Application of Combined Wavelet Transformation and Neural Network in Electrical System Malfunction Detection of Engine

Abstract

Engine failure is a critical issue for drivers and often requires substantial experience to diagnose and resolve effectively. Attempting repairs based on guesswork or uncertain causes can lead to significant time loss and high costs. Recently, Artificial Intelligence (AI) models, particularly those based on Artificial Neural Networks (ANNs), have shown promising performance in fault diagnosis. This study focuses on detecting two common faults in internal combustion engines—cylinder misfire and complete cylinder failure—both typically caused by problems in the ignition system. A model referred to as WANN (Wavelet+ Artificial Neural Network) is proposed, which uses coefficients are derived from vibration signals by wavelet transformation. The WANN achieved over 90% classification accuracy in identifying ignition-related faults. To evaluate the model's generalizability, the WANN is also tested on a different engine, successfully classifying fault types with acceptable accuracy. Notably, the model accurately detected ignition faults in a vehicle-mounted engine, demonstrating its robustness and practical utility.

This capability allows mechanics and technicians to accurately pinpoint the fault type, leading to more efficient and cost-effective repairs. Therefore, the proposed method offers a reliable and intelligent solution for diagnosing ignition system faults in automotive applications.

Keywords: Ignition System Malfunction, Wavelet Transformation, Artificial Intelligence Model, Diagnosis, Internal Combustion Engine

1- Introduction

In advanced vehicles working by internal combustion engines and station engines used in power plants, mines, refinery industries, etc. the diagnosis systems had been industrialized to identify subsystem or engine element has malfunction or does not its task due to failure. Repair cost reduction and maintenance can be executed by condition monitoring of the engine through working. In fact, condition monitoring can increase the durability and reliability of them. Some methods of Fault detection are developing continually such as dynamical model based, statistical models, or artificial intelligent models such as Fuzzy Logic (FL), Artificial Neural Networks (ANN), Deep Learning and etc. The ANN models imitate human brain learning ability. Like as human training, the ANN emulate to learn with samples or examples. In reality, the ANN utilizes input-output data sets to execute training, and then internal nodes weights are set to represent output with lowest error. Hence, the ANNs have been employed for prediction and estimation, or classification of faults regards to features. The mentioned aspects make it suitable tool for fault analysis and fault classification [1-5].

To distinguish fault of internal combustion engine, naturally conditioned vibration signals acquired of block engine are treated by the ANN method. Improving accuracy of ANN models requires to select proper input parameters or derive features show variations perfectly. One choice is feeding ANN by statistical features which are deriving from time or frequency domains vibration signal [4], and second solution is decomposing vibration signal by a mathematical transformer such as Laplace Transformation, Fourier Transformation, or Hilbert Transformation to find diversion point in original signal to show behavior differences. So, hybridizing ANN with other algorithms make it superior in performance in terms of accuracy. For example, in a research, neural network is integrated by Genetic algorithm to diagnose fault in a HCCI engine [6]. In another investigation, regression method and neural network is compounded to detect engine faults [7]. Moreover, the integration of ANN by decision tree method shows improved in fault diagnosis and classification [8,9]. The integration of Particle Swarm Optimization by ANFIS model is evaluated in engine to improve the accuracy of diagnosis process [10 and 11]. The intend of hybridizing ANN to other techniques of identification is increased because ANN cannot satisfy purpose of diagnosis alone [12-15]. The combination of ANN to other algorithms is based on aspects of second algorithm refer to its ability in simplification of computing or increasing number of features provided for supporting the ANN [15-20].

Among AI-based methods, Artificial Neural Networks (ANNs) have shown considerable promise due to their ability to learn complex, nonlinear relationships from data. However, ANNs alone often struggle with raw, high-dimensional, and noisy signals, such as engine vibration data, which can limit their diagnostic accuracy. To address this, hybrid approaches that combine signal processing techniques with machine learning have been developed. In particular, wavelet transform has emerged as a powerful tool for fault diagnosis due to its ability to analyze non-stationary signals in both time and frequency domains simultaneously. Unlike Fourier transform, which provides only frequency information, wavelet transform offers multi-resolution analysis, making it ideal for capturing transient features and localized signal anomalies that are indicative of faults [26,27].

