CONTINUOUS IDENTIFICATION OF A FOUR-STROKE SI ENGINE

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Abstract

Compact engine models often consist of a set of nonlinear differential equations which predict the time development of the mean value of the engine state variables (and perhaps some internal variables): such models are sometimes called mean value engine models. Currently a great deal of attention is focused on constructing such continuous time models and on finding their parameters. This paper shows, that it is possible to identify an engine model from a linearised version of a mean value model for a CFI four-cycle spark ignition (SI) engine. Such an approach is useful because it preserves a physical understanding of the engine throughout the identification stage. Afterwards the identification results are available for general dynamic engine studies.

The identification techniques discussed in this paper include classical methods (step response) as well as modern statistical methods (Kalman filtering and Maximum Likelihood estimation). These techniques have been applied to a four cylinder SI engine. The results include an identification of the most important parameters and time constants of the engine. These are of interest for the construction of engine simulation models, for control studies and condition monitoring applications.

1. Introduction

In spite of the great interest which exists in identifying the parameters of engines (and in particular spark ignition engines), there is very little work of this nature reported in the literature. This is mainly because

1. an engine is a nonlinear system which is difficult to describe physically and
2. an engine is a very noisy control object which requires the use of advanced dynamic statistical identification techniques.

These difficulties are reflected in the rather spare collection of literature references in this area and in the large variety of engine and engine model types treated in that which is available. The models identified range from very simple continuous or discrete transfer function models to linearised continuous mean value engine models. Mean value engine models are continuous dynamic models which predict the mean value of important engine variables several engine cycles.

Among the simplest types of model identified one can mention those which have appeared in connection with adaptive control studies. Examples of such models are the work of Olsson, et. al., (1981) and Wellstead and Zanker, (1981). Both the models and the identification techniques in such models are very simple and unsophisticated as an adaptive algorithm is meant to run on-line, in parallel with an operating engine. The physical content of the models and their accuracy is correspondingly limited.

Wellstead, et. al., (1978) have used a simple continuous transfer function model in their digital frequency response identification of a turbocharged diesel engine. Frequency response methods were also used by Chin and Coats, (1986) to identify the dynamics of an SI engine transformed to the crank shaft domain. Such investigations are very useful at isolated operating points and reasonable engine transfer functions can be obtained. The procedure is however very time consuming both as regards experimental time as well as computer analysis.

Time domain identifications have been undertaken by Hopkins and Borcherts, (1980), Morris, et. al., (1981) and Cao, et. al., (1986). The approach of Hopkins and Borcherts (1980) is to use simplified discrete difference equations and Landau's model reference adaptive algorithm. This yields reasonable results for a single engine at different operating points, but yields very little physical understanding of the model obtained or of its parameters. Morris, et. al., (1981) use the same approach but start with a more physical model. While this does yield results which can be interpreted physically, the discretization of the engine model involved collects the desired engine parameters into discrete transfer function coefficients which are difficult to unravel. Cao, et. al., (1986) use an RLS algorithm to estimate engine parameters directly in a discrete model. While this algorithm is useful on line, the models identified are simple difference equation approximations to the physical engine.

This paper describes an identification of a continuous time linearised engine model using Maximum Likelihood (ML) methods. The ML algorithm is used in conjunction with a Kalman filter to estimate the states and noise covariances iteratively for the ML algorithm. The identified parameters are those of a continuous rather than a discrete time model. While this is a large algorithm which is used off-line here, it can be converted into a recursive form. In any case it does yield physical engine parameters with good accuracy at widely spread operating points.

2. Model Formulation

In order to successfully estimate parameters in a model of a dynamic system, it is very important at the experimental design stage to define the frequency ranges of the important dynamic engine subsystems. This has to be done, since for practical estimation it is not possible to estimate simultaneously time constants which differ too widely at the same time. In the table below, the characteristic frequency ranges of the most important SI engine subsystems are tabulated.

engine subsystem	subsystem bandwidth		
temperature changes	~	0.01	Hz
rotational dynamics	~	0.2	Hz
fuelflow dynamics	~	2.	Hz
manifold filling	~	20–200	Hz
noise from crankshaft rotations	~	20–80	Hz
noise pulses from piston	~	30–170	Hz
noise from bearings, gear etc.	~	400–600	Hz

Table 1: The characteristic frequency ranges of the most important subsystems of a SI engine (Collacott, 1977 pp 170–178; Hendricks and Sorensen, 1990).

