Data Driven Seal Wear Classifications using Acoustic Emissions and Artificial Neural Networks

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ABSTRACT

The work presented in this paper is built on a series of experiments aiming to develop a data-driven and automated method for seal diagnostics using Acoustic Emission (AE) features. Seals in machineries operate in harsh conditions, and 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 this study, we implemented a data-driven diagnostics approach which utilizes AE measurements along with light weight Artificial Neural Networks (ANN) as a classifier to investigate the performance and resources (hardware & software) required for implementing a real-time soft sensor unit for monitoring seal wear condition. We used a feedforward multilayer perceptron ANN (Scaled Conjugate Gradient- SCG algorithm) that is trained with the back propagation algorithm, which is a popular network architecture for a multitude of applications (automotive, oil and gas, electronics). We benchmark the developed method against previous work conducted based on Support Vector Machine (SVM), and we compare ANN performance in classifying the running condition of seals in hydraulic cylinders by applying it to both raw (full frequency spectrum) and down sampled frequency measurements. The experiments were performed at varying pressure conditions on a hydraulic test rig that can simulate fluid leakage conditions like that of hydraulic cylinders. The test cases were generated with seals of three different conditions (unworn, semi-worn, worn). From the AE spectrum, the frequency bands were identified with peak power and by heterodyning the signal. This technique results in 10X down sampling 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 general set of 16 time and frequency domain features were designed. Then a training set was developed using relevant set of features (4, 5, and 16 features). The data was used to train the ANN (70% training – 30% test & validation) and SVM (60 % training - 40% test and validation). Classification of down sampled measurements, both ANN and SVM were able to accurately classify the status irrespective of the pressure conditions, with an accuracy of ~99% with execution time less than seconds. Therefore, the proposed approach can be applied as part of an automated seal wear classification technique based on AE and ANN/SVM and can be used for real-time monitoring of seal wear in hydraulic cylinders.

Keywords: Hydraulic cylinder, Piston rod seals, Fluid leakage, Acoustic emission, Artificial neural networks.

1. INTRODUCTION

Hydraulic cylinders are linear actuators that are used in a wide variety of material handling applications because they provide high pressure and stable speed rate with low energy consumption (Totten 2011). Stability and efficiency of hydraulic cylinders can be affected due to fluid leakage. Fluid leakage in hydraulic cylinders is mainly due to seal wear, and can affect pressure response, stick-slick of the piston which can further reduce designed efficiency of hydraulic cylinders (Li et al. 2018). Therefore, a maintenance strategy that can identify the seal wear in hydraulic cylinder at initial stages is required. Compared to the reactive and preventive maintenance strategies, condition-based maintenance considers the current health of the system before proposing the maintenance action. Therefore, in this study we propose a condition-based maintenance strategy that can identify the seal wear and classify the seal wear severity in hydraulic cylinders.

In recent times, attempts have been made to develop robust condition monitoring techniques to monitor seal wear using pressure, vibration, torque, and acoustic emission (AE). For example, (Goharrizi and Sepehri 2011), and (Zhao et al. 2015), monitored the fluid leakage in hydraulic cylinder using pressure sensor and wavelet analysis. (Goharrizi and Sepehri 2011), proposed the root mean square (RMS) feature extracted from level two coefficient to monitor internal leakage and RMS feature extracted from level four coefficient to monitor external leakage, respectively. (Zhao et al. 2015), observed that, displacement signal of the piston rod in hydraulic cylinders was observed to be more sensitive in monitoring hydraulic fluid leakage when compared to pressure signal. In the other work, (Goharrizi and Sepehri 2012), monitored fluid leakage in hydraulic cylinders using pressure sensor and the Hilbert Huang Transform (HHT) technique. The instantaneous magnitude of the first intrinsic mode function (IMF) was proposed as a feature to monitor internal fluid leakage rate. (Petersen et al. 2000) used vibration sensor to monitor seal wear in hydraulic cylinders. The vibration energy (dBVrms) feature was proposed to monitor changes in loading condition and seal wear condition. With increasing loading condition, dBVrms increased, whereas with increasing seal wear condition, dBVrms reduced. (Ramachandran and Siddique 2018) monitored aging of rotary seals using friction torque sensor. Time domain features were extracted from the torque sensor to monitor the seal ageing condition. Features such as mean, RMS, peak and square mean rooted absolute amplitude (SRA) decreased with increase in seal ageing, whereas features such as impulse factor, crest factor and margin factor increased with seal ageing. (Chen, Chua, and Lim 2007), and (Shanbhag et al. 2020) proposed the use of AE to monitor seal wear. (Chen, Chua, and Lim 2007), observed a linear relationship between the RMS feature and the internal fluid leakage rate. Whereas (Shanbhag et al. 2020), proposed the band power and power spectral density (PSD) features to identify fluid leakage due to semi-worn and worn seals. From literature, it can be noted that robust signal-based features have been proposed for seal wear diagnostics.

