Modelling internal combustion engines via identification techniques

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Abstract

This paper deals with the identification of NARX (Nonlinear Autoregressive eXogenous) models for describing the pressure inside the intake manifold and the crankshaft speed of Internal Combustion car engines. The proposed method is based on stepwise regression and has been applied to real data collected on a 1200cm^3 commercial engine. A number of experimental results witness the applicability of the approach.

1 Introduction

The development of reliable Internal Combustion (IC) engine dynamic models is of crucial importance for the synthesis of control strategies coping with more and more challenging requirements on fuel consumption, vehicles' driveability, performance and pollutant emissions, see e.g. [1] for a recent survey on this topic. At the same time, thanks to the increasing availability of computing power it is now possible to implement on-board monitoring and diagnosis techniques for improving vehicle maintainability and repairability, see e.g. [2]. Also these fault detection and diagnosis methods call for the knowledge of simple and reliable engine models. However, IC engine modelling is still an open field of research due to the antithetical needs of describing a very complex, nonlinear system and deriving simple model structures suitable for the control synthesis or diagnosis phases [3].

A common approach to the development of IC engine models is to resort to Mean-Value Models (MVM), which are basically derived from physical laws complemented by identification techniques for the estimation of the unknown parameters, see e.g. [4]-[5]. In these models, the pressure p inside the intake manifold, and the crankshaft speed n are described as functions of the external manipulated variables, namely the position α of the stepper motor directly linked to the idle by-pass valve shaft, the spark advance ψ, and the relative air/fuel ratio λ. The main drawback of MVM is the need to determine the functional dependence of some quantities, such as the friction and pumping powers, on the primary state and input variables n, p, α, ψ, λ. The tuning of the model calls also for the identification of some parameters, such as the volumetric and the thermal efficiencies or the flow coefficient though the throttle body. The identification task can be successfully accomplished at the cost of collecting data in expensive and time consuming dynamic test bench experiments, see e.g. [5]-[7].

For all the above reasons, it is of great interest to develop efficient algorithms for the identification of reliable engine models from raw data collected on-board. The approach here proposed is to resort to the identification of NARX models describing the dynamics of n and p in a set of operating conditions ranging roughly from *650 RPM* (Revolutions Per Minute) to *1100 RPM* for the crank shaft speed and from *250 mbar* to *360 mbar* for the manifold pressure, which constitute a wide neighbourhood of idle speed conditions. NARX models have been already used in [2], [8], for the development of on-board diagnosis techniques.

The identification method here proposed has been applied to various sets of data collected on a commercial 1200cm^3 IC engine. NARX models in the crank-angle domain have been identified starting from time histories of n, p obtained by imposing step changes of different size and at different times to α, ψ, λ. The crank-angle (θ) basis instead of the time basis has been adopted since it is commonly recognized that in the angle basis idle speed controllers and fault detection methods are easier to design and calibrate, besides being more robust with respect to variations due to time and deterioration, see e.g. [9], [10].

2 The NARX model and the identification method

2.1 Parameter estimation and structure selection

Consider a general discrete-time nonlinear system with one output y and m inputs u_1, u_2, ..., u_m. It has been shown in [11], [12] that, under very mild assumptions, the system can be locally described by the model

$$y(t) = f(y(t-1), ..., y(t-n_y), u_1(t-1), ...,u_1(t-n_{u1}), . u_m(t-1), ...,u_m(t-n_{um})) \qquad (1)$$

In (1) n_y and n_u denote the maximum lags in the output and input and $f(\cdot)$ is a nonlinear function, a-priori unknown. Expanding $f(\cdot)$ as a polynomial of degree M, model (1) can be written as [13]:

$$y(t) = \sum_{i=0}^{r} \beta_i x_i(t) \qquad (2)$$

where r depends on $m, M, n_y, n_{ui}, i=1,...,m$. The parameters β_i, $i=0,...,r$ are coefficients to be suitably identified, $x_0=1$ and $x_i(t)$, $i=1,..., r$, are monomials made up by (delayed) outputs and/or inputs. In the following, $\beta=[\beta_0 \quad \beta_1 \ ...\beta_r]$ will denote the vector of unknown parameters, and

$$\varepsilon(t) = y(t) - \sum_{i=0}^{r} \beta_i x_i(t) \qquad (3)$$

will denote the residual sequence.

