MODELS FOR THE DESIGN AND OPTIMIZATION OF CNG INJECTION SYSTEMS

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Abstract

The need of improved performances in mechatronic systems calls for the integrated design of the mechanical, electronic and control subsystems. In this framework, simulation can help in attaining the optimal solution, as it allows to evaluate the effect of changes even at early stages of the design process. In this paper, we tackle the problem of a proper choice of a model for the integrated design and optimization of a mechatronic system, i.e. the injection system for a Compressed Natural Gas Engine. In particular, two models that are obtained by using different approaches and characterized by different level of details are compared. The first one is developed within the AMESim® environment, an advanced multi-domain modelling/optimization tool for the virtual prototyping of the physical/geometrical characteristics of fluid-mechanical systems. The resulting model can be regarded as a virtual prototype, as similar as possible to the actual final hardware, and is assumed as a reliable representation of the real system. Then, with reference to this prototype, a reduced order state space model is determined, which is more suitable for designing a controller or to speed up the design optimization process. A comparison study involving the proposed models is performed in terms of fidelity, range of validity and computational efficiency, showing that the system development can take advantage of a proper choice of the system model at different stages of the design optimization processes.

Keywords: MDO, Modeling Injection System, CNG, AMESim®

Presenting Author's Biography

Carlo Meloni received the degree in Electronics Engineering from the Università La Sapienza (Rome) in 1997. He received a Ph.D. in Operations Research from the same university in 2000, then he joined the Università Roma Tre as post-doctoral fellow in Operations Research. In July 2002 he became Assistant Professor of Systems Engineering at the Politecnico di Bari. He took part in research projects promoted by academic organizations and companies. Recently, he has been involved in a research project for the design and optimization of common rail engine parts, in co-operation with Fiat Research Center, Valenzano Branch, Bari, Italy.

1 Introduction

The optimized development of a mechatronic system is not always feasible, as it calls for the proper dimensioning of the mechanical, electronic and embedded control subsystems, and requires the knowledge of the interactions of the basic components and sub-systems for different operating conditions [1]. To this end, a deep analysis considering the system as a whole and its transient behavior seems necessary. According the current approach, the main problem is decomposed into several sub-problems, which are solved separately. The partial solutions are then put together leading, in general, to a sub-optimal solution. In this framework, simulation represents an essential tool for designing and optimizing mechatronic systems. In fact, it can help in getting closer to the optimal solution, by integrating the steps involved in the whole design process, giving tools to evaluate the effect of changes in the mechanical and the control subsystems, even at early stages of the design process. Available or suitably built models may be exploited for the geometric optimization of components, the design and test of control systems, the characterization of new systems.

Since models are application oriented, none of them has absolute validity [2]. A compromise between accuracy in describing the most important phenomena and simplicity of representation would be helpful to obtain a more manageable model, still valid for each working condition. To precisely predict the real system behavior, the model could be too complex to be profitably used. The derivation of appropriate models for the system dynamics can take advantage of domain specific simulation environments, requiring a reduced effort to designers. Models that differ for complexity and accuracy can be defined to take into account the main physical phenomena at various accuracy levels. From the control engineer point of view, the use of detailed modeling tools allows the safe and reliable evaluation of the control systems, which usually are designed considering simplified models. Moreover, the construction of accurate models in a general purpose environment could be a complex and stressful process if a deep knowledge of the system under study is not achieved.

In this paper, we compare two models [3, 4], which are obtained by using different approaches and characterized by a different level of details, to optimize the design of a Compressed Natural Gas (CNG) injection system. The first one is developed within the AMESim® environment [5], an advanced multi-domain modelling/optimization tool for the virtual prototyping of the physical/geometrical characteristics of a Compressed Natural Gas (CNG) injection system. We used this tool to obtain a virtual prototype, as similar as possible to the actual final hardware, that could be assumed as a reliable representation of the real system. Then, with reference to this prototype, we also determined a reduced order model in form of a state space model, more suitable for analytical (or empirical) tuning of the pressure controller of the CNG injection systems or to speed up the design optimization process. This model has been implemented in the MATLAB environment. Using the virtual prototype in early design stages enabled the evaluation of the influence of the geometrical/physical alternatives on the reduced model used for the controller tuning.

