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IDENTIFICATION OF MANIFOLD TWO-PHASE FUEL FLOW MODEL IN A SPARK IGNITION ENGINE WITH KALMAN FILTER AND LEAST SQUARE METHODS

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In this paper the identification of the two-phase fuel flow model in the intake manifold for a spark ignition engine is approached. The dynamic model is part of an integrated system of models with hierarchical structure, ranging from phenomenological to neural network approaches, for the analysis and the optimal design of engine control strategies in automotive engines, which is actually in use by a major automotive supplier.

Two different techniques for the estimation of model parameters are compared: ***i)*** a classical least square method and ***ii)*** a Kalman filtering approach. The former approach requires a set of off-line identifications performed through the generation of air-fuel ratio transients for each engine operating condition. Model parameters are then identified via inverse modeling approach using non linear least square techniques and stored in a look-up table in the ECU. The second technique consists in the design of a non-linear observer based on an extended Kalman filter. This latter approach can be applicable in on-line operations in order to estimate both states and parameters of the dynamic model.

The study has been performed on a set of 35 air-fuel ratio dynamic transients generated on a dynamic test bench for a spark ignition Alfa Romeo 1.4 litres with 4 cylinders, equipped with a IAW multi-point ECS. A train of square waves has been imposed on the nominal injection time pulse width in order to generate the air-fuel ratio strength excursions.

Both techniques allow to predict the observed values with good accuracy, consistently with the physical processes occurring in the region interested by the fuel injection. The results obtained from the two techniques are discussed and compared, and the emerging advantages of the Kalman filtering approach are shown.

1 GENERAL

In the last decade, increasing attention has been devoted to the study of transient phenomena relating to the operation and the design of Engine Control Systems (ECS), in order to design suitable compensation strategies for mixture strength excursions and to assure good conversion levels for pollutant gases in catalytic converters. An accurate control of Air fuel ratio is required both in steady state and transient conditions and this goal can only be achieved estimating correctly the air mass flow at the injector location and injecting the fuel in the right amount and with the appropriate time dependence. Many engine dynamic models have then been described in literature, characterized by different structures, goals and complexity. They range from very detailed fluid-dynamic models [1], [2], utilized for engine development, to simpler black-box models [3], mainly used for control system design.

At an intermediate level of complexity, an important role is played by the "Mean Value Engine Models" [4], [5], [6], [7], [8], [9], [10], [11]. They allow to describe the dynamics of both the air and the fuel flows making use of the mean values of the most important engine variables, and can achieve a good level of accuracy within a wide range of engine operating conditions, with limited computational demand. These features make them particularly suitable for control system design and also for on-board real-time applications [7], [9], [25], [26], [27]. A mean value model able to evaluate fuel consumption and emissions in a driving cycle for a SI engine has been proposed by the Authors [12]. The model describes the dynamics of air and fuel in intake manifold and, unlike other models in literature, taking also into account the effects of cylinder thermal dynamics on emissions, due to the fact that during a typical transient an engine does not operate in thermal equilibrium. The model has been applied to the study of mixture strength excursion during transients and to the development of suitable compensation strategies in order to precisely achieve the target air-fuel ratio. Thanks to its limited computational demand, the model has been used to optimize both static control maps and dynamic compensation strategies by mathematical programming techniques, considering complex driving cycles and the effects of constraints on emissions, knock and driveability.

Moreover, a stochastic model describing the non-linear effects due to random errors in sensors and actuators, previously applied to steady-state engine optimization , has been included in the dynamic engine optimization [13]. These studies show how robust control strategies which reduce performance deterioration, due to the not ideal operation of the ECS, can be designed.

In this paper, the experimental validation of the sub-model describing the dynamics of fuel in intake manifold is presented, and the identification of the corresponding parameters is performed making use of both a classic least square technique and a non linear observer based on an extended Kalman filter. In the following, the model structure and the most significant results are reviewed. Experimental facilities are described and the results of model identification are presented and discussed.

2 FUEL FILM DYNAMIC MODEL

The purpose of the fuel film sub-model is to describe the fuel transport from injection location to engine port through a mean value approach. It is coupled with a filling emptying sub-model describing the air flow dynamic within a Mean Value Engine Model for the prediction of the mean value of the main engine external (manifold pressure, engine speed) and internal (volumetric and internal efficiency) variables dynamically in time.

For both single and multi-point spark ignition engines, a two phases fuel flow occurs in the intake manifold, with a thin film of fuel on manifold walls and droplets transported by the main flow of air and fuel vapour [5], [7], [14], [15]. It is assumed that ***i)*** at any instant uniform conditions exist throughout the intake manifold, ***ii)*** a fraction D_f of the injected fuel is deposited on the wall as liquid film, ***iii)*** the evaporation rate, proportional to the fuel mass in the liquid film, can be modeled considering a first order process with time constant t. The fuel flow entering the combustion chamber $\dot{m}_{f,e}$ is obtained (Figure 1) by considering both the vapour flow $\dot{m}_{v,e}$ and a liquid flow $\dot{m}_{L,e}$ (Couette flow). The mass balance for liquid (m_L) and vapour (m_v) can be expressed by the following system of ODE's:

$$\dot{m}_L = D_f \dot{m}_{f,i} - \frac{m_L}{t} - \dot{m}_{L,e} \tag{1}$$

$$\dot{m}_v = (1 - D_f)\dot{m}_{f,i} + \frac{m_L}{t} - \dot{m}_{a,e}\left(\frac{m_v}{m_a}\right) \tag{2}$$

The fuel flow entering the combustion chamber is:

$$\dot{m}_{f,e} = \dot{m}_{v,e} + \dot{m}_{L,e} \tag{3}$$

The last term in eq. (2) represents the vapor flow rate $\dot{m}_{v,e}$ as function of the fuel mass in the vapor phase and of a characteristic manifold time constant t_m.

$$\tau_m = \frac{m_a}{\dot{m}_{a,e}} = \frac{1}{\dot{m}_{a,e}} \frac{p_m V_m}{R T_m} \tag{4}$$

In the present work, the liquid film flow through the intake valves has been considered proportional to the amount of liquid mass present on the manifold walls by means of the constant L_f, while the process is supposed governed by the air mass flow:

$$\dot{m}_{L,e} = L_f \dot{m}_{a,e} m_L = \frac{m_L}{\tau_{L,f}} \tag{5}$$

From this relation the term $L_f \dot{m}_{a,e}$ corresponds to the inverse of a time delay constant $\tau_{L,f}$. In the literature a more detailed model has been used by Matthews et al. [16] based on the physical description of Couette motion and geometrical parameters. Apart from physical flow parameters (i.e. viscosity and density of air and fuel) their relationships account for a quadratic dependence of liquid film flow with respect to the fuel liquid mass, an inverse quadratic dependence on manifold pressure and a direct dependence with air mass flow to the power 1.75.

