Automated and Rapid Seal Wear Classification Based on Acoustic Emission and Support Vector Machine

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ABSTRACT

Seal wear in hydraulic cylinders results in fluid leakage, and instability of the piston rod movement. Therefore, regular inspection of seals is required using automated approaches to improve productivity and to reduce unscheduled maintenance. In literature, successful attempts have been made using acoustic emission-based condition monitoring to classify the seal wear. However, limited attempts have been made to implement automated approaches to classify seal wear using acoustic emission features. Therefore, this article presents an automated approach for rapid and computationally economical diagnosis of seal wear using acoustic emission. The experiments were performed at varying pressure conditions on a hydraulic test rig that can simulate fluid leakage conditions similar to that of hydraulic cylinders. From the acoustic emission spectrum, the frequency bands were identified with peak power and by heterodyning the signal. This technique results in 10X downsampling without losing the information of interest. Further, the signal was divided into smaller "snapshots" to facilitate rapid diagnosis. In these tests, the diagnosis was made on short-time windows, as low as 0.3 seconds in length. A set of time and frequency domain features were designed, and the Support Vector Machine (SVM) was trained on 60 % of the test cases generated with seals of three different conditions. The SVM was able to accurately classify the status irrespective of the pressure conditions, with an accuracy of ~99 %. Therefore, the proposed automated seal wear classification technique based on acoustic emission and SVM can be used for real-time monitoring of seal wear in hydraulic cylinders.

Keywords: Piston rod seal, Fluid leakage, Acoustic Emission, and Support Vector Machine.

1. INTRODUCTION

Reciprocating hydraulic seals play a crucial role in preventing fluid leakage in hydraulic cylinders. In hydraulic cylinders, a typical rod seal system consists of a wiper, excluder seal, primary seal, secondary seal, and rod bearing elements. Whereas a piston seal system includes piston seal and piston bearing elements. Seal wear in a hydraulic cylinder can result in internal and external fluid leakage. Internal fluid leakage due to seal wear can cause a) reduction of force exerted by the cylinder b) instability of the piston rod movement, and c) reduction in linear velocity. Whereas external fluid leakage due to seal wear can result in all the problems associated with internal leakage in addition to d) increased risk of injury to the operator due to fluid spill e) fire hazard risk, and f) environmental contamination. Considering the risk associated with internal and external fluid leakage, it is important to avoid unpredictable failure of seals (Barillas et al., 2018; Shanbhag et al., 2021; Zhao & Wang, 2019). Machine learning techniques have been used widely for condition monitoring processes and in combination of different sensor data measurement, including AE method (Ince et al., 2010). Thus, machine learning in combination with AE method, would enable development of rapid and accurate assessment of condition monitoring method of the current health of the seal and can also automatically classify different stages of seal wear.

In the literature, numerous attempts have been made to study fluid leakage due to seal wear from hydraulic cylinders using different condition monitoring techniques. For instance, several attempts have been made to monitor fluid leakage using a pressure sensor. Pressure signal-based features as residual pressure error (An & Sepehri, 2005), Root Mean Square (RMS) from the level two and level four Wavelet coefficients (Goharrizi & Sepehri, 2011), Wavelet packet energy variance (Zhao et al., 2015), Energy from the frequency band (Tang et al., 2010), Instantaneous value from the first Intrinsic Mode Functions (IMF's) (Goharrizi & Sepehri, 2012), state estimation error from the Adaptive Robust Observer (ARO) technique (Garimella & Yao, 2005) were proposed to monitor fluid leakage. Using the pressure sensor-based condition monitoring technique, it was possible to identify fluid leakage as low as 0.124 L/min. In other literature, the feasibility of a vibration sensor to monitor fluid leakage due to seal wear was assessed (Tan et al., 2000; Yunbo et al., 2001). Vibration-based feature dBVrms was proposed to monitor fluid leakage due to seal wear. In recent times, the Acoustic Emission (AE) sensor is used extensively to monitor fluid leakage because of its high frequency range. AE based features such as RMS, mean frequency, median frequency and band power were proposed to monitor fluid leakage due to seal wear (Chen et al., 2007; Shanbhag et al., 2020b, 2020a). Using AE-based features, it is possible to monitor fluid leakage as low as 1.0 L/min (Chen et al., 2007). It is evident from the literature that a sufficient number of studies has been conducted to monitor fluid leakage using different sensor-based features. However, few studies have been proposed for automatically classifying the seal wear using signal-based features in combination with machine learning techniques.