The integration of wavelet transforms with neural networks—commonly referred to as Wavelet Neural Networks (WNNs) or hybrid wavelet-ANN models—has been explored in various engineering applications, including bearing fault detection, gearbox monitoring, and structural health assessment [28,29]. In engine diagnostics, wavelet-based methods have been used to extract discriminative features from vibration, acoustic, and pressure signals [30,31]. However, most prior studies have focused on specific engine subsystems or simplified laboratory conditions, with limited validation under real-world operational environments [32,33]. Moreover, the selection of optimal mother wavelets and network architectures often lacks systematic justification, which can affect the reproducibility and robustness of the proposed methods. By hybridizing Wavelet Transformation and ANN, the efficiency of the ANN model improves, and classification ability will be enhanced. Current work aims to present this idea and study about its performances to make comparison to previous work [4].

2- Methodology

To establish a none parametric dynamical model which is integrating the Wavelet Transformer and ANN, and it must able to detect faults of IC engine, vibration signals of engine block were acquired as stated in [4 and 24].

A stationary four-stroke engine, recognized as M13GS, is considered for indoor testing. The engine is fixed on a stand, and vibration data is gathered under both normal operating conditions and with ignition system faults. Initially, the investigations were conducted for 9 iterations when engine worked by constant revolution speed as 1000RPM [21]. These tests involve normal firing in all cylinders, misfiring and no firing in first, second, third, and fourth cylinders. Then, similar to mentioned tests [4], trials are repeated in 2000 and 3000 RPM. To monitor of the engine revolution speed, the diagnosis apparatus known as *Diag 2000* is employed. Totally, 27 sets of the vibrational data are gathered from the engine block vibration throughout the tests listed in Table. 1. Furthermore, noise filtering and signal conditioning are applied as reported in [4].

Table 1. Various tests were conducted in normal firing, misfiring and no firing

1000RPM	N1	MSF1-A	MSF2-A	MSF3-A	MSF4-A	WSP1-A	WSP2-A	WSP3-A	WSP4-A
2000RPM	N2	MSF1-B	MSF2-B	MSF3-B	MSF4-B	WSP1-B	WSP2-B	WSP3-B	WSP4-B
3000RPM	N3	MSF1-C	MSF2-C	MSF3-C	MSF4-C	WSP1-C	WSP2-C	WSP3-C	WSP4-C

In this table, N is revolution speed of in engine, and MSF is number of cylinder with misfire. Moreover, WSP is showing the cylinder with spark problem.

2-1- Proposed WANN Model

WANN Model was created by hybridizing discrete wavelet transformation (DWT) and artificial neural network. Actually, the time domain signal of the engine vibration is decomposed to some sub bands, and wavelet coefficients were obtained. These wavelet coefficients were fed into the ANN as the inputs. The steps of establishing the model is described in following.

2-1-1- Selecting Proper Feature Vector

The accuracy of wavelet-based models depends on selecting Mother Wavelet. The suitable Mother Wavelet must have most similarity to the signal which is decomposed. The continuous wavelet transform decomposes a signal f(t) into shifted (Translation) and scaled versions of the mother wavelet ψ by starching signal (Dilation).

In brief, simultaneous analysis of the vibration signal by means of continuous wavelet transform is based on energy function. In mathematical statement, it is convolution of the input data function and Mother Wavelet:

$$CW(a,b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{\infty} f(t) \cdot \psi^{*}\left(\frac{t-b}{a}\right) dt \tag{1}$$

Like as other mathematical transformation, wavelet has invers transform which is definite to:

$$f(t) = \frac{1}{C_{\psi}} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} CW(a,b) \cdot \frac{1}{a^{2}} \cdot \psi\left(\frac{t-b}{a}\right) dadb \tag{2}$$

Also, definition of C_{ψ} is:

$$C_{\psi} = \int_{0}^{\infty} \frac{|\psi(\omega)|^{2}}{\omega} d\omega \langle \infty \tag{3}$$

The coefficients, $W_x(a,b)$, are function of a and b, which is demonstrating high frequency components for narrow wavelets. In opposite, wide wavelets coefficients belong to low frequency. Desecrate Wavelet Transform is given by:

$$DW(j,k) = \sqrt{2^j}\int_{-\infty}^{+\infty} f(t)\cdot\psi^*\left(2^j t - k\right)dt \tag{4}$$

