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UTILIZATION OF NEURAL NETWORKS FOR OBSERVING THE INTERNAL COMBUSTION ENGINE'S FUNCTION

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Abstract. *This paper will describe a method for determining the functioning parameters of the internal combustion engine (ICE), such as pressure in cylinders or the air-fuel ratio. Direct measuring of the internal combustion engine's functioning parameters requires expensive sensors, the installation of which inside the engine presents big technical difficulties. Although inefficient from economical point of view, the last method is often used with the modern automobiles.*

Introduction

The main parameter that characterises the internal combustion engine's functioning is the air-fuel relation (or the Lambda factor). This parameter is directly proportional to the air quantity and fuel quantity relation:

$$Lambda = \frac{1}{14{,}7} \cdot \frac{airquantity}{fuelquantity}$$

(at normal pressure and temperature)

So, given a air-fuel ratio of 14,7:1, Lambda equals 1. This 14,7:1 relation is called stoichiometrical and corresponds to the air and fuel quantities needed for a complete combustion. For a higher quantity of fuel, Lambda<1, and the mixture is called rich. For a higher quantity of air, Lambda>1, and the mixture is called lean. The maximal power is obtained when Lambda approximately equals 0,9. The minimal fuel consumption is obtained when Lambda approximately equals 1,1.

Current engines reduce emission levels to within legislative limits by converting the exhaust gases into less toxic products using three-way catalytic converters. For optimum effect, three-way catalytic converters require that the Lambda-ratio is closely maintained at stoichiometric (unity). In modern engines, a Lambda-sensor, mounted in the exhaust stream, determines whether the Lambda is above or below unity from the amount of oxygen present. The Engine Control Unit uses this to adjust the fuel pulse width to keep the Lambda-ratio approximately at unity. Power units currently under development, for example the gasoline direct injection engine, may involve operation in lean of stoichiometric regions of the characteristics of the engine. The lambda-sensor that is installed in most production vehicles has a voltage-lambda characteristic which effectively makes it a binary device. It can be used to indicate whether the value of lambda is above or below unity, but it is unable to provide an accurate analogue measurement of air-fuel ratio. Accurate measurements can be made using what are referred to as wideband lambda-sensors, but they are very expensive, and in fact, even the currently-used binary lambda sensor represents an undesirable cost penalty.

The functioning regime of the engine that determines a minimal pollution of the environment is also very important. It is obvious that a minimal quantity of the combustion resultant substances is to be obtained when the combustion is complete, that is when Lambda approaches 1.

