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Data Driven Engine Model Identification and Real-Time Adaptation

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***Abstract*— New model-based engine identification and adaptive control algorithms are introduced. In a first attempt to reduce the development time, control-oriented models are employed to represent engine processes. Model parameters are automatically identified for nominal engine operating conditions. To reduce model temperature sensitivity, such as during cold conditions, a scheme for real-time fast adaptation of model parameters is proposed. To maintain a high quality of control under all operating conditions, slow adaptation of model parameters is used to counteract the effects of engine-to-engine variations and at the same time to compensate for the effect of component aging and degradation. Experimental results for the implementation of the control algorithm performance in a vehicle with a V8 engine are presented and discussed.**

***Index Terms*— System identification, Parameter adaptation, Kalman filter, Engine control**

I. Introduction

Combustion engine modeling and identification is considered in this paper. The modeling and identification of engines may follow several approaches. For the least complex representation of engine models applicable for control design, we rely on a combination of physical as well as grey-box modeling. In this approach that relies on mean-value models, parameter estimates are obtained using real vehicle data including information from all sensors and actuators.

The same identification scheme is also used for real-time estimation of model parameters. A major part of the effort for engine calibration and control requires accurate cylinder charge estimation. Systematic methods for the air charge estimation were developed and tested in realistic engine operating conditions. Model parameters associated with the system and subsystems are proposed. Only the data collected during the driving cycle is used for modeling. Consequently, the identification procedure can easily be adopted for on-line engine operation. This in turn allows model adaptation to gradual parameter variations. The associated engine modeling techniques have been presented in the literature over the past two decades. The mean value engine models are regarded as sufficient and appropriate for control purpose [1], [2] and this type of model is used in this paper.

An engine model identification procedure, based on the driving cycle data, was the subject of research in [3]. However, it presented the model for the idle speed control, which implies that only a restricted range of engine speeds and loads were considered. Event-based sampling is employed throughout this paper and has numerous advantages over time-based sampling [4]. There are also disadvantages associated with the main system noise resulting from the engine pumping fluctuations [5].

The identification procedure is split in two distinct parts: (i) intake manifold model identification (air charge model) using upstream engine sensor information from the driving cycle sensors data (section III) and, (ii) fuel path identification using the measured air-fuel ratio (also referred to as "Lambda") from the driving cycle data (section IV). The air-fuel ratio models developed have been validated using three different sets of criteria: an integrated absolute, integrated squared error and a correlation between the measured and estimated variables. Depending on the complexity of the model structure selected, various measures of accuracy are developed and presented. Good model accuracy is achieved as more measured variables and model parameters are incorporated in the model structure. These measures include the transient as well as the steady state errors in the air-fuel ratio model during the arbitrary driving cycle. These models are used for predictive feedforward fuel control and also subsequent vehicle test presented later in the paper.

As mentioned, the identification procedure uses only the driving cycle data. In this paper the driving cycle data are collected from a V8 naturally aspirated engine. The engine was controlled using dSpace rapid prototyping controller (Autobox) with the control algorithm set up to achieve sufficient lambda excursions for a well-posed identification.

Different schemes for fast parameter adaptation to compensate for the effect of temperature sensitivity due to cold operating conditions, as well as slow parameter adaptation for component aging and degradation, are proposed and tested in a vehicle. The same slow adaptation scheme allows for engine-to-engine variations and provides compensation so that a more uniform controller performance can be achieved across a family of engines [9-11].

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II. SYSTEM MODEL STRUCTURE

The structural block diagram of the spark ignition engine model with the relevant measured signals is shown in Fig. 1 and also Fig. 2. The inputs to the model are the throttle angle setpoint (*SP* [V]) signal and the fuel pulse width (*FPW* [ms]) command. For the throttle sub-system, the indicated throttle position (*TPS* [V]), mass airflow rate ($\dot{m}_{at}$ [g/s]), ambient pressure (P_a [kPa]) and temperature (T_a [K]) are measured. the For intake manifold, intake manifold pressure (P_{im} [kPa]) and intake manifold gas temperature (T_{im} [K]) are available. In the exhaust manifold the gas pressure (P_{em} [kPa]) and gas temperature (T_{em} [K]) and the exhaust gas lambda (commonly referred to as air-fuel ratio AFR) at the exhaust valve location (λ_0), and before the catalytic converter λ are measured. The engine speed N [rev/min] is also available. The data is logged with an event-based sample time of 90 degrees.

