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# Derivative free optimization method and physical simulations coupled with statistical models for transient engine calibration

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## Abstract

Nowadays, automotive manufacturers have to deal with strong constraints: lowest fuel consumption, emission-control legislation and driver requests for driveability and performance. For this purpose, the classical engine has evolved towards a very complex system combining many hi-tech components with advanced control strategies. It leads to an increasingly complexity of the underlying optimization issue.

The classical method to perform this optimization is to use statistical response surface models obtained from optimally designed experiments at test bench in steady-state conditions. In this approach, the transient effects observed during the driving cycle are not taken into account.

A promising idea to include these transient effects in the optimization process is to couple physical modelling of the engine (to get the conditions in the combustion chamber before each combustion event) with statistical models (to obtain engine-out emissions after this combustion event). Powertrain system simulation is shown to provide a helpful tool to reach this objective thanks to a good compromise between accuracy and low CPU time.

A dedicated parameterization of the engine maps and a Derivative Free Optimization method is then used to minimize the cumulative fuel consumption and pollutant emissions, under combustion noise constraints, on a driving cycle.

An application on a real dataset obtained at automated test-bench for a diesel engine is presented.

## 1. Introduction

Future regulations enforcement concerning emissions, customers requirements and economic competition lead to higher constraints on internal combustion engines development.

It paves the way for increasing complexity in terms of design and control. Diesel engines, with many sophisticated devices for air loop as well as for injection system, have now potentially thousands of control parameters to be calibrated. Fast and reliable tuning of these parameters are key issues for engine manufacturers.

The first stage of the calibration process consists in basic engine maps tuning for steady-state conditions. The conventional method for engine map optimization is based on statistical engine models depending on control parameters obtained from optimally designed experiments at test bench in steady-state conditions. The cumulative emissions on the driving cycle computed with these models are optimized ([1], [2]). In this approach, one assumes a quasi static engine behaviour on engine speed

and load trajectory, indeed the transient effects during the driving cycle are not taken into account.

Engine physical model coupled with statistical and control models is a promising solution to deal with the transient effects optimisation. Eventually the real air and fuel trajectories during the driving cycle could be used as inputs to optimise the control parameters to fulfil noise and emissions targets. Powertrain system simulation, with phenomenological 0D combustion and air loop models, appears as a good compromise between accuracy and low CPU time for engine physical modelling. One of the main challenges concerns the coupling process in order to limit CPU time and loss of accuracy.

Usual optimisation algorithms require derivatives of optimised functions which are not available for such models. Moreover, the large size of the optimization problem (number of parameters for engine map description) prevents from approximating these derivatives by perturbation techniques (finite differences). Hence a derivative free optimization method whose efficiency has been highlighted in several application areas ([3]), is proposed to tackle this topic.

Thus this paper focuses on the calibration process (design of experiments, statistical modelling of engine responses), engine physical models, to couple those models and to design of adequate optimization tools .

## **2. Experimental data and statistical modelling**

### **2.1. Description of the test case**

The engine used during this study is a 1.6 litre four-cylinder Diesel engine (DV6 ATED 4 from PSA Peugeot-Citroën). This engine has a maximum power output of 66 kW. The bore and the stroke of this engine are respectively of 75 mm and 88.3 mm. The compression ratio is 18:1. It is a turbocharged engine with a high pressure cooled exhaust gas recycling circuit. It has a second generation injection system using Bosch CRI 2.2 injectors with injection pressure as high as 1600 bar. The exhaust line has a conventional Euro4 Diesel oxidation catalyst (DOC) and is not equipped with a Diesel particulate filter (DPF).

Moreover, this study is part of a project concerning the use of biofuels to deal with the issues of energy diversification and greenhouse gas emissions. Therefore an Ethanol based Diesel fuel was chosen; the fuel formulation is deeply described in the reference [4]. The vehicle and the powertrain were not modified to use this blend but the engine calibration was updated as explained in previous publications [4], [5].

The most significant point concerning the facilities is the use of a dynamic test bench driven by Morphée® for the reproduction of normalised European driving cycle (NEDC). Such equipment and procedure have been detailed in a previous paper [4]. The test cell provides all the equipment required for transient tests (fuel consumption, opacimeter for smoke measurement) and the design of the fluid circuits has been optimised to ensure good vehicle behaviour reproduction.

## 2.2. Experimental data

Different approaches to tune engine maps are proposed to deal with the high number of parameters to optimise and to reduce this time-consuming task during the development process. These methods (local, mixed and global) based on mathematical models and Design of Experiments (DoE) were compared in previous publication [6]. Global modelling approach for calibration, considering load and speed as parameters, reduces time spent for whole calibration workflow because an unique DoE is necessary to model engine responses for entire domain (or several DoE if this domain is divided in several zones with common parameters) [7]. In fact the global method considers the trace of the driving cycle (load and speed) as inputs of the models of the engine responses. Figure 1 shows the operating area chosen for the calibration in the speed/load area.

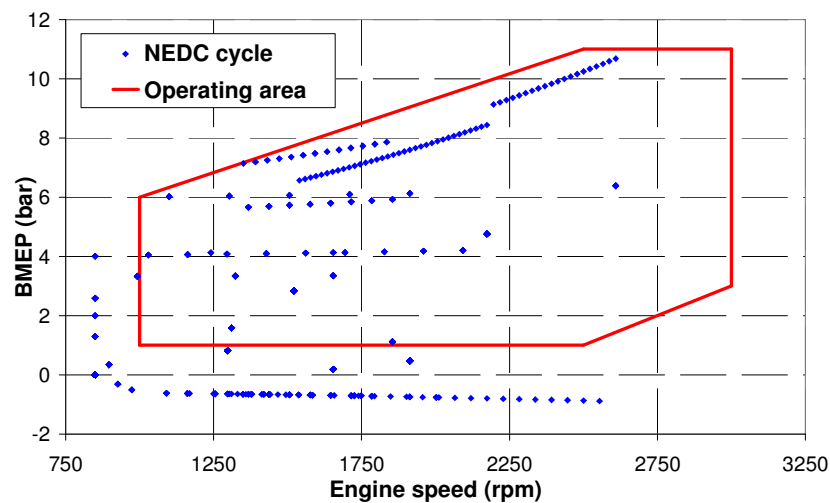


Figure 1: Engine speed and load area for global method

The next stage consists in defining the operating space of each engine control parameter. Concerning injection parameters, previous experiences [7] show that fixed boundaries or simple linear limits compared to the original maps could be a suitable answer to ensure a sufficient potential of optimization.

The main issue involves the air loops limits. It is required to have a wide enough operating space close to the physical domain (to ensure a high potential of optimization) and to make it easy to model. Four air limit parameters should be defined: two for the boost pressure (maximum and minimum limits) as well as two for the air mass flow. Three limits are physical ones and could be straightforwardly obtained. To determine the last one (minimum air mass flow), different criteria could be chosen (air fuel ratio, stability, etc.). Then each limit should be modelled, in this case with low degree polynomial. The accuracy of the model is illustrated in Figure 2 for the minimum air flow limit by comparing experiences used for the modelling (blue crosses) and the validation points (red circles). The coefficient of determination  $R^2$  as well as the root mean squared error (RMSE) show the good estimation obtained with the model.

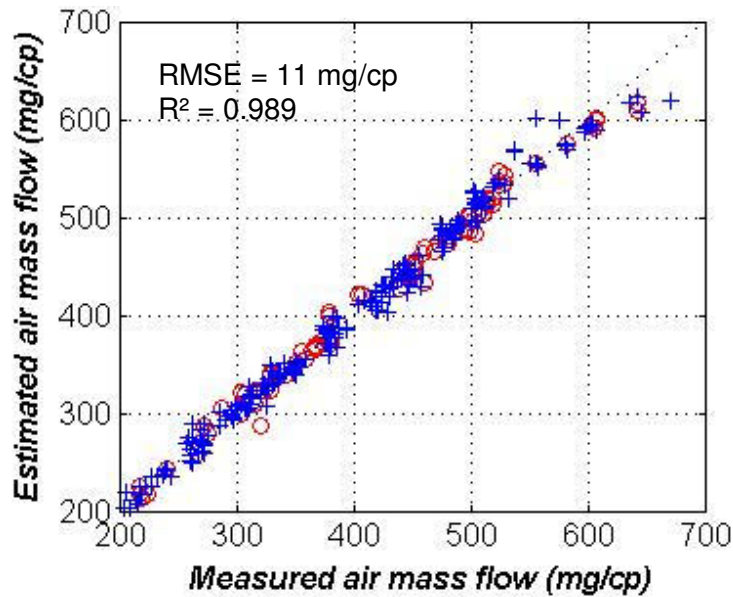


Figure 2: Comparison of estimated and measured minimum air mass flow limit. Blue crosses correspond to experimental data used for modelling whereas red circles are validation points.