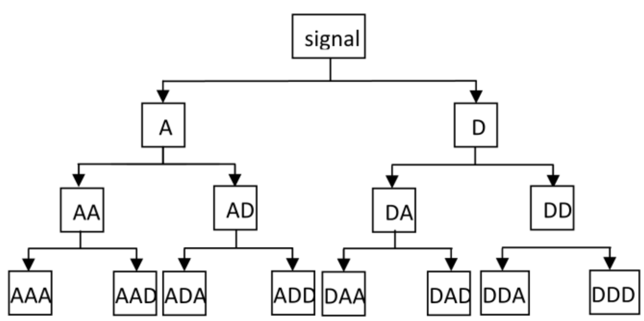
Where DW(j,k), j, and k are matrix of the coefficients, scale of the frequency domain, and time shift of the Mother Wavelet, respectively.

Wavelet packet transform (WPT) represents decomposes approximations with detail. In first step, two packets are created by decomposing of the signal: A and D. First term is belonging to component in low frequency and second term is related to higher frequency element of the signal. In second step of decomposition, sub packets are generated as AA, AD, DA, and DD. This process of decomposition continues to form WPT tree. The mathematical expression of the WPT is:

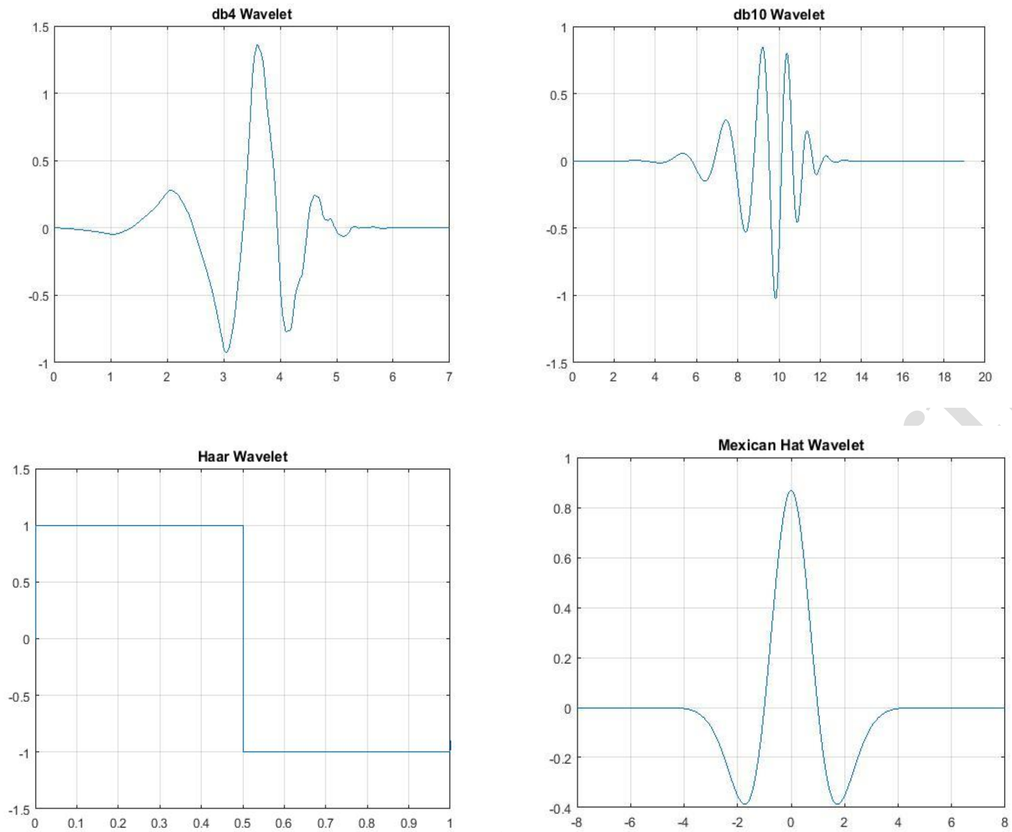
$$W_{j,k}^{n}(t) = 2^{j/2} W(2^j t - k), \quad j,k \in Z \tag{5}$$

Where j and k are belonging to scale and time shift, respectively.