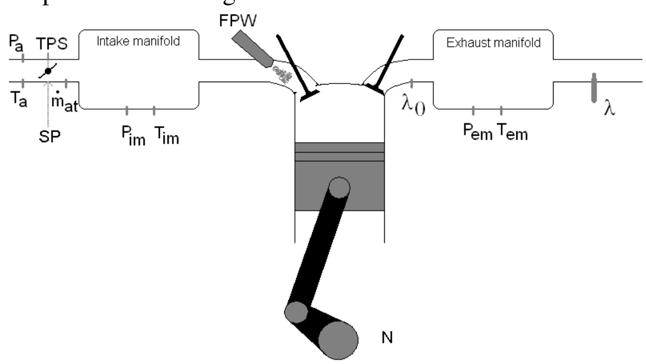

Fig. 1: System Diagram

An identification methodology for the subsequent system blocks shown in Fig. 2, is introduced in the next sections. The intake manifold subsystem that includes the throttle is identified before the fuel delivery and exhaust manifold/lambda in carried out.

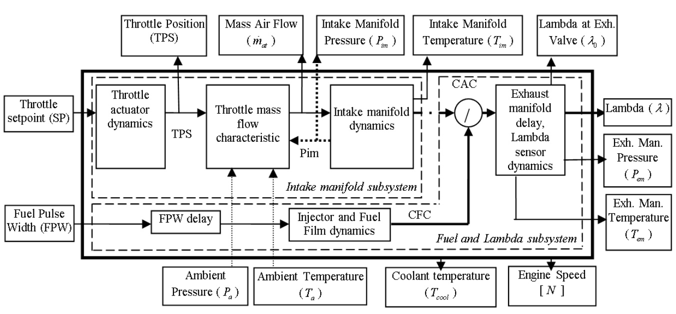

Fig. 2: System Block Diagram

The cylinder air charge estimate obtained from the intake manifold model is used as a parameter for fuel path identification. This methodology removes the non-linearity associated with the ratio computation that is inherent to the model structure and provides a manageable identification algorithm with desired convergence properties.

III. THE AIR INTAKE MODEL IDENTIFICATION

A. *Throttle actuator*

The throttle is controlled by its local controller at higher than the main (engine control system) sampling rate. The throttle actuator's internal feedback controller already provides a linearizing effect, therefore a relatively simple model provides sufficient accuracy. The input to the throttle actuator (Electronic Throttle) is the setpoint command SP_n supplied either by the driver or the engine controller (PCM). The model of the throttle dynamics is a discrete-time system scheduled with engine speed (as event-based sample time is inversely proportional to the engine speed) and provides the throttle position TPS_n as the output.

$$\begin{aligned} TPS_{n+1} &= -p_1(N_n)\cdot TPS_n - p_2(N_n)\cdot TPS_{n-1} + \\ &+ p_3(N_n)\cdot SP_n + p_4(N_n)\cdot SP_{n-1} \end{aligned} \tag{1}$$

The least-squares fitting method was used for the parameter identification.

B. *Throttle flow rate*

The throttle flow rate model captures the relationship between the actual throttle position and the mass air flow. The flow is characterized by one-dimensional isentropic compressible flow equation for flow across the orifice. The flow $\dot{m}_{at}$ is computed as a function of the throttle position (*TPS*), and other engine/ambient parameters.

$$\dot{m}_{at} = C_d \cdot A_{th} \cdot f\left(R_{th}, \alpha_0, \kappa, TPS, P_a, P_{im}, R_{air}, T_a\right) \tag{2}$$

The model is constructed out of physical constants/dimensions (e.g. radius R_{th}, offset angle α_0, ratio of specific heats κ) and the lookup-table $C_d = C_d\left(P_{im}/P_a, \alpha\right)$. As the throttle flow is almost static function of measured parameters, the lookup-table is constructed using the regression over the available data with an extrapolation to fill the gaps.