Assuming that N observations are available, the Least Squares (LS) estimate β^{LS} of β is

$$\beta^{LS} = \arg\min_{\vartheta} \sum_{t=1}^{N} \varepsilon(t)^2$$

If the nonlinear model structure (2) is assigned, the estimation problem is trivially solved by means of standard algorithms. A much more challenging problem is determining the optimal structure of the model, that is what powers and delays of what variables should be included in the model (2). Indeed, it is apparent that even for small values of m, M, n_y and n_{ui}, $i=1,...,m$, the number r of possible monomials (and regressors) tends to explode.

A simple, yet effective, approach to the optimal structure selection (OSS) problem is to divide the data into two subsets $\{y^{id},u^{id}\}$ and $\{y^v,u^v\}$ which will be used for identification and validation respectively. Given alternative model structures, the identification data are used to estimate their parameters. Among the identified models, one chooses the one that minimizes a suitable performance index, typically a sum of squared residuals (SSR), computed on the validation data.

In the present paper, the OSS problem is solved using a stepwise regression algorithm, see e.g. [14]. For a given model structure, once the estimate β^{LS} has been obtained using the identification data, the simulated output $y^s(t)$ is computed by applying the validation input signal u^v to the identified model. In other words

$$y^s(t) = \sum_{i=0}^{r} \beta_i^{LS} z_i(t) \qquad (4)$$

where β_i^{LS} is the i-th entry of the estimated vector β^{LS} and the z_i's in (4) correspond to the x_i's in (2) provided that the terms y, u in the definition of the x_i's are substituted by analogous terms y^s and u^v, respectively. Correspondingly, the simulation residuals $\varepsilon^s(t)$ are

$$\varepsilon^s(t)=y^v(t)-y^s(t) \qquad (5)$$

Letting N_v be the number of validation data, the quality of the identified model is measured by the SSR relative to *simulation*

$$SSR^s = \sum_{t=1}^{N_v} \varepsilon^s(t)^2 \qquad (6)$$

The overall stepwise regression technique can be summarized as follows

1. Define a family of candidate regressors x_i, $i=0,...,r$ and identify $r+1$ models with only one regressor at a time. Select the most significant regressor, that is the one that minimizes the SSR^s criterion (6).

2. Temporarily extend the model by including one at a time each of the remaining regressors, estimate the model parameters and compute the corresponding SSR^s.

3. Include in the model the regressor producing the greatest decrease of SSR^s with respect to that of the previously selected model. If there are no regressors whose inclusion reduces the SSR^s, go to step 5.

4. Consider one at a time all the regressors included in the model and check whether their elimination reduces the SSR^s. In the affirmative, eliminate the regressor and proceed to check the others. When this step is completed go to step 2.

5. Stop.

<u>Remark 1</u> Stepwise regression provides only a suboptimal solution of the OSS problem. In fact, the

procedure only guarantees that the final model will be *locally* optimal in the sense that it performs better (according to SSR^s) than all the models whose structure differs for one regressor (added or subtracted) at most. Nevertheless, given the prohibitive cost of performing an exhaustive search over all possible model structures, the stepwise regression strategy is widely applied and often leads to more than satisfactory results.

Remark 2 The stepwise regression scheme adopted in this paper is different from the standard one in that the residuals computed on a validation data set are used to accept (or reject) the candidate regressors, while it is more common to adopt "subjective" (e.g. statistical) criteria such as the F-test or "objective" criteria such as AIC, see [14] and the references quoted there. The use of a cross-validatory performance index seems more robust with respect to the statistical assumptions that are needed by other criteria.

