DESIGN AND IMPLEMENTATION OF SEQUENTIAL STATE LOGIC FOR PNEUMATIC VALVE MONITORING USING PIEZO FILM SENSORS

by

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ABSTRACT

MITHUN YERRA. Design and implementation of sequential state logic for pneumatic valve monitoring using piezo film sensors (Under the direction of DR. ASIS NASIPURI)

Valve malfunctioning is a serious concern in industries and other production units that rely on processes requiring controlled operation of valves. This thesis considers the design of sequential state logic for condition monitoring of pneumatic valves using low-cost, non-invasive and flexible piezo film sensors. The main contribution of this work is to extract features from the signals captured using these sensors for monitoring externally, and design a simple and robust signal processing algorithm to effectively detect/categorize the actuation events of healthy valves. Acoustic signatures obtained from the piezo film sensors are used to determine the behavior of the valves under operation. Performance evaluations of the proposed algorithm are conducted using MATLAB, on a laboratory testbed installed at Energy Production and Infrastructure Center (EPIC) building, UNC Charlotte. Results indicate that the proposed algorithm can effectively detect actuation events with less fault alarms and missed detections. This work also considers the analysis of a defective valve and suggests approaches to detect leaks, using sequential state logic.

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I would like to dedicate my thesis to Dr. Asis Nasipuri, who has given me an opportunity.

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CHAPTER 1: INTRODUCTION

Valve malfunctioning is a serious concern in industries and other production units that rely on processes requiring controlled operation of valves. Malfunctioning valves can potentially impact human health and safety, affect production yields, and cause environmental risks. For these reasons, valves are frequently removed from service for maintenance. The cost for pulling a valve for maintenance is the same no matter whether the valve is good or bad. A study [1] reported that over 50% of typical maintenance activities are unnecessary. Moreover, some maintenance actually reduces equipment reliability. In short, too much of work done by maintenance teams is unnecessary, unproductive, or even counter-productive sometimes. An effective alternative is to develop autonomous valve monitoring systems that continuously monitor status signals for analysis of the operating status of valves. It becomes apparent that the introduction of non-destructive evaluation techniques will significantly reduce the cost of the preventive maintenance program [2, 3]. Fortunately, with the advent of microprocessor-based valve instrumentation and sensor technology, the health of control valve assemblies became much more visible. In other words, today's smart valve technology enables fault detection and analysis while the valve is in normal operation – online and in service [4].

Basically, a typical valve monitoring system mainly comprises of a set of sensors (e.g., sound, vibration, etc.) to capture signals from the valves/pipes. A wide variety of sensors are available in the market and nowadays, the deployment of wireless sensor networks are replacing traditional wired switch boxes, thereby contributing to major advancements in condition monitoring systems.

This work presents the design and implementation considerations to successfully monitor the healthy status of valves and detect leaks, if any. Moreover, the monitoring system considered here is non-invasive, in the sense that it does not require fundamental modifications to the valves. This is achieved through snap-on sensors that can detect the signals for monitoring externally. Indeed, the sensors selected makes the monitoring system cost effective with respect to the cost of the valve, which costs less than $100. In this regard, this thesis report focuses on the development of signal processing techniques for condition monitoring of pneumatic valves through theoretical analysis and experimental tests. Acoustic signatures obtained from the low-cost piezo film sensors are used to get the behavior of the valves under operation. Results are presented using MATLAB, by implementing the proposed algorithm on the signals collected on an experimental testbed, installed at Energy Production and Infrastructure Center (EPIC) building, UNC Charlotte.

1.1 Objective and Proposed Design Approaches

The proposed valve monitoring system is equipped with piezo film sensors to determine the status of valves. Signals, using these sensors are captured for various valve operations for monitoring. Hence, the issues that will be addressed in developing the algorithm for valve monitoring include:

- To determine a unique, consistent and distinguishable signal profiles/parameters that could effectively categorize the actuation events – opening and closing of a healthy valve, with/without medium flowing through the pipes and thereafter, to design the logic.

- To check for the applicability of the above logic in case of unhealthy/defective valves and then, to develop an algorithm for leak detection.

These specific design issues are explored in two different ways:

1.1.1 Classifiers based on Spectral Estimation:

This approach deals mainly with the frequency content of the signals in categorizing the actuation events of a valve. It is expected that the closing of the valve has relatively more high frequency content, whereas relatively more low frequency content for the opening of the valve. This observation was used to classify the events. Initially, we obtain the Power Spectral Density (PSD) of the specific parts of signals corresponding to opening and closing of valves. All the signals are analyzed over the frequency band of 0-7 kHz. This frequency band is then split into two sub bands and estimates the power separately in the two sub bands. Finally, the total power contained in the sub bands are compared against each other with the two actuation events – opening and closing of the valve. Based on the power concentration in the two sub bands, this approach attempts to categorize the events This will be discussed in great detail in the Chapter 4. Finally, this happened to fail in some cases and hence another approach has been developed.

1.1.2 Sequential State Logic based on Short-Time Energy (STE) Profiles:

In contrast to the above, this method focuses on the energy content of the signals in time-domain. STE profiles of the signals are computed, and consistent and distinguishable patterns for the opening and closing events were determined. Thereafter, these profiles are categorized using pattern recognition techniques. This turned out to be successful in monitoring the healthy status of the valves and in indicating leaks. This will be discussed in Chapters 5 and 6.

1.2 Scope and Organization of Thesis

Considering the basic design issues involved in a typical condition monitoring system, the work presented in this thesis report initially focuses on the feature extraction of the signals captured using the sensor. This has been accomplished by attempting to analyze the signal characteristics in both time and frequency domain. A sufficiently large set of experiments were performed on a healthy valve primarily, to better understand the behavior of the healthy valve. This has been done by operating the valve without any medium flowing, and later with water. Gradually, similar kind of analysis has been extended to defective valves. In the beginning, a commercially available off-the-shelf contact microphone has been used to record the signals. But, later on, due to several other factors like inconsistency in the signal characteristics due to its hardware design, inflexibility with the test environment, and high cost, a piezo film sensor has been chosen to continue the analysis. This sensor yielded impressive results and seemed that this could also serve as a wise option to extend the study to multi-sensor analysis, if required in future, due to its low cost and flexibility.

To account for the significant and sufficient information, this thesis report is organized into seven chapters. The Chapter 2 sheds some light on the current valve monitoring systems, intrusive sensors and the related work done on this. A basic overview of the experimental testbed with all the hardware and software needed for the analysis will be discussed in Chapter 3. Chapter 3 also provides an exhaustive analysis of the time domain signals from the sensors mounted at different positions on the valve, with respect to medium flowing through the pipes. This signal analysis provides a basic understanding on the actuation events of the valve and its operation. It also discusses on how the location of sensor on a valve also plays a key role in the design of a condition monitoring system. Chapter 4 presents the spectral analysis of the sensor signals. Based on this analysis, this chapter focuses on the approach of classifiers based on spectral estimation in condition monitoring of pneumatic valves. Chapter 5 discusses about the envelope analysis of the signals in time domain and their signal processing aspects to categorize the actuation events of valves. This chapter attempts to present a sequential state logic based on short-time energy profiles of the signals, to detect and categorize the opening and closing operations of a healthy valve. Also, the design of the proposed algorithm and test results are discussed here. In Chapter 6, the logic proposed in Chapter 5 is analyzed using a defective valve and certain approaches towards detection of leaks, are discussed here. All the chapters include enough plots clearly explaining the characteristics of the signals in perspective to the valve operation. The Chapter 7 concludes the thesis work and suggests future work for further research.

CHAPTER 2: RELATED WORK

In the modern day economics, oil and gas has become one of the significant commodities. Hence, since many years, huge infrastructures using pipelines are being deployed in the transportation of these fluids world-wide. Valves find applications in these kind of large infrastructure based industries, including food processing, sterilizer construction, etc. Though the application may vary, as with any other component, the valves must operate properly and reliably when called upon to perform their design function [5, 6]. Several approaches and techniques had been developed to monitor the status of the valves and detect anomalies.

2.1 Basic Design of a typical Condition Monitoring System

The design of any condition monitoring system involves certain basic steps – Data Acquisition, Feature Extraction, Logic Implementation and Decision Making, as shown in Figure 2.1. Every phase in the process plays a significant role in designing a robust and cost-effective condition monitoring system. Briefly:

- **Data Acquisition** primarily focuses on the sensing method and the type of the sensor. The various sensing methods like acoustic emission, vibration sensing, etc., has their own advantages and drawbacks, specific to a particular application. Moreover, the different types of sensors and their deployment in a particular environment poses their own challenges, as will be discussed in the succeeding sections. Therefore, this phase can play a major role in deciding the cost, size of the monitoring module and in addition to that, may put forward challenges to the next phases depending on the techniques/principles used to capture the status signals.

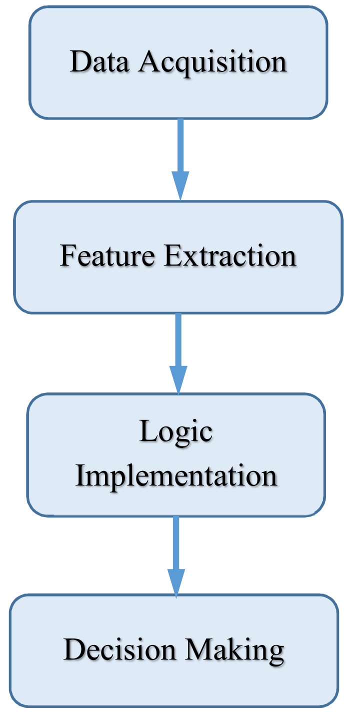


Figure 2.1: Basic steps involved in a typical condition monitoring system

- **Feature Extraction** needs a keen observation and analysis of various signal characteristics from a large set of data. Basically, this phase demands the consistency of certain parameter/signature of the signal, which needs to be verified and validated over many observations and iterations to reach a conclusion. There are numerous approaches to encounter this challenge, which determines the effectiveness and reliability of the algorithm.

- **Logic Implementation and Decision Making** collectively determines the efficiency and robustness of a condition monitoring system. Exhaustive consideration of all the possible cases can possibly reduce fault alarms and missing detections.

In short, the effectiveness of any condition monitoring system mainly depends on the type of sensors employed, and the data processing algorithms designed to analyze the signals obtained from the sensors. Considering these design challenges phase-by-phase, there are many ideas that had been proposed for condition monitoring in different applications.

2.2 A Brief Overview of Current Valve Monitoring Systems

Valve Monitoring Systems (VMS) in the literature can broadly be classified into invasive and non-invasive. A non-invasive VMS attempts to check the valve condition using the data acquired from the sensors mounted on the valve/pipe externally. On the other hand, the invasive VMS often employs pigging devices that are inserted from one end and extracted from the other end of the pipeline. Sometimes, this category can also entail drilling holes or cutting the pipe, in order to install maintenance devices. Therefore, invasive VMSs are inflexible and often disrupt the operation of the pipeline [7, 8]. In addition to this, the invasive sensors are relatively more expensive due to its design, to withstand different medium pressures and, to be resistant enough to medium for sufficiently long period.

2.2.1 Sensing Techniques

Various techniques had been proposed for the condition monitoring of valves, making use of sensors that detect acoustic emission (AE) [9, 10], dynamic Pressure (DP) [11] and vibration [12]. All these methods do not disrupt the normal operation of the valves/pipelines. In fact, many researchers had suggested their diagnosis algorithms for valve monitoring using more than one different technique like a combination of acoustic emission sensor, magnetic flux sensor and ultrasonic sensor, etc. [13].

The journal [14] on measurement and control discusses that Acoustic Emission (AE) is a promising technique for the non-invasive monitoring and characterization of material structures and processes. Indeed, this provides the principle of a sensing method that is passive, continuous, sensitive and capable of *in situ* monitoring. Acoustic Emission is the phenomenon of radiation of elastic waves within a material, by rapid release of localized stress energy. Unlike most other Non-Destructive Testing (NDT) techniques, instead of supplying energy to the object under examination, it simply listens for the energy released by the object. Because of the versatility of the AE technique, it has many industrial applications like assessing structural integrity, detecting flaws, testing for leaks, etc., and is used extensively as a research tool [15]. Acoustic emission of materials including fiber-reinforced composites, aluminum, steel and glass can be performed with contact microphones of piezo film. These can continuously monitor structures for 0.1 – 1 MHz acoustic emission. Piezo film being broad- band responds well at these frequencies [16].

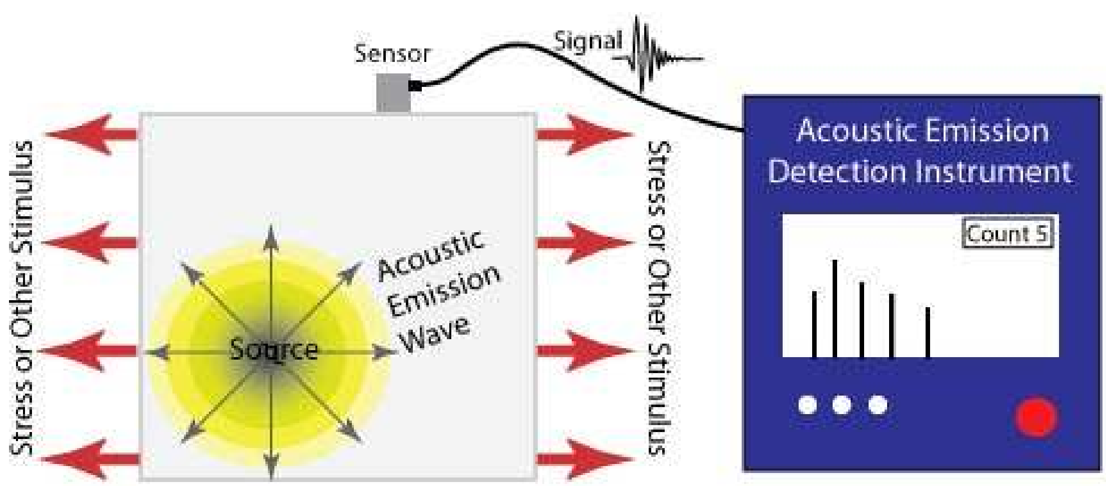


Figure 2.2: Radiation of acoustic waves from the material under stress, with sensor capturing them (Picture Courtesy: IOWA State University, NDT Resource Center)

Figure 2.2 clearly illustrates the sensor mounted on some material to capture the elastic waves generated from it under stress.

2.2.2 Feature Extraction Techniques

Signal analysis is one of the most important methods used for condition monitoring and fault diagnostics, whose aim is to find a simple and effective transform to the original signals [17]. Signals obtained from the sensors are expected to be non-stationary, as they depend on various factor such as location of the valves, change of environment, etc. Many signal parameters [18] like root mean square (RMS) value, rise time, ring-down counts, peaks, kurtosis, Fast Fourier Transform (FFT), Short-Time Fourier Transform (STFT), etc., were analyzed. The relative significance of the various parameters involved is important, because it indicates the strengths, weaknesses and potential for the applications of the methods used in the experiments. Important comparisons may be made in relation to the properties of the fluid on the results obtained [19].

Considering these inputs, a commercially available off-the-shelf microphone sensor, in the beginning and later on, a low cost piezo film sensor were selected and used to study the behavior of a pneumatic valve, manufactured by Burkert Fluid Control Systems. The entire setup, well-suitable for an exhaustive study and to design a feasible valve monitoring system, has been installed at The University of North Carolina at Charlotte (UNC Charlotte). Last year, a large set of experiments were performed on correlating the signals recorded at different actuation events of the valve for many iterations, to study, primarily the healthy condition of valves. The study concluded that the position of sensor on the valve plays a key role, as observed that different positions produce slightly different signal characteristics. It has also been reported that the time-domain, as well as the frequency-domain correlation analysis could not yield effective results and therefore, correlation would not be the best criteria to detect/categorize the actuation events of the valve and hence, for the status monitoring of valves.

Therefore, this work attempts to research on simple and robust signal processing techniques that could effectively detect/categorize the actuation events of a pneumatic valve. Thereupon, the report also proposes an algorithm to monitor the healthy condition of valves and detect leaks, if any. Moreover, the design of the algorithm is based on signals acquired using a low cost piezo film sensors, thereby making this an economically effective solution to the problem of valve malfunctioning. The designed algorithm has been implemented using MATLAB and tested over several iterations on an experimental testbed.

CHAPTER 3: EXPERIMENTAL TESTBED FOR THE ANALYSIS OF SENSOR SIGNALS FROM VALVES

3.1 Experimental Setup

A well-established experimental setup facilitates in performing rigorous experiments and replicable testing, which is required to develop a laboratory proof-of-concept demonstration to evaluate the feasibility and performance of an algorithm. As mentioned earlier, a laboratory testbed, as shown in Figure 3.1 has been developed for the investigation and characterization of signals corresponding to Burkert pneumatically operated valve.

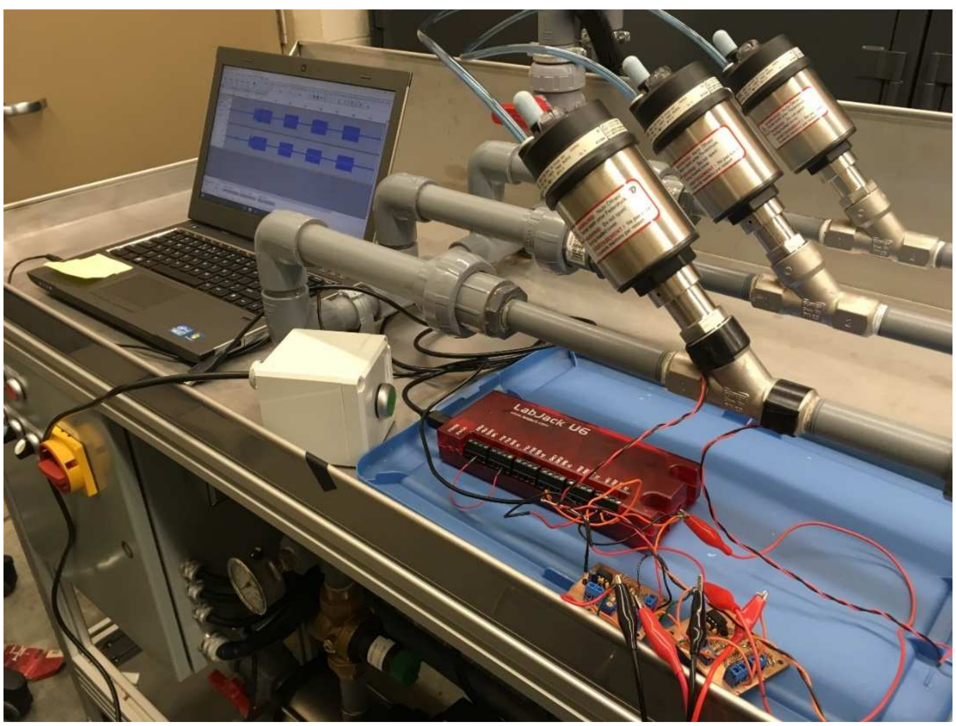


Figure 3.1: Laboratory testbed

The testbed was developed and delivered by Burkert Fluid Control Systems and appropriate sensors and interface circuits were developed and included for the acoustic signal analysis at UNC Charlotte. The testbed delivered by Burkert Fluid Control Systems comprises of a complete valve setup well-suitable to study and conduct experiments to develop an effective monitoring system. As depicted in Figure 3.1, it comprises of three pneumatic valves attached to three pipes in parallel. These three valves can be actuated in different combinations by a Programmable Logic Controller (PLC). The setup comprises of air compressor with pressure gauge, and remote switch required to actuate the valves. It also includes a water pump, with pressure gauges at the inlet and outlet pipes.

Figure 3.1 shows three pneumatic valves, one of which is tied with two piezo film sensors (appearing in black color) at two locations on the valve. Suitable signal conditioning circuit with preamplifier has been built and connected to these sensors. The setup has a remote switch to actuate the valve(s). This setup allows to perform experiments by setting different medium pressures up to 120 psi. Data acquired from the sensors using laptop is analyzed using MATLAB.

3.2 Type of Valve and its Actuation Events [20]

The investigation and characterization of the signals is done corresponding to the Burkert 2/2 – way Angle-seat pneumatically operated valve (Type 2100), as shown in Figure 3.2. This valve consists of a pneumatically actuated piston and this is a normally closed valve, meaning that the valve stays in a close state by default and need to actuate it pneumatically to open, thereby allowing medium to flow through. Figure 3.3 clearly depicts the internal movement of piston against medium flow (in blue color) during the actuation events – normal opening and closing of the valve.

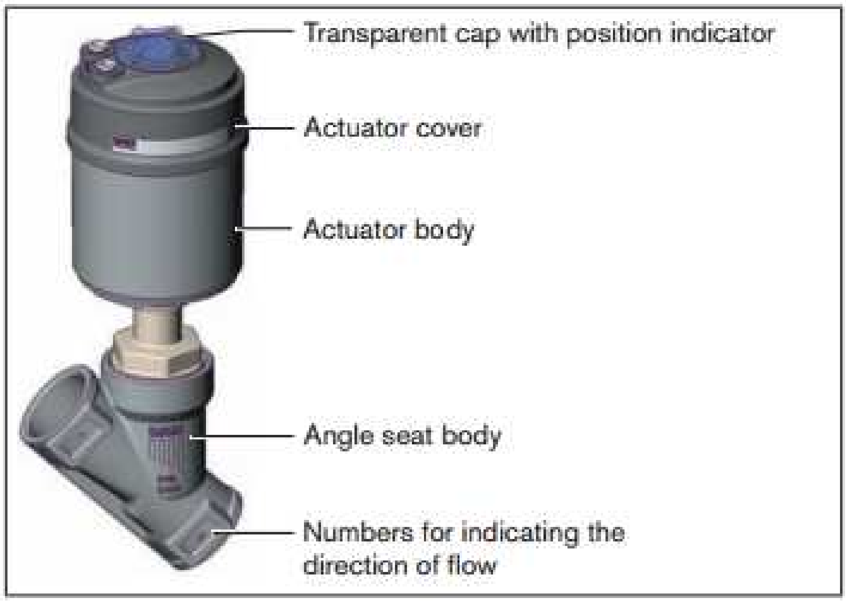
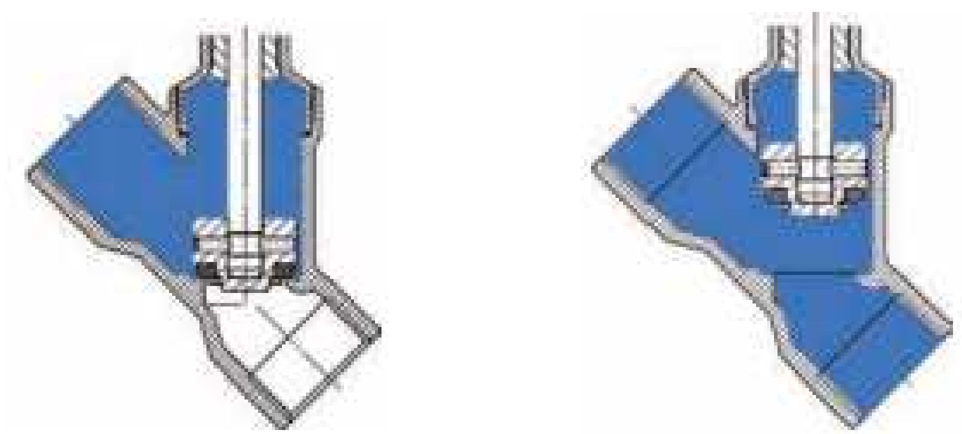


Figure 3.2: Angle seat valve type 2100, structure and description
(Source: Burkert Manual – Type 2100 2/2 – way Angle Seat Valve)



(a) Valve in close state (b) Valve in open state
Figure 3.3 Piston movement during actuation events – close and open
(Source: Burkert Manual – Type 2100 2/2 – way Angle Seat Valve)

3.3 Types of Sensors

Being motivated by the promising acoustic emission (AE) technique, initially, a commercially available off-the-shelf contact microphone was selected to investigate the signal characteristics.

