Jurnal Kejuruteraan 31(2) 2019: 287-294
https://doi.org/10.17576/jkukm-2019-31(2)-13

Pattern Recognition for HEV Engine Diagnostic using an Improved Statistical Analysis

(Pengiktirafan Corak untuk Diagnosis Enjin HEV menggunakan Analisis Statistik yang Telah Ditambahbaik)

Nor Azizi Ngatiman* & Mohd. Zaki Nuawi
Faculty of Engineering and Built Environment, Universiti Kebangsaan Malaysia, Bangi, Selangor, Malaysia
Mohd Irman Ramli
Faculty of Mechanical and Manufacturing Engineering Technology, Universiti Teknikal Malaysia Melaka, Durian Tunggal, Melaka, Malaysia
**Corresponding author: azazi@utem.edu.my*

Received 18 October 2018, Received in revised form 6 March 2019
Accepted 17 July 2019, Available online 31 October 2019

ABSTRACT

Detecting early symptoms of engine failure is a crucial phase in an engine management system to prevent poor driving performance and experience. This paper proposes a Hybrid Electric Vehicle (HEV) engine diagnostics using a low-cost piezo-film sensor, an analysis with improved statistical method and verification by a Support Vector Machine (SVM). The current engine management system is unable to evaluate the performance of each cylinder operation. Eventually, it affects the whole hybrid vehicle system, particularly in the mode of charging and accelerating. This research aims to classify the combustion to monitor the condition of sparking activity of the engine by using the Z-freq statistical method. Piezo-film sensors were mounted on the Internal Combustion Engine (ICE) wall of each hybrid vehicle for vibration signal measurements. The engine runs at different speeds, the vibration signals were then recorded and analysed using the Z-freq technique. A machine learning tool referred to as Support Vector Machine was used to verify the classifications made by the Z-freq technique. A significant correlation was found between the voltage signal and calculated Z-freq coefficient value. Moreover, a good pattern was produced within a consistent value of the engine speed. This technique is useful for the hybrid engine to identify different stages of combustion and enable pattern categorisation of the measured parameters. These improved techniques provide strong evidence based on pattern representation and facilitate the investigator to categorise the measured parameters.

Keywords: Hybrid engine diagnostic; Pattern recognition; Piezo-film sensor; Statistical signal analysis; Z-freq

ABSTRAK

Pengesanan tanda-tanda awal kegagalan enjin merupakan fasa kritikal di dalam sistem pengurusan enjin bagi mengelakkan penurunan prestasi enjin dan pengalaman pemanduan. Artikel ini mencadangkan diagnostik enjin kenderaan elektrik kacukan (HEV) menggunakan penderia filem piezo yang berkos rendah, analisis menggunakan kaedah statistik yang telah ditambahbaik dan penentusahan dengan mesin vektor sokongan (SVM). Sistem pengurusan enjin sedia ada tidak mampu menilai prestasi setiap silinder enjin. Akhirnya ia memberi kesan kepada keseluruhan sistem kenderaan kacukan, terutamanya semasa mod pengecasan bateri dan pemecutan. Tujuan utama kajian ini adalah untuk mengklasifikasikan proses pembakaran dalam bagi memantau aktiviti percikan palam pencucuh pada enjin menggunakan kaedah statistik Z-freq. Penderia filem piezo dilekatkan pada setiap dinding enjin kacukan untuk pengukuran isyarat getaran. Kemudian, enjin akan dihidupkan pada beberapa kelajuan dan isyarat getaran akan direkodkan dan dianalisis menggunakan teknik Z-freq. Alat pembelajaran mesin yang dinamakan mesin vektor sokongan telah diaplikasikan bagi menentusahkan pengaplikasian yang dibuat melalui teknik Z-freq. Korelasi yang penting telah dijumpai di antara isyarat voltan dan nilai pekali Z-freq yang dikira. Tambahan lagi, corak yang baik telah dihasilkan dengan nilai konsisten untuk kelajuan enjin. Teknik ini berguna untuk pengenalpastian tahap proses pembakaran dalam enjin bagi kenderaan kacukan dan membolehkan perwakilan kategori corak parameter yang telah diukur. Teknik yang telah ditambahbaik ini akan menjadi bukti kukuh untuk perwakilan corak dan memudahkan pengkaji mengklasifikasikan parameter yang diukur.

Kata kunci: Diagnostik enjin kacukan; Pengiktirafan Corak; Penderia filem piezo; Analisis isyarat statistik; Z-freq

INTRODUCTION

The introduction of the Hybrid Electric Vehicle (HEV) is an alternative strategy to reduce fuel consumption in transportation and other industrial applications. It ensures emission reduction and guarantees excellent performance such as increasing power or diminishing vibration (Enang & Bannister 2017). A few countries have executed rigorous regulations to limit environmental issues and energy usage of vehicles on the road (Puchalski 2015). The automobile divisions worldwide have shifted their consideration towards insignificant usage of petroleum while trying to achieve the most effective use of electrical power (Babu & Ashok 2012). Thus, it has turned into the most important innovation, and a vital concern of the researchers in this field of study (Fajri et al. 2013; Hannan et al. 2014; Zhu & Wayne 2013). In a hybrid vehicle, two prime movers are commonly used, namely electric motor and Internal Combustion Engine (ICE) that coupled in different ways and referred to as hybrid architecture. In addition, ICE performs a primary function that supports the activities of high voltage battery charging, vehicle acceleration assisting, hill climbing or boosting the car (Lai & Ehsani 2013).

