# A MODEL BASED CONTROL OF COMPRESSED NATURAL GAS INJECTION SYSTEMS

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Keywords: Modeling injection systems, Common Rail, CNG, Pressure control.

Abstract: Low fuel consumption and low emissions are key issues in modern internal combustion engines design. For this reason, an effective on-line control of the injection process requires the mathematical equations describing the system dynamics. The inherent nonlinearities make the modeling of the fuel-injection system hard to accomplish. Moreover, it is necessary to trade off between accuracy in representing the dynamical behavior of the most significant variables and the need of reducing complexity to simplify the controller design process. In this paper we present a second order lumped parameters model of a Compressed Natural Gas injection system for control system synthesis and analysis. Based on the proposed model, we propose a generalized predictive controller to regulate the injection pressure, which guarantees good performances and robustness to modeling errors.

## 1 INTRODUCTION

Today it is a widely accepted opinion that performances of internal combustion engines strictly depend on fuel injection dynamics and metering of air/fuel mixture (Heywood). Owing to a better control on air/fuel ratio, the innovative Common Rail injection system remarkably reduces noxious emissions, consumptions and noise in Diesel engines, while improving efficiency and available power (Maione, 2004a). These goals are achieved by setting the injection pressure to a fixed value, while controlling injection timings electronically for different operating conditions.

It is also well known that, if compared to liquid fuels, the Compress Natural Gas (CNG) reduces polluting emissions of CO, NOx, HC and particulate of internal combustion engines, and guarantees their better efficiency, thanks to its good antiknock properties (Weaver). However, greater difficulties in metering make the use of CNG less worthwhile. This drawback can be overcome by applying the Common Rail technology to CNG engines and by using the injection control to improve performances. However, improving the controllers design process requires a quite accurate model for predicting the system behavior.

Injection system models for Diesel engines are mainly based on three different approaches. The straightest one is founded on fluid-dynamic simulation packages like AMESIM, which encompasses libraries of mechanical components, and requires precise knowledge of the system geometrical data (Mulemane). Although the resulting models provide an accurate representation of system dynamics, which is appropriate for mechanical design, they are not in the form of mathematical equations useful for control purposes. Different classes of models descend from identification processes based on real data. They guarantee a good prediction of the system behavior if nonlinear functions are exploited (Maione, 2004b). Finally, some injection system models are based on equations describing the physics underlying the process. Basically, this approach leads to Partial Differential Equations or high order representations, which are certainly not suitable for control purposes (Cantore), (Kouremenos), (Maione, 2004a).

However, to the best authors knowledge, there is lack of studies carried out for modeling and controlling gaseous fuel injection systems. In this paper we propose a simple lumped parameters model describing only main fluid-dynamic phenomena of the CNG injection system. It is in the form of a second order state space representation suitable for designing controllers of the rail pressure. Moreover, we also stress that tuning the parameters of the model requires a minimal set of the system geometric data. Finally, on the basis of this model


Maione B., Lino P. and Rizzo A. (2005).
A MODEL BASED CONTROL OF COMPRESSED NATURAL GAS INJECTION SYSTEMS.
In *Proceedings of the Second International Conference on Informatics in Control, Automation and Robotics - Robotics and Automation*, pages 132-137
DOI: 10.5220/0001158401320137

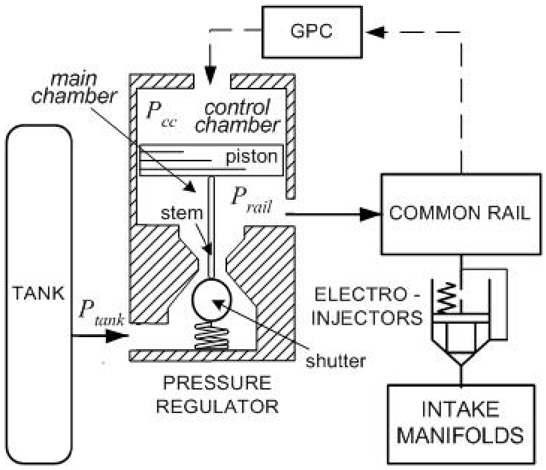


Figure 1: Block scheme of the CNG Common Rail injection system

we show how to design a Generalized Predictive Controller (GPC) for the rail pressure which parameters directly descend from the model equations (Rossiter).

