Incorporation of Neuro-Fuzzy Knowledge for Fast Measurement of Combustion Engine Maps

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ABSTRACT: Map-measurements of internal combustion (IC) engines concerning torque, emissions and other effects are essential for the design and application of the engine control system. With the rising number of engine input- and output variables, however, the measuring efforts rise exponentially and can require up to several weeks. State-of-the-art approaches usually measure equidistant grids in the multidimensional input space (load, speed, injection angle, exhaust gas recirculation (EGR), blade position of variable turbine geometry turbochargers (VTG), etc). This paper proposes an extraction of only relevant measuring points by a neuro-fuzzy pre-analysis of data from a comparable engine. The chosen data is then sorted according to its temperature behavior in order to reduce time due to waiting for stable temperatures. During the actual measurement, new temperature levels are reached faster by use of a temperature controller and the measuring time can further be reduced by means of output models.

KEYWORDS: combustion engines, neuro-fuzzy methods, dynamic modeling, parameter estimation

1. INTRODUCTION

IC engines are controlled mainly based on stationary curves and 3D maps. Fast and accurate measurements of combustion engines with respect to their torque and emission behavior are of high interest in order to reduce development time. Increasing the number of input values, however, the required time rises enormously since exponentially more measurement points have to be evaluated. Therefore, it can take up to several weeks to complete a full measurement of a combustion engine [1,2].

This paper proposes a procedure allowing to reduce the time necessary for measurement of multiple input multiple output behavior of modern IC engines. While state-of-the-art approaches usually measure equidistant grids in the multidimensional input space, the presented method chooses the most important measuring points by using a-priori knowledge taken from neuro-fuzzy models of similar engines.

In a second step, the chosen points are sorted according to the expected (exhaust or engine) temperature of the respective measurements. In case of fast static temperature changes between two operating points, higher dynamic injection rates are used in order to reach the new temperature sooner. Thereby, the delay times for reaching constant temperatures can considerably be shortened.

Finally, the dynamics of output variables, which are assumed to have PT_X behavior, are estimated and adapted to the measurements on-line. This saves additional time since it is not necessary to wait until static behavior of the output values is reached. The values for $t \to \infty$ can entirely be predicted in advance.

2. CHOICE OF RELEVANT MEASUREMENT POINTS

Equidistant grid measurements do not inherently consider the nonlinearitites of the underlying process and therefore, more points are being measured than needed for an exact model of the process. With the a-priori knowledge of a similar IC engine, however, the most relevant points properly representing the nonlinearity of the process can be extracted from the following neuro-fuzzy approach.

The local linear model tree algorithm (LOLIMOT) partitions the input space of a nonlinear process into subspaces where local linear models are estimated. Starting with an initial model which is valid over the whole input space, splits along every input-dimension are tested and the one leading to the lowest model error is performed resulting in two local linear models (LLM). In every following step, the worst LLM concerning its respective local error is chosen for further refinement and again, all possible divisions are tested. Figure 1 shows the first four iterations of the tree construction. For further details concerning the neuro-fuzzy system refer to [3,4]

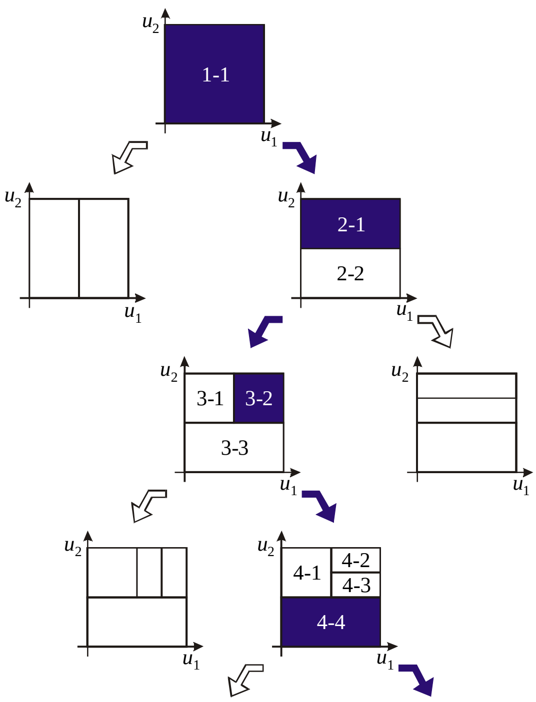

Figure 1: Tree construction algorithm

Thus, the model is automatically adapted to the nonlinearity of the process because refinements are done at regions where local linear models fail to approximate the local nonlinearity. The structure of the model tree therefore explicitly contains structural information on the nonlinearities of the process.

