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Automated misfire diagnosis in engines using torsional vibration and block rotation

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Abstract. Even though a lot of research has gone into diagnosing misfire in IC engines, most approaches use torsional vibration of the crankshaft, and only a few use the rocking motion (roll) of the engine block. Additionally, misfire diagnosis normally requires an expert to interpret the analysis results from measured vibration signals. Artificial Neural Networks (ANNs) are potential tools for the automated misfire diagnosis of IC engines, as they can learn the patterns corresponding to various faults. This paper proposes an ANN-based automated diagnostic system which combines torsional vibration and rotation of the block for more robust misfire diagnosis. A critical issue with ANN applications is the network training, and it is improbable and/or uneconomical to expect to experience a sufficient number of different faults, or generate them in seeded tests, to obtain sufficient experimental results for the network training. Therefore, new simulation models, which can simulate combustion faults in engines, were developed. The simulation models are based on the thermodynamic and mechanical principles of IC engines and therefore the proposed misfire diagnostic system can in principle be adapted for any engine. During the building process of the models, based on a particular engine, some mechanical and physical parameters, for example the inertial properties of the engine parts and parameters of engine mounts, were first measured and calculated. A series of experiments were then carried out to capture the vibration signals for both normal condition and with a range of faults. The simulation models were updated and evaluated by the experimental results. Following the signal processing of the experimental and simulation signals, the best features were selected as the inputs to ANN networks. The automated diagnostic system comprises three stages: misfire detection, misfire localization and severity identification. Multi-layer Perceptron (MLP) and Probabilistic Neural Networks were applied in the different stages. The final results have shown that the diagnostic system can efficiently diagnose different misfire conditions, including location and severity.

1. Introduction
Misfire is a very common combustion fault for IC engines and over many years there have been continuing advances in vibration signal based misfire diagnostics. Most of the researchers studied the torsional vibrations of the crankshaft and tried to find their relationship with the combustion conditions in cylinders. Zhang[1] used “synthetic speed” to set up a linear relationship between rotational speed and in-cylinder pressure. More recently, Deshazeille et al. [2] studied the torsional mode effects in a twenty cylinder engine and developed an analytical model with flexible crankshaft. They also proposed the use of the most sensitive Fourier coefficients (real and imaginary parts) of the torsional vibration signals as condition indicators. Some researchers used the translational acceleration signal on the engine block to recover the cylinder pressure [3, 4], but this method

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requires the design of an inverse filter and measurement of the transfer functions from inner cylinder wall to block surface. Even though the existing research found some patterns from the vibration signals in misfire conditions, the implementation of these diagnostic techniques normally requires an expert to interpret the analysis results. In this paper, an automated misfire diagnostic system was developed. ANNs were applied to identify and localize the misfires in different cylinders. The inputs to the networks are the selected features from the analysed results, for both torsional vibration of the crankshaft and angular accelerations of the engine block (roll). The measurements are simple and straightforward. The angular acceleration is calculated from two linear acceleration signals on the engine block. In order to get the sufficient data for training the networks, based on the thermodynamic and mechanical principles of IC engines, models were built in simulation packages, mainly in the AMESim Imagine Lab framework, to simulate different conditions, rather than doing a lot of experiments on the test rig, and the models were updated from a limited number of experiments (normal and misfire). Before building the simulation models, some parameters were calculated from experiments, including the inertia properties of the engine parts and whole engine, and the stiffness and damping properties of the engine suspension (mounts).

2. Experiments, signal processing and feature selection

Vibration tests were carried out on a four-cylinder Toyota 3SFE engine. The firing sequence of the engine is 1-3-4-2. Five accelerometers were used to record the vibration on the surface of the engine block. The layout of accelerometers is shown in Figure 1(a). Two Bently Nevada 3300 proximity transducers were used to pick up the once-per-rev tacho signal and the ring gear encoder signal (tooth passage). For the once-per-rev pickup, a small piece of steel was glued on the flywheel with its position corresponding to the top dead centre of cylinder 1 (see Figure 1(b)). Because there are 120 teeth on the ring gear, the proximity probe records 120 pulses each revolution. The cylinder pressure was measured by a Kistler measuring spark plug with integrated cylinder pressure sensor 6117B. Three constant speed conditions were selected for the engine tests: 1500rpm, 2000rpm and 3000rpm. For each speed, there are three different load conditions: 50Nm, 80Nm, 110Nm.

