DEVELOPMENT AND IDENTIFICATION OF A HIERARCHICAL SYSTEM OF MODELS FOR RAPID PROTOTYPING OF SI ENGINES

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The structure of a hierarchical system of models for model based optimization and rapid prototyping of control strategies in automotive spark ignition engines is presented. The advantages of a distributed and hybrid modeling approach are discussed, in order to meet the conflicting goals of high flexibility and precision with limited experimental cost and computational time.
The critical role played by the identification phase is discussed, and a comparative analysis of the estimation procedures adopted during model validation is presented, analyzing their connections with the model development process.

1. INTRODUCTION

Many models for the study and the design of internal combustion engines (ICE's) have been proposed in literature, in order to assist the development of automotive engines with performance complying with future pollution control regulations. The most evident effect of this effort is perhaps represented by the development of comprehensive 3-D models, which try to describe all the relevant phenomena relating to engine operation and emission formation at the maximum allowed level of detail. The use of such models can be precious in order to consider the mutual influence of geometrical and operating parameters on the complex fluid-dynamics and thermo-chemical phenomena involved in engine operation, and in particular for the design of engines based on innovative concepts. But, in spite of their increasing diffusion and of some spectacular results, it could be hazardous to conclude that their use would represent the ultimate solution for all applications in the ICE's sector, at least in next future. The practical utility of these models, which require very high computational power, may be questionable in those cases where many repeated computations are involved, as in design applications. Moreover, their quantitative precision, which require an appropriate "balanced precision" in all their sub-models, could even be inadequate for some applications[26].
By a literature analysis on the models devoted to engine control applications, an articulate picture emerges concerning structure, goals and complexity [1,4,5,9], ranging from input-output black-box models, mostly oriented to control design, to gray-box mean-value models, with a simplified description of the most relevant physical processes [1,2,3], up to complex 3-D fluid-dynamic models [4,5]. These classes of model substantially differ in terms of computational time and experimental data required: for the validation of the simplest black-box models, hundreds or thousands of engine data could be needed to compensate for the lack of physical information, resulting in high experimental effort and lower model flexibility; on the other hands, the computational cost of the detailed 3-D models is not yet compatible with most control applications, and their predictivity still questionable[26].
From these considerations, it emerges that in many cases a suitable solution could be represented by the adoption of a mixed approach, in order to combine the advantages of various kind of models. The proper model structure, with a balanced role of a-priori theoretical knowledge and experimental information, would critically depend on objectives, resources and context of the work (fig.1).
It is also clear that, once the exclusive recourse to fully predictive physical models is excluded for some of the above mentioned reasons, a key role is played by proper use of experimental information during model development and validation. But, while well established identification techniques for models characterized by regular mathematical structures are generally available[16,13,14], the identification of the parameters and, mainly, of the structure of mixed or hybrid "non parametric" models has not been so extensively investigated[25]. Moreover, apart from a certain lack of methodological assessment, some sort of "philosophical" resistance to the use of systematic procedures for model identification may be argued, especially in those disciplinary contexts where the final objective is represented by the development of fully predictive models, to not be contaminated by "hybrid" methodologies. Therefore, in many cases the comparison with experimental data, when present, is usually made only at the end of modeling work, with little interaction on model structure development.

