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Statistical Processing of Engine Vibration Signals for Knock Diagnosis

A. Uma Mageswari and R. Vinodha
Department of Electronics and Instrumentation Engineering, Annamalai University, Chidambaram, Tamil Nadu, India

Key words: Discrete Wavelet Transform (DWT), knock, kurtosis, skewness, crest factor

Corresponding Author:
A. Uma Mageswari
Department of Electronics and Instrumentation Engineering, Annamalai University, Chidambaram, Tamil Nadu, India

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Abstract: The wavelet transform is the powerful tool used in the field of signal processing. Many works have been contributed to wavelet transform in the last two decades and in precise in this decade, the researchers have thrown a number of works in the field of signal processing based on wavelet transform. This paper extends the idea of Discrete Wavelet Transform (DWT) in knock signal detection which is experienced in SI engine. Due to abnormal combustion, the engine produces a pinging noise which is termed as Knock signal. The knock signal should be identified earlier since the frequent occurrence of the knock signal would damage the engine. In this work the statistical parameter of a knock signal such as kurtosis, skewness and crest factor is determined by employing the DWT. The experimental result shows that the proposed system dominates the results produced by conventional transform.

INTRODUCTION

In a spark-ignition engine, knock occurs when a portion of the air-fuel mixture ahead of the spark-initiated flame front spontaneously combusts (Borg *et al*., 2005). This causes very high local pressures which propagate in the combustion chamber, hence setting the entire engine block in vibration. The pressure wave is formed as a result of increase in pressure and energy released during vibration. The imperative characteristics of both vibrations occur during the knocking and oscillation of pressure in the cylinder is that their resonant frequency will decrease with time. This vital feature will contribute to the detection of knock as illustrated by Zhang and Tomota (2000). The crisis related to knock like pollution is overcome by advance detection of knock (Park and Yang, 2004). The prevention measure for detonation is shown by Stankovic and Bohme (1999) as we can use fuel with high octane numbers, reduction of pressure and temperature in the cylinder and controlling the time of ignition. The Engine parameters that affect the occurrence of knock are.

Compression ratio: Auto-ignition is made possible with high compression ratio. If the mixture of fuel-air is compressed to high pressure and temperature, ignition will be initiated automatically even before the spark ignition.

Engine speed: Auto-ignition takes more time for the engine with low speed. In contrast to this, the loss of heat is very less if the speed of engine is high and in turn this would increase the temperature of the gas. Finally the gas with high temperature will advance to Auto-ignition.

The structural vibration signal is the basis for the planned detection scheme and this vibration signal can be detected and measured with accelerometer (Molinaro *et al*., 1992). The knock sensor responds to the acceleration of the engine block at its mounting location. The response from the sensor is dominated by low SNR. The low SNR is experienced as result of masking the knock signal with various other vibrations (Borg *et al*., 2005). The aim of this paper is to detect the knock signal by incorporating the Discrete Wavelet Transform (DWT). The real-time realization of the proposed system is made possible by fixing the accelerometer in the car engine.

The feature parameter of the detected vibration signal is analyzed by using the wavelet transform. The wavelet transform made the analysis easy by forming the segments of long and complicated signal which is detected by the accelerometer. The proposed method outperforms the results achieved by conventional transform and the practical application shows that it could contribute to the future engine knock signal detection.

MATERIALS AND METHODS

Mathematical analysis of dft, stft and wavelet transform

Discrete fourier transform: The Discrete Fourier Transform (DFT) operates on periodic sampled time domain signal and it correlates the input time domain samples with its basis function (sine and cosine waves). The fundamental analysis equation for obtaining the N-point DFT is as follows:

$$X(k) = \frac{1}{N}\sum_{n=0}^{N-1} x(n) e^{-j2\pi nk/N}$$
$$X(k) = \frac{1}{N}\sum_{n=0}^{N-1} x(n)\left[\cos(2\pi nk/N) - j\sin(2\pi nk/N)\right] \quad (1)$$

The correlation of a sine/cosine wave of any frequency other than that of the basis function produces a zero value for both ReX(1) and ImX(1) as shown in Fig. 1. A similar procedure is followed when using the inverse DFT (IDFT) to reconstruct. The disadvantage in DFT is that it assumes signal is periodic. Therefore, when measured signal is non-periodic, spectral leakage occurs. Further, DFT also reveals only frequency information and it does not tell us, at which time these frequency components exist.

