

Aerodynamic drag optimization of a high-speed train

J. Muñoz-Paniagua, J. García

► To cite this version:

Muñoz-Paniagua, J., & García, J. (2020). Aerodynamic drag optimization of a high-speed train. *Journal of Wind Engineering and Industrial Aerodynamics*, 204, 104215. doi:10.1016/j.jweia.2020.104215

Published Version.

Published 2020 September 01

Archivo Digital UPM houses in digital format the academic and scientific documentation (theses, pfc, articles, etc.) generated at the institution and makes it accessible through the Internet, within the framework of the Budapest Open Access Initiative and the Berlin Declaration, of which the Universidad Politécnica de Madrid is a signatory.

El **Archivo Digital UPM** alberga en formato digital la documentación académica y científica (tesis, pfc, artículos, etc..) generada en la institución y la hace accesible a través de Internet, en el marco de la Iniciativa por el Acceso Abierto de Budapest y la Declaración de Berlín, de la que es signataria la Universidad Politécnica de Madrid.

AERODYNAMIC DRAG OPTIMIZATION OF A HIGH-SPEED TRAIN

J. Muñoz-Paniagua and J. García

*Departamento de Ingeniería Energética
Escuela Técnica Superior de Ingenieros Industriales, Universidad Politécnica de Madrid
C/ José Gutiérrez Abascal 2, 28006, Madrid, Spain
e-mail: le.munoz@upm.es

Key words: Shape Optimization, High-speed train, Genetic Algorithm, Surrogate model, SAS

Abstract. *This paper considers the optimization of the nose shape of a high-speed train to minimize the drag coefficient in zero-yaw-angle conditions. The optimization is performed using genetic algorithms (GA) and is based on the Aerodynamic Train Model (ATM) as the reference geometry. Since the GA requires the parameterization of each optimal candidate, 25 design variables are used to define the shape of the train nose and, in particular, to reproduce that of the ATM. The computational cost associated to the GA is reduced by introducing a surrogate model in the optimization workflow so that it evaluates each optimal candidate in a more efficient way. This surrogate model is built from a large set of simulations defined in a Latin Hypercube Sampling design of experiments, and its accuracy is improved each optimization iteration (online optimization). In this paper we detail the whole optimization process, ending with an extensive analysis of results, both statistical (analysis of variance (ANOVA) to identify the most significant variables and clustering using Self-Organized Maps (SOM)), and aerodynamic. The latter is performed running two accurate simulations using Scale-Adaptive Simulation (SAS) turbulence model. The optimal design reduces the drag coefficient a 32.5% of the reference geometry.*

1 Introduction

Reducing energy consumption is still demanded for trains even when these are the most efficient mean of transport in the use of energy. One contributor to the consumption of the energy put into a high-speed train (HST) is the aerodynamic drag, which takes a more relevant role as the cruise speed is increased. The aerodynamic drag of a HST has been object of study in Baker (2010) and Choi et al. (2014), while Schetz (2001) and Raghunathan et al. (2002) have estimated the contribution of different constructive elements of a HST to the total aerodynamic drag. Although not a HST, Orellano and Schober (2006) and Osth and Krajnovic (2014) have investigated the aerodynamic drag for other different type of trains like regional and freight trains, respectively. Recently, most of the attention has been paid to the slipstream of a HST, Baker et al. (2012); Bell et al. (2014); Muld et al. (2012); Hemida et al. (2014), which is directly related to the train nose shape under zero-yaw-angle incident flow. Consequently, an a priori simple scenario like a train in open air under front wind has still attracted much interest from researchers.

Once the flow structures are pictured, it is possible to propose a geometric modification that can improve the aerodynamic performance of trains. For streamlined trains at speed around 300 km h^{-1} , 80% of the total resistance is caused by external aerodynamic drag, Schetz (2001). So, any modification that could reduce the aerodynamic drag might be important for the global performance of the train. In this sense, it is possible to obtain appreciable variations of the drag changing the train nose and tail shape as indicated in Raghunathan et al. (2002) and Orellano (2010), suggesting there is potential to aerodynamically optimize the nose of a HST.

The optimization of aerodynamic properties of high-speed trains has traditionally been handled as a trial-and-error procedure, which is very expensive in terms of computer and designer time. Advanced optimization algorithms try to use the information extracted from these previous analyses while, at the same time, present a new strategy to solve the problem based in a more automated fashion. Among the first studies considering high-speed trains optimization are the studies of Krajnovic (2009) and Vytla et al. (2010), resolving different single-objective optimization problems in open air using genetic algorithms (GA) and a geometric parameterization of two and five design variables, respectively. Oh et al. (2018) also uses a GA for shape optimization but instead considers design-by-morphing with three design variables (or weights) which actually mean two degrees of freedom. The pressure pulse generated by trains passing by and the side force under crosswind are minimized in Munoz-Paniagua and Garcia (2019) using also three design variables. A multi-objective optimization problem is solved in Suzuki and Nakade (2013) for a five-design-variables nose shape parameterization, and the same complexity of geometry parameterization is adopted in Shuanbao et al. (2014) and Li et al. (2016), where Free-Form Deformation (FFD) is considered. Meanwhile, Orellano (2010) considers the drag-crosswind multi-objective optimization problem for a sixty-design-variables

parameterization and GA. Jakubek and Wagner (2012) considers adjoint methods for the minimization of the pressure pulse generated by passing the train head, while Munoz-Paniagua et al. (2015) uses also the adjoint method for the minimization of the aerodynamic drag. In the case of trains in tunnels, a more intense work has been observed for the optimization of the nose shape, which is accomplished in, among others, Kwon et al. (2001), Lee and Kim (2008) and Kikuchi et al. (2011) to reduce the micro-pressure wave at the tunnel exit, while Munoz-Paniagua et al. (2014) optimizes the nose shape to reduce the maximum pressure gradient at the entry of the tunnel using GA. Thus, the interest of aerodynamic shape optimization for high-speed trains and the development and application of advanced optimization methods for train aerodynamics is evident. In particular, it is found that there is not available any detailed study of the aerodynamic optimization of the nose shape of a train involving a large number of design variables for the parameterization of the geometry.

1.1 The scope of the study

- The main objective of this paper is the application of GA for the minimization of aerodynamic drag of a HST subjected to front wind, presenting the set-up of the optimization approach introduced in this paper, where a geometric parameterization in computer-aided design (CAD), the construction of a Radial Basis Function (RBF) metamodel for optimal candidates evaluation and accurate flow simulations using computational fluid dynamics (CFD) are automated to speed up the GA process.
- Global optimization methods like the GA are generally used with low-dimension design spaces (i.e. low number of design variables). Here a twenty-five-design-variables shape parameterization of the nose of a high-speed train is proposed, which is flexible enough to be adapted to different train noses while accurate enough to represent the original shape by a set of design variables.
- The third objective is to take advantage of all the information used for and contained in the metamodel required by the GA to yield insight into the design space nature. An analysis of variance (ANOVA) test completes it. These results let us obtain a relationship between drag and the most significant design variables, as well as determine which are the most dominant variables and if any correlation between them is detected.
- Once the optimization process is finished, the optimal solution is compared to the initial design. An unsteady simulation for each case using the SAS turbulence model is run. SAS has only been recently applied for train aerodynamics in Garcia et al. (2015), Wang et al. (2017) and Munoz-Paniagua et al. (2017), so it is encouraging the industrial interest this second-generation URANS turbulence model might generate.

