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RESEARCH ARTICLE

Establishing Statistical Correlation Between Sensor Signature Features and Lubricant Solid Particle Contamination in a Spur Gearbox

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ABSTRACT This paper aims to predict the severity of solid particle contaminants present in the lubricant in a Spur Gearbox using Vibration, Acoustic Emission, and Sound Signature features. Sensor signatures are acquired at various contaminant conditions of lubricant with different speed and load conditions. Statistical Features are extracted in the time domain, and feature ranking is carried out using the analysis of variance approach. Statistical models are developed using the selected features of Sound, Acoustic Emission, and vibration separately and fusing the features in the feature level. Decision Trees and Support Vector Machine algorithms are used in this study to build statistical models. AE features have a good correlation with lubricant conditions compared to sound and vibration features. The feature-level fusion approach predicts the lubricant conditions with more than 99% accuracy. The feature-level fusion models built using dominant features are computationally efficient without compromising the prediction ability.

INDEX TERMS Condition monitoring, machine learning, acoustic emission, vibration signature analysis, feature level fusion, lubricant solid particle contamination.

I. INTRODUCTION

Proper lubricant and lubricant methods reduce friction, wear, and contact fatigue and improve the mechanical system's efficiency and durability [1]. Lubricant oil contamination is one of the critical causes of equipment failure and machine downtime. Lubricant oil contamination is influenced mainly due to external and internal factors [2]. External factors include the presence of dust and moisture in the external environment. The change of lubricant or poor condition of joints and seals causes the external agents, namely dirt, dust, metal oxide particles, sand particles, fibers, and water molecules, to access the lubricant, leading to deteriorating the condition of the lubricant. External factors are common issues and can be controlled. In rotating machines, due to wear and tear, solid particles enter the lubrication system and cause severe damage to the lubricant condition over a period. The size and concentration of the solid particles play a crucial role

in affecting the performance of the mechanical system. In a mechanical system, typical machine elements such as gears, bearings, engine pistons, seals, etc., are subjected to severe abrasive wear, surface fatigue, noise, and vibration due to solid particle contamination, which results in loss of reliability, breakdowns, and reduction in service life [3], [4], [5].

In the gearbox, lubricant plays a vital role, acts as a film-like layer, and reduces the friction between the gear teeth. The change in the lubricant's viscosity affects the thickness of the layer between the gear teeth, resulting in the development of stress concentration in the gear tooth [6], [7]. The molecular structure of the gear is getting distorted due to stress concentration and initiates wear and sub-surface cracks which lead to spalling and pitting in gear. Due to wear and tear, the shredded metallic particles are mixed with the lubricants and get contaminated. The contaminants in the lubricant pass through the gear teeth and influence the wear in the gear tooth. Lubricant contamination is one of the major causes of the failure of the gearbox. The progress of the defect due to lubricant contamination in the

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mechanical system leads to catastrophic failure of the rotating machinery.

It is essential in critical operations to monitor the conditions of crucial parameters of the lubricant; thereby, condition-based maintenance can be carried out to avoid any catastrophic failures, which result in savings in terms of time and money. Faults or defects in a gearbox are predicted using the level of vibration, noise, oil analysis, and visual inspection. Condition Monitoring (CM) systems are highly reliable and collect information continuously about the condition of the rotating machinery components such as gears, bearings, couplings, etc. Many CM approaches utilize sensor information to identify the fault conditions of mechanical parts. Sensors, namely accelerometers, microphones, piezoelectric, optical, and dynamometers, are used to determine fault conditions [8]. This study focuses on identifying the lubricant conditions in a typical spur gearbox. It is expected that gearboxes are subjected to breakdown due to lubrication and operational issues. Lubrication issues include inadequate lubrication, solid particle contamination, increased lubricant temperature, and the presence of sludge. Operational problems are due to higher load and speed conditions, inadequate maintenance, shaft and gear misalignments, and installation issues. Among these issues, lubrication contamination plays a significant part in the failure of the gearbox. Lubricant in a gearbox should be monitored periodically for the healthy operation of the gearbox. This research focuses on predicting solid particle contamination in a spur gearbox. Solid particle contamination is intentionally added to the lubricant, and the gearbox is made to run at different load and speed conditions. This study uses Decision Trees (DT) and Support Vector Machine (SVM) algorithms to predict the lubricant conditions using vibration, AE, and sound sensor signatures.

The novelty of the proposed work includes a) use of multiple sensors, namely microphone, accelerometer, and piezoelectric AE sensors, to predict the lubricant conditions in a spur gearbox, b) Adopting feature-level fusion methodology to improve the classification ability of machine learning algorithms, and c) 44 lubricant conditions are established by varying the particle size, concentration, gearbox speed, and load. Sensor signature features are extracted, dominant features are chosen, and statistical models are developed using machine learning algorithms to predict all 44 conditions of the lubricant.

II. LITERATURE REVIEW

Lubricant Condition Monitoring (LCB) is an important activity in rotating machines to ensure the quality of lubricant and timely replacement of the lubricant before the lubricant loses its property. A review of lubricant condition monitoring has been presented by Wakiru *et al.* [9]. Lubricant degradation factors, namely water contamination, particle contamination, and oxidation for various applications such as gearbox, hydraulic systems, engines, compressors, and turbines, were reviewed in their study. The review highlighted the effectiveness of statistical, artificial intelligence,

model-based, and hybrid approaches for lubricant condition monitoring. Different types of sensors used to monitor the lubricating oil conditions, namely Gill, MetalSCAN, inductive pulse, bulk capacitance, ultrasonic, and active pixel sensors, are reviewed in [10]. It is highlighted in their study that particle contamination in lubricants is the primary cause of failure of mechanical systems. A detailed review of online monitoring of oil debris in rotating machinery has been carried out in [11]. The review has been done by classifying the sensors based on their operating principle, viz. a) Magnetic, b) Electrical, c) Optical, and d) Acoustics. Myshkin and Markova [12] concluded in their extensive study that sensors integrated with Artificial Intelligence (AI) methods would improve the accuracy and reliability of diagnosing and predicting lubricant conditions.

Solid particle contamination in lubricants is one of the severe contamination forms in a lubricant used in rotating machinery. Solid particles in lubricants damage the contact surfaces through abrasion, erosion, and fatigue wear mechanisms. Solid particles of various sizes and shapes are inducted into lubricant as a) debris during maintenance, b) dust or soot from the environment, and c) metal particles due to wear mechanism. Solid particle contamination in a journal bearing has been investigated by Boucherit *et al.* [13]. It is understood from their study that solid particle contamination has a substantial impact on friction, surface deformation, and flow rate of the lubricant. Shan and Hirani [7] observed that the degradation of lubricant quality is an indicator of the health of the gearbox. The experimental studies concluded that solid particles in a lubricant increase the wear and fatigue in the tooth of the gear in a gearbox. It is also observed that lubricant contamination increases the temperature of the lubricant and the mechanical system's vibration amplitude [3], [14].

Vibration-based methods have a good correspondence in identifying faults in bearings and gearboxes due to the degradation of lubricants and solid particle contamination. Faults developed in the gearbox are typically diagnosed by monitoring the condition of the lubricant, wear debris, and vibration level [15]. Wear debris analysis is an offline method, and laboratory analysis is required to identify the lubricant condition [16]. Zhu *et al.* [17] developed a wear debris sensor prototype for real-time lubricant condition monitoring. Wear particles of size 50 microns were detected by the sensor. A detailed wear debris morphological study has been conducted and presented in [18]. It was found that an increase in the number of wear particles and average wear mass influences the gear tooth surface damage. Lubricant monitoring is an offline process that involves laboratory analysis to test the physical and chemical properties of the lubricant. The maintenance cost of machinery can be reduced by 30% by effectively monitoring the lubricant and timely replacement [19]. Unscheduled machinery downtime is also minimized by effective monitoring of the lubricant conditions. A 3D-Hall effect sensor identifies the metallic solid particle in a lubricant used in gearbox application [20], [21] for condition-based maintenance.

Lubricant contamination influences the vibration levels of the system. Off-line, sensor-based lubricant condition monitoring systems are used to identify the lubricant conditions in real time. The time and frequency spectrum of the vibration data is often used for fault identification and diagnostics. Fault conditions in a spur gearbox have been investigated by Ebersbach *et al.* [15] using vibration and wear debris analysis. The vibration approach effectively predicts the fault conditions, and wear debris analysis identifies the wear modes. Loutas *et al.* [22] studied the health condition of the gearbox by integrating vibration, AE, and oil debris data. Their study implemented a data fusion approach, and the gearbox's health conditions were assessed in time, frequency, and wavelet domains.

Feng *et al.* [23] proposed a reliable gear wear prediction model using a vibration-based approach. It is observed from their study that the wear process in a spur gear can be effectively monitored using vibration parameters on a real-time basis. Using the proposed approach remaining useful life of the gear can be identified. The vibration-based model proposed by the authors predicts the failure modes in the spur gear with reasonable accuracy. Feng *et al.* [24] reviewed gear wear monitoring and prediction techniques focusing on vibration-based approaches. It was indicated in their research that much of the current research in vibration-based monitoring concentrates on identifying abrasive wear-induced profile change. It is also suggested in their study that abrasive wear, fatigue pitting, and adhesive wear also need to be addressed in developing models for predicting the failure modes and remaining useful life of the gearbox system. It can be concluded that sensors such as accelerometers precisely capture the gear wear conditions. The abrasive wear, localized fatigue, pitting in gear, and solid particle contaminants influence subsurface damages in the lubricant. Monitoring the lubricant using sensors-based approaches helps identify the conditions of the lubricant in real-time, replace the lubricant at the right time, and avoid the catastrophic failures of mechanical elements in a gearbox.

Along with the vibration approach using accelerometers to sense the vibration levels, piezoelectric and current sensors were also used to identify the fault condition in a gearbox [25]. Experimental studies have been carried out, and a statistical correlation has been established between the pitting state of the gear tooth and features of current, vibration, and AE signatures. KNN classifiers trained with features of vibration and AE signatures predict the pitting and good condition of the gearbox with an accuracy of 94%. Yao *et al.* [26] proposed an AE-based fault detection in a planetary gearbox. It was found that the fault detection ability of AE is better compared to vibration signatures in extracting weak fault features. A review on AE-based gear fault diagnosis is presented in [27]. AE-based diagnostic methods are also effective in tool condition monitoring and rotary machine fault diagnostics [28], [29]

The Remaining Useful Life (RUL) of the lubricating oils considering solid particles in the oil, has been studied by

Valis *et al.* [30]. A meta-model was developed using Neural Network (NN) and Fuzzy Inference Systems (FIS) to predict the level of particle contamination lubricant. Pan *et al.* [31] recently proposed an integrated data and knowledge-based system using the NN model for predicting oil conditions. Their study considered randomness and uncertainty in the input data. The oil's viscosity, Total Base Number (TBN), and solid particles viz. Zn, Fe, and Cu were considered parameters for studying oil degradation. The change in the health state of the planetary gearbox has been studied with wear debris present in the lubricant using image analysis [32].

To improve models' reliability and prediction ability, AI approaches are increasingly used in the field of condition monitoring. In the AI paradigm, Machine Learning (ML) methods are becoming popular since the algorithm learns, makes, and improves decisions based on experience. There are two types of machine learning: supervised learning and unsupervised learning. The model must be trained in supervised learning with the known input and output response. Once the model is trained, response for the input conditions can be predicted. There are many supervised learning methods implemented to lubrication health monitoring, such as a) Logistic Regression [9], [33], [34], [35], [36], b) Decision Tree [37], [38], c) Neural Network [39], [40], [36], [41], [42], [43], [44], and d) Support Vector Machines [36], [45]. In unsupervised learning, the input data doesn't have a response. These data are fed into the machine learning algorithm to train the model. The trained model predicts the response for the given input data. Some of the important unsupervised learning methods implemented in lubricant health monitoring problems include a) Principal Component Analysis [46], [47], [48] and b) Cluster Analysis [49], [50], [51], [52].