In recent times, studies have been conducted to diagnose the seal wear condition and classify seal wear severity using signal-based features and data classification or machine learning techniques. For example, (Tang, Wu, and Ma 2010) used wavelet transform with back propagation neural network (BPNN) to analyse the pressure signal and classify different internal leakage severity levels in hydraulic cylinders. Using this method, the authors classified non-leakage, mild leakage, and severe leakage. (Ramachandran and Siddique 2019) used time domain features from the torque signal as an input to the multi-layered perceptron neural network (MLP-NN). Using this technique, an accuracy of 92.86% was achieved in classifying seal wear. In the other work, (Ramachandran, Keegan, and Siddique 2019), used features from force signal such as maximum force during compression cycle and maximum tension force during the tension cycle to monitor seal degradation. The features from the force signal were used as inputs to the hybrid particle swarm optimization-support vector machine (PSO-SVM) model in classifying seal wear. (Zhang and Chen 2021), proposed AE and the complete ensembled empirical model decomposition (CEEDMAN) technique in classifying different leakage severities such as small, medium, and severe leakage. Using the proposed technique, an accuracy of 93% was observed in classifying different leakage severities. (Kandukuri et al. 2021) used AE and the support vector machine (SVM) for classifying unworn, semi-worn and worn seals. The proposed technique was able to classify the seal wear with an accuracy up to 99%.

From literature we can note that, several attempts have been made to propose diagnostics with machine learning techniques. However, few attempts have been made in studying seal wear classification using artificial neural network (ANN) with AE features as input. Therefore, in this paper, we propose a new methodology in classifying seal wear using AE features and ANN, and we compare the performance of the developed technique with that of the SVM technique. In this paper, the AE data obtained from the tests conducted by (Shanbhag et al. 2021) is used to train, test and validate the ANN model.

2. METHODOLOGY

2.1. Experimental details

The experiments to study seal wear were conducted on a custom-built hydraulic test rig (see Figure 1-a)), that consists of an electro-mechanical cylinder and a hydraulic cylinder head. The hydraulic test rig closely replicates the piston rod and seal interactions, and fluid leakage like that of a hydraulic cylinder. The extension and retraction movement of the piston rod in test rig are driven by a spindle and a nut, that converts rotary motion to translatory motion. A schematic view of the cylinder head (pressurized flange) is shown in Figure 1-b). It consists of three bearing strips to withstand any arising side loads (not present in this study), and piston rod seals acts as fluid sealings. The fluid pressure in the test rig is controlled using pressure relief valves and the pressurized fluid for the cylinder head is supplied through a hydraulic power unit (HPU). A servomotor encoder is used to control the piston rod movement and also record the number of times the piston moves through the cylinder head. At both ends of the extension and retraction strokes there is a dwell time of one second (Stroke length: 600 mm). For the seal wear classification study, only the piston rod seal at the top of the cylinder head (See Figure 1-b)) was replaced with unworn, semi-worn and worn seals (seal material: Polyether-based polyurethane elastomer). Although seal wear in itself is a continuous process, we choose to investigate the detection capability at specific state of wear. The reason is that the detection process should ideally be economical (computationally cheap) to be realized across multiple units in the industry. It may not be feasible to continuously monitor the signals, only periodic monitoring using AE can classify the seal state and that itself serves as valuable information for maintenance. The unworn seal had no scratches, the semi-worn seal had minor scratches and the worn seal had major scratches on their surfaces (See Figure 2 a)-c)). Fluid leakage was observed when semi-worn and worn piston rod seals were used in the cylinder head (See Figure 2 d)-e), Fluid type used in test rig: Water glycol. Throughout the experimental study, speed was kept constant at 100 mm/s, and each experiment was conducted for five strokes. For each seal condition experiments were conducted at four pressure conductions: 10, 20, 30, and 40 bar.