The paper is organized as follows. In section 2, the methodology used for solving the optimization problem is described. This encompasses the GA work-flow and the numerical

set-up, including a brief description of the nose shape parameterization and its validation. Section 3 presents the main results from the optimization process (in two steps) and the (statistical) post-processing. The optimized design is simulated in section 4 with the SAS turbulence model for a better comparison of the flow around it with respect to that of the initial design. Finally, section 5 is devoted to the summary of the study.

2 Methodology

The optimization method selected to solve this aerodynamic problem is the genetic algorithm (GA). GA, introduced by Holland (1975) and developed by Goldberg (1989), is a technique that mimics the mechanics of the natural evolution. Once a population of potential solutions is defined, three operators (selection of the fittest, reproduction or crossover and mutation) are applied, fig. 1. Iteratively, a new population is generated and better results are obtained until a solution closer to globally optimal solution is reached. The combination of the survival-of-the-fittest concept to eliminate unfit characteristics with a random information exchange and the exploitation of the knowledge contained in old solutions permit GA to effect a search mechanism with efficiency and speed. GA are englobed in zero-order methods, based on direct evaluations of the objective function. This is an advantage compared to first-order methods that need the calculation of the first derivative of the objective function. However, the large number of evaluations required when using GA is a disadvantage that minimizes its power, moreover when compared to the adjoint method, Munoz-Paniagua et al. (2015). Nevertheless, the simplicity and robustness of this optimization method put the GA into a prevailing position, specially for this problem where the nature of the flow is not so complex.

To minimize the problem of the large number of evaluations required by the GA, which directly depends on the dimensionality of the design space, a simple while at the same time robust, geometric parameterization is proposed. Additionally, the CFD solver call is substituted by a metamodel or surrogate model. The present increase of the computational power is not sufficient to conceive a thorough search of the design space using accurate simulations. This situation leads to the introduction of an approximate model whose computational cost is much lower than the relative to the CFD simulation. In fig. 1, the optimization work-flow is represented. This scheme refers to an online optimization, where after the end of the GA optimization process, the best solution found by the surrogate-based optimizer is evaluated and verified, and this new simulation is added to the initial database that was used to fit the coefficients of the metamodel.

Blocks 1 and 2 from fig. 1 are related to the pre-optimization issues, namely the shape parameterization and the construction of the metamodel or surrogate-model. The parameterization is performed using CATIA[®] software and it is thoroughly explained in section 2.4. The construction of the metamodel is done using MINAMO[®] software, in which it is also implemented the GA code and where the statistical post-processing of the optimization results can be performed. CFD simulations are run in ANSYS Fluent[®].

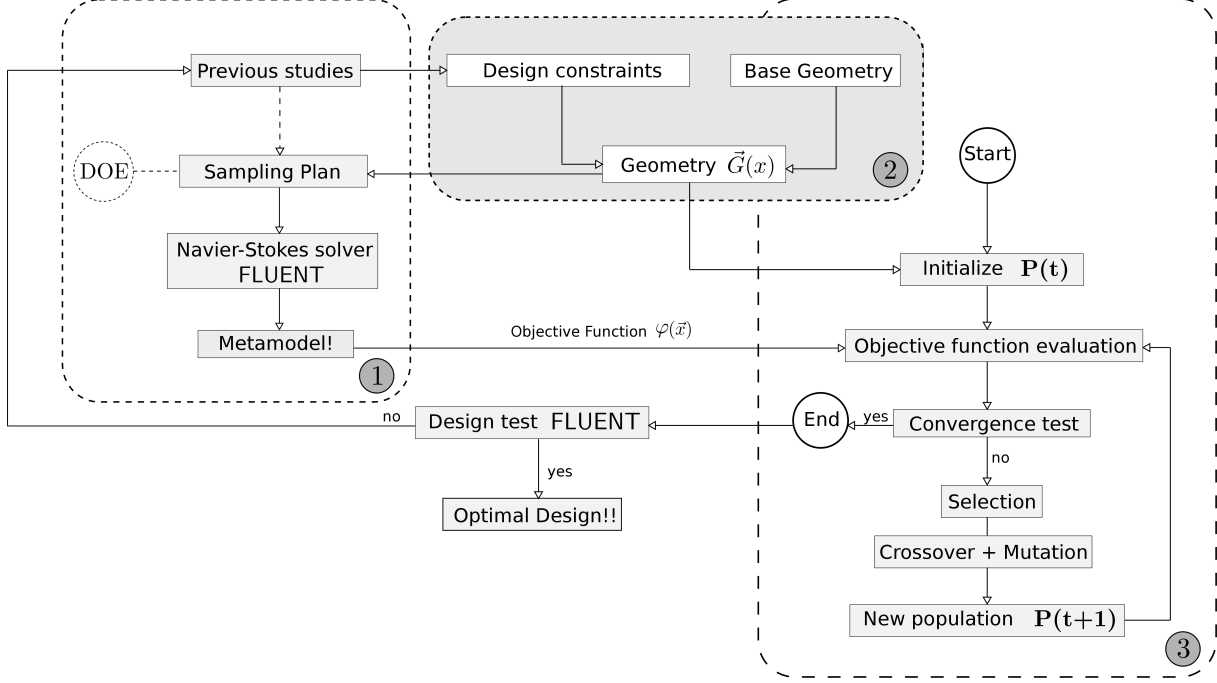


Figure 1: Schematical representation of the whole optimization workflow

2.1 Metamodel definition

The expensive cost of running (complex) engineering simulations makes it impractical to rely exclusively on numerical codes for the purpose of aerodynamic optimization, in particular when GA is applied. By using approximation models or metamodels, the expensive simulation model is replaced and so the GA process is speed up. A variety of metamodeling techniques exist, and an excellent comparison and review of these methods can be found in Simpson and Peplinski (2001). Among those implemented in MINAMO[®], the metamodel technique chosen is the tuned radial basis function network (TunedRBFN). A default RBF uses a linear combination of m radial basis functions

$$\hat{y}(\mathbf{x}) = \sum_{i=1}^m \omega_i \phi(|\mathbf{x} - \mathbf{x}_i|) \quad (1)$$

to approximate the response $y(\mathbf{x})$. $\phi(d_i)$ is called the radial basis function, such that the radial distance d_i is defined as $d_i = |\mathbf{x} - \mathbf{x}_i|$ centered at the point $\mathbf{x}_i$. The norm $||$ is the Euclidean distance and ω_i is the weight of radial basis function i in the linear combination aforementioned. While several radial basis functions exist, MINAMO[®] works mainly with two, namely the multiquadratic and the Gaussian basis functions. These basis functions are defined in terms of the radial distance d_i (implicitly the center $\mathbf{x}_i$) and the spread $\mathbf{r}_i$. Consequently, apart from setting the weights in equation (1), the number of hidden units