Three important lubrication oil degradation feature includes a) water contamination, b) solid particle contamination, and c) oxidation. This paper focuses mainly on lubricant contamination due to solid particles. Solid particle contamination is primarily due to metal debris formation because of friction and wear in mechanical elements. The presence of solid particle contaminants in the lubricants significantly influences friction. The friction between solid particles with the rotating gear tooth results in abrasive wear, indentation, and pitting. Abrasive wear results in scratches and sharpening of the gear tooth. Indentation is due to the hard particles in the lubricant rolled over by the contacting gear surface. Indentation results in plastic deformation in a localized area. Pitting is a surface fatigue phenomenon due to rolling and sliding contacts. Abrasive solid particle contaminants in the lubricant aggravate the pitting process. The increased concentration of solid particles results in an increased wear rate. The flow rate of the solid particles varies from tooth to tooth leading to the source of vibration. The size and concentration of the solid particles in lubricant, load, and gear operation speed significantly influence the life of the gearbox. By identifying the condition of the lubricant, it is possible to predict the health state of the gearbox. Lubricant

oil analysis and wear debris analysis are popular methods to identify the condition of the lubricant. But these methods are offline approaches, and it is difficult to determine the conditions of the lubricating oil in real time.

Over the years, researchers have developed sensors-based methods to monitor the lubricant's condition, which has led to the development of real-time monitoring systems. Sensor signatures such as vibration, AE, sound, temperature, current and voltage, and force are being used in condition monitoring of rotating machinery. Vibration-based analysis of lubricant conditions is one of the widespread methods. AI models built with machine learning algorithms predict the fault conditions in rotating machines with good accuracy and reliability. Research on predicting solid particle contamination using AI-based ML approaches may lead to the developing of online lubricant condition monitoring systems. Literature focussing on developing ML models using features extracted from vibration and AE signatures to identify the lubricant conditions is limited. The present study focuses on developing statistical models using ML algorithms to predict lubricant conditions with varying sizes and concentrations of solid particles.

III. OBJECTIVES AND METHODOLOGY

A. OBJECTIVES

The main objective of this study is to predict the lubricant conditions in a spur gearbox. A sensors-based approach is followed in this study. Vibration, AE, and sound sensors are used to acquire the signatures from the gearbox. Sensor signatures are captured under good lubricant conditions and lubricant with solid particle contamination. Various lubricant conditions are established by varying the size of the solid particle and its concentration. Experiments were carried out, and sensor signatures were captured at different load and speed conditions. The acquired sensor signatures are processed further in the time domain, and statistical features are extracted. The feature selection is carried out using univariate analysis. The extracted features of vibration, AE, and sound are used to train the machine learning algorithms. This study uses two ML algorithms, namely CART and Support Vector Machines (SVM), to predict the lubricant conditions. ML algorithms are trained separately using the features of sound, AE, and vibration, and feature level fusion is also carried out to train the ML algorithms to improve the classification accuracy.

B. METHODOLOGY

The proposed experimental setup and methodology adopted in this study to meet the objectives are illustrated in Fig.1. Schematic diagram of the experimental setup is shown in Fig. 2. The proposed methodology involves the following steps:

Step 1: Establishing experimental setup consisting of spur gearbox, Machine Control Unit (MCU), drive for the gearbox, transmission system, couplings, bearings, torque controller and dynamometer, tri-axial accelerometer for sensing

vibrations, piezoelectric sensors for acquiring AE signals, microphone for sensing sound signature, Data Acquisition System (DAS) for AE, vibration and sound signatures, and signal processing software and hardware.

Step 2: Sensors are calibrated as per the standards to acquire the signature of vibration, AE, and sound.

Step 3: Establish lubricant conditions. A total of 44 lubricant conditions are established with varied particle size, the concentration of solid particles, gearbox load, and speed of operation.

Step 4: Conduct experiments with good lubricant free from solid particle contamination and acquire the signatures of vibration, AE, and sound.

Step 5: Conduct experiments with lubricant added with solid particles of varied size and concentration and acquired the signatures of vibration, AE, and sound.

Step 6: Convert the analog signatures of vibration, AE, and sound signatures into digital using relevant DAS and signal processing hardware and software.

Step 7: Extract statistical features from the time domain sound, vibration, and AE signatures.

Step 8: Select dominant features using univariate analysis and rank the features.

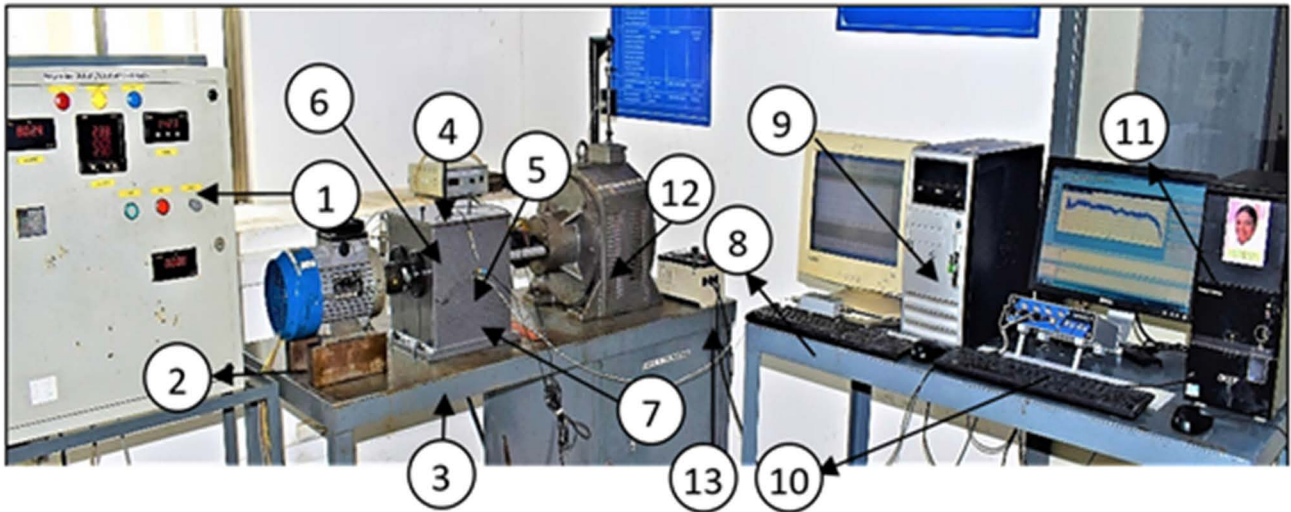
Step 9: Choose suitable ML algorithms to build statistical models to predict the lubricant conditions. CART and SVM algorithms are used in this study to build the classifiers.

Step 10: Train the CART and SVM Classifiers separately using the statistical features extracted from sound, vibration, and AE signatures.

Step 11: Adopt a feature-level fusion approach and train the CART and SVM Classifiers using fused sound, vibration, and AE features.

Step 12: Test the CART and SVM algorithms trained with features of sound, vibration, and AE separately and fused features. Confusion Matrix is constructed, and the prediction ability of the classifier is tested using well-known measures.

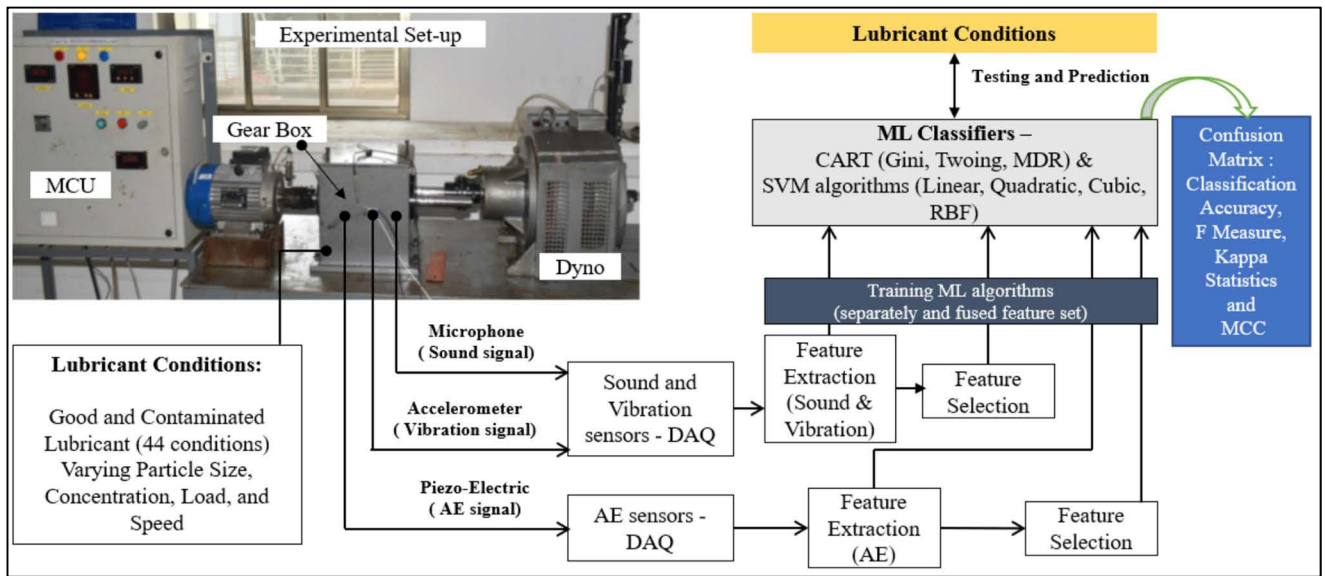
The major components of the experimental setup fabricated in this study are the gearbox, transmission system, sensors, and signal processing hardware and software. A gearbox has been designed and fabricated for the variable speed AC drive of 1.5 kW. The gearbox comprises a pair of healthy spur gears arranged in parallel consisting of 36 nos. teeth, 2.5mm module, and 20° pressure angle. A variable speed AC motor is coupled with the gearbox through a driving shaft. The motor speed is varied through Motor Control Unit (MCU). The experiments were conducted by fixing the drive speed at 800 rpm and 1300 rpm, respectively. The motor and the driving shaft are connected through flexible coupling to reduce misalignment and power loss. An eddy current dynamometer is coupled with the driven shaft of the gearbox through a rigid coupling to induce loads on the gearbox. Experiments were carried out at different load settings of 5 N-m and 7 N-m, respectively. Loads are generated by adjusting the current flow using a torque controller. The dip type method is used for lubricating a pair of gears under different gearbox speed and load conditions. Key joints are used in the gearbox system to



Note:

1 – Motor Control Unit (MCU); 2 – AC Motor; 3 – Gear Box; 4 – Speed Controller; 5 – Microphone; 6 – Accelerometer; 7 – Acoustic Emission Sensor; 8 – AE Pre-Amplifier; 9 – AE Data Acquisition System and Signal Processing unit; 10 – Vib-Pilot (DAQ for sound and Vibration signature); 11 – Sound and Vibration Signal processing unit; 12 – Dynamometer; 13 – Torque Controller

a) Photograph of the Experimental setup available at Amrita Viswa Vidyapeetham (Amrita University)



b) Methodology

FIGURE 1. Photograph of the experimental setup and methodology.

develop a relative rotation between the two parts and enable torque transmission.