3.3.1 CM-01B Contact Microphone Sensor [21]

The CM-01B contact microphone, as shown in Figure 3.4, uses sensitive but robust PVDF piezo film combined with a low-noise electronic preamplifier to provide a unique sound or vibration pick-up with buffered output. The design minimizes external acoustic noise while offering extremely high sensitivity to vibration applied to the central rubber pad.

Figure 3.4: CM-01B contact microphone

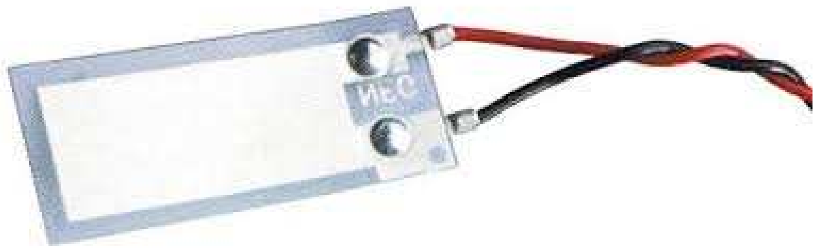
As this microphone is designed to sense only the vibrations applied to the central rubber pad, it is observed through a series of experiments that the signal characteristics are largely dependent upon the pressure applied to attach it to the valve/pipe. This resulted in inconsistency of signals measured during valve operations and hence, we came up with an alternative of using a piezo film sensor, which of course CM-01B also uses internally. Moreover, this is very cheaply available, as almost 10-12 times less expensive than CM-01B. Additionally, its ready availability in the form of film made it more flexible to use at any location on the valve/pipe.

3.3.2 Piezo Film Sensor [22]

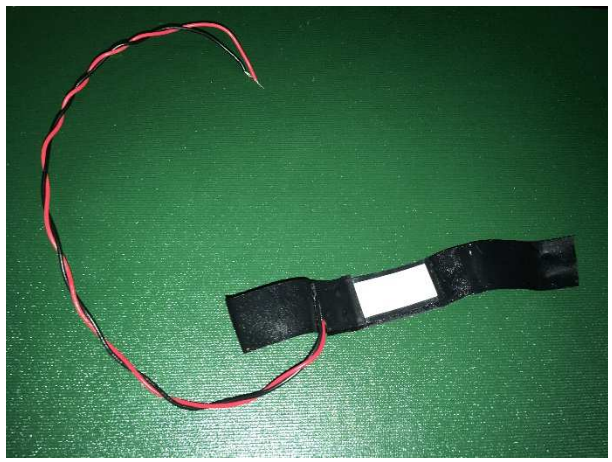
Piezoelectric effect is the ability of certain materials to develop an electric charge in response to applied mechanical stress. In the 20 years since the discovery of piezoelectric polymer, the technology has matured, practical applications have emerged from a long list of possibilities, and the rate of commercialization of the technology is accelerating [16]. Due to its flexibility, lightweight, wide frequency range, high mechanical strength, etc., it had got a huge set of applications – impact sensors, vibration sensing, ultrasound applications and many more. Recently, piezo electric film has become available for various non-intrusive fluid dynamic applications. It offers ease of applications and distributed measurements while exhibiting broad band electro-acoustical characteristics.

As shown in Figure 3.5 (a), piezo films are readily available in the market with leads attached. It has been attached to electrical tape as shown in Figure 3.5 (b), thereby making it suitable to tie to any position on the valve/pipe for experimental purposes. As mentioned earlier, we can see in Figure 3.1 that one of the valves is tied to two piezo film sensors using electrical tape.

Because piezo film is both piezoelectric and pyroelectric, some provision must be made to eliminate—or at least reduce—the effect of unwanted signals. The primary principles of signal conditioning include filtering, averaging and common-mode rejection. A properly designed interface circuit plays a key role in the optimization of piezo film sensors. The applications of piezo film span from toys to military sensors and interfacing to electronics is highly application dependent. By considering these facts and following the guidelines [16], a signal conditioning circuit along with a preamplifier has been built by Mr. Sanketh Shingte.



(a) Piezo film sensor with leads attached



(b) Piezo film sensor attached to electrical tape (for experimental purposes)
Figure 3.5: Piezo Film Sensor

Operation down to fractions of Hz can be achieved using either conventional charge amplifiers or, since signal levels are relatively high, simple high impedance FET buffer circuits. Here, Field Effect Transistor (FET) is used to electronically interface with piezo film. To facilitate the experimental process, preamplifier was built with a wide range of gain over 1 – 500, controllable using a potentiometer.

3.4 Related Software and Hardware

Data from sensors, which are interfaced to signal conditioning circuit and preamplifier, has been acquired using a set of software and hardware, after which analysis is done using MATLAB.

3.4.1 Audacity [23]

Audacity is a free open source digital audio editor and recording computer software application available Windows, OS X, Linux and other operating systems. Figure 3.6 shows the recording of an audio, at a certain sample rate, using Audacity.

In addition to recording audio, its features include:

- Importing and exporting to WAV, AIFF, MP3 and various other file formats
- Editing via cut, copy and paste
- Recording and playing back sounds
- Multitrack mixing
- Audio spectrum analysis using the Fourier Transform algorithm
- Noise reduction, and many more

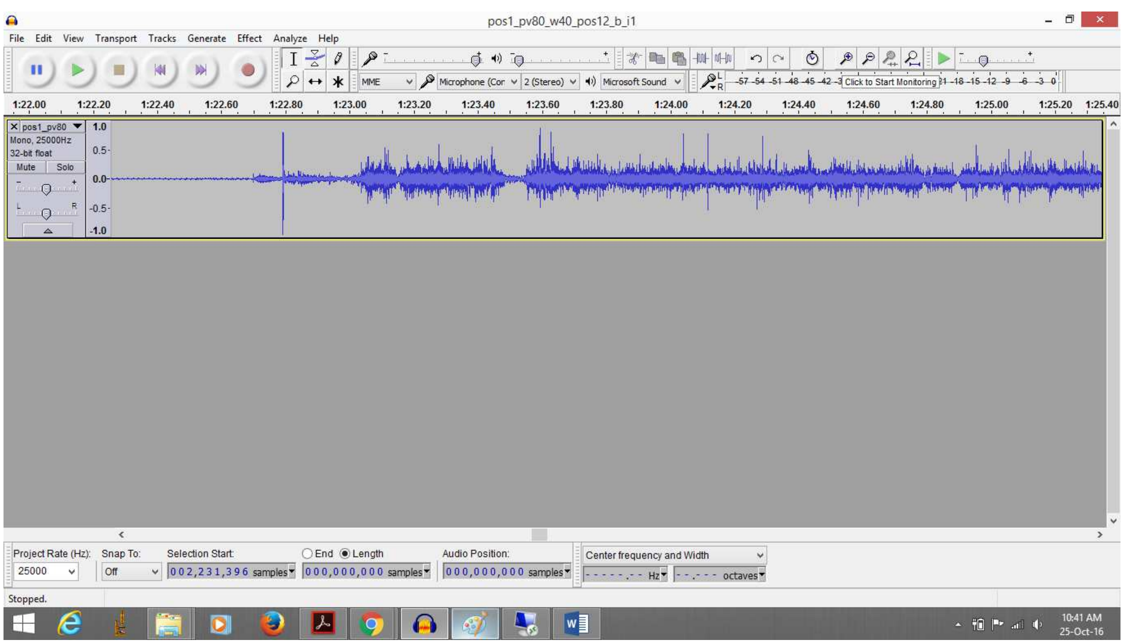


Figure 3.6: Audio recording using Audacity

3.4.2 Labjack DAQ [24]

A high performance multifunction Data Acquisition Module (DAQ) with USB, Labjack U6, as shown in Figure 3.7, was selected to record data from multiple sensors simultaneously. It has 14 analog inputs and 2 analog outputs, with 20 digital I/O. The maximum input range is ±10 volts, with software selectable gains of x1, x10 and x100. Each analog input can be measured single-ended or differentially in even/odd pairs. Analog input resolution is 16 bits at maximum speed (~20 µs conversion time), increasing to 18+ bits at lower speeds.

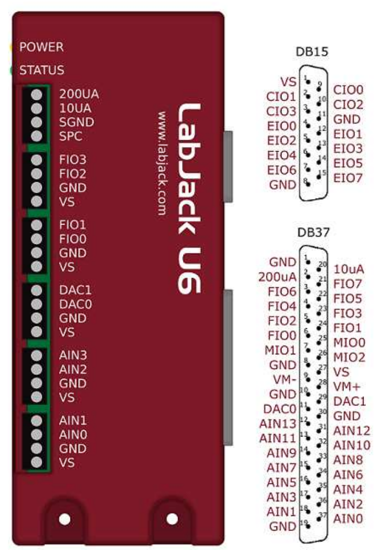


Figure 3.7: Labjack U6 DAQ
(Source: Labjack Manual)

Stream mode is used to scan the inputs for continuous data. The scan rate specifies the interval between the beginnings of each scan. The samples within each scan are acquired as fast as possible. As samples are collected by the Labjack, they are placed in a buffer on the Labjack, until received by the host. Stream mode is generally used at 10 scans/second or faster. Stream mode is not supported on the hi-resolution converter, that is, resolutions 9-12 are not supported in this mode. This has a maximum rate that varies with resolution from 4 ksample/s at 18 bits to 50 ksamples/s at 16 bits.

Stream mode is generally best for maximum-throughput applications where latency is not so important. Data is acquired very fast, but to sustain the fast rates it must be buffered and moved from the LabJack to the host in large chunks. For example, a typical stream application might set up the LabJack to acquire a single analog input at 50,000 samples/second. The LabJack moves this data to the host in chunks of 25 samples each. The Windows UD driver moves data from the USB host memory to the UD driver memory in chunks of 2000 samples. The user application might read data from the UD driver memory once a second in a chunk of 50,000 samples.

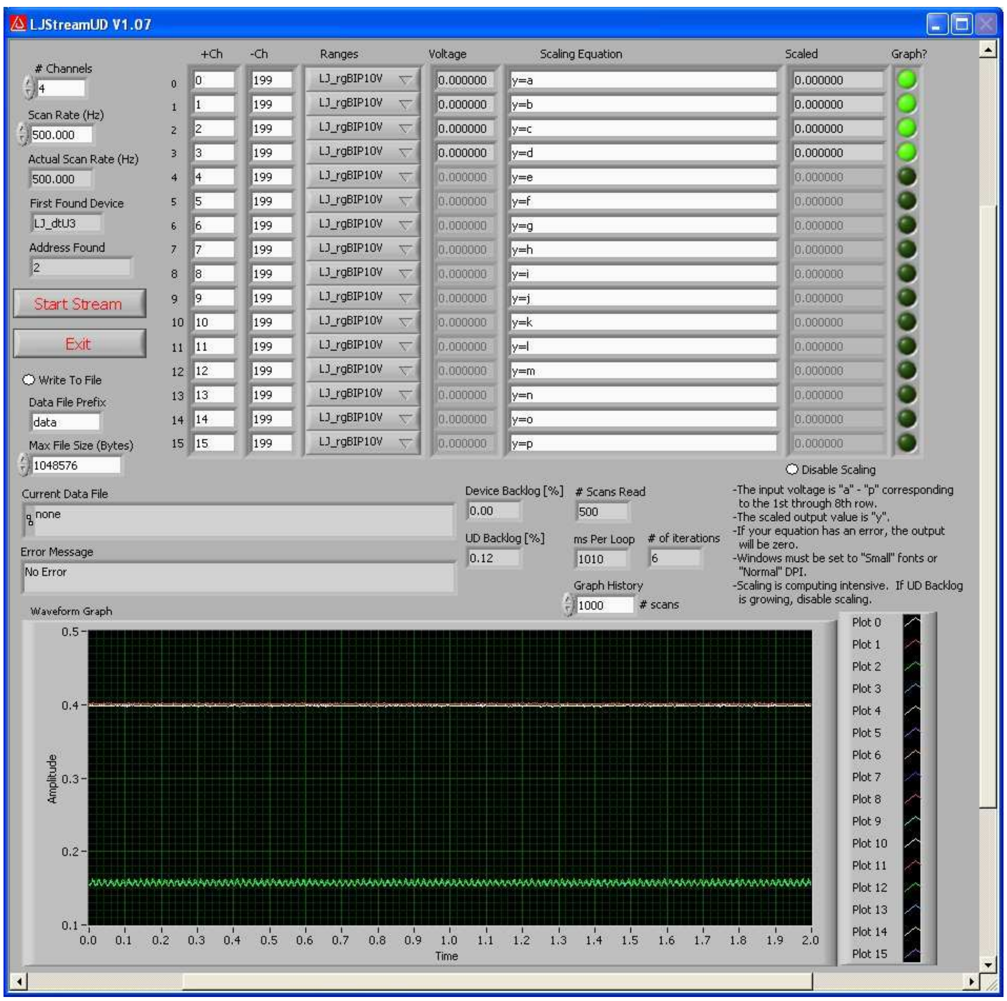


Figure 3.8: LJStreamUD application showing data being recorded from 4 channels (Source: Labjack Manual)

The computer has no problem retrieving, processing, and storing, 50k samples once per second, but it could not do that with a single sample 50k times per second. This is accomplished using the application LJStreamUD on Windows. LJStreamUD is a simple ready-to-run executable that streams up to 16 input channels from a single Labjack DAQ. It displays selected channels on a graph, as shown in Figure 3.8, and writes data to file.

3.5 The Analysis of Sensor Signals

Although the data acquisition may appear simple, particular caution is required for the interpretation of the data as pressure fluctuations [22], resulting in the generation of acoustic signals. This section presents an analysis of the signals acquired from the piezo film sensors during various valve actuation events, and their interpretations to the physical operation of the valve. As mentioned in Chapter 2, the location of the sensor on the valve plays a key role in signal analysis. Keeping this in mind, two suitable locations were chosen, and signals recorded at these locations are investigated to develop an algorithm for condition monitoring of the valve. Figure 3.9 shows suitable locations on the valve that are considered for signal analysis. Also, piezo film sensors attached to the valve using electrical tape is depicted in the figure.

From now, the entire investigation on signals correspond to the signals captured using piezo film sensors (not CM-01B sensor) at these locations (Positions-1 and 2) on a Burkert 2/2 – way Angle-seat pneumatically operated valve (Type 2100). The signals are recorded at 25 kHz sampling rate with 16 bit resolution. It may be noted that a series of experiments were also done with CM-01B. However, it was later replaced by the flexible, low-cost piezo film sensors. The signal conditioning circuit that is interfaced to these piezo film sensors is similar to that built internally in CM-01B contact microphone. The data from the CM-01B have not been included in the report, for brevity, and only the signals captured using piezo film sensors have been presented here. [A clear note will be mentioned there itself, if there is going to be any illustration on the signals captured by CM-01B, in the further sections of this document].

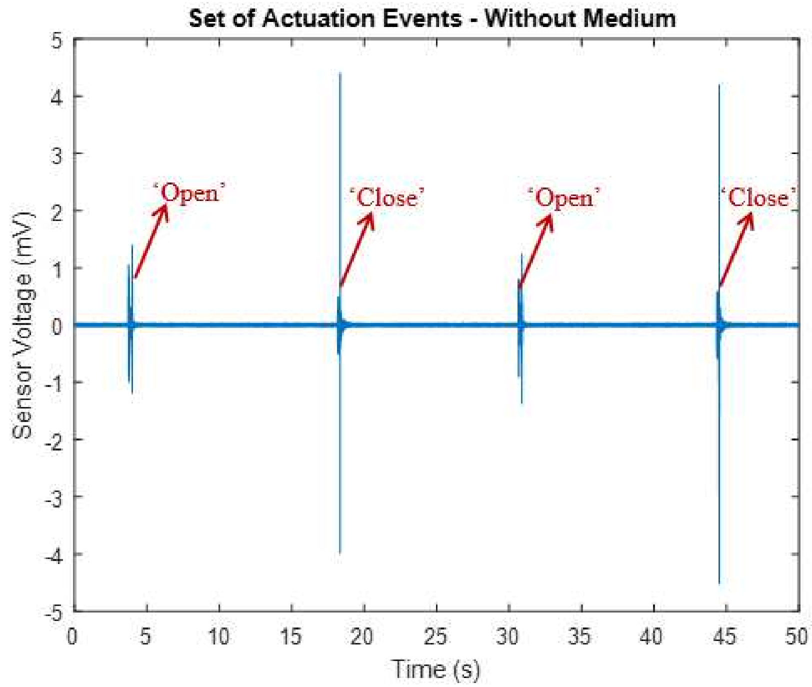
(a) Positions on the valve to place the sensors

(a) Valve after attaching sensors at the corresponding locations
Figure 3.9: Pneumatic valve before and after mounting sensors

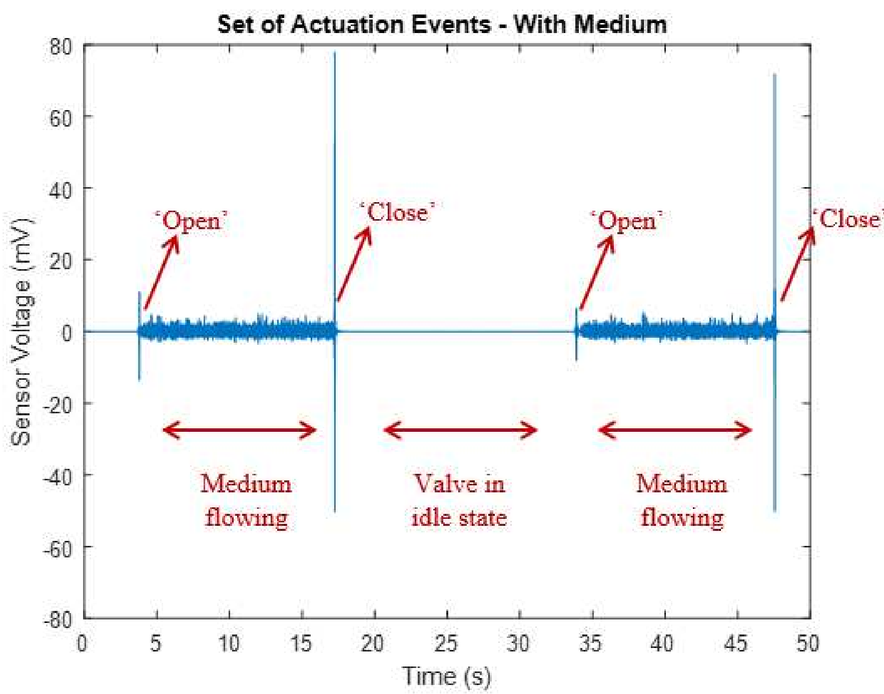
As discussed in the objectives in Chapter 1, the investigation was carried out step-by-step, by initially analyzing the signals during its actuation events – opening and closing of the valve without medium, and then with medium (regular water has been used as medium), for a healthy valve. After reaching to some sensible conclusions, similar analysis has been carried out with a defective valve, which will be discussed in Chapter 6.

3.5.1 A Broad view of Sensor Signals

Figure 3.10 (a) and (b) depicts analog signals captured by using piezo film sensors at a certain position, during the valve actuation events, i.e., opening and closing of the valve. The 'Open' and 'Close' labels in the figures represent the opening and closing events of the valve. A difference can be observed from these plots, with respect to the flow of medium. There is a great rise in signal strength of the signals during open and close events when medium is flowing, as compared to that without any medium. In a broad perspective, it is clear from the plots that signals corresponding to open and close events of the valve, may have some additional characteristics when medium flows through the valves. This can be clearly understood when we look into the signals for specifics. A more keen observation of signals specific to just the open event and close event separately, with and without medium would give us a better understanding of their characteristics, which is done in the succeeding sections. These signals are plotted by normalizing with the approximate gain of the amplifier.



