Neural Network Nonlinear Modeling of a Common Rail Injection System for a CNG Engine

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Abstract: - In this paper, nonlinear dynamical black-box models of a common rail injection system for a CNG engine are developed. In particular, the common rail pressure dynamics is modeled on the basis of three input signals, easily and cheaply measurable on board a vehicle. The nonlinear model is identified by means of Multi Layer Perceptron neural networks. Both non-autoregressive (NMAX) and autoregressive (NARMAX) models have been developed, showing satisfactory performance.

Key-Words: - Internal combustion engines, CNG, Injection systems, Nonlinear Modeling, Identification, Neural Networks.

1 Introduction

Reducing pollutant emissions from engines is important to avoid the problems of a severe environmental pollution. For this purpose, strictly limits on the emissions are necessary [10]. At the same time, car manufacturers are in competition for improving performance in terms of drivability, safety, fuel consumption, reliability, noise reduction, power.

Recently, manufacturers have given a significant contribution to noise and consumption reduction, as well as torque and power performances improvement, by controlling the injection system, which attends to feed the motor with the proper amount of fuel in any operational condition. A thorough design of control strategies for the injection system greatly affects the combustion mechanism [13], [9], [3]. The development of control strategies for the injection system requires a mathematical model describing the dynamics of most significant variables. Simulation models increase the knowledge of the system and provides a better understanding of the relationships between variables. Moreover, simulation models can predict the effect of changes on the engine operational parameters and the influence of the control action on the behavior of the injection system. Hence such models allow to shorten the time for designing the control schemes, and avoid unnecessary solicitations to the actual system during the tuning procedure.

Obtaining a mathematical model for automotive systems is not a trivial task. First of all, it is necessary to trade off between accuracy in representing the dynamical behavior of the most significant variables and a low computational effort. Furthermore, the model has to be suitable for the control approach to be used. For example, high order models could be inadequate for control purposes.

The injection system consists of electro-mechanical elements, each of them accomplishing specific tasks and interacting with each others, so that a highly non linear process results. Nevertheless, often to develop a control strategy, a complete representation of all the internal dynamics may not be required.

The straightest way to model the injection systems is the use of a fluid-dynamic simulation software, such the AMESim package [4], on the basis of system geometrical data [1], [11]. This simulation environment is based on block libraries of mechanical elements, able to simulate complex fluid-dynamic phenomena. 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.

Some injection system models for diesel [5], [9] and Compressed Natural Gas (CNG) [8] engines are based on equations describing the physics underlying the process. Following the Eulerian theory, each element of the system is first considered as a control volume and modeled separately, and then it is included in a pertinent way into the entire system. Then the fuel dynamics within each control volume can be derived by a proper mix of ideal gas law, conservation of the mass, conservation of energy and dynamic equilibrium equations [12], [14]. This approach leads to a distributed parameters representations, describing the system through sets of partial differential equations, or to a nonlinear state space representations. The main drawback of these methods is that, sometime, it is impossible to have a detailed insight of the geometry of the system components, in particular of the valves and the injectors, or it is difficult to model nonlinear interactions between the system variables.

However, the injection control leave apart the accurate representation of fuel dynamics in each subsystem. To this end, there are identification techniques leading to black box models, with a complexity adequate to the problem. For example, the method proposed in [6] identifies the dynamic characteristics of an electro-mechanical fuel metering system, leading to a third order transfer function representation. It relates the control signal to the axial displacement of a metering sleeve connected to the injector, without considering the fuel pressure variations and, consequently, the injection accuracy. So far, these approaches have not been extensively used for the identification of the injection systems, as they need a proper set of measured data on the real system.

