CONDITION MONITORING OF A SMALL FOUR STROKES PETROL ENGINE USING VIBRATION SIGNAL ANALYSIS

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ABSTRACT

This research is concerned with the studies of technique to monitor conditions of a small, four- stroke, petrol engine using vibration signal analysis based on time domain and crank angle domain. Vibration signals detected from the engine have been tested to describe engine processes such as intake and exhaust valve operations, ignition process, combustion process, etc. In this study, vibration signals are used to study the small petrol engine processes which can lead to application in monitoring various faults of intake and exhaust valves. Abnormal conditions of intake and exhaust valves were simulated by adjusting various valve clearance conditions. It is found that vibration signal analysis employing statistical analysis with various parameters i.e. mean, variance, root mean square, and energy content, to determine the main valve events such as Intake valve open (IVO), Intake valve close (IVC), Exhaust valve open (EVO) and Exhaust valve close (EVC) for the 90 degree crank angle intervals, gives better results than those calculated from the entire signal. The covariance analysis method on vibration signal using mean, variance and root mean square could be used to predict all intake valve clearance fault conditions but only some cases of exhaust valve clearance fault conditions.

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CHAPTER 1

INTRODUCTION

1.1 EVOLUTION OF MAINTENANCE PHILOSOPHIES

Machinery maintenance in industry has evolved from breakdown maintenance to time-based preventive maintenance. Presently, the predictive and proactive maintenance philosophies are the most popular. Breakdown maintenance was practiced in the early days of production technology and was reactive in nature. Equipment was allowed to run until a functional failure occurred. Secondary, damage was often observed along with a primary failure. This led to time-based maintenance, also called preventive maintenance. In this case, equipment was taken out of production for overhaul after completing a certain number of running hours, even if there was no evidence of a functional failure. The drawback of this system was that machinery components were being replaced even when there was still some functional lifetime left in them. This approach unfortunately could not assist to reduce maintenance costs. Due to the high maintenance costs when using preventive maintenance, an approach to rather schedule the maintenance or overhaul of equipment based on the condition of the equipment was needed. This led to the evolution of predictive maintenance and its underlying techniques.

Predictive maintenance requires continuous monitoring of equipment to detect and diagnose defects. Only when a defect is detected, the maintenance work is planned and executed. Today, predictive maintenance has reached a sophisticated level in industry. Till the early 1980s, justification spreadsheets were used in order to obtain approvals for condition-based maintenance programs. Luckily, this is no longer the case. The advantages of predictive maintenance are accepted in industry today, because the tangible benefits in terms of early warnings about mechanical and structural problems in machinery are clear. The method is now seen as an essential detection and diagnosis tool that has a certain impact in reducing maintenance costs, operational vs repair downtime and inventory hold-up. In the continuous process industry, such as oil and gas, power generation, steel, paper, cement, petrochemicals, textiles, aluminum and others, the penalties of even a small amount of downtime are immense. It is in these cases that the adoption of the predictive maintenance is required above all. Through the years, predictive maintenance has helped improve productivity, product quality, profitability and overall effectiveness of manufacturing plants. Predictive maintenance in the actual sense is a philosophy – an attitude that uses the actual operating conditions of the plant equipment and systems to optimize the total plant operation. It is generally observed that manufacturers embarking upon a predictive maintenance program become more aware of the specific equipment problems and subsequently try to identify the root causes of failures. This tendency led to an evolved kind of maintenance called proactive maintenance. In this case, the maintenance departments take additional time to carry out precision balancing, more accurate alignments, detune resonating pipes, adhere strictly to oil check/change schedules, etc. This ensures that they eliminate the causes that may give rise to defects in their equipment in the future. This evolution in maintenance philosophy has brought about longer equipment life, higher safety levels, better product quality, lower life cycle costs and reduced emergencies and panic decisions precipitated by major and unforeseen mechanical failures.

Putting all this objectively, one can enumerate the benefits in the following way:

Increase in machine productivity: By implementing predictive maintenance, it may be possible to virtually eliminate plant downtime due to unexpected equipment failures.

Extend intervals between overhauls: This maintenance philosophy provides information that allows scheduling maintenance activities on an 'as needed' basis.

Minimize the number of 'open, inspect and repair if necessary' overhaul routines: Predictive maintenance pinpoints specific defects and can thus make maintenance work more focused, rather than investigating all possibilities to detect problems.

Improve repair time: Since the specific equipment problems are known in advance, maintenance work can be scheduled. This makes the maintenance work faster and smoother. As machines are stopped before breakdowns occur, there is virtually no secondary damage, thus reducing repair time.

Increase machine life: A well-maintained machine generally lasts longer.

Resources for repair can be properly planned: Prediction of equipment defects reduces failure detection time, thus also failure reporting time, assigning of personnel, obtaining the correct documentation, securing the necessary spares, tooling and other items required for a repair.

Improve product quality: Often, the overall effect of improved maintenance is improved product quality. For instance, vibration in paper machines has a direct effect on the quality of the paper.

Save maintenance costs: Studies have shown that the implementation of a proper maintenance plan results in average savings of 20–25% in direct maintenance costs in conjunction with twice this value in increased production.

Principles of predictive maintenance or Condition-based maintenance

Predictive maintenance is basically a condition-driven preventive maintenance. Industrial or in-plant average life statistics are not used to schedule maintenance activities in this case. Predictive maintenance monitors mechanical condition, equipment efficiency and other parameters and attempts to derive the approximate time of a functional failure.

A comprehensive predictive maintenance program utilizes a combination of the most cost-effective tools to obtain the actual operating conditions of the equipment and plant systems. On the basis of this collected data, the maintenance schedules are selected. Predictive maintenance uses various techniques such as vibration analysis, oil and wear debris analysis, ultrasonics, thermography, performance evaluation and other techniques to assess the equipment condition.

Predictive maintenance techniques actually have a very close analogy to medical diagnostic techniques. Whenever a human body has a problem, it exhibits a symptom. The nervous system provides the information – this is the detection stage. Furthermore, if required, pathological tests are done to diagnose the problem. On this basis, suitable treatment is recommended in a similar way, defects that occur in a machine always exhibit a symptom in the form of vibration or some other parameters. However, this may or may not be easily detected on machinery systems with human perceptions. It is here that predictive maintenance techniques come to assistance. These techniques detect symptoms of the defects that have occurred in machines and assist in diagnosing the exact defects that have occurred. In many cases, it is also possible to estimate the severity of the defects. The specific techniques used depend on the type of plant equipment, their impact on production or other key parameters of plant operation. Of further importance are the goals and objectives that the predictive maintenance program needs to achieve.

1.2 MOTIVATION FOR THE CONDITION MONITORING

Demand for condition monitoring of machinery has advanced at a rapid pace in recent year. This has been driven primarily by the requirement within industry to improve the effectiveness of assets that is the necessity to extract maximum profit from minimum investment in plant and equipment. This translates into a need to attain high levels of asset availability, reliability and performance whilst minimizing unplanned downtime and the cost of maintenance.

The condition monitoring of machinery has long development history from the earliest methods based on the experience and background knowledge of operators/technicians to modern methods using intrusive or non-intrusive sensors with diagnostics strategies. Condition monitoring of machinery is the measurement various parameters related to the mechanical condition of machinery (such as vibration, bearing, temperature, oil pressure, oil debris, and performance), which makes it possible to determine whether the machinery is in normal or failure mechanical condition. If the mechanical condition is abnormal, then condition monitoring makes it possible to determine the cause of the problem. The necessary analysis is normally performed at laboratory in batches and requires specifics equipment rendering it not particular amenable to continuous or on-line monitoring. Many continuous condition monitoring methods rely on combinations of various intrusive sensors such as those for pressure, fuel flow and temperature. Condition monitoring is used in conjunction with *predictive maintenance*, for example maintenance of machinery based on an indication that a problem is to occur. In many plants predictive maintenance is replacing *run-to-breakdown maintenance* and *predictive maintenance* (in which mechanical parts are replaced periodically at fixed time intervals regardless of the machinery's mechanical condition) [1]. Predictive maintenance of machinery avoid unexpected catastrophic breakdowns with expensive or dangerous consequences, deduces the number of overhauls on machines to a minimum thereby reducing maintenance costs, eliminates unnecessary interventions with the consequent risk of introducing faults on smoothly operation machines, allow spare parts to be ordered in time and thus eliminates costly inventories and reduces the intervention time thereby minimizing production loss. Because the fault to be repaired is known in advance, overhauls can be scheduled when most convenient. Amongst the non-intrusive methods, vibration analysis is possibly the most common one used in machinery and diesel engines [3]. Measurement of airborne sound radiation has also shown a potential of monitoring diesel engines [4-13]. Both vibration and sound have benefits in section-based condition monitoring applications because the installation of sensors is simple and the hardware is of low to medium specification.

This motivation uses vibration measurement for conditions monitoring of machinery. Vibration is a parameter which can be used to predict the broadest range of faults in machinery most successfully. This description includes such as selection of an appropriate monitoring method for four-stroke petrol engines, establishment of a condition monitoring program, fault detection, time domain analysis interpretation, fault diagnosis, special analysis techniques, trend analysis and the use of computers in condition monitoring programs. The ability of current monitoring technique to monitor and diagnose all known faults and conditions is limit, particularly for processes which have traditionally been considered difficult to monitor. The demand for improved diagnostic information combined with advances in sensor technology, signal processing and computation power, and lower costs, mean that it is now possible to consider new techniques which may offer greater diagnostic capabilities. The potential of vibration monitoring to reveal information about process condition in four-stroke petrol engine is investigated in this thesis.

1.3 RESEARCH OBJECTIVES

This thesis has studied vibration analysis methods for a condition monitoring of a small four-stroke, single cylinder, and petrol engine with capacity of 125 CC using vibration signals.

- To study condition monitoring technique of a small 4-stroke petrol engine using vibration signal.
- To study signal processing techniques to diagnose the valve clearance of a small four-stroke petrol engine. The signal processing techniques are used to diagnose vibration signal in time-domain and crank angle domain with some statistical parameters such as mean, standard deviation, root mean square etc.

1.4 THESIS METHODOLOGY

The thesis is organized in 5 chapters, the contents of which are summarized as follows

Chapter 1: Introduction

The chapter introduces the general background of condition monitoring of machinery, engine and the place of the vibration monitoring in this context. The objective of this research and the claimed contribution to knowledge are also identified.

Chapter 2: Literature review

This chapter citation reviews the published literature on condition monitoring of internal combustion engines (ICE) and other machinery using vibration signature and other type of sensors as appropriate. The various simple and advanced technique analysis used for fault monitoring of engines are also reviews that are the techniques of vibration monitoring. The chapter concludes with an identification of the thesis topic of current knowledge of vibration monitoring of machines.

Chapter 3: Vibration monitoring techniques and Experiment

This chapter describes the theory of signal processing technique and explains the general vibration signature and mathematical model for deterministic and nondeterministic techniques are used in this research including techniques for the purpose of analysis.

Chapter 4: Experimental result and Discussion

This chapter provides detail of experiment of this research and the vibration signature measurement apparatus. Then, this chapter presents the result of vibration analysis form a small four strokes petrol engine and identifies characteristic of fault signals detection to determine the statistical parameter. Finally, this chapter present and discusses the experimental result and analysis techniques that follow the objective of this research.

Chapter 5: Conclusion and Future Work

A brief summary of the work, the result presented in the thesis, the main finding and achievements of this research are given, along with recommendation for possible future studies.

CHAPTER 2

LITERATURE REVIEW

2.1 INTRODUCTION

In general, condition monitoring relies on selecting a measurable parameter which will change when the condition of a machine deteriorates. An extremely wide definition covered sensor selection and signal processing and interpretation. Fault detection is one of the main reasons for condition monitoring of rotating machinery. The most common diagnostic technique is based on vibration analysis. This chapter reviews the use of vibration monitoring of engine and operation condition process and other machinery for various fault condition in order to establish the state of knowledge against which this current work is set. The processing techniques that are used to extract information from the vibration signal, such as statistical parameter feature and time waveform feature are discussed, and the last section summaries state of knowledge for selection technique for use in this thesis and then identifies the thesis target.

The first part is concerned mainly vibration monitoring for various simulated fault conditions such as abnormalities in combustion process, although other monitoring techniques using various types of sensors to diagnose in typical engine and rotating machinery are also described and their relative advantages and disadvantages are discussed. Finally, associated fault diagnoses are discussed the state of knowledge that used for the research objective.

2.2 CONDITION MONITORING OF ENGINE AND MACHINERY

This section is concerned with identifying the state of knowledge of vibration monitoring of four-stroke engines and rotating machinery. The first part is concerned mainly with vibration monitoring for various common engine fault conditions such as mechanical impact event and abnormalities in combustion or injection processes, although other monitoring techniques using various types of sensors to diagnose faults in four-stroke engines are also described and their relative advantages and disadvantages are discussed. Finally, examples of classical techniques of vibration monitoring for rotating machinery, and associated fault diagnosis are discussed, including rolling element, gears, and reciprocating machinery.

2.2.1 Vibration Monitoring of Four-Stroke Engines

Condition monitoring of four-stroke engines using vibration signal analysis has been introduced over the past many years. Monitoring of surface vibration via accelerometers has proven to be an effective technique for condition monitoring. This is particularly true for rotating machinery, where fault detection usually consists of identifying rotational speed frequencies or their harmonics [18]. Application towards reciprocating machinery is not quite as straightforward although it has been suggested by A. Autar [19] that vibration signature analysis provides by far the most information about internal engine condition. Vibration analysis has been used for fault detection both small and large engines, being sensitive, for example, to combustion faults [2, 5-6], liner scuffing [7-8], and exhaust valve leaks [12-13].

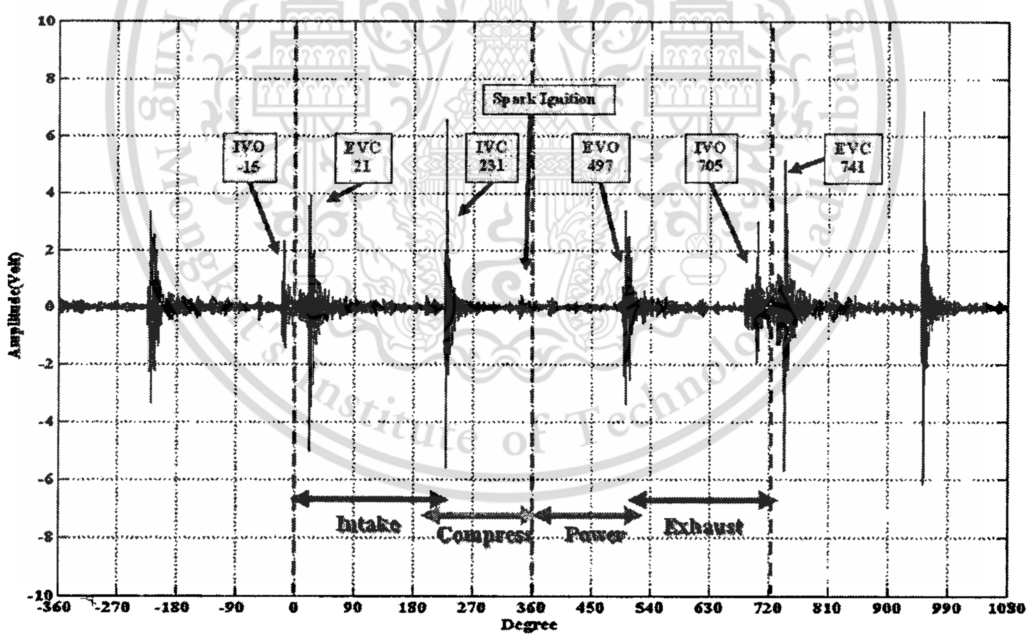


Figure 2.1: Example of vibration signal and related processes recorded at cylinder head of a small four-stroke diesel engine.

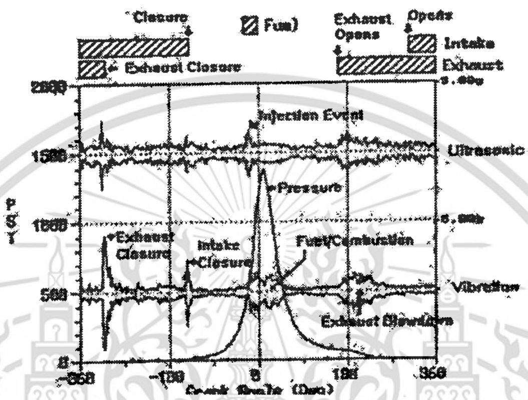
In the four-stroke petrol engine cycle, each stroke (intake, compression, power and exhaust) consists of series of processes, which are related to mechanical movement and fluid flow activities in the engine, i.e. those coming from exhaust valves, intake valves, sprak ignitions and other ancillary equipment. Figure 2.1 shows a typical raw vibration signal obtained from an accelerometer attached on the cylinder head of a small four-stroke, single cylinder, petrol engine. The IVO, IVC, EVO and EVC represent intake valve opening, intake valve closing, exhaust valve opening, and exhaust valve closing event, respectively. The 0 and 180 degrees represent TDC (Top Dead Center) and BDC (Bottom Dead Center), respectively.

Engine surface vibration results from excitation forces associated with operational events such as mechanical impacts, fluid flows and friction [14]. The simplest form of analysis is to compare an observed signature against a reference indicative of normal operation. Deviations of amplitude or timing of expected events, or the appearance of unexpected events, combined with knowledge of engine operation, can be used to diagnose engine performance or condition. Other process variables such as temperatures and pressures are often used to aid and strengthen this process. Analysis of vibration signatures has allowed diagnostic information to be obtained about processes such as fuel injection [2, 13, 22] combustion and diesel engine knock [13, 24, 25], valve operation [2, 13, 22] and tribological failure of crosshead bearings [26]. Further fault detection capabilities have been demonstrated through the reconstruction of fault detection in engines which will be discussed in the later section.

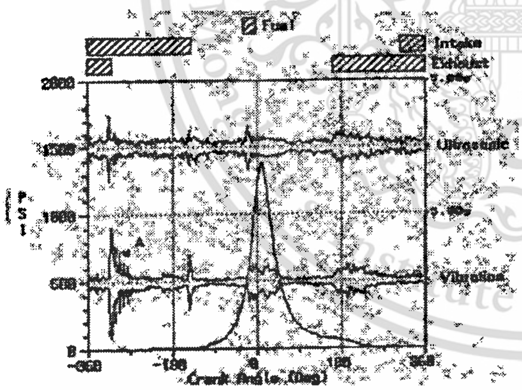
Fault detection in four-stroke diesel engines is a common topic of vibration diagnosis. B. R. Long, and K. D. Boutin [2] described a number of case studies where vibration and ultrasound signature analysis were used to diagnose a variety of faults including valve bouncing, damaged exhaust valve lifter, improper tappet setting, valve seating problems and faulty fuel injection in Figure 2.1. In both cases, fault diagnosis was achieved through comparison to reference normal signals. However, there were ambiguities as to the instrumentation used, particularly regarding the location of sensors and the acquisition of the ultrasonic signals. Nevertheless, the advantages and increased diagnosis potential over conventional monitoring techniques were clear. G. Chandroth [21] further showed through the use of an artificial neural network that a variety of commonly occurring valve and injector faults in a small, twin-cylinder engine could be identified through analysis of vibration signals.

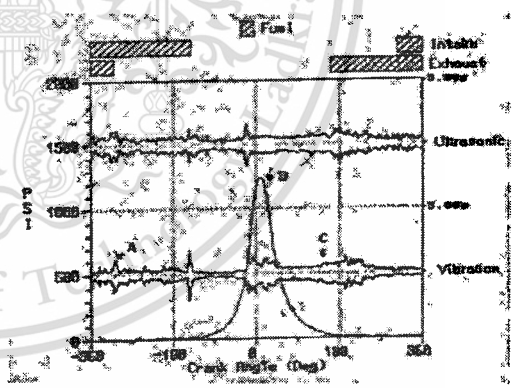
B. R. Long, and K. D. Boutin [2] demonstrated that measurements of vibration and ultrasound could be used to identify faults including piston slap, scuffing and exhaust valve fault. The signal characteristics of normal operation were first established, as shown in Figure 2.2a.

Changes in the signals were then attributed to the development of faults, for instance, strong vibration spikes occurring coincident with either maximum cylinder pressure or maximum lateral piston force were deemed indicative of piston slap. Vibration events occurring symmetrically about TDC, shown in Figure 2.2b by events marked A and B, were believed to indicate liner scuffing or scoring. High vibration and ultrasonic energy coinciding with decreasing cylinder pressures, as shown in Figure 2.22c, were considered symptomatic of exhaust valve not seating properly.



(a) Normal vibration pattern





(b) Exhaust valve bouncing and closure

(c) Exhaust valve not seating properly

Figure 2.2: Vibration and ultrasonic signals

An array of accelerometers that used to survey surface vibration characteristics of a large two-stroke diesel engine was used by S. Sasaki [22]. The origins of most activities were coming from injector, combustion or valves. Using additional TDC, shaft encoding and in-cylinder pressure signals, the events in the vibration signals were mapped to their respective mechanical and fluid sources. This process was aided through approximate source location using array characteristics, for example, vibration events resulting from exhaust valve activity were more prominent in signals acquired from the upper cylinder liner and exhaust valve housing components.

In general, vibration monitoring does have other problems, mainly regarding event isolation and the resulting signal to noise ratio. With regards to engines, some events generated during a cycle of one cylinder can have marginal separation and when events originating from other cylinders are considered. Then, the levels of event overlap can make focused analysis difficult. R. K. Autar [19] noted that this was common for small, multi-cylinder engines. Means by which events could be separated were elucidated to, with the example given of signal isolation through careful filtering. It was also observed that much random noise was present in vibration signals [19]. A. Albarbar [29] concurred that the diagnostic information was dominated by both background and interference noise and proposed methods such as coherent filtering techniques and adaptive noise cancelling to improve this situation.

H. Li and B. J. Stone [40] described the application of a time domain systems approach to the modeling of a reciprocating engine. The engine model includes the varying inertia effects resulting from the motion of the piston and con-rod. The cylinder pressure measured under operating conditions was used to force the model and the resulting motion was compared with the measured response. The results obtained indicate that the model was very good.

One of common topic of four-stroke diesel engine using vibration diagnostics is in-cylinder pressure monitoring. Vibration signals have also been used to reconstruct the in-cylinder pressure trace. This has been accomplished successfully for both single (R. B. Randall et. al. [26, 27]) and multi-cylinder engines (G. Zurita [28]) by operating under steady-state conditions. This technique was based on the presumption that transient vibrations were generated by the pressure waveform during the combustion phase. Therefore, if the transfer function relating the forcing pressure wave to the surface acceleration response could be identified then the inverse of this function could be used to reconstruct the pressure trace. However, not all attempts have been successful. P. M. Azzoni [16] commented that pressure reconstruction based upon vibration measurements was unsatisfactory. However, similar analysis using ICAV measurements produced better results. F. Gu [5, 6] further questioned the ability of vibration-based reconstruction methods to estimate the compression phase and a transfer function was constant during the service life of an engine.

Y. Gao and R. B. Randall [41] studied the time waveform of engine cylinder pressures that was the most useful parameter in evaluating cylinder working procedures, such as compression, combustion and expansion in a diesel engine. Unfortunately, direct measurement of cylinder pressure signals was impractical because installing pressure transducers was difficult as well as uneconomical for general use. Therefore, indirect derivation or reconstruction of such signals from externally measured engine vibration was desired. Different procedures have been developed to reconstruct cylinder pressures from externally measured vibration responses. In this paper, the theories of existing procedures were reviewed. Also the Laplace transform (LT) was used to design a time-domain smoothing technique. The properties of this technique were investigated theoretically. Then it was applied to reconstruct cylinder pressures from response vibrations measured externally on a single-cylinder diesel engine, and the results obtained corresponded well with the measured pressure waveforms.

A common topic of vibration diagnosis for four-stroke diesel engines is monitoring of injector operation. A non-intrusive solution is particularly attractive since other techniques such as needle lift and fuel-line monitoring are intrusive. F. Gu and A. D. Ball [12, 13] reported that needle impacts and high pressure fluid flows were the principle vibration sources during injector operation. It was also noted that the measured vibration response was influenced by the dynamic properties of the injector body and less so by other potential noise sources such as combustion. They proceeded to show that the timing of injector events could be extracted from the vibration signal and that these were similar to those obtained from simultaneous needle lift measurements.

Tribological failure on a crosshead bearing in a large, two-stroke, diesel engine has been investigated by T. Kitahara *et al* [25]. Lubrication condition and applied load were varied to assess if lubricant film failure and the beginning of severe metal-to-metal contact could be detected prior to complete seizure. They found that vibration events were generated when the reciprocating speed between the bearing surfaces was momentarily zero and oil film thickness was at a minimum. When the oil supply was stopped, the level of vibration at these points increased progressively in amplitude. Similar observations were made when loading was progressively increased under normal lubricating conditions. These abnormal vibration spikes were attributed to severe metal-to-metal contact that was precursor to complete seizure. It was noted that this could be used to provide early warning of problems so to allow remedial measures to be taken.

A method for improving knock detection in spark ignition engines using vibration signals and pattern recognition has been described by F. Molinaro and F. Canstanié [23]. The aim was to improve upon techniques whereby knock was deemed to occur if abnormally high-energy vibration was observed in a windowed period. The disadvantage of an energy-based approach was that the knock-induced vibration had to be detected against a background of other sources and this could result in a very poor signal to noise ratio, especially at high engine speeds. A further method for knock detection through extraction of both time and frequency domain parameters was outlined by A. Ghasemloonia and M. Behzad [24].

J. B. Roberts [42] introduced a new method of linearised fitting. Parametric stochastic models of pressure variations of each cycle during the combustion region of a spark ignition petrol engine were described. The technique was based on stochastically fitting the combustion models to the covariance function of the measured pressure fluctuations, obtained by averaging over the entire ensemble of measured cycles. Comparisons for two specific combustion models with corresponding results obtained by deterministic fitting on a cycle-by-cycle basis showed that the new method gave a similar degree of fit, but with much improved computational efficiency. It was also demonstrated that the degree of fit to the data could be further improved by modelling the residual error between the data and the combustion models in terms of Chebyshev polynomials. The parameters in these polynomials may be determined by stochastic fitting. The technique has wider applications in the condition monitoring of rotating machinery.

2.2.2 Vibration Monitoring of Rotating Machinery

Most rotating machines produce low levels of vibration when they are designed properly. During operation, all machines are subjected to fatigue, wear, deformation and foundation settlement. These effects cause an increase in the clearances between mating parts, misalignments in shafts, initiation of cracks in parts and unbalances in rotors – all leading to an increase in the level of vibration deterioration, which causes additional dynamic loads on bearings and gears boxes. As time progresses, the vibration levels continue to increase, leading ultimately to the failure or breakdown of the machine. The common types of fault or operating conditions that lead to increased levels of vibration in machines include bent shafts, eccentric shafts [50], misaligned components [50], unbalanced components [50], faulty bearing [50,54,55], faulty gears [54-55,60,63,65], impellers with faulty blades[50] and loose mechanical part [51].

Several methods can be used to monitor the condition of a machine, as indicated in Figure 2.3. Aural and visual methods are the basic forms of monitoring techniques in which a skilled technician, having an intimate knowledge of machines, can identify a failure simply by listening to sounds and visually observing large amplitudes of vibration produced by a damaged machine. Similarly, device ranging from magnifying glasses to stroboscopes are used to visually monitor the condition of a machine. Current and Voltage Monitoring can be used to for the condition monitoring of electrical drives such as large generators and motors.

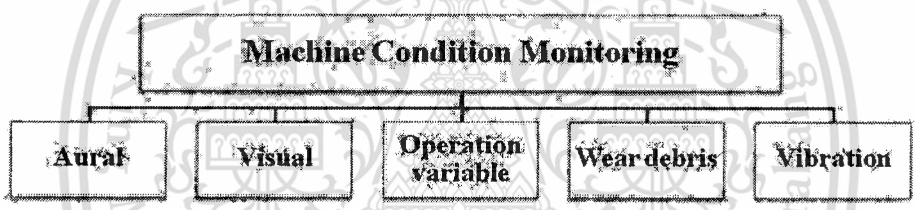


Figure 2.3: Machine Condition Monitoring Technique

In the operational variables method of monitoring, also known as performance or duty cycle monitoring, the performance of a machine is observed with regard to its intended duty. Any deviation from performance denotes a malfunction of the machine. Temperature monitoring involves measuring the operational or surface temperature of a machine. This method can be considered as a kind of operational variable method. A rapid increase in the temperature of a component, occurring mostly due to wear, is an indication of a malfunction such as inadequate lubricant in journal bearings. Temperature monitoring uses such devices as optical pyrometers, thermocouples, thermography, and resistance thermometers. In some cases, dye penetration are used to identify cracks occurring on the surface of a machine. This procedure requires the use of heat-sensitive paints, known as thermography paints, to detect surface cracks on hot surfaces. In such cases, the most suitable paint matching of the expected surface temperature is selected.

Wear debris is generated at relative moving surfaces of load-bearing machine elements. The wear particles that can be found in the lubricating oils or grease can be used to assess the extent of damage. As wear increases, the particles of the material used to construct machine components such as bearing and gears can be found in increasing concentration. Thus the severity of the wear can be assesses by observing the concentration (quantity), size, shape and color of the particles indicates how they have been.

The aforementioned techniques are based on human and technician. In other hand, vibration monitoring of rotating machine using non-intrusive sensors can be used to describe about the fault detection clearer than visual and aural technique of person. Many researchers afford improvement and developing technique for predictive symptom of rotating machines. For example, failures in rolling bearings are a classical problem in a number of different types of machinery, and the use of vibration monitoring is relatively mature. A number of investigators have recently turned to applying vibration analysis techniques to detect defects on rolling element bearings. In recent years, there has been a considerable amount of attention paid to the analysis of cyclostationary signals [31], primarily in the field of communications and electrical engineering. However, limited applications in mechanical engineering have also been reported [32]. The latter paper was one of the first research to apply the principles of cyclostationarity to bearing signals, but it did not demonstrate clear results in the spectral correlation, possibly because the frequency range chosen was below resonances excited by the bearing faults.

R.B. Randall [30] described one of the most successful techniques for diagnosing faults in rolling element bearings which called ‘envelope analysis’, where the envelope of the signal (obtained by amplitude demodulation), rather than the raw signal itself, was frequency analysed to detect the bearing fault frequencies [32]. The reasons for the advantage of this approach have been explained qualitatively [33], but not quantitatively. One of the aims of this paper was to give a quantitative evaluation of the degree to which information about bearing faults could be extracted by frequency analysis using the raw signal. Another aim was to demonstrate the relationship between the classical envelope analysis (and in particular, analysis of the squared envelope) and spectral correlation analysis, which are one of the tools used to characterise cyclostationary signals. The third aim was to point out how experience was already gained by using envelope analysis that could be used to improve results obtained by spectral correlation of cyclostationary signals more generally.

H. Yang et al [34] investigated the task of condition monitoring and fault diagnosis of rolling element bearing was often cumbersome and labour intensive. Various techniques have been proposed for rolling bearing fault detection and diagnosis. The challenge, however, was efficiently and accurately extract features from signals acquired from these elements, particularly in the time–frequency domain. They presents an application of this new basis pursuit method in the extraction of features from signals collected from faulty rolling bearings with inner race and outer race faults. Results obtained using this new technique were compared with discrete wavelet packet analysis (DWPA) and the matching pursuit technique. Basis pursuit was represented features with very fine resolution and sparsity in the time–frequency domain thus rendering easier interpretation of the analysed results. The technique also improved the signal to noise ratio so that subsequent fault detection and identification could be conducted with confidence.

The vibration signal of a gearbox carries the fault signals in gears. As such early fault detection of gearbox is possible by analyzing vibration signals using various signal processing techniques. E. B. Halim et al [35] investigated time synchronous averaging could extract the periodic waveforms of a noisy vibration signal, whereas wavelet transformation was able to characterize the local features of the signal at different scales. This paper proposed a new technique, time domain averaging across all scales, which combined the time synchronous average and wavelet transformation to extract periodic waveforms at different scales from noisy vibration signals. The technique efficiently cleaned up noise and detected both local and distributed faults simultaneously. A pilot plant case study was presented to demonstrate the efficacy of the proposed technique.

However, F. Xianfeng [36] who studied demodulation that is an important issue in gearbox fault detection. Non-stationary modulating signals increase difficulties of demodulation. Though wavelet packet transform has better time–frequency localisation, because of the existence of meshing frequencies, their harmonics, and coupling frequencies generated by modulation, fault detection results using wavelet packet transform alone are usually unsatisfactory, especially for a multi-stage gearbox which contains close or identical frequency components. Their work proposed a new fault detection method that combines Hilbert Transform [37] and wavelet packet transform [38-39]. Both simulated signals and acquired vibration signals collected from a gearbox dynamics simulator were used to verify the proposed method. Analysed results showed that the proposed method was effective to extract modulating signal and helped to detect the early gear fault.

In this section, the successful detection of mechanical and fluid flow activities related to processes in machinery i.e. fluid flow, mechanical impact, which are typical phenomena in four-stroke engines and rotating machinery using vibration analysis has been discussed. A number of faults or abnormal conditions in machinery have been identified using accelerometer. To diagnose fault conditions, knowledge of physical phenomena of machinery operation under normal and simulated fault conditions are necessary. Then, patterns or features related to machinery conditions can be extracted from the signals. The methods used for interpreting accelerometer signals are described in more detail in the next section.

2.3 DIAGNOSTIC METHODS

This section emphasizes on diagnostic methods used to classify fault symptoms and severity based on sensor inputs. The initial condition monitoring technique applied to engines involved fault detection through the use of human, sound, smell, touch and sight. It is not too difficult to imagine that reliance on human perception alone is often uncertain and imprecise. This, combined with the increasing complexity of engines, has necessitated the other investigated methods to monitoring engine operation. The result is that a wide range of measurement and analytical techniques have been developed to measure and process data into a form where it can be interpreted with regards to engine condition. These ranges of systems trend from basic operational parameters to sophisticated technique that require a high level of human expertise to fully automated, on-line monitoring systems which fuse data from many raw data of separate engine measurement. Due to the continual demand for better-quality diagnostic information, developments in measurement and monitoring techniques are ongoing, with a number of new technique, such as vibration monitoring, actively being pursued.