In present paper, Mexican Hat Wavelet, Haar Wavelet, Symlets 8, DB 4 (Daubechies) and DB10 are evaluated as mother wavelet and applied as the ANN inputs. Because the ANN can detect the trend of variations [22-25]. Fig.1 (a) shows flowchart of signal decomposing to sub bands. Proposed mother wavelets used to break up signals are exposed in Fig. 1 (b).



(a)



(b)

Fig. 1 Mother Wavelet employed to obtain coefficients, (a) flowchart of signal decomposing to sub bands, (b) proposed mother wavelets used to break up signals

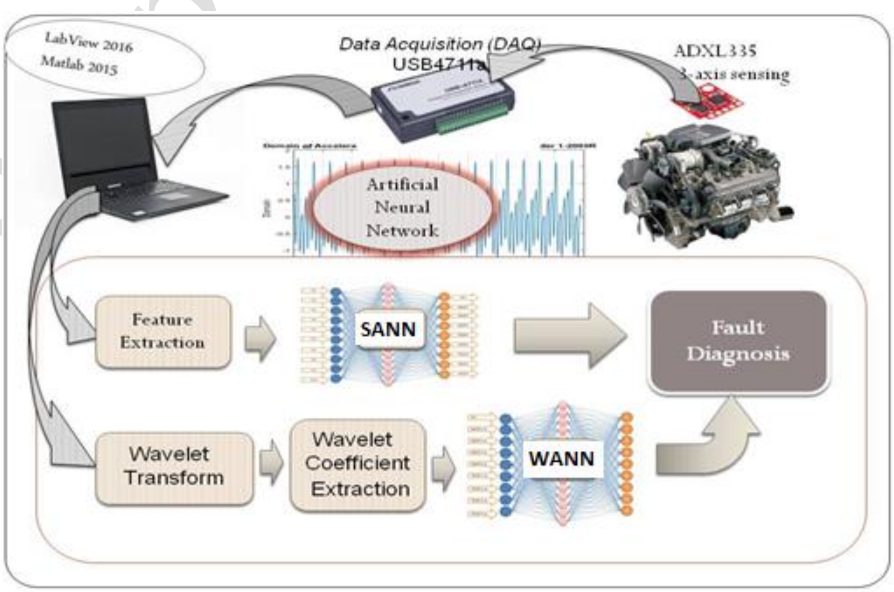
3- Results and Discussions

3-1- Topology of the WANN Model

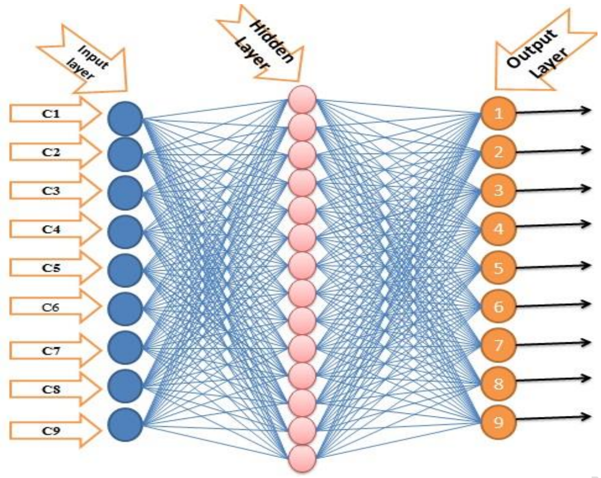
Firstly, the vibration signal is decomposed by Wavelet pocket transform to reach some coefficients. The ANN model fed by the wavelet coefficients includes 9 inputs nodes (wavelet coefficients). Different number of hidden layers are trailed. Schematic architecture of WANN (ANN+Wavelet) is exhibited in Fig.2. Sixty-five percentages of data were entered to the WANN model through the training step, and 15% of data was employed in validation step. Various training algorithms are evaluated in terms of accuracy. In previous work [4], statistical features were derived from time domain signal and entered as inputs in neural network to identify fault of ignition system. It called SANN (Statistical+ Artificial Neural Network). Similar to the SANN model [4], in current work, the Levenberg – Marquardt Algorithm showed superior performance as can be seen in Fig. 3. The correlation ratio was overtaken 0.9844. In order Fig. 4 to Fig. 6 and Table 2 demonstrate the performance of the WANN model and their errors by all training algorithms. Consequently, DB10 was chosen as the best mother wavelet in the WANN model which is integrated to ANN by 30 hidden layer refer to Fig.6.

