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To cite this article: A A Azrin *et al* 2021 *IOP Conf. Ser.: Mater. Sci. Eng.* **1092** 012030

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An overview of the spark plug engine profile in a spark ignition engine

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Abstract. The main concern regarding on the spark plug usage is their ignition efficiency and lifetime capabilities. This article reviews on the spark plug engine profile in a spark ignition. An intelligent practical approach needs to be developed to be the indicator to know when the spark plug should be changed. Due to its promising effect on the spark ignition engine, the study of spark plugs profile is increasing day by day. For safety, mechanical vibration of a vehicle is a very important phenomenon. Moreover, it specifically affects passenger comfort in some applications. Due to the effects on vehicle structure components and passenger comfort as well as safety, the mechanical vibration through the spark ignition engine has acquired great significance. However, there are many problems in researching existing running engines with a spark ignition system, such as slower ignition, increased cyclic variance and possible misfire. The higher spark energy will improve the ignitibility, but due to electrode corrosion, the life of the spark plug will decrease, and electrodes serve as a sink of thermal energy that will affect the spark plug's health. For instance, the conditions such as the spark plug gap, the plug thickness and the carbon dissipated on the spark plug that influences the output of a spark ignition, are highlighted in this article.

1. Introduction

In automotive industry, vibration is one of the major issues that has always been highlighted as a concern of engine developers. This is because vibration has a huge influence on the driving comfort of the passengers. Passenger comfort will be significantly increased when the undesired vibrations is attenuated. The vibration of a vehicle can be generated from various factors such as broken motor mount, faulty adjusted fuel intake system, faulty timing belt, lose or disconnected hoses and etc. When a vibration problem is not



solved, it will lead to more serious issues that will result in a breakdown of a vehicle. Engine vibration of vehicles commonly caused by worn out or faulty sparkplugs. Dirty sparkplugs (or worn out) will cause the engine vehicle to misfire or else not properly fire which causes the excitation of forces originated from the engine. This can be revised by replacing new sparkplugs or other spark correction or compression improvement.

Engine is considered as the core part in of vehicle, involves many complex mechanisms that provide power to the drive. The importance of spark ignition engine and their useful life has proved that its maintenance and fault diagnosis are vital [1]. Monitoring of engine condition is an effective method of preventing a vehicle from breaking down. Among the many parts of spark ignition engine such as engine block, pistons, crankshaft and etc., ignition system plays a significant role in an engine. An ignition system requires spark plug to deliver the current to the combustion chamber of a spark ignition from an ignition system to ignite the mixture of compressed air-fuel.

2. Literature review

2.1. *Effects of spark plug on spark ignition engine*

The spark plug effects on spark ignition engine has been extensively studied. For an optimal engine efficiency and performance, the spark plugs of your engine should be in a clean condition without destroying the electrodes [2]. In a comprehensive literature review of spark plug effects on spark ignition engine, Patane et. al found that when spark plugs get fouled, it will change how the engine runs. A foul or bad spark plug is coated with a material like tar, gasoline or carbon, or one that is blistered from running too hot [3]. D. Jung et. al reported that driving with foul or poor spark plugs will cause problems for the car which may lead to engine breakdown [4]. Symptoms with poor spark plugs can include:

- a) Engine misfires
- b) Knocking
- c) Hard starts
- d) Reduced gas mileage

Besides fouled spark plugs, the increasement of the spark plug gap contributes to common faults of spark ignition (SI) engines that causes the deterioration in engine performance. For example, the phenomenon such as misfire and knock causes by pre-ignition from the spark plug gap fault that lead to postponed between two electrodes. The spark plug gap increment growth result in requires higher ignition voltages. Unfortunately, the high ignition voltage may harm the electrical system of the engine. Generally speaking, this fault in SI engines can be considered as a major electrical device flaw [5], [6].

2.2. *Vibration signal monitoring*

In the past years, many researchers have studies and investigated on the fault recognition of spark plug in SI engine. In the research on spark plug fault recognition, many methods have been implemented. The research by Antoni et al. has suggested an approach using vibration analysis of internal combustion engine [7]. Vibration analysis is commonly used for monitoring the condition of spark ignition engine [8]. Interpreting a complex vibration signal is a dynamic procedure involving advanced preparation and practise. To further investigate the role of vibration signal in engine condition monitoring, S. B. Devasenapati et. al converted the acquired analog vibration signals to digital signals using an analogue-to-digital converter [9] and discrete data files are then processed on the device for further processing [10].