The diagnostic activities should not neglect any defects that occurred. Most of the detected fault symptoms of the internal combustion engine are due to the vibrations generated by frictions between the cylinder liner and piston ring. A statistical technique exhibits it can be applied to perform signal analysis in the case study. Evaluation of statistical parameters provides a fault sign of the components in a machine, for instance, the rotating or vibrating parts (Delvecchio, Bonfiglio & Pompoli 2018). I-kaz™ is an alternative to the statistical signal analysis which was developed by the researcher to calculate the degree of data scattering that refers to the data centroid for dynamic signal analysis. Furthermore, it is also utilised as an effective monitoring method for the tool life, bearings, and automotive gearbox (Yunoh et al. 2013). In the extension to further analyse the time domain is the application of frequency domain data into the signal analysis by utilising a statistical method called Integrated-Kurtosis-Frequency based for Z-filter (Z-freq). This technique is explored to extract more information from the raw signal acquired through experiments using data acquisition equipment.

ICE is regarded as the most likely component to fail. Many researchers used their methods to study the problems that occur and the impact on ICE especially on engine performance while at the same time maintaining the consistency of the operation (Sinnasamy et al. 2017; Yadav, Tyagi et al. 2011). Condition monitoring is the main activity to diagnose the failure of machines, which were addressed by researchers from the past to the present because early detection can avoid the most significant problem on the machine. Condition monitoring is a vital technique used to monitor vibrations and noise in the engine. The strain sensor is utilised for data measurement of the engine block, and the statistical method is used for data analysis (Delvecchio et al. 2018). The advantage of condition monitoring is that it allows maintenance to be scheduled, or other actions to be taken in order to prevent the consequences of failure. This activity can prolong the lifespan of an engine (Tahan, Tsoutsanis, Muhammad & Abdul Karim 2017). Three useful elements in condition monitoring are data acquisition, data processing, and decision-making or recommendation (Schramm et al. 2018). If the fault is detected early, better proficient engine monitoring can be produced. A recent study by researchers proved there was no correlation between engine status and statistical analysis especially when it was installed on a hybrid vehicle (Enang & Bannister 2017).

The time domain represents what happens to parameters such as magnitude, voltage, current, velocity or acceleration of the system versus time. The desired signal can be produced from the waveform by gathering the amplitudes, frequencies and phases of sine waves correctly. The frequency domain representation of a signal is called the spectrum. In the frequency domain, small components are easy to see because they are not masked by larger ones. The frequency domain provides an essential tool for analysing vital information (Heath 2018).

The primary transducers used in the mechanical work include accelerometers, strain gauge and piezoelectric. This application presents the idea of time and frequency. Notably, there are three main areas in fault diagnosis: 1) fault detection; 2) fault isolation; and 3) fault identification. The condition monitoring of ICE relied on the experience of skilled technicians, yet the decision-making process was exceptionally subjective. Among them, the broadly utilised method for condition monitoring and diagnosis of bearings is vibration monitoring. Essentially, acoustic signals are preferred over others since they are airborne. In such a manner, it also observed that working in the time domain poses many problems such as lack of information and embedded noise in certain frequency pockets. It was solved by taking the Fourier transform signal to be analysed in the frequency domain (Nason 2018).

METHODOLOGY

Z-FREQ STATISTICAL METHOD

Initially, the random signals are categorised into the r-th order of moment M_r. M_r for the discrete signal in the frequency band can be written as equation (1) below:

$$M_r = \frac{1}{n}\sum_{i=1}^{n}(f_i - \bar{f})^4 \quad (1)$$

where: M_r = r-th order of moment
n = number of sample
f = frequency

Kurtosis is the fourth order of statistical moment, a global signal that is sensitive to the spikiness of the measured data. For discrete data sets, the kurtosis value is written as equation (2) below:

$$K = \frac{1}{n\sigma^4}\sum_{i=1}^{n}(f_i - \bar{f})^4 \quad (2)$$

where: K = kurtosis value
σ = standard deviation

The kurtosis value is approximately 3.0 for a Gaussian distribution. Higher kurtosis values designated the occurrence of extreme values and established in a Gaussian distribution.

Kurtosis analysis was used to detect fault symptoms because of its sensitivity to high magnitude (Fadli Ahmad, Dirhamsyah, Nuawi, Mohamed & Wahid 2016). Based on this, the Z-freq method provides a 2-D graphical representation of its coefficient result. The time domain signal was decomposed into two frequency mobs, the x-axis represents low frequency (affix), and the y-axis represents high frequency (annex). Affix mob consists of frequency mob from $0f_{max}$ to $0.5f_{max}$ and annex mob consists of frequency mob from $0.5f_{max}$ to $1.0f_{max}$. Z-freq measures the data distance to signal centroid which is determined by equation (3):

$$Z^f = \frac{1}{n}\sqrt{K_{afx}s_{afx}^4 + K_{anx}s_{anx}^4} \quad (3)$$

where: Z^f = Z-freq value
K_{afx} = kurtosis for affix frequency mob
s_{anx} = standard deviation for annex frequency mob