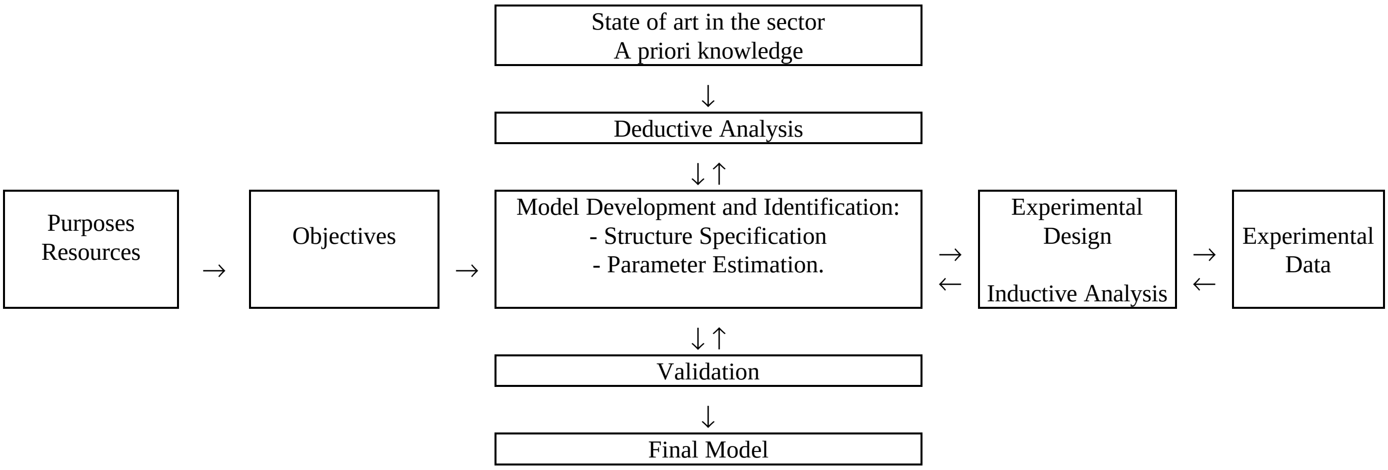

Fig.1 - Scheme of the modeling process.

Some significant semantic differences may be also noticed: rather than to model "identification", which refers to a well established discipline, the more vague term "calibration" is often used[27]; moreover, little attention is sometimes paid to detailed description of techniques used for parameter estimation[26], as well as to statistical significance of the results. Because of these reasons, in spite of the potential advantages of the models with mixed and hybrid approach, their development and validation are likely more affected by empiricism, with wider recourse to euristic techniques.

In the following chapters the structure of a distributed systems of models for the rapid prototyping of engine control strategies is presented, analyzing the mutual interactions among the various modeling modules and those with the experimental data, and focusing the most relevant aspects related to model validation and to parameter identification.

2. A HIERARCHICAL MODELLING APPROACH

A hierarchical model structure has been developed by the authors for the optimal design of engine control strategies [6]. The final objective is the development of rapid prototyping procedures for the design of the control strategies for an automotive engine of assigned geometry, able to be used in an industrial framework and to reduce by a substantial factor the time and the experimental cost involved by the design process. The general structure of the models is shown in fig.2.

At inner level, a gray-box mean-value dynamical model [8,9] has been developed, that predicts the effects of given control strategy over performance and emission of an engine/vehicle system during an arbitrary driving cycle. This model can consider the following dynamic effect, characterized by increasing time constants: (i) air flow dynamics and (ii) two phase fuel flow dynamics in the intake manifold, and (iii) thermal dynamics of cylinder wall temperature and their effects on emissions. This model can be used both for simulation and for optimization analysis [10]. The stochastic effects due the non ideal operation in sensors and actuators can be also predicted, and robust strategies can be designed via stochastic optimization approach [8]. These models are linked within the computer code ODECS (Optimal Design of Engine Control Strategies), which is now in use by Magneti Marelli [10].

At higher level, phenomenological models are used to simulate in off-line mode engine performance and emissions in steady-state conditions. Thanks to their built-in physical information, these models could be validated with a limited recourse to experimental data. The data computed by phenomenological models can be used to instruct the faster inner level of models, which in turn are used for optimal design of engine control strategies [6,].

In order to reduce the empiricism in the choice of both experimental and numerical[24] conditions to be investigated during the validation of the various levels of models, interactive experimental design techniques have been developed [7]. These techniques can significantly reduce the experimental (or numerical) cost by interactive selection of the next condition to be investigated, minimizing the expected value of the volume of the confidence region of model parameters. An application to the identification of black-box models for engine fuel consumption has shown that the amount of experimental data can be reduced of about a factor 3 with respect to conventional techniques, or, conversely, higher modeling precision can be achieved with given experimental effort[24].

