Air-Fuel Ratio Measurement in an Internal Combustion Engine using a Neural Network

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Abstract

Accurate measurement of the air-fuel ratio in a spark-ignition internal combustion engine is desirable for precise control of the engine but difficult to achieve economically because of the unavailability of low-cost sensors. This paper describes research which aims to develop the spark plug as a sensor for the measurement of the air-fuel ratio. The method involves recording the time-varying voltage waveform at the spark plug. The shape of this waveform is influenced by the combustion activity in the cylinder, which in turn, is dependent on a number of factors, of which one is the air-fuel ratio. After signal-enhancement by pre-processing algorithms, the data is analysed by a neural network. The outcome of the analysis is the prediction of the air-fuel ratio. As the spark plug is already installed in the engine, the additional instrumentation cost is low. The paper describes the effects of differing neural-network training file sizes and discusses measures which could be taken to overcome the effects of variations in other engine parameters.

I. INTRODUCTION

Monitoring the combustion phenomena occurring in the cylinder of an internal combustion engine can provide information which can be used for the control of the engine and also in the diagnosis of fault conditions. A robust, low-cost method of monitoring combustion phenomena would be of great interest to engine manufacturers. However, many current combustion-monitoring techniques are too expensive for incorporation into production engines.

Methods of determining a range of parameters have been described in the literature, including statistical timing parameters, flame burn rates and temperature, air-fuel ratio, NOx levels, the onset of engine knock, cyclic variations and combustion abnormalities such as misfire [1, 2, 3, 4, 5].

Optical sensors have the potential to detect a wide range of combustion phenomena of interest [1]. However, the installation of the sensor involves changes to the shape of the combustion chamber, leading to the possibility that the combustion itself will change with consequent degradation in performance.

The cylinder pressure can be related to a number of quantities of interest. Measurement can be achieved by the insertion of a sensor into the cylinder head. However, this is again an invasive procedure, potentially itself leading to changes in combustion. Additional problems also occur, in that the sensor often must be water-cooled, leading to expense, and that it suffers from reliability problems [2].

As the spark plug is in direct contact with the combustion processes, a number of researchers have suggested it for use in the gathering of combustion-related data. The ionic current method has been investigated by a number of researchers. A bias voltage of approximately 100V is applied to the spark plug after the initiation of combustion. The combustion phenomena are assessed by monitoring the ionisation current in the gases due to this bias. Zhao and Ma [2] have proposed a spark plug ionisation (SPI) detection circuit which is incorporated into the secondary winding of the ignition coil. The system enables ionic currents to be monitored via the spark plug. The data obtained permits the detection of knocking combustion and engine cyclic variations. However, the results published exhibit a very wide spread of data due to random fluctuations and this would be likely to make automated analysis of the data difficult. Ohashi et al. [4] describe the use of ionic currents for knock and mis-fire detection in a modified production gasoline engine. An et al. [5] have used Principal Components Analysis (PCA) in association with a statistical classifier to analyse ionic current data.

While a number of researchers have reported investigating the ionic current technique in the research laboratory, the practical problems inherent in applying the bias have prevented the system from being widely adopted for use in production vehicles. For example, the high voltage diodes which are often required are expensive and prone to break-down. In addition there are difficulties in obtaining measurements of sufficiently high accuracy.

II. COMBUSTION MONITORING USING THE SPARK-PLUG VOLTAGE

A continuing research project at the University of Brighton, involves an investigation into the use of the time-varying voltage waveform at the spark plug for monitoring combustion phenomena and engine parameters. The project aims to use spark-plug data in conjunction with other measured engine information to create a *virtual sensor* system to determine combustion parameters of interest. One quantity which is of particular interest is the air-fuel ratio, often expressed as the *lambda value* where a lambda of unity corresponds to an air-fuel ratio of approximately 14.7 to 1.

The use of the spark-plug voltage waveform for combustion monitoring has some characteristics in common with the ionic-currents technique. However, it has the advantage that no bias voltage supply is required and the problems inherent in switching the bias supply in and out of circuit are obviated.