The mixture strength of the flow entering the engine is then computed:

$$\alpha = \frac{\dot{m}_{a,e}}{\dot{m}_{f,e}} \tag{6}$$

The block diagram for the fuel dynamics is reported in fig.2. The described model has been derived from general physical consideration and can be applied for the modeling of any arrangement: continuous or pulsed, throttle-body or port fuel injection apparatus. These systems are, indeed, characterized by different values of τ, D_f and by the manifold geometry [7]. Experimental tests have shown the dependence of D_f upon other state variables such as throttle opening position and rpm which can make the system of equations non linear. This matter has been treated by Hendricks and Sorenson, [7] who report a weak dependence of D_f from *rpm* and a stronger influence of τ only for continuous injection system. The results presented in previous papers [12] have been obtained assuming a throttle body injection system with τ=1 [sec.] and D_f =0.3, in agreement with literature data [5], [7].

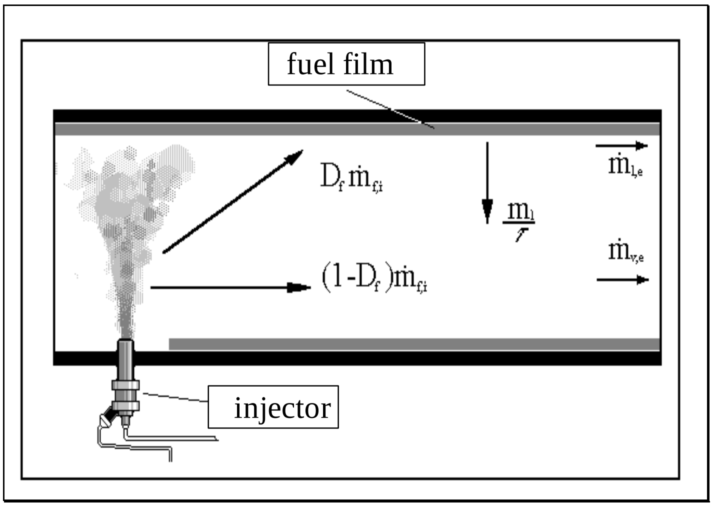

Figure 1 - Fuel film process in the intake manifold

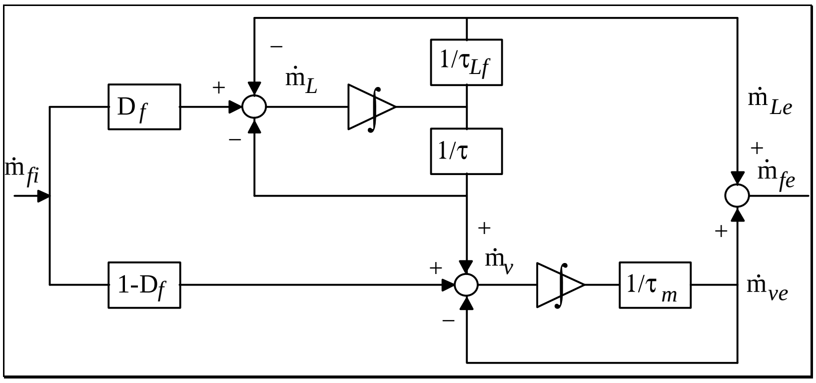

Figure 2 - Block diagram of the fuel film dynamic model

3 EXPERIMENTAL MODEL VALIDATION

In order to assess the validity and the reliability of the simulation model, the predicted results must be compared with corresponding experimental data. The procedure followed in the present study is such that each submodel is tested independently from the whole model. Hence all the engine control variables are kept constant except the ones directly related to the physical phenomena described by the submodel undertesting. Different experimental tests have been carried out, and the corresponding manoeuvres are simulated in the calculation. In this way, measured data are consistent with the simulations and the occurrence of uncorrelated effects and errors, arising when the engine is run under a general test cycle, can be avoided.

The engine used for the present experimental investigation is a 1.4 litres Alfa Romeo 4 cylinders Boxer, equipped with a Weber IAW multi-point ECS. The control technique implemented in the ECU relies on the classical speed-density approach, where the air mass flowing into the engine is calculated once are known the engine speed, manifold pressure and ambient air temperature [17].

The engine is mounted on an Assing automatic dynamic test bench with DC motor. Throttle valve position and engine speed are controlled in closed loop by a computer which allows to reproduce standard or arbitrary vehicle/engine test cycles, with a quite precise control of engine speed around its target values. Therefore, simple manoeuvre at constant rpm can be performed, with step variations of throttle opening. Maximum *rpm* variations of about 5% during throttle step transient tests have been found.

To modify the engine control variables (i.e. spark advance, injection time and transient strategy constants) the ECU has been coupled with an AVL-MCS system which allows the remote control of all variables. This equipment gives also the possibility of acquiring simultaneously engine parameters (i.e. throttle position, rpm, manifold pressure, engine temperature, etc.). The main advantages in using this device are represented by the fact that the signals correspond to the ones used by the ECU in controlling the engine and are already filtered and treated to take into account sensor drift and hysteresis. Besides, no triggering procedure is needed. The acquisition frequency is up to 100 Hz.

In order to validate the manifold two phases fuel flow engine model, the instantaneous air fuel ratio should be known, to evaluate the amount of the injected fuel mass flowing into the engine. This measurement has been performed by an HITACHI proportional AFR sensor, whose signal has been acquired with a Data6000 device at a frequency of 250 Hz. Steady state air mass flow is measured by a laminar Ricardo flow-meter.

