Multi-objective constrained optimization of engine maps

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Abstract

Nowadays, automotive manufacturers are submitted to strong constraints in engine calibration: lowest fuel consumption, emission-control legislation and driver requests for driving comfort and performances. These constraints lead to an increasingly complexity of the engines and thus an increasingly number of parameters to be tuned, making the empirical engine calibration by a scan of parameter values impossible at engine test-bench. New methodologies in automated engine calibration based on statistics and optimization have emerged in order to limit the number of experimental tests to be run.

The optimization problem of engine calibration consists in the determination of engine tuning parameter maps that minimize the cumulated fuel consumption and pollutant emissions, under combustion noise constraints, on a driving cycle.

The usual way to get this result is to select specific operating points representing this cycle in the engine working range and to define upper bounds applied on the different engine responses (allocations) for each of them, in order to obtain a weighted sum of these local responses respecting the global targets. The underlying problem is a multi-objective optimization problem: different compromises between fuel consumption, noise and pollutant emissions on each operating point are possible. We propose an adapted optimization method based on the MO-CMA-ES method (Multi-objective Covariance Adaptation Evolution Strategy) which takes into account the non trivial limits of the engine parameter variation domains and some robustness constraints.

An other point addressed in this paper is the map optimization which consists in a global optimization of engine responses cumulated on the driving cycle. This method avoids the cumbersome choice of allocations for each considered operating point and includes directly the map regularity constraints in map parameterizations.

Finally, application on real dataset obtained at automated test-bench for a diesel engine are presented.

1 Introduction

Engine calibration consists in fulfilling the engine tuning maps that are used in engine controls of the vehicle, i.e. in defining the optimal tuning of parameters used by engine control strategies. Due to the highly increased number of these parameters (especially for diesel engines but spark ignition engines are following the same trend) and the reduction of the development schedule available for the calibration process, manual tuning of engine parameters is now replaced by mathematically assisted calibration process. Such a process is based on the design of experiments with associated modeling methods, in order to reduce the number of tests used to build engine response models depending on engine control parameters, and optimization techniques to determine the optimal settings within the model definition domain ([10], [3], [11], [1]). In order to perform the tests in a more productive way, these mathematical techniques are generally associated with test automation, requiring well controlled measurement methods and reliable test equipments.

This paper describes the optimization methods developed for this application and illustrates their effectiveness on a real case of a common rail diesel engine. The first section introduces the classical steps of the calibration process and discusses the associated difficulties. In the second section, we adapt the Multi-Objective Covariance-Adaptation Evolution Strategy method, proposed by [5], for solving the optimization problem associated with a given engine operating point defined by the engine speed and the engine load. In the third part, an integrated approach is proposed in order to directly optimize the engine maps on the whole driving cycle (associated with legislation norms) instead of the individual optimization of each engine operating point.

2 Engine calibration

2.1 Sketch of the engine calibration process

The emission calibration workflow is classically divided into three steps ([10]):

1. a preliminary phase consists in choosing a sample of operating points (referred to as *OP* in the following) to be studied and emissions targets associated with each OP, these targets being called *allocations* hereafter.
2. the optimization of engine responses on each OP according to these targets,
3. the fulfilling of the maps with a smoothing step between these optimal settings.

The preliminary step deduces from a simple model of the vehicle the trajectory of the driving cycle in the engine speed-load operating domain (see Figure 1). A limited number of specific Operating Points are chosen to represent the cycle in the engine working range. Figure 1 gives an example of NEDC (New European Driving Cycle) simulation and a selection of 16 OP. The cumulated levels of pollutant emissions along the cycle are computed as weighted sums of the pollutant emissions for each chosen OP. Note that the transient effects during the cycle as well as the effect of the warming up of the engine and of the after-treatment on the emissions are not taken into account in these weighted sums. They must be introduced when defining the objective of optimisation (the allocation) for each OP.

Phase 2 consists of five steps:

i) defining the domain of variations of the engine control parameters ([2]: this is an essential step of the process as it defines the validity domain of the models. The complexity of the models to be used for engine response depends on the size of this domain: for tiny domains low order polynomials are usually sufficient to accurately model engine responses. However, choosing too small domains leads to difficulty in coherently fulfilling sub-optimal engine maps ([1]).

ii) building the test matrix: various types of experimental designs can be used to build a test matrix: D-Optimal, space filling... The choice of the type of design as well as the number of tests to be done are directly correlated with the assumed complexity of the model and thus with the size of the considered domain. D-Optimal test designs are often used with hyper-cubic tiny domains ([10]).

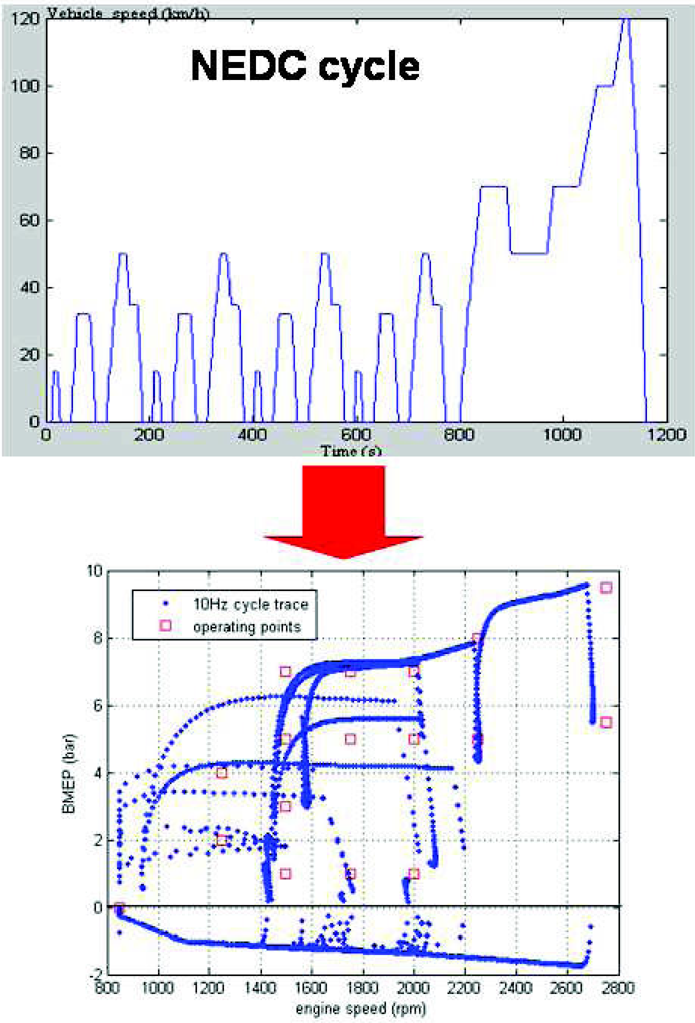


Figure 1: Simulation of the cycle from European legislation (NEDC: New European Driving Cycle) and selection of operating points

iii) running this test matrix on the test bench: as the tests are predefined, the experiments can be performed in an automated way, which drastically improves the productivity of the global process. In this case, special attention must be paid to the validation of the experimental data.

iv) modeling the engine responses: the type of mathematical models depends on the complexity of the engine responses and on the size of the domain. As already mentioned, reducing the size of the parameter variations may lead to difficulties to build coherent optimal engine maps from the obtained optimal settings in those tiny domains. Often, low order polynomial functions are used coupled with D-optimal design of experiments. For some response as particulates or CO emissions, this type of models may be too limited, then non-parametric response surfaces may be chosen as RBF or kriging ([11]). We will not detail this step of the calibration process in this paper, the reader may find more details on this topic in [1] or in [2].

v) optimizing the engine control parameters to meet the allocations. The problem may be formulated as a classical mathematical problem of optimization under constraints or as a multi-objective optimization (searching for compromises between antagonist objectives) as it is detailed in the following section. For this classical approach, the optimization is performed one OP after the other, considering the allocations of each OP as constraints. We refer in the following to this optimization problem as the OP optimization problem.