By drawing on an extensive range of sources, M. Khazae et. al make use of vibration signal data for engine condition monitoring. The vibration signal is first received by sensor then transmitted from time

domain to time-frequency domain. The author achieved 98% classifier accuracy which can be identified as a high potential method for industrial application [11]. Other authors [12]–[14] question the usefulness of such an approach.

A novel method to vibration monitoring of internal combustion engine by cyclo method has been presented in their study. They assessed the combustion process from vibration measurements and demonstrates how the exploitation of cyclostationarity obviates several related difficulties. Considering all of the evidence they obtained, they found out that the solution to spark plug fault diagnosis lies in by passing the classical hypothesis of stationarity or quasi-stationarity by explicitly modelling the type of non-stationarity involved achieved through the paradigm of cyclostationarity. Similarly, using this method, they established a fault diagnosis for a four-stroke compression ignition engine [15].

Meantime, Wang et al. found a method to diagnose a diesel engine fault using an adaptive wavelet packet which involved vibration signals [16]. Fuel injection faults have been determined in this study by ensemble empirical mode decomposition (EEMD) and correlation dimension (CD) approaches. The lead of the combination of EEMD and CD is that classifiers are not needed to identify the types of diesel engine fault. This method has overcome the challenges of detecting fault states when more fractal dimensions occurred too close to each other.

2.3. Ignition signal monitoring

On the other hand, Vong et al. used introduced a method called Fuzzy and Probabilistic Simultaneous-Fault Diagnosis (FPSD) to identify some failures automotive engine [17]. This new FPSD integrates fuzzification, decision-by-threshold and pairwise probabilistic multi-label sorting. This method is particularly useful that the important and hard task of engine simultaneous-fault-diagnosis are effectively resolved based on qualitative symptom identification. Another advantage of FPSD is feasible and inexpensive.

2.4. Feature extraction and feature selection

The signals recorded from the spark plug contain a large amount of number of data points and could not be used as classifier inputs, as high-dimensional data increases computational complexity, making it very difficult for the classifier to train [18], [19]. Any statistical features should be added to reduce dimensionality of the data. In the present analysis, the de-noised acoustic and vibration signals were implemented with seventeen features. It should be noted that after testing different signal processing methods such as discrete wave-let transformation (DWT), it was found that highest accuracy of recognition was achieved by applying these features to the time-domain de-noised signals, as also stated in [20]. It is known that these features can be used to diagnose all mechanical components for fault, and do not belong to a particular system. Sakthivel et al. [8], for example, used some of the features for mono-block centrifugal pump fault diagnostics. In another study, Widodo et al. used a variety of features for fault diagnosis of low-speed bearing [21]. Some of these features were used by Ebrahimi and Mollazade [10], Khazaee et al. [22] and [23] to diagnose tractor starter motor and planetary gearbox failures, respectively. In a petrol engine, Devasenapati et al. [9] used a variety of features to define misfire. A strong and effective classifier should have the following characteristics:

- a) It should have good ‘predictive accuracy’; it is the ability of the model to correctly predict the data.
- b) It should have good speed.
- c) The computational cost involved in generating and using the model should be as low as possible.
- d) The level of understanding and insight that is provided by classification model should be high enough.
- e) It should be ‘robust’; robustness is the ability of the model to make correct predictions given the noisy data or data with missing values. (Insensitive to noise in the data.)

2.5. Classification method

2.6.1. Dempster-Shafer (D-S) evidence theory

D–S evidence theory is one of the most powerful tools for fusing classifiers. This theory was inspiration of many studies in fusion of noisy and uncertain data to reach the best results. D–S theory was developed by Shafer in 1976 for completing the Dempster's theories in possibilities [24]. Let define $X = \{h_1, h_2, \dots, h_k\}$ which X is a finite set of possible hypotheses. This set is referred to the frame of discernment or the power set. The Basic Probability Assignment function is the most important function in the evidence theory which is known by m or BPA. This function assigns a value in $[0, 1]$ to set A where the BPA of null set is 0. BPA function is defined as follows [25]. In 2001, C. Parikh et. al conducted a case study based on D-S evidence theory on condition monitoring application of diesel engine cooling system [26]. The studies by Basir and Yuan applied data fusion technique to diagnose an internal combustion (IC) engine for fault [27]. Using D–S theory, they collected data from four different sensors and attached the data obtained. They noted that the simultaneous use of multiple sources of information and also the D–S theory as a device for modelling and fusing multi-sensory pieces of validation that will significantly improve the accuracy of fault detection increasing the engine quality.