In recent times, monitoring of reciprocating seals, and rotary seals using data-driven techniques have gained significant research attention. In the literature (Ramachandran et al., 2019) used Particle Swarm Optimization (PSO) with SVM to monitor fluid leakage due to wear of reciprocating seals. Features from force signals were used as an input for the PSO-SVM model. Mean Square Error (MSE) and Mean Absolute Error (MAE) were lower for the PSO-SVM model when compared to the Genetic Algorithm (GA)-SVM and Optimized Distributed Gradient Boosting System (XGBoost). In the other work (Ramachandran & Siddique, 2019) a Multi-Layered Perceptron Neural Network (MLP-NN) model was used for the seal wear classification. Torque-based features such as RMS, peak, mean, and Square Mean Rooted Absolute Amplitude (SRA) were used as inputs for the MLP-NN model. The classification accuracy of 92.86 % was observed for the MLP-NN model when compared to the logistic (89.29 %) and random forest classifiers (89.29 %). To monitor internal leakage in hydraulic cylinders (Zhang & Chen, 2021) proposed optimization deep belief network (DBN) combined with the Complete Ensemble Empirical Model Decomposition with Adaptive Noise (CEEMDAN) technique to classify the AE signal acquired when the system was not leaking, and at different severities of internal leakages such as small, medium and severe internal leakage. Using the proposed method, a classification accuracy of up to 93 % was observed.

From literature, it is evident that several seal wear classification studies have been conducted using a combination of condition monitoring approaches and machine learning techniques. However, to the authors' knowledge, there exist limited attempts to classify the external leakage due to different types of seal wear using AE and automated classification techniques. Therefore, this article proposes an automated classification technique based on AE features and the SVM technique. To this end, experiments were conducted on a hydraulic test rig under various pressure conditions with seals at three different degrees of wear; unworn, semi-worn and worn. The recorded AE signal of each stroke is then processed to produce features based on time and frequency domain, serving as input to the SVM classifier.

2. METHODOLOGY

2.1. Experimental details

A custom-built test rig was used in this study, consisting of an electromechanical cylinder and a hydraulic cylinder head, to conduct experiments for studying different types of seal wear using AE, –see Figure 1-a). The test rig was designed to simulate the fluid leakage conditions due to seal wear that is typically observed in hydraulic cylinders. The movement of the piston rod (extension and retraction strokes) is driven by a spindle and nut that converts rotary to translatory motion. As shown in Figure 1-b), the pressurized flange consists of three bearing strips to withstand arising side loads, the piston rod seals act as fluid sealing. The pressurized fluid for the flange in the test rig is supplied through the hydraulic power pack and pressure is controlled through pressure relief valves. A servomotor encoder is used in the test rig to control the piston rod position and to record the number of times the piston rod passes through the pressurized flange. There is dwell time of one second at both ends of the piston rod stroke i.e. between changing from extension and retraction and vice versa.

Table 1. Process parameters.

Setup	Hydraulic test rig
Seal material	Polyether-based polyurethane elastomer
Coating on piston rod	Cladded coating of a cobalt-based alloy
Fluid	Water glycol
Speed	100 mm/s
Pressure	10, 20, 30, 40 Bar
Stroke length	600 mm
Number of strokes	5
AE data acquisition	1 MS/s
AE amplifier gain	40 dB
Seal condition	Unworn, Semi-worn and worn

