

Optimizing the Calibration of a Turbocharged GDI Engine through Numerical Simulation and Direct Optimization

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ABSTRACT

Different optimization strategies for the optimization of the calibration of a turbocharged GDI engine through numerical simulation were analyzed, aiming to evaluate the opportunities offered by direct optimization techniques.

A one-dimensional fluid dynamic engine model was used to predict engine performance, taking into account knock and exhaust temperature constraints.

Air fuel ratio, spark advance, boost pressure and cam phasing were optimized by means of different optimization strategies, including direct search as well as numerical methods.

Both full load (with maximum bmep targets) and part load (with minimum bsfc targets) were considered.

The potential for remarkable improvements (up to 10% bmep increase at full load and 8 g/kWh bsfc decrease at part load) in comparison with the baseline engine calibration was highlighted, and a ranking between different optimization methods was obtained, based on the requested computational efforts and on their capabilities to handle constrained optimization problems.

INTRODUCTION

In recent years the widespread diffusion of turbocharged Gasoline Direct Injection (GDI) engines, often equipped with Variable Valve Timing (VVT) devices [1,2,3], has lead to a remarkable increase in the number of calibration parameters also for SI engines, highlighting the need of proper

optimization tools in order to solve complex calibration problems which are far beyond the simple bi-parametric search for lambda - spark advance optimal combination at full load that has represented for many year the standard calibration issue for SI engines [4,5]. The traditional “one parameter at a time” approach to calibration thus has become more and more obsolete and unsuitable to address modern calibration issues, making it impossible to estimate the interactions among different factors.

Moreover, quite often the selection of the best calibration parameters is not only a matter of the final engine calibration, but should be addressed from the earliest stages of the engine development, due to the interactions between calibration and design parameters.

Computer Aided Engineering conveniently offers the possibility to overcome the limits of the traditional approach, thanks to the constantly improving capabilities of simulation tools, which can nowadays provide a kind of “virtual test bench” not only for the optimization of engine design parameters such as for instance port or valve geometries, but also for the optimization of a number of calibration parameters [5,6].

The common approach to engine calibration consists in a preliminary exploration of the parameters' domain, carried out by means of Design of Experiments techniques in order to obtain a simple algebraic approximation (generally with a polynomial structure, obtained by means of the least squares method), of both the objective function and the system constraints. This relatively simple function can then be easily

managed through commercial or even home-made optimizers to refine the calibration finding a local optimum [7, 8].

The use of reliable engine simulation tools allows the building of a virtual prototype and paves the way to a quite different approach to the Design of Experiments, not only by dramatically reducing the costs of the experiments, but also by greatly simplifying the problem of the selection of the parameters' levels, since there is no material constraint on the values that can be assumed by the parameters once a reliable model has been built and validated.

On the contrary, the use of a virtual model makes the experimental planning completely free, its definition being subject to analytical considerations only, since no configuration has to be discarded due to hardware limitations.

Since simulation models are capable to realize whatever variation of the independent variables, there is no need to carry out the calibration on a polynomial fitting of spare data, but, as long as the model maintains its accuracy, the optimization process can be performed directly on the real system response.

The aim of this work is therefore the evaluation of the potentialities offered by direct optimization techniques coupled with engine fluid-dynamic simulation codes for the optimization of the calibration of a turbocharged direct injection spark ignition engine with variable valve timing.

The choice of the optimization procedure is a crucial factor that may remarkably affect the results of the optimization process: different techniques have been conceived and implemented aiming to solve different kind of problems with specific structures, and it is not likely that each method can achieve correct results regardless the system characteristics.

Moreover, internal combustion engine calibration entails not only simple optimization problems, but usually requires the treatment of constrained problems.

Finally, also the computational cost of the solution should be considered as an important issue: methods that rapidly produce good results if engaged in optimization of polynomial objective functions may require a number of model executions unsuitable for use in direct optimization.

The performance of different optimization algorithms will therefore be evaluated, and a ranking will be obtained, based on the requested computational efforts and on their capabilities to handle constrained optimization problems.