4 PARAMETRIC ANALYSIS

The main problem related to the analysis of fuel flow submodel arises from the presence of the parameters D_f , t and L_f in the system of equations (1), (2) and (5). These parameters characterize the dynamic behaviour of each engine with respect to the two phase fuel flow into the manifold, playing thus a key role in designing the compensation strategy to reduce the lean and rich air-fuel ratio excursions during throttle transient manoeuvre. D_f, τ and L_f or $\tau_{L,f}$ are not directly measurable on the engine neither derivable from steady-state analysis of experimental data. Thus, the determination of these parameters must be done applying an identification technique which uses the mathematical submodel in conjunction with dynamic engine test data. The submodel system considered is the one described by equations (1,4,5).

In order to evaluate the influence exerted by the main model parameters τ e D_f on the AFR simulated response, a parametric analysis has been carried out, neglecting the Couette Flow influence [17]. The analytical solution of the equation system (1,4,5) has been derived for a step input transient of the injected fuel flow ($\Delta\dot{m}_{f,i} = (\dot{m}_{f,i})_{t>0} - (\dot{m}_{f,i})_{t=0}$) and the AFR response has been computed through the following relationship:

$$\alpha = \frac{\dot{m}_{a,e}}{-\Delta\dot{m}_{f,i} D_f \frac{\tau}{\tau-\tau_m}\left(\exp\left(-t/\tau\right)-\exp\left(-t/\tau_m\right)\right)-\Delta\dot{m}_{f,i}\exp\left(-t/\tau_m\right)+\left(\dot{m}_{f,i}\right)_{t>0}} \qquad (7)$$

the analysis has been performed modifying in turn the two parameters τ and D_f, and the results are presented in the figures 3 - 4.

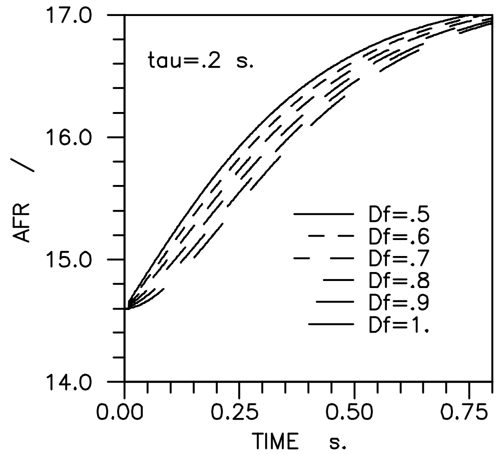

Figure 3 – D_f influence on AFR response to a step transient of injected fuel flow.

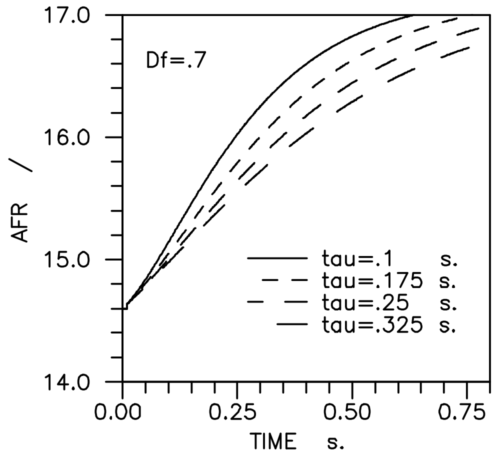

Figure 4 - τ influence on AFR response to a step transient of injected fuel flow.

The figures 3-4 show that the two parameters τ e D_f exert strong influence on different part of the modeled AFR transient. The time constant τ is responsible for the time it takes the system transient to decay without any substantial influence on the first part, which is controlled by D_f. This behavior is furthermore confirmed by observing the computed gradient at the time t=0, which does not depend on the time constant τ:

$$\left(\frac{d\alpha}{dt}\right)_{t=0} = K\frac{D_f - 1}{\tau_m} \quad \textit{with} \quad K = \dot{m}_{a,e}\frac{\Delta\dot{m}_{f,i}}{\left(\dot{m}_{f,i}\right)^2_{t=0}} \qquad (8)$$

Since D_f is mainly responsible for the initial transient modeling, the identification procedure could be affected by a time lag between input and measured signal induced by engine cycle, exhaust gas mixing and transportation process and EGO sensor time response. Therefore an accurate signal processing has to be done in order to avoid too high D_f values which are not compatible with the fuel film dynamics.

5 PARAMETER IDENTIFICATION

For the parameter identification, the selected experiment procedure consists in the analysis of the dynamic fuel flow response generated by a set of step variations in the injection time. These square wave variations are imposed on the nominal time injection value stored in μ-p map in correspondence of the tested values of engine speed and throttle position. During the experiment the air mass flow can be assumed constant and consequently the air-fuel ratio changes only for the variation of injected fuel [9], [17]. This latter is computed from the measured value of injection time, according to a correlation determined by steady state experimental data:

$$\dot{m}_{f,i} = f(t_{inj}, n) \tag{9}$$

Two different techniques have been proposed for parameter identification: ***i)*** a classic least square method and ***ii)*** a non linear observer based on an extended Kalman filter.

Since both the identification procedures are based on the comparison between measured and simulated AFR response, a great attention has to be paid in tuning the two signals in the time domain in order to account for time delays due to ***i)*** engine cycle, ***ii)*** gas mixing phenomena in the exhaust manifold, ***iii)*** gas transportation from engine port to EGO sensor location and ***iv)*** EGO sensor time response [26].

The effect of engine cycle can be described by the following relationship:

$$\Delta t_c = \frac{30}{rpm} \tag{10}$$

The time delay due to gas transport from engine port to EGO sensor location has been evaluated through the mass balance applied to the exhaust manifold, neglecting the filling-emptying effects during transients and assuming a one-dimensional flow:

$$\Delta t_{gt} = \frac{l_1}{U_1} + \frac{l_2}{U_2} \quad U_1 = \frac{\dot{m}_{a,e}}{4 r_{ex} A_1} \frac{1+a}{a} \quad U_2 = \frac{\dot{m}_{a,e}}{r_{ex} A_2} \frac{1+a}{a} \tag{11}$$

where l and A represent manifold lengths and sections respectively, U and r_{exh} are exhaust gas speed and density respectively, while footnotes 1 and 2 are referred to different parts of the exhaust manifold.