The sophistication of a condition monitoring system are fundamentally similar in that they rely upon the measurement of parameters that vary either directly with the physical deterioration of a component, or indirectly from the effects of deterioration. For example, measurements include variables such as pressures, temperatures and exhaust emissions, together with other signals that result from these variables, such as engine surface vibration, crankshaft speed fluctuation and engine noise level. In many cases, the measured signal fluctuates continuously during each engine cycle and is on the basis of a cyclic signature.

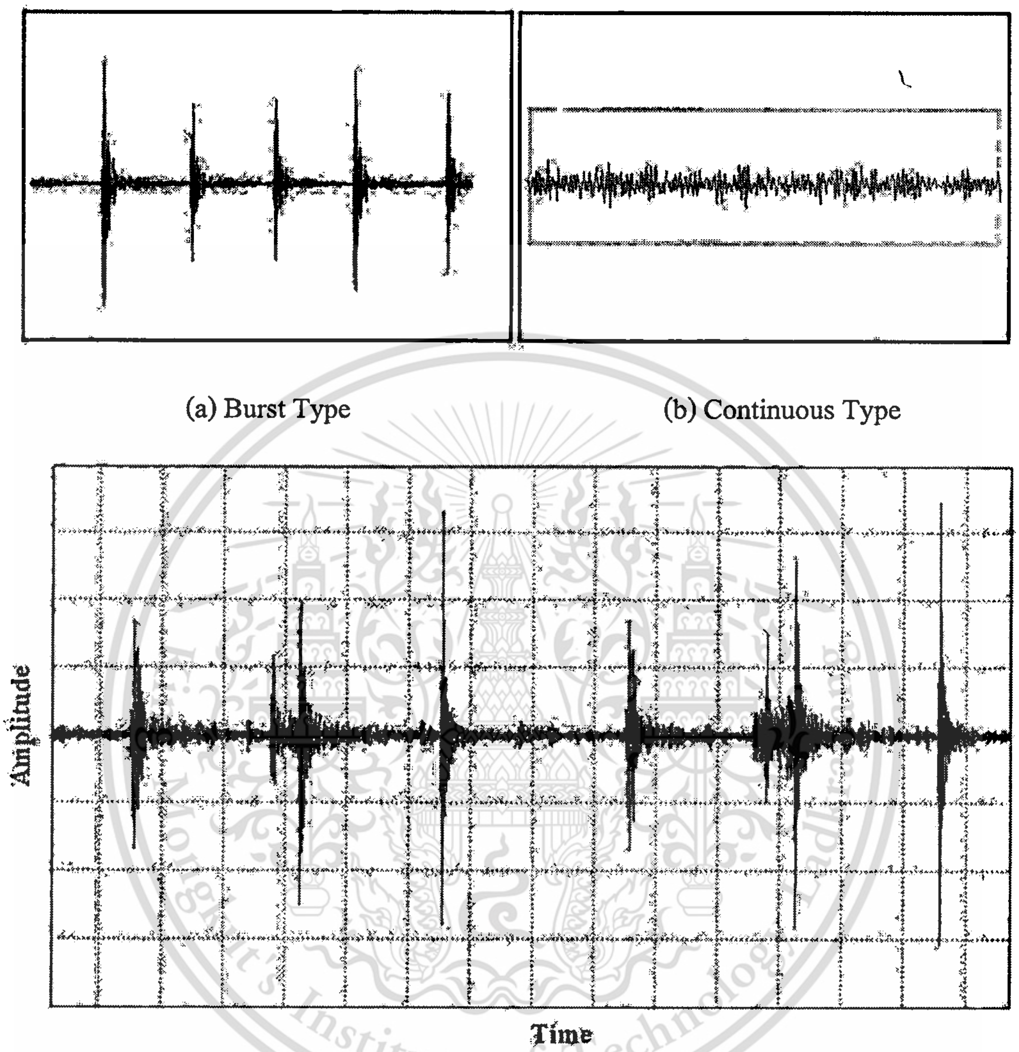
2.3.1 Deterministic Method

Deterministic methods use more or less sophisticated mathematical simulation models based on physical processes to predict the behavior of machinery for both healthy and faulty conditions and then use more or less direct measurements to assess condition. To develop a monitoring system based on these methods, it is necessary to encode some level of knowledge of the machinery and the processes into the diagnostic system. One example of this approach is given by F. Gu [12, 13] who have developed a dynamic model to estimate injection parameters including fuel injection pressure, fuelling rate and timing. They used a two-mass, vibro-impact model to describe characteristics of a single-stage, hole-type, direct injection, diesel fuel injector. This model was based on needle motion during an injection period and consisted of four effects; compression or relaxation of the needle seat, the retraction and advance of the needle seat, the impact of the needle with its back stop, and spring seat and needle separation. They suggested that the use of this model permitted analysis of both the needle impact behavior and the general dynamics of the fuel injection process. The model was validated by measuring the needle lift from the injector of a diesel engine in a laboratory test. They noted that some parameters used in the model were unable to be obtained directly from the injector, such as the contact stiffnesses and the damping ratios. Thus, a trial and error approach was used to estimate these parameters until the predicted needle lift from the model was close to the measured needle lift. The motion of the injector needle was controlled by the flow of high pressure fuel within the injector so that the models of fuel flow, injection rate and pressure in the nozzle chamber were defined. Gu et al [12, 13] concluded that the peak amplitude of the first needle opening impact from the model could be used to estimate the initial pressure and initial fuel delivery. Furthermore, the experimental study using a vibration signal confirmed that the peak amplitude of the vibration signal had a linear relationship with fuel supply line pressure which was similar to the results obtained from the model.

As mentioned previously, Douglas [45] has studied the relationship between Instantaneous Crankshaft Angular Velocity (ICAV) waveform and output power on large two-stroke, marine diesel engines. The ICAV waveform represented cyclic variations about the mean engine speed due to the compression and expansion strokes associated with each cylinder and were measured from a shaft encoder mounted on the end face of the flywheel of the engines. They suggested that the in-cylinder pressure end the resulting indicated torque was a major factor that affected the ICAV fluctuations. The relationship of the ICAV waveform and output power was related to the torque balance equation of the engine which was defined using the inertia of the system, the angular position of the crankshaft, the indicated torque, the inertial torque due to the reciprocating mass and the piston motion, and the external load torque. They noted that when the in-cylinder pressure increased, the indicated torque in the torque balance equation increased, resulting in increased power output, and then the amplitude of the indicated torque waveform increased. Thus, the magnitude of the crankshaft acceleration fluctuations increased with increasing power and the magnitude of the fluctuations in the ICAV amplitude increased. The power output could be directly related to the ICAV amplitude. They showed that the experimental results of the ICAV waveform were in a good agreement with the assumption mentioned above. In addition, the standard deviation calculated from the ICAV waveform could be used to indicate power output of the engines.

2.3.2 Statistical Method

Analysis of observed signature generally aims to detect deviations from the normal. This can present major challenges. Signal changes relating to component or process deterioration have to be detected from the background of normal signal variation that arise from operation over the engine range, i.e. varying speeds, ambient conditions, etc. The requirement for incipient fault detection further adds complexity as this may involve discrimination between subtle features in signals. However, early detection is an essential criterion of an ideal condition monitoring system as advanced stage fault, although easier to detect due to larger deviation from the norm, may require immediate attention. Additionally, accurate root cause diagnosis of fault in an advanced state can be difficult due to that cause-and-effect nature of fault propagation. A further aspect of the condition monitoring process is to understand a physical explanation for identified signal change and in doing so, determine whether a fault is present and if so, the nature and severity of that fault.



(c) Raw vibration signal acquired from a running engine

Figure 2.4: Example of various types of vibration signals

There are two types of vibration signals. The first is burst-type signal, where the signal consists of clearly defined 'events' as shown in figure 2.4(a). These events are characterised by amplitude significantly larger than the background level. Distinct sharp signal rises and closes to exponential decays, and individual pulse are usually well separated in the time-domain. The second type is continuous signal. This occurs when burst generation is so rapid that the signal appears continuous and resolution of individual events is not possible as shown in Figure 2.4(b).

Typically, signals acquires from machinery will be a combination of both to varying degrees. An example of vibration signal measured from the surface at cylinder head of a running engine is shown in Figure 2.4(c). It can be seen that a number of overlapping burst and continuous types of varying amplitudes are evident.

2.3.2.1 Time Domain analysis

There are various means by which vibration signal can be processed and evaluated in order to extract useful information for condition monitoring. The most common method for achieving is time-domain characterization of burst type events through extraction of waveform parameter. A further problem with applying threshold-based analysis to machinery monitoring is that burst type activity is often accompanied by a high level of continuous signal. If the burst activity is generated from a fault-related source, such as the early signs of wear or mechanical impact, this may effectively be buried in the continuous signal, which can make identification via threshold-analysis difficult. Therefore, to fully preserve the possibility of incipient fault detection and to better understand vibration signal generated from machinery, continuous and mixed vibration signal should be analysed through other means.

Vibration signal is a measurement parameter used extensively in vibration monitoring. However, the calculation of signal energy is a parameter that can be used to describe information from acquired vibration signals. For this work, energy content is taken as the area under the absolute value of vibration signal, as defined in Equation (2.1).

$$E = \int_{0}^{t} x^2(t)dt \tag{2.1}$$

Where $x(t)$ is the vibration signal amplitude in volts, t is time in seconds and E is the signal energy in $V^2 \cdot s$.

Vibration signal can be transformed from time domain signal to crank angle signal. Then, energy content of crank angle signal is calculated from Equation (2.2)

$$E = \int_{a}^{b} x(\theta)^2 d\theta \tag{2.2}$$

Where $x(\theta)$ is the amplitude of crank angle domain signal, again given in arbitrary units, θ is angular position in degrees, E_θ is the crank angle domain of signal energy and a, b are crank angle positions.

A further parameter widely used to indicate energy is the Root Mean Square (RMS) value of the vibration signal, calculated using Equation (2.3)

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2} \tag{2.3}$$

Where x is the data at a discrete point (or time) and N is the total number of data in the selected time period.

This can be applied as post-acquisition processing in which the RMS value of a burst type event for each successive time window is calculated. Otherwise, a signal averaging circuit can be built into an acquisition equipment which continually calculated RMS value over a sliding time period. This allows data acquisition at a lower, more conventional thereby bringing about a significant reduction in data size. This can be beneficial when analysis of many hundreds or thousands of length acquisition is considered as analysis of raw waveforms can be extremely computationally intensive.

Further, simple statistical parameter are commonly used to describe signals such as the mean ($\bar{x}$), standard deviation (s), and variance (s^2), as defined in Equations (2.4), (2.5) and (2.6), respectively. These can be applied to a whole signal, to section, or windows, of a signal, or to determine variation between sets of signals.

$$\bar{x} = \frac{1}{N}\sum_{n=1}^{N} x_n \tag{2.4}$$

$$s = \sqrt{\frac{1}{N-1}\sum_{n=1}^{N}(x_n - \bar{x})^2} \tag{2.5}$$

$$s^2 = \frac{1}{N-1}\sum_{n=1}^{N}(x_n - \bar{x})^2 \tag{2.6}$$

Other statistical indicators often used are the skewness, kurtosis, crest factor, impulse, clearance and shape factor.

2.3.2.2 Frequency Domain analysis

Frequency domain analysis offers further options for investigation of vibration signals, and is a proven technique for machinery diagnosis. This has been established through a long association with vibration monitoring where spectral analysis is considered as one of the principal analytical tool used in many commercial monitoring packages.

In general, frequency analysis involves the decomposition of time series data into the frequency domain. This is typically achieved as an estimate through an algorithm known as the Fast Fourier Transform (FFT). For many applications, this method alone is sufficient to describe the signal. However, other algorithms have been developed using the FFT in order to estimate the distribution of the signal energy in the frequency domain. This is known as the Power Spectral Density (PSD) and the Welch PDS estimated.

Regarding condition monitoring, frequency spectra analysis can be similar to time-domain analysis. Deviations from the expected normal condition may be indicative of faults. Some frequency contents are directly associated with aspects of normal machine such as running speed or resonance, however, the development of faults may result in the emergence of discrete frequencies which can be related to the physical behavior of the machine. Frequency contents of vibration spectral analysis can be used to distinguish between different types of source mechanism. This may be beneficial to investigation of events of unknown origin. A further approach is commonly used to filter unwanted signal from the original signal. If the filter is careful constructed, this can allow increased focus on specific events through enhanced signal-to-noise ratio.

Irrespective of which method is used to estimate spectral contents, a singular usage cannot satisfactorily describe how non-stationary signals, such as vibration signals, vary with time. Therefore, to overcome this, techniques which combine time and frequency analysis are widely used, with the simplest being the Short Time Fourier Transform (STFT). This implements the FFT algorithm at time increments through the signal using a sliding window approach. Other methods for time-frequency analysis include wavelet decomposition, a spectral decomposition technique which returns scale and variable resolution in both time and frequency axes.

The aforementioned spectral analysis tools are generic techniques which are usually applied towards the raw vibration signal. However, for machinery monitoring and particularly for rotating and reciprocating machinery, there is merit in applying these techniques towards the vibration signal analysis.

2.3.3 Pattern Recognition Method

Other approaches exist for vibration signal processing which are applicable for burst and continuous signals. Many of these methods are considered attractive to condition monitoring as they introduce some form of automation to the analysis processes and therefore lend themselves well to real-time monitoring. Also, they can be adapted to quickly handle large amounts of data and to identify changes in signals, or signal features which do not conform to the expected case. A further point is that many of these processes are purely statistical in nature, and require minimal interpretation of the complex vibration signal with regard to the material or component behavior. Hence, they are generic and transferable over application as they are borne out in the wide range of data processing problems. The analysis techniques are usually applied such as speech recognition, machine vision, etc.

A technique often used for isolating significant features from large and complex datasets is Principal Components Analysis (PCA) [43]. This is a form of higher-level statistical analysis whereby variance is analysed and a simplified description of the data is returned which preserves as much statistical relevant information as possible. The removal of redundant features is deemed desirable especially for the large datasets which vibration monitoring usually generates, as it permits the application of further statistical classification and diagnostic aids.

Independent Component Analysis (ICA) [44] is further signal isolation techniques, and is considered an extension of PCA. It assumes that the measured signal is a composite of separate signals which can be resolved using ICA algorithm based upon the assumption that the signals are statistically independent. The outcome is the source signals and also a measure of their separation effectiveness, i.e. how strongly they appear in the measured signal. This technique is especially useful for extracting low level, or hidden signals, which may otherwise be obscured by dominant source.

Pattern recognition techniques are extensively used in condition monitoring applications, either using simple time domain parameters or in combination with feature extraction or other analytical processes. The overall aim with pattern recognition is to ascertain through comparison of measured signal parameters against a reference bank in which signals over varying conditions are mathematically and statistical well-defined. A best-match is identified and the acquired signal is then classified as representative of that particularly condition. One drawback with this process is that in order to minimize misclassification is require of all condition that may be encountered. This may be impractical due to the many different operating and fault scenario. Hence, the pattern recognition process may be limited to differentiation between normal and abnormal conditions.

Artificial Neural network have regular been used to recognise and classify complex fault patterns without requiring a great deal of prior knowledge about processes, signals, or specific fault patterns. Neural networks are structured in layers of interconnecting processing elements (neurons), with the behavior of the network determined by the weights with each connection. These weights can be adaptively trained using example signals to associate a particular input pattern to an output classification. Hence, if something is similar to that pattern is presented again then the network will recognize it and return the appropriated output. Many output possibilities can be programmed in this manner and it is not unusual to have several processing layers in order to achieve an output classification. Neural networks are adept at handling large amounts of in a short period of time and are therefore useful for real-time analysis and for data fusion, i.e. the amalgamation of information obtained from a variety of sensory inputs.

Further generic signal processing tools include fuzzy logic and expert systems. Fuzzy logic is a technique used when fault threshold values for conventional time domain and frequency domain analysis are felt too rigid to suit the complex nature of mechanical condition monitoring. Expert systems is a term used to describes the application of knowledge-based procedures and programs that are the equivalent to the knowledge, or reasoning processes, that would be expected from human experts in particular field.

2.4 SUMMARY STATE OF KNOWLEDGE

Accelerometer has been shown an important in condition monitoring and diagnostics not only in structural integrity but also, increasingly, in rotating and reciprocating machinery. Vibration signal acquired form accelerometer has been applied to condition monitoring of four-stroke diesel engines and has been used successfully to identify various conditions such as combustion, valve fault, injector faults and liner scuffing. The fault conditions have been identified by monitoring the change of statistical or waveform features extracted from the vibration signal. Additionally, pattern recognition methods have been applied to improve fault identification, including PCA, ICA and neural network.

In the light of this, the current research attempts to find a way to gain more understanding of vibration wave transmission is four-stroke petrol engines in order to obtain more detailed information from the detected signal. In addition, the effects of abnormal signal form four-stroke engines will be studied to find a way to determine the relationship between normal condition and abnormal condition from the simulated fault at the valve. Most of the published work uses crank angle and TDC signals to map the vibration events from the time domain onto the crank angle domain so that each known mechanical process in the engine cycle can be compared to the events in the vibration signal. This thesis has studied vibration analysis methods for a condition monitoring of a small four-stroke, single cylinder, and petrol engine with capacity of 125 CC using vibration signals. The signal processing techniques are used to diagnose vibration signal in time domain and crank angle domain with some statistical parameters such as mean, standard deviation, root mean square, variance, skewness, kurtosis, and covariance components.

CHAPTER 3

VIBRATION MONITORING TECHNIQUES AND EXPERIMENTS

3.1 INTRODUCTION

This chapter is introduced about the types of signals and fundamentals of signal processing which are the science of applying transformations to measurements, to facilitate their uses by an observer or a computer, and digital signal processing (DSP) is the enabling technology for applications across all disciplines and sectors. The study of sound and vibration is highly dependent on the use of special-purpose signal analysers or software packages. The accessibility and convenience of DSP analysis modules and procedures can sometimes create a deceptive air of simplicity in often complicated phenomena. It is important that practitioners, while availing themselves of the full range of DSP capabilities, should have a clear understanding of the fundamentals of the science of signal processing and so be fully aware of the assumptions, implications and limitations inherent in their analysis methods. Signal processing and analysis involves the three phases of data acquisition, processing and interpretation (of the results of the processing) and, of course, all three are linked in any application. The last phase is naturally very much related to the subject under investigation, but the first two may be discussed independently of specific applications. A vast body of theory and methodology has been built up as a consequence of the problems raised by the need for data analysis. This is often referred to as "signal analysis" or "time-series analysis" depending on the context. The choice of methodology is often reliant on some prior knowledge of the phenomenon being analysed. This usually relates to classifying the characteristics of the data and the way in which the data may be modeled owing to knowledge of (or assumptions about) the way in which the data may have been generated. This section considers signal and system characteristics that underpin signal processing.

Signal processing is the name given to the procedures on measured data and is also used to reveal the information contained in the measurements. These essentially rely on various transformations that are based on mathematical model and implemented using digital techniques. The wide availability of software to carry out digital signal processing (DSP) with such ease now pervade all areas of science and engineering. This chapter will describe the typical signal and technical analysis such as the data acquisition system, the signal processing technique and the interpretation of vibration signal acquired from petrol engines.

3.2 VIBRATION SIGNALS

3.2.1 Descriptions of Physical Signal

To observe data representing a physical phenomenon will be referred to as a time history or a time series signal. Example of signals are temperature fluctuation in a room indicated as a function of time, voltage variations from a vibration transducer, pressure change at a point in an acoustic field, etc. The physical phenomenon under investigation is often translated by a transducer into an electrical equivalent (voltage or current) andis displayed on an oscilloscope. It might appear as shown Figure 3.1. This is an example of a *continuous (or analogue)* signal.

In many cases, data are *discrete* owing to some inherent or imposed sampling procedure. Data might to be characterized by a sequence of numbers equally spaced in time. The sampled data of the signal in Figure 3.2 are indicated by the crosses on the graph shown in Figure 3.2.

Figure 3.1: A typical continuous signal obtained from a traducer output [51]

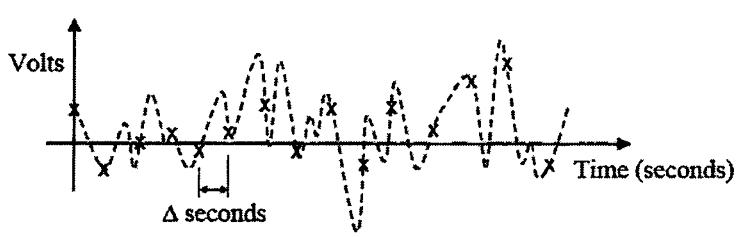


Figure 3.2: A discrete signal sampled at every Δ seconds (marked with $\times$) [51]

For continuous data, the notation $x(t)$, $y(t)$, etc. are used and for discrete data, various notation are used, e.g. $x(n\Delta), x(n), x_n$ $(n = 0,1,2,...)$.

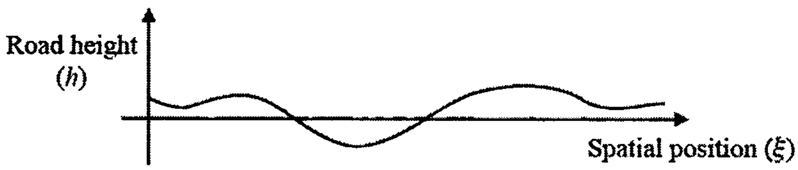


Figure 3.3: An example of a signal with unnatural independent variable [51]

In certain physical situations, 'time' may not be the natural independent variable; for example, road roughness as a function of spatial position, i.e. $h(\xi)$ as shown in Figure 3.3. However, for uniformity, we shall use time as the independent variable in all discussions.

3.2.2 Classification of Signal

Time histories can be broadly categorized as shown in Figure 3.4. A fundamental difference is whether a signal is *deterministic or random,* and the analysis methods are considerably different depending on the 'type' of the signal. Generally, signal are mixed, so the classifications of Figure 3.4 may be easily applicable, and thus but the choice of analysis methods may not be apparent. In many cases, some prior knowledge of the system (or the signal) is very helpful for selecting an appropriate method. However, it must be remembered that his prior knowledge (or assumption) may also be a source of misleading the results. Thus, it is important to remember the first principle of data reduction.

The result of any transform imposed on the experiment data shall incorporate and be consistent with all relevant data and be maximally non-committal with regard to unavailable data.

It would seem that this statement summarizes what is self-evident. But how often do we contravene it – for example, by 'assuming' that history is zero outside the extent of a captured record.

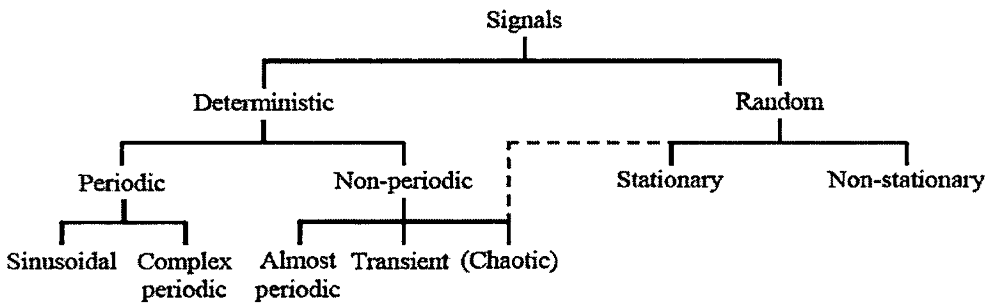


Figure 3.4: Classification of signals [51]

Nonetheless, we needs to start somewhere and signal can be already classified as being either *deterministic* or *non-deterministic*. Deterministic signal are those whose behavior can be predicted exactly. As an example, a mass- spring oscillator is considered in Figure 3.5.

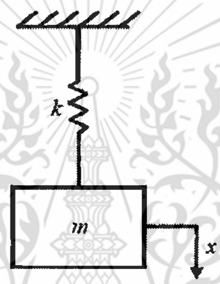


Figure 3.5: A simple mass-spring system

The equation of motion is $m\ddot{}$ 0 (x is displacement and $\ddot{}$ is acceleration). If the mass is related from rest at a position $x(t) = A$ and at time $t = 0$. Then, the displacement signal can be written as

$$x(t) = A\cos\left(\sqrt{k/m}\cdot t\right) \quad t \geq 0 \tag{3.1}$$

In this case, the displacement $x(t)$ is known exactly for all time. Various types of deterministic signal will be described later.

Non-deterministic signals are those whose behavior can not be predicted exactly. Some example is vehicle noise and vibration on a road, acoustic pressure variation in a wind tunnel, temperature records at a weather station, etc. Various terminologies are used to describe these signals later section, namely random process (signals), time series and the study of this signal is called *time domain analysis*. Analysis approaches such as statistical analysis method will be described in the next section.

The classification of data as being deterministic or random signal might be debatable in many cases and the choice must be made on the basis of knowledge of the physical situation. Often signals may be modeled as being a mixture of both, e.g. a deterministic signal 'embedded' in unwanted random disturbances (noise).

In general, the purpose of signal processing is the extraction of information from a signal, especially when it is difficult to obtain from direct observation. The principle of extracting information from a signal has three key stages (i) acquisition, (ii) processing, and (iii) interpretation. To a large extent, signal acquisition is concerned with *instrument*, and we shall treat some aspects of this e.g. **analogue to digital conversion**. However, we shall assume that the signal is already acquired, and concentrated on stage (ii) and (iii).

As described above, the deterministic signal can be classified as show in Figure 3.4. In this figure, chaotic signals are not considered. The sinusoidal signal and more general periodic signals are combined together. So, deterministic signals are now classified as periodic, almost periodic and transient and some basic characters.

There are two basic type of vibration signal as shown in the Figures 2.1 and 2.4. The first is burst-type signal, where the signal consists of clearly defined 'events' as shown in Figure 2.4(a). These events are characterised by amplitudes significantly larger than the background level. Distinct sharp signal rises and closes to exponential decays, and individual pulse are usually well separated in the time-domain. The second type is continuous signal. This occurs when burst generation is so rapid that the signal appears continuous and resolution of individual events is not possible. Typically, signals acquires from machinery will be a combination of both varying degrees, for example, Figure 2.4(b) shows a vibration signal measure from the surface at cylinder head of a running engine in which a number of overlapping burst and continuous types of varying amplitude are evident.

3.3 VIBRATION ANALYSIS TECHNIQUE

This section describes some parts of signal processing theory that can used to analyse vibration signals obtained from the firing engine. The major techniques are based on time domain analysis and statistical analysis techniques.

3.3.1 Gaussian Distribution

This is probably the most important distribution, since many practical processes can be approximated as Gaussian (see a statement of the central limit theorem below). If a random variable X is normally distributed, then its probability distribution is completely described by two parameters: its mean value, μ_x and variance, σ_x^2 (or standard deviation σ_x), and the probability density function of a Gaussian distribution is given by [49,52]

$$p(x) = \frac{1}{\sigma_x \sqrt{2\pi}} e^{-(x-\mu_x)^2/2\sigma_x^2} \tag{3.2}$$

If $\mu_x = 0$ and $\sigma_x^2 = 1$, then it is called the 'standard normal distribution'.. For $\mu_x = 0$, some examples of the Gaussian distribution are shown in Figure 3.6

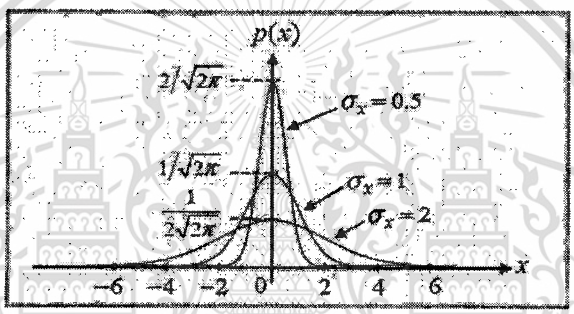


Figure 3.6: Probability density function of Gaussian distribution [51]

The importance of the Gaussian distribution is illustrated by a particular property: let $X_1, X_2, \ldots$ be independent random variables that have their own probability distribution as n gets large, regardless of their individual distribution of X_k. This is a version of the so-called *central theorem*. Moreover, it is interesting to observe the speed with which this occurs as n increase.

For a Gaussian bivariate process (random variable X and Y), the joint probability density function is written as

$$p(x,y) = \frac{1}{2\pi} \cdot \frac{1}{|S|^{1/2}} \exp[-\frac{1}{2}(\nu - \mu_\nu)^T S^{-1}(\nu - \mu_\nu)] \tag{3.3}$$

where

$$S = \begin{bmatrix} \sigma_x^2 & \sigma_{xy} \\ \sigma_{xy} & \sigma_y^2 \end{bmatrix}, \ \nu = \begin{bmatrix} x \\ y \end{bmatrix} \text{ and } \mu_\nu = \begin{bmatrix} \mu_x \\ \mu_y \end{bmatrix}$$

Also $\mu_x = E[X]$, $\mu_y = E[Y]$, $\sigma_x^2 = E[(X-\mu_x)^2]$, $\sigma_y^2 = E[(X-\mu_y)^2]$ and $\sigma_{xy} = E[(X-\mu_x)(Y-\mu_y)]$ (this is discussed shortly).

3.3.2 Bivariate Processes

The concept of moments generalizes to bivariate processes. For example, the expected value of the product of two variables X and Y is

$$E[XY] = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} xyp(x,y)dxdy \tag{3.4}$$

This is a generalization of the second moment. If we centralize the process (i.e. subtract the mean from each) then

$$Cov(X,Y) = \sigma_{xy} = E[(X-\mu_x)(Y-\mu_y)] = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty}(x-\mu_x)(x-\mu_y)p(x,y)dxdy \tag{3.5}$$

$E[XY]$ is called the correlation between X and Y, and $Cov(X,Y)$ is called the *covariance* between X and Y. They are related by

$$Cov(X,Y) = E[XY] - \mu_x\mu_y = E[XY] - E[X]E[Y] \tag{3.6}$$

Note that the covariance and correlation are the same if $\mu_x = \mu_y = 0$. Some definitions for joint distributed random variables are given below. X and Y are:

(a) *Uncorrelated* if $E[XY] = E[X]E[Y]$ (or $Cov(X,Y) = 0$)

(Note that, for zero-mean variables , if X and Y are uncorrelated, then $E[XY] = 0$)

(b) *Orthogonal* if $p(x,y) = p(x)p(y)$.

(c) *Independent* (statistically) if $p(x,y) = p(x)p(y)$.

Note that, if X and Y are *independent*, they are *uncorrelated*. However, uncorrelated random variables are not necessarily independent. For example, Let X be a random variable uniform distribution over the rage -1 to 1, note that the mean value $E[X] = 0$. Let another random variable $Y = X^2$. Then, obviously $p(x,y) \neq p(x)p(y)$, i.e. X and Y are dependent (if X is known, Y is also known). But $Cov(X,Y) = E[XY] - E[X]E[Y] = E[X^3] = 0$ shows that they are uncorrelated (and also orthogonal). Note that they are related *nonlinearly*.

An important measure called the *correlation coefficient* is defined as

$$\rho_{xy} = \frac{Cov(X,Y)}{\sigma_x \sigma_y} = \frac{E[(X-\mu_x)(Y-\mu_y)]}{\sigma_x \sigma_y} \tag{3.7}$$

This is a measure (or order) of a *linear* relationship between two random variables, and the correlation coefficient has values in the range $-1 \leq \rho_{xy} \leq 1$. If $|\rho_{xy}| = 1$, the two random variables X and Y are 'fully' related in a linear manner, e.g. $Y = aX + b$, when a and b are constants. If $|\rho_{xy}| = 0$, there is no linear relationship between X and Y. Note that the correlation coefficient detects only linear relationships between X and Y. Thus, even if $\rho_{xy} = 0$, X and Y can be related in a nonlinear fashion (see that above example, i.e. X and $Y = X^2$, where X is uniformly distribution on -1 to 1).

3.3.3 Probability Density Moments

Probability density moments are single-number indices (descriptors), similar to the time-waveform indices except they are based on the probability density function. Odd moments (first and third, mean and skewness) reflect the peak position of probability density function that is relative to the mean. Even moments (second and fourth, standard deviation and kurtosis) are proportional to the spread of the distribution. Perhaps, the most useful indices is the kurtosis, which is sensitive to the impulsiveness in the vibration signal and therefore sensitive to the type of vibration signal generated in the early stages of a rolling-element-bearing fault [54]. Because of this characteristic sensitivity, the kurtosis index is a useful fault detection tool. However, it is not good for trending. As a rolling-element-bearing fault worsens, the vibration signal becomes more random, the impulsiveness disappears, and the noise floor increases in amplitude. The kurtosis then increases in value during the early stages of a fault, and decreases in value as the fault worsens.