The choice of the mother wavelet is a critical step in wavelet-based feature extraction, as it directly influences the quality of the decomposed signal components and, consequently, the classification performance of the hybrid WANN model. In this study, several candidate mother wavelets—including Mexican Hat, Haar, Symlets 8, Daubechies 4 (DB4), and Daubechies 10 (DB10)—were systematically evaluated based on the following quantitative criteria:

1. **Regression Coefficient (R-value)**: The overall regression coefficient obtained during the training, validation, and testing phases was used as a primary indicator of model accuracy. As presented in Table 2, DB10 combined with the Levenberg–Marquardt training algorithm achieved the highest overall correlation coefficient (0.9844), outperforming other wavelets across multiple training algorithms.
2. **Mean Squared Error (MSE)**: The MSE was monitored to assess the model's convergence and generalization capability. DB10 exhibited the lowest MSE (0.4126×10^{-4}) during validation when trained with the Levenberg–Marquardt algorithm, indicating superior learning stability and minimal prediction error.



(a)



(b)

Fig. 2 (a) the flowchart of establishing the WANN, (b) Schematic architecture of WANN

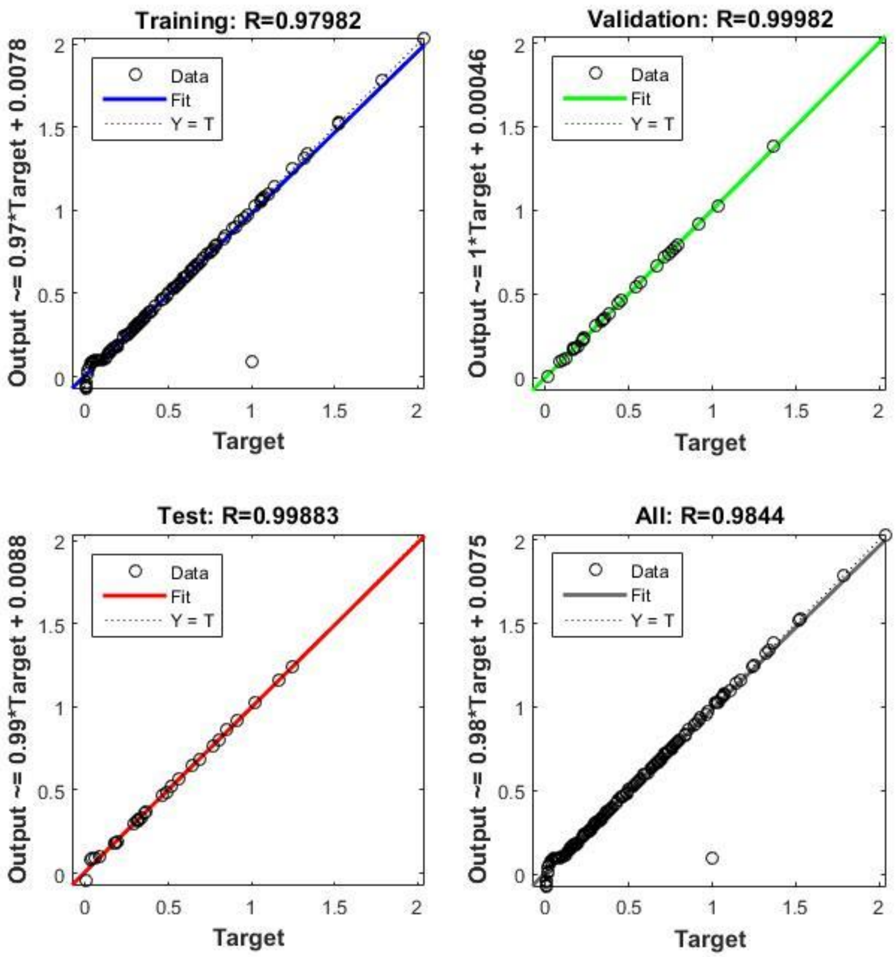


Fig. 3 The performance of WANN in training, validation, test steps and overall in terms of correlation ratios (signal decomposed by DB10)

