NONLINEAR ON-LINE IDENTIFICATION OF A 4-CYLINDER FUEL INJECTED ENGINE

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Abstract. *A fuel injected engine is a highly nonlinear system, because it presents time delays that vary inversely with engine speed and is time-varying due to aging of components and environment changes, such as engine warm-up after a cold start. The engine dymanic equations are usually derived from steady-state map data and other empirical information and, hence, entail a great deal of uncertainty. In this paper we propose an on-line identification algorithm for estimating the engine speed and manifold pressure. Based on Lyapunov arguments and by using a robust modification of the gradient methodology it is proved that the engine speed and manifold pressure estimation errors coverge to zero, assymptotically, whereas the parameter error remain bounded, even in the presence of bounded disturbances.*

Keywords*: on-line identification, nonlinear estimators, fuel injected engine*

1. INTRODUCTION

Several schemes for controlling the speed of fuel injected engines have been proposed in recent years (Vachtsevanos et al., 1993; Puskorius and Feldcamp, 1994; Powell et al., 1998; Powellt and Hrovatt, 2000; Yu and Li, 2001; Yu et al., 2001; Sun et al., 2005). These works are mainly based on the previous knowledge of the systems dynamic, which is usually derived from steady-state map data and other empirical information, or also, by on-line identification techniques to approximate the unknown nonlinearities of the engine, such as neural networks (NN) and fuzzy systems (FS). However, the aforementioned techniques have several drawbacks: 1) traditional modeling is based on empirical information, as for instance steady-state maps, and then entail an enormous deal of uncertainty, with a negative impact on the control performance (Puskorius and Feldcamp, 1994; Vachtsevanos et al., 1993); 2) identification techniques based on neural networks, such as radial basis function NN (Sanner and Slotine, 1992), which are mainly used in identification-based control algorithms, have poor interpolation capability and requires large number of basic functions for tackling with multidimensional network inputs (Rysdyk and Calise, 2005); 3) NN-based identification models do not provide any physical insight on the process under consideration (Ge et al., 2002), and 4) all aforementioned works are incapable of guaranteeing the convergence of the residual speed and manifold pressure estimation errors to zero.

Based on a passivity framework (Sontag and Wang, 1995), in Yu and Li (2001) adaptive laws for the weights of linear in the weights dynamic NN were proposed to ensure convergence of the speed and manifold pressure estimation errors to a neighborhood of the origin. It was showed that robust techniques such as dead-zone and σ-modification (Ioannou and Sun, 1995) are not necessary to ensure stability of gradient descent algorithms for weight adjustment in the presence of modeling error and bounded disturbances. In order to improve the approximation capability, nonlinear in the weights dynamic NN have been used to parameterize a 1.6 liter, 4-cilinder fuel injected engine, as reported in Yu et al. (2001). Based on the stability proof, learning laws for the weights were chosen to guarantee that the state errors were all bounded.

Recently in Vargas and Hemerly (2007), a robust modification for the weight adaptive law in neuro-identification problems was proposed to ensure, in contrast to the literature, that the prediction error converges to zero in the presence of approximation error and disturbances. The adaptive law consisted of a leakage modification of a standard gradient descent algorithm. However, in contrast to commonly leakage modifications (Ioannou and Su, 1995) which aim at stability in the presence of approximation errors and disturbances, the leakage term was introduced for, in addition to stability, ensuring that the state error converges to zero. It was proved by using usual Lyapunov arguments and an adaptive bounding technique (Polycarpou, 1996) that the state error converges asymptotically to zero, whereas the others error signals remain bounded. However, some assumptions on the design parameters, which can be hard to be verified in practice, are necessary to ensure convergence to zero.

In this paper, motivated by the previous facts, we propose an on-line identification algorithm, without NN, for estimating the main parameters in the engine, and in addition, for ensuring the state error convergence to zero, even in the presence of internal and external disturbances. Based in the methodology introduced in Vargas and Hemerly (2007) and a 1.6 liter, 4-cilinder fuel injected engine model proposed by Powell and Cook (1987), it is proposed an identification model and parameter adaptation law that ensure bounded identification of the manifold and rotational constants and, at the same time, the asymptotical convergence of the speed and manifold pressure to the true values. Since the proposed method is valid to any operation points, in contrast to others models derived from steady-state map data and other empirical information, and it ensures convergence, is very adequate for identification-based control purposes.

