Closed-Loop Ignition Control Using On-line Learning of Locally-Tuned Radial Basis Function Networks

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Abstract

Increasing demands of low emissions and low fuel consumption of modern spark ignition combustion engines require new ways for an optimal control of the ignition timing. Instead of classical open-loop strategies cylinder pressure sensors are used for an adaptive control of the ignition point. A linear feedback controller is designed as well as an on-line adaptive neural feedforward controller, the latter is trained during regular operation, i.e. no test cycles are required. The control algorithms were implemented and tested in a research automobile. Experimental results showed that the proposed neural network is very effective in learning the engine's nonlinearities and in compensating for manufacturing tolerances and aging. The designed adaptive feedforward control improves efficiency and fuel consumption.

Keywords: Spark Timing, Ignition Control, Cylinder Pressure Sensor, RBF Network, On-line Learning

1 Introduction

The objective of ignition control is to achieve optimum engine efficiency in the presence of changing engine and environmental conditions. State-of-the-art systems use open-loop strategies to set production engine spark timing. The data for spark timing is stored in the form of look-up tables in the vehicle's on-board computer. The database values are initially determined from analysis of a nominal engine under fixed environmental conditions. However, the measured relationship at the time of the first installation does not imply that the relationship holds during the whole life of the system. Aging effects, manufacturing tolerances or a changing environment usually change the plant characteristics and lead to a suboptimal performance.

Due to progress in cost-effective combustion pressure sensors [8] and in dedicated signal processing capability, combustion feedback control systems are now possible for production vehicles. In this article, a linear feedback controller and a combination of a linear controller and an adaptive feedforward structure are designed and compared. The adaptive feedforward structure is represented by a normalized radial basis function network, which can be trained using the controller output as a teacher signal. The learning process of this network is performed during regular operation of the system (i.e. no test cycles required) by just collecting and processing input-output pairs at the current operating point.

The article is structured as follows: Section 2 describes the evaluation algorithm of cylinder pressure signals for ignition control, Section 3 explains the control architecture. In Section 4 radial basis function networks and the learning algorithm for on-line training are introduced. Section 5 gives some experimental results.

2 Cylinder Pressure Based Ignition Control

Generally factors that influence spark timing are engine specifications like configuration of combustion chamber, operating conditions like engine speed, load, temperature, and exhaust gas recirculation flow rate, as well as ambient conditions such as air temperature, air pressure and humidity in the atmosphere. Accordingly, in order to determine optimum spark timing by the mapping method, extensive tests are required to examine at least several of the factors mentioned above. However, since it would be extremely difficult and time consuming to measure *all* the parameters, and since manufacturing tolerances, aging, and fuel quality cannot be detected, the performance of these open-loop strategies based on nominal engine mapping data is suboptimal.

Rather than measuring all the parameters known to affect the spark, or inferring the state of combustion from the response of a remotely located sensor, combustion pressure measurements offer a real-time signature of the combustion process. By measuring and controlling the *result* of the spark timing many variables that affect the combustion process can be compensated on an individual cylinder basis

[11, 12].

Not only thermodynamic analysis but also extensive experimental results showed that optimum engine efficiency from each combustion event can be accomplished by controlling the crankshaft angle position of 50 % conversion of energy [1, 7, 9]. In [1] it has been shown that the crank angle (CA), at which 50 % of energy of one cycle is converted, is most optimal in efficiency at approximately $8° - 10°$ CA after Top Dead Center (TDC) – which is approximately a constant for all spark ignition engines and for all operating conditions. Energy conversion can also be described by Mass Fraction Burned (MFB) of the cylinder charge at a specific crank angle which can be approximated by

$$MFB(\alpha) \approx \frac{p_{fired}(\alpha)}{p_{motored}(\alpha)} - 1 \qquad (1)$$

where $p_{fired}(\alpha)$ denotes the measured cylinder pressure at a certain crank angle α, and $p_{motored}(\alpha)$ denotes the cylinder pressure without combustion (motored pressure) [9]. The latter is the component of the cylinder pressure which is due to the piston motion. It can be reconstructed by assuming a polytropic compression [7].

