NEURAL NETWORKS MODELS USAGE IN METHODS FOR COMBUSTION PROCESS INFORMATION EXTRACTION IN IC ENGINES

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Summary: *The In-cylinder pressure profile contains valuable information on the combustion process and its availability is greatly desirable in closed loop IC Engine control systems. The low lifetime and high costs of the currently available sensors are still preventing high-volume production of in-cylinder based engine control system. This paper deals with the potentials of Artificial Neural Networks (ANN) and their application in combustion features extraction, based solely on the crankshaft angular speed measurements. The focus of this paper is put on two concepts of ANN, based on a radial basis function (RBF) and a local linear Neuro-fuzzy models (LLNFM) and their applicability in virtual sensing of crucial combustion process parameters. Training and validation of the suggested ANN models is based on comprehensive engine test bed data set.*
Keywords: *engine combustion analysis, neural networks, combustion features extraction.*

1. INTRODUCTION

In-cylinder pressure signal contains valuable information on complete working process in the internal-combustion engine. Since the signal origin is located in the sole centre of the engine's combustion process, it contains essential information on process thermodynamics and is a very desirable as a feedback signal for a closed loop combustion process control algorithms. The reason, why are so many researchers focused on exploitation of in-cylinder pressure and its importance is simply, but effective, described by A.K. Oppenheim, who compared it with the engine hearth beats and its measurements and analysis as an engine cardiology [1].

There are numerous applications in which data, extracted from the measured in-cylinder pressure, can be used like: spark advance control, detection of detonative

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combustion, misfire detection, detection of intake and exhaust phase discrete events, EGR control (on lean mixture side limits), even distribution of fuel/mixture to cylinders, estimation of air mass induced to cylinders, shortening of cold start engine warm-up time, indicated torque estimation, enhancements and shortening of engine calibration procedures, implementation in fault detection algorithms and so on.

Despite estimations, from more than a decade, that the in-cylinder pressure based engine control systems will be available in high-volume production engines very soon, this prediction is still optimistic and far away from full implementation. The main reason for this can be found in high costs of in-cylinder pressure sensors because they have to provide long endurance in very harsh conditions. Studies conducted through the project *Aeneas* ([2]) derived some conclusions that benefits of in-cylinder pressure based engine control systems are evident in terms of enhanced engine's characteristics but not enough to justify, economically, its high-volume implementation. Although ready and available, these systems are still waiting for the future.

In the meantime, a lot of research is focused on other, but readily available signal sources, which have a potential to provide information, with acceptable quality, on the in-cylinder combustion process. Sources like ionization currents, vibrations, effective torque and crankshaft speed are only intermediary related to the in-cylinder working process thus requiring higher efforts in data processing and, often, only limited results.

2. CRANKSHAFT ANGULAR SPEED AS A SOURCE OF COMBUSTION PROCESS INFORMATION

The crankshaft rotational speed and in-cylinder pressure are related through the differential equation which describes dynamics of the crankshaft mechanism motion. Crankshaft angular acceleration is a result of the summed action of torques: gas T_g, mass T_m, friction T_f and load torque T_l. The friction torque T_f originates from the friction forces within the engine and the load torque T_l acts as an external load, acting on the crankshaft and opposing the effective torque generated by the engine. These torques are related through the torque balance equation, which in general, for single cylinder takes the form:

$$J\ddot{\theta} = T_g(\theta) + T_m(\theta, \dot{\theta}, \ddot{\theta}) + T_f(\theta) + T_l(\theta) \tag{1}$$

where θ is the crank angle and J denotes the crankshaft's moment of inertia. Information on combustion process is nested in in-cylinder pressure which is part of the gas torque T_g:

$$T_g(\theta) = p_g(\theta) \cdot A_p \cdot \frac{ds}{d\theta} \tag{2}$$

where $p_g(\theta)$ is the in-cylinder absolute pressure, A_p is the piston area and s denotes the piston displacement.

The mass torque represents the influence of inertia of crankshaft mechanism parts on its dynamics. Depending on variable inertia of oscillating parts this torque component additionally amplifies already non-linear relations between the crankshaft angular speed and in-cylinder pressure signal [3]. Having on mind two-mass connecting rod modelling approach mass torque can be evaluated as:

$$T_m(\theta,\dot{\theta},\ddot{\theta}) = (-J_A(\theta) + m_B r^2)\cdot\ddot{\theta} - \frac{1}{2}\cdot\frac{dJ_A(\theta)}{d\theta}\cdot\dot{\theta}^2 \tag{3}$$

where the $J_A(\theta)$ is varying inertia of oscillating mass m_A with respect to the crankshaft axis, and m_B denotes the rotating mass on a crankshaft side.