Further delay in the mixture formation process are produced by the injection system which is responsible for mixing process taking place in the intake manifold. Due to the full-group injection strategy, the amount of fuel is injected twice within an engine cycle and simultaneously for all the cylinders, thus resulting in about half amount of fuel delivered when the intake valves are closed. This process produces a smoother response of the injected fuel to the engine with respect to the input step signal. Moreover, further mixing process between the burned gas from each cylinder take place in the exhaust manifold. Both these effects result in a smooth response in the measured AFR signal, as it is shown in Figure 5, and have been modeled by means of an average performed over the last 4 engine cycles.

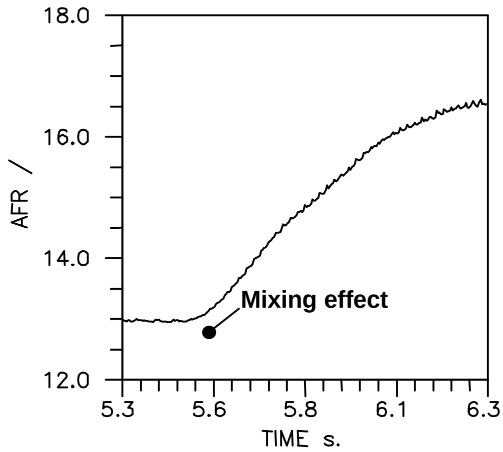

Figure 5 – Initial transient in the measured AFR signal

5.1 Least square method

The least square method relies on the minimization of a quadratic error function, defined as the difference between the measured air-fuel ratio at engine exhaust outlet and the corresponding value obtained from the simulation as function of D_f, τ and L_f:

$$\boldsymbol{E}\left(\boldsymbol{D}_f, \tau\right) = \int \left(\alpha_{meas}(\boldsymbol{t}) - \alpha_{calc}\left(\boldsymbol{D}_f, \tau, \boldsymbol{t}\right)\right)^2 \boldsymbol{dt} \qquad (12)$$

The optimal parameter D_f, τ and L_f are the ones that minimize the function (9):

$$\min_{D_f, \tau} \boldsymbol{E}\left(\boldsymbol{D}_f, \tau\right) \qquad (13)$$

with the inequality constraints:

$$0 < \boldsymbol{D}_f < 1, \tau > 0 \quad \textbf{\textit{and}} \quad \boldsymbol{L}_f > 0 \qquad (14)$$

The non-linear constrained minimization problem (8), (9) and (10) has been solved by applying the Augmented Lagrangian Approach with a Quasi-Newton technique [9], [17], [18].

5.2 Extended Kalman filter

Unlike the least square method described in the previous section the application of a non-linear observer would allow to estimate on-line both model states and parameters, leading to the design of an adaptive control system [20], [21], [22].

For a model based control system to achieve high level of performance, model parameters have to be identified accurately over a wide range of engine operating conditions. This goal could be reached by designing a non linear observer which allows to utilize both the model based control laws and the measurements from the real system and identifies the required model parameters using input-output data. The adoption of on-line system identification would offset the effects of engine age, wear, environmental condition and, referred to practical engine application, also the problems related to engine to engine component differences due to manufacturing tolerances [23], [24], [25], [27].

The non linear observer is designed assuming as physical system the fuel film model represented by equations (1, 2 and 4), neglecting Couette flow contribution, adding two further virtual states referred to the parameters to be identified, and state noise disturbances:

$$\dot{t} = w_1 \qquad (15)$$

$$\dot{D}_f = w_2 \qquad (16)$$

$$\dot{m}_L = D_f \dot{m}_{f,i} - \frac{m_L}{t} + w_3 \qquad (17)$$

$$\dot{m}_v = (1 - D_f)\dot{m}_{f,i} + \frac{m_L}{t} - \frac{m_v}{t_m} + w_4 \qquad (18)$$

State noise w_1 and w_2 represent model parameter variations with engine wear and operating conditions (throttle opening, engine speed, manifold pressure, etc..), while w_3 and w_4 account for the mean value model appressimation (i.e. neglecting periodic fluctuations).

The fuel flow to the engine is derived from the AFR signal measured by EGO sensor and is assumed as the measurement on the real system; it is modeled as the vapor flow to the engine computed in equation 3, adding white noise in order to account for sensor and measurement disturbances.

$$z = \dot{m}_{f,e} + v_m = \frac{m_v}{t_m} + v_m \qquad (19)$$

Starting from the dynamic fuel film model and adding the correction through the experimental measurement, the non linear observer is described by the following equations:

$$\dot{t} = k_1 (z - \dot{m}_{f,e}) \qquad (20)$$

$$\dot{D}_f = k_2 (z - \dot{m}_{f,e}) \qquad (21)$$

$$\dot{m}_L = D_f \dot{m}_{f,i} - \frac{m_L}{t} + k_3 (z - \dot{m}_{f,e}) \qquad (22)$$

$$\dot{m}_v = (1 - D_f)\dot{m}_{f,i} + \frac{m_L}{t} - \frac{m_v}{t_m} + k_4 (z - \dot{m}_{f,e}) \qquad (23)$$

Thus the feedforward estimation is performed by computing the fuel film model; the observer is tuned through a comparison between estimated and measured output, by means of the Kalman gains k_i which are computed minimizing the error propagation in the Riccati equation [21], [22]:

$$\dot{P} = AP + PA^T + Q - KRK^T \qquad (24)$$

where $\boldsymbol{A}$ is the State matrix, $\boldsymbol{Q}$ and $\boldsymbol{R}$ are the state noise and measurement noise variance matrices respectively and $\boldsymbol{P}$ is the error covariance matrix.

A block diagram of the extended Kalman filter is reported in Figure 6, where the connections between feedforward model estimation and feedback from the system measurement are shown.

