Modeling and Control of a Compressed Natural Gas Injection System

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Abstract: - The application of new technologies in the automotive field has highly improved the performances of internal combustion engines. In particular, applying electronic control to the fuel injection system has improved dynamic performances and reduced noxious emissions, noise and fuel consumption. To achieve this goal it is necessary to exactly meter the injected fuel by controlling both the injection pressure and the injectors opening time. On the other hand, to develop a suitable control strategy for the injection system, it is necessary a mathematical representation, describing the dynamics of most significant variables. In this paper we propose a fast and simple model of a Compressed Natural Gas injection system to predict the system dynamics with a good accuracy for different operating conditions. We also present a comparison between simulation and experimental data to validate the results. Then we use this model to design a fuzzy logic controller of the injection pressure. Simulation experiments show that the fuzzy logic controller can cope with system nonlinearities, guaranteeing better performances than classical PI controllers.

Key-Words: - Internal combustion engines, CNG, Injection systems, Fuzzy control.

1 Introduction

Recent restrictive regulations concerning internal combustion engines have encouraged automotive companies and researchers to propose innovative solutions, reducing noxious emissions and employing cleaner fuels, particularly gaseous ones. E.g. the EURO 4 regulations, that will become effective in Europe by 2005, will impose a 50% reduction of main polluting combustion products. Hence it will be difficult to satisfy restrictions by exploiting the present technology [9].

For many types of vehicles, compressed Natural Gas (CNG) represents the most promising choice among alternative fuels. In fact, thanks to its good antiknock properties and low exhaust emissions, particularly of CO, NOx, HC and particulate, CNG has a better efficiency than other fuels used in spark ignition engines. The main drawbacks of CNG, however, are large space requirements for high autonomy and difficulty of exact metering. To guarantee the requested power for engine speed and load and the lowest fuel consumption it is necessary to provide the engine with the correct air-fuel ratio [3]. The fuel delivery technology has evolved from early mechanical driven to recent electronically controlled systems, which allow the injection device to optimize the mixture formation. In particular, the innovative Common Rail injection system under development at the FIAT Research Center (CRF), Valenzano site, accomplishes this task by setting the injection pressure to a reference value and by controlling injection timings electronically for different operating condition. Nevertheless, the injection control needs the knowledge of mathematical equations of the system dynamics. In other words, to predict the system behavior and get better knowledge for the controllers design process it is necessary to have a model. The main obstacle for the injection system modeling is the plant non-linearity. Moreover, to describe pressure dynamics and fluid dynamic phenomena in every working condition, it is necessary to evaluate a large number of parameters.

Thanks to their simple structure, standard PI controllers are widely used in automotive applications. Nevertheless, they don't guarantee a satisfactory behavior in injection systems, which are highly non linear. Namely in these systems, controller performances depends on the operating point, and on the influence of the ageing of mechanical parts and environmental conditions. More complex and non linear control approaches can overcome these problems giving higher robustness and performances than PI controllers. Inherently non linear features of fuzzy logic controllers (FLCs) can be suitably exploited to derive a control action that guarantees a satisfactory behavior for different operating conditions. Moreover, as the FLCs structure is based on if-then linguistic rules, the tuning procedure could be made easer by exploiting the expert knowledge of the process to be controlled [1].

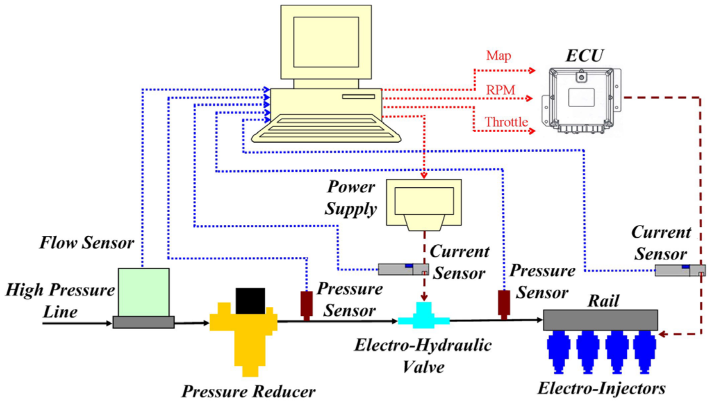

Fig. 1: Block scheme of the CNG Common Rail Injection System.

