Comparison of linear and nonlinear system identification approaches to misfire detection for a V8 SI engine

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This paper presents simple and practical methodologies for early engine misfire detection. Two diagnostics models, one based on standard linear system identification approaches and a second using a novel nonlinear extension of the linear approaches, involving a multilayer perceptron neural network, were investigated. The models were validated using crankshaft angular velocity measurements taken from a V8 cylinder, 4.2 litre spark ignition engine. The models’ performance was compared and analysed. This paper shows that standard linear approaches are capable of detecting engine misfire with sufficient accuracy, though they require high model order to accommodate the nonlinear nature of the IC process. Therefore, a nonlinear extension to the model is presented. It is shown that this model extension provides a more compact and simple model structure with better capabilities to handle the nonlinearities.

Topics: vehicle diagnostics, modeling and simulation technology, sensors/actuators black-box technology

1. INTRODUCTION

Stringent emissions regulations pioneered by the California Air Resource Board (CARB) have forced automotive manufacturers to develop automotive engines that are not only highly reliable and efficient but also environmentally-friendly. Any type of fault that causes an increase in the emissions level above the legislated value has to be detected at the earliest possible stage. This includes engine misfires, especially the intermittent case, which is notoriously difficult to detect. Intermittent misfires happen at irregular intervals and often for a short period of time which means they can be undetected by the engine management systems (EMS). This type of misfire creates a series of undesirable effects. These may cause severe damage to the catalytic converter, especially when the unburned mixtures reach the converter and produce excessive heat that can melt it. The non-functional catalytic converter will then fail to filter out the toxic exhaust gases, in violation of the emissions regulations. This situation is economically costly and in the long run may deteriorate engine performance, and can be hazardous to the environment.

The problem of detecting engine misfires has been addressed by many researchers, notably in the work of Förster et al. [1], Kiencke [2], Ilkiová, et al. [3], and Cavina et al. [4], to name a few. Their work discussed various mathematical representations of crank angular velocity measurements to detect engine misfire. This type of approach falls into the popular category of model-based fault diagnosis methods. A good overview of engine misfire diagnostics based on crankshaft angular velocity measurements can be found in Williams [5]. Recently, Isermann [6] gave details on the application of model-based fault detection and diagnosis. He stated how the improvement of reliability, safety and efficiency for advanced methods of supervision, fault detection and fault diagnosis becomes increasingly important for many technical processes, especially for safety related ones. A further highlight in the model-based field was given by Mills III [7] at the SAE World Congress 2005, where the usefulness of automotive data for diagnostics purposes was presented. With the advanced data acquisition existing in most modern automotive vehicles, the ‘luxury’ of obtaining abundant measured sensor/actuator signals can now be rigorously explored for diagnostics purposes.

This paper presents results of a collaborative research project between IARC and Jaguar Cars Ltd., UK. The objective is to investigate simple and practical methodologies for early misfire detection in the operation of automotive internal combustion engines. Two diagnostics models, one based on standard linear system identification approaches and a second using a novel nonlinear extension of the linear approaches, involving a multilayer perceptron (MLP) neural network, were investigated. The models were validated using crankshaft angular velocity measurements taken from a V8 cylinder, 4.2 litre spark ignition engine. The models’ performance was compared and analysed. This paper shows that standard linear approaches are capable of detecting engine misfire with sufficient accuracy, though they require high model order to accommodate
the nonlinear nature of the internal combustion process. Therefore, a nonlinear extension to the model is presented. It is shown that this model extension provides a more compact and simple model structure with better capabilities to handle the nonlinearities.

The organization of this paper is as follows: section 2 discusses the design of experiment process; section 3 presents the methodology for misfire detection, where two misfire detection approaches are proposed; section 4 presents detailed discussion of the results obtained with the proposed misfire detection approaches; and, finally, Section 5 summarizes and concludes this paper.

2. DESIGN OF EXPERIMENT

The purpose of misfire monitoring is to detect any misfire, including any possible pattern at any engine speed. Crankshaft speed sensor [1-5] is the most frequent component used to provide an accurate measurement of crankshaft angular velocity to detect engine misfire. The design of experiment process in this study used the above method, where crankshaft angular velocity measurements were taken from a vehicle equipped with a V8 cylinder, 4.2 litre spark ignition engine. The vehicle was tested under various speed and load driving conditions on a chassis dynamometer to simulate a realistic on-road situation. The dynamometer was setup in "speed control mode", to control the vehicle's speed. The vehicle was set in various gears and the load on the engine was then adjusted using the throttle position to give the appropriate engine speed. For the misfire diagnostic, only two variables are required to be logged, one is the measure of time taken by the crank angle to move through 30 degrees and the second is an identification counter which is used to determine which cylinder has firing.