Table 2. The WANN correlation ratios by various training algorithms and various Mother Wavelets

Training Algorithm	**Criteria of comparison**	**DB10**	**DB4**	**SYM8**	**HAAR**
Train lm	correlation ratio in Overall	0.9844	0.99992	0.97722	0.98012
	Regression in Validation	0.99982	0.99768	0.99862	0.98076
	Error(MSE)	0.4126*e-4	9.4881*e-3	3.6393*e-3	2.0093*e-1
Train rp	correlation in Validation	0.99837	0.99967	0.99157	0.99921
	Error(MSE)	9.4792*e-4	0.27644	0.23749	٠.566144
	correlation ratio in Overall	0.98427	0.99765	0.99315	0.9877
Train bfg	correlation in Validation	0.99719	0.99768	0.99997	0.98076
	Error(MSE)	0.9478*e-3	1.9569	6.0415*e-4	1.16151
	correlation ratio in Overall	0.98347	0.99986	0.99488	0.99982
Train scg	correlation in Validation	0.99564	0.99981	0.99837	0.99984
	Error(MSE)	0.3862*e-4	9.0953*e-2	3.9929*e-2	1.0256
	correlation ratio in Overall	0.98841	0.99997	0.99	0.99968
Train cgb	correlation in Validation	0.99994	0.99968	0.99685	0.99982
	Error(MSE)	1.2851*e-5	2.6444*e-1	7.0572*e-2	1.39243

DB: Daubechies wavelet, SYM: Symlets wavelet, HAAR: Haar wavelet

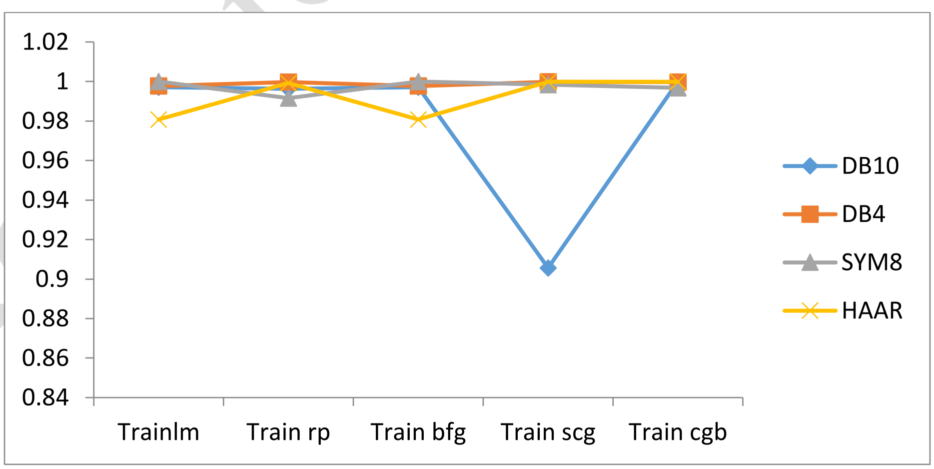


Fig. 4 The WANN correlation ratios by various training algorithms and various Mother Wavelets