The scope of this work is limited to establishing a statistical correlation between sensor signature features and lubricant conditions. For every lubricant condition, healthy spur gears are considered, and it is ensured that there is no gear defect while acquiring the sensor signature. The solid particle contamination in the lubricant may lead to wear,

localized fatigue, and pitting in the gear tooth throughout the gearbox's operation. In this study, we have not allowed the experiments for a longer duration to induce measurable wear or any other defect in the gear tooth or other components of the gearbox. If the gears are faulty, faulty gear condition signature features must be considered to develop the statistical model; thereby, lubricant and defective gear conditions can be predicted.

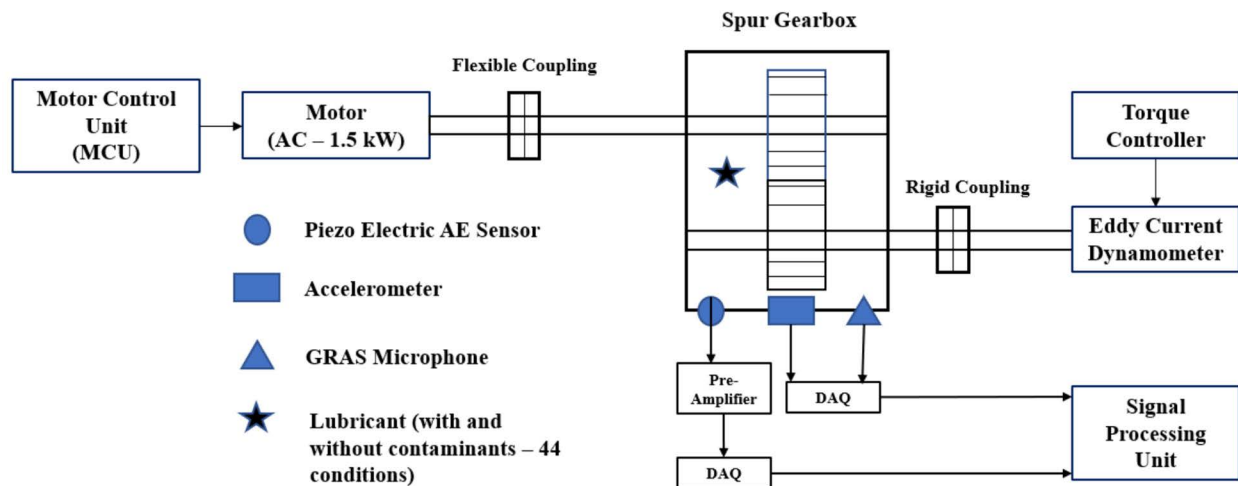


FIGURE 2. Schematic diagram of experimental setup.

C. SENSORS AND DATA ACQUISITION

Three different types of sensors were used in this study, viz. a) accelerometer for acquiring vibration signals, b) piezoelectric sensors for acquiring AE signals, and c) microphone for acquiring sound signatures. Sound, vibration, and AE data points are acquired from a total of 44 experimental conditions in this study for developing machine learning models by conducting experiments for 100 sec for every condition.

A dytran 3273A2 triaxial accelerometer with the frequency range of 42 Hz to 10000 Hz is used in this study to acquire the vibration signature of various lubrication conditions. A sampling rate of 8192 kHz is used in this study to collect the vibration data. The duration allowed for sampling the vibration data is 100 sec. Since there are 44 test cases, the total no. of vibration data points acquired by using vibration sensors during the experiments is 36,044,800 [$8192 \times 100 \times 44$].

The 'GRAS 40PH Free-field Array microphone, which has a frequency range of 5kHz to 20kHz, is used for sound signature acquisition. A sampling rate of 8,192 kHz is used in this study to collect the sound data. The duration allowed for sampling the sound data is 100 sec. Since there are 44 test cases, the total no. of data points acquired by using AE sensors during the experiments is 36,044,800 [$8192 \times 100 \times 44$]. For data acquisition, a 4-channel 'm+p VibPlot' hardware is used for vibration and sound data conversion and analysis.

A 'Micro 30D' differential AE sensor is used in this study to capture AE signals generated during the gearbox operation at various lubrication conditions. The frequency range of the sensor varies from 10 kHz to 400 kHz. The sampling rate used for collecting the AE data is 1 MHz. The AE measurement chain consists of preamplifiers, Data Acquisition System (DAS), and 'AEWin' software for signal processing. The duration allowed for sampling the AE data is 100 sec. Since there are 44 test cases, the total no. of data points acquired by using the AE sensor during the experiments is 45,056,000 [$10240 \times 100 \times 44$].

IV. LUBRICANT CONDITIONS

Experiments were carried out by considering varied particle sizes and concentrations. For every concentration level and particle size, two levels of experiments were carried out by varying load and speed of rotation. The gear was made of Grey Cast Iron material. Grey Cast Iron consists of other alloying materials, namely Si, Mn, P, and S, along with Fe and C. Contaminant in lubrication oil is primarily due to the wear of the gear material. The contaminant's size and concentration increase will deteriorate the gearbox's condition [2].

In this study, Fe and SiC particles are added as a contaminant in the lubricant. The remaining materials, such as Mn, P, and S, are at meager levels in grey CI, so it is neglected in the analysis. The particle sizes (in microns) used to establish lubricant conditions are 5, 37, 74, 100, and 149 microns. Based on the gear material's chemical composition, the proportion of the solid particle contaminants (weight %) was chosen considering 93% of Fe and 7% SiC. Two levels of concentrations (C1: 8 grams and C2: 16 grams) of solid particles are considered for every particle size. The concentration level C1 consists of 7.44 g of Fe and 0.56 g of SiC. The concentration level C2 consists of 14.88 g of Fe and 1.12 g of SiC. The size of the SiC particles considered in this study is 10 microns.

The particle size considered in this study is based on the investigation made by Boucherit *et al.* [13]. It was found that the particle average size of 75 microns influences the wear over the gear tooth surface. The wear also accelerates when the mass of the solid particles increases. Experiments are conducted with two-speed conditions at 800 rpm and 1300 rpm, respectively, and two load conditions at 5 N-m and 7 N-m, respectively. Experiments were also performed without adding solid particles in lubricant by varying the load and speed. The experimental design is shown in Table 1. Experiments are carried out for all conditions, and sensor data is acquired for 100s. The gearbox was filled with the lubricant

TABLE 1. Lubricant conditions – experimental design.

Lubricant Condition	Solid Particle				Gearbox Condition	
	Particle Size, Microns		Concentration, % Wt., grams		Speed, rpm	Load, N-m
	Fe	SiC	Fe	SiC		
1	-	-	-	-	800	5
2	-	-	-	-	800	7
3	-	-	-	-	1300	5
4	-	-	-	-	1300	7
5	5	10	7.44	0.56	800	5
6	37	10	7.44	0.56	800	5
7	74	10	7.44	0.56	800	5
8	100	10	7.44	0.56	800	5
9	149	10	7.44	0.56	800	5
10	5	10	7.44	0.56	800	7
11	37	10	7.44	0.56	800	7
12	74	10	7.44	0.56	800	7
13	100	10	7.44	0.56	800	7
14	149	10	7.44	0.56	800	7
15	5	10	7.44	0.56	1300	5
16	37	10	7.44	0.56	1300	5
17	74	10	7.44	0.56	1300	5
18	100	10	7.44	0.56	1300	5
19	149	10	7.44	0.56	1300	5
20	5	10	7.44	0.56	1300	7
21	37	10	7.44	0.56	1300	7
22	74	10	7.44	0.56	1300	7
23	100	10	7.44	0.56	1300	7
24	149	10	7.44	0.56	1300	7
25	5	10	14.88	1.12	800	5
26	37	10	14.88	1.12	800	5
27	74	10	14.88	1.12	800	5
28	100	10	14.88	1.12	800	5
29	149	10	14.88	1.12	800	5
30	5	10	14.88	1.12	800	7
31	37	10	14.88	1.12	800	7
32	74	10	14.88	1.12	800	7
33	100	10	14.88	1.12	800	7
34	149	10	14.88	1.12	800	7
35	5	10	14.88	1.12	1300	5
36	37	10	14.88	1.12	1300	5
37	74	10	14.88	1.12	1300	5
38	100	10	14.88	1.12	1300	5
39	149	10	14.88	1.12	1300	5
40	5	10	14.88	1.12	1300	7
41	37	10	14.88	1.12	1300	7
42	74	10	14.88	1.12	1300	7
43	100	10	14.88	1.12	1300	7
44	149	10	14.88	1.12	1300	7

TABLE 2. Lubricant specification.

S.No.	Parameters	Specifications	units	Remarks
1	Type	Hydraulic oil	-	IS: 493-1981
2	Capacity	4	Liters	(35% immersion of gear)
3	Density	0.878	Kg/L	-
4	Viscosity@40°C	64-72	cSt	-
5	Viscosity@100°C	88	cSt	-
6	Flash point	175	°C	-
7	Pour point	0	°C	IS 6552 – 1972
8	Viscosity Index	90	-	-

of two liters, and experiments were conducted without adding solid particle contaminants under two different speeds and load conditions. Later, lubricant was drained, contaminants as per the details given in Table 1 were added to fresh lubricant for every experiment, and corresponding sensor signatures were captured. The specification of the lubricant used in this study is given in Table 2.

V. FEATURE EXTRACTION AND FEATURE SELECTION

A. FEATURE EXTRACTION

The traditional statistical method has been employed to extract the features from the time domain signatures of sound,

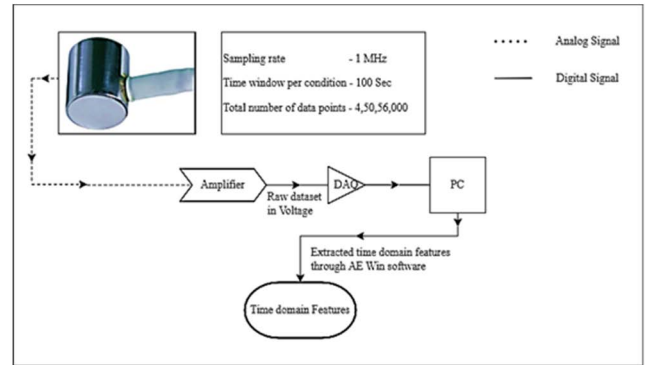


FIGURE 3. Methodology of feature extraction for AE signature.

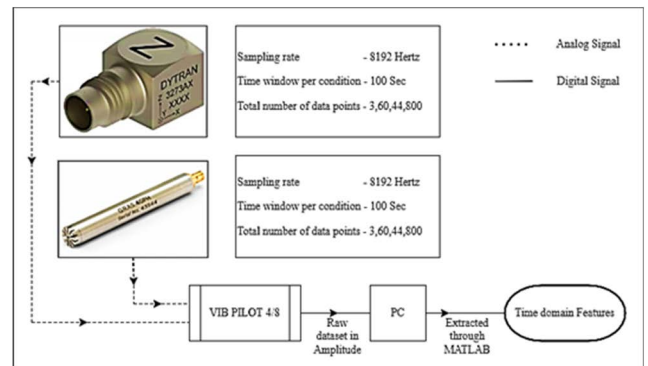


FIGURE 4. Methodology of feature extraction for sound and vibration signatures.

vibration, and AE [53]. Vibration signals are acquired using a triaxial accelerometer with a sampling rate of 8192 Hz. Sound signals are acquired using a ‘GRAS- 40PH’ microphone with a sampling rate of 8192 Hz. AE signals are captured using a piezoelectric sensor with a sampling rate of 1 MHz. The analog signals are converted into digital signals for feature extraction. The data acquisition methodology for AE is shown in Fig.3. Fig.4 shows the methodology adopted for acquiring sound and vibration signatures.