Short time fourier transform: All the real time signals like vibration signal from any rotating machinery or engine are Non-stationary signal and therefore time-frequency analysis method is needed to analyze such kind of signals. Then multiply the signal with a window function whose width is equal to the small segment of the signal where it is stationary and then Fourier Transform is taken for the product. The short time Fourier transform of a function x(t) is given by:

$$STFT_X^{\omega}(t, f) = \int\left[x(t) * \omega^*(t, t')\right] * e^{-j2\pi ft} dt \quad (2)$$

The advantage of STFT over DFT is that along with frequency components, time localization is also known. But the disadvantage is fixed window size. Time/Frequency localization depends on window size. Once a particular window size is chosen, it will be the same for all frequencies. Narrow window leads to poor frequency resolution and Wide window gives poor time resolution (Polikar, 2002).

Wavelet transform: The wavelet transform has proven to be very effective in analyzing a wide class of signals

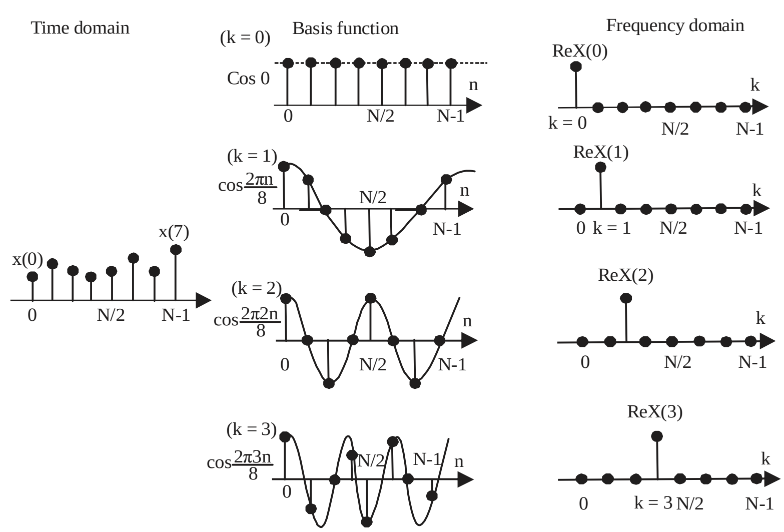

Fig. 1: Correlation of time samples with basis function using DFT

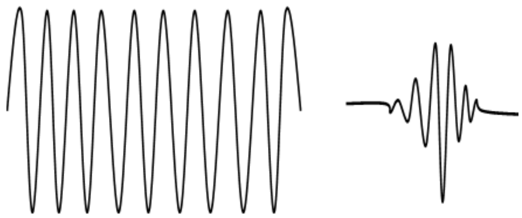

Fig. 2: Sinusoid basis function in DFT and wavelet basis Function in WT

that appear in practical applications but are not well matched by the Fourier basis (Fiolka, 2006). WT overcomes the preset resolution problem of the STFT by using a variable length window. Narrow window could be used at high frequencies for better time resolution and wider windows at low frequencies for better frequency resolution. Wavelets are functions that “wave” above and below the x-axis, having varying frequency, limited duration and an average value of zero. This is in contrast to sinusoids, used by fourier transform which have infinite energy as shown in Fig. 2. In wavelet transforms, Wavelets are used as basis function, unlike the sinusoids which are the basis function in DFT.

