Use of block pseudo angular acceleration for engine misfire diagnosis

Jian Chen (1), Robert B. Randall (2)

(1) Mechanical & Manufacturing Engineering, UNSW, Sydney 2052, Australia
(2) Mechanical & Manufacturing Engineering, UNSW, Sydney 2052, Australia

ABSTRACT

A study has shown that misfire causes angular rotations of the engine in its mounts, dominated by roll motions around an axis parallel to the crankshaft, and that it is possible to detect and quantify misfire using this. This can be a viable alternative to measuring torsional vibration of the crankshaft, possibly using accelerometers already mounted for other monitoring purposes. By making a kinematic/kinetic model of the engine as a rigid body in the engine mounts, and updating it on the basis of a small number of measurements, it has been found possible to simulate misfires of different severities and locations, and use the simulated angular accelerations to train neural networks to recognise a much wider range of faults than the small number of measurements used to validate the model. The paper describes the successful use of this approach for misfire detection and diagnosis in a 4-cylinder spark ignition engine.

INTRODUCTION

Vibration based condition monitoring techniques have long been successfully applied to rotating machines, typically operating at constant speed and load in various industries. However, the application of condition monitoring on IC (internal combustion) engines or similar reciprocating machinery developed slowly. That is partly because they often operate at variable speed and load, and remotely from a central monitoring station. Another source of difficulty with engines is that the signals are fundamentally different from those of high speed rotating machines, with information about faults carried not only by patterns of frequency content, but also by variations in temporal patterns. Misfire is a very common combustion fault in IC engines and over a number of years there have been continuing advances in vibration signal based misfire detection. There are mainly two approaches: one is based on torsional vibration of the crankshaft (eg Williams 1996, Yang 2001), and the other is based on translational acceleration signals measured on the engine block (eg Ball 2000, Macian 2009). The first requires special transducers to be mounted, the simplest being some kind of shaft encoder, which can be as simple as a proximity transducer detecting passage of teeth on the ring gear.

On the other hand accelerometers are often mounted on the engine to detect other faults such as piston slap, bearing knock or combustion knock and it could be convenient to use them as an alternative to detect misfire. A small number of studies have shown that misfire causes angular rotations of the engine in its mounts, dominated by roll motions around an axis parallel to the crankshaft, and that it is possible to detect and quantify misfire using this.

A general problem with automated diagnosis, for example based on artificial neural networks (ANNs) is that the latter require large amounts of data to train them, and this cannot be acquired from experiencing actual failures in practice (because these do not cover the full range of fault types, locations and severities to be guarded against) in particular at different stages of the failure process. Artificial faults can be seeded in the laboratory, but once again it is not feasible or economical to generate a sufficiently wide range of cases to cover all eventualities. Walters of Rolls-Royce pointed this out in a paper in 2011 (Walters 2011), and stated that it was becoming much more economical to use numerical simulation instead. Numerical simulation is proving to be a viable way of generating data to train neural networks to diagnose and make prognosis of faults in machines. In reference (Randall 2009), the main examples given were for simulation of faults in gears and bearings in rotating machines. There was also a small section on faults in reciprocating machines, in particular IC engines, but this was basically limited to combustion faults, which had been shown to affect the torsional vibrations of the crankshaft. An example was given for simulation of misfire in a large 20-cylinder diesel engine (Desbazeille 2010).

The current paper takes up the possibility of using block rotations for the diagnosis and classification of IC engine combustion faults, using simulated data to train the networks and then test them on real response data.

SIMULATION MODEL

Engine kinematic/kinetic model

The engine used for testing and simulation was a Toyota 3S-FE 4-cylinder 4-stroke spark ignition engine, shown mounted in its test rig in Fig. 1.