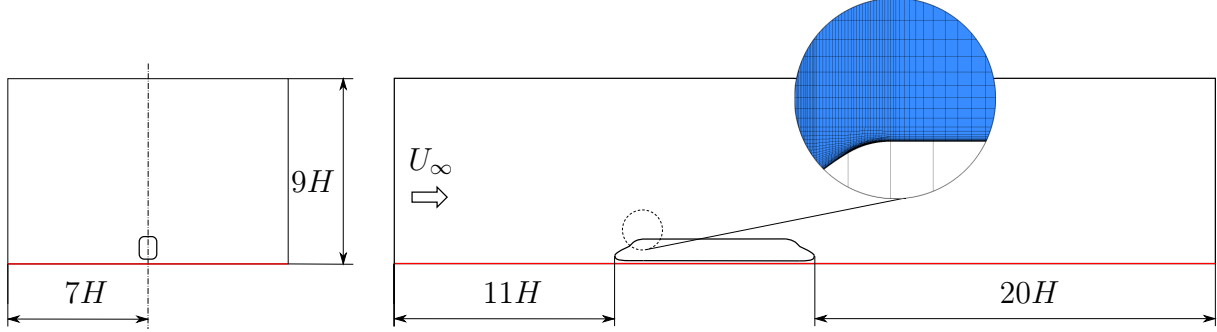


Figure 2: Computational domain. The flat ground boundary is colored in red. It is included also a detail of the mesh refinement in the train surface.

m , the spread $\mathbf{r}_i$ and the centers $\mathbf{x}_i$ are the other parameters to be defined. The TunedRBF implements a tuning so that it is not required a priori definition of these parameters and the type of basis function, Sainvitu et al. (2013). A leave-one-out based heuristic is used to select the radial basis function and to adjust the the spread. The number of hidden units is set equal to the size of the design of experiments N (section 2.2), and the centers do coincide with the sampling points.

2.2 Design of experiments

The metamodel is constructed with a sampling plan of the design space. This sampling plan is called design of experiments (DoE) and will be used to fit the parameters of the metamodel. MINAMO[®] features various DoE techniques, among which Latinized Centroidal Voronoi Tessellations (LCVT), Saka et al. (2007), is used in this paper. An initial database of $N_0 = 80$ samples is considered for the construction of the first metamodel, and this dataset is enlarged during the optimization process taking advantage of the MINAMO[®] adaptive DoE capability. This helps reducing the computational cost of constructing an accurate metamodel as it locally increases the sampling intensity where it is required depending on the response values observed at previous iterations. In particular, besides the optimal solution obtained at each optimization step, it is included in the database an additional point from regions where the model exhibits its maximum error, with the error indicator provided by a leave-one-out procedure, Sainvitu et al. (2013).

2.3 Numerical set-up and boundary conditions

The computational domain is an hexahedral box inside which the train is arranged as indicated in fig. 2. The inlet is placed $11H$ upstream the train head, the outlet is $20H$ far from the tail and the lateral walls are $7H$ far from the train longitudinal symmetry plane. The height of the domain reads $9H$. The domain boundaries do not interfere with the flow around the vehicle and are in good agreement with the European Normative, en1 (2009). The ground clearance is set as $0.15H$. An uniform velocity profile is set at the inlet, with

$U_\infty = 50 \text{ m s}^{-1}$. Uniform pressure is imposed at the outlet, and symmetry condition is set at the sides and top of the domain. The ground is moving with U_∞ . No-slip condition is set at the train surface. The Reynolds number based on the inlet velocity and the train height is $\sim 1.3 \times 10^7$. An incompressible, steady, turbulent flow simulation is considered. Simulations are run using ANSYS Fluent[®] CFD software. For the level of detail desired in this study, and due to the considerable computational cost of the optimization problem, the authors have limited themselves to two-equations turbulence model. Nevertheless, in section 4, a more advanced turbulence model is considered for a further analysis of the optimal solution. Here, the $k-\omega$ SST turbulence model is used, with second-order upwind momentum. The standard wall functions implemented in ANSYS Fluent[®] are used at the ground and on the train surface. A grid-independence analysis was performed, resulting in $y^+ = 100$ and Δx^+ , in terms of wall units y^+ , of 25-250, where $y^+ = u_\tau y / \nu$, being u_τ the wall friction velocity and ν the kinematic viscosity of the air ($\nu = 1.45 \times 10^{-5} \text{ m}^2 \text{ s}^{-1}$).

2.4 Nose shape parameterization

2.4.1 3-D parameterization

As it is observed in fig. 1, geometry parameterization requires a base geometry and the specification of the design constraints, which is achieved from the experience of previous studies. Here, it is selected the Aerodynamic Train Model (ATM) as the base or reference geometry, Orellano and Schober (2006). This is a simplified model of the leading control unit of the ICE 2 train (class 808) of Deutsche Bahn AG. This geometry is widely accepted among the train aerodynamics community as a reference geometry, and has been object of study in García et al. (2017). The leading car is followed by a simplified end-car which has the same shape as the nose. No details as pantograph, bogies, partial bogies skirts, plough underneath the front-end or inter-car gap are included.

The optimization problem is restricted to the design of the nose of the train, thus all the optimal candidates will be attached to the same cylindrical (train) body and so, the cross-section of the train body is kept constant for all the geometries. Nevertheless, it is important to remark the fact that, because of the symmetry of the train, the tail is also optimized in the same way as it is done in the train head. Consequently, both ends will change during the optimization. Figure 3 plots the spline that captures the cross-section shape. Its height H_t and width W_t are considered as reference dimensions for the following geometrical definition. From Raghunathan et al. (2002), the maximum value of the nose length at which it is possible to observe significant differences in the drag coefficient, when front wind is considered, is two times the train width. Therefore, the length of the train nose L is set to this value. These three dimensions define the cuboid containing the train nose volume. The clearance between the ground surface (i.e. top of rail or TOR) and the underbody of the train is set to c , while the distance from the nose tip at which the bottom of the train is assumed to be flat is set to l_{base} . The train length L_{train} is also kept constant during the optimization. These reference dimensions are presented

in Table 1. Taking advantage of the longitudinal symmetry of the train, only one half is considered for parameterization. For the sake of brevity, the whole description of the shape parameterization is not detailed in this paper. Instead, just the considered Bézier curves that define the side view, front view and top view of the train nose, with their corresponding control points and the variables involved in their definitions are indicated and plotted in fig. 3. We propose the application of Bézier curves, Farin (1993), to define the geometry of a three-dimensional high-speed train nose in combination with Rho section boxes approach, Rho et al. (2009). Bézier curves are highly suited for shape optimization, as they can describe a curve in a very compact form with a small set of design variables, Samareh (2001). Comparing them with Hicks-Henne functions used in Kwon et al. (2001) and Lee and Kim (2008), they have a simpler formulation by means of polynomial functions. Moreover, the characteristics of the curve are strongly coupled with the underlying polygon of control points, simplifying the link between parameters and real design variables. Compared with the power functions considered in Rho et al. (2009), it is avoided to deal with coefficients which physical meaning is not explicit. The convex hull of the Bézier control polygon contains the curve. This property is very useful, especially in defining the geometric constraints, Samareh (2001).

Constant	Physical meaning	Value
H_t	Height of train body from TOR	3856.3 mm
W_t	Width of train body ($W_t = 2w_t$)	3000.0 mm
L	Length of train nose (i.e. from nose tip to connection of nose-train body)	6000.0 mm
c	Clearance. Distance between TOR and train bottom	271.0 mm
l_{base}	Distance from nose tip of beginning of flat bottom side*	720.0 mm
B_{base}	Width of flat bottom side** ($B_{base} = 2b_{base}$)	1300.0 mm
l_0	Distance from origin of coordinates to start of roof Bézier curve*–	1750.0 mm
L_{train}	Length of train body (i.e. from end to end)	35577.7 mm

Table 1: Reference values of design constants extracted from ATM model and used for the shape parameterization. *This reference value is used to define end of side-view profile (control point $\mathbf{P}_{11}$). **This value is used to define the end of front-view profile at the hood (control point $\mathbf{P}_{20}$). *– This value is used to capture the shape of the ATM roof (control point $\mathbf{P}_1$).