3. ADVANTAGES OF A DISTRIBUTED MODEL STRUCTURE

The evidence that the performance and emissions of an internal combustion engines are influenced by almost all geometric and operating variables could represent a valid reason to develop comprehensive models, which could in principle take into account all the mutual influences of the engine variables on engine operation.

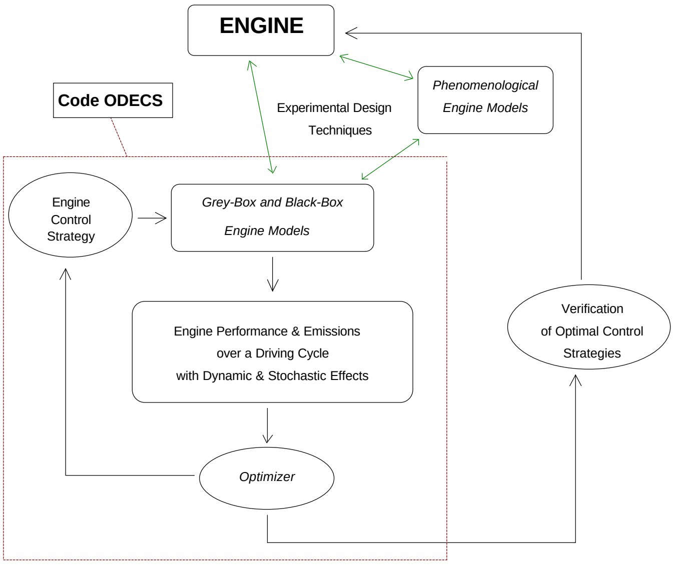

Figure 2 – A hierarchical model structure for engine control design.

In spite of its evident advantages, this approach has also some drawbacks. In an homogeneous model, the mathematical structure is often imposed by only part of the phenomenology, while simpler approaches could be followed to take into account the effects of other variables and phenomena. This fact can lead to unnecessary mathematical complexity and computational power demand. Other important implications refer to model validation: while it would be possible in principle to estimate all model parameters by making inferences on model output by classical non linear least square techniques (e.g. Levenberg and Marquard algorithm [16,19]), the circumstance that almost all output variables are influenced by all parameters and the presence of correlation between them may often prevent from finding solutions with some statistical significance. This kind of result has been found in a recent application of thermodynamic combustion models to ICE's [19], where the differences between computed and measured pressure values were used to estimate unknown engine parameters: in many cases (e.g. cylinder wall temperature and heat transfer coefficients) it was not possible to estimate the parameters, and high value of cross correlation resulted.

A more convenient approach would therefore consist in the development of a sequential structure of modules, rather than as a single comprehensive block. This approach, at the cost of a more articulate work during model design phase, could allow to avoid redundant mathematical complexity during computations and to offer a substantial advantage in the validation phase: in this case it would be possible to identify the values of the model parameters just acting on the appropriate module, so limiting the uncertainty due to mutual influences and correlation among the variables.

The structure adopted for the phenomenological engine models, which are in turn embedded in the hierarchical structure shown in fig.2, is represented in fig.3. Different functional blocks are used, to describe (i) the air flow into the intake manifold, (ii) the closed valve in-cylinder cycle, via two-zone thermodynamic combustion model, (iii) temperature stratification in the burned gas region via a multi-zone model, (iv) the emission formation and (v) engine mechanical losses. The connections between the modules, with the main input and output variables and the corresponding model parameters are synthetically shown, while for a detailed description of the models the reader is addressed to the references reported in tab.I.

4. MODEL VALIDATION AND PARAMETER IDENTIFICATION

A detailed description of model parameters and on identification methods for each modeling module is presented in tab.I. It can be observed that in most cases the identification of the model parameters can be performed in cascade (e.g.A1-A2-A3-A4), so limiting both computational time and estimation uncertainty.

Although the identification methods used for each case can appear quite different, some common features can be recognized. The functional dependence of the model parameters is mostly related to the nature of the models. In case of phenomenological models, the estimated parameters p, which represent some physical variables, are usually defined over the single i-th engine operating condition. Since in most cases their values cannot be assumed constant over the entire operating range, they are in turn expressed as function of the operating variables v_i, by means of further parameters β. Instead, the parameters of the black-box models, which do not have a precise physical meaning, are usually defined over the entire operating range.