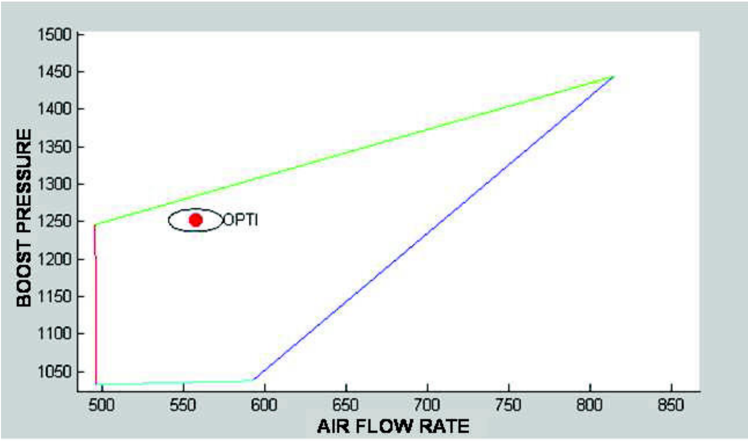


Figure 2: Projection of the domain of parameter variations in the (boost pressure, air mass) plane. The limits of the domain are generally modeled by linear constraints on the engine control parameters. The ellipse indicates the parameter dispersions (here projected on the 2D space) modeled by a multidimensional Gaussian probability law. The ellipse should remain in the engine physical domain in order to avoid that any control parameter takes some value outside this domain after the implementation in the control unit.

When the optimal settings are found, the last step consists in integrating them in the reference engine maps (if available) or building maps from these settings on the whole engine operating domain (see Table 2 for examples of engine maps). For the drivability of the target vehicle and because sharp evolution of air loop parameters are not easily feasible during transient, it is necessary to provide smooth engine maps. Thus, the settings are often moved away from their optimal values in order to build smooth engine maps, especially for air loop parameters. This smoothing process can be performed with respect to local constraints (such as maximum gradients), as well as to keep some predefined shapes. The difficulty of this step is thus to remain as close as possible to the local optima while preserving a smooth shape of the map, in order to keep all the benefits of the optimization work and satisfy the targets. This delicate step is usually time consuming and is likely to deteriorate the work performed during the optimization phase by providing sub-optimal engine tunings. This is the motivation for our proposal of an integrated method of map optimization described in section 4.

2.2 The OP optimization problem formulation

The OP optimization problem consists in minimizing some engine responses under constraints on other engine responses whereas the engine control parameters are kept inside the domain usually modeled by linear constraints coupling the parameters (see Figure 2). It leads to the following multi-objective constrained optimization problem:

$$\begin{cases} \min\limits_{p \in \mathbb{R}^{N_p}} (f_1(p), f_2(p), \dots, f_m(p)) \\ \\ \text{subject to} \\ l \leq Ap \leq u \\ f_1(p) \leq s_1 \\ f_2(p) \leq s_2 \\ \dots \\ f_d(p) \leq s_d \end{cases} \tag{1}$$

In turbo-diesel engine, a classical bi-objective optimization problem concerns the NOx/particulates trade-off. It could be formulated as the minimization of the particulate emissions and the NOx emissions under constraints on fuel consumption (CO_2 emissions), on CO and HC emissions and engine noise level. Generally, this multi-objective optimization problem (1) is replaced by a constrained optimization problem where only one of the objective is effectively minimized, the other being constrained to remain below some thresholds:

$$\begin{cases} \min\limits_{p \in \mathbb{R}^{N_p}} (f_i(p)) \\ \\ \text{subject to} \\ l \leq Ap \leq u \\ f_j(p) \leq s_j \quad j \in [1, d] \end{cases} \tag{2}$$

This constrained single-objective optimization problem (2) is then solved by a classical Sequential Quadratic Programming method run several times with different initial points to search for the global optimum.

3 Solving the OP multi-objective optimization problem

In this section, we present a method to solve the constrained multi-objective problem (1). It is based on the algorithm proposed by [4] namely the Multi-objective Covariance Matrix Adaptation Evolution Strategy method (MO-CMA-ES).
The MO-CMA-ES method belongs to the class of evolution strategy methods which allow to solve global optimization problems. These methods are popular for their ability to find a global minimum but their slow convergence rate is often criticized. In [5], Hansen has proposed the CMA-ES method for optimization of real-space functions, based on an original mutation operator that increases the convergence rate thanks to the adaptation of the mutation distribution at each generation.

3.1 CMA-ES method for single-objective optimization

In the CMA-ES evolutionary algorithm, a new population is created from the current population by generating realizations of a Gaussian probability law

$$x_k^{(g+1)} \sim \mathcal{N}\left(m^{(g)}, \sigma_k^{(g)2} \cdot C_k^{(g)}\right) \tag{3}$$

where $m^{(g)}$ is the barycenter of the best μ individuals with respect to the objective function to be minimized,

$$\begin{aligned} &m^{(g)} = \sum_{i=1}^{\mu} w_i x_{i:\lambda}^{(g)}, \\ &\text{with } \sum_{i=1}^{\mu} w_i = 1 \text{ and } w_\mu \leq w_{\mu-1} \leq \ldots \leq w_1 \leq 1, \end{aligned} \tag{4}$$

$x_{i:\lambda}^{g}$ being the i^{th} best individual of the current population $x^{(g)}$ with respect to the function to be minimized. The next population is thus directed towards the best points.
An ideal choice for the covariance matrix would be the inverse of the Hessian matrix of the objective function, the idea proposed by Hansen is then to approximate this matrix as for a Quasi-Newton method but without any computation of the derivatives. The update formula for the covariance matrix is then

$$C^{(g+1)} = (1 - c_{cov})C^{(g)} + c_{cov} \sum_{i=1}^{\mu} w_i \left(\frac{x_{i:\lambda}^{(g+1)} - m^{(g)}}{\sigma^{(g)}} \right) \left(\frac{x_{i:\lambda}^{(g+1)} - m^{(g)}}{\sigma^{(g)}} \right)^T \tag{5}$$

which amounts to adding to the current covariance matrix a μ-rank term that takes into account the repartition of the best μ individuals of the new population. An other update formula is proposed by Hansen which does not take into account only the last iteration as in (5) but all the previous iterations from the beginning.
In the same way, an update formula of the standard deviation is built: the main idea is here to avoid that two consecutive iterations lead to a displacement of the barycenter of the population $m^{(g)}$ in the same direction, replacing these two iterations by one with a larger standard deviation would have been a better choice. Likewise, a small standard deviation is preferred to a large one which leads to two iterations with opposite displacements of the barycenter of the population. The reader is referred to [5] for more details. Figure 3 illustrates on a 2D single-objective optimization example the adaptation of the covariance matrix and of the standard deviation leading to an efficient evolution of the population toward the global minimum.

3.2 MO-CMA-ES method for multi-objective optimization

Adapting the CMA-ES method to multi-objective optimization requires the definition of new criteria to define what is a *good* and a *bad* individual for selection step of the evolutionary algorithm (see [4]). Two criteria are implemented in MO-CMA-ES:

1. A classical criterion for multi-objective optimization is the Pareto dominance:

   Definition 1. *An individual x is said to dominate another individual x', which is symbolized by $x \prec x'$, if and only if*

   $$\begin{cases} \forall m \in \{1, ..., M\} : f_m(x) \leq f_m(x') \\ \exists m \in \{1, ..., M\} : f_m(x) < f_m(x'). \end{cases} \tag{6}$$

   Definition 2. *The set of Pareto optimal points of the set X is thus defined by the set $\{x \mid \quad \nexists x' \in X : x' \prec x\}$.*