(a) Without Medium



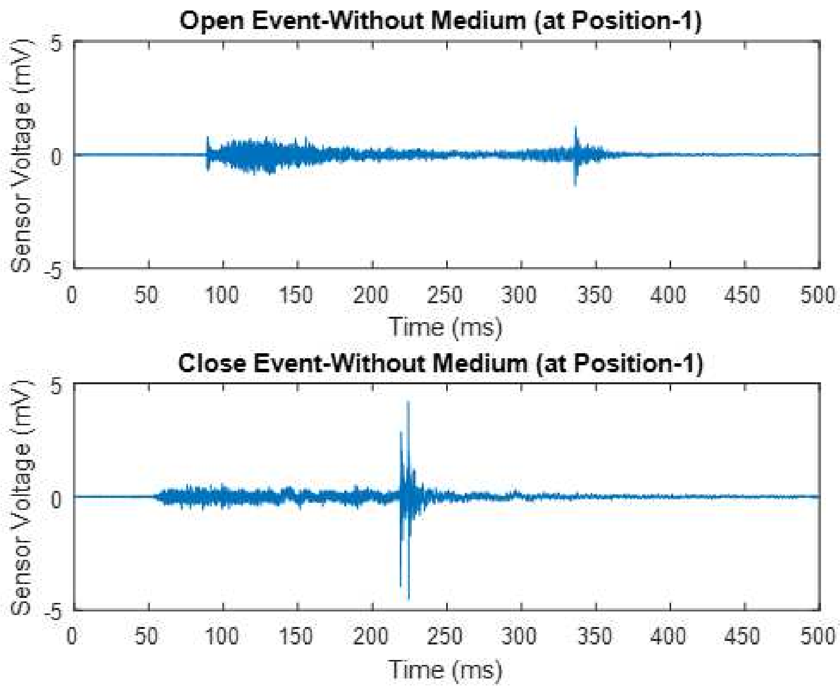
(b) With Medium

Figure 3.10: Sensor signals during opening and closing of the valve (with/without medium)

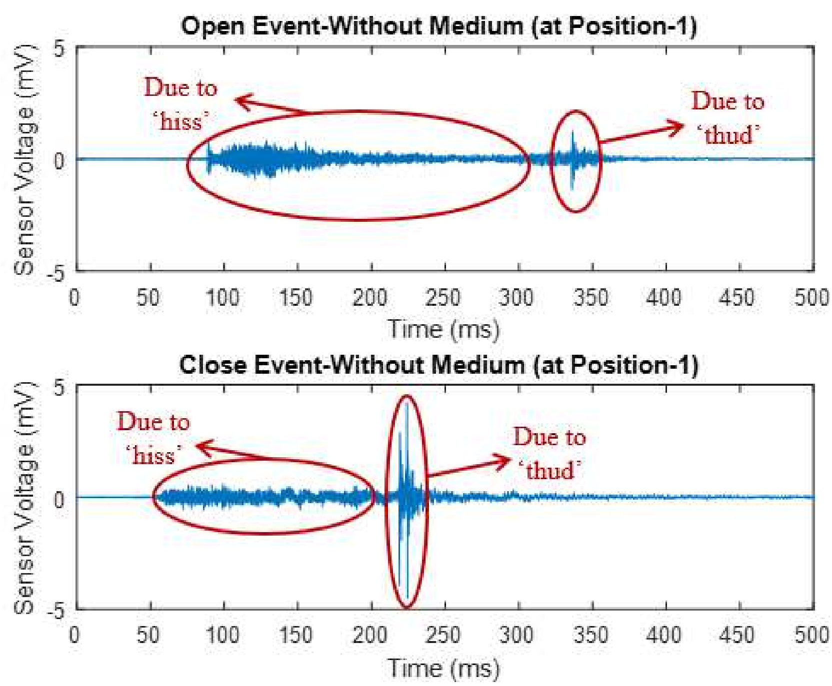
3.5.2 A Close look at the Sensor Signals

To better understand signals from the sensors, and how they reflect the pneumatic valve movements, the valve is first operated without any medium flowing. The signals recorded during the opening and closing of the pneumatic valve are shown in Figure 3.11. As these are recorded while no medium was flowing, these are expected to only reflect the acoustic signal generated from the mechanical actions during valve actuation movements. These mechanical actions can be described as follows. When a valve is opened, the piston inside the valve is pushed to the top due to spring action (as this is a normally-closed valve). This produces a hissing sound. Then, the metal part of the piston hits the metal surface inside the valve, which generates a 'thud' like sound is produced. This activity lets the valve to open completely. During closing, a similar process goes on resulting in producing sounds like 'hiss' and 'thud'. One thing to be noted here is that, during both the events, thuds occurs at the end.

The corresponding signals with medium (water) flows are depicted in Figures 3.12 and 3.13, which clearly depicts the signal portions of open and close events, that are added due to medium. To get a clear picture of the signal characteristics, these figures have been plotted with different amplitude scales to illustrate the effect of the medium. The signals captured at Posiiton-2 are depicted in the figures 3.14 and 3.15. The portions of the signals pertaining mainly due to medium may also be caused due to fluid hammers. Fluid hammer is a pressure surge or wave caused when a fluid in motion is forced to stop or change direction suddenly.

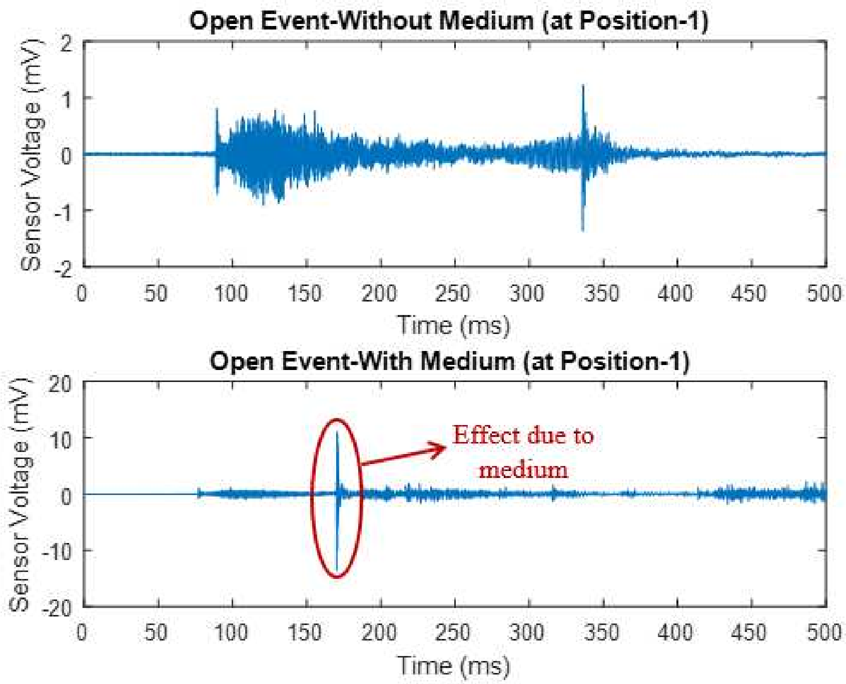


(a) Open and Close signals

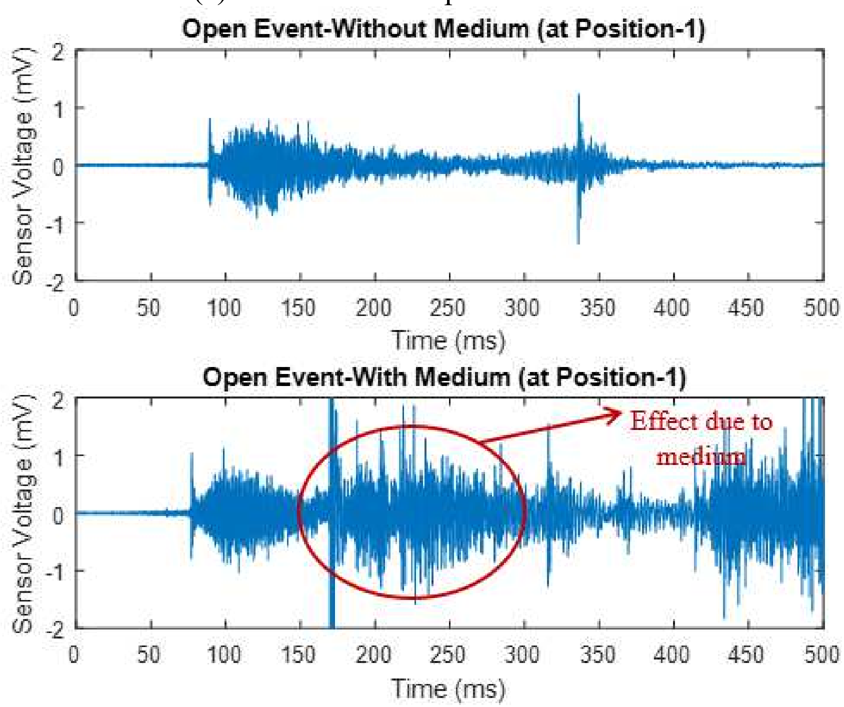


(b) Signals depicting the valve movements

Figure 3.11: Signals corresponding to open and close events of a healthy valve without medium (at Position-1)

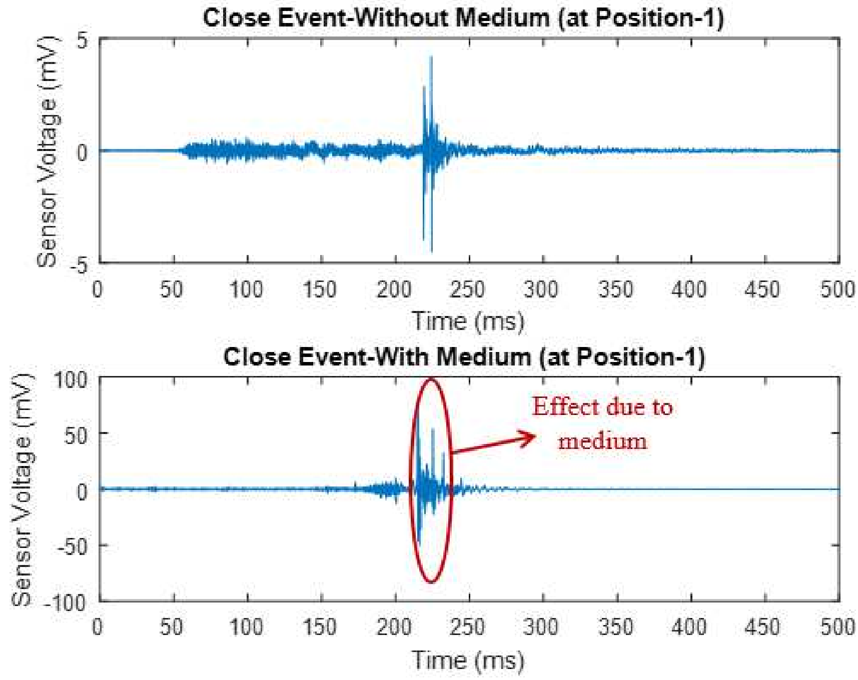


(a) On different amplitude scale

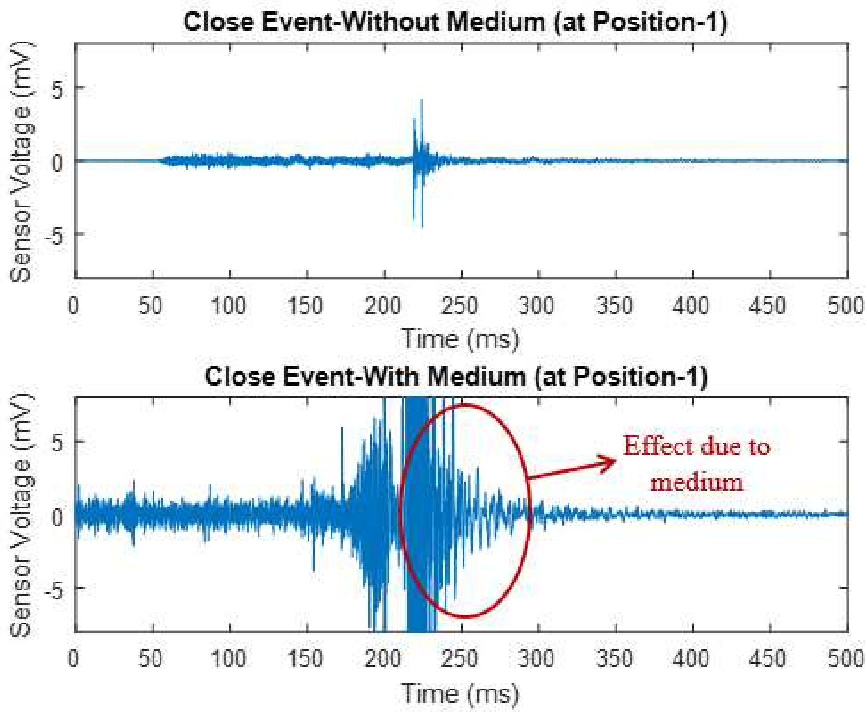


(b) On same amplitude scale

Figure 3.12: Signals corresponding to open events showing the effect of medium (at Position-1)

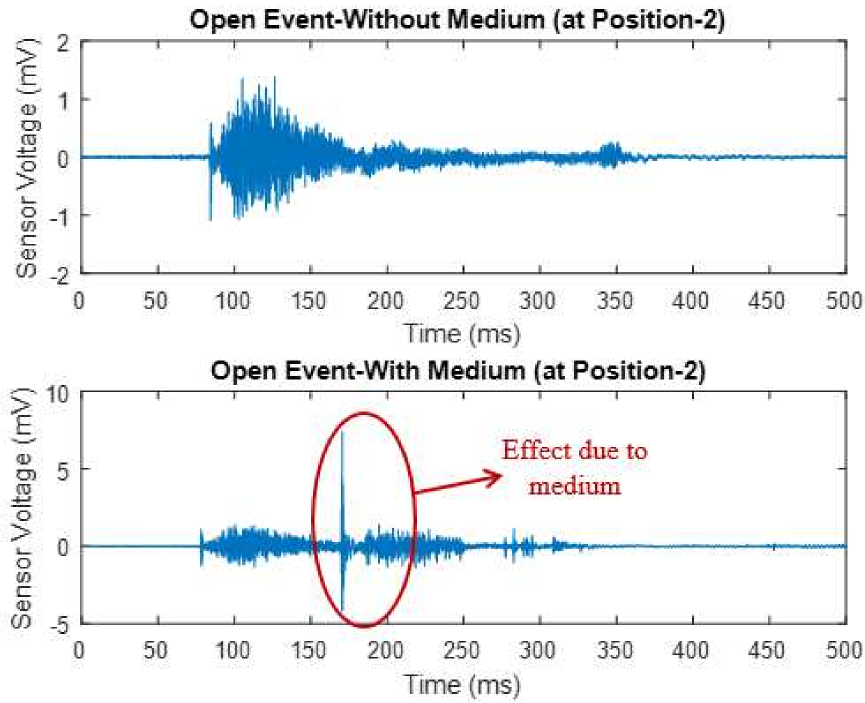


(a) On different amplitude scale

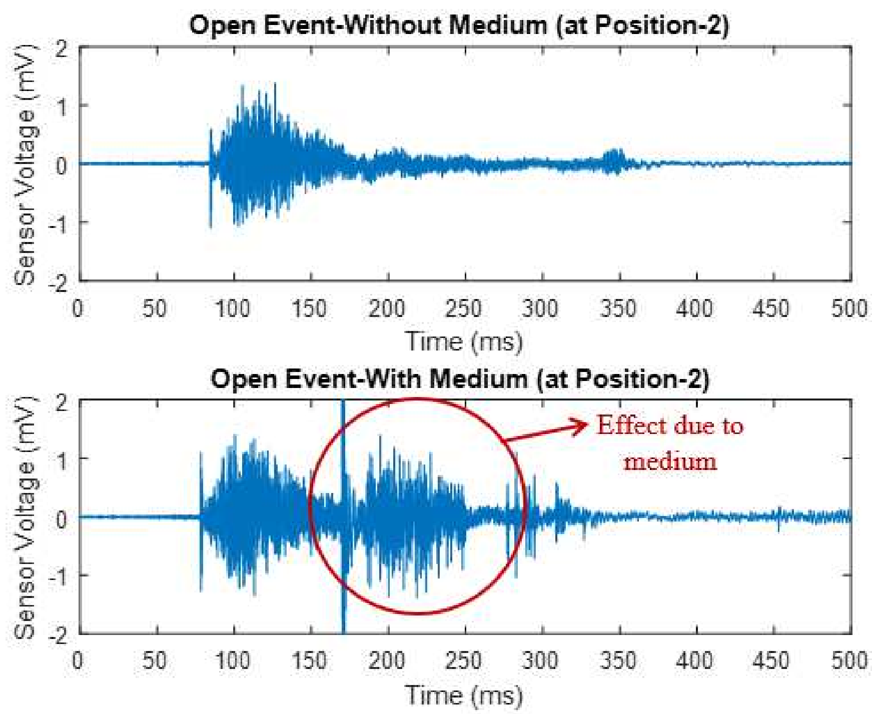


(b) On same amplitude scale

Figure 3.13: Signals corresponding to close events showing the effect of medium (at Position-1)

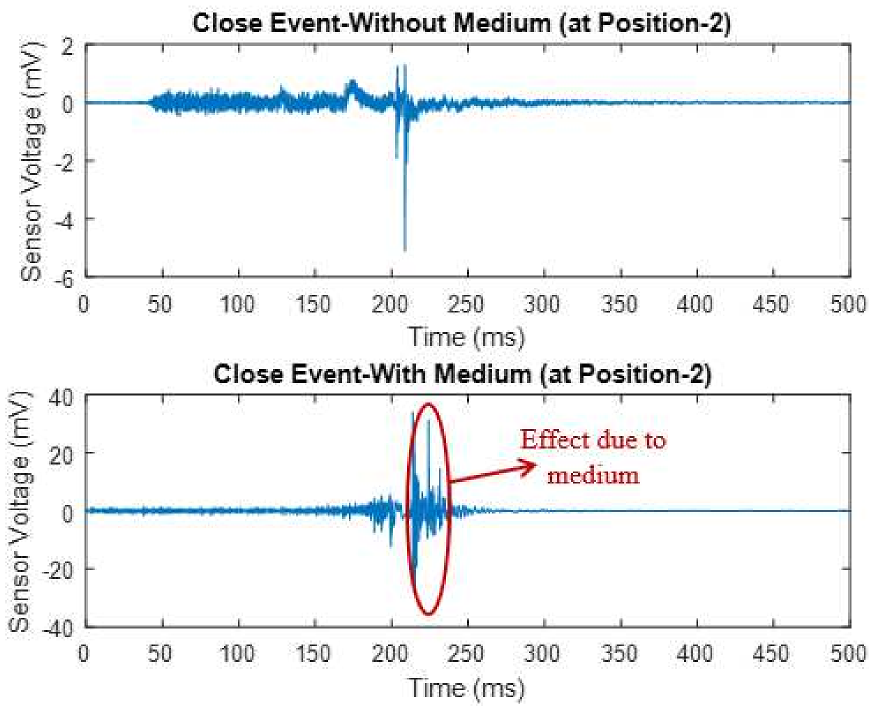


(a) On different amplitude scale

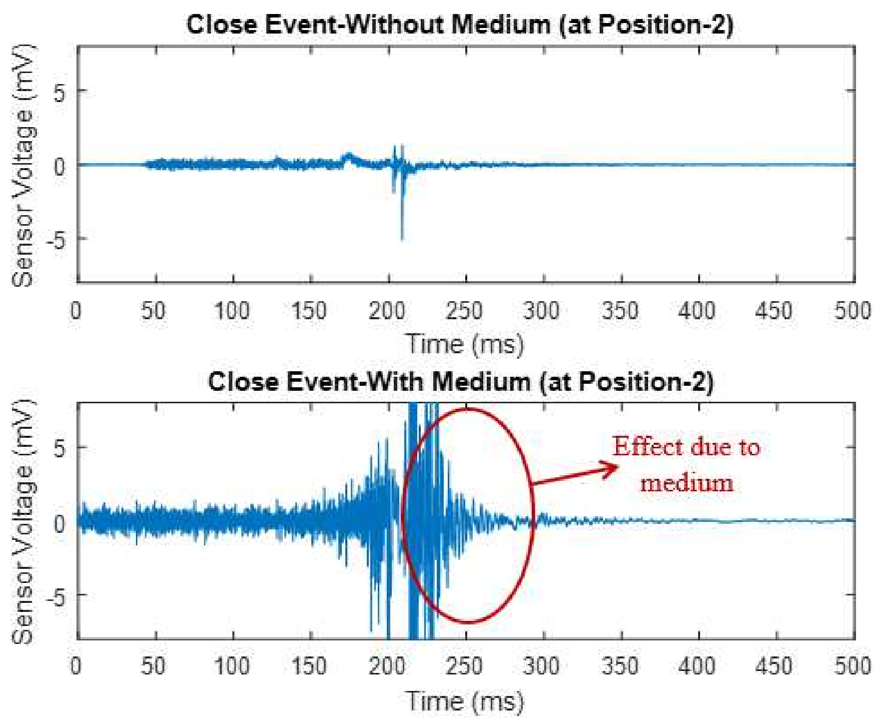


(a) On same amplitude scale

Figure 3.14: Signals corresponding to open events showing the effect of medium (at Position-2)



(a) On different amplitude scale



(a) On same amplitude scale

Figure 3.15: Signals corresponding to close events showing the effect of medium (at Position-2)

3.5.3 Observations

From the time-domain signals illustrated in the figures in the previous section, it is observed that:

- The sounds due to thuds are less audible at Position-2 than at Position-1.
- The effect due to medium is less significant at Position-2 than at Position-1.
- As compared to an open event, a close event is more impacted by the medium as s evident from the above figures. This is due to the fact that sensors capture the sounds produced by the valve movement along with those produced due to the flow of medium, until thuds occurs, this is when the event successfully completes, as mentioned earlier.

It is often the case that useful information can be obtained from the available data through feature extraction, either in the time or the frequency domain. Conceptually, the idea of feature extraction is to find those parameters that give the most important information about the condition of the system and discard the rest [25]. Thus, having obtained a basic idea on the signals that sensor captures, during the normal opening and closing of the valve, the next chapters present the approaches to extract some features that specifically determine signatures of the actuation events. Thereby, attempts to propose an algorithm based on proposed feature extraction ideas, have been performed, both in the frequency and time domains, to monitor the condition of valves.

