

On-Board Fuel Identification using Artificial Neural Networks

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ABSTRACT

On-board fuel identification is important to ensure engine safe operation, similar power output, fuel economy and emissions levels when different fuels are used. Real-time detection of physical and chemical properties of the fuel requires the development of identifying techniques based on a simple, non-intrusive sensor. The measured crankshaft speed signal is already available on series engine and can be utilized to estimate at least one of the essential combustion parameters such as peak pressure and its location, rate of cylinder pressure rise and start of combustion, which are an indicative of the ignition properties of the fuel.

Using a dynamic model of the crankshaft numerous methods have been previously developed to identify the fuel type but all with limited applications in terms of number of cylinders and computational resources for real time control.

The purpose of the current work is to overcome these limitations and to present how Artificial Neural Networks expand the capability of utilizing engine speed signal for fuel identification by using main combustion characteristics such as firing peak cylinder pressure and peak pressure rise rate.

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INTRODUCTION

The combustion process can be controlled by continuously monitoring the pressure variation inside the cylinder using a pressure transducer and by adjusting the ignition timing to maintain a safe peak cylinder pressure while assuring low exhaust emissions and good fuel economy. Nevertheless, pressure transducers are expensive and their use on powered vehicles is prohibitive. A less expensive way to obtain information about combustion characteristics such as ignition delay, peak cylinder pressure and its location is to measure the instantaneous crankshaft speed and extract from this measurement the information regarding combustion characteristics.

The flexibility of running safely multiple fuels on an engine is a desirable but also a challenging task. For commercial vehicles this task is supported by the necessity to reduce the dependency on foreign oil. For military vehicles this flexibility is required to allow them to run properly on any fuel available on the battlefield. Furthermore, the use of alternative and renewable fuels has great potential to increase energy sustainability. For each type of fuel, optimal engine operation requires a specific control strategy regarding injection pressure, injection timing and injection duration. Nevertheless most manufacturers calibrate their diesel engines according to ULSD (Ultra Low Sulfur Diesel) specifications. Therefore when

fuels having different cetane numbers, heating values, densities, volatilities or bulk moduli are used, their properties should be estimated and the injection strategy accordingly adjusted such as to ensure safe and efficient operation of the engine.

Numerous techniques have been performed to reconstruct the cylinder pressure from the instantaneous crankshaft speed measurement. Using engine angular velocity and its derivative as inputs in a MLP (Multi-Layer Perceptron) artificial neural network, F.Taglialatela et.al. [1] estimated the in-cylinder pressure peak value and its location, but not the entire pressure trace. An example of pressure curve computation by stochastic estimation techniques using crankshaft position, speed, acceleration and motoring pressure is illustrated by Y. Guezennec et. al [2]. D.Taraza et.al. [3][4][5][6][7] correlated the harmonic components of the crankshaft speed to the harmonic components of the gas pressure torque which is directly related to the in-cylinder pressure. F. Ponti et.al [8] used a baseline model and a Frequency Response Function (FRF) to correlate engine speed with torque. The computation time of pressure estimation was reduced by D. Brand et.al. [9] using as inputs not only engine speed, but also air-fuel ratio, inlet manifold pressure and spark advance timing. C. Kallenberger et.al. [10] estimated the IMEP on a multiple cylinder engine using both one engine speed and one in-

cylinder compression pressure trace. F. Mocanu et.al. [11] developed several fuel identifying methods, all with limited applications. In this case, using a dynamic model of the crankshaft, the authors proposed a Model-Based Recognition Method which reconstructed the cylinder pressure trace and estimated the fuel type in a reasonable manner. The technique cannot be implemented for real time controls on engines having more than one cylinder, because of the large amount of computations required in a very short period of time. A second option called Direct Recognition method [11], with shorter computational time, assuming that the crankshaft is a rigid body, provided less satisfactory results for peak pressure and its location. A third method [11], the Start of Combustion Approach, yielded fairly accurate values for the start of combustion / ignition delay. Unfortunately, this technique cannot be applied on engines having more than four cylinders due to an increased torsional disturbance produced by other cylinders when a cylinder is firing.