Continues wavelet transform: If x(t) is a given function, then continuous wavelet transform of the function is expressed as:

$$CWT_{X(\tau,a)} = \frac{1}{\square\sqrt{a}}\int X(t)\times\varphi^*_{\tau,s}(t)dt \quad (3)$$

Where:
$\tau\rightarrow$ = Translational factor (time)
$a\rightarrow$ = Scale factor

When a>1, the signal is dilated; when a<1, the signal is compressed. The complete CWT is obtained for all values of the scaling parameter. When large scale is selected, the resulting $\psi_{\tau,s}(t)$ become low frequency wavelet functions and spread out in time and vice versa (Albarbar, 2013). To detect localized characteristic frequency, the magnitude of wavelet transform at different dilations varies periodically at a rate of the characteristic frequency of a certain defect. At low frequency, high scale is chosen which gives a non-detailed global view of the acquired knock signal. For higher frequencies, low scale is chosen which gives a detailed view of the signal. At lower scale, the wavelet is compressed and is used to detect the rapidly changing details. The main disadvantages of the CWT are heavy redundancy and computational complexity (Fiolka, 2006) as far as the reconstruction of the signal is concerned. This leads to the discrete wavelet Transform where the scaling factor ‘a’ and the Translational factor ‘b’ are sampled.

Discrete wavelet transform: The Discrete Wavelet Transform (DWT) tracks the changes in frequency content of a signal as a function of time. DWT is a convolution of the input data sequence with a set of functions generated by the mother wavelet. DWT of the signal x(t) is defined as:

$$DWT_X(iT_S, a) = a^{-1/2}\sum_{n=1}^{N} x(nT_S)\varphi^*\left(\frac{(n\text{-}i)T_S}{a}\right) \quad (4)$$

Where:
$N\rightarrow$ = No. of samples
$T_S\rightarrow$ = Sampling period

$$x[n]*h[n] \;\; \sum_{x=-\infty}^{\infty} x[k]*h[n\text{-}k] \quad (5)$$

The filters of different cutoff frequencies are used to analyze the signal at different scale. The signal is passed through a series of high pass filter to analyze the high frequencies and low pass filters to analyze the low frequencies. Therefore, Eq. 5 becomes:

$$Y[n] = \sum_{k=-\infty}^{\infty} h[k]\times x[2n\text{-}k] \quad (6)$$

The first level of decomposition can be mathematically expressed as:

$$Y_{high}[k] \;\; \sum_n x[n]\times g[2k\text{-}n] \quad (7)$$

$$Y_{low}[k] \;\; \sum_n x[n]\times h[2k\text{-}n] \quad (8)$$

Both the filter is related by:

$$g[L\text{-}1\text{-}n] = (\text{-}1)^n\times h[n] \quad (9)$$

$$Y_{high}[k] = \sum_n x[n]\times g[\text{-}n+2k] \quad (10)$$

$$Y_{low}[k] = \sum_n x[n]\times h[\text{-}n+2k] \quad (11)$$

The reconstruction of the original signal can be derived from:

$$x(n) \;\; \sum_{kx-\infty}^{\infty}\left(y_{high}[k]\times g[\text{-}n+2k]\right)+\left(y_{low}[k]\times h[\text{-}n+2k]\right) \quad (12)$$

The Fig. 3 illustrates the decomposition of the original signal at each level of filtering and sub-sampling. In Fig. 3, g[n] is the low-pass approximation coefficient; h[n] is the high-pass detail coefficient. In detail coefficient, the time resolution is good. In approximated