## 2 STATE SPACE MODELING OF THE CNG INJECTION SYSTEM

The main elements of the CNG injection system are a fuel tank, storing high pressure gas, a controlled pressure regulator, a common rail and four electro-injectors. The regulator reduces the pressure of the fuel supplied by a tank, and sends it to the common rail, feeding the electronically controlled injectors. Then the injectors send the gas to the intake manifolds to obtain the proper air/fuel mixture (Figure 1).

The large volume of the common rail helps in damping the oscillations due to the operation of both pressure regulator and injectors. So it ensures a constant pressure as requested by a correct metering of the injected fuel. In fact, the injection flow only depends on rail pressure and injection timings, which are precisely driven by the Electronic Control Unit (ECU). The output signal of a pressure sensor inside the rail is processed to close the control loop.

The pressure regulator consists of a main chamber with a variable inflow section, which depends on the axial displacement of a spherical shutter over a conical seat, and of a control chamber, whose pressure is regulated by a solenoid valve. A piston between the two chambers provides the seal for the main valve shutter. The equilibrium of the applied forces determines piston and shutter dynamics (Smith) (Figure 1). In particular, the control chamber pressure is regulated by varying the driving current *duty cycle* (*d.c.*) among a control period, making the valve opened and closed in turn: in this way is possible to control the fuel flow from the tank towards the rail. Finally, to maintain an equilibrium condition in steady state operation, the fuel in the control chamber is sent to the main circuit through an high resistance orifice.

To model the CNG injection system we consider two control volumes having a uniform, time varying, pressure distribution, i.e. the regulator control chamber and the rail circuit. We consider the tank pressure as an input rather than a state variable as its measure is always available on board as it is related to the fuel supply. Furthermore, it is likely to assume equal injection and rail pressures, so that electro-injectors are not modeled apart, but included in the rail circuit as control electronic valves. Finally, we assume a constant temperature in the whole injection system, so that the system dynamics is completely defined by the pressure variations in the control chamber and the rail circuit.

Continuity equation and perfect gas law (Zucrow) lead to the state equations of control volumes. In particular the perfect gas law is:

$$p = mRT/V \tag{1}$$

where $p$ is the control volume pressure, $R$ the gas constant, $T$ the temperature and $m$ the fuel mass stored in the instantaneous volume $V$. We can neglect possible volume changes due to mechanical part motions (for example in the control chamber) without sensibly affecting the model accuracy. Hence the derivative of (1), immediately gives the continuity equation:

$$\dot{p} = \frac{RT}{V}\left(\dot{m}_{in} - \dot{m}_{out}\right) \tag{2}$$

where $\dot{m}_{in}$ and $\dot{m}_{out}$ are the input and output mass flows, which sum has to be equal to the overall mass change in the control volume. Integrating the equation (2), after the evaluation of mass exchanges, yields the pressure in the generic control volume.

By considering mass flows through control chamber and regulator inlet orifices as isentropic transformations and by applying momentum equation, we get the following equations, depending on the output/input pressure ratio $r = p_o/p_i$ (Zucrow):

$$\dot{m}_{in} = c_d \rho_{in} A \sqrt{\frac{2kRT}{k-1} \cdot \left[ r^{\frac{2}{k}} - r^{\frac{k+1}{k}} \right]} \tag{3}$$

$$\dot{m}_{in} = c_d \rho_{in} A \sqrt{kRT \cdot \left( \frac{2}{k+1} \right)^{\frac{k+1}{k-1}}} \tag{4}$$

where $A$ is the outlet section surface, $\rho_{in}$ is the intake gas density and $k$ is the gas elastic constant. Equation (3) holds if $r > 0.5444$ and refers to subsonic speed flows, while equation (4) holds if $r \leq 0.5444$ and refers to sonic speed flows. The effect of non-uniformity of the mass flow rate is accounted for by a discharge coefficient $c_d$.