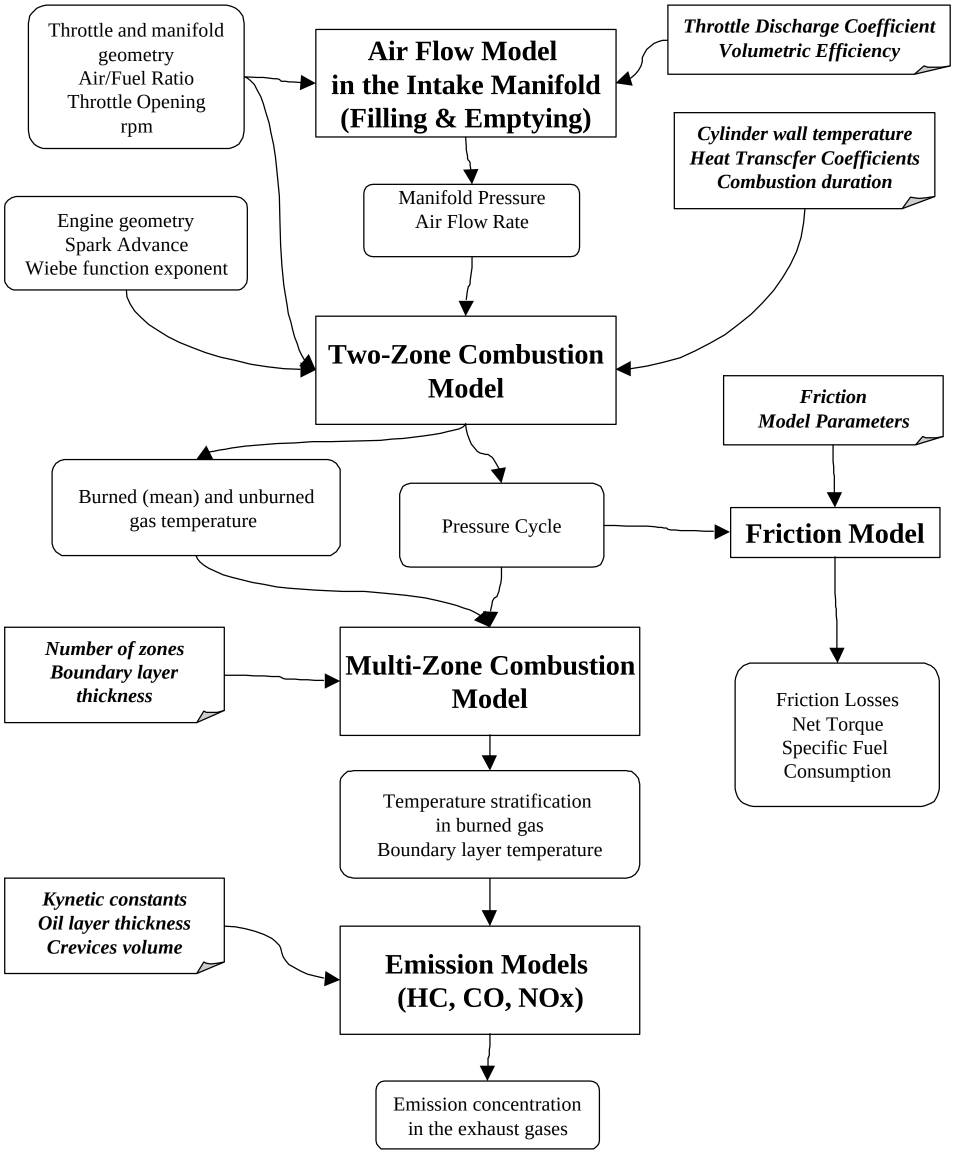

Figure 3 – Engine phenomenological models: modules **(in boldface)**, input and output data, model parameters *(in Italic)*

According to the information content related to the adopted inference criteria, two different cases can therefore occur.