Two different types of tests were conducted under normal running and misfire conditions. For this study, intermittent engine misfire was considered. The intermittent misfire condition was generated by disabling the ignition signal to a specific cylinder at a frequency of 1 in 100 firings or, for a given cylinder, generating a misfire every 12 to 13 ignition events from the following sequence of firing order: 1A-1B-4A-2A-2B-3A-3B-4B.

3. METHODOLOGY FOR MISFIRE DETECTION

Using normal running data, two types of diagnostic models were investigated. The first type was built using standard linear system identification approaches [8]. The second type was a nonlinear extension of the first model type.

3.1 Linear approaches

Initial investigation considered the use of linear time series models for the reason of simplicity. Two methods were proposed: (i) autoregressive (AR) and (ii) autoregressive moving average (ARMA). They were chosen to create the first type of the diagnostics models, taking the form

\[ y(t) = - \sum_{i=1}^{na} a_i y(t-i) \]  

\[ y(t) = - \sum_{i=1}^{na} a_i y(t-i) + \sum_{j=0}^{nc} e_j (t-j) \]  

respectively, where \( na \) and \( nc \) denote the model order, \( a_i \) are the coefficients to be identified and \( e_j \) in Eq.(2), are disturbance terms to compensate for the lack of flexibility in Eq.(1) by describing the equation error as a moving average of white noise [8].

3.2 Nonlinear approach

The nonlinear diagnostics model was a nonlinear extension of the linear models in section 3.1, aimed at improving the ability of the diagnostics model to capture both linear and nonlinear characteristics of the combustion process. Using the information gathered from the most dominant coefficients of the linear model, a simple nonlinear extension model, structured as a multilayer perceptron (MLP) neural network, was developed. It used 5 previous measurement vectors as an input and a current measurement as a target (output), i.e. \( y(t) = f(y(t-1), y(t-2), y(t-3), y(t-4), y(t-5)) \), as depicted in Fig. 1.

This structure was then trained using a Levenberg-Marquardt training algorithm [9] with various numbers of hidden nodes to determine the best network architecture. The best architecture, in terms of the smallest sum-squared error (SSE) value, was formed by a network structure of 5-10-1 (5 input nodes, 10 hidden nodes containing sigmoid functions and 1 target node containing a linear function) as shown in Table 1. This network was further initialized 10 times to find the best weight structure capable of ‘generalizing’ an unknown input once the network has been trained, prior to conducting a validation process, i.e. to perform misfire detection. Fig. 2 illustrates the training performance of the model as a function of iteration.
The proposed nonlinear extension model can be written as

\[ y = g(u, w) = \sum_{j=1}^{N_h} w_j^2 f(x) \quad \text{and} \quad x = \sum_{i=1}^{N_i} w_i^1 u_i + b_j \]  

where \( N_h \) and \( N_i \) are the number of hidden layers and input neurons respectively, \( y \) is the network output and \( u_i \) is the \( i^{th} \) element of the input vector

\[ u = [y(t-1) \quad y(t-2) \quad y(t-3) \quad y(t-4) \quad y(t-5)]^T \]

defined from 5 consecutive tap delays of the current output, \( y(t) \). The overall weights vector, \( w \) comprises of: \( w_j^2 = \) the weight between the \( j^{th} \) neuron in the hidden layer and output neuron, \( w_i^1 = \) the weight between the \( i^{th} \) input and the \( j^{th} \) hidden layer neuron, and \( b_j = \) the bias on the \( j^{th} \) hidden neuron. The sigmoid activation function \( f(x) = \left(1 + e^{-x}\right)^{-1} \).

### 4. RESULTS AND DISCUSSION

Once the model has been developed, the next step is to perform a validation process. This section presents the results of intermittent misfire detection using both linear and nonlinear approaches. A sample of measurement signals in critical engine operating condition is presented. Analysis and performance comparison is discussed.

#### 4.1. Analysis of linear approaches

Initial analysis, based on the measured output signals and their 10-step ahead predicted model output, showed that the AR model had a slightly better performance in comparison to the ARMA model by 0.03% fit subject to normal data (i.e. AR\{30\} showed 80.4% fit followed by ARMA\{30;4\} with 80.37% fit, where \{\} represents the model order). This means that higher order linear models were required for misfire detection. The model was then validated using a sample of measurement signals in critical engine operating conditions.