The pressure regulator inlet flow section $A_r$ is the lateral surface of a truncated cone and depends on shutter and piston axial displacement $h_s$ (i.e. the cone height):

$$A_r = \left[ d_s + 0.5 \cdot h_s \sin\left(2\beta_s\right)\right] \cdot \pi h_s \sin\beta_s \tag{5}$$

where $\beta_s$ is the slope of the conical seat and $d_s$ is the minimal seat diameter. The shutter and piston dynamics are determined by applying the Newton's second law of motion to the forces acting upon each of them. If we neglect the viscous friction term, the piston and the shutter inertias due to the large hydraulic forces, we can write the force balance:

$$\sum_i p_{si} A_{si} - k_s h_s + F_{so} - F_c = 0 \tag{6}$$

where $p_{si}$ is pressure acting on the to surface $A_{si}$, if we assume that pressure gradients are applied to the flow minimal section. Moreover, $k_s$ is the spring constant, $F_{so}$ is the spring preload, i.e. the force applied when the shutter is closed. Finally, $F_c$ is the coulomb friction. Hence, we get $h_s$ from equation (6) and then $A_r$ from (5).

The shutter displacement of the electro-hydraulic valve regulates the flux incoming in the control chamber. As its inertia is negligible, we assume that the inlet section can be completely opened or closed, depending on the actual driving current (energized/not-energized circuit), and calculated using the equation (5), with $h_s = \{0, h_{max}\}$.

Since the flow between control chamber and rail circuit can be considered stationary, it is determined by the following equation (Zucrow):

$$\dot{m}_{out} = c_d c_L A \sqrt{\rho_{out}\left(p_{in} - p_{out}\right)} \tag{7}$$

where $c_L$ takes into account the effect of kinetic energy losses in the nozzle minimal section $A$. Equation (7) assumes that no reversal flows occur.

The injectors opening time intervals are set by the ECU, in dependence of engine speed and load. The whole injection cycle takes place in a 720° interval, with a 180° delay between each injection command. Since in this model we neglect the injectors opening and closing transients, we express the injectors flow section as $ET{\cdot}A_{inj}$, where $ET$ (Energizing Time) is a square signal with a variable period and equal to 0 or 1 depending on injection timings. This simplification does not introduce a considerable error, while reduces the system order and computational effort. As critical flow condition always holds, the injection mass flow has to be calculated applying equation (4).

Equations (1)-(7) can be rewritten in a state space form:

$$\begin{cases} \dot{x}_1(t) = a_{11}u_1(t) \cdot u_2(t) + \\ \qquad - a_{12}\sqrt{x_2(t) \cdot \left[x_1(t) - x_2(t)\right]} \\ \dot{x}_2(t) = a_{21}u_1(t) \cdot \left[b_1 x_1(t) - b_2 x_2(t) + \right. \\ \qquad \left. - b_3 u_1(t) - b_4\right] - a_{22}x_2(t)u_3(t) + \\ \qquad + a_{23}(t)\sqrt{x_2(t) \cdot \left[x_1(t) - x_2(t)\right]} \end{cases} \tag{8}$$

where $a_{ii}$ are constant coefficients. The set of inputs and state variables is:

$$x(t) = \left[p_{cc}, p_{rail}\right]^T, \; u(t) = \left[p_{tank}, d.c., ET\right]^T \tag{9}$$

where $p_{cc}$, $p_{rail}$ and $p_{tank}$ are the control circuit, common rail and tank pressures respectively. The system of non linear equations (8) can be solved given the inputs and the initial conditions, and completely describes the system dynamics in terms of control volume pressures.

## 3 A GENERALISED PREDICTIVE CONTROL LAW FOR THE RAIL PRESSURE REGULATION

Model Predictive Control techniques are based on the idea of predicting output from a system model and then to impress a control action able to drive the predicted output to a reference trajectory (Rossiter). We assume that the system is represented by an ARIMAX (*AutoRegressive Integrated Moving Average eXogenous*) model:

$$A\left(q^{-1}\right) \cdot y(t) = B\left(q^{-1}\right) \cdot u\left(t-1\right) + \xi\left(t\right)/\Delta \tag{10}$$

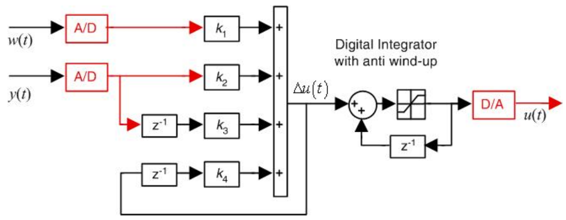


Figure 2: The GPC scheme for the rail pressure control

where $u(t)$, $y(t)$, and $\xi(t)$ are the control action, the system output and a zero mean white noise respectively, $A(q^{-1})$ and $B(q^{-1})$ are polynomials in the shift operator $q^{-1}$, and $\Delta$ is the discrete derivative operator $(1\text{-}q^{-1})$. The corresponding $j$-step optimal predictor is (Rossiter):