Extending the model, described by equation (1), with the multibody lumped mass model (Fig. 1) results in more accurate model which can be described, in matrix form as [4]:

$$\mathbf{J}\cdot\underline{\ddot{\theta}} + \mathbf{C}\cdot\underline{\dot{\theta}} + \mathbf{K}\cdot\underline{\theta} = \underline{T_g}(\theta) + \underline{T_m}(\theta,\dot{\theta},\ddot{\theta}) + \underline{T_l}(\theta) + \underline{T_f}(\theta) \tag{4}$$

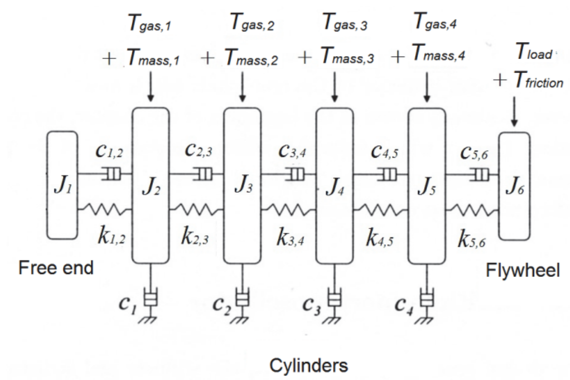

Fig. 1 *Torsional crankshaft lumped mass model for four cylinder engine*

The mass torque T_m can be successfully estimated since it depends on crankshaft speed i.e. acceleration, which is readily available in the engine management system, and the set of parameters defining the dynamic behaviour of the mechanism. Following this idea, Moskwa [5] suggested an introduction of, so called synthetic variables, which can be used to eliminate, as far as possible, nonlinear influence of mass torque from equation (1) leading to establishment of more straightforward relation between crankshaft speed and combustion process.

Introduction of a variable, which represents the estimated sum of the gas and load torque, with a rough assumption that the friction torque can be incorporated in the lumped mass damping losses, opens the possibility for on-line calculating of the synthetic signal rich in combustion information content:

$$T_{synth}(\theta) = \sum_N \left(\mathbf{J}\cdot\underline{\ddot{\theta}}_{m*} + \mathbf{C}\cdot\underline{\dot{\theta}}_{m*} + \mathbf{K}\cdot\underline{\theta}_{m*} - \underline{T_m}(\theta,\dot{\theta},\ddot{\theta})\right) \tag{5}$$

3. ANN AS A CORE STRUCTURE OF THE VIRTUAL IN-CYLINDER PROCESS SENSOR

Artificial neural networks (ANN) are featured with strong capabilities to establish functional approximation of the highly nonlinear correlated data, and therefore, have a great potential to be exploited in models of virtual in-cylinder process sensors. ANN strength of complex processing is founded in their structure which, in fact, mimics the massively parallel-distributed processing virtue of a brain [6] by using multiple interconnected processing units.

There is variety of ANN architectures but, within a scope of potential usage in engine control units and management systems, ANN's which can provide small, fast and compact numerical models are the most interesting ones. Therefore the focus is put on the Radial Basis Function (RBF) ANNs and Neuro-fuzzy based models, since they are able to achieve same or even better performance than widely used MLP networks, but with more compact structures.

RBF networks, (Fig. 2 left), have one hidden layer. The main processing units of this layer are the neurons with implemented activation function, which is often (as in this study) a Gaussian RBF. The network k-th output is calculated as:

$$y_{k_{RBF}} = \sum w_{jk} \cdot e^{-\frac{\left\| x - c_j \right\|^2}{2 \cdot \sigma_j^2}} \tag{6}$$

where w_{jk} are the weighing coefficients, c_j denotes the centre of the j-th Gaussian function, and σ_j its width. The learning method, used for the estimation of the RBF network weights and biases is based on the Orthogonal Least Squares algorithm (OLS).

