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Neural Network Techniques for Monitoring and Control of Internal Combustion Engines

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Abstract

Engine manufacturers are constantly striving to find new and improved techniques for the monitoring and control of motor-vehicle engines. The aim is to achieve reduced exhaust emissions and superior fuel economy. Intelligent-systems techniques, such as neural networks and fuzzy methods, are attractive for application in this area because of their capabilities in pattern-recognition, modelling and control. For this reason, the use of neural networks in the monitoring and control of motor-vehicle engines is becoming an area of research which is receiving increasing attention from both the academic and commercial research communities. This paper reviews the way in which neural networks can be applied to gasoline or spark-ignition motor vehicle engines for combustion monitoring, on-board diagnostics and enhanced control strategies. It also describes research in these areas being carried out at the Transfrontier Centre for Automotive Research at the University of Brighton.

Introduction

There are two recurrent themes in the area of motor-vehicle engine design, fuel economy and the reduction in harmful exhaust emissions. Europe, the United States, and much of the rest of the world, have legislative controls which govern the permissible levels of pollutants in the exhaust of Internal Combustion (IC) engines [1]. Maintaining these standards in current engines demands strict control of operational parameters using a microprocessor-based Engine Management Systems (EMS) or Engine Control Unit (ECU).

The EMS implements control strategies which aim to achieve optimum efficiency and high output power when required, while at the same time maintaining low emission levels. At the same time, in a gasoline or spark-ignition engine, the EMS must operate the engine in a region favourable to the operation of a three-way catalytic converter, which further reduces the harmful content of the exhaust. The engine must also exhibit good transient response and other characteristics desirable to the operator, known among motor manufacturers as *driveability,* in response to movements of the driver's main control, the throttle or accelerator pedal. The EMS governs the amount of fuel admitted to the engine (the fuel-pulse width), the point in the cycle at which the mixture is ignited (the ignition timing), the amount of exhaust gas recirculated (EGR), and other parameters in advanced engine designs, for example, the valve timings. It selects values for these parameters from measured quantities such as speed, load torque, air mass flow rate, inlet manifold air pressure, temperatures at various points, and throttle angle.

The EMS has a further role, in that legislation in the US and now in Europe demands an on-board diagnostic (OBD) system. The OBD system must indicate when emissions do not conform to standards, or when fault conditions occur which could lead to excessive emissions.

Research is taking place to develop improved engine control by incorporating neural networks and other intelligent-systems techniques into the EMS. The contribution of the neural network can be categorised into three areas which are explored in this paper:-

- Neural networks have a role in interpretting data from sensors already present in the engine, or available at low additional cost, so as to extract new information. An example of this is combustion monitoring using the spark plug, which is described later.
- Neural networks can be used for the detection of specific *signatures* from new or existing sensors in OBD systems in order to detect and identify fault conditions.
- Neural networks, and the related technology, *fuzzy systems*, can be valuable in the implementation of advanced control strategies.

Combustion Monitoring using the Spark Plug

The use of the spark plug as a combustion sensor in gasoline or spark-ignition (SI) engines appears attractive when compared to other sensory methods. Many techniques, such as pressure measurements or light emission recording by fibre-optics, require that the combustion chamber be modified and this can itself affect the combustion. Secondly, engines are extremely price sensitive and additional sensors can only be provided if they are economically justifiable in terms of the improvements they provide.

The spark plug is already present in a gasoline engine, eliminating the need to make any potentially detrimental modifications to the cylinder head or combustion chamber and avoiding additional costs. As the spark plug is in direct contact with the combustion, it is an excellent witness to the combustion process. Analysing the spark-plug voltage and current waveforms therefore potentially provides a robust and low-cost method for monitoring phenomena in the combustion chamber.

The method of using the spark plug as a combustion sensor which has received most attention is known as the *Ionic Current* method. This has been investigated for measuring combustion pressure, air-to-fuel ratio (AFR) and the detection of fault conditions such as misfire and knocking combustion.