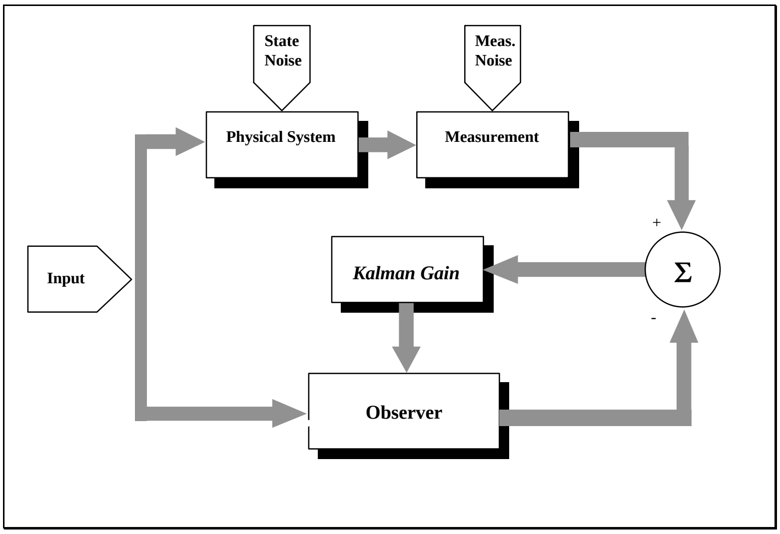

Figure 6 – Block diagram of the extended Kalman filter

6 RESULTS

In the present section the results obtained using both least square method and Kalman filtering for engine fuel flow and model parameters estimation will be discussed and compared. The proposed techniques have been tested in off-line mode through a comparison with a set of experimental transients referred to 35 different engine operating conditions, ranging from 1500 to 2500 rpm for the engine speed and from 10 to 70 Nm for the Load Torque. Each transient has been performed varying injection timing from lean to rich mixtures with constant throttle opening, and measuring the AFR at EGO sensor location [9], [17].

6.1 Least square method

In Table 1, Table 2 and Table 3 the identified values of t, D_f and $t_{L,f}$ are reported. The comparison between measured and modeled AFR response shows a satisfactory accuracy over the whole data set, as it is shown in Figure 7 where the transient referred to 50 Nm and 2500 rpm is reported. From experimental evidences the fuel film dynamics exhibits different response ranging from rich to lean mixture or inversely from lean to reach, as it was already mentioned by Hendricks and Sorenson; this behavior is mainly due to different physical mechanisms controlling the evaporation process for different two phases fuel equilibrium conditions. Unfortunately such differences can not be modeled by the proposed fuel film model which describes in the same way both rich to lean and lean to rich transients; nevertheless the design of a model reproducing two different behaviors would result in an excessive computational demand not compatible with the purposes of the present application.

Table 1 - t identification results

t [*s*]	Torque [*Nm*]						
rpm	10	20	30	40	50	60	70
1500	0.27	0.13	0.11	0.15	0.27	0.68	1.85
1750	0.22	0.15	0.18	0.25	0.34	0.30	0.53
2000	0.21	0.20	0.14	0.21	0.30	0.46	0.31
2250	0.20	0.14	0.21	0.17	0.29	0.50	0.72
2500	0.59	0.17	0.18	0.22	0.24	0.26	0.30

Table 2 - D_f identification results.

D_f [/]	Torque [*Nm*]						
Rpm	10	20	30	40	50	60	70
1500	0.73	0.93	0.97	0.78	0.68	0.47	0.44
1750	0.61	0.78	0.71	0.58	0.50	0.50	0.53
2000	0.86	0.81	0.93	0.73	0.66	0.45	0.53
2250	0.74	0.93	0.67	0.84	0.66	0.49	0.47
2500	0.59	0.86	0.79	0.70	0.58	0.59	0.66

Table 3 - $t_{L,f}$ identification results.

$t_{L,f}$ [*s*]	Torque [*Nm*]						
Rpm	10	20	30	40	50	60	70
1500	8.55	3.06	1.36	2.05	2.05	1.72	1.57
1750	14.4	6.78	15.1	3.43	4.82	10.2	2.34
2000	2.49	6.66	1.84	1.25	3.03	3.47	3.04
2250	2.63	2.59	2.39	7.36	4.73	3.60	2.78
2500	2.03	2.74	11.2	3.00	7.17	4.71	1.91

In order to evaluate the engine variables which mainly influence model parameters, a correlation matrix has been computed (Table 4), evidencing a poor influence of engine speed and quite strong correlation with respect to engine load conditions (torque, manifold pressure, air flow). A poor correlation of Couette flow time constant with almost all engine variables is also evident.

Table 4 - Correlation matrix

	Torque	Engine Speed	Man. Press.	Air Flow	t	D_f	t_{Lf}
Torque	1.00	0.01	0.98	0.84	0.47	-0.69	-0.24
Engine speed	0.01	1.00	-0.15	0.52	-0.18	0.02	-0.03
Manifold Press.	0.98	-0.15	1.00	0.74	0.52	-0.69	-0.27
Air flow	0.84	0.52	0.74	1.00	0.25	-0.55	-0.19
t	0.47	-0.18	0.52	0.25	1.00	-0.61	-0.23
D_f	-0.69	0.02	-0.69	-0.55	-0.61	1.00	-0.02
t_{Lf}	-0.24	-0.03	-0.27	-0.19	-0.23	-0.02	1.00

In Figure 8 and Figure 9 the comparison between measured and modeled AFR response referred to a rich to lean mixture transient are shown. The response smoothness due to gas mixing effects has been correctly reproduced even with low D_f values, thanks to the signal averaging procedure used and previously described. The simulated response has been modeled both accounting and neglecting for the Couette flow, in order to evaluate its influence on the simulated curve. From a previous analysis [17] the error committed by neglecting the Couette flow resulted to be significant only in few cases. Furthermore, from Table 3, the time constant related to the Couette flow is much greater than the time constants related to fuel film evaporation (t) and vapour transportation into the engine (t_m). These considerations lead to the conclusion that neglecting the Couette flow in the fuel film model would result in a reduced number of model parameters to be identified without affecting significantly the model prediction performance level.

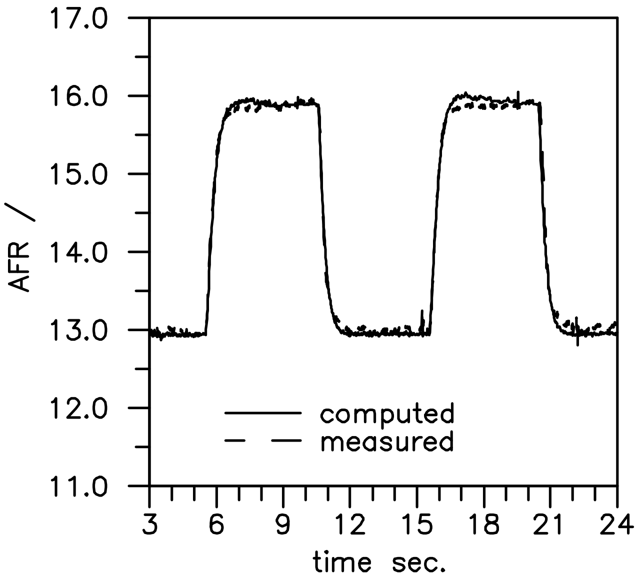

Figure 7 – Comparison between measured and simulated AFR; Load Torque=50[Nm], Engine Speed=2500[rpm], t =0.23[s], D_f=0.54.