Computational Consideration of Moments

We now indicate some ways in which the moments described above might be estimated from measured data. No attempt is made this stage to give measures of the accuracy of these estimates. That will be discussed later. [49, 52]

Suppose we have a set of data ($x_1, x_2, ..., x_N$) collected from N measurements of a random variable X. Then the *sample mean* $\bar{x}$ (which estimated the arithmetic mean, μ_x) is computed as

$$\bar{x} = \frac{1}{N}\sum_{n=1}^{N} x_n \tag{3.8}$$

For the estimation of variance s_x^2, one may use the formula

$$s_x^2 = \frac{1}{N}\sum_{n=1}^{N}(x_n - \bar{x})^2 \tag{3.9}$$

However, this is estimator usually underestimates the variance, so it is a *bias* estimated. Note that $\bar{x}$ is present in the divisor. $N-1$ is more frequency used. This gives an *unbiased* sample variance, i.e.

$$s_x^2 = \frac{1}{N-1}\sum_{n=1}^{N}(x_n - \bar{x})^2 \tag{3.10}$$

where s_x is the sample standard deviation. Since

$$\sum_{n=1}^{N}(x_n - \bar{x})^2 = \sum_{n=1}^{N} x_n^2 - 2N\bar{x}^2 + N\bar{x}^2$$

The following computationally more efficient form is often used:

$$s_x^2 = \frac{1}{N-1}\left[\left(\sum_{n=1}^{N} x_n^2\right) - N\bar{x}^2\right] \tag{3.11}$$

The above estimation can be generalized, i.e. the *k*th sample (raw) moment is defined as

$$m_k' = \frac{1}{N}\sum_{n=1}^{N} x_n^k \tag{3.12}$$

Note that $m_1' = \bar{x}$ and m_2' is the mean square value of the sample. Similar the *k*th sample central moment is defined as

$$m_k = \frac{1}{N}\sum_{n=1}^{N}(x_n - \bar{x})^k \tag{3.13}$$

Note than $m_1 = 0$ and m_2 is the (biased) sample variance. As shown in the above equation, the divisor N is usually used as the sample moments for the estimation of skewness and kurtosis coefficients. The following biased estimators are often used:

$$Skew = \frac{\frac{1}{N}\sum_{n=1}^{N}(x_n - \bar{x})^3}{s_x^3} \tag{3.14}$$

$$Kurt = \left(\frac{\frac{1}{N}\sum_{n=1}^{N}(x_n - \bar{x})^4}{s_x^4} \right) - 3 \tag{3.15}$$

Where, the sample standard deviation is

$$s_x = \sqrt{\frac{1}{N}\sum_{n=1}^{N}(x_n - \bar{x})^2}$$

Finally, for bivariate process, the sample covariance is computed by either

$$s_{xy} = \frac{1}{N}\sum_{n=1}^{N}(x_n - \bar{x})(y_n - \bar{y}) = \frac{1}{n}\left[\left(\sum_{n=1}^{N} x_n y_n\right) - N\overline{xy}\right] \text{(biased estimator)} \tag{3.16}$$

or

$$s_{xy} = \frac{1}{N-1}\sum_{n=1}^{N}(x_n - \bar{x})(y_n - \bar{y}) = \frac{1}{N-1}\left[\left(\sum_{n=1}^{N} x_n y_n\right) - N\overline{xy}\right] \text{(unbiased estimator)} \tag{3.17}$$

Note that although we have distinguished the biased and unbiased estimators (the divisor is N or $N-1$), their differences are usually insignificant if N is 'large enough'.

3.4 EXPERIMENTAL PROCEDURE AND APPARATUS

This section is representation of the test rig that is used for testing. There are two testing engines used in this study. The first engine, "Engine A", was a 100 CC, four-stroke, single cylinder, petrol engine removed from an old engine as shown in Figure 3.7. The carburetor components were removed and the remaining components such as crankshaft, piston, valve components and other ancillary equipments of this engine were driven by an electric motor without the spark ignition process. This engine can be used to study the mechanical processes such as intake/exhaust valve operation using vibration signals. All information obtained from vibration signals can help to understand intake/exhaust valve operation.

The second engine, "Engine B" was a 125 CC, four-stroke, single cylinder, petrol engine. The engine shown in Figure 3.8 was the running engine and used to simulate various engine conditions such as normal, intake valve clearance fault and exhaust valve clearance fault conditions. Vibration signals obtained from this engine were used to study mechanical and fluid flow processes in the engine cycle.

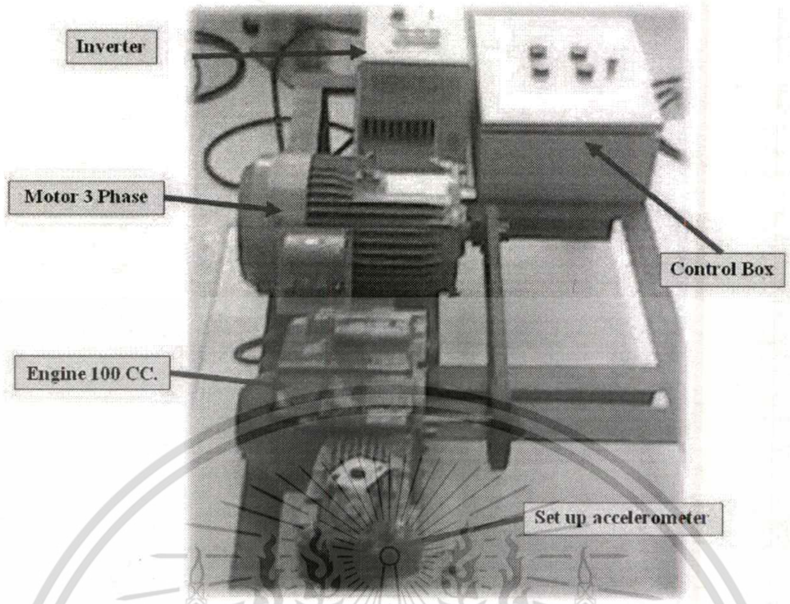


Figure 3.7: a four-stroke, petrol engine driven by 3-phase electric motor

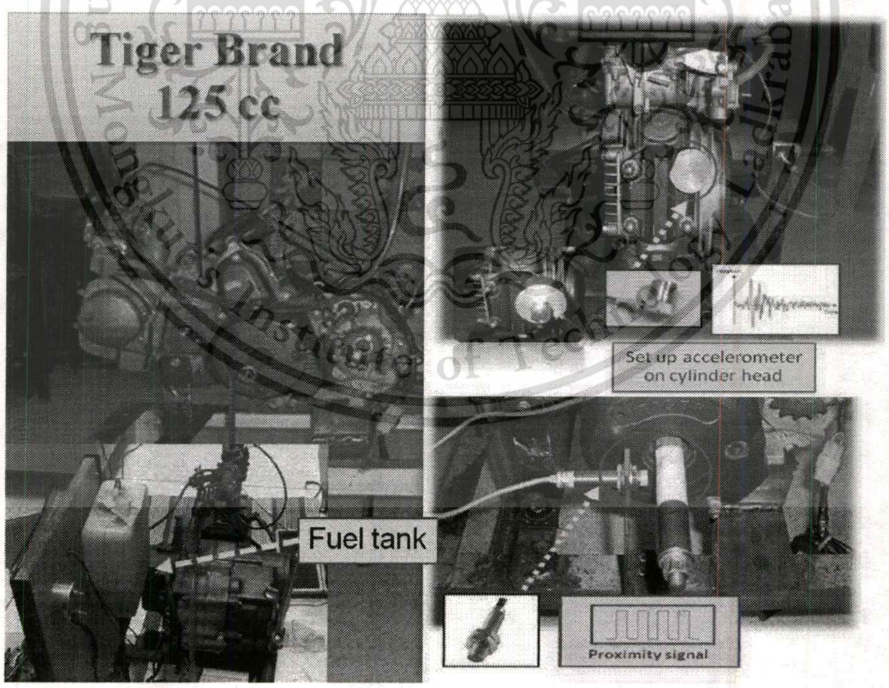


Figure 3.8: a Tiger brand, four-stroke, single cylinder, petrol engine

The vibration and TDC signals were acquired from an accelerometer and a proximity sensor, respectively using LabVIEW program. A schematic diagram of data acquisition (DAQ) system is shown in Figure 3.9. This system consists of an accelerometer with a charge amplifier, a proximity sensor, a terminal block, and a DAQ card with in-house developed LabVIEW software installed in a notebook computer. In this study, National Instruments (NI) DAQ card, 12-bit, PCMCIA-6024E was used to acquire and digitize both vibration and crank angle signals which were recorded with sampling frequency of 100 kHz and saved into files for later analysis. The vibration signals were measured from an Bruel & Kjaer accelerometer (more detail in appendix A), Model 4371 attached on the cylinder head stud of the small petrol engine as shown in Figures 3.7 and 3.8. An in-house designed aluminum clamp was used to hold - accelerometer at the same axis of the piston motion and the proximity sensor was attached to measure one pulse per revolution from a shaft connected to the main crankshaft of the engine as shown in Figure 3.10. This crank angle signal gives two pulses every one engine cycle which is represented the piston position at top dead center (TDC) of the intake and power strokes, respectively. All calculations were averaged over 2000 cycles for all testing conditions of this work.

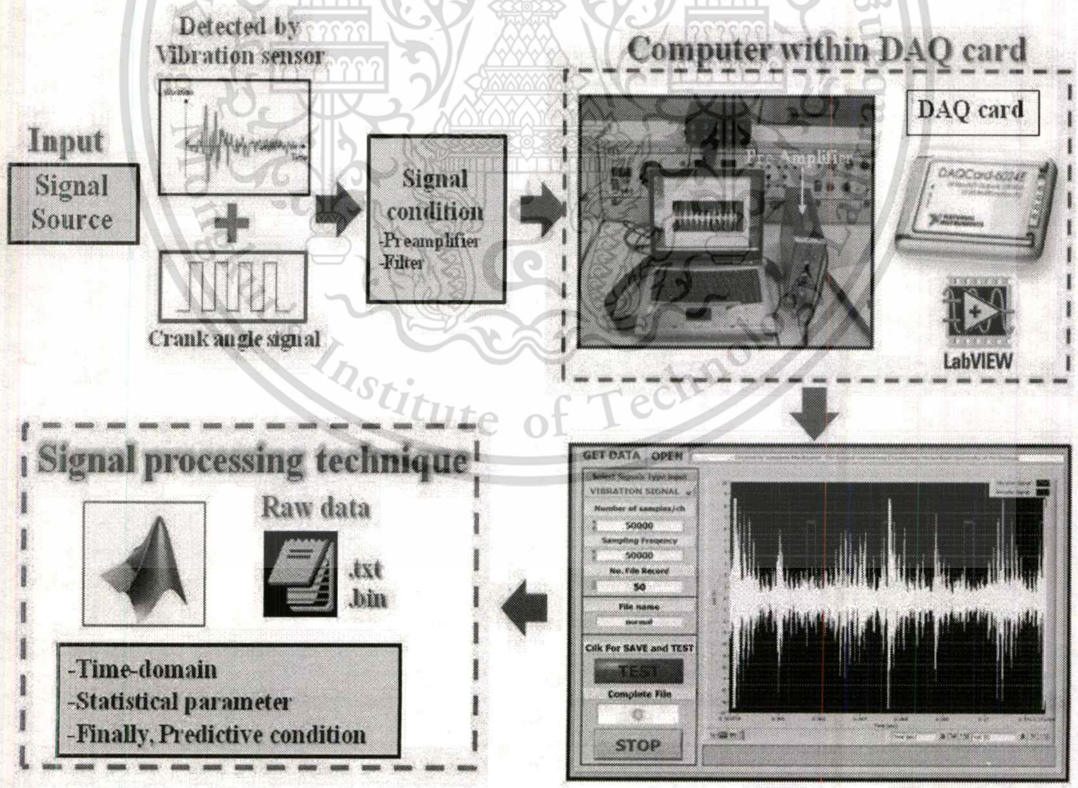


Figure 3.9: A schematic diagram of data acquisition system

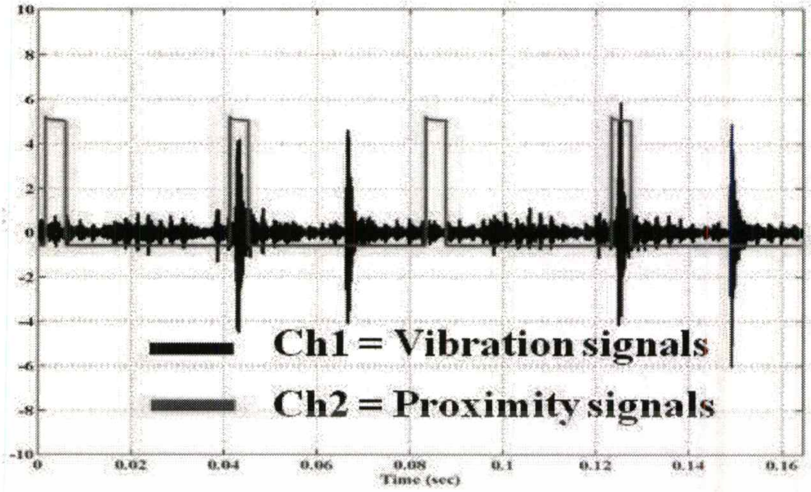


Figure 3.10: Typical vibration signal acquired from a four-stroke, petrol engine Example of vibration and TDC signals.

A small, single cylinder, four strokes petrol engine, Tiger brand, with capacity of 125 CC was used and run at speed of 1500 rpm, no load with various conditions such as the intake and exhaust valve clearance fault conditions as shown in Figures 3.11 and 3.12, respectively. Typical spark plug gap used in this engine was 0.8 mm. All fault conditions were simulated on the engine as follows:

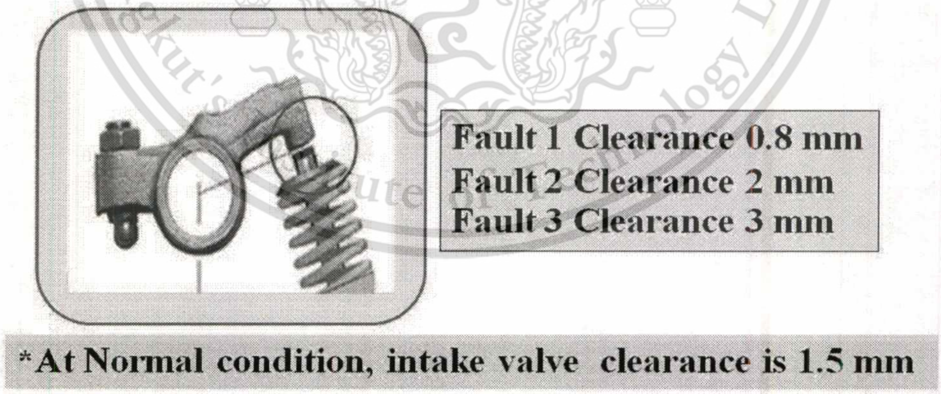


Figure 3.11: Various simulated intake valve clearance fault conditions

Figure 3.12: Various simulated exhaust valve clearance fault conditions

- Simulated various intake valve (IV) clearance fault conditions (Figure 3.11) i.e. IV Fault1 = 0.8 mm, IV Fault2 = 2 mm and IV Fault3 = 3 mm. Typical intake valve clearance of this engine is 1.5 mm.
- Simulated various exhaust valve (EV) clearance fault conditions (Figure 3.12) i.e. EV Fault1 = 1 mm, EV fault2 = 2.5 mm and EV fault3 = 3 mm. Typical exhaust valve clearance of this engine is 2 mm.

3.5 SUMMARY

The focus of this chapter is based on the definition and description of fundamentals of vibration signatures, signal types, vibration monitoring and fault diagnosis techniques. The reasons and justification behind the adoption of any techniques are also presented. The motivation behind the decision making in regarding to various applications is both research and technical. Both of these aspects are discussed, with the emphasis being on the technical side. Topics considered in detail include transducer selection and mounting location, recording and analysis instrumentation, and display formats and in-house analysis methods (specifically, time domain and statistical methods). The discussion of fault detection is based primarily on standard method in the time and frequency domains. The overall knowledge is used to the concept and fundamental technique in this thesis.

CHAPTER 4

EXPERIMENTAL RESULTS AND DISCUSSION

4.1 INTRODUCTION

This chapter describes the experimental results and discussion of various experiments such as valve timing simulation on the motor engine (the engine was driven by an electric motor) and intake/exhaust valve clearance faults on the firing engine (the real petrol engine). Typical vibration sources in the engine are mechanical and fluid flow activities from the intake/exhaust valve processes, combustion process, ignition process and ancillary equipment. Vibration signals acquired in time domain on the cylinder head of the engines were analysed using statistical analysis methods, signal energy and the covariance method. The analysis methods were used to determine various parameters from recorded vibration signals such as mean, variance, skewness, kurtosis, RMS and signal energy. Each parameter was determined from vibration signals using the whole cycle and each main valve events. The results and discussion of each analysis method based on time domain are discussed in this chapter. In addition, the illustration of various intake/exhaust faults has been applied using the covariance method.

4.2 RESULTS AND DISCUSSION OF EXPERIMENTS ON THE MOTOR ENGINE

Typical engines, used in a motorcycle or a passenger car, provide the rotating power to drive the wheels through the transmission and driving axles. All vehicle engines, both petrol and diesel engines, are classified as internal combustion engines because the combustion or burning takes place inside the engine. Typical cycle of internal combustion engine composes of four strokes which are intake, compression, power and exhaust strokes. Each stroke consists of a series of processes which are related to mechanical and fluid flow activities in the engine, i.e. those coming from the injectors, the exhaust valves, the inlet valves and other ancillary equipment.

Although, both petrol and diesel engines are internal combustion engines, the power strokes of both engines are different. The power stroke of the petrol engine starts when the compressed air/fuel mixture is ignited by a spark plug but the power stroke of the diesel engine starts when the piston compresses air and reaches the top dead centre (TDC), fuel is injected at just the right moment and ignited, forcing the piston back down. In this work, single cylinder, four-stroke, petrol engines were used to study about the mechanical and fluid flow processes and to investigate intake/exhaust valve clearance faults using vibration signals. The next section will be described the results and discussion of the experiments on the motor engine and the firing engine using various signal analysis techniques.

For all engine tests, vibration signals in time domain were resampled to the crank angle domain by using a TDC signal or a timing signal. An advantage of vibration signals on the crank angle domain is that mechanical events in the engine cycle can be identified easily. The resampled signals were always referenced to the crank angle at top dead centre (TDC) of the intake stroke. Using the timing signal, the number of data points for each crank angle degree was determined. This could be assumed that the engine speed was constant within each degree of rotation. Thus, vibration signals acquired from various experiments could be resampled directly from the time domain to the crank angle domain until the entire engine cycle (720 degrees) was obtained. These vibration signals could be mapped onto the same scale and the signals associated with mechanical events could also be compared with signals acquired from the engine with different testing conditions.

The first experimental study was to investigate intake/exhaust valve operation events using vibration signal acquired from the four-stroke, single cylinder, petrol engine with engine capacity of 100 cc (which called "motor engine") so that all mechanical movement and impact could be investigated. This engine was operated by electric motor so only valve movement and ancillary equipment movement (no ignition and combustion processes) could be detected using vibration signals. In this experiment, vibration signals were acquired from an accelerometer attached on the cylinder head of the engine and the crank angle signal was recorded using a proximity sensor located on the crankshaft of the engine given two pulses per one engine cycle.

Figure 4.1 shows the typical valve timing of the motor engine. EVC, IVC, EVO and IVO events represent exhaust valve closing, intake valve closing, exhaust valve opening and intake valve opening events, respectively and are occurred at 15, 220, 495 and 710 (or -10) degrees ATDC of the intake stroke, respectively. The example of a vibration signal was acquired from the motor engine with running speed of 950 rpm as shown in Figure 4.2. This signal was mapped onto the crank angle domain so that EVC, IVC, EVO and IVO can be identified easily. Electrical noise also can be seen in recorded vibration signals. The study of the motor engine can help to identify the main events produced by the main valve operation in the engine cycle. It is expected that the high amplitude signals may be the mechanical impact of intake/exhaust valve operation and the low amplitude signals may be the combination of the piston movement, fluid flow activities and electrical noise. This result is similar to Long and Boutin [2] who pointed out that there were three types of sources that gave rise to vibration signals; mechanical impacts which produced sharp vibration patterns; gas leaks which occurred over a longer period of time and had a lower amplitude; and roughness or friction which was described by a noisy low amplitude pattern.

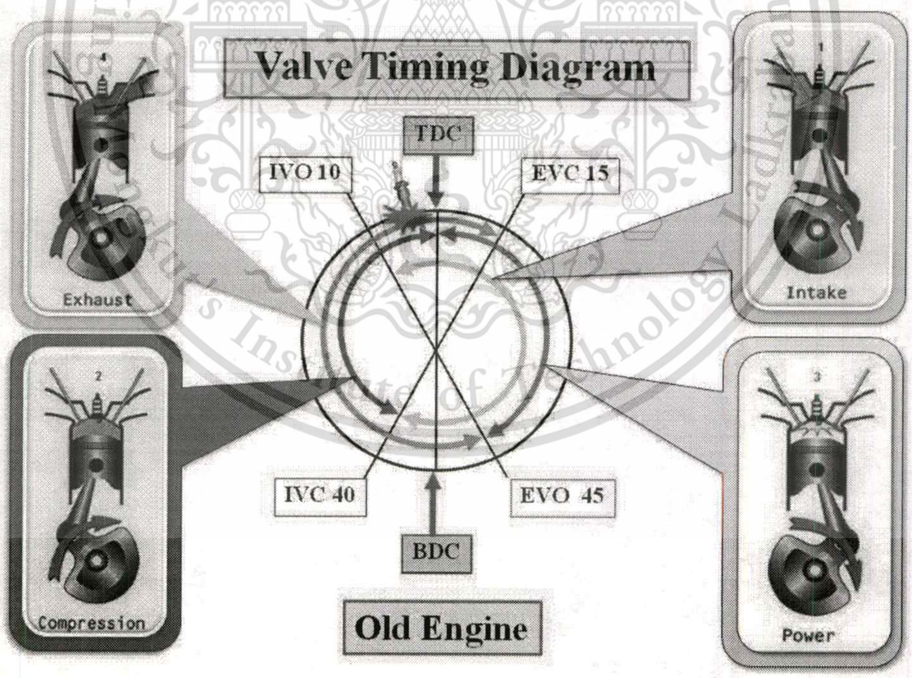


Figure 4.1: Valve timing diagram of the motor engine

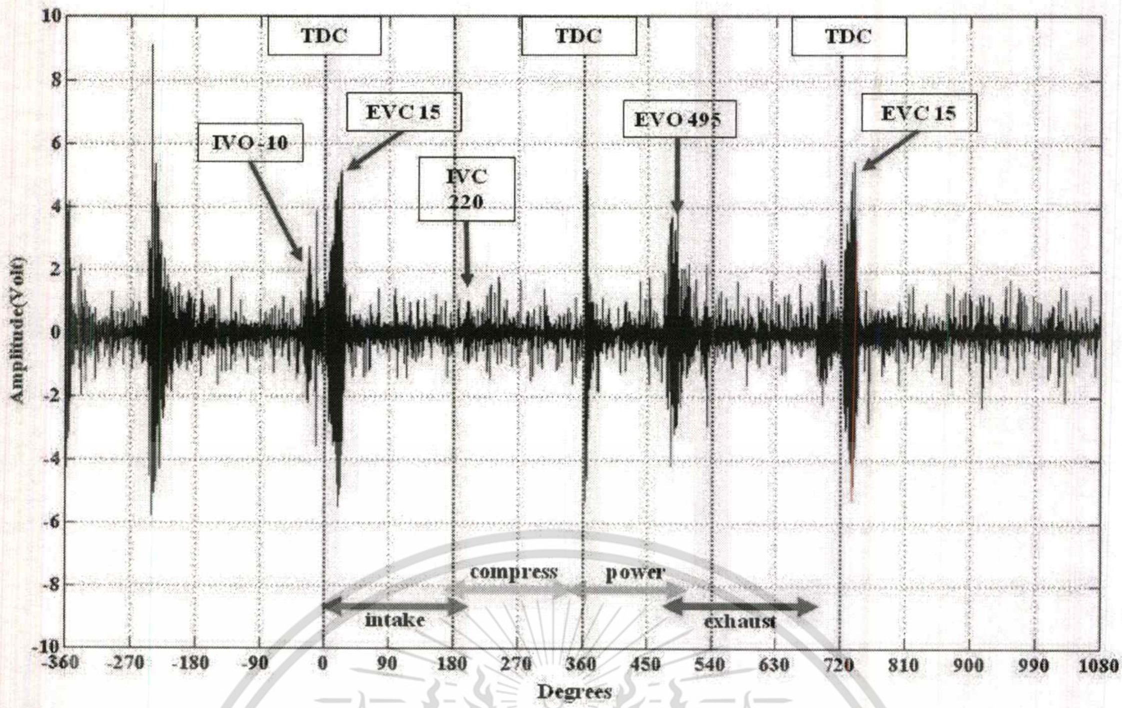


Figure 4.2: Example of vibration signal acquired from the motor engine with speed of 950 rpm

4.3 RESULTS AND DISCUSSION OF EXPERIMENTS ON THE FIRING ENGINE

The second experimental study was to investigate the real operation of four-stroke, single cylinder, Tiger brand, petrol engine with capacity of 125 cc which can be called as "Firing engine". In this experiment, the firing engine was run at speed of approximately 1500 rpm. Typical vibration signal, acquired from the firing engine, is difficult to identify the engine processes such as intake/exhaust valve operation and ignition process. The crank angle signal or TDC signal could help to identify the main events of running engine as mentioned above. The vibration signal could be mapped onto a crank angle domain using a crank angle signal as shown in Figure 4.3. Vibration signal and crank angle are shown on the vertical and horizontal axes, respectively. Crank angle at 0 degree represents piston position at TDC of the intake stroke. All main four strokes described in Figure 4.3 are intake, compression, power and exhaust strokes associated with crank angles at 0-180, 180-360, 360-540 and 540-720 degrees ATDC, respectively. IVO, IVC, EVO, EVC represent inlet valve open, intake valve close, exhaust valve open and exhaust valve close, respectively. The strongest events shown in vibration signal are the intake/exhaust valve operation events.

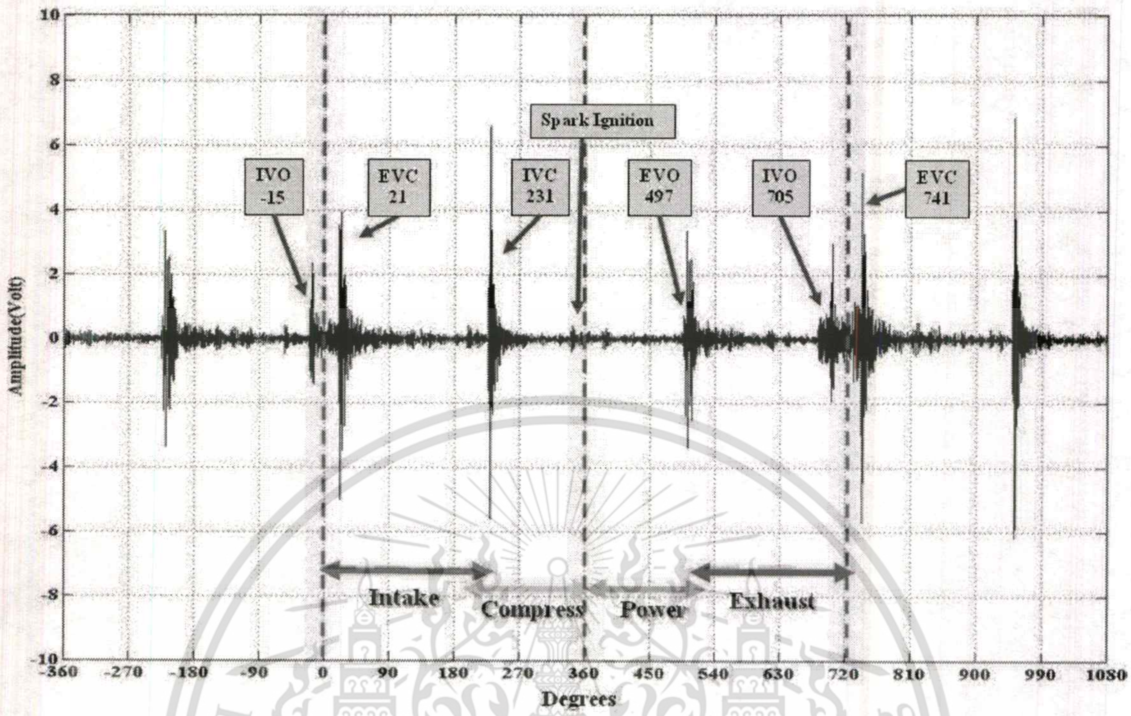


Figure 4.3: Vibration signal based on crank angle domain acquired from firing engine with speed of 1500 rpm

For greater resolution, amplitude of each recorded vibration signal was enveloped as seen in Figures 4.4-4.5 so that signal amplitude can be easily compared. Typical vibration signal acquired from the engine at the normal condition are shown in Figures 4.4(a) and 4.5(a) with the engine setting-up parameters such as intake valve clearance of 1.5 mm, exhaust valve clearance of 2 mm and spark plug gap of 0.8 mm. The main operation events such as the IVO, IVC, EVO and EVC events can be seen clearly at around 705 (or -15), 231, 497, and 21 degrees ATDC, respectively. It can be seen that the IVC and EVC events are greater than other events because the closing impact of both valves produces more signal amplitudes than other engine processes. Typical spark ignition event, which occurs at approximately 345-355 degrees ATDC, is unable to identify easily as seen in Figures 4.4(a) and 4.5(a) because this event is unclear with small signal amplitude close to noise level.

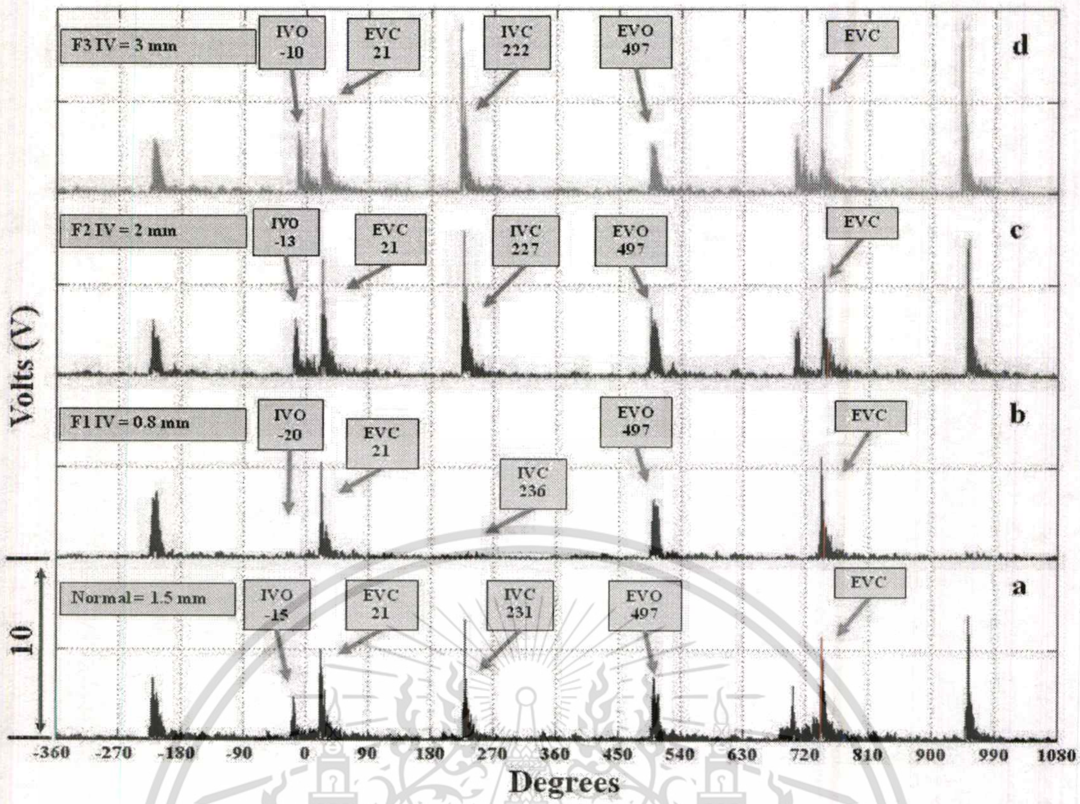


Figure 4.4: Example of vibration signals acquired from the firing engine at speed of 1500 rpm with various testing conditions of the intake valve faults.

Normal IV (b) F1 IV (c) F2 IV and (d) F3 IV

Various simulated faults of intake valve clearances can be seen in Figures 4.4(b)-4.4(d). Normal IV, F1 IV, F2 IV and F3 IV represent intake valve clearances at normal condition of 1.5 mm, intake valve clearance fault of 0.8 mm, intake valve clearance fault of 2 mm and intake valve clearance of 3 mm, respectively. When intake valve clearance is greater than at the normal condition, the IVO event is delayed around 2-5 degrees and the IVC event is occurred early around 4-9 degrees as seen in Figures 4.4(c)-4.4(d). From Figure 4.4(b), when valve clearance is smaller than at normal condition, the intake valve is opened early at approximately 700 (or -20) degrees ATDC. The IVC event is delayed and closed at around 236 degrees ATDC. This IVC event is difficult to identify because valve clearance is too small. Thus, the closing impact may have not enough energy to produce high amplitude of vibration signal.

For various simulated faults of exhaust valve clearances, Normal EV, F1 EV, F2 EV and F3 EV represent exhaust valve clearance at the normal condition of 2 mm, exhaust valve clearance fault of 1 mm, exhaust valve clearance fault of 2.5 mm and exhaust valve clearance of 3 mm, respectively. The EVC events for all test conditions occur at the same location around 21 degrees ATDC as seen in Figure 4.5. It can be seen that the more exhaust valve clearance is, the greater signal amplitude of the EVC event can be seen in vibration signals. When exhaust valve clearance is greater than at normal condition as seen in Figures 4.5(c) and 4.5(d), the EVO event is delayed and amplitude of this event can be seen clearer than at the normal state (Figure 4.5(a)) and at exhaust valve clearance of 1 mm (Figure 4.5(b)).

