10th World Congress on Structural and Multidisciplinary Optimization
May 19 - 24, 2013, Orlando, Florida, USA

CAD-based large scale shape optimization method with intensive simulations

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1. Abstract

Current design loops for shape optimizations allows significant improvements in relation to the functions that need to be optimized, and are widely used in industry. Among these approaches, parametric shape optimization allows rapid enhancement of the shape, on the condition that the design space is confined enough in order to be explored within a reasonable computational time.

This paper introduces a CAD-based large-scale shape optimization method for products requiring intensive simulations, for instance in CFD. Many CAD failures occur due to either direct geometric constraints or software bugs, so a SVM method is used to classify geometries (admissible or inadmissible shapes). Then a D-optimal design chooses k admissible geometries. The objective function evaluation of these shapes is firstly assessed with a simplified continuum. In parallel, a base of meta-parameters is built. The number of meta-parameters is defined according to the final computational cost that is intended. These meta-parameters are generated by an artificial neural network pre-trained on a sample set of geometries.

Subsequently, the previous meta-parameters are used to rapidly reach a limited design space close to the optimum thanks to conventional methods for optimization. Finally, interesting points are computed and simulated with the full continuum. To prove the efficiency and accuracy of the method, the workflow schedule is applied on shape optimization of a car body. The objective is to optimize the drag coefficient.

2. Keywords: Shape optimization, Parameterization, Meta-parameters, Multi-fidelity.

3. Introduction

Within the framework of mechanical products, designers aim at finding an optimal shape with regard to a set of multiphysics constraints such as aerodynamics, aeroacoustics, thermo-mechanics, aesthetics, etc.

The development process in CFD today is based exclusively using CAD models. Current design loops begin with the drafting of technical specifications, followed by the definition of the available volume for the design space. A pre-study is then conducted to define the architecture of the part. The next step is to create the initial geometric model: the working drawing is evaluated through numerical evaluations with regard to each engineering field involved in the study. The analysis of the results identifies the necessary changes to enhance the initial model. In the end, a design that fulfills most requirements is adopted, completing the design loop.

During the research of the optimal shape, this loop is repeated sequentially several times to cover a larger design space. The optimum obtained during this process corresponds to an overall compromise with regards to the requirements. Advanced methods try to use an optimization on the CAD parameters of the design that allows enhancing the shape of the geometry, with the exception that the design space should be confined enough in order to be explored within a reasonable computational time.

To cover a design space as large as possible, i.e. the one offering the most freedom, it is necessary to have an extremely flexible geometry. To achieve this, it is worth multiplying the geometric parameters that define the shape. The multiplication of parameters increases the effort needed to determine the influence that variation of each parameters have on design sensitivity. This limitation makes it very difficult to design a generic CAD model that adheres to a large neighborhood of solutions, all while restricting the number of parameters.

In an industrial context, due to the lack of parameterization approaches, the complexity of large-scale parametric optimizations and the short design lead-time, the roll-out methods in optimization face difficulties.

4. State of the art

Within the framework of mechanical part design, shape optimization is usually used to reduce design time and provide a reliable and efficient powerful solution to avoid expensive experiments. A wide range of approaches are available to perform such optimizations. According to [1, 2], these approaches can be classified into three categories: shape optimization, topology optimization and parametric optimization. Each kind of shape optimization has its pros and cons that are summarized in table 1.

The ability of an optimization method to provide an innovative and efficient design depends on the initial geometric parameterization. Both shape and topologic parameterizations provide a larger design space than parametric optimization (sizing optimization) but this is done to the detriment of the computational resources required. On the other hand, increasing the number of parameters in a geometric optimization (CAD) involves the increase of the design space, which entails an increase in the number of optimization loops.

The parameterization for shape optimization relies on the displacement of the initial grid nodes [3, 4]. Thus, the optimal shape design is given by a mesh deformation of the initial part. This parameterization allows a wide domain of exploration that depends on the initial design, the initial discretization of the part and the allowed range of displacement for the nodes. The underlying idea of topology optimization is to find the optimal density distribution in an initial design space [5]. Since the parameters of this method are the density of each element, the topologic parameterization depends on the initial discretization of the design space. This space has no physical meaning. Parametric optimization (CAD) is based on a set of dimensions (radii, lengths...) which allows changes to the geometry thanks to a design table [6].