For control and condition monitoring applications the fuel flow and rotational dynamic subsystems are the most important identification objects. This is because the fuel flow dynamics are of great significance for air/fuel ratio (λ) control, while the crank shaft dynamics determine an engine's drivability characteristics. The crank shaft dynamics also reflect the condition of the engine. Temperature effects will be ignored here.

The model for the crank shaft speed is based on a linearization proposed by Cook and Powell (1987). In this continuous mean value model, it is possible to neglect the injection to power delay. For a four cylinder, four–stroke engine this delay is $T_{ip} = 30/n[\mathrm{rpm}]$. At 3000 rpm this delay is ~ 0.01 sec which, when compared to the time constant for the rotational dynamics $\tau_r \sim 4$ sec, is negligible.

The fuel flow dynamic submodel for a CFI engine has been identified in the literature using classical identification techniques (Aquino, 1981). It has not yet been the subject of a study using modern techniques. For this study Aquino's model (with modifications) has been used as the basic identification object. The model is a semi empirical representation of the behavior of the fuel film in the intake manifold. It is assumed that the intake manifold is heated by the engine coolant. A block diagram of the fuel flow subsystem is shown at the top of figure 1.

As indicated on the figure, the injected fuel mass flow, $\dot{m}_{fi}$, divides into two contributions: a vapor phase mass flow, $\dot{m}_{fv}$, and a liquid phase mass flow, $\dot{m}_{ff}$ (which is the fuel film). The proportion of the fuel which goes into the fluid phase is X ($0 \leq X \leq 1$) while the remaining proportion ($1 - X$) is entrapped in the air stream as vapor. The time constant, τ_{fv}, which describes the dynamics of the entrapment process is expected to be of the same order as the manifold filling dynamics. The time constant, τ_{ff}, describes the mean evaporation time for the fuel film flow from the intake manifold.

In order to complete the fueling dynamics submodel, a model for the dynamics of the lambda sensor (and its associated electronics) must be given. Lambda is the air/fuel mass ratio normalized with the ratio at stoichiometric conditions: $\lambda = \dot{m}_a/(\dot{m}_f L_{th})$, where $L_{th} = 14.67$ is the mass ratio for a stoichiometric mixture, $\dot{m}_a$ is the air mass flow and $\dot{m}_f$ is the fuel mass flow at the cylinder intake valve. The dynamics of the lambda sensor will be approximated by a pure time delay, Δt, in this paper for simplicity. Thus $\lambda_{\Delta t}$ is lambda measured by a linear lambda sensor, delayed the time Δt, which is the delay time for exhaust gases to pass through the exhaust valves and down to the lambda sensor.

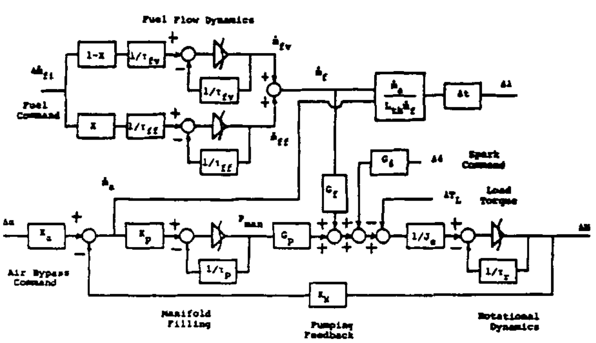

Fig. 1: Block diagram of the overall engine model. All input and state variables are linearized around their mean values, i.e., $\Delta z = z - \bar{z}$ ($\bar{z}$ is the mean value of z). In this block diagram the process and measurement noises are omitted for clarity. Noise is of course included in the state space formulation and considered in the model estimation.

3. Measurement Setup

The experiments were conducted on a four cylinder, four–stroke, 1.1L Ford CFI engine mounted on an eddy current dynamometer. The engine was fully equipped with sensors for all the relevant engine input and output variables. The air/fuel ratio was measured with a NTK Micro Oxivision MO—1000 Air/Fuel Ratio Meter with its own linear λ sensor. All engine inputs and outputs were connected to a PC—AT based data acquisition system. All experiments were conducted under open loop conditions.