The time-domain sound and vibration features extracted from the time domain signal are mean, sum, median, mode, min., max., variance, RMS, kurtosis, skewness, and std. deviation. A total of 13 AE features extracted in this study are avg. rise time, count, amplitude, avg. frequency, RMS, avg. signal level, counts to peak, reverberation frequency, initial frequency, signal strength, absolute energy, frequency centroid, and peak frequency. A typical AE wave and its significant parameters are shown in Fig.5. Details of AE measurements and important AE feature parameters are presented in [54].

B. FEATURE SELECTION

The feature selection process weighs the extracted features concerning the data points of all the conditions to reduce the computational cost and improve the model performance [55], [56]. A detailed survey on feature selection methods is presented by Chandrashekar and Shahin [57]. Important techniques in feature selection in supervised learning include intrinsic methods using decision trees, wrapper

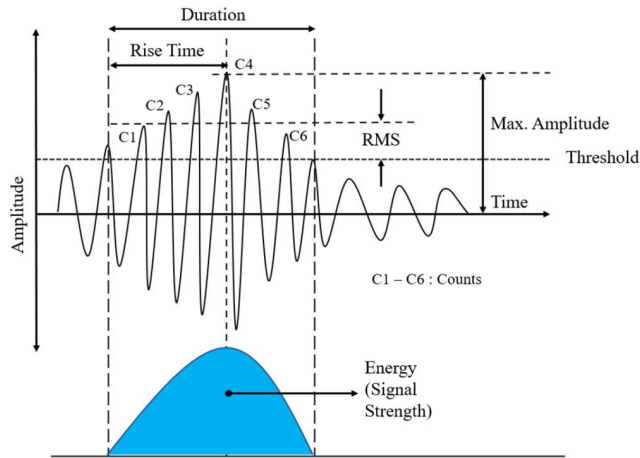


FIGURE 5. Typical AE wave and major AE parameters.

approach, filter method, and embedded method. Filter methods are implemented for many practical applications due to their simplicity. For selecting dominant features, filter-based techniques use statistical measures to assess correlations or dependencies between input variables. Feature selection guidelines based on input and output variable is given by Butcher and Smith [58]. For a numerical input variable and categorical output variable, correlation-based approaches are used.

One-way analysis of variance (ANOVA) is used in this study to validate feature importance. It examines the relationship between a categorical predictor and continuous numerical data. Feature importance is accomplished by comparing the mean of each predictor category in a feature population and determining the degree of differentiability between them. The One-way ANOVA method tests null hypotheses on equal means. It uses the 'F' statistic, a between-group and within-group variability ratio. The value of the 'F' statistic becomes roughly equal to 1 under the null hypothesis. 'F' statistic follows an F-distribution when the null hypothesis is true, and the obtained value must exceed the critical value to reject the hypothesis. F-distribution with $\alpha = 0.05$ is typically considered, and the feature's F-value is compared with the F-critical value. The F-value should be greater than F-critical, and the p-value should be the least to get the best feature to compute the future score. Based on the feature score, feature raking is carried out.

Selected features from the sound signal features are standard deviation and skewness. From vibration signature, std. deviation, min., mode, max., sum, mean, median, and RMS features are selected. In the case of AE signature, RMS, ASL, count, A-Frequency, signal strength, amplitude, and absolute energy are chosen. The selected set of features is used to train the machine learning algorithms.

VI. LUBRICATION CONDITION PREDICTION USING MACHINE LEARNING ALGORITHMS

Two machine learning approaches, namely Classification and Regression Tree (CART) and Support Vector Machine

(SVM), are used to predict the lubricant conditions. CART algorithms are implemented with split criteria viz., gini, twoing and maximum deviance. SVM algorithms are implemented with linear and nonlinear kernel functions. Machine learning models are built with features of vibration, sound, and AE separately and fused features of vibration, sound, and AE. Well-known performance measures are used to evaluate the prediction ability of the models developed in this study.

CART and SVM algorithms list in one of the top 10 machine learning algorithms identified by the IEEE International Conference on Data Mining (ICDM, <http://www.cs.uvm.edu/~icdm/>). Breiman *et al.* [59] proposed a CART algorithm for solving classification and Regression problems. CART application exists in almost all fields, such as electrical engineering, biology, medical research, sociology, condition monitoring, etc. [60]. Advantages of CART include a) can handle missing data, b) training the algorithm with lesser computational cost, and c) constructing features dynamically. The authors of this research also implemented this algorithm for weld quality monitoring and grinding wheel condition monitoring problems [61], [62] and found that CART is one of the competitive algorithms for classification problems. The good performance of the CART algorithm motivated the authors to attempt to implement it in this research.

The SVM algorithm proposed by Vapnik [63] is one of the most robust and accurate methods for classification. SVMs are originally proposed for constructing linear classifiers. Off late, SVM uses a variety of kernel functions to model higher dimensional nonlinear models to classify the data. Data that cannot be classified by linear SVM can be transformed into higher dimensional space to find the optimal separating hyperplane using kernel functions. A detailed review has been done by Cervantes *et al.* [64], focusing on the types and applications of SVM for classification. In this study, 44 classes of lubricant conditions were established, and corresponding sound, vibration, and AE signature features were used to build the statistical models. SVM algorithms can use kernel tricking to classify the data that are not linearly separable. Kernel functions in this study transform the data into higher dimensional space and classify the raw data, which are not linearly separable. In this study, linear and nonlinear kernels, such as quadratic, cubic, and gaussian (Radial Basis Functions (RBF), are implemented to compute the classification accuracies of classifiers.

A. TRAINING AND TESTING OF MACHINE LEARNING ALGORITHMS

Machine learning algorithms were implemented in the MATLAB environment. Features of all 44 classes are combined into a single data set to train different classification models. The 'K' fold cross-validation method is used for testing and training purposes. This method divides the initial population into 'k' subsets. This method is an iterative process; in each iteration, one of the subsets is taken for testing purposes, and the remaining is used for training. Unlike the holdout

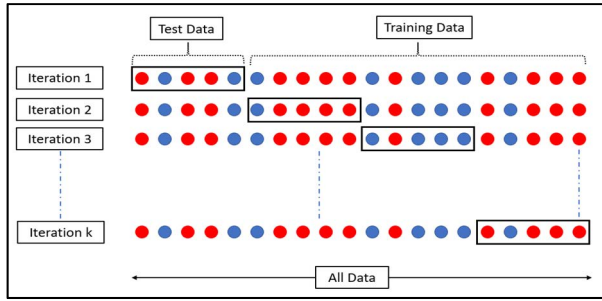


FIGURE 6. k-fold cross-validation (k=5).

method, every data point in the initial population gets trained. As shown in Fig.6, there will be a total of ‘k’ iterations. Here in this study, a 10-fold cross-validation method is used.

B. PERFORMANCE MEASURES

The confusion matrix is the key to evaluating the performance of the classifier, and it works based on the values of True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) concerning each class. A 10-fold cross-validation technique is used to train machine learning models. Some important performance measures used to test the ML algorithms are accuracy, misclassification rate, kappa statistics, precision, recall, F-measure, and Mathews Correlation Coefficient (MCC). Various measures for assessing the quality of classifiers are presented in [65] and [66].

Accuracy: Percentage measure of correctly classified instances for all instances, and it’s calculated using the equation (1):

$$Accuracy = (TP + TN)/(n^+ + n^-) \tag{1}$$

where n^+ indicates the sum of true positive and false negatives (TP + FN) and n^- indicates the sum of true negative and false positive (TN + FP) instances.

The possibility of misclassification occurs between the classes, and the misclassification rate is one of the important factors in acquiring the best classification performance, and it is obtained using the equation (2):

$$Misclassification\ rate = (FP + FN)/(n^+ + n^-) \tag{2}$$

Kappa statistics: It measures inter-rater agreement of the instances [67]. A kappa coefficient value ranges from -1 to +1. A kappa value of ‘1’ indicates the classifiers are in complete agreement, and the value ‘0’ shows no agreement. Kappa statistics are computed using the equation (3).

$$Kappa\ value, k = \frac{(P_r(A) - P_r(E))}{(1 - P_r(E))} \tag{3}$$

where $P_r(A)$ is the actual observed agreement and $P_r(E)$ is the expected agreement.

Precision: It classifies the correct instances among the instances that are classified as positive, and it is calculated using the equation (4):

$$Precision = (TP)/(TP + FP) \tag{4}$$

Recall: It measures the true positive of correctly classified instances, and it is the percentage of relevant information, and it is computed using the equation (5):

$$Recall = (TP)/(TP + FN) \tag{5}$$

F-measure: It shows the rate of the robustness of the classifier by using precision and recall values. F-measure is calculated by using the equation (6):

$$F - Measure = \frac{(2 \times Precision \times Recall)}{(Precision + Recall)} \tag{6}$$

MCC (Matthews Correlation Coefficient): It is a more reliable statistical rate and produces a high score only if the prediction obtained good results in all the four confusion matrix categories (true positives, false negatives, true negatives, and false positives). MCC is computed using equation (7), as shown at the bottom of the next page. MCC coefficient value ranges from [-1, +1], and the highest value of ‘1’ indicates the classifier as perfect.

VII. LUBRICATION CONDITION PREDICTION USING THE CART ALGORITHM

Classification and Regression Tree (CART) is the simplest machine learning algorithm used for prediction in classification or regression type problems [59]. A decision tree consists of three types of nodes a) root node, b) decision node, and c) leaf node. The root node is the initial node from which the splitting of the data points starts, and further branching or splitting takes place at decision nodes. Leaf nodes are the final nodes where further splitting is not possible. Each node is split based on the best feature, which can give the most homogeneous child nodes. The practice of dividing a node into several sub-nodes to create relatively pure nodes is known as node splitting or simply splitting. The splitting criterion decides when to split and where to split nodes. There are several approaches: gini impurity, twoing rule, and Maximum Deviance Reduction (MDR).

Gini impurity: This metric indicates how frequently pieces of data are classified wrongly. Equation (8) can be used to compute the gini index value.

$$G(i) = 1 - \sum p(i)^2 \tag{8}$$

$p(i)$ is a ‘n’ observed portion of classes at “i.”

Maximum deviance reduction: The CART tree measures the impurity of the node and splits the tree. It can be computed using equation (9).

$$MD(i) = - \sum p(i) \times \log_2 p(i) \tag{9}$$

Twoing rule: Twoing criterion splits the classes into two superclasses to find the best Gini split to optimize the impurities in the overall classes. It is computed by using equation (10)

$$T(i) = p(L) \times p(R) \times \left(\sum |L(i) - R(i)| \right)^2 \tag{10}$$

$L(i)$ and $R(i)$ indicate the portion of representatives of the class “i” on the left and right of the tree after the node split.

TABLE 3. Performance measures of CART algorithm trained using sound signature features.

Performance measures / Split criterion	Gini impurity		Twoing rule		MDR	
	A	B	A	B	A	B
Accuracy	0.51	0.66	0.50	0.67	0.50	0.66
Misclassification rate	0.50	0.35	0.50	0.33	0.50	0.34
F-Measure	0.63	0.74	0.49	0.74	0.53	0.76
Kappa statistics	0.59	0.72	0.49	0.73	0.52	0.74
MCC	0.19	0.45	0.02	0.46	0.04	0.49

Note:
A – Model trained with all features; B – Model trained with selected features using one-way ANOVA method; MCC - Matthews Correlation Coefficient

TABLE 4. Performance measures of CART algorithm trained using vibration signature features.

