B. TECH. PROJECT REPORT

On

Condition Monitoring of Hydraulic Direction Control Valve

BY

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DISCIPLINE OF MECHANICAL ENGINEERING

INDIAN INSTITUTE OF TECHNOLOGY INDORE

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Condition Monitoring of Hydraulic Direction Control Valve

A PROJECT REPORT

Submitted in partial fulfilment of the

Requirements for the award of the degree

of

BACHELOR OF TECHNOLOGY

in

MECHANICAL ENGINEERING

Submitted By:

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Guided By:

Dr. Pavan Kumar Kankar

INDIAN INSTITUTE OF TECHNOLOGY INDORE

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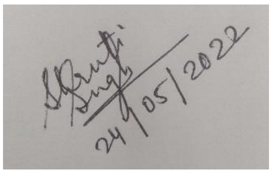
CANDIDATE’S DECLARATION

I hereby declare that the project entitled “Condition Monitoring of Hydraulic Direction Control Valve” submitted in partial fulfillment for the award of the degree of Bachelor of Technology in ‘Mechanical Engineering’ completed under the supervision of Dr. Pavan Kumar Kankar (Associate Professor), IIT Indore is an authentic work.

Further, we declare that we have not submitted this work for the award of any other degree elsewhere.



Shruti Singh

CERTIFICATE by BTP Guide

It is certified that the above statement made by the students is correct to the best of my knowledge.

Dr. Pavan Kumar Kankar

Associate Professor, Discipline of Mechanical Engineering

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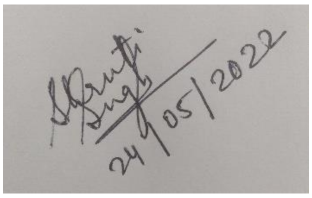
Preface

This report on “Condition Monitoring of Hydraulic Direction Control Valve" is prepared under the guidance of Dr. Pavan Kumar Kankar.

Through this report, I have developed and compared two models based on Machine Learning and Deep Learning technologies for fault detection in hydraulic 2-way direction control valve.

I have tried to the best of my abilities and knowledge to explain the content in a lucid manner. I have also added figures and experimental data to make it more illustrative.



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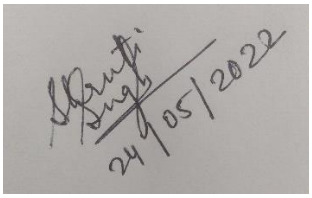
I wish to thank Dr. Pavan Kumar Kankar for his supervision and valuable guidance throughout this project. His constructive criticism and motivation pushed me to give my best to elaborately analyse the subject and bring novelty in this project. Also, I am very thankful to Dr. Ankur Miglani for his constant support and suggestions during the course of project. I would also like to thank Jatin Prakash (PhD student) for guiding me through every step of the way. It is their help and support, due to which I have been able to have a detailed study of switching behavior in hydraulic valve and develop models to predict its faulty conditions.

Lastly, I thank all faculty members and batchmates of Mechanical Engineering Department for without their support, this report would not have been possible.



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Abstract

In hydraulic systems, directional valves are responsible for regulating the flow of the fluid. Solenoid operated valves do so by mechanical movement of spool inside valve by the virtue of electromagnetic force generated by the applied control current. The deterioration in control current leads to the degradation in electromagnetic force and thus the spool takes longer to initiate as well as terminate the switching position. This delay or lag potentially causes the pressure, flow and power fluctuation and unintended impacts on the system. This project presents a comparative analysis of detecting these anomalies by acquiring pressure signals across the valve using extreme gradient boost (XGBoost) and 1-Dimensional Convolution Neural Network (CNN). Four handcrafted statistical features and four fractal dimensions train XGBoost whereas 1-D CNN with six hidden layers utilizes the raw signal of net pressure change across the valve. XGBoost predicts the switching behaviour at an accuracy of 99.68% and 1-D CNN performs at its maximum possible accuracy (100%). The very narrow gap signifies the nearly equal significance of both of these different category classifiers. As XGBoost cannot handle the raw signals, the pre-processing increases the time-consumption while 1-D CNN using its deep architecture efficiently maps the complexity of the hydraulic system using pressure signals and is robust to noisy data.

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1. Introduction

1.1 Introduction to Direction Control Valves

Nowadays, hydraulic systems are used in various industrial and mobile applications like manufacturing, robotics, heavy machinery, etc. The increase in the demand for high-end performing machineries, noise-resistant operation has led to the deployment of complex systems at the industrial scale. Hydraulic systems offer these characteristics and also provide a flexible routing as fluids are flexible to flow. Additionally, the incompressibility of the fluid makes these systems highly efficient with a negligible or very low power loss during the operation. A basic hydraulic system must consist of an electrical motor to run the pump which creates the flow in the system. The direction of the flow gets controlled, regulated and routed by valves. Valves do so by switching the position of the spools inside it. This switching in position is achieved either by mechanical or electrical excitation. Most of the hydraulic systems employ the electrically excited hydraulic valves for regulating the flow of the fluid being more precise and quicker than the mechanical excitation. These valves are often referred as servo-actuated valves or solenoid valves. Depending on the types of valves, they may be further pronounced as servo-operated direction control valve, proportional relief valve etc. Direction control (DC) valves are more generally used for reliable flow management of the hydraulic fluid. They achieve their desired functionality by switching the spool position and connecting different ports.

1.2 Motivation Behind Project

Any deviation from the optimal switching condition either due to delay or incomplete movement of the spool in DC valve may trigger undesirable flow and pressure fluctuations in the system. It affects the speed, direction, and acceleration of the actuator, which may induce fatigue in system components resulting in degraded power transmission ability of the system. Also, discrepancies in the fluid flow such as uneven or discontinuous flow leads to several impacts like an unexpected jolt in the actuator movement. To ensure system reliability and reduce maintenance downtime, it is imperative to monitor hydraulic DC valve switching condition.

Also, for fault detection in real time, data collected from industrial sensors can have noise because of the external environment interferences or impaired sensor configurations. This demands a requirement of a model that is robust in handling noisy data. One of the aims of this project is to propose a method that can be easily applied for remote condition monitoring of hydraulic components.

1.3 Organization of Report

This thesis report is organized as following: Chapter 2 details the literature review on works done previously on hydraulic valves and recent advanced artificial intelligence technologies being applied in predictive maintenance of mechanical systems. The experimental setup of hydraulic circuit is mentioned in Chapter 3. Chapter 4 describes the acquisition of pressure signals and switching characteristic pressure fluctuations for distinct switching conditions (optimal and faulty) of DC valve. Chapter 5 describes the monitoring of switching behaviour using XGBoost. Initially, it explains four statistical features followed by four fractal dimensions. The tuned hyperparameters using random search method for training XGBoost are also listed in this section. The next chapter discusses the adopted architecture of the 1D CNN layers used for prediction of the switching behaviour of the DC valve. The overall methodology adopted in the project is briefed in Chapter 7. Comparative results for XGBoost and 1D CNN with previously developed models are shown in Chapter 8. Chapter 9 marks the final step of the project i.e., deployment of the model. Chapter 10 concludes the report by listing the key findings of the study.

1.4 Flowchart of Adopted Methodology

The methodology adapted in this project is shown in Fig. 1.