In this paper we develop a nonlinear black-box model [7] for the rail pressure in a CNG engine. We use Multi Layer Perceptron (MLP) neural networks [2] to identify a nonlinear model wich shows good prediction accuracy and low computational effort. Thu, it is suitable for a further development of control strategies for the injection system. In particular, an accurate prediction of the rail pressure on a suitable time horizon allows the implementation of predictive control schemes on the rail pressure, which should be kept constant at any time. To allow an effective implementation of predictive control schemes, the inputs of the model are quantities which are easily and cheaply measurable with standard sensors already produced and installed on board of vehicles.

To generate the data for the system identification phase we exploit in this work an accurate 8^{th} order mathematical model developed by the authors and presented in [8]. It is based on the Eulerian theory mentioned above and its parameters are determined or detected by known geometrical data. We use this model due to the lack of suitable experimental data; however, this approach gives us important directions on how to choose the I/O data set from the real system and to assess the suitability of the approach, in view of future developments, when an experimental setup will be available.

2 System Description

The CNG Injection System is composed of a tank, a mechanical pressure reducer, an electro-hydraulic valve, a common rail and four electro-injectors (Fig. 1), see [8] for details. A set of sensors displaced among the circuit allow to measure tank, reducer and rail pressures, as well as current absorptions of the electro-hydraulic valve and the injectors.

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 20 bar. The reference pressure is regulated by the equilibrium of the forces acting upon a mobile piston located inside the reducer chamber. It is coupled with the spherical shutter whose axial displacement controls the inlet section. Pressure forces push the piston at the top, while elastic force of a preloaded spring pushes it

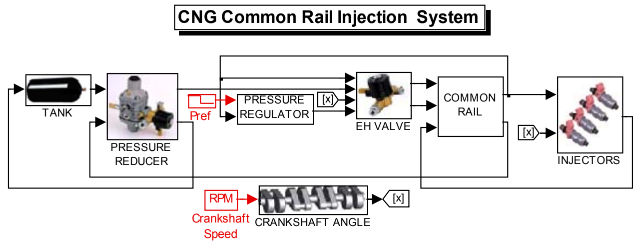


Fig. 1: Block scheme of the CNG Common Rail Injection System.

down and causes the shutter to open. The spring preload value sets the desired equilibrium reducer pressure: if the pressure exceeds the reference value the shutter closes and reduces the gas inflow, 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 so that the pressure in the reducer chamber increases.

An electro-hydraulic valve regulates the flow from the reducer pressure towards the common rail. The valve encompasses an electromagnet, with a mobile anchor, and a spherical shutter, integral with the anchor. In a non energized condition, a preloaded spring action against the hydraulic force makes the shutter and the anchor remain closed, and blocks 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.

To sum up, the common rail is a constant control accumulator connected to injectors. Its main task is to reduce pressure fluctuations due to mechanical part motions and injection flows. The injected fuel amount depends on the injector opening time and pressure [8]: the former is set by the Electronic Control Unit (ECU) according to the engine speed, the latter is almost equal to that in the rail and hence can be regulated by controlling the electro-hydraulic valve.

A complete injection cycle takes place in a 720° angular interval and consists of four injections starting every 180°. The injectors driving command is a square signal energizing the solenoid valve that attends to change the outlet section. In comparison to system dynamics, opening and closing transients are negligeable.

3 Nonlinear Model Identification

In this section, the nonlinear model of the rail pressure is presented. The model is developed through the usual steps of system identification, i.e.: input selection, experiment definition and data collection, selection of the model structure, model identification, model validation [7].

The selection of the input variables is a primary task in the definition of a model. The aim of the proposed model is the development of model-based control algorithms for the rail pressure. To this aim, models must be simple enough, with both static and dynamic good performance, and based on simple, easily accomplished, measurements. Most of the producers require for their prototypes control schemes using a limited number of cheap and commercially available sensors, possibly identical to those already adopted in current automotive systems. Therefore, input variables must be chosen among those that have a good influence on the output trend, and must be easily (cheaply) measurable.

After a thorough phase of investigation, three variables have been selected as candidate inputs for the model.

