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ENGINE KNOCK DETECTION BASED ON WAVELET PACKET TRANSFORM AND SPARSE FUZZY LEAST SQUARES SUPPORT VECTOR MACHINES (SFLS-SVM)

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ABSTRACT

The intensity of knock detection techniques is detected by using the combination of microphone sensors and sequence of filtering techniques, which are identified the type of engine vibration sound. However, the other knock detection methods, such as using wavelet transform and support vector machines, are failed to accurate time detection and the exact identification. This paper proposed wavelet packet transform (WPT) and sparse fuzzy least squares support vector machines (SFLS-SVM) techniques for better accurate time detection and the exact identification. WPT acts as a tool to analyze the characteristics of the knock signals in the decomposition levels. To find the exact intensity of knock detection, sparse fuzzy least squares support vector machines (SFLS-SVM) is introduced. SFLS-SVM works efficiently in the stepwise selection, forward expansion phase and backward exclusion phase for every step. The SFLS-SVM algorithm is extremely fast as compared with the Fourier transform (FT), Wavelet Transform (WT) and Wavelet Packet Transform (WPT)

KEY WORDS
Knock Detection, wavelet packets transform (WPT) and sparse fuzzy least squares support vector machines (SFLS-SVM)

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INTRODUCTION

Now-a-days, Engine control systems are intended to minimize fatigue emissions while increasing power and fuel economy. The capability to increase power and fuel economy by optimized spark timing for a given air ratio or fuel ratio is restricted by engine knock. Detecting engine knock and controlling combustion timing to tolerate an engine to keep running at the knock threshold gives the best power and mileage. Typical ignition occurs when a gaseous combination of air and fuel is ignited by the sparkle plug and blazes easily from the position of ignition to the cylinder walls.

The competence efficiency is an imperative parameter for an engine. The competence efficiency of the engine is enhanced with an augment in compression ratio (CR) as predicted by thermodynamic study of best motor engine cycles. Yet, raising the CR also enhances the susceptibility to knock [1]. The condition with specific temperatures and weights of pressure in an engine cylinder after the sparkle ignition, the clean gas zone, situated in front of the fire front might produce one or more auto ignitions and some of them disintegrate into non-linear pressure weights waves or knock [2].

Most importantly engine knock causes the majority of the unusual burning in an engine [3], for instance polluting, exasperating passengers by the uncomfortable metallic noises and obliterating engine parts in extreme knock condition. In this way, early detection of knock is most important to lessen pollution and other issues.

There are a few disadvantages of the filtering concepts. Extracting the knock segment split into the resonance frequencies by basic pass-band filters is not adequate both to appraise the knock and to enhance the signal-to-noise ratio (SNR). Additionally the values of resonance frequency are capacity of the crank angle, and the vicinity of noise, like cam shocks, is complex to evacuate. With a specific end goal to overcome those issues, time-frequency approaches [4-7], the short-time Fourier transform (STFT), the promising method wavelet transform [8-10], are modified by number of researchers.
Support vector machine (SVM) [11-12] is proposed method that intends to solve classification pattern issues, where it is utilized to discover a hyperplane $h \cdot x$ that can isolate two class designs with the greatest edge. This is because maximizing the two-class edges is proportionate to minimizing the upper bound on the model's simplification error. Because of the high computational complexity usually concerned in illuminating the Quadratic Programming (QP) issues in the dual-space in SVM, least-squares support vector machine (LS-SVM) was proposed by changing the inequality limitations in conventional SVM with a two- standard.

This paper proposed wavelet packet transform (WPT) and sparse fuzzy least squares support vector machines (SFLS-SVM) techniques for better accurate time detection and the exact identification. WPT acts as a tool to analyze the characteristics of the knock signals in the decomposition levels. To find the exact intensity of knock detection, sparse fuzzy least squares support vector machines (SFLS-SVM) is introduced. SFLS-SVM works efficiently in the stepwise selection, forward expansion phase and backward exclusion phase for every step. The SFLS-SVM algorithm is extremely fast as compared with the SVM.
Section-II describes the wavelet packet transform (WPT); Section-III explains sparse fuzzy least squares support vector machines; Section-IV describes the proposed method algorithm; Section-V discusses the result, and finally concludes the paper in section-IV.