Remark 3 In the above procedure the *SSR* is computed on the validation data in a simulation experiment where the measured validation outputs are not used to simulate future outputs. In other words, the validation criterion is an "output error" one, see e.g. [15]. Conversely, the parameters are estimated from the identification data by minimizing the prediction error according to an "equation error" philosophy, see again [15]. This discrepancy is justified by the fact that equation error models, being linear-in-the-parameters, result in easy identification algorithms. However, as far as an output error performance index is more realistic, it is convenient to solve the OSS problem resorting to simulation-based criteria. In so doing, it is guaranteed that the obtained model will be able to provide realistic simulations of the physical phenomenon.

2.2 Identification of the pressure dynamics

For completeness, as many regressors as possible should be considered a-priori; on the other hand this may imply a prohibitive computational burden. The approach here adopted is to first identify a model for the pressure dynamics and select its candidate regressors by resorting to physical considerations. To this end, recall that a reliable and quite simple MVM of the pressure inside the intake manifold is, see e.g. [4],

$$\frac{dp}{dt} = \frac{dp}{d\theta}\frac{d\theta}{dt} = \frac{dp}{d\theta}n = -\frac{V\eta pn}{120\overline{V}} + \frac{RTm}{\overline{V}} \qquad (7)$$

where V and $\dot{m}$ are the engine displacement and the manifold port-passage volume respectively, T is the intake manifold air temperature (which is assumed to be almost constant in warmed-up conditions), R is the gas constant, η is the volumetric efficiency and $\dot{m}$ is the air mass flow through the throttle plate. In (7) the term $\dot{m}$ can be modeled as an isoentropic flow of a compressible gas in a pipe, see e.g. [5]. However, this requires the knowledge of the throttle and by-pass open area as well as the measure of the pressure at the inlet port of the intake manifold, which is in contrast with the goal of identifying a model from data collected on-board. On the other hand, experience has shown that in most cases one can assume a simple quadratic dependence on α, that is

$$\dot{m} = \beta_0 + \beta_1\alpha + \beta_2\alpha^2 \qquad (8)$$

As for the volumetric efficiency η, in [6] it has been shown that a suitable polynomial model is

$$\eta = \beta_3 + \beta_4 p + \beta_5 p^2 + \beta_6 n + \beta_7 n^2 + \beta_8 n^3 \qquad (9)$$

Then, by combining (7)-(9) and using the Euler discretization rule, it easily turns out that the candidate regressors to be considered for identification in the crank angle domain are p, p^2, p^3, np, n^2p, n^3p, n^{-1}, αn^{-1}, $\alpha^2 n^{-1}$, besides a constant term which is always worth considering in the identification of nonlinear models, see [11]. Since the number of candidate regressors is small, the stepwise regression method of Section 2.1 can be applied to obtain with a negligeable effort the discrete-time model in the crank angle domain

$$p(\theta)=f_p(p(\theta-1),n(\theta-1),\alpha(\theta-1)) \qquad (10)$$

where the sampling instants coincide with the cylinders' top dead center. The model (10) is then used to compute the simulated pressure transient p^s on the validation data as follows

$$p^s(\theta)=f_p(p^s(\theta-1),n^v(\theta-1),\alpha^v(\theta-1)) \qquad (11)$$

2.3 Identification of the crankshaft speed dynamics

The identification of a suitable discrete-time model for n of the form

$$n(\theta)=f_n(p(\theta-1),n(\theta-1),\alpha(\theta-1),\psi(\theta-1),\lambda(\theta-1))$$

poses two basic problems: the first concerns again the a-priori selection of the candidate regressors, while the second is due to the requirement that the connection of the identified submodels (10) and (12) is representative of the overall engine dynamics, that is the overall model (10), (12) is a reliable simulator of the engine.