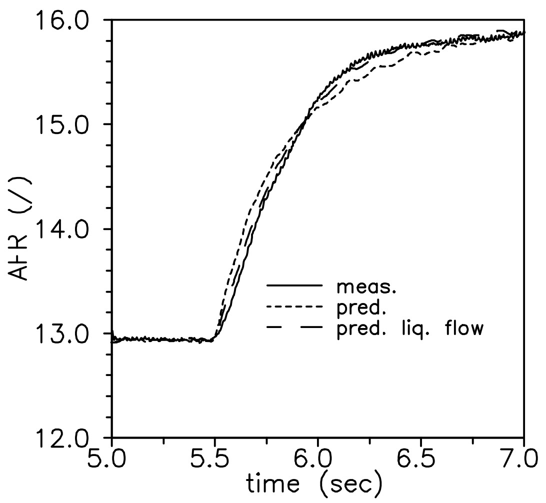

Figure 8 – Comparison between measured and simulated AFR for a rich to lean mixture transient. Load Torque = 70 [Nm], Engine Speed=2500[rpm], t =0.30[s], D_f=0.66.

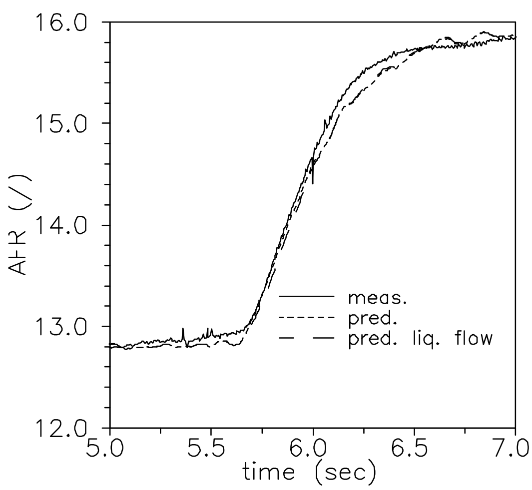

Figure 9 – Comparison between measured and simulated AFR for a rich to lean mixture transient. Load Torque = 20 [Nm], Engine Speed=1750[rpm], t =0.15[s], D_f=0.78.

Since the general purpose of the current application is the development of a model based control system, the determination of a black-box polynomial regression for fast t and D_f estimation is needed. Starting from the correlation matrix, the manifold pressure has been selected as independent engine variable due to its strong correlation with respect to both engine operating conditions and model parameters. In Figure 10 and Figure 11 t and D_f identification results are plotted versus manifold pressure. The dotted curves represent the estimated values by means of polynomial regressions:

$$\tau = -1.3256 + 9.395\frac{P_m}{P_0} - 18.56\left(\frac{P_m}{P_0}\right)^2 + 11.8\left(\frac{P_m}{P_0}\right)^3 \quad R^2 = 0.64 \qquad (25)$$

$$D_f = 0.448 + 0.944\frac{P_m}{P_0} - 1.1\left(\frac{P_m}{P_0}\right)^2 \quad R^2 = 0.53 \qquad (26)$$

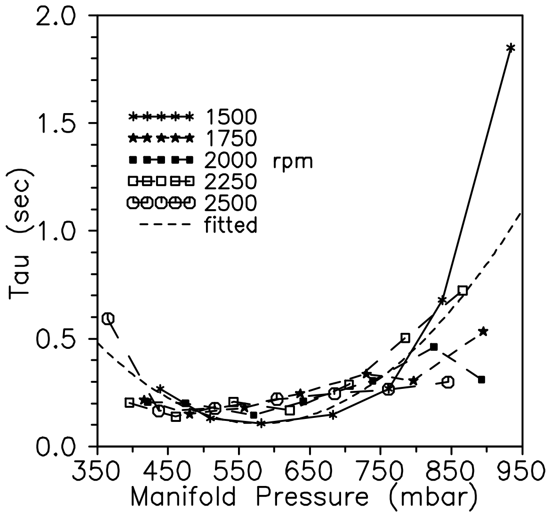

Figure 10- τ identification results vs. manifold pressure. The dotted line is the regression curve eq. (25).

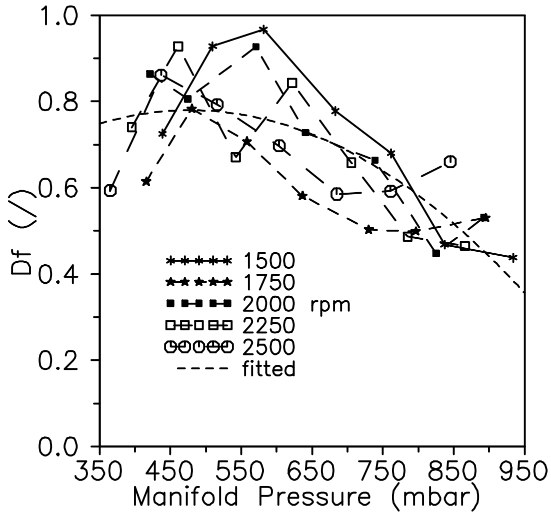

Figure 11- D_f identification results vs. manifold pressure. The dotted line is the regression curve eq (26).

6.2 Kalman filtering

As it has already been mentioned in the previous section, a non linear observer is mainly designed to be used on line for the development of a model based control system. Nevertheless since the purpose of the current work is to compare two different identification methodologies, the observer has been tested in off-line mode through a comparison with a set of measured transient data.