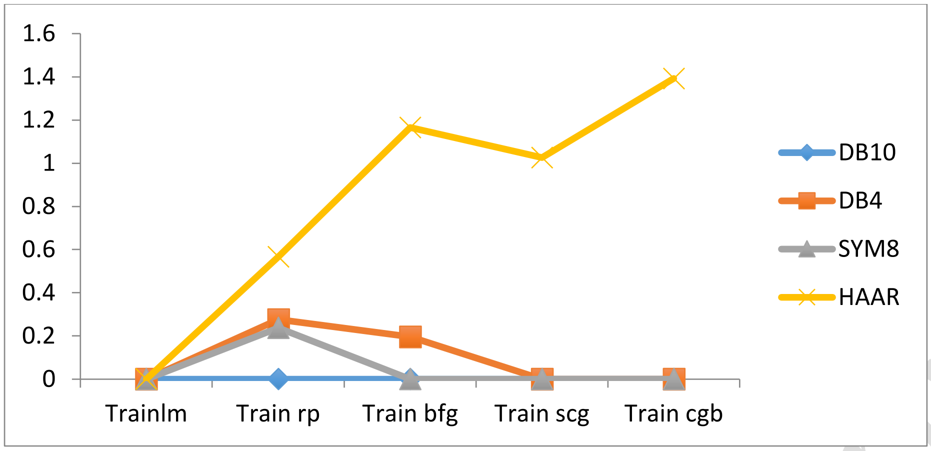


Fig. 5 The Error of the WANN models by different Mother Wavelets

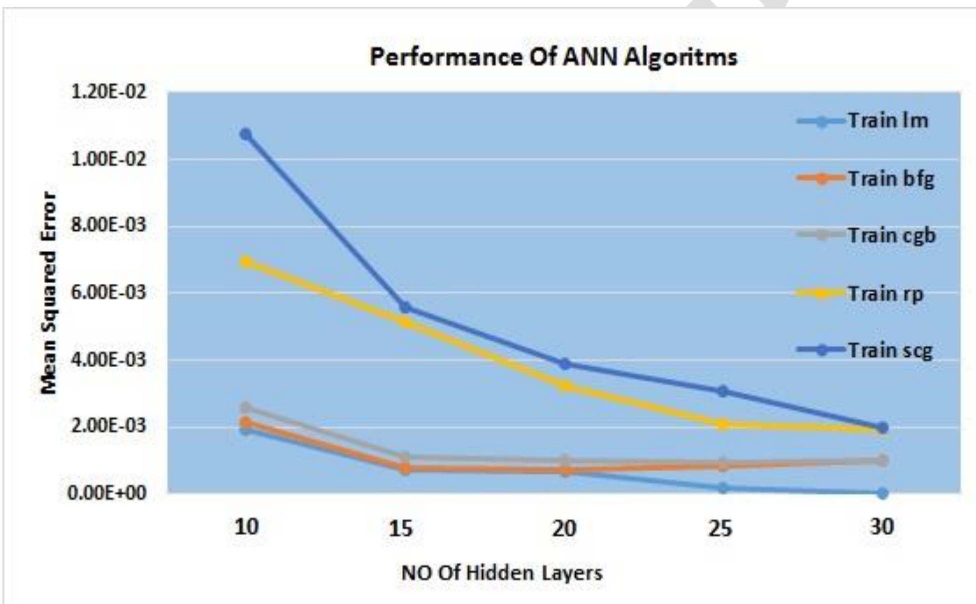


Fig. 6 The means squared error of the WANN model by DB10 with different number of the hidden layers

3-2- Evaluation of WANN Model

Subsequently WANN model is trained by data collected from a test engine fixed on test rig, for better valuation of model efficiency, additional engine mounted on vehicle like to test rig engine is tested to predict of fault type in cylinder. The outcomes of this assessment are revealed in Fig.7. The prediction of type of fault by WANN is very closed to actual class of faults. When speed revolution of engine is 1000 RPM, first point of diagram, normal firing is distinguished by WANN. The Second point to fifth point show misfiring in one cylinder of the first to forth cylinder of engine block. The sixth point to tenth point illustrates no fire in one of the block cylinders. As can be seen in Fig.7, the convergence of actual fault type and diagnosed by WANN is high and is more efficient in comparison to SANN [4]. Consequently, it can be used for this purpose in this type of engine.

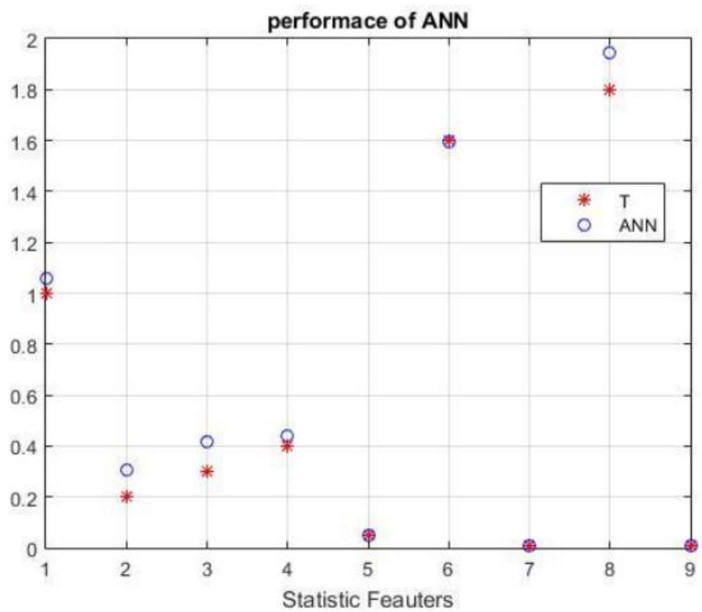


Fig.7 the performance of WANN in fault diagnosis of engine (T denotes test result)