Starting from the ATM geometry, the main idea is basically to capture the most characteristic dimensions of the train nose, and following the restrictions included in the European regulations on Technical Specifications for Interoperability (TSI), tsi (2006) and the section boxes proposed in Rho et al. (2009) define a robust but accurate parameterization of the ATM. The nose is divided into four section-boxes, namely the roof, windshield, hood and underbody (lower part of the nose tip). In consequence, four Bézier curves are used for the outline of the two-dimensional view (i.e. xz -curves), see fig. 3. A quadratic Bézier curve is used to outline the roof profile as it is not expected a big curvature for this section. Therefore, three control points are used for such quadratic curve ($\mathbf{P}_1, \mathbf{P}_2, \mathbf{P}_3$). The windshield is again sketched by a quadratic Bézier curve. The practical difficulty of producing a windowpane with two curvatures (what drives to the existence of an inflexion

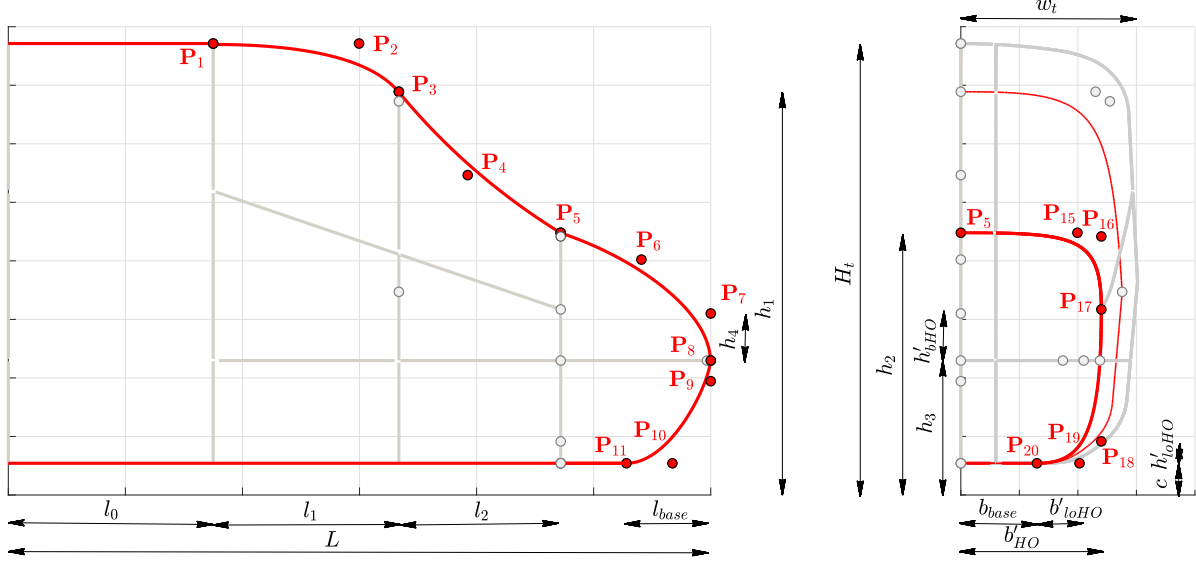


Figure 3: Side and front view of (a very simplified sketch of) the nose shape parameterization. In red color, the Bézier curves corresponding to each view are sketched. For the sake of clarity, in the side view the four Bézier curves with their control points at the symmetry plane are plotted, while in the front view information is limited to the hood. The rest of control points are plotted in grey, as well as auxiliary curves in each view. Besides, the design constants introduced in table 1 and some of the most representative design variables are also included in the drawing.

point) makes a quadratic curve enough for its outline. Consequently, three control points are required and, once $\mathbf{P}_3$ is already defined, only $\mathbf{P}_4$ and $\mathbf{P}_5$ are introduced. The hood is represented by a cubic Bézier curve. The ATM is considered as the base design for this optimization study, but the design space is not restricted to this type of nose configuration, where continuity C^1 is observed at any point of the two-dimensional (side-view) nose profile. In order to take into account beak-like train nose designs (e.g. AVE S-102 train model, see fig. 4), four control points are utilized. Indeed, a cubic Bézier curve is chosen because of its simplicity and flexibility to reproduce an inflection point in a curve. While control point $\mathbf{P}_5$ is given from the windshield curve, $\mathbf{P}_8$ represents the nose tip, whose coordinates are defined by the nose length L and the design variable h_3 . The lower part of the nose tip is defined by a cubic Bézier curve, and so four control points are used. While $\mathbf{P}_8$ is already defined, the other end point ($\mathbf{P}_{11}$) is also already defined by the clearance between the bottom of the train and the ground, and by the base distance l_{base} . The other two control points, $\mathbf{P}_9$ and $\mathbf{P}_{10}$, define the curvature of the lower part of the nose tip. The three-dimensional representation of the train nose is achieved by defining front-view profiles (i.e. yz -curves) and a top-view profile. For the front view, the reference cross-section sampled from the ATM geometry is not enough, and more profiles are required. Two more cross-sections are considered, these placed at the starting point of the windshield and hood curves, respectively. Thus, points $\mathbf{P}_3$ and $\mathbf{P}_5$ give the x -coordinate of

desVa	Physical meaning	Min	Max	Units
l_1	Dimension of the roof (x -coord. of $\mathbf{P}_3$)	700	2000	mm
h_1	Height at which starts the windshield (z -coord. of $\mathbf{P}_3$)	3000	3600	mm
α_1	Curvature at the connection nose – car body by slope of line $\mathbf{P}_2 - \mathbf{P}_3$	$\frac{\pi}{20}$	$\frac{\pi}{6}$	-
l_2	Horizontal dimension of the windshield. (x -coord. of $\mathbf{P}_5$)	1000	1500	mm
h_2	Height at which starts the hood (<i>i.e.</i> end of window) (z -coord. of $\mathbf{P}_5$)	0.85	1.25	-
k_2	Windshield curvature	0.30	0.70	-
α_3	Shape of hood by slope of line $\mathbf{P}_5 - \mathbf{P}_6$	$\frac{\pi}{12}$	$\frac{\pi}{4}$	rad
h_3	Height of the nosetip (z -coord. of $\mathbf{P}_8$)	800	1300	mm
h_4	(Vertical) bluntness of the nose end (z -coord. of $\mathbf{P}_7$)	250	500	mm
k_3	Hood curvature	0.20	0.80	-
α_5	Inclination of the underbody surface (z -coord. of $\mathbf{P}_9$)	0.30	0.80	-
l_4	Relative size of the spoiler (x -coord. of $\mathbf{P}_{10}$)	150	400	mm
h_{bWS}	Height related to b_{WS} (z -coord. of $\mathbf{P}_{14}$)	1500	1800	mm
γ_{WS}	Maximum width of windshield (b_{WS}) with respect to w (y -coord. of $\mathbf{P}_{14}$)	$\frac{\pi}{90}$	$\frac{\pi}{22.5}$	rad
h_{bHO}	Height (above h_3) of maximum width of the hood (z -coord. of $\mathbf{P}_{17}$)	0.75	0.90	-
b_{HO}	Width of the hood with respect to b_{WS} (y -coord. of $\mathbf{P}_{17}$)	0.85	1.00	-
h_{upWS}	Sets z -coord. of $\mathbf{P}_{13}$ relative to h_1 and h_{bWS}	0.85	1.00	-
k_{upWS}	Roundness of the A-pillar in the windshield region (y -coord. of $\mathbf{P}_{12}$)	0.80	1.00	-
β_{WS}	Slope of side surfaces in the windshield region (y -coord. of $\mathbf{P}_{13}$)	0.00	0.10	rad
h_{upHO}	Sets z -coord. of $\mathbf{P}_{16}$ relative to h_2 and h_{bHO}	0.85	1.00	-
k_{upHO}	Roundness of the A-pillar in the hood region (y -coord. of $\mathbf{P}_{15}$)	0.70	0.90	-
h_{loHO}	Curvature of lower side edge in the hood region (z -coord. of $\mathbf{P}_{18}$)	150	300	mm
b_{loHO}	Width of train bottom (y -coord. of $\mathbf{P}_{19}$)	350	500	mm
b_{peak}	(Horizontal) bluntness of the nose end (y -coord. of $\mathbf{P}_{23}$)	800	1100	mm
k_{peak}	Curvature of the nosetip (top view)	0.85	1.00	-