In automotive applications, as in many different engineering areas, expensive computer simulation models are often employed in the design optimization process of complex systems. Aiming at reducing the high computational costs payed for running the simulation model, the use of several approximation techniques (also called surrogates or metamodels) have been proposed in the literature to assist the main optimization process. Metamodels are often used to obtain approximations of expensive objective or constraint functions. However, integrating metamodels in a computational optimization process based on classical, evolutionary or meta-heuristic optimizers is not straightforward and different model management issues emerge in order to coordinate optimization strategies and approximation efforts. At this aim, a number of implementations proposed in the literature supports the use of successive approximation models of a costly fitness function and enables different strategies - usually referred to as metamodel management - to integrate and manage the metamodels in the optimization process. Successive approximations can be obtained dynamically improving a metamodel either adopting some progressive DOE fill-in scheme. or using more accurate simulation models in successive stages of the optimization process. Clearly, the issue to find the trade-off between metamodel accuracy, overall computational efficiency and solutions quality has to be addressed carefully playing a central role in the design optimization process.

The paper is organized as follows. In Sections 2 and 3 the case study and the considered models are presented, respectively. Section 4 reports on a validation analysis performed by comparing simulation and experimental data to evaluate the models performances, either in time and frequency domains and by means of statistical tools. Section 5 compares the models regarded as tools involved in the integrated design and optimization process, by considering the computational effort, the range of validity and the effect of simplifying assumption on overall behaviour of the models. Finally, in Section 6 some conclusions are given.

2 The Case Study

In internal combustion engines equipped with the Common Rail injection system the accurate metering of the air/fuel mixture strictly depends on the injection pressure regulation. Accuracy in metering is difficult to be achieved especially for Compressed Natural Gas (CNG) injection systems, as the gas compressibility makes the fuel delivery process more complex. The optimal design of the CNG injection system is not a trivial task, and could take advantage of the use of appropriate models during each stage of the development process.

We consider a system composed of the following elements (Fig. 1): a fuel tank, storing high pressure gas, a mechanical pressure reducer, which includes a main

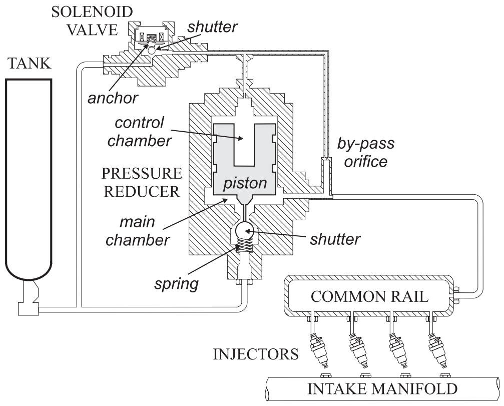

Fig. 1 Block scheme of the common rail CNG injection system

chamber and a control chamber, a solenoid valve and the fuel metering system, consisting of a common rail and four electro-injectors. The fuel from the pressure reducer directly flows towards the rail, and the solenoid valve regulates the intake flow in a secondary circuit including the control chamber. The injection flow only depends on rail pressure, which is almost equal to the main chamber pressure, and injection timings, which are precisely driven by the Electronic Control Unit, so that it can be controlled by acting on the solenoid valve, as described in the following.

The variable inflow section of the pressure reducer is varied by the axial displacement of a spherical shutter coupled with a moving piston. Piston and shutter dynamics are affected by the applied forces: gas pressure in the main chamber acts on the piston lower surface pushing it at the top, and gas pressure in the control chamber pushes it down and causes the shutter to open. When the solenoid valve is energized, the fuel enters the control chamber, causing the pressure on the upper surface of the piston to build up. As a consequence, the piston is pushed down with the shutter, letting more fuel to enter in the main chamber, where the pressure increases. On the contrary, when the solenoid valve is non-energized, the pressure on the upper side of the piston decreases, making the piston to raise and the main chamber shutter to close under the action of a preloaded spring [6, 3].

3 Modeling the CNG Injection System

3.1 Low Order State-Space Model

By following the Eulerian approach [7] to derive the state-space model of 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. The tank pressure is considered 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 [3]. With x_1, x_2, p_{tk} the control chamber, the rail and the tank pressures, respectively, and u_1, u_2 the signals driving the solenoid valve and the injectors, respectively, the CNG injection system can be represented by the following 2^{nd} order state space model [3]:

$$\begin{cases} \dot{x}_1(t) = c_{11}p_{tk}(t)u_1(t) - c_{12}\sqrt{x_2(t)[x_1(t) - x_2(t)]} \\ \dot{x}_2(t) = c_{21}p_{tk}(t)[c_{24}x_1(t) - c_{25}x_2(t) - c_{26}p_{tk}(t)+ \\ \qquad - c_{27}] - c_{22}x_2(t)u_2(t)+ \\ \qquad + c_{23}\sqrt{x_2(t)[x_1(t) - x_2(t)]} \end{cases} \tag{1}$$

where c_{ii} are constant coefficients. The system of non linear equations (1) completely describes the system dynamics in terms of control volume pressures.