To keep the engine at the desired identification (operating) point, the engine was given constant input biases (fuel flow, spark angle BTDC and throttle angle). For the step response experiments a deterministic square wave perturbation was superimposed on the desired input, with a maximum amplitude of ±10% of the relevant bias level. In the statistical identification experiments a corresponding PRBS (Pseudo Random Binary Sequence) perturbation was superimposed. The PRBS signal may switch between two constant levels only at certain equally spaced time intervals , $t = 0, T_{prbs}, 2T_{prbs}$ .... Its frequency characteristics are determined by selecting the time period T_{prbs} and the order of the signal, n. These parameters determine the frequency limits for the signal. A useful rule of thumb is , that it is possible to estimate time constants in the interval $T_{prbs}/10 < t < 2nT_{prbs}$ (Madsen, 1988) given a reasonable sampling period, T_s. For the experiment to be reviewed, $T_{prbs} = 0.5$ sec and $n = 6$ have been selected, thus it should be possible to estimate time constants in the approximate interval 0.05 sec to 6 sec. In order to avoid aliasing effects, all the data logging channels are prefiltered with identical fourth order analogue filters, with a bandwidth of 20 Hz. The sampling frequency was selected as four times this bandwidth, i.e., $T_s = 0.0125$ sec.

3.1 Classical Identification Experiments

Before initiating a series of experiments aimed at using complicated identification algorithms, it is always advisable to attempt to use simpler classical methods. This is desirable in order to check the feasibility of the basic model and to see what problems might arise in the use of a more sophisticated method.

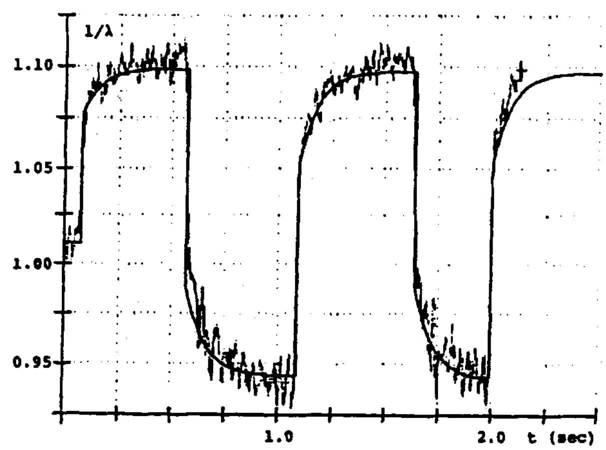

Fig. 2: The result of a step response test. For comparison the simulation result from an equivalent deterministic square wave input is plotted together with the experimental time response.

The results of a typical classical step response test are displayed on figure 2. The fuel injector is being driven here by a rather large manually generated square wave perturbation with an amplitude which is ±10% of the fuel bias amplitude. $1/\lambda$ is plotted proportional to the intake valve fuel mass flow. Thus the dynamic port fuel flow is being observed directly in this experiment. For comparison the response of the model of figure 1 (with $\tau_{fv} = 0$) to an equivalent square wave input is plotted together with the experimental results. The time delay Δt has been suppressed for clarity. Here the throttle angle is 43.5° and the crank shaft speed is 3380 rpm. The time constant, τ_{ff}, for the simulation is 0.25 sec and the proportion of fuel which goes into the fluid phase, X is 0.22. It may be seen that the agreement is excellent during the entire experiment except for a small deviation at the beginning of the lean excursions of the square wave. This is due to the slight physical differences between rich and lean evaporation conditions. Figure 2 and a large number of similar results suggest that the simple model gives a sufficient description of the physics of the intake manifold. The results of the step response tests also show that due to noise and the response time of the λ sensor, it is very difficult to obtain sufficiently accurate parameter estimates in this way. In order to obtain greater accuracy it is necessary to resort to more advanced methods.

4. Maximum Likelihood Method for Parameter Estimation

The maximum likelihood method is used to solve the parameter estimation problem. This section describes how the parameters of the continuous engine model are found by using discrete measurements and the maximum likelihood method. As a starting point the model is reformulated as a linear stochastic state space model, where the stochastic portion accounts for discrepancies of the model compared to the true system. Secondly, the discrete version of the continuous stochastic model is obtained in order to evaluate the likelihood function. The likelihood function is then expressed as a product of conditional densities, which are evaluated by using a Kalman filter. Numerical methods have been used for the optimization of the likelihood function. The asymptotic properties of the maximum likelihood estimator make possible a parallel evaluation of the uncertainty of the estimated parameters.