$$\hat{y}(t+j\,|\,t) = G_j\left(q^{-1}\right)\cdot\Delta u(t+j-1) + \\ + F_j\left(q^{-1}\right)\cdot y(t) \tag{11}$$

where $G_j(q^{-1})$ and $F_j(q^{-1})$ are polynomials in the shift operator $q^{-1}$. Let $f(t+j)$ be the component of $y(t+j)$, which only depends on known values at time $t$. We can express (11), for $j$=1, …, $N$, in matrix form as $\hat{\mathbf{y}} = \mathbf{G}\tilde{\mathbf{u}} + \mathbf{f}$, where $\hat{\mathbf{y}}$ = $[\hat{y}(t+1), \ldots, \hat{y}(t+N)]^{\mathrm{T}}$, $\tilde{\mathbf{u}}$ = $[\Delta u(t), \ldots, \Delta u(t+N-1)]^{\mathrm{T}}$, and $f$ = $[f(t+1), \ldots, f(t+N)]^{\mathrm{T}}$ and $\mathbf{G}$ is a lower triangular $N\times N$ matrix. If $\mathbf{w}$ = $[w(t+1), w(t+2), \ldots, w(t+N),]^{\mathrm{T}}$ is a sequence of future reference-values, we introduce a cost function taking into account the future errors:

$$J = E\left\{\left(\mathbf{G}\tilde{\mathbf{u}} + \mathbf{f} - \mathbf{w}\right)^{\mathrm{T}}\left(\mathbf{G}\tilde{\mathbf{u}} + \mathbf{f} - \mathbf{w}\right) + \lambda\tilde{\mathbf{u}}^{\mathrm{T}}\tilde{\mathbf{u}}\right\}$$

where $\lambda(j)$ is a sequence of weights on future control actions. The minimization of the cost function $J$ with respect of $\tilde{\mathbf{u}}$ gives the optimal control law for the prediction horizon $N$:

$$\tilde{\mathbf{u}} = \left(\mathbf{G}^{\mathrm{T}}\mathbf{G} + \lambda\mathbf{I}\right)^{-1}\mathbf{G}^{\mathrm{T}}\left(\mathbf{w} - \mathbf{f}\right) \tag{12}$$

As the first element of $\tilde{\mathbf{u}}$ is $\Delta u(t)$, the current control action is:

$$u(t) = u(t-1) + \mathbf{g}^{\mathrm{T}}\left(\mathbf{w} - \mathbf{f}\right) \tag{13}$$

where $\mathbf{g}^{\mathrm{T}}$ is the first row of $(\mathbf{G}^{\mathrm{T}}\mathbf{G}+\lambda\mathbf{I})^{-1}\mathbf{G}^{\mathrm{T}}$; at each step the first computed control action is applied and then the optimization process is repeated after updating all vectors.

We apply the above concepts to design a GPC for the rail pressure. We assume the *d.c.* as control variable and the rail pressure itself as output respectively. As the GPC law gives the change with respect of the previous control action, it is necessary to use an integrator to get the whole input to be applied. Since this signal is bounded in the range [0, 100%], we have introduced an anti wind-up system to avoid undesired oscillations in the control loop. To tune the GPC for the rail pressure, the proposed model is linearized considering different equilibrium points. Linearization is justified by the aim of the control action to keep the pressure close to a reference value, in dependence of the working conditions, set by the driver power request, speed and load. From the state space linearized models we derive a transfer function representation that is finally discretised by a first order holder, leading to a family of ARX models in the following form:

$$\left(1 + a_1 q^{-1}\right)\cdot y(t) = \left(b_0 + b_1 q^{-1}\right)\cdot u(t-1)$$

The GPC control that derives is:

$$\Delta u(t) = k_1 w(t) + \left(k_2 + k_3 z^{-1}\right) y(t) + k_4 \Delta u(t-1)$$

where $[k_1, k_2, k_3, k_4]$ depends on $N$ and $N_U$, and the related control scheme is depicted in Figure 2.

# 4 SIMULATION RESULTS

We have carried out extensive simulations in MATLAB/Simulink environment to evaluate the effectiveness of the proposed approach, considering different operating conditions, in terms of speed, load and rail pressure.