Performance measures / Split criterion	Gini impurity		Twoing rule		MDR	
	A	B	A	B	A	B
Accuracy	0.66	0.62	0.67	0.63	0.66	0.62
Misclassification rate	0.35	0.38	0.33	0.37	0.34	0.38
F-Measure	0.74	0.66	0.74	0.73	0.76	0.71
Kappa statistics	0.72	0.65	0.73	0.70	0.74	0.69
MCC	0.45	0.30	0.46	0.41	0.49	0.38

Note:
A – Model trained with all features; B – Model trained with selected features using one-way ANOVA method; MCC - Matthews Correlation Coefficient

A. PERFORMANCE OF CART ALGORITHM

The CART algorithm is trained using the three splitting criteria separately, and the performance measures are obtained. The results obtained from CART using different splitting criteria, with and without feature selection, are presented in Table 3-5 for sound, vibration, and AE signatures, respectively. The performance measures are computed using the confusion matrix derived from the trained model.

It is found that the CART model trained using the AE feature can predict the lubricant conditions with an accuracy of around 83%. The CART algorithm trained using vibration features predicts the lubricant condition with an accuracy of about 65%. The CART model trained with selected sound features using the one-way ANOVA method produces an accuracy of 65%. It was noticed that in the case of CART models developed with sound features, feature selection improves the classification accuracy. In the CART model trained with vibration features, feature selection does not improve the classification accuracy. In the case of the

TABLE 5. Performance measures of CART algorithm trained using AE signature features.

Performance measures / Split criterion	Gini impurity		Twoing rule		MDR	
	A	B	A	B	A	B
Accuracy	0.72	0.72	0.83	0.83	0.83	0.83
Misclassification rate	0.28	0.28	0.17	0.17	0.17	0.17
F-Measure	0.85	0.85	0.91	0.91	0.90	0.90
Kappa statistics	0.84	0.83	0.90	0.90	0.89	0.90
MCC	0.69	0.68	0.81	0.81	0.79	0.80

Note:
A – Model trained with all features; B – Model trained with selected features using one-way ANOVA method; MCC - Matthews Correlation Coefficient

CART model trained with AE features, the feature selection doesn't influence the models' prediction ability. Twoing and maximum deviance criteria have improved the performance of the CART models compared to the gini criterion only in the case of the model trained with AE features. Overall, models trained using AE features predict the lubricant conditions better than models trained with sound and vibration features. Other measures such as MCC, Kappa, and F-measure also indicate better performance of CART models trained with AE features.

VIII. LUBRICATION CONDITION PREDICTION USING SUPPORT VECTOR MACHINE (SVM) ALGORITHMS

A. BINARY SVM CLASSIFIER

The Support Vector Machine (SVM) is a popular supervised learning technique [63]. SVMs are used to solve both linear and nonlinear classification problems. The main aim of the SVM classifier is to optimally split the n-dimensional space (formed by the predictor variables) using linear or nonlinear boundaries so that future data points can be correctly placed in their respective category. A hyperplane is a name for the optimal choice boundary, and the nearest data points to the hyperplane are called support vectors. Initially, the input datasets with 'n' predictors are represented in an n-dimensional space. Then divide this space into different classes using hyperplanes. For the selection of optimal hyperplane, the distance between the considered plane and the nearest data points (support vectors) are considered. This distance is known as the margin. The maximum margin will ensure the increased robustness of the model. The plane with the maximum margin is selected as an optimum hyperplane. SVM approaches this as an optimization problem for maximum margin and minimum misclassification. A typical linear binary classifier indicating margin and support vectors is shown in Fig.7.

$$MCC = \frac{(TP \times TN) - (FP \times FN)}{\sqrt{(TP + FP) \times (TP + FN) \times (TN + FP) \times ((TN + FN))}} \tag{7}$$

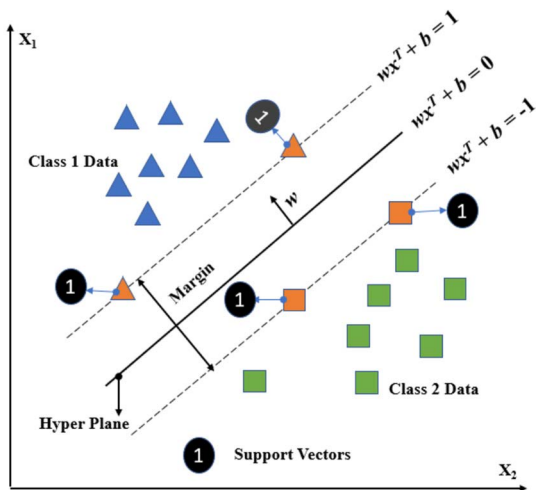


FIGURE 7. SVM linear binary classifier.

In most cases, the linear boundary will not be able to classify the data efficiently. In such cases, kernel functions are used. However, the kernel function transforms data into a higher dimensional space where linear separation is possible.

B. WORKING OF MULTICLASS SVM

Support Vector Machines (SVM) doesn't support multiclass classification natively. SVM supports binary classification and distinguishing data points into two classes. The same principle is utilized for multiclass classification after breaking down the multiclassification problem into multiple binary classification problems [68]

Two approaches, namely 'one to one' and 'one to rest' or 'one to all', are used to construct multiclass prediction models. Hyperplanes are constructed between every two classes in the 'one-to-one' approach. For example, for a 3-class problem, separate SVMs are used to classify data belonging to a) class 1 and class 2, b) class 1 and class 3, and c) class 2 and 3 separately. The no. of SVMs constructed using this procedure is $(N(N-1)) / (2)$, where 'N' is the total no. of classes. In this study, the One-to-Rest approach is used to classify the data belonging to every test case., A hyperplane is generated to separate data points belonging to a particular class and all other data points belonging to different classes at once. The classification process incorporates all data points (feature values) into account and makes them into two groups. One group belongs to data points of a particular class, and another belongs to data points of the remaining classes. No. of classifiers built in the 'one to rest' approach is equal to no. of classes. Compared to 'one to one', the computational complexity of the 'one-to-rest' approach is less.

For example, as shown in Fig.8 (three class problems), the dark blue line (hyperplane) tries to maximize the separation between blue points (class 1) and all other points at once (red points – class 2 and green points - class 3). The procedure is repeated by constructing hyperplanes separately, maximizing

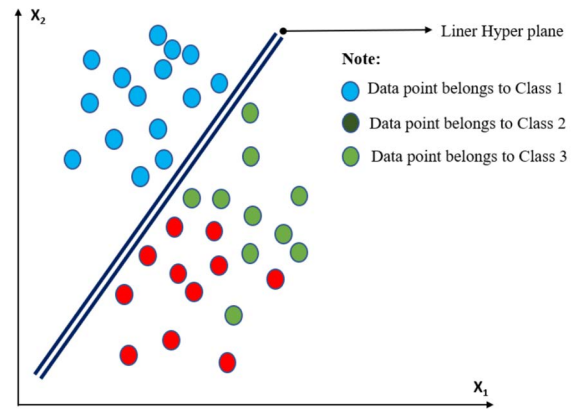


FIGURE 8. Working of multi-class SVM (One to rest).

the separation between a) green points (Class 3) and other classes (blue points – class1 and red points -class 2) and b) red points (Class 2) and other classes (blue points – class1 and green points -class 3).

The problem considered in this study consists of 44 classes of data acquired using sensors corresponding to lubricant conditions. Using the 'one to rest' approach, the classifier uses 44 SVMs, and each SVM predicts the membership in one of the 44 classes. Different Kernel functions other than linear such as quadratic, cubic, and Radial Basis Function (RBF) kernel functions, are implemented in this study to compute their classification accuracy. Implementation of Multi-Class SVM has been carried out in Matlab Environment Performance of classifiers is compared by building ML models considering a) all feature data points of a sensor separately, b) selected feature data points using a one-way ANOVA approach, and c) fused feature data set.

C. SVM PARAMETER SETTING

Models are built using the functions available in Classifier Matlab Toolbox. Some of the critical parameters influencing the results are a) box constraint parameter value, b) kernel function, c) kernel scale parameter, and d) multiclass SVM model building approaches.

Box Constraint: Box constraint parameter controls the maximum penalty imposed on margin-violating observations and aids in preventing overfitting. Increasing the box constraint leads to assigning fewer support vectors, tighter margins, minimizing the no. of misclassifications, and increased training times. Decreasing the box constraint parameter allows more constraint violations [69]. The typical value of the box constraint level is in the range [0.001,1000]. The value of the box constraint parameter is varied, with a minimum value of 0.001 and a maximum of 1000. Experiments are conducted with values 0.001, 0.01, 1, 10, 100 and 1000. Experimental trials were conducted to fix the box constraint parameter using a specific case data set acquired using an AE sensor. The misclassification rate of algorithms is recorded for different kernel functions chosen in this study. While

TABLE 6. Box constraint parameter setting.

BCPV	Kernel function							
	Linear		Quadratic		Cubic		Gaussian (RBF)	
	MCR, %	CT (sec)	MCR, %	CT (sec)	MCR, %	CT (sec)	MCR, %	CT (sec)
0.001	31.2	7.58	30.1	84.35	23.9	133.44	10.6	71.76
0.01	10.7	8.33	5.4	71.76	4.4	125.81	4.6	96.17
0.1	7.9	12.76	3.7	64.07	3.2	118.73	3.9	101.16
1	4.1	45.08	3.2	65.51	3.4	122.73	3.9	94.35
10	4.4	175.21	2.9	75.21	3.9	123.72	4.6	105.44
100	5.3	170.83	3.4	88.96	4.6	131.06	4.1	121.77
1000	5.8	229.56	3.7	112.28	4.4	128.63	4.4	167.12

Note : BCPV – Box Constraint Parameter Value; MCR – Mis-Classification rate; CT- Computational Time

training, the model kernel scale mode was chosen as ‘Auto’. The ‘Auto’ option in the Matlab-Classifer toolbox utilizes the heuristic program to fine-tune the kernel scale parameter for all the kernel functions chosen in this study. The ‘one to all’ multiclass method was selected for model construction for all kernel functions used in this work. A 10-fold cross-validation method is used to train and test data. The misclassification rate of the SVM algorithm with different kernel functions is shown in Table 6. It is observed from the results that the box-constraint parameter value of ‘1’ predicted the lubricant conditions with good accuracy for SVM models built using kernel functions, namely linear, cubic and RBF. It is also observed that increasing the box-constraint value increases the training time required for most models. For all SVM models built using AE, vibration, and sound features, the box constraint parameter value of ‘1’ is chosen in this study.

Kernel functions, namely linear, quadratic, cubic, and gaussian (Radial Basis Function), were used to build the models for predicting the 44 lubricant conditions. The exact relationship (linear or nonlinear) between the observed and labeled data is not known initially. To deal with this, along with linear kernel, nonlinear quadratic, cubic, and gaussian kernel functions are used in this study.

Kernel scale: Kernel scale is a scaling parameter for the input data. The input data is recommended to be scaled with respect to a feature before being applied to the Kernel function. When the absolute values of some features range widely or can be large, their inner product can be dominant in the Kernel calculation. Shin *et al.* [70] studied optimizing Kernel scale parameters for training Machine Learning Classifiers for a user authentication system. It was found in their research that for linear, cubic, and gaussian models, a heuristic procedure (Grid Search) implemented in Matlab provides a good prediction ability of their models. We have also implemented a similar procedure to choose the kernel scaling parameters. Details of the parameter setting are shown in Table 7.

D. PERFORMANCE OF SVM ALGORITHMS

SVM is trained with linear and nonlinear kernel functions with and without feature selection using sound, vibration, and AE feature data. Details of the results are given in

TABLE 7. SVM parameter setting.