4. Conclusion

This study successfully developed and validated a hybrid WANN (Wavelet-Artificial Neural Network) model for the intelligent diagnosis of ignition-related faults in internal combustion engines, specifically targeting cylinder misfire and complete cylinder failure. By integrating Discrete Wavelet Transform (DWT) for feature extraction with a multi-layer perceptron ANN for classification, the proposed methodology addresses key limitations of standalone ANN models in processing raw, non-stationary vibration signals.

The WANN model demonstrated superior diagnostic performance, achieving a high overall classification accuracy of over 98% for the two targeted fault types across multiple engine speeds (1000, 2000, and 3000 RPM). A systematic evaluation of five candidate mother wavelets (Mexican

Hat, Haar, Symlets 8, DB4, DB10) revealed that the Daubechies 10 (DB10) wavelet, coupled with the Levenberg-Marquardt training algorithm, yielded the optimal configuration. This configuration produced a regression coefficient (R-value) of 0.9844 and the lowest mean squared error (0.4126×10^{-4}) during validation. Crucially, the model's robustness was confirmed through cross-validation on a different, vehicle-mounted engine, where it maintained high diagnostic accuracy, correctly identifying normal operation, single-cylinder misfires, and complete cylinder failures under real-world operating conditions.

Practical Implications:

The primary contribution of this work is a practical, data-driven tool for the automotive maintenance industry. The WANN model translates complex vibration analysis into a reliable, automated diagnostic decision, offering several tangible benefits:

1. Enhanced Diagnostic Precision and Efficiency: By providing mechanics with a highly accurate fault classification (misfire vs. no-fire and identifying the affected cylinder), the system reduces diagnostic time, eliminates guesswork, and prevents unnecessary part replacements.
2. Enablement of Predictive Maintenance: The model's sensitivity to early fault signatures, such as intermittent misfires detectable in vibration patterns, allows for proactive intervention before a minor ignition issue escalates into a major engine failure, thereby increasing vehicle reliability and reducing long-term ownership costs.
3. Foundation for On-Board Diagnostics (OBD) Enhancement: The computational efficiency of the trained WANN model makes it a strong candidate for integration into next-generation OBD systems or portable diagnostic tools, moving beyond generic fault codes to provide specific, actionable intelligence about the ignition system's health.

Limitations and Future Research Directions:

While the results are promising, this study acknowledges certain limitations that outline clear paths for future research:

1. Scope of Faults and Operating Conditions: The model was validated for two specific ignition faults under controlled and steady-state RPM conditions. Future work should expand the fault dictionary to include other common issues (e.g., fuel injector faults, valve train problems) and validate performance under transient engine operations (acceleration, deceleration, variable load).

2. Model Generalizability and Data Dependency: The performance was validated on a limited set of engines. Extensive testing on a wider variety of engine makes, models, and ages is necessary to ensure broad applicability. Incorporating larger, more diverse datasets from real-world fleet operations would further enhance model robustness.
3. Towards Real-Time Deployment and Explain ability: Future research should focus on optimizing the model architecture for embedded, real-time processing. Additionally, employing Explainable AI (XAI) techniques would be invaluable to interpret which specific wavelet coefficients (and thus which time-frequency features of the vibration signal) are most influential in the diagnosis, building crucial trust with end-users and providing deeper insights into the failure mechanics.

In conclusion, the WANN framework presents a significant step forward in intelligent engine fault diagnosis. By effectively marrying the multi-resolution analysis capability of wavelets with the pattern recognition power of neural networks, it offers a robust, accurate, and practical solution. To transition from a successful proof-of-concept to a widely adopted industrial tool, subsequent efforts must address the challenges of expanded fault coverage, validation across diverse platforms, and integration into the next generation of vehicle health monitoring ecosystems.

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