Z^f coefficient was formulated based on the normal order of Daubechies signal decomposition. The HEV engine signal monitoring activity is illustrated in the flowchart as shown in Figure 1. Initially, the vibration data were measured from the engine wall using four piezo-film sensors for every cylinder and the data acquired using vibration analyser at a high sampling rate of 51.2 kHz. The engine speeds for measurement varies from as low as 1000 rpm, 1500 rpm, and 2000 rpm to as high as 2500 rpm at on stand mode. This highest speed is enough because of a safety issue. Then, the collected signal was decomposed into two frequency bands, namely affix (low frequency) and annex (high frequency). Affix frequency band defines the frequency between zero and half of the maximum frequency, while the annex frequency band means the frequency from half of the maximum frequency to the maximum frequency range. The activity followed with the calculation of kurtosis values and standard deviations for every single signal, the calculation of Z-freq coefficient for each sensor for different engine speeds and this value is verified by using the Support Vector Machine (SVM) tool. A classification using machine learning was used to distinguish between each engine speed. The training will be repeated until it produces acceptable results during verification stage. Lastly, the scattering of Z-freq value was represented in a 2-D graphical scattering plot using simulation software. The produced pattern can be determined as identical or not based on this 2-D plot. The whole process was categorized into three phases; first is the signal acquisition by vibration analyzer, second is the analysis by simulation software and lastly is the result verification for future prediction. The verified result can be used for other engines with the same parameters.

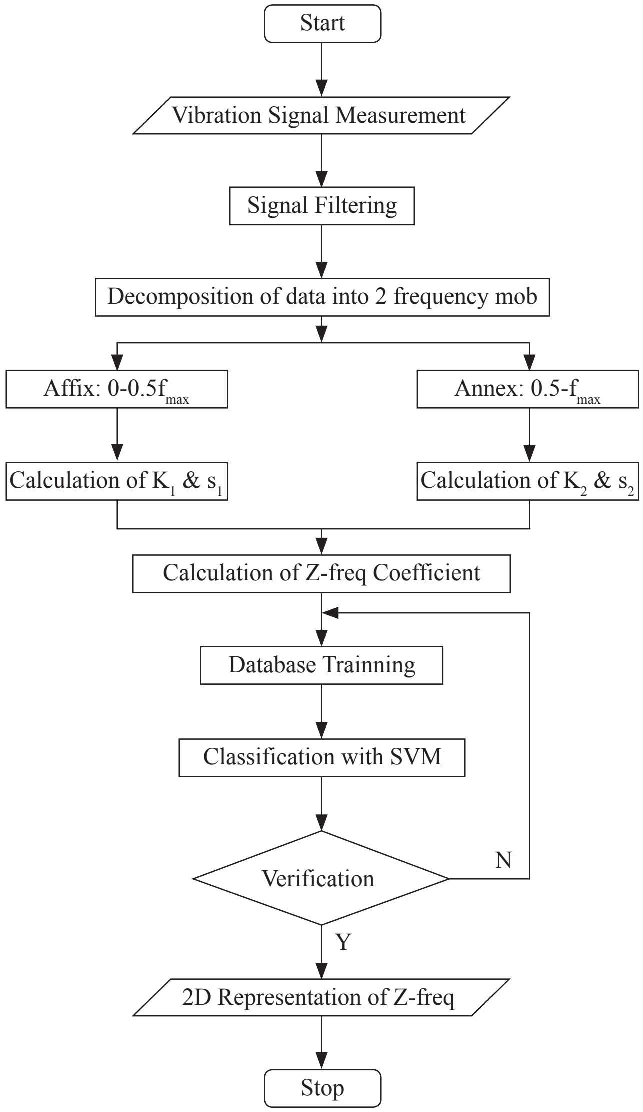

FIGURE 1. HEV Engine Diagnostics Process Flow

SUPPORT VECTOR MACHINES

This proposed vehicle engine diagnosis used the Support Vector Machine (SVM) for classification with the Z-freq feature extraction. A total of 240 data was segregated for training and testing at a ratio of 70:30. SVM in machine learning falls under supervised learning models with an algorithm that analyses data and recognises patterns, used for classification and regression analysis (Maxwell, Warner & Fang 2018). The trained data sets were classified using the same control setting as shown in Table 1.

TABLE 1. Support Vector Machine Control Setting

Description	Specification
Method	Cross Validation
Kernel Function	Linear
Multiclass Method	One-vs-One
PCA Percent Variants	95

All safety procedures were performed while handling high voltage battery, during calibration of equipment, and other noises that affect the signal monitoring processes. Any electrical-related work must take into account electric shock, short circuit and arc fault impact. Measurements should not be performed on live electrical components. A few measurements were conducted, and the average value was calculated.

The sensors were connected to a vibration analyser using BNC cables. Then, the output from the vibration analyser was recorded using the data acquisition software installed in the computer. The filtered signal was then analysed using the proposed new statistical technique by using the MATLAB software. Figure 2 shows the flow of the signal acquisition process for the hybrid vehicle's engine that was used in this experimental activity.