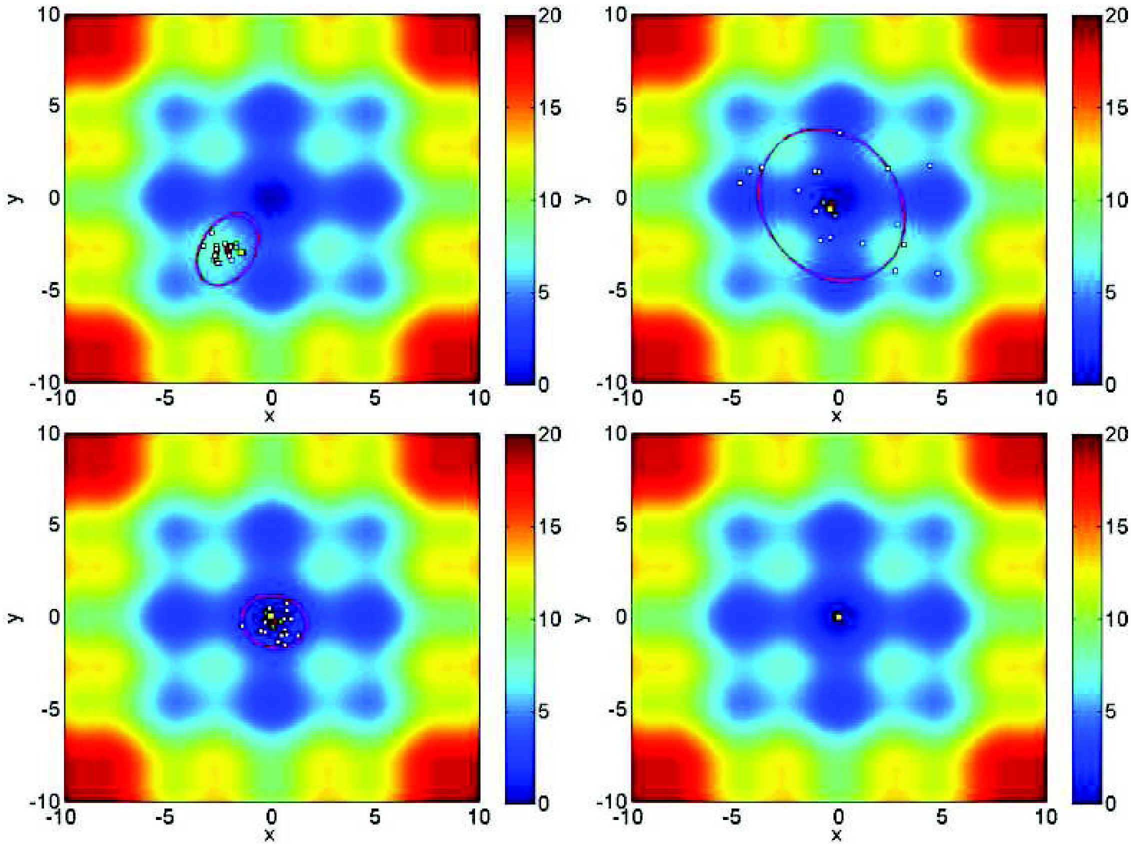


Figure 3: An application of CMA-ES method on the analytical function $f(x,y) = \frac{x^2+y^2}{10} - \frac{1}{2}\left(\cos(\frac{2\pi}{5}x) + \cos(\frac{2\pi}{5}y)\right) + 3$. From top left to bottom right, the population at iterations 1, 5, 8 and 20 are represented. The ellipse represents the 95%-isovalue of the Gaussian probability density of the mutation operator with the adaptive covariance matrix.

The Pareto front is composed of the values taken by the objectives for all the Pareto optimal solutions. Examples of Pareto fronts are given in Figure 5. The individuals of a given population A are sorted by their non-dominance level. The non-dominated solutions of A are given by:
$ndom(A) = \{a \in A \,|\quad \nexists a' \in A : a' \prec a\}$.
We consider that these non-dominated solutions have a non-dominance level of 1. Recursively, we define the points of non-dominance level equal to 2 as the non-dominated points of the population A without the non-dominated solutions. We thus obtain the recursive definition:

$$\begin{array}{l} ndom_i(A) = ndom(dom_{i-1}(A)) \\ \text{with } dom_i(A) = dom_{i-1}(A) \backslash ndom_i(A) \text{ and } dom_0(A) = A. \end{array} \tag{7}$$

2. The second criterion is a diversity criterion of the solutions to obtain an uniform repartition of the solutions along the Pareto front. A measure of the dominance hyper-volume at a non-dominated solution is defined by considering the surface of the rectangles defined in Figure 4 (one rectangle for each non-dominated point).

Combining these two criteria allows to sort the individuals of the current population with respect to the multiple objectives and then to apply the CMA-ES update formula of the covariance matrix adaptation for the mutation. For more details on the MO-CMA-ES method, the reader is referred to [4].

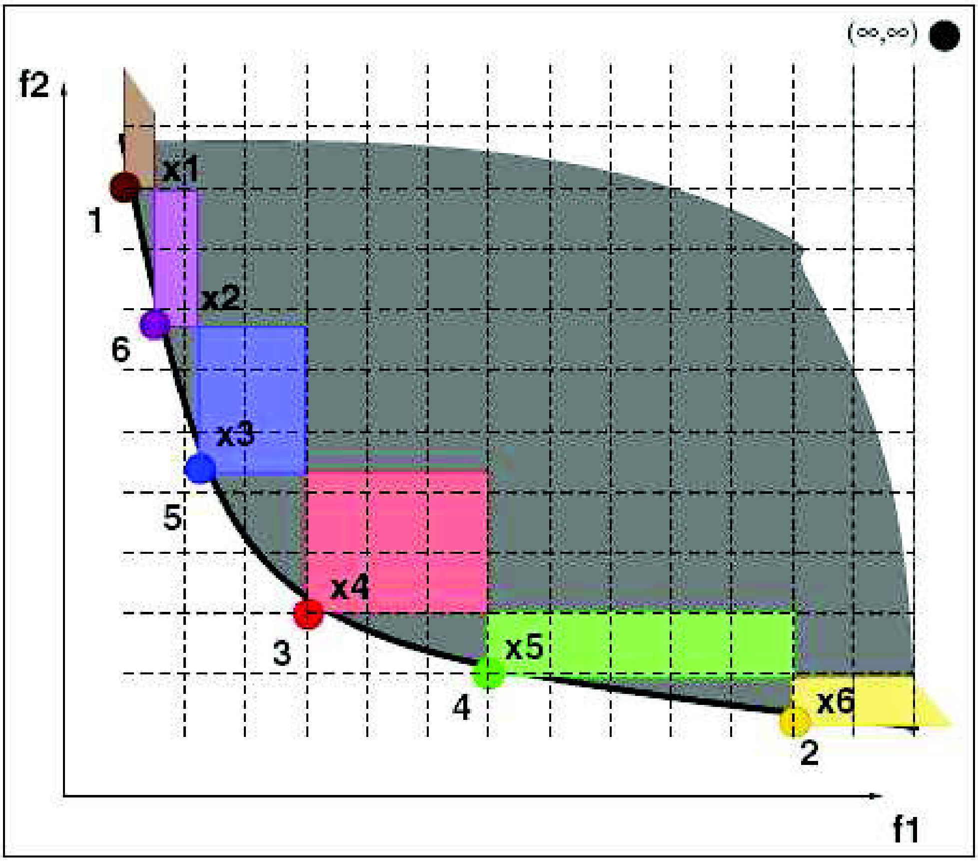


Figure 4: Contributing dominance hyper-volumes for the evaluation of the diversity criterion

3.3 Application of MO-CMA-ES method to a real case of engine calibration

In this section we present results obtained from a real dataset associated with a turbo-diesel engine. We consider the optimization problem (1) at a given engine operating point (1750 rpm - 1 bar). Models of the engine responses have been built from experimental data, the tests being designed thanks to a classical D-optimal criterion: the models are cubic polynomials.

The optimization is performed on 6 engine control parameters: the main injection timing, the pilot fuel injection quantity, the pilot injection timing, the fuel injection pressure, the mass air flow and the boost pressure.

The optimization objectives are the particulate emissions and the NOx emissions, CO2, HC and CO emissions and the engine noise being constrained to remain smaller than a given threshold. Linear constraints defining physical limits of the domain of variations of the parameters are introduced. These linear constraints may take into account the parameter dispersions, these new constraints are denoted by robustness constraints hereafter.

Thus, the multi-objective optimization algorithm has been modified to deal also with linear and non linear inequality constraints: they have been introduced via a l_1 penalization term added to the objectives (if the i^{th} constraint is not satisfied, the misfit with the bound is added to the objective functions, the penalization weight varying during the iterations).