An alternative method, currently being investigated at TCAR, is called *Spark Voltage Characterisation* which involves neural-network analysis of the time-varying spark voltage waveform. Current research involves the use of neural networks to predict the AFR with promising results, and the possibility of use for combustion fault detection.

Ionic Current Monitoring Systems

In the ionic current system, the spark plug is used as a sensor during the non-firing part of the cycle. This is done by applying a small bias voltage of about 100 volts to the spark plug and measuring the current. This current is due to the reactive ions in the flame which conduct current across the gap when the voltage is applied. The ions are formed during and after combustion, and the type and amount of ions present is dependent on the combustion characteristics. The ionization current is also dependent on the pressure, temperature etc. and therefore is rich in information but very complex [2].

The ionic-current waveform has three notable peaks. The first is due to the ignition pulse. The second is the flame front passing through the gap. The third, termed post flame, correlates with the pressure signal and is used for spark timing control and gas temperature sensing around the spark gap [3]. Much work has been done on the use of ionic currents for monitoring combustion, mainly to estimate combustion pressure, and thus act as a replacement for combustion pressure sensors. Ion current systems have also been proposed for AFR and ignition-timing estimation, and misfire and knocking detection [4, 5]. More recently, neural networks have been applied to the analysis of ionic-current data for spark-advance control and AFR estimation [6,7].

The ionic-current method appears attractive because only minor modifications are required to adapt the engine. However, high-voltage diodes or other switching methods are needed to isolate the ionic-current circuitry from the ignition system and these have been prone to failure in the past. The 100V power supply is also an additional component which is required and the cost of any additional component must be carefully justified.

Spark Voltage Characterisation using Neural Networks

The Method

Spark Voltage Characterisation (SVC) is a combustion monitoring technique which offers an alternative to the ionic-current method. Using the spark plug as the combustion sensor, this technique has many of the advantages of the ionic current method. However, as the method involves analysing the ignition voltage waveform itself, it eliminates the need for an additional bias power supply, and for the associated high-voltage switching circuitry.

TCAR is engaged in the investigation of spark voltage characterisation as a method for combustion monitoring, for example for the determination of air-fuel ratio (AFR). Accurate measurement of AFR is desirable, but not currently achievable in production engines due to the high cost of sensors. A low-cost accurate method of determining the AFR in the cylinder would have a great appeal to the motor industry. The method also could potentially be extended to the measurement of in-cylinder pressure.

The SVC method of AFR estimation involves the use of a neural network to associate the time-varying voltage waveform at the spark plug with the AFR measured by the exhaust gas analyser.

Data Capture and Synchronisation

The SVC method requires a data-capture system which allows desired portions of the spark plug voltage waveform to be recorded in a repeatable manner. Synchronisation circuitry has been developed to allow this to be done. Figure 1 shows the essential elements of a gasoline engine ignition system. The ignition coil is essentially a high voltage transformer, increasing the battery voltage (approximately 12V) to between approximately six and 25 kV. The contact breaker was once universally a mechanical component, but in electronic ignition systems is replaced by a semiconductor switch such as an automotive specification transistor or thyristor.