The spark-plug voltage waveform has a number of predictable phases. As the spark pulse is generated by the ignition system the potential difference across the gap rises to between approximately six and 22 kV, before breakdown occurs. Breakdown is accompanied by a fall in voltage, giving a characteristic voltage spike of approximately 10us in duration. This is followed by a glow discharge region of a few milliseconds duration which appears as the tail of the waveform.

Empirical observation of the spark-plug voltage characteristic has shown that variations in engine parameters lead to changes in the shape of the voltage characteristic. Some of the reasons for these changes are discussed in a later section of this paper. Although the general shape of the characteristic is predictable, the detailed variations which occur as the engine parameters vary are not. In addition, random variations occur between sparks even when the engine parameters are kept constant. For these reasons, analysis of the spark-voltage data is not amenable to the use of scalar parameters or conventional classifiers. However, encouraging results have been obtained by the use of adaptive techniques, for example, neural networks.

Neural networks are frequently used as classifiers in pattern-recognition applications. Neural networks possess a number of specific qualities which make them invaluable in pattern classification applications and which are not easily achieved by other means. For example, they can automatically perform knowledge abstraction and statistical analyses on data which is presented to them and this information becomes encoded into the internal structure of the network. They can generalise so as to respond correctly even in the presence of noise or uncertainty. The ability of the neural network to act as a trainable pattern classifier has been exploited where there has been a need to correlate characteristic voltage or current signatures with some physical phenomena. The ability of neural networks to generalise give them a resistance to noise which is useful in situations where random variations in signal are problematic.

Previous papers by the author and associates have described the use of neural networks to correlate the signatures formed by the spark plug voltage waveforms with specific values of air-fuel ratio [6,7] and some of the practical problems, due to electrical noise, the high voltages encountered and lack of stability in the engine, have been reported [8,9]. It has been found that the neural network can differentiate between various categories of air-fuel ratio (lambda = 1.0, 1.2 or 1.4 respectively) with a success rate of up to approximately 90% provided load, speed etc., were held constant [6,7]. A number of neural network architectures have been investigated in this application, including the multi-layer perceptron (MLP) and the radial basis function (RBF) network.

The aim of the experimental work reported here was to investigate the effects of different neural network training regimes on a MLP network, in order to obtain improvements in the ability of the system to determine the air-fuel ratio, and to gauge the suitability of this architecture for use in this application.

III. Experimental Work

A. Method

The experimental work was conducted using an engine test-cell which is being developed to allow investigation into the application of a range of intelligent techniques to engine control. Early work on the development of a fuzzy logic control kernel for this engine has been previously described [9].

The engine was a single-cylinder type with a capacity of 98.2cc. The engine was modified to enable manual adjustment to be made to the air-fuel ratio, which was measured using an exhaust gas composition analyser. The ignition timing was fixed at 24 degrees before top-dead-centre. A regenerative electric dynamometer provided an adjustable load. Instrumentation and data-capture circuitry was installed to allow engine parameters and spark signatures to be recorded.

The experimental method used involved recording sampled spark waveforms for various values of lambda, at specific values of engine speed. The data was pre-processed and then placed in a training file. This was used in conjunction with neural-network pattern-classification to correlate the waveform signatures with the corresponding lambda values. The neural network used was a multi-layer perceptron (MLP) executing a cumulative back-propagation learning algorithm. The code for this was written in-house in the C language.

Training files were created at three different engine speeds, 2800 rpm, 3500 rpm and 4200 rpm. Correspondingly, separate test files were created at these speeds so that the neural network could be tested on unseen data after training.

B. Training using the Raw Data

Firstly, the raw spark data was used in training the neural network. Very small learning coefficients were required in order to prevent oscillatory behaviour in the sum-of-squares error during training. Convergence was extremely slow and the training process, judged by a termination criterion of a satisfactorily low sum-of-squares error, was not reached in a 24 hour training period. This prevented results from being obtained. The difficulty in obtaining satisfactory convergence with raw training data was not surprising given previous experience with an MLP.