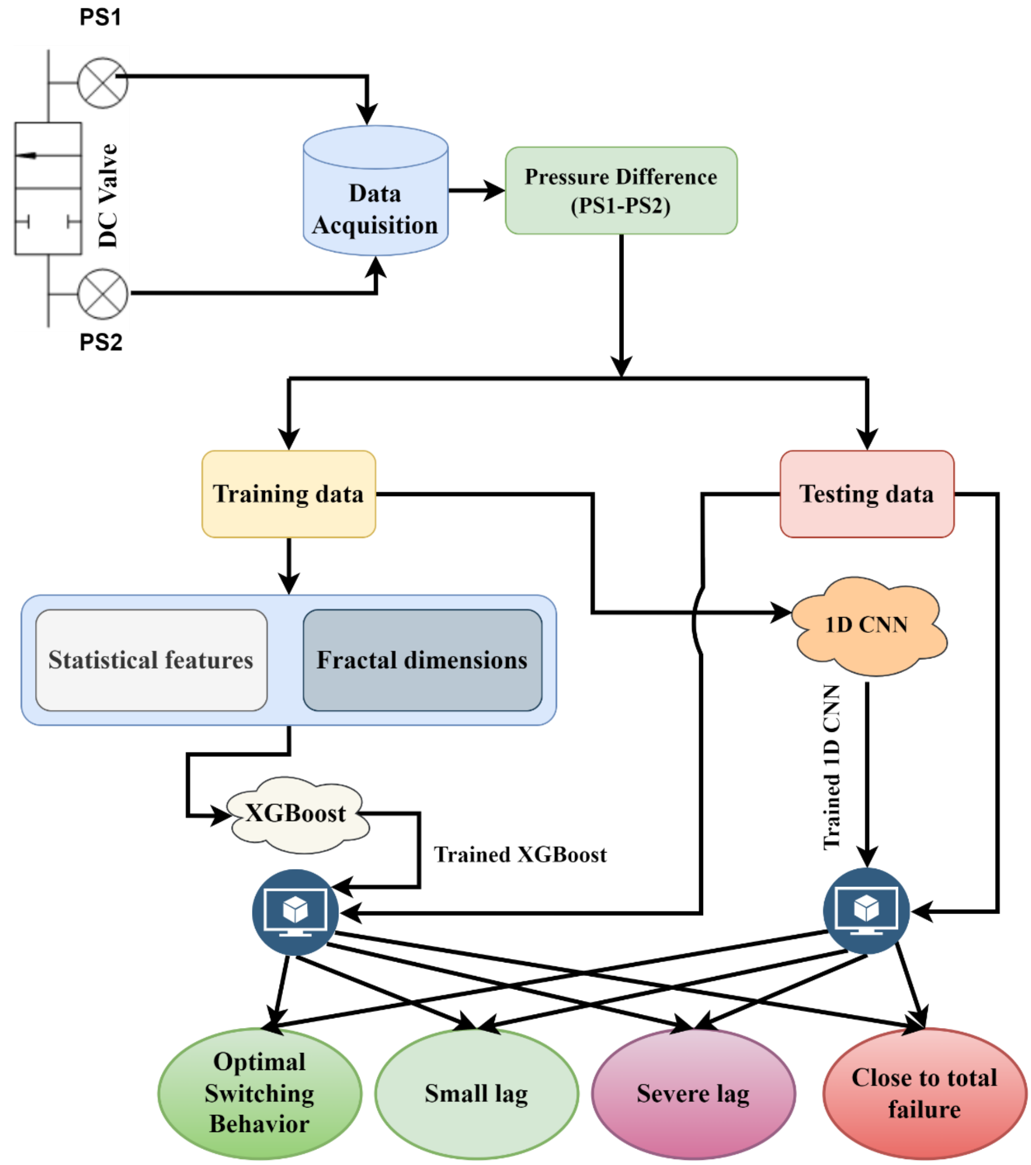


Fig. 1 Methodology adopted to determine the switching characteristic of the valve

2. Literature Review

2.1 Monitoring of Hydraulic Valves

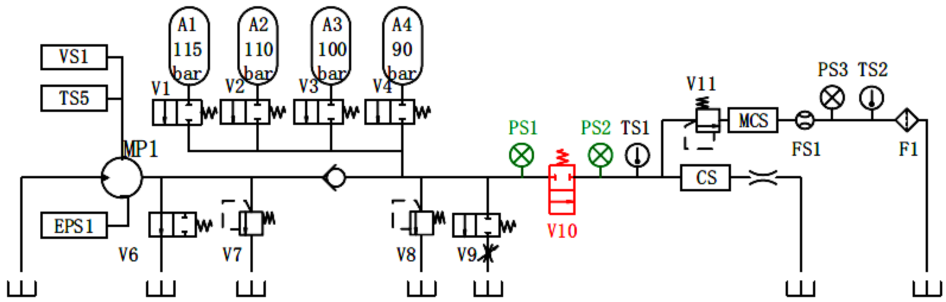
The monitoring methodologies for the mechanical and electrical systems broadly classifies as either model-based fault diagnosis [1] or data-driven fault diagnosis [2]. To date, various attempts have been made to study the static and dynamic characteristics of the hydraulic valves. Out of these, Maiti et al. [3] studied the steady and dynamic characteristic of a 2-stage proportional relief valve. They varied the input voltage and achieved a linear relationship between input voltage and solenoid force generated by it. Topcu et al. [4] developed a fast-switching electro-pneumatic valve with a switching time of 4.5 ms. They further reported that the switching time of the valve can be enhanced by applying an overdriving current to the solenoid coils. On the aspect of data-driven based fault detection in the switching valves, Vianna et al. [5] estimated the degradation in servo-valves by applying Fading Extended Kalman filter considering a single failure owing nozzle blockage. Folmer et al. [6] presented a data-driven approach to detect faults resulting from spool wear by comparing the standardized flow coefficients. They considered the wear and the contamination of the valve plug (spool). Cao et al. [7] developed non-dimensional artificial neural networks (NDANNs)-based model to estimate the flow force and rates at different levels of pressure drop and valve openings. This is also compared with conventional flow-field models. Lei et al. [8] implemented principal component analysis (PCA) and XGBoost to the pressure signals across a direction control valve to identify its switching faults. Literature search reveals that the valve health monitoring has been mainly demonstrated using conventional data driven approaches, and therefore, there is dearth of information on the applicability of more advanced technologies like deep learning.

2.2 Machine Learning Technologies

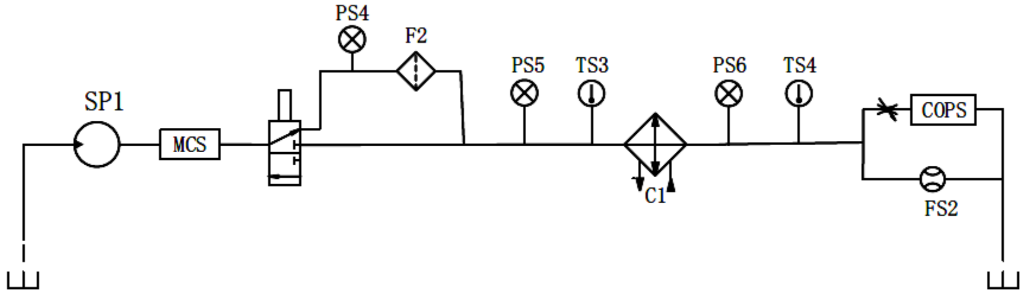
eXtreme Gradient Boosting (XGBoost) algorithm is one of the most effective ensemble classifier known for its low computational complexity, fast analysis, and high predictive metrics [9]. As evident, XGBoost is a boosted algorithm that combines weak learners sequentially to make them together a strong learner and has wide applicability in different fault detection problems. Convolution Neural Network (CNN) is one such deep learning neural network used to analyse the visual imagery dataset (2-Dimensional data) [10]. CNN eliminates the manual feature extraction of the input as convolution layers performs so by moving the kernel over the data itself. The conventional 2-D CNN can be tuned and adapted to learn features from time domain signal (1-Dimensional signal) by moving the kernels in the convolution layer in one-direction only preserving the complex learning capabilities of CNN. In literature, 1D CNN has shown state-of-the-art results in monitoring the associated system using electrocardiogram (ECG) data [11] and raw motor data [12]. Advancement in predictive maintenance and real-time decision-making is done by implementing cloud, internet of things, artificial intelligence, etc. in the context of Industry 4.0 [13].