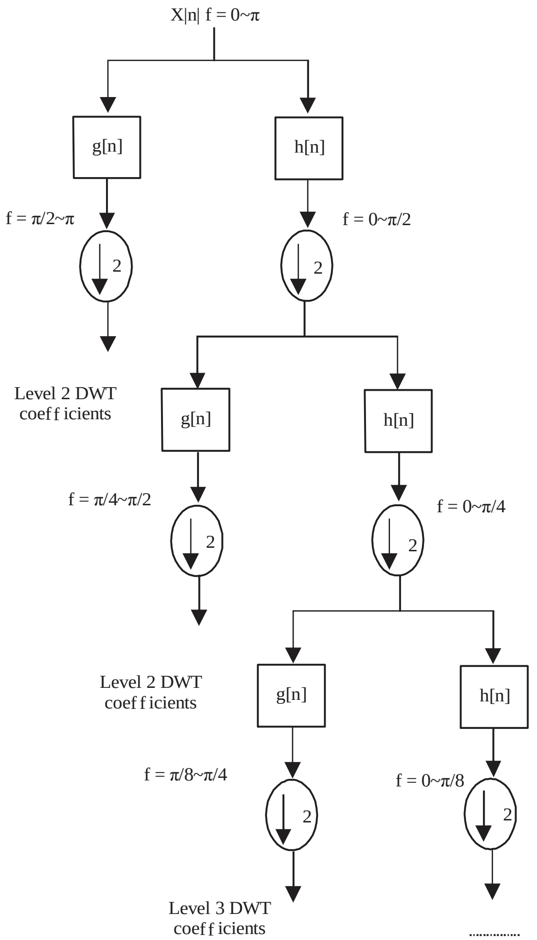

Fig. 3: Three level decomposition using DWT

coefficient, the frequency resolution is good. The decimation process is undergone for getting the time resolution signals. The larger the dilation scale goes, the more multiplications and additions are needed (Kikuchi *et al*., 1993).

The DWT is very suitable for knock detection systems, since the knock signal can be observed in discrete scales (Borg *et al*., 2006). Also the acquired knock is a transient phenomenon consisting of several resonances with decreasing resonance frequencies (Matz and Hlawatsch, 1998). As shown in the Fig. 3. The DWT is computed by successive low pass and high pass filtering of the discrete time-domain signal.

Signal statistics: Detonation can be examined by statistical parameters such as crest factor, kurtosis, skewness, RMS value of the signal. The crest factor corresponds to the ratio between the crest value (maximum absolute value reached by the representative function of the signal during the considered period of time) and the R.M.S. value (efficient value) of the signal and can be expressed as:

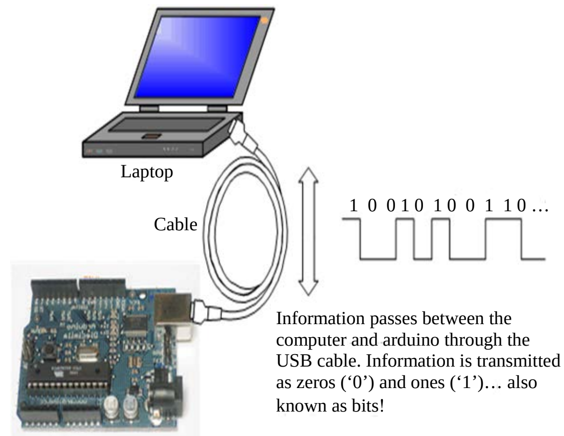

Fig. 4: Three level decomposition using DWT

$$\text{Crest factor} = \frac{\text{Crest value}}{\text{RMS value}}$$

High crest factor indicates a low signal to noise ratio. The crest factor and the energy depend inversely on each other (i.e., if crest factor is large then the signal contains less energy and vice versa). The time-domain signal which contains the vibratory amplitude can be determined by the kurtosis and in addition the impulsiveness of the signal can be detected. The kurtosis can be determined by second and fourth order statistic moment (i.e., M2 and M4) and signal amplitude x(n) for n sample. The expression is as follows:

$$\text{kurtosis} = \frac{M_4}{M_2^2} = \frac{(1/N)\sum_{n=1}^{N}\left(x(n)-\tilde{x}\right)^4}{\left[(1/N)\sum_{n=1}^{N}\left(x(n)-\tilde{x}\right)^2\right]^2}$$

In the context of machine fault detection, a high kurtosis value indicates the presence of faults in a rotating mechanical system. To evaluate the symmetry and the third order moment we can compute the Skewness. The probability density function with longer right side and left side is indicated by positive and negative skewness value, respectively.