Some of the main challenges when using the global modelling approach concern complex constraints for description of parameter variation domain (e.g. non-linear) and increased number of parameters to manage. Thus dedicated statistical tool and method should be used to take into account these issues. This process was described in previous reference [5]. After defining the speed and load boundaries as explained previously, the values of these parameters are fixed; this permits to determine acceptable values for injection parameters and then air loop limits depending on other parameters could be given. The most valuable experience is determined by using a *Maximin* criterion (maximization of minimal distance between experimental points). Finally, the global DoE includes also the corners of the operating space, some mono parametric variations and a space filling.

### 2.3. Global modelling of the engine responses

Modelling the complex engine response surfaces requires to use advanced statistical models instead of standard polynomial models. In this case the choice of kriging for modelling was the most relevant since it is flexible and takes into account the experimental repeatability and the spatial dependency providing therefore consistent values for close operating points. A total of 1200 experiences, added to 100 points for repeatability and 200 points for validation of the models, were performed.

The engine responses that are modelled are : HC, NO<sub>x</sub>, CO, CO<sub>2</sub> and PM emissions (g/h), combustion noise (dB) and fuel consumption (kg/h). The statistical criteria are satisfying for all models except HC and PM emissions. Concerning PM emissions, the oxygenated fuel used for these tests implies near-zero soot emissions and there is a lack of accuracy of the measurement device for these levels. Concerning HC emissions the bad repeatability is the main explanation of the poor quality of the model. Some examples of validation of the estimated value from the model are given in Figure 3 and in Figure 4. First NO<sub>x</sub> emissions model is validated with experimental specific tests. CO<sub>2</sub> emissions estimation during monoparametric variations are repre-

sentative of test bench results in Figure 4. In fact, for the different emissions, the models show good trends and consistent estimated levels.

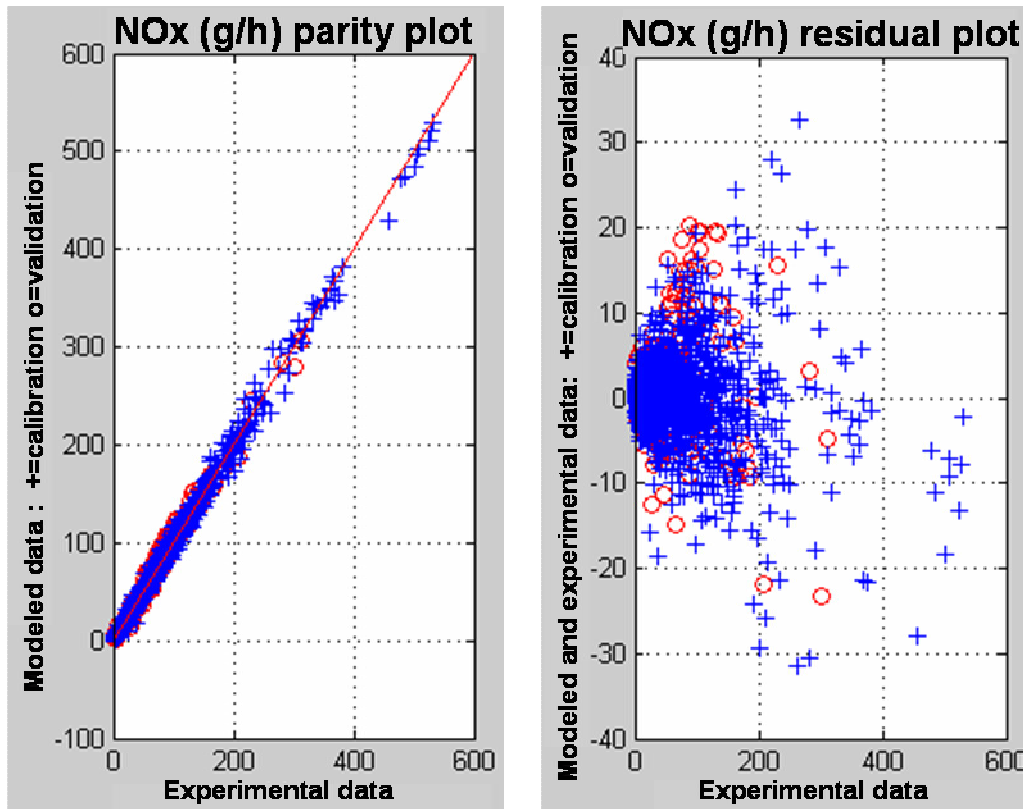


Figure 3: NOx emissions model validation. Blue crosses correspond to experimental data used for modelling whereas red circles are validation points.

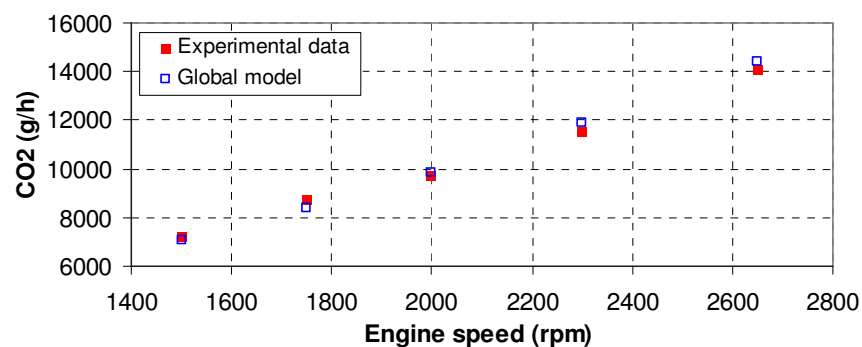


Figure 4: Comparison of estimated and measured CO<sub>2</sub> emissions on an engine speed variation

### 3. Coupling physical engine simulator with statistical models

IFPEN is strongly involved in powertrain modelling and simulation to support technological development. It develops specific libraries (IFP-Engine, IFP-Drive and IFP-Exhaust) in the LMS.IMAGINE.Lab AMESim environment which includes a large set of commercial libraries used for various applications, in particular for control strategy development, validation and pre-calibration as it is presented in [8].

The purpose of this section is the coupling of a physical engine simulator with statistical models and control algorithm model in order to have both well representative transient effects and accurate pollutants model. The complete engine simulator is based on the LMS.IMAGINE.Lab AMESim platform with in particular the use of the IFP-Engine library. Its description and validation are given in the following sections.

### **3.1. Complete engine simulator creation and validation in steady state**

#### **1. Combustion model**

##### *IFP-Barba phenomenological combustion model*

In this study, a combustion model based on the Barba approach [9][10][11] is chosen to compute the combustion heat release rate. In this approach, the combustion process is divided into two parts. In a first step, the fuel is burnt using a pre-mixed model with the hypothesis of flame propagation in the pre-mixed zone. When the pre-mixed zone is burnt, the remaining fuel is oxidized using a mixing controlled combustion model.

Using a simple example with a pilot and a main injection, different steps can be isolated during the combustion. At the beginning of the pilot injection, the combustion model is initialised and the different variables are computed. During injection, the auto-ignition delay is computed and the injected fuel is introduced in the premixed zone.

The auto-ignition delay is defined at the beginning of the injection and is computed using a simple Arrhenius law. When the auto-ignition delay is reached at the end of the phase, the pre-mixed combustion starts. In a first step, the ascendant part of the combustion heat release rate (burning mode 1) is generated by the flame propagation in a turbulent field. Then, because of the multiplication of the auto-ignition sites, the hypothesis of the propagation of a single flame in the pre-mixed zone is no longer valid and the flame interactions must be modelled (burning mode 2), leading to a reduction of the total flame surface.