3. Experimental Setup

The experimental dataset for pressure signals used in this project is obtained from the UC Irvine Machine Learning Repository [14]. The considered hydraulic test rig comprises of a primary working circuit (Figure 2-a) and a secondary cooling-filtration circuit (Figure 2-b) connected by a common reservoir.



(a) Hydraulic system for the primary working circuit.



(b) Hydraulic system for the secondary cooling-filtration working circuit.

Fig 2. Circuit diagram of the considered hydraulic test rig [9]

The hydraulic circuit (see Fig. 2) consists of numerous components like pump, accumulator, control valves like DC valve (V10), proportional relief valve (V11), cooler (C1). Various pressure sensors (PS) and temperature sensors (TS) are installed on the either side of the cooler to acquire the data for monitoring the hydraulic system. Data from different sensors are acquired at different sampling rate varying from 1-100Hz.

4. Data Analysis

This study focuses on the data acquired using PS1 and PS2 (shown in green colour in Fig. 2a) located at inlet and outlet of a 2-way DCV (shown in red colour in Fig. 2a) respectively, at a sampling frequency of 100 Hz for 60 seconds. Initially, the valve remains in OFF condition where pressure transducer PS1 records high pressure (~190 bar), while sensor PS2 senses zero pressure. At time t =10 seconds, when the valve spool switches to a new position and the valve opens, the upstream pressure PS1 starts reducing while the downstream pressure PS2 (see Fig-3a) increases. Fig. 3b shows the temporal variation of both the pressure signals during the switching operation for four different switching conditions namely "Optimal switching, small lag, severe lag, and close to total failure" with increasing degree of severity. Since the magnitude of the control current supplied to the solenoid actuator governs the spool movement, to simulate these fault conditions, the control current is varied at 100 %, 90 %, 80 % and 73 % of the nominal value respectively. Fig. 3c shows the temporal variation of pressure difference ($\Delta PS = PS1 - PS2$) across the valve for four different switching conditions. It is evident that the less is control current than optimal value, the larger is the delay is triggering spool movement for switching. This delay is termed as the lag in the switching of a direction control valve.

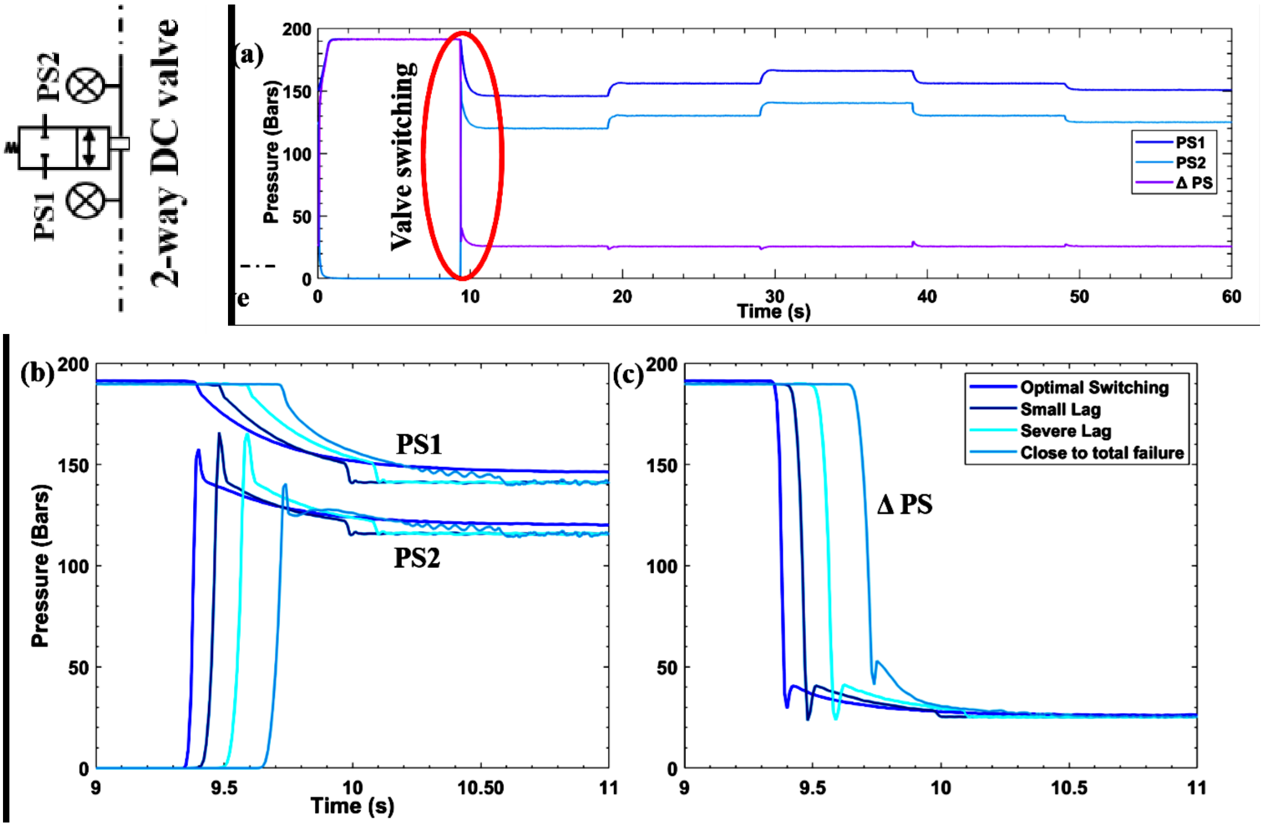


Fig 3 (a.) Pressure signals as acquired by PS1 and PS2, Zoomed view of (b.) pressure transient in PS1 and PS2, (c.) Net pressure change

At optimal switching condition, the valve starts to switch at ~9.3th second (see Fig. 3b) while under the faulty conditions, there is a noticeable delay. For instance, at the switching condition of close to total failure, switching starts at ~9.7th second due to the lower control current to the solenoid, which in turn generates lower electromagnetic force for spool movement. With a decrease in the control current while the switching delay increases, the pressure difference attains a constant, steady-state value (~25 bar after 10.5 s) irrespective of the switching condition. However, the transient pathways that lead to this steady-state value depend on the switching condition. Specifically, under optimal switching there is a gradual reduction in PS1 with no pressure fluctuations, while under small lag and severe lag conditions there are small scale fluctuations in PS1, and under close to total failure condition there are noticeable largescale fluctuations in the PS1 signal.