CHAPTER 4: CLASSIFIERS BASED ON SPECTRAL ESTIMATION

In this chapter, we will focus on the spectral characteristics of the signals representing the healthy actuation events of the valve. This requires estimation of the power spectral density (PSD) of these random signals, as it gives the distribution of power of a signal over a set of frequencies. According to the Wiener-Khincthine theorem [29], it is known that, the power spectrum of a wide sense stationary random process can be obtained from the autocorrelation function as follows,

$$S_X(\omega) = \sum_{k \to -\infty}^{\infty} r_X(k) e^{-jk\omega} \tag{4.1}$$

Here,

$S_X(\omega)$ represents the power spectral density,

$r_X(k)$ is the autocorrelation sequence, and

ω is the angular frequency

For discrete time signals, the autocorrelation sequence, over a finite interval, say $n = 0,1,...N-1$ can be estimated using,

$$r_X(k) = \frac{1}{N} \sum_{n=0}^{N-1} x(n+k) x^*(n) \;;\; k = 0,1,...N-1 \tag{4.2}$$

Therefore, if $x(n)$ is known for all *n*, then power spectrum can be estimated by determining the autocorrelation sequence using Eq. (4.2). However, there are two challenges with this approach. First, the amount of data that one has to work with is never unlimited and, in many cases, it may be very small [26]. Such a limitation may be an inherent characteristic of the data collection process.

The approaches for estimating power spectral density can be categorized into non-parametric methods and parametric methods. Non-parametric methods typically estimate the power spectrum through the Fourier transform of some estimate of the autocorrelation. Parametric methods are typically based on some model such as Autoregressive model or ARMA models. Periodogram is a basic method to estimate the power spectrum as it is easy to compute, but it is limited in its ability to produce an accurate estimate of the power spectrum, particularly for short data records [26]. There are several methods for improving the simple Periodogram, like Bartlett method by averaging a number of periodograms, Blackman-Tukey method by applying a window to the estimated sample correlation function and Welch method by combining windowing and averaging [27]. Welch method is used here to estimate power spectral density of the signals corresponding to the actuation events of the valve.

4.1 PSD Estimation:

Power Spectral Density is estimated using Kaiser window. Its analysis is shown in Figure 4.1, in time and frequency domains for different values of attenuation parameter, β. Larger absolute values of β result in greater stopband attenuation, or equivalently greater attenuation between the main lobe and the first side lobe. Here, the side lobe attenuation, α (dB), is expressed in terms of β, according to the Eq. 4.3.

$$\beta = \begin{cases} 0.1102(\alpha - 8.7), & \alpha > 50 \\ 0.5842(\alpha - 21)^{0.4} + 0.07886(\alpha - 21), & 50 \ge \alpha \ge 21 \\ 0, & \alpha < 21 \end{cases} \quad (4.3)$$

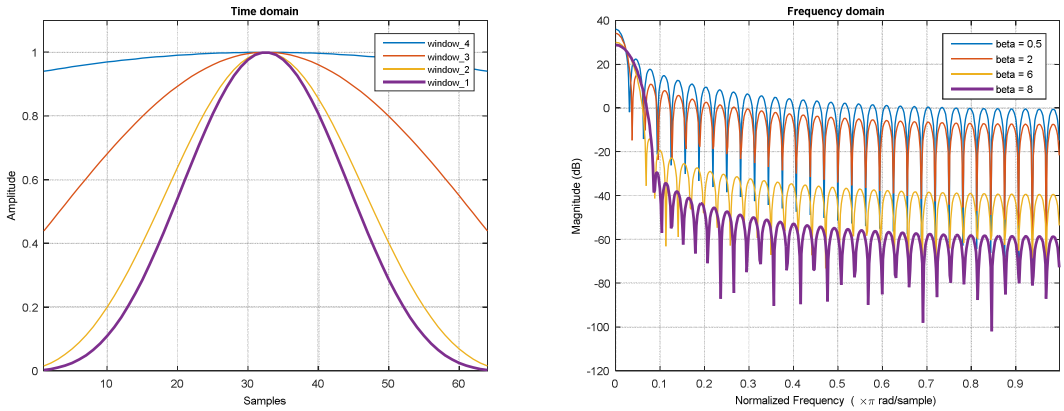
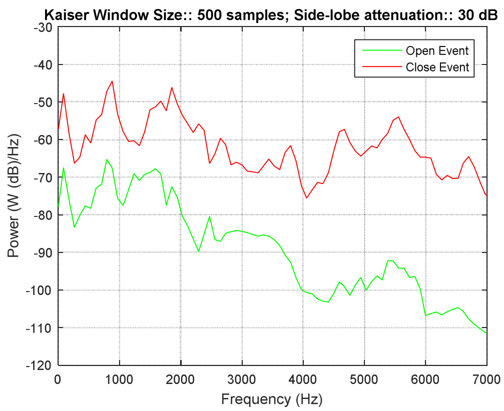


Figure 4.1: Analysis of Kaiser window in time and frequency domains for different β

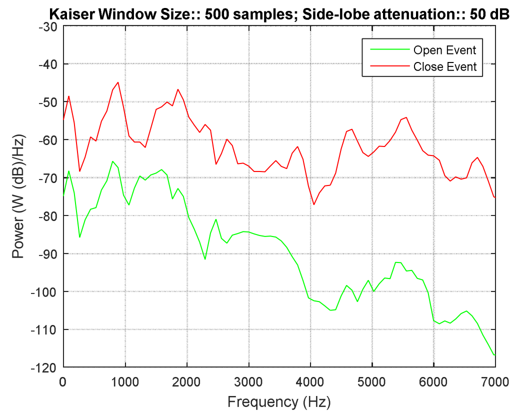
By experimenting with different window sizes and side lobe attenuations, as shown in Figure 4.2, it is observed that considering a window size of 1100 with a side lobe attenuation of 50 dB would be suitable to better understand the frequency content of these signals. In this analysis, ten instances are averaged to get the PSD estimates considering only the thuds of the open and close events. To easily distinguish between open and close signals in the figure, we use green color to represent the characteristics of an open event and red color to represent that of the close event.

This approach has been extensively experimented with CM-01B sensor by mounting the sensor at different locations, perhaps 4 to 5. The PSD estimates of open and close thuds, without medium, are shown in Figure 4.3. These plots indicate that the close event has more power concentrated at high frequency components as compared to that of an open event.

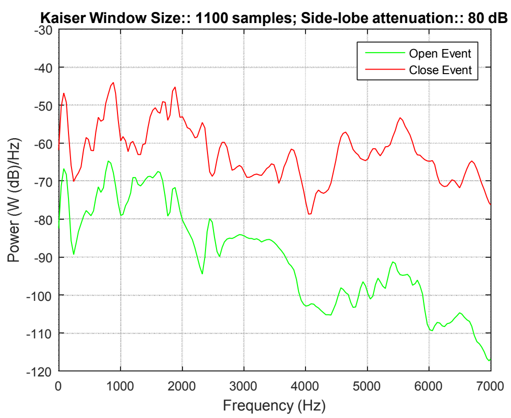
Figure 4.4 shows the PSD estimates of the open and close thuds in the presence of medium flow. Similar to the case without any medium, these plots also support the fact that the close event has high frequency content than the open event, although this effect is less pronounced in this case. Based on this idea, an approach to classify these events by considering the spectral content, has been explored.



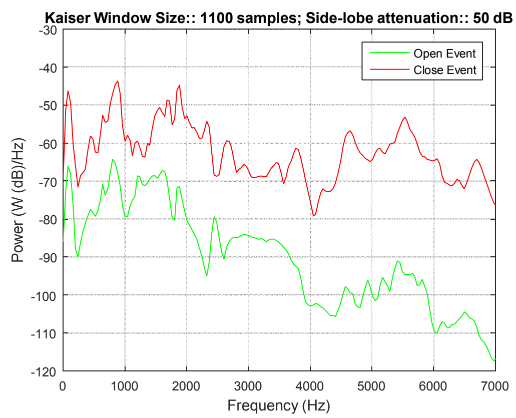
(a) Window size: 500 samples;
Side-lobe attenuation: 30 dB



(b) Window size: 500 samples;
Side-lobe attenuation: 50 dB

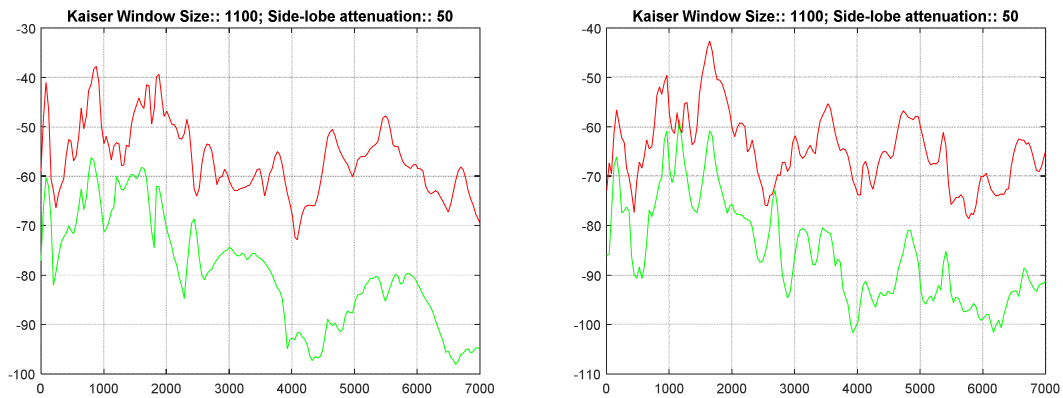


(c) Window size: 1100 samples;
Side-lobe attenuation: 50 dB



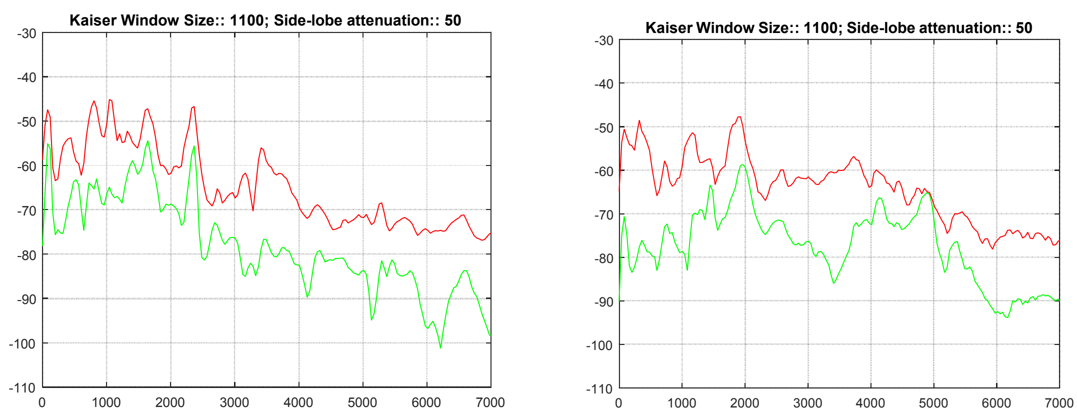
(d) Window size: 1100 samples;
Side-lobe attenuation: 80 dB

Figure 4.2: PSD estimates with different window sizes and side-lobe attenuations



(a) Iteration – 1 (b) Iteration – 2

Figure 4.3: PSD estimates without medium (green – open; red - close)



(a) Iteration – 1 (b) Iteration – 2

Figure 4.4: PSD estimates with medium (green – open; red - close)

4.2 Classifiers

We apply a classifier based event detection scheme is shown in Figure 4.5. Initially, 1024 samples of thuds corresponding to open and close events are taken to find its Fast Fourier Transform (FFT). Then, the magnitude of their frequency components are squared to get the power associated with the frequency components. Here, the analysis is done over the frequency band of 0 – 7 kHz. The power obtained is normalized over this frequency band for unity power. Now, two sub-frequency bands are selected as (0 – 3 kHz) and (3 – 7 kHz), over which the obtained power is integrated separately to get the classifiers C_1 and

C_2. Finally, these classifiers are plotted and analyzed to categorize the actuation events of the valve.

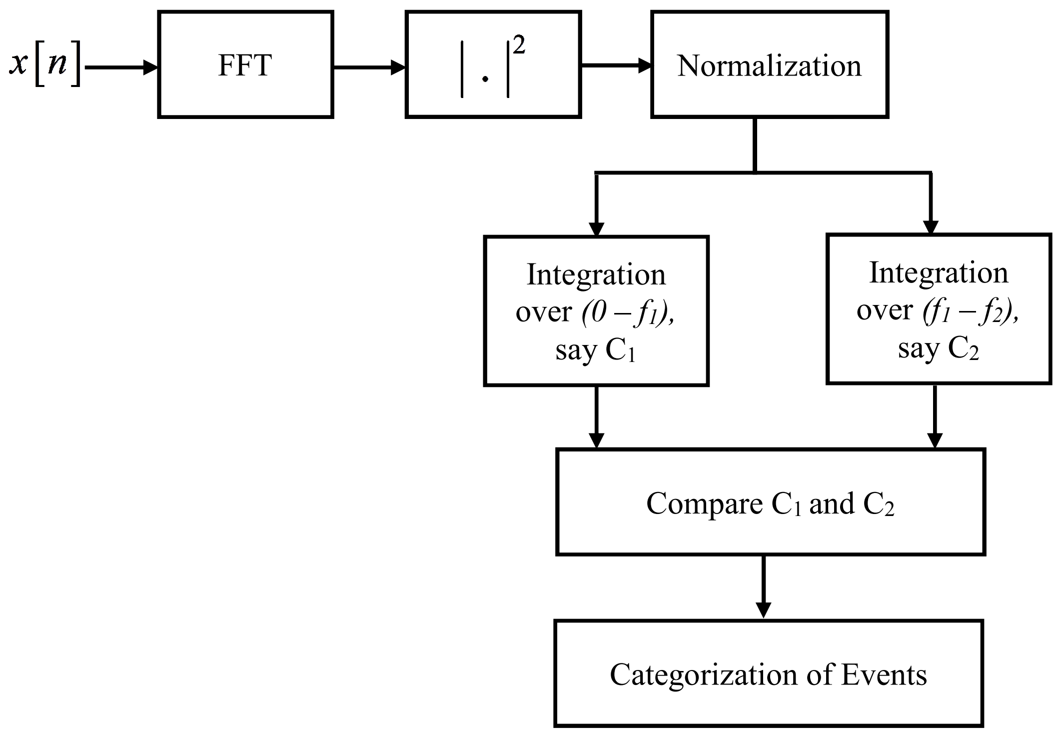
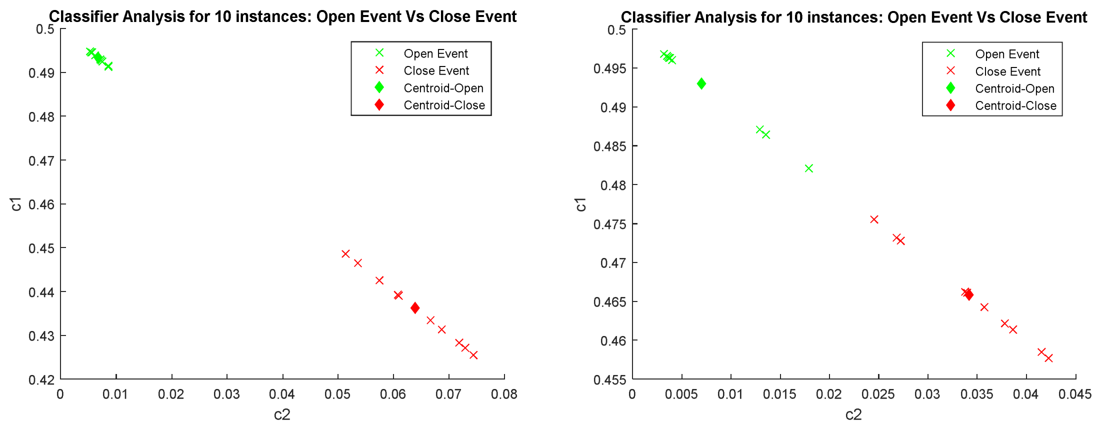


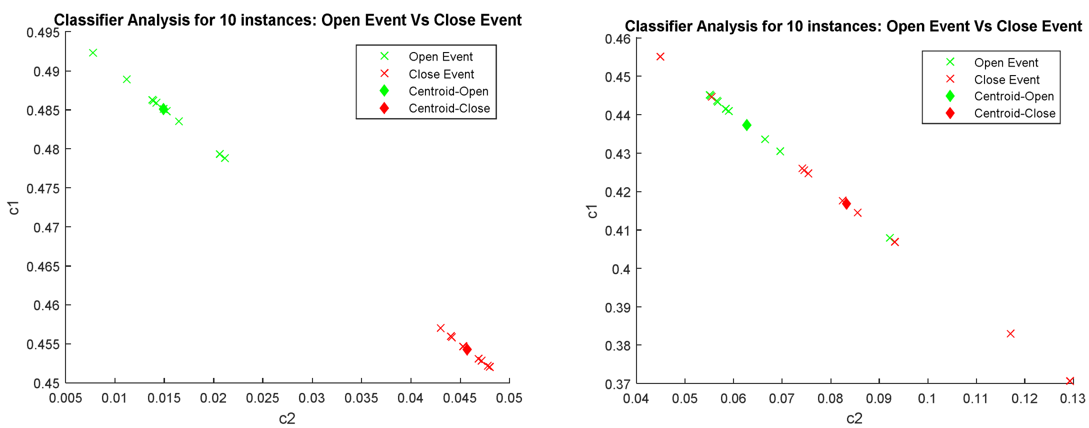
Figure 4.5: Block diagram of the Classifiers approach

The choice of $f_1 = 3\ kHz$ was obtained from experimental tests for obtaining the best distinctions between open and close events. The classifiers are plotted by taking 10 instances of open and close events as per the process explained above. In the plots, the green color represents an open event and red color, a close event. The centroid of all these 10 distributions of C_1 and C_2 can be seen in the plots, shown in Figure 4.6. These plots indicate that in the absence of any medium, the open events have more power at lower frequency components. In contrast, the exact opposite is observed for close events. Therefore, similar analysis is done by considering the instances of the events with medium, as shown in Figure 4.7.



(a) Iteration – 1 (b) Iteration - 2

Figure 4.6: Classifiers of Open and Close events without medium
(green – open; red - close)



(a) Iteration – 1 (b) Iteration - 2

Figure 4.7: Classifiers of Open and Close events with medium
(green – open; red - close)

These experiments were conducted many times using CM-01B sensor by mounting it at various positions on the valve, as mentioned before. But, as seen from Figure 4.7, there were some inconsistent data points that can be noticed in Figure 4.7 (b). As a matter of fact, some results completely contradict the expected behavior. Therefore, it has been inferred that the proposed classifiers based on energy content in different frequency bands is not suitable to these kind of signals. Hence, a new approach using envelope analysis of the signals was proposed, which we will be discussing in the next chapter.

CHAPTER 5: SEQUENTIAL STATE LOGIC BASED ON SHORT-TIME ENERGY PROFILES

The measured AE signal is a rich source of temporal information [28]. The signal duration, distribution of the peak amplitude, arrival time differences of the signal at different sensors, average repetition rates, individual signal amplitudes and energy of the signal are all important characteristics [5]. Time domain envelope analysis consists of the examination of the variations in the signal strength, statistical distribution of the values of signal amplitudes, etc. This chapter initially presents the investigation of the short-time energy profiles of the signals and then, attempts to categorize the actuation events of the valve using pattern matching techniques.

5.1 Short-Time Energy (STE) Estimation:

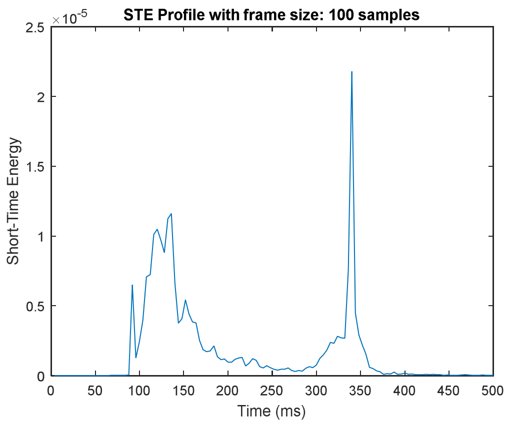
The short-time energy of any signal may be computed by dividing the signal into frames of *N* samples and computing the total squared values of the signal samples in each frame. Splitting the signal into frames can be achieved by multiplying the signal by a suitable window function (here rectangular window), as:

$$E_m = \sum_{\forall n} \left[x[n] w[m-n] \right]^2 \qquad (5.1)$$

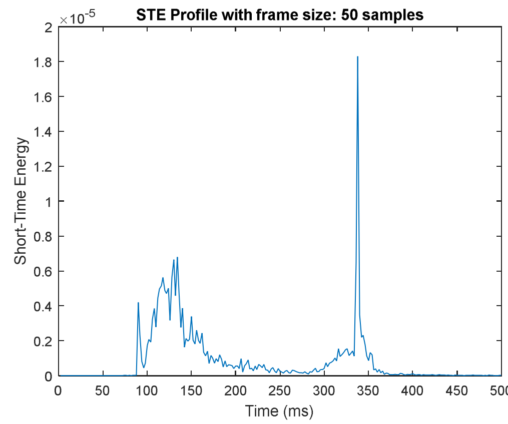
where, $x[n]$ is a signal sample, and

$$w[n] = \begin{cases} 1; & 0 \le n \le N\text{-}1 \\ 0; & elsewhere \end{cases}$$ is a rectangular window.

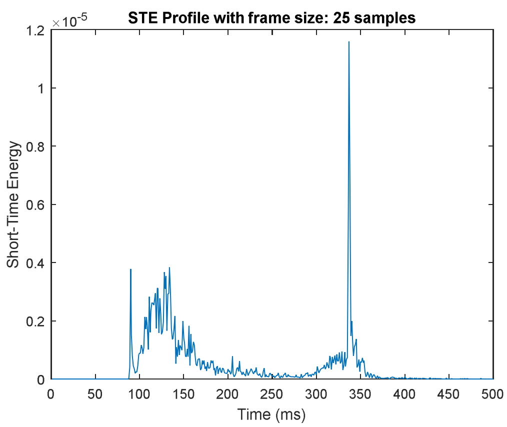
The choice of the window size affects the short-time energy and therefore, we wish to have a short duration window to be responsive to rapid amplitude changes. But a window that is too short will not provide sufficient averaging to produce accurate energy function.