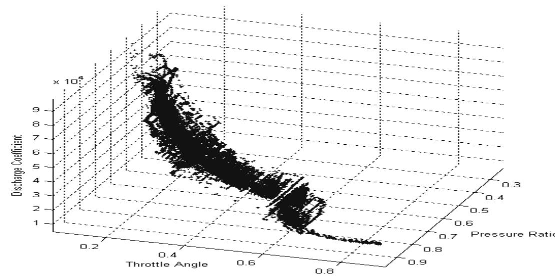

Fig. 3: Data points in Lookup-Table coordinates from the FTP driving cycle

C. *Intake manifold dynamic model*

The intake manifold is represented by two types of models. The first, one-state model employs only the mass conservation law.

$$P_{im,n+1} = \left(1 - \frac{V_{cyl}}{V_{im}}\eta\left(P_{im,n}, N_n\right)\right)P_{im,n} + \frac{R_{air}T_{im,n}T_{s,n}}{V_{im}}\dot{m}_{at,n} \tag{3}$$

The second type, two-state model, employs both: mass and energy conservation law and is more non-linear, but offers better accuracy.

$$P_{im,n+1} = \left(1 - \frac{\kappa}{V_{im}} V_{cyl} \eta_n\right) P_{im,n} + \frac{\kappa R_{air} T_{a,n}}{V_{im}} T_{s,n} \dot{m}_{at,n} + \frac{\kappa - 1}{V_{im}} T_{s,n} \dot{Q}_{ext}$$

$$T_{im,n} = \left(1 - \frac{\kappa}{V_{im}} V_{cyl} \eta_n \left(1 - \frac{1}{\kappa}\right)\right) T_{im,n} +$$

$$\left(T_{im,n} \frac{\kappa R_{air} T_{a,n}}{V_{im} P_{im,n}} - T_{im,n}{}^2 \frac{R_{air}}{V_{im} P_{im,n}}\right) T_{s,n} \dot{m}_{at,n} + T_{im,n} \frac{\kappa - 1}{V_{im} P_{im,n}} T_{s,n} \dot{Q}_{ext,n}$$

$$T_{im\ measured,n+1} = \left(1 - \tau_{InvTemp} T_{s,n}\right) T_{im\ measured,n} + \tau_{InvTemp} T_{s,n} T_{im,n}$$

$\dot{Q}_{ext} = h_0 \left[T_{wall} - T_{im}\right]$ - heat transfer equation (4)

The port air flow rate is given by the following model:

$$\dot{m}_{ac,n} = \frac{V_d}{120 R_{air} T_{im,n}} \eta\left(P_{im,n}, N_n\right) P_{im,n} N_n \quad (5)$$

The unknown parameters estimation was carried out with the extended Kalman filter. The identification was carried out off-line based on FTP and US06 driving cycle data. To pre-condition the data in order to ensure convergence (remove cyclic components from the process noise) a sampling interval of one engine cycle (8 events) was used in some cases. After validation of the one-state and two-state models, it was clear that the two-state model gave better results. The following procedure for parameters identification was established:

1. The volume of the intake manifold is identified using the one-state model with cycle-sampled data.
2. The heat-transfer parameters and temperature-sensor time constant (if not known) are identified – using the two-state model and cycle sampled data.
3. Employing constant parameters identified in stage one and two, the volumetric efficiency is estimated and the lookup table built that describes the volumetric efficiency as a function of intake manifold pressure and engine speed.

The port (or cylinder) airflow rate is computed from equation (7). The cylinder air charge (CAC) is computed from the equation (6) representing the air that enters cylinders over the time of one event (i.e. 90°).

$$m_{ac,n} = \dot{m}_{ac,n} T_{s,n} \quad (6)$$

IV. Fuel Delivery and Lambda Model

With the knowledge of the CAC, the fuel delivery path (with the FPW delay, injector parameters and fuel film dynamics) and the lambda path (with the exhaust manifold transport delay and the lambda sensor dynamics) is identified.

The in-cylinder air-fuel ratio represents both the air and fuel path. The non-linearity associated with the division (ratio) may cause problems during identification since the system operating point changes over a wide range during the driving cycle. To circumvent this problem, the intake manifold is identified separately and the lambda measurement is used for an identification of the fuel delivery parameters only. In this way the problem of additional non-linearity associated with lambda representing the ratio of two unknown variables is eliminated.

A. System delays

The fuel injection delay results from the pulse width modulation used for the fuel measuring and the injection strategy. The injection takes place before the cylinder intake takes place. This introduces a time delay that lasts about six engine events.

