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ESTIMATING PRESSURE PEAK POSITION AND AIR-FUEL RATIO USING THE IONIZATION CURRENT AND ARTIFICIAL NEURAL NETWORKS

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ABSTRACT

We propose two artificial neural network models which use the ionization current for estimation of the position of the pressure peak and the air-fuel ratio.

The pressure peak position model produces estimates on a cycle-by-cycle basis for each of the cylinders. These estimates are twice as good as estimates obtained from a linear model.

The air-fuel ratio model uses the universal exhaust gas oxygen sensor as reference; it produces estimates that are ten times better than estimates obtained from a linear model.

INTRODUCTION

To optimize the performance and reduce the emission levels of an internal combustion engine one needs some measurements of the combustion process quality. These measurements are, e.g., the air-fuel ratio (AFR) and the position of the pressure peak (PMAX).

The AFR can be used in a feedback control loop as shown in several papers, see [Bush94] [Hasegawa94] and references therein. To achieve optimal performance from the three-way catalytic converter, the AFR has to be kept within a window as small as 0.1 air/fuel ratios around the stoichiometric level [Heywood88]. To achieve such precision, the measurement need not only be accurate but also continuous, as in the case of the universal exhaust gas oxygen sensor (UEGO). However, the UEGO sensor has two drawbacks, the price is too high for mounting in commercial automobiles and the sensor dynamics are slow. The latter makes it difficult to use for control under transient conditions. Furthermore, if the sensor would be mounted in a commercial car it would be difficult to achieve good control on a cylinder to cylinder basis, unless one sensor per cylinder were mounted. This is due to individual components such as fuel injectors and intake port geometries. Difference between individual cylinders in the air fuel mixture in the order of ± 7% is reported in [Heywood88]. There is thus a need for a cheap cycle-by-cycle, individual cylinder measurement.

The PMAX can be used to achieve optimal ignition timing as shown in [Eriksson96] [Eriksson97]. Optimal ignition timing can boost the efficiency by 5% and increase the power by 10%. Conventionally the PMAX has been measured using piezo-

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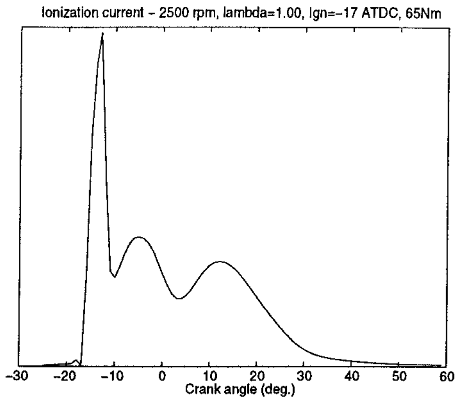

Figure 1: Typical ionization current. The curve is an average over 100 consecutive combustion cycles under constant external conditions.

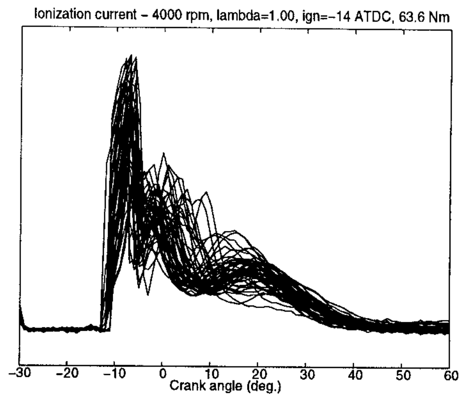

Figure 2: 50 consecutive ionization currents for the same conditions. The variations make it difficult to interpret the signal on a cycle-by-cycle basis.

electric pressure sensors mounted within the cylinder; however, this is expensive and another technique would be desirable.
In a previous paper [Linde95] we show that the AFR of a two-stroke chain saw engine can be estimated using the ionization current measured over the conventional spark plug[1]. In this paper we show that both the AFR and PMAX can be estimated on a four stroke Opel 1600cc engine. The prominent features of the ionization current signal, figure 1, are the cheap electric measurement setup and the lack of need for mounting extra sensors within the cylinder. The drawback is the high noise level, figure 2. We have choosen non-linear feed-forward artificial neural networks (ANN)[2] to model the problem.