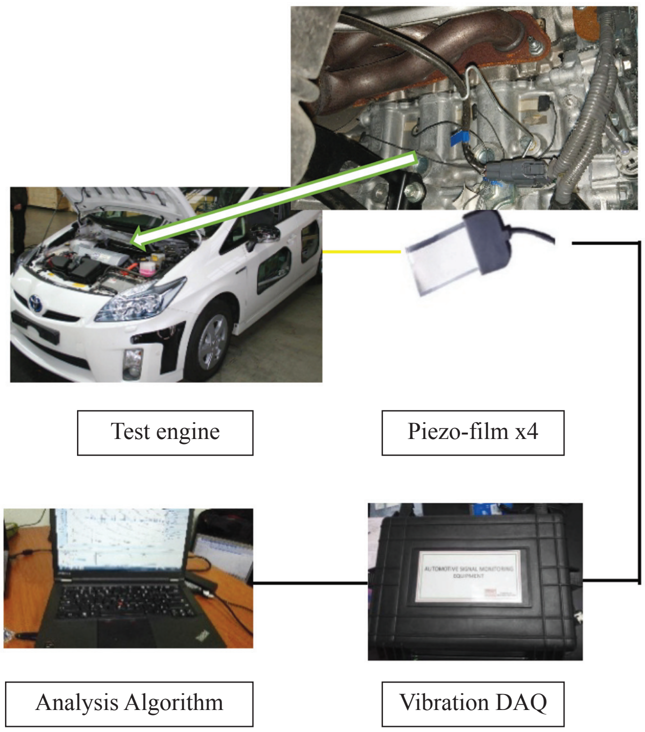

FIGURE 2. Hybrid Vehicle Engine Signal Acquisition Process Flow Diagram

PIEZO-FILM SENSOR INSTALLATION

While studying the vibrations of the object, it was found that one of the most sought after transducers is piezo-film. The most common type is the shielded piezo sensor. It comes with a shaped plastic housing and 18" of a coaxial link. One of the film components is a screen printed with silver ink and folded over on itself, accorded a self-protecting of the transducer area. It is vital to be used in high EMI environments to ensure accurate data collection. Another criterion is that it has a broad frequency response (C. Zhang & Wang 2012).

The piezoelectric sensor is a command sensor that leads the energy from the piezoelectric material. The energy can be produced through vibration and form an electric charge. From the explanation by (S. Zhang & Yu 2011), there is a feature of a piezoelectric sensor that includes non-moving part: the structure is simple, reliable, lightweight and has a

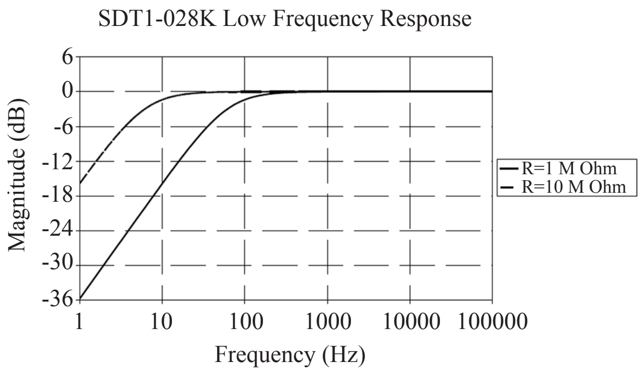

FIGURE 3. Characteristic of low frequency response for piezo-film sensor

high signal-to-noise ratio. Figure 3 shows the characteristic of a low-frequency response for the piezo-film sensor used.

The preliminary step of this activity was installing the transducer by attaching it to the wall of the hybrid internal combustion engine's body using the tape-assisted technique. One of the piezoelectric vibration transducers known as piezo-film sensor together with its specifications is depicted in Table 2. The size of the sensor is perfectly fitted to the engine wall.

TABLE 2. Piezo-film Sensor Specification

	Sensor Parameters	Specifications
1.	Type	SDT shielded piezo sensors
2.	Minimum Impedance	1MΩ
3.	Preferred Impedance	10MΩ
4.	Output @ 10MΩ	Min 15V
5.	Operating temperature	0°C to + 70°C
6.	Dimension	L × W × H: 28.6 × 11.2 × 0.13

HYBRID VEHICLE TEST SETUP

In hybrid vehicles, the classification depends on high-voltage systems and performance level, which are the micro-hybrid system, mild-hybrid system and strong-hybrid system. The ICE and electric motor operate variably to propel the vehicle, depending on its operating conditions and required torque level. The control unit determines the driving torque outputs. Every operating mode is determined by the type of interaction between the combustion engine, electric machine, and stored energy which are the internal combustion, hybrid, purely electric, generator, boosting and regenerative braking. In some cases, the internal combustion engine becomes a primary mover and its performance is inevitable.

In order to measure signal data using vibration analyser, the most popular Hybrid Electric Vehicle (HEV) with Vehicle Identification Number (VIN) was used. This test vehicle was set up with proper safety procedures, and all precautions were considered such as using high voltage Class A glove up to 1000V, tagged insulated cable, natural environment, and assisted by well-trained technicians. These test hybrid vehicle specifications are depicted in Table 3. All hybrid systems were fully functional so that any disturbances were taken into consideration during measurements. This vehicle is a 2015 model with the third-generation hybrid system that was developed by the manufacturer.