When the main injection starts, the model creates a new pre-mixed zone for the main injection and computes the auto-ignition delay. The definition of the pre-mixed zone is similar to that of the pilot injection.

As for the first injection, the auto-ignition delay of the main injection is computed from the beginning of the injection, leading to the beginning of the combustion. The auto-ignition model is the same as for the pilot injection, but thanks to a higher pressure and temperature, the auto-ignition delay is smaller and reached before the end of the injection.

As the auto-ignition delay is reached before the end of the injection, the fraction of fuel available in the premixed zone is lower than for the pilot injection. The combustion process is the same as for the first injection.

In parallel to the pre-mixed combustion mode, the remaining injected fuel starts to burn progressively with a mixing controlled combustion model. In this burning mode, the combustion is piloted by the mixture speed between the injected fuel and the surrounding air. Generally, the mass of fuel burnt in this mode is defined with a simple equation depending on the turbulent kinetic energy. In order to enlarge the range of applications of this combustion model, there is the possibility to compute more injections and combustions.

### Combustion model set up

A single cylinder simulator with closed valves is used to calibrate the combustion chamber. The calibration is made between Intake Valves Closure (IVC) to Exhaust Valve Opening (EVO). The initial in-cylinder thermodynamic conditions are defined using the experimental results for the steady state points. The advantage of this approach is to lower the error generated by the air path on the in-cylinder conditions at the IVC.

Concerning the thermal transfers, a Woschni model is used [12]. In order to fit correctly the combustion, the wall temperatures are functions of the BMEP with the following law :

$$T_{wall} (K) = \frac{100}{19} * BMEP(bar) + 450 - \frac{100}{19} \quad (1)$$

To set up correctly this combustion model, 9 points are chosen among the 218 available in the engine map (cf. Figure 5 – red surrounded crosses). The calibration process consists in fitting the simulated cylinder pressure on the experimental one for each operating condition. Then a validation on the whole operating points is done. Only one set of parameters is used for all the engine map.

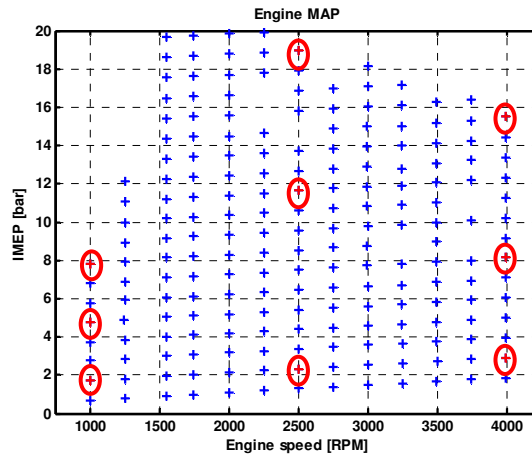


Figure 5: Engine map. 9 points (red circles) are chosen among the 218 available to calibrate the combustion model

The cylinder pressure curves shown in this paper (cf. Figure 6) are three out of the nine points used for the calibration of the combustion model (cf. Figure 5 – red surrounded crosses) . The four experimental cylinder pressures are in blue and the mean of the four is in dashed black. The simulated cylinder pressure is in red. In this paper, all the comparisons are made between the mean experimental cylinder pressure and the simulated one.



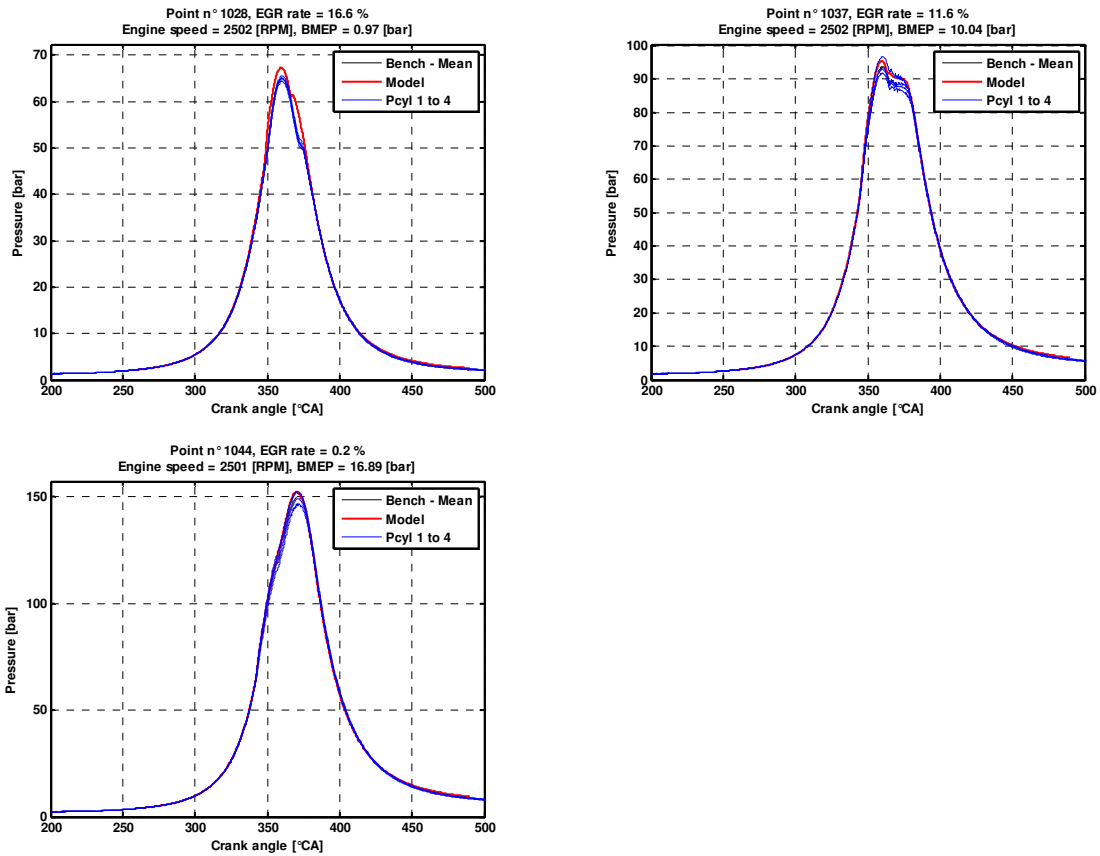


Figure 6 : Cylinder pressure – 2500 RPM – BMEP = 1, 10 and 16.9 bar. The four experimental cylinder pressures are in blue and the mean of the four is in dashed black. The simulated cylinder pressure is in red.

In order to define the combustion model accuracy, five criteria are chosen :

- IMEP : +/- 1 bar
- Max pressure : +/- 4 bar
- Max pressure angle : +/- 2 CA
- ISFC : +/- 5 %
- Noise : +/- 2 dB

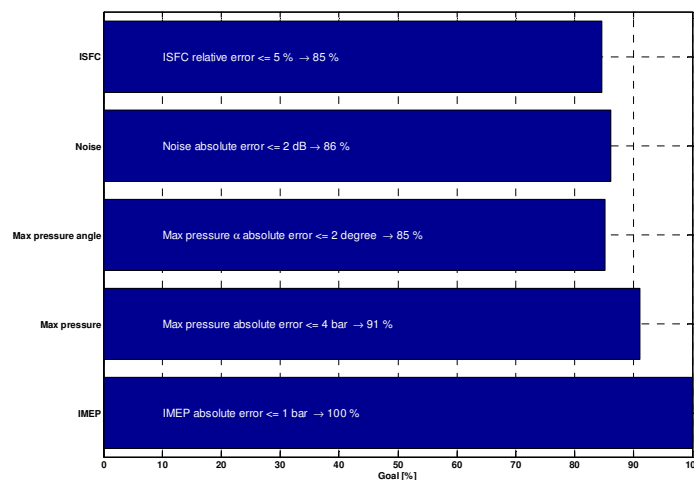


Figure 7 : Percentage of points matching the criteria to check combustion model accuracy

The cylinder pressures of the model are visually closed to the cylinder pressures of the bench. Moreover as described in the Figure 7 the percentage of points matching the criteria are high. It must be reminded that these results are obtained with only one set of parameters for the whole engine map.