THE IONIZATION CURRENT

It has been shown that it is possible to extract information about several quality properties of the combustion process in a cost effective manner from the ionization current, see [Auzins95]. Examples are misfire detection, knock detection, cam phase sensing, AFR estimation, and PMAX estimation. Misfire detection and individual cylinder knock detection are already implemented in commercial automobiles.
The measurement of the ionization current is made by applying a voltage over the gap of the spark plug, and the current is measured on the secondary side (low voltage) of the ignition coil. To have individual measurements from the cylinders, each cylinder must be equipped with one ignition coil. The coils have to be able to deliver a short high energy spark, so that the spark duration does not overlap with the period in the combustion process one wants to measure.
The ionization current is formed by a number of factors; in the first phase of the combustion cycle the formation of compounds which affect the ionization current is rather complicated, and the full process is not known. In the later part of the combustion cycle the most influential compound that shapes the ionization current is NO; in this stage the pressure also influences the signal. A more detailed general chemical and physical analysis of the ionization current can be found in [Saitzkoff96] and is studied more directed towards the AFR and the PMAX in [Reinmann97] and [Saitzkoff97], respectively.

The ionization current signal, figure 1, has three phases; the ignition phase, the flame front phase, and the post flame phase.
The ignition phase is in the range from ignition

[1] The technique for measuring the ionization current using the spark plug is patented by Mecel AB which is a subsidiary company of General Motors.

[2] A general introduction to ANNs can be found in e.g., [Haykin94].

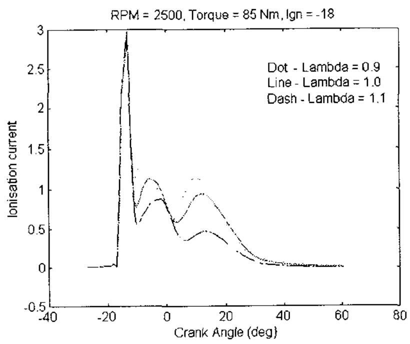

Figure 3: Ionization current vs. air-fuel ratio. The slope of the second peak correlates with the air-fuel-ratio. The curves is an average over 100 consecutive combustion cycles under constant external conditions.

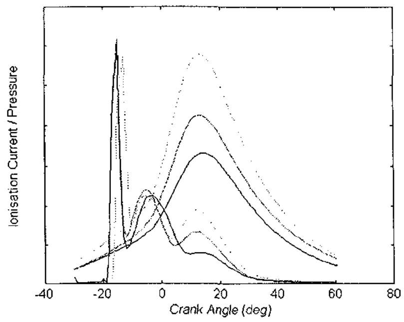

Figure 4: Ionization current vs. Cylinder pressure. The third peak of the ionization current correlates with the cylinder pressure peak. The curves is an average over 100 consecutive combustion cycles under constant external conditions.

to about 10 degrees after ignition, the high peak of the ionization current shows mainly coil ringings due to capacitance and inductance of the coil and cable.

In the flame front phase, between 10 and 20 degrees after ignition, the slope of the peak depends on the development of the flame; the derivatives of the slopes show correlation to the air-fuel ratio, as shown in figure 3.

The post flame phase begins after about 20 degrees after ignition and continues until no more ions are present in the spark plug gap. The signal in this phase depends mainly on the pressure development within the cylinder. The positions of the peaks in the ionization current show clear correlations with the cylinder pressure peak position, as shown in figure 4.

ESTIMATION OF THE PRESSURE PEAK POSITION

By using the ionization current we can achieve measurements of the activity within each of the cylinders. Estimating the PMAX on a cycle-by-cycle basis makes it possible to control the ignition in order to achieve optimal ignition timing. Further, the cycle-by-cycle interpretation makes it possible to control the ignition efficiently even under transient conditions.