In Figure 12 and Figure 14 the comparison between measured and identified AFR transients for two different operating condition are reported as a sample from the whole data set of 35 transients investigated. The AFR is simulated using the instantaneous value of both parameters τ and D_f , whose the time history along the transient is reported in the Figure 13 and Figure 15 for the two cases considered, respectively. The analysis of both Figure 12 and Figure 14 shows the satisfactory level of precision reached for each transient, confirming the correctness of the procedure developed. It is worth to remember that the parameters identification is achieved on line, while the parameters found via the Least Square Technique are computed making use of a minimization technique which in turn requires many model evaluations over the transient (eq. 1,2 and 4). On the other hand the Kalman filtering procedure allows to evaluate the instantaneous value of the parameters dynamically ensuring the best local precision for the simulation and making it eligible as one of the most reliable method for on-line application. This latter consideration is also confirmed considering the limited computational demand. From the analysis of the parameters curves (Figure 13 and Figure 15) the values attained along the transient change during time confirming the consideration already stated before about the different two phases fuel flow behavior which depends on both local fuel and engine states.

In order to make the results obtained comparable with the ones found via the Least Square Technique, the mean value of τ and D_f have been computed for each transient and reported as function of manifold pressure and engine speed in the figure 16 and 17 respectively. In the first figure the evaporation time constant presents comparable absolute values ranging from 0.2 to 0.6 [s] in both cases; nevertheless, a slight decreasing trend with the manifold pressure is detected, while the Least Square Technique results (fig. 10) exhibit an opposite trend with a slight increase with the manifold pressure. Regards to D_f, the trend resulted from the previous procedure is confirmed and the range of absolute values are quite similar (0.5 ÷ 1) (Figure 11 and Figure 17); nevertheless the values estimated via Kalman filter exhibit a more marked tendency to saturation for low pressure values (Figure 17), with respect to the results obtained via LS technique (Figure 11). Due to its local optimum estimation, the Kalman filtering technique is more sensitive to the time lag between measured and estimated signals; therefore D_f saturation tendency can be avoided by describing more accurately the gas mixing process and by the adoption of a proper model for EGO sensor dynamic response.

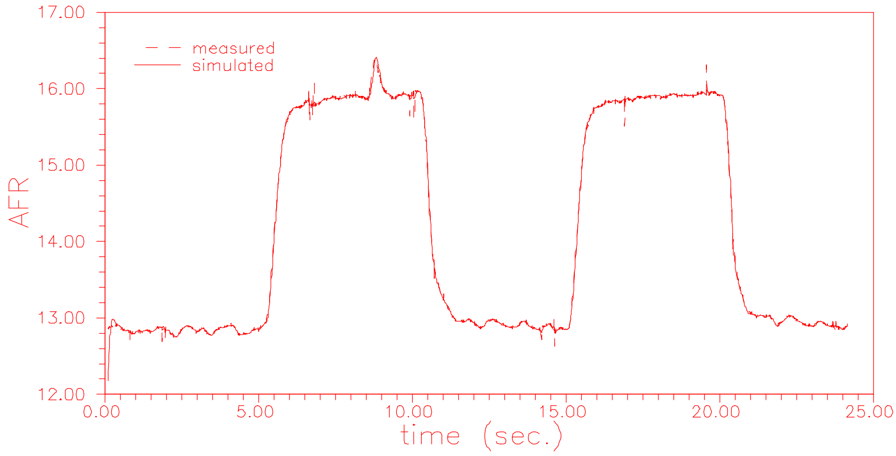

Figure 12 – Comparison between measured and simulated AFR response. Load torque = 20 [Nm], Engine speed = 1750 [rpm].

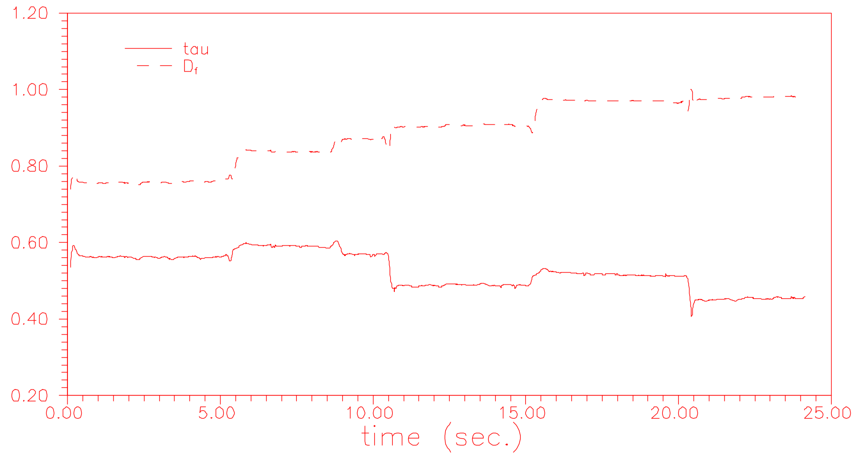

Figure 13 – t and D_f identification. Load torque = 20 [Nm], Engine speed = 1750 [rpm].

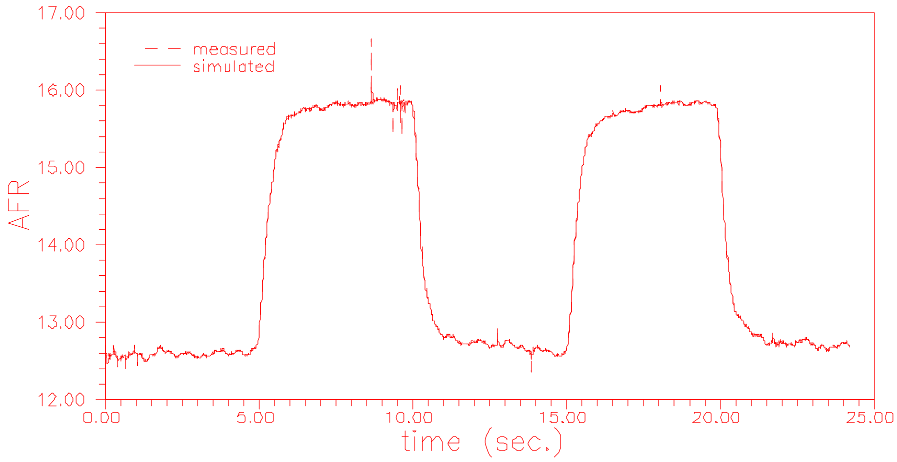

Figure 14 – Comparison between measured and simulated AFR response. Load torque = 50 [Nm], Engine speed = 1750 [rpm].