In this case too, recall (see again [4]) that a widely accepted MVM of n is

$$\frac{dn}{dt}=\frac{dn}{d\theta}\frac{d\theta}{dt}=\frac{dn}{d\theta}n=\frac{H_u\eta_b\dot{m}_f}{nI}-\frac{P_b+P_f+P_p}{nI} \qquad (13)$$

where H_u is the fuel heating value, $\dot{m}_f$ is the injected fuel mass flow, I is the total moment of inertia loading the engine, η_b is the indicated efficiency and P_b, P_p and P_f are the brake, pumping and friction powers respectively. In [4] it has also been argued that the loss power P_p+P_f can be described as

$$P_p+P_f = n(\beta_{10}+\beta_{11}n+\beta_{12}n^2)+np(\beta_{13}+\beta_{14}n) \quad (14)$$

while the indicated efficiency can be viewed as due to four effects, nearly independent, and quadratic in n, p, λ, ψ respectively, that is

$$\eta_b=(\beta_{15}+\beta_{16}n+\beta_{17}n^2)(\beta_{18}+\beta_{19}p+\beta_{20}p^2)(\beta_{21}+\beta_{22}\lambda+\beta_{23}\lambda^2)(\beta_{21}+\beta_{22}\psi+\beta_{23}\psi^2) \quad (15)$$

Finally, the term $\dot{m}_f$ in ideal (steady-state) conditions coincides with $\dot{m}/\lambda$ and its dependence upon α directly follows from (8). By combining (8), (13)-(15) and by using the Euler discretization rule, it it is possible to select the a-priori candidate regressors for the crankshaft speed.

The problem of deriving an overall model, composed by (10) and (12) and representative of the engine dynamics, is solved as follows. Assume to be at step 2 of the stepwise regression technique described in Section 2.1: a candidate model structure of the form (12) has been chosen and the problem is to assess the capability of the last candidate regressor included into the model to improve the model performance according to an output error criterion. Then, two modifications in the basic algorithm of Section 2 are introduced:

(i) in the identification phase, the regressors, instead of depending on p^{id}, depend on

$$p^s(\theta)=f_p(p^s(\theta-1),n^{id}(\theta-1),\alpha^{id}(\theta-1))$$

where f_p is the (previously identified) model of the pressure dynamics;

(ii) in the validation phase, the crankshaft speed n is simulated by using the overall model (10)-(12) feeded by α^v, ψ^v, λ^v, that is

$$n^s(\theta)=f_n(p^s(\theta-1),n^s(\theta-1),\alpha^v(\theta-1),\psi^v(\theta-1),\lambda^v(\theta-1))$$

$$=f_n(f_p(p^s(\theta-2),n^s(\theta-2),\alpha^v(\theta-2)),n^s(\theta-1),\alpha^v(\theta-1),\psi^v(\theta-1),\lambda^v(\theta-1)) \quad (16)$$

In so doing, at step 3 of the stepwise regression procedure, the selection of the regressor minimizing the SSR^S value amounts to optimizing the accuracy of the overall model (10) and (12) in *simulating* both the pressure and the crankshaft speed dynamics.

3 Experimental setup

The experimental data were collected on a commercial car with a $1200cm^3$ engine with four valves per cylinder. The car was equipped with a development Electronic Control Unit (ECU) with serial link to an external PC based development kit in order to perform data acquisition. The collected data were subsequently transformed in the crank angle domain.

The experiments were performed with warm engine ($TH20=90^0C$) and the clutch not coupled. Closed-loop idle control, λ control and knock control were disabled. The ECU was programmed in order to generate pre-assigned stimuli (time-histories) on the control variables: α, ψ and λ. The acquired data were the control variables and the relevant outputs p and n.

4 Identification results

In all the identification experiments, data scaling was used by considering the variables $n_n=n/1000$; $p_n=p/300$; $\psi_n=\psi/10$; $\alpha_n=\alpha/60$, $\lambda_n=\lambda/14.5$. For identification purposes, λ was varied in the range [14.9,17.5], variations of alpha were imposed in the range [45,83], while the variations of ψ were limited to the range [3^o,16^o]. The models identified according to the procedure described in Section 2 are :

Model of the pressure dynamics

$$p_n(k)=0.0743\alpha_n(k-1)n_n^{-1}(k-1) + 0.0311n_n^{-1}(k-1) + 0.8874p_n(k-1) - 0.0032p_n^3(k-1) \quad (17)$$