The ionization current was sampled at every degree of the combustion cycle, resulting in 92 samples per combustion cycle (-30 to 61 degrees relative to top dead center (TDC)). A window of the ionization current was chosen, from 6 degrees ATDC to 35 degrees ATDC, the part where the ionization current shows the best correlation with the pressure, figure 4. In order to further minimize the representation of the ionization current, we use principal components analysis (PCA), see e.g. [Haykin94], and retain the first 7 PCA variables which hold 99.5% of the energy of the original signal. Another useful property of PCA is decorrelated variables. In addition to the PCA variables, the model takes the RPM, torque, and ignition as input variables. The model uses a linear output corresponding to the position of the pressure peak in degrees ATDC. This makes a total of 10 inputs and one output.

The ANN model was trained using the RPROP algorithm [Riedmiller93]. To prevent the model from overfitting to the noise, early stopping was used as a method of regularization.

The results are compared with both a linear model and residual variance estimated by the the $\delta-$test [Pi94]. The $\delta-$test is a method for finding variable dependencies using conditional probabilities of vector component distances.

Table 1 shows an estimate of the best possi-

Model	NMSE	δ-test
ANN Model	0.212 ± 0.016[3]	0.233 ± 0.004
Linear Model	0.406 ± 0.013	0.410 ± 0.007

Table 1: Performance of the two PMAX models. The ANN model performs about 2 times better than the linear model. (The $\pm$ part is the confidence limits based on the size of the dataset.)

ble residual variance, which is equivalent to the normalized mean square error,

$$NMSE = \frac{1}{\sigma_Y{}^2} \frac{1}{N} \sum_{k=1}^{N} (Y(k) - \hat{Y}(k))^2 \qquad (1)$$

where $\sigma_Y{}^2$ is the variance of the reference, Y and $\hat{Y}$ are the reference and the estimate, respectivly.
In the table the performance of a linear model and an ANN model with 15 hidden neurons are also shown. The results of the linear model and the ANN model are calculated using a hold out data set, i.e., data points used for neither fitting nor selecting the models. The ANN model perform twice as good as the linear model, and the NMSE are within the margin of error of the optimal NMSE estimated by the $\delta-$test.
Figure 5 shows the residual of the ANN model. The correlation between the estimated PMAX and the measured PMAX is shown in figure 6.

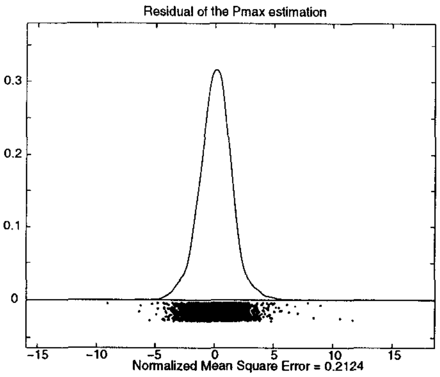

Figure 5: Residual of the pressure peak estimation. The residual are based on a hold out data set which was not used for building the model.

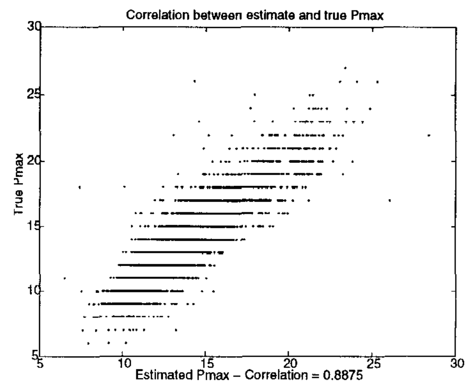

Figure 6: Correlation between the estimated PMAX and the measured PMAX. The correlation shown here is based on a hold out data set which was not used for building the model.

ESTIMATION OF THE AIR-FUEL RATIO

The model for estimating the AFR is similar to the one we use for estimating PMAX. The difference is the slow dynamics of the UEGO sensor, in comparison with the ionization current. Since we have no feasible option other than using the UEGO, we must compensate for the averaging effect that the sensor introduces. The compensation we do here is to average over several consecutive ionization currents. We thereby model the UEGO sensor instead of the true cycle-by-cycle AFR.