Experimental setup: An acknowledged procedure in today's automobile is to mount acceleration sensors on the engine body to measure sound in the form of a distorted version of pressure signal inside the cylinder (Carstens-Behrens and Bohme, 2001). Keeping this in mind a simple experimental setup which consists of the spark ignition engine, Arduino kit, laptop with LabVIEW software and its interface with the Arduino as shown in the Fig. 4 have been developed. LabVIEW interface for Arduino (LIFA) Software interfaces the LabVIEW Software with Arduino kit. Detonation is actually an acoustic vibration signal from an engine body in commercial vehicles (Jonathan *et al*., 2006). Therefore an accelerometer is attached to the engine which measures the vibration signals. Arduino converts vibration signal into binary waveform which is processed by a program developed by means of LabVIEW Software. The sampling frequency was set at 1024 kHz.

RESULTS AND DISCUSSION

The result of the proposed system is evaluated and compared with the results based on conventional transformations. In order to evaluate the outcome of the proposed system, we have calculated the vital characteristics of knock signal such as skewness, kurtosis and crest factor. The hardware setup is made as shown in the experimental setup. The knock signal from the engine is detected by the accelerator and it is bypassed to Software (LabVIEW) through the Arduino and the detected signal is shown in Fig. 5.

To make the signal analysis, complex-free, precise and accurate, we, have to determine the transformed signal and the FFT transform of the detected knock signal is shown in Fig. 6-10. In our proposed system, Discrete