Table 2: Meaning of the design variables (desVa) used in the nose shape parameterization, and range of variation of each one. Units help identifying lengths, angles and non-dimensional parameters.

the profiles contained in these yz -planes. Each profile is divided into two parts, namely upper and lower, so that four curves besides the reference cross-section help defining the three-dimensionality of the train nose. The division of each profile into two parts let us introduce different curvature to the upper and lower part. The point for the maximum width in each profile is the one considered to divide the profile. No continuity C^1 condition is imposed at that point. Tangency is imposed at the symmetry plane connection to avoid cusps when the whole train is represented. This behavior is reinforced by the use of auxiliar splines, copy of the symmetry plane Bézier curves and shifted ± 300 mm with respect to the symmetry plane, see fig. 3. The lower part of the windshield front-view profile is defined not by a Bézier curve but just as a geometric transformation of the lower part of the reference cross-section. This simplification is adopted based on the fact that the distance between these two cross-sections might be small enough so as to expect a slight variation of the curvature. As a consequence, no additional design variables are required for the definition of this curve. Meanwhile, the upper part of the windshield and the two parts of the hood front-view profiles are given by cubic curves, so that four control points are required for each curve. ($\mathbf{P}_3, \mathbf{P}_{12}, \mathbf{P}_{13}, \mathbf{P}_{14}$) are used for the former, while ($\mathbf{P}_5, \mathbf{P}_{15}, \mathbf{P}_{16}, \mathbf{P}_{17}$) and ($\mathbf{P}_{17}, \mathbf{P}_{18}, \mathbf{P}_{19}, \mathbf{P}_{20}$) are used for the hood front-view curves. Finally, an extra cubic Bézier curve is considered to control the slenderness of the train nose tip and to define the three-dimensional shape of it. This curve introduces three new control points ($\mathbf{P}_8, \mathbf{P}_{21}, \mathbf{P}_{22}, \mathbf{P}_{23}$).

Table 2 summarizes the meaning and function of the design variables in the nose shape

parameterization, as well as the range of variation of each design variable. The range of variation of these twenty-five design variables is defined so as to include the ATM design and to represent a wide variety of nose geometries.

2.4.2 Validation of the geometric parameterization

Robustness and precision of the proposed parameterization are tested in this subsection. Apart from the simplified ICE2 train nose, two more commercial high-speed trains are considered to validate the parameterization robustness. These are the Spanish high-speed train TAV350, from Bombardier and Talgo, and the French TGV, from Alstom. Only information of the lateral-side view is available, so validation is restricted to check if the set of Bézier curves can reproduce the train shape satisfactorily. Being aware of this limitation, by modifying the control points positions and setting the constants to capture the train shape in question, a very accurate representation can be obtained, see fig. 4. The parameterization is flexible enough to fit different geometries while keeping itself as simple as possible.

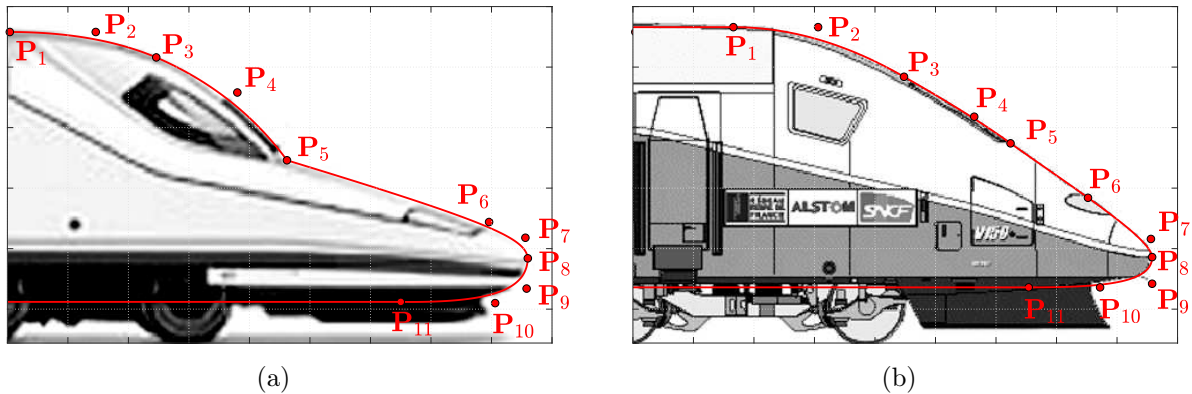


Figure 4: Validation of the parameterization robustness by representing two commercial high-speed trains and the generated Bézier curves. In (a) the Spanish high-speed train AVE is depicted. In (b) the French TGV is represented. Red lines refer to the lateral-side profile. Red dots are the control points used to draw the Bézier curves.

To validate the parameterization accuracy, a comparison of the pressure flow field and velocity at the train surface is performed between the original ATM geometry and the one resulting by the parameterization and Bézier curves aforementioned. The numerical set-up for these simulations is that introduced in section 2.3. The pressure field around the nose of both trains is presented in fig. 5. Small differences are observed close to the top point of detachment and along the hood, which result into a variation of 0.95% of the total drag, assumed as negligible.