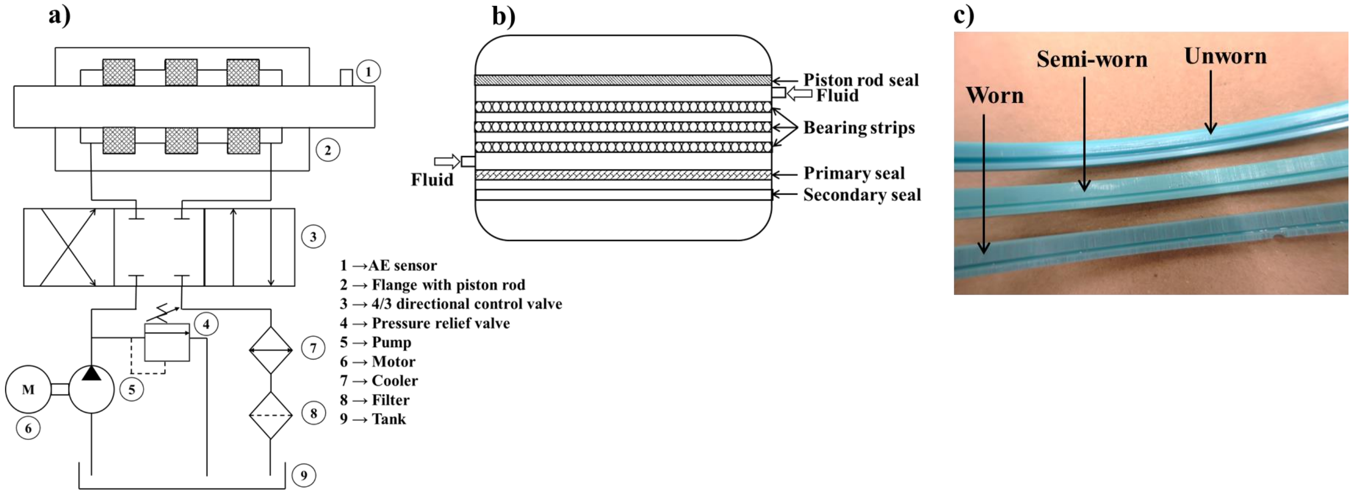

Figure 1. a) Circuit diagram of hydraulic test rig, b) Schematic front view of piston rod seal and bearing strips arrangement in the cylinder head, c) Piston rod seals used in the study.

To perform condition monitoring studies, only the upper piston rod seal was replaced with unworn seal (no grooves), semi-worn seal (minor grooves) and worn seal (major grooves). Fluid leakage was observed in the test rig for all the experiments when semi-worn or worn seal was used in the cylinder head (Figure 1-c)). For each seal condition, experiments were performed for five strokes and at four different pressure conditions (10, 20, 30 and 40 Bar). Each stroke consists of full extension and retraction of piston rod in either direction (600 mm). Other parameters are summarized in Table 1.

2.2. AE data acquisition details and bandpass filtering

In this study, the AE sensor (AE frequency range: 50-400 kHz and resonant frequency: 150 kHz) was mounted on the piston rod because the piston rod is in direct contact with the piston rod seal. To secure a good signal transfer path, the AE sensor was mounted on the piston rod using adhesive bond and industrial duct tape. The AE sensor was connected to the AE channel in data acquisition setup via a pre-amplifier (Gain: 40 dB) using a five-meter-long coaxial cable. The AE data acquisition for all the experiments was performed at 1 MS/s. In the previous condition monitoring studies conducted by (Shanbhag et al., 2020a), the AE frequency range related to seal wear was observed to be in the AE frequency range of 50-100 kHz. Therefore, all the AE signals were subjected to bandpass filtering in the AE frequency range of 50-100 kHz. The AE signal after bandpass filtering for the unworn, semi-worn and worn seals are represented in Figure 2 a)-c). The maximum amplitude of the AE signal for the semi-worn and worn seals is higher compared to that of the unworn seal. However, the maximum amplitude of the AE signal of semi-worn and worn seals is nearly same. Therefore, Power Spectral Density (PSD) is calculated from the bandpass filtered AE signal to understand the difference between AE signals recorded from experiments performed using unworn, semi-worn and worn seals (Figure 2-d)). From the PSD plot, the maximum magnitude for the worn seal>semi-worn seal>unworn seal. However, classification based solely on PSD was found to be insufficient for automation specially under varying pressure conditions. Therefore, additional features extracted from time and frequency responses were evaluated.