Based on the cylinder pressure signals (actually only pressure pulse is needed), the tacho pulses corresponding to the top dead centre of the exhaust stroke were removed and only the tacho pulses corresponding to the top dead centre of the firing stroke were kept. When synchronously averaging all signals, the modified tacho signals were used for the order tracking. The pressures were measured in different cylinders to check the pressure uniformity. The averaged pressure data was also used to update the combustion chamber pressure of the simulation models in the following section. The torsional vibration signal is obtained by phase demodulation of the ring gear encoder signal. The unwrapped phase angle demodulated from the first harmonic of the encoder signal represents the torsional vibration signal of the crankshaft when divided by the number of teeth (120) to get it in terms of the angular displacement of the shaft. Next the angular displacement of the shaft was
differentiated to get the angular velocity. Finally the angular velocity was synchronously averaged for pairs of cycles (to check the validity of the average).

The roll rotation of the engine block was analysed from the average of a pair of acceleration signals. The signals from accelerometers 5 and 7 were subtracted to remove the translational components. The subtraction results were divided by the distance between the two measurement points to calculate the pseudo angular acceleration of the block. It is called pseudo angular acceleration because the measurement points are not in line with the centre of gravity (CG) of the engine (their line is not parallel to the principal axis of the engine either) and the calculated angular acceleration is mixed with other rotational motions. However, in the simulation model, if the angular accelerations about the CG are simulated, it will be easy to calculate the accelerations at the measurement points 5 and 7, and finally get the simulated pseudo angular accelerations.

The results of the torsional vibrations at 1500rpm/80Nm and the pseudo angular accelerations at 1500rpm/50Nm are taken as illustrative examples in Figure 2 and Figure 3 respectively. The X axes in the figures are the sampling numbers, whereas the modified tacho signals at the bottom of each figure give more useful information about the time sequence. In order to compare with the simulated waveform, higher harmonics of averaged pseudo angular acceleration was considered in comparison with the former work [5].

The most important thing for the engine misfire detection is to find suitable features from the processed data. The amplitudes and phases of the first five harmonics of one firing cycle were investigated for both the torsional vibration method and block angular acceleration method. In the former work [5, 6], when the first five harmonics are shown in polar diagram (the first five harmonics are enough for the misfire diagnostics, because the first harmonic indicates most information in the cycle frequency and the fourth harmonic indicates most information in the firing frequency), it has been found that the amplitudes of the first and forth harmonics can be used as the features to detect the misfire and identify the severity (the ratio of two amplitudes). The phase of the first harmonic can be used to localize which cylinder has misfire. If the misfire happens in a different cylinder, the difference of the phase of the first harmonic between them is 90 degrees in a polar diagram [5] (where a complete cycle or two revolutions is represented as 360 degrees). For the pseudo angular acceleration method, it is also found that even when the misfires happen in the same cylinder, the
phases of the first harmonic vary with speed. This is because the combustion force frequencies change at different engine speed, but the frequency response functions of the engine block, based on fixed rigid body modes, do not change. Therefore, it is necessary to measure the frequency response functions of the engine block on the test rig and study the rigid body modes of the engine before the simulations. It should be noted that the same applies for torsional vibrations in cases where the crankshaft is not rigid, as in [2].

3. Inertia property and rigid body mode test
The mechanical inputs of the simulation model include the dimensions of the engine components, such as the bore and stroke of piston, length of connecting rod, but more importantly, the inertia properties of the components. There are two common methods to extract inertia properties from vibration signals [7]: massline method and modal property method.