Table 1: Comparison between different types of shape optimization

Optimisation type	Parameters	Number of parameters	Design space	Topologic changes	Manufacturing process
Shape	Nodes position	$-$	$+++$	$++$	$+$
Topology	Elements density	$-$	$+++$	$+++$	$-$
Parametric (CAD)	Set of dimensions	$+$	$+$	$+$	$+++$

Another important aspect for parameterization is its ability to integrate a given manufacturing process [7, 8, 9, 4]. A solution provided by a shape optimization has to be post-processed in order to meet manufacturing constraints. The post-processing step generally deteriorates the performance of the theoretical solution since it had not been taken into account during parameterization and optimization steps. A solution provided by a parametric optimization is disposed to respect the manufacturing process since it is directly implemented into the geometry parameterization.

The purpose of this paper is to present a framework for shape optimization, which implements a parametric optimization (CAD) without limiting the number of geometric parameters. We propose to master the amount of necessary evaluations by the use of meta-parameters, without degrading the quality of the convergence to an optimal design.

5. Description of the proposed workflow schedule

The proposed method is based on a CAD model, developed from a dead geometry (stemmed from a neutral format such as IGES, STEP). The CAD model meets a hierarchical construction and allows parameterizing rapidly a dead geometry. It includes manufacturing constraints. Parameter ranges are defined according to engineering rules. There is no restriction regarding the number of parameters p. From this model, a set of several thousand geometries is chosen by using Design of Experiments techniques and are generated. Many CAD failures occur due to the generation of inadmissible geometries. These failures are due to either direct geometric constraints and so on that are difficult to express mathematically or due to a software bug. Then, these geometries can be:

- classified by using a Support Vector Machines technique with a rate of 90% (due to software bugs). This solution is chosen if the number of geometries in the initial set is inferior to a thousand. Then, k-geometries for simulations are chosen in this novel design space by a D-optimal design that seeks to minimize the covariance of the parameter estimates.

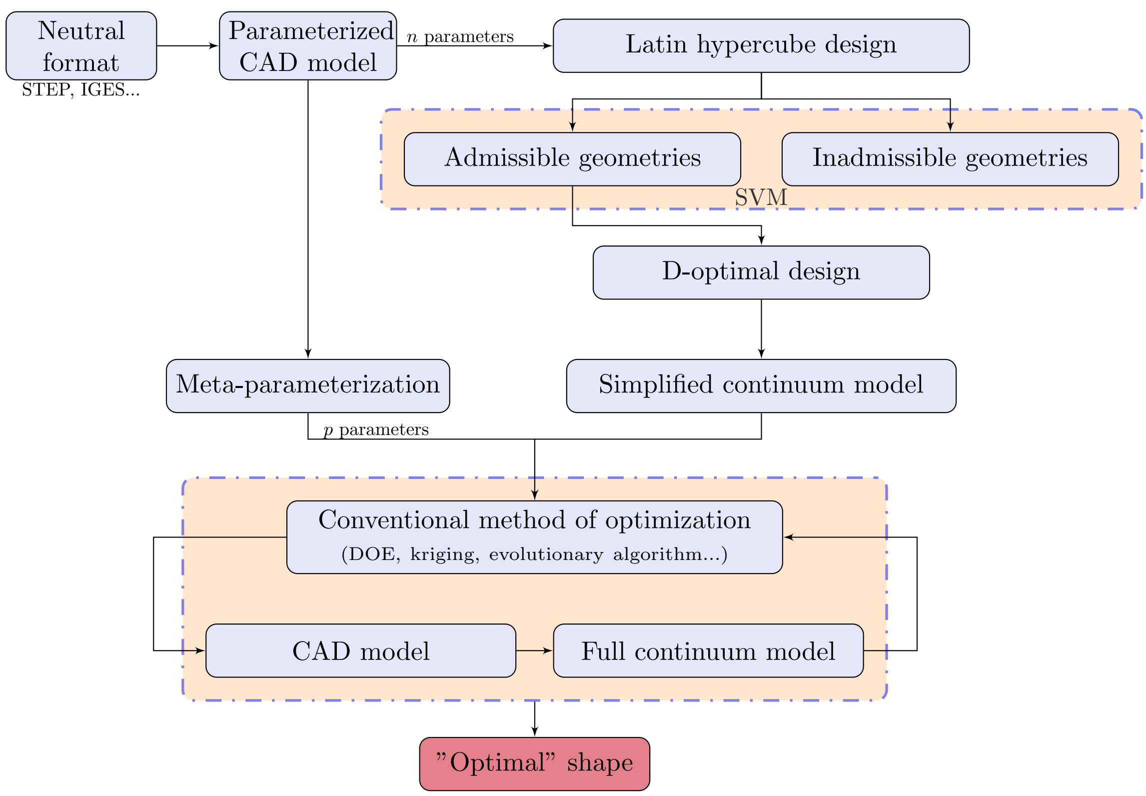
- or directly used in a D-optimal design that chooses k-geometries from the set of admissible shapes by using a row-exchange algorithm.