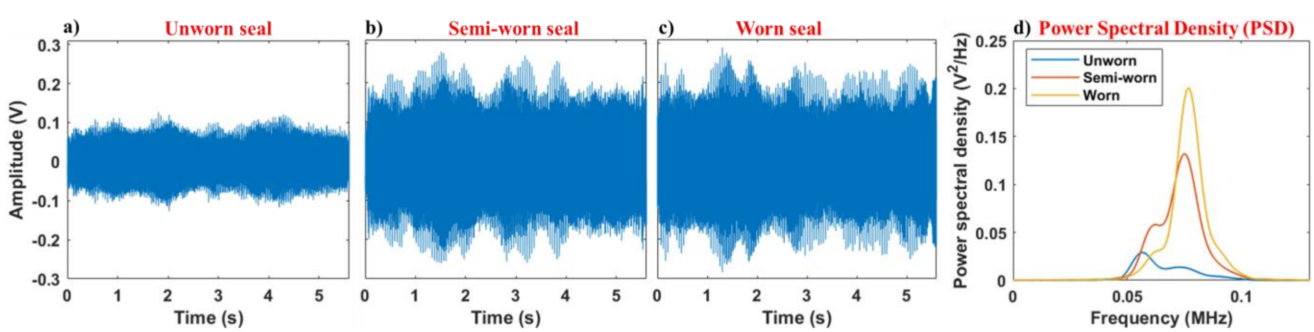

Figure 2. Bandpass filtered AE signal due to a) unworn seal, b) semi-worn seal and c) worn seal; d) PSD plot calculated from the Figure 2 a)-c) (Bandpass filtered range=50-100 kHz, Pressure=20 bar, Stroke number=2, AE signal from extension of rod).

2.3. Processing AE signal

Raw AE signals are sampled at a very high sample rate of 1 MS/s. Such high sample rate entails significant storage usage besides requiring high computational power for signal processing and communication. As the peak energy content was observed only in the range of 50-100 kHz, a bandpass filter was applied to isolate this band in the AE signal. The signal processing steps prior to supplying features to the SVM classifier is described in Figure 3. After detecting the peak power band in the AE signal, the heterodyne operation is performed. In heterodyne operation, the Fast Fourier Transform (FFT) of the signal is calculated and the frequency band of interest, namely 50-100 kHz is shifted to the origin, and the remainder of the FFT amplitudes are set to zero (Bechhoefer, 2018). In this way, a new FFT is obtained that contains the frequency content of interest but is downshifted to 0 – 50 KHz. The inverse FFT is then calculated, and the new signal can be down sampled to a new sample rate of 100 kHz while holding all the information of interest. This approach resulted in a reduction of file size by ~70%, which is highly beneficial for further exploration of data-driven techniques for health state classification and storing data for online monitoring. The resultant signal is split into short-time windows of as low as 0.28 s. Further, several time and frequency domain features are calculated on these short-time windows of AE signal.