These fluctuations in pressure sensor data can be attributed to several factors such as contamination, silting, mechanical or operator failure. When hard particles get between the spool and its mating bore causing it to jam, the optimal amount of force required to move the spool increases. Silting, similar to contamination involves soft contamination like varnish and sludge, leading the sliding force required to bring movement in the spool to increase. Thus, the change in magnitude of the forces caused by silting and the time-to silt can be inferred as causes of impeded spool faults. Also, the small parts inside a DCV like springs, pins, washers, and detent devices are prone to breakage causing mechanical failure in valve leading it to jam or stick. A DCV uses external signal operators, common types of which are- electrical (solenoids), mechanical (levers and rods), hydraulic and pneumatic (pistons) to change spool position. So, if not the mechanical problem inside the valve, a failure in operator is likely to avert spool to slide properly which is how the dataset is acquired for this study that is to be used to troubleshoot the deteriorated operation of valves and monitor fault diagnosis.

While it is possible to detect the switching condition by capturing the trends and features with such highly time-resolved signals (a sampling rate of 100 Hz), in practice, these measurements are acquired either using simple pressure gauges or with pressure transducers at nominal sampling frequencies in the order of 10 Hz [15], which cannot capture such fluctuations. Therefore, an automated machine learning approach is required for monitoring the switching condition of valves. This is the focus of following sections 3 and 4, which demonstrate the efficacy of XGBoost and 1D-CNN for predicting the switching condition with a high accuracy.

5. Monitoring using XGBoost

This section details the methodology for predicting the switching condition of a hydraulic valve by extracting four statistical features (section 3.1) and four fractal dimensions (section 3.2) to train XGBoost.

5.1 Statistical features

Statistical features derive the information associated with the statistic and the distribution of the signal under consideration (pressure difference signals in this study), and thus are worthwhile for training a machine learning model. Section 3.1 describes the root mean square, standard deviation, skewness and kurtosis for the considered data set along with their mathematical formulas [16-18].

i. **Root Mean Square (RMS):** RMS, often is called the quadratic mean. It is calculated as the square root of the arithmetic mean of the squares of the numbers. The mathematical formula for RMS is given in Eq. 1.

$$RMS = \sqrt{\frac{1}{N}\sum_i {X_i}^2} \tag{1}$$

where, N is the number of data points in a signal $\{X_1, X_2, \dots, X_N\}$.

ii. **Standard Deviation (σ):** The standard deviation measures the dispersion of a dataset relative to its mean. It is measured as the square root of variance. If the data points are farther from the mean, there is a higher deviation within the data set. The mathematical formula for standard deviation is given in Eq. 2.

$$\sigma = \sqrt{\frac{\sum_i^N (X_i - \bar{X})^2}{N}} \tag{2}$$

where, $\bar{X}$ is the mean of series and N is the number of data points in signal $\{X_1, X_2, \dots, X_N\}$.

iii. **Skewness:** In a signal, skewness signifies the distortion or asymmetry of the data from a normal distribution. The distribution of the data can be either left or right skewed. Thus, skewness is a measure of the extent to which a given distribution differs from a normal distribution. The mathematical formula for skewness is given in Eq. 3.

$$Skewness = \frac{1}{N}\sum_{i=1}^{N}[\frac{(X_i - \bar{X})}{\sigma}]^3 \tag{3}$$

where $\bar{X}$ is the mean of series, σ is the standard deviation and N is the number of data points in signal $\{X_1, X_2, \dots, X_N\}$.

iv. **Kurtosis:** Kurtosis is measurement of how the tails of a distribution varies from the tails of a normal distribution. It can also be described as an identification of whether the tails of a given distribution contain extreme values. The mathematical formula for kurtosis is given in Eq. 4.

$$Kurtosis = \frac{1}{N}\sum_{i=1}^{N}[\frac{(X_i-\bar{X})}{\sigma}]^4 \quad (4)$$

where $\bar{X}$ is the mean of series, σ is the standard deviation and N is the number of measurements $\{X_1, X_2, \dots, X_N\}$.

5.2 Fractal Dimensions

The term 'fractal dimension' is a measure to figure out the complexity of a system using the measured or acquired data. It is a non-integer value and is used as a measure of nonlinearity in time-series data. This indication can be useful in analyzing non-stationary and non-periodic signal data for better diagnosis performance [19]. It is viable that the pressure signals acquired across the valve does neither exhibit periodicity nor exhibits regularity. Thus, fractal dimension is a good measure to analyze the nonlinearity in the acquired pressure signals. Numerous fractal Dimension estimation techniques such as Higuchi's Fractal Dimensions [20], Petrosian's Fractal Dimensions [21], Katz's Fractal Dimensions [22], Detrended Fluctuation Analysis (DFA) [23], etc have been employed in various applications such as image characterization [24, 25], biomedical applications [26, 27], dynamic analysis of mechanical systems [16], etc. In this study, four different aforementioned Fractal Dimensions i.e., Higuchi's FD, Petrosian's FD, Katz's FD and Detrended Fluctuation Analysis (DFA) are used to quantify the nonlinearity of the pressure signal data obtained across a DC valve.

i. **Higuchi Fractal Dimension:** Higuchi's algorithm [20] for Fractal Dimension estimation is based on the evaluation of mean value of curve length by considering segments of *k* samples. The following steps are employed for HFD calculation methodology-

Step 1: For a finite set of time series data at a regular interval *n*: $X_1, X_2, \dots, X_n$, a new time series X_k^m of *k* sets is constructed from the given instances as in Eq. 6.

$$X_k^m = X_m, X_{m+2k}, \dots, X_{m+[\frac{n-m}{k}]} \quad (6)$$

where *k=1,2,…,*k_{max} , *m=1,2,…,k* and [] is the Gauss' notation.

Step 2: The average curve length of each of the time series X_m is then estimated as given in Eq. 7.

$$L_m(k) = \sum_{j=1}^{\frac{n-m}{k}} [X_{m+jk} - \frac{X_{m+(j-1)k}(N-1)}{\left[\frac{N-m}{k}\right]k}] \tag{7}$$

where N is the total length of the data sequence and $\frac{(N-1)}{[(N-m)/k]k}$ is a normalization factor.

Step 3: The step 2 is reiterated for k ranging from 1 to k_{max} yielding sum of the average curve lengths as given in Eq. 8.

$$L_{avg}(k) = \sum_{m=1}^{k} L_m(k) \tag{8}$$

Step 4: The curve is said to be fractal with dimension FD if L_{avg} is found to be proportional to k^{FD}. The k_{max} is obtained from a range of values ranging from 1 to 100 using methodology proposed by Polychronaki et al [28]. The HFDs are calculated for each of p values for a synthetic Weierstrass sequence which is calculated as given in Eq. 9.

$$W_H(x) = \sum_{i=0}^{M} \lambda^{-iH} \cos\cos 2\pi\lambda^i x \qquad 0 < H < 1 \tag{9}$$

where H is related to the theoretical fractal dimension as $FD_{th} = 2 - H$. Using each of the k_{max} values, fractal dimensions are evaluated for Weierstrass cosine sequences. The mean square error (MSE) is evaluated for each case to get the estimation accuracy of the Higuchi fractal dimension. The variation of MSE with k_{max} as shown in Fig. 4 indicates that the error is minimized for the value of 4. Therefore, k_{max}=4 is chosen to find HFD for the pressure signal in this study.