4.1 Linear Stochastic Models in State Space

The dynamics of the engine can be parameterised via the linearized state space model in continuous time

$$\frac{dX}{dt} = A\,X + B\,U \qquad (1)$$

where X is the state–vector and U is the input vector.

Some description of the discrepancies between the model (1), and the true variation of the states is introduced by adding a noise term. Then the model of the engine dynamics is described by the stochastic differential equation

$$dX = A\,X\,dt + B\,U\,dt + dw(t) \qquad (2)$$

where the m'th dimensional stochastic process w(t) is assumed to be a process with independent increments. With the purpose of calculating the likelihood function, w(t) will be further restricted to be a Wiener–process with the incremental covariance $R_1'(t)dt$.

In general, the measured or recorded variables are a subset of the state variables, and the measurements are encumbered with some measurement errors. Thus it is assumed that only a linear combination of the states are measured. Let Y denote the measured or recorded variables, then the measured variables are written

$$Y(t) = C\,X(t) + e(t) \qquad (3)$$

where C is a matrix, which specifies which linear combination of the states that are actually measured. The term e(t) is the measurement error. It is assumed that e(t) is normal distributed white noise with zero mean and variance R_2. Furthermore it is assumed that w(t) and e(t) are mutually independent.

4.2 From Continuous to Discrete Time

The observations are discrete. Hence, the continuous model has to be evaluated at discrete time intervals in order to calculate the likelihood function. For the present method, where the system is assumed to be described by the stochastic differential equation (2) it is possible analytically to perform an integration, which under some assumptions exactly specifies the system equation in discrete time.

For the continuous model (2) the corresponding discrete model is obtained by integrating the differential equation through the sample interval $[t, t+\tau]$. If U(t) is constant in the sample interval the sampled version of (2) can be written exactly as the following discrete model in state space form

$$X(t+\tau) = \phi(\tau)\,X(t) + \Gamma(\tau)\,U(t) + v(t;\tau) \qquad (4)$$

where

$$\phi(\tau) = e^{A\tau}\quad , \qquad \Gamma(\tau) = \int_0^{\tau} e^{As}\,B\,ds$$

$$v(t;\tau) = \int_t^{t+\tau} e^{A(t+\tau-s)}\,dw(s)$$

On the assumption that w(t) is a Wiener process, $v(t;\tau)$ becomes normally distributed white noise with zero mean and covariance

$$R_1(\tau) = E[v(t;\tau)\,v(t;\tau)'] = \int_0^{\tau} \phi(s)\,R_1'\,\phi(s)'\,ds$$

If the sampling time is constant, the stochastic difference equation can be written

$$X(t+1) = \phi\,X(t) + \Gamma\,U(t) + v(t) \qquad (5)$$

where the time scale now is transformed in such a way that the sampling time becomes equal to one time unit.

4.3 Maximum Likelihood Estimates

In the following it is assumed that the observations are obtained at regularly spaced time intervals, and hence that the time index t belongs to the set {0, 1, 2, ..., N}. N is the number of observations. In order to obtain the likelihood function we introduce

$$\mathcal{Y}(t) = [Y(t), Y(t-1), ..., Y(1), Y(0)]'$$

i.e. $\mathcal{Y}(t)$ is a matrix containing all the observations up to and including time t. Finally, let θ denote a vector of all the unknown parameters — including the unknown variance and covariance parameters in R_1 and R_2.

The likelihood function is the joint probability density of all the observations assuming that the parameters are known, i.e.

$$\begin{aligned} L'(\theta; \mathcal{Y}(N)) &= p(\mathcal{Y}(N)\,|\,\theta) \qquad (6)\\ &= p(Y(N)\,|\,\mathcal{Y}(N-1),\theta)\;p(\mathcal{Y}(N-1)\,|\,\theta)\\ &= \left[\prod_{t=1}^{N} p(Y(t)\,|\,\mathcal{Y}(t-1),\theta)\right] p(Y(0)\,|\,\theta) \end{aligned}$$

where successive applications of the rule $P(A \cap B) = P(A|B)\,P(B)$ are used to express the likelihood function as a product of conditional densities.