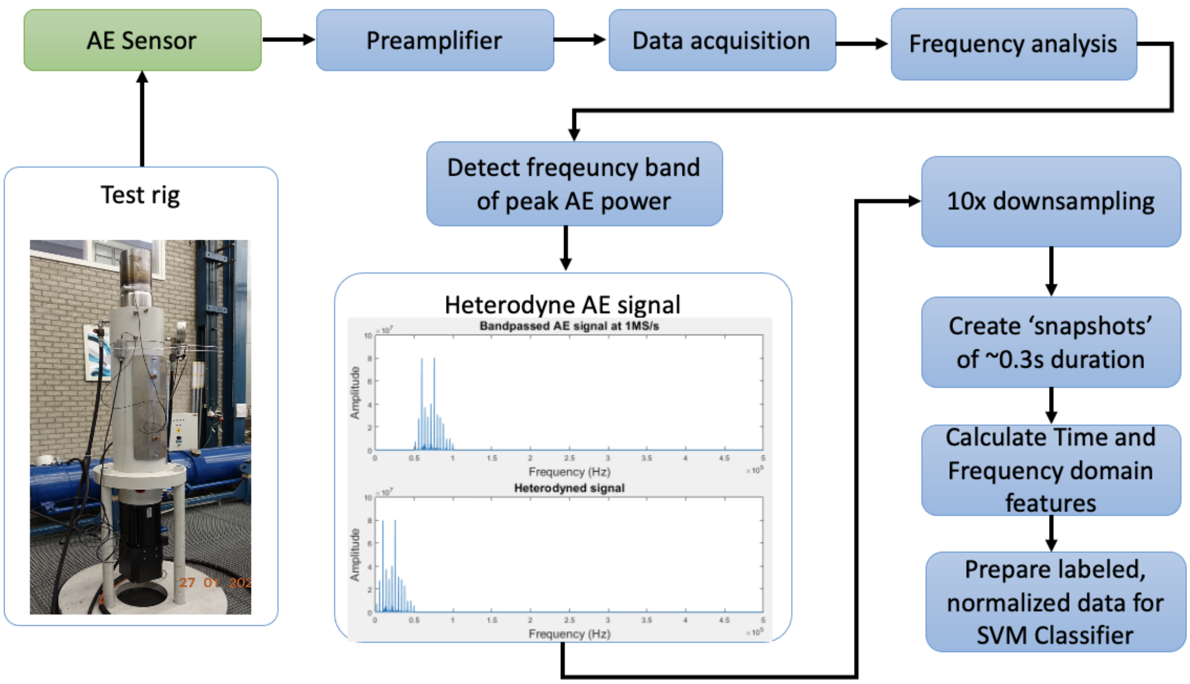

Figure 3. AE signal processing procedure.

2.4. Time and frequency domain features

To automate the classification of the health state of the seals, a set of time and frequency domain statistical features are generated (Table 2). In an earlier work (Shanbhag et al., 2020b) showed that AE band power and power spectral density could be utilized for separating the three seal wear conditions. However, to improve the robustness of the automated detection in short time window using an SVM classifier, several other statistical features were introduced to accomplish rapid and autonomous detection. These features form an *n*-dimensional feature space for fault classification using SVM. These are statistical measures often used for feature extraction on vibration signatures such as mean, standard deviation, RMS and higher order moments such as skewness (3rd), kurtosis (4th), crest factor, and spectral spread. These features are calculated on time-domain ($\delta_1 - \delta_8$) and on frequency domain ($\delta_9 - \delta_{16}$). These features were earlier tested with vibration signatures (Li et al., 2011) and current signatures (Kandukuri et al., 2019) and proven to be capable of capturing the statistical properties of the signal for automated classification.

2.5. SVM Classifier

In the previous section, a set of 16 features based on the time and frequency domain statistical parameters of the AE signal have been calculated. Since the tests are performed using known fault severities, the SVM classifier may be trained using a portion of the data. Then, the remaining data may be utilized to test the SVM classifier to determine the health stage and classifier performance. This process is detailed in Figure 4. The SVM classifier is chosen because of its mathematical rigor unlike black-box models like artificial neural networks. Besides, SVM's complexity does not increase with data dimensionality unlike its counterparts as decision tree classifiers, besides being highly efficient on large datasets (Dobrzycki et al., 2019). The SVM classifier distinguishes classes by drawing an optimum hyperplane in a multidimensional hyperspace spanned by the feature set. This is achieved by solving an optimization problem (Vapnik, 2000). The mathematical formulation of the linear SVM classification for two class (binary) case is discussed in this section. However, the same concept can be extended to multiclass linear and nonlinear problems. Consider the training dataset with inputs $x_i \in \mathbb{R}^m$ and binary outputs $y_i \in \{\pm 1\}$ and $(x_i, y_i) \in \mathbb{R}^m \times \{\pm 1\}$, $i = 1,2, \dots N$.

Through training, the SVM classifier derives a decision function given by

$$f_{w,b}(x) = \mathrm{sgn}(wx + b),$$

where w is the coefficient vector and b is the bias of the hyperplane and sgn is the binary signature function. Ideally, the following condition should be satisfied by the hyperplane of the classifier:

$$y_i(wx_i + b) \geq 1, \quad i = 1,2, \dots N.$$

Table 2. Time and frequency domain features calculated on AE signal snapshot.