3.2 Virtual Prototype - AMESim Model

AMESim is a virtual prototyping software produced by IMAGINE S.A. [5], which is oriented to lumped parameter modeling of physical elements, interconnected by ports enlightening the energy exchanges between pairs of elements and between an element and its environment. AMESim enables the modeling of components from different physical domains and the integration of these different elements in an overall system framework. It also guarantees a flexible architecture, capable of including new components defined by the users [4].

The AMESim model is developed by considering the following assumptions. The pressures distribution within the control chamber, the common rail and the injectors is uniform, and the elastic deformations of solid parts due to pressure changes are negligible. The pipes are considered as incompressible ducts with friction and a non uniform pressure distribution. Temperature variations are taken into account, affecting the pressure dynamics in each subcomponent. Besides, only heat exchanges through pipes are considered, by properly computing a thermal exchange coefficient. The tank pressure plays the role of a maintenance input, and it is modeled by a constant pneumatic pressure source. Finally, to simplify the AMESim model construction some supercomponents have been suitably created, collecting elements within a single one (Fig. 2). For further details on the AMESim model of the CNG injection system refer to [4].

4 Validation of the Proposed Models

To assess the models validity, a comparison between simulations and experiments, in terms of time responses and frequency analysis has been carried on. Equation (1) has been solved on a 1.8GHz Pentium IV within the MATLAB/Simulink environment, by using a fourth order Runge-Kutta method with a 10^{-4} integration time step. The AMESim model has been deveoloped within the AMESim 4.2 package by using a mixed variable step integration method, which is declared by the producer as the most efficient method for these kind of

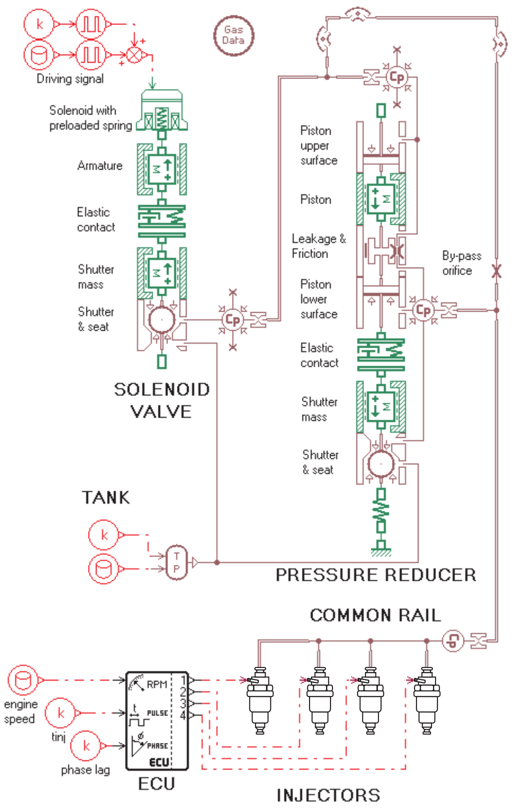

Fig. 2 AMESim model of the common rail CNG injection system

problems.

Firstly, with constant injectors driving command and constant tank pressure, the system response to step variations of the duty cycle of the valve driving signal has been determined. The operating conditions are a 2400rpm engine speed and 8ms injectors exciting time interval, when two opposite duty cycle step variations are applied (3%-9%, 9%-3%), at 1.5s and 28s time instants respectively. Fig. 3 compares the state-space model simulation results with the performed experiments.With a positive step variation, the pressure increases in the control chamber (see Fig. 3(a)), making the regulator inlet section to stay open longer. As a consequence of the larger mean air inflow coming from the compressor, the rail pressure raises (see Fig. 3(b)). Conversely, with a negative step reducing the duty cycle, both the control chamber and the rail pressures fall to lower levels. As shown in Fig. 3(c), the pressure in the control chamber has an oscillating behavior within the control period: the pressure increases (decreases) when the solenoid valve is open (closed). Shortening the control period could smooth away these pressure variations.