Fired and motored (polytropic) pressure of an exemplary combustion cycle are shown in Figure 1. In Figure 2 the approximation of MFB according to (1) is compared to MFB calculated by thermodynamic analysis of the cylinder pressure. In the presented control system the value of MFB is calculated at 9° CA after TDC by means of the approximation mentioned above. Since the pressure signals are very noisy, a moving average filter is applied to the measurements of 10 cycles. The control objective is to keep MFB(9°) at 50 %.

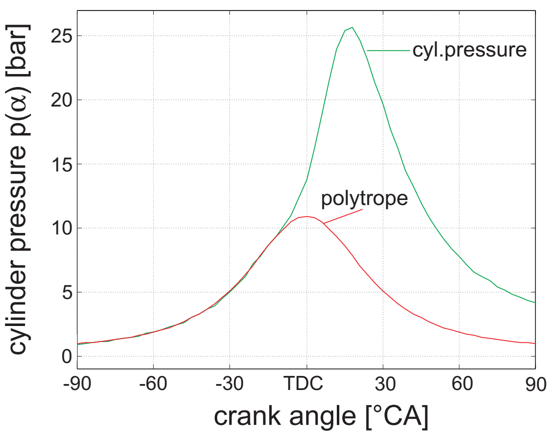

Figure 1: Fired and motored (polytropic) cylinder pressure signals

3 Control Structure

Automotive combustion engine control systems have to cope with fast changing operational conditions and an extremely nonlinear system behavior. This is the major reason why in state-of-the-art systems nonlinear input-output mappings are applied for ignition control. An approximate value of the ignition points of all cylinders is basically determined by the engine load (a normalized value calculated from the intake manifold pressure signal) and the engine rotational speed. This conventional input-output-map is depicted on the upper right-hand side of Figure 3. In a first step this conventional feedforward control was enhanced by adding a linear (PI-type) feedback controller for each cylinder. The linear controllers modify the ignition point of the corresponding cylinder such, that at a specified crank angle (9° after TDC) exactly 50 % of the fuel is burned (MFB(9°)=0.5). The PI controllers and the cylinder pressure evaluation are shown in the lower part of Figure 3.

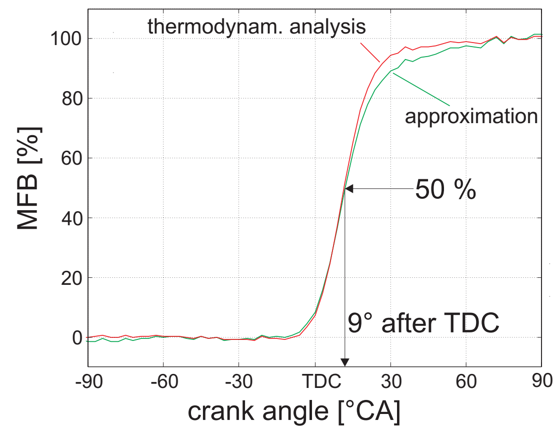

Figure 2: Approximation of MFB in comparison to thermodynamic analysis

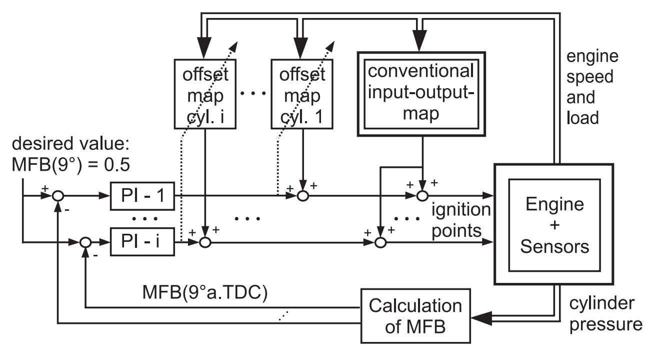

Figure 3: Structure of ignition control system

These feedback controllers lead to good performance under steady state and slowly time variant operating conditions. However, they cannot be tuned with high control effort. This is due to the fact, that after ignition of the air-fuel mixture, the combustion cannot be influenced any further. Therefore ignition time can only be computed for the next cycle, based on measurements from the present engine cycles. Therefore a dead time of one cycle is inherent. Moreover as there exist significant cycle fluctuations even under steady operating conditions, the results of cylinder pressure evaluation of several engine cycles have to be averaged (we used a moving average over 10 cycles). Because the system error usually differs from one engine operating condition to another, during engine transients it takes a certain amount of time for the PI controller to „integrate" to a new ignition time.

