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# ROBUST, PREDICTIVE, NEURO FUZZY, MULTIPLE MODEL TECHNIQUES TO CONTROL THE AIR-TO-FUEL RATIO IN NATURAL GAS ENGINES

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***Abstract.*** *The recent announcement of the existence of giant natural gas fields near the largest Brazilian cities has put the automotive usage of the gas under strong expectatives. Use of natural gas as an alternative fuel is pursued since long time and for passenger cars an expressive number of feasible solutions are already implemented. On the other hand, the transformation of middle or big engines, as those used on buses and trucks, to run on natural gas did not reach the same performance specially when one considers pollutant emissions. This paper deals with the design of robust(LMI), predictive (GPC), optimal (LQR) Multiple Model based controllers to maintain the stoichiometric air-to-fuel ratio in order to guarantee the efficiency of the catalitic converter and, in consequence, low emission levels, even in the occurence of large transients. Switching techniques, including a new Neuro-Fuzzy approach, are proposed and simulated on a numerical environment that corresponds to the dynamic model of a typical bus engine converted to use natural gas instead of Diesel oil.*

***Keywords:*** *Internal Combustion Engine , Natural Gas, GPC Controller, LQR Controller, LMI Controller, Multiple Models, Fuzzy Logic.*

## 1. Introduction

Regulations concerning pollutant emissions from internal combustion engines (ICE) and the increasing oil prices in the international markets have been driving factors for the development of modern engines, some running in alternative fuels. Many control technologies have been added to fuel injection and ignition systems in order to achieve the desired figures of low fuel consumption and low pollutant emission (Moskwa and Hedrick, 1992; King and Watson, 2000). For example, in the case of light engines fuel passenger cars, advanced material and control technology made possible the use of compressed natural gas (CNG), a type of fuel with a small contribution to the power matrix all over the world. On the other hand, the transformation of medium and heavy engines, as those used on buses or trucks, remains problematic since these engines are submitted to acceleration transients most part of the time. In consequence, they produce more emissions and there is a lack of equipments to manage that, in a time that the national state oil company announces the existence of giant natural gas fields near the largest Brazilian cities, a fact that puts strong expectations on the spreading use of natural gas.

As part of a large project aiming to make feasible the use of CNG on urban buses, IPT and Escola Politécnica / USP teams have been dealing with topics such as the design of new combustion chambers or natural gas fuel injection and ignition control systems under transient conditions. This work is related to this last topic and describes the design of different controllers to regulate the air-to-fuel ratio. In other words, an efficient mean to reduce pollutant emissions corresponds to the use of a 3-way catalitic converter combined to near stoichiometric mixtures on the injection system (the other is the use of lean burn mixtures). This combination implies a complex control problem since a 1% deviation in the air-to-fuel ratio relative to the stoichiometric value may correspond to a 50% degradation in the catalitic converter efficiency (Dan Cho and Oh, 1993) and a considerable increase of emissions mainly $NO_x$. Therefore, a quite accurate fuel injection and ignition control system implemented through electronic means is a need. Several control strategies have been investigated based on robust (LMI), predictive (GPC) and optimal (LQR) approaches (Freitas Jr, 2003) coupled to Multiple Models techniques to take into account the non-linear engine behavior (Fleury et al., 1999a). Neuro Fuzzy and Error Model based switching methods have also been analyzed (Starr, 2003; Freitas Jr, 2004) because of the loop sensitivity to abrupt changes in the models. The results achieved on a numerical simulator show that robust or predictive approaches work very well even for long excursion transients but a controller as simple as a LQR one requires some additional cares to reach a performance similar to the other controllers.

## 2. Engine Model

A simplified engine simulation model for control and identification purposes has been designed based on a real six cylinders, six liters diesel bus engine converted to compressed natural gas (CNG) use (Otto spark cycle). Three main modules are used to describe its behavior with good accuracy: intake manifold, combustion dynamics and torque and rotational inertias. This model is implemented in Matlab- Simulink™ environment, as shown in Fig. 1.