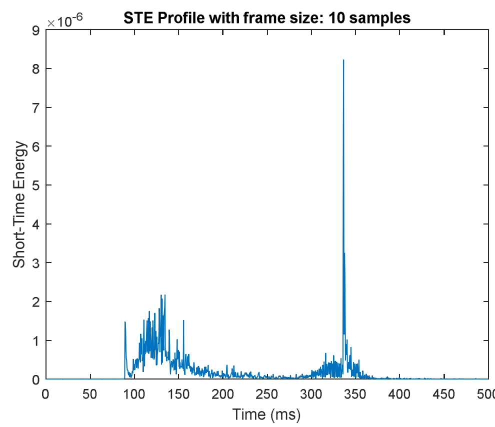
(a) Frame size: 100 samples



(b) Frame size: 50 samples



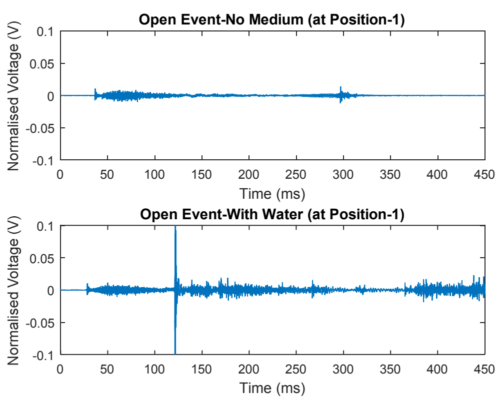
(c) Frame size: 25 samples



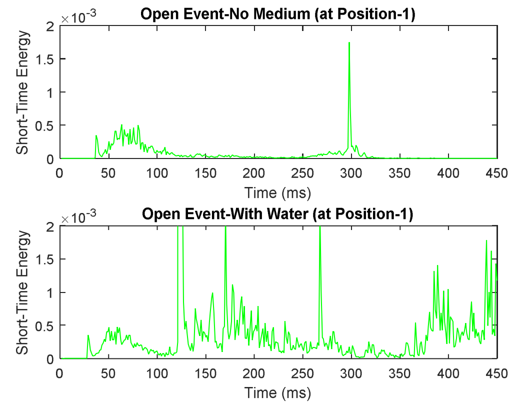
(d) Frame size: 10 samples

Figure 5.1: Short-Time Energy profiles for different frame sizes

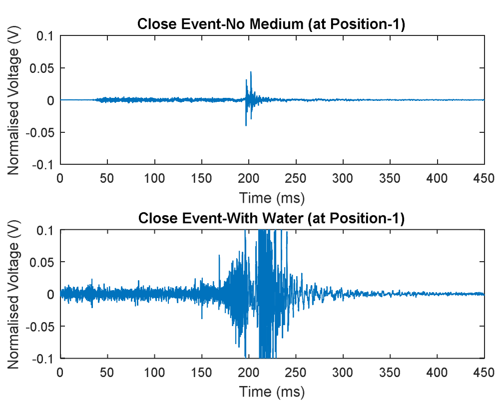
Figure 5.1 shows the short-time energy profiles of a signal for the open event similar to that in Figure 3.11, for different window lengths (frame sizes). It can be observed from the figure that the details of the signal are not clearly revealed by the profiles with window lengths – 100 and 50, whereas the frame size of 10 samples is unnecessary as it is giving too much of redundant information. Therefore, a frame size of 25 samples looks informative enough to extract the features of the signal and will be considered for further analysis. Analysis of the characteristics of the actuation events of the valve and effect due to the medium are investigated based on their STE profiles.



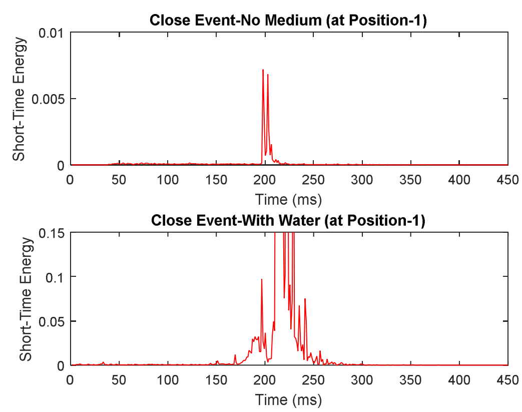
(a) Sensor signal of an open event



(b) STE profile of an open event



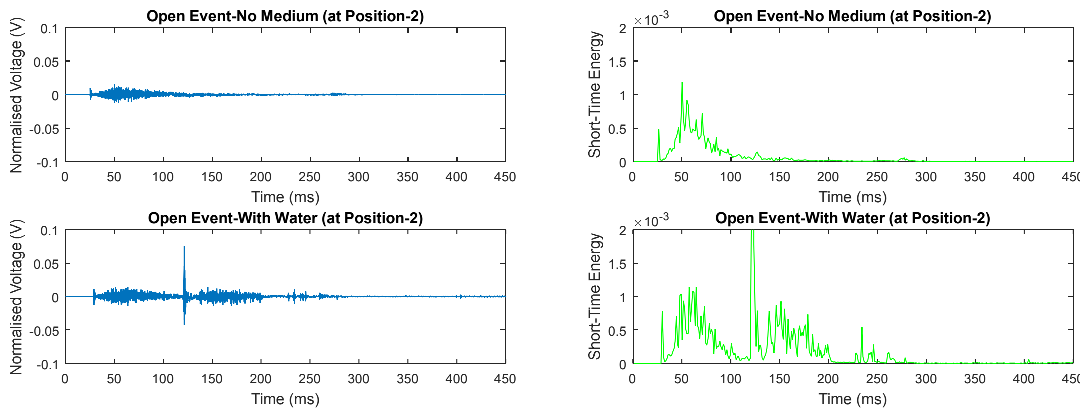
(c) Sensor signal of a close event



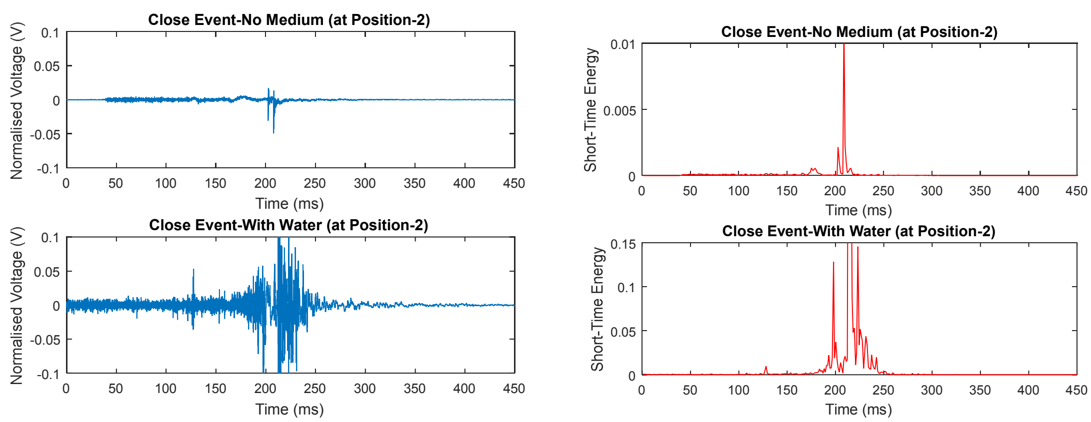
(d) STE profile of a close event

Figure 5.2: Open and Close events' signals with their STE profiles at Position – 1 (with and without medium)

Figure 5.2 shows the STE profiles of open and close events of a healthy valve at Position-1. The left column of the figure shows the analog signals captured by the piezo film sensor, and the figures toward the right shows their corresponding STE profiles (green – open, red – close, as mentioned earlier). We observe that these STE profiles are good at showing clearly the effect due to medium during the events. Similar profiles at the Position-2 are shown in Figure 5.3. One more thing that can be noticed from these figures is that the sound due to thud is very much less audible at Position-2.



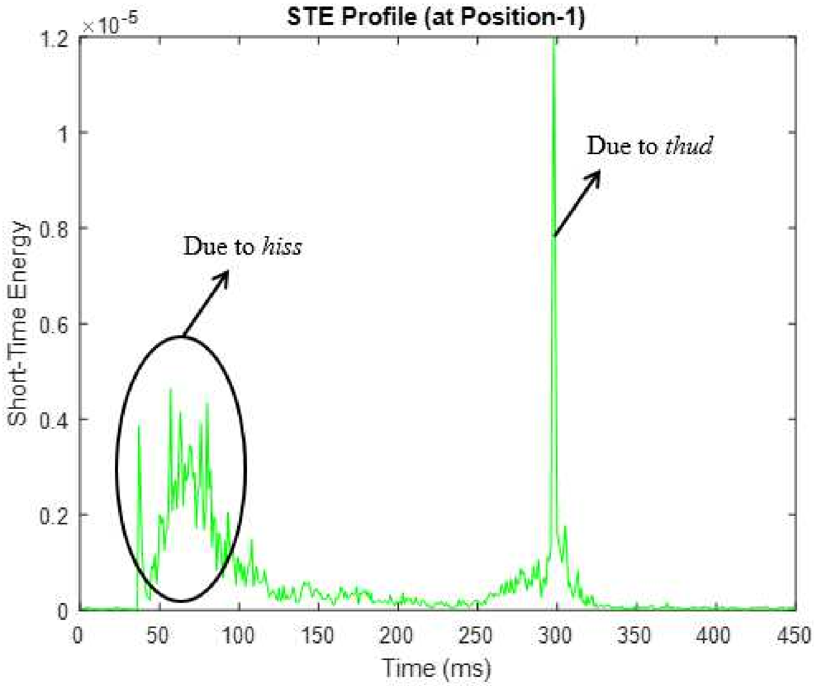
(a) Sensor signal of an open event (b) STE profile of an open event



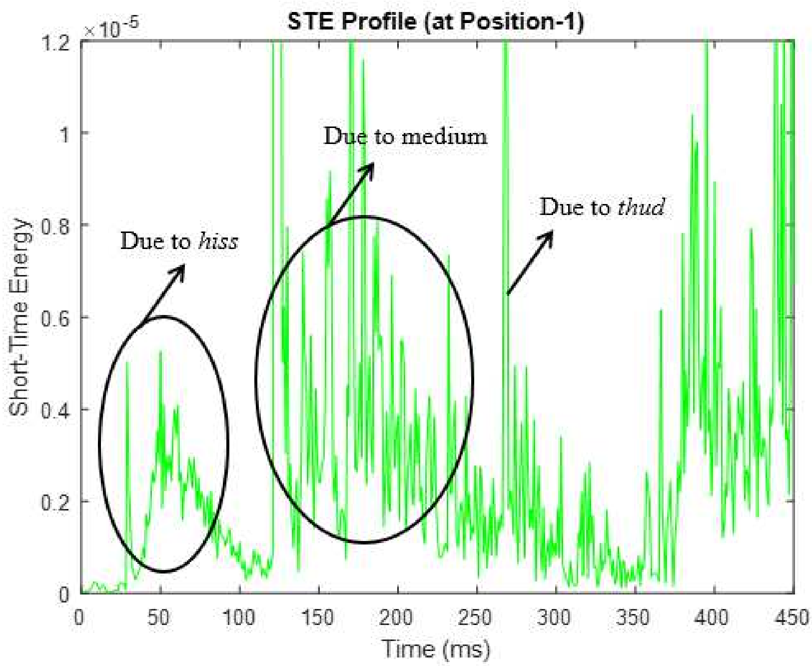
(c) Sensor signal of a close event (d) STE profile of a close event

Figure 5.3: Open and Close events' signals with their STE Profiles at Position – 2 (with and without medium)

To get a better understanding on these STE profiles and their specifics to the open and close events of the valve, we will look a bit closer into these profiles, as depicted in Figure 5.4 and Figure 5.5. These figures clearly depict the portions of the profile that correspond to the sound produced by the valve and that produced by medium. This kind of analysis lets us know the signatures of the actuation events of the valve and the effect due to medium separately. As discussed earlier, the STE profiles clearly depict the thud at Position – 1 and its absence at Position – 2. Similarly, Figures – 5.6 and 5.7 shows the STE profiles of a close event at Position – 1 and Position – 2 and their comparison with and without medium.

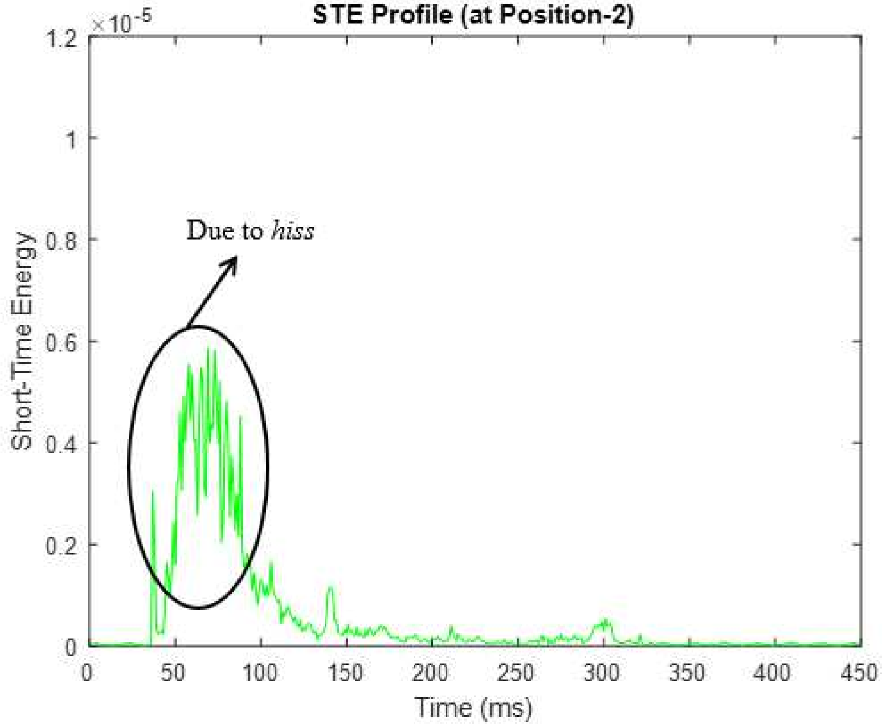


(a) Without medium

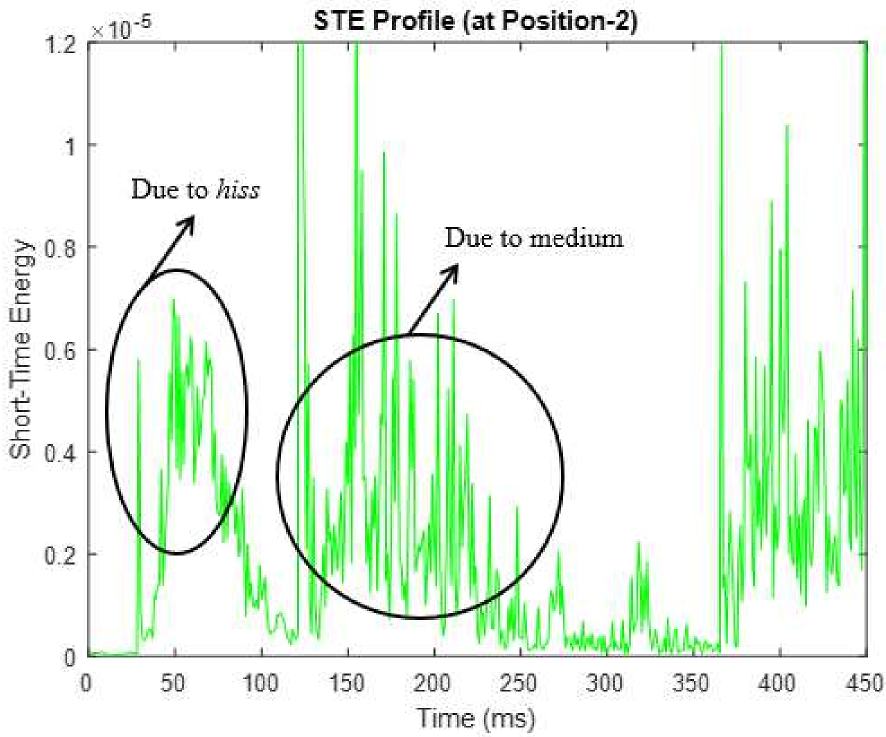


(b) With medium

Figure 5.4: A close look into STE profiles of an open event at Position – 1 (with and without medium)

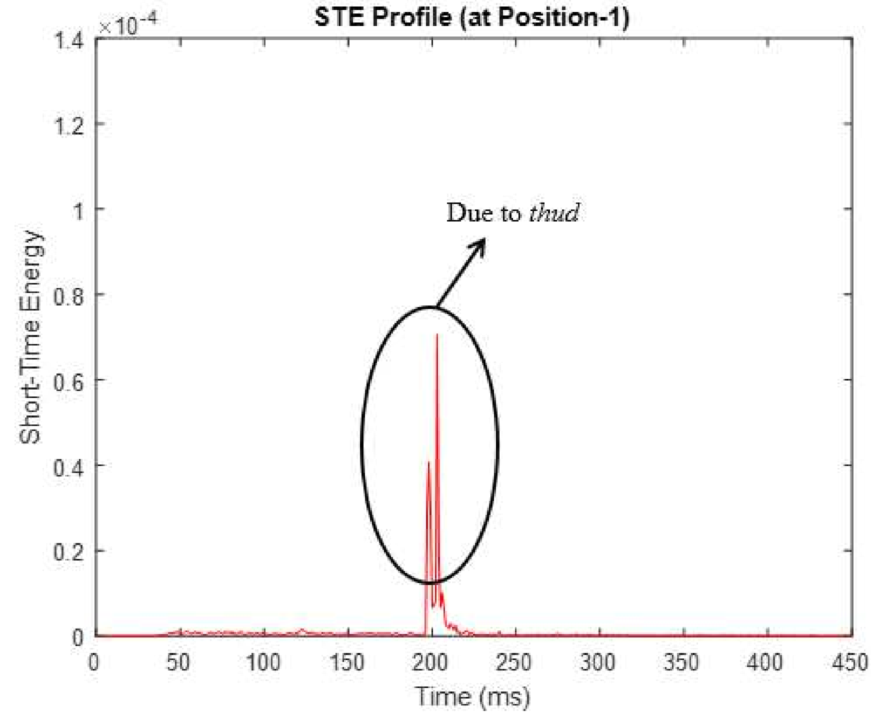


(a) Without medium

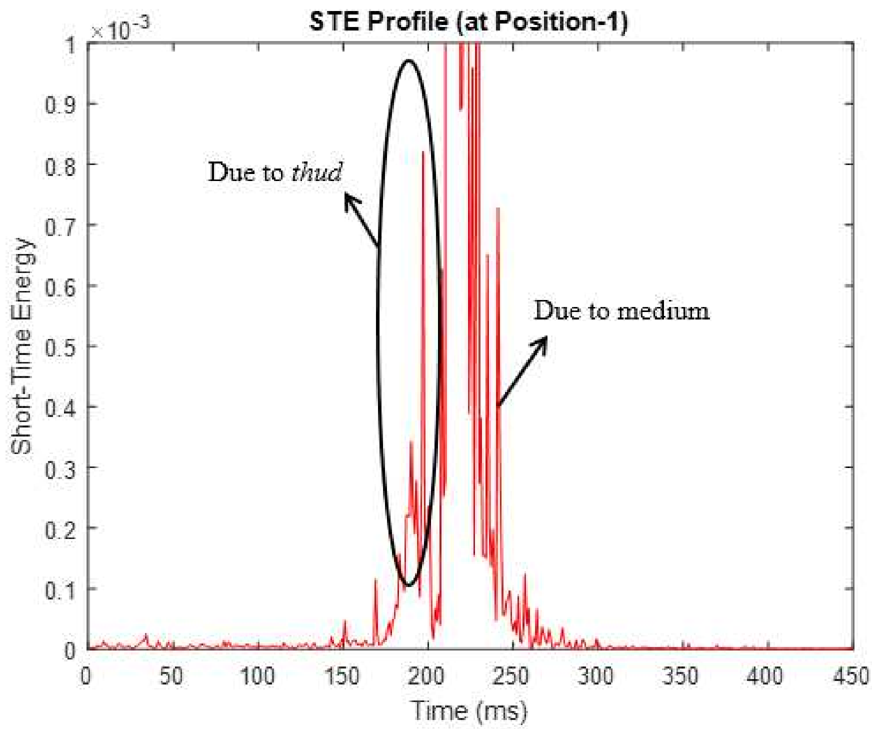


(b) With medium

Figure 5.5: A close look into STE profiles of an open event at Position – 2 (with and without medium)

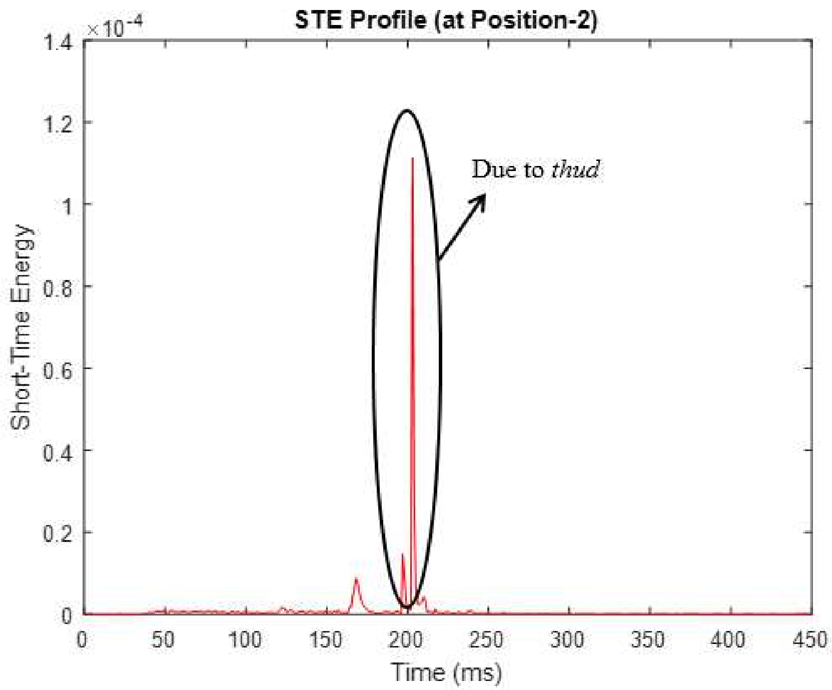


(a) Without medium

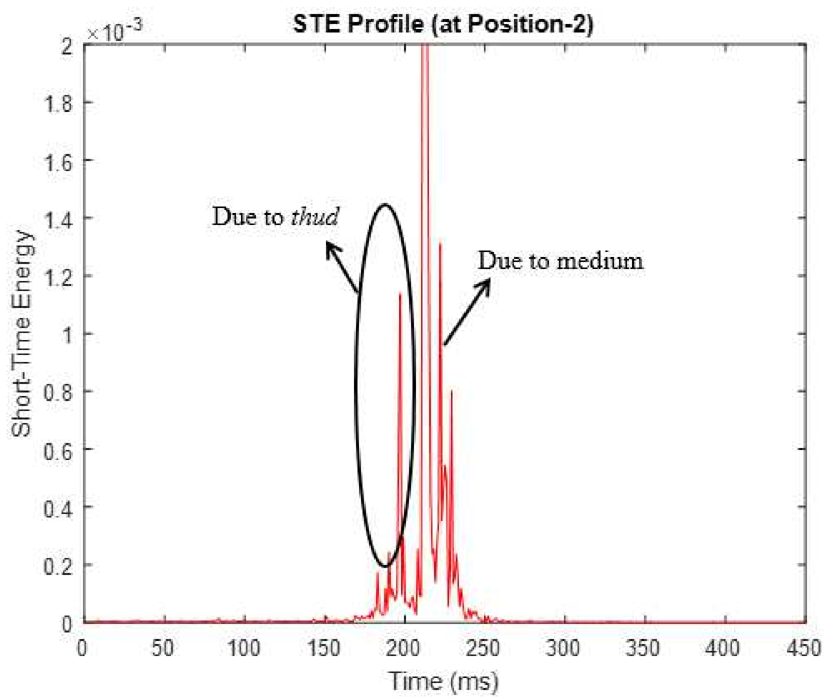


(b) With medium

Figure 5.6: A close look into STE profiles of a close event at Position – 1 (with and without medium)



(a) Without medium



(b) With medium

Figure 5.7: A close look into STE profiles of a close event at Position – 2 (with and without medium)

After analyzing the signals obtained from a sufficiently large number of iterations, it is observed that the close and open STE profiles are consistent with that of the typical patterns shown in Figures – 5.4 to 5.7. Moreover, the pattern of the close STE profiles are more distinct rather than the amplitude values because the effect of medium on close events is a bit more and inseparable in comparison to that of the open events.