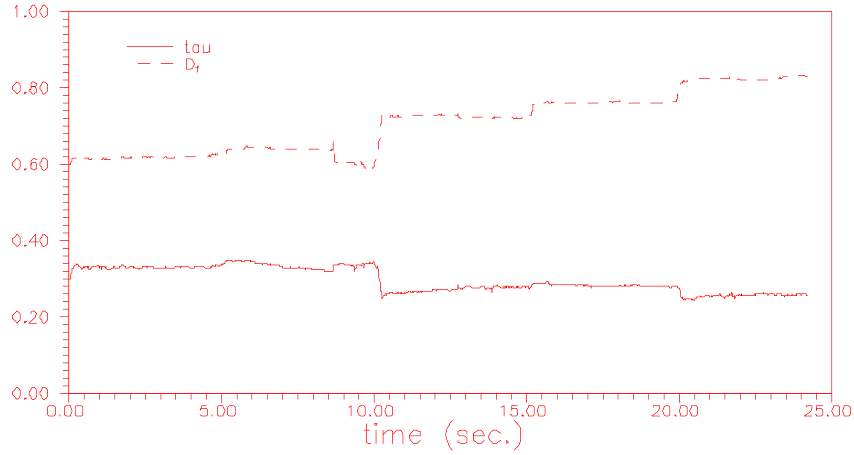

Figure 15 – t and D_f identification. Load torque = 50 [Nm], Engine speed = 1750 [rpm].

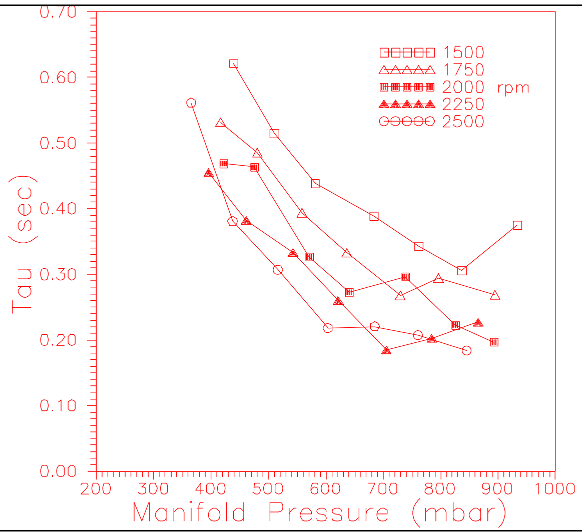

Figure 16 - t identification results vs. manifold pressure.

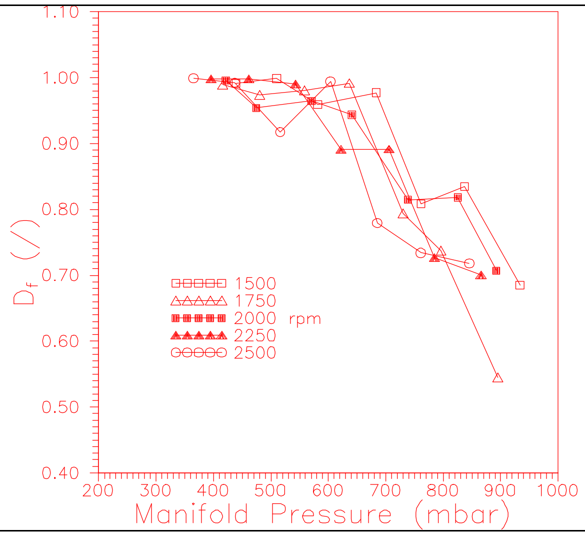

Figure 17 - D_f identification results vs. manifold pressure.

7 CONCLUSIONS

The parameter identification of a fuel film dynamic model for a spark ignition engine has been conducted by means of two different techniques. The dynamic model accounts for both the injected fuel impinging on manifold walls and the fuel film evaporation, via two parameters describing the fraction of injected fuel going onto the manifold walls and the evaporation time constant.

The first method uses a classical identification procedure based on a Least Square technique in conjunction with a minimization method. Its application over a wide set of transient experimental manoeuvres has allowed to derive two polynomial regression expressing the model parameters as function of engine speed and intake manifold pressure. The least square technique relies on a global optimum criteria with respect to each transient, without accounting for local specific fuel dynamic behavior. However, the trends found out for both the parameters are in accordance with the basic phenomenology of the processes taking place inside the intake manifold. In order to precisely achieve the target air fuel ratio, this approach could be used to derive a look-up table to be used for model based compensation strategies derived by inverting the fuel film model.

The stressed need to design a model based control system which could be able to guarantee the target air/fuel ratio even during transient conditions and even accounting for engine wear and environmental condition, has led to the opportunity to come out with an alternative identification technique. This goal, has been accomplished by designing a non linear observer based on an extended Kalman filter, which allows to estimate on line the local optimal value of each parameter along the transient, through a comparison between model estimation and a direct measurement on the system. The combined use of feedforward model estimation and on line feedback from system measurement makes the observer to cancel measurable disturbances and delays, and leads to an adaptive control methodology.

The results obtained by Kalman filtering identification are still consistent with the physical fuel flow behavior and a similar range for the estimated parameter values has been observed with respect to the LS technique results. Slight differences for the evaporation time, which is almost constant in the LS application, while it exhibits a decreasing trend with respect to the intake manifold pressure in the actual case, have also been detected. A stronger tendency to saturation for D_f emerged, probably due to lacking precision in time lag modeling. Further investigations are then required to analyze and avoid these effects.

Because of their different theoretical and computational features the proper applications of both methods have to be envisaged. Since the least square technique cannot be applied on line, its identification results can only be used to realize a look-up table without accounting for engine wear and age and without maintaining engine model accuracy over a wide range of operating conditions. Nevertheless, due to its simplicity this technique is appropriate to be used for off-line simulations. On the other hand, due to its adaptive properties, the Kalman filtering approach seems to be suitable for the design of model based control system, though its development require a detailed analysis of state and measurement noises bandwidth. Furthermore an accurate modeling of the sensor dynamics and of the measurement line is also needed in order to account for time lags and to compare appropriately model output and system measurement.

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