The in-cylinder air-fuel ratio is determined by the amount of the air and the fuel that enters the cylinder at each event. The homogeneous charge is compressed, combusted and finally released through the exhaust valves. This takes six engine events. A further delay is introduced by the exhaust manifold and pipes. This time delay is variable; it is inversely proportional to the exhaust gas flow rate.

Using the air mass flow into the cylinder the volume gas flow out of the cylinder is obtained. For this purpose the ideal gas law is used. It is assumed that, on average, the stoichiometric Air-Fuel ratio is maintained. Using the exhaust manifold pressure P_{EM} and the exhaust manifold gas temperature T_{EM} measurements, the volume of the gas entering the exhaust manifold over one engine event is given by the following expression. It is assumed that the ideal gas constant for the exhaust gas equals $R_{EM} = 0.2862$ [kJ/kgK].

$$V_{cyl,n} = \left(m_{a,n} + \frac{1}{AF_{stoich}} m_{a,n}\right) \frac{R_{EM} T_{EM,n}}{P_{EM,n}} \quad (7)$$

The discrete time delay $k_{EM,n}$ at time n is implicitly given by the following equation:

$$V_{EM} = \sum_{i=n}^{n+k_{EM,n}} V_{cyl,i} \quad (8)$$

The meaning of the equation (8) is that the exhaust gas has to be pushed out of the exhaust manifold with a volume V_{EM} by gases leaving the combustion chamber in the next engine events.

The mathematical representation of the variable time delay is quite complicated. In the state-space model additional states are introduced, and the output equation matrix changes the position of the unity element. The exhaust manifold volume may either be measured or identified from the data if an additional lambda measurement at the valve location is provided.

B. The injector, fuel film dynamics and air-fuel ratio model

The fuel film dynamics are modeled by the first-order X-τ model [[6], discretized and combined with the injector model:

$$m_{w,n+1} = \left(1 - {T_{s,n}}/{\tau_n}\right) m_{w,n} + X_n k_{fi,n} \left(FPW_{fi,n} - O_{fi,n}\right) \quad (9)$$

$$m_{fc,n} = \frac{T_{s,n}}{\tau_n} m_{w,n} + \left(1 - X_n\right) k_{fi,n} \left(FPW_{fi,n} - O_{fi,n}\right) \quad (10)$$

The input to model is the time of injector opening. The output provides the cylinder fuel charge mass.

The X and τ parameters and the injector gain k_{fi} are defined as functions of other engine parameters. These are assumed to be linear functions of the intake manifold pressure and engine speed. The injector gain is defined as a state-dependent function of the battery voltage, the intake manifold pressure and engine speed. The fuel film model is employed with the following injector model and fuel film dynamics coefficients.

$$k_{fi,n} = k_{1,fi,n} + k_{2,fi,n} P_{im,n} + k_{3,fi,n} N_n + k_{4,fi,n} P_{im,n} N_n + k_{5,fi,n} P_{im,n}{}^2 + k_{6,fi,n} N_n{}^2 + k_{7,fi,n} U_{batt,n}$$

$$\frac{1}{\tau_n} = \frac{1}{\tau_{1,n}} + \frac{1}{\tau_{2,n}} \cdot P_{im,n} + \frac{1}{\tau_{3,n}} \cdot N_n$$

$$X_n = X_{1,n} + X_{2,n} P_{im,n} + X_{3,n} N_n$$

The extended Kalman filter was used for off-line parameters estimation with FTP and US06 driving cycle data. The satisfactory data fit was achieved with datasets collected from warmed-up engine.

The air-fuel ratio is simply a ratio of the cylinder air charge and cylinder fuel charge. To obtain so-called lambda, the air-fuel ratio is scaled by the stoichiometric lambda ratio.

$$\lambda_n = \frac{m_{ac,n}}{m_{fc,n}} \frac{1}{\lambda_{stoich}}$$

The air-fuel ratio is measured in the exhaust manifold by the lambda sensor. The sensor is modeled by a first-order lag with a time constant was determined to be $\tau_\lambda = 125[ms]$ and is in line with manufacturer's datasheet.

C. Model on-line adaptation with extended Kalman filter

Some model parameters are not measured directly and the intake manifold wall temperature defined as an externally provided parameter needs to be estimated on-line. The same applies to the parameters of the identified model that are not necessarily constant. Fortunately, it is possible to use extended Kalman filter on-line for parameter adaptation. In the results presented in this paper the intake manifold wall temperature and injector gain component $k_{1,fi}$ are estimated on-line. It is also possible to adapt other parameters – like $X_{1,n}$, $\frac{1}{\tau_{1,n}}$, however these parameters were assumed constant in the results presented here.