In this paper, we propose a fuzzy control scheme to regulate the injection process in a CNG internal combustion engine. To this end, we derive a model of the CNG injection system using the equations describing the physics underlying the process. The model parameters can be easily determined or detected by known geometric data. We compare simulation and experimental results to validate the model, which shows a good accuracy in the predicted behavior. The proposed FLC derives from the equivalence with PI controllers. This procedure allows to easily get a linear controller that is made non linear in a subsequent step, by modifying I/O Membership Functions (MFs) and applying a gain scheduling technique. In this way it is possible to take advantage from a non linear control surface. We perform simulation tests, in Matlab/SIMULINK environment, to show that the proposed regulator significantly improve the performance of PI controllers.

2 The Case Study

We consider a system with the following elements: a fuel tank, storing high pressure gas, a mechanical pressure reducer, an electro hydraulic valve and the fuel metering system, consisting of a common rail (CR) and four electro-injectors (see Fig. 1). The pressure reducer receives fuel from the tank at a pressure in the range between 200 and 20 bars and reduces it to a value of about 10 bar. Then the electro hydraulic valve suitably regulates the gas flow towards the CR to control pressure level and transients, and to damp oscillations due to injections. Finally the electronically controlled injectors send the gas to the intake manifold to obtain the proper fuel air mixture.

The CR is a constant volume accumulator connected to electro-injectors and the pressure reducer. A pressure sensor inside the rail supplies a signal which is processed to drive the injectors and which closes the control loop. The injection and the rail pressures are almost equal, while the intake manifold is at atmospheric pressure. As critical flow condition always holds during injections (see section 3 for details), the injected fuel amount doesn't depend on the intake manifold pressure, but only on rail pressure and injection timings. The latter are precisely driven by the ECU. Conversely, pressure regulation is not a trivial task to accomplish.

The pressure reducer consists of a chamber with a variable inflow section, that depends on the axial displacement of a spherical shutter; the volume of the chamber is variable because of the motion of a piston coupled with the shutter. Piston and shutter dynamics are affected by the applied forces equilibrium. In particular, act on the shutter tank and reducer pressures, viscous friction and the piston reaction. Atmospheric and reducer pressures push the piston at the top, and elastic force of a preloaded spring pushes it down and causes the shutter to open. The spring preload value has to be chosen to set the desired equilibrium reducer pressure: if the pressure exceeds the reference value the shutter closes and the gas inflow reduces, preventing a further pressure rise; on the contrary, if the pressure decreases, the piston moves down and the shutter opens, letting more fuel to enter and causing the pressure to go up in the reducer chamber. A conceptual scheme of the reducer is depicted in Fig. 2, showing the pressures involved.

The electro hydraulic valve encompasses an electromagnet, with a mobile anchor, and a spherical shutter, integral with the anchor. In a non energized condition, the shutter and the anchor remain closed under a preloaded spring action against the hydraulic force, and block the gas flow towards the rail. As the electromagnetic circuit is energized, the magnetic force overcomes the spring preload: the anchor and the poles come together and the pressure force shuttles the sphere to open the supply port. When the solenoid circuit is de-energized, the anchor is forced down and the shutter is pushed against the seat. In this way, varying the supplying voltage duty cycle among the injection period and making the valve opened and closed in turn regulates the rail pressure.

In the literature some Diesel injection system models take into account complex fluid mechanics phenomena [4], [6], [7]. On the base of physical considerations, these approaches lead to distributed parameters representations, describing the system through sets of partial differential equations, or propose a high order nonlinear state space representation. However they are not suitable to develop a control strategy for the rail pressure because, in general, they request high computational resources. A different way to model the injection system is the use of a fluid-dynamic simulation software, such the AMESim package [5], based on block libraries of mechanical elements, and able to simulate complex fluid-dynamic phenomena. In this case, the greatest difficulty is the need of details of valves and injectors geometry, not always available. Moreover, despite of good prediction capabilities of such models, they cannot be used for control purposes, as they do not give any mathematical representation of the process dynamics.

In this paper we propose a mathematical model of the CNG injection system which is quite simple, as it is based on a lumped parameters representation and, on the other hand, it is enough accurate to predict the system behavior to design a rail pressure controller.

3 Model Description

According to Eulerian approach, to develop the injection system model we consider a set of control volumes in which the fluid thermodynamic properties can be considered spatially constant but time variant; such properties can be derived from ideal gas law, conservation of the mass, conservation of energy and dynamic equilibrium equations [10], [11]. If we assume the gas temperature constant, we can describe the fluid dynamics by the pressure in the following control volumes: the fuel tank, the pressure reducer and the common rail. We assume that injectors pressure is equal to that of common rail. In other words, we consider them just as control valves, and reduce the system order without sensibly affecting the model accuracy.