The PhD project of the lead author (JC) was carried out in the context of an ARC (Australian Research Council) Linkage project, supported by the Belgian company LMS International, now part of the Siemens group. LMS software was used for much of the modelling in the project, both the 1D package AMESim, and the 3D package Virtual.lab. These LMS packages are normally used for designing new machines, and the application to fault simulation is novel. AMESim was used for the two misfire models, one using torsional vibration of the crankshaft and the other using angular acceleration of the engine block. The latter is the only one considered here. AMESim provides a number of templates for different machines, and the one used here was for an IC engine with standard kinematics, where the subcomponents, engine block,

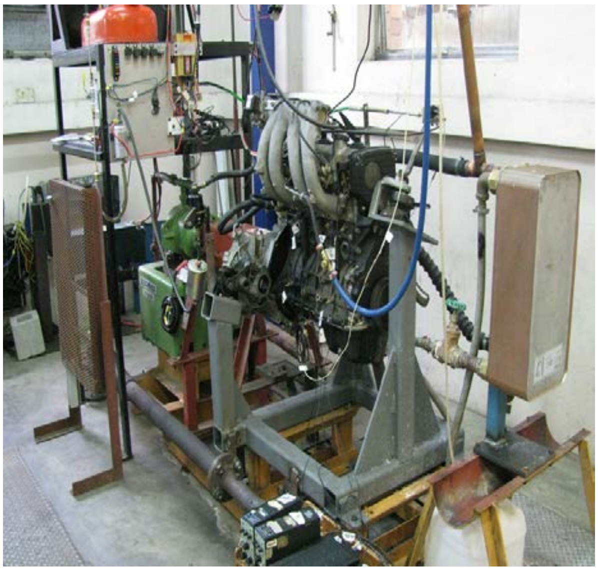

Figure 1 The engine test rig at UNSW

crankshaft, connecting rods, pistons, were modelled as rigid bodies with perfect joints. The engine block was supported in three engine mounts, modelled as linear springs and dampers, whose rotational DOFs (degrees of freedom) were considered negligible in their effect on the engine. The inputs to the model were the time-varying cylinder pressures in each cylinder, and a flywheel was attached to the end of the crankshaft to limit torsional vibrations. The actual load was applied by a Froude fluid dynamometer, with controllable speed and load.

The dynamic properties of the engine and its components were determined from a mixture of experimental methods and computations. The rotational inertias of the engine block, connecting rod, and whole assembled engine were measured experimentally using the so-called “mass-line method” (eg Lee 1999). The inertial properties are estimated from an over-determined set of equations by a least-squares method, based on the constant mass lines between the highest rigid body mode of the support and the lowest elastic mode of the test object (Fig. 2) for a range of FRFs between reference DOFs in all three directions.

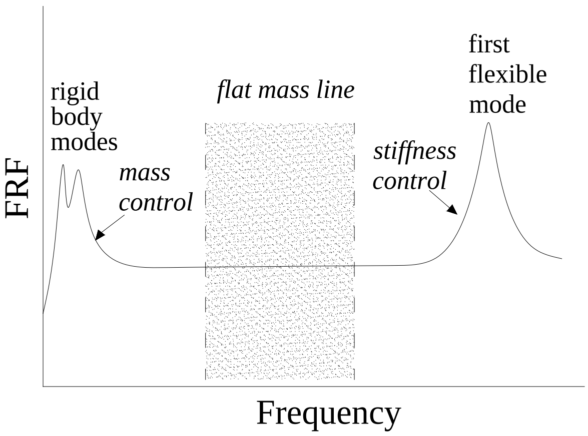

Figure 2. Showing a typical mass line in an FRF

The inertia matrix of the whole engine, as mounted on the rig with attachments, was estimated again using the modal property method, with which the stiffness matrix of the supports could be estimated at the same time from the identified rigid body modes of the mounted engine. The damping matrix, assumed proportional, was also estimated from the modal analysis of the rigid body modes. The inertias of minor components were estimated from CAD drawings. The final dynamic model was adjusted slightly by trial and error to give a good match between measured and calculated rigid body mode frequencies, and response amplitudes. Note that the position of the global centre of gravity could not be determined very accurately by the mass-line or modal

