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Modern Methods in Engine Knock Signal Detection

Azher Razzak Witwit[a,*], Azman Yasin[b], Mohd Azman Abas[c], Horizon Gitano[d]

[a]*University Utara Malaysia (UUM), Kuala lumpur, Malaysia*
[b]*University Utara Malaysia (UUM), Kedah, Malaysia*
[c]*PROTON Powertrain Dept, Shah Alam, Malaysia*
[d]*University Science Malaysia (USM), Penang, Malaysia*

Abstract

In this paper, a review is given of some of the modern methods in the detection of knock in internal-combustion engines and some comparisons are made between these methods and the effectiveness of each one of them is indicated through a statement of the advantages and disadvantages of each method. In this way it will be possible to clarify how to deal with the original signal and the associated signal noise through some of the modern algorithms in the field of soft computing such as an Artificial Neural Network (ANN), Genetic Algorithms (GA), Wavelet Transform (WT), Fuzzy logic, Supported Vector Machine (SVM) and some statistical methods.

Keywords: Artificial Neural Network; Fuzzy logic; Genetic Algorithms; Supported Vector Machine; Wavelet Transform.

1. Introduction

Knocking is a process that presents a challenge for many engineers and researchers to achieve the characteristics of quality and to meet customer satisfaction through the achievement of efficiency in the engine. A design that avoids the occurrence of knocking is not an option, but this involves the use of high cost excellent quality fuel, a low compression ratio, and high-efficiency control strategies to avoid knocking. It is important to manipulate the compression ratio and spark advance to accommodate knocking, as the knocking process leads to

* Corresponding author. Tel.: +60174471347
E-mail address: azherwitwit@yahoo.com

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reduced engine performance. In order to achieve an efficient control system such a method must include an effective signal detection system in order to keep the knocking signal under control. Several strategies to improve performance include an effective production control system that allows the engine to work near the knocking borderline. This is a requirement for an accurate knock detection system.

2. What is Engine Knock?

Control systems are designed in modern engines to minimize exhaust emissions while maximizing power and fuel economy. The ability to maximize power and fuel economy by optimizing spark timing for a given air/fuel ratio is limited by engine knock. Knock detection and the control of ignition timing to allow an engine to run at the knock threshold provides the best power and fuel economy. Normal combustion occurs when a mixture of air / fuel is ignited by use of a spark plug and the combustion flows smoothly from the point of ignition to the walls of the cylinder.

Engine knock, or detonation, occurs when the temperature or pressure in the unburned air/fuel mixture (end gases) exceeds a critical level, causing auto ignition of the end gases. This produces a shock wave that generates a rapid increase in cylinder pressure. Damage to pistons, rings, and exhaust valves can result if fixed heavy knocking occurs. Additionally, most automotive customers find the sound of a heavy engine knock undesirable. There are many factors that affect the occurrence of knocking, including mechanical, electrical, environmental and misuse. The factors can be clarified that influence knocking through analysis of a fishbone diagram as given below in fig. 1.
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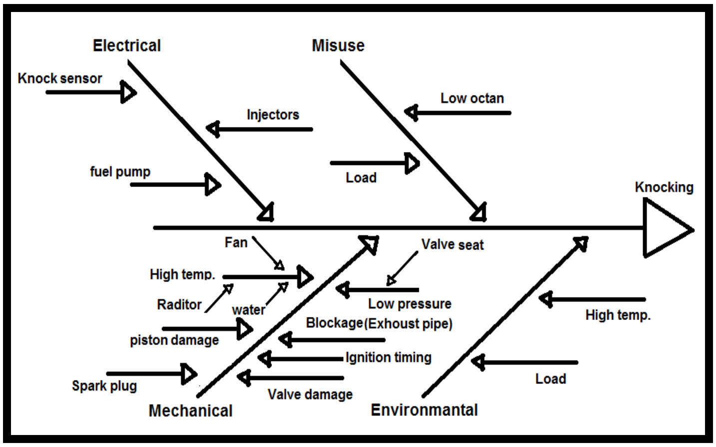