The massline method is suitable for the scenario when the rigid body modes and the first elastic mode are well separated. The dynamic equation for a free-free body with respect to the centre of gravity is:

\[
\begin{bmatrix}
F_x \\
F_y \\
F_z \\
M_x \\
M_y \\
M_z
\end{bmatrix} =
\begin{bmatrix}
m & 0 & 0 & 0 & 0 & \pi_{xv} \\
0 & m & 0 & 0 & 0 & \pi_{yv} \\
0 & 0 & m & 0 & 0 & \pi_{zv} \\
0 & 0 & 0 & I_{xx} & -I_{yx} & -I_{xz} & \alpha_x \\
0 & 0 & 0 & -I_{xy} & I_{yy} & -I_{yz} & \alpha_y \\
0 & 0 & 0 & -I_{xz} & -I_{yz} & I_{zz} & \alpha_z
\end{bmatrix}
\begin{bmatrix}
\pi_{vx} \\
\pi_{vy} \\
\pi_{vz} \\
\pi_{xv} \\
\pi_{yv} \\
\pi_{zv}
\end{bmatrix}
\]  

(1)

The subscript \(c\) indicates the values about CG, \(m\) and \(o\) appearing in the following section mean the values about the measurement points and the point of origin of the coordinates respectively. When the measured object is excited by hammer or shaker, the accelerations of the points on the surface of the object are measured. The motion of the CG can be calculated from the measured accelerations by:

\[
\begin{bmatrix}
\pi_{mx} \\
\pi_{my} \\
\pi_{mz}
\end{bmatrix} =
\begin{bmatrix}
1 & 0 & 0 & 0 & z_m & -y_m \\
0 & 1 & 0 & -z_m & 0 & x_m \\
0 & 0 & 1 & y_m & -x_m & 0
\end{bmatrix}
\begin{bmatrix}
\pi_{xv} \\
\pi_{yv} \\
\pi_{zv} \\
\pi_{xv} \\
\pi_{yv} \\
\pi_{zv}
\end{bmatrix}
\]  

(2)

In real measurements, the transformation matrix in equation (2) is always overdetermined, so the least squared method is used to “average” the accelerations at the origin. The force/moment and the accelerations about the CG can be related to the force/moment and the accelerations at the origin by unknown variables - the coordinates of CG; consequently the equation (1) can be changed to equation (3) [7]. From the equation (3), the coordinates of CG can be solved first, and the moment of inertia can be calculated later. Usually the Frequency Response Functions (FRFs) are the final results from measurements instead of the accelerations and forces, but the equation (3) can be rewritten in terms of FRFs by dividing by the forces on each side of the equation.

\[
\begin{bmatrix}
F_{xv} - m\pi_{xv} \\
F_{yv} - m\pi_{yv} \\
F_{zv} - m\pi_{zv} \\
\gamma_{xv} F_{yv} - z_v F_{xv} \\
\gamma_{yv} F_{zv} - x_v F_{yv} \\
\gamma_{zv} F_{xv} - y_v F_{zv}
\end{bmatrix} =
\begin{bmatrix}
0 & -m\alpha_x & m\alpha_y & 0 & 0 & 0 & 0 & 0 & 0 \\
-\alpha_x & m & 0 & -m\alpha_y & 0 & 0 & 0 & 0 & 0 \\
-\alpha_y & 0 & m & 0 & -m\alpha_z & 0 & 0 & 0 & 0 \\
0 & -F_{xv} & -F_{yv} & \alpha_x & 0 & 0 & -\alpha_y & 0 & -\alpha_z \\
-\alpha_y & 0 & -F_{yv} & F_{xv} & \alpha_y & 0 & 0 & -\alpha_x & -\alpha_z \\
-\alpha_z & 0 & 0 & -\alpha_x & -\alpha_y & F_{xv} & F_{yv} & 0 & \alpha_z \\
\end{bmatrix}
\begin{bmatrix}
\pi_{xv} \\
\pi_{yv} \\
\pi_{zv} \\
\pi_{xv} \\
\pi_{yv} \\
\pi_{zv}
\end{bmatrix}
\]  

(3)
An advanced test software package (based on massline theory), such as LMS test lab, can accurately calculate the inertia properties from the measured FRFs. Moreover, the software can also take into account the influence of the lower residue of the elastic modes when the separation between the rigid body modes and bending modes is not very clear. For the inertia property test of the whole engine, there are 7 reference dofs and 21 response dofs. The setup of the test is shown in Figure 4 and the point of origin of the coordinate system is the output point of the crankshaft.