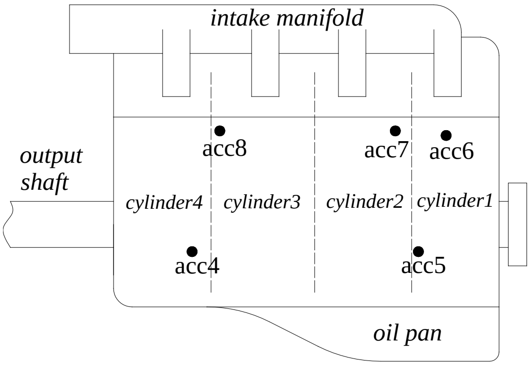

Figure 3. Accelerometer layout on the engine.

property methods, although it is known exactly for the computational model. For this reason it was decided to use “pseudo angular acceleration” of the block rather than the actual angular acceleration about the crankshaft axis. The pseudo angular acceleration was determined as the difference between the linear accelerations measured at the top and bottom of the engine (points 5 and 7 in Fig. 3) divided by the vertical difference between them. The outputs of the AMESim model were the linear accelerations of the centre of gravity of the engine, and the rotational accelerations about it, but these were transformed into linear accelerations at the measurement points, from which the pseudo angular accelerations could be calculated.

Simulations of cylinder pressure

During the compression and expansion phases of the engine cycle, the cylinder pressure is given by:

$$P(\theta) = P_0 \left(\frac{V_0}{V(\theta)} \right)^{\gamma} \tag{1}$$

where $P(\theta)$ and $V(\theta)$ are the instantaneous cylinder pressure and volume, respectively, and $P_0(\theta)$ and $V_0(\theta)$ are the pressure and volume at the start of the process. γ is the polytropic exponent, which is typically 1.3 for compression and 1.25 for expansion (Kuo 1996).

During the combustion phase, use was made of Wiebe’s empirical functions for burn rate $w(\theta)$ and heat release $Q(\theta)$ as functions of crank angle θ (Ghojel 2010), viz:

$$w(\theta) = \frac{6.908(m_v + 1)}{\theta_d} \cdot \left(\frac{\theta}{\theta_d} \right)^{m_v} \cdot e^{-6.908(\theta/\theta_d)^{m_v+1}} \tag{2}$$

and

$$Q(\theta) = w(\theta) \cdot r_{comb} \cdot m_{fuel} \cdot LHV \tag{3}$$

where m_v is Wiebe's combustion characteristic exponent, θ_d is the combustion duration in degrees, r_{comb} is the combustion efficiency, m_{fuel} is the fuel injection quantity which can be looked-up from the fuel injection map of the engine, LHV is the lower heating value of the fuel, normally 43.9MJ/kg for petrol.

Figure 4 shows simulated pressure curves for normal combustion, 50% misfire and 100% misfire.

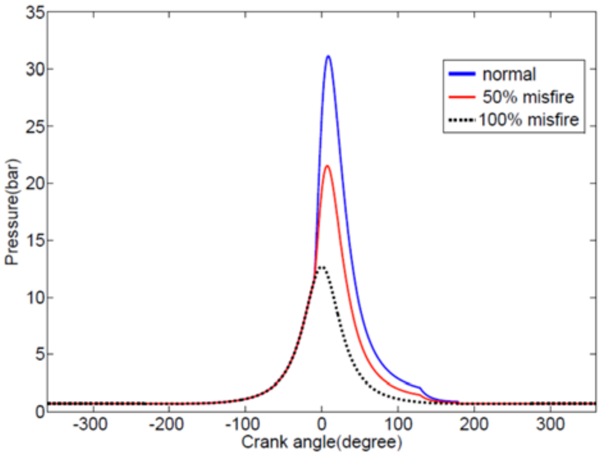

Figure 4. Estimated cylinder pressure for different amounts of misfire

EXPERIMENTAL MISFIRE TESTS

Tests were carried out on the engine mounted as shown in Fig. 1. The injection and firing of the engine was managed by a special engine control unit (ECU) Motec M800. By controlling the dynamometer, three constant speed conditions were selected: 1500rpm, 2000rpm and 3000rpm. For each speed, there were three different load conditions: 50Nm, 80Nm, 110Nm. Removing the ignition lead from the spark plug is the most direct way to simulate 100% misfire, but 50% misfire was simulated by controlling the ECU. Cylinder pressure could be measured (in one cylinder at a time) using a Kistler measuring spark plug, with integrated cylinder pressure sensor, type 6117B. Measured pressures were reasonably consistent in all cylinders, and were used to validate the simulated pressures, as in Fig. 4, for different speeds and loads. The pressure was not significantly reduced even in the case of oversize piston clearance, which was used in another series of tests for the effects of piston slap.