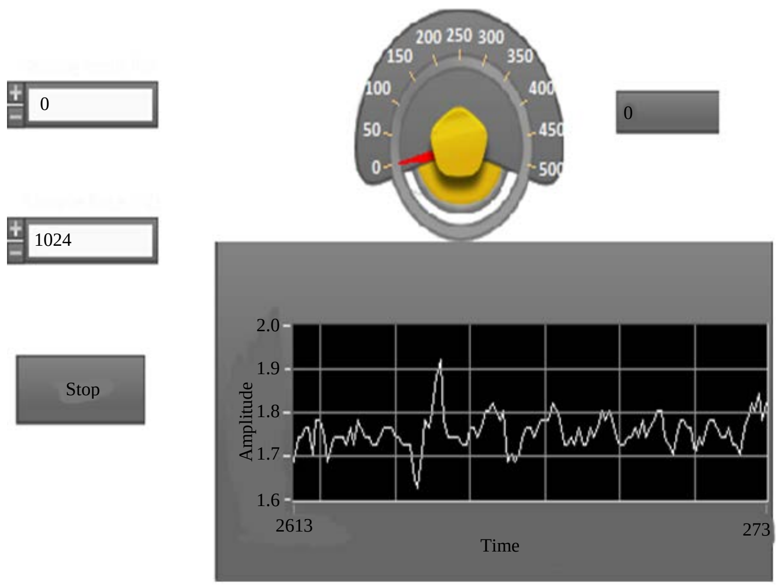

Fig. 5: Detected signal

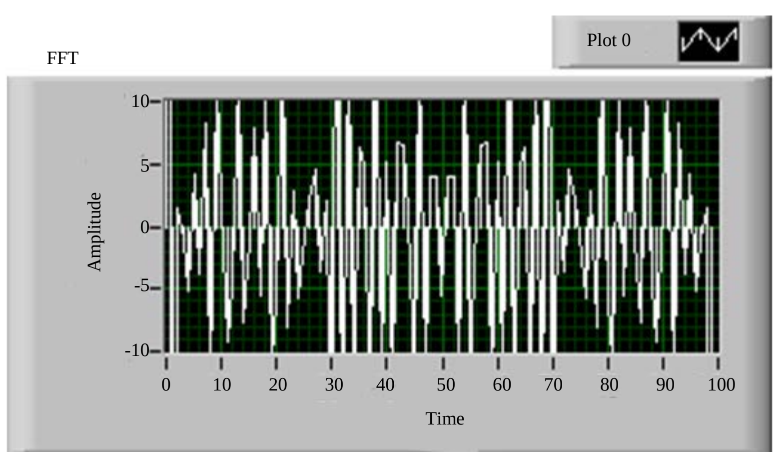

Fig. 6: FFT output of the detected signal

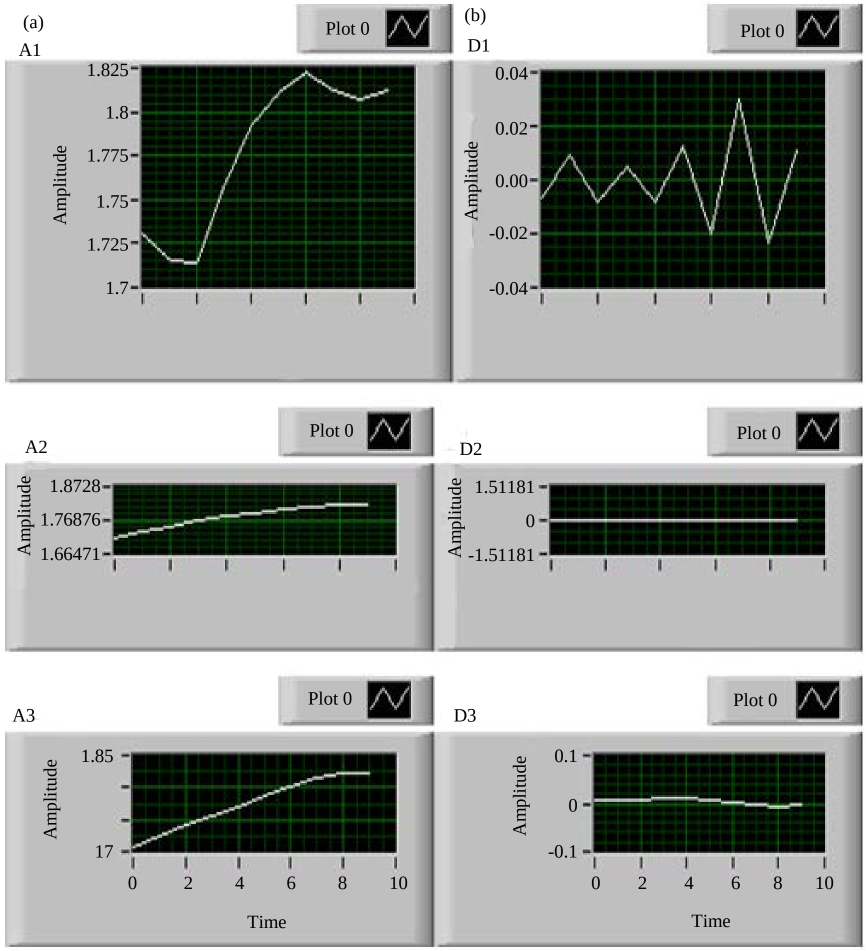

Fig. 7(a, b): Approximation and detailed coefficients

kurtosis

1.813772	2.249391	1.774706	1.625098	6.899576	1.840319
1.429568	4.715149	1.661513	1.260942	1.853878	1.847380
6.650281	2.702665	4.224191	2.705590	1.763011	1.900575
1.196014	2.206745	1.747756	2.205864	2.292080	1.796361
2.329177	3.225028	1.349646	2.627363	1.871172	2.853047
1.906891	7.753359	1.763610	4.693611	3.151098	1.811856
1.501624	2.087431	1.814779	3.176961	1.981525	1.848299
1.916173	2.199009	4.313161	1.712922	1.760853	1.899426
2.768349	2.690022	3.665243	2.866129	1.729750	2.175123
1.335348	3.209620	1.757483	2.813842	2.683559	1.809598
1.948596	5.325817	3.525633	2.778136	1.702923	1.908193
4.300344	4.026130	1.442263	4.311930	1.822837	1.887930
6.921457	3.622509	4.354695	1.623826	1.786345	1.870152
6.717256	3.788744	3.734597	4.095930	1.808506	1.810901
1.791772	2.503333	1.728642	4.256632	4.666411	1.790044