OPTIMIZATION METHODS

The logic followed for the solution of the optimization problem is what distinguishes different algorithms, and their

performance depends on the system they are called to study. Each logic best fits a particular category of systems, so the best results are obtained when appropriately coupling the analyzed system and the optimization algorithm.

Understanding the characteristics of both the analyzed system and the optimization algorithm, and so choosing the correct method for optimization is certainly the first and most important step to be taken when approaching a numerical optimization problem.

The wide range of optimization methods can be subdivided into three main categories: explorative, direct search and numeric methods.

EXPLORATIVE METHODS

Explorative methods imply a systematic exploration of the variables domain, that should be managed in the correct way. The most common logics for exploration conduction are statistic or genetic.

The former implies probabilistic calculation of the distributions of the interesting features of the objective function, such as the distribution of local optima or the generation of new points to explore, so that exploration can be leaded to converge around an esteemed global optimum.

The latter aims to simulate the genetic evolution theory, treating points coordinates as binary chromosomes, performing crossing and mutations among the population, then evolving to next generations by means of "natural" selection of the fittest. The sequence of generations will be stopped when the requested convergence is reached, by convergence meaning a sufficiently low improvement rate in the objective function.

Such logics best apply to complex response surfaces, when random factors are involved in the definition of the objective function, and the presence of several local optima creates "traps" that are difficult to be avoided. This requires instruments that are somehow capable to take into account the unpredictable nature of the phenomenon, actuating appropriate logics to lead the exploration.

A visually effective example of the problem is the search for the lowest valley in a mountain area. Two coordinate directions, N-S and W-E, are the independent variables; the geodetic height is the objective function. No privileged search direction can be found a priori, nor one could ever be sure that the valley found is actually the lowest.

DIRECT SEARCH

Direct search methods are based on iterative algorithms. The solution is searched for by following a path in the variables domain moving to the next point along the direction in which

the objective function improves, reducing the step size at each iteration until reaching the desired minimum dimensions. What distinguishes the different methods within this category is the choice of the moving direction: the simplest possibility is to move alternatively along the directions of the coordinate axes of the variables space. More sophisticated methods are capable to choose by themselves the best direction at each iteration, performing a local exploration of the area around the current point in order to evaluate the local gradient and move along this direction: in this way the path to the optimal solution can be significantly shortened.

The best application of direct search algorithms comes when studying smooth and continuous objective functions. The strength of direct search algorithms is their speed and robustness, when applied to well fitting systems: if a unique optimum exists it will always be found in a limited number of iterations. On the contrary, these methods do not fit to discontinuous systems nor to systems with more than one local optimum, being unable to distinguish between local and global stationary points, and thus leading to results which are strongly dependent on the search starting point.

NUMERICAL METHODS

When the analytical expression of the function to be optimized is known, numerical methods can be used. Depending on the shape of the function, different algorithms can be used to find the exact analytical solution to the problem. In this category the most common problems are those in which both the objective function and the constraints are a linear function of the independent variables (linear programming, solved through the simplex method), or those featuring a quadratic objective function (quadratic programming, solved through a sequence of simple minimization problems along different directions, until reaching the absolute minimum). The construction of the different algorithms and the demonstration of the existence and uniqueness of the solution are described in detail in specific publications [9,10] and will be not further discussed here for the sake of brevity.

Whenever the analytic expression of the function to be optimized is unknown, numerical methods can be applied to an approximation of the system response: optimization techniques perform an exploration of the area surrounding the point of interest, and then calculate a quadratic approximation of the objective function and move to the next point. The solution of a sequence of quadratic programming problems brings to the solution of the optimization problem for an unknown function.

DESIGN OF EXPERIMENTS

Finally, it should be pointed out that gaining a first general knowledge of the system response to a number of parameters

as well as better understanding interactions among parameters can often be helpful, both in case of local exploration performed to build the approximation of the objective function and in case of global exploration carried out to choose the best starting point for optimization.