Results show that the model well approximates the real system behavior both during the steady state condition and during both the rising and drop transients. The waves amplitude difference between experiment and simulation in Fig. 3(c) depends on simplifying assumptions, in fact and it is smaller for the AMESim model, which considers both the 2nd order dynamics of solenoid valve shutter and piston, and gives better results (Fig. 4(c)). Moreover, higher frequency, superimposed rail pressure oscillations due to injections within a cycle occurs (see Fig. 3(d)). In this case, simulation results obtained using the state space model exhibits wider oscillations than experiments, synchronously with the solenoid valve operations. Modeling assumptions, indeed, considered the reducer main chamber and the common rail as a whole control volume. Consequentially, the decoupling effect of the main chamber volume with respect to pressure disturbances propagating towards the rail was not taken into account. In addition, the distributed losses along the pipes connecting common rail and pressure reducer were neglected. However, a detailed representation of these phenomena would require a PDE description.

The same experiment has been performed considering the AMESim model, as shown in Fig. 4. The comparison shows a good accordance of simulation and experimental results, and a more accurate representation of the oscillating behavior than the previous case.

Such accuracy can be also evaluated by performing a frequency analysis on experimental and simulated pressure signals (Fig. 5). The main component of the oscillation of experimental pressure in the control chamber (Fig. 5(a)) is clearly due to solenoid valve operation, and different high frequency components seem to be high order components (with multiple frequencies of the main component) of the same saw-tooth oscillation (Fourier analysis shows that the amplitude of these components almost decreases as in Fig. 5(a)). The higher amplitude component of experimental rail pressure oscillation (Fig. 5(b)) can be correlated to injectors operations, which cause a $v \cdot 6 \cdot 720/n = 80$Hz oscillation for the considered working conditions ($v =$ 2400rpm, $n = 4$, being n the number of injectors). The simulated control chamber pressure obtained by using the state-space model correctly includes all the harmonics of the experimental signal, even though with a higher power content (Fig. 5(c)). However, due to the simplifications related to the main chamber and rail representation, the frequency content of simulated the rail pressure signal is different from the experimental one (Fig. 5(d)). From figures 5(e) and 5(f) it is evident that the AMESim model can better represent the frequency content of both control chamber and rail pressures.

A second test is performed to assess the reliability of the proposed models in predicting the system dynamics for variable operating conditions. To this aim, the system behavior for a constant load (resulting in a 3ms injectors opening time interval), while varying engine speed and solenoid valve driving signal has been evaluated. The engine speed varies according ramp profiles, while the duty cycle abruptly changes within the interval $[1\%, 13\%]$. Figures 6(a)-6(b) and 6(c)-6(d) compare experimental results with those obtained with the detailed AMESim model and the low order state-space model, respectively. In both cases, there is a good accordance of the resulting dynamics with the expected behavior.