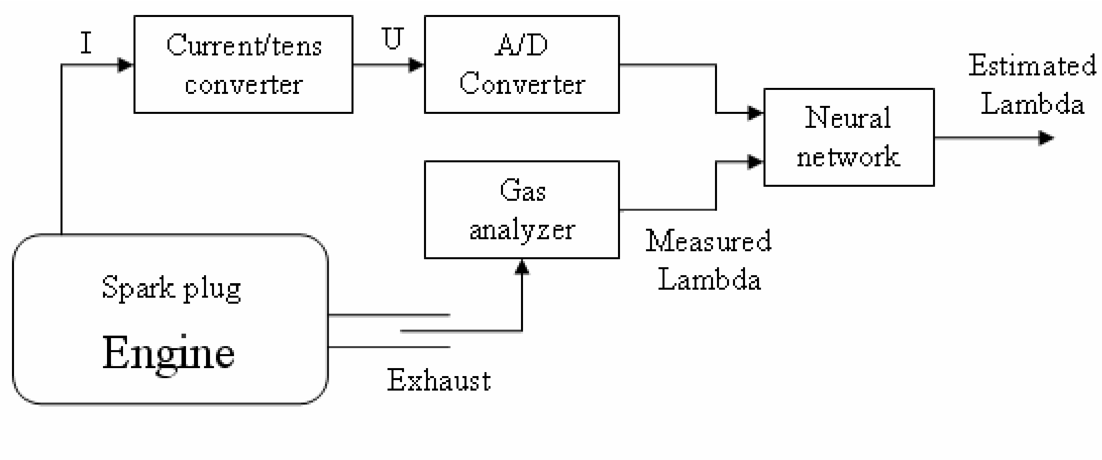

Fig. 1. System for neural network usage

So, knowing the current Lambda value, we have the possibility to modify in real time the behaviour of the engine in accordance to certain optimization requirements (for example: minimal pollution, maximal power, minimal fuel consumption, etc.). This adjustment can be made within an automatic closed-loop system that is immune to perturbations and is more precise than the open-loop system. Most engines command systems use open-loop because of the impossibility of measuring the regulated variable – the Lambda factor.

The existence of a cheap method for a precise measuring and the further regulation of the air-fuel relation would allow a considerable reduction of the polluting gas emission as well as a fuel economy. Though not considered a sensor, the engine spark plug is in direct contact with the burning processes that take place in the cylinder. The analysis of the tension variation in time at the spark plug jacks would be a convenient method for observing the phenomena inside the engine.

The most frequent method for utilizing a spark plug as a sensor is the so-called ionic current method[1]. This method is especially used for measuring the pressure inside the cylinders, the air-fuel relation, as well as for detecting some disturbances, such as late ignition or cylinder knocking.

In ionic current measuring system, the spark plug works as a sensor only during that part of the cycle when it is not used for mixture ignition. During this period, a continuous tension of 100V is applied on the spark plug jacks and then the current is to be measured. This current appears due to the reactive ions from the flame that lead the current between the two electrodes of the spark plug. Ions keep forming during the ignition as well as after that. The type and the quantity of the formed ions depend on the ignition process characteristics. The ionization current depends also on pressure, temperature, etc., and as a result it carries a great amount of information on the processes inside the engine, and in consequence this signal is very complex. This is why the signal analysis brings many difficulties, and the classical methods of signals processing are no longer efficient. In this case, the neural networks represent the most adequate solution, due to their capacity of treating complicate forms signals and of finding the correspondence between the incoming signal and the estimated dimensions.

These neural networks possess a set of specific characteristics, which describe them as a priceless mathematic instrument in recognizing a model (Fig. 1).

Some of their important characteristics are the reaction capacity to an unknown signal, the possibility of extracting new information and statistic data from the analyzed information, as well as the possibility to react to a signal with errors.

The neural networks contribution in observing the internal combustion engine functioning is the capacity of predicting the looked-for parameters, which in this case is the estimation of the Lambda parameter. With this purpose a device for analysing the concentration of some substances from the exhaust gas is introduced into the exhaust tube. Applying these characteristics at the neural network entrance, we obtain the real Lambda vector (the gas analyser) $V_n = (v_1, v_2, \ldots, v_n)$, measured at different time intervals, as well as the estimation vector from the transducer $V_n^{'} = (v_1^{'}, v_2^{'}, \ldots, v_n^{'})$. Some types of neural networks are known to have some specific properties that could solve the upper given problem taking as an example the many levels perceptron (Fig. 2) (MLP). The many levels perceptron is a static network but it is adapted for processing dynamic data[3].

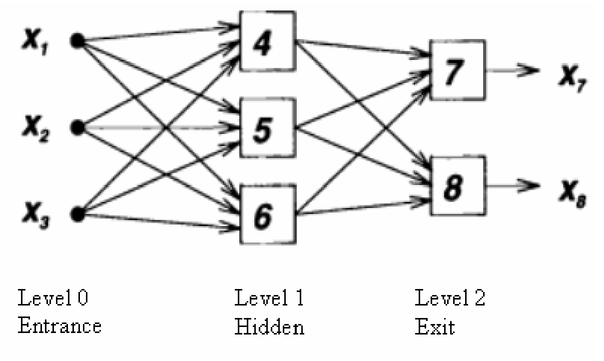

Fig. 2. The structure of a many-level perceptron

We may consider that the MLP network casts a vector with n elements from the entrance in a n-dimensional space. The vectors that belong to different classes, occupy different regions of this entrance space.