Fig. 8: Computed kurtosis

skewness

0
0

-0.182388	0.370101	0.953322	0.533875	0.319365	-0.32642
0.110250	0.550153	0.312890	0.127353	-1.88860	0.347249
0.382576	-1.134421	0.483890	-0.13783	-0.34933	-0.39509
1.774537	0.592846	1.056572	-0.03885	0.336927	-0.19630
0.379404	-0.535231	0.260834	-0.12908	0.111990	0.383151
0.193946	-1.153439	0.236936	-0.39426	-0.38652	0.199573
-0.691556	-1.637939	-0.29471	1.588283	0.188853	-0.37379
-0.242119	-0.373948	-0.02546	0.422109	0.326842	0.367381
0.057466	-0.602009	1.193512	0.327689	0.330244	-0.20077
-0.811019	0.770962	-1.32701	-0.89357	-0.30683	-0.23370
-0.399130	0.673113	-0.25966	0.455090	0.055477	-0.37684
-0.106934	1.386827	0.569299	0.095728	0.281999	-0.21239
-1.496362	0.171418	-0.57113	-0.00502	0.357175	0.402909

Fig. 9: Computed skewness

crest factor

1.027505	1.921158	1.039402	1.799701	1.023369	1.950318
1.041919	2.494842	1.047310	2.146176	1.019848	2.138966
1.043079	2.809971	1.047762	2.571369	1.019764	2.420450
1.048083	2.641202	1.051783	2.724798	1.023025	2.437868
1.047087	2.804882	1.051184	2.449948	1.024348	2.510715
1.043884	2.972968	1.048108	2.506286	1.022290	2.748819
1.061539	6.819698	1.121832	5.149499	1.030697	4.839090
1.060441	7.285998	1.121008	5.486147	1.030725	5.142765
1.057652	7.725531	1.118259	5.782856	1.028237	5.453116
1.056739	8.142935	1.117314	6.015863	1.027666	5.746746
1.056394	8.535339	1.116801	6.230438	1.027091	6.004815
1.056399	8.907038	1.116733	6.414258	1.026964	6.246703
1.079551	7.468532	1.123277	6.360738	1.134047	5.540381
1.077074	7.747136	1.120846	6.594388	1.131841	5.744726
1.076785	8.014934	1.120684	6.800023	1.131917	5.942537

Fig. 10: Computed crest factor

wavelet transform is used to compute the timing and frequency information of the knock signal. The determined approximation coefficients (i.e., A1, A2 and A3) and detailed coefficients (i.e., D1, D2 and D3) are shown in Fig. 7. Figure 8 shows the determined kurtosis for the detected knock signal. In similar, the skewness of the knock signal is shown in Fig. 9. Finally, both RMS value and Crest value is used to determine the Crest factor and the result is shown in Fig. 10.

CONCLUSION

This study contributes to the detection and analysis of the knock signal in the engine. The knock signal is captured by the accelerometerand forwarded to LabVIEW through Arduino board for analysis based on the statistical parameter such as skewness, kurtosis and crest factor. From the experimental result, we can conclude that the proposed system of analyzing the statistical parameter of the vibration signal from the SI engine based on Discrete Wavelet Transform (DWT) outperforms all the results based on the conventional transforms. As of now, we have employed the DWT for the analysis and in the future the work can be extended by deploying the wavelet packets for analyzing the statistical parameters.

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