Fig. 1. Knock problem

Researchers [1] have presented an innovative way to analyze the knock signal in spark ignition engines (SI) to improve the signal to noise ratio (SNR). The Method involves analyzing the structural vibration of the engine by using the time-frequency domain. The time-frequency representation of the signal is then used to define several schemes characterized by a greater SNR than current methods. One researcher in the course of his research indicated that the problem of knock detection can be improved by using a time-varying signal detection scheme and that the proposed method can estimate the difference in resonance frequencies in the signal by a joint time and frequency representation. A detector is then designed which has the ability to effectively follow the frequencies of vibration in the knock signal although this method depends on the choice of an appropriate threshold limit value, and generally this is effective for an engine speed where the signal-to-noise ratio is high. Generally, all signal detection methods include detection statistical formulas, where either the signal is found when crossing the threshold or non-existent if less than a threshold. The researcher compared between four statistical methods in knock detection analysis:

1- Band-pass filtering based methods.
2- Detection based on the Wigner-Ville Distribution (WVD).
3- Detection using the cross WVD.
4- Detection schemes based on the Choi-Williams distribution (CWD).

The following results have been obtained in Table 1:

Table 1.

Method	SNR
Conventional BPF	1.1942
WVD, Simple FM	1.5678
WVD, Modified FM	1.4683
XWVD	1.9985
CWD, Simple FM	1.4458
CWD, Modified FM	1.2546
XCWD	2.1656

From the table above, it can be seen that the two methods that depend on the WVD show a better performance than the traditional methods using a Band-Pass filter (BPF) scheme. As anticipated, the method based on XWVD gives the best performance. Using the same construction analysis, the distribution of Choi-Williams was used to obtain a quantitative measure, and the results summarized as above. Researchers [2] have presented an experimental study carried out to develop a new method for the detection of knocking by using signals from a spark ignition (SI) engine. The signals are (cylinder pressure, sound pressure, block vibration). As a first step, the harmonious knocking frequencies were identified by analysing the cylinder pressure signal under a wide range of operating conditions of the engine. As long as these frequencies are independent of the operating conditions of the engine and the standard deviation of these frequencies is small, three filters are designed to process the knocking of the engine.

A new method called the Sum of Divided Band-Pass (SDBP) filtering method was proposed to determine the density of knocking and the removal of noise. Varying and significantly changing the knocking density in the case of a running engine, the knock sensor location and the characteristics of the gasoline, and others all contribute to the knocking phenomenon. In order to work on the knock control system properly in a car, it is required to determine the appropriate threshold value that can be applied under any conditions. This global threshold is created by analysing the distribution of the intensity of non-dimensional knocking. This threshold is created by analysing the distribution density of non-dimensional knocking, which is obtained by the non-dimensional version of the SDBP method referred to as the NSDBP method. This threshold and the new method (NSDBP) significantly contribute to improve future knock control systems of spark ignition engines (SI).

2.1 Support Vector Machine (SVM)

The Support Vector Machine (SVM) is a hot topic in current research, being used in a variety of research areas to solve a multitude of different learning and classification problems. For instance, combustion engine knock detection, handwriting recognition and 3D computer vision object detection. SVMs are suited to such a wide variety of tasks as they operate by identifying optimal features in order to improve the division of a feature space by concentrating on the most important features. SVMs attempt to split the feature space into two distinct classes, via a hyperplane decision surface.

2.1.1 Application of SVM

One of the methods of classification for the detection of knocking has been tested using a new algorithm from the field of Support Vector machine (SVM), which has been sourced from the field of statistical learning theory.
One of the obstacles faced by the support vectors, especially Adatron, is that they tend to produce classification systems that need to call upon many computations. The reason for this is due to the large number and the dispersion of the support vectors.

In 1999, a group of researchers [3] developed a new technique to classify and detect knocking by the use of a Support Vector Machine (SVM), which promised a good general performance in addition to the (SVM) maintaining some limits, such as the generalization error and the convergence of learning which gave a greater stability than learning algorithms in neural networks. However there is a single obstacle in the (SVM) and Adatron especially. This is because the process tends to produce classification systems that require a large computational effort for recall. The reason for this is the large number of scattered support vectors. Therefore it is proposed to remove the less important vectors by adjusting the training data and re-training steps to avoid the reduction of the performance of the classifier.