Since both v(t) and e(t) are normally distributed, the conditional density is also normal. The normal distribution is completely characterized by the mean and the variance. Hence, in order to parameterize the conditional distribution, we introduce the conditional mean and the conditional variance as

$$\hat{Y}(t|t-1) = E[Y(t) \mid \mathcal{Y}(t-1), \theta] \ , \tag{7}$$

$$R(t|t-1) = V[Y(t) \mid \mathcal{Y}(t-1), \theta] \tag{8}$$

respectively. Equation (7) is the one step prediction and (8) the associated variance. Furthermore, it is convenient to introduce the one step prediction error (or innovation)

$$\epsilon(t) = Y(t) - \hat{Y}(t|t-1) \tag{9}$$

Using (6) — (9) the logarithm of the conditional likelihood function (conditioned on Y(0)) becomes

$$\log L(\theta; \mathcal{Y}(N)) = -1/2 \sum_{t=1}^{N} \left[\log \det R(t|t-1) + \epsilon(t)' \, R(t|t-1)^{-1} \epsilon(t) \right] + \text{const.} \tag{10}$$

The conditional mean $\hat{Y}(t|t-1)$ and the conditional variance $R(t|t-1)$ are calculated recursively by using a Kalman filter (e.g. Åström, 1970). The Kalman filter requires initial values, which describe the prior knowledge about the states of the system in terms of the prior mean and variance

$$\hat{Y}(1|0) = E[Y(1)] = \mu_0$$

$$P(1|0) = V[Y(1)] = V_0$$

For a given set of parameters, θ, the likelihood function is evaluated by using the Kalman filter for a calculation of the the conditional mean and variance. The maximum likelihood estimate (ML estimate) is the set $\hat{\theta}$ which maximizes the likelihood function. For the optimization of the likelihood function the IMSL routine DB2ONF (1988) was used.

An estimate of the uncertainty of the parameters is obtained by the fact that the ML estimator is asymptotically normally distributed with mean θ and variance

$$D = H^{-1} \tag{11}$$

where the matrix H is given by

$$\{h_{lk}\} = -E\left[\frac{\partial^2}{\partial\theta_l \, \partial\theta_k} \log L(\theta; \mathcal{Y}(N))\right]$$

An estimate of D is obtained by equating the observed value with its expectation and applying

$$\{h_{lk}\} \approx -\left[\frac{\partial^2}{\partial\theta_l \, \partial\theta_k} \log L(\theta; Y(N))\right]\Big|_{\theta=\hat{\theta}} \tag{12}$$

The above equation is thus used for estimating the variance of the estimates. If an estimated variance is large compared to the actual estimated value for a parameter, this indicates that probably this parameter can be eliminated from the model (the parameter is equal to zero). An asymptotic test can be based on the t–distribution.

The estimated models are evaluated both statistically and physically. The latter is discussed in the next section. The statistical methods used for evaluation rely on the fact that if all the systematic variation is described by a specific model, then the residuals will be white noise sequences. Both tests in the auto– and cross correlation functions, and tests in the frequency domain were carried out. A further description of test procedures is found in e.g. Box and Jenkins (1976).

5 Results

Since the engine inputs were perturbed one at a time (while the others were kept constant), it was possible to identify submodels of the total model one after the other. Most attention was concentrated on the fuel flow submodel, because of it's great importance and deficient coverage in the literature.

The parameters of the model were estimated for 6 points in the normal engine operating region, for varying values of the throttle angle. In the experiment with perturbations in the injected fuel, the air flow is assumed to be constant, thus a straight–forward way of measuring the fuel flow into the cylinder intake valves, was again just to invert lambda. This value is proportional to the fuel mass flow.

$$1/\lambda_{\Delta t} = \frac{L_{th} \dot{m}_f}{\dot{m}_a} e^{-s\Delta t} = \text{const} \cdot \dot{m}_f \, e^{-s\Delta t} \ , \text{ where } \dot{m}_a \simeq \text{const.}$$

The state space formulation of the submodel is

$$\begin{bmatrix} d\dot{m}_{fv} \\ d\dot{m}_{ff} \end{bmatrix} = \begin{bmatrix} -1/\tau_{fv} & 0 \\ 0 & -1/\tau_{ff} \end{bmatrix} \begin{bmatrix} \dot{m}_{fv} \\ \dot{m}_{ff} \end{bmatrix} dt + \begin{bmatrix} (1-X)/\tau_{fv} \\ X/\tau_{ff} \end{bmatrix} \dot{m}_{fi} dt + \begin{bmatrix} dw_{fv}(t) \\ dw_{ff}(t) \end{bmatrix} \tag{13}$$

$$1/\lambda_{\Delta t} = [K_b \ \ K_b] \begin{bmatrix} \dot{m}_{fv}(t-\Delta t) \\ \dot{m}_{ff}(t-\Delta t) \end{bmatrix} + e(t) \tag{14}$$

where $w_{fv}(t)$ and $w_{ff}(t)$ are Wiener–processes, with incremental variances σ_{11}^2 and σ_{12}^2, and e(t) is normal distributed white noise, with variance σ_2^2 (see figure 1).