The equations describing the pressure variations inside the control volumes combine the ideal gas law and the conservation of mass equations:

$$\frac{dP}{dt} = \frac{RT}{V}\left(\dot{m}_{in} - \dot{m}_{out} - \rho \frac{dV}{dt}\right) \tag{1}$$

where P is the control volume pressure, R the gas constant, T the temperature, $\dot{m}_{in}$ and $\dot{m}_{out}$ the input and output mass flows and ρ is the gas density in the instantaneous volume V; the derivative at the second member takes into account volume changes due to mechanical parts motion (for example in the pressure reducer), if these changes occur. The pressure in the generic control volume can be calculated by integrating the equation (1), after the evaluation of mass exchanges.

We consider mass flows through orifices adiabatic transformations and apply the conservation of energy equation in the computations; in general, the following equations hold, depending on the output/input pressure ratio $p_r = p_{out}/p_{in}$ [11]:

$$\begin{cases} \dot{m} = c_d \rho_{in} a A \cdot \sqrt{\dfrac{2}{k-1}\left[(p_r)^{\frac{2}{k}} - (p_r)^{\frac{k+1}{k}}\right]} & \text{if} \quad p_r > \left[\dfrac{2}{k+1}\right]^{\frac{k}{k-1}} \\ \dot{m} = c_d \rho_{in} a A \cdot \sqrt{\left(\dfrac{2}{k+1}\right)^{\frac{k+1}{k-1}}} & \text{if} \quad p_r \le \left[\dfrac{2}{k+1}\right]^{\frac{k}{k-1}} \end{cases} \tag{2}$$

where a is the speed of sound, A is the outlet section surface, ρ_{in} is the intake gas density, c_d is flow coefficient, taking into account losses, and k is the gas elastic constant; the former equation refers to subsonic speed flows, the latter to sonic speed flows.

The reducer inlet flow section A_r is the lateral surface of a truncated cone and depends on shutter and piston axial displacements h_r (i.e. the cone height). As mentioned in the previous section, for describing the shutter and piston dynamics we consider the forces acting upon each of them according to Newton's second law of motion. To this end we write:

$$M_r \frac{dh_r}{dt} = \sum_i P_{ri} \cdot A_{ri} - k_r h_r + F_{ro} - F_r - F_{rb} \tag{3}$$

where M_r is the overall shutter and piston mass, P_{ri} is pressure acting on the to surface A_{ri}, k_r is the spring constant, F_{ro} is the spring preload. Moreover, F_r is the coulomb friction, assumed to be constant and evaluated through lab measurements and F_{rb} is a viscous friction term, depending on speed. Furthermore, as we are interested to overall forces acting on the shutter, we assume that pressure gradients are applied to the flow minimal section.

We use the same approach to compute the common rail inlet section, regulated by the electro hydraulic valve. In this case, in the equation describing the shutter and anchor motion we have considered the magnetic force F_{vm}, while we have neglected the coulomb friction. Hence, the Newton's second law of motion becomes:

$$M_v \frac{dh_v}{dt} = \Delta P_v \cdot A_v + F_{vm} - k_v h_v + F_{vo} - F_{vb} \tag{4}$$

where h_v and M_v are the shutter/anchor axial displacement and overall mass respectively, $\Delta P_v \cdot A_v$ is the net force acting upon the shutter surface A_v, k_v is the spring constant, F_{vo} is the spring preload, F_{vb} is the viscous friction. To calculate F_m we have to write the equations governing the magnetic circuit, obtaining:

$$F_{vm} = \frac{1}{2\mu_0} A_m B^2 \tag{5}$$

where B is the density of the magnetic flux φ, that is generated by the solenoid current due to applied voltage v, μ_0 is the air permeability and A_m is the gap cross-sectional area. Finally, after computing the shutter axial displacement, it is straightforward to obtain the minimal flow section surface.

The injectors opening time intervals are settled by the electronic control unit (ECU), depending on engine speed and load. The whole injection cycle takes place in a 720° interval, with a 180° delay between each injection command. In this model, we neglect the injectors opening and closing transients, therefore only two conditions can occur: injectors closed or opened with a flow section A_{inj}. This simplification do not introduce a considerable error, while reduces noticeably the computation time. As critical flow condition always holds, the injection mass flow has to be calculated applying the second of equations (2) and multiplied by a variable period square signal ET, equal to 0 or 1 depending on injection timings.