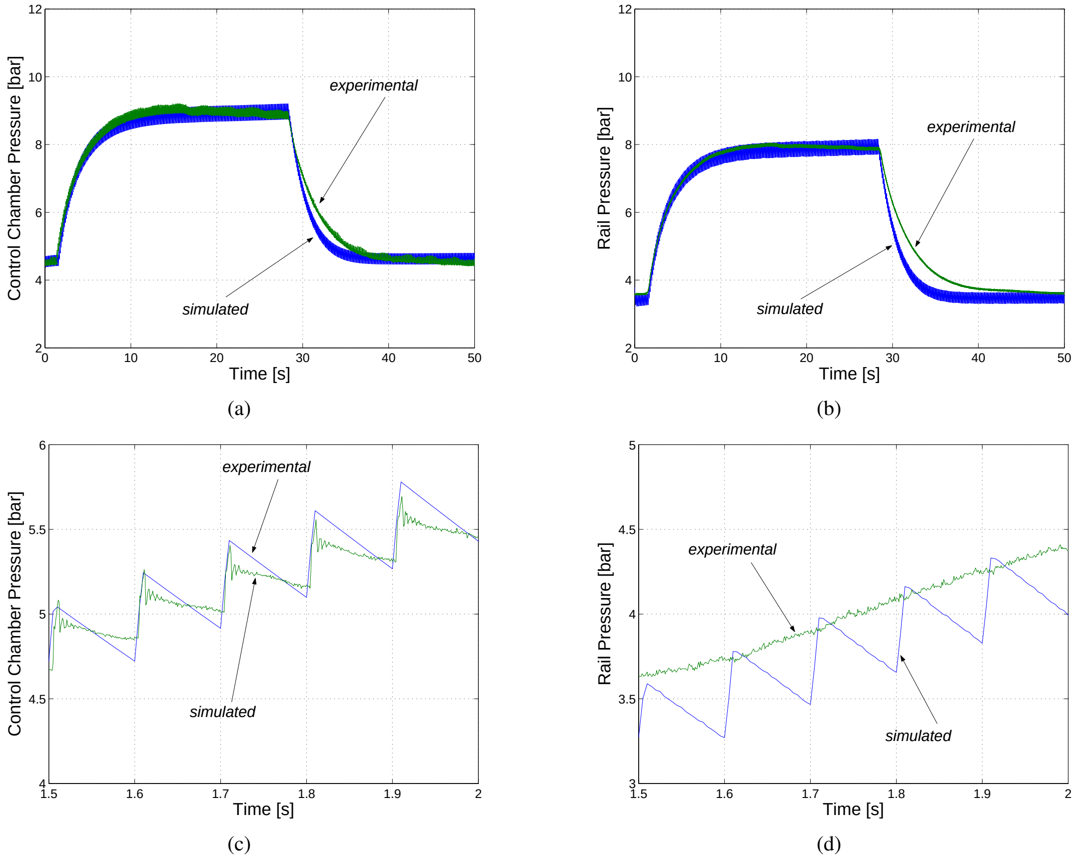

Fig. 3 State-space model and experimental results with duty cycle step variations and constant injectors driving signal; (a) control chamber pressure; (b) rail pressure; (c) detail on control chamber pressure; (d) detail on rail pressure.

Even if the AMESim model can better represent the rail pressure dynamics than the state-space model, in particular for low pressure values and slow transient, as in the initial time interval. However, a maximum error of 10% confirming the state-space model validity can be tolerated considering that the computational effort is a crucial parameter to be taken into account.

5 A Comparison Study from the Optimization Perspective

Some considerations can be drawn from results presented in the previous section. The design process requires the optimization of some geometrical parameters, which affect both the system steady state and the transient behavior. The different level of detail in representing the system makes the considered models suitable for exploring different aspects of the design process.

The first concern about the models performances is related to the computational effort required to solve the model equations. As expected, the state-space model is lesser demanding than the AMESim model, as requires 1.05s to simulate 1 second of system operations using the MATLAB normal mode. The simulation time reduces to 0.23s using the MATLAB accelerator mode. Besides, by using the same configuration, the AMESim simulation is performed in about 45s. The comparison of the computational effort suggest the use of the AMESim model only if accuracy is a crucial point during the optimization process, e.g. to choose from different final solutions.

As for the mechanical system dynamical performances, we refer to indices introduced in [8]. The first two dynamical indices consider the variability of the common rail pressure due to solenoid valve and injectors operations, respectively. In fact, by varying the system geometry, the same step variation of solenoid valve driving signal or injectors opening time causes a different steady state pressure change. Clearly, these two indices could be contrasting. The former, given by the least square of the difference between the actual rail pressure and the initial steady state pressure $l.s.(p_{mc})$, expresses the disturbance rejection capabilities of the system. The latter, given by the pressure change δp_{mc} due to a step variation of the control action, represents the system sensitivity to control action. In both cases, the dynamical model has to correctly represent only the steady state system behavior induced by input step changes. Thus, a precise representation of pressures oscillating behaviors is not mandatory, and both the proposed state-space model and the AMESim model can