The results are presented in Figure 5 : two optimizations are compared, one without taking into account the parameter dispersions and one with the robustness constraint which consists in taking into account the possible dispersion of the engine control parameters when applied on the vehicle. This dispersion is modeled by an uncorrelated Gaussian probability law, thus by

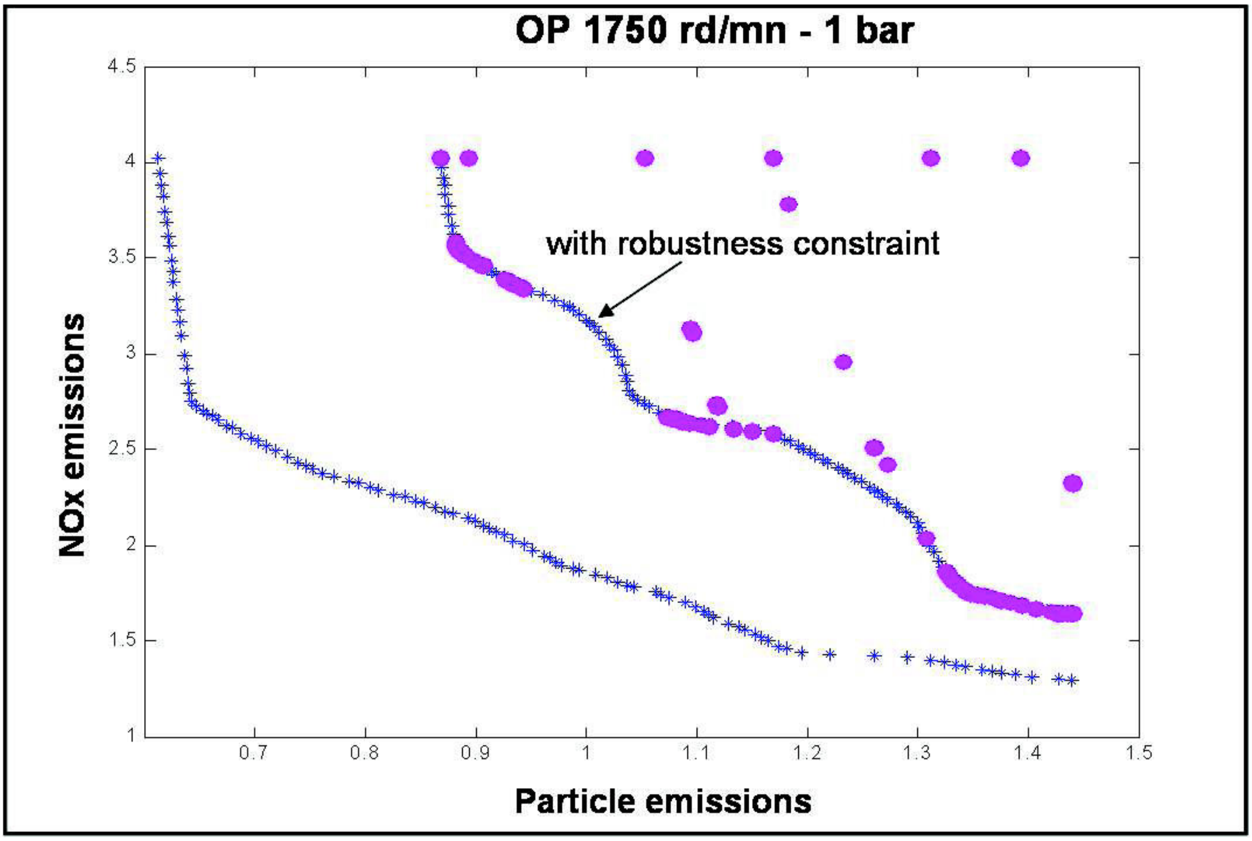


Figure 5: Pareto fronts (stars) obtained with the MO-CMA-ES method for the OP 1750 rd/mn - 1 bar. The front at the right side of the Figure is associated with an optimization taking into account the parameter dispersion (robustness constraints that ensure the effective engine control parameter values to remain inside the engine physical domain). The other front results from an optimization without these constraints. The dots are solutions obtained by single-objective optimizations (weighted sum of the two objectives) associated with different initial points and different penalization weights.

one standard deviation by parameter. As shown in Figure 2, a vicinity of the engine setting is defined and this vicinity should remain inside the physical limits. The impact of this constraint is noticeable in Figure 5 by an important shift of the Pareto front and a modification of its shape. Engine experts were very interested in the different compromises between the two objectives that have been obtained by the multi-objective optimization method. The points indicated with dots are associated with successive runs of a local single-objective optimization with different initial points and with a weighted sum of the two objectives (different weight values have been tested). We notice that these optimizations lead to points not located on the Pareto front: these points are some local minima. Moreover, as expected, the points obtained on the Pareto front are located on the convex parts only.

The MO-CMA-ES method has performed on this example 3 times more evaluations of the objective functions than the local optimization with different initial points and different weights. Even if this performance is already very encouraging, some work on the stopping criteria may reduce the number of evaluations of MO-CMA-ES.

4 Solving the map optimization problem

In the classical calibration process described in section 2.1, the engine map building in the smoothing step is delicate and time consuming. In this section, we propose an alternative method that consists in directly optimizing the cumulated engine responses over the cycle via deformations of the engine maps themselves instead of optimizing individually the selected OP and building afterward the engine maps by the smoothing step. The map optimization problem is formulated as

$$\begin{cases} \min\limits_{m^p \in \mathbb{R}^{N_p}} \displaystyle\int_0^T F_i\left(r(t), c(t), m^{p_1}(r(t), c(t)), m^{p_2}(r(t), c(t)), \ldots, , m^{p_{N_p}}(r(t), c(t))\right) dt \\ \\ \text{subject to} \\ l(r,c) \leq A m^p(r,c) \leq u(r,c) \\ \displaystyle\int_0^T F_j\left(r(t), c(t), m^{p_1}(r(t), c(t)), m^{p_2}(r(t), c(t)), \ldots, , m^{p_{N_p}}(r(t), c(t))\right) dt \leq S_j \\ \quad j \in [1, d] \end{cases} \tag{8}$$

where $(r(t), c(t))$ indicate the trajectory of the cycle within the engine speed-load domain, F_i is the 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.

The objectives to be minimized (or constrained) are the engine responses cumulated on the considered driving cycle: the cumulated responses may be either the weighted sums of the local models defined at chosen representative OP or the integral of global models defined on the whole operating domain (depending on engine speed and engine load or some models defined on zones depending on the parameterizations: for instance number of injections). The latter formulation allows a finer optimization with a fine sample of the integrals in (8). Additional smoothing constraints such as global smoothing constraints (to preserve the regularity of the original maps) or more local constraints (for example limits on the gradients of the maps) can also be introduced. Note that, as with local optimization problem, the transient effects are not taken into account in engine response modeling and must be introduced when defining the objective of global optimization.

4.1 Modeling the engine maps

The formulation (8) requires an adapted parameterizations of the engine maps that must be flexible enough to model the very different shapes of engine map surfaces (Figure 6) and should not require too many parameters to limit the number of unknowns in the optimization process. LoLiMoT models ([9], [3]) seem to be a good compromise between flexibility, accuracy and complexity: some very simple local models (linear or bilinear) are combined by a weighted sum

$$m(r,c) = \sum_{i=1}^{M} \hat{m}_i(r,c)\Phi_i(r,c) \text{ with } \hat{m}_i(r,c) = \omega_{0i} + \omega_{ri} r + \omega_{ci} c \tag{9}$$

where the weights $\Phi_i(r,c)$, normalized Gaussian functions, control the degree of smoothness of the global surface:

$$\Phi_i(r,c) = \frac{\mu_i(r,c)}{\sum_{j=1}^{M} \mu_j(r,c)} \text{ with } \mu_i(r,c) = \exp\left(-\frac{1}{2\alpha}\frac{(r - {r_i}^0)^2}{\sigma_i^{r2}} + \frac{(c - {c_i}^0)^2}{\sigma_i^{c2}}\right) \tag{10}$$