2. PROBLEM FORMULATION

Consider an engine model operating under idle (Powell and Cook, 1987) described by

$$\dot{P} = k_p\left(\dot{m}_{ai} - \dot{m}_{ao}\right) + v_1 \tag{1}$$

$$\dot{N} = k_n\left(T_i - T_l\right) + v_2 \tag{2}$$

where

$\dot{m}_{ai} = \left(1 + k_{m1}\theta + k_{m2}\theta^2\right)g(P)$,

$\dot{m}_{ao} = -k_{m3}N - k_{m4}P + k_{m5}NP + k_{m6}NP^2$,

$g(P) = \begin{cases} 1 & P \le 50.6625 \\ 0.0197\sqrt{101.325P - P^2} & P > 50.6625 \end{cases}$,

$T_i = -39.22 + 325024 m_{ao} - 0.0112\delta^2 + 0.635\delta + (2\pi/60)(0.0216 + 0.000675\delta)N - (2\pi/60)^2 0.000102N^2$,

$T_l = (N/263.17)^2 + T_d$, $m_{ao} = \dot{m}_{ao}(t-\tau)/(120N)$, $k_p = 42.40$, $k_n = 54.26$, $k_{m1} = 0.907$, $k_{m2} = 0.0998$,

$k_{m3} = 0.0005968$, $k_{m4} = 0.1336$, $k_{m5} = 0.0005341$, $k_{m6} = 0.000001757$,

P is the manifold pressure (kPa),

N is engine speed (rpm),

δ is the spark advance (degrees),

θ is the throttle angle (degrees),

$\dot{m}_{ai}$ is the mass flow rate into the manifold,

$\dot{m}_{ao}$ is the mass flow rate out of the manifold and into the cylinder,

T_d are disturbances which act to the engine as unmeasured accessory torque (N-m)

T_i is the internally developed torque (N.m),

T_l is the load torque made up of accessory torque T_d and shaft torque (N.m),

$g(P)$ is a manifold pressure influence function,

m_{ao} is the air mass in the cylinder,

τ is a dynamic transport time delay,

k_p is a manifold dynamics constant,

k_n is a rotational dynamics constant, and

v_1, v_2 are bounded internal or external disturbances.

The meaning of the main variables of the model is showed in Fig. 1 (Vachtsevanos et al., 1993). For a more detailed discussion on the engine dynamic and equations above see Puskorius and Feldcamp, (1994) and the references therein.

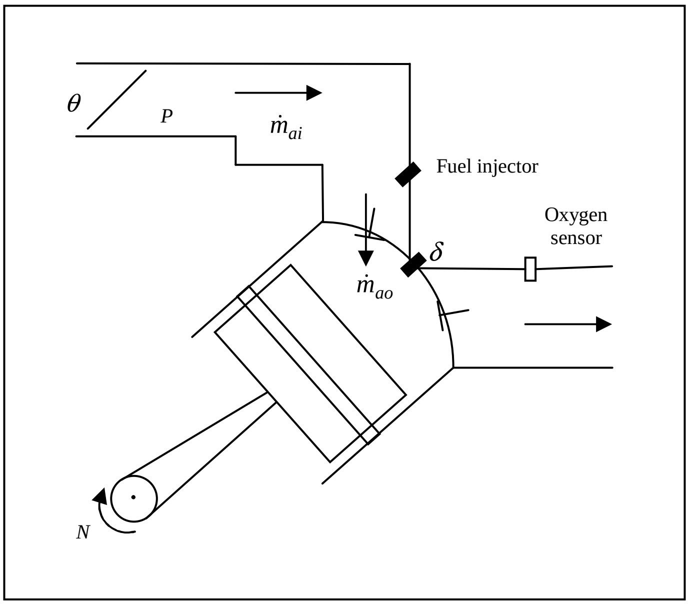

Figure 1. The main engine subsystem.