- *Engine Speed*, in Revolutions Per Minute (RPM) of the crankshaft. When the engine speed increases, the injector opening time increases according to a look-up table set by the manufacturer. Consequently, the rail outflow increases and the rail pressure decreases.
- *Duty Cycle* of the regulator valve opening with respect to one injection cycle (720° of crankshaft rotation).
- *Fuel Tank Pressure*. This pressure has a decreasing trend, as the fuel is burned into the engine. As the tank pressure decreases, the rail pressure tends to decrease. The pressure reducer at the output of the tank is installed to reduce the effect of the changes in the tank pressure and keep the fuel outflow at a constant pressure, but nonlinear dynamics in the reducer prevent the output pressure to be constant. Therefore, the tank pressure still influences the rail pressure.

It is well known that in identification problems, data must be carefully selected, as identified models cannot provide more information than that provided by data. In our case, since an analytical model in the state-space generates data, input can be suitably chosen to stimulate the modes of the response in the frequency band of interest and with peculiar signal trends.
In particular:

- We have assigned a decreasing trend to the tank pressure, and tuned on experimental data, according to typical fuel consumption rates.
- We have chosen the engine speed, which is actually set by the driver, according to typical driving profiles containing accelerations, decelerations and steady phases.
- Duty cycle is an actuation signal of a closed-loop scheme rather than an exogenous signal. For generating this signal, we have pursued three strategies:
  - Simulating the system in open loop and imposing on the duty a pseudo-random trend;
  - Simulating the system in closed loop and generating the duty through a Proportional-Integral control scheme;
  - Simulating the system as in the previous point, and consider the PI-generated signal as a start point. Further, the signal is enriched through some post-processing and the system simulated again in open loop by using the new duty cycle signal.

After a thorough analysis phase, the third choice for the generation of the duty cycle trend has been adopted.

Fig. 2 shows the data set adopted for the identification of the model. Data have been sampled at 1 kHz; this sampling frequency is suitable for control purposes. The dataset, which consists of 296.000 points, has been split into two halves, used for learning and testing, respectively.

The aim of this paper is to build a dynamical model able to predict the trend of the rail pressure on the basis of the input selected above. Two kind of models have been taken into account: a *Nonlinear Moving Average with exogenous inputs* (NMAX) model, and a *Nonlinear AutoRegressive Moving Average with eXogenous inputs* (NARMAX) one.

The first model considered does not take as input past regressions of the output. After an extensive trial-and-error phase, the model with best performance has been selected as:

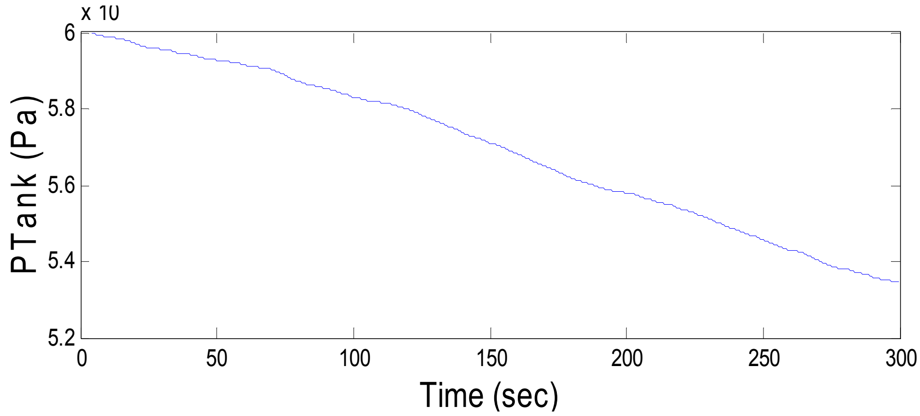
$$prail(k+1) = f\,[ptank(k), ptank(k-1), RPM(k), RPM(k-1), duty(k), duty(k-1)] \qquad (1)$$

The unknown function f in eq. (1) has been interpolated with a Multi Layer Perceptron (MLP) neural network on the basis of the data shown above. The first half of the dataset has been used for training the model, the remainder has been used for testing.
The neural network has therefore six inputs and one output. A trial-and-error phase led to best performance with a network with five neurons in the hidden layer. Performances are satisfactory, as shown in Fig. (3), which illustrates a comparison between predicted and actual output, the residual, the histogram of the residual, and the autocorrelation function of the residual. All these tests were passed successfully.