To achieve high bandwidth control, the presented control system is enhanced in a second step by using an adaptive neural feedforward controller for each cylinder, which memorizes the appropriate offset values of the corresponding cylinder at the specific operating condition, i.e. the engine speed and load. The outputs of the linear controllers serve as teacher signals for the adaptation of the adaptive neural networks as it can be seen in Figure 3. Hence, in operation all three components, the production look-up table, the PI-controllers and the neural net based offset look-up tables are active.

4 Radial Basis Function Networks

Neural networks [5] can be used for the identification and control of nonlinear dynamic systems. Often neural controllers are first trained in an off-line procedure, by applying appropriate test signals to the process. Since a compensation is required not only for manufacturing tolerances, but also for aging and wear, a training algorithm has been developed, which allows training of the network during regular operation of the system, i.e. no test cycles are allowed. This can be achieved by locally tuning of Radial Basis Function (RBF) networks. They are well-suited for on-line adaptation because RBF networks are linear in their output weights. Due to the better interpolation and extrapolation properties a *normalized* RBF network is employed, i.e. the basis functions form a partition of unity. A short introduction of the network design and the learning algorithm is given in the following.

An RBF network is defined as a linear combination of radial basis functions

$$y(\underline{x}) = \sum_{i=1}^{M} w_i \Phi_i(\underline{x}, \underline{c}_i, \sigma_i) \tag{2}$$

where w_i denote the output weights associated with each of the M basis functions Φ_i. $\underline{x} = [x_1 \ x_2 \ \cdots \ x_n]^T$ is the input vector, $\underline{c}_i = [c_{i1} \ c_{i2} \ \cdots \ c_{in}]^T$ are the vectors of the center coordinates of the M basis functions, and σ_i denote the widths of the basis functions, respectively. A very popular choice for the radial basis function is the Gaussian

$$\begin{aligned} G_i(\underline{x}, \underline{c}_i, \sigma_i) = \exp\Bigg(-\frac{1}{2}\Bigg(\frac{(x_1 - c_{i1})^2}{\sigma_i^2} + \\ \frac{(x_2 - c_{i2})^2}{\sigma_i^2} + \ldots + \frac{(x_n - c_{in})^2}{\sigma_i^2}\Bigg)\Bigg) \end{aligned} \tag{3}$$

which was used here in its normalized form:

$$\Phi_i = \frac{G_i}{\sum_{j=1}^{M} G_j} \, . \tag{4}$$

Due to this normalization the neural networks form a partition of unity [13] to improve the interpolation properties and makes the network less sensitive to the choice of the widths σ_i.

4.1 Learning Algorithm for the Output Weights

If basis functions are used that decay to zero with increasing distance from its center, and if the value of the basis function is sufficiently small at a certain distance from its centre, local support can be achieved. In view of reducing calculation power for later use in automotive applications, a very simple learning algorithm, the Normalized Least Mean Squares (NLMS) rule was chosen [3] for adaptation of the weights of the neurons:

$$w_i^{\mathrm{new}} = w_i^{\mathrm{old}} + \mu \cdot e(\underline{x}) \cdot \frac{\Phi_i(\underline{x})}{\sum_{j=1}^{M} \Phi_j^2(\underline{x})} \, . \tag{5}$$

$e(x)$ denotes the error between the correct value and the old network output. The gain factor μ must be within the range $0 < \mu < 2$. However, appropriate values vary between 1 for fast learning and $\mu \ll 1$ for robustness against measurement noise. In our case, $\mu = 0.002$ was chosen.

In order to improve robustness against noise and to avoid over-fitting, a dead zone with a minimal error value for parameter adaptation was set to $\pm 1°$ CA [6].

4.2 Determination of the RBF Centers and Widths

The normalized RBF network shall be used as a nonlinear feedforward correction of the linear PI feedback controller. This correction depends on the operating point defined by the engine load and the engine speed. Thus, the neural network operates on a two-dimensional input space. Since for secure and robust operation of the neural network based feedforward controller only the linear output weights shall be adapted on-line, the nonlinear network parameters – the centers and standard deviations – have to be fixed a priori.