By defining $x = [P \quad N]^T$, $u = [\theta \quad \delta]^T$, the engine model (1)-(2) can be rewritten as

$$\dot{x} = \overline{W}\pi(x,u) + \overline{h}(x,u,t) \tag{3}$$

$$\pi = \begin{bmatrix} \dot{m}_{ai} - \dot{m}_{ao} \\ T_i - (N/263.17)^2 \end{bmatrix} \tag{4}$$

$$\overline{W} = \begin{bmatrix} k_p & 0 \\ 0 & k_n \end{bmatrix}, \ \overline{h} = \begin{bmatrix} v_1 \\ v_2 - k_n T_d \end{bmatrix} \tag{5}$$

where $x \in \Re^2$ is the state vector, $u \in \Re^2$ is the control input, $\overline{W}$ is an unknown parameter matrix, $\overline{h} \in \Re^2$ is a vector of time varying uncertain variables, which includes T_d and others internal or external disturbances.

We assume that the following can be established

Assumption 1: For all $t \geq 0$

$$\left\| \overline{h}(x,u,t) \right\| \leq \overline{h}_0 \tag{6}$$

where $\overline{h}_o \geq 0$ is an known constant.

Remark 1: To avoid confusion, we define $\overline{h}_0$ to be the smallest constant such that (6) are satisfied.

The goal is to design an on-line identifier for the system (1)-(2), which ensures asymptotic estimation of the states, even in the presence of internal or external disturbances.

It should be highlighted that system on-line identification is important not only to predict the behavior of the system, but also for providing an appealing system parameterization, which can later be used in the synthesis of control algorithms, since mathematical characterization is often a prerequisite to controller design.

3. IDENTIFICATION MODEL AND STATE ERROR EQUATION

We start by presenting the identification model and the definition of the relevant errors associated with the problem.

Note that (3) can be rewritten as

$$\dot{x} = BW\pi(x,u) + h(x,u,t) \tag{7}$$

where $B \in \Re^{2\times 2}$ is a scaling matrix defined as $B = diag(b_i)$, $b_i \neq 0$, $h = \bar{h} + (\overline{W} - BW)\pi$, and W is a properly selected parameter matrix. It should be noted, based on (6), that for all $t \geq 0$ we have $\|h(x,u,t)\| \leq h_0$ for some positive constant h_0.

Remark 2: The matrix B provides an additional degree of freedom for shaping the transient performance.

The structure (7) suggests an identification model of the form

$$\dot{\hat{x}} = A(\hat{x} - x) + B\hat{W}\pi(x,u) \tag{8}$$

where A is a stability matrix, $\hat{x}$ is the estimated state, and $\hat{W}$ is the estimated parameter. It will be demonstrated that the identification model (8), along with the adaptation law for $\hat{W}$, to be stated in the next, ensures asymptotic convergence of the state error, even in the presence of disturbances.

Remark 3: A drawback with identification models based as (8) is that they are not suitable for prediction, since such schemes can only work on-line, because their weights cannot converge to the ideal ones (Yu et al., 2001). The proposed identification model (8) also suffers from this. However, similarly to other models, for instance these based on neural networks, it is relevant for identification-based control. Moreover, the parameterization (8) allows the establishment of a state error equation which is later used in the stability analysis.

Define the state estimation error as $\tilde{x} := \hat{x} - x$. Using (7) and (8), we formulate the state estimation error equation as follows:

$$\dot{\tilde{x}} = A\tilde{x} + B\tilde{W}\pi(x,u) - h(x,u,t) \tag{9}$$

where $\tilde{W} := \hat{W} - \overline{W}$.

4. ADAPTIVE LAW AND STABILITY ANALYSIS

The adaptive laws in this section are based on a Lyapunov-like analysis, and ensure bounded estimation errors. In addition, we show asymptotic convergence of the prediction error in the presence of approximation error and disturbances. The proposed adaptive law employs ε_1-modification (Ioannou and Sun, 1995), with a dynamic leakage gain to ensure robustness against approximation error and disturbances. Dynamic leakage gains have been used in Chai and Tao (1994) and Vargas (1997) where robust adaptive control of linear plants and on-line identification of dynamical systems, respectively, were studied.
Before presenting the main theorem, we state a fact, remark and lemma, which will be used in the stability analysis.