TABLE 3. Engine test specification

Aspects	Specification
HEV Model	Toyota Prius
Vehicle identification number	ZVW30-196651
Engine	1.8L Atkinson cycle
Engine compression ratio	13.0:1
Engine maximum power	73kW @ 5200 rpm
Engine maximum torque	142Nm @ 4000 rpm
Electric motor maximum voltages	650VAC
Electric motor maximum power	60kW
Electric motor maximum torque	207Nm

SIGNAL ANALYSIS

Piezo-film sensor is very susceptible to heat and vibration during monitoring activities. Furthermore, the temperature of the engine wall can reach up to 90°C due to frictions between engine components when the hybrid electric vehicle engine is running, and the result sometimes leads to imprecise reading. This heat effect is unavoidable, and a rigid plate was applied to isolate some heat, and a filtering process was installed to reduce unwanted noise caused by the measurement equipment.

RESULTS AND DISCUSSION

The new statistical analysis was used by implementing kurtosis and standard deviation application into the frequency domain of the converted signal acquired from the data acquisition. Four types of engine speed were recorded to study the characteristic of the analysis result. Each test was conducted using a sampling rate of 51,200 Hz to detect all events occurred during the signal capturing processes. A four-stroke which utilises intake, compression, power, and exhaust is involved in the internal combustion engine for a hybrid vehicle. The data in Figure 4 presents the collected and plotted signals into the time domain, then, converted into the frequency domain and zoomed in to measure the four-stroke process quantitatively. As can be seen from this figure, an engine speed of 1000 rpm results in 0.06 s/rev in the simulation and shows an accurate desired value of each revolution time experimentally. The most interesting aspect of this graph is the samples obtained from the vibration analyser can distinguish different engine speeds by observing and calculating the peak-to-peak time value. Overall, from Table 4, it can be be concluded that 1000 rpm gains 0.06 s/rev, 1500 rpm is 0.04, 2000 rpm is set out at 0.03 s/rev, and lastly 2500 rpm gets 0.024 s/rev. Another interesting point to note is that for each power stroke, the signal creates a peak and it repeats harmonically after all four-stroke processes occurred. The second lower peak can be seen on the stroke for exhaust because the valve was opened at that particular time and the cylinder location was at the top position. The calculation for the revolution time is shown in Table 4. There is a significant positive correlation referring to the time domain on the random graph pattern which is easier to see where the peak signal is at a low speed, and the peak becomes closer as the speed increases. Based on the representation as shown in the frequency domain graph, it can be concluded that the magnitude of frequency increases significantly as the hybrid engine speed increases at the low-frequency area. It also can be clearly seen that the magnitude of frequency at high frequency slowly increases as the speed increases which contribute to the Z-freq value.

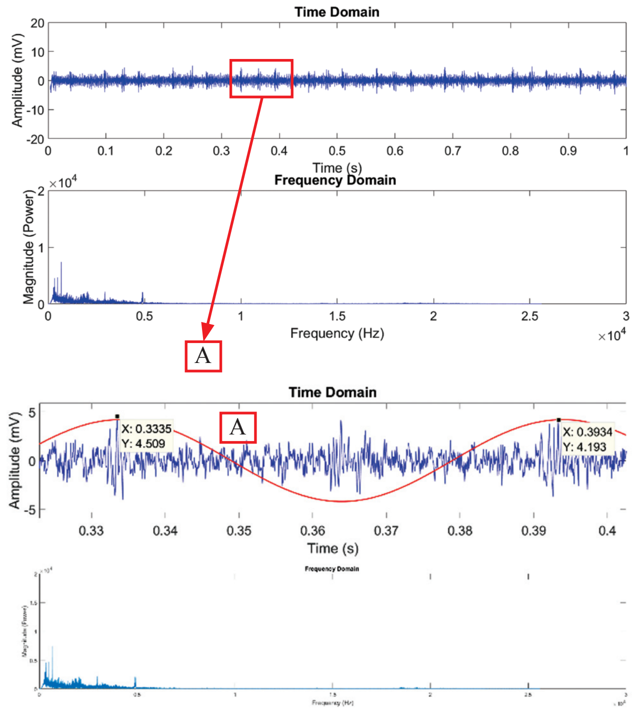

FIGURE 4. 1000 rpm experimental data C1

TABLE 4. Total Time/Revolution for Simulation and Experimental Activity

rpm	rev/s	s/rev	Time	x2	x1
1000	16.67	0.060	0.060	0.3933	0.3335
1500	25.00	0.040	0.040	0.5079	0.4682
2000	33.33	0.030	0.029	0.623	0.594
2500	41.67	0.024	0.024	0.5751	0.5515

In regard to this observation, there is no clear peak to another peak representation if there is no complete compression and power stroke during ICE sparking activities (pre-ignition, ignition and post-ignition). It also leads to imbalance and incomplete high voltage battery charging (storage system) or boosting the vehicle (acceleration).

As mentioned in the previous finding, the pattern of the hybrid vehicle engine also can be displayed in the scatter diagram as shown in Figure 5 (a-d). The significant pattern is presented in the graphs below. There are two axes in which the x-axis represents the low-frequency distribution, and the y-axis represents the high-frequency distribution. It was hypothesized that the scattering of frequency magnitude becomes wider for both low and high frequencies as the engine speed increases. It is because of in the frequency domain, the distribution of high-frequency data appears to increase slowly in frequency magnitude. The scatter is clearly seen as discussed, and shown in Figure 5a for 1000 rpm and Figure 5d for 2500 rpm. The vibration level of the engine wall increases proportionally, detected by every piezo-film sensor. The number of Z-freq value is also identical and increases in line with the size of the pattern generated.