In the second method – the modal property method, the inertia properties are extracted from the measured six rigid modes (the poles and mode shapes). In order to extract six separated rigid modes from the measurements, the suspension should be not too “soft”. The modal parameters were firstly identified by some modal analysis techniques, such as PolyMax [8]. Next, there are two ways to calculate the inertia properties. The first considers that the damping of the suspension is proportional damping [7, 9]. The parameters can be derived from the mode shapes under unity modal mass (normal mode shapes). The second approach considers general non-proportional damping and all parameters can be related to the poles and mode shapes under unity modal A [10]. The details of different mode shape scaling: under unity modal mass and unity modal A can be found in reference [11]. Obviously, the mass matrix and stiffness matrix of the suspension can derived in both ways, but the second one can also solve for the damping matrix of the suspension so the mode shapes under unity modal A were applied for the parameter extraction of the suspension of the engine on the test rig. The state transmission matrix is the essential equation of the second approach [10]:

$$
\begin{bmatrix}
-M^{-1}C & -M^{-1}K \\
I & 0
\end{bmatrix}
\begin{bmatrix}
[\phi]^* \\
[\lambda]^*
\end{bmatrix}
= 
\begin{bmatrix}
[\phi] \\
[\lambda]
\end{bmatrix}
$$

(4)

$$
[\phi] = \begin{bmatrix} [\phi_1] \\ [\phi_1]^* \end{bmatrix}, \quad [\lambda] = \begin{bmatrix} [\lambda_1] & 0 \\ 0 & [\lambda_1]^* \end{bmatrix}
$$

Here, the $\lambda_j$ is pole matrix and $\phi_j$ is the unit-A mode shape matrix ("*" means their conjugates). If all modes are complex modes, the following two equations [10] can be derived from equation (4):

$$
[M]^{-1}[C] = -\text{Re}(\{[\phi], [\lambda], [\phi]^*\})
$$

(5)

$$
[M]^{-1}[K] = \text{Re}^2(\{[\phi], [\lambda], [\phi]^*\}) + \text{Im}^2(\{[\phi], [\lambda], [\phi]^*\})
$$

(6)

By the diagonal characteristic and zero elements in the matrices, the M, K and C matrices can finally be obtained.
Because the individual rigid body modes are not always separated from each other and there are inconsistencies in the measured FRFs, the results calculated by the modal property method are less accurate than those by the massline method under real experimental conditions. Therefore the massline method was applied to get accurate inertia properties of the components and whole engine. The modal property method was used to extract the properties of the suspension. The boundary conditions are complicated for the engine on the test rig, and the connected exhaust pipe and coolant hoses etc., increase the difficult of extracting accurate suspension properties. When calculating the suspension properties by the modal property method, the mass matrix in equations (5) and (6) was firstly corrected by the results from the massline method, then the stiffness matrix and damping matrix were calculated in the next step. Because the coordinate difference of accelerometers 5 and 7 in the X direction is small in comparison with the difference in the Z direction (see figure 1), the pseudo angular accelerations contain mostly roll motion. The derived stiffness matrix and damping matrix were further optimized to make the roll motions in the simulation as close as possible to those in the experiments.

4. Simulations

Misfire means abnormal cylinder pressure (no combustion or partial combustion), so the simulation of cylinder pressure is essential for all simulation models. The regular cylinder pressure is the combination of compression pressure and combustion pressure. The compression pressure can be derived from the polytrophic formula and the combustion pressure can be calculated by classic Wiebe’s functions [12]. The burn rate $w(\theta)$ and heat release $Q(\theta)$ about the crank angle are written as:

$$w(\theta) = \frac{6.908(m_+ + 1)}{\theta_d^m} \left(\frac{\theta}{\theta_d}\right)^m e^{-6.908(\theta/\theta_d)^m-1}$$

(7)

$$Q(\theta) = w(\theta) \cdot r_c \cdot m_{fuel} \cdot LHV$$

(8)

Where, $\theta$ is the crank angle, $m_+$ is Wiebe’s combustion characteristic exponent, $\theta_d$ is the combustion duration in degree, $r_c$ is the combustion efficiency, $m_{fuel}$ is the fuel injection quantity and it can be looked-up from the fuel injection map of an engine. $LHV$ is the lower heating value of the fuel. The combustion pressure $P_{comb}$ can be calculated step-by-step with finite angle degree increase:

$$P_{comb}(\theta + \Delta \theta) = \frac{V(\theta)^{\gamma-1}}{V(\theta)} \left( Q(\theta) + P_{comb}(\theta) \frac{(\gamma+1) \cdot V(\theta) - \gamma \cdot V(\theta + \Delta \theta)}{\gamma - 1} \right)$$