WAVELET PACKET TRANSFORM (WPT)

Wavelet packets are a specific linear combination of wavelets. They appearance bases that hold a lot of the orthogonality, smoothness and area properties of their parent wavelets[13]. The coefficients in the

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direct combinations are processed by a recursive method, with the outcome that developments in wavelet-packet bases have less computational complexity.
As of late, the WPT has been proposed as an important new device in signal analysis and processing. Wavelet transform is a high-quality solution in the both frequency domains and time domains, synchronously, and can remove more information in the time domain at unusual frequency bands. The WPT has been utilized for on-line monitoring of the process. The WPT can decompose the existing signal into different levels in distinctive time windows and frequency bands; the components, subsequently, can be considered as feature elements of the original signal.

To decompose an existing signal, which is a one-dimensional (1-D) discrete-time signal, an easy and quick method is required for calculation of WT coefficients of the signal. In the first level of wavelet decomposition, a signal can be decomposed into an approximation and detail coefficients, confirmed in [Fig. 1]. In second level of wavelet decomposition, the coefficient of the approximation is again decomposed into approximation and detail coefficients, and then it repeats the level of procedure.

In WPT, approximations coefficients and details coefficients can be part, demonstrated in [Fig. 2]. In WPT theory, the low pass coefficient (approximation coefficient) component and high pass coefficient (detail coefficient) component outputs can be iterated into further separating. Accordingly, the WPT achieves more than one wavelet packet at a specified scale at the importance of high pass filter. Anyhow the low pass filter does again at every level in wavelet transform. The final level of the wavelet packet decomposition is the time representation of the signal. At every last level, the tradeoff between resolutions of the both time and frequency can be expanded. Subsequently, the WPT acquires an exact frequency resolution than the WT.

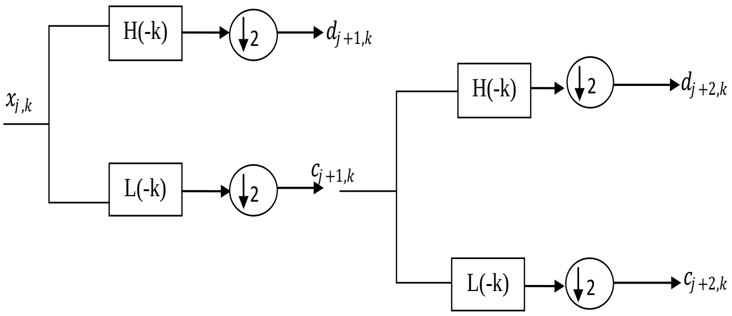

Fig. 1: Decompositions of wavelet transform.

For a predefined succession of signals $x_{j,n} \in K$ at scale j, the approximation coefficients can be effected by filtering $x_{j,n}$ with the low-pass wavelet filter $L = \{l_t\}$ and then sub inspected by two

$$c_{j+1,k} = \sum_n l_{n-2k}\, x_{j,n} \qquad (1)$$

Because of low-pass filtering, a few details would have been lost from $x_{j,n}$, which could be registered by filtering $x_{j,n}$ with the high-pass wavelet filter $H = \{h_t\}$ and then sub sampled by two

$$d_{j+1,k} = \sum_n d_{n-2k}\, x_{j,n} \qquad (2)$$

Here $d_{j+1,k}$ is the detail coefficient.
For that reasons, mathematical equations (1) and (2) are measured as a decomposition signal onto an orthogonal, and measured the reconstruction can be summed up the orthogonal projections.

$$x_{j,n} = \sum_n l_{n-2k}\, c_{j+1,k} + \sum_n h_{n-2k}\, d_{j+1,k} \qquad (3)$$

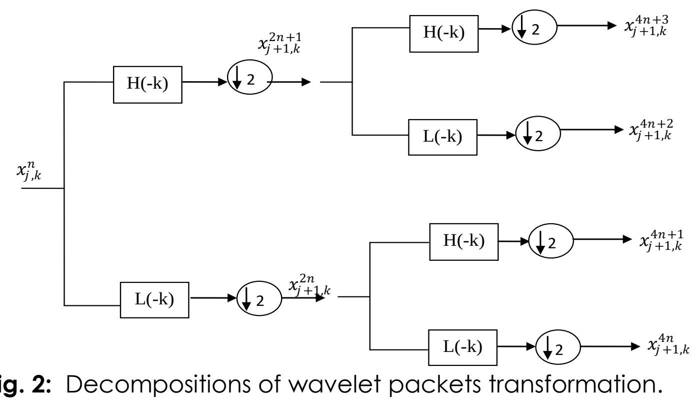

Fig. 2: Decompositions of wavelet packets transformation.