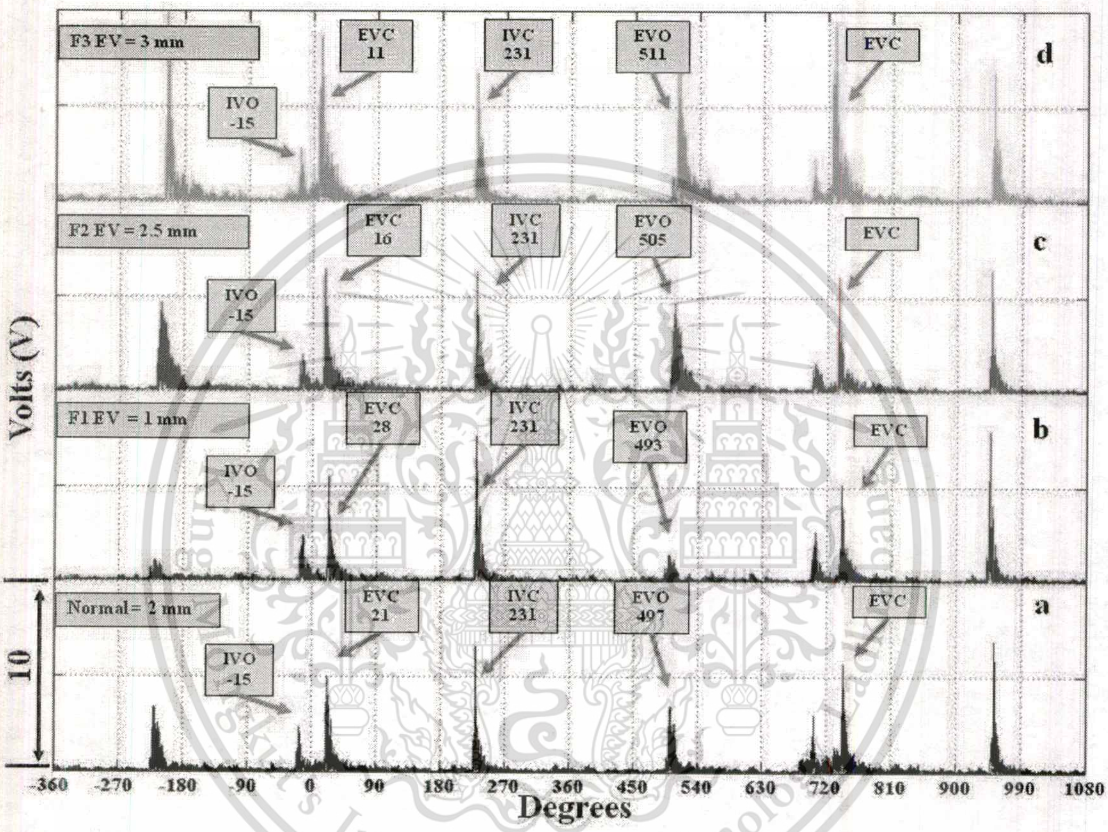


Figure 4.5: Example of vibration signals acquired from the firing engine at speed of 1500 rpm with various testing conditions of the exhaust valve faults.

(a) Normal EV (b) F1 EV (c) F2 EV and (d) F3 EV

This may be because the increasing valve clearance was leading to the rising in-cylinder pressure when the piston was moving forward to TDC of the exhaust stroke. Thus, the activity of exhaust gas gave more energy to produce more information in vibration signals. For condition of exhaust valve clearance of 1 mm as seen in Figure 4.5(b), the EVO event is difficult to identify because in-cylinder pressure may not have enough energy to produce vibration signal. It can be seen the delayed open of the exhaust valve and the early close of the exhaust valve are seen in

Figures 4.5(c)-4.5(d), when the exhaust valve clearance is greater than at normal condition. However, when the exhaust valve clearance is smaller than at normal condition, the exhaust valve is opened early and exhaust valve closing is delayed as seen in Figure 4.5(b). Typical spark ignition events as seen in Figures 4.4-4.5 are occurred at approximately 345-355 degrees ATDC. The spark ignition event is unable to identify and amplitude of this event is closed to noise level because the spark ignition and combustion processes, which are the main activities of this event, gave signal amplitude less than the closing impact of valve.

Vibration signals acquired on the firing engine were able to use to analyse on both time domain and crank angle domain and also described the processes of the firing engine with no load at speed of 1500 rpm. For simulated fault conditions with various valve clearances, vibration signals were able to identify the valve operation events generated from both intake and exhaust valves. However, the increasing and decreasing of the intake/exhaust valve clearance could be determined using theory of cam profile. This method can be used to show a displacement diagram of the intake/exhaust valves of each valve clearance, and then valve timing diagram of each valve can be created.

Cam profile displacement was used to validate about the valve operation. Displacement at each cam rotation angle was determined to compare between cam profile theory and experimental testing. First, Theory is calculated by Equations (4.1)-(4.2). The simple harmonic motion can be generated by a cam displacement (L) and a common from to use for a displacement diagram. Cams with this type of transition motion are formed the basic equation as follows.

$$y = c_o + c_1 \cos(c_2\theta) = c_2\left(1 + \frac{c_1}{c_2}\cos(c_2\theta)\right)$$

The displacement, velocity, acceleration, and jerk diagram shown in Figure 4.6. Simple harmonic motion produces sine velocity curve and a cosine acceleration curve. There is no discontinuity at the transition point, so that θ is defined for all angles between zero and β . The equation for a rise starting from $\theta = 0$ and ending at $\theta = \beta$ and $y = L$ are

$$y = \frac{L}{2}\left(1 - \cos(\frac{\pi\theta}{\beta})\right) \tag{4.1}$$

The equation for the return from $\theta = 0$, $y = L$ to $\theta = \beta$ and $y = 0$ are

$$y = \frac{L}{2}\left(1 + \cos(\frac{\pi\theta}{\beta})\right) \quad (4.2)$$

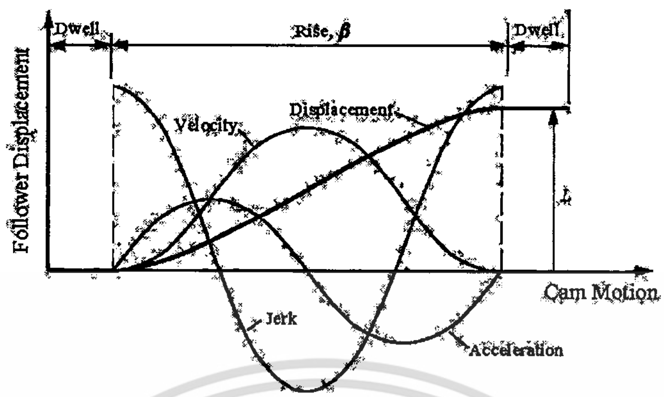


Figure 4.6: Shape of the displacement, velocity, acceleration and jerk curve for simple harmonic motion [69]

A simple harmonic displacement diagram can be generated graphically by drawing a semicircle in the vertical axis and dividing it into an even number of segments. The cam motion axis is then divided into the same number of even increments of the horizontal lines with the corresponding vertical lines give the location of points on the simple harmonic curve. This construction is shown in Figure 4.15 for the construction, note that

$$\frac{\Delta\alpha}{\Delta\theta} = \frac{180}{\beta} \quad (4.3)$$

Where β is the cam rotation for the follower to move from 0 the L. With the advent of computers, the graphical procedure is typically used only for schematic representations of simple harmonic motion.

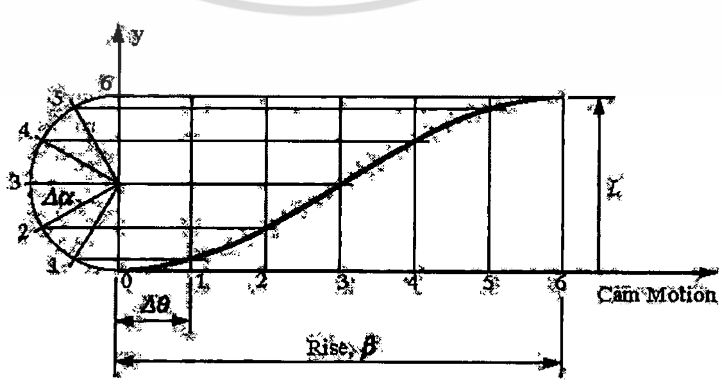


Figure 4.7: Graphical construction of displacement diagram for a simple harmonic rise [69]

This section is represented a comparison of the result between theory and experiments. The intake/exhaust valve opening and closing events are the main events of this study. A displacement diagram for the cam follower of the testing engine was generated using Equations (4.1) - (4.3) so that intake/exhaust valve open and close positions could be determined. Then, acquired vibration signals were mapped on to crank angle domain and the intake/exhaust valve operation events were compared with the positions shown in the displacement diagram.

For various valve clearance conditions of the intake and exhaust valves, the plot between displacement of the intake and exhaust valves and crank angle can be seen in the Figures 4.8 and 4.9, respectively. Follower IV, Normal IV, F1 IV, F2 IV and F3 IV shown in Figure 4.8 represent valve clearances of 0, 1.5, 0.8, 2 and 3 mm, respectively. Follower EV, Normal EV, F1 EV, F2 EV and F3 EV shown in Figure 4.9 represent as valve clearance of 0, 2, 1, 2.5 and 3 mm, respectively. Both displacement diagrams of intake/exhaust valves were generated by using the Equations (4.1)–(4.2). When the intake/exhaust valve clearance is smaller than at normal condition (i.e. F1 IV and F1 EV), the intake/exhaust valve opens earlier and the closing of intake/exhaust valves is delay. On contrary, when the intake/exhaust valve clearance is greater than at normal condition (i.e. F2 IV, F3 IV, F2 EV and F3 EV), the intake/exhaust valve openings are delay and intake/exhaust closings are earlier.

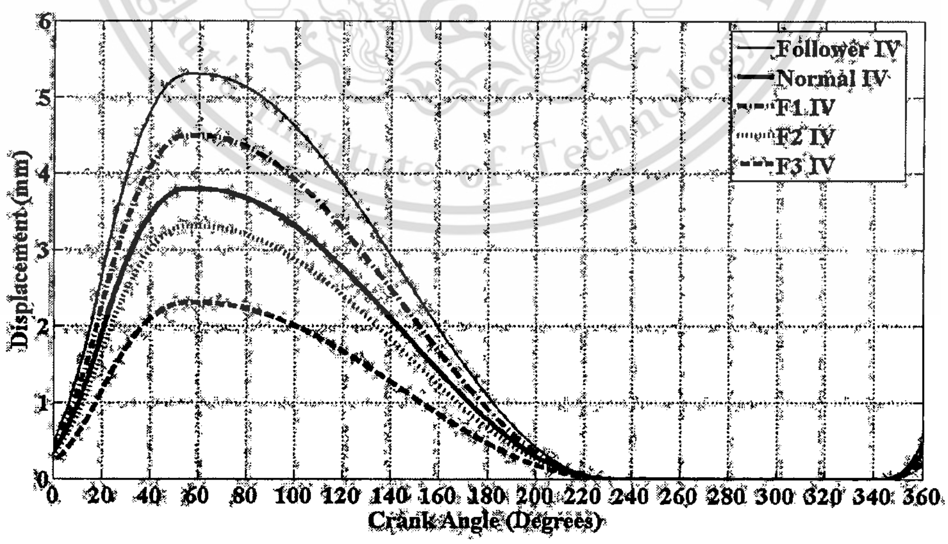


Figure 4.8: Displacement diagram for the intake valve with different valve clearances

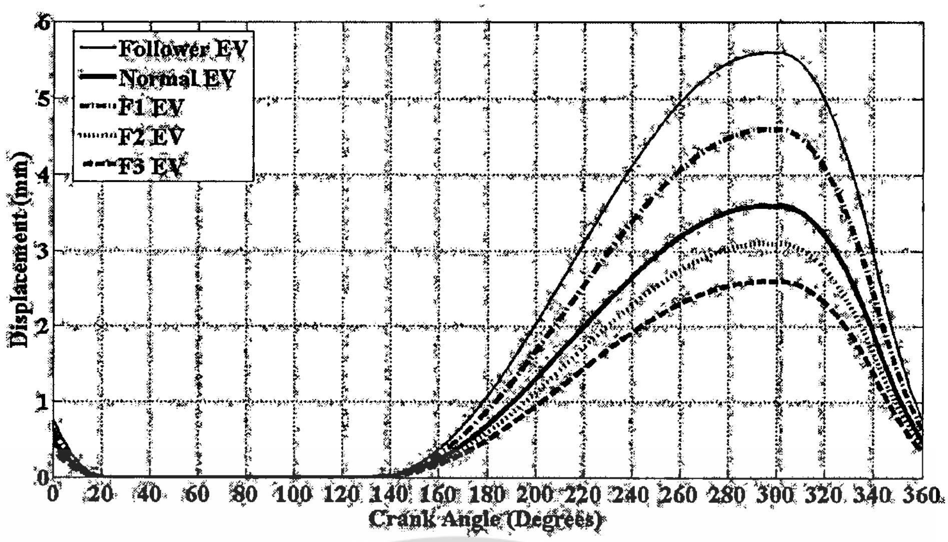


Figure 4.9: Displacement diagram for the exhaust valve with different valve clearances

The result of the vibration signals can also be indicated the different between smaller clearance and bigger clearance and easily to identify. Although, the vibration signal can be used to identify but the illustration of the displacement of cam follower can help to understand about the main valve operation events with both intake valve and exhaust valve fault conditions. Acquired vibration signals of various valve clearance conditions can be indicated the valve operation events with the difference between smaller clearance and greater clearance.

The comparison results between theory and experiment of the intake/exhaust valve timing positions can be summarised in Table 4.1. The detailed results of Table 4.1 can be seen in Appendix C. Although, the detected valve operating positions are slightly different because their positions were determined from acquired vibrations on the engine. However, the trend of both theoretical and experiment results are similar. It can be seen from both theory and experimental results. When the intake/exhaust valve clearances are smaller than at normal condition (i.e. F1 IV and F2 EV), the intake/exhaust valve openings are earlier and the intake/exhaust closings are delay. On contrary, when the intake/exhaust valve clearances are greater than at normal condition (i.e. F2 IV, F3 IV, F2 EV and F3 EV), the intake/exhaust valve opening are delay and the intake/exhaust valve closing are earlier.

Simulated faults of intake valve clearance			Simulated faults of exhaust valve clearance		
Description	**Theory (degs)**	**Experiment (degs)**	**Description**	**Theory (degs)**	**Experiment (degs)**
N IVO	-15 (705)	-15 (705)	**N EVO**	497	497
N IVC	231	231	**N EVC**	21	21
F1 IVO	-19 (701)	-20 (700)	**F1 EVO**	491	493
F1 IVC	235	236	**F1 EVC**	26	28
F2 IVO	-12 (708)	-13 (709)	**F2 EVO**	500	505
F2 IVC	228	227	**F2 EVC**	18	16
F3 IVO	-6 (713)	-10 (710)	**F3 EVO**	503	511
F3 IVC	222	222	**F3 EVC**	15	11
Valve clearances of the intake valve			**Valve clearances of the exhaust valve**		
Normal IV	1.5	**mm**	**Normal EV**	2	**mm**
F1 IV	0.8	**mm**	**F1 EV**	1	**mm**
F2 IV	2	**mm**	**F2 EV**	2.5	**mm**
F3 IV	3	**mm**	**F3 EV**	3	**mm**

Table 4.1: Summary of the intake/exhaust valve timing positions between theoretical and experimental results

To obtain more information about the petrol engine processes, the vibration signals were analysed using signal energy technique. The signals shown in Figures 4.10-4.11 were calculated using Equation (2.1). The energy content was calculated every crank angle degree to cover the entire engine cycle. It can be seen that the plot of energy contents with each testing condition can be seen easier with smooth signal. The typical events shown in Figures 4.10-4.11 can be identify by comparing with valve timing of the firing engine which are IVO, IVC, EVO and EVC events. These valve events can be seen clearly at approximately 705, 231, 497 and 21 degrees ATDC, respectively. All the findings as described in Figures 4.4-4.5 also can be seen in Figures 4.10-4.11. However, the spark ignition event is unable to identify. This is because the spark ignition and combustion activities may not have enough energy as mentioned before.

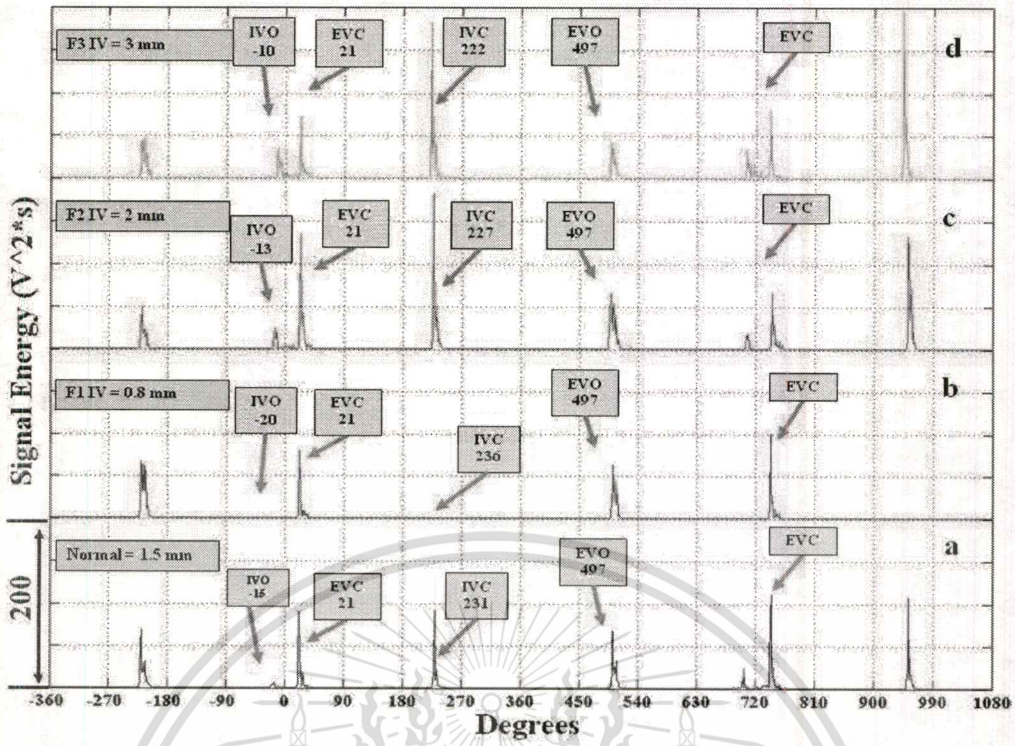


Figure 4.10: Example of signal energy with various testing conditions of the intake valve.

(a) Normal (b) IV F1 (c) IV F2 and (d) IV F3.

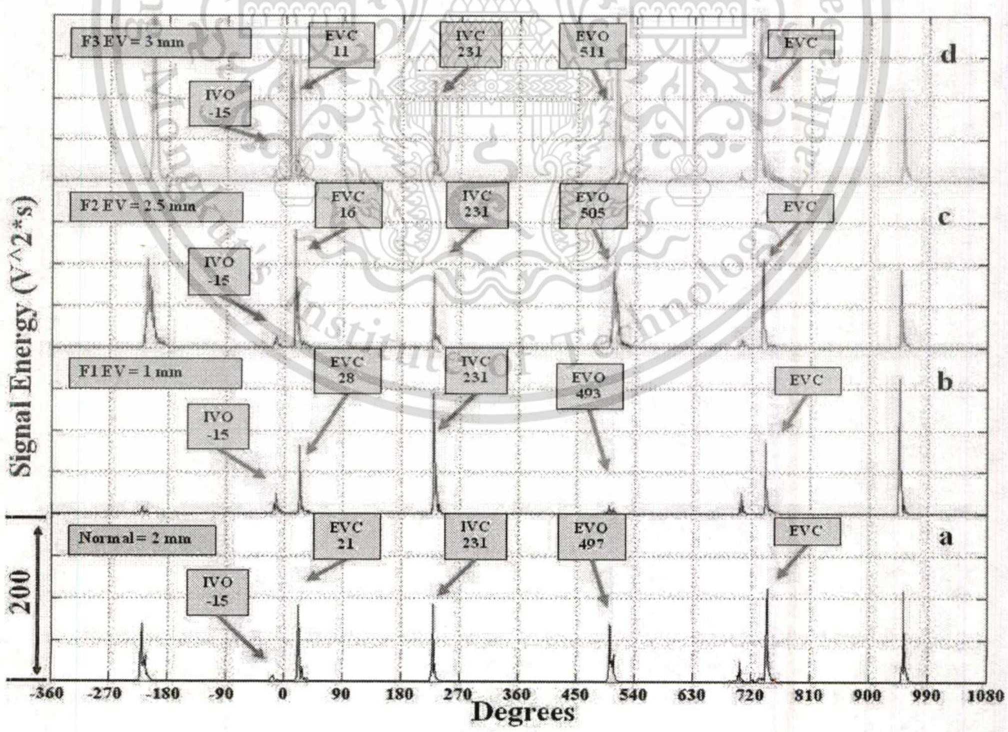


Figure 4.11: Example of signal energy with various testing conditions of the exhaust valve.

(a) Normal (b) EV F1 (c) EV F2 and (d) EV F3.

This section is represented the result of the time domain analysis techniques that applied to determine various parameters from acquired vibration signals on the firing engine. In this study, parameters used in analysis are mean, variance, skewness, kurtosis, root mean square (RMS), energy content, and covariance. All of these parameters can be indicated engine state at normal condition and other fault conditions. This work was applied the statistical analysis techniques to analyse vibration signals acquired from the cylinder head of the firing petrol engine. The time domain analysis based on statistical techniques can be used to identify and separate the main events associated with mechanical and fluid flow processes of the engine.

For statistical analysis techniques, acquired vibration signals were determined absolute values of the signals and then, statistical parameters such as mean, variance, skewness, kurtosis and RMS were determined using Equations (3.2)-(3.17). Each statistical parameter of each experimental condition was averaged over 200 cycles. Figures 4.12-4.16 are the bar charts of the result for each statistical parameter: mean, variance, skewness, kurtosis and RMS, respectively. The horizontal axis and vertical axis represent testing conditions and statistical parameter, respectively. The errorbar shown in Figures 4.12-4.16 is represented the standard deviation of each parameter and the short line in the middle of each errorbar is the mean of each parameter. It can be seen that mean, variance and RMS can only be used to identify a group of faults occurred at the intake valve or exhaust valve but they could not be used to separate each fault condition. In the results, skewness (Figure 4.14) and kurtosis (Figure 4.15) of all testing conditions give similar values so it is difficult to identify intake/exhaust valve clearance faults with both parameters. The variation of each statistical parameter can be seen in each plot because when engine was running, engine speed varied approximately 1500 $\pm$100 rpm. These may cause the variation of vibration signal amplitudes from cycle to cycle.

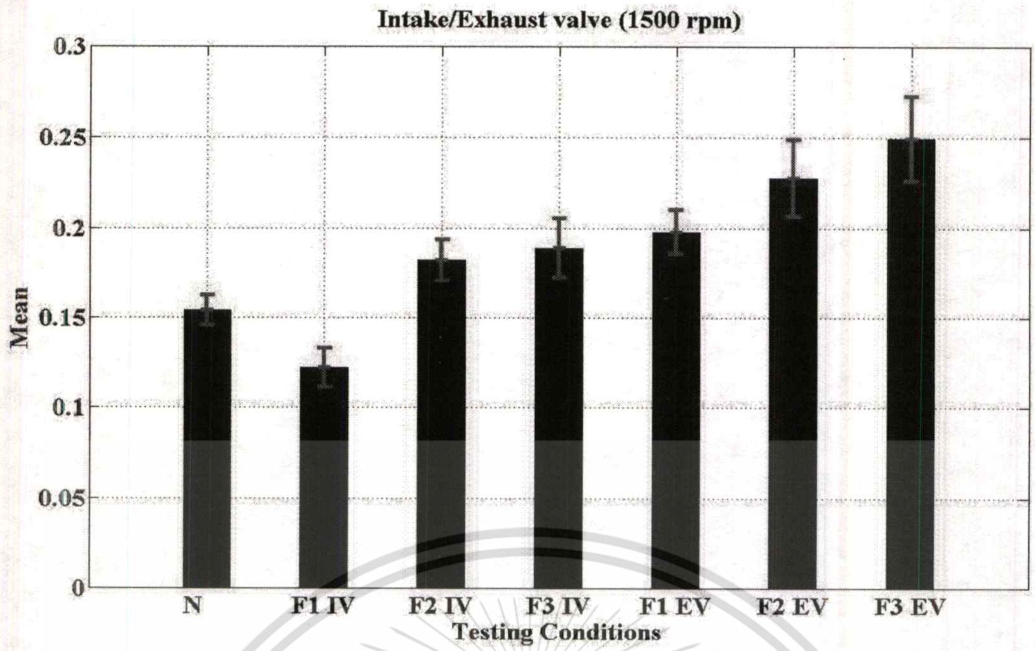


Figure 4.12: The bar plot of mean for the IV/EV events with various testing conditions.

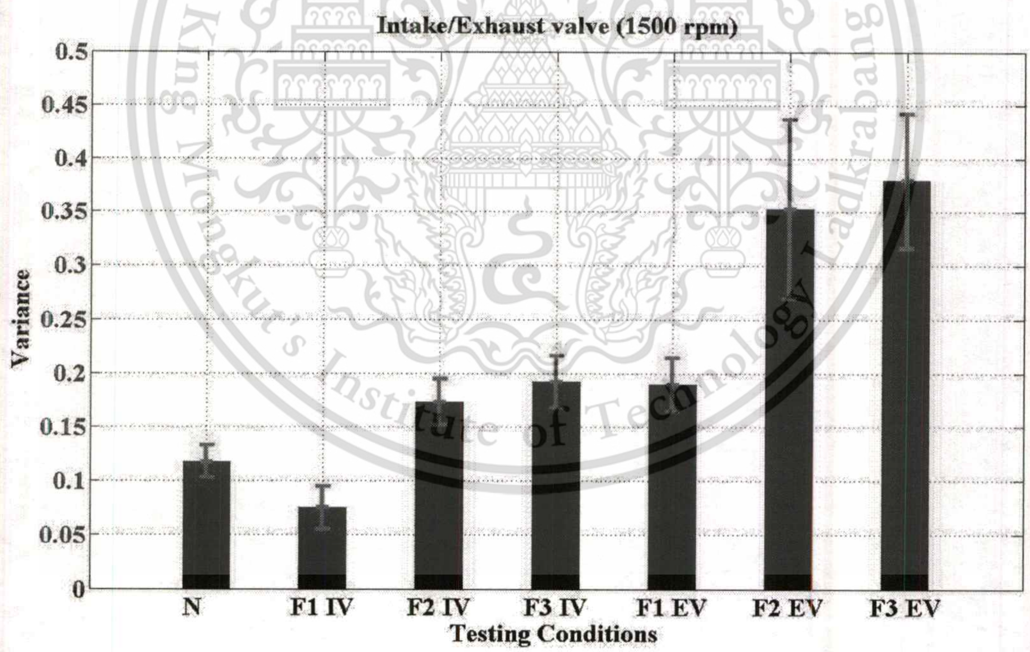


Figure 4.13: The bar plot of variance for the IV/EV events with various testing conditions.

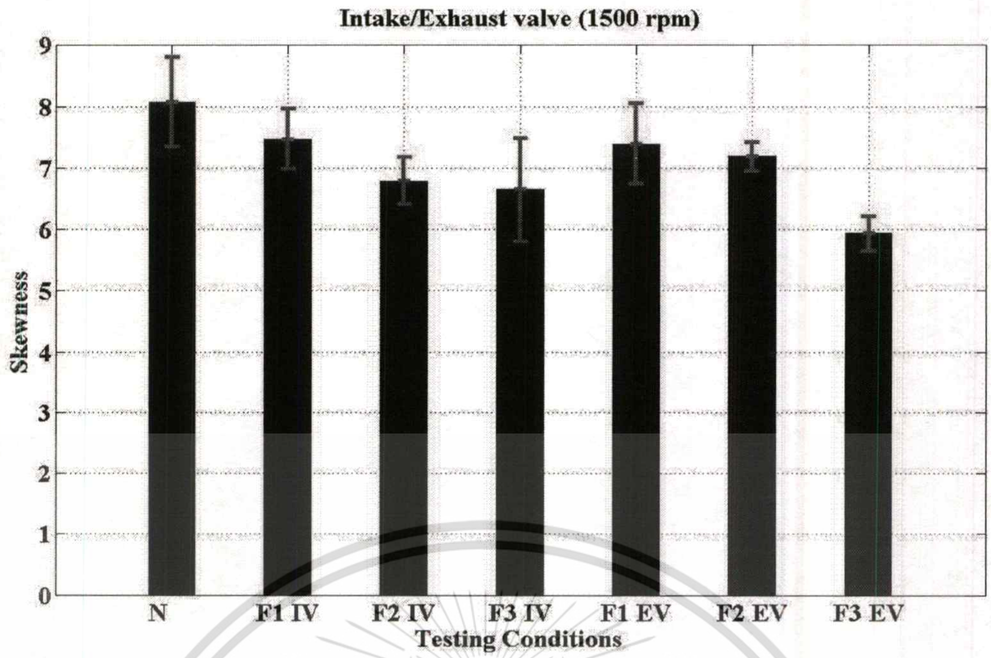


Figure 4.14: The bar plot of skewness for the IV/EV events with various testing conditions.

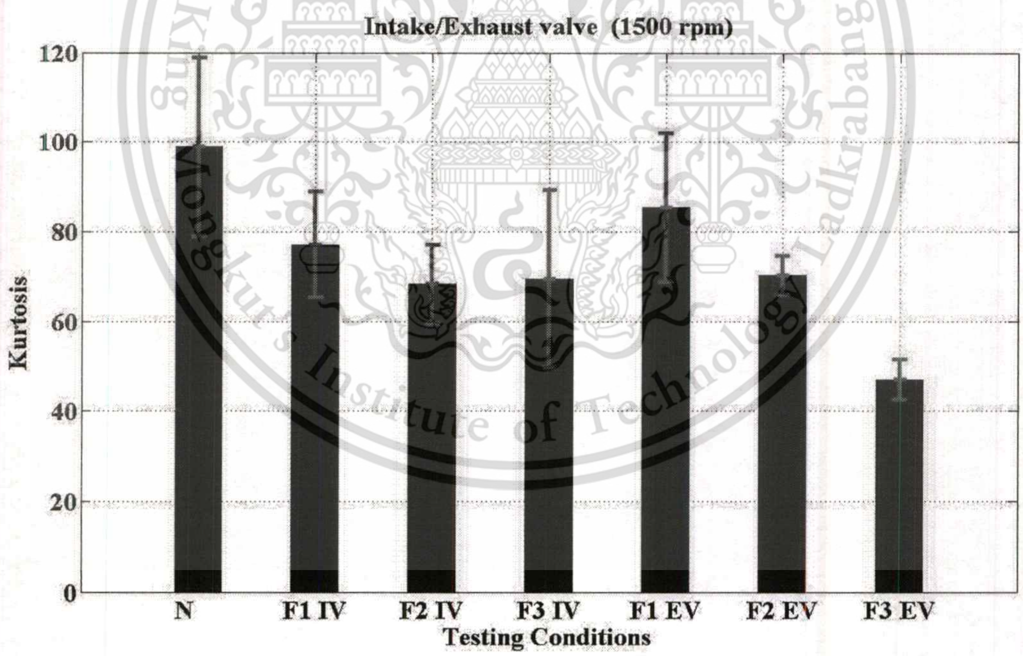


Figure 4.15: The bar plot of kurtosis for the IV/EV events with various testing conditions.

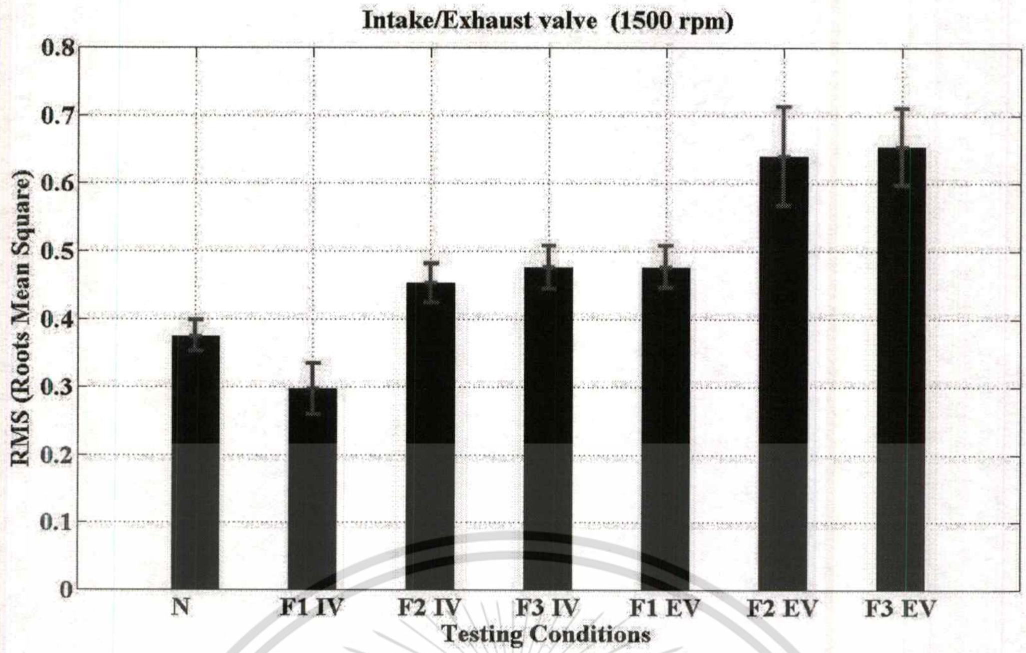


Figure 4.16: The bar plot of RMS for the IV/EV events with various testing conditions.

To improve the results of the statistical analysis method, recorded vibrations were windowed only the main valve operation events. The window size used was 90 degrees for each main event such as 0-90, 180-270, 450-540, and 630-720 degrees for the IVO, IVC, EVO, and EVC events, respectively. In this section, mean, variance and RMS were used in analysis because skewness and kurtosis were not suitable for predicting fault as mentioned in previous section. Bar charts of mean, variance and RMS for various intake valve testing conditions are shown in Figures 4.17-4.19, respectively and for exhaust valve testing conditions are shown in Figures 4.20-4.22, respectively. The greater variation of mean, variance and RMS can be seen in the results of EVO/EVC events as shown in Figures 4.28-4.30, respectively. These may be because of variation of an engine speed that may cause uncertainty of mechanical and fluid flow processes during each engine cycle. Mean, variance and RMS of both intake and exhaust valve testing conditionws increase with valve clearance. This statistical analysis method base on windowing of the main valve events gives better results than the technique that determined all above mentioned parameters from each entire engine cycle. The use of single parameter could not be used to predict all simulated faults of this study. However, it is possible to predict a group of faults that occurred at the intake valve or the exhaust valve. In addition, the combination of statistical parameters is possible to use for predicting faults of the intake and exhaust valves.