Unlike in lattice-like datafields where a grid structure is used to determine the active interpolation nodes, the centres of the RBF network can be arbitrarily placed in the input space. A clustering algorithm was used to place the RBF centers in only those regions of the input space where data is present. The standard k-means clustering algorithm [2, 10] was used in this case. The widths of the basis functions are determined using a „nearest-neighbor" algorithm. Figure 4 shows the distribution of datapoints and the 46 RBF centers [1] obtained by k-means clustering in the input space for an exemplary test cycle. The corners of the operating regime were used as additional centers.

[1] The appropriate network complexity was determined empirically in this example

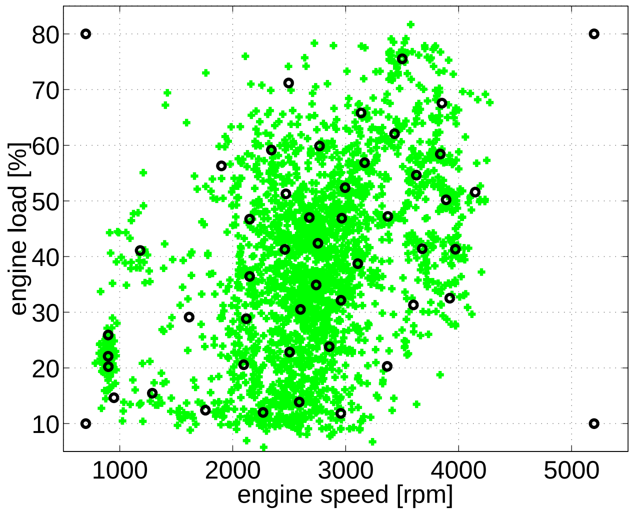

Figure 4: Determination of centers of RBF-neurons by clustering (the circles and crosses correspond to the centers of the RBF-neurons and to the operating condition of this test cycle, respectively)

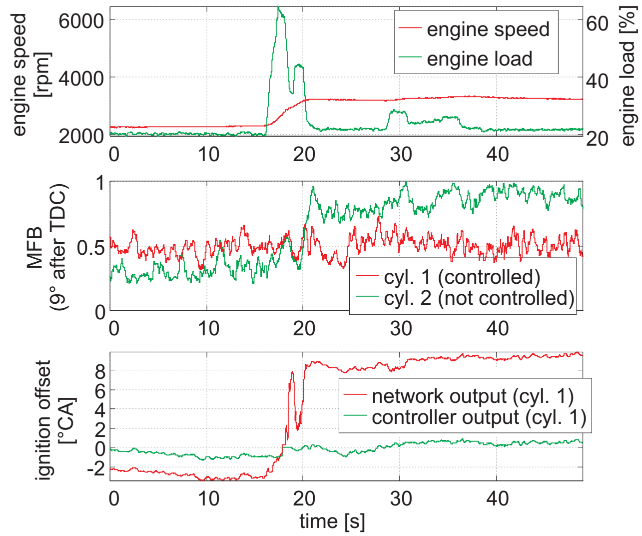

Figure 5: Experimental results during rapid change of operating condition, for one cylinder controlled, and one cylinder without control

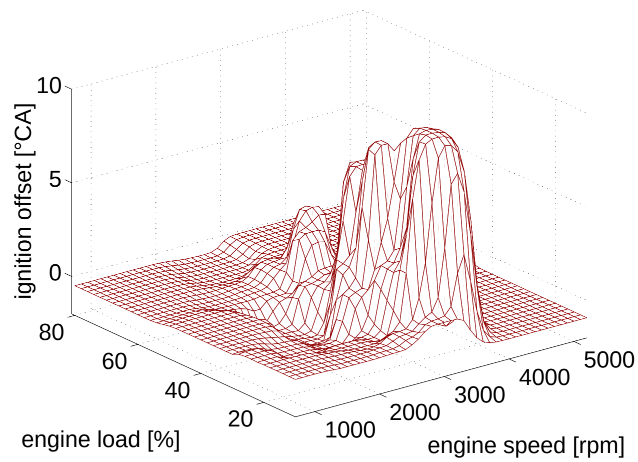

Figure 6: RBF-network of the controlled cylinder (positive values imply a delayed ignition point)

The distribution of neurons in the input space was identical for all cylinders since beforehand no information concerning possible nonlinearities of the system are available. The positions of the neurons were hold constant, only the weight parameters $w_i$have to be adapted. Therefore a fast convergence is achieved.