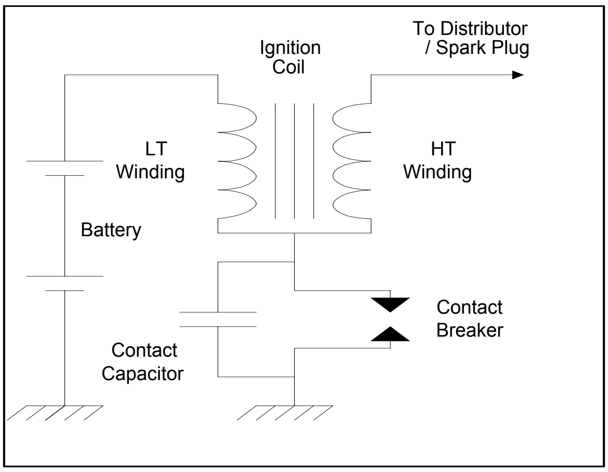

Figure 1: The Ignition System

The contact breaker closes and current builds up in the low-tension (LT) winding of the coil resulting in the storage of energy; however, the speed at which this occurs is limited by the resistance of the coil. At an appropriate point in the engine cycle, when a petrol-air mixture has been injected into the cylinder via the inlet valve, and compressed so that the piston lies just before top-dead-centre, the contact breaker opens. The magnetic field in the coil collapses rapidly, with an equally rapid change in magnetic flux, and a high voltage pulse is induced into the high-tension (HT) side of the coil, igniting the petrol-air mixture. The resulting combustion drives the power stroke of the engine.

Each cylinder in a four-stroke engine experiences one power stroke for every two revolutions of the crank- shaft. In a multi-cylinder engine a distributor can be used to switch the ignition pulse to the correct cylinder. Alternatively, there may be multiple coils and no distributor. In a *wasted-spark* system each cylinder receives a spark once every crank-shaft revolution. This requires multiple coils, in a multi-cylinder engine, but enables the distributor to be dispensed with, and is common practice. Single cylinder engines also commonly use this principle, as it allows the ignition system to be triggered directly from the crankshaft

Figure 2 shows the form of the spark plug voltage waveform for approximately 720 degrees of crank angle in a wasted spark ignition system. The waveform shows four distinct spark events: 'b' and 'd' correspond to pulses which are obtained when the contact breaker closes. The voltage which these reach is limited because the coil resistance limits the rate of change of flux. If these pulses are troublesome, perhaps giving rise to misfire or erroneously-timed ignition, they may be suppressed.

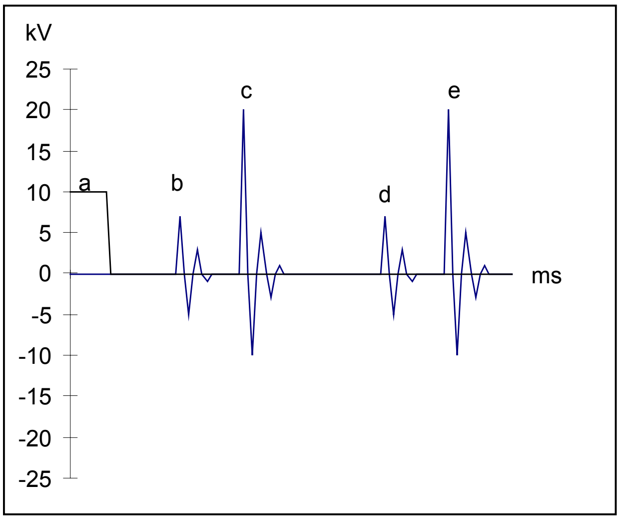

Figure 2: Spark voltage waveforms for a wasted-spark ignition system

Pulses 'c' and 'e' are the high-voltage pulses which occur when the contact breaker opens. Pulse 'c' is timed to occur some time before the piston reaches top-dead-centre and initiates combustion. The combustion takes time to develop and the ignition timing delay allows for the time required for the combustion pressure to reach its maximum. Pulse 'e' occurs during the exhaust stroke and has no effect. All of these pulses exhibit dampedresonant behaviour because the ignition system possesses capacitive and lossy-inductive elements. Each occupies a few milliseconds in time.

For successful analysis of the spark waveform, it is necessary to ensure that it is possible to select portions of the waveform which contain relevant information. For example, it may be desired to capture only the firing spark, ‘c’, or perhaps only the wasted spark, ‘e’. Triggering using the spark voltage waveform is unreliable, due to random variations between sparks, and unlikely to be successful in this respect.