2.6.2. Least square support vector machine (LS-SVM)

Support vector machine (SVM) is a well-known and popular method in classification and regression applications. In the past decade, SVM has successfully been applied in pattern recognition problems such as machine fault diagnosis, speech verification, text detection, and prediction. SVM is based on structural risk minimization (SRM) which minimizes the upper bound of the generalization error. Hence, SVM is claimed to have good generalization capability for classification purposes [31].

2.6.3. Artificial Neural Network (ANN)

ANN is one of the most frequently used methods of artificial intelligence in pattern recognition, fault detection, data classification, etc. In decision making and recognition they are designed to imitate humans. ANNs may identify the associated patterns between the collection of input data and the respective target values. ANNs are useful for knowing the rotary machines' certain status or state of service. In her study of investigating an intelligent filter for bearing fault diagnosis, Zarei et. al [32] spotted bearing defects of induction motors by using ANN. He found that the vibration signal with filtered component gave better fault classification result.

There are several different ANN types at the moment. There may be variations in topology, functions, hybrid models, agreed values, learning algorithms, etc. However, the back-spread algorithm is one of the most common ANN models in which the network receives inputs from neurons in the input layer, and the output of the network is supplied by the neurons on the output layer. The difference between real and predicted outcomes is then calculated (error). Finally, the back-propagation algorithm eliminates this error so that the ANN knows the training data set [33]. The most important layer in ANN design is hidden layer that should be defined by trial and error [34]. The number of hidden layer neurons can be determined by iterative or random selection.

The maintenance of IC engines is vital to ensure its life cycle sustainability. Hence, they are crucial for monitoring its condition from time to time and for identifying its fault diagnosis. Vibration and acoustics, among various methods of condition monitoring. Both methods are common and necessary in practical applications analyses techniques. These techniques are usable effectively and reliable in engine control. As most failures may affect and alter engine sound and vibration behaviours. A considerable amount of literature has been published on fault diagnosis and engine condition monitoring by employment of the acoustics and vibrations analyses [6], [32], [35]. The defect of bearing type could be determined by vibration

measurement analyses as well as engine fault diagnosis. Table 1. shows the objectives, method used and results obtained by literature that studied fault diagnosis in engine.

Table 1. Engine technical review on fault diagnosis.

Objective	Method	Findings	Reference
Develop methods for spark plug fault recognition	-Implement of acoustic and vibration signal using combination of classifier and sensor fusion. -Wavelet de-noising to remove noise signal -ANN/LS-SVM to classify -D-S evidence to improve accuracy	-The performance of spark plug fault detection method has improved -The usage of vibration and sound signals has improved the engine condition monitoring diagnosis system	[1]
Study effect of energy supply procedure, electrode size, spark channel radius and gap on minimum ignition engine (MIE)	-kinetics of chemical -electrode heat loss	-The hydrogen-air mixture content influenced by energy supply procedure	[5]
Examine combine load and vibration-based fault diagnosis to obtain monitoring system of a bearing	Fusion accelerometer and a load cell	-Load cell is useful for ball bearing health detection -Accelerometer is useful for location of fault detection	[6]
Analysing vibration signal for engine condition monitoring	-Assessing from vibration measurements -Demonstrates the exploitation of cyclostationarity	The solution by passing the standard guess of stationarity or quasi-stationarity by modelling the type of non-stationarity involved	[7]
Using decision tree for fault recognition of centrifugal pump	-Extraction and classification of features with decision tree algorithm	-fault affects the performance of the pump adversely	[8]
Identifying misfire in a four-stroke engine	-Piezoelectric accelerometer	-Accuracy decreased at elevated speeds.	[9]
Classifying fault and vibration monitoring	-Adaptive Neuro-Fuzzy Inference System	-Adaptive neuro-fuzzy inference systems found in various industrial and commercial applications	[10]
Combined classification of acoustic and vibration signals for fault diagnosis using Dempster-Shafer evidence theory	- Dempster-Shafer evidence theory	-High accuracy (98%) and the safety range	[11]
Diagnosis vibration using Neural Network and Wavelet Analysis	-Reduce background noise with The Wavelet Noise Reduction - Obtain useful characteristic vectors using Wavelet Decomposition	-Methods applied into the inlet and exhaust system of diesel engine	[12]
Induction motor fault recognition using current and vibration signals	-Dempster-Shafer theory	-Achieving reliable classifiers requires good feature extraction and selection techniques	[14]
Investigate the combustion process (cylinder pressure trace) as indicator to engine condition monitoring	-Reconstruction of the pressure trace -Deconvolution by make the inverse filter robust by cyclostationary process	Optimal inverse filter is periodically varying for the pressure trace under 3 conditions: (i) cyclostationary noise, (ii) variability of random structure, and (iii) variation of periodic input-output	[15]