There were 15 cases in the normal condition and 21 cases for misfire conditions (including 2 cases with 50% misfire), as shown in Table 1.

Table 1. Details of misfire tests

Normal	Misfire	
15 in total	100% misfire 19 in total,	50% misfire 2 in total,
	9 (cylinder 1) 7 (cylinder 2) 3 (cylinder 3)	2 (cylinder 1)

COMPARISON OF SIMULATION WITH MEASUREMENT

Normal condition

Figure 5 compares measured and simulated pseudo angular accelerations in normal condition for two different speeds and loads (note that the x-axis is crank angle degrees, not time). The simulation is lacking some higher harmonic information, but the first harmonic is very similar.

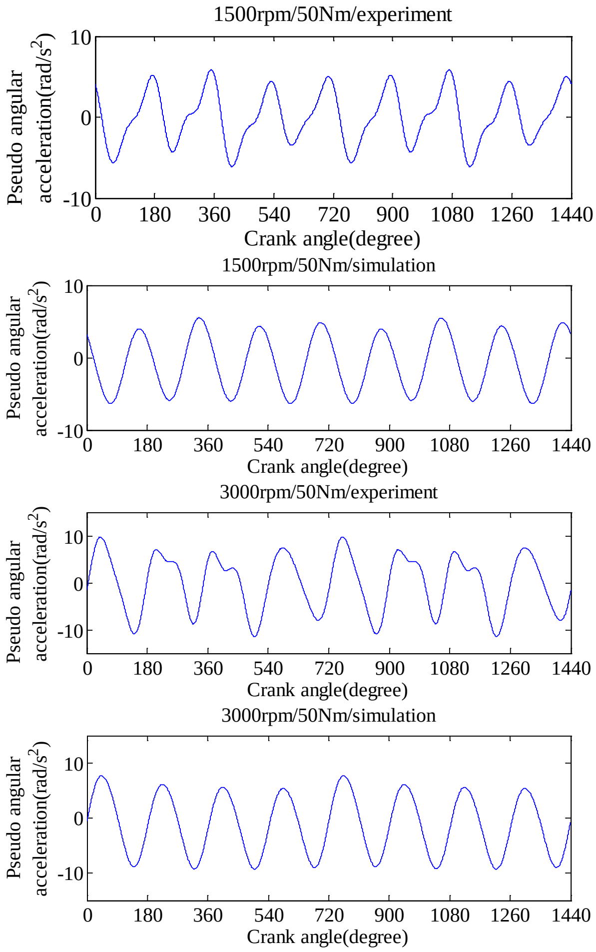

Figure 5. Experimental and simulated pseudo angular accelerations of engine block under normal conditions

In fact, on the basis of the experimental measurements it had been decided that the most appropriate parameters to use for detecting and evaluating misfires were the amplitude and phase of the low harmonics of the motions, with the amplitude (ratios) indicating severity of the misfire, and the phase indicating the affected cylinder. Phase was measured relative to a datum of TDC (top dead centre) cylinder 1, firing stroke. In normal condition the fourth harmonic (firing frequency) dominates (as in Fig. 5), while with misfire in a single cylinder the first harmonic (cycle frequency or half rotational speed) dominates. This was found to be appropriate for analysis of the torsional vibration signals (inspired by Desbazeille 2010), and with very similar results for the pseudo angular acceleration. It will be seen in what follows that the simulations are even closer to the measurements in terms of these dominant harmonics.