Figure 3 shows a data-capture and synchronisation system that has been developed at TCAR for the investigation of spark characterisation. Most modern engines have a sensor, normally inductive, which determines the rate of rotation of the crank-shaft, and also indicates the top-dead-centre position once every crank-shaft rotation. A wasted-spark ignition electronic ignition system can be synchronised by the signal from this sensor, with a delay applied to ensure the correct ignition timing. A sensor which detects the cam-shaft position can be used to generate a synchronisation signal once every 720 degrees of crank angle, but a cam-shaft sensor is not always fitted as a standard engine component.

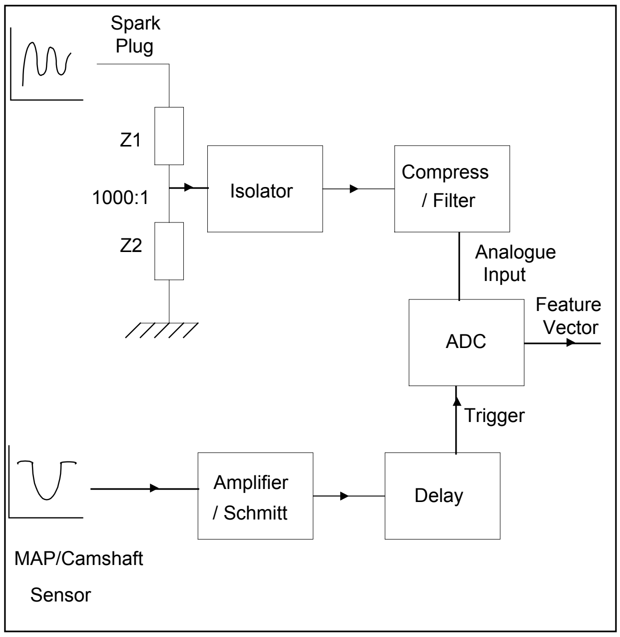

Figure 3: Data capture and synchronisation system

An alternative method which has been found to be convenient is to fit an inexpensive piezo-electric pressure transducer to the inlet manifold. This sensor is used to measure the Manifold Air Pressure (MAP) and so detect the opening and closing of the inlet valve, corresponding to pulse ‘a’ in Figure 2. The inlet valve closes at approximately bottom-dead-centre, corresponding to approximately 65 degrees of crank angle before the ignition point. In the data-capture system used for this work, the output of the MAP sensor, subjected to suitable signal conditioning, is used as a reference. The point at which data capture begins is determined by a delay, the length of which is adjusted according to the speed to correspond to a fixed number of degrees of crank-angle. The desired portions of the signal at the spark plug due to the firing or non-firing spark can be selected by changing this delay.

The high-tension signal from the spark plug is reduced in voltage by a potential divider formed from impedances Z_1 and Z_2. The reduced-voltage signal is then pre-processed, compressed and filtered, and digitised. A feature vector is produced for each ignition spark; these are stored and used in training the neural network.

Multi-Layer Perceptron (MLP) and Radial Basis Function (RBF) networks are under investigation for this application and a number of different neural network training regimes are being evaluated. Initially, the engine was adjusted to run at a particular speed and AFR. A large number of digitised spark voltage data records were captured and stored. The process was repeated for different speeds and AFRs. The neural network was trained using a portion of this data, and tested using the unseen remainder.

Experimental work initially involved the use of multi-cylinder engines. However, current work makes use of a test-rig based on a 98.2 cc single-cylinder engine with electric dynamometer. The ignition timing is fixed at 24 degrees before top-dead-centre. Semi-automatic adjustment of the petrol-air mixture is possible and the resulting AFR is measured by an exhaust gas analyser. TCAR has attracted European Union funding and the support of a prominent firm of engine design consultants situated local to the University, resulting in the provision of a Hydra research engine for future work.

Results

Using a multi-cylinder engine and random spark waveform capture it has been found that the neural network can differentiate between various categories of air-fuel ratio (lambda ratio = 1.0, 1.2 or 1.4 respectively) with a success rate of up to approximately 90% provided load, speed etc., were held constant [8].