Here, filters h_t and l_t are supposed to satisfy

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$$h_t = (-1)^t h_{1-t}, \sum_n h_t = \sqrt{2}, \sum_n h_t h_{t+2\varepsilon} = \delta_{0,\varepsilon},$$
$$\delta_{0,\varepsilon} = \begin{cases} 1, \varepsilon = 0 \\ 1, \varepsilon \neq 0 \end{cases}$$

Here t ∈ Z, ε ∈ Z.
In WT, every single level can be decomposed by transient the preceding approximation coefficients as high pass filters (HPF) and low pass filters (LPF). In any case, WPT decomposit, both the high frequency and low frequency coefficients have been decomposed. The WPT coefficients equations can be distinct as

$$x^{2l}_{j+1,k} = \sum_n l_{n-2k}\, x^l_{j,n} \qquad (4)$$
$$x^{2l+1}_{j+1,k} = \sum_n h_{n-2k}\, x^l_{j,n} \qquad (5)$$

The reconstruction can be done as

$$x^l_{j,n} = \sum_n l_{n-2k}\, x^{2l}_{j+1,k} + \sum_n h_{n-2k}\, x^{2l+1}_{j+1,k} \qquad (6)$$

Here, l is the space serial number in scale j. For J scale decomposition, the WPT decomposition makes 2^J sets of coefficients rather than $J + 1$ sets of coefficients for the WT. On the other hand, due to the down sampling process the number of coefficients is still same and no redundancy is there.
For effortlessness and efficiency, a node $x^{2l}_{j+1,k_{j+1}}$ or $x^{2l+1}_{j+1,k_{j+1}}$ can be written as the linear combination of the nodes at scale j. From the equations (4) and (5), it can be characterized as

$$x^{2l}_{j+1,k_{j+1}} = \frac{\sqrt{2}}{2}\left(x^l_{j,k_j} + x^l_{j,k_{j+1}}\right) \qquad (7)$$
$$x^{2l+1}_{j+1,k_{j+1}} = \frac{\sqrt{2}}{2}\left(x^l_{j,k_j} - x^l_{j,k_{j+1}}\right) \qquad (8)$$

Here, $= 0, 1,\ H = \{h_0, h_1\},\ L = \{l_0, l_1\},\ l_0 = \frac{\sqrt{2}}{2}, l_1 = \frac{\sqrt{2}}{2}, h_0 = \frac{\sqrt{2}}{2}, h_1 = -\frac{\sqrt{2}}{2}$, it can be seen that $k_j = \left[\frac{k_0}{2^j}\right]$,

SPARSE FUZZY LEAST SQUARES SUPPORT VECTOR MACHINES (SFLS-SVM)

Aspire of this paper is that a new fuzzy rule-based system is developed based on a SFLS-SVM learning mechanism with the representation structure appeared in [Fig. 3].

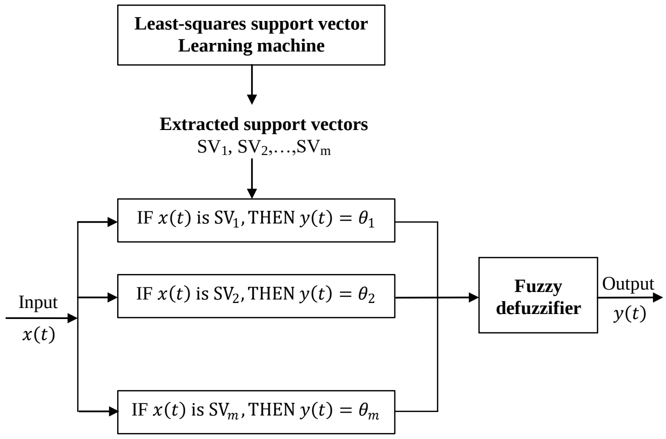

Fig. 3: The structure of the sparse fuzzy least squares support sector machines (SFLS-SVM).