Since this node distribution accounts for the data distribution during normal operation, adaptation holes", i.e. areas of the input space where the network does not reflect the actual plant characteristics, are very unlikely to occur.

5 Experimental Results

The control algorithm and cylinder pressure evaluation were implemented under MATLAB/Simulink and run on a rapid-prototyping system as described in [4]. The engine of the test vehicle was based on a baseline engine, basically cylinder pressure sensors have been installed, and a modified engine control unit was used. The developed controller worked at a sampling time of 0.005 s. After initialization of the network parameters, a 5-minute sequence of network training was performed during normal driving conditions. Figure 5 illustrates the resulting behavior for a fast change of the operating condition. The upper diagram shows the operating condition. Starting from an engine speed of about 2200 rpm, after 15 s an acceleration is carried out. This can be seen in an increase of the engine speed, as well as in a step of the engine load during acceleration.

The filtered MFB at 9° CA after TDC is shown for two cylinders in the second diagram. One of the two cylinders worked in closed-loop as described in Figure 3, the other cylinder worked in open-loop, i.e. the ignition point was determined by the conventional input-output map. It can be seen that the MFB of the controlled cylinder remains around 0.5, i.e. at 9° after TDC approximately 50% of fuel is burned. The value of MFB of the second cylinder deviates from the optimal value. At the second operating condition most of the fuel of this cylinder is already burned (approximately 80 %). The third diagram shows the two components of the offset value of the first (controlled) cylinder, which are added to the ignition point defined by the open-loop system, i.e. the static input-output map. Positive values imply a delay of the ignition point determined by the open-loop system. The neural network reacts immediately to the changing operation condition (feed-forward control). Since the weights of the network have already converged to their optimal values for the operating points that occur in this experiment, the output of the linear controller remain close to zero. The considerable stochastic cycle fluctuations of the combustion can be seen for both cylinders.

Unlike many other neural network type controllers, the parameters of the RBF based neural controller can be easily interpreted and supervised. For two-dimensional problems the parameters can be displayed as input-output map as it was done in Figure 6 for the ignition offset values of the RBF network as it was used for the test cycle in Figure 5. Positive values of the ignition offset imply a delayed ignition, i.e. later crankshaft angles. It can be seen that in a large part of the operating domain a considerable delay of the ignition point was necessary, in order to optimize the ignition point of this cylinder. This means, that the ignition point determined by the conventional (state-of-the-art) feedforward controller was over-advanced, thus resulting not only in a higher fuel consumption, but also in higher exhaust gas emissions. Unlike classical lattice-like input-output maps, the trained RBF network produces a smooth surface despite of considerable nonlinearities.

6 Conclusions

The demand for improved engine performance and efficiency has inspired the development of a closed-loop control system for ignition control based on the measured combustion pressure. The pressure signals of each cylinder are evaluated and linear feedback controllers have been developed on a individual cylinder basis, to keep the 50 % point of energy conversion at its optimal value. In order to obtain optimal control performance also during transient conditions, an adaptive neural network was implemented, which is trained during regular engine operation, and which works in parallel to the linear controller. The proposed control system was implemented and tested in a test vehicle using a rapid-prototyping system. It showed good results also during transient conditions.

The control algorithms are simple to implement, no extensive off-line-training procedures are necessary, and the neural network can be easily interpreted and supervised by representing as 3D-mapping. The benefits of such a control system for ignition timing are improved fuel economy and increased torque by compensating for manufacturing tolerances, fuel variations, and engine wear. By this way also exhaust gas emissions can be improved. In addition, the complexity and cost of engine calibration can thus be reduced. The availability of cost-effective cylinder pressure sensors, dedicated signal processors, and advanced control algorithms makes these closed-loop control systems possible for today's production SI engines. The control system can also be used to correct and adapt the production look-up table by pressure sensors during experimental implementation phase. I.e. the pressure sensors are only required for the experiments.

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