Time domain	Significance	Frequency domain	Significance
$\delta_1 = \sum_{n=1}^{N} \frac{x(n)}{N}$	Mean value of signal in time domain.	$\delta_9 = \sum_{k=1}^{K} \frac{s(k)}{K}$	Mean value of the amplitudes of frequency response.
$\delta_2 = \sqrt{\sum_{n=1}^{N} \frac{(x_n - f_1)^2}{N}}$	Variance of the signal in time domain.	$\delta_{10} = \sum_{k=1}^{K} \frac{(s(k) - \delta_9)^2}{K}$	Variance in the frequency response.
$\delta_3 = \sqrt{\sum_{n=1}^{N} \frac{x(n)^2}{N}}$	RMS value (energy) of the signal in time domain.	$\delta_{11} = \sum_{k=1}^{K} \frac{(s(k) - \delta_9)^3}{K}$	Non-normalized 3rd order moment of the frequency response.
$\delta_4 = \max(\lvert x(n) \rvert)$	Max value of the signal	$\delta_{12} = \sum_{k=1}^{K} \frac{(s(k) - \delta_9)^4}{K}$	Non-normalized 4th order moment of the Fourier response.
$\delta_5 = \frac{\sum_{n=1}^{N} (x(n) - \delta_1)^3}{\delta_2^3 (N-1)}$	Normalized 3rd order moment (skewness) of the signal. A measure of asymmetry of distribution around its mean.	$\delta_{13} = \frac{\sum_{k=1}^{K} k s(k)}{\sum_{k=1}^{K} s(k)}$	The features $\delta_{13} - \delta_{16}$ are statistical features taking into account the spectral location of the frequency content. The features are similar to mean, variance, skewness and kurtosis, but are sensitive to the region in the spectrum where the frequency content is present.
$\delta_6 = \frac{\sum_{n=1}^{N} (x(n) - \delta_1)^4}{\delta_2^4 (N-1)}$	Normalized 4th order moment (kurtosis) of the signal. Denotes the spikiness or impulsive nature of the signal.	$\delta_{14} = \sqrt{\frac{\sum_{k=1}^{K} (k - \delta_{13})^2}{K}}$	
$\delta_7 = \frac{\delta_4}{\delta_3}$	Crest factor - Ratio of max value to the total energy of the signal. A signal with high max value and low overall energy is indicative of narrow-band disturbances.	$\delta_{15} = \frac{\sum_{k=1}^{K} (k - \delta_{13})^3 s(k)}{K \delta_{14}^3}$	
$\delta_8 = \frac{\delta_4}{\left(\frac{1}{N} \sum_{n=1}^{N} \sqrt{\lvert x(n) \rvert} \right)^2}$	Clearance factor – ratio of max value to the squared mean value of square roots. This factor typically decreases with increase in faults, eg. in bearing faults.	$\delta_{16} = \frac{\sum_{k=1}^{K} (k - \delta_{13})^4 s(k)}{K \delta_{14}^4}$	
Where $x(n)$ is the signal time series, $n = 1,2, \dots N$.		Where $s(k)$ is the frequency spectrum, $k = 1,2, \dots K$.	

Among the hyperplanes satisfying the equation, the optimal hyperplane is the one with maximum distance to the closest point. Based on the structural risk minimization inductive method, the training of the SVM is to minimize the guaranteed risk bounds as follows:

$$\min J(w, e, b) = \frac{1}{2} w^T w + \frac{1}{2} C \sum_{i=1}^{N} e_i^2,$$

where e_i is a slack variable, $e_i \geq 0$, which accumulates the error in case an optimal solution is infeasible. The SVM algorithm considers only the boundary data to define the optimal hyperplane, making it highly efficient even with large sets of data and dimensionality. The SVM can work with both linear and nonlinear classification problems. For the classification of seal health, a quadratic SVM is employed.