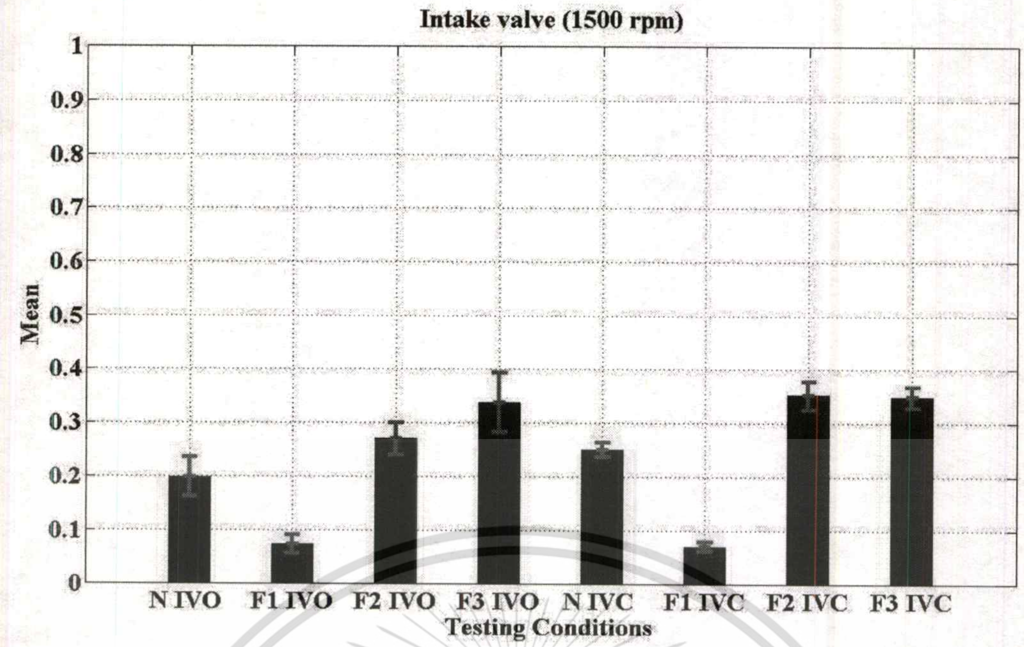


Figure 4.17: Bar chart of mean value for the IVO/IVC events with various testing conditions

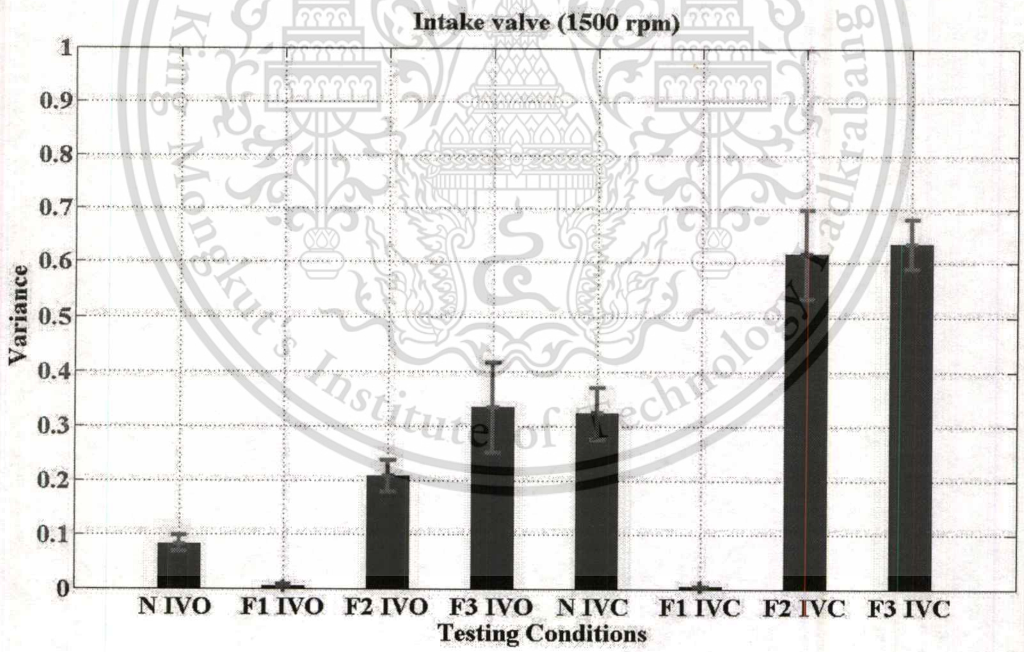


Figure 4.18: Bar chart of variance for the IVO/IVC events with various testing conditions

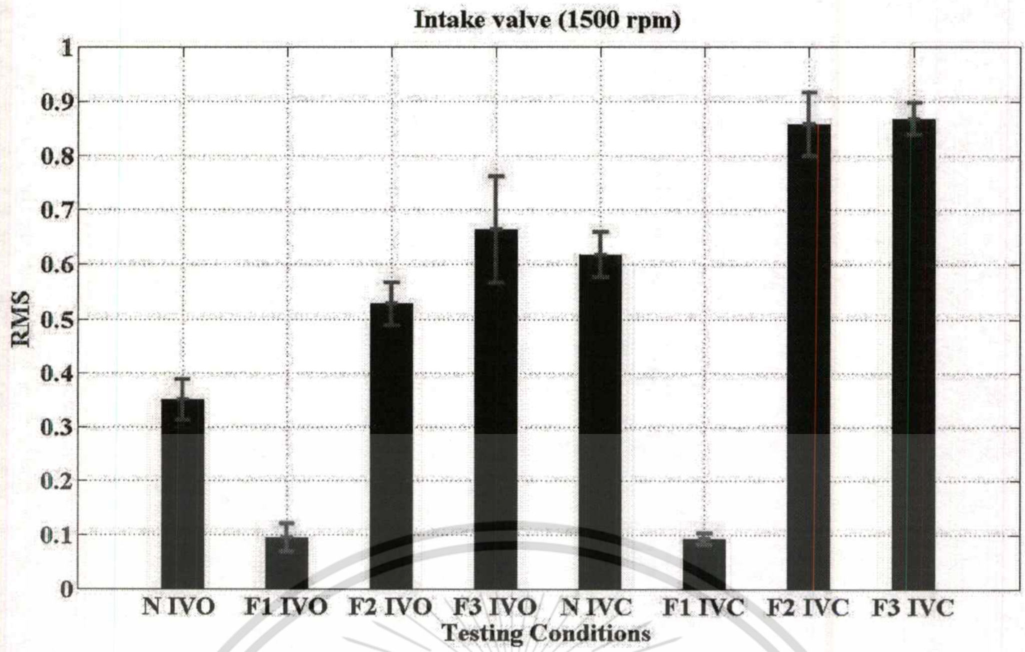


Figure 4.19: Bar chart of RMS value for the IVO/IVC events with various testing conditions

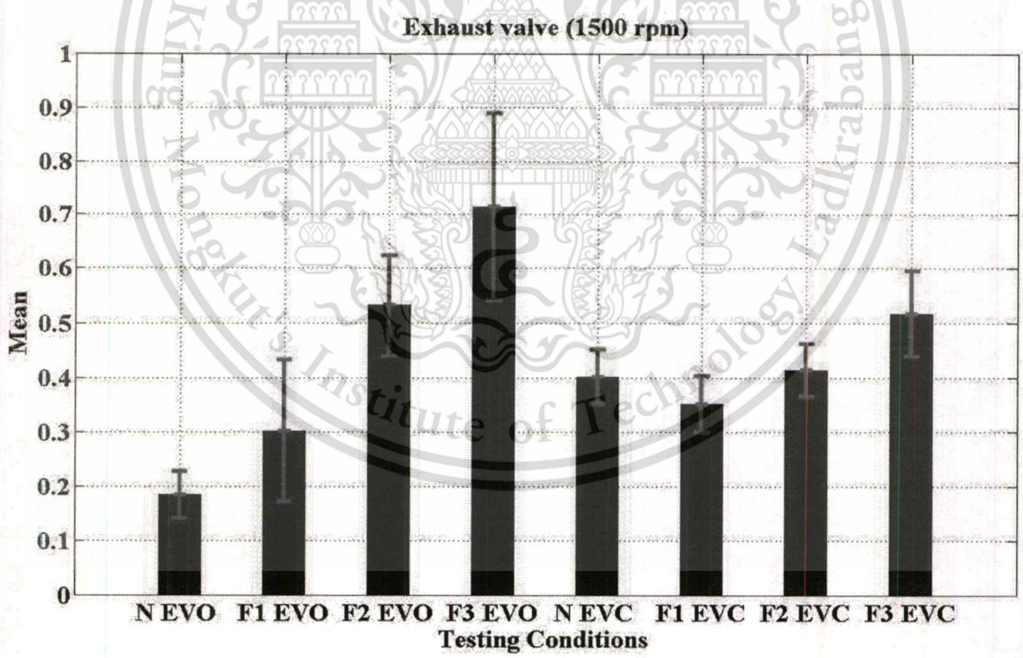


Figure 4.20: Bar chart of mean value for the EVO/EVC events with various testing conditions

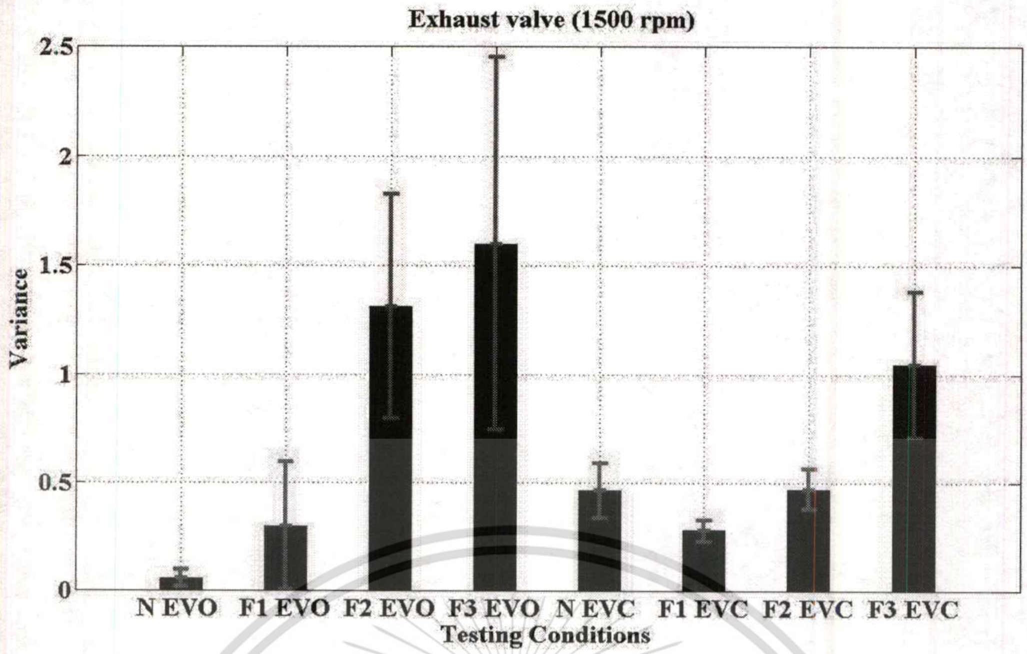


Figure 4.21: Bar chart of variance for the EVO/EVC events with various testing conditions

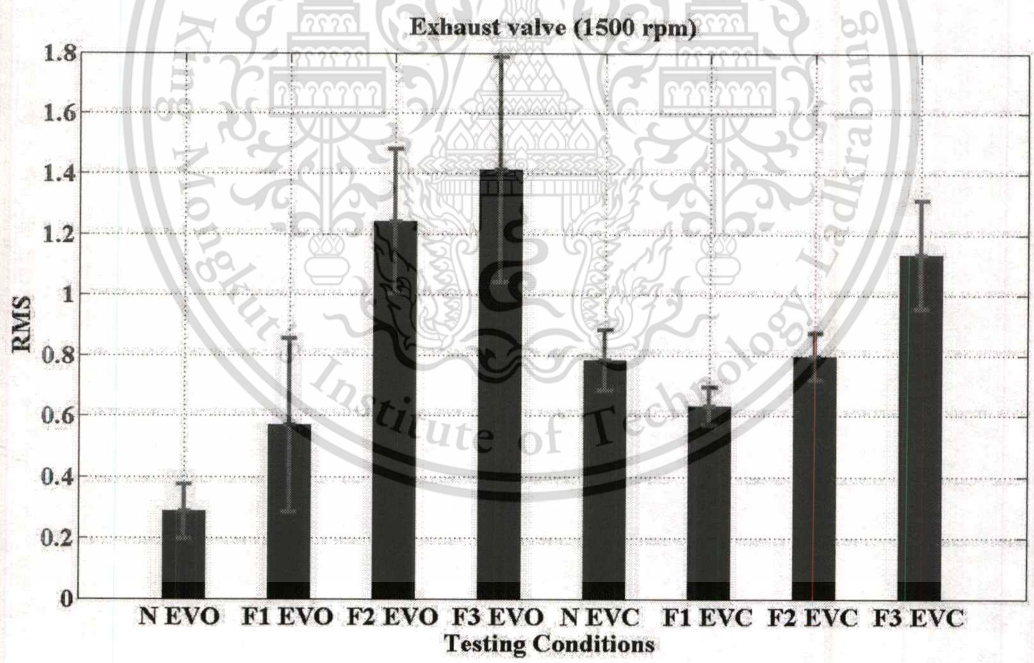


Figure 4.22: Bar chart of RMS value for the EVO/EVC events with various testing conditions.

As mentioned before, the analysis method based on windowing of the main valve events gives better results than the methods that determined various parameters from each entire engine cycle. The signal shown in Figures 4.10-4.11 were windowed only the main events and the window size was approximately 90 degrees for each main event such as 0-90, 180-270, 450-540, and 630-720 degrees for the IVO, IVC, EVO, and EVC events, respectively. Energy contents of the IVO and IVC events with various testing conditions were calculated using the trapezoidal rule method as shown in Figure 4.23. Normal IV, F1 IV, F2 IV and F3 IV represent various intake valve clearance conditions of 1.5, 0.8, 2 and 3 mm, respectively. The energy contents of the IVO and IVC events at the normal condition are approximately 51 and 331 V^2s. It can be seen that when valve clearance is greater than at the normal condition, the energy contents of the IVO and IVC events are greater than at the normal condition. The energy contents of the IVC events are greater than the IVO events for all testing conditions. The errorbars shown in Figure 4.23 are represented the variation of energy contents. It can be seen that the more intake valve clearance is, the greater variation energy content is. For the simulated tests of exhaust valve clearance faults as shown in Figure 4.24, the results of signal energy are similar as discussed in the results of various intake valve clearance faults. The reference energy contents for the EVO and EVC events at the normal condition are approximately 133 and 293 V^2s. The energy contents of both EVO and EVC events trend to increase with increasing of exhaust valve clearance. The variation of energy contents for the EVO/EVC events are greater than for the IVO and IVC events. It can be seen that energy contents of the IVO, IVC, EVO and EVC events could be used as indicators to identify valve clearance fault conditions by comparing the energy content of each current state with the normal state.

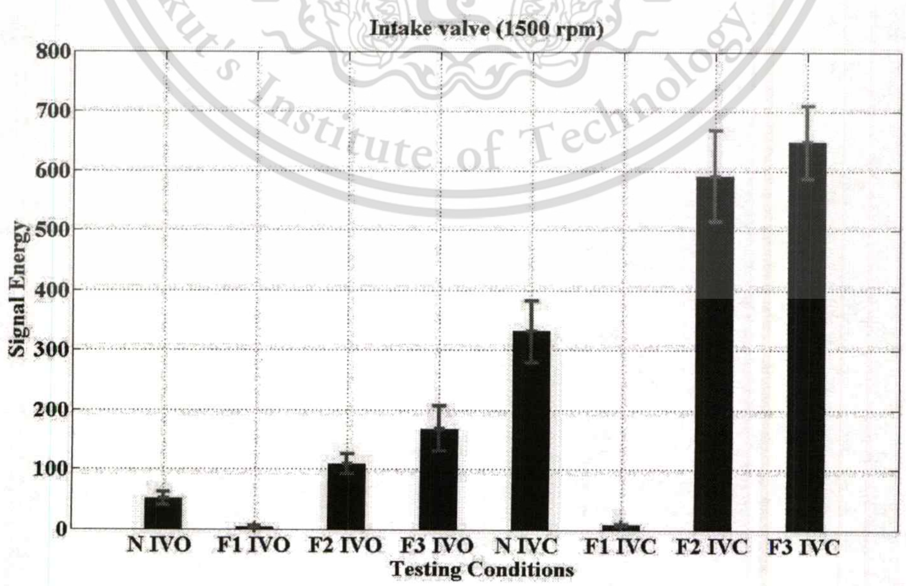


Figure 4.23: Bar chart of energy contents of the IVO/IVC events with various testing conditions.

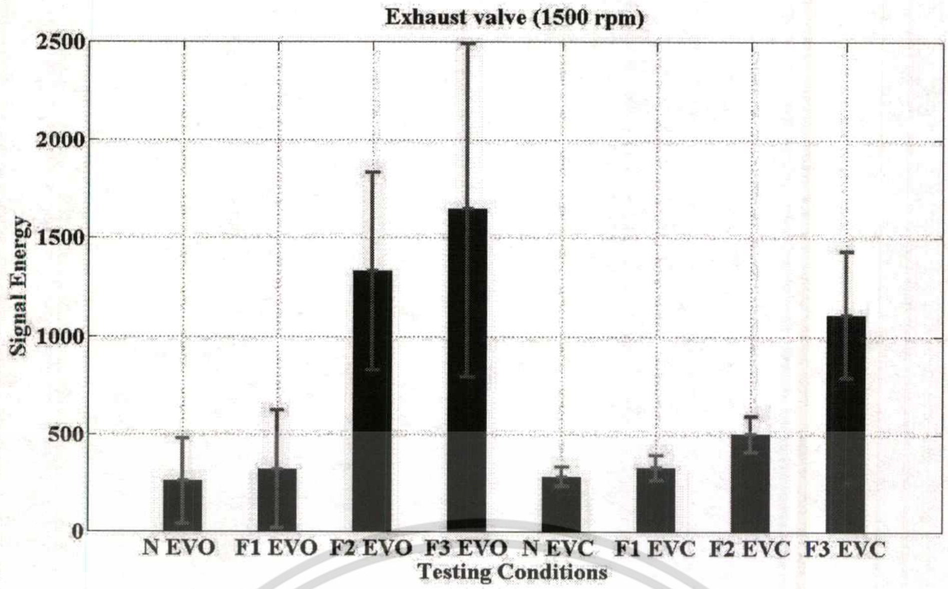
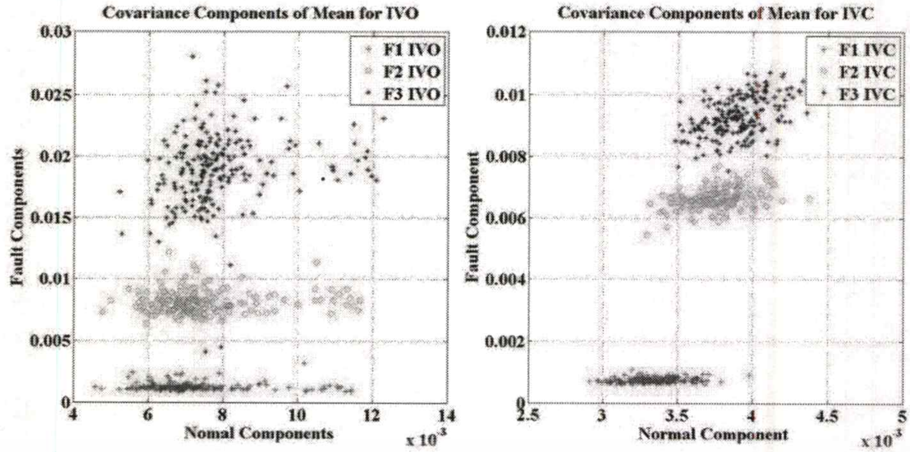


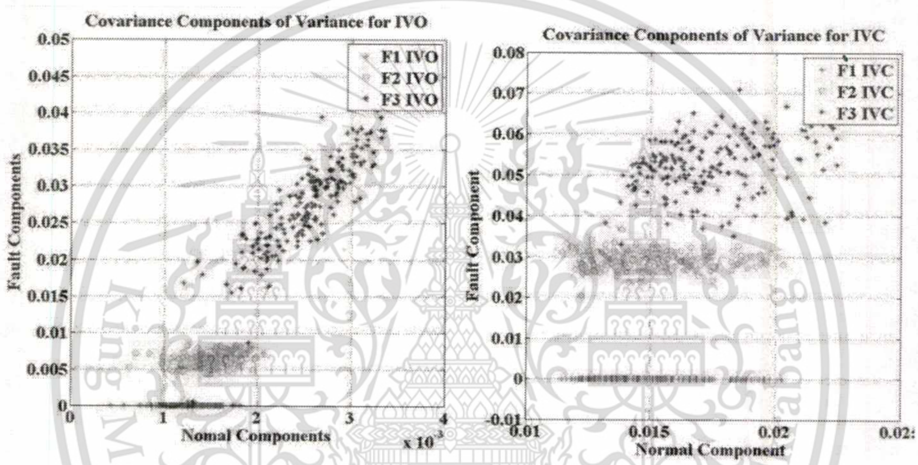
Figure 4.24: Bar chart of energy contents of the EVO/EVC events with various testing conditions.

The statistical parameters (i.e. mean, varience and RMS) and energy contents of each main valve operation event discussed above are difficult to classify various faults using single parameter. To improve fault prediction, a technique called "Covariance (COV)" can be used to identify various faults. Covariance analysis method is used to assess how strongly the data are related to one another. In this study, mean, varience, RMS and energy contents were used as input data to determine covariance between normal condition and each fault condition using Equation (3.15). The results of covariance are shown in Figures 4.25-4.27 with the normal components on the horizontal axis and fault components on the vertical axis. It can be seen that F1 IV, F2 IV and F3 IV are seperated evidently into three groups using the covariances of mean, varience and RMS for the IVO and IVC events as shown in Figure 4.25. The covariance of mean, variance and RMS increases with increasing of the intake valve clearance. The covariance of mean, variance and RMS of the EVO and EVC events are shown in Figures 4.26. The covariance of mean, variance and RMS of the EVO event is scattered so that they are unable to classify exhaust valve clearance faults exactly. For the EVC events, the covariances of variance and RMS are possible to classify exhuast valve clearance faults. The covariance of mean is not able to classify exhuast valve clearance faults. The use of the covariance of mean, variance and RMS for the IVO/IVC events give a better fault classification than for the EVO/EVC events. These may be because of the high variation of vibration signal acquired during the exhaust stroke of the petrol engine cycle. The mechanical impact of the exhaust valve and fluid flow activities of the exhuast gas through the exhaust port may vary from cycle to cycle so detected vibration signal of the EVO/EVC events may also give high variation of vibration amplitude.

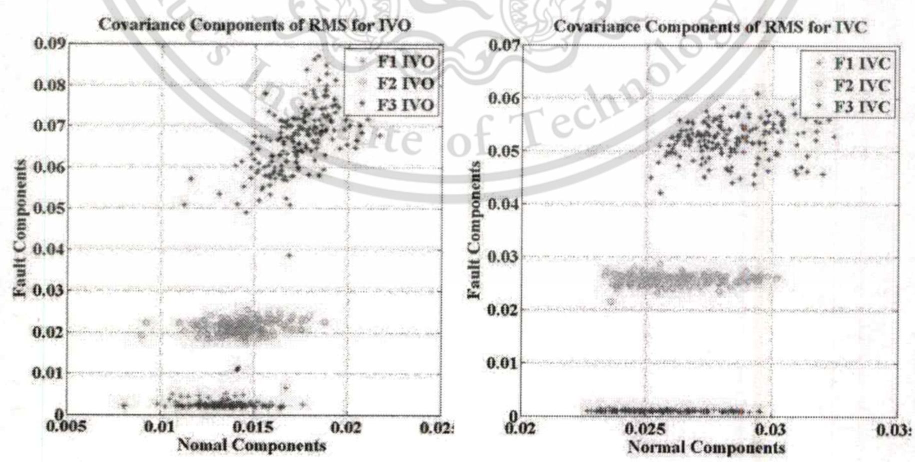
The covariance of energy contents for the IVO/IVC events give almost the same results of the covariance of mean, variance and RMS as discussed above. The covariance of energy contents for the IVO event can be separated into three groups for F1 IV, F2 IV and F3 IV, respectively. However, for the IVC event, the results for F2 IV and F3 IV are mixed together so these are difficult to separte both faults from each other. For the EVO/EVC events, the covariance of energy contents are similar to the results as discussed above. It is not perfectly used to classify exhuast valve clearance faults. It is evident that the covariance analysis method based on the IVO/IVC and EVO/EVC events with more than single parameter can be used to classify various intake and exhaust valve clearance faults.



(a) Mean

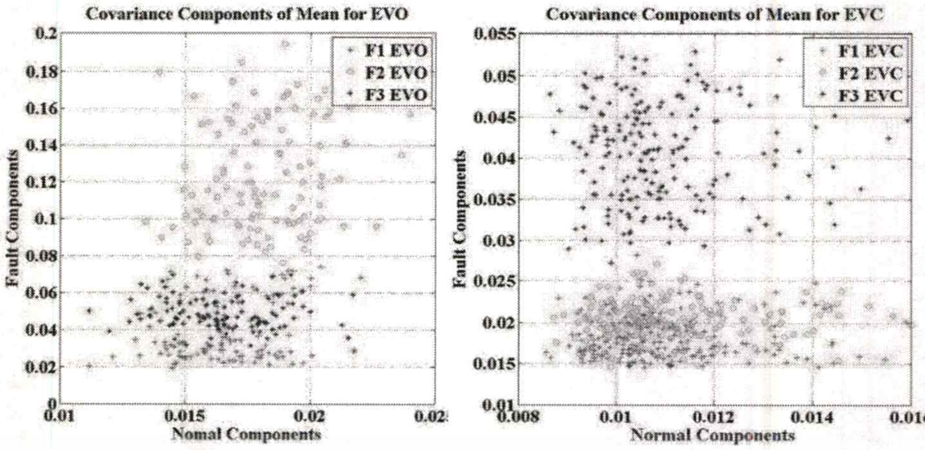


(b) Variance

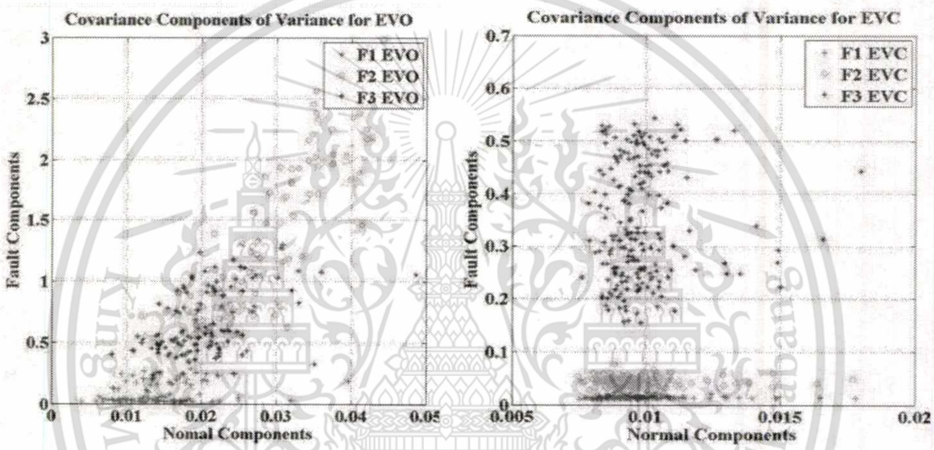


(c) RMS

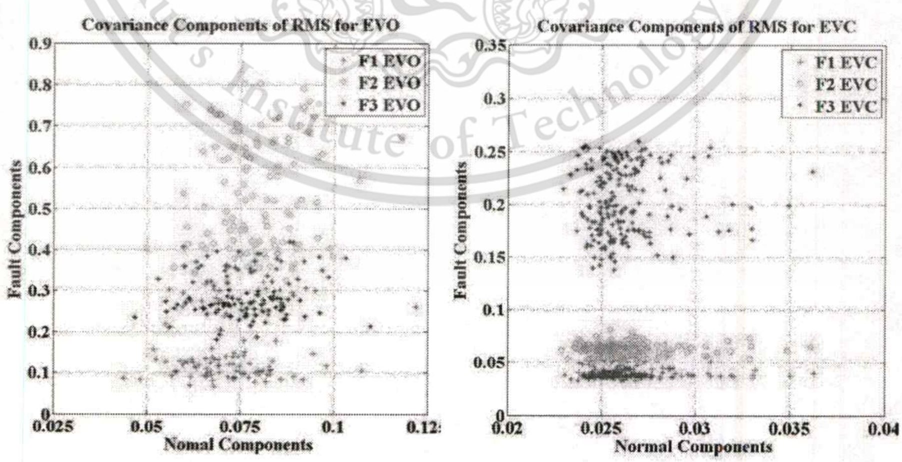
Figure 4.25: Covariance components of mean, variance and RMS for the IVO/IVC events with various testing conditions



(a) Mean

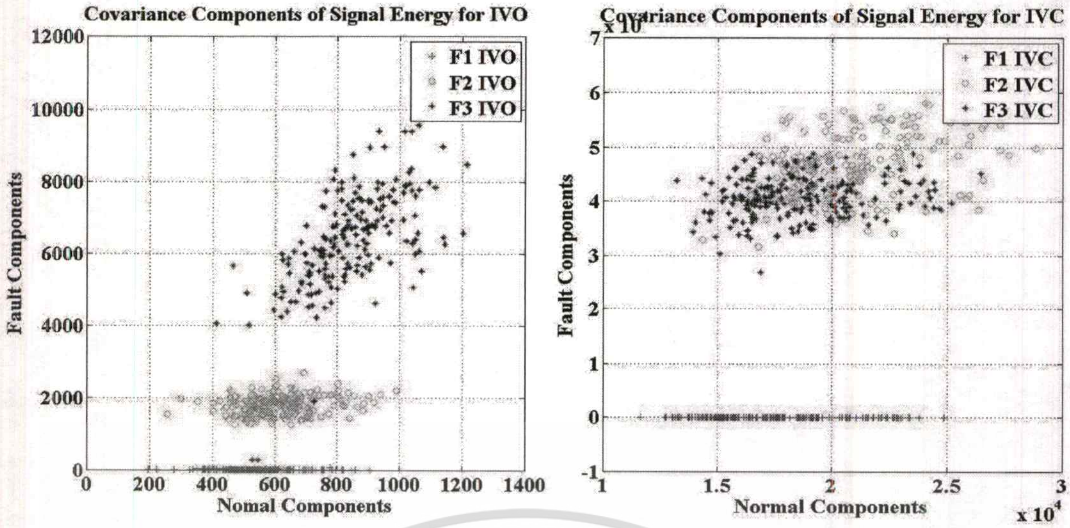


(b) Variance

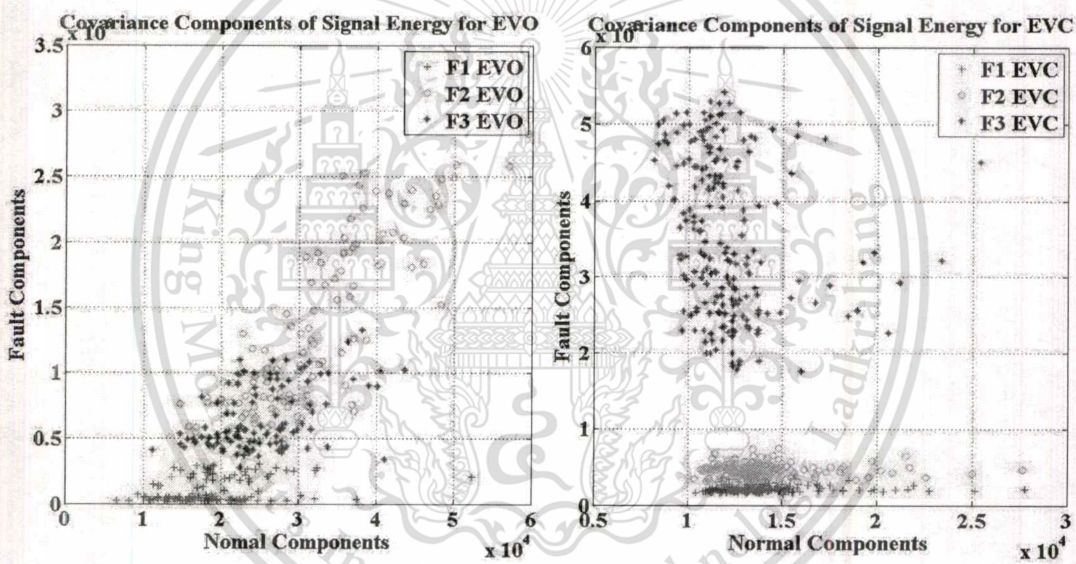


(c) RMS

Figure 4.26: Covariance components of mean, variance and RMS for the EVO/EVC events with various testing conditions



(a) IVO/IVC events



(b) EVO/EVC events

Figure 4.27: Covariance components of energy contents for main valve events with various testing conditions (a) IVO/IVC events and (b) EVO/EVC events

4.4 SUMMARY OF EXPERIMENTS

This chapter has been concerned with the signal processing techniques used to predict intake/exhaust valve clearance faults on the small, four-stroke, petrol engine. Two experiments were carried on small four-stroke, petrol engines. Two signals, a vibration signal and a timing signal, were acquired from an accelerometer and a proximity sensor, respectively. The experiment of the motor engine (an engine was driven by an electric motor) was used to study the mechanical processes of the intake/exhaust valve operation including valve timing diagram of the small engine. The experiment of the firing engine (a real engine) was used to study condition monitoring techniques for predicting various intake/exhaust valve clearance faults. Various signal processing techniques have been used to analysis acquired vibration signals such as statistical method (i.e. mean, variance, skewness, kurtosis and RMS), signal energy and covariance method. In the analysis, acquired vibration signals were converted from time domain into crank angle domain using the timing signal (TDC signal) so the mechanical and fluid flow activities in the engine cycle could be identify easily. Vibration signals also were used to determine energy content per degree so that the engine processes could be easily identified. The statistical analysis methods based on mean, variance, skewness, kurtosis and RMS were used to analysis vibration signals using the entire engine cycles and the windowed main valve events (the IVO, IVC, EVO and EVC events). The covariance of each parameters such as mean, variance, RMS and energy contents has been applied to classify various intake/exhaust valve clearance faults. The use of statistical analysis method and the covariance method is able to predict various faults of intake/exhaust valve clearances.