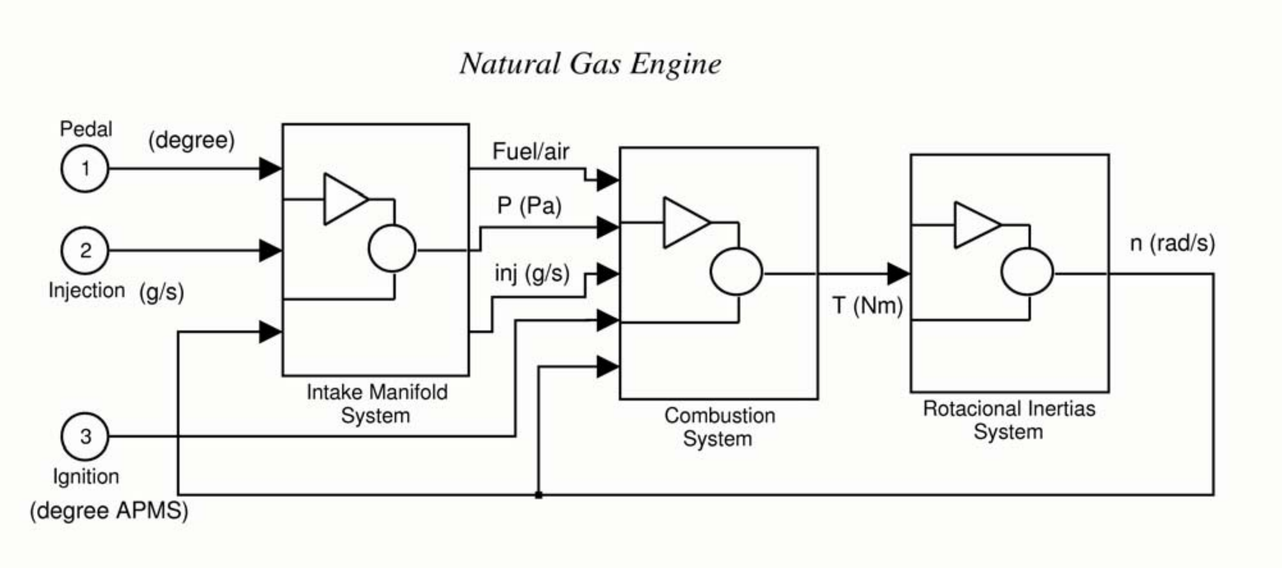


Figure 1. Natural Gas Model Engine

In order to design a model based controller, a linear or non linear mathematical model of the plant has to be available. A non linear model has been implemented as in the scheme above and used in several works of the group (Lopes, 1996; Fleury et al., 1999b; Freitas Jr, 2003). In this paper the three control techniques multiple model GPC, LQ and LMI, use different switching strategies to change between linearized models. The GPC approach is based on a priori identified linearized models for several butterfly valve angles. From the other side, the LQR and LMI controllers require state space linearized models for the same valve apertures.

The air mass flow through the butterfly valve is considered as a compressive flow through an orifice and given by:

$$va_b = \begin{cases} 0{,}06502 \cdot A(\alpha) \cdot p^{0{,}714 \cdot \left(1 - \frac{p}{10^5}\right)^{0{,}143}} & \text{if } p > 5{,}28 \cdot 10^4 \text{ Pa} \\ 186{,}7579 \cdot A(\alpha) & \text{if } p \le 5{,}28 \cdot 10^4 \text{ Pa} \end{cases} \tag{1}$$

where $A(\alpha)$ corresponds to the valve area:

$$A(\alpha) = 2{,}5 \cdot 10^{-3} \cdot \pi \cdot \left( \frac{3 - 2 \cdot \cos(\alpha) - \cos^2(\alpha)}{16} \right) \tag{2}$$

and $p$ to the pressure in the manifold.

The fuel mass flow through injection valve $vc_a$ is modeled as a transport delay relative to the air flow in the butterfly valve plus a smoothing factor represented by a first order function (Moskwa and Hedrick, 1992). This leads to

$$vc_a = \frac{1}{0{,}01 \cdot s + 1} \cdot e^{-0{,}01 \cdot s} \cdot vc_b \tag{3}$$

The fuel-to-air ratio in the butterfly valve is defined by

$$\Phi_b = 14{,}5 \cdot \frac{vc_b}{va_b} \tag{4}$$

where the 14,5 factor is a scale factor that represents the stoichiometric air-to-fuel ratio. From the other side, the symbol $\Phi_e$ will be used to designate the burnt mixture that, after combustion, reaches the exhaust manifold and is sensed by the lambda sensor.