Table 2: The estimation results are shown with the standard error of the estimates in brackets. n is the engine speed in rpm, α is the throttle angle in degrees. The values of the delay, Δt, and the two time constants are in seconds. The constant K_b is in sec/g and the two process variances are in $(g/sec)^2$.

exp.	n	α	$\hat{\Delta t}$	$\hat{\tau}_{fv}$	$\hat{\tau}_{ff}$	$\hat{X}$
f1	2931	29.5	0.0625	0.0750 $(2.45 \cdot 10^{-5})$	0.375 $(2.79 \cdot 10^{-6})$	0.175 $(8.24 \cdot 10^{-3})$
f2	3562	32.8	0.0375	0.0788 $(4.19 \cdot 10^{-5})$	0.338 $(6.94 \cdot 10^{-3})$	0.184 $(3.35 \cdot 10^{-2})$
f3	2655	24.8	0.0750	0.0902 $(5.63 \cdot 10^{-2})$	0.211 $(6.56 \cdot 10^{-2})$	0.073 $(8.05 \cdot 10^{-2})$
f4	3275	29.2	0.0500	0.0916 $(1.75 \cdot 10^{-2})$	0.275 $(1.82 \cdot 10^{-3})$	0.150 $(1.22 \cdot 10^{-1})$
f7	3201	36.5	0.0375	0.0799 $(5.37 \cdot 10^{-5})$	0.288 $(3.49 \cdot 10^{-3})$	0.218 $(1.48 \cdot 10^{-2})$
f8	2676	24.7	0.0750	0.0928 $(4.22 \cdot 10^{-5})$	0.289 $(9.98 \cdot 10^{-5})$	0.067 $(6.56 \cdot 10^{-4})$

exp.	$\hat{\sigma}_{11}^2 \cdot 10^{-2}$	$\hat{\sigma}_{12}^2 \cdot 10^{-3}$	$\hat{\sigma}_2^2 \cdot 10^{-4}$	$\hat{K}_b$
f1	0.1098 $(2.12 \cdot 10^{-7})$	0.3910 $(1.04 \cdot 10^{-8})$	1.2570 $(2.84 \cdot 10^{-9})$	0.8421 $(1.06 \cdot 10^{-5})$
f2	0.3591 $(1.66 \cdot 10^{-4})$	0.1206 $(2.04 \cdot 10^{-5})$	1.2190 $(2.31 \cdot 10^{-9})$	0.7211 $(7.80 \cdot 10^{-6})$
f3	0.0751 $(1.14 \cdot 10^{-5})$	1.2010 $(4.20 \cdot 10^{-7})$	0.8106 $(3.57 \cdot 10^{-6})$	1.1937 $(3.71 \cdot 10^{-2})$
f4	0.1978 $(2.85 \cdot 10^{-4})$	2.4760 $(1.46 \cdot 10^{-3})$	0.6732 $(1.44 \cdot 10^{-7})$	0.8568 $(1.31 \cdot 10^{-1})$
f7	1.6750 $(1.66 \cdot 10^{-4})$	0.2281 $(2.04 \cdot 10^{-5})$	0.2091 $(2.31 \cdot 10^{-9})$	0.6495 $(7.80 \cdot 10^{-6})$
f8	0.1333 $(1.52 \cdot 10^{-7})$	0.6240 $(4.24 \cdot 10^{-8})$	0.7682 $(1.11 \cdot 10^{-8})$	1.1609 $(1.36 \cdot 10^{-4})$

It can be observed that for some of the parameters a close relation exists between the parameter values and the operating point. For example, the delay is less for higher engine speed: this is shown on figure 3.