We have performed a first set of test to check the model effectiveness to predict the system behavior. Firstly, we have considered constant engine speed and load, resulting in constant injectors driving command, and constant tank pressure. Then we have evaluated the system response to *d.c.* step variations. Figure 3 shows the simulation results for a 40 bar tank pressure, 2400 rpm engine speed and 8 ms injectors exciting time interval, when two opposite 6% *d.c.* variations are applied, the first one starting from a 3% value, occurring at 1.5 s and 28 s time instants respectively. When applying the first step variation, a pilot circuit pressure increment occurs, causing the regulator inlet section to stay open longer. As a consequence, the larger mean fuel inflow coming from the tank raises the rail pressure. Conversely, when the *d.c.* is reduced by the second step, the pilot pressure drops and the rail pressure diminishes too. A picture magnification points out the pilot and rail pressures oscillating behavior within the 100 ms control period: the pressure increases when the solenoid valve is opened, while decreases when it is closed. Further simulations may show that shortening the control period attenuates these pressure variations.

Fig. 4 depicts model output for constant 40 bar tank pressure and 9% *d.c.* and a varying injectors driving signal. Simulation starts from a steady state condition corresponding to a 2200 engine speed and 3 ms injectors exciting time interval within the injection cycle. At time 4.5 s we have applied a 4000 rpm speed step, and raised the injection time interval to 12 ms, so that the applied *d.c.* is no longer able to maintain the initial rail pressure, because of the more injected fuel amount. Besides, the fuel flow between main and pilot circuit causes the pilot circuit pressure to decrease. At time 21 s we have applied a complete *cut-off*, i.e. we have kept the injectors closed in the whole injection cycle: pilot and rail pressures rise because the fuel is no more sent to the intake manifolds. In conclusion, we observe that the accordance of the resulting dynamics with the expected behavior shows the model validity.

A second set of tests investigates the GPC performances. To this end, we consider a 100% set-point variation, to evaluate the rail pressure response. We have tuned all the tested controllers referring to models linearized at the starting equilibrium point. Figures 5 and 6 show the rail pressure dynamics when the system is controlled by a GPC with $N = 5$ (0.5s) and $N = 15$ (1.5s) prediction horizons respectively, and a $N_U = 1$ (0.1s) control horizon for both cases. We have also compared the linear and nonlinear model responses with the above controllers. Clearly, increasing prediction horizon results in a sluggish response, while considerably decreases pressure overshoot, which is strongly desirable. Further simulations may show that increasing the control horizon does not result in a better rail pressure behavior.

Figures 7 and 8 compare the GPC with a standard PI controller, tuned according the Ziegler-Nichols rules. To evaluate the controllers robustness to model uncertainties, we have tuned them by considering a 3 bar rail working pressure (Figure 7). Then we have assumed a different operating condition (Figure 8), holding the same parameters. We have considered the linear system response for the GPC, since it almost coincides with the nonlinear one. Compared with the PI controller, the proposed regulator grants lower pressure overshoot and oscillation amplitude. PI parameters are tuned for a narrow working range, while the fact that the dynamic performances of the GPC are independent from the set-point demonstrates the superiority and robustness of such control approach.

# 5 CONCLUSIONS

In this paper we have presented a simple lumped parameters control-oriented model of a CNG injection system. The model equations describe the main fluid-dynamic phenomena and require a minimal set of geometric data. By using the model equations, we have designed a linear Generalized Predictive Controller to regulate the injection pressure, and then we have compared its performances with those obtained with a standard PI controller. The proposed controller structure is simple enough for on-line computation and simulation results validate the control approach. Future work will concern a narrow model validation through lab tests and the implementation of a nonlinear control strategy.

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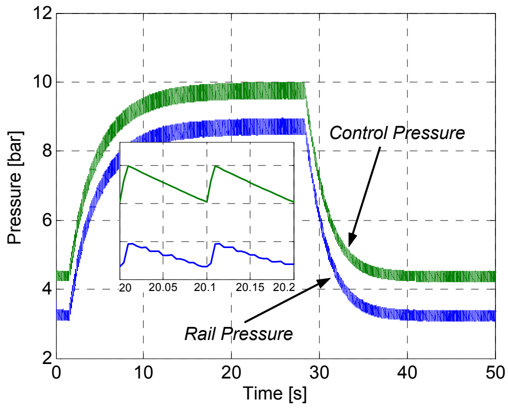