The manifold pressure dynamics $p$ is a function of the difference between the mass air flows at the injection valve and at the butterfly valve, given by

$$\dot{p} = 43624000 \cdot va_b - \frac{1{,}35}{\pi} \cdot n \cdot p \tag{5}$$

The net torque generated by the ICE is supposed to depend on the engine rotation, on the mass fuel flow through the intake valve and on the engine efficiency (an experimental curve)

$$T_{ind} = 4{,}0 \cdot 10^7 \cdot vc_a \cdot Ef \cdot \frac{1}{n} \tag{6}$$

where *Ef* is the engine volumetric efficiency and $vc_a$ is given by:

$$vc_a = \frac{5{,}4 \cdot 10^{-3}}{174496 \cdot \pi} \cdot n \cdot p \tag{7}$$

The engine rotation is calculated by the difference between the net torque and the load and friction torques, where the last two torques are assumed to change linearly with the rotation. Admitting that the engine moment of inertia is $J=120 Kg\ m^3/s^2$, the corresponding equation is given by:

$$\dot{n} = (4{,}0 \cdot 10^7 \cdot vc_a \cdot Ef \cdot \frac{1}{n} - 2{,}22 \cdot n + 66{,}3) \cdot \frac{1}{120} \tag{8}$$

After making the necessary mathematical simplifications, a state space non linear model for the CNG engine can be written as (Freitas Jr, 2003):

$$\dot{x}_1 = -300 \cdot x_1 - 20000 \cdot x_2 + vc_b \tag{9}$$

$$\dot{x}_2 = x_1 \tag{10}$$

$$\dot{x}_3 = -2 \cdot n \cdot x_3 + \frac{1265096 \cdot 10^6 \cdot \pi}{27 \cdot n \cdot p} \cdot \left(-x_1 + 200 \cdot x_2\right) \tag{11}$$

$$\dot{x}_4 = -200 \cdot x_4 + 4 \cdot n \cdot x_3 - \frac{1265096 \cdot 10^6 \cdot \pi}{27 \cdot n \cdot p} \cdot \left(-x_1 + 200 \cdot x_2\right) \tag{12}$$

$$\dot{p} = va_b \cdot 4{,}364 \cdot 10^7 - \frac{1{,}35}{\pi} \cdot n \cdot p \tag{13}$$

$$\dot{n} = \left(8{,}0 \cdot 10^9 \cdot \left(-x_1 + 200 \cdot x_2\right) \cdot Ef \cdot \frac{1}{n} - 2{,}22 \cdot n + 66{,}3\right) \cdot \frac{1}{120} \tag{14}$$

and the algebraic equations:

$$\Phi_b = 14{,}5 \cdot \frac{vc_b}{va_b} \tag{15}$$

$$\Phi_e = 400 \cdot x_4 - 4 \cdot n \cdot x_3 + \frac{1265096 \cdot 10^6 \cdot \pi}{27 \cdot n \cdot p} \cdot \left(-x_1 + 200 \cdot x_2\right) \tag{16}$$

The control techniques that require explicit plant models, as LQR and LMI, rely on linearized approximations of Eq. (9) to (16) for different acceleration pedal positions, that is, for different values of the $\alpha$ angle in Eq. (2). The model bank required for the Multiple Model implementation is composed by linearized versions calculated using a vector of steady state values of $x_1, x_2, x_3, x_4, p, n, vc_b$ and for each chosen value of the $\alpha$ angle of the butterfly valve.