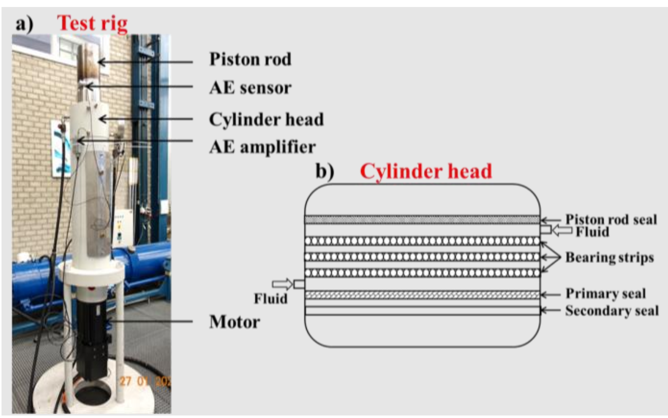

Figure 1. a) Hydraulic test rig, b) Schematic view (view) of cylinder head showing arrangement of piston rod seal and bearing strips.

2.2. AE data acquisition details and bandpass filtering

The AE sensor was mounted on the piston rod for all the experiments as shown in Figure 2-a), as the piston rod is in direct contact with the piston rod seal. The type of AE sensor used in this study was a mid-frequency sensor with resonant frequency at 150 kHz and frequency range of 50-400 kHz. The AE sensor was mounted on the piston rod using an adhesive glue and industrial duct tape to secure a good signal path. The AE sensor was connected to an external pre-amplifier with a gain of 40 dB, and the pre-amplifier was further connected to data acquisition system using co-axial cable. For all the experiments the AE data acquisition was performed at 1 MS/s. In the previous work conducted by (Shanbhag et al. 2021) the AE frequency range that originates from the piston rod seal was observed to be in the frequency range of 50-100 kHz. Therefore, to filter out the frequency range of other parts that are present in the test rig (e.g., spindle, piston rod and bearing strips), heterodyne process was used prior to calculating time and frequency domain features. In the heterodyne process the fast Fourier transform (FFT) of the signal is calculated and the frequency band of interest (50-100 kHz) is shifted to the origin and remainder of the signal amplitudes in the frequency domain are set to zero (Bechhoefer 2018). A new FFT is calculated, that contains the frequency of interest, but the spectrum is downshifted to 0-50 kHz. Later, the inverse FFT is calculated, and the new signal is down sampled to a new sample rate of 100 kHz, without compromising the information of interest. This technique resulted in reduction of file size by approximately 70%. This reduction in data volume while keeping the frequency content of interest is of significant practical use in monitoring multiple actuators in industrial implementation. The resultant signal is further split into short-time windows as low as 0.28s. From the short time window signals, the time domain and frequency domain features are calculated (Table 1). The implemented technique is beneficial for further research to implement during online monitoring and to perform condition monitoring of parts. Figure 3 represents the methodology adopted for signal processing.