4.1 LOCAL ESTIMATION - CORRELATION

This approach can be used if the inference criteria (i.e. the objective function of the related optimization problem) are enough informative to allow the identification of all model parameters for each operating conditions, on local basis. In such case, when the parameters are defined over the single operating condition, the problem can be split in two steps: (i) determination of local optimal value of the parameters p_i, in each operating conditions, and (ii) determination of a correlation $p=p(\beta,v)$ between the optimal values of model parameters and the operating conditions, which allow to use the model in predictive mode. This condition is verified when the inferred variable is represented by a function of time, with (virtually) infinite dimensionality. In this case, for each for the N operating conditions, the optimal value of model parameters p can be found by Least Square techniques by minimization of a functional:

$$\min_p \int [f(p,v)-f^*(v)]^2 dt \qquad i=1,N \tag{1}$$

With reference to table I, this approach has been used for the identification of heat transfer coefficients (A2) and then of combustion time (A3), starting from pressure cycle; and to determine the parameters of the dynamic model for two-phase fuel flow in the intake manifold (C), starting from mixture strength transient response. In the latter case, the local estimation is affected by the uncertainty due to some degree of cross correlation between the two variables.

A local estimation can be also performed in case of identification of cylinder wall temperature (A1) by processing measured pressure data during compression stroke. In this case, an algebraic relationship can be derived to express a net adiabaticity condition between gas and cylinder walls, and the wall temperature is assumed equal to the temperature of the gas at the crank angle where the instantaneous polytropic compression exponent is equal to the corresponding adiabatic iso-entropic one [18].

In a second phase, a correlation between the optimal model parameters p* and the operating conditions v can be found, via regression techniques:

$$\min_\beta \sum[p(\beta,v_i)-p_i^*]^2 \qquad (2)$$

4.2 GLOBAL ESTIMATION - DECOMPOSITION

In other cases, the inferred variables could do not contain enough information to allow the estimation of the model parameters on local basis. Within this work, different examples can be lead to this case: the determination of model parameters for black-box models for fuel consumption and emissions (B), for the air flow in the intake manifold (D2), for mechanical losses (F) and for engine emissions via phenomenological model (A4). In these cases, the functional form of model parameters should be found by simultaneous analysis of the entire set of data.

In case that model parameters β are defined over the whole operating range, the solution of the following LS problem would be required:

$$\min_\beta \sum[f_i(\beta,v_i)-f(v_i)^*]^2 \qquad (3)$$

If the physical parameters p are defined over the i-th operating condition, the specification of a functional relationship $p=p(\beta,v_i)$ between parameters p and the operating variables v would be needed and the problem can be formulated as follows:

$$\min_\beta \sum[f_i(p(\beta,v_i),v_i) -f(v_i)^*]^2 \qquad (4)$$

In both cases, the determination of the optimal values of the parameters β requires repeated model computation over the set of experimental conditions, to solve the non linear regression problem; and, possibly, the estimation of statistical significance of the solution. For real cases ($N\approx300$, $M=10\div50$), many thousands of model evaluations could be necessary. Moreover, the entire process should be repeated each time that a different functional structure has to be assumed, since most of the information achieved to arrive at the solution of the previous problems can not be utilized.

This approach can be practically used only if the model has a simple mathematical structure, as in the case of the black-box models, while an excessive computational cost would be required for complex physical models, as in case of engine emissions (A4). A two-step decomposition approach has been therefore proposed to solve this latter problem. In a first phase, a simpler model (i.e. 2nd order Taylor polynomial) is built to describe the effects of "physical" model parameters p on output data (i.e. emissions), by computation of first and second derivatives; in a second phase, the functional form of the correlation between "physical" parameters and operating data is found via non linear regression techniques, using the approximate model; thanks to the substantial reduction of model complexity and to a proper parametric description of the functional relationships, the most significant variables can be selected via stepwise approach. A detailed description of the technique can be found in previous papers [11,17].