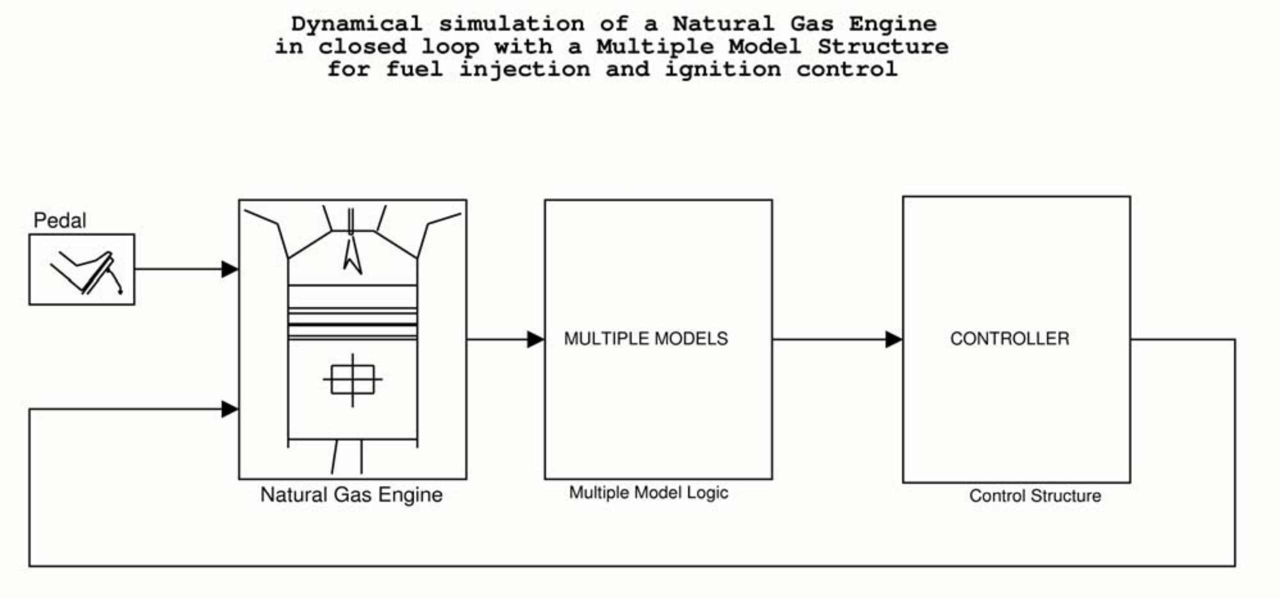


Figure 2. Natural Gas Engine Simulator

Figure 2 shows a schematic diagram of the simulator which comprises ICE, controller and Multiple Models switching logic used to develop controller designs under any of the control techniques. The butterfly valve transients commanded by the accelerator (input block on Fig. 2) is modeled as a first order transfer function, corresponding to the mean time a typical driver requires to change the accelerator pedal:

$$G_{ped} = \frac{1}{s + 0,4} \tag{17}$$

## 3. Multiple Model Structure

A linear model in each of the controllers is valid just for a narrow region around an operating point. Therefore, if one intends to achieve good performance under transient conditions, the model for control calculations must change according to different operating regions. Model tuning can be done by a Multiple Model strategy where the accuracies of several stored models are compared and the most adequate model to that particular condition is implemented.

The Multiple Model techniques have been used for nonlinear system control since the 70's with good results (Narendra et al., 1995). The nonlinear engine model represents the real system for this simulation study. The map of the engine is divided in 17 areas for Multiple Models calculation, where each area corresponds to one predefined angle of the valve butterfly opening, increasing of 10° (minimum flow) to 90° (maximum flow). The linear models are obtained then (by identification, in the case of GPC and by linearization, in the cases of LQ and LMI) for each area and implemented in the block of Multiple Models Logic (Fig. 2).

The structure of each one of GPC, LQ e LMI controllers is presented in the next section.

## 4. The GPC Controller

In this work, the basic GPC proposed by Clarke et al. (1987a and b) and adapted by Lopes (1996) for the engine applications is used. It is based on a discret linear time-invariant system with two inputs and two outputs represented by the polinomial form:

$$A(q^{-1})\cdot y(t)=B(q^{-1})\cdot u(t-1)+\frac{C(q^{-1})}{\Delta}\cdot\xi(t) \tag{18}$$

where

- *y(t)* is a 2 x1 vector that represents the temporal sequence of the plant output;
- *u(t)* is a 2 x1 vector that represents the temporal sequence of the plant input;
- $\xi(t)$ is a 2x1 vector that represents a Gaussian white noise of the plant input;
- $A(q^{-1})$, $B(q^{-1})$ and $C(q^{-1})$ are polinomial square matrix of order 2 representing the plant model description;
- $q^{-1}$ is the delay operator, that is, $q^{-1}\cdot f(t)=f(t-1)$ for any temporary sequence;
- $\Delta$ is a polinomial diagonal matrix: $\Delta=\begin{bmatrix}1-q^{-1} & 0\\ 0 & 1-q^{-1}\end{bmatrix}$, reminding that $(1-q^{-1})\cdot f(t)=f(t)-f(t-1)$, then each diagonal element of $\Delta$ is the differential operator;
- $I$ is the 2 order identity matrix.