5.2 Design of Sequential State Logic:

Motivated by the consistency of the short-time energy profiles of both the open and close events, we propose a sequential state logic to categorize the events. This involves some pre-processing of the STE profiles, after which, the logic is applied for condition monitoring. This implementation can be explained by the block diagram in Figure 5.8.

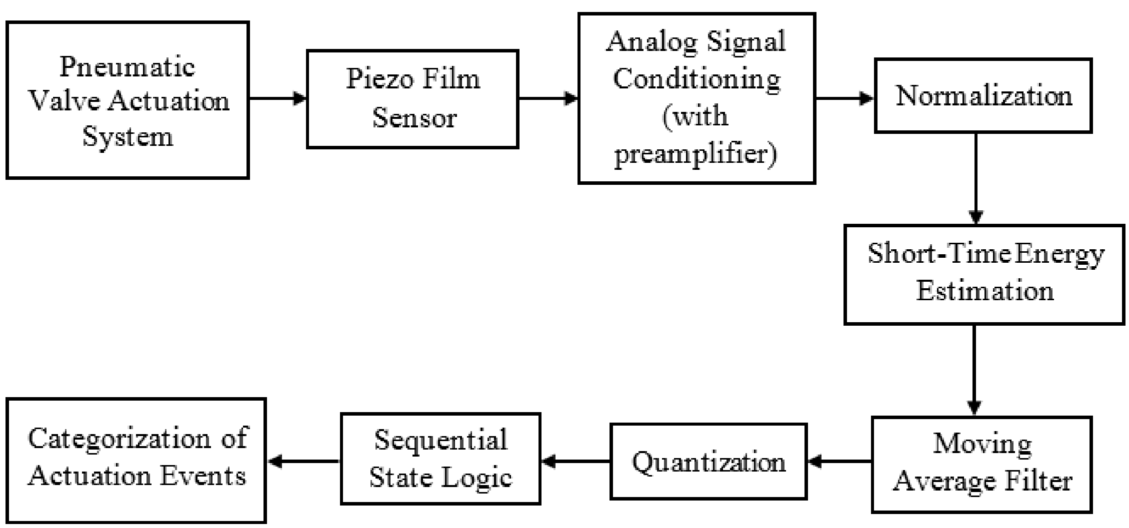


Figure 5.8: Block diagram to categorize events using sequential state logic

The different steps involved in the process are:

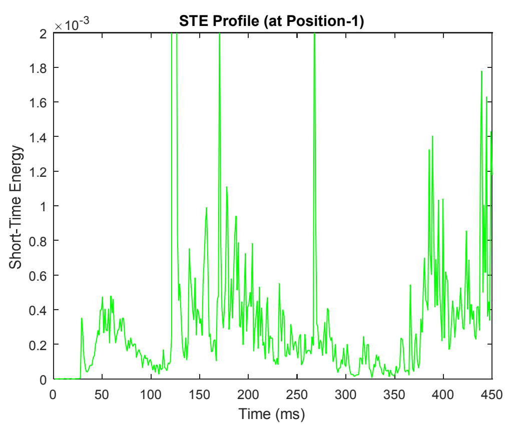
5.2.1 Normalization:

While capturing the data from sensors, a preamplifier may be required, as mentioned earlier in Chapter 2. Basically, the signals are normalized to compensate with any gains introduced by analog signal conditioning circuits and any other, to assist sensors. During the implementation of this logic using MATLAB, the signals are normalized with the gain set by preamplifier.

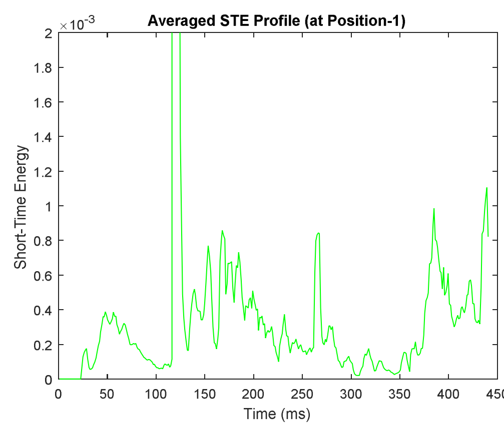
Short-Time Energy profiles are computed, as discussed in the section 5.1, after normalization.

5.2.2 Moving Average Filter:

As evident from Figures 5.4 – 5.7, the STE profiles comprise sharp fluctuations and need to be low-pass filtered to effectively match the patterns. Upon testing the logic on several iterations, a 4-point averaging was adopted for easy detection. Figure 5.9 shows the averaging of a given STE profile for an open event. Figures 5.10 and 5.11 show the averaged STE profiles for 4 iterations of open and close events, respectively.

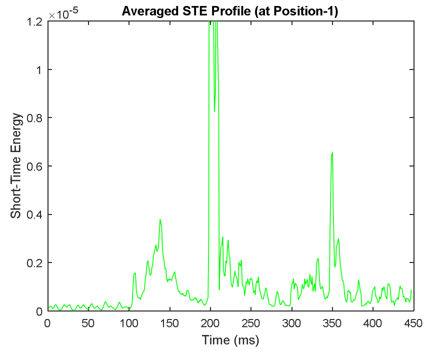


(a) STE profile

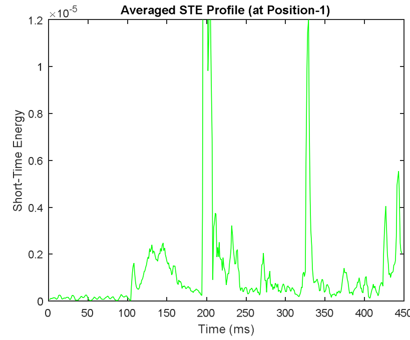


(b) Averaged STE profile

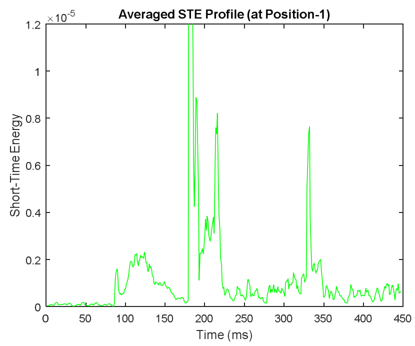
Figure 5.9: Averaging of an STE profile



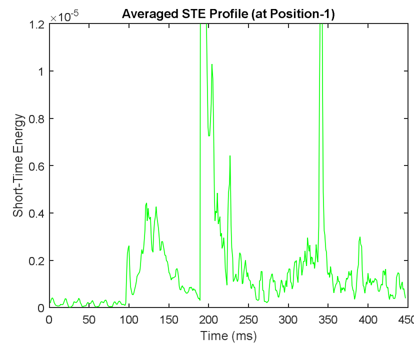
(a) Iteration – 1



(b) Iteration - 2

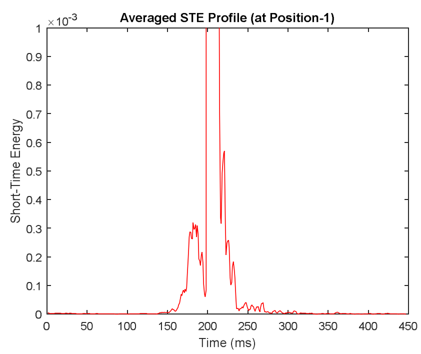


(c) Iteration – 3

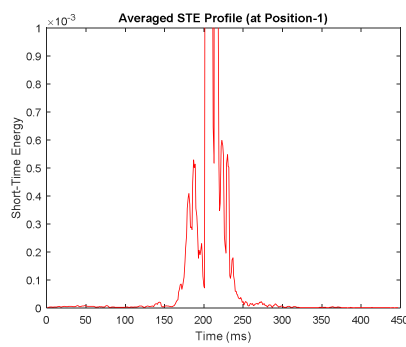


(d) Iteration - 4

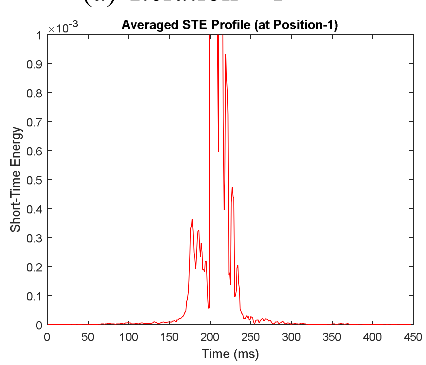
Figure 5.10: Averaged STE Profiles for 4 iterations of an open event



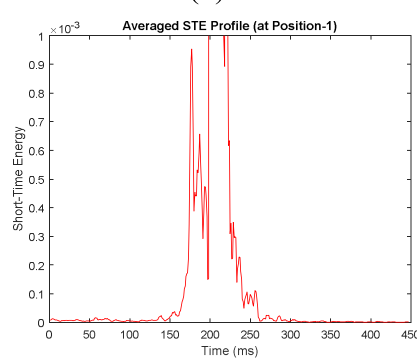
(a) Iteration – 1



(b) Iteration - 2



(c) Iteration – 3



(d) Iteration – 4

Figure 5.11: Averaged STE Profiles for 4 iterations of a close event

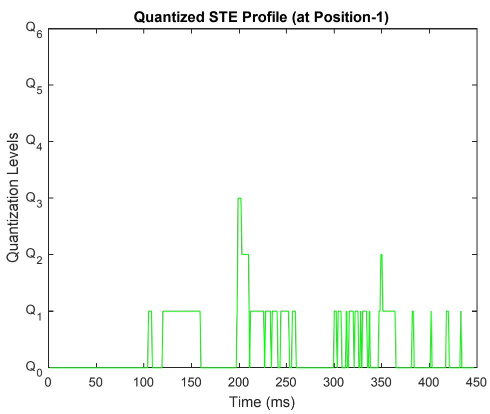
5.2.3 Quantization:

The open and close profiles in the Figures 5.10 and 5.11 are unique and distinguishable. Hence, quantization is done to distinguish these kind of patterns. Quantization is done in such a way that any signal coming from the sensor would fall into one of the 6 quantization levels (Q_0 to Q_5) defined as per Table 5.1. The minimum and maximum values represent the averaged STE values normalized as mentioned above. The Figures 5.12 and 5.13 show the quantized STE profiles of the open and close events respectively. From these figures, it is determined that an open event may be described by 3 quantization levels - Q_0, Q_1 and Q_2 and a close event may be described by another set of 3 quantization levels – Q_2, Q_3 and Q_4.

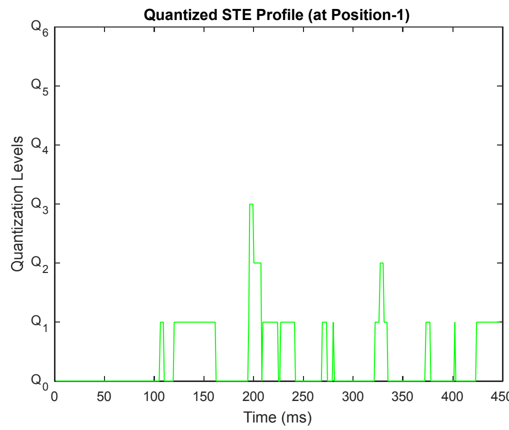
Table 5.1: Quantization levels

Q	Minimum	Maximum
Q_o	0	1×10^{-6}
Q_1	$>1\times10^{-6}$	6×10^{-6}
Q_2	$>6\times10^{-6}$	3.5×10^{-5}
Q_3	$>3.5\times10^{-5}$	2.4×10^{-4}
Q_4	$>2.4\times10^{-4}$	1.4×10^{-3}
Q_5	$>1.4\times10^{-3}$	0.03

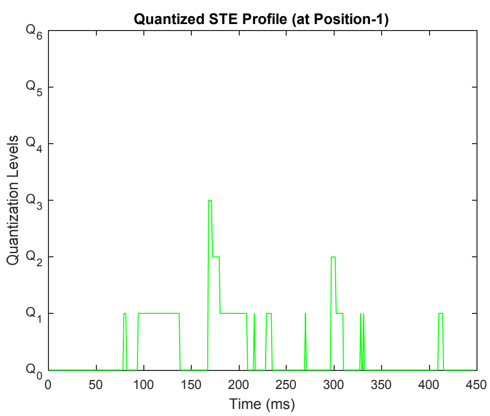
Experimental tests were performed to determine the range of values for these quantization levels that generate consistent sequences of open and close events, which are shown in Table 5. Each event may then be identified by detecting the corresponding sequences of quantized values or states. This is implemented by a sequential logic. It basically detects the events based on the occurrence of the sequence of pre-defined quantization levels for specific events. The time elapsed between the successive levels also plays a key role in determining whether the event has occurred or not.



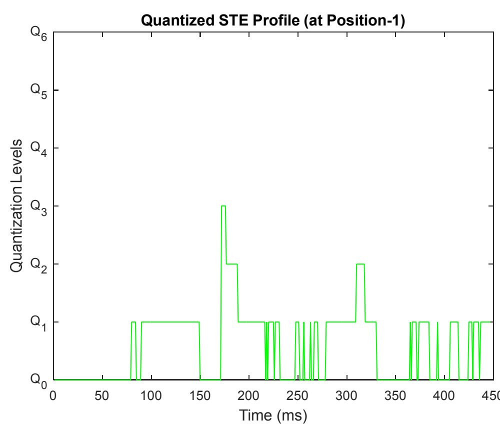
(a) Iteration – 1



(b) Iteration – 2



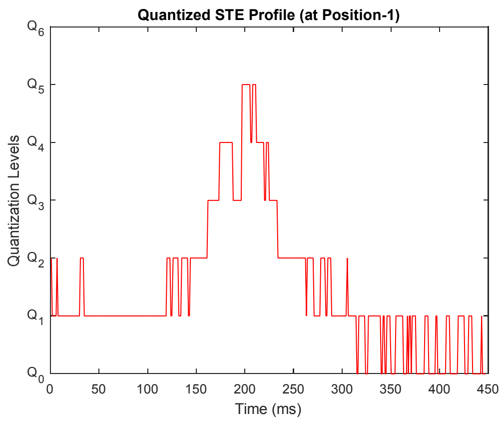
(c) Iteration – 3



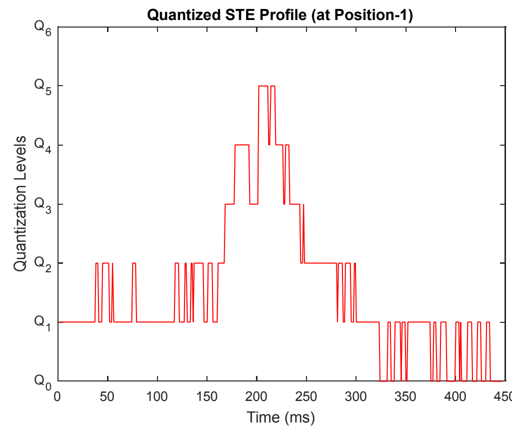
(d) Iteration – 4

Figure 5.12: Quantized STE profiles for 4 iterations of an open event

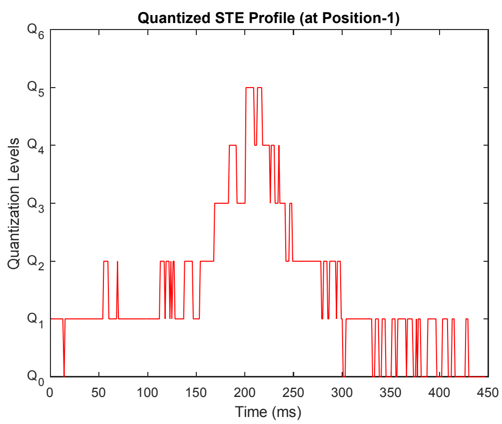
Having obtained the consistent quantized profiles as shown in Figures 5.12 and 5.13, sequential logic were designed for both the open and close events, which are explained using Figures 5.14 and 5.15. For either of the events, all the corresponding intermediate states need to be sequentially detected. That is, the open event gets declared only if all the states starting from 0 to 6 are sequentially passed. Similarly, all the states from 0 to 3 need to be sequentially passed for the detection of a close event.



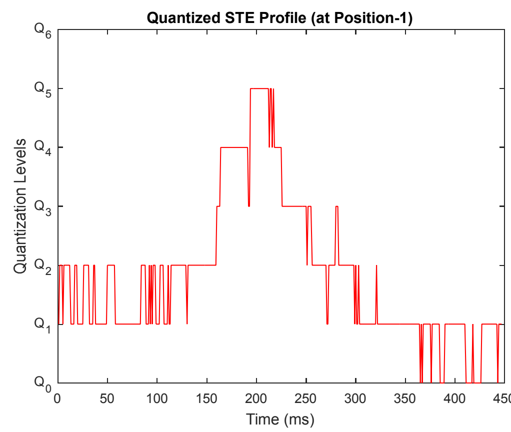
(a) Iteration – 1



(b) Iteration – 2



(c) Iteration – 3



(d) Iteration – 4

Figure 5.13: Quantized STE profiles for 4 iterations of a close event

It must be noted that successful traversal of a state requires that the system remain in that state for a given duration of time. For instance, the open state-0 is detected only if Q_0 state is met and if it remains in this state for a duration of τ_{o0} . After open state-0 being detected, if Q_1 is met, then open state-1 is detected. If the system remains in open state-1 for a period of τ_{o1} and then if it goes to Q_0 again, then the open state-2 is detected. Similarly, the occurrence of all the other intermediate states satisfying their respective time parameters would end up in declaring an open event. One thing is to be noted here that after open state-5, the logic waits for a time period of τ_{o5} without checking for any other open states and then goes on checking for the open state-6 and finally declaring the open

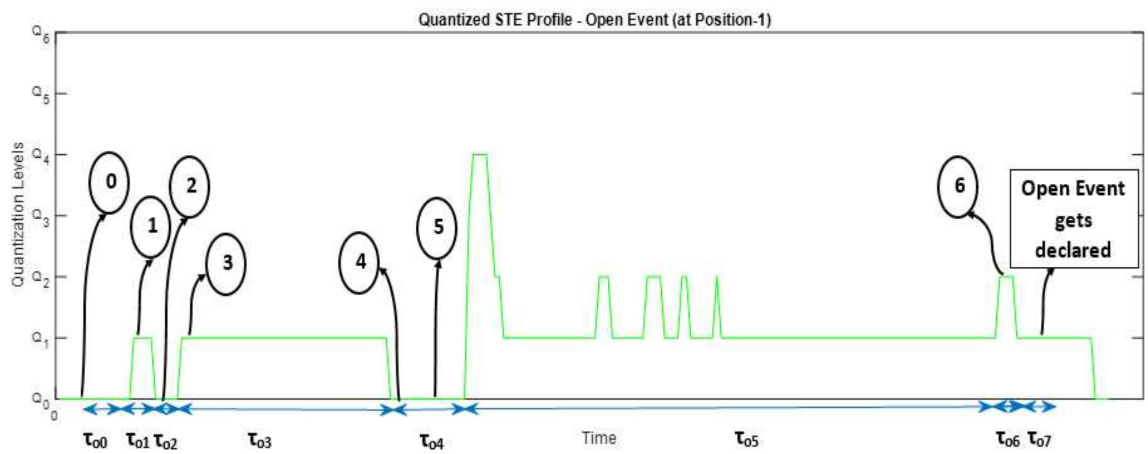


Figure 5.14: Sequential state logic flow diagram to detect open event for a healthy valve

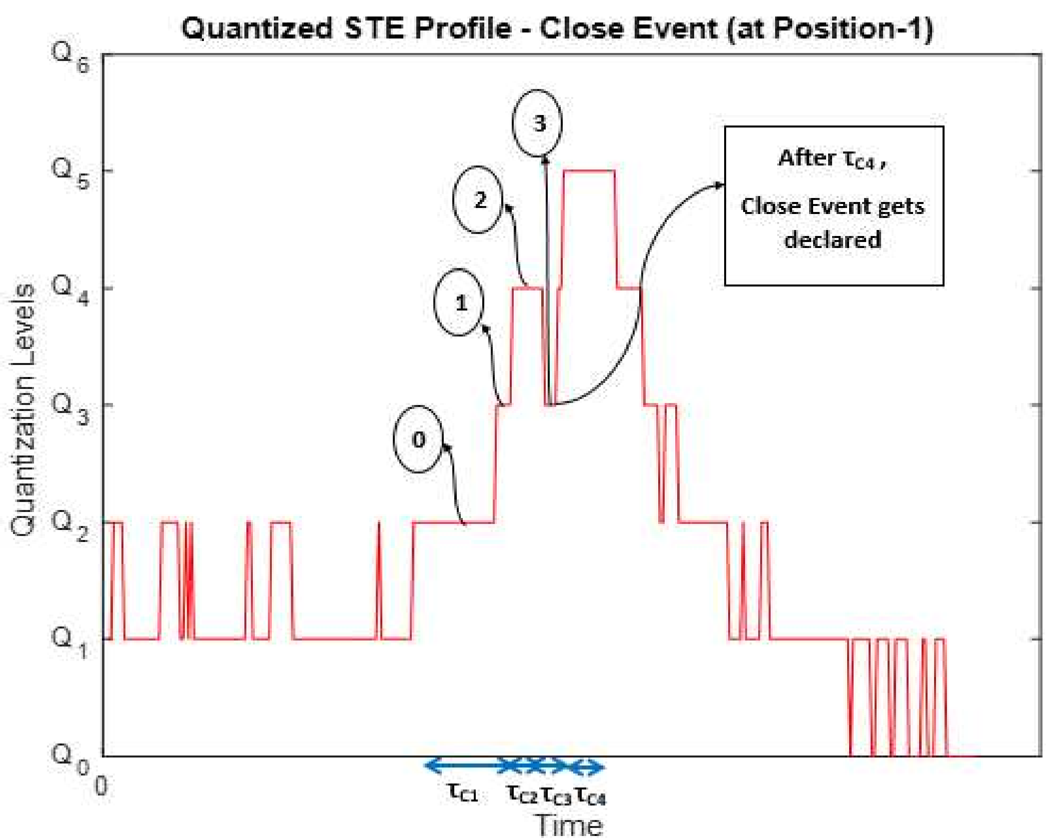


Figure 5.15: Sequential state logic flow diagram to detect close event for a healthy valve

event. Similarly, the close event gets declared after the logic encounters all the intermediate states from close state-0 to close tate-3 meeting all the corresponding time factors as well. If any state does not get detected within the specified timeouts, then the logic resets itself from the open state -0 or close state-0. The tables 5.2 and 5.3 give the ranges of the time durations that were obtained from experimental tests to successfully detect an open/close events of the valve. Approximately 100 instances of open and close events were considered for obtaining these values.