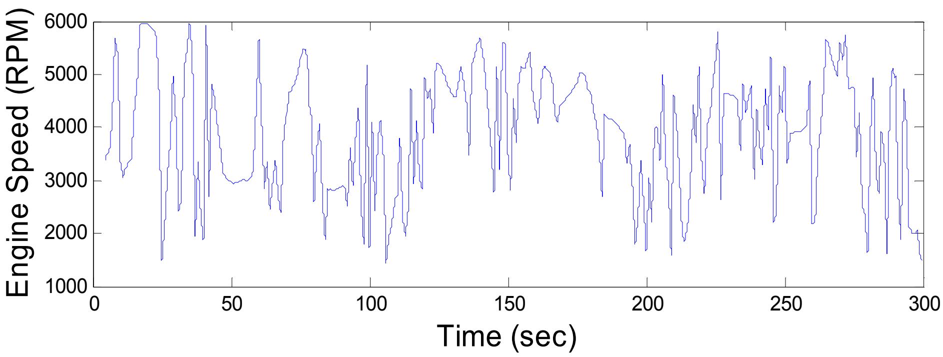
To improve the modeling performance, a NARMAX model has been selected as follows:

$$prail(k+1) = f\,[ptank(k), RPM(k), duty(k), prail(k)] \qquad (2)$$

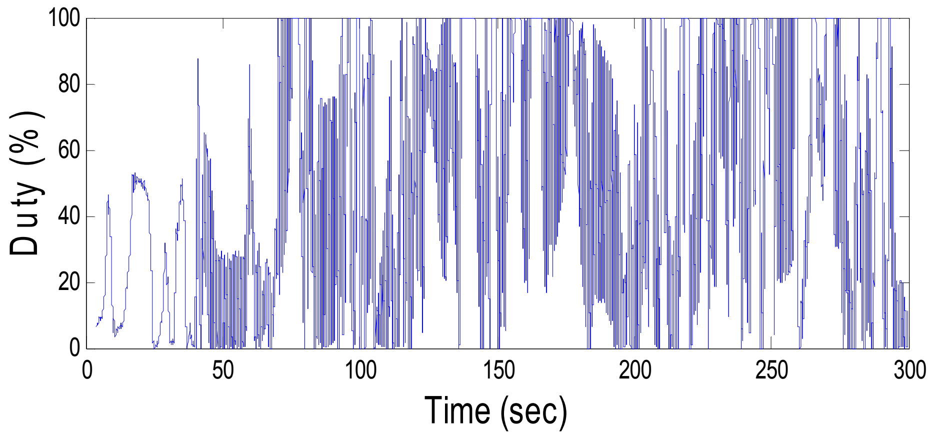
The unknown function f in equation (2) has been interpolated with a Multi Layer Perceptron (MLP) neural network on the basis of the data shown above. The first half of the dataset has been used for training the model, the remainder has been used for testing.