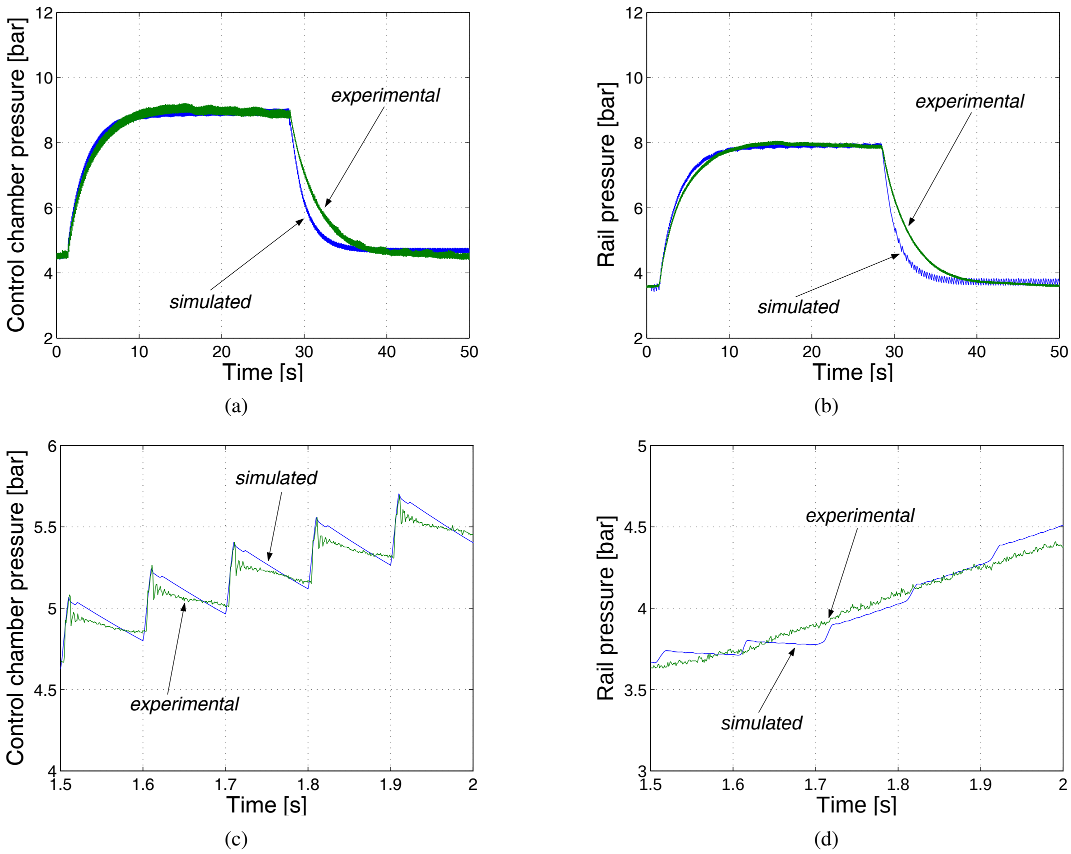

Fig. 4 AMESim model and experimental results with duty cycle step variations and constant injectors driving signal; (a) control chamber pressure; (b) rail pressure; (c) detail on control chamber pressure; (d) detail on rail pressure.

be suitably employed to compute the indices. A second performance index ($\sigma(p_{mc})$) is obtained by considering the injection pressure standard deviation with respect to the mean value during steady state conditions, and gives a measure of the control and rail pressures oscillating behavior within the control period, which influences the injection process. A proper dimensioning of the common rail and pipes volumes depends on a correct evaluation of this index, depending on the model accuracy. According to results obtained in the previous section, the AMESim model is more appropriate than the state-space model for the evaluation of this index.

The analysis of the models can be concluded by considering the static performance indices used during the optimization process, as in [8]. These indices are used for the optimal design of the injection system in terms of friction forces reduction, gas leaks reduction, improvement of system disturbance rejection capabilities, improvement of pressure and mechanical parts dynamics. The optimization process is performed on a set of geometrical parameters which affect the overall system behavior, which can be reliably evaluated only if a model including the entire set of design parameters is available. In fact, different designs could results in the same dynamical behavior in simulation, if the model does not include the entire set of optimized variables. In our case, the state-space model only considers the data needed to compute flows between volumes and pressure variations, while does not take into account friction effects, wave propagation phenomena and heat exchanges, which affect the above mentioned indices.

6 Conclusions

In this paper, two different models of a CNG injection system have been analysed and compared to assess their feasibility for inclusion in a multidisciplinary optimization tool. Different performances in terms of low computational effort and accuracy in predicting the real system behavior call for a different utilization of the considered models, in order to optimize the design process. In particular, the state-space model developed in the MATLAB/Simulink environment guarantees a good prediction on the mean system dynamics requiring a considerably lower computation time, but lacks in representing high frequency dynamics due to wave propagation phenomena. It also neglects temperature variation that could affect the prediction accuracy for particular operating conditions. On the other hand, the AMESim model can detail complex fluid dynamic phenomena to detriment of simulation time. These considerations suggest the use of the state-space model for a rough tuning and the AMESim model for the fine