The main benefit is not only trying to reduce the error in the test group, but also aims to reduce the complexity of the system as long as the error can be determined and fixed at a lower value such as zero. Thus, the result of SVM is to reduce the upper limit of the risk of non-classification of the invisible data. This is done by maximizing the margin. This means that the hyperplane used in the classification will have the highest distance between the hyperplane and the boundaries of the class points. The hyperplane is determined by the points on the border called the Support-vectors. A non-linearity function is defined by the kernel function which is used to project the input data to a higher dimensional space, where the linear decision is taken in the end.

From the results, the researchers compared the SVM method with the conventional neural networks such as a multilayer perceptron in a real-world application and concluded that SVM could potentially improve the classification more successfully than neural networks.

2.2. Wavelet and Wavelet Transform (WT)

A Wavelet is a small wave (window function) of finite length [4]. The wavelets are used to build a basis in which are represented the details that are gained between a resolution and the next finer one. A Wavelet Transform (WT) (in its continuous or discrete version) represents a signal as a sum of wavelets with different locations and scales [5]. Wavelet Transform analysis uses small wavelike functions known wavelets, in fact a 'local' wavelike function is a more accurate description of a wavelet. Such WT are used to transform the signal under investigation into another representation which gives the signal information a more useful form. This transform for a signal is known as a wavelet transform. Mathematically, it can be said that the wavelet transform is a convolution of the wavelet function with the signal. In other words, the wavelet transform is a way to convert a function or a signal to any other format either to make certain features of the original signal more tractable and to have greater clarity, or to enable the original data set for the description to be more succinct [6].

A wavelet can be manipulated in two ways, where by the wave could move to different locations on the signal, and it can also be stretched or shrunk (squeezed) as in Fig. 2. and Fig. 3.

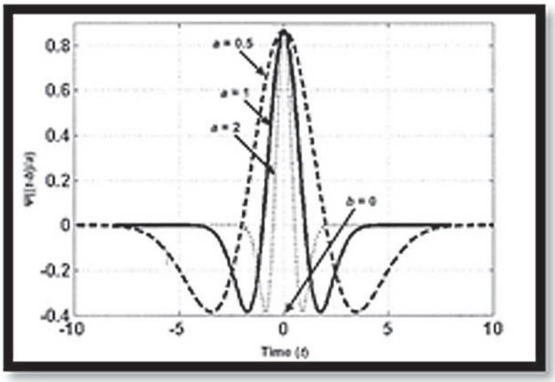

Fig. 2. Stretching (a = 0.5) and squeezing (a= 2) of the Mexican Hat wavelet function.

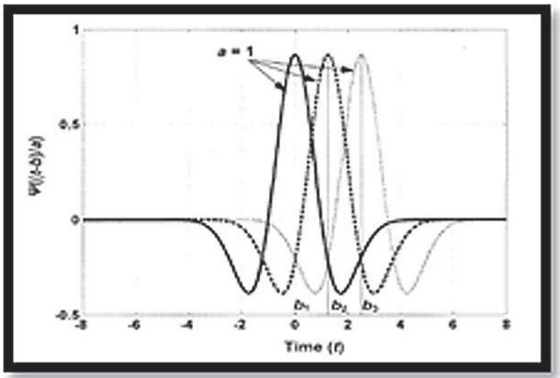

Fig. 3. Translation (b_1 via b_2 to b_3) of the Mexican Hat wavelet function.

If the wavelet form matches the signal well then the scale and location will be obtained along with a high conversion value (large transform value). If, however, the wavelet and the signal do not correlate well, this does not produce a high conversion value, and a low transform value is obtained. See Fig. 4. [6],[7].