D. Slow correction of the Cylinder Air Charge mode

During the identification of the fuelling and lambda models, the cylinder air charge (CAC) was assumed to be given by the intake manifold model. In the case of model structure mismatch (either for CAC or fuel models) or measurement errors the lambda model becomes inaccurate.

The following equations for the in-cylinder fuel-air ratio are established according to the simplified diagram in Figure 4:

$$\left(m_{fc,n} / m_{ac,n}\right)_{\text{measured}} = \frac{\delta_2 m_{fc,n}}{\delta_1 m_{ac,n}} \quad \text{(in "Engine" block)}$$

$$\left(m_{fc,n} / m_{ac,n}\right)_{\text{nominal}} = \frac{m_{fc,n}}{m_{ac,n}} \quad \text{(engine model inside of the controller)}$$

Now, define a correction coefficient as a ratio of the reconstructed fuel-air and the value computed from the nominal model:

$$\delta = \frac{\left(m_{fc,n} / m_{ac,n}\right)_{\text{measured}}}{\left(m_{fc,n} / m_{ac,n}\right)_{\text{nominal}}} = \frac{\delta_2 m_{fc,n}}{\delta_1 m_{ac,n}} \Big/ \frac{m_{fc,n}}{m_{ac,n}} = \frac{\delta_2}{\delta_1}$$

The aim is to make sure that the in-cylinder air-fuel ratio is at stoichiometry:

$$\frac{\delta_2 m_{fc,n}}{\delta_1 m_{ac,n}} = \left(m_{fc,n} / m_{ac,n}\right)_{\text{Stoich}} \rightarrow m_{fc,n} = \frac{\delta_1}{\delta_2} \cdot m_{ac,n} \cdot \left(m_{fc,n} / m_{ac,n}\right)_{\text{Stoich}} \quad (11)$$

From the above it is clear that the amount of the fuel that is required to enter the cylinder may be calculated from the following expression:

$$m_{fc,n} = \frac{m_{ac,n} \cdot \left(m_{fc,n} / m_{ac,n}\right)_{\text{Stoich}}}{\delta}$$

Finally, the fuel dynamics inverse is carried out and with the injector model a Fuel Pulse Width command is computed.

The correction coefficient $\delta = f\left(P_{im}, N\right)$ is constructed as a lookup table. Depending on the engine speed and load an adaptation of the corresponding element of the lookup table is carried out. For the given operating conditions the following on-line adaptation procedure is used:

$$\delta_{LUT(i,j)} = \sigma \delta_{LUT(i,j)} + \left(1 - \sigma\right) \delta$$

where: *i,j* are the coefficients associated with the P_{im} and N

σ is the forgetting coefficient, usually 0.99…0.999

The above adaptation accumulates a long history of data measured into each of the lookup table entries. It's a slow mechanism working only after long operation of the algorithm.

E. Fast feedback correction

Since the lookup-table adaptation is intended to provide a slow response to the variations, additional mechanism that removes intermittent model errors is required. Also, an influence of the unmeasured external factors like the fuel quality, humidity and the engine model variation must be accounted for. The variations which do not depend upon the intake manifold pressure and the engine speed are also corrected by the additional algorithm. The system diagram is presented in Figure 4. The fast adaptation uses the inverse of lambda measurement. The inverted lambda value is compared with the setpoint and the error signal is used as an input to the gain scheduled PI controller. The output of the controller is used as a multiplicative correction coefficient for the feedforward signal.

V. Engine Test Results

The driving cycle tests were carried out using the controller based on the identified model. The on-line adaptation with all three aforementioned mechanisms was implemented to eliminate model mismatches that are inevitably present due to structure limitations. The engine model employed by the controller uses the model pre-identified from the off-line driving cycle data. The controller was built using Simulink™ and implemented using dSpace® rapid prototyping controllers. The FTP driving cycles were used for validation of the model. One of the test driving cycles was starting with a cold engine and covering the warm-up stage while the second began with the engine already warmed-up. The cold-engine cycle results are particularly interesting, as the nominal (off-line) engine model was identified with warmed-up engine data and the adaptation was crucial for the engine operation under considered model-based control strategy. The schematic diagram describing the controller integration with three adaptation mechanism is shown in Figure 4.