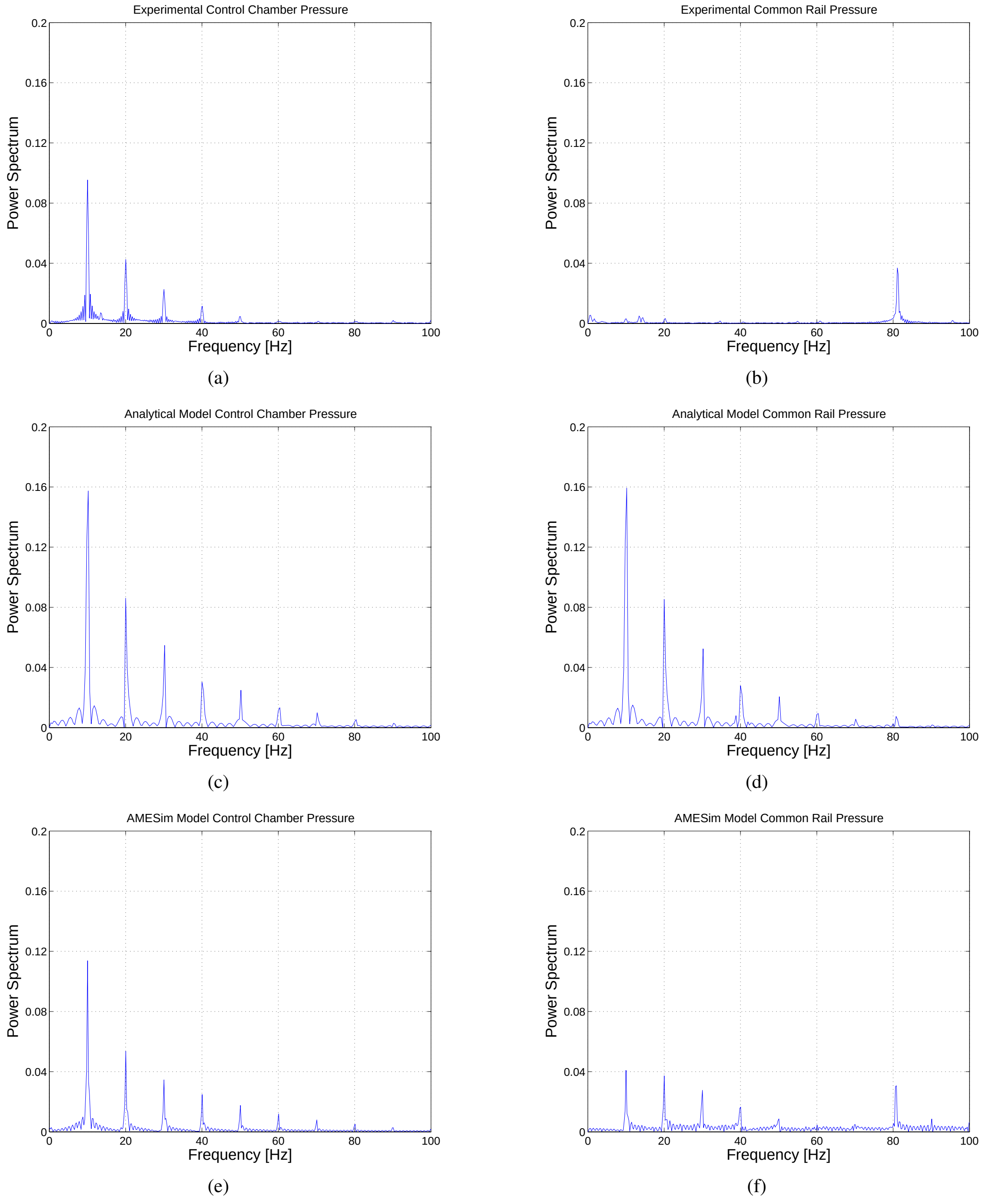

Fig. 5 Power spectrum of the control chamber and common rail pressures (a) Experimental control chamber pressure; (b) Experimental rail pressure; (c) State-space model control chamber pressure; (d) State-space model rail pressure; (e) AMESim model control chamber pressure; (f) AMESim model rail pressure;