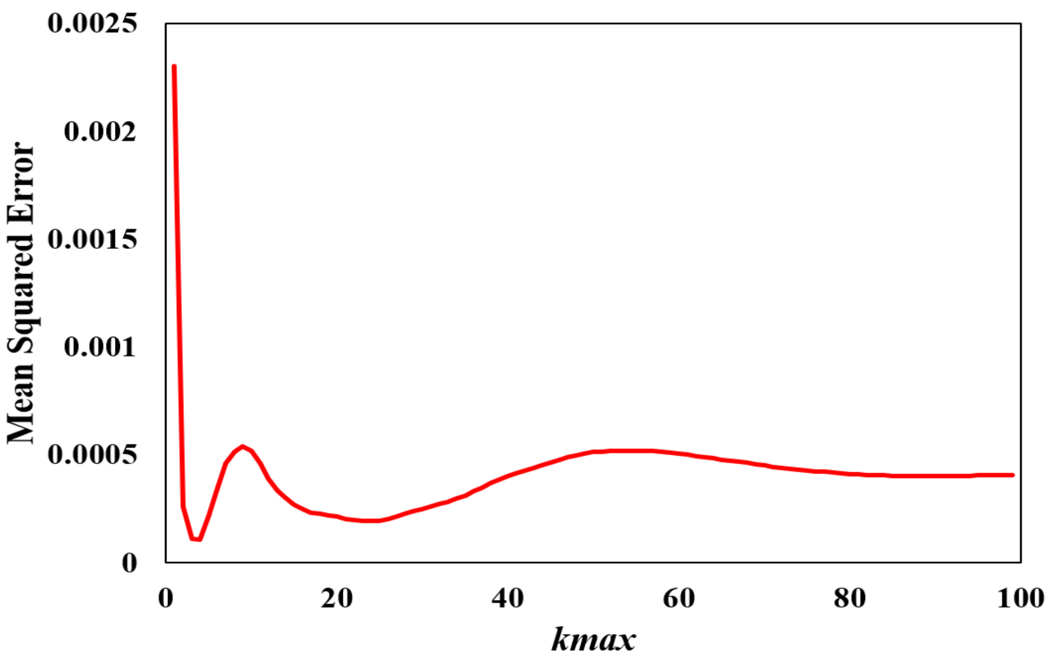


Fig. 4 Variation of k_{max}versus Mean Squared Error

ii. **Petrosian Fractal Dimension:** One of the simplest and fastest method of FD estimations is Petrosian's algorithm [21], derived using the mathematical formula mentioned in Eq. 10.

$$PFD = \frac{k}{k + \frac{k}{k+0.4\times N_d}} \tag{10}$$

where, k is the length of sequence and N_d denotes the number of sign changes in the slope of the signal.

iii. **Katz Fractal Dimension (KFD):** Katz's algorithm for FD estimation is operated by discretization of space based on the Mandelbrot fractal dimension (MFD) [22], which is measured for a planar curve as mentioned in Eq. 11.

$$MFD = \frac{\log L_t}{\log d} \tag{11}$$

where, $L_t = \sum_{i=1}^{N-1} ||T_{i+1} - T_i||$ and $d = ||T_{i+1} - T_i||$ with T representing a point on the curve and N represents the overall number of points over the curve. Katz proposed the following modified mathematical relation as given in Eq. 12 for the measurement of fractal dimension using the average distance a amongst two successive points.

$$KFD = \frac{\log \frac{L_t}{a}}{\log \frac{d}{a}} \tag{12}$$

iv. **Detrended Fluctuation Analysis (DFA):** DFA is a measure that quantifies the fractal scaling and correlation properties of non-stationary signals [23]. This non-linear feature also has the capability of distinguishing different intrinsic disturbances caused in a system. Calculation of DFA requires the following steps:

Step 1: For a finite length N of time series data at a regular interval $X_1, X_2, \dots, X_n$, a new time-series is generated using the given instances as in Eq. 13.

$$Y_i = \sum_{j=1}^{n}[X_j - \bar{X}] \tag{13}$$

where $\bar{X}$ is the mean of values in X.

Step 2: The obtained time-series is divided into time windows of length "t" samples each. Then for each window, a local least squares straight-line fit is calculated by minimizing the squared errors. The root-mean-square deviation from the trend using Y_i which indicates the resulting piecewise sequence of straight-line fits., the fluctuation, is measured as given in Eq. 14.

$$DFA_t = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(X_i - Y_i)^2} \tag{14}$$

5.3 Extreme Gradient Boosting (XGBoost)

XGBoost (Extreme Gradient Boosting algorithm) is an ensemble learning method, first introduced by Tianqi Chen in 2014 can be described as an efficient open-source implementation which performs using decision trees that are gradient boosted. This algorithm is introduced for high speed and performance [9]. XGBoost refers to a class of ensemble machine learning algorithms constructed by adding decision trees one at a time to the ensemble and fit using any arbitrary differentiable loss function and gradient descent optimization algorithm. It sequentially combines weak learners to produce a powerful learner with a lower bias and variance. For a given dataset: $D = \{(x_i, y_i)\}$ $(|D| = n, x_i \epsilon R^m, y_i \epsilon R)$ where, *m* is the number of features and *n* is the number of examples, the model uses *K* additive functions to train the output as given in Eq. 15 [28].

$$\widehat{y_i} = \sum_{k=1}^{K} f_k(x_i) \tag{15}$$

where, each f_k corresponds to an independent tree structure with specific number of leaves and weights. With appropriate tuning of the parameters for the decision trees, the model is trained such that the regularized objective loss function as expressed (l) in Eq. 16 gets minimized. l is a differentiable convex loss function and Ω is a penalty parameter that penalizes the complexity of the model at every iteration.

$$L(\phi) = \sum_i l(\widehat{y_i}, y_i) + \sum_k \Omega(f_k) \tag{16}$$

The statistical features and fractal dimension for the differential pressure signal are used to train the XGBoost Classifier for fault diagnosis in valves. 70% of the data is used to train the model and remaining are used as the testing data. To remove the biasness of the model, 10-fold cross validation has been employed and to maintain the generality in the data splitting, *stratified* is set to be true. The hyper parameters of the XGBoost Classifier are tuned using Random Search cross-validation and the optimal hyper parameters are listed in Table 1. The training accuracy of XGBoost is found to be 99.36% and the testing accuracy for predicting the valve switching condition using remaining 30% of the data is found to be 99.68%. The precision, recall and f1-score are 99.52, 99.63 and 99.58 respectively.

Table 1 Tuned hyperparameters using random search for training XGBoost

Hyperparameters	Value	Hyperparameters	Value
alpha	0.0025	*max_depth*	38
bootstrap	TRUE	*max_features*	sqrt
colsample_bytree	1	*min_child_weight*	3
gamma	0.013	*min_samples_split*	7
learning_rate	0.065	*n_estimators*	1333

6. Monitoring using 1-D Convolution Neural Networks

6.1 1-D Convolution Neural Network

The conventional Convolution Neural Network (CNN) was first described in Lenet-5 architecture and used on image data. This is also called as 2D CNN as the kernel slides along 2-dimensions over the data. The kernel can be understood as a filter that extract features from the images. Thus, a CNN does not need a manual feature extraction and the raw data can directly be used in CNN [10]. The relatively new version of CNN specifically suited for handling 1D data is called as 1D Convolution Neural Network. In 1D CNN, the kernel slides along only one dimension. Due to this property of 1D CNN, it has been proven to be a reliable deep learning approach for monitoring the condition of machines and their components like bearings, gears etc. [29, 30]. In a CNN architecture, there are number of layers that defines the depth of the model and also it highly influences the classification performance of the model. Few of the studies have reported the superiority of compact 1D CNN in classification of labelled signals. These includes classification of ECG signals [31, 32], high power circuitry [33], power engines [34] structural health monitoring and structural damage detection [35, 36].