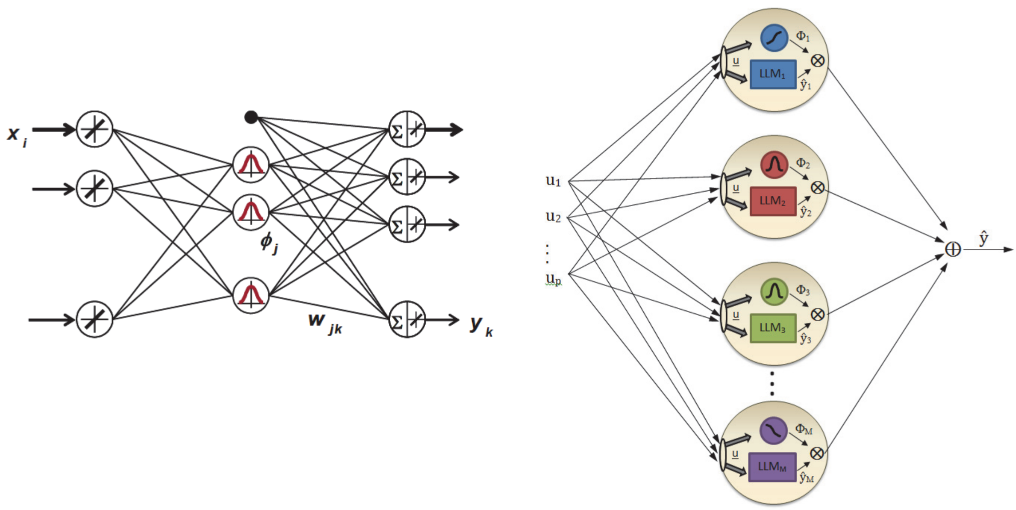

Fig. 2 *Structures of RBF (left) and LLNFM (right) ANN models*

Neuro-fuzzy (NF) models are hybrid models which involve fuzzy models in neural networks based structure. The advantage of local linear NF models, is their capability to model complex nonlinearities by superposition of several very simple models – linear functions. LLNF model is comprised of locally valid linear models $L_i(\underline{u})$ placed over partitioned input space vector $\underline{u}$. Validity of each linear model is further defined by validation function $\Phi_i(\underline{u})$ (Fig. 2 – right). The output of the LLNFM is defined as:

$$\hat{y} = \sum_{i=1}^{M} L_i(\underline{u}) \cdot \Phi_i(\underline{u})$$
$$L_i(\underline{u}) = \sum_{i=1}^{p} w_{i0} + w_{i1} \cdot u_1 + \ldots + w_{ip} \cdot u_p \tag{7}$$

where *M* is the number of the local linear models and w_{ij} are the parameters of the i-th linear submodel and $u_1 \ldots u_p$ are the elements of the input vector $\underline{u}$. The validity function, often used, is a normalised Gaussian function. The training of the LLNFM is conducted by emplyment of Local Linear Model Tree alghorithm (Lolimot), which is introduced by Nelles [7]

3.1 Estimation of the MFB50 by means of ANN based virtual sensors

Anticipated accuracy of ANN based models is related to the amount and the quality of the data acquired for its training and testing. Extensive set of data is acquired through engine test bed measurements conducted on a 1.4 MPI engine (DMB) on more than 140 working points, evenly spaced through its operational field [8]. Data are used for training the ANN models which are employed as virtual sensors of cyclic MFB50 combustion feature (the position of 50% of mass fraction burned) [9]. In order to take into account the parameters, which significantly influence the combustion process, cycle averaged pressure in the intake manifold $\overline{p}_{im}$ and the cycle averaged crankshaft speed $\overline{n}_{eng}$ are added to the input vector which takes the form:

$$\underline{u}^{(i)} = \left[T_{synth,map}^{(i)}, \overline{n}_{eng,map}^{(i)}, \overline{p}_{im,map}^{(i)}\right] \tag{8}$$

where (i) designates each engine cycle. All three signals, comprising the input vector, are mapped into the range [-1 1], as usual in the ANN input data preparation process. In order to identify the optimal structure of the RBF network, a series of numerical tests were conducted by changing the maximum number of neurons used $M \in \{7 \ldots 14\}$, and the spread parameter (spread $\in \{3 \ldots 10\}$), defining the width of Gaussian RBF. Similarly, within the LLNF model, the number of local models were varied ($M \in \{2 \ldots 7\}$) with simultaneous variation of the validation function width ($\sigma_L \in \{0.2 \ldots 0.5\}$). All models were trained with 30% of available data while the rest of 70% were used for model validation.

The performance indicator used, was the standard deviation of MFB50 estimating error (see eq. 9) where *N* is the number of input vectors available for training / validation (number of engine cycles) while estimating error is designated as Δ_{MFB50}.

$$\sigma_{\Delta_{MFB50}} = \sqrt{\frac{1}{N-1} \cdot \sum_{N} \left(\Delta_{MFB50} - \overline{\Delta}_{MFB50}\right)} \tag{9}$$

LLNF model achieved the most promising results. Model with only 5 local linear models and requirements for T_{synth} sampling resolution of only 6° CA (within the angular window of ±40° TDC) achieved standard deviation of MFB50 estimation as low as 0.33° CA. Having on mind that method for estimation of MFB50, with deviation which is less than 0.5° CA can be used in closed loop spark ignition control [10], gives some encouraging thoughts that ANN based virtual in-cylinder combustion sensors have a potential for employment in engine management systems.

4. CONCLUSION

Both RBF and LLNF models demonstrated very good performance in estimating the MFB50 with excellent generalization capabilities. Designed LLNF and RBF models outperform the minimum allowable error variation and provide acceptable inputs for the closed-loop spark advance control system. Compared to RBF, LLNF models are able to provide the same performance with more compact structure and smaller number of neurons. Since this affects their execution speed, LLNF models are more appropriate for the implementation in the engine ECUs. The reduction of the input vector size, by reducing the angular resolution of the synthetic torque variable, enabled the more compact design of the LLNF model with only 5 neurons. Further reduction of the neural network structure input vector, based on the information content extraction, could lead to the additional model size reduction and processing requirements which can be even more acceptable to the modern engine control units.

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