Fact 1: Let $W, W_0, \hat{W}, \tilde{W} \in \Re^{2\times 2}$ and $\overline{C} \in \Re^{2\times 2}$ be a diagonal matrix such that $\overline{C}^T\overline{C} = C$, where $C = diag(c_i)$, $c_i > 0$. Then, with the definition of $\tilde{W} = \hat{W} - W$, the following equalities are true:

$$\begin{gathered} 2tr\tilde{W}^T C(\hat{W} - W_0) = \|\overline{C}\tilde{W}\|_F^2 + \|\overline{C}(\hat{W} - W_0)\|_F^2 - \|\overline{C}(W - W_0)\|_F^2 \\ 2tr\hat{W}^T W_0 = \|\hat{W}\|_F^2 + \|W_0\|_F^2 - \|\hat{W} - W_0\|_F^2 \end{gathered} \tag{10}$$

Remark 4: The first equality in (10) leads to the following inequality:

$$2tr\left[\tilde{W}^T C(\hat{W} - W_0)\right] \geq c_{i\,min}\|\tilde{W}\|_F^2 + c_{i\,min}\|\hat{W} - W_0\|_F^2 - c_{i\,max}\|W - W_0\|_F^2 \tag{11}$$

where $c_{i\,max} = max(c_i)$ and $c_{i\,min} = min(c_i)$.

Lemma 4.1: Let a scalar bounding function be given by

$$\dot{\hat{\psi}} = -\gamma_\psi \|\tilde{x}\| \left[2\alpha_1 l(\hat{\psi},\psi)\hat{\psi} - \alpha_2 \left(\|\hat{W}\|_F^2 + \|W_0\|_F^2 \right) - 2\alpha_1 l(\hat{\psi},\psi)\psi \right] \tag{12}$$

where

$$l(\hat{\psi},\psi) = \frac{2l_0}{\hat{\psi}+\psi} \tag{13}$$

and $\gamma_\psi, l_0, \alpha_1, \alpha_2, \psi > 0$. Then, subject to the condition

$$\hat{\psi}(0) \geq \delta\psi \tag{14}$$

where $\delta = \dfrac{4\alpha_1 l_0 + \alpha_2 \|W_0\|_F^2}{4\alpha_1 l_0}$, the bounding function is lower bounded, for all $t \geq 0$, by

$$\hat{\psi}(t) \geq \delta\psi \tag{15}$$

Proof: Consider the Lyapunov-like function

$$V_\psi = \hat{\psi}\,\gamma_\psi^{-1}\hat{\psi}/2 \tag{16}$$

By taking the derivative of (16) along (12) we obtain

$$\dot{V}_\psi = -\hat{\psi}\|\tilde{x}\| \left[2\alpha_1 l\,\hat{\psi} - \alpha_2 \left(\|\hat{W}\|_F^2 + \|W_0\|_F^2 \right) - 2\alpha_1 l\,\psi \right] \tag{17}$$

Furthermore, based on (12) and (14) it follows that $\hat{\psi}(t) > 0$ for all $t \geq 0$. Then, with the definition (13), the Lyapunov derivative (17) can lower bounded as

$$\dot{V}_\psi \geq -2\alpha_1 l\,\hat{\psi}\|\tilde{x}\|[\hat{\psi} - \delta\psi] \tag{18}$$

Hence, if $\hat{\psi} \leq \delta\psi$ we have $\dot{V}_\psi \geq 0$, which implies that the bounding function is directed towards the outside or boundary of the region $\{\hat{\psi} \mid \hat{\psi} \leq \delta\psi\}$. Consequently, based on (14), it follows that $\hat{\psi} \geq \delta\psi$ for all $t \geq 0$.

□

We now state and prove the main theorem of the paper.