Table 5.2: Time parameters for an open event

τ	Min. (ms)	Max. (ms)
τ_{o1}	3	7
τ_{o2}	2	13
τ_{o3}	38	64
τ_{o4}	4	40
τ_{o5}	150	150
τ_{o6}	2	2
τ_{o7}	1	1

Table 5.3: Time parameters for a close event

τ	Min. (ms)	Max. (ms)
τ_{c1}	1	7
τ_{c2}	2	20
τ_{c3}	5	30
τ_{c4}	1	1

5.2.4 Deviations in the Quantized templates:

The consistency of the sequential state based event detection was tested by repeating experiments multiple times. One of the objectives was to analyze common deviations of the state transitions from that of the standard templates in Figures 5.14 and 5.15. These deviations can occur due to many reasons, such as noise, averaging and quantization that would not let the pattern to exactly match the ideal template. This means that averaging sometimes may not smooth the raw STE profile properly. Quantization of this kind of averaged profiles may let the quantization levels jump to the undesired levels – immediate higher or lower levels. Some of the observed deviations are shown in Figure 5.16 for open event and in Figure 5.17 for close events. These are successfully dealt with by writing some special logic boxes and tested using MATLAB.

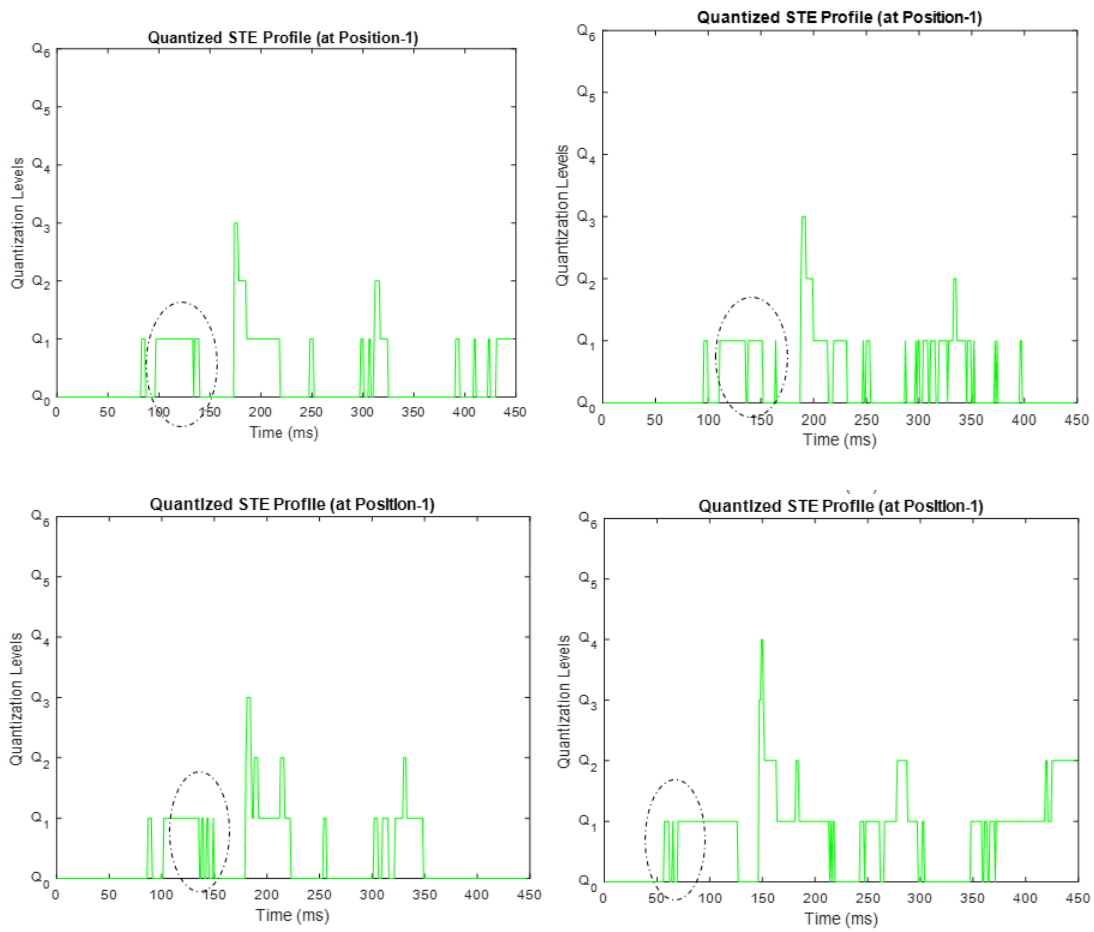


Figure 5.16: Deviations observed in the quantized STE profile of an open event

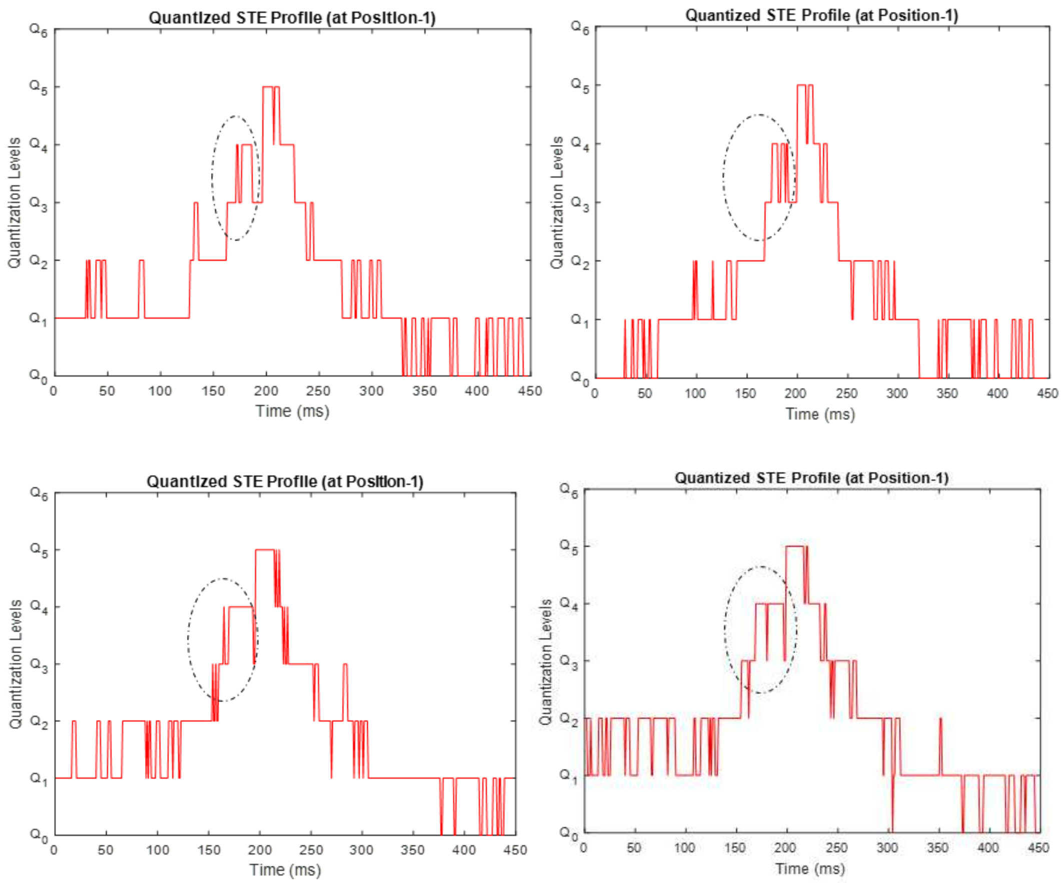


Figure 5.17: Deviations observed in the quantized STE profile of a close event

5.2.5 Results using MATLAB:

The sequential logic has been implemented in MATLAB and tested for about 125 instances. Figure 5.18 shows the intermediate states and declaration of the events, when a series of actuation events are tested. And, Figure 5.19 shows an overall picture of the performance of the sequential state logic to detect/categorize the events, by considering false alarms and missed detections from the experiments. It can be observed that the false alarm rate and missed detection rate for an open event are approximately 6% and 0%, respectively, from a test involving 129 actual events. And for the close event, the result shows 100% detection efficiency without any false alarms and missed detections, from a similar test involving 129 actual events.

```
Editor - F:\Courses\WSNVM\Attempts\pattern_recog_logic_healthy_defective.m
Command Window
OPEN STATE - 2 detected!
OPEN STATE - 3 detected!
OPEN STATE - 4 detected!
OPEN STATE - 5 detected!
OPEN STATE - 6 detected!
Open Event occured at 54min 39.4550s
33
CLOSE STATE - 1 detected!
CLOSE STATE - 2 detected!
CLOSE STATE - 3 detected!
Close Event occured at 54min 54.9590s
CLOSE STATE - 1 detected!
CLOSE STATE - 1 detected!
OPEN STATE - 1 detected!
OPEN STATE - 2 detected!
OPEN STATE - 3 detected!
OPEN STATE - 4 detected!
OPEN STATE - 5 detected!
OPEN STATE - 6 detected!
Open Event occured at 55min 10.1760s
33
CLOSE STATE - 1 detected!
CLOSE STATE - 1 detected!
CLOSE STATE - 1 detected!
CLOSE STATE - 2 detected!
CLOSE STATE - 3 detected!
fx Close Event occured at 55min 25.3850s
```

Figure 5.18: A command window of MATLAB showing the intermediate states and declaration of events

```
CLOSE STATE - 3 detected!
Close Event occured at 66min 33.6170s
CLOSE STATE - 1 detected!
CLOSE STATE - 1 detected!
CLOSE STATE - 1 detected!
Actual No. of Open Events - 129
No. of Open Events Detected - 137
No. of Fault Alarms for Open - 8
No. of Missed Detections for Open - 0
Actual No. of Close Events - 129
No. of Close Events Detected - 129
No. of Fault Alarms for Close - 0
No. of Missed Detections for Close - 0
fx >>
```

Figure 5.19: A command window of MATLAB showing the performance of the detection scheme using the sequential state logic

CHAPTER 6: ANALYSIS OF THE DEFECTIVE VALVE

As seen in the previous chapter that the proposed sequential state logic was working well to detect /categorize the actuation events of a healthy valve. This chapter attempts to propose some approaches for leak detection or detection of faults in the valve. Initially, a specific type of fault was simulated in the laboratory by inserting wires of varied thickness so as to obstruct the normal operation of the valves, and experimented and analyzed a series of data from this kind of faulty simulated behavior. In due course, one of the valves developed a real fault, which enabled us to carry on experiments on fault detection. This chapter will mainly discuss the behavior of the defective valve based on plots and comparisons with the healthy valve.

6.1 Healthy Valve Vs Defective Valve

We first try to analyze and compare the sensor signals from the healthy and defective valves. Chapter 5 provides an exhaustive information on the characteristics of the time domain signals and their corresponding STE profiles of a healthy valve. In the case of a defective valve, some variations in these signal characteristics are expected. There will be medium flow even though the defective valve is in closed state. Due to this, a significant signal strength is observed all the time from the sensors irrespective of the actuation events of the valve. Therefore, some distortions can be expected in the signals captured during both the open and close events. This also affects the pattern of their STE profiles.

Similarly, PSD estimates of the events also show difference in their characteristics as compared to that of a healthy valve. The rise in signal strength which is due to leak is also reflected in their corresponding PSD estimates. As discussed earlier, a continuous leak is noticed even when the valve is in closed state. This corresponds to rise in the power, which results in different characteristics of the PSD during the closed state.

Therefore, the analysis of time domain signals, their STE profiles and PSD estimates is done to detect the leak and distinguish it from a healthy valve. To clearly understand, these investigations are being presented in a compare/contrast form in this chapter. This kind of analysis helps us to clearly catch the differences in the characteristics and draw the valid conclusions.

Figure 6.1 clearly compares the open events of a healthy valve with that of the defective valve. By looking at these plots at Position-1, we observe that the signal due to a thud is much less prominent for the defective valve. Also, during the starting of open event, the STE profile looks distorted as the sensor captures the sound produced by the leak along with the piston movement, as clearly visible from time domain signals. The signals at Position-2, as shown in Figure 6.2, also exhibit similar characteristics except that the distortion is very less as compared to that at Position-1.

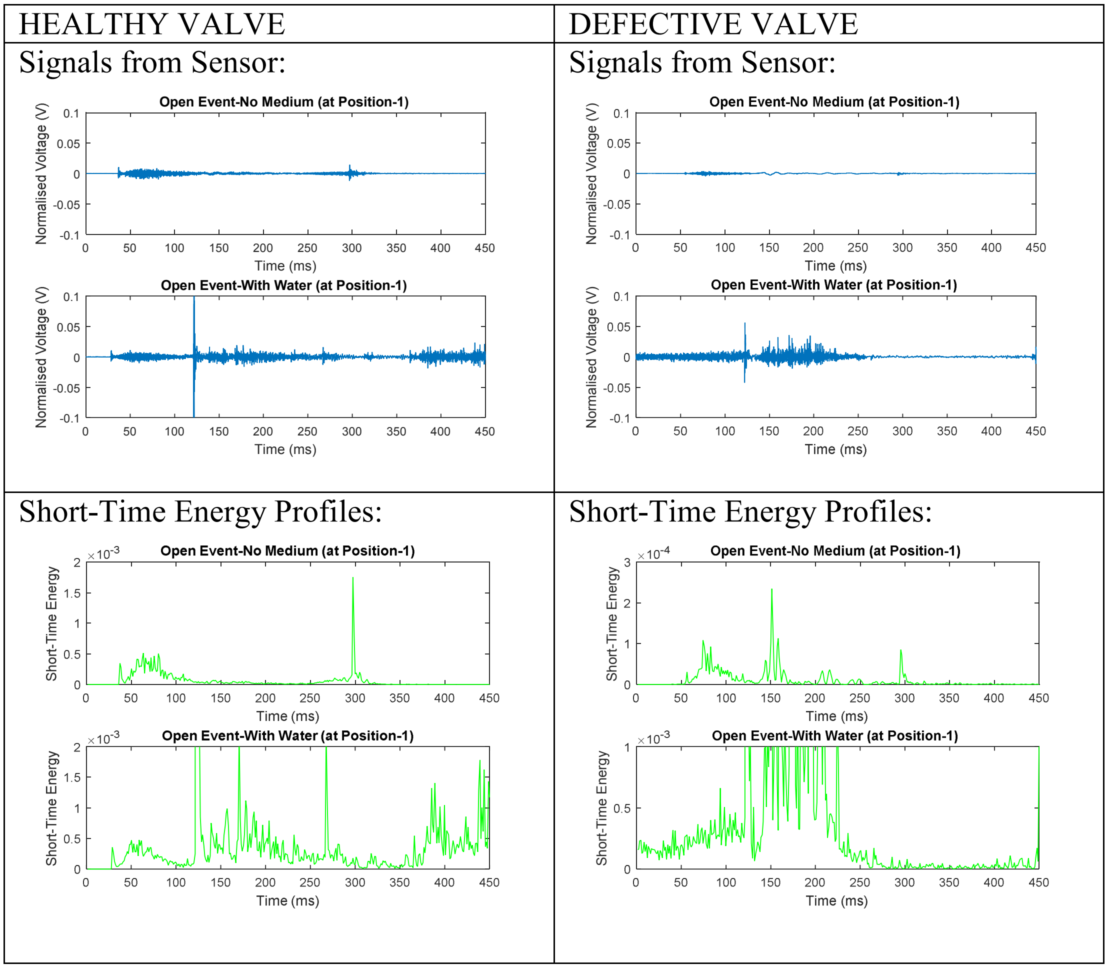


Figure 6.1: Comparison of open event of healthy Vs defective valve
(at Position - 1)

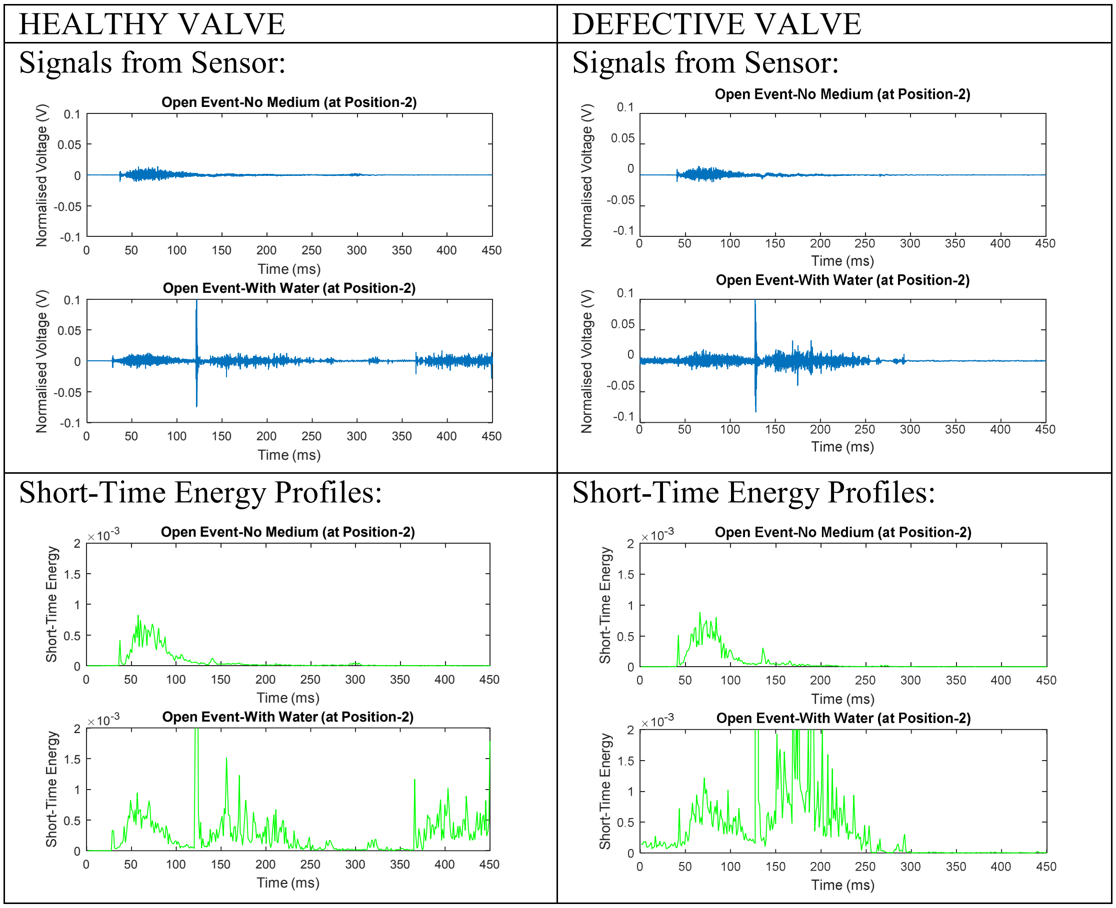


Figure 6.2: Comparison of open event of healthy Vs defective valve (at Position - 2)

Similar to the Figures 6.1 and 6.2, Figures 6.3 and 6.4 depicts the relative characteristics of the close event for a healthy and defective valve. These figures show the time domain signals and their corresponding STE profiles captured by the sensor at the Positions – 1 and 2. As compared to the open events, envelope profiles of the close events of the defective valve are not expected to deviate much from that of the healthy valve. This is because, the medium has a dominating effect on these signals until the valve is completely closed. As discussed in Chapter 2, the thud lets the valve to completely close. Hence, the portion of the close signals captured until the thud occurs, have similar characteristics for both healthy and defective valve. The signals corresponding to the close event at Position – 2 also behaves in a similar way, as shown in Figure 6.4.

One important observation in the case of the valve with this kind of defect is that the piston does not touch the bottom of the valve. This makes the thud of the close event less audible. Due to this, the portion of signal due to the thud is relatively weak. This can be clearly noticed from Figure 6.5, which depicts the averaged STE profile of a close event of a healthy valve in comparison to that of a defective valve.