## 2. Steady state engine model

Figure 8 presents the complete engine simulator. The whole air path with the turbo-charger, the charge air cooler, the exhaust line and the EGR loop is modelled. After its tuning the combustion model is embedded in this complete engine simulator.

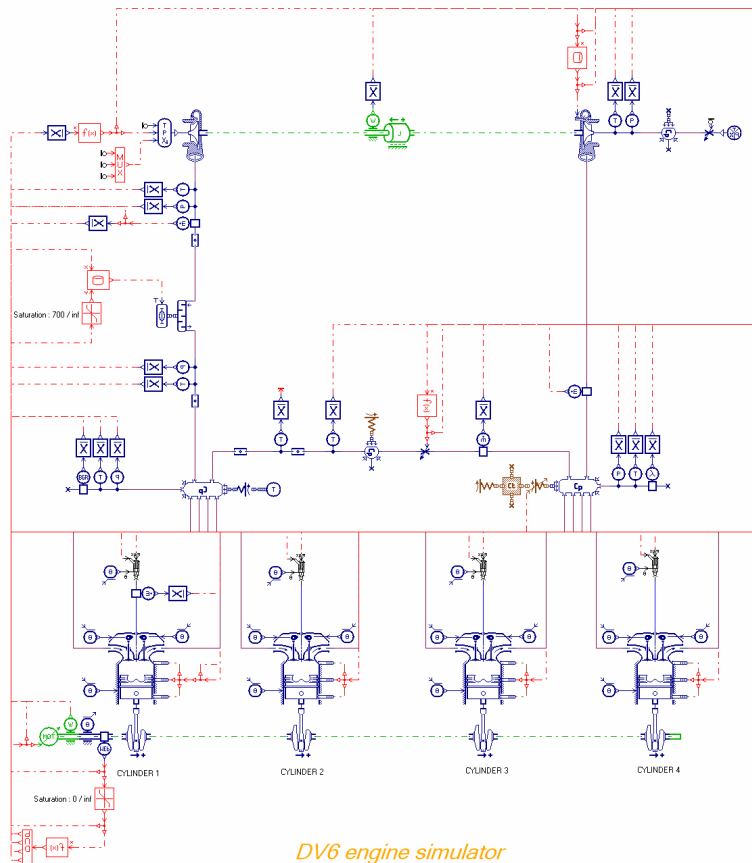


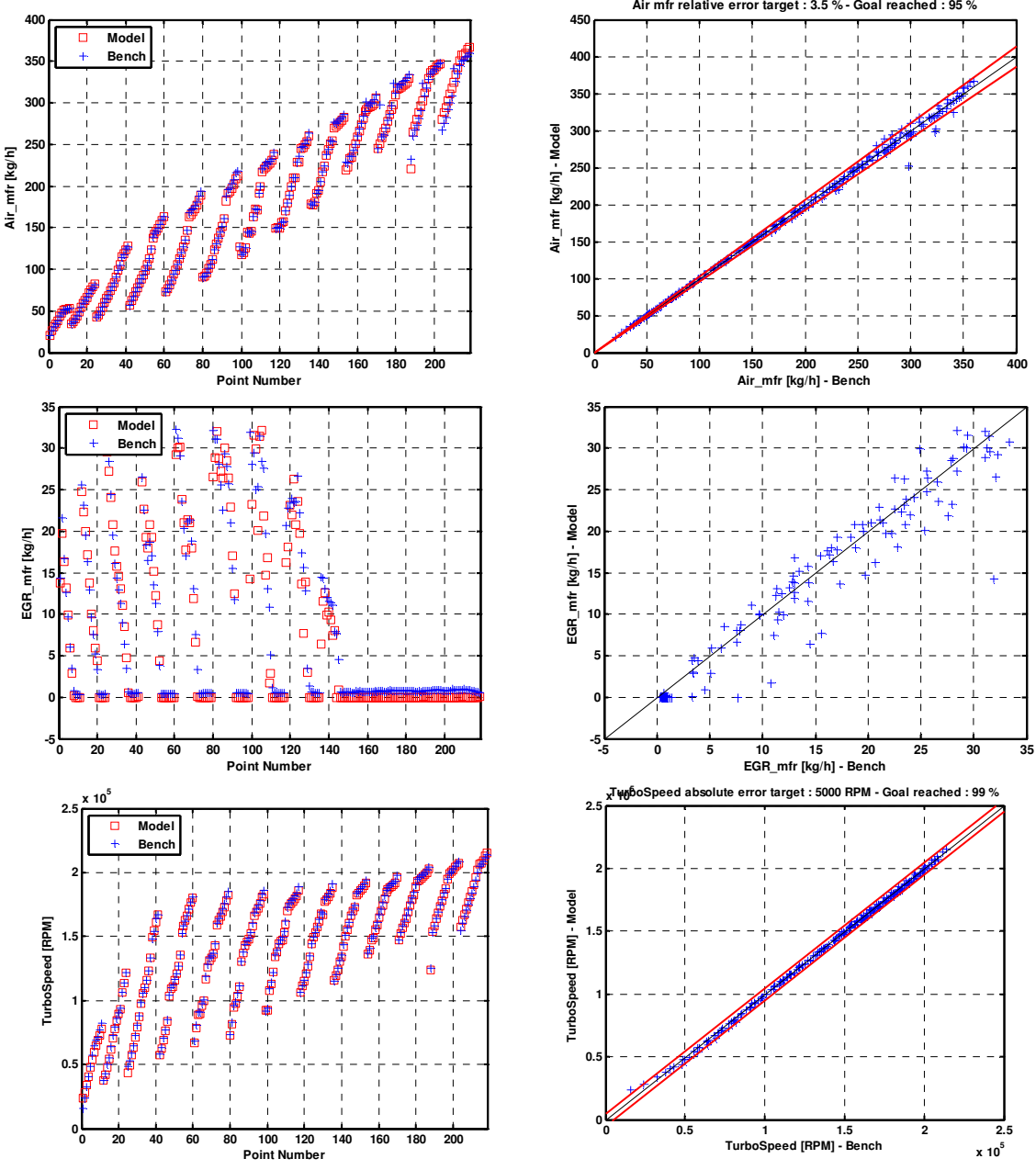
Figure 8 : Four-cylinder simulator in AMESim environment

In order to validate the behaviour of the complete engine simulator, it is coupled with a simple control implemented in Matlab Simulink. Two PID controllers regulate the engine : one for the intake manifold pressure with the control of the VNT position and one for the air mass flow rate with the control of the EGR valve position.

In order to appreciate the quality of the results, some criteria are defined :

- Intake manifold pressure (P2S) : +/- 0.05 bar
- Intake manifold temperature (T2S) : +/- 10 K
- Exhaust manifold pressure (P3) : +/- 0.2 bar
- Exhaust manifold temperature (T3) : +/- 30 K
- Air mass flow rate : +/- 3.5 %
- IMEP: +/- 1 bar

The Figure 9 presents results obtained with the engine simulator on the 218 measurement points. The presented results are air mass flow rate, EGR mass flow rate, turbo speed and IMEP. On left figures, blue crosses represent experimental data and red squares model results for each operating point. On right figures, model results function of experimental data are plotted. Red lines represent criteria to respect.