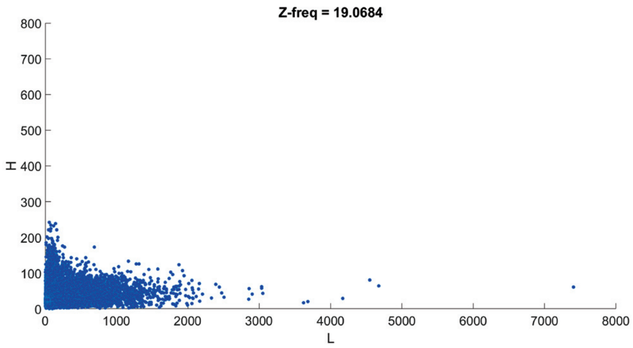

FIGURE 5a. 1000 rpm Z-freq representation

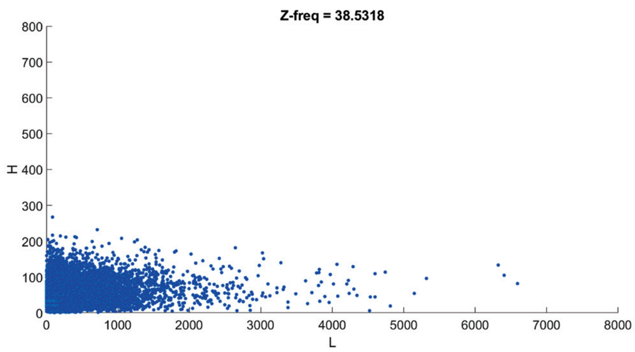

FIGURE 5b. 1500 rpm Z-freq representation

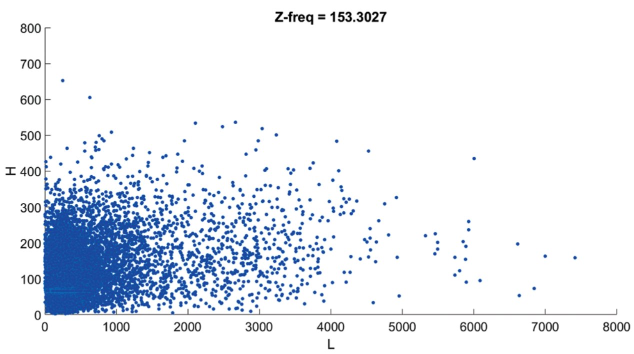

FIGURE 5c. 2000 rpm Z-freq representation

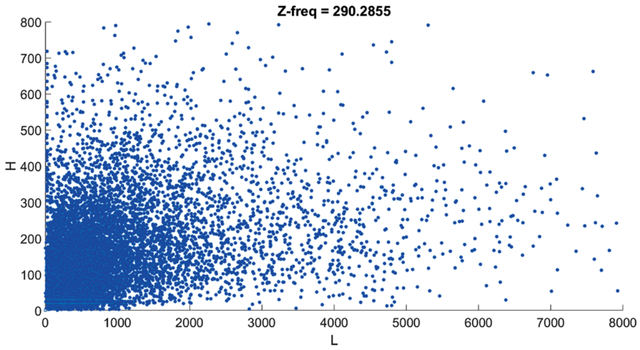

FIGURE 5d. 2500 rpm Z-freq representation

A recent study found that the Z-freq value increased significantly over the engine speed and that value is also identical for each speed at a certain average as shown in Figure 6. On the other hand, Z-freq coefficient shows a downward pattern from Channel 1 (cylinder 1) to Channel 4 (cylinder 4) because of the effect from the nearby timing chain. The experiment did not detect any effects except the timing chain rotation at that moment.

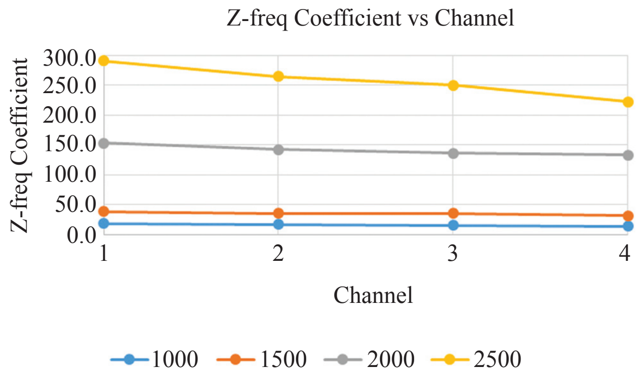

FIGURE 6. Z-freq plot for different channels

Figure 7 compares the Z-freq value obtained from the measurements of each sensor's channel for all different speeds from 1000 rpm, 1500 rpm, 2000 rpm to 2500 rpm. It is apparent from this figure that the coefficient value increases as speed increases. It also shows a slow increment in the Z-freq coefficient for 1500 rpm because the engine runs smoothly but becomes noisy during the observation phase.