The model represented by the Eq. (18) is known in the literature as CARIMA models - Controlled Auto Regressive and Integrated Moving Average, where the *A*, *B* and *C* matrices are obtained through the systems identification.

GPC Controllers are based on the optimization of the quadratic performance index *J* that utilizes explicitly a predictor of future outputs until a prediction horizon, based on the plant, is reached. The expression for the performance index is:

$$J=E\left\{\sum_{k=N_i}^{N_f}\left[y(t+k)-y_r(t+k)\right]^2+\sum_{k=0}^{N_u}\left[\Gamma\left(\Delta u(t+k-1)\right)^2\right]\right\}$$

where $N_i$ is the initial prediction horizon, $N_f$ is the final prediction horizon, $N_u$ is the control horizon, $y_r$ is the reference outputs vector and $\Gamma$ is the weight in the control variations.

The control actions are admitted null after a control horizon is reached. For this reason, GPC is classified usually as a strategy of finite horizon predictive control, based on model. In this article, only unrestricted GPC is used. Furthermore, the values of initial prediction horizon, final prediction horizon and control horizon are assumed as 3, 8 and 2, respectively. This way, an analytical control law can be obtained, instead of the case that includes state restrictions where only quasi-optimal numeric solutions can be reached. The main aspects about the GPC application to the control of the air-fuel ratio are discussed in Lopes (1996).

The polinomial structure of the GPC controller allows the use of a switching logic strategy of the Multiple Models theoretically more efficient than the formulation in state spaces as required by LQR and LMI controllers. This occurs because, in MMGPC all the 17 linear models are running simultaneously and therefore 17 error functions are sampled at regular time intervals. Supposing that, at a given instant, the *i*-th model has the least absolute value among the calculated error functions, the switching logic commands the change from the current model to the *i*-th model. The control actions for the next step are then calculated based on the *i*-th model and the same procedures are repeated in the subsequent time intervals.

## 5. The LQ Controller

Linear Quadratic (LQ) design is known as a simple design technique (Zhou and Doyle, 1998) which other advanced methods as GPC has originated from. Since the results achieved with GPC were considered very good, the decision in using LQR seemed to lead to "cheap" controllers with a "little degrated" performance when compared to GPC. We have designed a lot of MMLQ but never got near the GPC performance. This has changed with a different, new switching method based on a Neuro-Fuzzy approach (Starr, 2003) which uses a non-linear interpolation that takes into account besides the opening angle of the butterfly valve, the positions of each controller in the state space and the distance from the current engine point of operation to each of the controllers.

The resulting switching laws are mainly based on heuristics defined in natural language and later translated into a series of formal and precise rules. In this case, the heuristics is that the closer the engine point of operation is from a given controller, the larger is the weight attributed to that controller. This produces a *N* rules basis, where *N* is the number of linear controllers. Gaussian Error Functions are then employed as a Fuzzy group to generate the inference function $\mu_i(x)$ as:

$$\mu_i(x) = \prod_{j=1}^{N} e^{-\left(\frac{x_j - x_{ij}}{\sigma_{ij}}\right)^2} \tag{20}$$

where the subscript *i* means rule *i*, the subscript *j* represents each of the components of the extended state vector and $\sigma_{ij}$ as the radius of the Gaussian function for that variable. An advantage in using Gaussian function as group of pertinence is that these functions are never equal to zero.