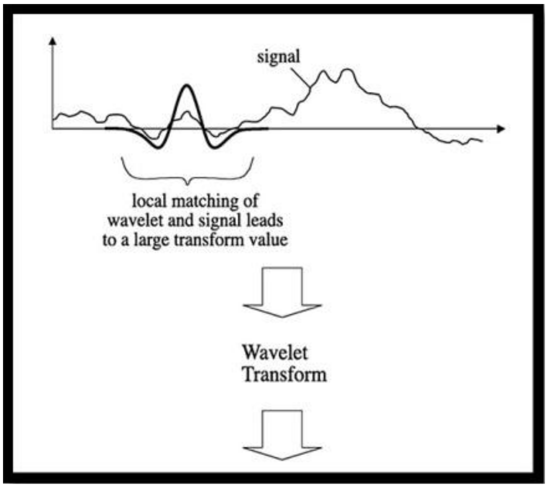

Fig. 4. Matching Wavelet and signal

To carry out the Wavelet transform, a local form of the wave is needed. In fact, a wavelet is a function *ψ(t)* that compensates for a certain mathematical formula. Note, through the above these functions are handled by translation (movement along the axis of time) and dilation (spreading out of the wavelet) to transform the signal to another form. This may appear simple and obvious to the eye over time and it scales easily. There are in fact, a large number of wavelets chosen for use in the analysis of the data and the best selection of a wavelet for a particular application depends on the nature of the signal being processed, and what is required from the analysis.

2.2.1. Application of WT

In one developmental study, [8] the researchers worked to improve the detection of knocking using the wavelet transform coefficients especially at a high-speed for a low signal-to-noise ratio (SNR). Traditional knock detectors use the signal-energy vibration of the engine. A knock signal is characterized as containing a set of resonance frequencies. The researchers chose two sets of wavelet transform parameters: The first set took into account only the mean value as a module for the wavelet transform, and the second set considered the maximum value and the position of the maximum value of the module of the wavelet transform. The pattern recognition system works with two classes: the existence of knocking and the absence of knocking. Choosing the rule of the distance of the centroids for the classification step it accomplishes the requirement to calculate the distance between the elements and the mean parameter vector of each class.

Using the classical energy parameter, the researchers obtain a well classified rate of 76.4 %. Fig. 4. and Fig. 5. give the results for the two sets of parameters for different scale factors a. If a scale factor of $2.6 < a < 3.4$ is chosen (see Fig. 5 and Fig. 6), the results of the classical energy parameter can be improved. The mean value gives a better classified rate than the maximum value. A 5 % improvement was obtained for the well classified result for a = 3.4. For the second set of parameters, the position of the maximum value does not improve on the knocking recognition obtained using the maximum value.

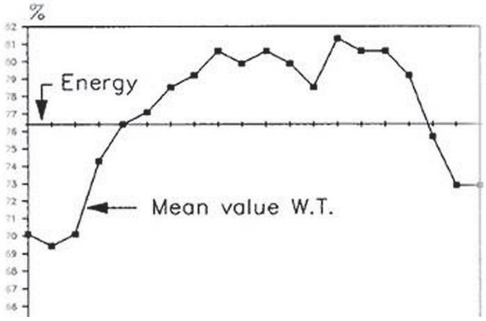

Fig. 5. Well classified rate versus of the scale factor. Mean value of module of WT.

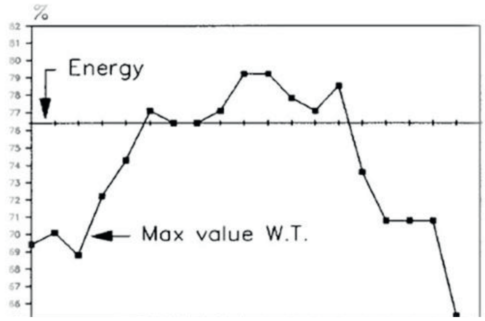

Fig. 6. Well classified rate versus the scale. factor. Maximum value of module of WT.

The researchers concluded that the parameters in the wavelet transform for pattern recognition can be successfully expanded for signals consisting of sinusoids in white Gaussian noise.
There are several drawbacks to the filtration methods. The extraction components of knocking through filters are not sufficient to guess the knocking as well as increasing the signal-to-noise ratio (SNR). In addition, the values of the resonance frequencies that are a function of the angle of crank and the presence of noise, such as CAM shocks, are difficult to remove. To overcome these problems, the time-frequency methods, such as the Wigner-Ville distribution and the promising method of wavelet transform have been adopted by some researchers.