CHAPTER 5

CONCLUSION AND FUTURE WORK

5.1 CONCLUSION

The main aim of this study was to develop the generic technique to monitor condition and performance of a small, four-stroke, petrol engine using vibration signals. It has been demonstrated through a range of experimental results that vibration technique has potential for investigating behavior of four-stroke, petrol engine. Typical recorded vibration signals consist of both burst and continuous signals associated with mechanical and fluid flow processes in the engine cycle. The vibration signal and crank angle signal could be used to map the main event (i.e. valve operation and spark ignition events) in the engine cycle. However, the knowledge of engine processes and signal processing techniques are necessary. The crank angle and signal energy analysis based on time domain technique were able to describe the main events by windowing the vibration signal so the engine condition was able to identify easily. The signal energy technique applied to the main valve operation events could helped to identify fault from acquired vibration signal of a firing engine. Also, the statistical parameter analysis with the covariance method could help to separate various intake/exhaust faults from each other.

In the previous chapter, the results of various tests on the small four-stroke engines have been discussed and the main conclusions of this work are as follows:

- At the 950 rpm, vibration signals from engine driven by electric motor could be used to study mechanical impact (i.e. the intake and exhaust valve operation) in the engine cycle. The valve timing of the intake and exhaust valve could also be identified in vibration signals.
- At the 1500 rpm, vibration signals acquired from the cylinder of the firing engine could be used to monitor engine conditions which associated with mechanical and fluid flow activities in the engine cycle.
- Vibration signals in time domain could be mapped into crank angle domain using TDC signal so that the intake valve and exhaust valve activities could be identify easily. In addition,

vibration signals in crank angle domain could be used to investigate various clearance faults of the intake and exhaust valves.

- The analysis methods used to determine mean, variance, skewness, kurtosis, RMS and energy content from vibration signal of the entire engine cycle could be used to predict various valve clearance faults of the intake and exhaust valves. However, skewness and kurtosis were able to predict a few cases of valve clearance faults of the intake and exhaust valves.

- The analysis method of mean, variance, RMS and energy content applied to determine the main valve events (i.e. IVO, IVC, EVO, EVC events) were able to predict various faults of the intake and exhaust valves and gave better prediction than those results, that determined all parameters from vibration signals using the entire engine cycle. This analysis technique applied to the IVO/IVC events could be identified various faults clearer than the EVO/EVC events.

- The covariance method using various parameters determined from the IVO, IVC, EVO and EVC events could be used to separate various faults. The covariance method based on mean, variance and RMS using IVO/IVC events was able to separate various intake valve clearance faults but using EVO/EVC events, it was able to separate some cases of exhaust valve faults.

- The use of single statistical parameter or energy content was unable to diagnose completely various faults. The vibration signal analysis of at least two parameters was possible to distinguish between various intake and exhaust valve faults on the petrol engine.

5.2 WORK IN THE FUTURE

The suggestions for future work are as follows:

- The four-stroke, four-cylinder, petrol engine: It is worth to investigate the complex engine processes of a four-stroke, four-cylinder, petrol engine in order to develop more powerful condition monitoring techniques using vibration signals.

- The analysis techniques: Vibration signal has been shown a capability of detecting various faults on the engine. The advanced analysis techniques (i.e. FFT, wavelets, pattern recognition and neural network etc.) can be applied to analyse vibration for more useful information to diagnose engine faults and also mechanical and fluid flow processes in the engine cycle.

- Monitoring with various sensors: Engine monitoring can be applied with other types of sensors to investigate engine state such as in-cylinder pressure, temperature, and sound so that the engine processes can be monitored more detailed information.

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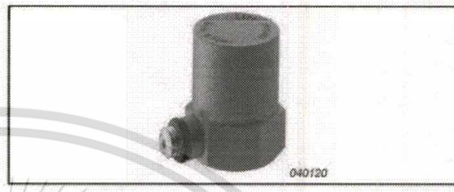
APPENDIX A

Accelerometer Data Sheet

PRODUCT DATA

Piezoelectric Accelerometer
Charge Accelerometer — Type 4371, 4371 S and 4371 V

FEATURES
- General purpose
- High sensitivity
- High frequency
- Vibration testing



Description

Type 4371 is a piezoelectric, DeltaShear®, Unigain® accelerometer with side connector. Type 4371 features 10–32 UNF receptacle for output connection and can be mounted on the object by means of a 10–32 UNF threaded steel stud.

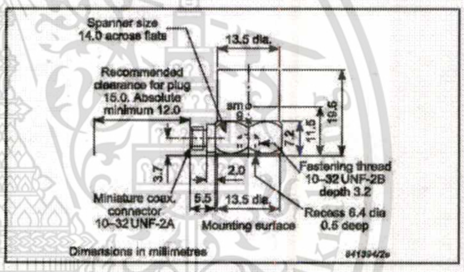
Characteristics

This piezoelectric accelerometer may be treated as a charge source. Its sensitivity is expressed in terms of charge per unit acceleration (pC/g).

The DeltaShear design involves three piezoelectric elements and three masses arranged in a triangular configuration around a triangular centre post. The ring prestresses the piezoelectric elements to give a high degree of linearity. The charge is collected between the housing and the clamping ring. The piezoelectric element used is a PZ 23 lead zirconate titanate element. The housing material is titanium.

Calibration

The sensitivity given in the calibration chart has been measured at 159.2 Hz and an acceleration of 10 g. For 99.9% confidence level, the accuracy of the factory calibration is ±2%.



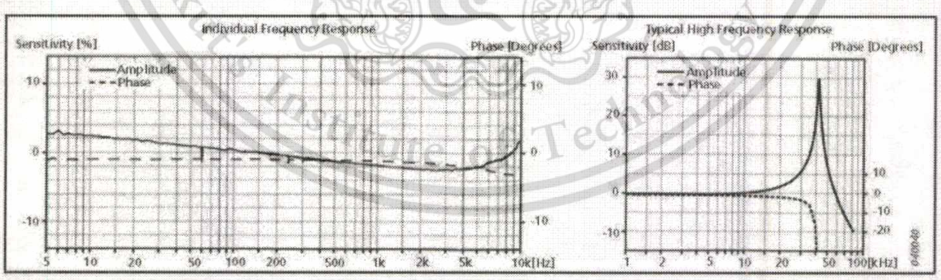


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Figure A.1: Accelerometer Data Sheet

Specifications – Charge Accelerometer Type 4371, 4371 S and 4371 V

	Units	4371/4371 S	4371 V
Dynamic Characteristics			
Charge Sensitivity (@ 159.2 Hz)	pC/g	9.8 ± 2%	9.8 ± 15%
Frequency Response		See typical Amplitude Response	
Mounted Resonance Frequency	kHz	42	
Amplitude Response ±10% [1]	Hz	0.1 to 12600	
Transverse Sensitivity	%	<4	
Transverse Resonance Frequency	kHz	15	
Electrical Characteristics			
Min. Leakage Resistance @ 20°C	GΩ	≥20	
Capacitance	pF	1200	
Grounding		Signal ground connected to case	
Environmental Characteristics			
Temperature Range	°C (°F)	–55 to 250 (–67 to 482)	
Humidity		Welded, sealed	
Max. Operational Sinusoidal Vibration (peak)	g pk	6000	
Max. Operational Shock (± peak)	g pk	20000	
Base Strain Sensitivity	Equiv. g/μ strain	0.002	
Thermal Transient Sensitivity	Equiv. g/°C (g/°F)	0.004 (0.022)	
Magnetic Sensitivity (50 Hz–0.03 Tesla)	g/T	0.4	
Physical Characteristics			
Dimensions		See outline drawing	
Weight	gram (oz.)	11 (0.39)	
Case Material		Titanium	
Connector		10–32 UNF	
Mounting		10–32 UNF × 3.2 mm threaded hole	

[1] Low-end response of the transducer is a function of its associated electronics

Ordering Information

Type 4371 includes the following accessories:
- Carrying box
- Calibration chart
- AO 0038: Low noise cable fitted with 10–32 connectors, 1.2 m
- 10–32 UNF threaded steel stud. Length 12.7 mm

Type 4371 S includes the following accessories:
- Carrying box
- Calibration chart
- AO 0038: Low noise cable fitted with 10–32 connectors, 1.2 m
- 10–32 UNF threaded steel stud. Length 12.7 mm
- UA 0078: Accessory box including:
  - Cementing stud, 10–32 UNF
  - EP610 input adaptor, TNC to 10–32 UNF microdot
  - Mounting magnet, 10–32 UNF thread
  - Case of beeswax
  - Insulating disk
  - Insulating stud
  - Steel stud 10–32 UNF × ½″
  - Tools

Type 4371 V includes the following accessories:
- Carrying box
- Calibration chart
- 10–32 UNF threaded steel stud. Length 12.7 mm

OPTIONAL ACCESSORIES
- AO 0038: 260°C Teflon® low-noise cable, 10–32 UNF, length 1.2 m (4 ft)
- AO 0122: 250°C, reinforced super low noise cable, 10–32, 3 m (10 ft)
- AO 0231: 260°C Teflon low-noise cable, 10–32 UNF/TNC, length 3 m (10 ft)
- AO 1382: Teflon low noise cable, double screened 10–32, 1.2 m (4 ft)
- DB 0544: 10–32 UNF Round tip
- JJ 0207: 2-pin TNC/10–32 UNF plug adaptor
- JP 0162: 10–32 UNF to TNC connector adaptor
- QA 0013: Hexagonal key for 10–32 UNF studs
- QA 0029: Tap for 10–32 UNF thread
- UA 0559: Mechanical filter for Accelerometer
- UA 0642: Mounting magnet and 2 insulating discs
- UA 0866: Cement stud 10–32 UNF 0.14 mm (set of 25)
- YG 0150: Steel stud 10–32/10–32 with flange
- YJ 0216: Beeswax for mounting
- YP 0080: Probe with sharp tip
- YP 0150: 10–32 UNF insulated stud. Length 12.7 mm
- YQ 2960: 0–32 UNF threaded steel stud. Length 12.7 mm
- YQ 2962: 0–32 UNF threaded steel stud. Length 7.62 mm

Brüel & Kjær reserves the right to change specifications and accessories without notice

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Germany (+49) 421 17 87 0 · Hong Kong (+852) 2548 7486 · Hungary (+36) 1 215 83 05 · Ireland (+353) 1 807 4083
Italy (+39) 0257 68061 · Japan (+81) 3 5715 1612 · Korea (+82) 2 3473 0605 · Netherlands (+31) 318 55 9290
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Figure A.2: Accelerometer Data Sheet

APPENDIX B

LabVIEW Program

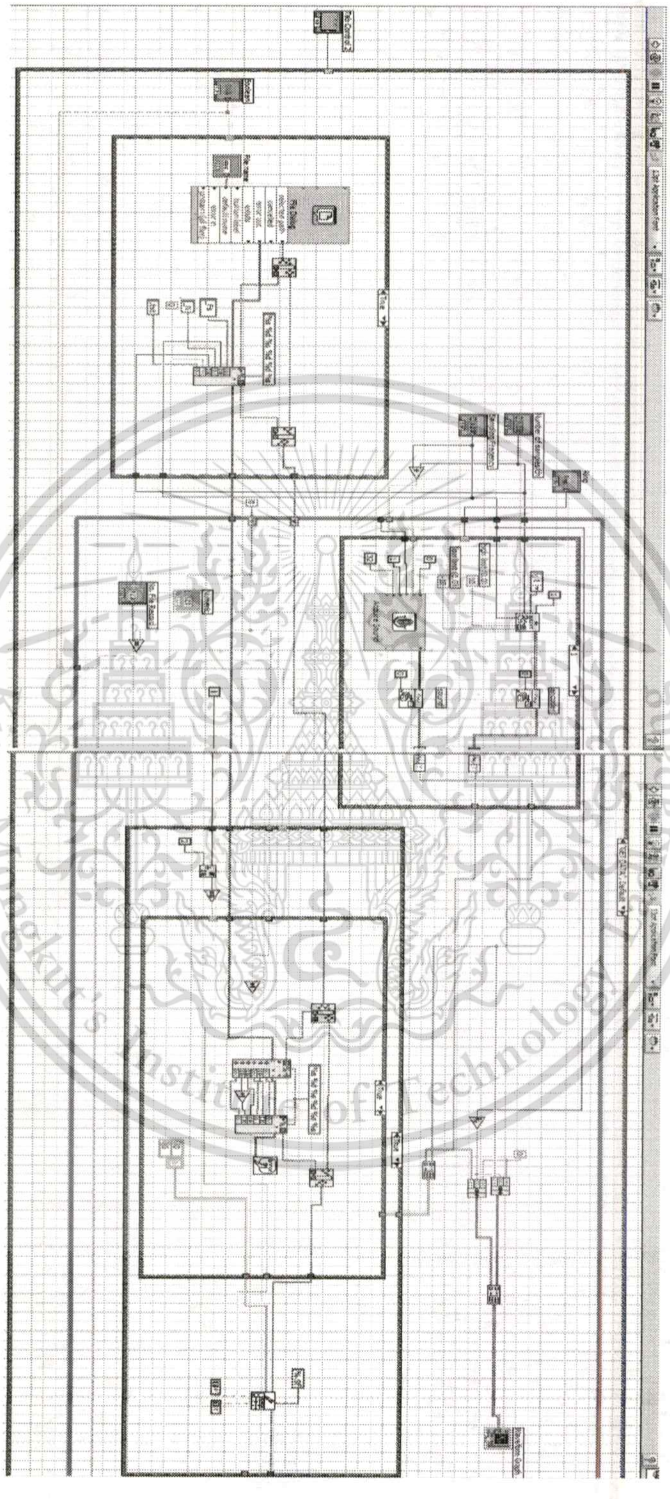

Figure B.1: Bock diagram of LabVIEW Programming using in the acquisition system.

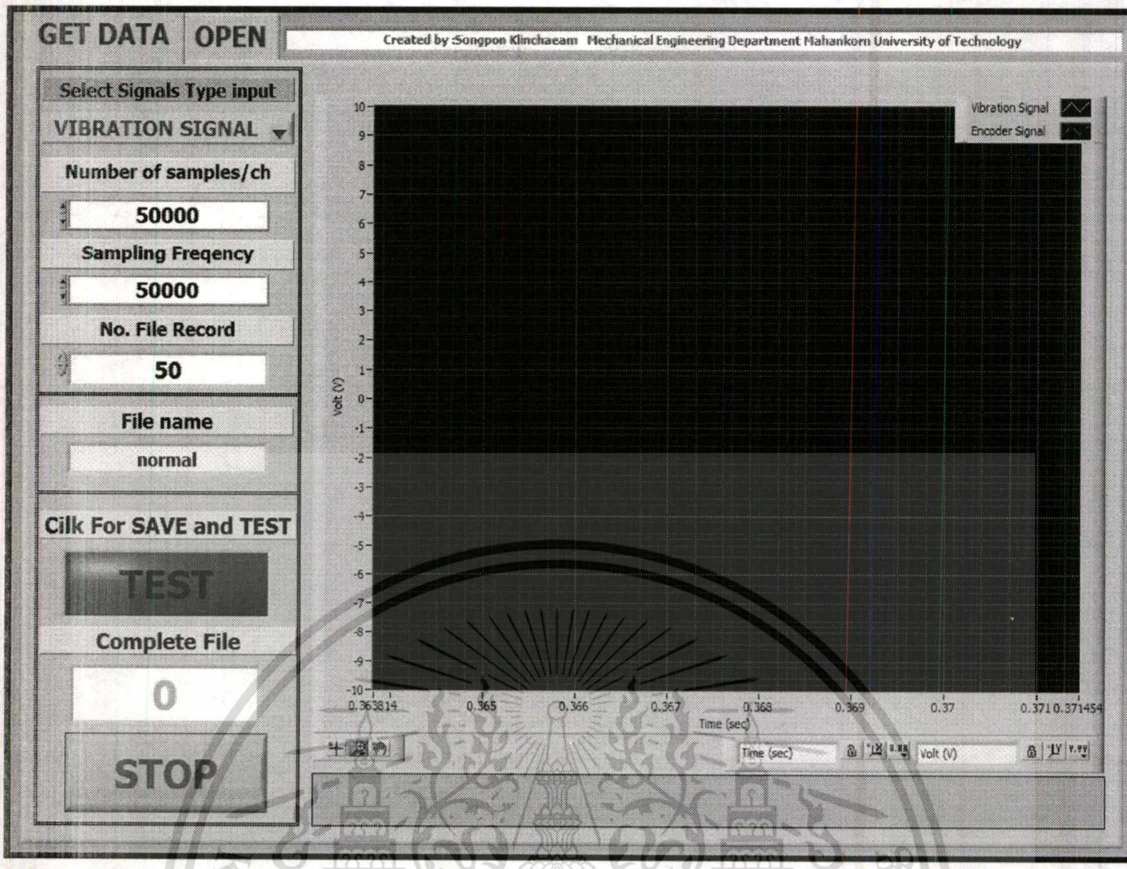

Figure B.2: Front panel of LabVIEW program using in the acquisition system.

APPENDIX C

Simulation of Intake and Exhaust valve displacement in each condition

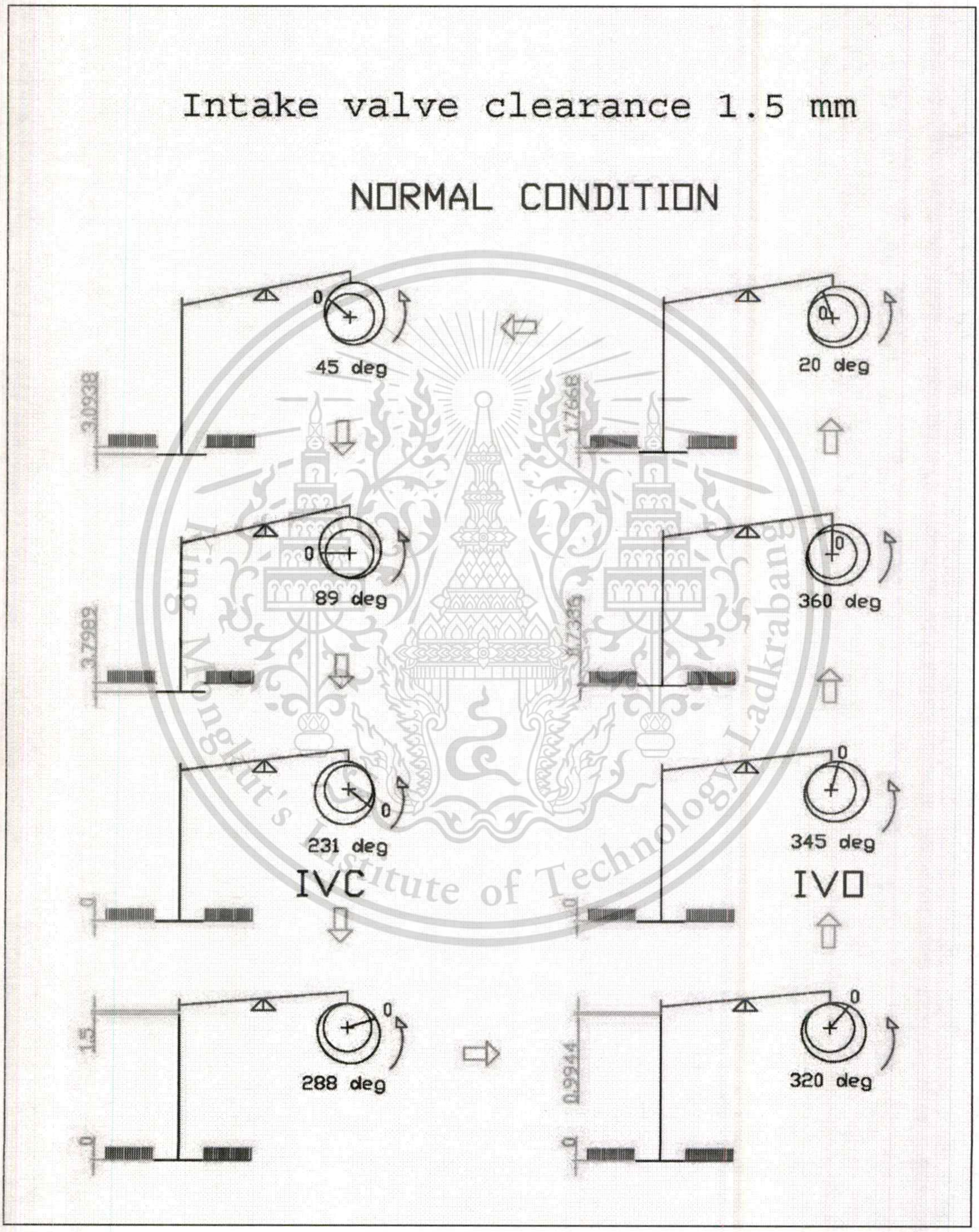

Figure C.1: Displacement of intake valve at various cam rotation angle of normal condition

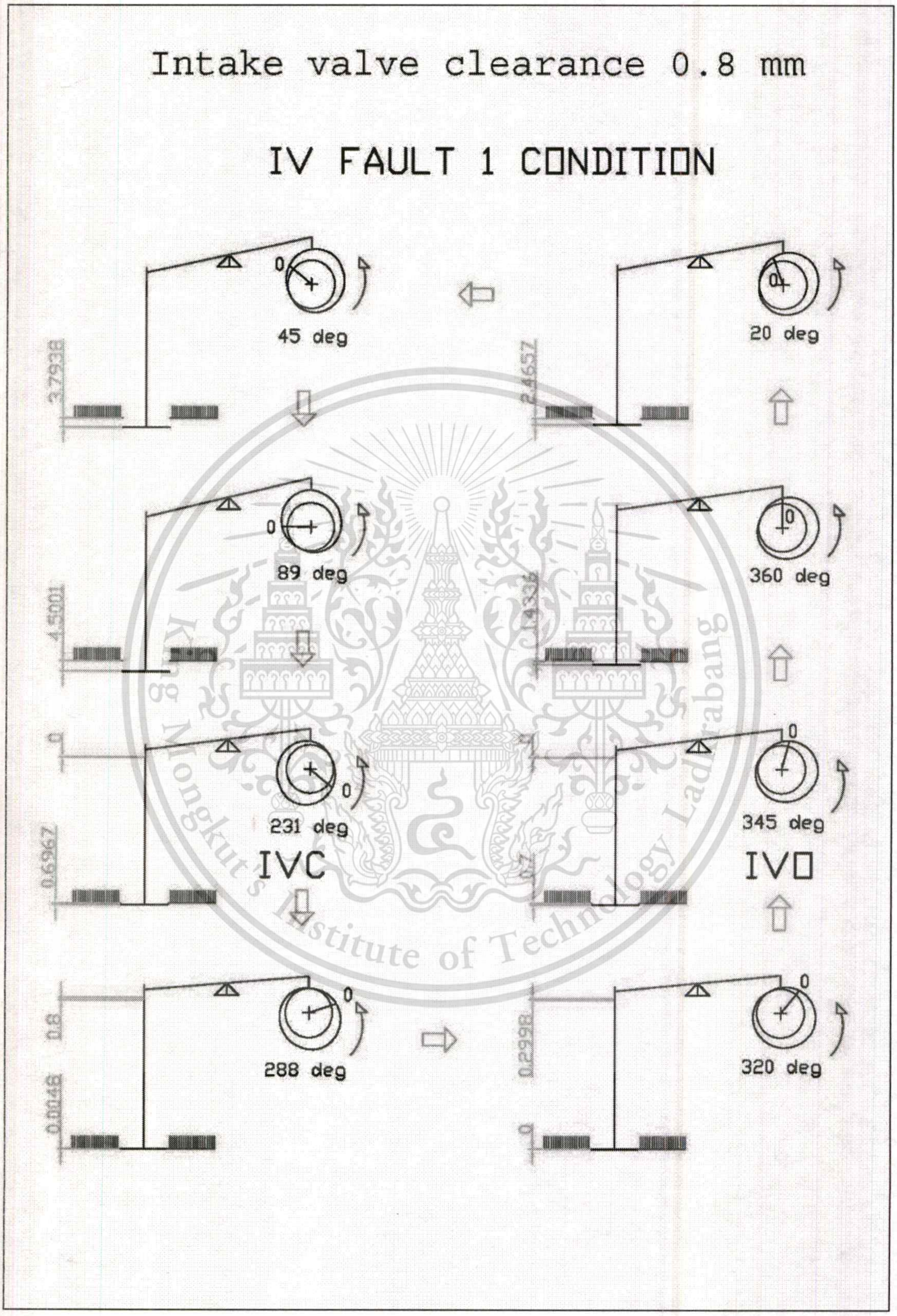

Figure C.2: Displacement of simulated fault 1 of intake valve at various cam rotation angles

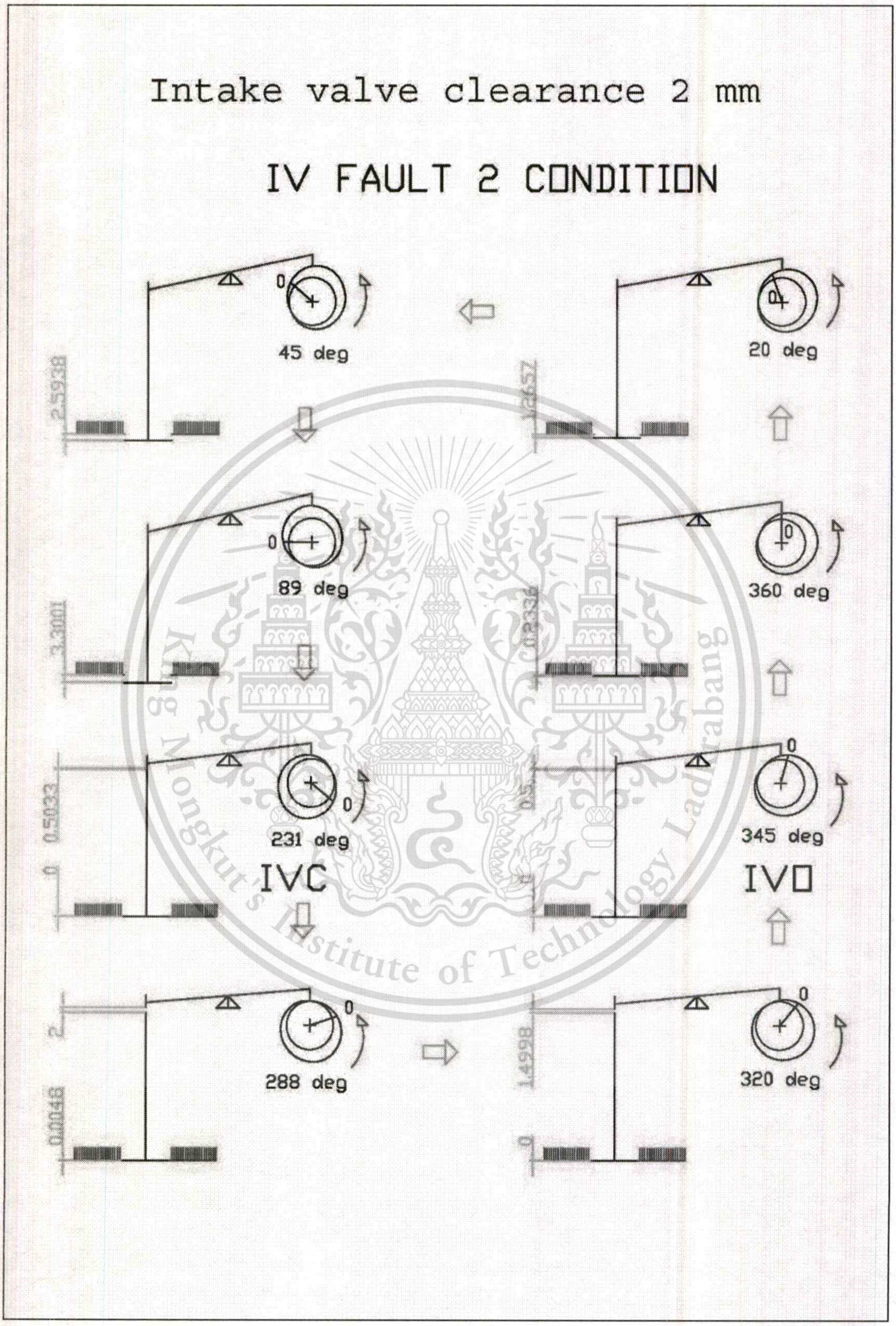

Figure C.3: Displacement of simulated fault 2 of intake valve at various cam rotation angles

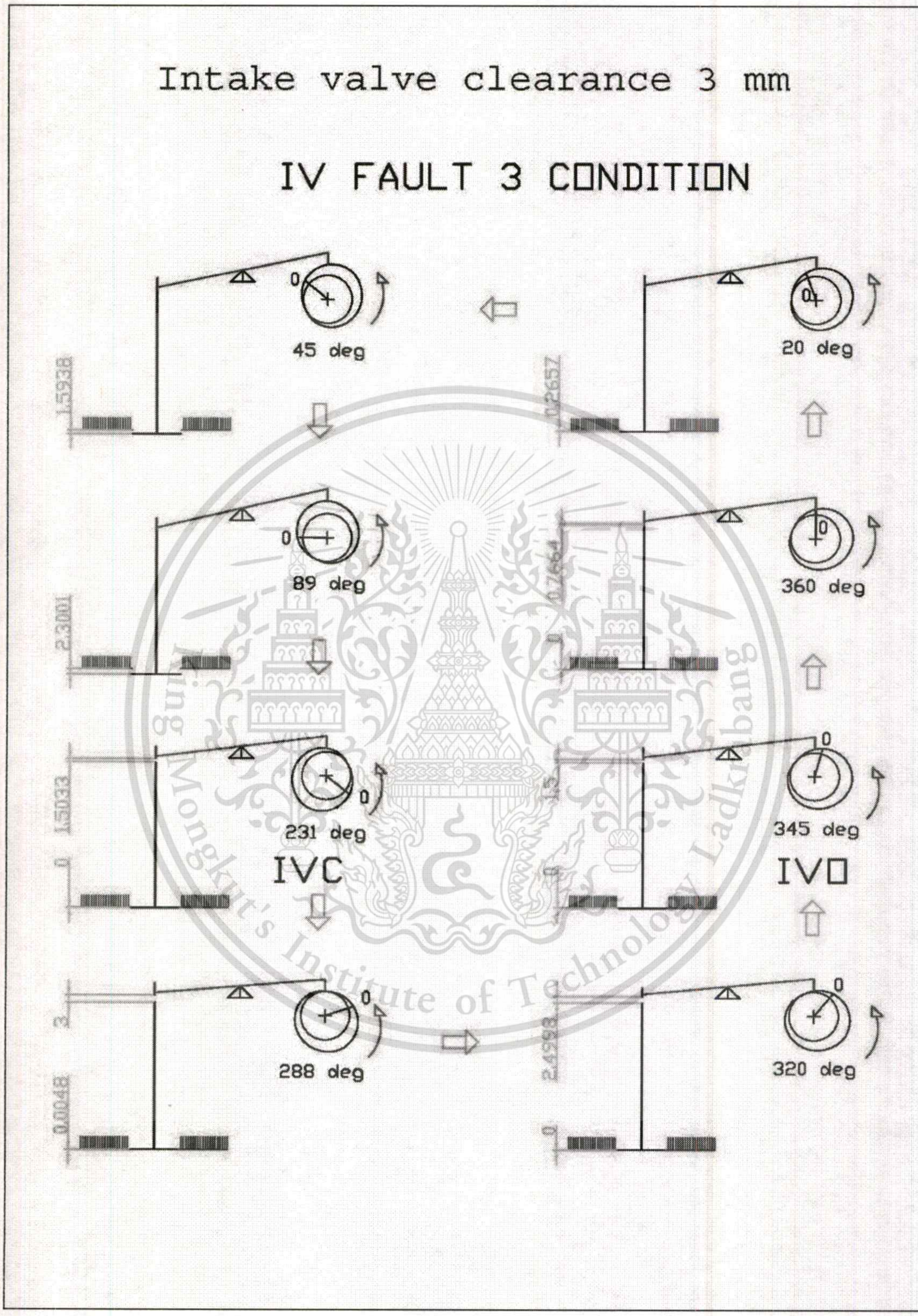

Figure C.4: Displacement of simulated fault 3 of intake valve at various cam rotation angles