Therefore, when accomplishing interpolation other controllers shall still influence in the answer since they use models linearized around operating points known with good accuracy. This fact induces an offset error, as large as the other controllers influence (this influence is represented for the values of $\sigma_{ij}$, one for each controller). To circumvent this problem a feedfoward neural network approach is used. This allows the application of backpropagation learning techniques, as used by (Brown and Harris, 1994), and the introduction of a weight matrix (Branco and Dente, 1998), leading to a controller structure given by:

$$\overline{u} = \frac{\sum_{i=1}^{N} \mu_i(\overline{x}_S)[W_i]\left([K_i]\overline{x} + u_{0i}\right)}{\sum_{i=1}^{N} \mu_i(\overline{x}_S)} \tag{21}$$

where $[W_i]$ is a diagonal square matrix of the same dimension as $[K_i]$.

The first step to design the controller corresponds to choose values for $\mu_i$. This was done using the already known stable points for each butterfly angle. On the other side, there is no efficient way to choose values for $\sigma_{ij}$. Following Fuzzy approaches, these parameters are calculated from a distance norm between different controllers in the state space. In other words, the $\sigma_j$ value of the *j*-th controller is calculated looking for the *i*-th controller with the operating point closer to the *j*-th and taking $\sigma_{ij}$ proportional to the distance between these points. In order to have valid values it is necessary that the various state variables have the same order of magnitude. Then, the state variables are reduced to the same scale through transformations that guarantee that the setpoints fall in a 0 to 1 interval. Instead of several $\sigma_{ij}$ for each rule, this method requires the calculation of just one value, $\sigma_i$. Besides that, instead of calculating several values of the Gaussian functions for each rule and after multiplying these values between them, one value of the Gaussian function and one value of an Euclidean norm are enough and the data processing becomes faster.

Based on this procedure, Eq. (21) becomes:

$$\mu_i(x) = e^{-\left(\frac{\left\| x_S - x_{Si} \right\|_2}{\sigma_i}\right)^2}$$

Numerical simulations have shown a great influence of $\sigma_i$ in the LQ Controller performance. Then, in the current version, we have decided to implement a scaled coefficient as

$$\sigma_i = \frac{d_i}{\xi_i} \tag{23}$$

where $d_i$ is the distance norm and $\xi_i$ the scale factor. Simulation results show that the lower the value of $\xi_i$ smoother is the engine response. On the other side, the offset becomes larger. Analysing the results the best value for $\xi_i$ was 0.5 since it provides the lowest off-set errors.

## 6. The LMI Controller

Considering a linear time invariant system modeled by the generalized plant:

$$\begin{cases} \dot{x} = A \cdot x + B_1 \cdot w + B_2 \cdot u \\ z_\infty = C_\infty \cdot x + D_{\infty 1} \cdot w + D_{\infty 2} \cdot u \\ y = C_y \cdot x + D_{y1} \cdot w + D_{y2} \cdot u \end{cases} \tag{24}$$

where $x$ is the state vector, $w$ is the disturbance vector, $y$ is the output vector and $z_\infty$ is a performance index to be minimized, one would like to design a controller of the type

$$\begin{cases} \dot{x}_k = A_k \cdot x_k + B_k \cdot y \\ u = C_k \cdot x_k + D_k \cdot y \end{cases} \tag{25}$$

In this case, the closed loop system is given by:

$$\begin{cases} \dot{x}_{close} = A_{close} \cdot x_{close} + B_{close} \cdot w \\ z_\infty = C_{close1} \cdot x_{close} + D_{close1} \cdot w \\ z_2 = C_{close2} \cdot x_{close} + D_{close2} \cdot w \end{cases} \tag{26}$$

The $H_\infty$ control problem through Linear Matrix Inequalities is solved by finding the $A_{close}, B_{close}, C_{close}$ and $D_{close}$ matrices that provide internal stability to the plant and simultaneously minimizes the objective function $J$ given by the $H_\infty$ norm of the transfer function ($T_{z_\infty w}$), from $w$ to $z_\infty$, that is:

$$J = \left\| T_{z_\infty w} \right\|_\infty = \max_w \bar{\sigma}\left[ T_{zw}(jw) \right]$$

The LMI switching logic is based on the butterfly valve position, where the supervisor chooses the linear model closer to a specific valve position, as in the GPC design. For the LMI ones, the inclusion of a module to estimate the injected fuel-mass based on the air volumetric flow through the butterfly valve is necessary. This is done by a mathematical model ($vz_{air}$) whose entries are the butterfly valve position and the intake manifold pressure. This case is the first where measurement of the manifold pressure is mandatory but in real world MAP (Manifold Air Pressure) sensors are implemented in several ICE versions.