2.3 Artificial Neural Network (ANN)

Artificial neural networks (ANNs) are defined as mathematical models which represent the biological process of a human brain. There are three main components in the ANNs; neurons or processing elements (PE), interconnections, and learning rules [9].
In other words the basic ANN model includes input nodes for the input parameters, weights connecting the input nodes to the summing neurons, an optional bias function feeding into each neuron, and a transfer function acting on the output of each neuron. The output of the transfer function can be either the output of the network or the input to the next layer of neurons.

A neuron is a component that processes data. It receives and processes input signals and continually passes its output to the next level of neurons. A single neuron may have more than one input but only one output. The output of a neuron depends on the input signals, weights of connections, threshold value and activation functions. The interconnection is a part of the network which propagates signals in a single direction from one neuron to the others or even to itself. The learning rules govern the change of the weight matrix in the network. Learning can be categorized into supervised and unsupervised learning. Supervised learning uses the data set that contains input vectors and corresponding output vectors to train the network while unsupervised learning relies on the local information and internal control within the network [9]. Artificial neural networks can be of many types such as the back propagation neural network, radial basis neural network, single layer and multiple layer networks. Neural networks have been shown to be an effective technique for modelling complex nonlinear processes. Since the operations of neural networks are in a parallel manner, their processing is fast. Unlike some other techniques such as nonlinear regression, neural networks do not require any a priori assumptions of the function [10].

2.3.1. Application of ANN

Some researchers [11] have suggested a way to detect knock using an ANN. This method differs from existing methods, where the wavelet coefficients are calculated and in addition, some statistical parameters are also calculated. These calculated parameters applied to a Neural network are called Self Organizing Maps (SOM) for the classification of the engine cycle through the influence of knocking, where some parameters are affected and other parameters are not affected. When the cycle reveals the affected engine knock this can be used to protect the engine from knocking in the following cycle. Discrete wavelet transforms (DWT) have been used in the signal processing, as well as using two sets of filters. The power that lies in this method is that it is able to provide modelling and analysis of the complex cases where it is possible that there could exist non-linear relationships for some of the variables.

Most of the production systems use either a single accelerometer or multiple accelerometers with univariate analysis. Each cylinder is mapped to a transducer which shows the closest correlation of the intensity of knocking calculated based on the methods appropriate for the cylinder. In this system it is proposed to use an array of nine transducers, and then conduct the analysis of knock intensity values obtained from this array by a multivariate connector.

2.4. Genetic Algorithms

A genetic algorithm (GA) is a heuristic technique used to find approximate solutions for difficult to solve problems through application of the principles of evolutionary biology to computer science. Genetic algorithms use biologically-derived techniques such as inheritance, mutation, natural selection, and recombination (or crossover). Genetic algorithms are a particular class of evolutionary algorithms.

Genetic algorithms are typically implemented as a computer simulation in which a population of abstract representations (called chromosomes) of candidate solutions (called individuals) to an optimization problem evolve towards better solutions. Traditionally, solutions are represented in binary as strings of 0s and 1s, but different encodings are also possible. The evolution starts from a population of completely random individuals and takes place in generations. In each generation, the fitness of the whole population is evaluated, multiple individuals are stochastically selected from the current population (based on their fitness), modified (mutated or recombined) to form a new population, which becomes current in the next iteration of the algorithm.

Genetic algorithms are inspired by Darwin's theory of evolution. The solution to a problem is solved by genetic algorithms by evolving.

The algorithm is started with a set of solutions (represented by chromosomes) called a population. Solutions from one population are taken and used to form a new population. This is motivated by the hope that the new population will be better than the old one. Solutions which are selected to form new solutions (offspring) are selected according to their fitness - the more suitable they are the more chance they have to reproduce. This is repeated until some condition (for example a number of populations or improvement of the best solution) is satisfied.

2.4.1. Application of GA

In 2011, a researcher [12] conducted a study which used a wavelet transform and a Genetic Algorithm to reduce noise and increase the efficiency of the filtration.

The selection of efficient parameters for wavelet signal de-noising, such as the wavelet function, decomposition levels, threshold function (method) and threshold selection rules play a major role in the success of the signal de-noising.