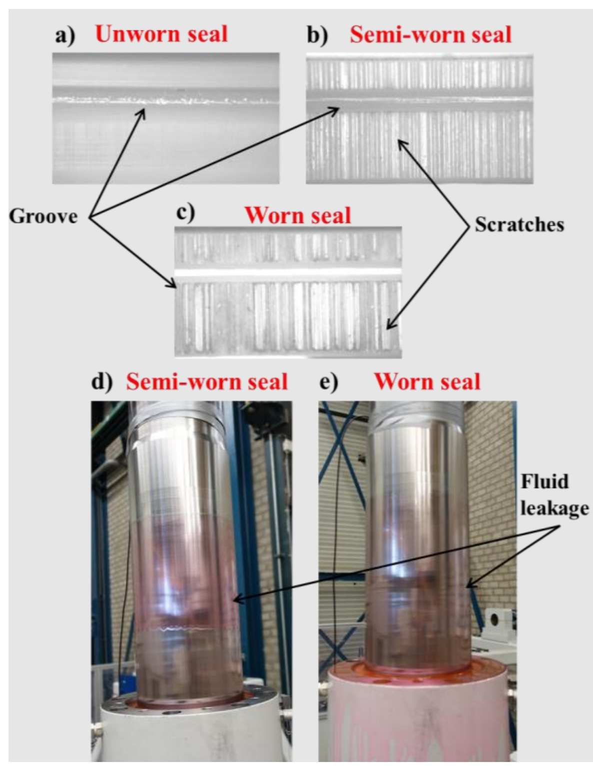

Figure 2. Microscopic camera images of piston rod seals: a) unworn, b) semi-worn, c) worn; fluid leakage on piston rod when d) semi-worn, e) worn piston rod seals were used. (Note: Instrument used take closeup image of a)-c)): Jenoptik ProgRes SpeedXT Core 3 CCD Microscope Camera, Pixel size: 3.45 µ.m X 3.45 µ.m).

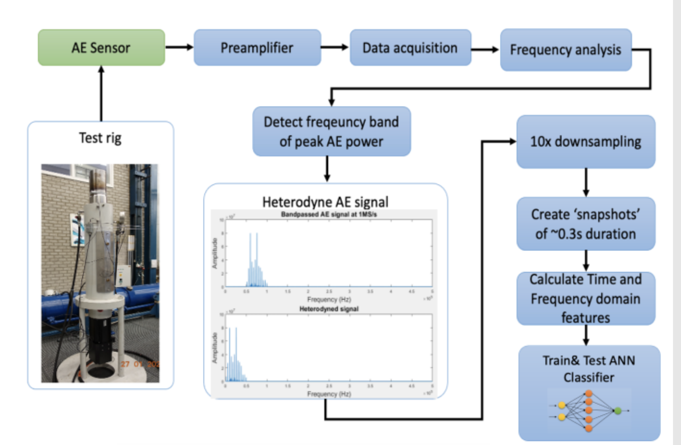

Figure 3. AE signal processing procedure.

Table 1.Time and frequency domain features calculated on AE signal snapshot. (Kandukuri et al. 2021).

Time domain	Frequency domain
$\delta_1 = \sum_{n=1}^{N} \frac{x(n)}{N}$	$\delta_9 = \sum_{k=1}^{K} \frac{s(k)}{K}$
$\delta_2 = \sqrt{\sum_{n=1}^{N} \frac{(x_n - f_1)^2}{N}}$	$\delta_{10} = \sum_{k=1}^{K} \frac{(s(k) - \delta_9)^2}{K}$
$\delta_3 = \sqrt{\sum_{n=1}^{N} \frac{x(n)^2}{N}}$	$\delta_{11} = \sum_{k=1}^{K} \frac{(s(k) - \delta_9)^3}{K}$
$\delta_4 = \max(\lvert x(n) \rvert)$	$\delta_{12} = \sum_{k=1}^{K} \frac{(s(k) - \delta_9)^4}{K}$
$\delta_5 = \frac{\sum_{n=1}^{N}(x(n) - \delta_1)^3}{\delta_2^3 (N-1)}$	$\delta_{13} = \frac{\sum_{k=1}^{K} k s(k)}{\sum_{k=1}^{K} s(k)}$
$\delta_6 = \frac{\sum_{n=1}^{N}(x(n) - \delta_1)^4}{\delta_2^4 (N-1)}$	$\delta_{14} = \sqrt{\frac{\sum_{k=1}^{K}(k - \delta_{13})^2}{K}}$
$\delta_7 = \frac{\delta_4}{\delta_3}$	$\delta_{15} = \frac{\sum_{k=1}^{K}(k - \delta_{13})^3 s(k)}{K \delta_{14}^3}$
$\delta_8 = \frac{\delta_4}{\frac{1}{N}\sum_{n=1}^{N}\sqrt{\lvert x(n) \rvert^2}}$	$\delta_{16} = \frac{\sum_{k=1}^{K}(k - \delta_{13})^4 s(k)}{K \delta_{14}^4}$
Where $x(n)$ is the signal time series, $n = 1,2, \dots N$.	Where $s(k)$ is the frequency spectrum, $k = 1,2, \dots K$.