Subsequent work using the small-capacity single-cylinder test rig, referred to above, showed that it was possible to improve on this, and obtain classification rates of about 95%, again with other parameters held constant [9, 10]. The effects of variations in speed were also investigated. A practical AFR system needs to be able to provide accurate measurements over a range of speed and load conditions. The enhancements in experimental facilities are intended to allow investigation and improvements in this area. Experimental results using the new synchronisation system, described above, will be made available later.

On-board diagnostics

The legislation in the US widely known as the *OBD2* legislation requires that the EMS incorporates on-board diagnostics (OBD) which are able to detect faults and combustion anomalies. Fault conditions which have the potential to damage the catalytic converter, for example misfire and knocking, which can cause fuel-contamination of the catalyst, must be detected, and a warning given to the driver.

Although misfire detection systems have been researched for some time, it has proved difficult to find a universal algorithm, with a low implementation cost, that can detect misfire with high accuracy and without false alarms in real time. Among many methods researched for misfire detection, crank-shaft speed fluctuation based methods are commonly used, due to low-cost signal availability, and adequate performance under most conditions. Recently neural networks have been investigated for the identification of signal-components which are characteristic of the occurence of misfire. A method which uses the neural interpretation of crankshaft-speed fluctuations has been described [11]. Ribbens, et al. propose a method where convential signal-processing techniques are suplemented by neural networks analysis for this purpose [12].

Engine knock detection is as important as misfire detection. Combustion efficiency is achieved by a high in-chamber compression ratio. However, knocking combustion places a limit on the compression ratio which can practically be achieved. To obtain high performance, engines have to operate close to the critical knock point and the EMS must incorporate a method of detecting the onset of knocking. Classical knock detection methods are based on accelerometers or acoustic transducers and analogue signal analysis. However, signal-to-noise ratio problems can be apparent, especially at high speeds. The use of modern micro-controllers in the EMS makes it possible to use advanced algorithms, for example neural networks or fuzzy logic, to extract more information from the accelerometer signal and more accurately anticipate the onset of knock [13, 14].

The use of the spark plug as a sensor for use in measuring AFR etc., has already been described, but it can also be used for sensing combustion anomalies [5]. At TCAR, the spark voltage analysis technique is being applied to the detection of mis-fire and is yielding interesting results.

Engine Modelling and Control Using Neural Networks

IC engines are dynamic systems with highly non-linear characteristics containing variable time-constant terms and delays. The abilities of intelligent-systems techniques, for example neural networks and fuzzy methods, to relate these non-linear properties makes them excellent tools in the modeling of engines [15]. For example, Ayeb, et al. discuss a method where static neural networks (SNN), time delayed neural networks (TDNN) and dynamic neural networks are used for modeling a SI engine [16].

Modelling can be used for engine simulation, but it can also be used in *virtual sensors.* If a model can be devised which relates engine parameters, then the quantities of interest which cannot easily be measured can be determined from those which are known. A virtual sensor could, for example, estimate AFR, which cannot economically be directly measured, from quantities such as speed, load, air flow rate, etc., which can be measured fairly easily. Atkinson et al. discuss a method where a neural network based system is used for predicting the engine performance, emission and fuel consumption. The method uses sensors already present on the engine to measure various parameters and an engine model based virtual sensor for estimating parameters that cannot be conveniently measured [17]. Frith et al. have described a method for estimation and control of AFR using a multiple neural-network modelling system [18]. A neural network based combustion-pressure analyser for controlling ignition timing [19] has been proposed, and a method has been described for controlling the AFR of direct injection (DI) combustion engines using neural networks [20]. Buamann et al. discuss a method where neural networks and fuzzy logic are used on a hybrid electric vehicle to coordinate powertrain components [21].