Model of the crankshaft speed dynamics

$$\begin{aligned}
n_n(k)= &- 0.0989 - 0.797p_n(k-1)\alpha_n(k-1)\lambda_n(k-1)\\
&+ 0.0268n_n^{-2}(k-1)p_n^2(k-1)\alpha_n^2(k-1)\lambda_n(k-1)\psi_n(k-1)\\
&+ 0.9879n_n(k-1) - 0.1007n_n^2(k-1)p_n^2(k-1)\\
&+ 0.0171\lambda_n^{-1}(k-1)\psi_n(k-1) + 0.0167\, n_n^2(k-1)\lambda_n(k-1)\\
&+ 0.2462n_n(k-1)p_n^2(k-1) + 0.0852\alpha_n(k-1)\lambda_n(k-1)\\
&- 0.0443n_n^{-1}(k-1)p_n(k-1)\alpha_n(k-1)\psi_n(k-1)\\
&- 0.0081\lambda_n^2(k-1)\psi_n(k-1) \qquad (18)\\
&- 0.0137n_n^{-1}(k-1)p_n(k-1)\alpha_n^2(k-1)\lambda_n^{-1}(k-1)\\
&- 0.0043\, n_n^2(k-1)\lambda_n^2(k-1)\psi_n^2(k-1)\\
&- 0.0053\, p_n^2(k-1)\alpha_n^2(k-1)\psi_n^2(k-1)\\
&- 0.416n_n(k-1)p_n(k-1)\lambda_n(k-1)\\
&+ 0.0133\, n_n^{-1}(k-1)p_n^2(k-1)\alpha_n(k-1)\psi_n(k-1)\lambda_n(k-1)
\end{aligned}$$

Experiment 1

With reference to the validation data, the transient of n and p and those of p^s and n^s provided by the joint simulation of the identified models (17) and (18) are reported in figs.1 and 2; correspondingly the computed *RMS* values are *21.1 RPM* and *6.76 mbar*. Note that in this experiment and in the following Experiment 3 the simulation is performed by feeding the inputs α_n^v, ψ_n^v, λ_n^v without using either p_n^v or n_n^v.

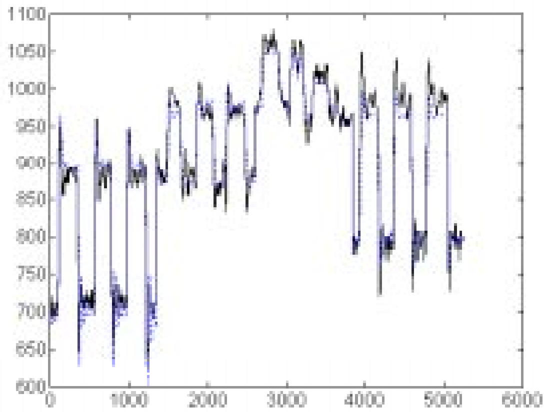

Figure A: *validation data* - transient of n and of the output n^s (dotted line) computed with the joint simulation of models (17) and (18).

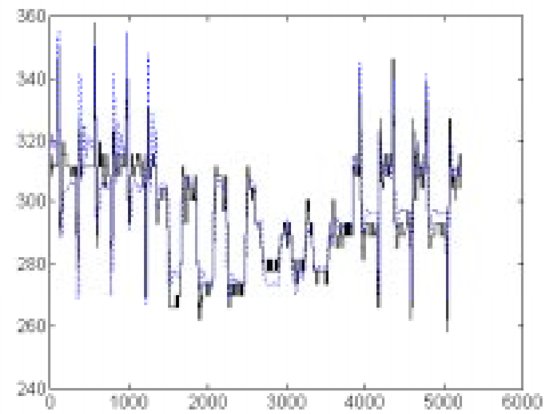

Figure B : *validation data* - transient of p and of the output p^s (dotted line) computed with the joint simulation of models (17) and (18).

Experiment 2

The one-step-ahead predictions of p and n provided by the joint use of the identified models (17) and (18) have been computed on the validation data. The obtained transients are reported in figs. 3 and 4; correspondingly the values of *RMS* are *6.22 RPM* and *1.78 mbar*.