Comparative as in SVM-based fuzzy systems [13], the fuzzy basis function (9) is selected as the mapping function (11) in the solution of SFLS-SVM, Comparative as in SVM-based fluffy frameworks [13] (where the portion capacity in SVMs is identified with the fluffy premise work), the fluffy premise capacity (9) is picked as the mapping capacity (11) in our proposed arrangement of SFLS-SVM,

$$N_i(x(t); W) = \frac{\mu_i(x(t); c_i; \sigma_i)}{\sum_{i=1}^m \mu_i(x(t); c_i; \sigma_i)} \qquad (9)$$

Where $W = [c_1^T, \sigma_1^T, \dots, c_m^T, \sigma_m^T]^T$ denotes the premise parameters vector. $\mu_i(x(t); c_i; \sigma_i)$ is the Gaussian membership function; which is defined in eq. (10)

$$\mu_i(x(t); c_i; \sigma_i) = \prod_{j=1}^n exp\left\{-\frac{1}{2}\left(\frac{x_j(t) - c_{i,j}}{\sigma_{i,j}}\right)^2\right\} \qquad (10)$$

Where $c_{i,j}$ is the centre of the i^{th} membership function with regard to the j^{th} input $(j = 1, \dots, n)$; i.e., $c_i = [c_{i,1}, \dots, c_{i,n}]^T \in \Re^n$ and $\sigma_{i,j}$ is the standard deviation of the i^{th} membership function with regard to the j^{th} input $(j = 1, \dots, n)$; i.e., $\sigma_i = [\sigma_{i,1}, \dots, \sigma_{i,n}]^T \in \Re^n$.

i.e.,$\varphi_i(x(t)) = N_i(x(t); W)$, to combine the two methods into a new sparse Least Square Support Vector Machine based fuzzy rule-based system. Note that normally the denominator of the fuzzy basis function (FBF) is uninvolved since the number of fuzzy rules is unknown in advance. There is no contravention of the soul of a fuzzy inference (FIS) system as depicted in [20], where the standard rule premises decide the certainty values for all rules, while the rule consequents allot the outcome of the inference system with the certainty values for the relating rules. Therefore, the support vectors extracted from the SFLS-SVM learning mechanism can be useful in producing the fuzzy IF-THEN rules that compare to the FBFs. In this way, the fuzzy systems can give suitable speculation capability over concealed information as in case of SFLS-SVM. Contrasting from the conventional Least Square SVM (LS-SVM) where all training samples serve as the SVs, a novel SFLS-SVM learning mechanism is proposed to generate rule determination in a fuzzy rule-based system. The average weighted defuzzification strategy can then be utilized to compute the general output of the fuzzy rule-based system, such that

$$f(X(t); W; \Theta) = \sum_{i=1}^{m} N_i(x(t); W)\theta_i \qquad (11)$$

Where $\Theta = [\theta_1, \dots, \theta_m]^T$ denotes the consequent parameter vector.

THE PROPOSED METHOD ALGORITHM FOR KNOCK DETECTION

1. The knock signal is defined as

$$x(t) = s(t) + n(t) = \sum_{p=1}^{P} a_p w_p(t) \cos\left(2\pi\left(\alpha_p t^2 + \beta_p t\right) + \phi_p\right) + n(t) \qquad (12)$$

2. The wavelet packet transform can be defined as $\phi_{2n} = \sqrt{2}\sum_k h_k \phi_n(2t-k)$ and $\phi_{2n+1} = \sqrt{2}\sum_k g_k \phi_n(2t-k)$. Here, the wavelet packets given by $\phi_{njk}(t) = 2^{j/2}\phi_n(2^j t - k)$.

3. The efficient learning mechanism of the SFLS-SVM is detailed as follows.

Step 1): Initialization. To start the learning process, the candidate pool $\Psi_0 = [\varphi_1, \dots, \varphi_m]$ is first generated by using all the training patterns as the potential rules or Support Vectors. Note that the initially selected pool Φ_0 is an empty matrix. The number of selected regressors is set to $k = 0$ and the two vectors $b^1 = [\varphi_1^T y, \dots, \varphi_m^T y]$and $d^1 = [\varphi_1^T \varphi_1, \dots, \varphi_m^T \varphi_m]$ are initialized.

Step 2): Forward expansion phase. The main task here is to select the most significant regressor from the candidate pool and to update the corresponding variables for the operations ahead.

1) According to the contribution of each candidate regressor computed from $\Delta \vec{J}_{k+1}(\varphi_i) = \frac{1}{2\mu}\frac{(b_i^{k+1})^2}{d_i^{k+1}+\mu}, i = k+1, \dots, m$, the one with the largest objective reduction is selected as the next regressor to be added into the regression matrix$\varphi_{k+1} = [p_1, \dots, p_{k+1}]$, i.e., $p_{k+1} = \arg\max_{i=k+1}^{m} \Delta \vec{J}_{k+1}(\varphi_i)$. The corresponding regressor p_{k+1} is then removed from the candidate pool and $\Psi_{k+1} = [\varphi_{k+2}, \dots, \varphi_m]$ set.