Figure 2 gives an idea of how this structural knowledge can be exploited for measuring engines with similar behavior. Making the assumption, that the nonlinearities of two engines are comparable concerning their respective locations, a reduced set of measuring points is sufficient in order to set up a model of the local linear model type.

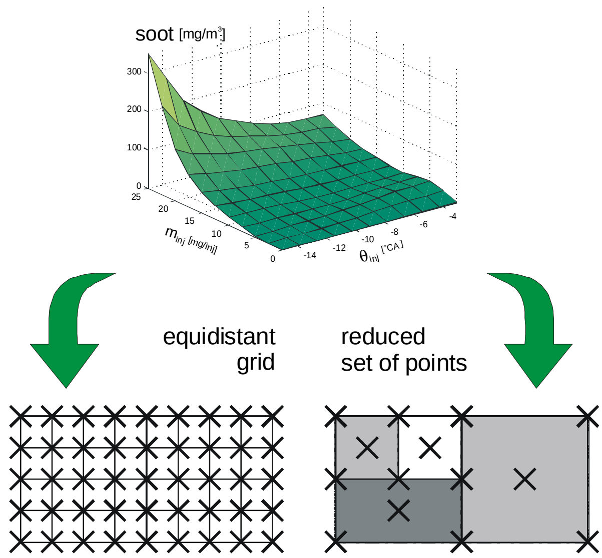

Figure 2: Full and reduced set of measurement points for a soot model

The nonlinearities of the measured soot formation in Figure 2 are higher for high injection rates and early injection angles. Consequently, a dense grid of measurements is needed to describe the process well enough in this area. On the other hand, the process shows a pretty linear behavior for late injection rates. Therefore, one local linear model is sufficient to represent the process in this area and only a small amount of measurements is required to estimate the parameters of the respective local model. The same density of measurements as in areas of high nonlinearities would lead to no additional accuracy and can therefore be omitted without loss of model quality.

Obviously, the nonlinear behavior of different output signals will be different. But, since all models should be deducted from the same data set, the measurement points of all respective output signals have to be superposed. Figure 3 illustrates the superposition of two output signals.

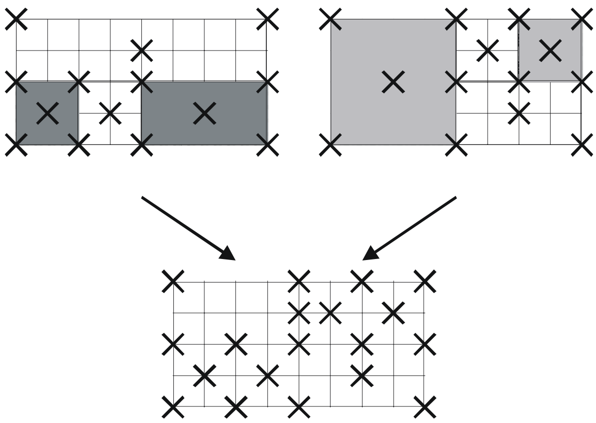

Figure 3: Superposition of two measurement sets to a common reduced set of measuring points

3. FAST MEASURING OF GIVEN OPERATING POINTS

3.1 Measuring order

After extracting all relevant measuring points using the presented neuro-fuzzy approach, the question arises how the measurement could be performed with minimal time effort. The thermal dynamics have to be considered very closely since the temperatures during the combustion and in the exhaust manifold significantly influence the emissions of the engine. In case of static map measurements, usually one has to remain in the present measuring point until the temperature (and therewith the output values) are more or less constant. In order to reduce the according waiting time, it is proposed to sort the extracted operating points according to their exhaust temperature rather than monotonically, stepwise varying the input variables.

As this exhaust temperature is not necessarily available for all extracted operating points, a nonlinear temperature model was implemented as shown in Figure 4. The model inputs are engine speed, injection rate and injection angle, equation 1,2. The temperature model is assumed to have PT_1 behavior.

$$\begin{aligned} T_{stat}(k) = \quad & r_{11} \cdot u_n + r_{12} \cdot u_n^2 \\ & + r_{21} \cdot u_m + r_{22} \cdot u_m^2 \\ & + r_{31} \cdot u_\Theta + r_{32} \cdot u_\Theta^2 \\ & + c_{gl} \end{aligned} \tag{1}$$

$$T_{dyn}(k) = a_1 \cdot T_{dyn}(k-1) + (1 - a_1) \cdot T_{stat}(k) \tag{2}$$

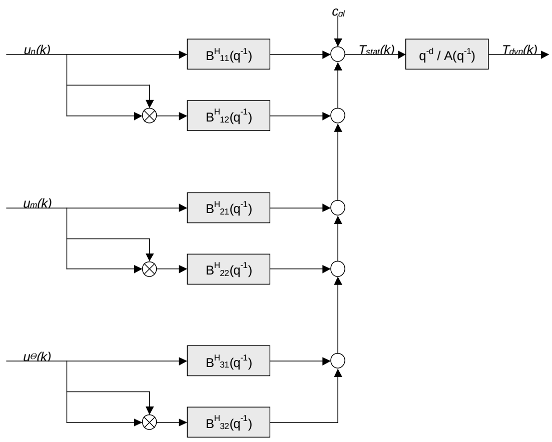

Figure 4: Structure of the dynamic temperature model (Universal Hammerstein model with three inputs)