Results with misfires

Figure 6 compares measured and simulated pseudo angular accelerations for two different speed and load conditions. The waveforms seem somewhat different, but it will be seen that the low harmonics are more similar. Note that there is a change in phase of the maximum reponse with speed, even though the misfire is always in cylinder 1. This is because the frequency response functions between forces (moments) and responses are constant because of the fixed rigid body modes, but the forcing frequencies (harmonics of the cycle frequency) vary directly with the speed. This was not the case for the

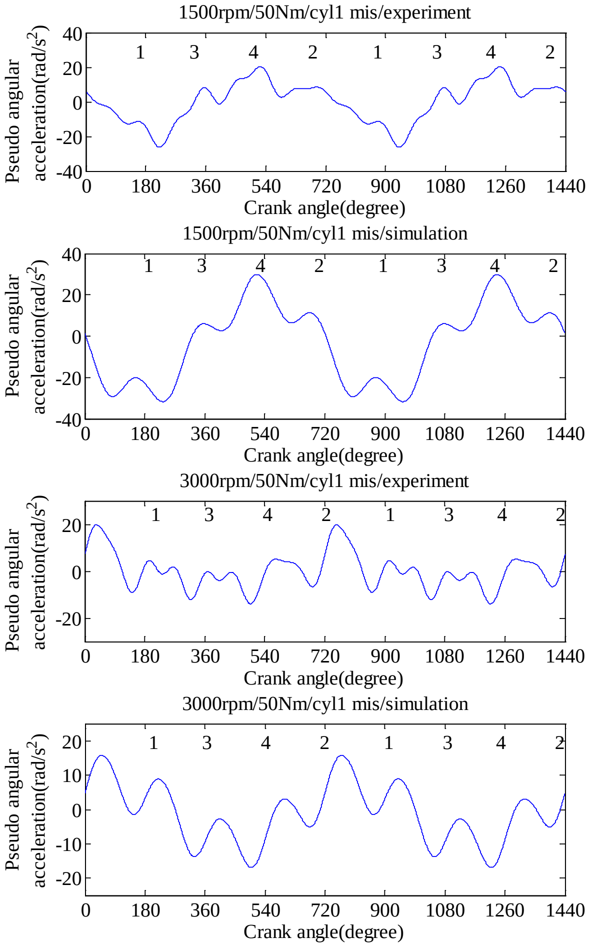

Figure 6. Experimental and simulated pseudo angular accelerations of engine block for misfire in Cylinder 1.

torsional vibrations measured at the same time as the rotational accelerations, because the crankshaft was effectively rigid, but something similar was found for torsional vibrations in (Desbazeille 2010), as the crankshaft was flexible on that large engine, and its torsional modes were within the range of excitations.

Figure 7 shows that the amplitudes and phases of the critical first and fourth harmonics of cycle frequency for the two speeds 1500 rpm and 3000 rpm are more similar than might appear from the waveforms of Fig. 6.

DIAGNOSIS USING ANNs

As mentioned in the Introduction, much research has shown that ANNs are a very efficient method to differentiate various faults in rotating machines (eg McCormick 1997, Samanta 2001). After training networks using a considerable amount of data, the ANNs can make judgments about inputs never before presented, based on the training data. However, large amounts of training data are required. In this paper it is proposed to use simulated data for this purpose, specifically based on the (pseudo) angular accelerations of the engine block. As discussed above, the input features to the networks are based on the amplitudes and phases of the low harmonics of the response waveform signals.