Kernel Function	Box Constraint parameter, C	Kernel parameter	Kernel Scaling	Multiclass SVM approach
Linear	Range : [0.001, 1000] Pilot studies are made to arrive at the value of C; C= 1	-	Kernel Scaling: Auto Model: Optimizable SVM Optimizer: Grid search (No. of grid divisions = 10)	One-to-all
Quadratic		Degree, d		
Cubic		Degree, d		
Gaussian (RBF)		σ (Spread)		

TABLE 8. Performance measures of SVM algorithm trained using sound signature features.

Performance measures / Kernel Function	Linear		Quadratic		Cubic		RBF	
	A	B	A	B	A	B	A	B
Accuracy	0.60	0.62	0.65	0.67	0.66	0.66	0.60	0.66
Misclassification rate	0.40	0.38	0.35	0.33	0.34	0.34	0.40	0.34
F-Measure	0.56	0.56	0.63	0.60	0.64	0.50	0.50	0.67
Kappa statistics	0.57	0.58	0.64	0.62	0.64	0.55	0.53	0.66
MCC	0.15	0.16	0.28	0.24	0.28	0.11	0.07	0.34

Note: A – Model trained with all features; B – Model trained with selected features using one-way ANOVA method; MCC - Matthews Correlation Coefficient

TABLE 9. Performance measures of SVM algorithm trained using vibration signature features.

Performance measures / Kernel Function	Linear		Quadratic		Cubic		RBF	
	A	B	A	B	A	B	A	B
Accuracy	0.81	0.68	0.83	0.68	0.71	0.54	0.80	0.64
Misclassification rate	0.19	0.32	0.17	0.32	0.29	0.46	0.20	0.36
F-Measure	0.87	0.66	0.62	0.12	0.00	0.00	0.87	0.67
Kappa statistics	0.86	0.66	0.68	0.39	0.37	0.28	0.86	0.66
MCC	0.73	0.33	0.38	0.28	0.39	0.53	0.73	0.32

Note: A – Model trained with all features; B – Model trained with selected features using one-way ANOVA method; MCC - Matthews Correlation Coefficient

Tables 8-10. In the case of models trained with sound signature futures, SVM models with quadratic, cubic, and RBF are better at predicting the lubricant conditions than the linear kernel function model. There is not much difference in the performance measures of the models trained with all the features and dominant features. In the models developed using vibration features, performance is better for models trained with all the features than those trained with dominant features. Classification accuracy of around 96% is achieved by the SVM models trained with AE features. Similar performance is noticed for all the models trained with all features

TABLE 10. Performance measures of SVM algorithm trained using AE signature features.

Performance measures / kernel Function	Linear		Quadratic		Cubic		RBF	
	A	B	A	B	A	B	A	B
	Accuracy	0.96	0.96	0.97	0.97	0.97	0.96	0.96
Misclassification rate	0.04	0.04	0.03	0.03	0.03	0.04	0.04	0.04
F-Measure	0.97	0.97	0.98	0.98	0.97	0.70	0.97	0.97
Kappa statistics	0.97	0.97	0.98	0.98	0.97	0.96	0.97	0.97
MCC	0.94	0.95	0.96	0.96	0.95	0.58	0.94	0.95

Note:
A – Model trained with all features; B – Model trained with selected features using one-way ANOVA method; MCC - Matthews Correlation Coefficient

and dominant features. Kernel functions also do not influence much in classifying the lubricant conditions.

IX. FEATURE LEVEL FUSION OF SOUND, AE, AND VIBRATION

In the feature level fusion method, features of ‘sound’, ‘vibration’, and ‘acoustic emission’ sensors are pooled into a single set. The combined data set is fed to the classifiers for signature analysis. Individual classifiers will have larger input data space, affecting classification accuracy. Feature level fusion gives advantages-like redundancy and complementarity [71]. Statistical features of sound, vibration and AE in the time domain are fused in feature levels. The fusion methodology adopted in this study is shown in Fig.9.

The algorithms employed are the CART decision tree with split criteria, namely gini, twoing, and maximum deviation, and Support Vector Machines with linear, quadratic, cubic, and Radial Basis Function.

A. PERFORMANCE OF CART ALGORITHM

CART algorithms are trained with all 37 fused sound, vibration, and AE features. The performance was also tested with fused dominant features. The performance of the CART algorithm is shown in Table 11. It is observed that twoing and maximum deviance criterions trained with fused features predict the lubricant conditions with an accuracy of around 92%. The model trained with dominant features doesn’t have a significant impact on improving the classification accuracy. It is to be noted that feature reduction significantly reduces the computation time complexity in the training and testing of the algorithms. The maximum deviance criterion achieves maximum classification accuracy of 93% with the CART model trained with all or dominant features. There is a reduction of 40% in time observed in the case of models trained with dominant features selected using the one-way ANOVA approach.

B. PERFORMANCE OF SVM ALGORITHM

SVM algorithms are trained with all 37 fused sound, vibration, and AE features. The performance was also tested

TABLE 11. Performance measures of CART algorithm trained using fused signature features.

Performance measures / Split criterion	Gini impurity		Twoing rule		MDR	
	A	B	A	B	A	B
	Accuracy	0.811	0.795	0.916	0.915	0.936
Misclassification rate	0.189	0.206	0.084	0.085	0.065	0.065
F-Measure	0.904	0.895	0.950	0.947	0.961	0.959
Kappa statistics	0.896	0.885	0.949	0.945	0.960	0.958
MCC	0.804	0.784	0.900	0.893	0.922	0.918
Comp. time (Sec)	33.605	17.528	27.231	15.630	39.416	23.447

Note:
A – Model trained with all features; B – Model trained with selected features using one-way ANOVA method; MCC - Matthews Correlation Coefficient

TABLE 12. Performance measures of SVM algorithm trained using fused signature features.

Performance measures / kernel Function	Linear		Quadratic		Cubic		RBF	
	A	B	A	B	A	B	A	B
	Accuracy	0.996	0.995	0.997	0.995	0.996	0.995	0.993
Misclassification rate	0.004	0.005	0.003	0.005	0.004	0.005	0.007	0.008
F-Measure	0.997	0.996	0.996	0.994	0.996	0.996	0.994	0.992
Kappa statistics	0.997	0.996	0.996	0.994	0.996	0.996	0.994	0.992
MCC	0.995	0.991	0.993	0.988	0.992	0.991	0.987	0.985
Comp. time (Sec)	581.901	418.972	616.361	417.066	554.392	472.797	734.212	598.227

Note:
A – Model trained with all features; B – Model trained with selected features using one-way ANOVA method; MCC - Matthews Correlation Coefficient

with fused dominant features. Four different Kernel functions, namely linear, quadratic, cubic, and RBF, are used to construct the model. It is observed that all SVM models trained with fused features are predicting the lubricant conditions with an accuracy of around 99%. Details are shown in Table 12. The other performance measures, namely F-measure, Kappa, and MCC, also prove the better performance of SVM algorithms than CART algorithms. The model trained with dominant features doesn’t have a significant impact on improving the classification accuracy. It is to be noted that feature reduction significantly reduces the computation time complexity in the training and testing of the algorithms.

X. RESULTS AND DISCUSSIONS

The overall comparison of results given by the CART and SVM algorithms is shown in Fig.10 for models trained with all features and dominant features. The comparison is based on the classification accuracy of algorithms. It is clear from the comparison that algorithms trained with fused features of sound, vibration, and AE are predicting the lubricant conditions with reasonable accuracy. When signature features are considered separately, AE based model outperforms models developed with sound and vibration features. From an algorithm point of view, SVM algorithms predict lubricant conditions better than decision tree algorithms. All the SVM models trained with fused sound, vibration, and AE achieve a classification accuracy of 99%. It is also noted that SVM algorithms trained with the AE feature exhibit

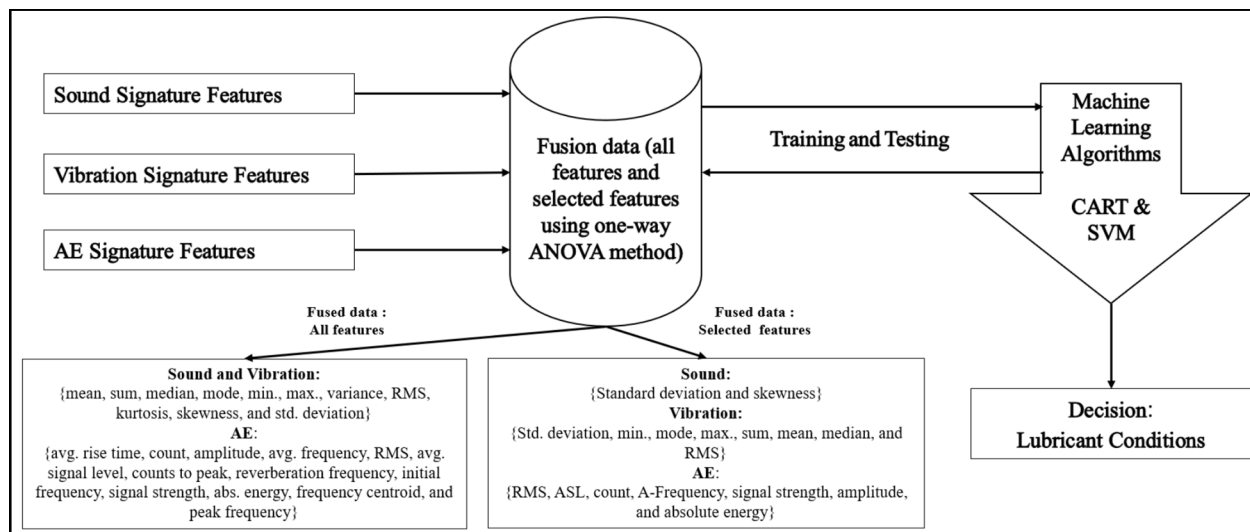


FIGURE 9. Feature level fusion methodology.

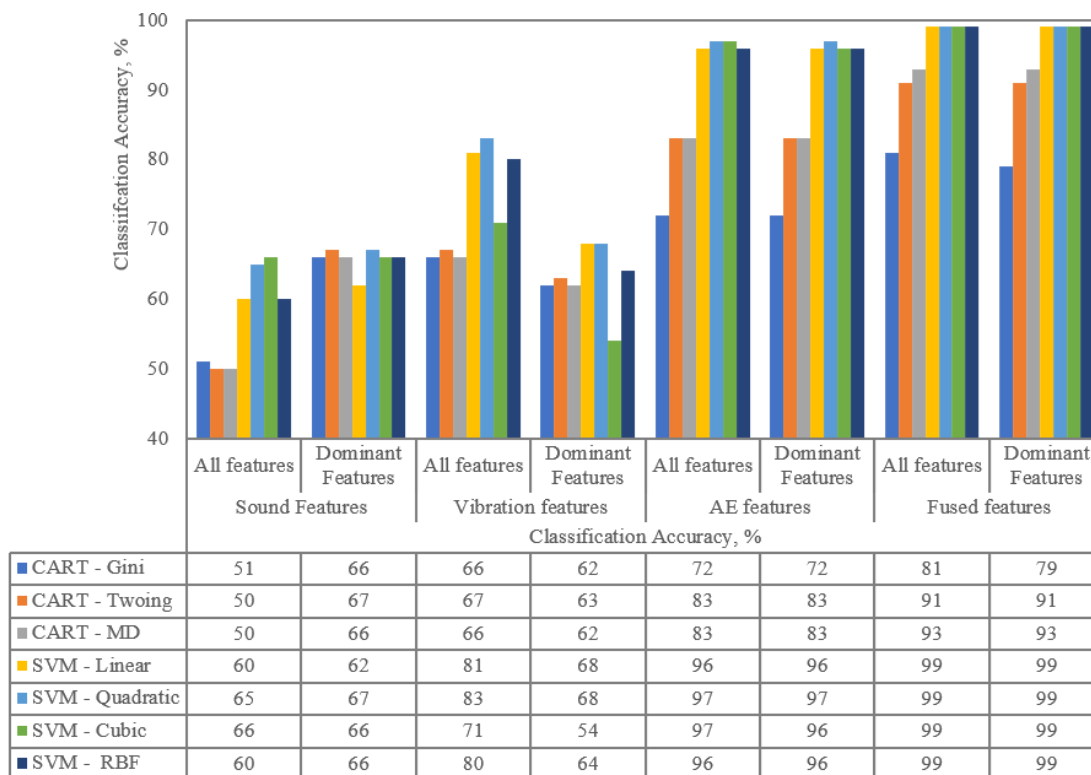


FIGURE 10. Comparative performance measures of CART and SVM algorithms.

good performance and predict the lubricant conditions with an accuracy of around 96%. It can be concluded that the excellent performance of the machine learning algorithm is due to the valuable information available in the AE signature pertaining to the conditions of the lubricant. AE sensor precisely captures a slight variation in the lubricant condition.