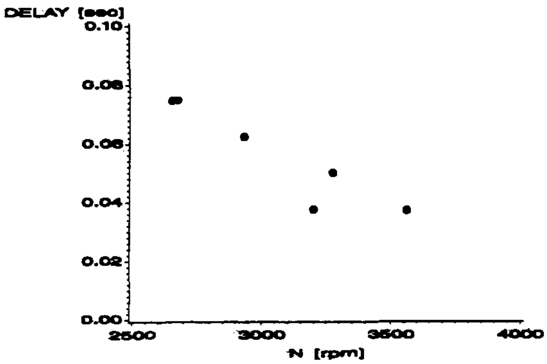

Fig. 3: A plot of the delay, Δt versus the engine speed. There is some quantization uncertainty, since the delay can only be estimated as whole number multipliers of the sampling time, i.e. $\Delta t = nT_s$.

Similarly the X parameter is obviously related to the throttle angle. A larger throttle angle implies a larger fraction of liquid fuel in the manifold, as shown by figure 4.

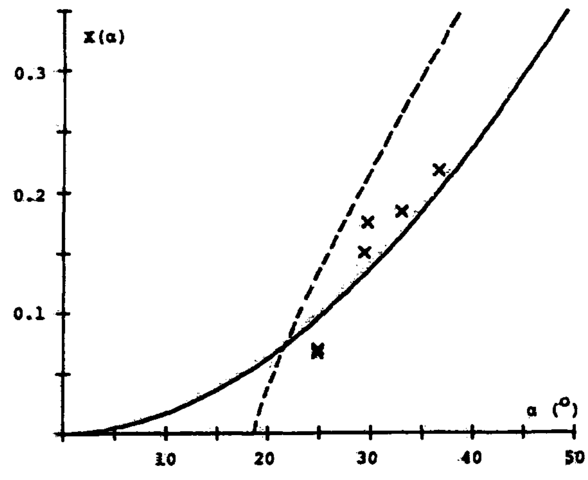

Fig 4: Identification of the function $X(\alpha)$ for the 1.1L Ford CFI engine. The expressions of Hendricks and Sorenson (———)(1990) and Wu, et. al.(– – – –)(1983) are plotted for comparison with the measured points (x's).

No obvious functional relationships are seen between the two time constants in the submodel and the operating point. The mean values for the two time constants in the operating region are $\tau_{fv} = 0.085$ sec and $\tau_{ff} = 0.296$ sec. Both time constants are sensibly constant from one identification run to another. Obviously the variance estimates of the process and measurement noise are varying. This is probably due to the different realizations of the noise processes from one experiment to another. In order to illustrate the performance of the model, figure 5 shows the one step predictions (performed by the Kalman filter) together with the observed output.

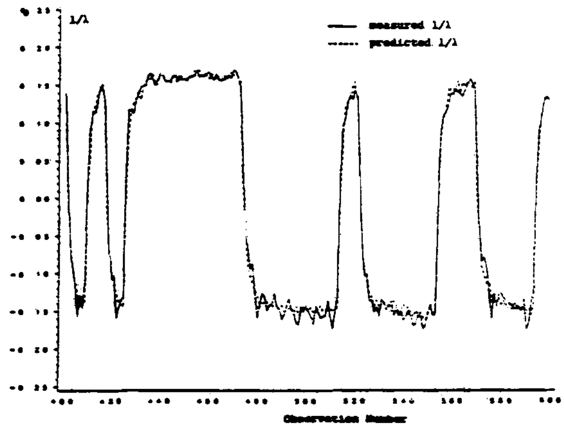

Fig. 5: A plot of the one step predictions and the measured values of $1/\lambda$ versus observation number. Notice that only a small part of the time series of observations is shown, otherwise it would be difficult to distinguish the curves. Sample time is 62.5 msec.