During the process of learning the neural network, a training file which contains the exemplar vectors is always attributed to the MLP network entrance in the iterative result of which a partition of space occurs in order to obtain a classification of all vectors. During the work phases, the vector to be classified is presented to the MLP network [2], which divides it into categories and determines where this vector is situated in the n-dimensional space. In most of the cases the hidden layer, a component part of the MLP network, consists of elements whose goal is to determine the Euclidian distance:

$\rho(x, y) = \sqrt{(x_1 - y_1)^2 + \ldots + (x_n - y_n)^2}$ followed by a Gauss Function for activation (Fig. 3)

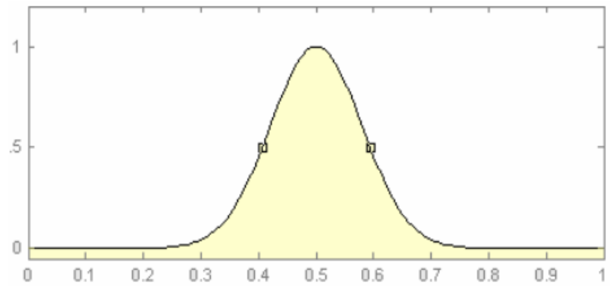

Fig. 3. Gauss function

A clustering algorithm is used for calculating the centre (position) of the cluster. In its elementary form, the exit level of the MLP network achieves a linear sum of the basic function values. The nonlinear transformation done by the basic neurons signifies the movement of the entrance vectors in a space with bigger dimension. Under some circumstances the vectors are easier to separate in a larger space, rather than in the space of their intrinsic dimension. The architecture of the neural networks depends a lot on the entrance space topology as well as on the comparison criteria.

The engine can be equipped with a dynamometer which presents the engine with a “dummy” load that can be varied as desired. The resulting load-torque can be measured and the output power calculated. The throttle setting and air-fuel ratio can be manually adjusted. The air fuel ratio that results from this adjustment is measured by an exhaust gas analyser. The ignition-system is modified by the addition of a high-voltage test-probe at the spark-plug to enable the

voltage to be measured and recorded. A current transformer is fitted to the high-tension line to permit the recording of current data.

A MLP network with one single hidden level and with the activation sigmoid function can be used to classify the transducer data. The learning through back propagation algorithm is applied to the MLP network during its usage. That is a training file which contains the classification needed data is required. The estimation vector from the transducer $V_n^{'} = (v_1^{'}, v_2^{'}, ..., v_n^{'})$ is created through measures at equal time intervals. Each vector is associated with an exit vector $Out_r = (0,0,1), Out_c = (0,1,0), Out_w = (1,0,0)$ showing whether the Lambda value measured by the gas analyser is enriched, equal to 1, or impoverished. Three sets of traducer vectors and respectively their exit vectors S_r, S_c, S_w are obtained. These vectors are combined in one single training file F={ S_r, S_c, S_w }. The MLP network is trained using the inverted cumulative propagation. The criteria used for determining the end of the training process is based on the principle of selecting a convergence value T_c of the neurons exiting data. It is possible that the neural network can indicate a rich, lean or correct mixture (Lambda = 0.9, 1.1 or 1.0 respectively) with a success rate of approximately 90% providing load, speed etc., as constant values. Owing to experimental difficulties in obtaining data, these results can be obtained with smaller training files than would be expected to give optimum discrimination. Much better results are desirable, a reasonable aim being 99% correct discrimination with a much smaller deviation of Lambda from stoichiometric, for example one or two percent, over a range of speed and load conditions. This in turn requires much larger quantities of training (and test) data. However, practical problems should be encountered in capturing the large amounts of training data required. The most serious is that the engine is required to maintain a constant value of Lambda for several minutes, so that a large number of representative voltage signatures can be captured, while in fact considerable drift in the Lambda value occurs over this time. An associated problem which may be encountered is that the simultaneous manual control of load, speed and Lambda become impracticable. In an attempt to facilitate close control of the Lambda value, to enable training data for the neural network to be collected, a feedback loop can be put in place from the Lambda sensor to enable closed-loop control.

References

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