CART algorithms with twoing and maximum deviance criteria can classify the lubricant conditions with 91% and 93% accuracy, respectively. The feature selection does not impact the classification accuracy of CART and SVM algorithms considering AE features separately and fused features of sound, vibration, and AE. Compared to models trained with AE features, the prediction ability of models trained

The confusion matrix of the best performing machine learning algorithm – Quadratic SVM, is shown in Table 13. For every condition, 1000 feature data points are given as input to train and test the SVM algorithm. The correctly classified instances are given in the diagonal of the confusion matrix. It is seen that lubricant condition no. 8 and condition no. 22 are predicted with 100% classification accuracy. It is to be noted that there are 44 conditions of lubricants with varying concentration, particle size, speed, and load conditions. Overall, it is observed that SVM is predicting all lubricant conditions with an accuracy of 99%, considering all 44 states. It is concluded that the proposed machine learning models predict the lubricant condition with good accuracy. Feature level fusion of sound, vibration, and AE improves the algorithms' prediction ability compared to models trained separately using sound, vibration, and AE signature features. Among the sound, vibration, and AE signature, AE signature features have better information content about the conditions of the lubricants.

XI. CONCLUSION

Sound, vibration, and AE signatures were acquired for 44 experimental circumstances representing various lubricant conditions involving varied particle sizes, particle concentrations, speeds, and loads in a spur gearbox. Statistical features extracted from the signatures are trained by considering features separately and fusing the signature in the feature level using CART and SVM algorithms. Feature selection was made using the one-way ANOVA approach, and dominant features were identified. The performances of the algorithms are compared by training algorithms using all features and dominant features. Pertaining to the CART algorithm, algorithms trained with AE feature data considering twoing and maximum deviance split criteria can achieve an accuracy of 83%. The prediction ability of the CART algorithms is improved by training the algorithm with fused sound, vibration, and AE features. The CART algorithm's maximum accuracy of 93.5% is achieved by considering the maximum deviance criterion.

Maximum classification accuracy of 99 % is achieved by all the variants of the SVM algorithm trained with fused sound, vibration, and AE features. Compared to CART algorithms, computational complexity is higher for SVM algorithms. Among sound, vibration, and AE features, AE features strongly correlate with the lubricant conditions. The One-Way ANOVA feature selection method reduces the computational complexity by around 25% without scarifying the classification accuracy.

Recommendation for future work:

a) It is observed that machine learning algorithms can predict lubricant conditions with reasonable accuracy; further study could be extended to develop a real-time lubricant condition monitoring system.

b) The present study used time domain statistical features for developing machine learning models. Further, frequency domain and time-frequency (wavelet) domain features may

be used to develop the models for predicting the lubricant conditions.

c) It is also noticed that the prediction ability of models developed using sound and vibration is less than AE-based models. Implementing suitable filtering techniques reduces external disturbances while acquiring sound and vibration sensor signals to improve the prediction ability of the models.

d) Identifying the remaining useful life of lubricants using a sensor-based approach is an important area to be researched further.

e) This study does not address gear tooth failure modes and other failure conditions of mechanical parts in a gearbox due to lubricant contamination. Further studies in this direction will help identify the remaining useful life of the gearbox.

REFERENCES

- [1] H. Liu, H. Liu, C. Zhu, and R. G. Parker, "Effects of lubrication on gear performance: A review," *Mech. Mach. Theory*, vol. 145, Mar. 2020, Art. no. 103701.
- [2] M. K. A. Ali, F. M. H. Ezzat, K. A. A. El-Gawwad, and M. M. M. Salem, "Effect of lubricant contaminants on tribological characteristics during boundary lubrication reciprocating sliding," 2017, *arXiv:1710.04448*.
- [3] M. R. Sari, A. Haiahem, and L. Flamand, "Effect of lubricant contamination on gear wear," *Tribol. Lett.*, vol. 27, no. 1, pp. 119–126, Jul. 2007.
- [4] G. K. Nikas, "A state-of-the-art review on the effects of particulate contamination and related topics in machine-element contacts," *Proc. Inst. Mech. Eng., J. J. Eng. Tribol.*, vol. 224, no. 5, pp. 453–479, Mar. 2010.
- [5] A. Bouchireb and M. R. Sari, "Effect of solid particles on gear tooth failure," *J. Central South Univ.*, vol. 22, no. 5, pp. 1667–1675, May 2015.
- [6] P. M. Ku, "Gear failure modes—Importance of lubrication and mechanics," *ASLE Trans.*, vol. 19, no. 3, pp. 239–249, Jan. 1976.
- [7] H. Shah and H. Hirani, "Online condition monitoring of spur gears," *Int. J. Condition Monitor.*, vol. 4, no. 1, pp. 15–22, Sep. 2014.
- [8] Y. Lei, N. Li, L. Guo, N. Li, T. Yan, and J. Lin, "Machinery health prognostics: A systematic review from data acquisition to RUL prediction," *Mech. Syst. Signal Process.*, vol. 104, pp. 799–834, May 2018.
- [9] J. M. Wakiru, L. Pintelon, P. N. Muchiri, and P. K. Chemweno, "A review on lubricant condition monitoring information analysis for maintenance decision support," *Mech. Syst. Signal.*, vol. 118, pp. 108–132, Mar. 2019.
- [10] X. Zhu, C. Zhong, and J. Zhe, "Lubricating oil conditioning sensors for online machine health monitoring—A review," *Tribol. Int.*, vol. 109, pp. 473–484, May 2017.
- [11] J. Sun, L. Wang, J. Li, F. Li, J. Li, and H. Lu, "Online oil debris monitoring of rotating machinery: A detailed review of more than three decades," *Mech. Syst. Signal Process.*, vol. 149, Feb. 2021, Art. no. 107341.
- [12] N. K. Myshkin and L. V. Markova, *Online Condition Monitoring in Industrial Lubrication and Tribology*, vol. 8. Cham, Switzerland: Springer, 2018.
- [13] H. Boucherit, B. Bou-Saïd, and M. Lahmar, "The effect solid particle lubricant contamination on the dynamic behavior of compliant journal bearings," *Lubrication Sci.*, vol. 29, no. 7, pp. 425–439, Nov. 2017.
- [14] D. D. Troyer and M. Williamson, "Effective integration of vibration analysis and oil analysis," in *Proc. Int. Conf. Condition Monitor.*, Swansea, U.K., 1999, pp. 411–420.
- [15] S. Ebersbach, Z. Peng, and N. J. Kessissoglou, "The investigation of the condition and faults of a spur gearbox using vibration and wear debris analysis techniques," *Wear*, vol. 260, nos. 1–2, pp. 16–24, Jan. 2006.
- [16] T. M. Hunt, *Handbook of Wear Debris Analysis and Particle Detection in Liquids*. Dordrecht, The Netherlands: Springer, 1993.
- [17] X. Zhu, L. Du, and J. Zhe, "A 3×3 wear debris sensor array for real time lubricant oil conditioning monitoring using synchronized sampling," *Mech. Syst. Signal Process.*, vol. 83, pp. 296–304, Jan. 2017.
- [18] A. K. Darpe and H. Hirani, "Classification of stages of wear in spur gears based on wear debris morphology," in *Proc. PHM Soc. Eur. Conf.*, vol. 5, no. 1, 2020, p. 9.
- [19] G. E. Newell, "Oil analysis cost-effective machine condition monitoring technique," *Ind. Lubrication Tribol.*, vol. 51, no. 3, pp. 119–124, Jun. 1999.
- [20] J. Manyala and M. Atashbar, "On-line lubricants health condition monitoring in gearbox application," *SAE Int. J. Fuels Lubricants*, vol. 6, no. 3, pp. 907–914, Nov. 2013.