Figure 3: Control and rail pressures for duty cycle step variations and constant engine speed and injectors ET

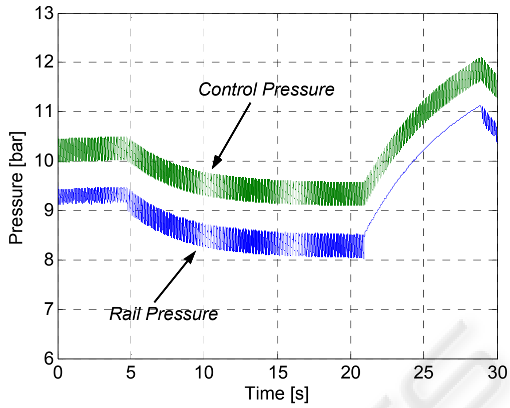


Figure 4: Control and rail pressures for engine speed and injectors ET step variations and constant duty cycle.

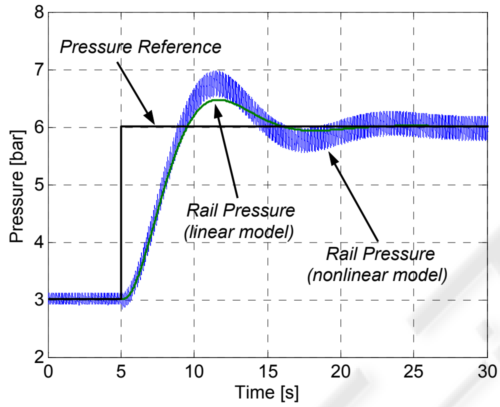


Figure 5: Rail pressure dynamics when the system is controlled by a GPC with $N = 5$ (0.5s) and a $N_U = 1$ (0.1s)

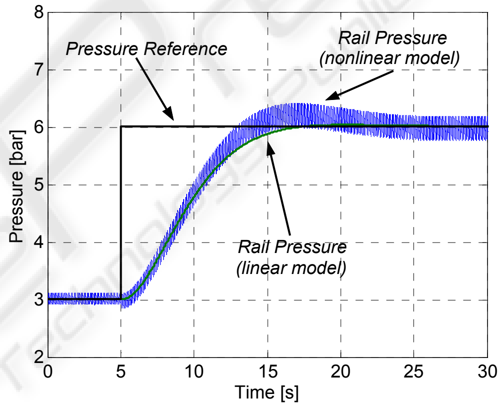


Figure 6: Rail pressure dynamics when the system is controlled by a GPC with $N = 15$ (1.5s) and $N_U = 1$ (0.1s)

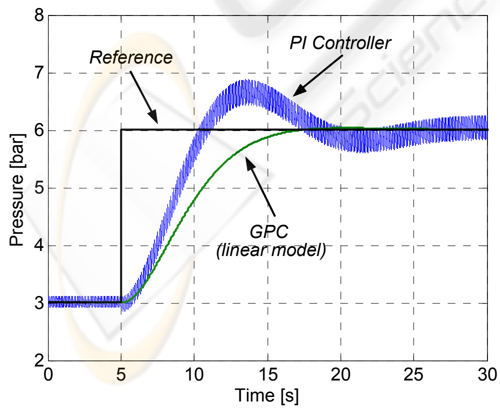


Figure 7: System step responses when controlled by a PI regulator and a GPC with $N = 15$ (1.5s) and $N_U = 1$ (0.1s)

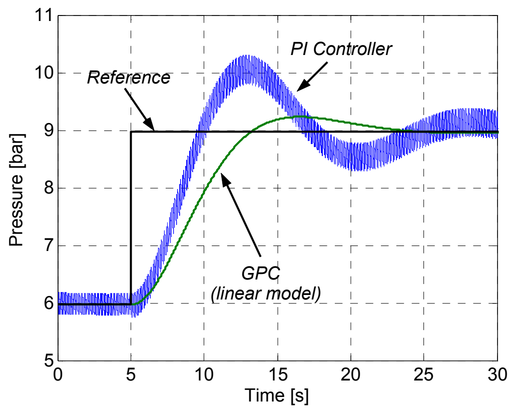


Figure 8: System step responses when controlled by a PI regulator and a GPC with $N = 15$ (1.5s) and $N_U = 1$ (0.1s), assuming model uncertainties