Theorem 4.1: Consider the class of nonlinear systems described by (7), which satisfy Assumption 1. Let the weight law be given by

$$\dot{\hat{W}} = -\gamma_W \left\{ 2C(\hat{\psi} - \psi)\left[\hat{W} - \left(I - \alpha_2 C^{-1} \right) W_0 \right] \|\tilde{x}\| + BK\tilde{x}\pi^T(x,u) \right\} \tag{19}$$

where $\hat{\psi}$ is given by (12), $\gamma_W > 0$, I is an identity matrix, $K = P^T + P$, P is the unique positive definite solution of the Lyapunov equation

$$L^T P + PL = Q \tag{20}$$

where $L > 0$ and $Q > 0$. Then, subject to the condition (14), and if

$$\psi = \frac{2\alpha_4 \|KB\|_F}{\alpha_1 l_0} \tag{21}$$

$$\alpha_2 \le c_{i\,min} \tag{22}$$

$$W^T W_0 \le 0 \tag{23}$$

$$\beta_1 \le \|W - W_0\|_F \le \beta_2 \tag{24}$$

where

$$\alpha_4 = \left\|B^{-1}\right\|_F h_0\,,\ \beta_1 = \frac{4\alpha_1 l_0}{\|W_0\|_F \sqrt{\alpha_2 c_{i\,max}}}\,,\ \ \beta_2 = \sqrt{\frac{\alpha_1 l_0}{2c_{i\,max}}}\,,\ \alpha_3 = \lambda_{min}(Q) \tag{25}$$

the error signals $\tilde{x}, \tilde{W}, \tilde{\psi}$ are uniformly bounded and $lim_{t\to\infty} \tilde{x}(t) = 0$.

Proof: Consider the candidate Lyapunov function

$$V = \tilde{x}^T P \tilde{x} + \tilde{W}^T \gamma_W^{-1} \tilde{W}/2 + \tilde{\psi}\,\gamma_\psi^{-1} \tilde{\psi}/2 \tag{26}$$

where $\tilde{\psi} = \hat{\psi} - \psi$.

By evaluating (26) along the trajectories of (9), (12) and (19), we obtain

$$\begin{aligned} \dot{V} &= -\tilde{x}^T \left(L^T P + PL\right)\tilde{x} - \tilde{x}^T Kh \\ &\quad - 2\tilde{\psi}\|\tilde{x}\|\,\tilde{W}^T C\left(\hat{W} - W_0\right) - 2\alpha_2 \tilde{\psi}\|\tilde{x}\|\tilde{W}^T W_0 \\ &\quad - 2\alpha_1 l\,\tilde{\psi}\hat{\psi}\|\tilde{x}\| + \alpha_2\left(\left\|\hat{W}\right\|_F^2 + \|W_0\|_F^2\right)\tilde{\psi}\|\tilde{x}\| + 2\alpha_1 l\,\psi\tilde{\psi}\|\tilde{x}\| \end{aligned} \tag{27}$$

By using Fact 1, the representation $2\tilde{\psi}\hat{\psi} = \tilde{\psi}^2 + \hat{\psi}^2 - {\psi^*}^2$, and (20), the Lyapunov derivative can be written as

$$\begin{aligned} \dot{V} &= -\tilde{x}^T Q\,\tilde{x} - \tilde{x}^T KB\left(B^{-1}h\right) \\ &\quad - \tilde{\psi}\|\tilde{x}\|\left[\left\|\overline{C}\,\tilde{W}\right\|_F^2 + \left\|\overline{C}\left(\hat{W} - W_0\right)\right\|_F^2 - \left\|\overline{C}\left(W - W_0\right)\right\|_F^2\right] + 2\alpha_2\tilde{\psi}\|\tilde{x}\|tr\left(W^T W_0\right) \\ &\quad - \alpha_1 l\left(\tilde{\psi}^2 + \hat{\psi}^2 - \psi^2\right)\|\tilde{x}\| + \alpha_2\left\|\hat{W} - W_0\right\|_F^2 \tilde{\psi}\|\tilde{x}\| + 2\alpha_1 l\,\psi\tilde{\psi}\|\tilde{x}\| \end{aligned} \tag{28}$$