C. Training with Pre-Processed Data

Two forms of pre-processing were applied to the spark data. Firstly, based on knowledge gained in previous experiments, each input vector presented to the neural network was tailored so that only relevant information was present. Data points corresponding to regions of the spark known to be unlikely to contain information were removed. Secondly, in order to enhance the signal-to-noise ratio, a filtering operator was applied to the data, the aim of which was to reduce random variations between contiguous spark waveforms.

Figure 1 shows the correct discrimination rate which was obtained at each of the three speeds. The graph shows that the discrimination rate is reduced at higher speeds. The sampling rate of the analogue to digital converter was not varied as the engine speed changed. This would effectively lead to a coarser resolution at higher speed which is likely to explain the reduced performance. Measures are in hand to link the sampling interval to the speed.

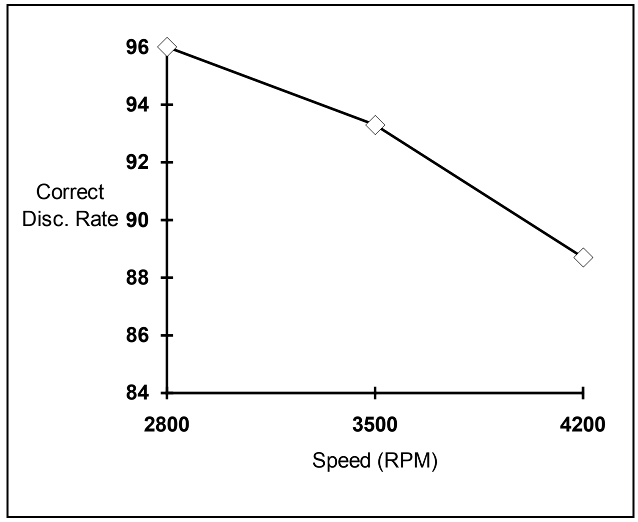

Figure 1: Discrimination rate using pre-processed data

D. Training File Size

The optimum number of training records (input-output vector pairs) in the training file of an MLP network has been the subject of much investigation, however, it has not proved amenable to formal analysis. It would be expected that a number of training vectors comparable with, or exceeding, the number of weights in the network would lead to good generalisation.

Given an MLP network with P, Q and R neurons in the input, hidden and output layers, respectively, the number of weights in the network, Nw, is given by:-

$$Nw = (P + 1) Q + (Q + 1) R \tag{1}$$

If the number of training records is Nt, then it would be expected that for good generalisation

$$Nt = S \, . \, Nw \tag{2}$$

The value s is the *normalised size* of the training file, where $1 < S < 10$. The optimum value of S depends on the application, which, in turn, determines the shape of the error surface. Generally, large values of S lead to better generalisation; however, adoption of this criterion often leads to a large training file size and long training times which may not be acceptable in practice.

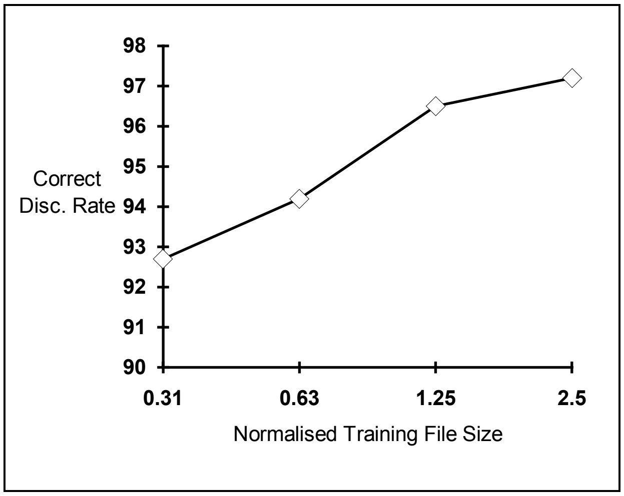

Figure 2: Graph showing neural network discrimination rate for different sizes of training files.

Figure 2 shows the variation in the ability of the neural network to correctly discern the air-fuel ratio with varying normalised training set size. As the normalised size increases the discrimination rate improves. However, although not shown quantitatively here, at the same time the convergence rate worsens and the training time rises very rapidly.