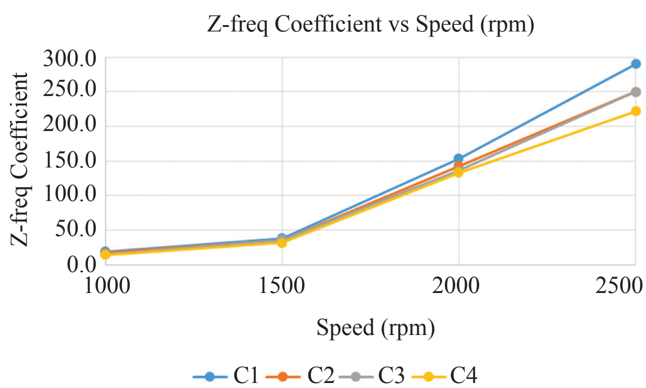

FIGURE 7. Z-freq plot for different engine speeds

TABLE 5. Summary of Z-freq values

Sensor's Channel	Z-freq coefficient values			
	1000 rpm	1500 rpm	2000 rpm	2500 rpm
Channel 1	19.1	38.5	153.3	290.3
Channel 2	17.1	35.9	142.5	264.8
Channel 3	15.7	35.9	135.9	250.0
Channel 4	14.1	31.8	133.1	222.1

All confusion matrices are summarized as shown in Figure 8. It explains that the accuracy of the Z-freq classifier is 95.5% of 200 Z-freq coefficients for all speeds from 1000 rpm, 1500 rpm, 2000 rpm to 2500 rpm. It proves that this coefficient can be used as a prediction method especially for speed and misfire activities.

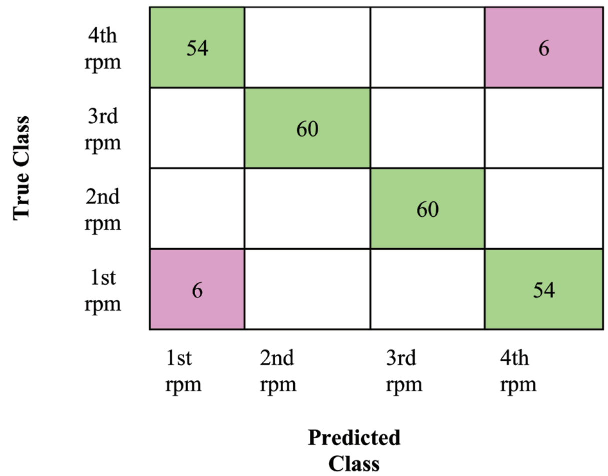

FIGURE 8. Confusion matrix for Z-freq coefficient

On the basis of this SVM confusion matrix for Z-freq coefficient, it can be concluded that the finding of Z-freq as a diagnosis tool is valid for future and real-time predictions. Of that, only 12 data were misclassified from a total of 240 Z-freq data, which contributed to 95% accuracy.

Compared to the existing vibration amplitude vs speed, and displacement vs frequency graph representation, there is no clear indication in the increment concerning speed and sparking activities. As expected, in the Z-freq representation, it is observed that the Z-freq value increases significantly and can be identified if abnormal sparking activity occurs. This improved the statistical analysis using an alternative piezoelectric sensor which is mainly to reduce the cost of condition monitoring, and also to save space for the sensor attachment encountered during the test procedure.

CONCLUSION

The present research aimed to apply a new statistical analysis technique for a hybrid vehicle engine monitoring activity using piezoelectric transducers called piezo-film and has been successfully determined. Initially, the time domain representation reviewed in detail the available information on the four-stroke process because of the high-frequency sampling rate. The research findings indicate the preliminary monitoring activities of four different engine speeds and spark plug malfunction were successfully conducted. The value of the Z-freq coefficient generated from the equation applied indicates a good pattern and a consistent value for the declared parameters. The study intends to identify any changes in parameters such as speed and condition of spark plug ignition as shown in Figure 4-8. The variation of Z-freq values is influenced by the amplitude and frequency of the engine. From this study, it can be deduced that the condition monitoring of hybrid vehicle engine is crucial as it affects other electrical components such as a three-phase motor, an inverter or a rectifier and a charging or a storage system.

RECOMMENDATION

A piezo-film sensor is a type of piezoelectric transducer similar to the accelerometer. Therefore, in the next phase, a comparison of performance between piezo-film and accelerometer will be carried out. Generally, operating modes such as hybrid mode, pure electric mode, generative mode, boosting mode and regenerative mode are much preferred for consideration as further research issues to make this monitoring system more accurate, efficient and reliable. This experimental activity can be conducted and accomplished in the autotronics laboratory once the equipment is fully upgraded. Furthermore, the simulation should be conducted in parallel with the field test run to improve the prediction activity in the future.

ACKNOWLEDGEMENT

First and foremost, I would like to express my special thanks to Associate Professor Dr. Mohd Zaki Bin Nuawi for his continuous guidance, encouragement, tolerance and advice during the development of this research. This research is supported by Acoustics Laboratory for the measurement hardware, software and Autotronics Laboratory for the test vehicle. Secondly, I wish to extend my special thanks to Faculty of Engineering and Built Environment, Universiti Kebangsaan Malaysia (UKM), Faculty of Engineering Technology, Universiti Teknikal Malaysia Melaka (UTeM), last but not least the Ministry of Higher Education Malaysia (MOHE) for the cooperation and funding until this research is successful. All their support is sincerely acknowledged and hugely appreciated.