2.3. Artificial Neural Networks (ANN)

The artificial neural networks computing technique is inspired by biological neuron processing. ANN models have been widely applied in various fields of science and technology involving time series forecasting, pattern recognition and process control (Zhang 2003) and (Manoonpong, Pasemann, and Roth 2007). There are multitudes of network types available for ANN applications and its choice depends on the nature of the problem and data availability (Dobrzycki, Mikulski, and Opydo 2019). Machine learning methods such as support vector machines (SVM) and ANN or Convolutional NN were used to analyse AE measurements in the domain of structural health monitoring related to wear and tear of equipment (Deshpande, Pandiyan, Meylan, & Wasmer, 2021; Zhao, 2021; Sikdar, Liu, & Kundu, 2022) . As the work in this paper is an extension to the research done by (Kandukuri et al. 2021) and (Noori et al. 2020) for addressing the need for reliable and accurate non-intrusive measurements for seal condition. The methods presented here may be used in many sectors satisfying all these requirements, yet some changes in these expected features may be seen in the practices of different seals, and changes might be necessary to adapt the current proposed method.

In this research, a feedforward multilayer perceptron ANN was utilized, that was trained with the backpropagation algorithm. In this type of network, the artificial neurons, or processing units, are arranged in a layered configuration containing an input layer, usually one "hidden" layer, and an output layer. Units in the input layer introduce normalized or filtered values of each input into the network. Units in the hidden and output layers are connected to all the units in the preceding layer. Each connection carries a weight factor. The weighted sum of all inputs to a processing unit is calculated and compared to a threshold value. Then activation signal is then passed through a mathematical transfer function to create an output signal, that is further sent to the processing units in the next layer. In this study, we used MATLAB – neural net fitting tool (NFTOOL) to carry out the data analysis and generating the ANN models (see Figure 4). The toolbox offers three options of shallow neural networks: Levenberg-Marquardt, Bayesian regularization, and Scaled Conjugate Gradient backpropagation. Due to the large size of the dataset, we used the Scaled Conjugate Gradient backpropagation algorithm (Møller, 1993). As it is also recommended in the NFTOOL documentation: "Scaled conjugate gradient backpropagation updates weight and bias values according to the scaled conjugate gradient method. For large problems, scaled conjugate gradient is recommended as it uses gradient calculations which are more memory efficient than the Jacobian calculations used by Levenberg-Marquardt or Bayesian regularization."[1]. The SCG - ANN architecture used consists of one hidden layer with five or 10 neurons.

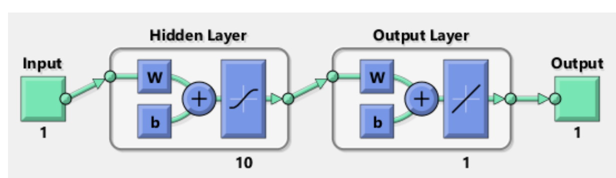

Figure 4. ANN Architecture using MATLAB NFTOOL.

[1] Neural Net Fitting, MathWorks documentation, https://se.mathworks.com/help/deeplearning/ref/neuralnetfitting-app.html

2.4. ANN model training and evaluation

In this study, we prepared three datasets to carry out the analysis and compare the inputs and SCG ANN models that would generate optimal results. The first dataset represents *filtered raw data* time series with 4096 X 63250 points of measurements. Second dataset represents *features filtered* time series with 13 X 63250 points of measurements. The third dataset represents *features filtered downsized* with 16 X 1200 points of measurements. The datasets were used for training, validating, and testing three ANN models created using the NFTOOL (See Figure 4) and used Scaled Conjugate Gradient algorithm to carry out the tests. Data from the AE sensor measurement, i.e., filtered frequency bands (4096 inputs), features filtered (raw 13 inputs or downsized 16 inputs) were used as input vector for the model. As for the output vector, the seal condition vector for every measurement was constructed manually to describe three operational conditions: worn (1), semi-worn (2) and unworn (3) (See Figure **5** for example of signal signature of the three seal conditions. The seal condition vector was set as the target vector for all the SCG ANN models' training. The dataset samples were divided into three sets used for training (70%), validation (15%) and testing (15%).