5. RESULTS

A wide experimental analysis has been performed in last years in order to validate the presented models, at Laboratories of Istituto Motori in Naples, within a cooperation with Magneti Marelli. The black-box models for fuel consumption and emissions have been validated over two sets of experimental data, respectively composed of about 1000 [9] and 400 operating conditions[10]. The dynamic models for air and fuel flow have been validated on a dynamic test bench, over about 40 conditions, and suitable correlation's have been derived for their use in predictive mode[2,3]. The thermodynamic model has been validated over more than 300 operating conditions, through identification of burning time, with a good level of agreement between measured and predicted data[6,11,17]. The results of the two-step identification procedure for emission models have shown that model precision is comparable with that obtained via conventional mapping procedures using black-box models, but with a drastic reduction of the experimental effort and with substantial computational time saving with respect to conventional identification techniques[11,17]. Two alternative models for mechanical losses have been proposed and validated over more than 400 engine conditions[21]. For a detailed analysis of model validation results, not compatible with the space constraints of this paper, the reader is addressed to the cited papers.

	Model/Phase	*Identified Parameters*	*Estimation method*
A1	Two zone Model – Compression Phase	Cylinder Wall Temperature	Estimation of polytropic index from pressure data (Adiabatic condition) [18]
A2	Two zone Model – Compression phase	Heat transfer coefficients (Woschni correlation)	Comparison of computed and measured pressure cycle (LS Minimization)
A3	Two zone model – Combustion phase	Combustion time (Wiebe function)	Comparison of computed and measured pressure cycle (LS Minimization) [15,17]
A4	Multi zone Model – Emission Models	Number of zones Boundary layer thickness Crevices volume Kynetic reaction constants	Comparison of computed and measured exhaust emissions over the whole range of operating data (via two steps decomposition approach) [11,17]
B	Black-box models for fuel consumption and emissions (steady-state)	Regression coefficients or Neural Network structure	Polynomial regressions and interpolation techniques 10– Neural Network [20] From steady-state experimental data or from physical model computations Interactive selection of input data via ED techniques [7]
C	Two-Phases Fuel Flow in the Intake Manifold	Injected Fraction to Wall Evaporation time constant Couette flow constant	Comparison of computed and measured A/F value in the exhaust gases for a transient injection step (LS minim.) [2,3] Kalman filtering estimation (in progress)
D1	Air Flow in the Intake Manifold (Filling & Emptying)	Discharge coefficients of engine valves	Comparison of computed and measured pressure in the open-valve cycle [22]
D2	Air Flow in the Intake Manif. (Filling & Emptying, Mean Value)	Discharge coefficients in the throttle valve Volumetric efficiency	Comparison of computed and measured values of mass flow rate in steady state conditions (polynomial regression) [6,10]
E	Cylinder wall thermal dynamics – Effects on emissions	Cylinder wall thermal inertia Correcting factor for emissions	Estimated by literature data [9,10] Can be estimated by transient thermal tests on dynamic test bench
F	Mechanical efficiency	Non linear regression parameters	Comparison of computed and measured mechanical losses over the whole range of operating data (LS minimization) [19]

Table I – Model parameters and identification methods

6. CONCLUSIONS

The structure of distributed system of models for the study and the design of control strategies in spark ignition automotive engines has been described. The conflicting constraints of limiting both experimental cost and computational time posed by the exigencies of rapid prototyping applications have been overcome by the development of a hierarchy of “fast” black-box and gray-box dynamical models, to be used for optimal design applications, with phenomenological models, to be used in off-line mode to instruct the previous model level.
The requirement of systematic methodologies to infer information from experimental data has been remarked, both in order to reduce time and cost through use of experimental design techniques and to derive consistent and statistically significant estimate for model parameters. The benefits due to the adoption of a sequential modeling structure during identification phase have been discussed, and the different used estimation techniques analyzed.

7. ACKNOWLEDGMENTS

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Nomenclature

β	Vector of the model parameters, defined over the whole operating range
M	Number of model parameters
N	Number of experimental conditions
P	Vector of the physical model parameters, defined over the i-th operating condition
V	Vector of Operating conditions

Subscripts

I	Index of the engine operating condition

Superscripts

*	Reference conditions