Equations (1)-(5) can be rewritten in a state space form:

$$\dot{x} = f(x(t), u(t)) \tag{6}$$

where the sets of inputs and state variables are:

$$\begin{aligned} x(t) &= \left[P_t, P_r, P_a, h_r, \dot{h}_r, h_v, \dot{h}_v, \varphi\right]' \\ u(t) &= \left[P_{atm}, v, ET, P_{im}\right]' \end{aligned} \tag{7}$$

The system of equations (6) can be solved on the base of inputs and initial conditions, completely describing the system dynamics in terms of pressures and motion of mechanical parts.

5 Rail Pressure Controller Design

In this section we propose a design procedure for a rail pressure Sugeno-type fuzzy controller: tuning a PI regulator with reasonable dynamic performances, building an equivalent fuzzy controller and, finally, modifying it to get a nonlinear control surface and to guarantee good performances in every operation point.

The discrete time PI control action is given by:

$$u_{PI} = K_P \left(e_n + \frac{K_i}{K_p} \sum_{j=1}^{n} e_j \cdot T_c \right) \tag{8}$$

where K_p is the proportional gain, K_i is the integral gain, T_c is the sample time. We have chosen the PI gains according to Ziegler-Nichols rules, and eventually we have tuned them by means of optimization algorithms. An equivalent fuzzy controller must have a linear control surface; this condition is obtained by a suitable choice of I/O MFs, inference rules and implication methods [2]. More precisely, rail pressure error and error change are inputs, and the control action change, i.e. duty cycle of the applied voltage, is the output. Since we use a velocity algorithm, we have to integrate output to compute the actual control action. To satisfy linearity condition input MFs are uniformly spaced triangles that do not overlap more than two at a time; the sum of membership degrees of two overlapped MFs is always equal to 1. Output MFs are singleton properly placed to obtain a plane control surface. Input MFs number affects those of inference rules and output MFs. Since we use 5 MFs for each input, we need 25 rules and output singletons (Table 1). Linearity condition holds only if inputs remain within universes of discourse; this can be obtained multiplying inputs by a constant K_{norm} and dividing each element in table 1 by $1/(K_p+K_i)$; consequently, output has to be multiplied by $(K_p+K_i)/K_{norm}$ to get the proper control action.

Finally, to guarantee a good behavior in different operation points, and in particular to improve the control action close to set point, the controller is made non linear adopting two different strategies: a scheduling of I/O gains is applied, depending on error values, and input MFs are modified, shifting the upper triangles vertices towards center of the universe of discourse. The resulting gain sets are:

$$\begin{cases} G_e^{st}, G_{\Delta e}^{st}, G_o^{st} \\ G_e^{tr}, G_{\Delta e}^{tr}, G_o^{tr} \end{cases} \tag{9}$$

where the first (upper) set is used close to set point, while the second (below) set is used in transient conditions. Once the fuzzy structure is designed, scaling factors are tuned by means of the Nelder-Mead optimization method [8] to get a fast response and low oscillations; to this end, we use integral time absolute error as a performance index.

6 Model Validation

We validate the proposed model using a large number of simulation tests and solving state space equations (6) in MATLAB/Simulink environment with a 4th order Runge Kutta algorithm.

Firstly, we have to check if the model is able to predict the steady state open loop system behavior. To this end, we choose different working points by setting engine speed, injection timings and tank pressure and then compare simulation and experimental results. Figures 3 and 4 depict reducer and rail pressures as well as injection flow rates for different tank pressures at 1990 and 6340 rpm engine speeds respectively. Simulation results are in good accordance with reference measured values. However, they exhibit some mismatching for injected flow rates at 6340 rpm, due to injector model simplification.

To evaluate model dynamics, we drive the electro hydraulic valve by a constant duty cycle, while keeping the engine speed constant at 1000 rpm. The solenoid exciting signal, which is applied for 24ms, is synchronized with only one injection. Fig. 5 depicts both experimental and simulated behaviors of rail and reducer pressures, as well as of electro hydraulic valve and injectors exciting currents in one injection cycle. Note that, due to mass flow towards common rail, pressure in the reducer chamber drops when the electro hydraulic valve is open. In conclusion, the model describes the reducer pressure dynamics with good accuracy. Comparing simulated and measured values of the current validates the valve magnetic circuit model.