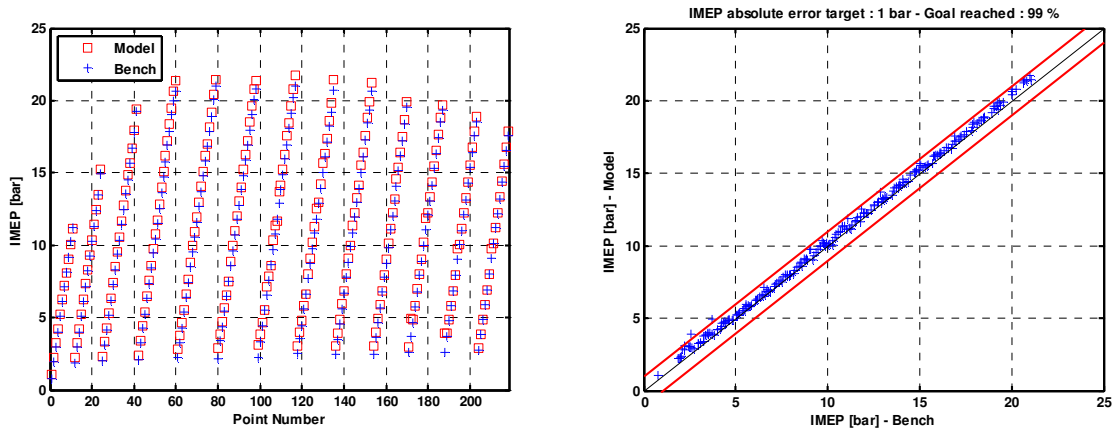


Figure 9: Steady state engine simulator results. Left figures : blue crosses represent experimental data and red squares modelled data results for each operating point. Right figures : red lines represent criteria to respect.

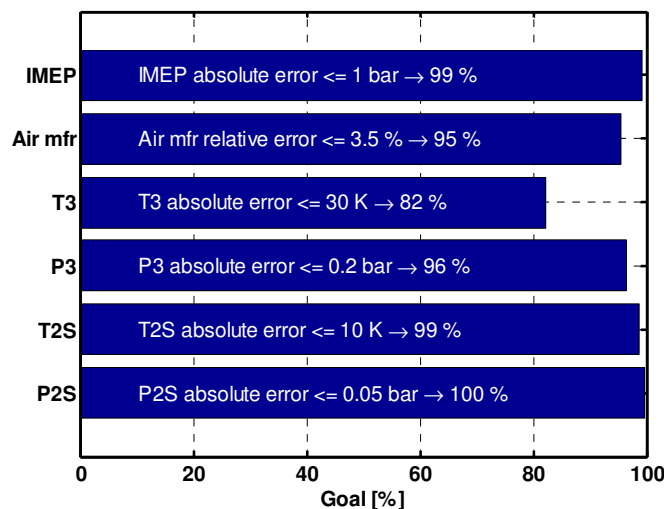


Figure 10: Percentage of points matching the criteria to check the complete engine model accuracy

Figure 10 gives the percentage of the points which respect the criteria on IMEP, air mass flow rate and intake and exhaust manifold temperatures and pressures. According to these criteria, results are consistent with test bench data and the complete engine simulator can be considered as set up.

### 3.2. Coupling with statistical models : presentation and validation on NEDC cycle

Figure 11 presents a way to estimate pollutant emissions during a transient thanks to a coupling between the AMESim simulator described in previously section, the engine control and the statistical models described in section 2.3. Inputs of these statistical models are air mass flow rate, intake manifold pressure, start of main injection, rail pressure, injected mass in the pilot injection, gap between pilot and main injection, BMEP and engine speed. The coupling is made with Matlab Simulink.

In this study, the real control software was not available. So, a basic open-loop control based on maps is used. Thus maps function of engine speed and total injected mass are used for the pilot and main start of injection, injected mass for the pilot injection, rail pressure, VNT and EGR valve positions.

A NEDC cycle was performed on this platform. As the optimization described in the next section is run on the EUDC part, only the results concerning EUDC are shown. Figure 12 presents comparison between virtual engine (in red line) and experimental data (in blue dashed line) for intake and exhaust manifold pressures (P2S and P3), air mass flow rate (Air\_mfr), fuel air equivalence ratio (FAR\_sonde), turbo speed (TurboSpeed), BMEP and CO<sub>2</sub>, CO, NO<sub>x</sub> and HC mass flow rates (CO2GH, COGH, NOxGH and HCGH). A comparison on cumulative emissions (NO<sub>x</sub>, CO<sub>2</sub>, CO and HC) is also presented in Table 1.

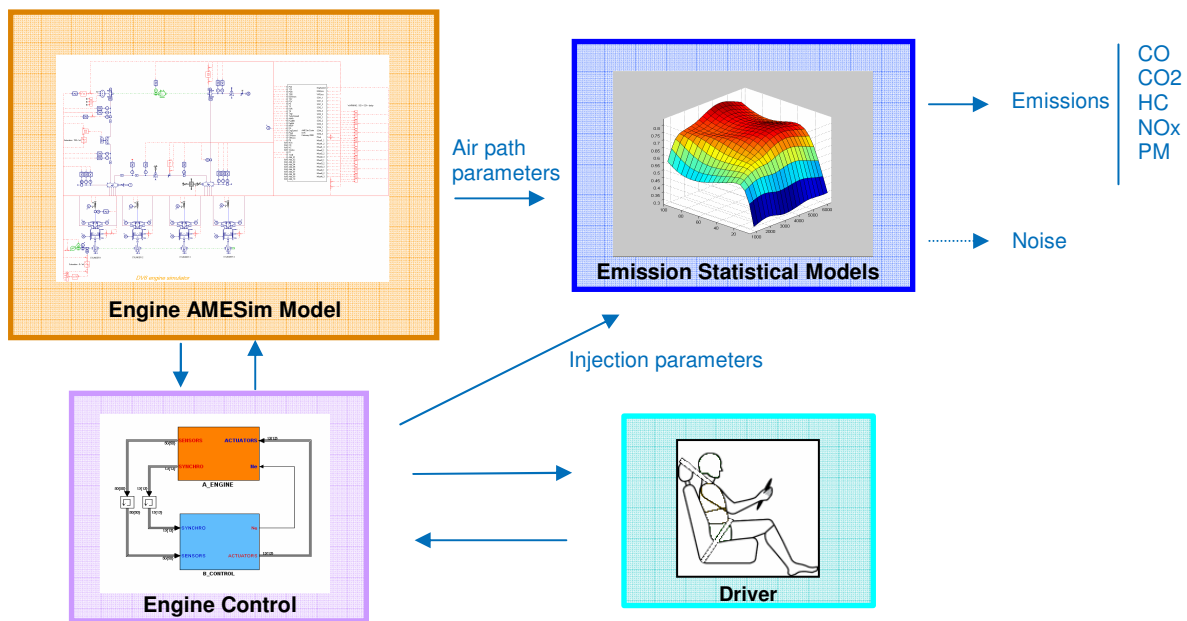
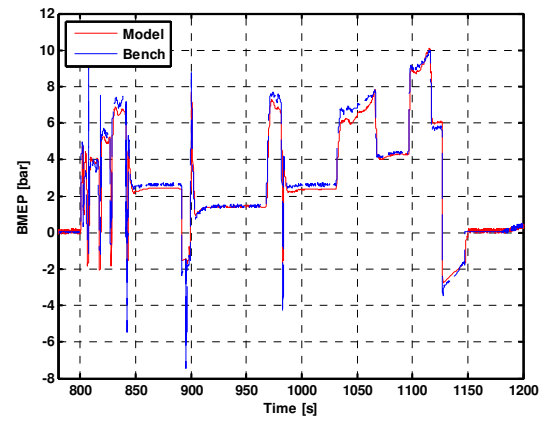
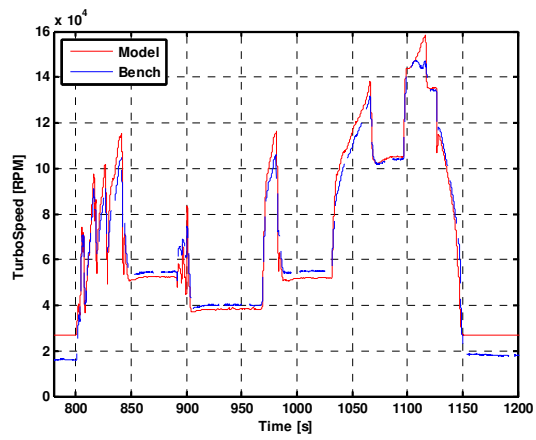
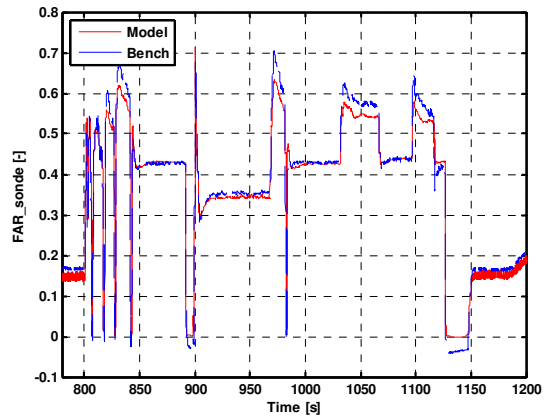
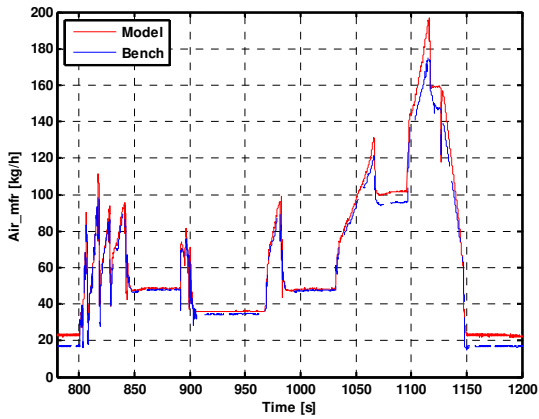
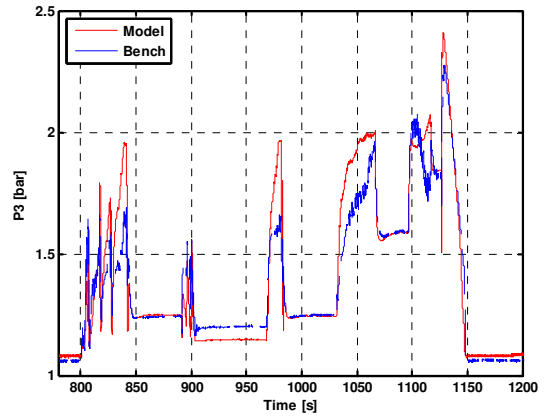
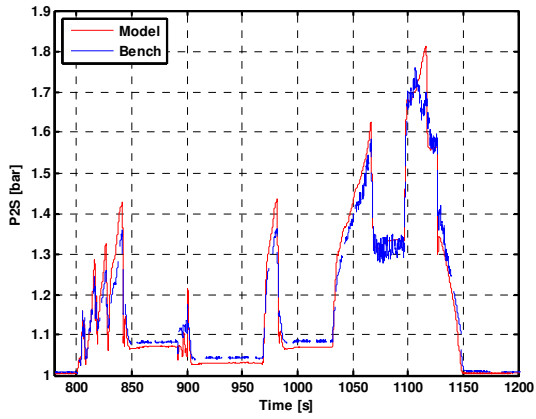