Secondly, the objective function evaluation can be assessed either with a fast model (saving computing time but less trustworthy) or with a slow model (time consuming but more accurate). Thus, we can learn more about the objective function by using the cheap model on a large number of geometries and then by using the full model on a limited set of interesting points. That is why both a model with a simplify continuum and one with a full continuum are defined. These models are fully automated. The automation of the computational workflow schedule includes the mesh generation, the physical model, its calculation and the post-processing. This allows making the most of high performance computing: parallel simulations are run automatically. Thus, a server is exploited to its full potential without any break in continuity. The previous k-geometries are simulated with the cheap model.

In parallel, CAD parameters (as known as user parameters) are used in an auto-associative feed-forward neural network to create a limited set of meta-parameters. These latter represent a combination of parameters having a similar influence towards the variation of shapes. In fact, the design space is reduced intelligently and rapidly, browsing an interesting subspace close to the optimum. The meta-parameters allow circumventing the difficulties of large-scale optimizations because the number of meta-parameters m is significantly below the number of geometric parameters p. So, the convergence to the optimum is slightly degraded.

These meta-parameters obtained are used in conventional methods for optimization (DOE, kriging, evolutionary algorithms...). Interesting points are computed and simulated with the full continuum. At the end, the design team can make better and faster choices. Figure 1 summarizes the workflow schedule.

Figure 1: Block diagram of the workflow schedule



5.1. Description of an industrial case

The proposed workflow schedule is applied to an industrial case. We focus on optimizing the external shape of a vehicle with respect to aerodynamic performance. This optimization is particularly time consuming: as a first step, a parametric model that mimics the design spirit needs to be created, i.e. it should respect the rays of light. As a matter of fact, the distinctive feature lines of a vehicle has to be preserved. Only modifications that mimic the design are allowed and these should increase the aerodynamic performance. After an optimization of the shape, we should be able to recognize the original design of the model (shape of the vehicle as envisioned) without any difficulty. Moreover, the CAD model should be stable while generating geometries from a design table; secondly, we need to be able to exploit the number of geometric parameters (hundreds). Influential physical parameters for the performances with headwind conditions are already known and engineering rules were created so that new designs meet these requirements in the early sketches. These engineering rules were correlated during wind tunnel experiments and are used for instance to define the profile of the rear quarter panels. What is more, they incorporate manufacturing constraints.

The objective is to reduce the carbon footprint of vehicles by minimizing the drag coefficient C_D, that is to say by optimizing the external shape of the vehicle. The drag coefficient is defined by Eq.(1). In the next paragraphs, we will particularly focus on the coefficient SC_D (cf. Eq.(2)) [10].

$$F_x = \frac{1}{2} \cdot \rho \cdot V^2 \cdot S \cdot C_x \tag{1}$$

$$SC_D = S \cdot C_D \tag{2}$$

with:

- S: frontal area
- ρ: density of the ambient air
- V: road speed

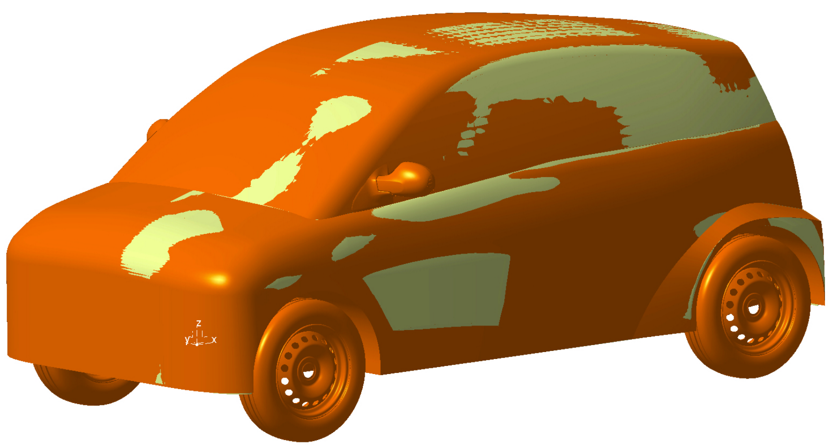
Between each design evolution during the development of a vehicle, the time allotted to evaluate the aerodynamic potential and to propose improvements of the shape is restricted to less than 3 weeks.

5.2. Development of the method

5.2.1. Parameterized geometric model of the vehicle

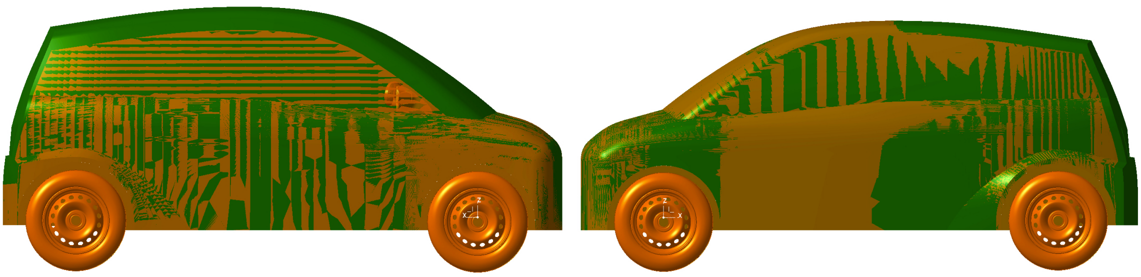
The starting point is a file with a neutral format (such as IGES or STEP) to which no specific information is attached. The first step of the method is to create a parameterized model of the body inspired by the engineering rules established with headwind conditions. The model must be as close as possible from the dead geometry in order to be validated by the wind tunnel experiments conducted previously (cf. figure 2).

Figure 2: Comparison between the dead geometry (sand color) and the parameterized geometry (orange color)



This model is defined by (100) physical parameters. In order to get the best possible reconstruction rate when generating new geometries, the model adopts a hierarchical and ordered construction that ensures stability while generating geometries from a design table. Initially, all physical parameters related to headwind conditions are integrated. Then, the model is enriched with other parameters in order to ensure both a maximum flexibility and scan a large design space. There is no restriction regarding the number of parameters. The validity of geometries in terms of physical sense is ensured by rules defined on and between parameters: parameter ranges are defined according to engineering rules and manufacturing constraints. Finally, all parameters are listed in a design table with their physical senses (angle of the windshield, wheelbase, overhang...) (cf. figure 3).

Figure 3: Variation of parameters



(a) Decrease of the overall height (b) Increase of the rear overhang

5.2.2. Geometric model of the wind tunnel

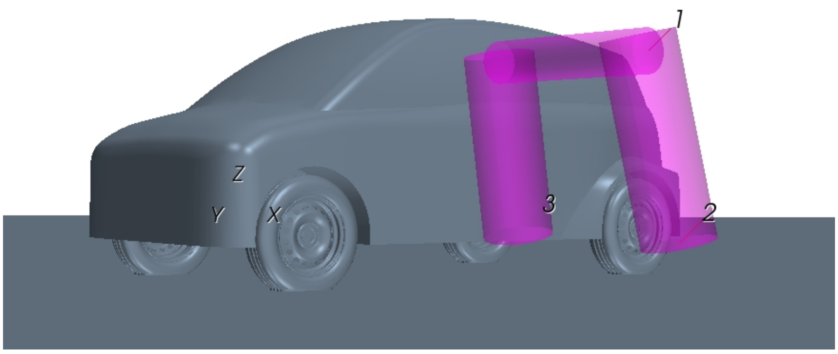
In order to compare numerical results with experimental results, the flow of the empty wind tunnel was measured to develop a numerical model able to reflect more accurately the real geometry.