Figures 6.6 and 6.7 depicts the signals when the valve is in closed state. Ideally, there should not be any leak for a healthy valve in closed state. Hence no energy levels are observed in the STE profiles after the close events. On the contrary, the signals from the defective valve show some energy content in their STE profiles after the close event. This is due to the fact that sounds produced due to leak are responsible for the rise in energy content of the signal. This behavior can also be observed by the corresponding PSD estimates, as depicted in Figures 6.6 and 6.7.

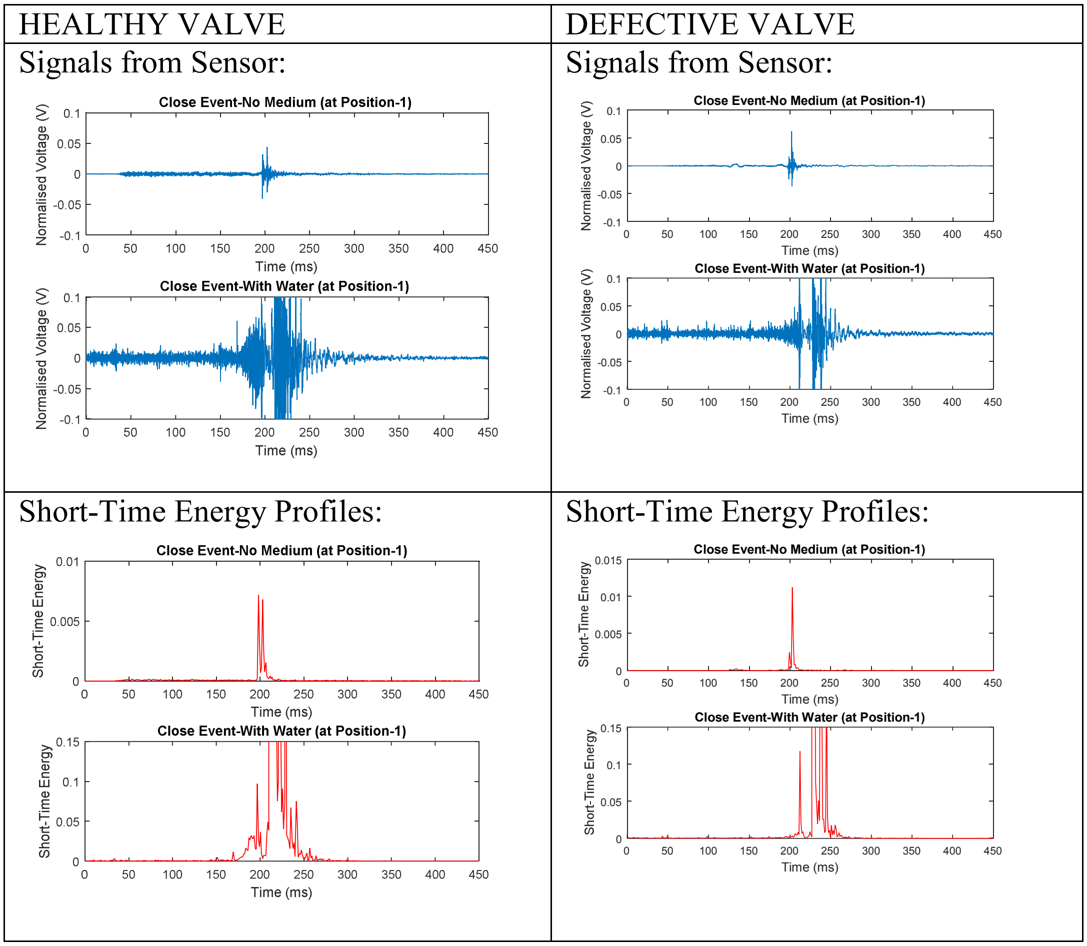


Figure 6.3: Comparison of close event of healthy Vs defective valve
(at Position - 1)

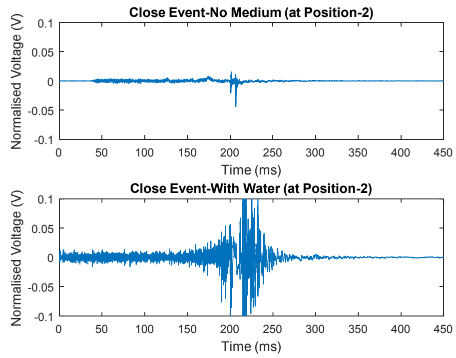
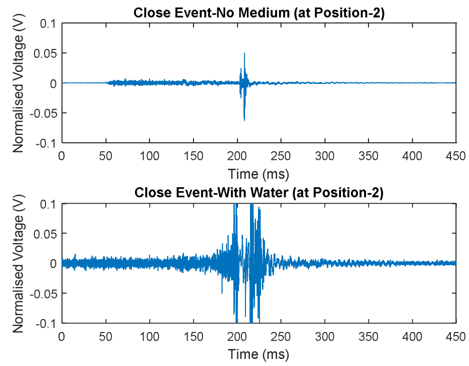
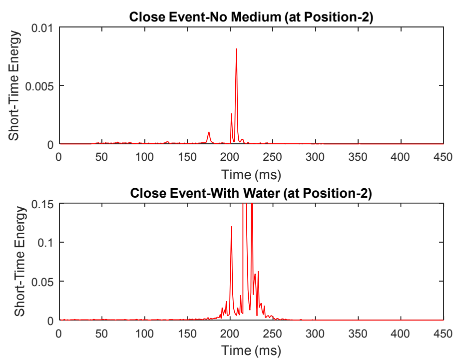
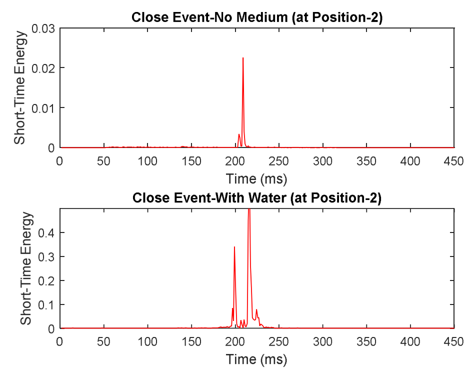
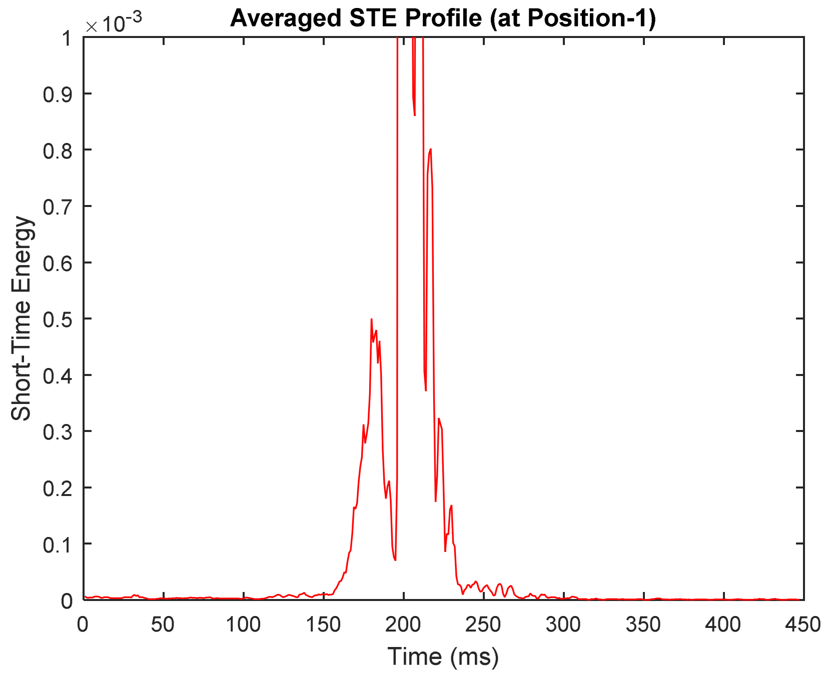
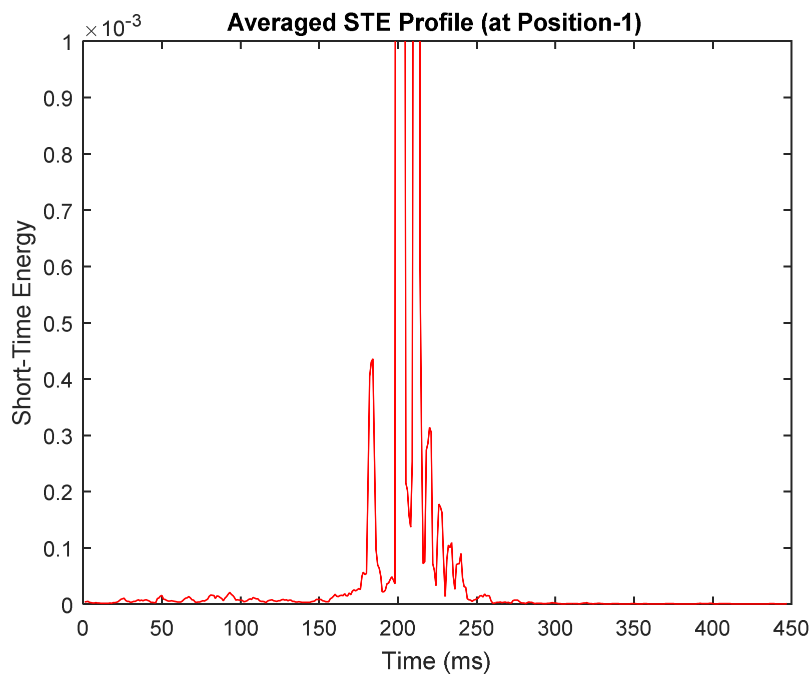
HEALTHY VALVE	DEFECTIVE VALVE
Signals from Sensor: 	Signals from Sensor: 
Short-Time Energy Profiles: 	Short-Time Energy Profiles: 

Figure 6.4: Comparison of close event of healthy Vs defective valve (at Position - 2)



(a) Healthy Valve



(b) Defective Valve

Figure 6.5: Averaged STE profile of close event of a healthy valve Vs defective valve

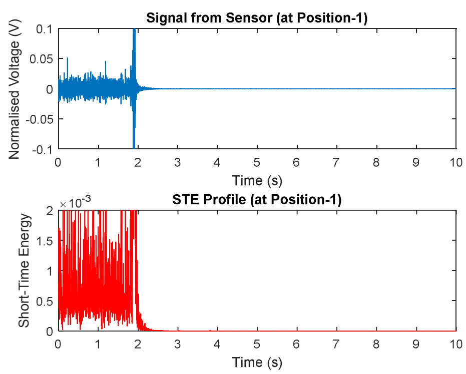
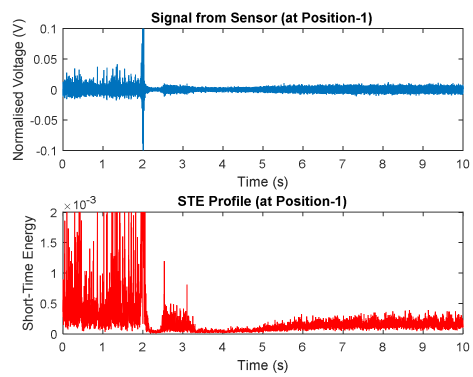
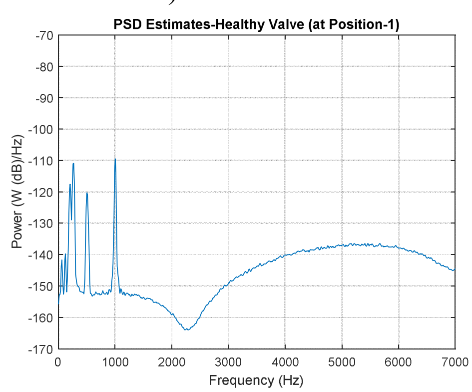
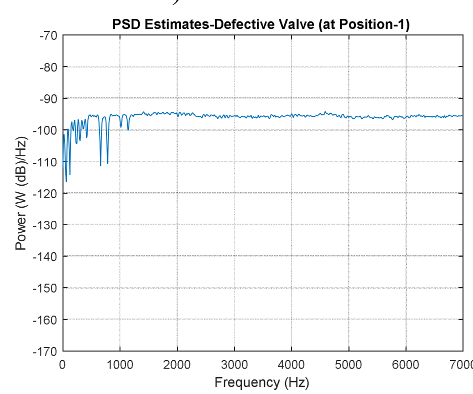
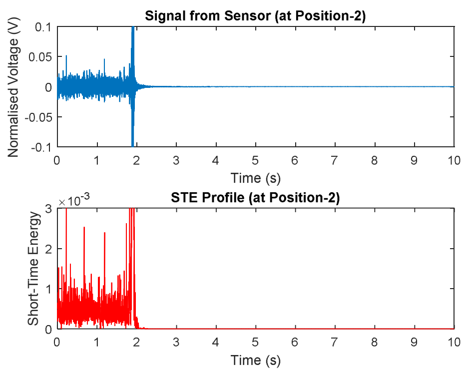
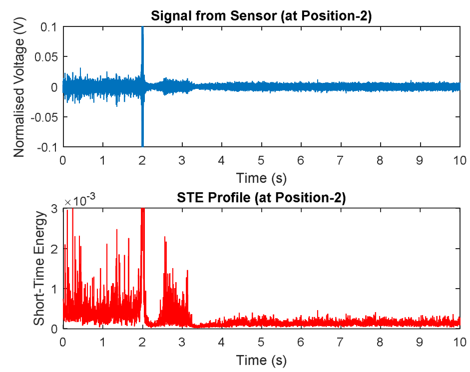
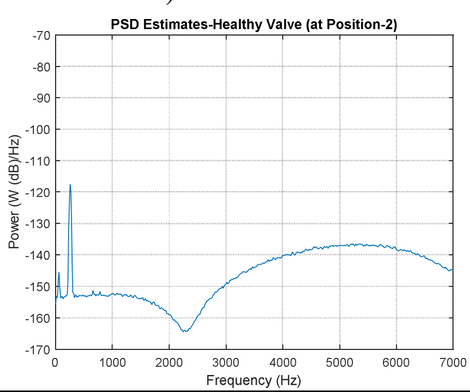
HEALTHY VALVE	DEFECTIVE VALVE
Analogue signal with corresponding STE Profile: 	Analogue signal with corresponding STE Profile: 
PSD Estimates (when valve is in ‘Closed’ state): 	PSD Estimates (when valve is in ‘Closed’ state): 

Figure 6.6: Comparison of healthy Vs defective valve in closed state (at Position - 1)

<table>
<tr><td>HEALTHY VALVE</td><td>DEFECTIVE VALVE</td></tr>
<tr><td>Analogue signal with corresponding STE Profile:


</td><td>Analogue signal with corresponding STE Profile:


</td></tr>
<tr><td>PSD Estimates (when valve is in ‘Closed’ state):


</td><td>PSD Estimates (when valve is in ‘Closed’ state):

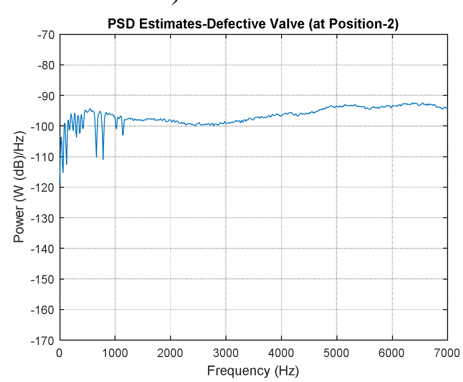
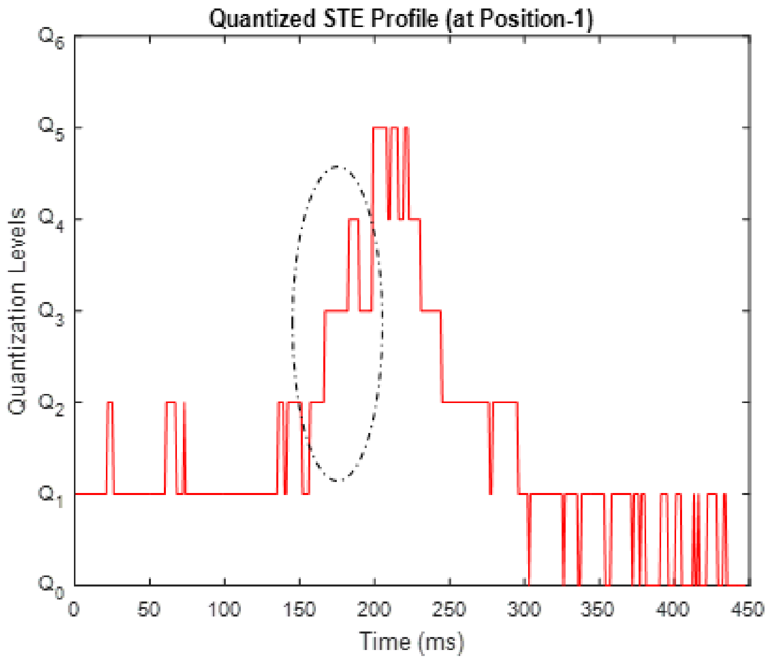
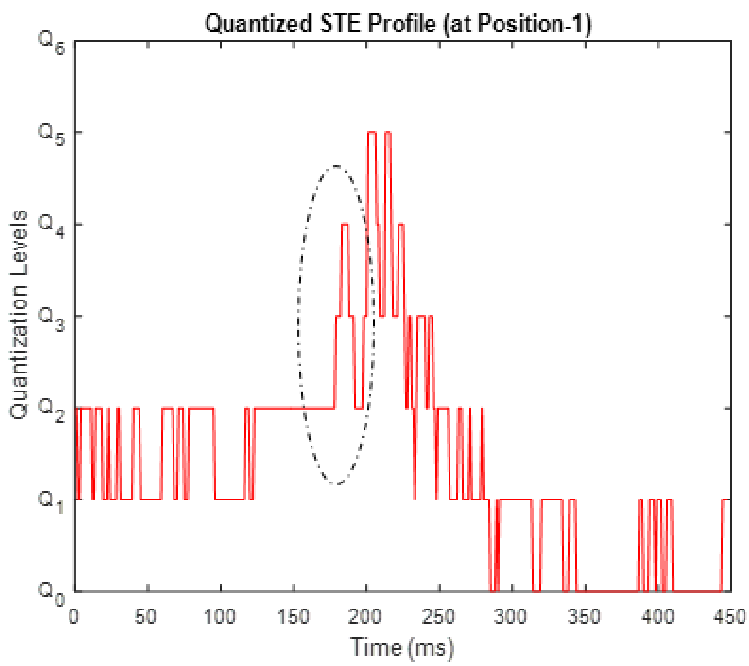

</td></tr>
</table>

Figure 6.7: Comparison of healthy Vs defective valve in closed state (at Position – 2)

Quantized STE Profiles:



(a) Healthy Valve



(b) Defective Valve

Figure 6.8: Quantized STE profiles of healthy Vs defective valve

6.2 Defect/Leak Detection

- As evident from Figures 6.1 and 6.2, due to lower distortion in Position – 2, that position is preferred over Position – 1 for detecting some intermediate states of open event of the defective valve. And from Figures 6.5 and 6.8, close event can be detected for the defective valve. Finally, from Figures 6.6 and 6.7, leak can be detected from the rise in energy after the close event. Basically, this requires a multi-sensor approach.
- PSD estimates of healthy and defective valves can also be used to assist in detecting leaks.

CHAPTER 7: CONCLUSIONS AND FUTURE WORK

7.1 Conclusions

This thesis presents a cost-effective engineering solution for condition monitoring of pneumatic valves using flexible piezo film sensors. The approach of classifiers based on spectral estimation yielded good results with the cases without any medium. But, it could not yield good results during medium flow, at all the positions considered. Therefore, a sequential state logic approach was developed to study the temporal characteristics of the signals corresponding to the actuation events of the valve. This is mainly focused on STE profiles and its' pattern recognition techniques to detect/categorize the events. This detection scheme is implemented and tested on about 100-150 instances recorded using piezo film sensors on an experimental testbed, installed in EPIC building, UNC Charlotte. Later on, a pneumatic valve of specific defect has been analyzed using the similar feature extraction parameters that were used for a healthy valve. The characteristics of the patterns of the events corresponding to the defective valve are consistent, and some ideas are proposed to detect leaks/defects, using the same logic.

Over years, there has been the application of smart technology in every field and hence, also in the condition monitoring of valves. The effectiveness of the algorithms/systems that use smart technology primarily focus on the type of sensors. As discussed in Chapter 2, some of the condition monitoring systems used invasive sensors. We have used highly sensitive, flexible, low-cost piezo film sensors in the process of developing a condition monitoring system. During experiments on extracting features of the signals captured using sensors, initially, techniques on spectral estimation were dealt with. But, they produced good results only with some specific cases of the study as discussed in Chapter 4. Hence, envelope analysis of signals was done, to first extract some parameters/signatures that could determine the healthy condition of the valves. A simple, but effective algorithm has been developed and design challenges were considered to efficiently develop the logic that could give more valid detections, that is, less percentage of false alarms and less percentage of missed detections. Chapter 5 discusses all these aspects in great detail, concluding with the results/performance evaluations, analyzed using MATLAB.

A special case of defective valve was considered and applicability of the sequential logic was discussed to detect defects/leaks, in Chapter 6. However, the issue of defects/leaks can be addressed by extending the sequential logic and exploring on multi sensor analysis.

7.2 Future Work

This research is one of its kinds in attempting to address the challenges to primarily explore for specific parameters/signatures that could be effectively used to monitor valve status externally.

Though the proposed logic was tested with a large set of data on an experimental testbed at UNC Charlotte, this research work leaves a large scope of future development to develop a global condition monitoring of valves:

- As discussed in Chapter 2, the proposed sequential logic was implemented and tested with the Burkert 2/2 – way Angle – seat pneumatically operated valve (Type

2100). Applicability of this logic is required to be tested with other kinds of pneumatic valves and electrically activated valves, as well.

- To extend the applicability of this logic to any type of valve, adaptive gain techniques can be used to decide the range of the STE amplitudes which are required to quantize the patterns.
- As the analysis was done on medium pressure of 40 psi, it is required to experiment with several other medium pressures and other types of medium, as well.
- Approaches on Multi-sensor techniques can be explored to effectively deal with different kinds of faults.

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