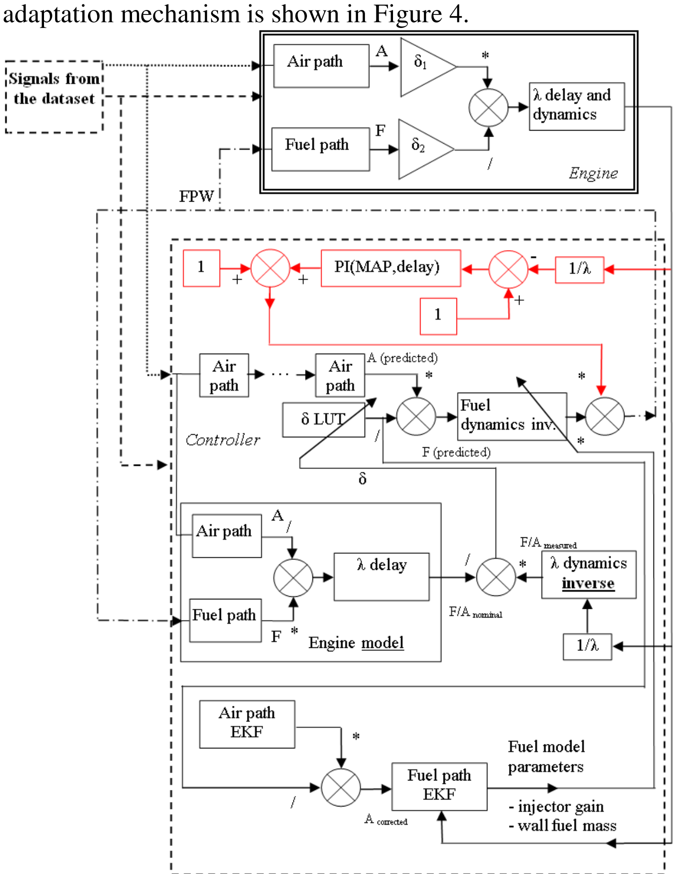

Fig. 4: Full system adaptation diagram

The intake manifold wall temperature estimation results are shown in Figure 5. Note that the variation of that parameter does reach unfeasibly low levels. However, this may be explained by the necessity to compensate for the heat transfer parameter mismatches that are present at certain operating conditions. The injector gain EKF estimation results are presented in Figure 6. Note that for the cold start conditions the estimated injector gain is below the typical level. This compensates automatically for the slow evaporation of fuel and vapor condensation on the cylinder walls. The slow correction coefficient extracted from gradually adapted lookup table is given in Figure 7. Such mechanism is designed to compensate for slowly developing system changes, but also captures systematic mismatches of the off-line identified model. The fast correction coefficient is plotted in Figure 8.