The researcher used an ECG signal distorted by standard white Gaussian noise, and selected a genetic algorithm to search for the best parameters for the wavelet signal de-noising problem. Fig. 7. below explains the hybrid algorithm.

Initially, the researcher entered a distorted ECG signal as well as wavelet de-noising parameters (Φ, L, β, λ, P). Secondly, an appropriate range value for the thresholding of the ECG signal was selected. This was followed by building the objective function, including the mean square error (MSE).

After that the optimal wavelet de-noising parameters were found, followed by a 1-D discrete wavelet transform for the noisy ECG signal to obtain the wavelet coefficients. Then the thresholding for the noisy coefficients in the ECG signal was applied with the optimal thresholds to obtain the modified new ECG components. Lastly, the de-noised ECG signal was rebuilt [12].

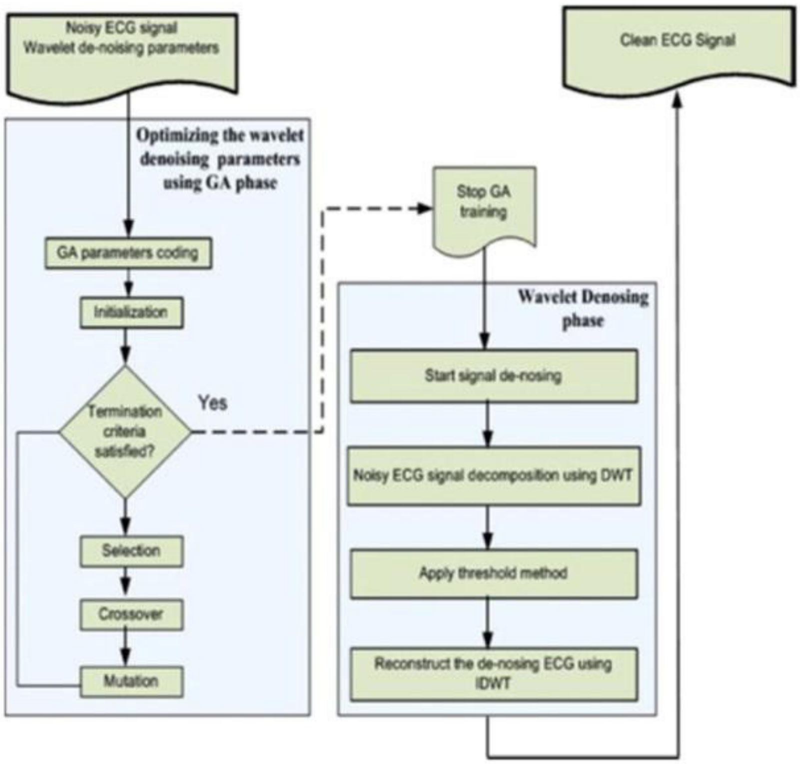

Fig. 7. Flowchart:- Wavelet improvement by GA.

2.5. Predictive Control

Researchers into this area [13] have stated that there are many parameters that are filtered from a pressure signal which can be filtered from band pass filters, which in turn can be used as indicators of knocking. One of these methods is the maximum amplitude of band pass filtered data [14]. Many knock indicators are obtained from a pressure signal, such as the integral of the absolute value of pressure oscillations or the integral of the value of the first derivative of pressure oscillations [15]. By use of these methods, knock detection as a sensitive function in micro-controller architecture can be used in the automotive field.

2.5.1. Fuzzy Logic

Fuzzy control is a tool to model the control of complex systems derived from the knowledge obtained from human experience, unlike ordinary expert systems. Fuzzy control systems do not require the consumption of time in the process of designing suitable algorithms for the display of human behaviour.

The fuzzy controller has four main components: firstly, the “rule-base” which holds the knowledge in the form of a set of rules of how best to control the system. Secondly, the inference mechanism evaluates which control rules are relevant at the current time and then decides what the input to the plant should be. Thirdly, the fuzzification interface simply modifies the inputs so that they can be interpreted and compared to the rules in the rule-base. Finally, the defuzzification interface converts the conclusions reached by the inference mechanism into the inputs to the plant. Fuzzy control is mostly a rule-based system, where the designer heuristically formulates a set of control rules, which makes the scope of fuzzy control narrower than general expert control systems. The main advantage is the relative simplicity with which fuzzy rule bases can be defined, refined or tuned.