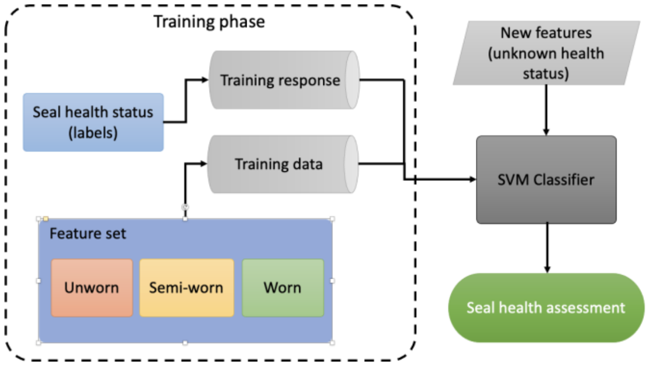

Figure 4. SVM classifier.

3. Result and Discussion

The short-time samples of AE signals were prepared, and the features described in Section 2.4 were calculated and labelled according to the known seal health condition as "Unworn", 'Semi-worn' and 'Worn'. The total dataset consisted of 1200 labelled samples equally distributed between the three health conditions and obtained under four different pressure conditions, 10, 20, 30 and 40 bar. The features described in Table 2 were calculated to produce the multidimensional hyperspace for the SVM classifier. To analyze the features, the mean values of all the 16 features were calculated over the entire sample set consisting of a total of 1200 samples (400 samples for each health condition). Further, the ratio of the mean of the features in the semi-worn and worn conditions are compared to the healthy. The results, shown in Figure 5, depict that a majority of the features present an increasing trend with the deterioration of the bearing seal. In particular, the time domain and frequency domain standard deviations (δ_2, δ_{10}), the time domain rms and peak value (δ_3, δ_4), the 3rd and 4th order moments in the frequency domain, $(\delta_{11}, \delta_{12})$,and the ratio of spectral spread of skewness (δ_{15}) appear to be highly sensitive to seal health variations. Although, the monotonicity in trend appears to be consistent over the mean values of the features, dimensionality reduction on the feature space did not result in similar accuracy with the SVM classifier, due to variations in the features in each time sample. Hence all the 16 features were considered to produce a high accuracy (>99%).

In this work, 60% of the data was used to train the SVM and 40% (480 cases) were utilized to test the SVM classifier. The training was performed using 'hold out' validation with randomized split and is repeated several times to ensure consistent accuracy. The box constraint for the SVM was set at 1. The training time for the SVM classifier was 7.6628 seconds, and the classification time of the trained classifier per case was 2.27E-4 seconds while the feature extraction per case as described in Section 2.3 was about 0.8 seconds. These metrics indicate that the trained classifier is suitable for rapid detection and classification of the seal condition. All the calculations were performed on an Intel Xeon X5660 CPU with 12 GB of ram.

The results from the classification are presented in the form of a confusion matrix in Figure 6, along with the true positive rates (TPR). The overall accuracy on the test cases were found to be 99.2%. The worn seals were accurately classified in all the cases irrespective of the pressure conditions, while in one case the unworn seal was classified as a semi-worn and the most errors were made in the classification of the semi-worn seal with one misclassification as an unworn seal and two misclassifications as worn. Compared to the literature, in this work a very high classification accuracy was observed in classifying different seal wear conditions in the hydraulic test rig (Table 3).

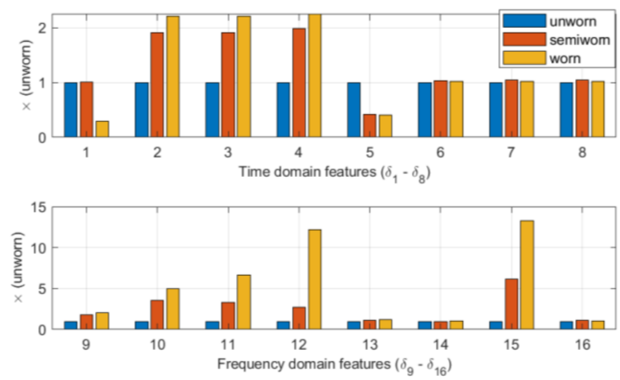

Figure 5. Variation of mean value of features depending on seal health.