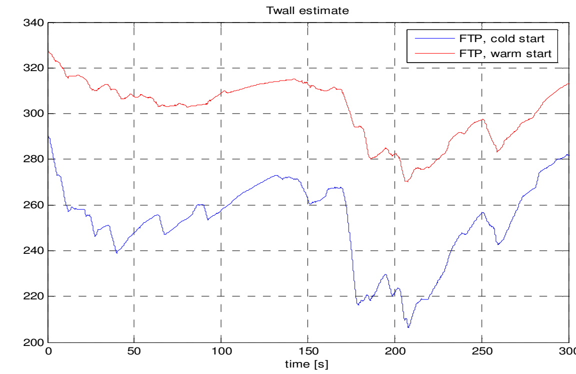

Fig. 5: Intake manifold wall temperature estimate

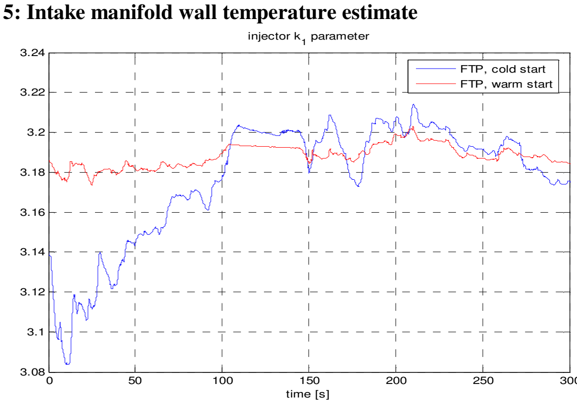

Fig. 6: Injector gain component k1 estimate

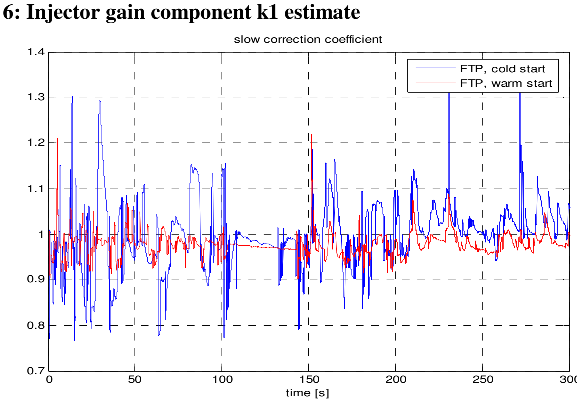

Fig. 7: Slow correction factor – from lookup table (adapted)

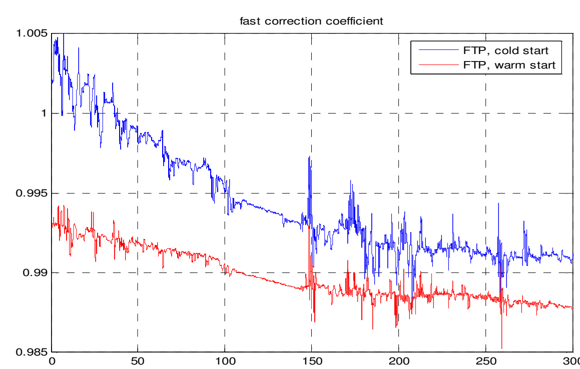

Fig. 8: Fast correction coefficient (from PI controller)

The coefficient is intended to capture rapidly occurring mismatches in either fuel or air delivery paths. Finally, the lambda control result with the adapted model is given in Figure 9. Note the differences between the cold and warm start driving cycles that are particularly significant in the first seconds of operation.

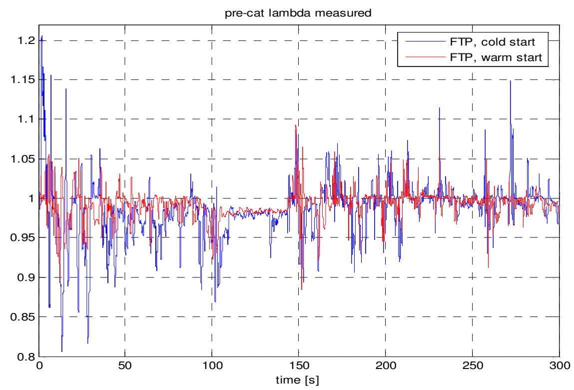

Fig. 9: Resulting pre-cat lambda measured

VI. CONCLUSIONS

The identification and feedforward control of combustion engines was presented. The methodology was aimed at developing a model with the minimum number of parameters. The data collected during the driving cycle was used for the modeling of the nominal model parameters. The identification procedure was also adopted for real-time operation. This in turn allowed slow model adaptation which is a highly desirable feature since engine parameters are subject to gradual change as a result of normal aging and degradation. The model was developed further with additional parameters introduced in the fuel film dynamics reflecting the effects of engine operating temperature. This is an important dependence especially for cold start conditions. Fast adaptation of engine parameters allowed fast adjustment of control system parameters due to changes in the operating conditions.

Real vehicle data was used in conjunction with physical models of engine processes and system identification techniques, to determine accurate engine models. This process is initially executed offline, however with more powerful microcontrollers adopted for engine control, some of the system identification and parameter estimation techniques will be able to run in real time. This has the advantage of more effective real-time compensation of modeling inaccuracies. In addition, the use of nonlinear models reduces the required memory, development time and effort in conventional fuel control systems where a large numbers of parameters are used to approximate the engine nonlinearities.

The air-fuel ratio models developed have been validated off-line and then during on-line run with a model-based controller. Good model accuracy was achieved as more measured variables and model parameters were incorporated in the model structure. The air-fuel ratio control system exhibits promising performance for further development and extension in the context of a multivariable engine control system. This will be the subject of future reports.

ACKNOWLEDGMENT

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