An estimation of the other submodel, describing variations in crank shaft speed when the throttle angle is perturbed has been performed to show the possibility of estimating other model parameters. The manifold pressure is joined as an output, since this value was actually measured. The manifold filling dynamics are very fast and can be neglected (the time constant for the rotational dynamics is around 4 sec while the time constant for the manifold filling is less than 0.02 sec). Hence it is less significant than both of the time constants in the fuel flow submodel. The resulting model in state space form is then

$$dN = [-1/\tau_r - G_P K_n / J_e] N dt + [G_P K_\theta \ -1/J_e] \begin{bmatrix} \theta \\ T_l \end{bmatrix} dt + dw(t) \tag{15}$$

$$\begin{bmatrix} N \\ P_{man} \end{bmatrix} = \begin{bmatrix} 1 \\ -K_n \end{bmatrix} N + \begin{bmatrix} 0 & 0 \\ K_\theta & 0 \end{bmatrix} \begin{bmatrix} \theta \\ T_l \end{bmatrix} + \begin{bmatrix} e_1(t) \\ e_2(t) \end{bmatrix} \tag{16}$$

where $w(t)$ is a Wiener process with incremental variance σ_1^2, and $e_1(t)$ and $e_2(t)$ are normal distributed white noise, with the covariance

$$R_2 = \begin{bmatrix} \sigma_{21}^2 & 0 \\ 0 & \sigma_{22}^2 \end{bmatrix}$$

The estimated parameters are shown below, with the associated standard errors in brackets.

$\hat{\tau}_r = 4.1358$ sec	$(1.08 \cdot 10^{-1})$
$\hat{J}_e = 0.6028$ (Nm s/rpm)	$(4.00 \cdot 10^{-5})$
$\hat{G}_P = 6.3570$ (Nm/kPa)	$(4.20 \cdot 10^{-2})$
$\hat{K}_n = 0.008746$ (kPa/rpm)	$(2.11 \cdot 10^{-6})$
$\hat{K}_\theta = 3.6403$ (kPa/°)	$(1.45 \cdot 10^{-2})$
$\hat{\sigma}_1^2 = 74.70$ (rpm)^2	$(2.17 \cdot 10^{-4})$
$\hat{\sigma}_{21}^2 = 14.43$ (rpm)^2	$(9.29 \cdot 10^{-4})$
$\hat{\sigma}_{22}^2 = 0.6988$ (kPa)^2	$(9.12 \cdot 10^{-5})$

It is seen, that the time constant for the rotating dynamics has been estimated to be $\tau_r = 4.1358$ sec. It is thus clear that with the method described here it is possible to estimate some parameters, that otherwise would be quite difficult to measure.

To demonstrate the overall performance of the model, a plot of the one step predictions performed by the Kalman filter is shown on figure 6 together with the observed values. The curves show very good agreement.

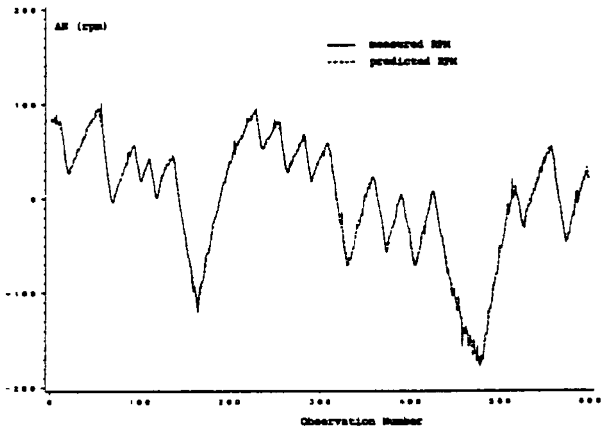

Fig. 6: One step predictions of the engine speed, N and the measured values of N versus observation number. The sample time is 62.5 msec.

6. Conclusions

In this paper a procedure has been proposed for the identification of continuous model for engine dynamics based on discrete time data. The fact that the model formulation and estimation take place in continuous time makes it easy to use physical intuition during the identification process. Thus the model can be iteratively improved by combining physical knowledge and statistical data analysis. In addition the accuracy of the parameters is estimated at the same time as the parameters themselves. The problem of sufficiency and over parameterization is readily answered by analyzing the residuals and by considering the variances of the estimates. The estimates of the noise variances are useful in constructing Kalman filters for condition monitoring and control applications.

There are a number of applications for the identification results themselves. It is clear that in finding the internal variables of an engine (such as the thermal and volumetric efficiencies), the algorithm above can be useful for condition monitoring applications. If the algorithm is written in a recursive form, it is possible to use it on–line in a microprocessor either at a service facility or (in a reduced form) in an on–board engine control microprocessor.

Currently the algorithm is in use to identify and refine a mean value engine model developed in part by one of the authors (Hendricks and Sorenson, (1990)). Here the method has made accessible some details of engine operation characteristics, which were only inaccurately known earlier. This has improved the quality of the nonlinear model for control studies.

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