Therefore, some optimization methods may often include an initial exploration of the variables domain in their routines.

Design of Experiments (DoE) techniques should therefore always be considered as a valuable option for a preliminary screening of the system behaviour.

ENGINE CHARACTERISTICS AND SIMULATION MODEL

The main engine characteristics are summarized in [Table 1](#) (see also [1] for more details).

Table 1. Main engine characteristics

Engine type	GDI Turbocharged
Cylinders	4 in-line
Displacement	1742 cm ³
Bore / stroke	83 / 80.5 mm
Compression ratio	9.5
Valves	DOHC, 4 valves/cyl. Intake and Exhaust Variable Valve Timing
Maximum power	169 kW at 5000 rpm
Maximum torque	340 Nm at 1900 rpm
Turbocharger	Single stage turbocharger with WasteGate

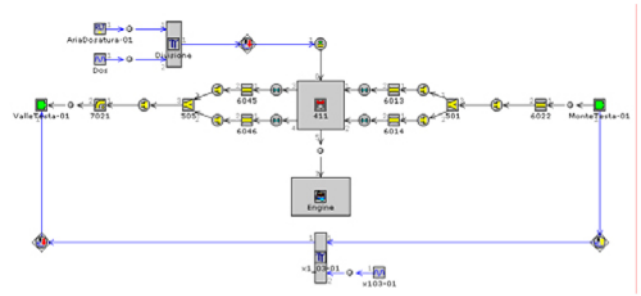
Computer simulations have been carried out using GT-POWER, a one-dimensional fluid dynamic code developed by Gamma Technologies Inc. for engine performance prediction. The general features of the code are described in detail in [11], and only a brief overview is here reported.

In GT-POWER the intake and exhaust systems are represented as a network of ducts connected by junctions. The junctions represent either physical joints between the ducts, such as area changes or volumes, or subsystems such as the engine cylinder.

The solution of the equations governing the conservation of mass, momentum and energy for each element of the network is then obtained using a finite volume scheme.

Pressure losses in ducts due to wall friction are automatically computed through a simple approach based on the Reynolds number, whereas losses in the junctions are governed by discharge coefficients, which can be either automatically computed by the code, according to junction geometry, or specified by the user, according to experimental data obtained

In the first phase of this work, aiming to compare different optimization methods, the complete engine model has been simplified to reduce simulation duration. This purpose has been achieved by considering a single cylinder in which the turbocharger has been replaced by means of a pressurized intake environment, coupled with a pressurized exhaust environment. The pressure levels of the two environments has been forced to vary according to a relationship reproducing the behaviour of a real turbocharger, as shown in the schematic model diagram which is reported in [Fig. 1](#).



As a matter of fact, a measure of knock intensity had always to be set as a constraint for the optimization processes, and the complexity of the phenomenon and its dependency on all the calibration parameters provided a chance to test optimizers when facing a highly non-linear constraint.

A number of empirical relationships have been proposed for the evaluation of the induction time, among which the most widely used is the correlation developed by Douaud and Eyzat [14], which is embodied in the standard GT-POWER knock model:

where P is the Precursor Reaction Rate Multiplier, ON is the fuel Octane Number, p the instantaneous cylinder pressure, A the Activation Energy Multiplier and T_u the instantaneous unburned gas temperature.

$$\tau = 17.68 \cdot \left(\frac{ON}{100} \right)^{3.402} \cdot p^{-1.7} \cdot e^{\frac{3800}{T_u}} \cdot \left(1 + \frac{G_{rg}}{(G_a) \cdot 0.76} \right) \cdot \left(\frac{A/F}{14.7} \right)^{0.33}$$

where G_{rg} is the residual gas mass at IVC, and G_a is the inducted fresh air mass at IVC.