Figure 11 : Description of the coupling between engine Control, engine AMESim model and emission statistical models



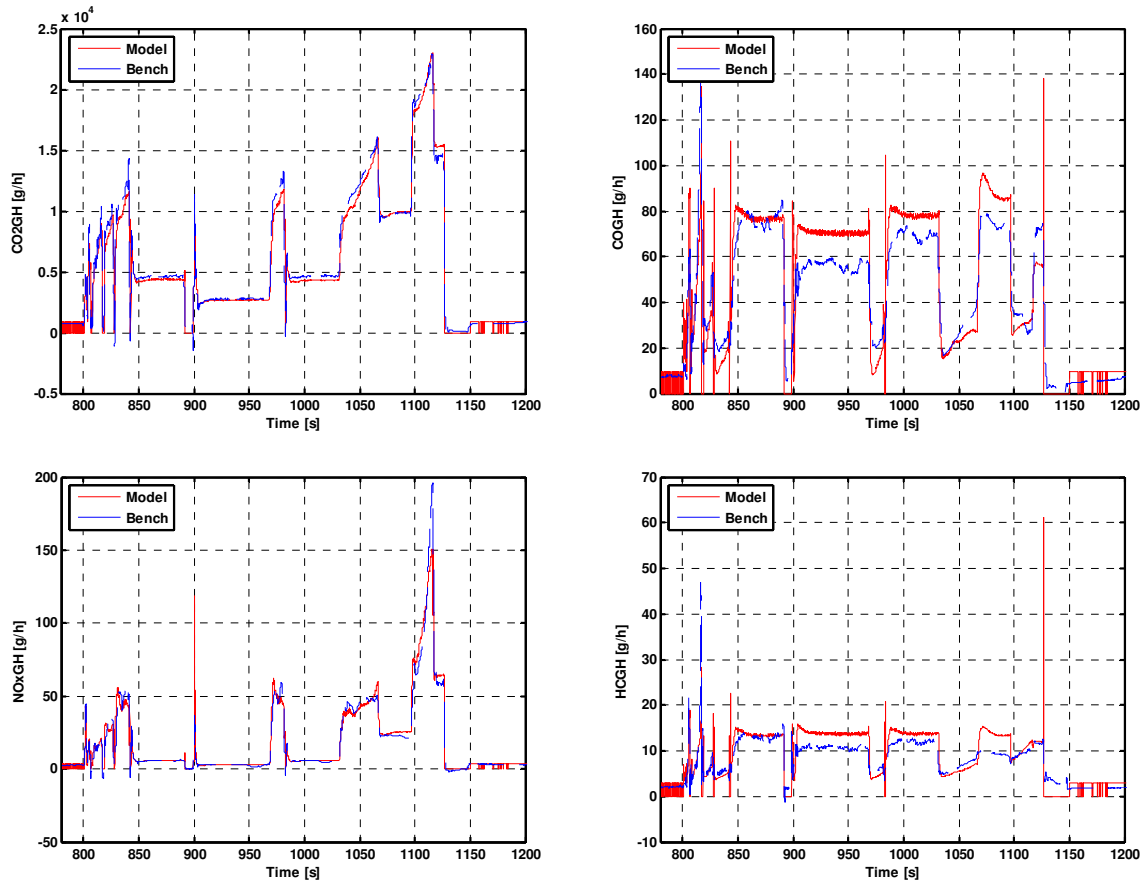


Figure 12 : Comparison between model (red line) and experimental (blue dashed line) data on EUDC

<i>EUDC cycle</i>	<b>NOx emissions</b>	<b>CO2 emissions</b>	<b>CO emissions</b>	<b>HC emissions</b>
<b>Bench</b>	100 %	100 %	100 %	100 %
<b>Virtual engine</b>	100 %	99 %	107 %	110 %

Table 1 Comparison of the cumulative emissions between model and experimental data on EUDC

Keeping in mind that engine control is different for experimental tests and simulation, one can conclude that the behaviour of the engine during the EUDC is well reproduced.

This virtual engine is sufficiently predictive to be used for an optimization process.

## 4. Engine map optimization with coupled models

### 4.1. Principle of engine map optimization

The engine map optimization consists in directly optimizing the cumulative pollutant emissions over the cycle via distortions of the engine maps instead of optimizing individually some selected operating points and building afterwards the engine maps by a smoothing step ([6], [13]).

Consequently, the objectives to be minimized (or constrained) are the engine responses cumulated on the considered driving cycle. The engine responses can be modelled by a global statistical model (as described in section 2) or by a physical simulator that models transient behaviour of the engine (as described in section 3).

The map optimization problem is formulated as

$$\left\{ \begin{array}{l} \min_{m^p \in \mathbb{R}^{N_p}} \int_0^T F_i(r(t), c(t), m^{P_1}(r(t), c(t)), m^{P_2}(r(t), c(t)), \dots, m^{P_{N_p}}(r(t), c(t))) dt \\ \text{subject to} \\ l(r, c) \leq A m^p(r, c) \leq u(r, c) \\ \int_0^T F_j(r(t), c(t), m^{P_1}(r(t), c(t)), m^{P_2}(r(t), c(t)), \dots, m^{P_{N_p}}(r(t), c(t))) dt \leq S_j \end{array} \right. \quad (2)$$

where :

- $(r(t); c(t))$  indicate the trace of the considered driving cycle within the engine speed-load domain,
- $F_i$  is the global model of the engine response  $i$  depending on the engine control parameters but also on the speed and load,
- $m^{P_i}$  are the 2D engine maps of the control parameters in the engine (speed, load) operating domain.