(9)

Where, $\gamma$ is the polytropic exponent (1.25) and $V(\theta)$ is the chamber volume. By changing the fuel injection quantity (multiplying by a given percentage), the cylinder pressure in different misfire conditions can be simulated. The cylinder simulation model was also updated by the averaged measured pressure in the experiments. Normal, 50% misfire and 100% misfire at different speeds/loads were simulated. The pressure curves for normal, 50% misfire and 100% misfire in a typical cylinder at 1500rpm/110Nm are shown in Figure 5.
The excessive rotation (roll) of the engine block is caused by the change of the torque acting on the engine block. The torque by a single cylinder about the crankshaft centre is [12]:

\[
T_b = \left[ F_p - m_p R \omega^2 (\cos \theta + \frac{R}{L} \cos 2\theta) \right] \frac{R}{L} \sin \theta \sqrt{1 + \left( \frac{R}{L} \sin \theta \right)^2} (L \cos \varphi + R \cos \theta) \\
\varphi = \frac{R}{L} \sin \theta + \frac{1}{6} \left( \frac{R}{L} \sin \theta \right)^3
\]  

(10)

Where \( R \) is the crank radius, \( L \) is the centre-to-centre connecting rod length, \( m_p \) is the mass of the piston, \( \omega \) is the speed of crankshaft in radians/s, \( F_p \) is the force from combustion. The abnormal pressure in the misfire conditions leads to the change in \( F_p \) and \( T_b \).

**Figure 5.** Pressure curves for normal and misfire conditions.

**Figure 6.** Simulated waveforms, with misfire in cylinder 1, at 1500rpm/50Nm.

Most of the simulations were built in LMS’s AMESim Imagine Lab software package. TRCS04A (2D crankshaft-piston with inertia and friction effects), TRVDENG03 (3D engine model) are the main models used in the simulation. For the torsional vibration, because the Toyota engine is a four-cylinder engine, the crankshaft can be considered as rigid, but the stiffness/damping models can be easily included into the simulations of a large engine with flexible crankshaft. As mentioned before, the direct simulation results of the block angular acceleration are about the CG, and they should be converted into pseudo angular accelerations (as measured) by transformation matrices, which are similar to the transformation matrix in the equation (2). Examples of the simulated results of torsional
vibration and pseudo angular acceleration in the cylinder 1 misfire and 1500rpm/50Nm are shown in Figure 6.

The pseudo angular acceleration is not pure roll and is mixed with other rotations. However, it can be assumed that the contact surface between the accelerometers and block are parallel to the X’-Z’ plane (about the CG), and the coordinates of accelerometers 5 and 7 in the Y direction are the same. As mentioned before, the coordinate difference of the two accelerometers in the X direction is small in comparison with the difference in the Z direction (see figure 1). Therefore, when the engine operates in the same speed/load and with the same misfire levels, even if the misfire happens in a different cylinder, the amplitudes of the first five harmonics of the pseudo angular acceleration (especially their relationship) should not change greatly.

The most important thing for the fault (misfire) diagnostics is to find the features to represent different misfires. For this reason, the first five harmonics of the simulation results were studied, for both torsional vibration and pseudo angular accelerations. It was found that the best features from the simulations (amplitudes of the first and fourth and the phase of the first harmonic) match with those from the experiments. The examples of the comparisons between the simulations and experiments are shown in Figures 7 and 8. In addition to the three measured speeds, the conditions at 1000rpm were also simulated.

![Figure 7](image1.png)  
**Figure 7.** Polar diagrams for torsional vibration of the cylinder 1 misfire at 1500rpm/80Nm.

![Figure 8](image2.png)  
**Figure 8.** Polar diagrams of pseudo angular acceleration of the cylinder 1 misfire at 1500rpm/50Nm.