As the model is also required as basis for a temperature controller, a dynamic Hammerstein model of second order was chosen which is refined on-line during the measurement by means of a recursive least squares algorithm with parameter vector Θ and the data matrix ψ according to equation 3, [5].

$$\underline{\Theta} = \begin{bmatrix} c_{gl} \\ r_{11} \\ r_{21} \\ r_{31} \\ r_{12} \\ r_{22} \\ r_{32} \\ a_1 \end{bmatrix}; \qquad \underline{\psi}(k) = \begin{bmatrix} 1 \\ n_{mot} \\ m_b \\ \Theta_{eb} \\ n_{mot}^2 \\ m_b^2 \\ \Theta_{eb}^2 \\ T_{dyn}(k-1) \end{bmatrix} \tag{3}$$

With this adapted model, the order of the measurement can be rearranged on-line if necessary.

3.2 Temperature controller

Now, a temperature controller varies the injection rate in order to approach the final expected temperature as soon as possible. The injection rate is used as input variable which is controlled in dependence whether the predicted temperature within a variable time horizon is higher or lower than the estimated final temperature. When reaching a given tolerance band around this temperature, the injection rate is set to the value of the respective operating point and the actual measurement can be started.

Figure 5 shows the performance of the temperature model which is used for two purposes: Firstly, it allows to dynamically predict the exhaust temperature as basis for the temperature controller. Secondly, the static temperature of the specific operating points are calculated (which could of course also be done by means of a static map).

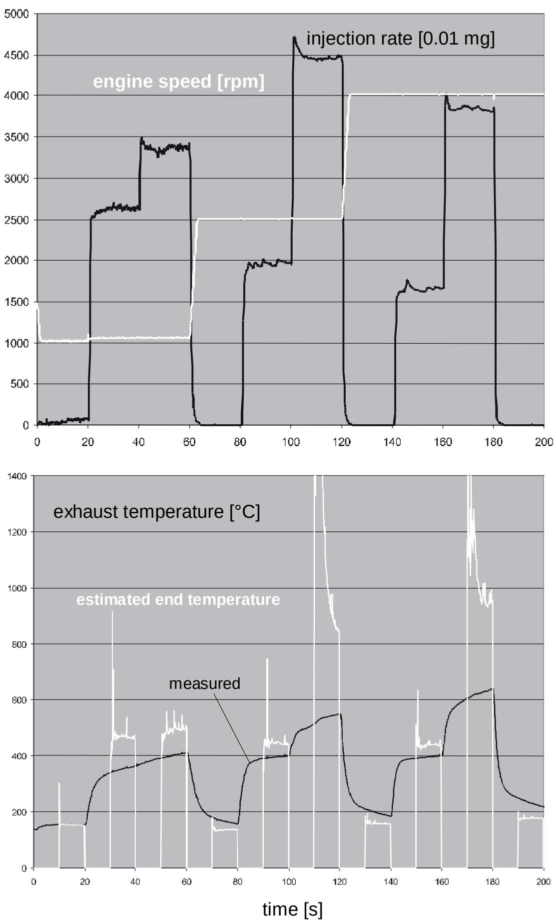

Figure 5: Temperature model for dynamic prediction and estimation of the statics

3.3. Output models

The remaining measurement time mainly depends on the delays due to the exhaust analysors. The respective delays were modeled as PT_1 or PT_2 systems for the analysors for HC, NO, NO_2, CO. The idea is to adapt a dynamic model for the output y according to equation 4 during the measurement.

$$y_{dyn}(k) = a_1 \cdot y_{dyn}(k-1) + a_2 \cdot y_{dyn}(k-2) + (1 - a_1 - a_2) \cdot y_{stat}(k) \tag{4}$$

with $\underline{\Theta} = \begin{bmatrix} c_{gl} \\ a_2 \\ a_1 \end{bmatrix}; \qquad \underline{\psi}(k) = \begin{bmatrix} 1 \\ y(k-2) \\ y(k-1) \end{bmatrix}$

Note that equation (4) is only valid for static inputs, i.e u(k) = u(k-1).