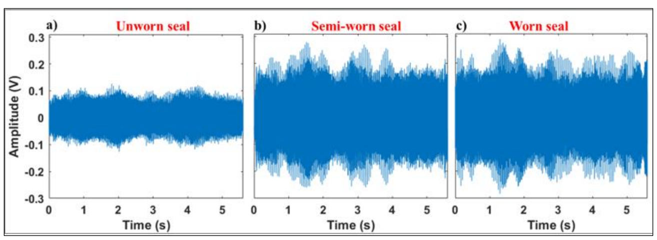

Figure 5. Signal signature samples for the seal conditions: unworn (3), semi-worn (2), and worn (1).

3. Result and discussion

The results for the analysis showed variation in classification accuracy when using different variable types or different number of variables as input to the ANN models. In addition, to implementing changes to the input vector of neural network model, we also implemented changes in the number of neurons to reach optimal results. The results for the different combinations of datasets and neural network models are listed in Table 2. Figure 6 shows the confusion matrix results for the used cases listed in Table 2. In Figure 7, we provide details related to the setup of the ANN model used in case #5, the ANN option used is SCG backpropagation options in NFTOOLS for the experiments. The NFTOOL provided us with different key performance indicators to learn about the model performance in relation to the classification accuracy, needed time for training, and other information, that would help understanding the model behaviour too. In Figure **7**, it shows the number of training epochs was 128 with ~0 second time for the training. The network used has 16 inputs, a hidden layer with 5 nodes and three outputs. Worth to mention, the time for training the SCG model in Case #1 using the raw data with 4046 inputs, was 3 minutes and 37 seconds with 110 epochs to finish the training. The training time using the downsized data, was ~0 sec for all cases.

We can observe from the results that using the ANN solution to classify condition of the seal is possible with a high accuracy rate, using all features (i.e., case #1, case #3, case #5) for filtered and downsized data. Furthermore, we can observe that in the case of using a subset (i.e., case #2, case #4, case #6) of the features from the downsized dataset, the ANN model was able to provide a high accuracy seal condition classification result. The experiments related to model tuning, we tried different options related to the number of inputs (4069, 13, 4, 5, 10), and number of hidden nodes (5 or 10 nodes). When used, there was no great improvement in the classification results. As for the number of inputs for the network, we experimented with different combinations of input features (i.e., raw data 4069, all 16 features, sub-set of features 5 features) to examine the impact of number of features' selection on the improvement of the classification results. As the results showed, that using part of the features set can yield good results. However, we have not experimented with different combinations to find the most representative set of features that can be used instead of the whole dataset, to optimize the solution further.

Furthermore, the shallow ANN is a lightweight neural network architecture, providing us with the ability to use the full dataset for the filtered data before (i.e., case #1 and case #2) and after downsizing, with a classification accuracy rate varying between 0.8-0.99. For training the ANN, a normal laptop was used (8 GB RAM, Intel Core i5 CPU, no GPU) , and the training times were approximately 0 seconds, except in the raw data Case #1. Thus, from automation and deployment of the method, shallow ANN is promising as it does not require specialized equipment to train the network and to later deploy it.

However, we can see, when we reduce the number of chosen features to five, and only use five neurons for the hidden layer in SCG-ANN model (using the options offered in NFTOOL setup wizard), the classification accuracy is impacted drastically, as the accuracy was reduced to 0.692. However, with 16 features, the network with five neurons provided the best accuracy classification results.

Hence to compare the developed method against previous work conducted using Support Vector Machine (SVM) (Kandukuri et al,2021), the ANN performance in classifying the seal condition by analysing both raw (full frequency spectrum) and down sampled frequency measurements were considered. The SVM results showed that worn seal condition 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. Compared to the test cases experiments in this paper, it can be observed that best case is Case #5, with overall classification accuracy of 99.3, and classification accuracy rate of 99.9% for unworn, 100% for semi-worn, and 98.8% for worn. As mentioned in section 1, Zhang and Chen (2021), proposed AE and the complete ensembled empirical model decomposition (CEEDMAN) technique in classifying different leakage severities such as small, medium, and severe leakage. However, the proposed technique, provided an accuracy of 93% in classifying different leakage severities.

In general, the classification of down sampled measurements, both ANN and SVM were able to accurately classify the status irrespective of the pressure conditions, with an accuracy of ~99% - 100% with execution time less than seconds. Therefore, the proposed approach can be applied as part of an automated seal wear classification technique based on AE and ANN/SVM and can be used for real-time monitoring of seal wear in hydraulic cylinders.