2) While all the previous k rows remain unchanged, the $(k+1)^{th}$ row of matrix A is calculated using $a_{k,i}$.

$$\text{Where } a_{k,i} = \begin{cases} \mu\, a_{i,k}/(a_{i,i}+\mu) - \sum_{j=i+1}^{k-1} a_{j,k}\, a_{j,i}/(a_{j,j}+\mu), & i = 1, \dots, k-1, \\ p_k^T p_k - \sum_{j=1}^{k-1} a_{j,k}^2/(a_{j,j}+\mu), & i = k, \\ p_k^T \varphi_i - \sum_{j=i+1}^{k-1} a_{j,k}\, a_{j,i}/(a_{j,j}+\mu), & i = k+1, \dots, m. \end{cases} \qquad (13)$$

3) The two vectors b^{k+2} and d^{k+2} are updated with entries from $k+2$ to m by using b^{k+1} and d^{k+1}, employed for selecting the $(k+2)^{th}$regressor from the candidate pool.

Step 3): Backward exclusion phase. The main purpose of this phase is to re-evaluate the contribution of each of the previously selected regressors.

1) The entries from 1 to $k+1$ for the two vectors c^{k+1} and $h^{k+1}$are updated, while the correspondingly remaining values in the two vectors are inherited from b^{k+2} and d^{k+2}.

2) The criterion $\Delta \overleftarrow{J}_{k+1}(p_r) = \min_{i=1}^{k} \Delta \overleftarrow{J}_{k+1}(p_i) < \max_{i=1}^{k} \Delta \overleftarrow{J}_{k+1}(\varphi_i)$ is used to decide whether to remove a regressor from the selected pool or not, and to determine which one is to be removed. If the criterion is not met, then set $k = k+1$ and go to Step 4). Otherwise, moves to the next step.

3) The regressor p_r is shifted to the last column of φ_{k+1} using a total of $k - r + 1$ interchanges between two adjacent previously selected regressors. Thus, a new regression context of $A \in \Re^{(k+1)\times m}$, $b^{k+2} \in \Re^m$, $c^{k+1} \in \Re^m$, $d^{k+2} \in \Re^m$, and $d^{k+1} \in \Re^m$ is produced as if pr was the last selected regressor in the regression matrix φ_{k+1}.

4) The criterion $\Delta \overleftarrow{J}_{k+1}(p_r) < \max_{i=k+2}^{m} \Delta \overleftarrow{J}_{k+1}^{*}(\varphi_i)$ is used to decide whether to remove a regressor from the selected pool or not. If none has to be removed, then set $k = k+1$ and the algorithm moves to Step 4). Otherwise, it goes to the next step.

5) The regressor p_r is removed from the selected pool and returned to the candidate pool, i.e., $\Phi_k = [\tilde{p}_1, \dots, \tilde{p}_k]$ and $\Psi_k = [\tilde{\varphi}_1, \dots, \tilde{\varphi}_k]$. The regression context $A \in \Re^{k \times m}$, $b^{k+1} \in \Re^m, c^k \in \Re^m, d^{k+1} \in \Re^m$, and $h^k \in \Re^m$ are then updated and the index k is set to $k - 1$.

Step 4): The learning process will terminate if some stopping criterion is met, such as a certain number of regressors have been selected or some tolerance value has been met. Similar to the stopping criterion commonly used in training neural networks and support vector machines, the tolerance for the maximum ratio of objective value reduction is used here. In detail, if the ratio $(J_k - \min_{i=1}^{k} J_{k+1}(\varphi_i))/J_k$ is less than a very small positive tolerance value (ρ), the generalization performance of the fuzzy systems will not be greatly improved by adding a new regressor. It should be noted that the stopping criterion used here is an important measure for the trade-off between the training accuracy (performance) and the model complexity (sparseness and interpretability) of the obtained fuzzy systems. If the stopping criterion is not met, the algorithm returns to Step 2).