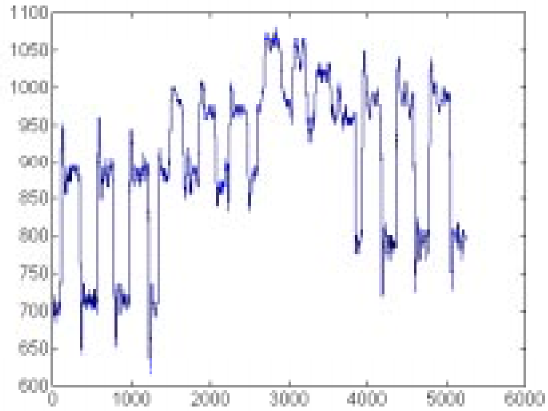

Figure C : *validation data* - transient of n and one step ahead prediction (dotted line) computed with the joint simulation of models (17) and (18).

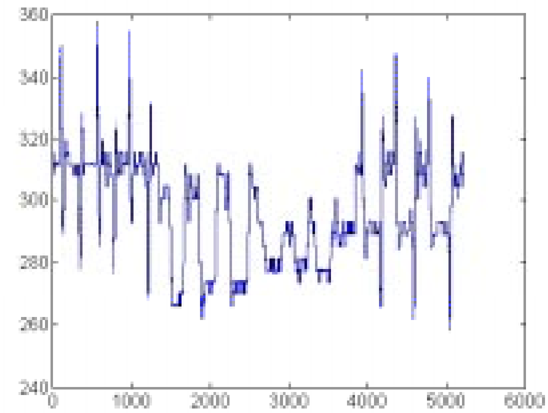

Figure D : *validation data* - transient of p and one step ahead prediction (dotted line) computed with the joint simulation of models (17) and (18).

Experiment 3

The performance of the identified models have also been tested by applying them to an extra set of data *S1*, different from those used in the identification procedure and in the validation one. Correspondingly, the transients of n^s and p^s reported in figs. 5, 6 have been determined. The *RMS* values are *20.43RPM* and *6.17mbar*.

5 Conclusions

This research is part of a wider project aimed at the development of idle speed control and diagnosis techniques for IC engines directly from data collected on-board. The results reported here show that the modelling phase can be effectively carried out through the identification of nonlinear input-output models. This conclusion is confirmed by the preliminary results obtained by applying the proposed approach also to the identification of a $1600cm^3$ engine, see [16].

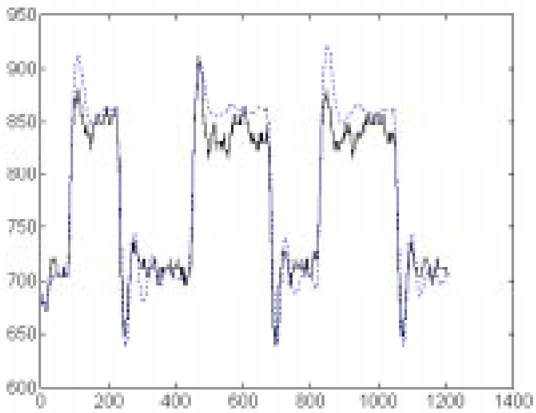

Figure E : *data set S1* - transient of n and of the output n^s (dotted line) computed with the joint simulation of models (17) and (18).

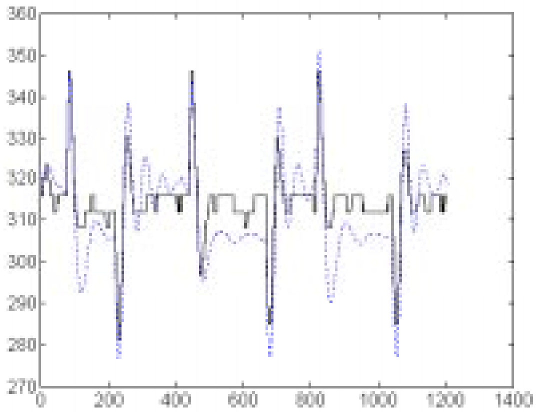

Figure F : *data set S1* - transient of p and of the output p^s (dotted line) computed with the joint simulation of models (17) and (18).

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