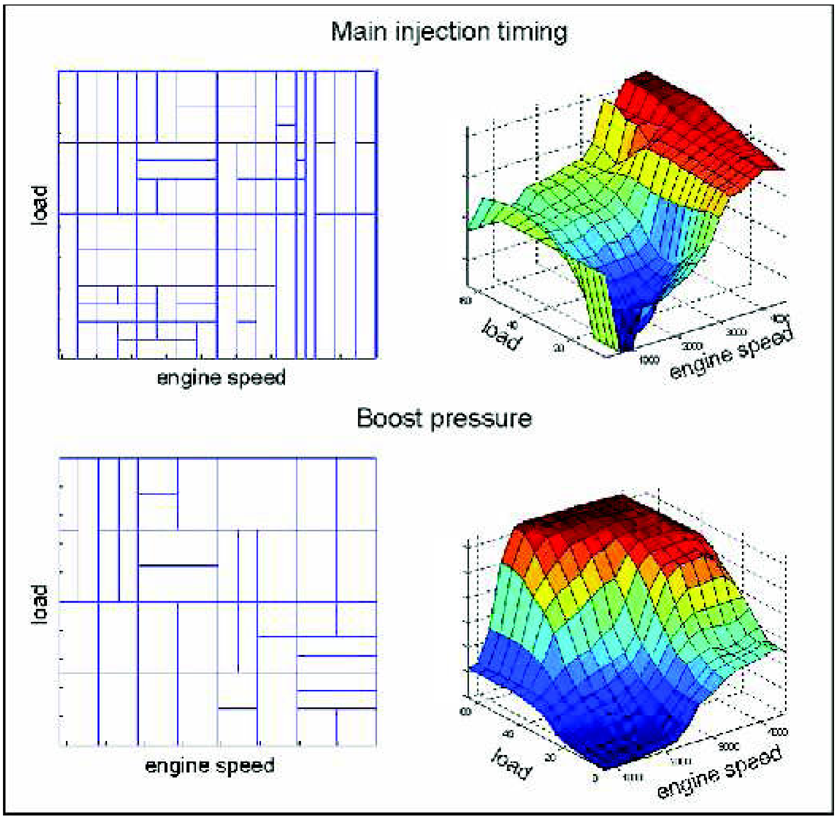


Figure 6: Examples of LoLiMoT parameterizations of engine map. Left: patching of the domain. A local linear model is defined on each patch. Right: the resulting surfaces modeled by LoLiMoT for two different engine control parameters from given discrete reference maps.

This representation allows an adaptive refinement of the surface: the patching associated with the definition domains of the local models may be refined during the optimization process. A finer patching allows a finer optimization (the number of degrees of freedom being increased) but may lead to a cumbersome optimization of a large number of parameters. The parametrization, namely the patch definition for LoLiMoT description of the maps should reflect the degree of smoothness the user expects for the maps: for some parameters like boost pressure, the map should remain smooth, for others like main injection timing, the smoothing constraint is not as strong.

Thus, from some reference engine maps or some a priori information, a LoLiMoT parametrization of each map of engine tunings is defined (Figure 6). The unknowns of the optimization are the LoLiMoT parameters (coefficients of local linear models $\omega_{.i}$ in equation (9)).

4.2 Application of map optimization on a real case

The map optimization has been applied on a turbo-diesel engine application. The optimization problem is defined as a constrained single-objective optimization problem where the cumulated CO2 emissions are minimized and the cumulated particulates, CO, HC and NOx emissions are constrained to remain under thresholds. Constraints are added to take into account the limits of the physical domain: linear and non linear inequality constraints as described in [2]. Different methods have been compared as described in Table 1:

- the **local method** is the most simple one but requires a smoothing step to build engine

Table 1: Engine map optimization methods to be compared

	Models	Optimized responses
Local method	local models (3^{rd} degree polynomials)	local responses for each OP, $\min\limits_{p\in\mathbb{R}^{N_p}} (F_1(p), F_2(p), \ldots, F_m(p))$
Mixed local method	local models (3^{rd} degree polynomials)	weighted sum of local responses $\min\limits_{m^p\in\mathbb{R}^{N_p}} \sum_{l=1}^{N_{OP}} \omega_l F_i^{(l)} \left(m^{p_1}(r_l, c_l), m^{p_2}(r_l, c_l), \ldots, , m^{p_{N_p}}(r_l, c_l)\right)$
Mixed global method	global/zonal models (kriging)	weighted sum of global responses $\min\limits_{m^p\in\mathbb{R}^{N_p}} \sum_{l=1}^{N_{OP}} \omega_l F_i \left(m^{p_1}(r_l, c_l), m^{p_2}(r_l, c_l), \ldots, , m^{p_{N_p}}(r_l, c_l)\right)$
Global method	global/zonal models (kriging)	integral over the cycle of global responses $\min\limits_{m^p\in\mathbb{R}^{N_p}} \int_0^T F_i \left(r(t), c(t), m^{p_1}(r(t), c(t)), \ldots, , m^{p_{N_p}}(r(t), c(t))\right) dt$

maps. This step may destroy the optimization work by modifying the obtained local optima at a set of 16 selected OP as explained in Section 2.1. The engine maps are sub-optimal maps because of the smoothing step but also because of the limited number of selected OP.

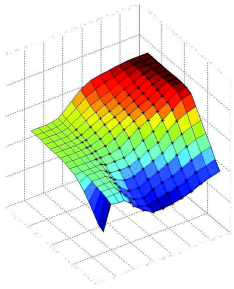
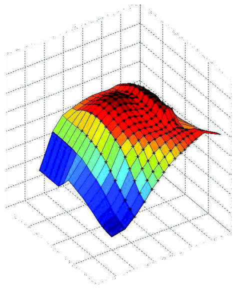
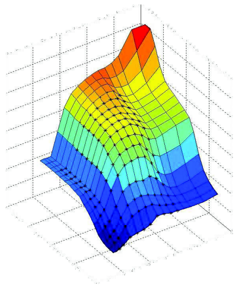
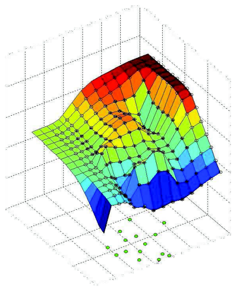
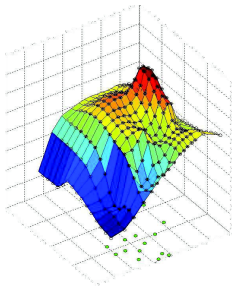
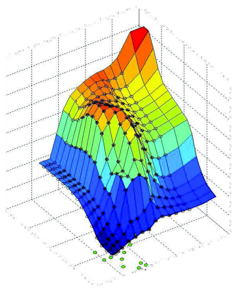
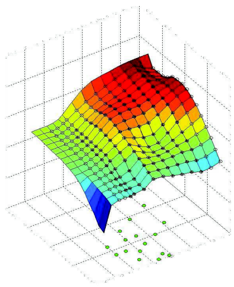
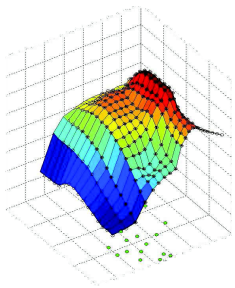
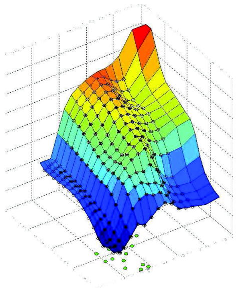
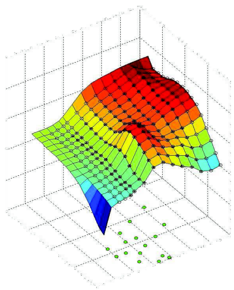
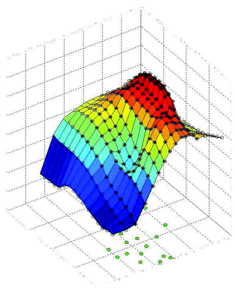
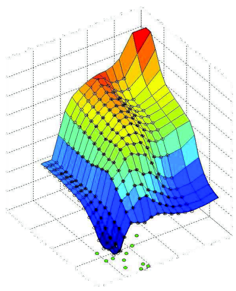
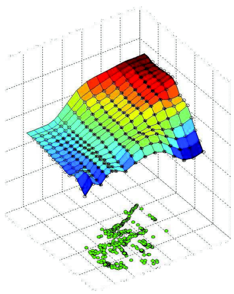
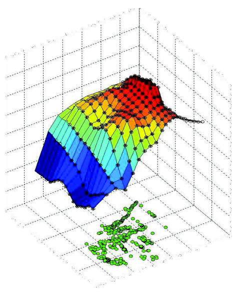
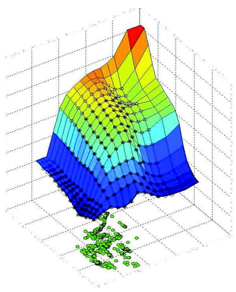
- the **mixed local method** allows to build optimized engine maps by a global map optimization on cumulated responses on selected OP, responses being modeled only locally on each selected OP. The models are cubic polynomials built from data obtained thanks to a D-optimal design. This method may suffer from a lack of accuracy because of the limited number of OP as for the local method but, on the contrary to the latter, this method avoids the delicate smoothing step.