The Shallow ANN advantage over the SVM approach that was followed in our previous study (Kandukuri et al. 2021) is the flexibility in configuring the ANN rapidly to improve classification accuracy results, with less required resources.

Table 2. Summary of the results for classifying the seal condition using AE sensor data, full samples and downsized.

Case #	Input and # of neurons	Accuracy
#1	• Filtered data – time series – 4096 X 63250 • Using 4096 inputs • Network size (10 hidden, 3 output)	0.81
#2	• Features filtered – 13 X 63250 • Using 4 features, namely (δ_6, δ_{10}, δ_{11}, and δ_{12}) / 4 inputs • Network size (10 hidden, 3 output)	0.867
#3	• Features filtered downsized – 16 X 1200 • Using all time and frequency domains 16 features / 16 input • Network size (10 hidden, 3 output)	0.856
#4	• Features filtered downsized – 16 X 1200 • Using 5 features, namely (δ_5, δ_6, δ_{12}, δ_{14}, and δ_{15})/ 5 input. • Network size (10 hidden, 3 output)	0.802
#5	• Features filtered downsized – 16 X 1200 • Using 16 features/16 inputs • Network size (5 hidden, 3 output)	0.993
#6	• Features filtered downsized – 16 X 1200 • Using only 5 features/5 inputs, namely, (δ_5, δ_6, δ_{12}, δ_{14}, and δ_{15}) • Network size (5 hidden, 3 output)	0.62

Figure 6. Confusion matrices for the results presented in Table 3. Seal condition codes: unworn (3), semi-worn (2), and worn (1).

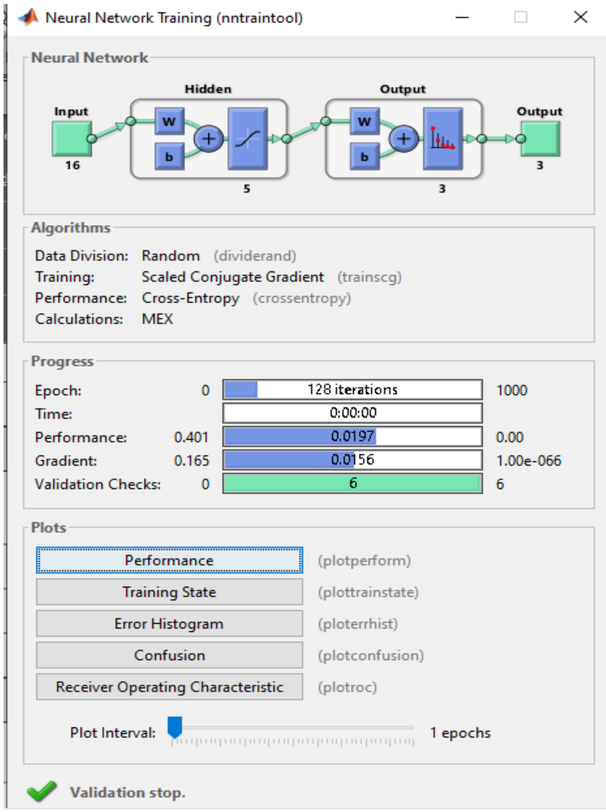

Figure 7. Details of ANN training and ANN architecture for case #5.

4. Summary

In this work we have presented an approach to apply a data-driven solution in combination with using shallow ANN to analyse AE sensor data. The goal was to classify accurately and in real-time the seal condition in a hydraulic cylinder to detect possible leakage. The work was based on a series of experiments carried out on customized test rig, in combination with a data pre-processing pipeline to reduce the size and the variable dimensions of the collected data, then applying machine learning methods for the analysis. In this part we successfully applied an ANN and reached high score of classification accuracy with negligent time for processing input variables with different variants (i.e., raw data to downsized flirted data). The resulted ANN models are easy to deploy and implement as a soft sensor on an edge device such as a Raspberry PI or Jetson Nano, attached to the monitored unit. The advantage is that data will be processed locally and only useful information about the seal condition will be transmitted over wireless or wired connection to the main or respective control system.

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