A potential problem with simulations is that they are inherently deterministic, whereas real measurements have a certain amount of variability for a numbr of reasons. The

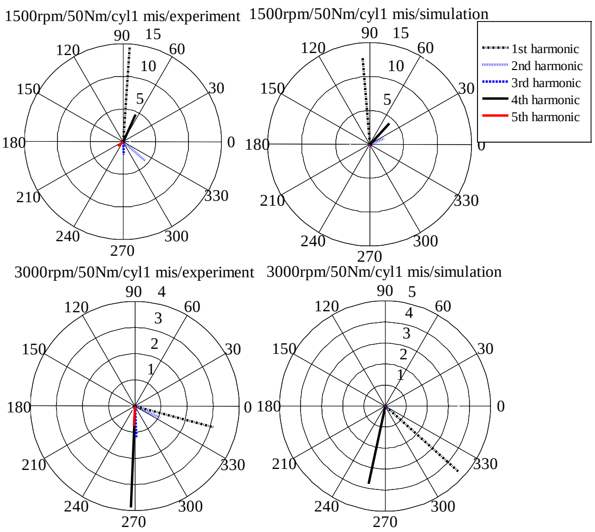

Figure 7. Polar diagrams of the experimental and simulated pseudo angular accelerations for misfire in Cylinder 1.

aprosach to that problem taken here is to use the limited number of actual measurements not only to validate the simulation models, but also to obtain a measure of the random variability, which is then applied to the feature vectors used to train the networks. In some cases, the data from a number of different situations, for example of speed and load, do not vary too greatly, and therefore this variability (also in the simulations) is included.

The system for the automated misfire diagnostics (as shown in Figure 8) was designed as a three-stage system. The first stage is to determine whether a misfire exists. The second stage identifies the cylinder which has a misfire, while in the third stage, based on the detection results, the severity of a misfire can be identified.

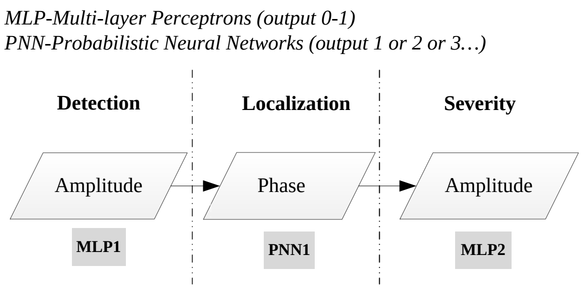

Figure 8. Structure of the three-stage ANN system

As is seen in Fig. 8, two different types of ANN are employed, MLP (multi-layer perceptron) networks and PNN (probabilistic neural networks). The MLP networks have a continuous output between 0 and 1, while the PNNs have discrete integer outputs (1, 2, 3…) to indicate the cylinder. In the initial study, it was desired not to restrict the measurement conditions more than necessary, so a fairly coarse limit was placed on severity identification. Since the only test cases were 50% and 100%, the ANNs were trained to recognise these two values. It would be possible to have finer gradations in severity identification, but this would probably involve making tighter restrictions on speed and load when the measurements are taken.

MLPs are described in many references and have the basic form shown in Figure 9. Two MLPs were designed: one for the fault detection (MLP1) and the other for the severity identification (MLP2). The MLPs consist of three layers: input, hidden and output. The number of hidden neurons of the MLPs was determined using a trial and error procedure (that shown in Figure 9 has 30 hidden neurons). I_w and b are respectively the weight and bias factors distributed to the

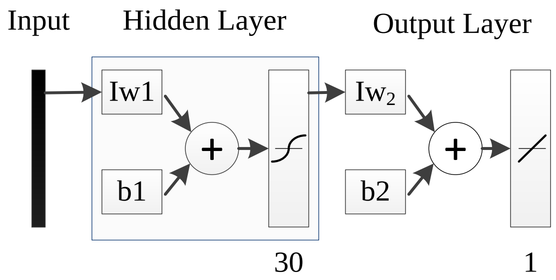

Figure 9. Typical layout of an MLP network

individual elements of the input feature vectors. Identifiers 1 and 2 indicate the different weight vectors and bias vectors for the hidden layer and the output layer. During the training stage, MLPs were led to a specific target output by adjusting the values of the connections (weights and bias) among the elements of the input vectors. The output of the MLPs is from 0 to 1. In the MLP1, output 0 means normal condition and output 1 for 50% and 100% misfire. In the MLP2, the output 0.5 represents 50% misfire and the output 1 represents 100% misfire.