2.5.1.1. Application of Fuzzy Logic

Researchers [13] have used this method in extracting indicators of knocking to be used as inputs for fuzzy logic, which is one method of control in the field of soft-computing. The researchers based their work on the oscillation of the pressure signal obtained from the cycle of the in-cylinder pressure, and then obtained digital pulses. The number and total duration of these pulses were used as indicators for the knock. Therefore, and with the fuzzy logic technical assistance, information will be obtained and the phenomenon of knock intensity determined. Compared with conventional systems that do not use soft-computing techniques, the fuzzy approach, when used to detect knocking, allows the determination of a non-linear relationship between input (knock indicators) and output (knock intensity level). In addition, the knock estimation algorithms which use fuzzy logic are easier to implement and require only a low level of computational time. However, despite these advantages, fuzzy logic uses a large number of rules in the rule set, which leads to complexity. In addition, the output of fuzzy logic remains close to the exact solution and it is subject to accuracy of the rule set and Membership functions. It is tedious to develop fuzzy rules and membership functions, which require prior knowledge. If a case is missed, the controller will not work properly. Further, the fuzzy outputs can be interpreted in a number of ways thus making analysis difficult, and it does not give generalizable results.

In 2011, researchers [16] built a control system that could manage the knocking of Diesel-Dual-fuel (DDF) engines which are the most complex form of conventional engines. The behaviour between the mixed compression engines and the ignition engines, which contain an engine DDF, led to the need for a more complex control system.

They used a novel control system, which relied on fuzzy logic for the organization of knock intensity at an appropriate level. The control system consisted of a fuzzy controller and a fuzzy decision maker. The fuzzy controller was used to control several actuators using a rule-base created from human experience, while the fuzzy decision maker examined the magnitude of each event issued by any actuator at a variety of operating points. The control system is designed to regulate several parameters including the amount of Compressed Natural Gas (CNG) (multipoint-injected at the intake ports) and diesel, diesel injection timing, rail pressure, throttle and exhaust gas recirculation (EGR) set points to run the engine near the border of knocking. The results showed that the DDF engine can be operated near the optimal points, and as a result can use a lot of CNG in most of the points of operation. See Fig. 8.

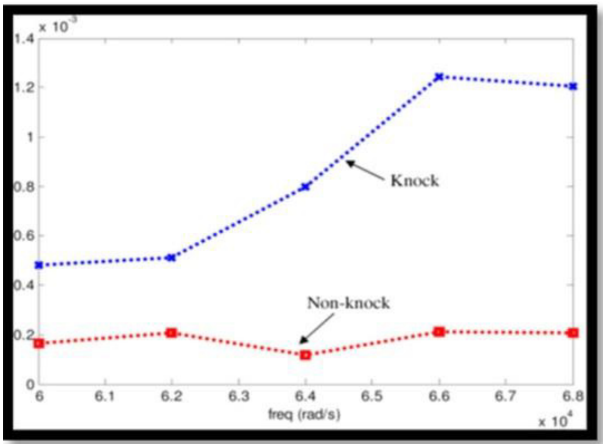

Fig. 8. Comparison of the magnitude A_{qi} between knock (blue) and non-knock (red)

Three test cases were used: no control, fuzzy controller only, and use of both the fuzzy controller and the fuzzy decision maker. Fig. 9. shows the knock intensity results of all three cases. The knock intensity threshold was set to 0.001 for all engine conditions. It can be seen that the use of both the fuzzy controller and the fuzzy decision maker delivered the best result in regulating the knock intensity. This is because with the fuzzy decision maker, the adjustment of all parameters can be done appropriately and speedily according to the current operating point.