- [21] J. O. Manyala and M. Z. Atashbar, "Development of particle contaminants monitor system for gearbox lubricant prognostics," in *Proc. IEEE SENSORS*, Oct. 2016, pp. 1–3, doi: [10.1109/ICSENS.2016.7808900](https://doi.org/10.1109/ICSENS.2016.7808900).
- [22] T. H. Loutas, D. Roulias, E. Pauly, and V. Kostopoulos, "The combined use of vibration, acoustic emission and oil debris on-line monitoring towards a more effective condition monitoring of rotating machinery," *Mech. Syst. Signal Process.*, vol. 25, no. 4, pp. 1339–1352, May 2011.
- [23] K. Feng, P. Borghesani, W. A. Smith, R. B. Randall, Z. Y. Chin, J. Ren, and Z. Peng, "Vibration-based updating of wear prediction for spur gears," *Wear*, vol. 426, pp. 1410–1415, Apr. 2019.
- [24] K. Feng, J. C. Ji, Q. Ni, and M. Beer, "A review of vibration-based gear wear monitoring and prediction techniques," *Mech. Syst. Signal Process.*, vol. 182, Jan. 2023, Art. no. 109605, doi: [10.1016/j.ymssp.2022.109605](https://doi.org/10.1016/j.ymssp.2022.109605).
- [25] R.-V. Sánchez, P. Lucero, R. E. Vásquez, M. Cerrada, and D. Cabrera, "A comparative feature analysis for gear pitting level classification by using acoustic emission, vibration and current signals," *IFAC-PapersOnLine*, vol. 51, no. 24, pp. 346–352, 2018.
- [26] J. Yao, C. Liu, K. Song, X. Zhang, and D. Jiang, "Fault detection of complex planetary gearbox using acoustic signals," *Measurement*, vol. 178, Jun. 2021, Art. no. 109428, doi: [10.1016/j.measurement.2021.109428](https://doi.org/10.1016/j.measurement.2021.109428).
- [27] M. S. Raghav and R. B. Sharma, "A review on fault diagnosis and condition monitoring of gearboxes by using AE technique," *Arch. Comput. Methods Eng.*, vol. 28, no. 4, pp. 2845–2859, Jun. 2021.
- [28] P. Krishnakumar, K. Rameshkumar, and K. I. Ramachandran, "Feature level fusion of vibration and acoustic emission signals in tool condition monitoring using machine learning classifiers," *Int. J. Prognostics Health Manage.*, vol. 9, no. 1, pp. 1–15, 2018, doi: [10.36001/ijphm.2018.v9i1.2694](https://doi.org/10.36001/ijphm.2018.v9i1.2694).
- [29] P. Krishnakumar, K. Rameshkumar, and K. I. Ramachandran, "Acoustic emission-based tool condition classification in a precision high-speed machining of titanium alloy: A machine learning approach," *Int. J. Comput. Intell. Appl.*, vol. 17, no. 3, Sep. 2018, Art. no. 1850017.
- [30] D. Vališ, J. Gajewski, and L. Žák, "Potential for using the ANN-FIS meta-model approach to assess levels of particulate contamination in oil used in mechanical systems," *Tribol. Int.*, vol. 135, pp. 324–334, Jul. 2019.
- [31] Y. Pan, Y. Jing, T. Wu, and X. Kong, "An integrated data and knowledge model addressing aleatory and epistemic uncertainty for oil condition monitoring," *Rel. Eng. Syst. Saf.*, vol. 210, Jun. 2021, Art. no. 107546.
- [32] W. Cao, H. Zhang, N. Wang, H. W. Wang, and Z. X. Peng, "The gearbox wears state monitoring and evaluation based on on-line wear debris features," *Wear*, vols. 426–427, pp. 1719–1728, Apr. 2019.
- [33] K. E. Spezzaferro, "Applying logistic regression to maintenance data to establish inspection intervals," in *Proc. Annu. Rel. Maintainability Symp.*, 1996, pp. 296–300.
- [34] F. D. Samirmi, W. Tang, and H. Wu, "Power transformer condition monitoring and fault diagnosis with multi-agent system based on ontology reasoning," in *Proc. IEEE PES Asia-Pacific Power Energy Eng. Conf.*, Dec. 2013, pp. 1–6.
- [35] J. Yan and J. Lee, "Degradation assessment and fault modes classification using logistic regression," *J. Manuf. Sci. Eng.*, vol. 127, no. 4, pp. 912–914.
- [36] J. Phillips, E. Cripps, J. W. Lau, and M. R. Hodkiewicz, "Classifying machinery condition using oil samples and binary logistic regression," *Mech. Syst. Signal Process.*, vols. 60–61, pp. 316–325, Aug. 2015.
- [37] D. Ide, A. Ruike, and M. Kimura, "Extraction of causalities and rules involved in wear of machinery from lubricating oil analysis data," in *Proc. 2nd Int. Conf. Digit. Inf. Process., Data Mining, Wireless Commun. (DIPDMWC)*, 2015, p. 16.
- [38] J. Wakiru, L. Pintelon, P. Chemweno, and P. N. Muchiri, "A decision tree-based classification framework for used oil analysis applying random forest feature selection," *J. Appl. Sci., Eng. Technol. Develop.*, vol. 3, no. 1, pp. 90–100, May 2018.
- [39] R. M. Balabin, E. I. Lomakina, and R. Z. Safieva, "Neural network (ANN) approach to biodiesel analysis: Analysis of biodiesel density, kinematic viscosity, methanol and water contents using near infrared (NIR) spectroscopy," *Fuel*, vol. 90, no. 5, pp. 2007–2015, May 2011.
- [40] M. Afrand, K. N. Najafabadi, N. Sina, M. R. Safaei, A. S. Kherbeet, S. Wongwises, and M. Dahari, "Prediction of dynamic viscosity of a hybrid nano-lubricant by an optimal artificial neural network," *Int. Commun. Heat Mass Transf.*, vol. 76, pp. 209–214, Aug. 2016.
- [41] G. S. Kapur, M. I. S. Sastry, A. K. Jaiswal, and A. S. Sarpal, "Establishing structure-property correlations and classification of base oils using statistical techniques and artificial neural networks," *Analytica Chim. Acta*, vol. 506, no. 1, pp. 57–69, Mar. 2004.
- [42] B. Basu, M. P. Singh, G. S. Kapur, N. Ali, M. I. S. Sastry, S. K. Jain, S. P. Srivastava, and A. K. Bhatnagar, "Prediction of biodegradability of mineral base oils from chemical composition using artificial neural networks," *Tribol. Int.*, vol. 31, no. 4, pp. 159–168, Apr. 1998.
- [43] H. J. Wei and G. Y. Wang, "Research of marine diesel Engine's state prediction based on evolutionary neural network and spectrometric analysis," *Adv. Mater. Res.*, vol. 346, pp. 339–345, Sep. 2012.
- [44] C. Sreepadha, A. K. Kumari, A. E. Perumal, R. C. Panda, K. Harshabardhan, and M. Aribalagan, "Neural network model for condition monitoring of wear and film thickness in a gearbox," *Neural Comput. Appl.*, vol. 24, nos. 7–8, pp. 1943–1952, Jun. 2013.
- [45] S. R. Chowdhury, R. Kumar, R. Kaur, A. Sharma, and A. P. Bhonekar, "Quality assessment of engine oil: An impedance spectroscopy based approach," in *Proc. IEEE Uttar Pradesh Sect. Int. Conf. Electr., Comput. Electron. Eng. (UPCON)*, Dec. 2016, pp. 608–612, doi: [10.1109/UPCON.2016.7894724](https://doi.org/10.1109/UPCON.2016.7894724).
- [46] W. Wang and W. Zhang, "A model to predict the residual life of aircraft engines based upon oil analysis data," *Naval Res. Logistics*, vol. 52, no. 3, pp. 276–284, 2005.
- [47] K. Sepcic, M. Josowicz, and J. Janata, "Determination of the principal volatile compounds in degraded engine oil," *Tribol. Lubrication Technol.*, vol. 60, no. 3, pp. 40–47, 2004.
- [48] H. B. Jun, F. L. Conte, D. Kiritis, and P. Xirouchakis, "A predictive algorithm for estimating the quality of vehicle engine oil," *Int. J. Ind. Eng. Theory Appl. Pract.*, vol. 15, no. 4, pp. 386–396, Dec. 2008.
- [49] Y. Gong, L. Guan, X. Feng, L. Wang, and X. Yu, "in-situ lubricating oil condition sensing method based on two-channel and differential dielectric spectroscopy combined with supervised hierarchical clustering analysis," *Chemometric Intell. Lab. Syst.*, vol. 158, pp. 155–164, Nov. 2016.
- [50] A. Wolak, G. Zajac, and W. Gołębowski, "Determination of the content of metals in used lubricating oils using AAS," *Petroleum Sci. Technol.*, vol. 37, no. 1, pp. 93–102, Jan. 2019.
- [51] D. Vališ, L. Žák, O. Pokora, and P. Lánský, "Perspective analysis outcomes of selected tribodiagnostic data used as input for condition based maintenance," *Reliab. Eng. Syst. Saf.*, vol. 145, pp. 231–242, Jan. 2016.
- [52] J. M. Wakiru, L. Pintelon, P. Muchiri, and P. Chemweno, "Analysis of lubrication oil contamination by fuel dilution with application of cluster analysis," in *Proc. 17th Int. Sci. Conf. Ind. Syst. (IS)*, Novi Sad, Serbia, 2017, pp. 4–6.
- [53] S. Ding, H. Zhu, W. Jia, and C. Su, "A survey on feature extraction for pattern recognition," *Artif. Intell. Rev.*, vol. 37, no. 3, pp. 169–180, May 2011.
- [54] H. Nakamura, M. Ohtsu, M. Enoki, Y. Mizutani, M. Shigeishi, H. Inaba, M. Nakano, T. Shiotani, S. Yuyama, and S. Sugimoto, *Practical Acoustic Emission Testing*. Tokyo, Japan: Springer, 2016.
- [55] A. S. Raghunath, K. T. Sreekumar, C. S. Kumar, and K. I. Ramachandran, "Improving speed independent performance of fault diagnosis systems through feature mapping and normalization," in *Proc. 15th IEEE Int. Conf. Mach. Learn. Appl. (ICMLA)*, Dec. 2016, pp. 764–767.
- [56] K. T. Sreekumar, K. K. George, C. S. Kumar, and K. I. Ramachandran, "Performance enhancement of the machine-fault diagnosis system using feature mapping, normalisation and decision fusion," *IET Sci., Meas. Technol.*, vol. 13, no. 9, pp. 1287–1298, Nov. 2019.
- [57] G. Chandrashekar and F. Sahin, "A survey on feature selection methods," *Comput. Elect. Eng.*, vol. 40, no. 1, pp. 16–28, Jan. 2014.
- [58] B. Butcher and B. J. Smith, "Feature engineering and selection: A practical approach for predictive models," *Amer. Statistician*, vol. 74, no. 3, pp. 308–309, 2020, doi: [10.1201/9781315108230](https://doi.org/10.1201/9781315108230).
- [59] L. Breiman, J. H. Friedman, R. A. Olshen, and C. J. Stone, *Classification and Regression Trees*. Brooks, 1st ed. New York, NY, USA: Taylor and Francis, 1984.
- [60] X. Wu, V. Kumar, J. R. Quinlan, J. Ghosh, Q. Yang, H. Motoda, G. J. McLachlan, A. Ng, B. Liu, P. S. Yu, and Z. H. Zhou, "Top 10 algorithms in data mining," *Knowl. Inf. Syst.*, vol. 14, no. 1, pp. 1–37, 2008.
- [61] D. S. B. Mouli and K. Rameshkumar, "Acoustic emission-based grinding wheel condition monitoring using decision tree machine learning classifiers," in *Advances in Materials and Manufacturing Engineering* (Lecture Notes in Mechanical Engineering), L. Li, D. Pratihari, S. Chakrabarty, and P. Mishra, Eds. Singapore: Springer, 2020, doi: [10.1007/978-981-15-1307-7_39](https://doi.org/10.1007/978-981-15-1307-7_39).
- [62] K. Rameshkumar et al., "Machine learning models for weld quality monitoring in shielded metal arc welding process using arc signature features," *SAE Int. J. Mater. Manf.*, vol. 15, no. 4, 2022, doi: [10.4271/05-15-04-0023](https://doi.org/10.4271/05-15-04-0023).
- [63] C. Cortes and V. Vapnik, "Support-vector networks," *Mach. Learn.*, vol. 20, no. 3, pp. 273–297, 1995.

- [64] J. Cervantes, F. Garcia-Lamont, L. Rodríguez-Mazahua, and A. Lopez, "A comprehensive survey on support vector machine classification: Applications, challenges and trends," *Neurocomputing*, vol. 408, pp. 189–215, Sep. 2020.
- [65] C. Ferri, J. H. Orallo, and R. Modroui, "An experimental comparison of performance measures for classification," *Pattern Recognit. Lett.*, vol. 30, no. 1, pp. 27–38, Jan. 2009.
- [66] D. Chicco and G. Jurman, "The advantages of the Matthews correlation coefficient (MCC) over F1 score and accuracy in binary classification evaluation," *BMC Genomics*, vol. 21, no. 1, pp. 1–13, Jan. 2020.
- [67] J. R. Landis and G. G. Koch, "The measurement of observer agreement for categorical data," *Biometrics*, vol. 33, no. 1, pp. 159–174, Mar. 1977.
- [68] J.-H. Hong and S.-B. Cho, "A probabilistic multi-class strategy of one-vs.-rest support vector machines for cancer classification," *Neurocomputing*, vol. 71, nos. 16–18, pp. 3275–3281, Oct. 2008.
- [69] M. Awad and R. Khanna, "Support vector machines for classification," in *Efficient Learning Machines*. Berkeley, CA, USA: Apress, 2015, pp. 39–66, doi: 10.1007/978-1-4302-5990-9_3.
- [70] J. Shin, M. R. Islam, M. A. Rahim, and H.-J. Mun, "Arm movement activity based user authentication in P2P systems," *Peer-to-Peer Netw. Appl.*, vol. 13, no. 2, pp. 635–646, Jun. 2019.
- [71] S. Cho, S. Binsaeid, and S. Asfour, "Design of multisensor fusion-based tool condition monitoring system in end milling," *Int. J. Adv. Manuf. Technol.*, vol. 46, nos. 5–8, pp. 681–694, Jan. 2010.



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