5.2.3. Simulation models

This second step aims at building an automated simulation model which takes the geometries of both the wind tunnel and the vehicle as inputs and gives the values of the drag coefficient as output. For each simulation, only the geometry of the vehicle is re-imported every time.

The geometries generated by the parameterized model revolve in a solution space round the dead geometry. Thus, the dead geometry is taken as reference. The mesh and refinement volumes are defined by this geometry. Refinement volumes must cover all geometries and are positioned to capture all separations of the boundary layer flow that may occur, particularly around the hood, the mirrors, the underbody and the rear (cf. figure 4). Mesh sizes are defined according to the existing engineering rules. A trimmer model is used, mostly made of hexahedral elements, with a prism layer mesher. Finally, the mesh contains 28 million elements.

Figure 4: Refinement volumes



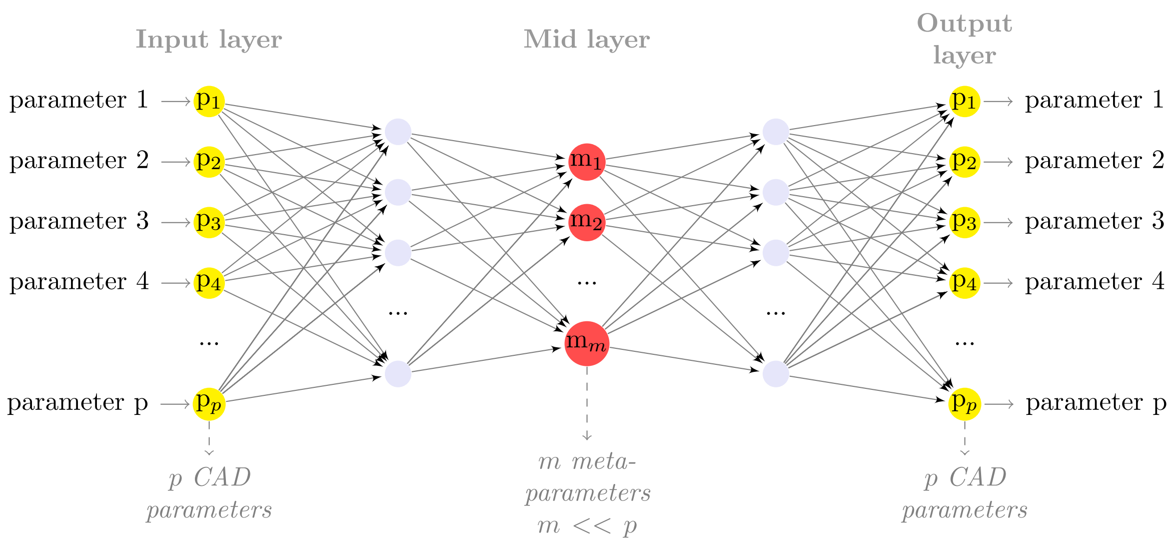
In order to have the same conditions as the experiments, it is assumed that the ground scrolls and that the air inlets of the vehicle are clogged.

In addition, it is necessary to capture the sensitivity of the measured physical quantity (SC_D) due to a geometric modification. These sensitivities are in the range of some thousandth of m^2 for the SC_D. Thus, the computer code should be enough predicative to validate the variations of the physical quantities. So, the simplify continuum uses a steady-state RANS method with a K-Omega turbulence model and the full continuum uses an unsteady DES method [11]. To save computing time, the full continuum runs previously the simplify continuum and uses the converged solution as initial solution.