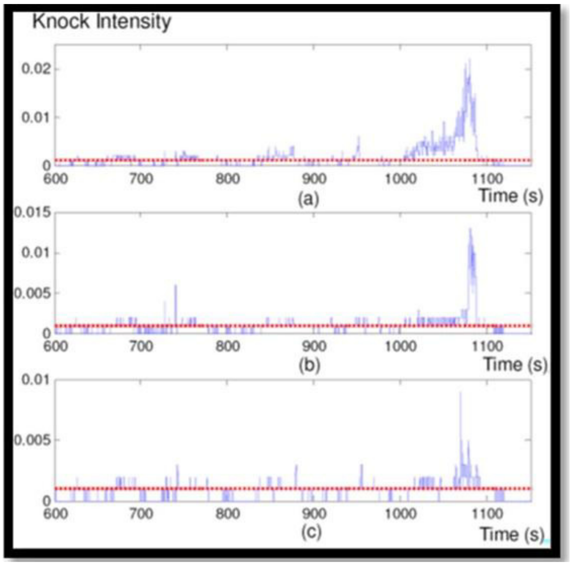

Fig. 9. Knock threshold values (red, dash line) and Knock intensity(blue, solid line) for three cases.
(a) No control. (b) Using only fuzzy controller.(c) Using fuzzy controller and fuzzy decision maker

The control system demonstrated an excellent result in regulating knock at appropriate intensity values. The use of both the fuzzy controller and the fuzzy decision maker enhanced the knock regulation performance to be better than when only the fuzzy controller was used. The engine was able to operate nearer to the optimum points, resulting in greater use of CNG. The success comes from the facts that:

- The control logic was based on expert human experience.
- Multiple parameters can be controlled at the same time.[16].

In 2004, researchers [17] hypothesized a fuzzy control system for gasoline engines. The researchers used a comparison made between the different spark advances and timing setting effects in determining the intensity of knocking. By using adaptation, in the light of the spark timing control function, the proper engine response can be attained, and the difference in spark advances is governed by a fuzzy control system under various cases that have been tested and examined. Researchers have experimentally achieved an improvement in the function of the timing of the spark in the Air/fuel ratio to a large extent, as the angle of the spark advance was controlled to make the engine work to follow the intensity of the knocking. The researchers explained that the proposed new system which used a fuzzy control system instead of a crisp system is the best in terms of higher stability and gives better results [17].

3. Conclusion

From the information given of the above methods to detect knocking, it is important to note that the statistical methods use Band Pass Filters (BPF) that rely on one or more of the resonant frequencies of the signal compression engine. When the speed of the rotation of the engine is slow these methods can be effective where the signal to noise ratio (SNR) is high. However, the signal-to-noise ratio becomes less important and is ineffective in the case of high speed rotation of the engine. This is in addition to the change in the resonance frequencies as a result of changing the engine compression ratio, and also changing the components of the fuel mixture (air/fuel), as well as the combustion of the mixture ratio and other reasons, such as the adoption of frequency representation or representation using time only. Therefore, all of these restrictions cause these methods to have difficulty in providing exact measurements for knock density detection. In order to improve the efficiency of the detection accuracy, these difficulties and limitations have to be overcome through the use of analysis based on the representation of time - frequency, such as the Wigner distribution. However, this method may not be effective when the pressure signal (knocking) has two or more resonance frequencies in which case the Wigner distribution will suffer from a Cross-Term. There are many ways to get rid of the cross term by using a method called the Gabor-Wigner transform or Cohen's class distribution, but the large amount of computation required in these methods make them ineffective. In order to overcome this obstacle and improve the efficiency of detection accuracy it is possible to use fuzzy logic technology which features easy application, and requires only a short computation time. Moreover, it provides relevant information when a severe knock takes place, and in a comparison between fuzzy logic and conventional systems for knock detection, the fuzzy logic allows the determination of the non-linear correlation between inputs (knock factors) and outputs (knock intensity). Wavelet transform (WT) discrimination can be used in conjunction with fuzzy logic as fuzzy logic by itself has several limitations which could preclude its use in some cases, especially where the performance of fuzzy logic sometimes makes it difficult to analyse nonlinear effects. Fuzzy logic relies heavily on the experience of real life, which is a critical factor in the success of such control devices where a lack of experience could hinder the process.

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