4. Finally, the output of the sparse fuzzy least square support vector machine detects the knock.

RESULTS TS AND DISCUSSION

[Table 1] describes the characteristics of the EF7 turbocharged engine. IKCO EF engines are 4 cylinder engines. The general structure of the engine is close to the PSA Group's Peugeot TU5JP4. EF7 turbocharged engine has 1648 cc displacement with 78.560 mm bore and 85 mm stroke. This engine was presented as EF7 dual-fuel at Engine Expo Stuttgart Germany in 2008.

Table 1: Description of the engine characteristics

Description	Value	Unit
Engine Model	EF7 turbocharged, gasoline	-
Displacement	1648	CC
Bore	78.56	Mm
Stroke	85	Mm
Compression ratio	11.1	-
Gasoline injection pressure	3.5	bar
Maximum power	215@2500rpm – 4500rpm	Nm
Maximum torque	110@5500 rpm	kW
Number of cylinders	4	-

The input knock signal, described in eq. (12) is applied to wavelet packet transform; the low frequency coefficient of the wavelet packet transform is applied to the SFLS-SVM for detect the knock signal. [Fig.4] shows the waveform of the input knock signal. Fig.5 shows the resultant waveform of the detected knock signal.

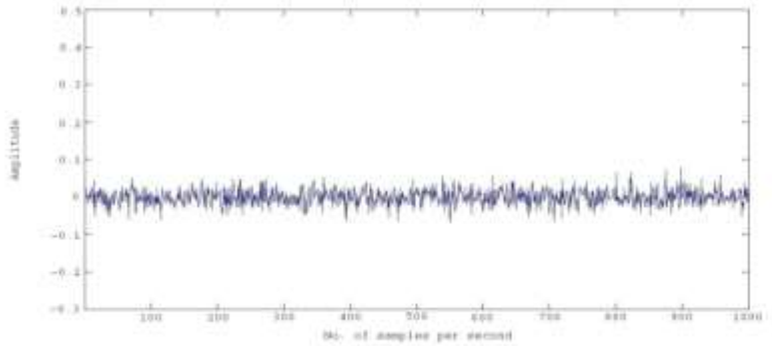

Fig. 4: Input knock signal.

[Table 2] compares the knock detection error rate of the proposed method with the other techniques. As compared with the other knock detection techniques, the proposed method gets better results than Fourier Transform, Wavelet Transform and Wavelet Packet Transform.

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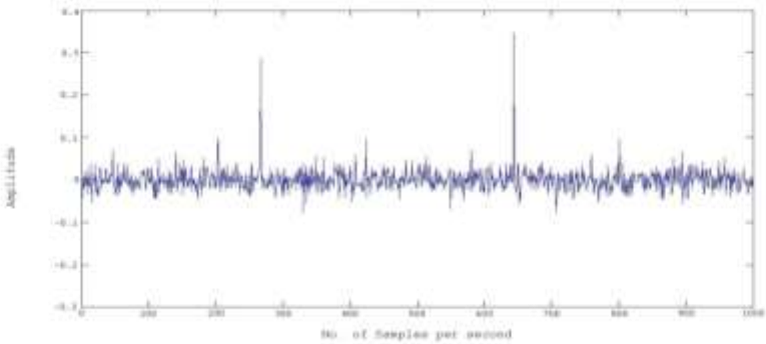

Fig. 5: Detected output of the knock signal.

Table 2: Comparison knock detection error rate of the proposed method with other techniques

Knock Detection Techniques	1000 revolution per minute Sampling Rate				
	150	200	250	300	350
Fourier Transform	74.60%	75.37 %	77.95%	77.34%	76.45%
Wavelet Transform	75.86%	76.43%	79.17%	78.05%	77.23%
Wavelet Packet Transform	77.85%	78.50%	81.25%	80.56%	79.42%
PROPOSED	**80.20%**	**81.5%**	**84.01%**	**83.7%**	**82.88%**

CONCLUSION

This paper concluded an advanced approach of knock detection by using WPT and SFLS-SVM techniques. This proposed method determines a knock index which represents the engine knock tendency. Due to the statistical behavior of knock, the proposed method not much focused knock detection on an every cycle. Hence, in the proposed method is applied up to two levels of the WPT which extracts statistical information of the acquired signals, then applied to the SFLS-SVM. As compared with the results of the other knock detection techniques, the proposed method gets better result. In future enhancement, mostly concentrate to reduce the complexity of the SFLS-SVM algorithm as well as focused on output smoothing.

CONFLICT OF INTEREST
There is no conflict of interest.

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FINANCIAL DISCLOSURE
None

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