Finally, the following definition of the knock index KI was used in order to evaluate knock intensity (see [11] for more details):

$$KI = 10000 \cdot A \cdot km \cdot \left(\frac{V_{TDC}}{V_I} \right) e^{-T_u/T_a} \cdot \max[0, (1 - (1 - \phi)^2)] \cdot T_{avg}$$

Where A is the Knock Index Multiplier, km the percentage of cylinder mass unburned at knock initiation, V_{TDC} the cylinder volume at TDC, V_I the cylinder volume at knock initiation, T_a the activation temperature, T_u the instantaneous unburned gas temperature, ϕ the equivalence ratio and T_{avg} the mass averaged induction time integral based on all of the surfaces in contact with unburned gases.

Afterwards, a preliminary check on the reliability of knock index KI was carried out, by comparing its response to the variations of the main engine calibration parameters, i.e. A/F ratio, spark advance, boost pressure and internal EGR.

Although the simulation results were not directly comparable with experimental data, due to different knock metrics, the calculated KI trends - which are shown in Figures 2,3,4,5 - appeared to be consistent with experimental trends reported in [16,17,18].

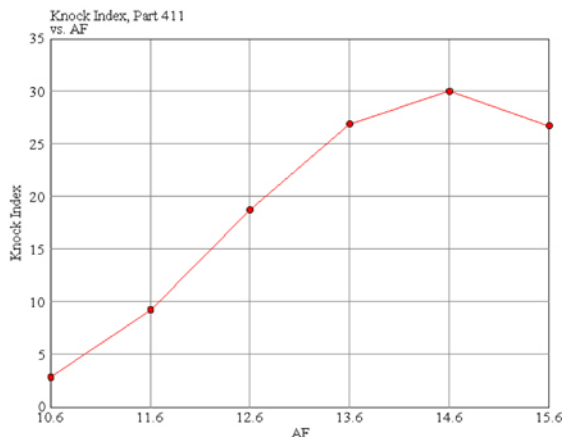


Figure 2. Calculated Knock Index as a function of A/F ratio at full load, 3000 rpm.

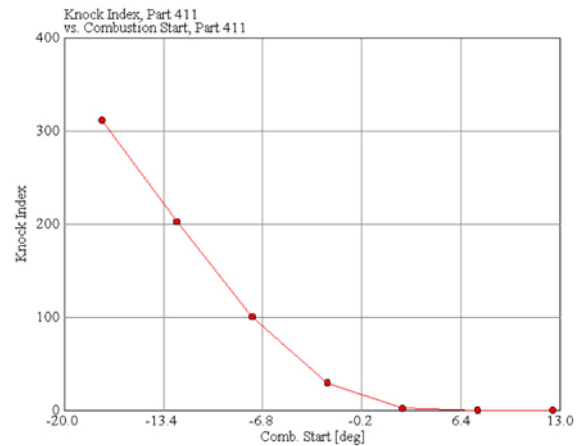


Figure 3. Calculated Knock Index as a function of Combustion Start angle (0 = TDC) at full load, 3000 rpm.

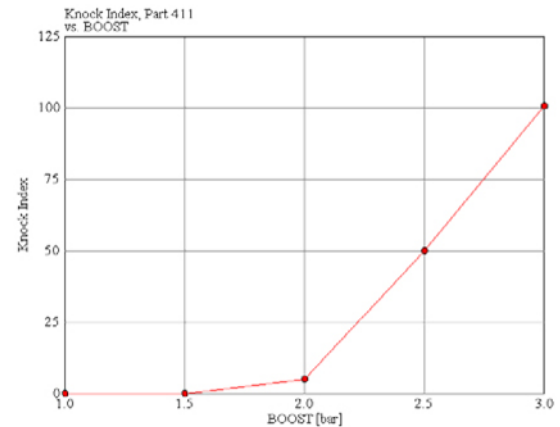


Figure 4. Calculated Knock Index as a function of boost pressure at full load, 3000 rpm.

A particular attention is required by the KI response to internal EGR, since, as shown in [18], end-gas autoignition is mainly affected by mixture temperature, so that KI is monotonically increasing with EGR ratio, because for such low percentages of internal residuals the charge dilution effect appears to be negligible.