E. The Effect of Speed Variations

In the previous experiments which have been described in this paper, the neural network has been trained using data obtained from the engine running at a fixed speed, and then it has been tested using new data obtained when the engine was running at the same speed. Figure 3 illustrates the performance of the network when data obtained when the engine was running at a particular speed was used in training the network, and then data obtained at a different speed was used for testing.

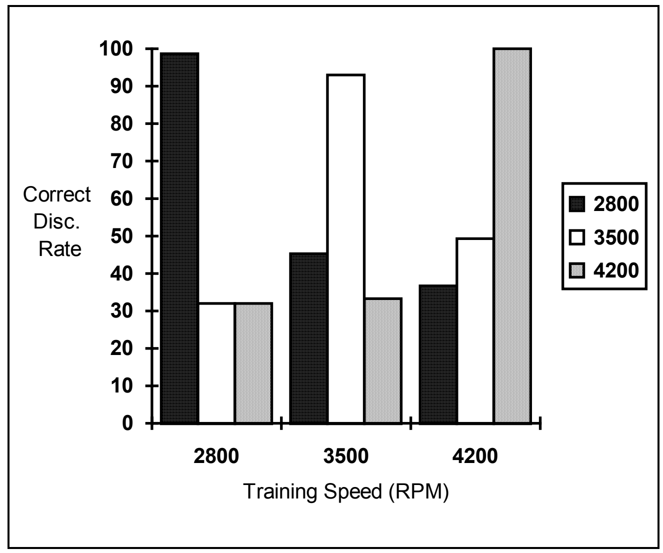

Figure 3: Discrimination rate obtained when the training and recall speeds were different.

Figure 3 shows that while the neural network was able to indicate the air-fuel ratio when the training and recall data were obtained when the engine was running at the same speed, only poor accuracy was achieved when the neural network was tested with data corresponding to different speeds.

In an attempt to gain an improvement to the accuracy of the system, a composite training file was constructed. Data obtained when the engine was running at 2800, 3500 and 4200 RPM was combined into a single training file. The network was then tested using individual recall files obtained at these speeds, but also at 3150 and 3900 RPM.

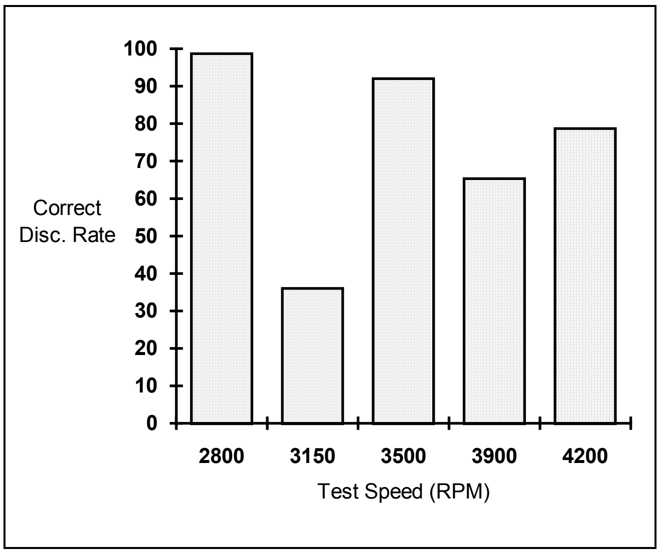

Figure 4: Training with an extended speed range

Figure 4 shows the results which were obtained.

Although reasonable accuracy was obtained at the speeds where data had been used for training the network performed poorly at the other speeds. The reason for this could be linked to the behaviour of the ignition system as speed changes. The ignition system of a conventional spark-ignition engine is based on a coil, which effectively functions as a transformer, and a contact breaker. The contact breaker may be mechanical, or may be a semiconductor device such as a transistor in the case of an electronic ignition system.

When the contact breaker closes current flows in the coil and energy is stored in the magnetic field which is produced. When the piston is at an appropriate point just before top-dead-centre the contact breaker opens again a voltage, $V = M\, dI/dt$ is induced, where M is the mutual inductance of the coil, and this causes breakdown in the spark-plug gap. The energy discharged into the air-fuel mixture before ignition, and into the plasma in the cylinder after ignition, depends on the energy stored in the coil, which in turn is the integral of the instantaneous current, I and the supply voltage Vs over the period for which there is current flowing in the coil.