Furthermore, by using Remark 4, condition (23), Lemma 4.1, and notation (25), the Lyapunov derivative (28) can upper bounded as

$$\begin{aligned} \dot{V} \le \|\tilde{x}\|\cdot\Big[&-\alpha_3\|\tilde{x}\| + \alpha_4\|KB\|_F \\ &- \tilde{\psi}\left(c_{i\,min}\left\|\tilde{W}\right\|_F^2 + c_{i\,min}\left\|\hat{W} - W_0\right\|_F^2 - c_{i\,max}\|W - W_0\|_F^2\right) \\ &- \alpha_1 l\left(\tilde{\psi}^2 + \hat{\psi}^2 - \psi^2\right) + \alpha_2\left\|\hat{W} - W_0\right\|_F^2 \tilde{\psi} + 2\alpha_1 l\,\psi\tilde{\psi}\Big] \end{aligned} \tag{29}$$

Further using (22) and rearranging terms, we obtain

$$\begin{aligned} \dot{V} \le \|\tilde{x}\|\cdot\Big[&-\alpha_3\|\tilde{x}\| - c_{i\,min}\tilde{\psi}\left\|\tilde{W}\right\|_F^2 - \alpha_1 l\,\tilde{\psi}^2 \\ &+ \alpha_4\|KB\|_F \quad + c_{i\,max}\tilde{\psi}\|W - W_0\|_F^2 \\ &- \alpha_1 l\left(\hat{\psi}^2 - \psi^2\right) + 2\alpha_1 l\,\psi\tilde{\psi}\Big] \end{aligned} \tag{30}$$

By employ the definition of ψ, see (21), recalling that $\tilde{\psi} = \hat{\psi} - \psi$, and using Lemma 5.1, (30) reduces to

$$\begin{aligned}\dot{V} \le \|\tilde{x}\| \cdot \Big[& -\alpha_3 \|\tilde{x}\| - c_{i\,min} \tilde{\psi} \|\tilde{W}\|_F^2 - \alpha_1 l \tilde{\psi}^2 \\ & + \left(\alpha_1 l_0 / 2 + c_{i\,max} \|W - W_0\|_F^2\right) \hat{\psi} - c_{i\,max} \psi \|W^* - W_0\|_F^2 \\ & - \alpha_1 l \hat{\psi}^2 + \alpha_1 l \psi^2 + 2\alpha_1 l \psi \tilde{\psi} \Big]\end{aligned} \tag{31}$$

which, by using (13), implies

$$\begin{aligned}\dot{V} \le \|\tilde{x}\| \cdot \Big[& -\alpha_3 \|\tilde{x}\| - c_{i\,min} \tilde{\psi} \|\tilde{W}\|_F^2 \\ & + \left(\alpha_1 l_0 / 2 + c_{i\,max} \|W - W_0\|_F^2\right) \hat{\psi} - c_{i\,max} \psi \|W - W_0\|_F^2 \\ & - \frac{2\alpha_1 l_0}{\hat{\psi} + \psi} \hat{\psi}^2 + 4\alpha_1 l_0 \psi^2 / \hat{\psi} \Big]\end{aligned} \tag{32}$$

Thus by using Lemma 5.1 and rearranging terms in (32), we finally obtain

$$\begin{aligned}\dot{V} \le \|\tilde{x}\| \cdot \Bigg\{ & -\alpha_3 \|\tilde{x}\| - c_{i\,min} \tilde{\psi} \|\tilde{W}\|_F^2 \\ & - \psi \left(c_{i\,max} \|W^* - W_0\|_F^2 - \frac{(4\alpha_1 l_0)^2}{\alpha_2 \|W_0\|_F^2} \right) \\ & - \frac{\alpha_1 \hat{\psi}^2}{\hat{\psi} + \psi^*} \left[l_0 - \left(l_0 / 2 + c_{i\,max} \|W^* - W_0\|_F^2 / \alpha_1 \right) \right] \\ & - \frac{\alpha_1 \hat{\psi}}{\hat{\psi} + \psi^*} \left[l_0 \hat{\psi} - \left(l_0 / 2 + c_{i\,max} \|W^* - W_0\|_F^2 / \alpha_1 \right) \psi^* \right] \Bigg\}\end{aligned} \tag{33}$$

It addition, we note from (24) that

$$\|W - W_0\|_F^2 \ge \frac{(4\alpha_1 l_0)^2}{\alpha_2 c_{i\,max} \|W_0\|_F^2}, \quad \frac{l_0}{2} \ge c_{i\,max} \|W - W_0\|_F^2 / \alpha_1 \tag{34}$$