Finally, we apply to the simulation model the pressure of the reducer and the duty cycle measured during two different speed transients with a 8 bar pressure reference. In Fig. 6(a) and Fig. 6(b) rpm variations from 2000 to 4000 (from 4000 to 2000) and from 2000 to 5000 (from 5000 to 2000) take place in 2 and 3 seconds, respectively. An enlarged window shows that the rail pressures trends during four injection cycles depict the pressure dynamics correctly. Slight differences are only noticeable during speed transients; this can be explained by considering simplification in the injector models.

Despite of good prediction capabilities, the proposed model requires a low computational effort. Simulation of a 720° injection cycle is performed in 0.24 s on a Pentium IV 1.8GHz with a 0.05° resolution.

7 FLC Performances

Using simulation we compare the proposed controller performances with that of a PI controller, which is tuned exploiting Ziegler-Nichols rules. Starting from a 3 bar pressure steady state condition, a 7 bars step reference is applied, while monitoring rail pressure and control action; the electro hydraulic valve drive signal is applied in a 720° interval. From Fig. 7 comes out that both control actions result in the same rise time, as duty cycle saturates at the maximum value causing the valve to be held opened during the transient. On the contrary, the pressure overshoot is remarkably reduced from 12% of the PI controller to 4% of fuzzy controller. Furthermore, fuzzy controller guarantees a better attenuation of pressure oscillations close to set point, thanks to its nonlinear surface. In both cases the same pressure ripple close to set point is the effect of the difficulties in compensating the pressure drops. Drops are due to individual injections, as the valve is only opened in the first part of the cycle while is closed in the remainder one.

8 Conclusion

In this paper we have proposed a CNG injection system model describing the physics underlying the process; the model is accurate enough to predict the dynamical behavior of most representative variables. Since the model takes explicitly into account the geometrical characteristics of the system, it can be easily adapted to different injection systems. We have used the proposed model to design a fuzzy controller for the rail pressure regulation. The simulation has shown that the fuzzy controller has better performances than PI controller.

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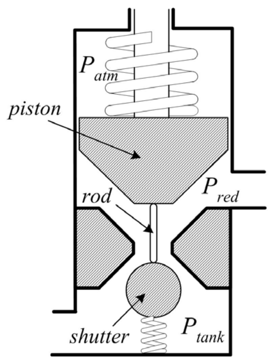


Fig. 2: Pressure Reducer conceptual scheme.

$\dot{e}$ / e	NB	NS	ZE	PS	PB
NB	$-K_p-K_i$	$-0.5K_p-K_i$	K_i	$0.5K_p-K_i$	K_p-K_i
NS	$-K_p-0.5K_i$	$-0.5K_p-0.5K_i$	$-0.5K_i$	$0.5K_p-0.5K_i$	$K_p-0.5K_i$
ZE	$-K_p$	$-0.5K_p$	0	$0.5K_p$	K_p
PS	$K_p+0.5K_i$	$-0.5K_p+0.5K_i$	$0.5K_i$	$0.5K_p+0.5K_i$	$K_p+0.5K_i$
PB	$-K_p+K_i$	$-0.5K_p+K_i$	K_i	$0.5K_p+K_i$	K_p+K_i

Table 1: Fuzzy Controller Rule Table.

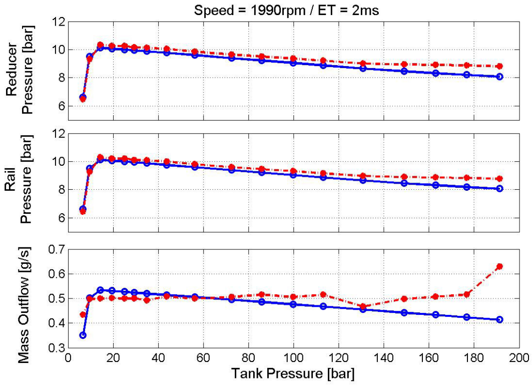
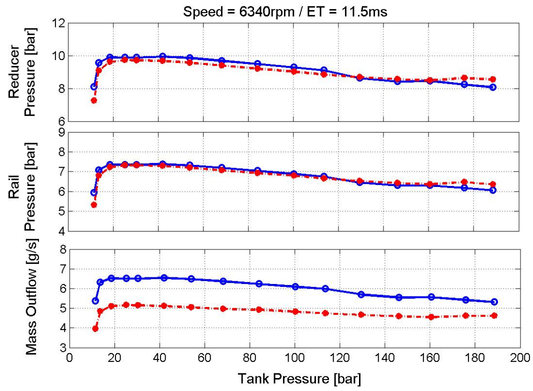
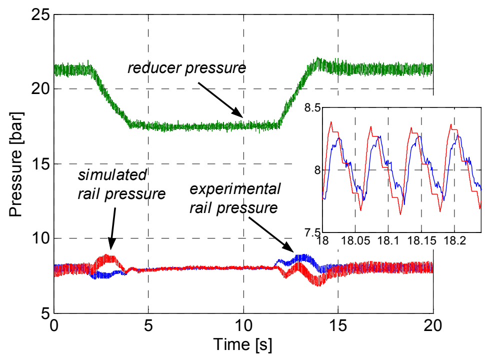