5.2.4. Creation of meta-parameters

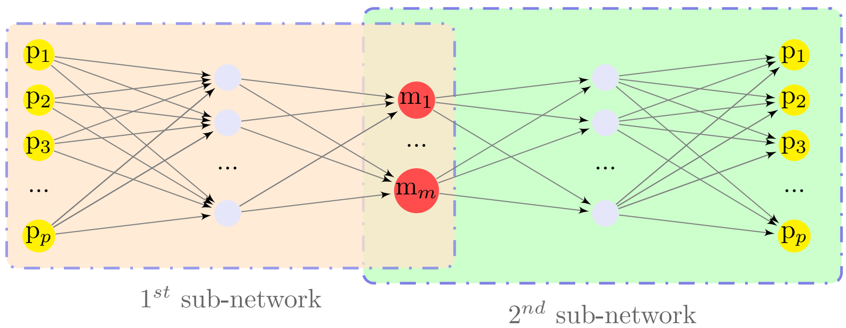
The meta-parameterization is achieved by the use of a feed-forward network. This kind of neural networks aims at performing an input dimensionality reduction in a nonlinear way.

Figure 5: Feed-forward network



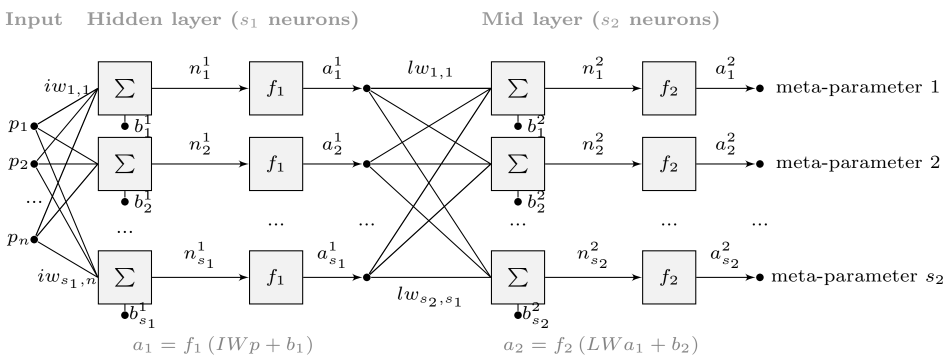
The network is made of layers composed of n_i neurons, whose inputs are the n_{i-1} neurons of the preceding layer. The input vector of the neural network is the p CAD parameters. The middle hidden layer has m neurons that corresponds to the meta-parameters [12], while the input and the output layers have p neurons. The network is trained on a learning set, constituted in our case by a matrix of admissible shapes. The aim is to minimize the mean squared error between the input and the output of the network. Ideally, the input and the output are equal.

Figure 6: Detail of the sub-network



The meta-parameters represent a combination of parameters having a similar influence towards the variation of admissible shapes. The number of meta-parameters is defined according to the time allotted to deliver the results. The 1^{st} sub-network performs a compression of the inputs and the 2^{nd} sub-network assures that the values of CAD parameters can be retrieved.

Figure 7: Symbolic version of the feed-forward network



Training the neural network leads to a network in which the middle hidden layer gives a m-dimensional representation that preserves as much information as possible. In order to allow the autoencoder to learn a nonlinear mapping, sigmoid activation functions are used [13]. Meta-parameters are computed with the equation Eq.(3):

$$a_2 = f_2\left(LWf_1\left(IWp + b_1\right) + b_2\right) \tag{3}$$

with:

- p: input vector
- IW et LW: weight matrices
- b^1 et b^2: bias vectors
- f_1 et f_2: transfert functions

6. Results - Discussion

6.1. Number of parameters

As mentioned earlier, the aim is to design a generic CAD model that adheres to a large neighborhood of solutions, so it should be flexible. The CAD model has about a hundred geometric parameters that characterize the external shape of the vehicle. The number of meta-parameters is defined according to the time allotted to deliver the results.

6.2. Design of experiments

As mentioned previously, when generating geometries with a CAD software, failures happen due to either direct geometric constraints (and so on) that are difficult to express mathematically or due to a software bug. So as to get an idea of the admissible volume, we need to generate several thousand geometries. Thus, we use a Latin Hypercube Sampling to generate a design table of 14.000 configurations. The CAD failure rate is about 30%, so we get about 10.000 admissible shapes.