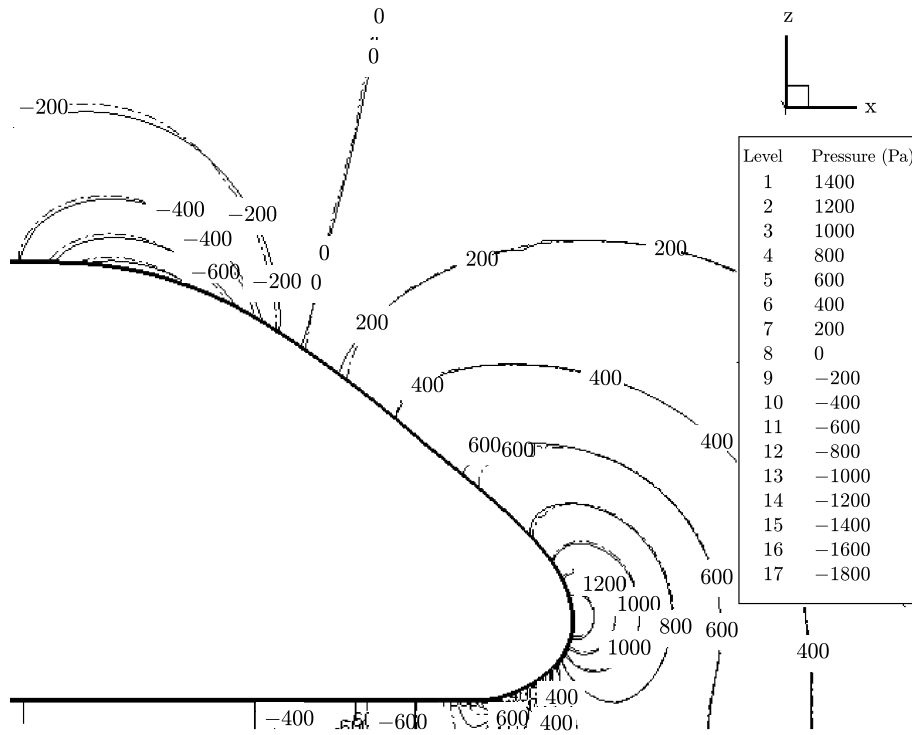


Figure 5: Comparison of the original ATM geometry and the one generated based on our parameterization based on the pressure field at the xz -symmetry plane. Solid lines refer to the original one, while dash-dot line refer to the generated one. Pressure is given in Pa.

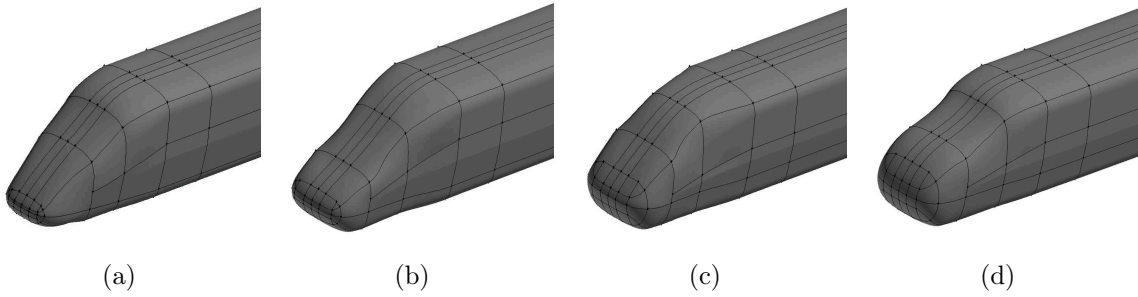


Figure 6: Examples of nose shapes obtained with the proposed geometry parameterization.

3 Discussion of results

3.1 Optimization

The single-objective optimization problem is solved in MINAMO[®] where, once the initial database is completed by CFD simulations, the first surrogate model is constructed and the optimization process starts. For the GA to work properly, some parameters are required to be set. These parameters are the cross-over probability, the mutation probability, the population size, the selection function or the elitism size among others. Here, the maximum number of generations is set to 100, while the population size is set to 400. Elitism is considered and the elitism size is 2. The selection function chosen is tournament and the size is 2. The rest of parameters are left as default, so the extrapolation range is set to 0.5 and the directed rate to 0.25; the mutation probability is set to 0.01, the mutation range to 0.1 and the mutation precision of 32 bits.

When the optimization ends, a (local) optimal solution is obtained, and this needs to accurately be evaluated to verify the predicted value of the objective function (based on the surrogate model) is satisfactory. For the sake of improving the prediction capability of the surrogate model, not only in the optimal region but also far from it, in MINAMO[®] two design points are selected at the end of each optimization step for an accurate simulation. Thus, the optimization is run as a compromise of two strategies, exploration and exploitation. The new simulation results are added to the database and, consequently, more information is available for the surrogate model to be enhanced and for the optimization method to find the optimal solution. Here, 25 steps are run during the online optimization, meaning 50 new design points are evaluated. The convergence of the drag coefficient is plotted in fig. 7, where the initial DoE is included as well. The optimal solutions and the maximum-prediction-error-region points are labelled as optimal solutions and additional samples, and are represented by dots and crosses, respectively. Failed experiments are also plotted since not all the optimal candidates included in the initial result into a converged solution. Concerning the initial design of experiments, the mean value is 0.161, while the ATM geometry presents a drag coefficient of 0.166, what indicates that the reference geometry is very close to the mean performance of the design space, and so confirms the choice of the range of the design variables.

Concerning the optimal solutions, a significant minimization of the drag coefficient respect to the reference value is observed even from the initial steps. Indeed, a convergence to a C_D of 0.122 is reached, leading to a reduction of the drag coefficient of the ATM of about 26%. This variation of the drag coefficient is in the order of magnitude indicated in Raghunathan et al. (2002), where differences of the aerodynamic drag of about a 33% were observed for a large set of train nose shapes, and Orellano (2010), who observed differences of the aerodynamic drag of about 25% from best-to-worst train nose design included in his study.

At the very first steps, there are some design points resulting from the optimization process that are considered as optimal solutions but are close to the reference value if

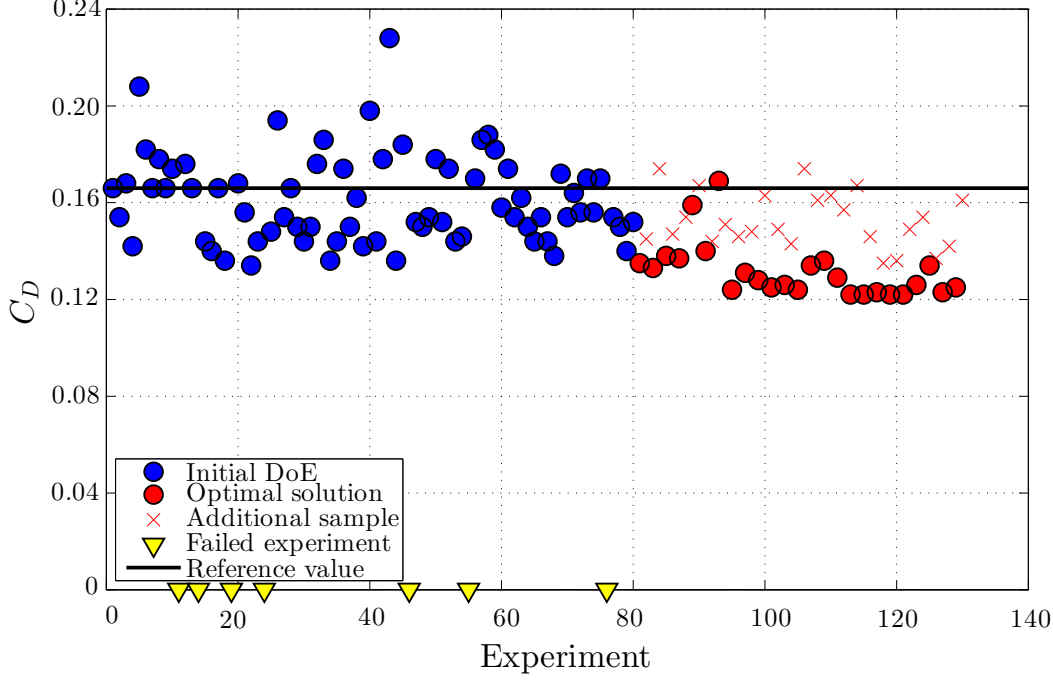


Figure 7: Evolution of drag coefficient along the initial optimization process.

not presenting a larger drag coefficient than the ATM one. It is evident that the surrogate model is not able yet to predict the actual drag coefficient of the design point in a very accurate way and so the GA gives an optimal solution which actually is not. The additional samplings help reducing the prediction error of the surrogate model, as the subsequent optimal solutions do reduce the drag coefficient compared to the reference value. Regarding the additional samplings distribution, some of them are very close to the reference value while others give even a larger drag. Thus, exploration is evident. Meanwhile, an important percentage of this subset is close to the (local) optimal solution, showing exploitation is also achieved.