To overcome these issues, a new technique, using Artificial Neural Networks, has been developed to be applied on any engine, regardless of the number of cylinders, including in those cases where the previous methods have failed. The Artificial Neural Network Method is able to identify four fuels (synthetic fuel S-8, jet fuel kerosene based JP-8, ultra-low sulfur diesel ULSD and bio-diesel soybean based B100) on a single-cylinder engine and three fuels (synthetic fuel S-8, ultra-low sulfur diesel ULSD, and bio-diesel soybean based B100) on a six-cylinder engine.

EXPERIMENTAL SETUP

The experiments were conducted on a single-cylinder Deutz 0.7 L engine and on a six-cylinder Mercedes MB900 7.2 L engine.

The 0.7 L Deutz engine, presented in Figure 1, having a mechanical injection pump, was equipped with a pressure transducer and a hollow shaft encoder at the flywheel end. The engine characteristics are presented in Table 1. A water dynamometer, connected through a driveshaft, provided the necessary resistance for engine testing.

Table 1. Single-cylinder Deutz 0.7 L engine characteristics

Displaced volume	0.7 L
Stroke	82 mm
Bore	80 mm
Max Torque	60Nm / 1300rpm
Max Power	12HP / 1500 rpm



Figure 1. Single-cylinder Deutz 0.7 L engine

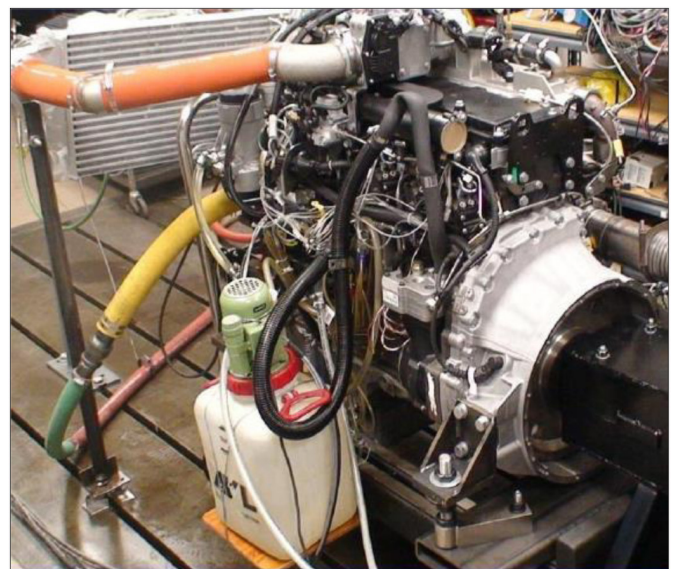


Figure 2. Six-cylinder Mercedes MBE900 7.2 L engine

The second engine under investigation was a six-cylinder Mercedes 7.2 L engine equipped with six individual unit injection pumps - Figure 2. This engine was heavily instrumented with pressure transducers, thermocouples, a shaft encoder at the flywheel end, intake, exhaust and fuel pressure transducers mounted on the high pressure lines.

The Mercedes 7.2 L engine specifications are presented in Table 2.

Table 2. Six-cylinder Mercedes MBE900 7.2 L engine characteristic

Displaced volume	7.2 L
Stroke	102 mm
Bore	106 mm
Max Torque	1100 Nm / 1400 rpm
Max Power	250 HP / 2000 rpm

TESTED FUELS

Four fuels were investigated in this research work, as follows: ULSD or Ultra-Low-Sulfur-Diesel, Synthetic fuel S-8, Jet fuel JP-8 kerosene based and soybean based Bio-diesel B100.