[3]The confidence limits estimated by bootstrapping.

The model for AFR estimation uses the same variables as the one we propose for the PMAX estimation, except for the averaging. The window of interest was chosen from 10 degrees after ignition to 60 degrees after ignition. The linear output corresponds to the AFR.
We use the same method for evaluation of the model as in the previous section; the ANN model was compared with both the $\delta-$test and with a linear model. Results are as shown in table 2. The ANN model performs an order of a magnitude better than the linear model, and the results are within the margin of error of the optimal NMSE estimated by the $\delta-$test.

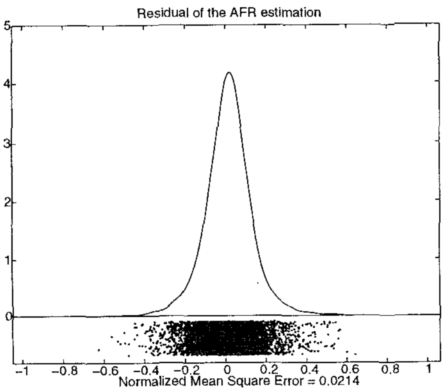

Figure 7: Residual of the AFR estimation. The residual are based on a hold out data set which was not used for building the model.

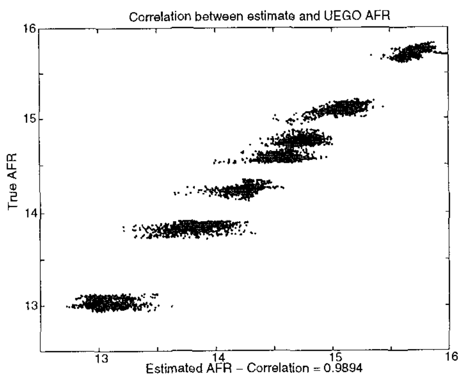

Figure 8: Correlation between the estimated AFR and the UEGO AFR. The correlation shown here is based on a hold out data set which was not used for building the model.

Figure 7 shows the residual of the ANN model. The correlation between the estimated AFR and the UEGO AFR is shown in figure 8.

DATA

The data was collected on a four cylinder 16 valve Opel 1600cc engine. The measurements were made using an AVL670, the pressure transducer used was of a piezo-electric type, and the UEGO sensor was an NGK TL-7111-W1 mounted 3 cm downstream from the exhaust valve.

[4] The confidence limits estimated by bootstrapping.

Model	NMSE	δ-test
ANN Model	0.021±0.001[4]	0.000±0.000
Linear Model	0.212±0.008	0.207±0.004

Table 2: Performance of the two AFR models. The ANN model performs about 10 times better than the linear model. (The ± part is the confidence limits based on the size of the dataset.)

RPM	13, 20, 22, 25, 25, 25, 40 (×100)
Torque	37.5, 19.1, 51.5, 45.0, 65.0, 85.0, 63.6
Ignition	-22, -23, -19, -20, -20, -18, -14
Lambda	0.90, 0.95, 0.98, 1.00, 1.02, 1.05, 1.10

Table 3: The operating points in the data set used for building and validating the models. A total of 49 × 500 data points were used.

The engine was run under seven different RPM, torque, and ignition conditions, and, within each of the conditions, seven different AFR. This results in a total of 49 operating points, listed in table 3. Data from 500 consecutive combustion cycles were collected for each of the operating points.

CONCLUSIONS

We have demonstrated that it is possible to use the ionization current signal to get good estimates of the air-fuel ratio and the position of the pressure peak for each individual cylinder. This allows independent control of the cylinders, and in the PMAX case even on a cycle-by-cycle basis. The AFR model produces an average of several consecutive combustion cycles, due to the slow dynamics of the UEGO sensor used as a reference, which degrades the performance of the control at transients.

The non-linear ANN models we propose produce significantly better estimates than linear models. In the AFR case, the ANN model is in the order of a magnitude better, and in the PMAX case, the ANN model is twice as good as the linear model. The models are also compared with a non-parametric test, the δ−test, which shows that the proposed ANN models are close to optimal, or even optimal.

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