The PNN is based on the weighted-neighbour method and was proposed by (Specht 1990). The distance is computed from the point being evaluated to each of the other points, and a radial basis function is applied to the distance to compute the weight for each point. The structure of a typical PNN is shown in Figure 10. The outputs of the PNN for the misfire diagnostics are the integer numbers 1, 2, 3 and 4, which directly indicate the cylinder number.

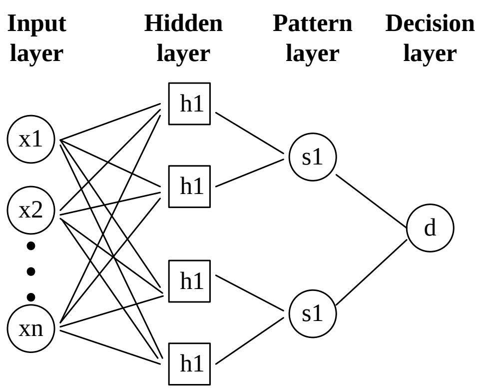

Figure 10. Typical layout of a PNN

Initially, the diagnosis was done with a mixture of test and simulated data. As discussed above, the amplitudes of the 1st and 4th harmonics were thought to be suitable input features for the MLP1. In order to investigate the effect of speed/load on the success of the networks, especially for the MLPs. Two input conditions were tried for MLP1; one was a four-element input condition (two amplitude features plus two speed/load elements) and the other was a two-element input condition (only two amplitude features). A fitness criterion was introduced to evaluate the performance of the MLP1:

$$Error = \sum_{i=1}^{N} \left| (ANN(i) - VAL(i) \right| \qquad (4)$$

where *ANN* is the output of the MLP and *VAL* is the corresponding target number. *N* is the total number in the test group (33). A higher fitness criterion means poorer MLP performance. Even though both feature sets gave excellent results, 100% correct, the 2-element set gave lower error, so the training of the MLPs purely by simulated data was restricted to the 2-element set. For the angular acceleration, as opposed to torsional vibration, the phases of the 1st harmonic with misfire are only fixed at a certain speed, so the inputs to the PNNs also contained two elements, phase and speed.

Finally, the networks were trained using only simulated cases and tested with the experimental cases. Thus, in the MLP1, the training group consisted of 84 simulated cases and the test group consisted of all 36 experimental cases. The final results for the MLPs and the PNN, with two input elements, are shown in Table 2.

Table 2. Diagnostic results

Detection (MLP1)	100%	
Localization (PNN)	100%	
	50% misfire	100% misfire
Severity (MLP2)	Output range 0.849 - 1.000	Output range 0.409 - 0.412

Restricting the maximum output of MLP2 obviously gives a bias, so this approach needs refinement. As mentioned above it should be possible to narrow the output range by restricting the allowable range of speed and load for the measurements.

CONCLUSION

A number of studies have shown that misfire causes angular rotations of the engine in its mounts, dominated by roll motions around an axis parallel to the crankshaft, and that it is possible to detect and quantify misfire using this. The location of the misfire is given by the phasing of the motion with respect to a cyclic reference (eg top dead centre, cylinder 1, firing stroke). Rather than measuring the actual angular acceleration about the longitudinal axis through the centre of gravity (which in general is not known exactly) it is possible to use a "pseudo angular acceleration" based on subtracting two linear accelerations measured near the top and bottom of the block. By making a kinematic/kinetic model of the engine as a rigid body in the engine mounts, and updating it on the basis of a small number of measurements, it has been found possible to simulate misfires of different severities and locations, and use the simulated pseudo angular accelerations to train neural networks to recognise a much wider range of faults than the small number of measurements used to validate the model.

In this paper, it is demonstrated that it is possible to use simulated data to train ANNs to detect and diagnose misfires usuing a 3-stage process: detection, localization, and determination of severity, with a separate ANN for each. The networks were trained entirely with simulated data, and tested entirely with measurement data, with 100% success rate on detection and localization, and a good result for severity determination. It shuld be possible to improve the latter by restricting the range of speeds and loads for which the measurements can be taken.

ACKNOWLEDGMENTS

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