The MAP sensor is modeled as a simple delay, as assumed by King and Watson (2000). These authors have observed that the lowest frequency for this type of sensor is 92 Hz when the highest depressurizations occur in the intake manifold. Then, the model is a delay with maximum time value of $\frac{1}{92}$ second and the air flow through the valve is obtained from:

$$vz_{air} = \begin{cases} 10^{-4} \cdot \left( -4 \cdot a^3 + 13 \cdot a^2 - a + 0{,}1 \right) \cdot \left( -5 \cdot 10^{-8} \cdot p^2 + 0{,}0054 \cdot p + 39{,}6 \right) & \text{if } p > 5{,}28 \cdot 10^4 \ Pa \\ -0{,}076 \cdot a^3 + 0{,}24 \cdot a^2 - 0{,}019 \cdot a + 0{,}002 & \text{if } p \le 5{,}28 \cdot 10^4 \ Pa \end{cases} \tag{27}$$

Equation (27) is also fed by an absolute pressure sensor and by the accelerator pedal position in order to determine the instantaneous air flow through the butterfly valve, that is required to calculate the fuel mass necessary to keep the stoichiometric mixture. In other words, the LMI controllers were designed under supervisory control strategies added to the multiple models scheme. In consequence, for transitory response, each control action is aided by the supervisory model in order to keep the stoichiometric mixture for the largest time interval, that is, to guarantee that the fuel/air ratio $\Phi_e$ has the least deviations in relation to the stoichiometric value.

## 7. Comparisons among MMGPC, MMLQ and MMLMI controllers

As described before, each control technique has required different switching strategies to tune the Multiple Models approach. For this reason, the results shown here synthetize, in just one case, a comparison between the best results for each of the three techniques. Several other figures should be found in other works of this group (Freitas Jr, 2003; Starr, 2003; Freitas Jr et al., 2004).

Figure 3 showns some of the ICE outputs for a severe 50° to 90° transient on the butterfly valve. From this figure one can observe that the MMGPC led to an error less than 3% relative to the stoichiometric values but the MMLMI has an even better performance with a excursion less than 2% . Besides that, the MMLMI controller shows a better settling time when compared to the MMGPC, that is, the first one requires 0,1 *s* to bring the fuel to air ratio back to the 1% zone while the second requires 0,15 *s*. The surprising performance is given by the Neuro Fuzzy switching MMLQ whose simulation has kept the $\Phi_e$ values inside the wright band (± 1%). From the other side, the MMLQ has shown the largest off-sets.