The Intelligent Engine Management System

Figure 5 illustrates a concept which is under development at TCAR, that of the Intelligent Engine Management System. The Intelligent EMS combines a neural-network based engine modelling system with a fuzzy control kernel. The modelling system forms a virtual sensor, which bases its estimates of AFR and other desired quantities on relatively slowly changing variables such as speed, MAP, air flow rate etc., but also on information obtained from spark voltage characterisation. The spark-voltage waveform potentially holds information which will allow an assessment of rapidly changing engine conditions, facilitating better transient response than might be expected from a virtual sensor based on long-time constant variables.

The fuzzy-control kernel is used to help overcome some of the problems which the complex characteristics of the engine poses for classical control methods [10]. Devising efficient control strategies is not straightforward and incorporating them into classical-model control systems poses many difficulties. While it is difficult to produce accurate mathematical models of the engine, there is a large body of heuristic knowledge of engine operation, and empirical observations may be carried out relatively conveniently. Fuzzy-control systems enable the exploitation of this heuristic operator-knowledge by the computer implementation of linguistically-based control strategies. They replace the classical mathematical model of a physical system by a heuristic piecewise approximation which is easily assimilated by the operator. Thus the fuzzy-control kernel will aid efficient calibration of the engine and allow a measure of rapid prototyping of the control strategies in the EMU.

Conclusion

The internal combustion engine is likely to be the most common motor vehicle power plant until well into the twenty-first century, although new variants such as the Gasoline Direct Injection (GDI) and High Speed Direct Injection (HSDI) Diesel engines may supplant more conventional engine variants. Engine designers and manufacturers are being set ambitious targets for fuel economy and exhaust emissions. To meet these targets the control regimes implemented by the EMS will have to increase in sophistication. Neural networks and other intelligent-systems techniques can be beneficially applied to the analysis of sensory data. They can also be helpful in achieving the non-linear mappings necessary for efficient engine modelling and control. In gasoline or spark-ignition engines, the neural-network analysis of data obtained from the spark plug promises to be a powerful technique for low-cost combustion monitoring and fault detection in OBD systems.

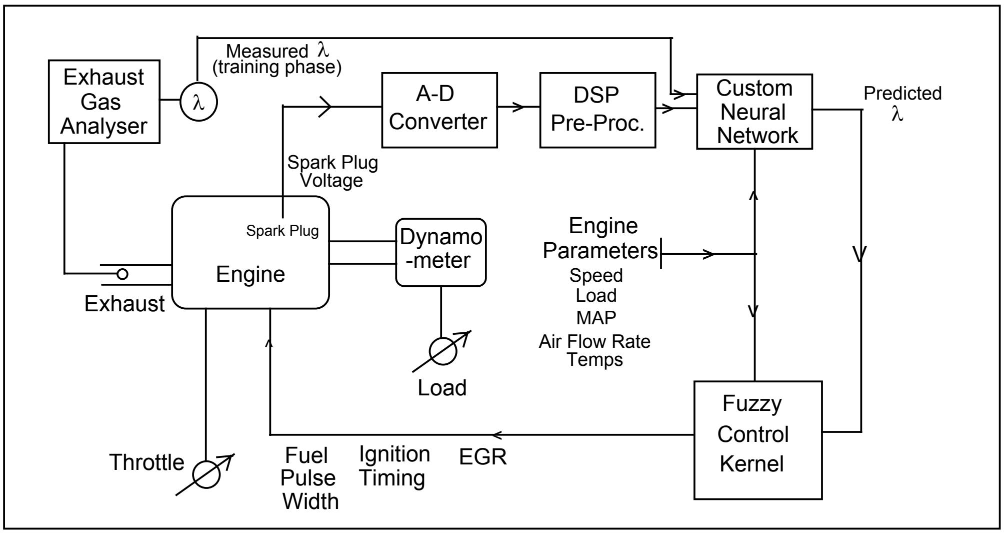

Figure 5: The Intelligent Engine Management System

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