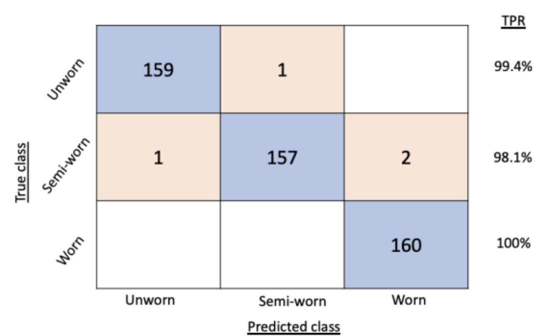

Figure 6. Confusion matrix showing test accuracy of SVM classifier.

Table 3. Comparison of classification accuracy with literature.

Literature	**Sensor**	**Technique**	**Maximum classification accuracy**
Ramachandran & Siddique, 2019	Torque	MLP-NN	92.86 %
Zhang & Chen, 2021	AE	CEEDMAN	93 %
*This paper**	AE	SVM	100 %

4. Conclusion

In this article, an automatic seal wear classification technique was proposed based on AE and SVM. Experiments were performed on a hydraulic test rig using different seal wear types and at different pressure conditions. The AE signal was processed using the bandpass filtered technique to filter out the noise due to other parts that were present in the test rig. From the bandpass filtered AE signal, a set of time domain and frequency domain features were extracted after pre-processing the signals to achieve data compression without loss of useful information. A quadratic kernel SVM classifier was trained and tested on AE data under three different seal wear conditions, and four different pressure conditions with very short time samples for rapid classification. Worn seal case was classified accurately under all the conditions, whereas accuracy of 99.4 % and 98.1 % were observed for the unworn and semi-worn cases, respectively. The high accuracy of seal wear classification using AE features and the SVM technique indicates that it can be used by the hydraulic industry for real-time monitoring of seal wear. The authors intend to further investigate automation of the peak energy band selection and data compression techniques in the future, towards development of continuous online monitoring and fault classification using AE signals.

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BIOGRAPHIES

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Dr. Vignesh. V. Shanbhag received his M. Tech in Manufacturing Engineering from Vellore Institute of Technology (VIT), India in 2015, and a joint PhD degree in Manufacturing Engineering from Deakin University (Australia) and Indian Institute of Technology, Madras (IIT-M, India) in 2019. He currently holds a Postdoc position at NORCE. His research interest includes condition monitoring of machine parts, quantification of machine tool defects using optical profilometer, and nano surface finishing of non-ferrous alloys.

Dr. Thomas. J.J. Meyer is the leader and coordinator of SFI mechatronics projects (Work package 5). Meyer holds a technical university of diploma of physical and chemical measurement technologies from the University of Bordeaux (FRA), a BSc in instrumentation system from Sheffield Hallam University (UK), and a M.Phil. & PhD in physics from Southampton University (UK). His primary research interest and recent industrial project work at NORCE focuses on the oil and gas industry with topics related to condition-based maintenance, conception of experimental rigs and development of harsh environment proof instrumentation.

Dr. Leo. W. Caspers got his MSc. in mechanical engineering at Eindhoven University of Technology in 1991. In 1995, he received his PhD in Engineering Sciences at the same institute. He is currently development manager at Bosch Rexroth B.V., focusing on the development of tribological systems, piston rod coatings and sensor systems for large hydraulic cylinders.

Dr. Nadia. S. Noori is a senior scientist at NORCE Norwegian Research Center, she is a Marie Skłodowska-Curie alumnus and holds a PhD in Electronics and Information Engineering from LaSalle-Ramon Lull University in Spain. She received her MSc in Computer and Control Systems from Baghdad University in 2002, in addition to engineering education, she holds a MASc in Technology Innovation Management from Carleton University, Ottawa-Canada. Her main focus in the field of automation in industrial applications is operational safety/security of cyber-physical systems, complex systems analysis.

Dr. Rune Schlanbusch received his MSc in Space Technology from Narvik University College (NOR) in 2007, and a PhD in Engineering Cybernetics from the Norwegian University of Science and Technology (NTNU) in 2012. He currently holds positions as Senior Researcher at NORCE and CTO at Machine Prognostics AS. His research interests include condition monitoring, condition-based maintenance, autonomy, nonlinear stability analysis and control design, rigid body dynamics and Multiphysics modelling and simulation.