An in-depth analysis of the evolution of the design variables values all along the optimization process lead to interesting conclusions. After 130 simulations, an ANOVA test let us know which are the most significant design variables and which is the influence of each one on the drag coefficient. A more detailed description is given in section 3.3. The width of the nose at the hood cross-section given by b_{HO} design variable, the design of the roof in terms of l_1 and α_1 , and the dimensions of the spoiler area, quantified by l_4 , seem to be the most dominant variables according to the ANOVA test. Meanwhile, design variables l_2 and γ_{WS} are in a second level but still show a relevant role. These six variables are plotted in fig. 8 versus C_D , where each variable is scaled between [0,1] so that $x^* = \frac{x - x_{\min}}{x_{\max} - x_{\min}}$. Minimum and maximum values for each variable are given in

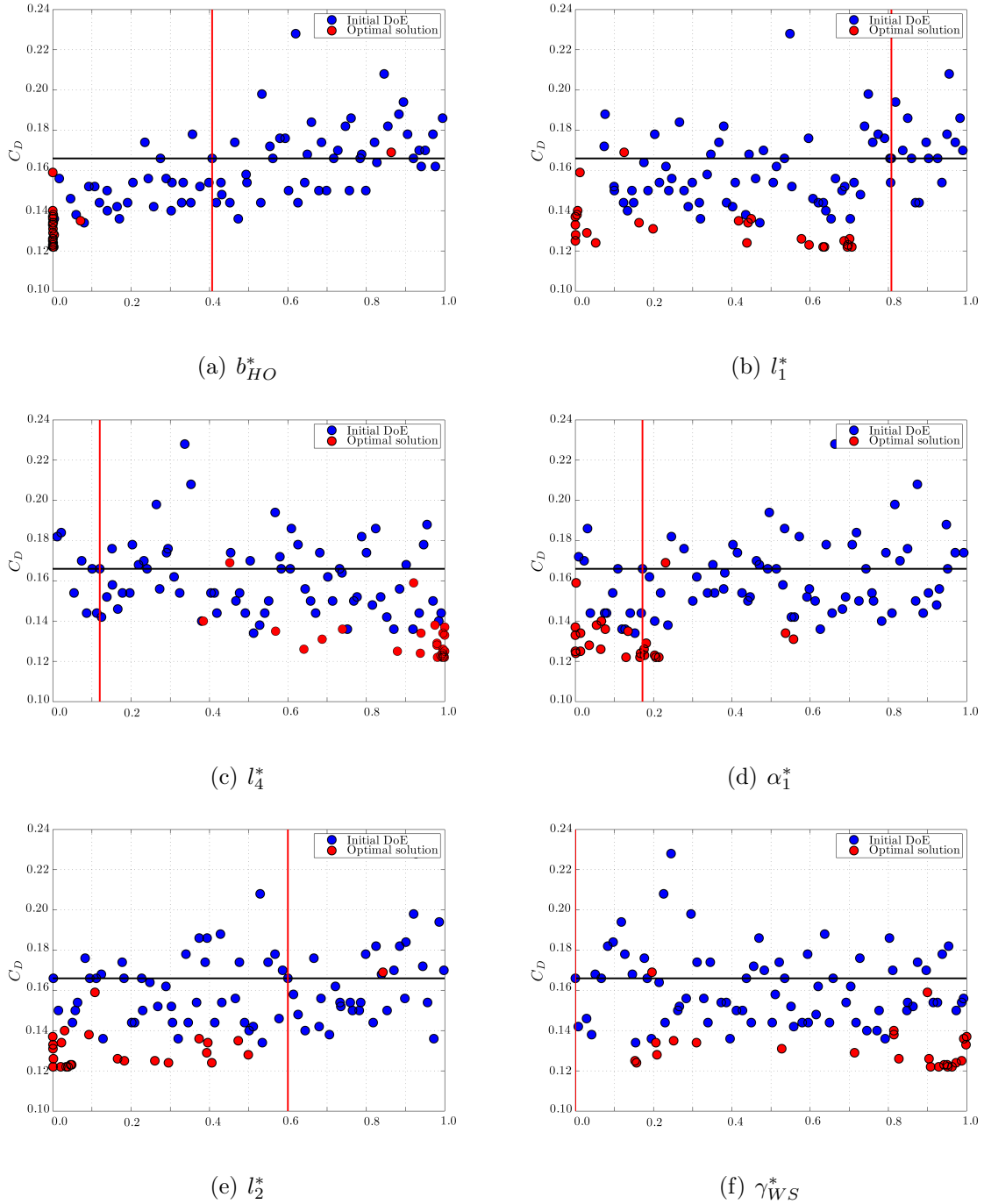


Figure 8: Drag coefficient as a function of the design variable for the initial database (blue) and the optimizational solutions during the first optimization (red).

Table 2. Blue dots refer to the initial DoE while red dots represent the optimal solutions from the optimization. For the sake of clarity, nor the additional samples obtained during the optimization steps neither the failed experiments are represented in fig. 8. Red and black solid lines correspond to the scaled value of the design variable for the ATM and the corresponding C_D , therefore it is possible to identify the initial train nose design. The concentration of dots around a certain value indicates the convergence for that variable. Such convergence is perceptible in most of the cases, being totally evident in the case of b_{HO} , where most of the optimal solutions dots are gathered in the lower bound. In the case of l_1 , two concentrations of dots are identifiable in the graphic, being the drag coefficient slightly lower for the case of $l_1^* \sim 0.7$. A similar feature is visible for α_1 , suggesting for this design variable not a big change from the original value. Instead, a significant variation of the reference value is observed for l_4 , l_2 and γ_{WS} . In these cases, the convergence to the optimal value is almost reached, although again this is not as evident as for b_{HO} . Thus, for the latter a modification of the range of variation is adopted. The bound of b_{HO} design variable is enlarged, setting a lower value for the lower bound of the range. Limited by the geometric constraints of the shape parameterization, such lower value is set to 0.7, so that the new range for b_{HO} is $[0.7, 1.0]$, given in absolute value.

3.2 Extended optimization

The variation of the range of b_{HO} requires to relaunch a DoE so that new design points are generated in the new region included to the design space, i.e. in the range $[0.7, 0.85]$, for the surrogate model to have information in that region. 30 extra design points are simulated in the extended region, leading to the extended DoE, and the resulting drag coefficient is plotted in fig. 9 for each of these design points. This extended DoE is represented by blue squares, showing the evolution from the initial DoE and the optimization. As the range of b_{HO} is limited to $[0.7, 0.85]$, all the experiments give a drag coefficient lower than the original one no matter which is the value for the rest of design variables. It is observed that the extended DoE spreads all over the extended region aiming to get as much information of the design space as possible. These 30 points are added to the initial 80 points from the initial DoE and to the 50 points obtained during the optimization, so now a database of 160 points is available for the surrogate model to be trained.