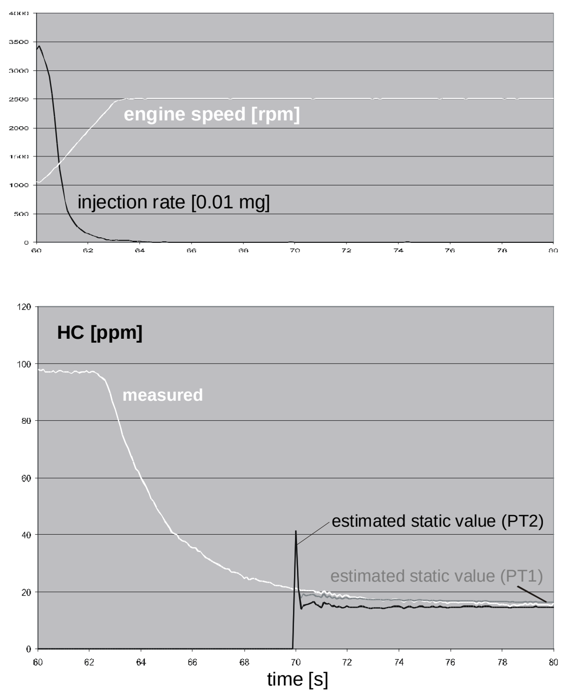

Figure 6: Output model for HC: measured and estimated static values

After a relatively short initialization time, the final measurement values are estimated based on the model and the data measured so far in the respective operating point.

Figure 6 shows the slow dynamics of the measured hydro carbons (HC). After some 10 seconds of initialization the dynamic output model is used to estimate the static value for HC. For this exhaust, the second order model shows significantly better results. It is able to estimate the static end-value very fast and accurately. The superiority in comparison to the first order model can be explained with an additional dynamic behavior of the HC-analysor (in addition to the process dynamics).

The output model allows to stop the measurement after some 12 seconds in the respective operating points instead of waiting another 10 seconds until the measured value reaches its final static values.

4. CONCLUSIONS

A series of strategies have been proposed in order to measure the emission behavior of a new IC engine in a more time-effective way. The proposed procedure is divided into an off-line pre-analysis of available data and the measurement itself.

Figure 7 illustrates the respective steps:

- In a pre-analysis of data from a comparable engine, the most relevant operating points to describe the nonlinearity of the process are extracted. Sorting these points according to their respective temperatures decreases the delay times due to temperature dynamics.

- The measurement itself is accelerated by two approaches: a temperature controller helps reaching the estimated static temperature of a new operating point more quickly. Additionally, the output dynamics are modeled on-line, so it is sufficient to measure only the first couple of seconds and then calculate the desired static output value of the respective operating point.

The presented strategies show the high potential of neuro-fuzzy methods and parameter estimation for fast engine measurements.

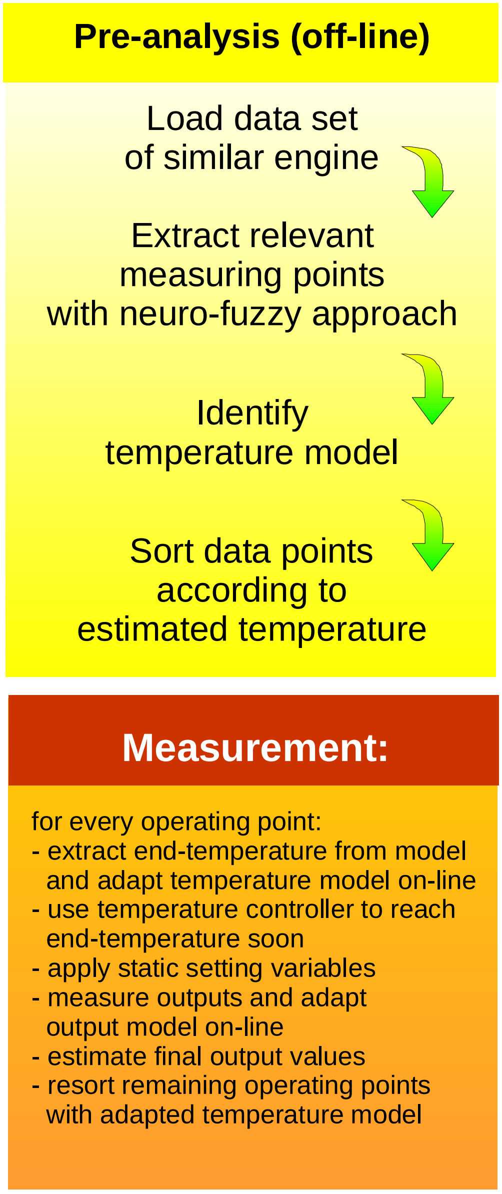

Figure 7: Procedure for fast measurement of IC engine characteristics

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