By substituting (34) into (33), and using Lemma 4.1, we arrive at

$$\dot{V} \le -\alpha_3 \|\tilde{x}\|^2 \tag{35}$$

Hence, the error signals $\tilde{x}, \tilde{W}, \tilde{\psi}$ are uniformly bounded. Further, since V is bounded from below and non increasing with time, we have

$$lim_{t \to \infty} \int_0^t \|\tilde{x}(\tau)\|^2 \, d\tau \le \frac{V(0) - V_\infty}{\alpha_3} < \infty \tag{36}$$

where $lim_{t \to \infty} V(t) = V_\infty < \infty$. Notice that with the bounds on $\tilde{x}, \tilde{W}, \tilde{\psi},$ and h, $\|\tilde{x}\|^2$ is uniformly continuous. Thus from (9), it follows that $\dot{\tilde{x}}$ is bounded. Hence by Barbalat´s lemma (Ioannou and Sun, 1995), we conclude that $lim_{t \to \infty} \tilde{x}(t) = 0$.

□

Remark 5: Conditions (14), (20), and (22) are trivial since them are defined by the user according to a desired performance. Condition (21) implies a previous knowledge of an upper bound for the disturbances, which is assumed in (6). Condition (23) is trivial since the matrix W is previously known. The previous knowledge of bounds for the modeling error and parameter is not peculiar to the proposed scheme. Most robust modifications in the literature, as for example, switching-σ, parameter projection, and dead-zone require *a priori* information on the plant or modeling error for ensuring stability, as reported in Ioannou and Sun (1995).

Remark 6: A sufficient interval condition for satisfying (24) can be formulated as

$$\frac{2c_{i\,max}}{\alpha_1}\left\|W - W_0\right\|^2 \leq \; l_0 \; \leq \frac{\sqrt{c_{i\,max}\alpha_2}\left\|W_0\right\|}{4\alpha_1}\left\|W - W_0\right\| \tag{37}$$

Observe that there is at least one way of selecting the design parameters to satisfy (37): by selecting a conservative $\left\|W_0\right\|_F$ (large enough) and, in the sequence, by adjusting $\left\|W - W_0\right\|_F$ (small enough).

Remark 7: Although the ultimate bound for the residual state error can be controlled to be asymptotically null by choosing appropriately some design parameters, as W_0 and *B*, it may be nontrivial to control the transient performance, due to the cross dependence between some design parameters, as shown in (22). Then, an extensive trial and error procedure may be needed.

5. SIMULATIONS

In this Section simulations are presented to show the application and the performance of the proposed method. We select θ as being a square wave with amplitude 20^o, frequency 0.25 rad/s, δ as a sine wave with amplitude 30^o, frequency 0.5 rad/s, T_d as a sawtooth wave with amplitude 10 N.m, frequency 0.5 rad/s, $\tau = 0$, and $x(0) = [10 \quad 500]^T$. The measurements of *P* and *N* are contaminated with two square waves of 1 Hz and amplitudes of 0.5 kPa and 10 rpm respectively. The performance in the estimation of the manifold pressure and engine speed are shown in Figures 2-3. We can see that the simulations confirm the theoretical results, that is, the algorithm is stable and the residual state error is small.