Then, k-geometries among these admissible shapes have to be chosen in order to be simulated. The results constitute a database for the optimization method. A D-optimal design is appropriate for calibrating a nonlinear model in experimental settings. It is generated by an iterative search algorithm and seeks to minimize the covariance of the parameter estimates for a specified model. This is equivalent to maximizing the determinant $D = |X'X|$, where X is the design matrix of model terms. In our industrial case, as we did not have any idea of the results, we have used a quadratic model (constant, linear, interaction, and squared terms).

6.3. Computational time

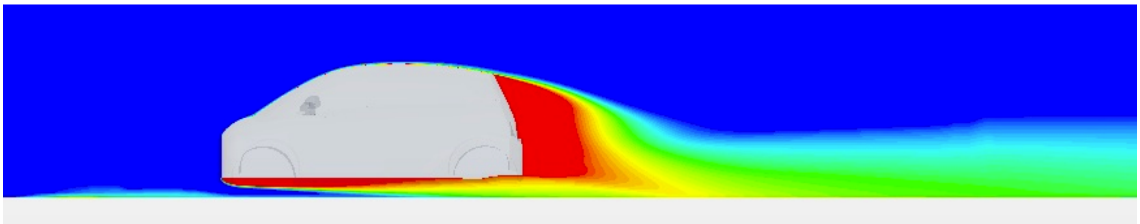
The entire optimization loop is automated, in order to make the most of high performance computing resources available. Each simulation is run on 64 cores and takes about 8 hours for completion for the simplify continuum, and 3 days for the full continuum; 10 simulations are run in parallel.

A complete design of experiments would need about 2^{100} calculations, which is impossible with current resources. Similarly, a fractional orthogonal plan would be time-consuming compared to the theoretical gains (few thousandths m^2 for SC_D).

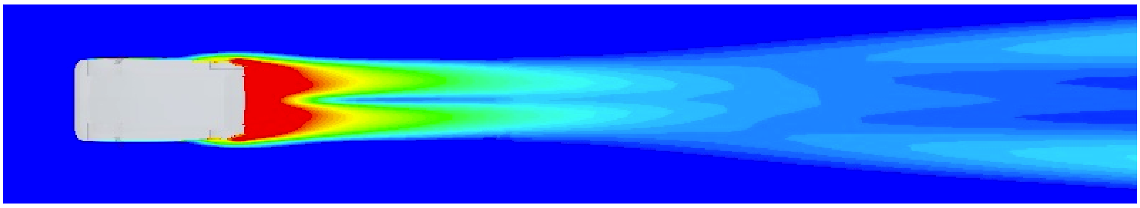
Our method provides the same gains in a fortnight. The number of meta-parameters is adjusted according to the time allotted to the study. With a limited number of meta-parameters, the initial problem is brought back to a usual problem on which conventional methods can be applied (kriging, etc.). We use a loop kriging-based method with the results of the previous k-simulations. Interesting points are computed by using the confidence intervals of the kriging and simulated with the full continuum.

6.4. Results of simulations

Figure 8: Dimensionless pressure coefficient Cp (cf. Eq.(4))



(a) Side view



(b) Top view

(c) Scale

$$C_p = \frac{p - p_\infty}{\frac{1}{2} \cdot \rho \cdot V_\infty^2} \tag{4}$$

with:

- p_∞: static pressure
- V_∞: free-stream velocity

The comparison of results with the experimental data gives an accuracy of the computer code in the range of 2%, that is to say about 0,010 m^2 for SC_D. This difference is reasonable knowing that the repeatability of a same experiment in the wind tunnel is in the range of $\pm$0,003 m^2 for the SC_D.

At the end, the gain for the coefficient SC_D is in the range of some tens of thousandths compared to the original shape.

7. Conclusion

We have presented in this paper a shape optimization method for products with a short design lead-time in an industrial context. New geometries are generated thanks to a parameterized model, without any restriction regarding the number of parameters that can be used. Some geometries are chosen by a D-optimal design and then simulations with a simplified continuum are run. CAD parameters are used in an artificial neural network to create a limited set of meta-parameters. The latter are used in a conventional method of optimization. Finally, interesting points are simulated with the full continuum. This method, breaking away from the usual industrial process, was applied on the shape optimization of a car body. The objective was to optimize the drag coefficient. Last, the results were compared with ones obtained by experiments in order to prove the efficiency and accuracy of the method.

8. References

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