Table 3. Physical and chemical properties of the tested fuels according to [12], [13], [14], [15], [40], [41], [42]

Property	Units	Fuels			
		ULSD (Ultra-Low-Sulfur-Diesel)	S-8 (Synthetic jet A fuel)	JP-8 (Jet Propellant 8 kerosene based fuel)	Bio-diesel B100
Physical properties					
Density at 40°C	Kg/m ³	837	750	810	884
Flash point	°C	64	46	56	68
Bulk modulus at 400 bar	MPa	1775	1484	1411	1680
Kinematic viscosity at 40°C	cSt (mm ² /s)	2.35	1.29	1.38	2.76
Lower heating value	MJ/Kg	42	44	43	40
Chemical properties					
Cetane number	-	46	56	31	44
Aromatic content	% by volume	31	0	12	0
Olefins content	% by volume	1	0	2	23

The physical and chemical properties are presented in Table 3. Each of these properties has a significant impact on the following processes such as fuel injection, break-up, atomization, ignition and combustion development, but the most important combusting properties are cetane number and volatility. The influence of the cetane number on the combustion process is probably best described in Figure 3 at 1500 rpm / 360 Nm (7.5 bar IMEP) where 4 (four) current probe signals show identical injection timing and duration for the four tested fuels: ULSD, JP-8, S-8 and bio-diesel B100. According to the rates of heat releases traces the 4 (four) fuels perform as follows: S-8, having the highest cetane number, CN 56, ignites first; it is followed by ULSD (CN 46), then by B100 (CN 44) and finally by JP-8 with the lowest cetane number (CN 31).

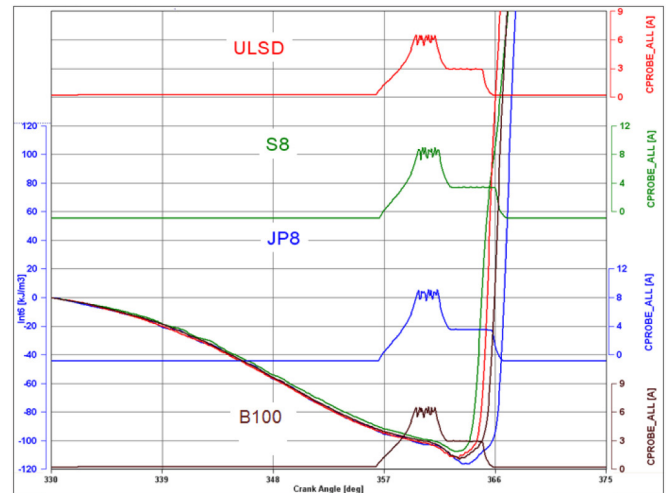


Figure 3. Rates of heat release at cylinder #6 (on the left) and injector current probes (on the right) for ULSD, S-8, JP-8 and B-100 at 1500 rpm, 360 Nm / 7.5 bar IMEP on Mercedes 6-cylinder engine MBE 900

Low cetane number and high volatility may increase premixed phase of combustion leading to high peak pressures and rates of pressure rise if injection timing is not adjusted accordingly. Optimal engine operation requires a specific control strategy for each type of fuel regarding injection pressure, injection timing and injection duration.

METHODOLOGY

Artificial Neural Networks (ANN) have been utilized in multiple research areas over the last years. According to [16], an artificial neural network is a machine designed to model the way in which the brain performs a particular task or function of interest. ANN-s have been trained to perform complex tasks such as function approximation, classification, and pattern recognition in various fields such as statistics, mechanics, electrical engineering, medical field, i.e. voice recognition or tumor classifications (benign or malignant based on cell descriptions) and the list does not stop here. There is no surprise that they can be used in fuel type identification. ANN-s are complex structures (Figure 4) and it is expected that the reader is familiarized with notions such as artificial neurons, weights, biases, transfer functions, activation function, performance function, perceptron, multiple perceptrons, neural networks training algorithms and so on.