		between pressure trace and vibration signature	
Application of several techniques for reciprocating diesel engine	-Using vibration signals -Fault detection and feature extraction by adaption of (a) WPT de-noising (b) CD (c) EEMD	-The techniques can extract impact signal from vibration -The type of fault can be identified even in high impact of unrelated vibration	[16]
Improvement of engine fault detection by simultaneous-fault diagnosis	-FPSD	Framework of FPSD resolves engine simultaneous-fault diagnostics	[17]
Fault diagnosis model of gear using EMD and multi-class TSVM	- EMD -TSVM	-Testing accuracy in multi-class TSVM is higher than multi-class SVM	[18]
Fault diagnosis of bearing	-Adaptive neuro-fuzzy inference -Multi-scale entropy	-High accuracy of fault categories classification and identification of fault severities	[19]
Multi-fault classification of bearing rolling element	- SVM) -discrete Meyer wavelet	- 100% accuracy	[20]
Fault diagnosis of low speed bearing	-RVM -SVM	- RVM is a reliable technique in low speed bearings fault diagnosis	[21]
Selecting features and fault diagnostics of roller bearing	-PSVM	-PSVM learn faster	[23]
Condition monitoring	-D-S theory	-predictive rates prevented mass assignment problem	[26]
Implementing multi-sensors data fusion to explore the engine fault diagnosis system	-2 methods of mass function calculation -Modified mass function	Data fusing from multi-sensors significantly improved fault diagnosis accuracy	[27]
Tuning least squares support vector machines on chaotic differential evolution	-LS-SVMs simulations on NARX (Nonlinear Auto Regressive with exogenous inputs)	-Optimal parameters are selected to establish efficient LS-SVM	[28]
Machine condition monitoring and fault diagnosis	- SVM	-Until 2006, used method develops towards problem-oriented domain and expertise orientation	[31]
Investigate filter for bearing fault diagnosis	-Artificial neural networks (ANNs). -RNFC filter	-Better classification of vibration signal with filtered component obtained	[32]
Comparing classification method for fault diagnosis	-PSD -KNN -ANN	-Used methods are effective in main engine fault diagnostics and an on-line condition monitoring	[33]

Develop a robust filtering algorithm in the natural environment of an auto workshop	- SVM	-Morlet wavelet is best wavelet to describe burst of acoustic signal	[35]
Investigate the normal combustion and knocking concepts in a SI engine	-2D digital imaging -Chemiluminescence visual techniques -UV to visible spectroscopy -Natural flame emission imaging	During knocking, ignition surface, end-gas temperature and pressure has increased	[36]
Fault diagnosis of induction machine	-W-SVM	-Used methods are effective only when being diagnosed running at constant speed and almost fully loaded (Douglas & Pillay, 2005).	[37]
Fault diagnosis rotating machinery using SVMs ensemble and improved wavelet package transform	- IWPT - SVM	-signal of 4096 samples, around three times faster computational time of IWPT (0.2500s) than traditional WPT (0.7420s)	[38]
Reviewing methods for binary classifiers	-binarization ensemble techniques	-great potential for industrial applications	[39]
Predicting coal terrain	-D-S theory -ANN	-coal seam terrain is predicted highly precise	[40]

3. Conclusion

This article was undertaken to review researches made on the spark plug engine profile in spark ignition engine. The spark plugs in this study had been tested at different chamber pressure, electrode gap, and filling size. From the data observation results between the theoretical part and experimental part, the experimental part indicates a relevant data that coincide with the theoretical part.

For the study of spark plug engine profile against the pressure, showed that increase of the pressure inside the chamber that will lead to decrease of the breakdown voltage, however as the breakdown voltage increased in pressure, it was recorded that the breakdown voltage started to increase. In comparison with the theoretical results, it can be said that the experimental results obeyed the theoretical graph despite the poles of the measuring device being switched causing the negation of the results. The standard deviation all of the tested condition varied at different pressure yield lower than 1 standard deviation from the mean.

For the case of spark plug engine profile against the spark plug electrode width it can be concluded that as the electrode gap reduces, the breakdown voltage increases linearly. The relevance of the findings can be supported by the previous finding that indicated the similar phenomenon. In the same time, it was also noted that with the decreasing of the electrode gap, here is an increase in the standard deviation of breakdown voltage. This results maybe owe to uneven filing on the sides of the electrode causing slight differences in the distance a spark must travel to reach the electrode during consecutive firing.

Acknowledgement

The authors would like to express their gratitude to the sponsorship by Universiti Malaysia Pahang under research university grants RDU1903101 and RDU191104.

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