- the **mixed global method** is very similar to the mixed local method with responses modeled globally on the operating domain. We use kriging models ([6], [8]) that allow to model complex responses and to take into account an estimate of measurement errors (see [2] for more details on the design of experiments). This method is not very interesting in practice: since we have at our disposal global models, an optimization of a finer sampling of the driving cycle is possible and should give more accurate results.

- the **global method** is the most complex method but the most accurate: it consists in the map optimization of the cumulated responses on a fine sample of the cycle (in our example, 1Hz sampling i.e. 1019 OP, see Figures 12 and 13). The models are the same as in the mixed global models.

As shown by Figures 7 and 8, the four methods match the constraints on the cumulated engine responses. Some of the engine maps obtained with these methods are displayed in Table 2: we observe that the maps obtained with mixed methods and global method are smoother than the maps obtained with local method. This is not surprising: the smoothing step of the local method is cumbersome, a compromise between smoothing and keeping the maps close to the local optima has to be found. A first advantage of the engine map optimization is thus the additional degree of freedom introduced by optimizing directly the cumulated responses instead of successive optimizations of local responses at each OP as in the local method. A response

Table 2: Examples of engine maps obtained with the different optimization methods. The green dots are the OP used to sample the integral of the cumulated responses (16 OP pr 1019 OP depending on the optimization method).

	Map of pilot fuel injection quantity	**Map of pilot injection timing**	**Map of fuel injection pressure**
Initial maps			
Local method			
Mixed local method			
Mixed global method			
Global method			

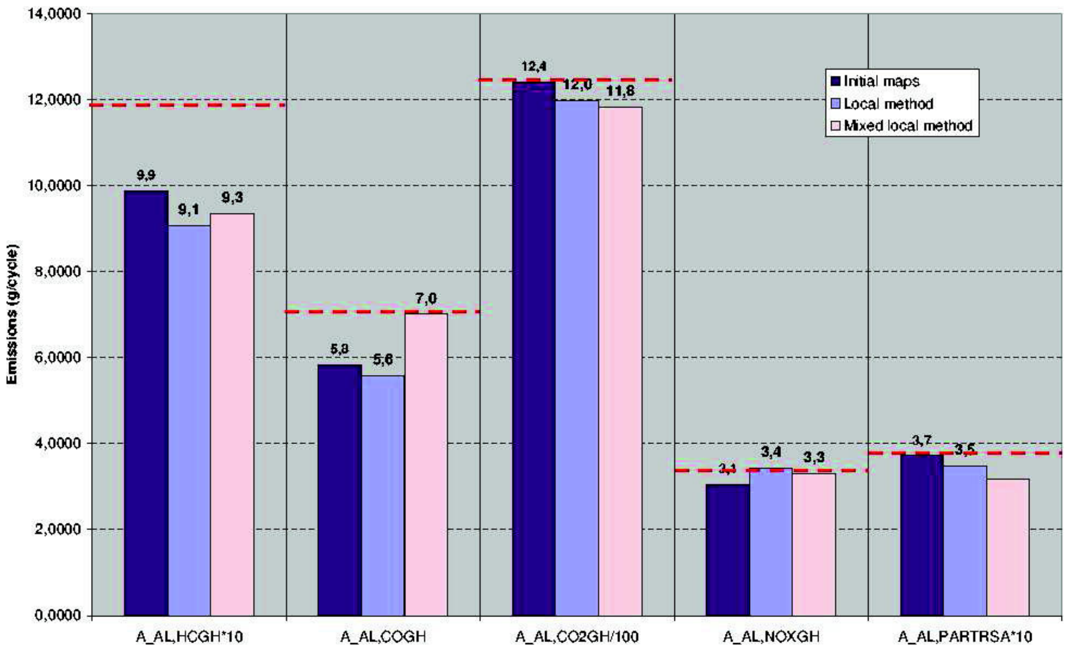


Figure 7: Comparison of results obtained by local method and mixed local method. The cumulated responses are computed by a weighted sum of 16 OP with local models. Upper bounds of engine responses introduced in optimization are displayed in dotted red lines.

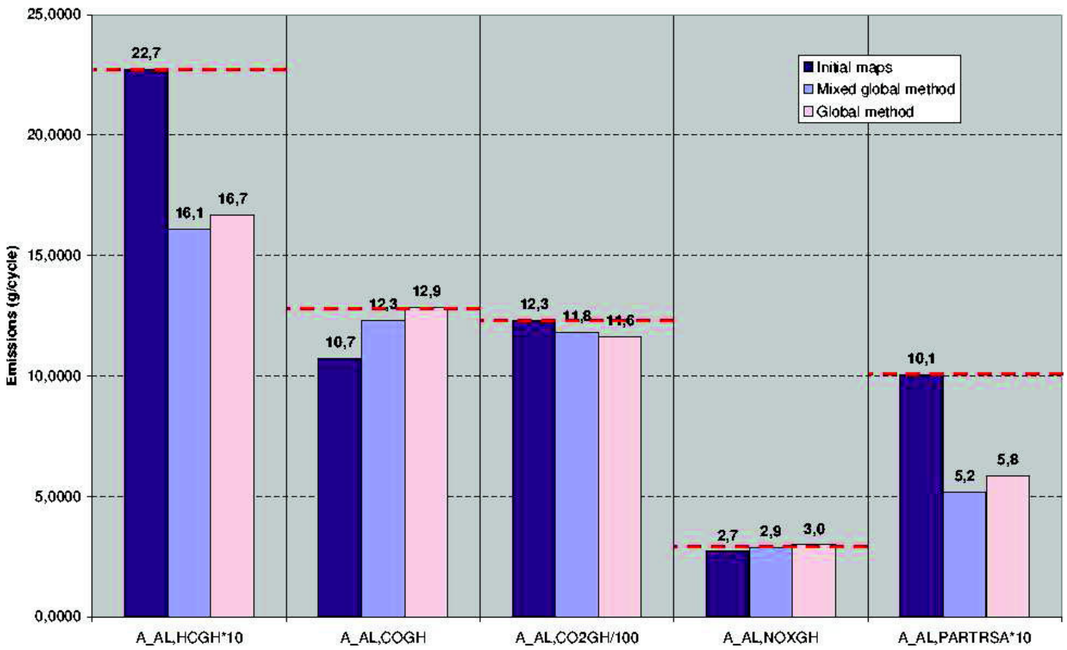


Figure 8: Comparison of results obtained with mixed global method and global method. The cumulated responses are computed by a 1Hz sampling of the integral of global models (1019 OP). Upper bounds of engine responses introduced in optimization are displayed in dotted red lines.

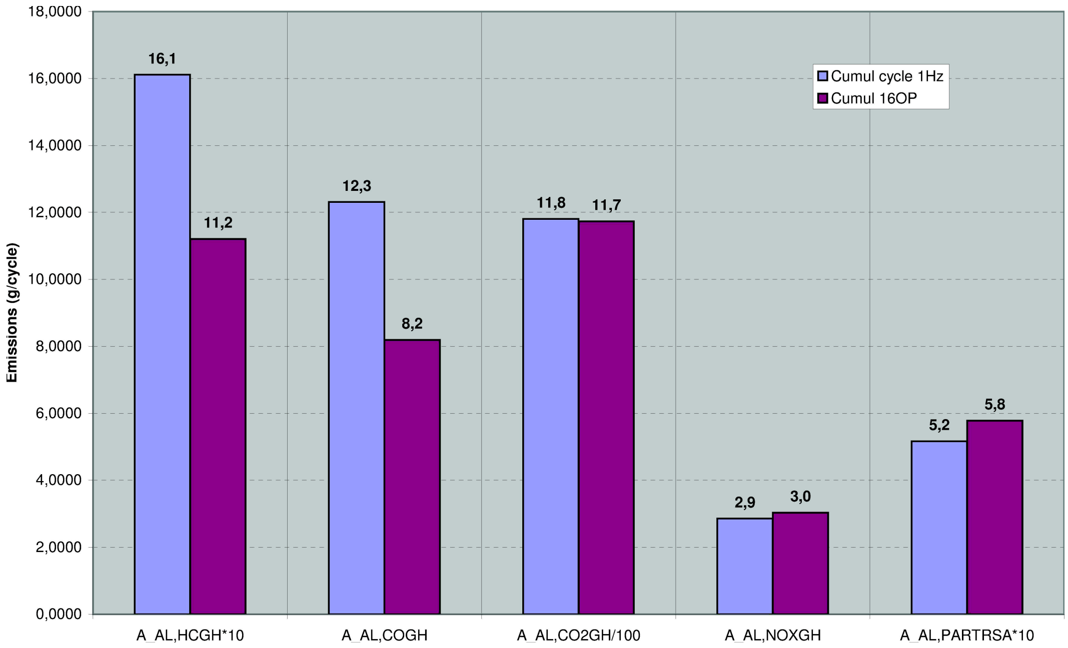


Figure 9: Comparison of estimation of cumulated responses on the driving cycle with a weighted sum of 16 OP and the integral with a discretisation of 1Hz (1019 OP).

at an OP may be slightly increased in order to keep the regularity of maps. We observe the gain on Figure 7: the mixed local method gives smoother engine maps (Table 2) and allows to obtain smaller CO2 emissions.