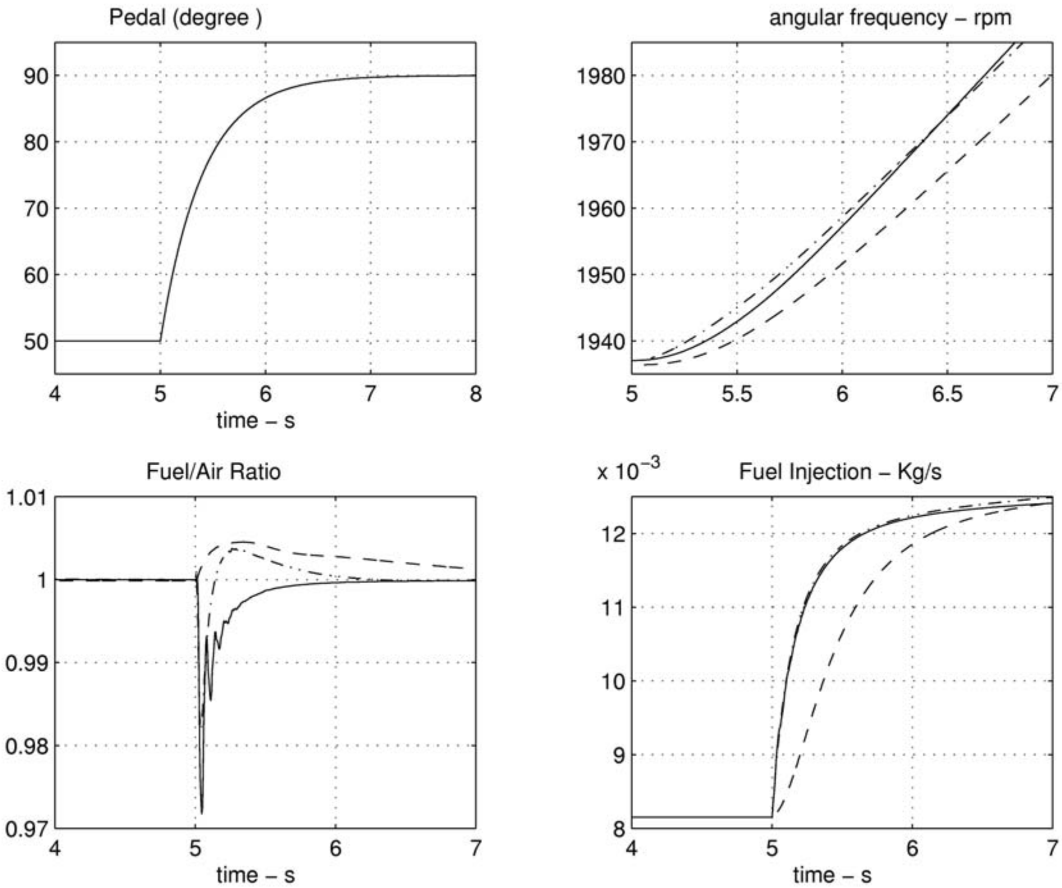


Figure 3. Comparison among fuel injection, angular frequency and fuel/air ratio ( $\Phi_e$ ) values of the MMGPC (solid line), MMLQ (dashed) and MMLMI (dashed dot) controllers, for 50° to 90° transient

The other graphics of the Fig. 3 show the performances for fuel injection and engine rotation for the 50°- 90° transient. One can observe that the MMLMI and MMGPC controllers have faster responses than MMLQ for these two figures of merit.

## 8. Conclusions

The achieved simulation results show that it is possible to control severe transient demands in a natural gas engine in short time intervals with no or quite small excursions out of the nominal operation values. Each design technique has required different treatments and exhibited different performances. The polynomial structure of the GPC technique has allowed the use of more intelligent switching strategies since it made possible the comparison between the 17 linearized models and, as a consequence, the choice of the best representation of the ICE dynamics in a given operating point. The consequence of a better switching logic is a larger processing time, a considerable disadvantage when dealing with a fast machine as an ICE. Another important observation concerning the actualized version of the MMGPC is the model dependency on the accelerator pedal position, on the load and on the rotation of the ICE. The old version relies on models depending just on the pedal position (Fleury et al, 1999a and 1999b). A practical implementation of the MMGPC shall also depend on an electronic package with large data processing capacity. From the other side, it shall require small number of sensors and actuators since it just needs the fuel to air ratio as an entry to generate fuel mass flow and ignition angle as outputs, that is, a MMGPC implementation shall use just lambda-sensors and fuel injectors. The LQ control structure has required the inclusion of other devices to give adequate performance when linked to the Multiple Models approach (Freitas Jr., 2003). The inclusion of the Neuro Fuzzy switching logic (Starr, 2003) has allowed the most uniform behavior of the ICE variables, eliminating undesirable peaks induced by model changes. Compared to the GPC controllers, a practical MMLQ implementation shall require an state observer in the control loop since the LQ control law is based in the knowledge of every state variables. The LMI control design is also based on linearized state space models and proposed as a $H_\infty$ controller where an Index of Performance is minimized using the usual LMI tools. For the development of the LMI controllers several switching strategies have been investigated (Freitas Jr., 2003) without significant results other than giving the hint of the need of a supervisory model to control the injected fuel mass flow during transient ICE operation. Numerical simulations carried during this research have shown that small errors in the injected fuel flow are the main reason to unstable ICE behavior. The supervisory control module shall require implementation of a MAP sensor, besides the lambda sensor and fuel injectors for practical use. This work points out the importance of the availability of good ICE models to get good fuel to air ratio controllers. If this is possible then it is also possible to control the pollution emission levels generated by natural gas ICEs in order to make them adequate to the stringent standards required by the authorities to enhance life quality in large cities.

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