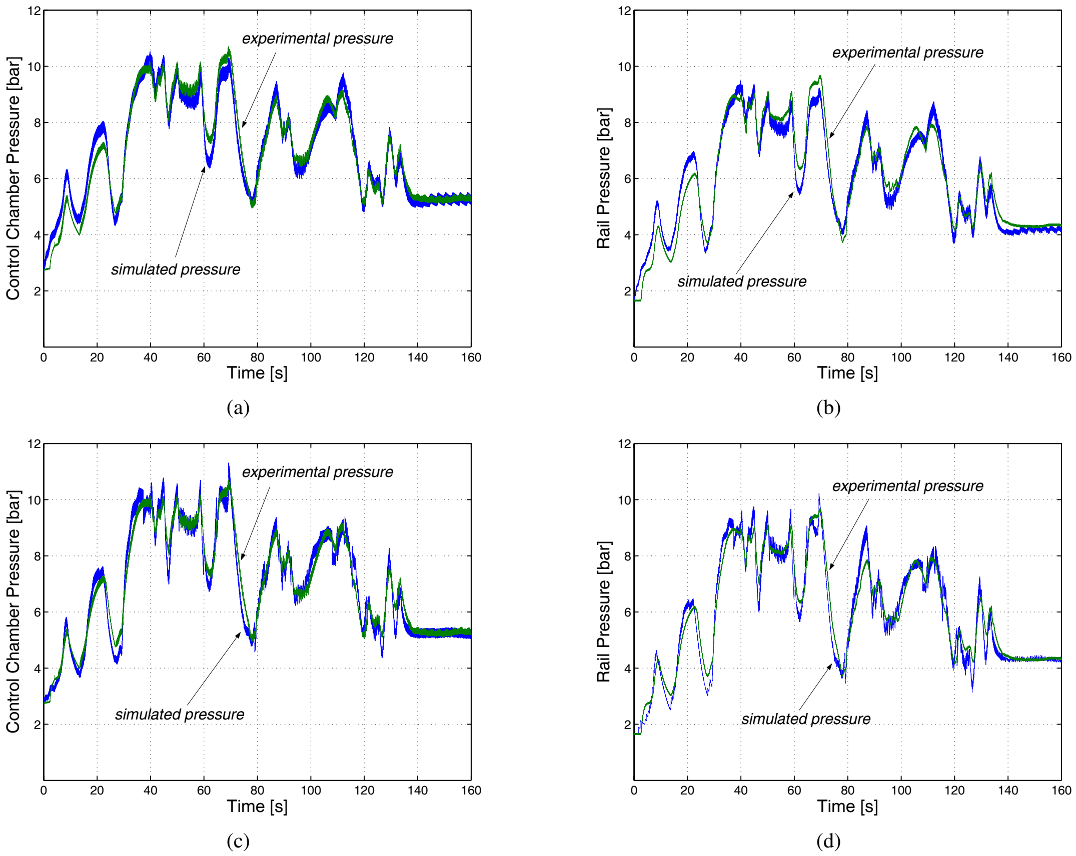

Fig. 6 Simulation and and experimental results when varying duty cycle and engine speed, with a constant $t_j = 3\text{ms}$; (a) State-space model control chamber pressure; (b) State-space model rail pressure; (c) AMESim model control chamber pressure; (d) AMESim model rail pressure.

tuning during or validation issues in the design process. In addition, a deep knowledge of these characteristics may guide the choices concerning the simulation-optimization scheme to adopt. Future work will regard a quantitative analysis of the influence of design parameters and working conditions (e.g. temperature, heat exchanges, etc.) on the dynamical indices.

7 References

[1] S.S. Joshi. The Need for a Systems Perspective in Control Theory and Practice. *IEEE Control Systems Magazine*, 6(19):56–63, 1999.

[2] J. van Amerongen and P. Breedveld. Modelling of Physical Systems for the Design and Control of Mechatronic Systems. *Annual Reviews in Control*, (27):87–117, 2003.

[3] P. Lino, B. Maione, C. Amorese, and S. De-Matthaeis. Modeling and Predictive Control of a New Injection System for Compressed Natural Gas Engines. In *Proceedings of IEEE CCA 2006 International Conference*, Munich, Germany, 2006.

[4] P. Lino and B. Maione. Integrated Design of a Mechatronic System. In *Proceedings of ICINCO 2007 International Conference*, Angers, France, 2007.

[5] IMAGINE S.A. *AMESim User Manual v4.2*. Roanne, France, 2004.

[6] C. Amorese, S. De Matthaeis, O. De Michele, and A. Satriano. The Gaseous Fuel Option: LPG and CNG. In *Proceedings of Int. Conference on vehicles alternative fuel system & environmental protection*, Dublin, Ireland, 2004.

[7] V. Streeter, K. Wylie, and E. Bedford. *Fluid Mechanics*. McGraw-Hill, New York, 9th edition, 1998.

[8] G. Dellino, P. Lino, C. Meloni, and A. Rizzo. Multidisciplinary Design Optimization of a Pressure Controller for CNG Injection Systems. In *Proceedings of IEEE CACSD 2006 International Conference*, Munich, Germany, 2006.