Finally, the estimate of cumulated responses on the driving cycle should be more accurate: as shown on Figure 9, the approximation of the integrals by a weighted sum on 16 OP gives very different results from the 1Hz discretisation. The choice of the 16 OP and the associated weights is cumbersome and may explain partly the differences. The accuracy of these approximations depends also on the accuracy of the models of the engine responses. The global models of the engine responses are not as accurate as the local models when considered locally. A special care should be taken in the validation of the global model.

Figure 8 illustrates the results obtained with mixed global method and global method: the method differs only by the discretisation of the driving cycle for computing the cumulated responses to be optimized (discretised with 16 OP or with 1019 OP for a 1Hz sampling). The results are very similar: for this example, the mixed global method does not suffer from the rough sampling of the cycle. Nevertheless, the cumulated CO2 emissions are smaller for the maps obtained by the global method. Figures 10 and 11 show the gain on the maps of the responses: the global method minimized more globally the CO2 emissions than the mixed global method. Figures 12 and 13 display the optimized engine settings and the gain on engine responses obtained with global map optimization.

5 Outlook

The methods proposed in this paper are based on experimental tests in stabilized conditions. The transient effects during the cycle as well as the effect of the warming up of the engine and of the post-treatment of the emissions are not taken into account during modeling process. They are only introduced in the definition of the objectives of optimization (the allocation for each OP

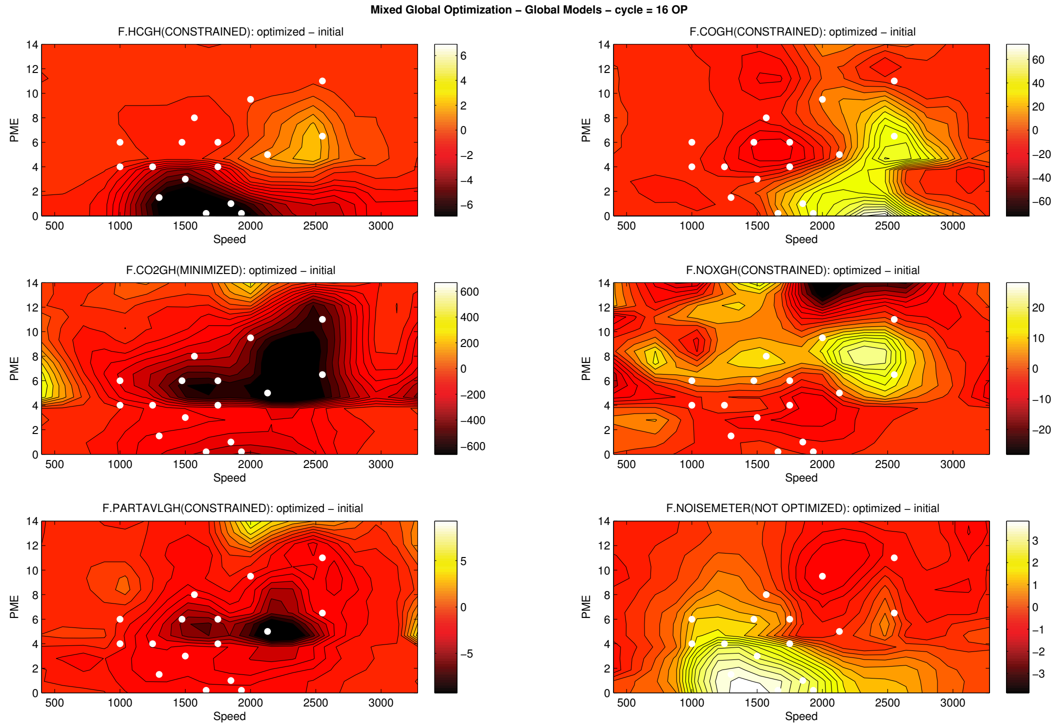


Figure 10: Maps of differences of engine responses (modeled by kriging global models) obtained with initial maps and maps obtained with mixed global methods. The white dots indicate the driving cycle OP.

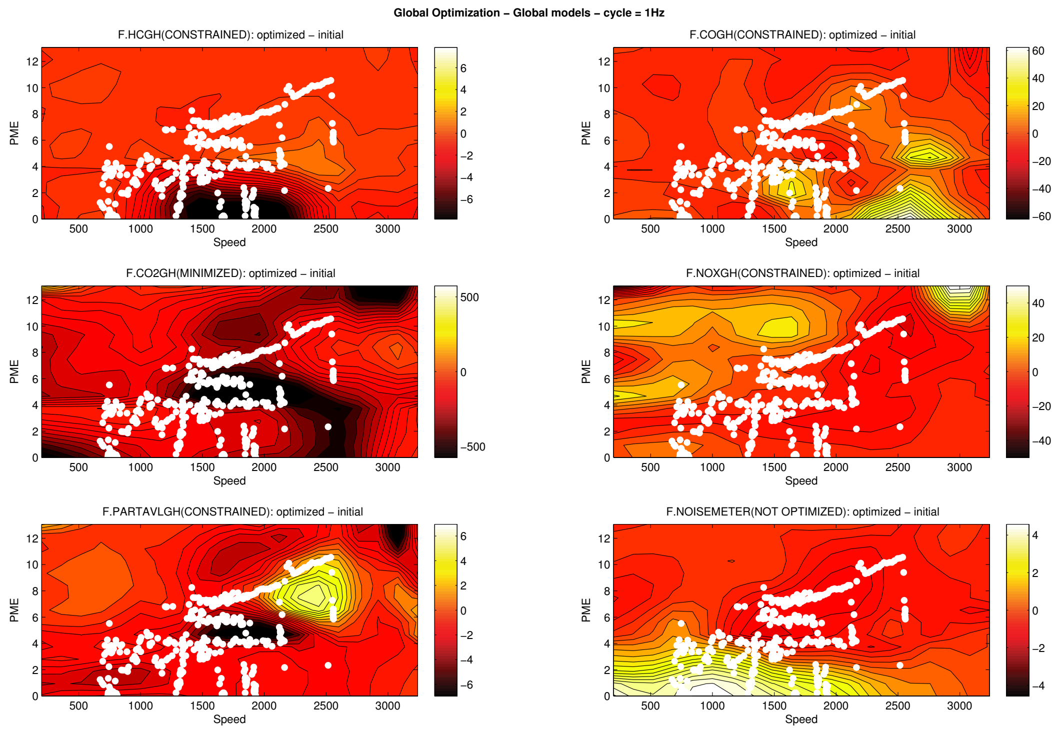


Figure 11: Maps of differences of engine responses (modeled by kriging global models) obtained with initial maps and maps obtained with global methods. The white dots indicate the driving cycle OP.

in local approach or the objectives of map optimization in mixed or global approaches), with empirical methods based on the know-how of engine experts. These methods consist generally of minimizing each emission target by transfer coefficient between hot and cold behavior and between stabilized and transient behavior. Such coefficient are often determined by experience on similar engines or preliminary tests.