Fig. 3 depicts the diagnostic process at low-load and high-speed operation (at 22% torque and 6000 rev/min) for AR (a) and ARMA (b), where the prediction error between the predicted and measured output is plotted. The occurrence of intermittent misfires is clearly seen and repeated at the same intervals.

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**Table 1: List of sum-squared error (SSE) value of the validation set to determine the best network structure**

<table>
<thead>
<tr>
<th>Network structure</th>
<th>SSE validation</th>
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<tbody>
<tr>
<td>5-2-1</td>
<td>0.1118</td>
</tr>
<tr>
<td>5-3-1</td>
<td>0.0557</td>
</tr>
<tr>
<td>5-4-1</td>
<td>0.0304</td>
</tr>
<tr>
<td>5-5-1</td>
<td>0.0206</td>
</tr>
<tr>
<td>5-6-1</td>
<td>0.0210</td>
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<tr>
<td>5-7-1</td>
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</tr>
<tr>
<td>5-8-1</td>
<td>0.0149</td>
</tr>
<tr>
<td>5-9-1</td>
<td>0.0090</td>
</tr>
<tr>
<td>5-10-1</td>
<td>0.0083</td>
</tr>
<tr>
<td>5-11-1</td>
<td>0.0102</td>
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<td>0.0092</td>
</tr>
<tr>
<td>5-15-1</td>
<td>0.0098</td>
</tr>
</tbody>
</table>

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Fig. 2: Training performance of the model as a function of epoch
Fig. 4 illustrates the corresponding intermittent misfires detection, extracted from previous figure, which occurred in cylinder 4B. The occurrence of the intermittent misfires which were repeated every 12-13 cycles are clearly visible. This is shown by strong violations across the threshold values. The results demonstrate that, using linear system identification approaches (AR and ARMA), this highly nonlinear process can be monitored with sufficient accuracy. Intermittent misfires are depicted by clear violation across the 99% threshold values.

4.2. Analysis of nonlinear approach

Although linear models have shown relatively good results, they required significantly high model orders (i.e. to a range of 30) to cope with the highly nonlinear nature of the process. Therefore, a simple nonlinear extension of these models (using a feed-forward neural network) was proposed to see if there was any improvement in terms of the simplicity of the model’s structure and its capability to detect misfire.

The nonlinear model built using Eq.(3) was then subjected to a validation process. The same data set used in Section 4.1 (at low-load 22% torque and high-speed 6000 rev/min driving condition) was applied here.

![Residual evaluation of intermittent misfire data](image)

**Fig. 5:** Residual evaluation (a) and illustration of intermittent misfire detection (b) using a proposed nonlinear extension approach.

Fig. 5(a) shows a mismatch between the predicted and measured output. This residual evaluation can be used to extract information from the process, i.e. for misfire detection. Fig. 5(b) shows the illustration of intermittent misfire detection based on previous residual evaluation. There are some clear and strong violations across the 99% threshold in an intermittent manner. The peaks correspond to misfiring cycles that intermittently occur in cylinder 4B, accurately detected by the proposed diagnostic model.

4.3. Comparison

In terms of overall performance, both models were capable of detecting engine misfire. The nonlinear model gave a clearer and crisper result in comparison to its linear counterparts as shown in Fig. 4 and 5, respectively. It is important to note that both linear and nonlinear models required ‘trial-and-error’ stages to determine their model orders or network structures. In terms of the computational load requirements, the nonlinear model required additional training time (to guarantee that the model has been trained to generalize unknown inputs with sufficient accuracy [9]) prior to the validation process. In contrast, once the model order had been identified, the linear models could be validated immediately. In terms of the model structure, the linear models required a significantly higher model order, whereas their nonlinear counterpart provided a more compact and robust structure, with better capabilities to capture the nonlinear characteristics of the process. Understanding the trade-off between the two proposed models will help the decision to choose particular model for implementation consideration.

5. CONCLUSIONS

This paper has demonstrated that both standard linear system identification models and their nonlinear extension using neural networks were capable of detecting engine misfires. The latter provided a more compact and robust model structure with better capabilities. It captured both linear and nonlinear characteristics of the combustion process effectively and efficiently. In comparison to most adopted current OBD misfire algorithms, which compare crank angle time deviations between cylinders to determine whether there has been a normal or a misfire condition, the proposed approaches conceptually offer (i) better efficiency, (ii) better accuracy and (iii) simpler results interpretation.

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