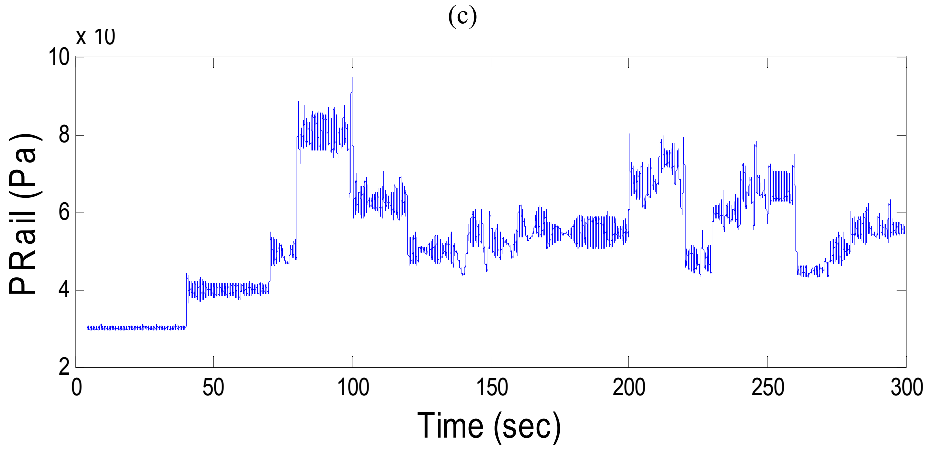
(a)



(b)



(c)



(d)

Fig. 2: Dataset adopted for identification. (a) Tank pressure, (b) Engine Speed, (c) Duty Cycle, (d) Rail pressure.

The neural network has four inputs and one output. A trial-and-error phase led to best performance with a network with twenty neurons in the hidden layer. It is not surprising that a NARMAX model performs extremely well on a one-step-ahead prediction. For this reason, performance evaluation in this case is not reported. For control purposes, a NARMAX model must perform a prediction along a time horizon sufficiently wide, to be suitable for predictive control schemes. In our model, the prediction horizon has been reckoned in 200 samples, which correspond to 0.2 seconds. This time interval is adequate for the implementation of predictive control strategies. Fig. 4 illustrates the satisfactory 200-step predictive performance along the whole testing dataset. A portion of Fig. 4(a) is magnified around a change in the working condition in Fig. 4(b). Also in this case, the model exhibits good accuracy.

4 Conclusion

Modern automotive systems require an intense modeling activity on all their subsystems for the development of control and diagnosis schemes. This paper deals with the development of nonlinear dynamical black-box models for the injection system of a common rail CNG engine. For this purpose, Multi Layer Perceptrons have been exploited to model the common rail pressure dynamics, leading to models with a prediction horizon suitable for the development of predictive control schemes.

The model has been identified on the basis on reliable data generated by a 8^{th} order state space model. Further work will concern some improvement of the performance of the existing model and its tuning with data collected on an experimental setup.