The amount of energy becomes speed-limited, because at higher speeds the time available for the storage on energy in the coil becomes reduced. In a magneto ignition system, the spark energy increases with speed, as the rate at which flux is cut increases.

Thus, in either type of ignition system the energy of the spark will vary with speed. The spark-plug voltage characteristic would, in turn, be expected to exhibit variations with speed. The inability of the neural network to characterise spark data recorded at speeds which had not been used during training, is not, therefore, surprising.

There are a number of methods which suggest themselves for overcoming this dependence on speed:-

- The neural network could be trained with spark data recorded for all speed conditions.
- The data could be pre-processed in such a manner that these speed-induced variations become insignificant.
- The neural network could be supplied with information about speed and other relevant engine parameters

Investigations into these alternatives is being carried out by the research group at the University of Brighton.

IV. Discussion - The Effect of Lambda on Spark Voltage Waveforms

The breakdown voltage across the electrode gap of a spark plug in an operating internal-combustion engine is dependent on the interactions of a multitude of parameters, for example, the combustion chamber and electrode temperatures, the compression pressure, the electrode material and configuration and the composition of the air-fuel gas mixture, [10, 11]. All of these factors may be attributed to physical properties and processes; for example, the composition of the air-fuel mixture influences the breakdown voltage mainly through temperature and pressure changes.

The spark plug cathode electrode temperature has a significant effect on breakdown voltage, due to increased electron emission at elevated temperatures. The maximum spark plug temperature, when keeping other parameters constant, is achieved when lambda is equal to 0.9, that is, the value for maximum power output [10]. Under lean, and to a lesser extent, rich mixture conditions, the voltage rises [11]; this is largely due to a reduction in the heat released by combustion [12]. Given a constant set of engine operating conditions, an increase in lambda results in an increased pressure at ignition which has been attributed to an increase in the ratio of specific heats (the gamma ratio) of the air-fuel mixture [12]; an increase in gas pressure results in a concomitant rise in breakdown voltage.

Changes in lambda, and therefore in breakdown voltage, lead to subtle changes in the overall shape of the typical ignition spark waveform. Given a constant ignition system energy, an increase in breakdown voltage results in more energy being used within the breakdown phase. This leaves less energy available for following phases of the spark, i.e. arc and glow discharge. The observed result is a reduction in the glow discharge duration.

To summarise, changes in lambda would be expected to influence both the breakdown voltage and the voltage characteristic of the arc and glow discharge phases. However, if the voltage characteristic of the spark is to be used to determine the lambda value, the effects of other parameters on the spark characteristic, for example temperature and pressure, must be accommodated.

V. Conclusions

The experiments described here have shown that the MLP neural network is capable of discerning small changes in lambda (~0.1) from the changes in spark waveform that occur, provided that other engine parameters are held constant. Changes in other engine variables, for example, load and temperature, are likely to be significant. In order to accommodate the effects of these changes it is probable that the values of these parameters will need to be supplied to the neural network.

Neural network models have been described in the literature [13, 14, 15]. These relate engine parameters such as the speed, load (manifold air pressure), temperatures etc. The *virtual sensor* system which is being developed under this project incorporates a neural network model of the engine but supplements speed, load etc., information with spark data. It is believed that this is an original concept.

The MLP network has proven useful in a range of applications, providing a compact representation of the problem space. Where the small training files are adequate for network learning or where execution platforms are available with high floating-point calculation rates, the network may be trained in practicable times. However, the large problem space inherent in a virtual sensor system for an engine is likely to necessitate the use of large amounts of training data. There must be a question about whether the standard MLP network executing a back-propagation algorithm will converge quickly enough for it to be usable in this application. Faster training algorithms have been investigated, including the *Class-Distributed* network which may be executed on a multi-processor platform [7, 16, 17]. An alternative to faster training neural networks could be to reduce the dimensionality of the training data (and the problem space) by the use of a mathematical transformation. Both of these are key areas of research into this problem.

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