Also, few of the previous authors have used time-domain signals to convert it into 2D images by using time frequency transformation like scalogram [37, 38], spectrogram [39, 40] etc. This transformation process increases the time consumption and the computational complexity of the model. For example, an image with $N\ x\ N$ dimensions convolves with $K\ x\ K$ kernel have a computational complexity ~ $O(N^2K^2)$, whereas for the corresponding 1D convolution (i.e., structured as same number of dimensions, N and K) the order of complexity is $\sim O(NK)$ [41]. Thus, it is evident that the complexity order also gets reduced significantly using 1D CNN and are easier and faster to train and implement. Fig. 5 shows the specialized neuron structure of the adaptive 1D CNN.

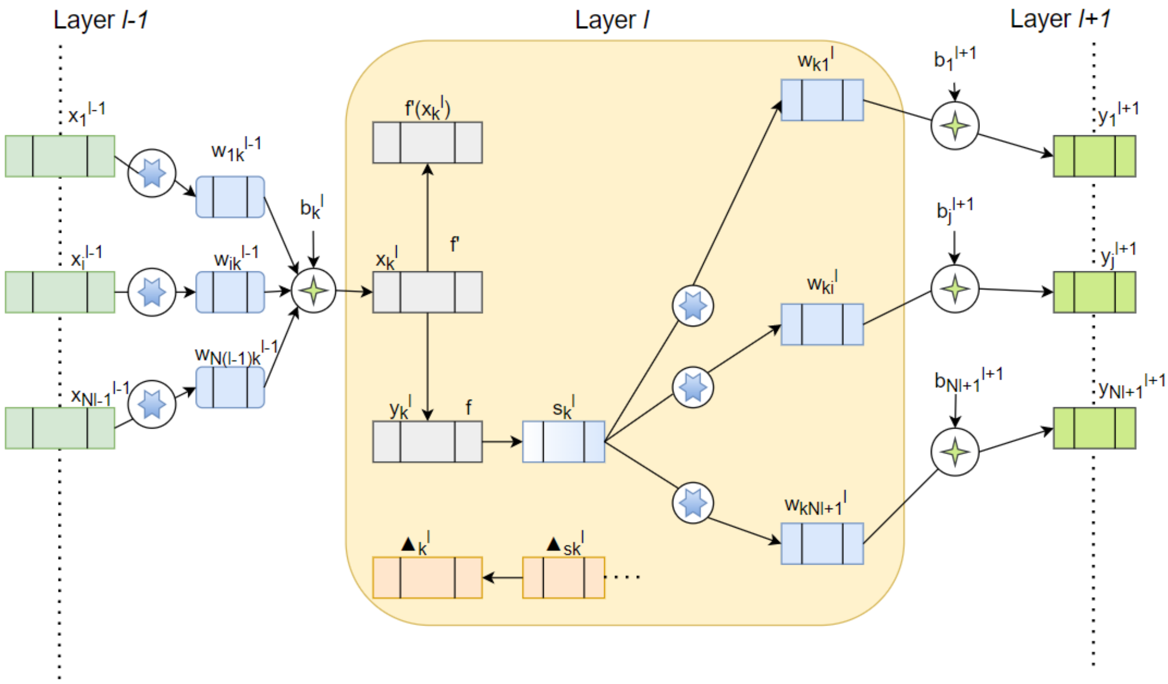


Fig. 5 Neuron structure of 1D CNN

The 1D forward propagation (FP) from convolution layer $l-1$ to the input of a neuron in layer l is expressed as given in Eq. 17.

$$y_k^l = b_k^l + \sum_{i=1}^{N_{l-1}} conv1D(w_{ik}^{l-1}, x_i^{l-1}) \tag{17}$$

where, x_k^l is input at layer l, b_k^l denotes the scalar bias of k^{th} neuron, s_i^{l-1} is the output of the i^{th} neuron at layer *l-1* and w_{ik}^{l-1} is the kernel from the i^{th} neuron at layer $l-1$ to the k^{th} neuron at layer l. As can be visualized in Fig. 6, the dimension of the input maps is gradually reduced by k-1, where k is the size of the kernel. For the back-propagation step, the calculations for back propagation of the error starts from the MLP output layer where the mean-squared error E_p for the input p is expressed as given in Eq. 18.

$$E_p = \sum_{i=1}^{N_L} (y_i^l - t_i^p)^2 \tag{18}$$

where, N_L is the number of classes, t_i^p denotes the target and $y_1^l, y_2^l, \ldots, y_{N_L}^l$ are the corresponding output vectors. The objective of the back propagation is to minimize the contributions of network parameters to this error and this step is performed iteratively using the learning factor, ε. This is applied for scaling weight and bias.

6.2 Proposed 1-D CNN architecture

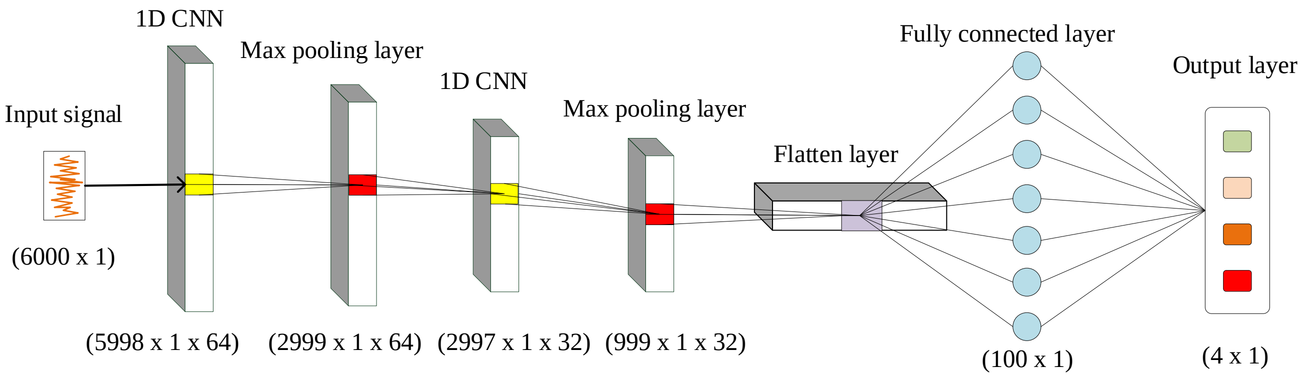


Fig. 6 Architecture of 1D CNN model for predicting switching behavior of the DC valve

Fig. 6 shows the architecture of the considered 1D Convolution Neural Network for predicting the degradation characteristics in the switching behavior of DC valves in hydraulic system. It contains a 1D CNN layer followed by a sub-sampling layer i.e., max pooling layer. Next, one more pair of 1D CNN and max pooling layer is stacked to fed input to the flatten layer. The flatten representation is passed along to the dense network (fully connected layer) which gives the input to the output layer.

The input data is fed to the first CNN layer. Every set of input data contains 6000 data points and the CNN layer employs 64 filters. Thus, the dimension of first CNN layer is shown as $5998\ x\ 1\ x\ 64$. Each of the CNN layer engraves an activation function placed after CNN layer and before the next layer. This activation function assists the model to learn the complex patterns in the data. *Rectified Linear Unit (ReLU)* is chosen as the activation function in the CNN as it prevents the vanishing gradient problem during learning. Next, the max pooling layer performs the sample-based discretization process for the data. It down-samples and reduces the dimensionality of the feature set. Next two hidden layers are 1D CNN layer and the max pooling layer respectively as shown in Fig. 7. The flatten layer employed after the max pooling layer flattens the multi-dimensional input tensor to a single dimension array before feeding it into the classification layer. The classification layer employs a fully connected layer (dense layer) that learns the non-linear combination of the high-level features represented by the convolution layers during the learning. The developed dense network in this CNN architecture contains 100 neurons. Based on these learning, the fully connected layer classifies the data to a class and passes the information to the output layer. Additionally, dropout regularization is introduced in the model after each convolution layer to avoid overfitting of neural networks. Thus, it offers an effective regularization method that reduces the overfitting of proposed model and improves the generalization error by randomly dropping out mentioned portion of nodes during training.