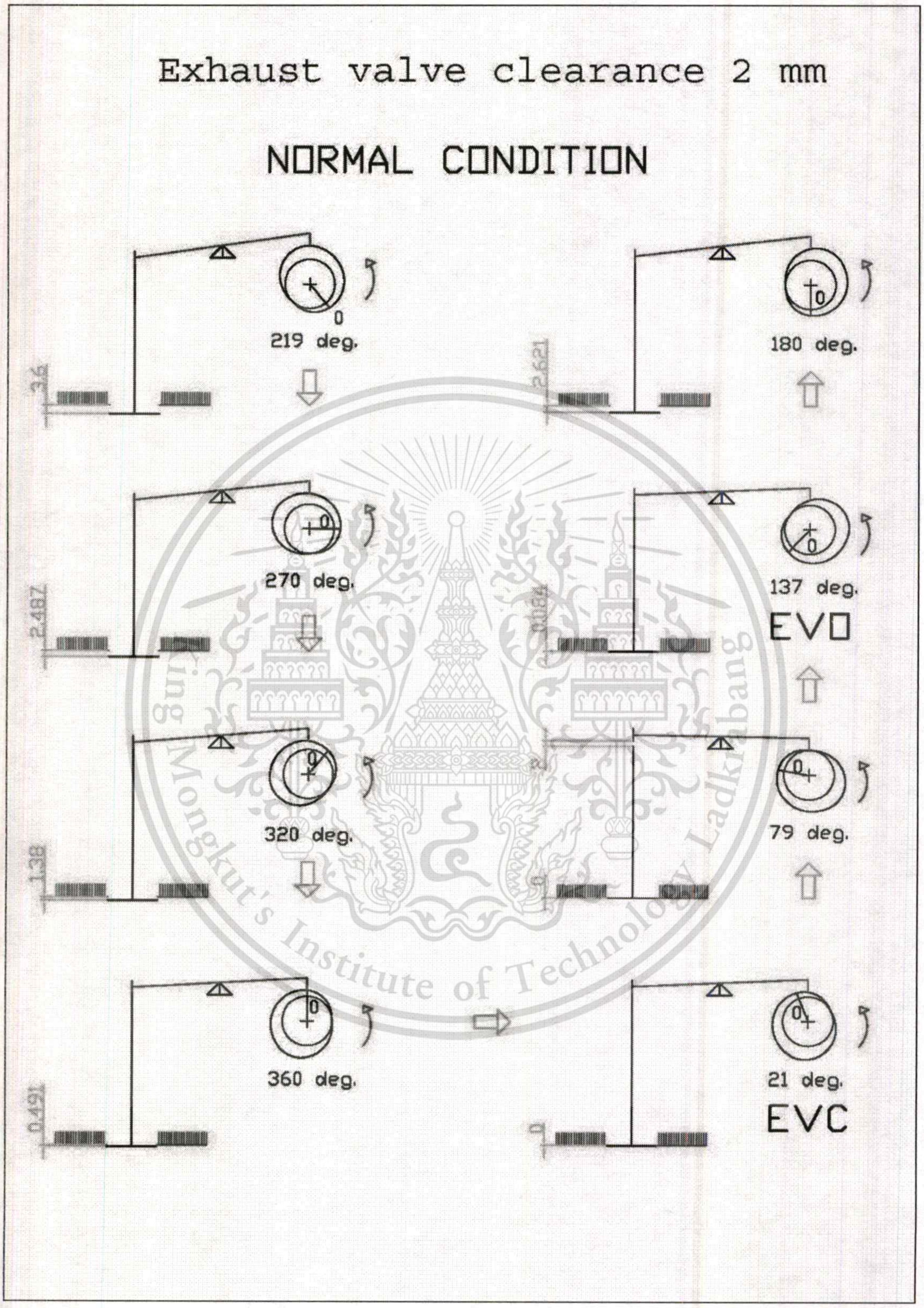

Figure C.5: Displacement of exhaust valve at various cam rotation angles of normal condition

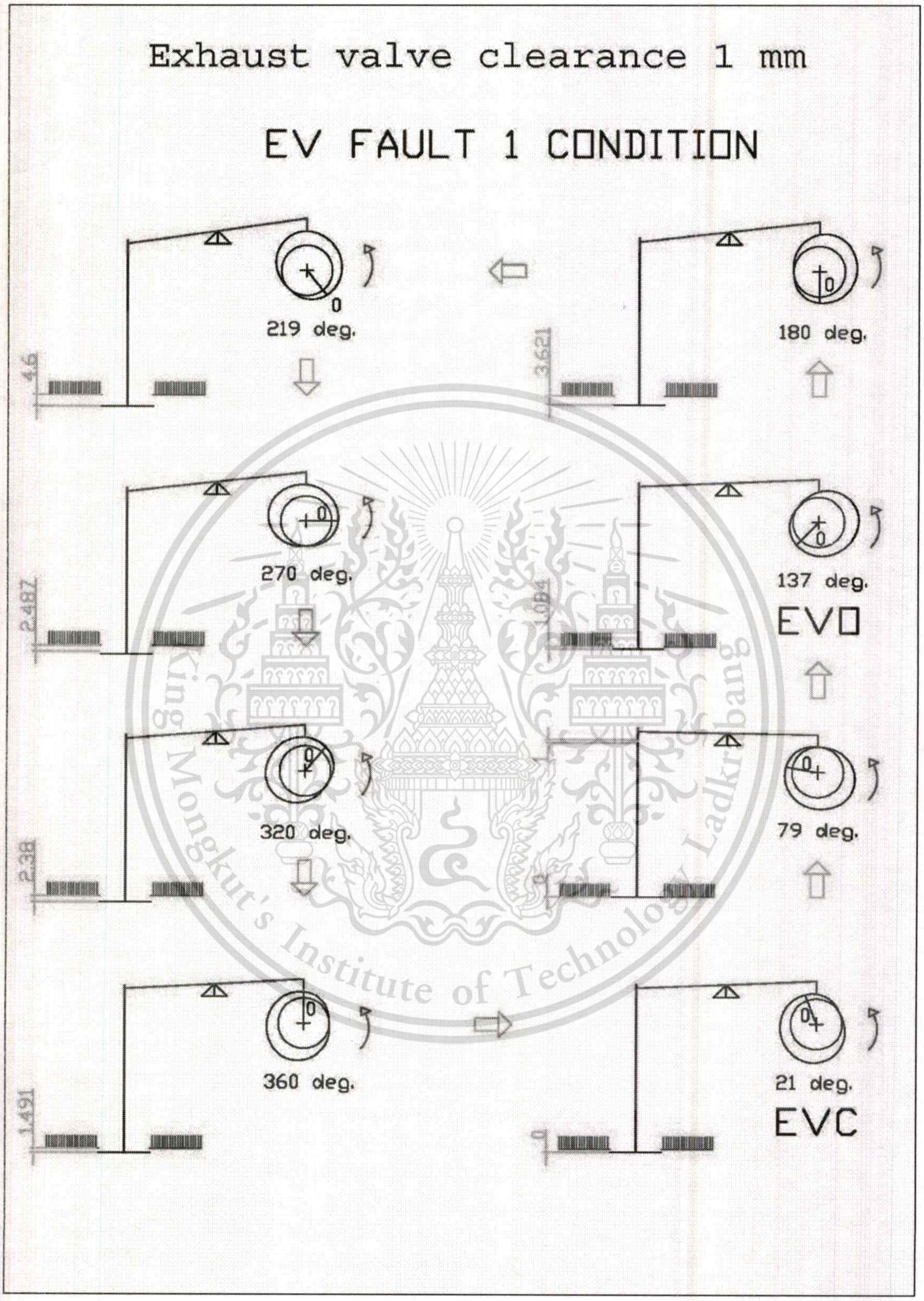

Figure C.6: Displacement of simulated fault 1 of exhaust valve at various cam rotation angles

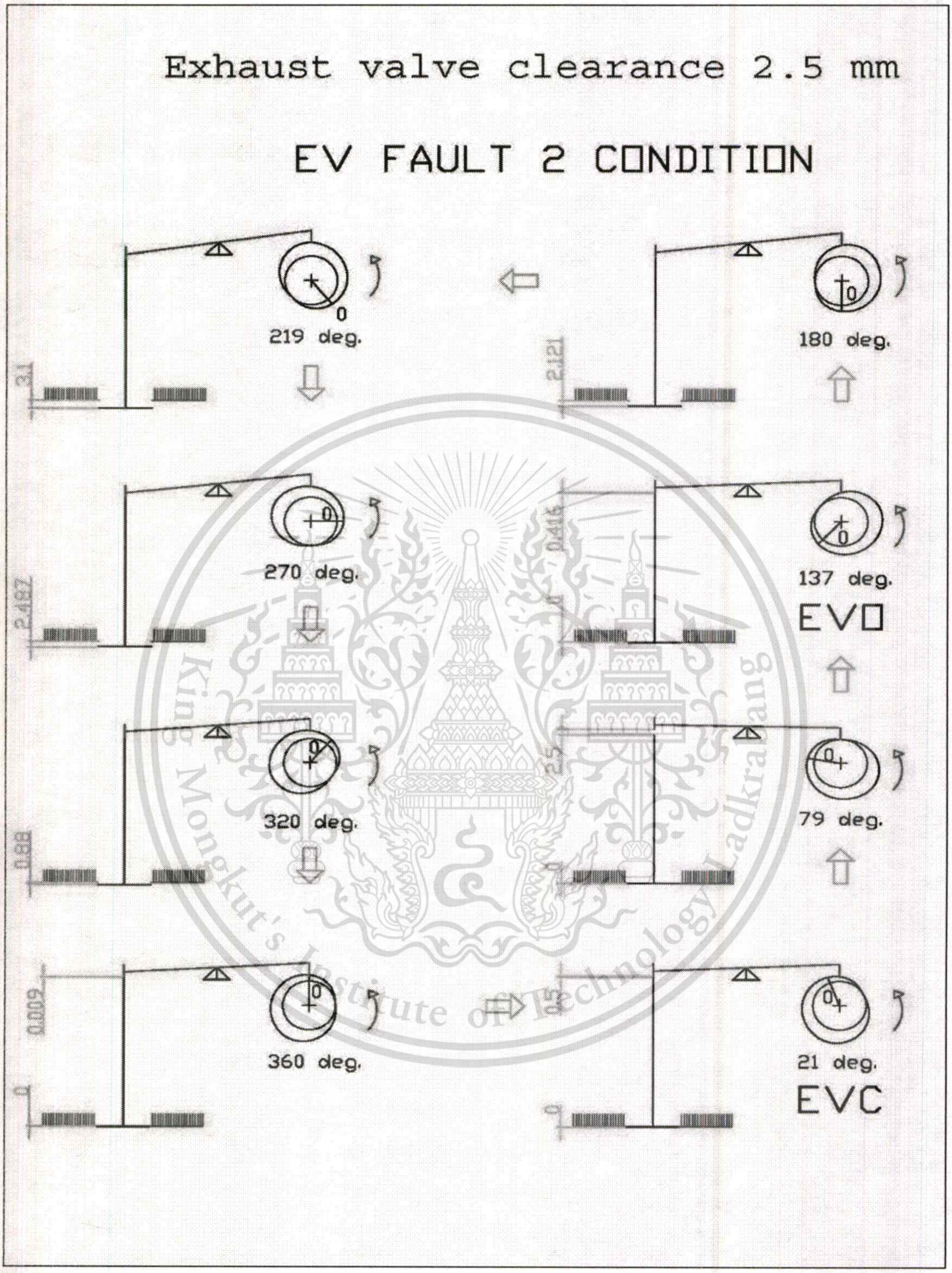

Figure C.7: Displacement of simulated fault 2 of exhaust valve at various cam rotation angles

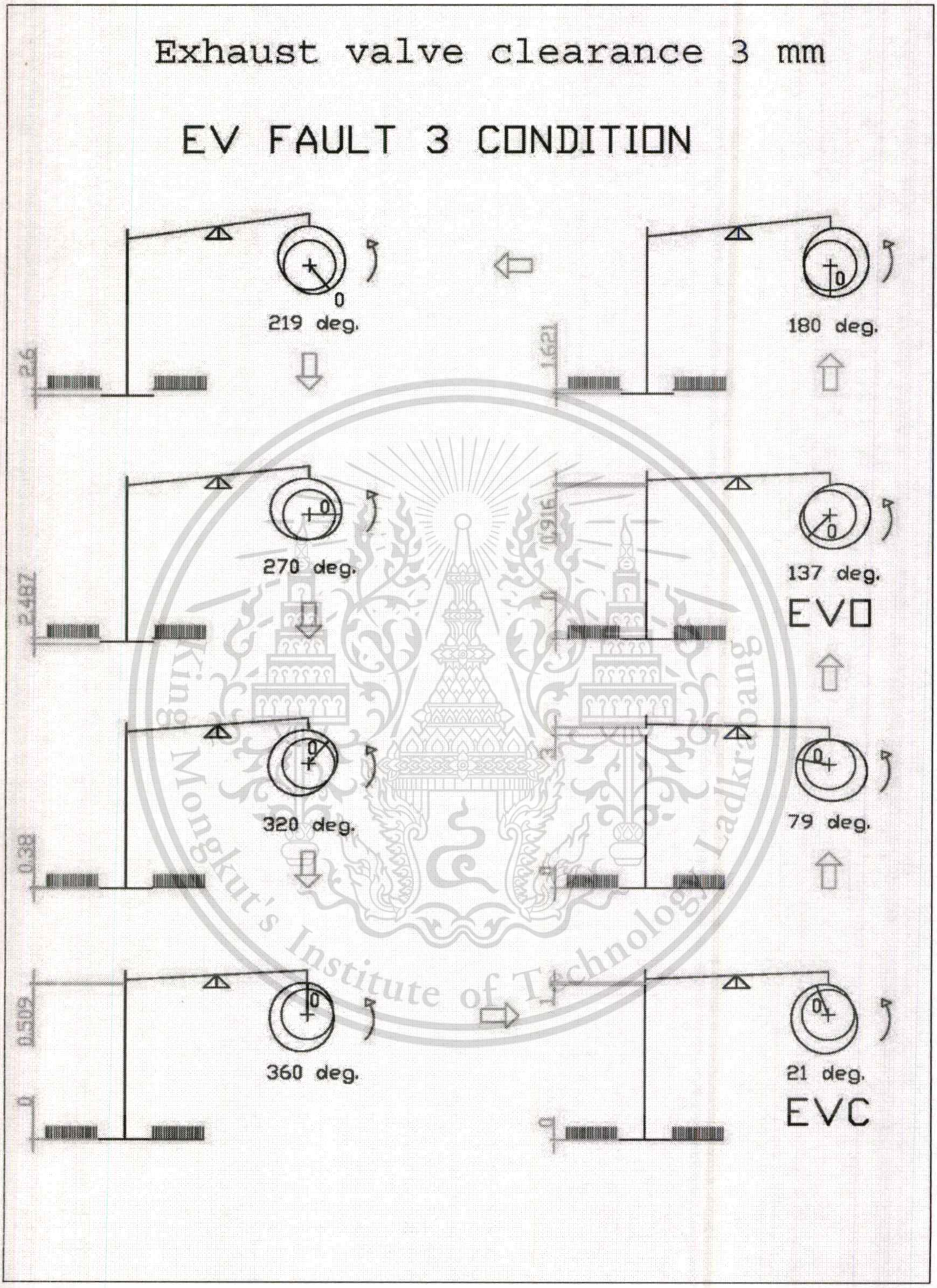

Figure C.8: Displacement of simulated fault 3 of exhaust valve at various cam rotation angles

BIOGRAPHY

Name: Mr. Songpon Klinchaeam

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Place of Birth: Singburi, Thailand

Education:

2003-2007: Bachelor of Engineering (B. Eng. First Class Honours) in Mechanical Engineering, Faculty of Engineering Mahanakorn University of Technology (MUT)

2007-2010: Master of Engineering (M. Eng. International Program) in Automotive Engineering, International College King Mongkut's Institute of Technology Ladkrabang (KMITL)

Honour and Scholarship:

2007-2009: Full scholarship for study in the master degree from National Science and Technology Development Agency (NSTDA)

Publications:

1. Klinchaeam S., and Nivesrangsan P., Ming Lokitsangtong., 'Condition monitoring of small four strokes petrol engine using statistical covariance parameter analysis', 2009., **13th International Annual Symposium on Computational Science and Engineering (ANSCSE 13)**, March 25 –27, 2009, Faculty of Engineering, Kasetsart University, Bangkok, Thailand. pp 366-373.

2. Klinchaeam S., and Nivesrangsan P., Ming Lokitsangtong., 2009., 'Condition monitoring of a small four strokes petrol engine using signal energy analysis' , **The 5th International Conference on Automotive Engineering (ICAE-5)**, March 30 – April 3, 2009, BITEC, Bangkok, Thailand.

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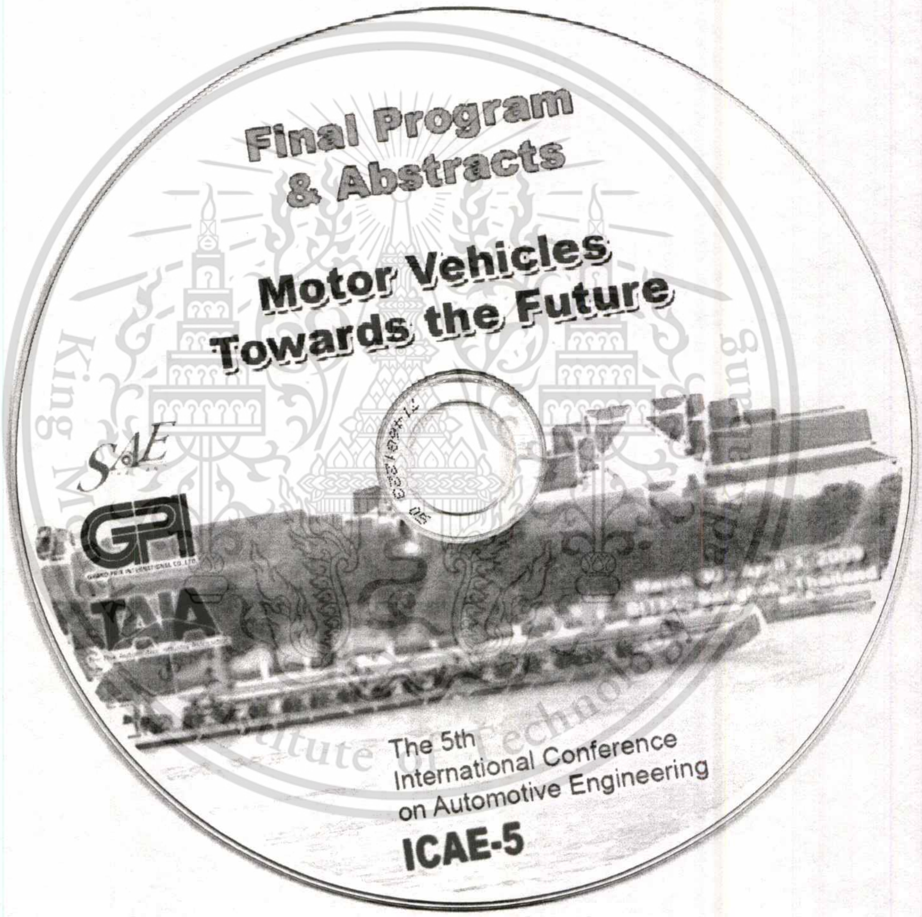
Final Program & Abstracts


Final Program
& Abstracts
Motor Vehicles
Towards the Future
SAE
GPI
TAIA
The 5th
International Conference
on Automotive Engineering
ICAE-5

Condition monitoring of a small four strokes petrol engine using signal energy analysis

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ABSTRACT

This paper studies condition monitoring method of a small four strokes, single cylinder petrol engine using vibration signal analysis based on time domain and crank angle domain. Vibration signals are acquired from the cylinder head of the engine and can be used to describe engine process such as intake/exhaust valve operations, ignition process, combustion process, etc. In this study, vibration signals are used to monitor various fault conditions in the engine such as intake/exhaust valve clearance faults and spark plug gap faults. Using energy technique to analyse recorded vibration signals, the main events related to engine operation can be describes easily and all fault conditions could also identify.

Keywords: condition monitoring, vibration signals, fault condition, intake/exhaust valves and spark plug, energy signal

INTRODUCTION

In the past decades, many successful efforts have been made to use vibration analysis as a means for condition monitoring of rotating machinery. A number of methods such as statistical analysis and time domain analysis etc. have been shown to offer high potential for the early detection of malfunctions and diagnosis of machines [1]. However, applications of internal combustion (IC) (diesel and petrol engines) using vibration signal have a problem of the complexity of the vibration signals and large amount of data. It was early realized that any effective approach dedicated to IC engines would have to cope with the highly transient nature of their vibrations [1-9]. This gave little scope to the classical methods which usually assume stationary (time invariance of statistical properties) of the vibrations and so cancel out all time information. This paper introduces an approach which takes into account the non-stationary nature of the vibration signals produced by a four strokes petrol engine. The key idea is to rephrase the prospect of vibration monitoring of a small four strokes petrol engines into the very general framework of cyclic stationary processes, which is perfectly suited for describing physical phenomena generated on a cyclic basis.

Non-intrusive sensor measurement techniques (i.e. vibration measurement technique) provide information in time domain and frequency domain that information related engine processes can be described to identify existing or impending problem by detecting deviations from a normal or an achievable condition in the engine cycle [1-9]. A challenge of engine monitoring system used in industry has to face with a large amount of recorded data that acquired using commercial or in-house developed software. These data can be analyzed using exist signal processing techniques to reduce number of data and to obtain some useful information to monitor engine conditions. Ideally, a condition monitoring program should mature to integrate techniques to reduce data from all sources and channel into a centralized system that produces information accessible to all levels of the preventive maintenance.

This paper has studied vibration analysis method for a condition monitoring of a small four strokes single cylinder with capacity 125 CC, petrol engine using vibration signals. The physical aspect of combustion characteristics of a spark ignition engine are every crucial for an engine performance and can be described using actual vibration signals and reference signal or top dead center signals .The analysis technique and data reduction produced normalized measure that can be used to analyze engine states. In This research engine monitoring techniques based on vibration signals acquired on a small petrol engine are used. The vibration signals can be acquired using the LABVIEW program. The accelerometer is attached on a surface of cylinder block by a magnetic clamp. Proximity sensor is used to record TDC signal. The signals are analyzed using time domain and crank angle domain techniques to determine various statistical parameter. Vibration signals detected on the petrol engine are related to events associated with some mechanical and fluid flow process in the engine cycle. These vibration signals can be mapped onto various processes associated with intake/exhaust valve operation, combustion and spark ignition are described in this research.

SIGNAL PROCESSING

Analysis of vibration patterns is an evaluation of vibration related to crankshaft angle and to obtain the understanding of various mechanical conditions in the engine cycle associated with gas leaks or mechanical impacts. Mechanical impacts, such as valve closure, produce sharp vibration patterns. [1-9] Gas leaks, however, typically occur over a longer period of time and have lower amplitude. In addition, gas leaks are usually affected by the changing pressure in the cylinder. Roughness or friction produces vibration that is characterized by a noise with low amplitude [1-5, 16-20]. Vibration pattern analysis of four strokes petrol engine involves the determination of the presence and absence of expected events associated with the engine processes which occur at measurable amplitude and at a specific time. Abnormal events based on mechanical experience and the maintenance history of the engine operation can be predicted using an engine knowledge, then, specific regions of the vibration pattern can be separated. The potential faults can be defined with the vibration pattern that anomalies in the signal pattern can be detected by comparison with a baseline normal condition pattern.

Signal analysis techniques used in this study are based on time domain and crank angle domain. The acquired, time domain, vibration signals can be converted into crank angle domain using reference signal that gave top dead center signal of an engine. So the main events related to petrol engine process can be identified. To obtain more information from the vibration signal, the signal energy technique is applied to identify various fault conditions. The signal energy can be calculated, as follow:

Signal energy

$$E_x = \int_0^t |x(t)|^2 dt \qquad (1)$$

Where: x_i is an element of data $x(t)$

$x(t)$ is time domain wave from

The signal energy can be used to analyse vibration signals, thus the engine state can be described.

EXPERIMENT

A small single cylinder, four strokes petrol engine, Tiger brand, with capacity 125 CC is used and run at speed of 1500 rpm with various conditions such as Intake/Exhaust valve clearance faults and spark plug clearance fault conditions is shown in Figure 1. All fault conditions were simulated on the engine as follows

1. Simulated fault at the Intake valve with various Intake valve (IV) clearance fault condition, IV Fault1 = 2 mm, IV Fault2 = 2.5 mm and IV Fault3 = 0.8 mm. Typical Intake valve clearance of this engine is 1.5 mm.
2. Simulated fault at the Exhaust valve with various exhaust valve (EV) clearance fault condition, EV Fault1 = 2.5 mm, EV fault2 = 3 mm and EV fault3 = 1 mm. Typical exhaust valve of this engine is 2 mm.
3. Simulated fault at spark plug (SP) with various clearance conditions, SP Fault1 = 1 mm, SP Fault2 = 1.4 mm and SP Fault3 = 2 mm. Typical spark plug clearance is 0.8 mm

Vibration signal and crank angle signal are acquired from accelerometer and proximity sensor, respectively using LabVIEW Program. A schematic diagram of data acquisition (DAQ) system is described in Figure 2. This system consists of an accelerometer with a charge amplifier, a crank angle sensor, a terminal block, and a DAQ card with in-house developed LabVIEW software installed in a notebook computer. In this study, National Instruments (NI) DAQ card, 12-bit, PCMCIA-6024E was used to acquire and digitize both vibration and crank angle signals, which were records with sampling frequency of 100 kHz and saved into files for later analysis. Vibration signal are measured using accelerometer attached on the cylinder head stud of the small petrol engine shown in Figure 3. An in-house designed aluminum clamp is used to hold Bruel & Kjaer accelerometer, Model 4371 at the same axis of the engine piston.

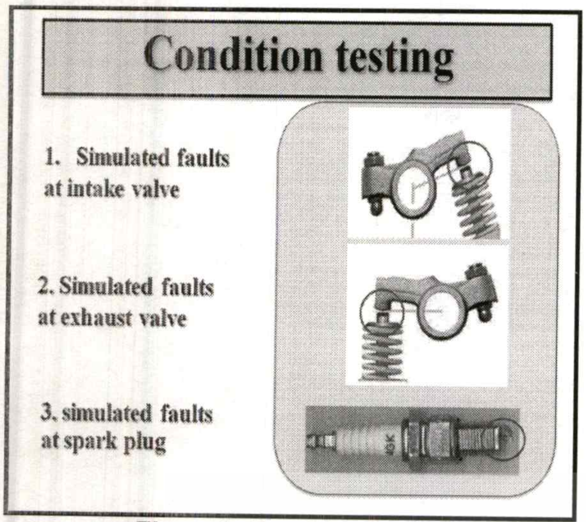

Figure1. Condition testing

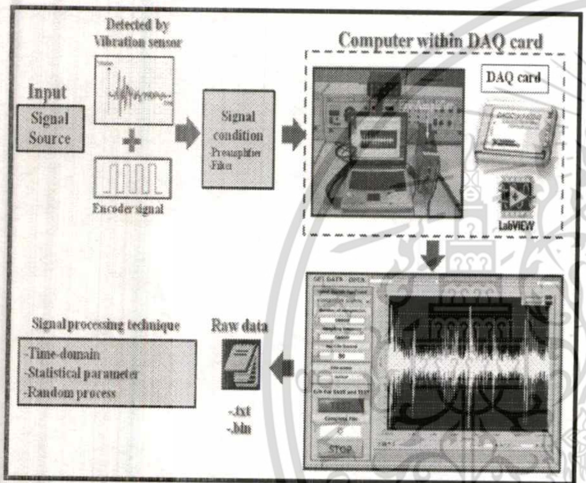

Figure2. A schematic diagram of data acquisition system

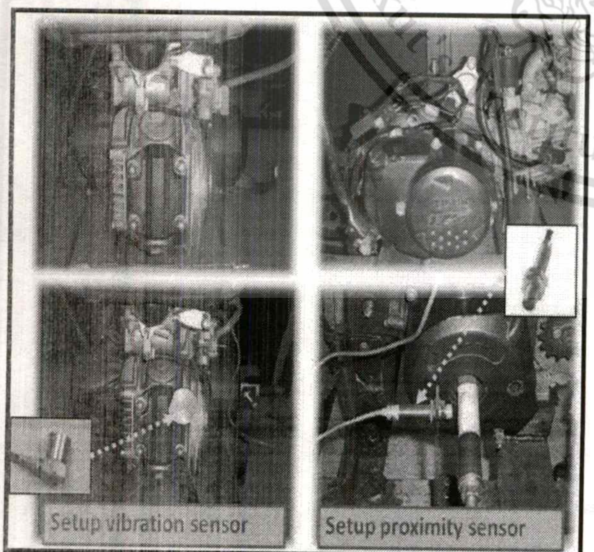

Figure3. A small four stroke petrol engine testing rig

A proximity sensor is attached to measure a one pulse per revolution from a shaft connected with the main crankshaft of the engine as shown in Figure 3. This crank angle signal gives two pulses every one engine cycle which is represented the piston position at top dead center (TDC) of intake and power strokes. All calculations were averaged over 2000 engine cycles

Typical main four strokes of the petrol engine are intake, compression, power and exhaust strokes as shown in Figure 4. The main mechanical events in the engine cycle are valve opening/closing events of intake and exhaust valves, respectively. For the intake stroke, Intake valve is approximately opened at 10-20 degrees before top dead center (BTDC) and closed at approximately 51-56 degrees after bottom dead center (ABDC). For the exhaust stroke, the open/close positions of exhaust valve occur at approximately 47-57 degrees BTDC and 15-21 degrees ABDC, respectively [12].

RESULT AND DISSCUSION

Typical time domain vibration signal is difficult to identify the engine processes such as valve operation and an ignition processes. The crank angle signal can help to eliminate the aforementioned problem. The vibration signal can be mapped onto a crank angle domain using a crank angle pulse given a pulse per revolution as shown in Figure 4. This signal was recorded at engine speed approximately 1500 rpm. Amplitude of vibration signal and crank angle location is shown on the vertical and horizontal axes, respectively. Crank angle at 0 degree represents piston position at TDC (Top Dead Center) of intake stroke. All four main strokes described in Figure 4 are intake, compression, power and exhaust strokes associated with crank angle at 0-180, 180-360, 360-540 and 540-720 degrees ATDC (After Top Dead Center), respectively. Valve operation events are the strongest event and can be shown in Figure5. IVO, IVC, EVO and EVC represent intake valve opening, intake valve closing, exhaust valve opening and exhaust valve closing event respectively. In order to obtain more information about the engine process of a petrol engine, the vibration signal is analysed using energy techniques.

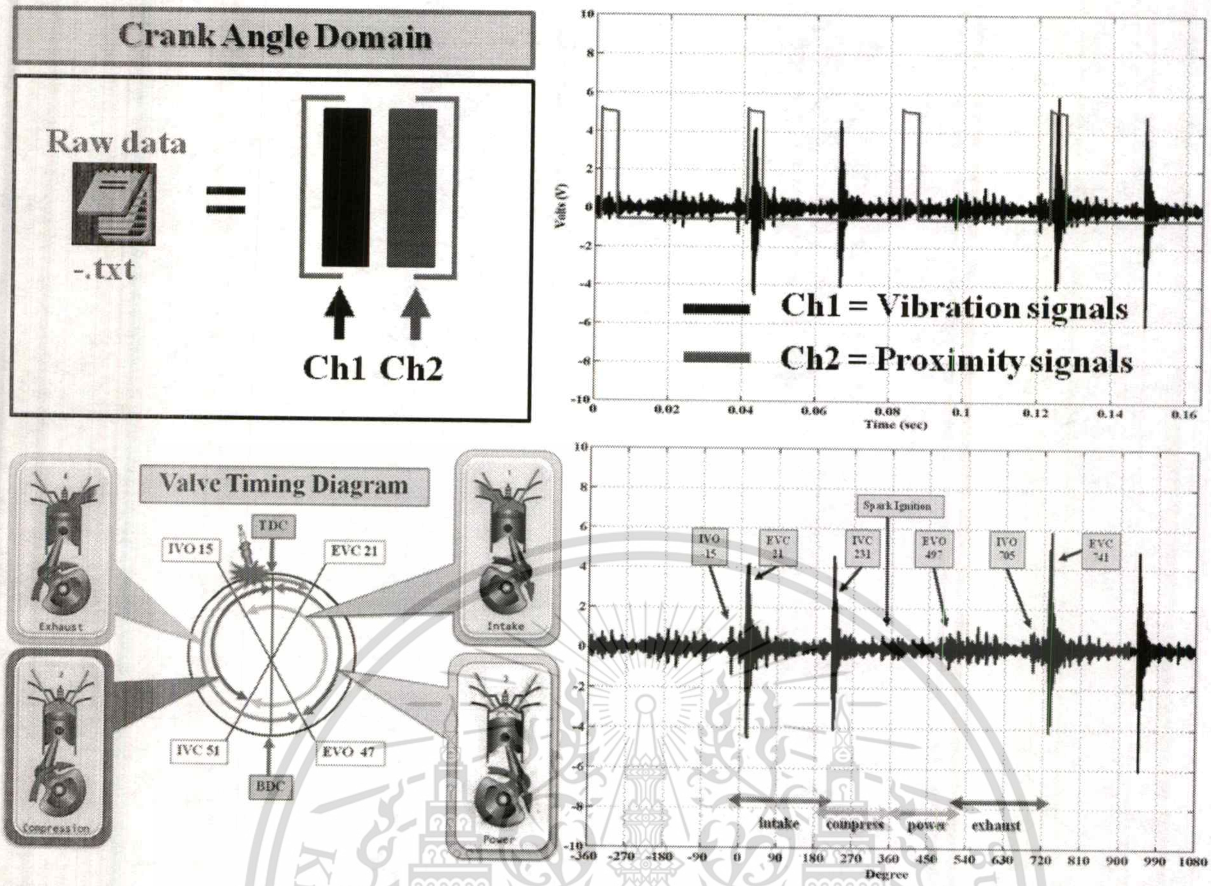

Figure 4 Typical valves timing diagram of a small four stroke petrol engine and a technique indices discrete data of time domain and converted to crank angle domain

The signal shown in figure 5 is calculated using equation (1). Energy of vibration signal is calculated every a crank angle degrees to cover the engine cycle. It can be seen that the vibration signal energy of each testing condition can be seen easier. The typical events shown in Figure 5 can be identify by comparing with valve timing of the testing engine which are IVO,IVC,EVO and EVC events. These valve events can be seen clearly at approximately 705, 231, 497 and 21 degrees ATDC.

For simulated fault tests of intake valve clearance fault conditions, typical IVO and IVC at normal condition occur at 705(-15) and 231 degrees ATDC, respectively as shown in Figure 5(A). When intake valve clearance is greater than normal stat 1.5 mm, The IVO event is delayed around 2-5 degrees and difficult to see as shown in Figure 5(A). However, the intake valve is early opened, when valve clearance is smaller than normal state. For IVC events, they occur at around 231 degrees ATDC and amplitude of signal is greater than other events. It can be include that only IVO event is affected by valve clearance and valve opening position of intake is delayed. For simulated fault test at exhaust valve clearance, EVC and EVO events occur proximately at 21 degrees and 497 degrees ATDC, respectively as shown in Figure 5(B). The EVC event for all test conditions occurs at the same location of 21 degrees ATDC. For EVO event it can be seen that when exhaust valve clearance is greater than normal conditions, EVO event is delayed. Amplitude of EVO event is difficult to identify when exhaust valve clearance is smaller than normal state.