New challenge is to develop methods allowing to take into account in a more robust way the behavior of the engine during transient operations (load, speed and/or thermal variations). Experimental methods are in development, based on the realization of transient operations at test bench, for example by using DoE. Such method could be proposed in addition to methods based on stabilized tests (map corrections to take into account transient effect) or be used directly to obtain optimal maps. Some others methods proposed in the literature are based on generating APRBS signals (Amplitude modulated Pseudo Random Binary Signals) at each operating point for the identification of the non-linearity of the engine ([7]). We also consider that coupling between experimental (statistical) models and physical modeling of the engine is a very promising way. The idea is to simulate the behavior of vehicle and engine in order to get the conditions in the combustion chamber before combustion(gas composition, injection behavior,...) and to use statistical models to obtain engine-out emissions. Such a simulation tool could be used for optimizing control parameters on the cycle, taking into account transient behavior.

6 Conclusions

In this paper, the optimization problems encountered in stationary engine calibration are addressed. The constrained multi-objective optimization has been successfully solved by the MO-CMA-ES method modified to handle inequality constraints. The performance of this method on the considered real case application is very encouraging. The resulting Pareto front gives to the engine experts a worth information on the possible compromises between antagonist engine responses as particulate emissions and NOx emissions of a diesel engine. In a second part, an other formulation of the engine map optimization is proposed based on a cycle optimization instead of an optimization at given engine operating points. This formulation allows to handle the smoothing constraints on the maps directly in the optimization process, thus to avoid the generally cumbersome step of map smoothing in classical engine calibration process. Results of a constrained single-objective map optimization have shown the efficiency of the method compared to local methods. A comparison of the different approaches on this example shows the efficiency of the map optimization. A next study will be to apply a multi-objective approach as for the OP optimization, the difficulty being the large size of the parameter space (500 parameters to describe all the engine maps). Taking into account transient behavior of the engine during optimization process by the use of dedicated tests or by the use of simulation tool is an other challenge for calibration engineers.

References

[1] Castagné M., Bentolila Y., Chaudoye F., Hallé A., Nicolas F. and Sinoquet D., Comparison of Engine Calibration Methods Based on Design of Experiments, Oil & Gas Science and Technology - Rev. IFP, Vol. 63, No. 4, pp. 563-582, 2008.

[2] Chaudoye F., Bentolila Y., Castagné M., Sinoquet D., Wahl F., Modelling engine operating space for DoE calibration methods, 5th IAV conference - DOE in Engine Development - Design of experiments, 2009.

[3] Hafner M. and Isermann R., The use of stationary and dynamic emission models for an improved engine performance in legal test cycles, International workshop on Modeling, Emissions and Control in automotive engines, Salerno, Italy, 2001.

[4] Hansen N., Igel C. and Roth S., Covariance Matrix Adaptation for Multi-objective Optimization, Evolutionary Computation, 15(1), p.1-28, 2007.

[5] Hansen N. and Ostermeier A., Adapting arbitrary normal mutation distributions in evolution strategies: The covariance matrix adaptation, In Proceedings of the 1996 IEEE International Conference on Evolutionary Computation, p. 312-317, 1996.

[6] Krige, D.G., A statistical approach to some mine valuation and allied problems on the Witwatersrand, Master Thesis, University of Witwatersrand, 1951.

[7] Martini E., Bachler J., Weber M., Maignan D., Michel S. and Collette Y., Dynamic Tuning: A new Approach for Fast Engine Emission Calibration, Diesel Engine 2006, Ecole Centrale de Lyon, May 31 and June 1 2006.

[8] Matheron, G., Principles of geostatistics, Economic Geology 58, 1246.1266, 1963.

[9] Nelles O., Non linear system identification, Springer-Verlag, 2001. and other modern development methods, Berlin, Germany, 2007.

[10] Röpke K., Gaitzsch R., Haukap C., Knaak M., Knobel C., NeSSler A., Schaum A., Schoop U., Tahl , DoE Design of Experiments, Methods and applications in engine development, Verlag Moderne Industrie, 2005.

[11] Seabrook J., Cornwell R., Mortimer P. and Edwards S., A Calibration Methodology to Ensure Low Variation in Emissions between Engines in Production, 4th IAV conference - DOE in Engine Development - Design of experiments, 2007.

Figure 12: The first and second figures from the top are respectively the engine speed and the MEP (Mean Effective Pressure) along the considered driving cycle. The other figures represent the optimized engine tunings along the driving cycle obtained by the global optimization method: from top to bottom, the injected air quantity, the fuel injection pressure, the pilot fuel injection quantity, the main injection timing, the pilot injection timing, the position of variable geometry turbine, the boost pressure.

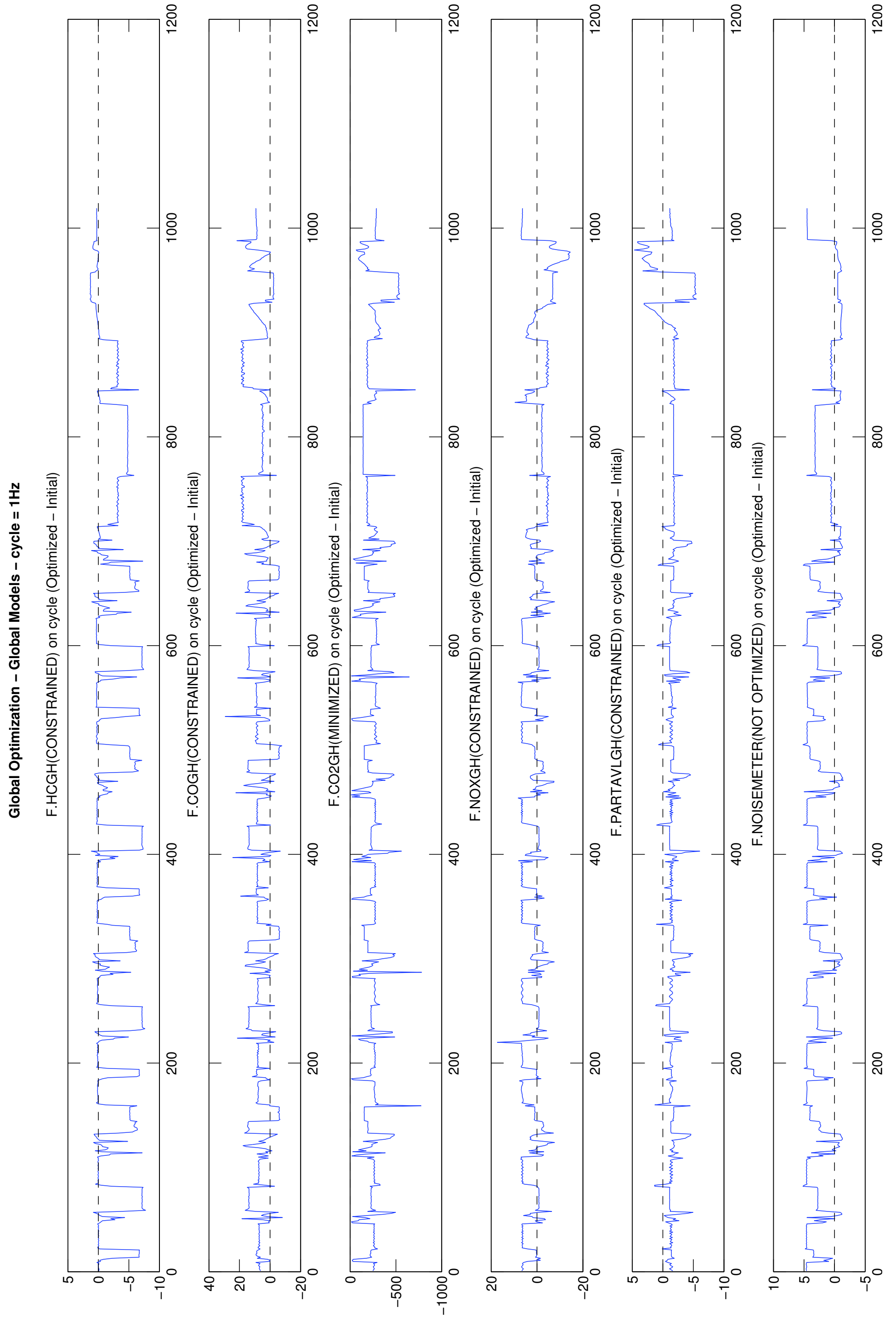


Figure 13: Optimized engine responses along the driving cycle obtained by the global optimization method: from top to bottom, HC, CO, CO2, NOx, particles emissions and noise.