Additional smoothing constraints such as global smoothing constraints (to preserve the regularity of the original maps), robustness constraints (to take into account parameter dispersions) and local constraints (for example limits on the gradients of the maps, or limits on engine noise response) are also introduced.

This formulation requires an adapted parameterisation of the engine maps,  $m^{P_i}(r, c)$ , in order to limit the total number of unknowns in the optimization process. For this application, an adapted discretization of the engine speed/engine load domain with a bilinear approximation in cells is implemented (see Figure 13):

$m^{P_i}(r, c) = \alpha_0 + \alpha_1 r + \alpha_2 c + \alpha_3 rc$  within a given cell with  $\alpha_0, \alpha_1, \alpha_2, \alpha_3$  determined from the 4 cell corners. Other map representations based on LoLiMoT (Local Linear Model Tree) are proposed in [13].



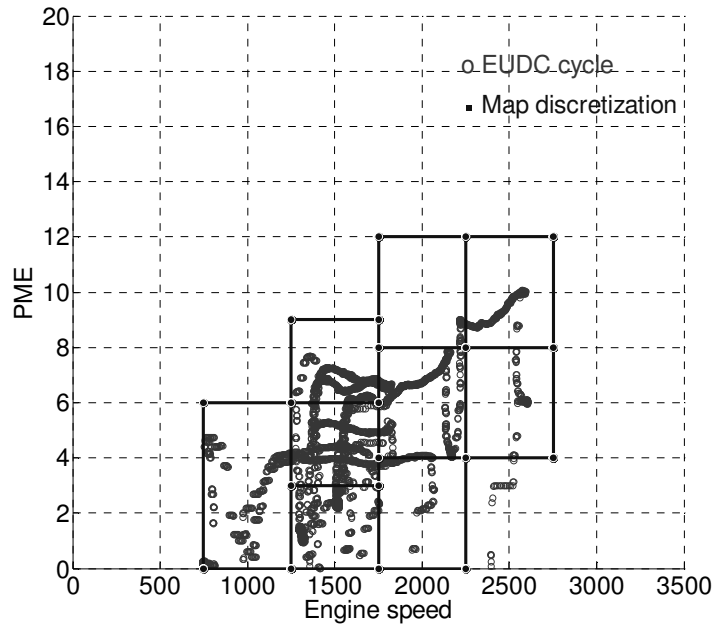


Figure 13 : Map discretization (for bilinear parameterization) in the engine (speed, load) operating domain and EUDC cycle trace.

#### 4.2. Derivative Free Optimization (DFO)

Problem (2) is a nonlinear constrained optimization problem which requires dedicated optimization methods to be solved. For engine responses modelled by statistical models, a classical SQP (Sequential Quadratic Programming) method is applied: first derivatives of objective function and constraints are available.

When the physical model described in section 3 is used, a Derivative Free Optimization method is implemented. In this case, no derivative of modelled engine responses is available and moreover simulations require a high computational effort (a couple of hours of calculation for one simulation).

Therefore, a dedicated optimization method is proposed, the SQA method (Sequential Quadratic Approximation), already applied successfully on several industrial applications [3].

This method is an extension of the DFO method proposed by Powell in [14] to nonlinear constrained problems: in order to save simulations, quadratic interpolating models are used as surrogate of the simulator responses. These quadratic models are minimized and updated thanks to additional simulations performed along the optimization process iterations. The main steps of the SQA algorithm are described in Table 2.

### **SQA Algorithm**

**Step 0. INITIALIZATION** A quadratic model (QM) of each optimized engine response is constructed in a neighbourhood of the initial guess, namely the trust region. They interpolate  $m$  points ( $n+2 \leq m \leq (n+1)(n+2)/2$  with  $n$  the number of parameters), obtained by evaluation of the engine simulator.

**Step 1. MINIMIZATION** At each iteration, we substitute in problem (2) engine responses with their associated QM and solve it within the trust region (TR).

**Step 2. EVALUATION and UPDATE of TR** We evaluate the engine responses at the solution of previous problem and update QM with this new point. The size of TR is also updated according to the predictivity of QM at this point :

- i. if predictions by QM are very closed to simulation results, TR is enlarged. Go to step 1.
- ii. if only the trend is correct, TR is not modified. Go to step 1.
- iii. else reduce TR and go to 3.

**Step 3. IMPROVEMENT OF QM** Choose and simulate a new point (evaluation of engine responses) in order to improve the accuracy of QM, update QM and go to 1.

*Table 2 Main steps of SQA algorithm: a DFO (Derivative Free Optimization) method for nonlinear constrained optimization.*

## **5. Application on EUDC driving cycle**

First, a quasi-static optimization (QSO) is applied. It is based on cumulative engine responses on the EUDC cycle (1 Hz discretization) modelled by global statistical models presented in section 2.3 (conventional optimization method is used, derivatives of objective and constraint functions being available for surface response models).

Four engine maps controlling injection are optimized: main injection timing, fuel injection pressure, pilot fuel injection quantity, pilot injection timing whereas mass air flow and boost pressure maps remain fixed to initial values. Bilinear modelling of maps allows to limit the number of map parameters to be optimized: 80 parameters.

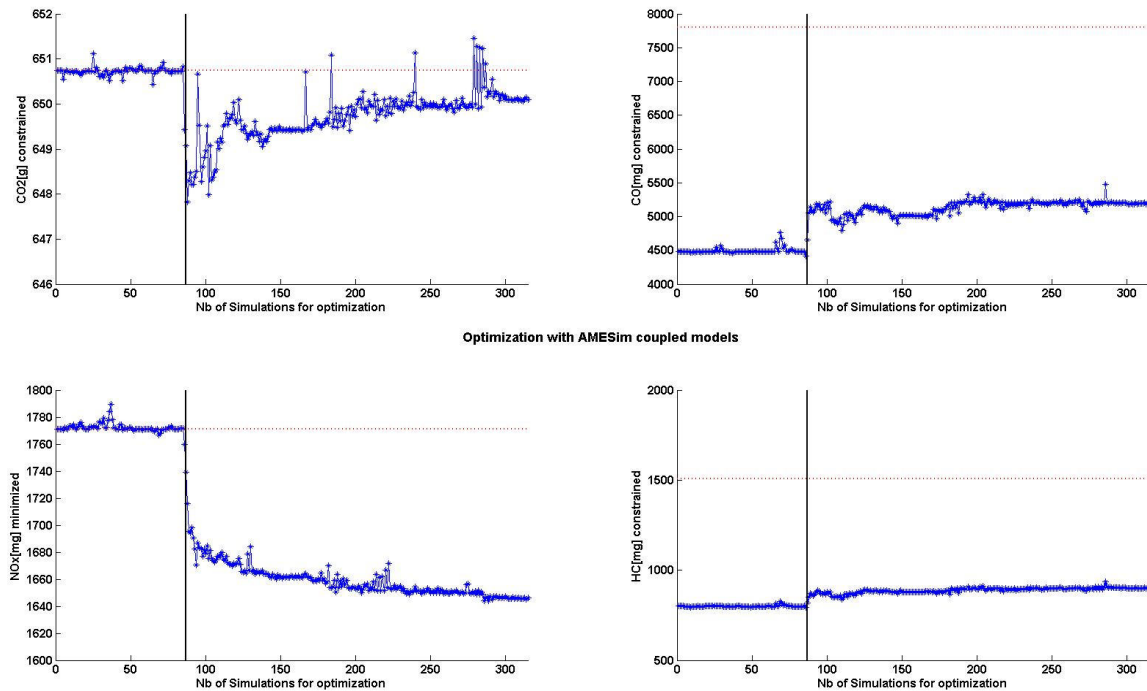
The minimized objective is the cumulative NOx emissions along the cycle, CO2 emissions are constrained to remain smaller or equal to the initial value, whereas an increase of 50% for HC and CO emissions is allowed.