The vibration signal of various condition of spark plug can be seen in Figure 5(C). The vibration signal are shown only ignition event at around 315-405 degrees ATDC. Typical spark plug clearance for this engine is approximately 0.8 mm. It can be seen that the spark ignition event is delay, when the spark plug clearance is increase. For the large clearance, the signal amplitude is small and difficult to identify from acquired signal. Typical spark ignition event is composed of spark ignition and combustion process which may not have enough energy to produce some detailed information in vibration signal.

From the aforementioned resulted result, it can be described about the behavior of an engine operation as seen in the vibration signals.

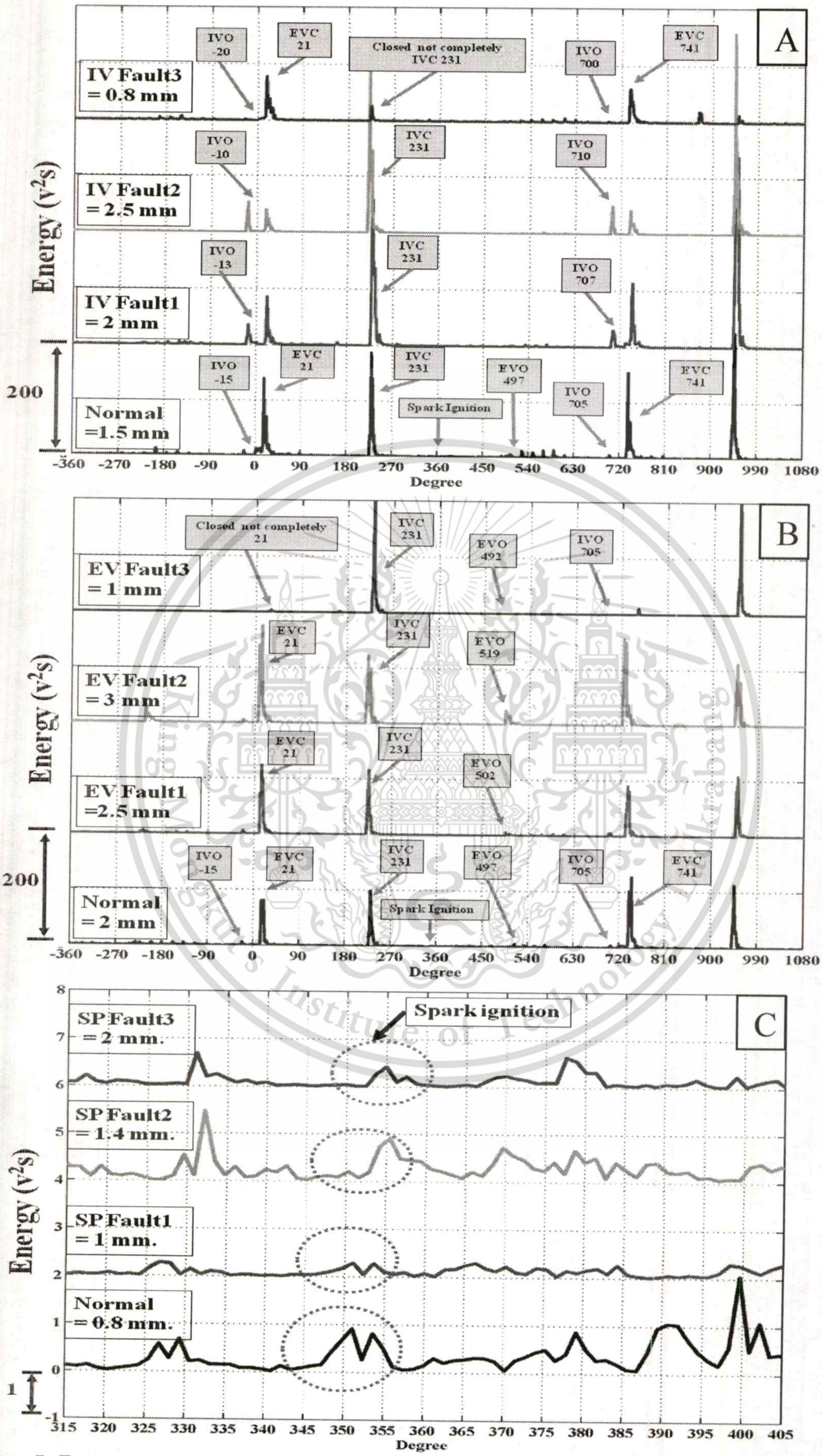

Figure 5. Energy per degree of vibration signal recorded from a petrol engine at 1500 RPM

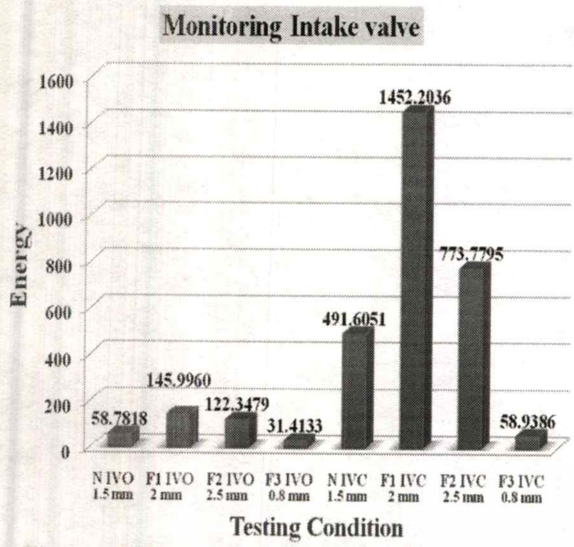

Figure 6 Energy of the IVO/IVC with various testing conditions

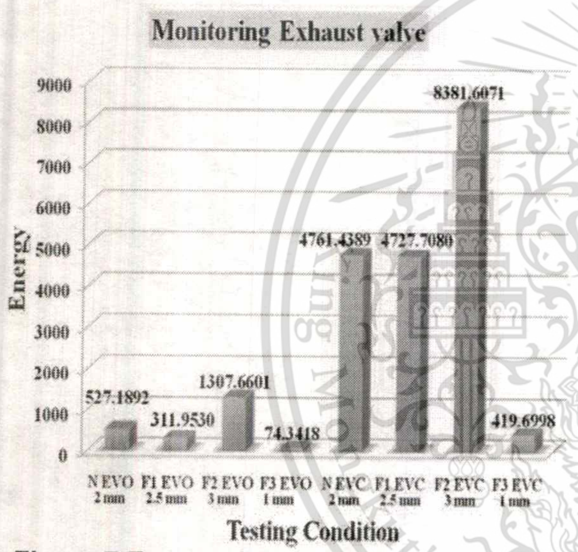

Figure 7 Energy of the EVO/EVC events with various testing condition

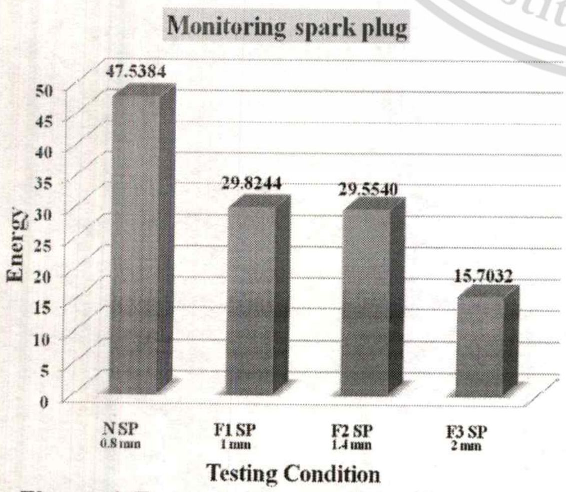

Figure 8 Energy of the spark ignition events with various testing conditions

All main events of engine operation can be seen on the crank angle domain using signal energy techniques to analyse by considering only the main component.

The statistical technique is used to describe the events to the engine operation to obtain information about the engine state. In this study, Energy signal is used to analyse signal shown in Figure 5. These signals are windowed only main events (i.e. IVO, TVC, EVO, EVC and SP) and the window size is approximately 90 degrees for each main events such as 0-90,180-270, 450-540, 630-720, and 315-405 degrees for IVO, IVC, EVO, EVC and SP events, respectively. Figure 6 shows the energy of IVO and IVC events of various test conditions N, F1, F2 and F3 is referred to normal, fault1, fault2 and fault3 with various valve clearance of 1.5,2,2.5 and 0.8 mm, respectively. From Figure 6, signal energy of NIVO, and NIVC event at normal condition are 58.7818 and 491.6051 and used as baseline values. It can be seen that when valve clearance is larger than normal condition, the signal energy of IVO and IVC events are greater than signal energy at normal condition. The signal energy of the IVC events is greater than the IVO events this is because of the impact of intake valve at the end of the intake stroke. Whereas the IVO events, impact of intake valve may not occur and only fluid flow activities may be presented in the vibration signal.

For the simulated test of exhaust valve clearance fault conditions as shown in Figure 7, it can be seen that the of signal energy is the same as discussed in the intake valve clearance condition. The signal energy of both EVO/EVC events is greater when exhaust valve clearance is bigger. At normal condition, valve clearance is 2 mm with signal energy of the EVC event (NEVC) about 4761.4389. When clearance is increase to 3 mm for valve clearance fault condition, the signal energy of the EVC event (F2 EVC) is increase to 8381.6071.

Figure 8 shows the signal energy of each testing condition of spark plug (SP) NSP, F1 SP, F2 SP and F3 SP represent normal, fault 1, fault2 and fault3 of spark plug conditions as described in experiment session. It can be seen that signal energy in Figure 8 can be used to identify spark plug fault condition. The signal energy is decrease when the spark plug gap is increase. However the energy of the SP event is smaller than the energy of the valve operation event because the spark ignition processes do not have enough energy to produce large amplitude of vibration signal as seen in valve operation processes.

CONCLUSION

It has been demonstrated through a range of experimental results that vibration technique shows a potential for investigating the behavior of a four strokes, petrol engine. Typical recorded vibration signals consist of both burst and continuous signals associated with mechanical and fluid flow processes in the engine cycle. The vibration signal can be used to map the main event (i.e. valve operation, combustion and spark ignition events) in the engine cycle. However, the knowledge of engine processes and signal processing techniques are necessary. The signal energy can be used to described the main events by windowing the vibration signal so the engine condition can be identify. The energy technique could be used to identify fault from acquired vibration signal of a running engine. For the future work, it is necessary to use more powerful techniques to improve a accuracy of an engine state monitoring.

ACKNOWLADGEMENT

The author gratefully thanks students of mechanical engineering department at Mahanakorn University of Technology for setting up the engine test rig and collecting some experimental data. The author would like to thank Asst. Prof. Ming Lokitsangtong and Dr. Pornchai Nivesrangsan for supervision, guidance, technical support, encouragement and friendship over the entire period of this study.

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Condition Monitoring of a Small Four Strokes Petrol Engine Using Statistical Covariance Parameter Analysis

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ABSTRACT

This paper studies condition monitoring method of a small four strokes, single cylinder petrol engine using vibration signal analysis based on time domain, crank angle domain and covariance of statistical parameter techniques. Acquired vibration signals on the cylinder head of the small petrol engine with capacity 125 CC can be used to study engine processes and abnormal conditions in the engine cycle such as intake/exhaust valve operations, ignition process etc. In this study vibration signals are used to study mechanical and fluid flow processes in the engine cycle of a small petrol engine. Vibration signals are applied to monitor abnormal conditions of rocker-arm intake/exhaust valves and spark plug.

Keywords: condition monitoring, vibration signals, fault condition, rocker-arm intake/exhaust valves and spark plug, statistical covariance parameter

INTRODUCTION

Condition monitoring technology for diesel engines has been developed in recent years. Diesel engine manufacturers and third-party vendors have developed techniques engine monitoring to determine and performance of diesel engines operation. A typical system is applied microprocessor based instrument and analysis software to monitor engine combustion characteristics, intake/exhaust valve operation, piston motion, cylinder, and liner conditions. Non-intrusive sensor measurement techniques (i.e. vibration measurement technique) provide information in time domain and frequency domain that information related engine processes can be described to identify existing or impending problem by detecting deviations from a normal or an achievable condition in the engine cycle [1-9]. A challenge of engine monitoring system used in industry has to face with a large amount of recorded data that acquired using commercial or in-house developed software. These data can be analyzed using exist signal processing techniques to reduce number of data and also to obtain some useful information to monitoring engine conditions. Ideally, a condition monitoring program should mature to integrate techniques to reduce data from all sources and channel than into a centralized system that produces information accessible to all levels of the preventive maintenance.

This paper has studied vibration analysis method for a condition monitoring of a small four strokes single cylinder with capacity 125 CC petrol engine using vibration signals. The physical aspect of combustion characteristics of a spark ignition engine are every crucial for an engine performance indicator and are covered in depth using actual vibration signals and proximity sensor to detect evolution of an engine running. The analysis technique and data reduction produced normalized measure that can be used to analyze engine states. In this research an engine monitoring techniques are interested by analysing vibration signals acquired on a small petrol engine. The vibration signals can be acquired using the LabVIEW program. The accelerometer is attached on a surface of cylinder block by a magnetic clamp. The signals are analyzed using time domain and crank domain techniques to determine various statistical parameters Vibration signals detected on the petrol engine are related to events associated with some mechanical and fluid flow processes in the engine cycle. These vibration signals can be mapped onto various processes associated with intake/exhaust valve operation, combustion and

spark ignition and will be described in this research.

SIGNAL PROCESSING

This section is described about the vibration analysis technique of a small four strokes petrol engine and involves the determination of the presence and absence of expected events associated with the engine processes which occurs at measurable amplitude at a specific time. The abnormal events associated with mechanical process and the maintenance history of the engine operation can be predicted from vibration signal using engine knowledge then, abnormal condition of engine can be isolated. Anomalies in the signal pattern can be detected by comparison with a baseline normal condition pattern. Signal analysis techniques used in this study are based on time domain and crank angle domain. These techniques are used to describe some statistical parameters such as, mean, variance, skewness and kurtosis. This research is introduced the method for a signal separation that used for fault classification. For the propose techniques, the signal is separated using covariance parameter of a random process [17-18].

Estimating the probability density

A theorem called the "law of large numbers" states that the probability for a random variable X an interval Δ can be approximated, If N is large enough, Then: (1) consider N independent random variables with the same probability distribution as X; an experiment is conducted, leading to the trials $x_1,...,x_N$,(2) the number n of values in these trials that belong to Δ is determined, (3) the approximation used for $\Pr(X \in \Delta)$ is n/N ;The quantity n/N is called the empirical frequency. This result can be used to estimate the probability density of $p_X(x)$ at the point x of the random variable X which is assumed to be continuous. By definition, we have:

$$\Pr(X \in \Delta) = \int_{\Delta} p_X(u)du \qquad (1)$$

Where Pr is the probability for the random variable X that belongs to the interval Δ, If Δ is a closed interval that small enough around the point x, we have $p_X(u) \approx p_X(x)$ and the second member is approximately equal to $p_X(x) \times l$, where l refers to the length of Δ. This leads us to a practical formula for estimating

$$p_X(x) \approx \frac{n}{Nl} \qquad (2)$$

Where n is the number of observed point inside the closed interval Δ and N is a number of samples.

Gaussian random vectors

Gaussian vector: $\{X_1,...,X_N\}$ are said to be n jointly Gaussian variables or the length n vector $[X_1,...,X_N]^T$ is Gaussian. If any linear combination of its components, $Y = a^T X$ for any $a=[a_1,...,a_n]^T$ is a Gaussian random variable. Probability distribution of a Gaussian vector can be shown that probability distribution of a length n Gaussian vector, with a length n mean vector **m** and a $(n \times n)$ covariance matrix, **C** has the characteristics function:

$$\phi_X(u_1,...,u_n) = \exp\left(jm^T u - \frac{1}{2}u^T Cu\right) \qquad (3)$$

Where $u=(u_1,\ldots,u_n)^T \in R^n$, u is any point of a random variable X_k, Let $x=(x_1,\ldots,x_n)^T$
If $\det(C)\neq 0$, C is covariance matrix, *the probability distribution's density has the expression.*

$$p_X(x_1,\ldots,x_n)=\frac{1}{(2\pi)^{n/2}\sqrt{\det(C)}}\exp\left(-\frac{1}{2}(x-m)^T C^{-1}(x-m)\right) \qquad (4)$$

For Gaussian case (non-correlation or independence) *if n jointly Gaussian variables are uncorrelated*, then they are independent. This is because if we replace $C=\sigma^2 I$ in expression equation (4), $p_X(x_1,\ldots,x_n)=p_{X1}(x_1),\ldots,p_{X2}(x_2)$ According to independent random variables , the variable are independent. Linear transformation of a Gaussian vector; Let $[X_1,\ldots,X_n]^T$ be a Gaussian vector with a mean vector m_X and a covariance matrix C_X the random vector $Y=AX+b$, where A and B are a matrix and vector respectively, with the ad hoc length is Gaussian and we have; $m_Y=Am_X+b$ and $C_Y=AC_XA^T$ in other words, the Gaussian nature of a vector untouched by linear transformations.

All of these equations are used for signal processing and using fault detection. The result can be described about the main events of the running engine at each evolution of normal speed.

EXPERIMENT

A small single cylinder, four strokes petrol engine, Tiger brand, with capacity 125 CC is used and run at speed of 1500 rpm with various conditions such as Intake/Exhaust valve clearance fault and spark plug clearance fault conditions as shown in Figure 1. All fault conditions were simulated on the engine as follows

(1). Simulated fault at the Intake valve with various Intake valve (IV) clearance fault condition, IV Fault1 = 0.08 inch, IV Fault2 = 0.1 inch and IV Fault3 = 0.03 inch. Typical Intake valve clearance of this engine is 0.06 inch.

(2). Simulated fault at the Exhaust valve with various exhaust valve (EV) clearance fault condition, EV Fault1 = 0.1 inch, EV fault2 = 0.12 inch and EV fault3 = 0.04 inch. Typical exhaust valve of this engine is 0.08 inch.

(3) Simulated fault at spark plug (SP) with various clearance conditions, SP Fault1 = 1 mm (0.039 inch), SP Fault2 = 1.4 mm (0.055 inch) and SP Fault3 = 2 mm (0.079 inch).

Vibration signal and Crank angle signal are acquired from accelerometer and proximity sensor, respectively using LabVIEW Program.

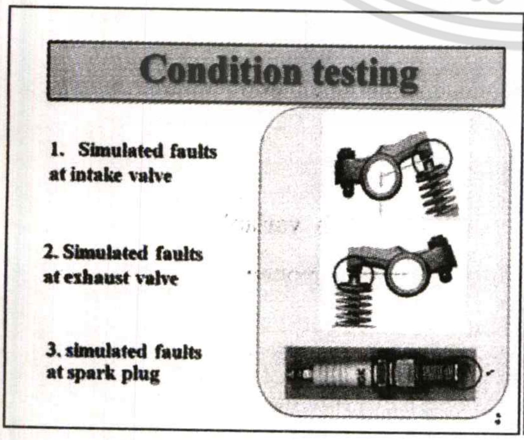


Figure 1. Condition testing

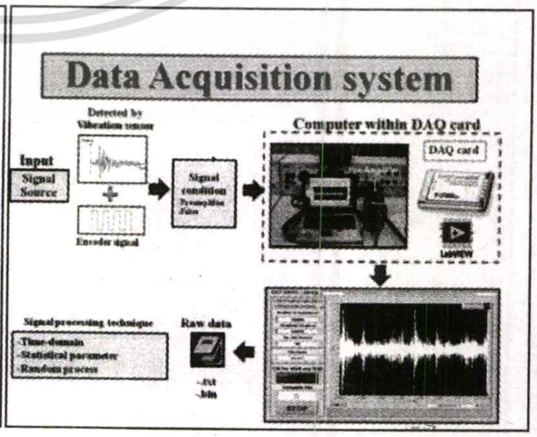
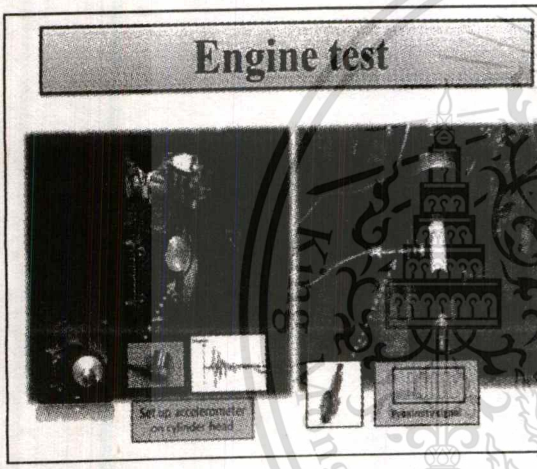


Figure2. A schematic diagram of data acquisition system

A schematic diagram of data acquisition (DAQ) system for monitoring the small four strokes, single cylinder, and petrol engine is described in Figure 2. This system consists of an accelerometer with a charge amplifier, a crank angle sensor, a terminal block, and a DAQ card with in-house developed LabVIEW software installed in a notebook computer. In this study, National Instruments (NI) DAQ card, 12-bit, PCMCIA-6024E was used to acquire and digitize both vibration and crank angle signals. Both signals were records with sampling frequency of 100 kHz and saved into files for later analysis. Vibration signal is measured using accelerometer attached on the cylinder head stud of the small petrol engine as shown in Figure 3. An in-house designed aluminum clamp is used to hold Bruel & Kjaer accelerometer, Model 4371 at the same axis of the engine piston. A proximity sensor is attached to measure a one pulse per revolution from a shaft connected with the main gear of the engine as shown in Figure 3. This crank angle signal gives two pulses every one engine cycle which is represented the piston position at top dead center (TDC) of intake and power strokes. All calculations associated with timing of mechanical processes were averaged over 2000 engine cycles.



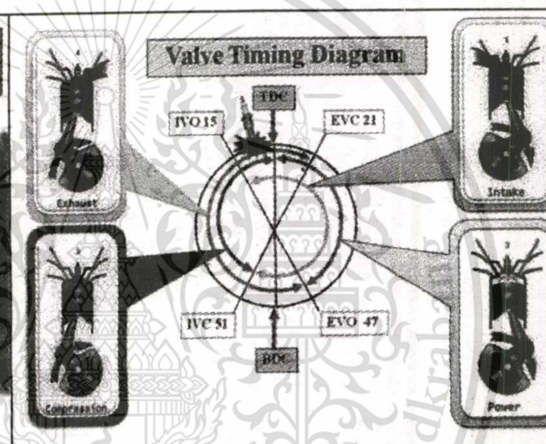


Figure 3. A small four stroke petrol engine testing rig

Figure 4. Typical valve timing diagram of a small four stroke petrol engine

Typical main four strokes of the petrol engine are intake, compression, power and exhaust strokes as shown in Figure 4. The main mechanical events in the engine cycle are valve opening/closing events of intake and exhaust valves associated with intake and exhaust strokes respectively. For the intake stroke, intake valve is approximately opened at 10-20 degrees before top dead center (BTDC) and closed at approximately 51-56 degrees after bottom dead center (ABDC). For the exhaust stroke, the open/closed positions of exhaust valve occur at approximately 47-57 degrees (BTDC) and 15-21 degrees (ABDC) respectively [12].

RESULT AND DISSCUSION

Typical time domain vibration signal is difficult to identify the engine process such as valve operation and an ignition processes. The crank angle signal can help to eliminate the aforementioned problem. The vibration signal can be mapped onto a crank angle domain using a crank angle pulse given a pulse per revolution as shown in Figure 5. This signal was recorded at engine speed of 1500 rpm. Amplitude of vibration signal and crank angle location is shown on the vertical and horizontal axes, respectively. Crank angle at 0 degree represents piston position at TDC (Top Dead Center) of intake stroke. All four main strokes described in Figure 4 are intake, compression, power and exhaust strokes associated with crank angle at 0-180, 180-360, 360-540 and 540-720 degrees ATDC (After Top Dead Center), respectively. Valve operation events are the strongest event and can be shown in figure5 IVO, IVC, EVO and EVC represent intake valve opening, intake valve closing, exhaust valve opening and exhaust valve closing event respectively. However, the valve timing is the strongest signal which composed of ignition and combustion processes.

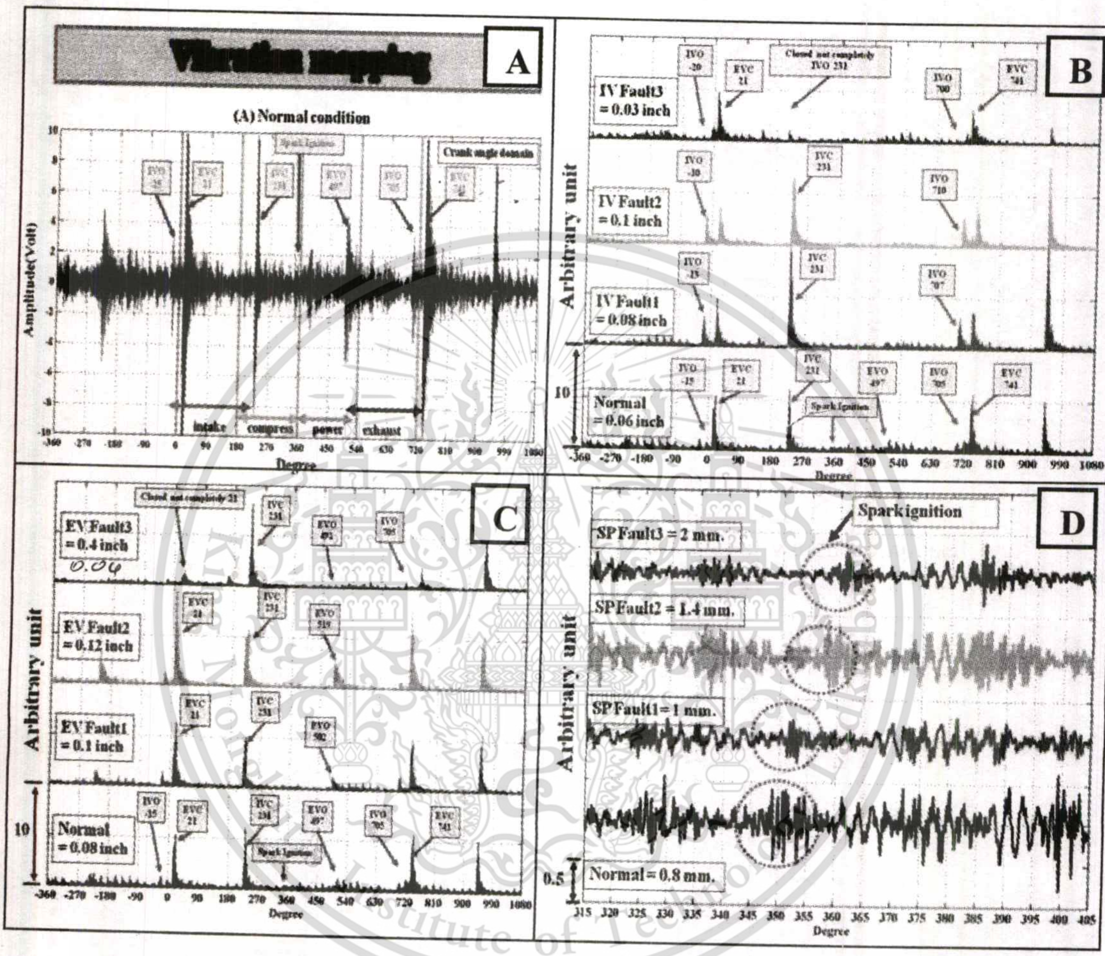


Figure 5. Vibration recorded from a small four stroke petrol engine at 1500 rpm normal evolution

The vibration signals shown in figure 5 can help to understand about the engine process of the small four stokes engine and can be used to identify abnormal condition from a running engine. Typical condition signal acquired from the engine at normal condition is shown in figure5(A) Main valve operation events such as IVO,IVC,EVO and EVC can be seen clearly at around 705 231 497 and 21 degrees ATDC. Spark ignition event occurs approximately 345-355 degrees ATDC as shown in figure 5(D) that event is unclear with a small signal amplitude.

For simulated fault of intake valve clearance, typical IVO and IVC at normal condition occur at 705(-15) and 231degrees ATDC respectively as shown in figure 5(B) When intake valve clearance is greater than normal state of 0.06 inch, The IVO event is delayed around 2-5 degrees. The IVO and IVC events are difficult to see as shown in figure5 (B).However the intake valve is early opened when valve clearance is smaller than normal state.

For simulated fault of exhaust valve clearance, typical EVC and EVO event occur proximately at 21 degree and 497 degree ATDC respectively as shown in figure 5(C). The EVC event for all test conditions occurs at the same location of 21 degrees ATDC. The more exhaust valve clearance is, the larger signal amplitude of EVC event can be seen in the vibration signal. For EVO event, it can be seen that when exhaust valve clearance is greater than normal condition; EVO event is delayed and amplitude of this event can be seen clearer and this difficult to identify EVO event when exhaust valve clearance is smaller than normal state.

The vibration signal of various condition of spark plug can be seen in figure5 (D). The vibration signal are shown only ignition event at around 315-405 degrees ATDC. Typical spark plug clearance for this engine is approximately 0.8 mm (0.031 inch). It can be seen that the spark ignition event is delay when the spark plug clearance is increase. For the large clearance the signal amplitude is small and difficult to identify from acquired signal. Typical spark ignition event compose of spark ignition and combustion processes. For the large clearance, the signal amplitude is small and difficult indentify because the spark ignition and combustion processes may not have enough energy to produce activities in combustion chamber.

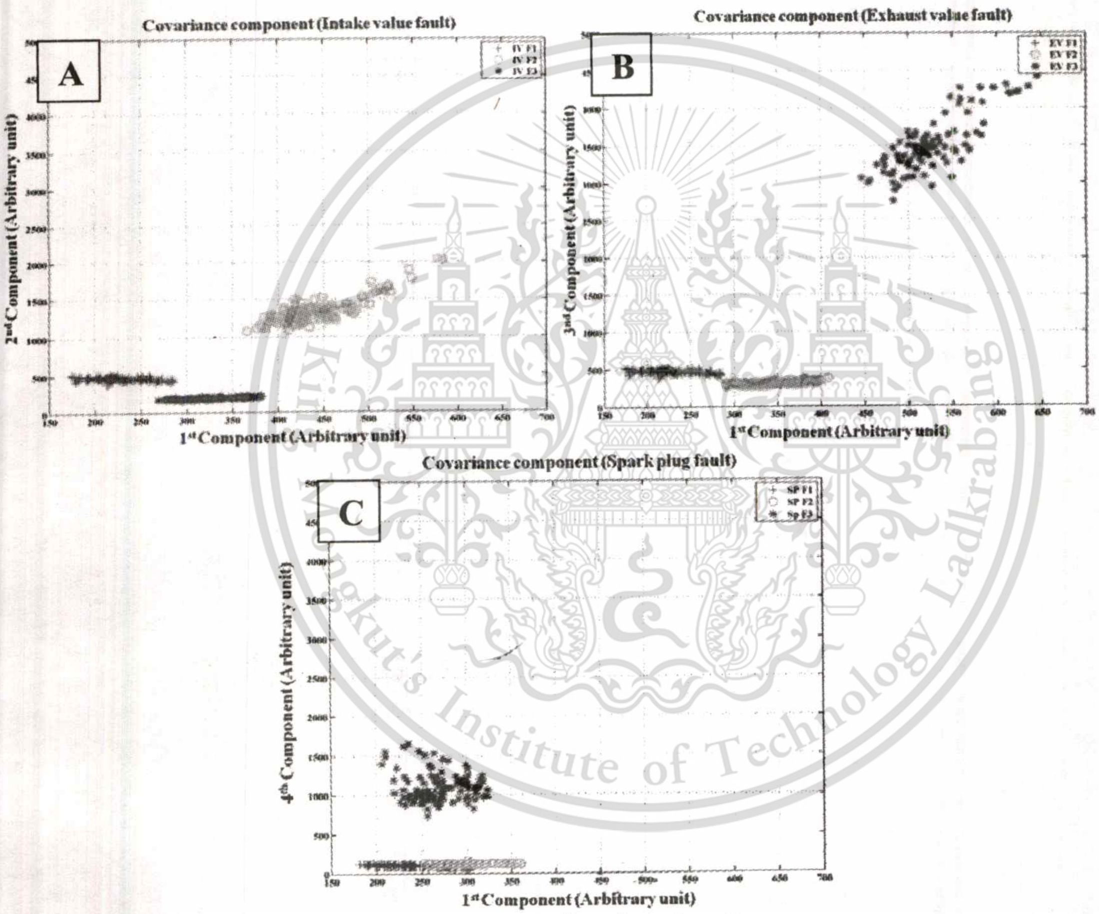


Figure 6. Covariance component of vibration signals

Figure 6, shows the experimental result about a statistical parameter using covariance parameter analysis technique as seen in equation (4). This technique can be used to separate a group of data that have statistical parameters for abnormal conditions. The covariance method base on PCA is applied to decide and select fault signals. Figure 6 (A), 2nd component of the intake valve fault condition can be separated from 1st component of the statistical parameter of normal condition. For Figure 6 (B), the 3rd component is a statistical parameter of the exhaust valve fault condition that for separated fault condition using the 1st component. The 4th

component is a statistical parameter of the spark plug fault condition as shown in figure 6(C) that can be separated fault condition using the 1st component. From Figure 6, it can be seen that all fault conditions of each can be separated using covariance components. The covariance component of each fault is shown as a group of result so that it is possible to identity each fault.

CONCLUSION

It has been demonstrated through a range of experimental results that vibration technique shows a promise technique for investigating of the behavior of a four strokes petrol engine. Typical recorded vibration signals consisted of both brush and continuous signals which associated with mechanical and fluid flow processes in the engine cycle. The vibration signal can be used to separate the engine states however the knowledge of engine processes and signal processing techniques and necessary the principle component analysis base on the covariance parameter could be used to separate the engine state without the knowledge of the engine processing. For the future work, it is necessary to use more abnormal techniques to improve accuracy of engine state monitoring.

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