REFERENCES

Babu, A. & Ashok, S. 2012. Algorithm for selection of motor and vehicle architecture for a plug-in hybrid electric vehicle. *Annual IEEE India Conference (INDICON)*, 875-878.

Delvecchio, S., Bonfiglio, P. & Pompoli, F. 2018. Vibro-acoustic condition monitoring of internal combustion engines: A critical review of existing techniques. *Mechanical Systems and Signal Processing* 99: 661-683.

Enang, W. & Bannister, C. 2017. Modelling and control of hybrid electric vehicles (A comprehensive review). *Renewable and Sustainable Energy Reviews* 74: 1210-1239.

Fadli Ahmad, M. A., Dirhamsyah, M., Nuawi, M. Z., Mohamed, N. F. & Wahid, Z. 2016. The study of polymer material characterisation using M-Z-N statistical analysis method. *Jurnal Kejuruteraan* 28(1): 9-18.

Fajri, P., Lotfi, N., Ferdowsi, M. & Landers, R. G. 2013. Development of an educational small scale hybrid electric vehicle (HEV) setup. *IEEE International Electric Vehicle Conference, IEVC 2013*.

Hannan, M. A., Azidin, F. A. & Mohamed, A. 2014. Hybrid electric vehicles and their challenges: A review. *Renewable and Sustainable Energy Reviews* 29: 135-150.

Heath, M. T. 2018. Chapter 12: Fast fourier transform. In *Scientific Computing*.

Karim, Z., Nuawi, M. Z., Ghani, J. A., Abdullah, S. & Ghazali, M. J. 2011. Optimization of integrated kurtosis-based algorithm for z-filter (I-Kaz TM) Coefficient Using Multi Level Signal Decomposition Technique. *World Applied Science Journal* 14(10): 1541-1548.

Lai, L. & Ehsani, M. 2013. Design study of parallel HEV drive train with full size engine. *2013 IEEE Transportation Electrification Conference and Expo: Components, Systems, and Power Electronics – From Technology to Business and Public Policy, ITEC 2013*, 1-6.

Liang, X., Zuo, M. J. & Hoseini, M. R. 2015. Vibration signal modeling of a planetary gear set for tooth crack detection. *Engineering Failure Analysis* 48: 185-200.

Maxwell, A. E., Warner, T. A. & Fang, F. 2018. Implementation of machine-learning classification in remote sensing: An applied review. *International Journal of Remote Sensing* 39(9): 2784-2817.

Nason, G. P. 2018. Stationary and non-stationary time series. In *Statistics in Volcanology*. *Special Publications of IAVCEI* 1: 129-142.

Othman, M. 2016. Experimental comparison of vibration and acoustic emission signal analysis using kurtosis-based methods for induction motor bearing condition monitoring. *Przegląd Elektrotechniczny* 1(11): 210-214.

Puchalski, A. 2015. A technique for the vibration signal analysis in vehicle diagnostics. *Mechanical Systems and Signal Processing* 56-57, 173-180.

Schramm, D., Mohamed Haris, S., Yat Sheng, K., Abdullah, S. & Omar, M. Z. 2018. Generation of artificial road profile for automobile spring durability analysis. *Jurnal Kejuruteraan* 30(2): 123-128.

Sinnasamy, Y., Yassin, M. R. M., Sa'at, N. A., Nain, H., Sutarji, F. A., Sulaiman, A. & Ahmad, K. A. 2017. Recognition of most common diesel engine condition monitoring methods. *Defence S and T Technical Bulletin* 10(3): 297-310.

Tahan, M., Tsoutsanis, E., Muhammad, M. & Abdul Karim, Z. A. 2017. Performance-based health monitoring, diagnostics and prognostics for condition-based maintenance of gas turbines: A review. *Applied Energy* 198: 122-144.

Vaughan, A. & Bohac, S. V. 2015. Real-time, adaptive machine learning for non-stationary, near chaotic gasoline engine combustion time series. *Neural Networks* 70: 18-26.

Widodo, A., & Yang, B.-S. 2007. Support vector machine in machine condition monitoring and fault diagnosis. *Mechanical Systems and Signal Processing* 21(6): 2560-2574.

Yadav, S. K., Tyagi, K., Shah, B. & Kalra, P. K. 2011. Audio signature-based condition monitoring of internal combustion engine using FFT and correlation approach. *IEEE Transactions on Instrumentation and Measurement* 60(4): 1217-1226.

Yunoh, M. F. M., Abdullah, S., Nuawi, M. Z. & Nopiah, Z. M. 2013. Durability analysis of motorcycle frame using fatigue i-kaz technique. *Applied Mechanics and Materials* 471: 213-217.

Zhang, C., & Wang, N. 2012. Aero-engine condition monitoring based on support vector machine. *Physics Procedia* 24: 1546-1552.

Zhang, S. & Yu, F. 2011. Piezoelectric materials for high temperature sensors. *Journal of the American Ceramic Society* 94(10): 3153-3170. ht

Zhu, Z. & Wayne, W. S. 2013. Mode and implementation of a hybrid control system for a 2-mode hybrid electric vehicle, *3605896*(November), 243. Retrieved from http://search.proquest.com/docview/1491165582?accountid=37552