The accuracy of the 1D CNN model is found to be 100% in predicting the switching behavior of the DC valve using the pressure difference data. Also, the precision, recall and f1-score for are equal to 100% respectively.

7. Methodology

As can be observed in the Fig. 1, the two pipelines, one with the ensemble machine learning model i.e., extreme gradient boosting (XGBoost) classification using manual feature extraction and the other deep convolutional neural network model are trained using preprocessed pressure signals. To determine switching condition of dc valve, the difference of the pressure signals obtained from the sensors positioned on either side of the 2-way direction control valve is fed as input. In pipeline 1, there is a feature extraction step in which four statistical features and four fractal dimensions are first extracted for the obtained difference in the pressure signals. The steps to calculate these features and dimensions are detailed in Chapter 5. The XGBoost Classifier is then trained on the obtained features with proper tuning of the hyperparameters using Random Search cross validation. Parallelly, the signal for obtained differential pressure is to be fed in the Deep 1D CNN architecture designed (as described in Fig. 6) for classification of hydraulic valves switching condition. The better performing model (1-D CNN) is then tested against differential pressure signal with artificial noise. Additive Gaussian White noise with different amplitudes generating 20dB, 15dB and 10dB signal-to-noise ratios (SNR) are introduced to original signals as can be visualized in Fig 7. The end-to-end deep learning approach with 1-D CNN architecture is then deployed on cloud along with the acquired data for remote condition monitoring and further analysis.

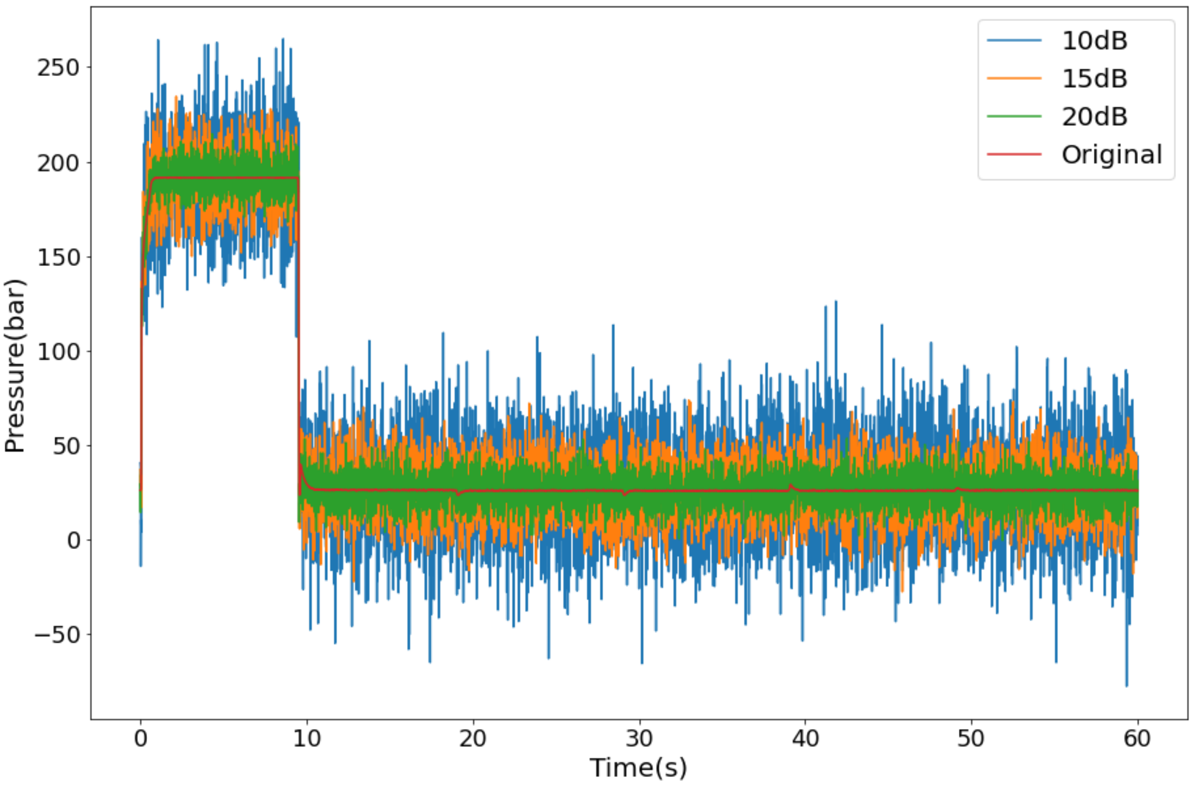


Fig. 7 Differential pressure signals with additive white gaussian noise

8. Results and Discussions

8.1 Comparison of Models Prediction Metrics

The classification metrics namely- accuracy, precision, recall and f1-score are obtained for the two pipelines, i.e., the first using feature extraction engineering and XGBoost classifier and the second based on 1-D CNN architecture are compared in Fig. These evaluation metrics, reflecting different condition monitoring requirements can be measured using formulas Eqs. [19-22]. For the condition monitoring system of DC valve equipped in a hydraulic system, a model with high recall will lead it to be alarmed for every fault but also cause lot of false alarms which is not preferable as this will increase operational cost because of unnecessary downtime. A high precision model, on the other hand, will avoid false alarms but also might miss to detect some faults causing the system to have inefficient working cases. Thus, the classifier is optimized for precision-recall tradeoff such that both precision and recall are maximized which can be expressed through f1-score of the model. Also, accuracy is another chosen metric because it has the most common and easy interpretation. Table 2 presents a comparison in the performance of PCA + XGBoost [8], feature extraction + XGBoost and 1-D CNN which can be observed in Graph 1.

$$Precision = \frac{|TP|}{|TP| + |FP|} \tag{19}$$

$$Recall = \frac{|TP|}{|TP| + |FN|} \tag{20}$$

$$f1\text{-}Score = 2 \times \frac{precision \times recall}{precision + recall} \tag{21}$$

$$Accuracy = \frac{|TP| + |TN|}{|TP| + |FP| + |FN| + |TN|} \tag{22}$$

where, TP- True positive, FP- False positive, TN- True negative, and FN- False negative

	Switching condition	PCA + XGBoost [8]	**Present work**	
			XGBoost	**1-D CNN**
Precision	Optimal switching	0.99	1	1
	Small lag	0.885	1	1
	Severe lag	1	0.96	1

	Close to total failure	1	0.982	1
Recall	Optimal switching	0.902	1	1
	Small lag	1	0.981	1
	Severe lag	0.975	1	1
	Close to total failure	0.99	0.97	1
f1-score	Optimal switching	0.944	1	1
	Small lag	0.939	1	1
	Severe lag	0.988	0.98	1
	Close to total failure	0.995	0.98	1
Accuracy		0.966	**0.996**	**1**