5. **Automated diagnostics**

Much research has shown that ANNs are a very efficient method to differentiate various faults of rotating machines [13-15]. After training networks using a considerable amount of data, the ANN can make judgments about inputs never before presented, based on the training data. For details of ANN refer to [16]. A three-stage system was designed for the automated misfire diagnostics. The first stage is the misfire detection stage. In the second stage, the neural networks localize which cylinder has a misfire. In the third stage, based on the detection results, the severity of the misfires is identified.
There are 120 cases in total, 36 cases from the experiments and the remaining 84 cases from the simulations. They were divided into two groups, one for the training of the networks (87 cases) and the remainder for test purposes (33 cases). The distribution of the different conditions is shown in table1.

|                  | for training | for test  |
|------------------|--------------|-----------|
|                  | normal       | 100% misfire | 50% misfire | normal       | 100% misfire | 50% misfire |
| from experiment  | 9 in total   | 1 in total, 6 in cylinder 1, 6 in cylinder 2, 2 in cylinder 3 | 6 in total | 5 in total, 3 in cylinder 1, 1 in cylinder 2, 1 in cylinder 3 | 1 in total, |
| from simulation  | 18 in total  | 39 in total, 11 in cylinder 1, 11 in cylinder 2, 9 in cylinder 3, 8 in cylinder 4 | 6 in total | 6 in total | 12 in total, 3 in cylinder 1, 3 in cylinder 2, 3 in cylinder 3, 3 in cylinder 4 | 3 in total, |

A fitness criterion was introduced to evaluate the performance of the MLPs:

\[
Error = \sum_{i=1}^{N} |(ANN(i) - VAL(i))| \\
(5)
\]

\[
Error \_ratio = \frac{Error}{N} \\
(6)
\]

Where, ANN is the output of the MLPs and VAL is the corresponding target number. N is the total number of the evaluation group (33). The final result for the misfire detection is 100% correct for both torsional vibration and pseudo angular acceleration methods. Because the pseudo angular acceleration is subject to more complicated influences and is more difficult to simulate, its fitness criterion is lower than those from the torsional vibration method. The comparisons are shown in table 2.

Due to their advantage for classification problems, probabilistic neural networks (PNN) were used to identify which cylinder has faults. The outputs of the networks are the integer numbers 1, 2, 3 and 4, which directly indicate the cylinder number. The final results have shown that the PNNs successfully localized which cylinder has misfire.
As analysed before, for the same speed/load and with the same misfire levels, the amplitude of the first five harmonics of the pseudo angular acceleration should have no big change for misfire in different cylinders (definitely, no change for the torsional vibrations either). Therefore, there is no need to develop new MLPs to identify the severity of the misfires after the localization stage and the results from the MLPs of misfire detection were further analysed. The results in the third column of table 2 have shown that the networks can accurately identify the severity of the misfires. Overall, the ANNs based on either torsional vibration or pseudo angular acceleration can efficiently detect and diagnose various misfires.

### Table 2. The results of ANNs.

|                | detection (MLP) | localization (PNN) | severity (MLP) |
|----------------|----------------|--------------------|----------------|
|                | 100% correct   | 100% correct       | 100% misfire    |
|                | error = 1.278  | output range       | output range    |
|                | error ratio = 0.0387 | 0.97-1             | 0.47-0.56       |
| torsional vibration |                |                    |                |
| angular acceleration | 100% correct | output range       | output range    |
|                | error = 3.528  | 0.93-0.99          | 0.42-0.66       |
|                | error ratio = 0.1069 |                |                |

6. Conclusions

An automated misfire diagnostic system was developed in this paper. Two methods, using the torsional vibration of the crankshaft and pseudo angular acceleration of the engine block, were studied. The system is based on ANN networks, which include three stages: misfire detection, misfire localization and severity identification. In order to get sufficient data for training the networks, the thermodynamic and mechanical principles of the engine were studied and simulation models were built up using advanced software packages. Only a limited number of tests were carried out to validate and optimize the simulation models. The inputs to the ANNs are the selected features from the processed vibration signals and consist of the data from both experiments and simulations. MLPs were used to detect the misfires and identify the severity. PNNs were applied to classify which cylinder has a misfire. It has been demonstrated that the automated diagnostics system performed very well. From the final results, even though the pseudo angular acceleration method is not so robust as the torsional vibration method (at least for a rigid crankshaft), both methods can efficiently detect and diagnose various misfires.

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