The optimization process is then applied but this time with physical AMESim model coupled with pollutant statistical models described in section 3.2 with DFO optimization method presented in Table 2. In order to save simulation computational time, the smallest number of interpolation points for a quadratic model:  $m=n+2$  is chosen for this application. This incomplete quadratic model is completed during optimization process with a constraint on model variations along iterations. Additional terms of the model are then determined. Therefore, as displayed in Figure 14, the initialization phase costs 82 simulations used to build the initial quadratic model. After this phase, the optimization work starts with a rapid decreasing of NOx emissions.

Results are presented in Table 3 and compared to results obtained with quasi-static optimization. The optimization coupled with the physical AMESim model, compared to the quasi-static optimization, enables to drop off the NOx emissions with a slight increase of HC and CO emissions. But they are still largely under the defined thresholds and even under initial maps results. CO<sub>2</sub> emissions remain close to the initial value.

Figure 15 compares engine emission traces on EUDC cycle for initial engine maps, QSO maps and maps obtained by optimization with coupled physical models. On 70-100km/h acceleration of EUDC cycle, one notices the gain of optimization considering transient effects compared to quasi-static optimization for NOx reduction. Nevertheless, globally, the NOx reduction is low due to the smoothness of EUDC cycle. Larger gains are expected on more realistic cycles.

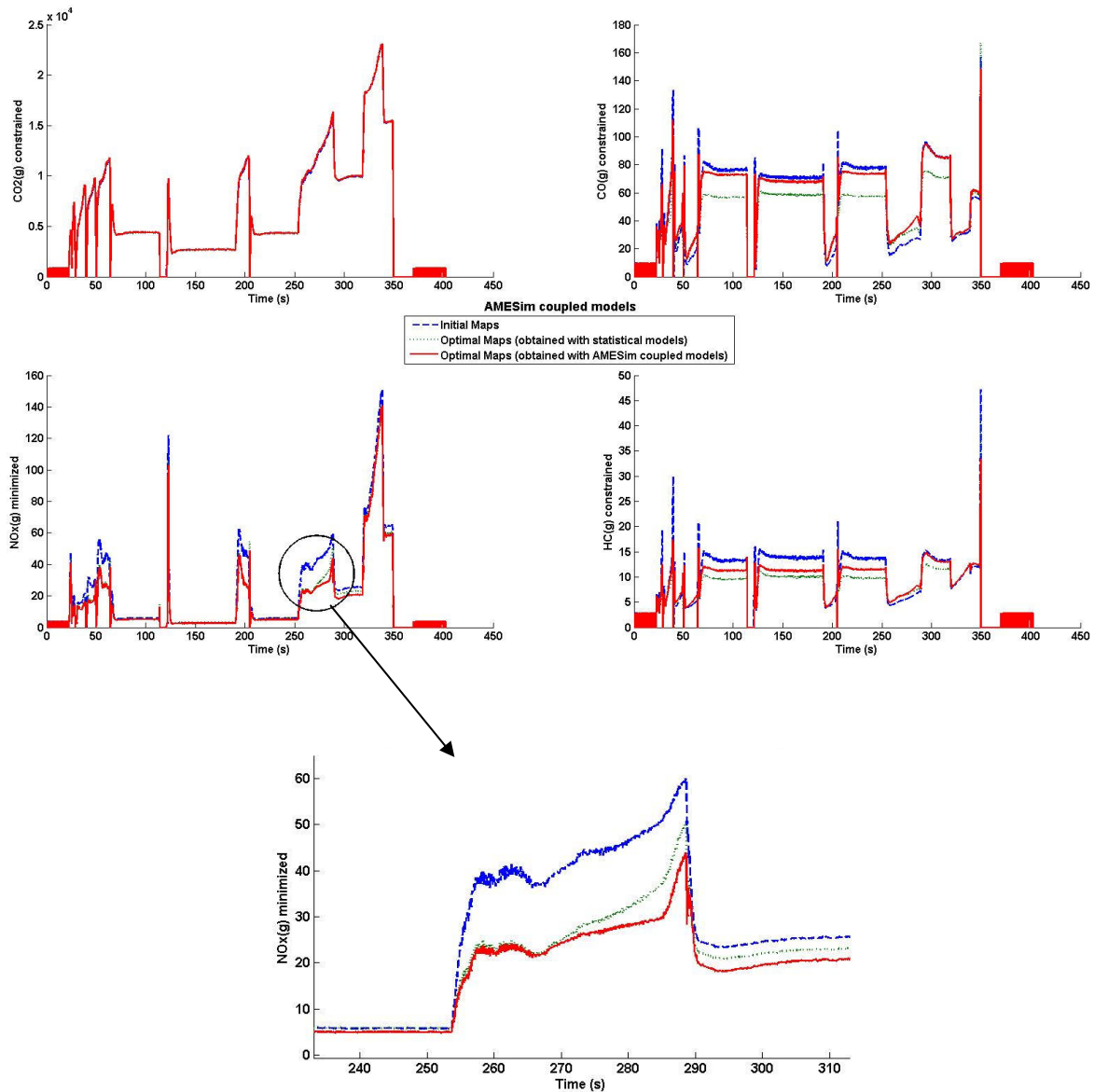
The physical AMESim model allows to take into account the transient effects of the air loop. It is then possible to take care of boost pressure lag for example to optimize the maps and not only to work on steady-state conditions.



*Figure 14 : Objective function decreasing and constraint satisfactions along SQA iterations (Derivative Free Optimization method). Dotted lines indicate upper constraint thresholds. The 82 first simulations belong to the SQA initialization phase (see algorithm in Table 2) to build the initial quadratic model.*

<i>Physical coupled models</i>	<b>NOx emissions</b>	<b>CO2 emissions</b>	<b>CO emissions</b>	<b>HC emissions</b>
<b>Threshold</b>	Minimized	100 %	150 %	150 %
<b>Initial maps</b>	100 %	100 %	100 %	100 %
<b>QSO Maps</b>	83.5 %	100 %	84.8 %	82.2 %
<b>Optimized maps</b>	78.0 %	100 %	99.9 %	89.7 %

*Table 3 Map optimization results with physical AMESim models coupled with statistical models*



*Figure 15 : Pollutant emissions (physical AMESim models coupled with statistical models) along EUDC cycle (1Hz discretization) for initial, Quasi-Static optimized maps, optimized maps (with physical models). (Bottom) Zoom on the 70-100km/h acceleration of EUDC cycle.*

## 6. Conclusions and outlook

Finally an innovative method has been presented to deal with transient effects on engine map calibration process on a Diesel engine, while performing only tests in steady-state conditions. It completes or replaces the standard quasi-static approach. The main features of the method consist in the different stages listed below:

- Obtain statistical models taking into account engine speed and load as parameters by applying advanced methodologies for domain definition, design of experiments and engine response modelling;
- Tune phenomenological 0D combustion and air loop models on a limited data set, then validate on the engine operating domain;
- Couple of statistical and physical engine models and engine control model to manage the effects of transient operations (especially regarding air loop parameters) on emissions;
- Adapt the formulation of the map optimization and design a derivative-free optimization algorithm to optimize engine responses on a driving cycle.

This methodology has been successfully applied to minimize NO<sub>x</sub> cumulative emissions on a EUDC cycle of a 1.6 litre engine with biofuel while maintaining initial CO<sub>2</sub> emissions. Nevertheless the results show that the potential of emission reduction remains low on EUDC cycle, because of the smoothness of such a cycle. Transient operations should become a key issue in engine calibration process since driving cycle might change from the NEDC to the World Light Duty Procedure (WLTP).

This method could also be helpful to optimize the engine control transient corrections (for example correction of injection parameters to compensate turbo lag).

One of key issues for system simulation emergence concerning optimization on driving cycles is to have both reduced CPU time and accurate models. Therefore multi-model multi-core simulation platforms ([15]) which allow to reach real-time computation for a virtual engine in keeping the same model accuracy will be investigated in further work.

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