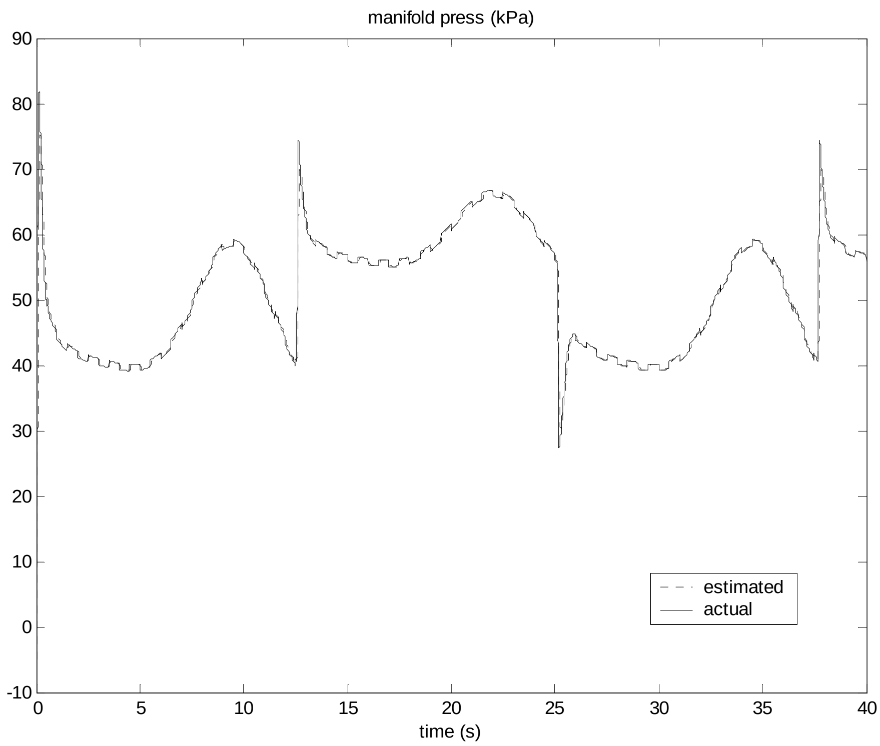

Figure 2- Performance in the estimation of *P*.

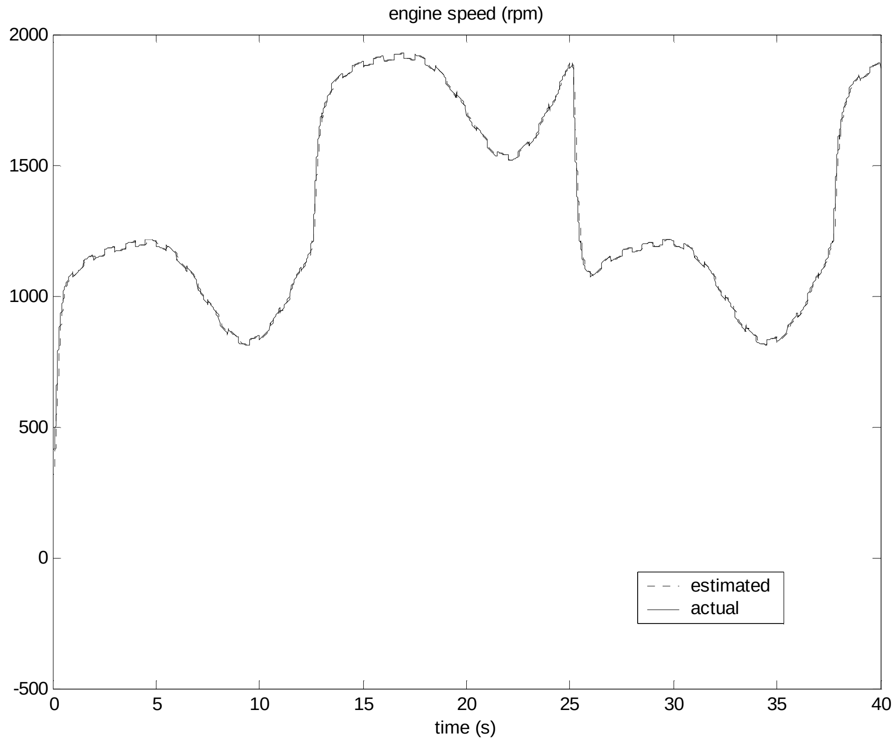

Figure 3- Performance in the estimation of *N*.

6. CONCLUSIONS

In this paper we have proposed an identification model and an associated parameter adaptation law for identifying the manifold and rotational constants and estimating the speed and manifold pressure of a 1.6 liter, 4-cilinder fuel injected engine. It was proved, by using Lyapunov arguments and an adaptive bounding technique, that the entire identification process is stable, ensuring both the estimation with bounded errors of the engine parameters and the convergence of the speed and manifold pressure estimations to their true values. Further results aiming adaptive observation and control are under investigation and will be opportunely reported.

7. ACKNOWLEDGEMENTS

The authors acknowledge the support from FINEP, and from the Reference Center of Gas Turbines of ITA, headed by professor João Roberto Barbosa.

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