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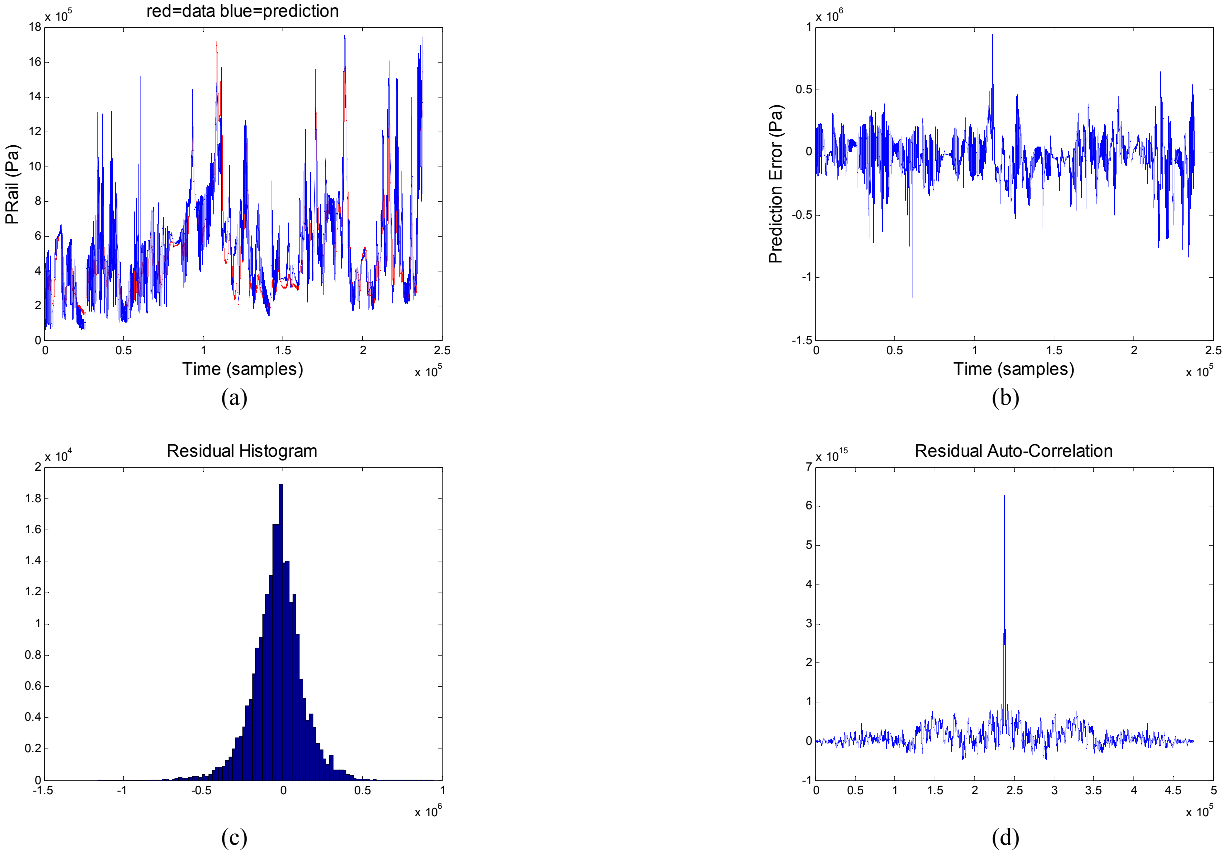

Fig. 3: Performance of a NMAX model implemented by a 6-5-1 MLP in terms of: (a) comparison of predicted and actual output, (b) residuals, (c) histograms of the residuals, (d) autocorrelation function of the residuals.

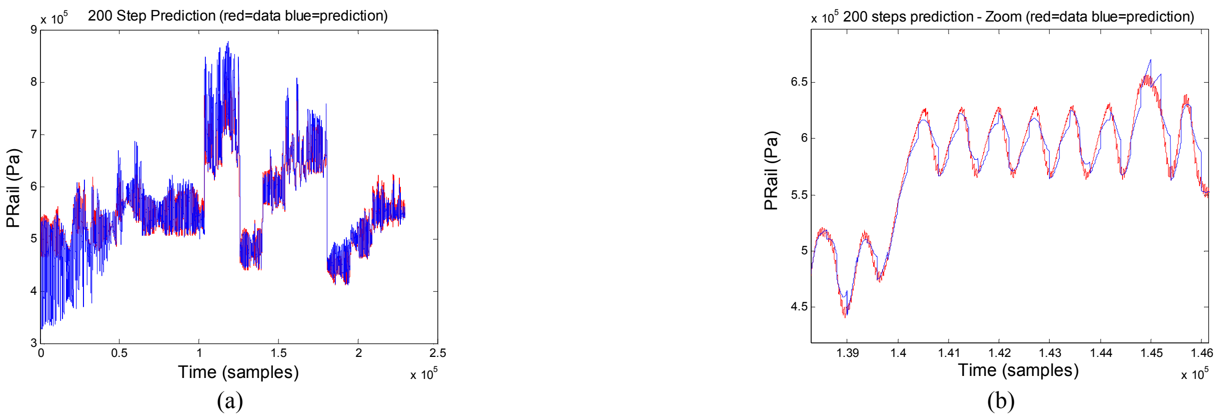

Fig. 4: Performance of a NARMAX model implemented by a 4-20-1 MLP in a 200 steps ahead prediction: (a) comparison of predicted and actual output along the whole test dataset, (b) zoom around a change in the operating condition..