Table 2 Comparison of XGBoost and 1D CNN for prediction of switching in DC valve

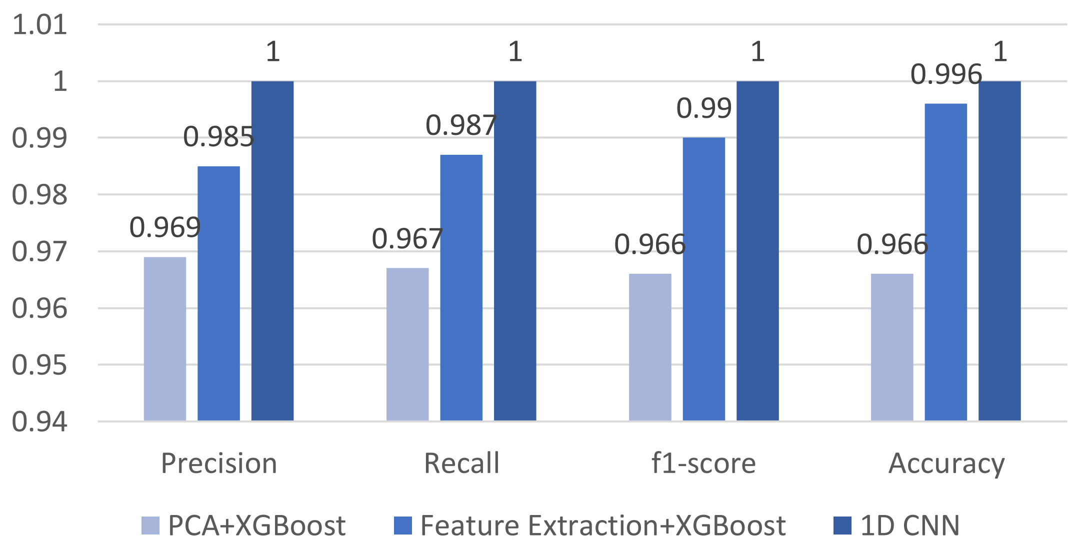


Fig. 8 Comparison of prediction metrics of models

8.2 Comparison of performance of models on noisy test data

For further validation of the proposed 1-D CNN deep learning model as a real-time fault detection model, it is tested on artificially deteriorated pressure sensor signals using Additive Gaussian White noise with different amplitudes generating 20dB, 15dB and 10dB signal-to-noise ratios (SNR). The comparative results are detailed in Table 3 and can be visualized clearly through Fig 9.

	ACCURACY (%)			
Model	Original	20dB	15dB	10dB
PCA + XGBoost [8]	96.6	93	82.2	76.8
1D CNN	100	100	89.27	87.16

Table 3 Comparison of performances of models on noisy test data

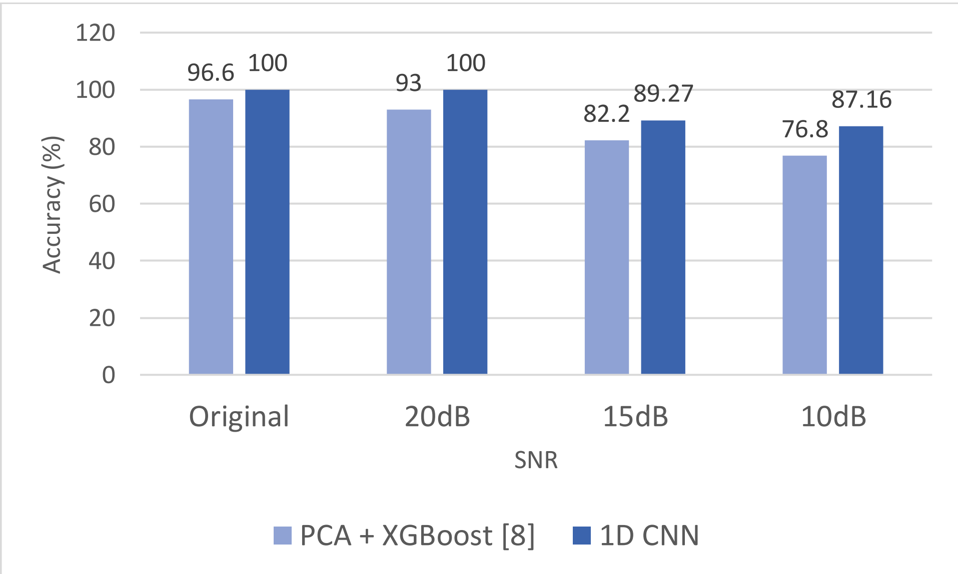


Fig. 9 Comparison of performance of models on noisy test data

9. Deployment of Model

One of the goals of this proposed model is to build a holistic framework which can be adapted to new systems conveniently. The 1-D CNN model is deployed on cloud for it to provide a theoretical basis and practical guidance for the fault diagnosis of hydraulic systems and the predictive maintenance of hydraulic components remotely. Acquired data is also stored on the cloud and can be easily used for further analysis. This allows for users to access and implement the proposed method in remote locations without much effort.

10. Conclusion

In the present study, a comparative methodology for monitoring the deterioration in the switching characteristics of a solenoid-actuated DC valve is proposed. The pressure signals acquired from the either side of the DC valve is used to obtain the differential pressure across the valve during switching operation. Subsequently, the effect of the switching on the working pressure and its transient behavior for small fraction of time is demonstrated. Followed by this, two different approaches (XGBoost trained with manually extracted statistical features along with fractal dimensions and 1-D CNN) are modeled and compared for their abilities to diagnose faults in switching behavior of DC valve in real-time. The major findings of this project can be listed as follows:

1. With a decrease in the control current to the solenoid actuator or increase in the severity of switching fault, the time delay to initiation of the switching increases, and fluctuations in the pressure signal increase.
2. The severity of fault present in the switching characteristics of valve used in a hydraulic circuit can be effectively monitored by the fluctuation patterns observed in signals of pressure sensors at the entry and exit of the valve.
3. Through manual feature extraction (statistical features and fractal dimensions) from the differential pressure signals for training the XGBoost model, a prediction accuracy of 99.68 % is achieved.
4. 1-D CNN is capable of learning complex and non-stationary features from the raw signal autonomously. With six hidden-layers, 1-D CNN employs unprocessed data and achieves a marginally better performance (100% accuracy) compared to XGBoost (99.68%).
5. By fusing feature extraction and selection steps into a single adaptive learning body, 1-D CNN model also succeeds in significantly decreasing time, cost and computational complexity of the fault detection system.
6. 1-D CNN architecture is simple and achieves a better accuracy without requiring pre-determined transformations, manual feature extraction or feature selection methods. This makes it a more adaptable framework which users can implement with minimal effort.
7. For real-time operational decisions, 1-D CNN proves to be a better classifier by showing better accuracies when tested with signals containing noise. Also, the compact architecture of 1D-CNN model makes it more appropriate for practical real-time hardware implementation.

8. The end-to-end deep learning model is deployed on cloud so that it can be conveniently adapted to altered conditions in hydraulic setup or occurrence of new faulty condition.

11. Limitations/Future Work

By accessing recent cloud computing developments, sufficient computing and storage resources can be accessed without requirement of physical data centers or servers. However, it has a drawback of low response time. Due to centralized computation, the data must be first transmitted to the cloud and the result is returned later. To overcome this issue, edge computing based on single board computer can be introduced. This will provide computation and storage resources near the data source leading the prediction model to have minimized latency, improved analysis speed and more efficient real-time decision-making.

Also, more complex learning models, such as CNN combined with LSTM can be studied to offer a better learning model for signals that require spatio-temporal representation. Approaches need to be discovered for them to work with incomplete sensor data issues that could arise from hardware malfunctions or during device replacement.

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