Fig. 3: Experimental (*--) and simulation (○) results at 1990 rpm and $ET = 2$ ms.

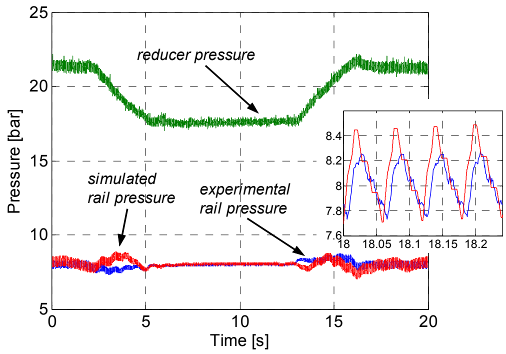


(b)

Fig. 4: Experimental (*--) and simulation (○) results at 6340 rpm and $ET = 11.5$ ms.

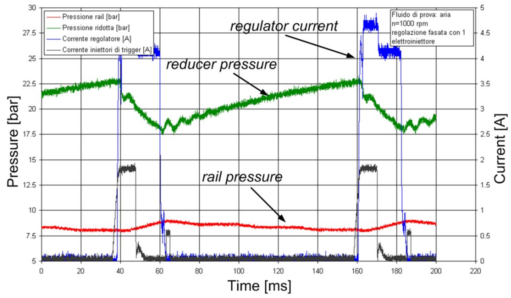


(a)

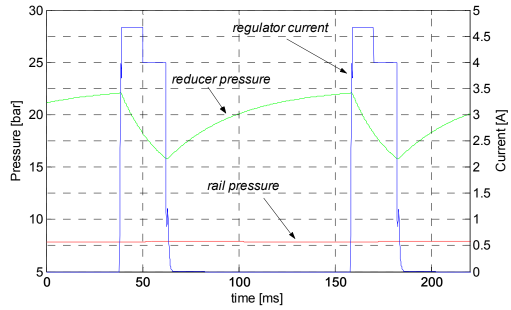


(b)

Fig. 6: Experimental and simulated rail and reducer pressures transients: (a) rpm variations from 2000 to 4000; (b) rpm variations from 2000 to 5000.

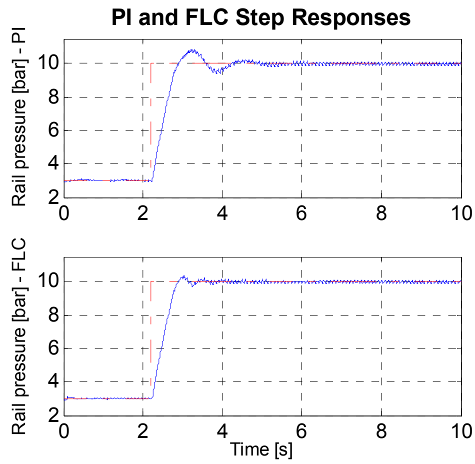


(a)

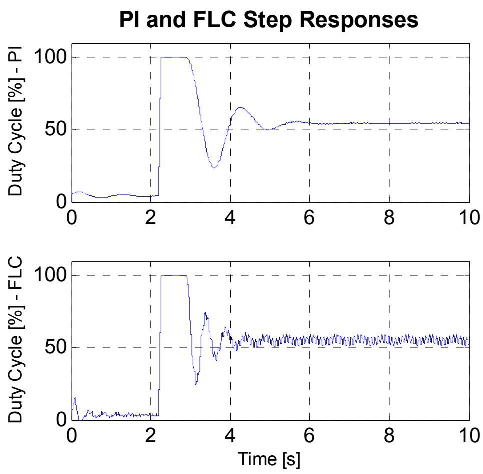


(b)

Fig. 5: Experimental (a) and simulation (b) results for a 720° control signal.



(a)



(b)

Fig. 7: PI and FLC regulators step responses: (a) rail pressures (b) control actions.