When the surrogate model is constructed, the optimization is relaunched with the updated bounds of design variable b_{HO} . Again an online optimization is considered, so that the optimal solution obtained from the optimization process is added to the database and the surrogate model is iteratively enhanced. 18 optimization steps are run. The evolution of the optimal solution at each optimization step is presented in fig. 9, represented by red squares. This optimization is labelled as extended optimization. Similar to the first optimization process, not only one but two design points are simulated after each optimization step. For the sake of simplicity, in fig. 9 it is not make any distinction between the optimal solutions and the additional samples as in fig. 7. Nevertheless, it is obvious that those points whose drag coefficient is not minimal correspond to the

additional samples. The spread of the latter indicates these points are added all along the design space although primarily far from the optimal region, as the drag coefficient is much larger than the optimal one, and sometimes even larger than the ATM one. Thus, exploration is confirmed all along the optimization process. On the other hand, the convergence of the drag coefficient for the optimal solutions confirms that the GA has already detected the region where the (global) optimal design is located. Small differences of the drag coefficient are observed for the last 10 steps, so it is concluded the optimization process has finished. The optimal solution is presented in fig. 10 compared to the reference one, while the values of the corresponding design variables are given in table 3, resulting into a drag coefficient of 0.112.

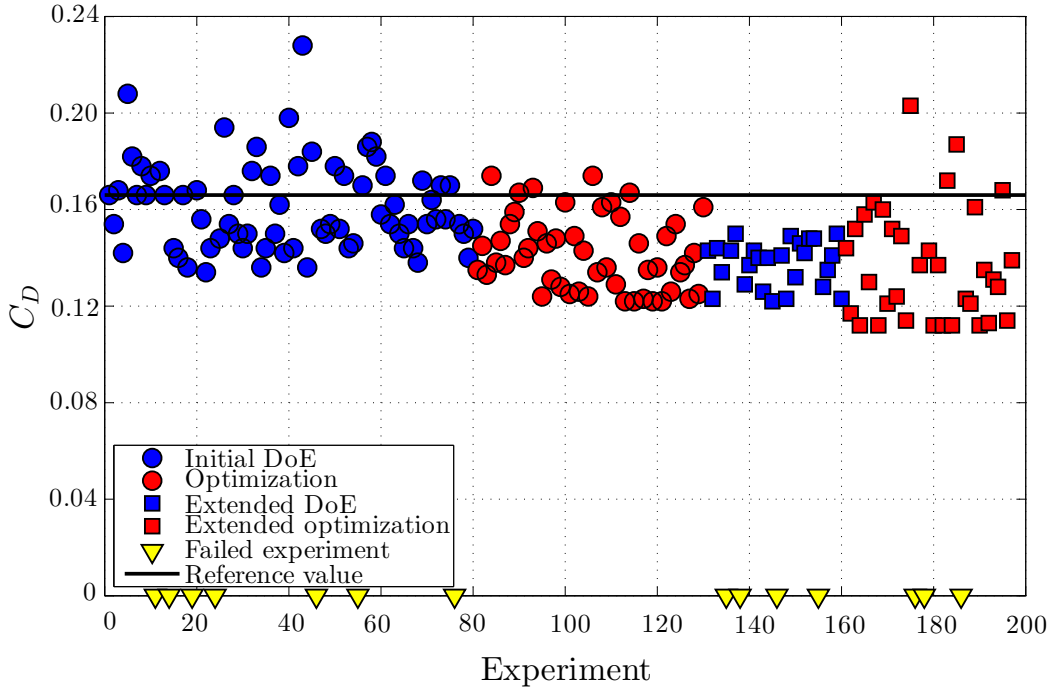


Figure 9: Evolution of drag coefficient along the full optimization process.

3.3 Analysis of results of the optimization

Any surrogate-based optimization problem relies heavily on the surrogate model prediction capability, as an optimal candidate is accepted or rejected depending on the predicted value of the objective function. So, it is necessary to check the accuracy of the surrogate model in terms of prediction. For this, the leave-one-out technique is used to estimate the correlation coefficient between the actual and predicted values of the objective function for each design point included in the database. The evolution of this correlation coefficient

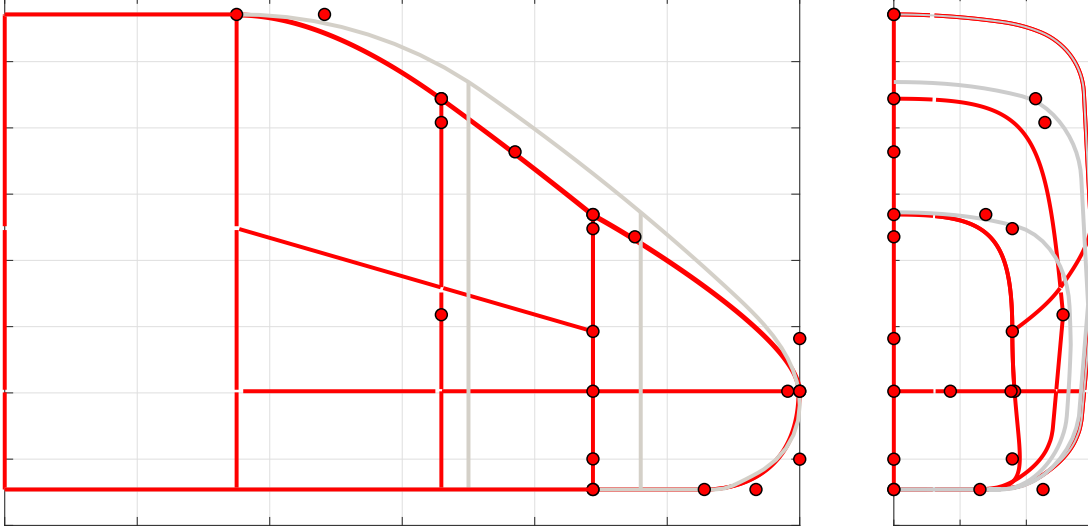


Figure 10: Comparison of optimal design (red) to the original or reference one (ATM) (grey).

desVa	ATM	Opt	h_{bWS}	1669.5	1589.7
l_1	1750.0	1545.3	γ_{WS}	0.035	0.136
h_1	3346.2	3220.3	h_{bHO}	0.816	0.782
α_1	0.22	0.19	b_{HO}	0.911	0.700
l_2	1300.0	1144.1	h_{upWS}	0.862	0.890
h_2	1.213	0.854	k_{upWS}	0.964	0.837
k_2	0.520	0.486	β_{WS}	0.030	0.094
α_3	0.680	0.488	h_{upHO}	0.867	0.879
h_3	906.0	1012.5	k_{upHO}	0.821	0.776
h_4	467.4	397.7	h_{loHO}	178.1	230.84
k_3	0.658	0.203	b_{loHO}	435.7	476.3
α_5	0.340	0.308	b_{peak}	1060.2	884.75
l_4	180.0	389.9	k_{peak}	0.937	0.942

Table 3: Design variables (desVa) values for the reference geometry (ATM) and the optimal one.

is depicted in fig. 11. Here, three database sizes are considered, each one of 80, 130 and 196 design points, respectively. These corresponds to the initial DoE, the addition of the (first) optimization experiments, and the full database once the extended optimization ends. It is significant the improvement of the prediction capability of the surrogate model from the initial DoE to the model obtained when the extended optimization ends. At this point, a correlation coefficient of 0.881 is obtained when outliers are removed, showing

the high reliability of the surrogate model, particularly in the region close to the optimal design.

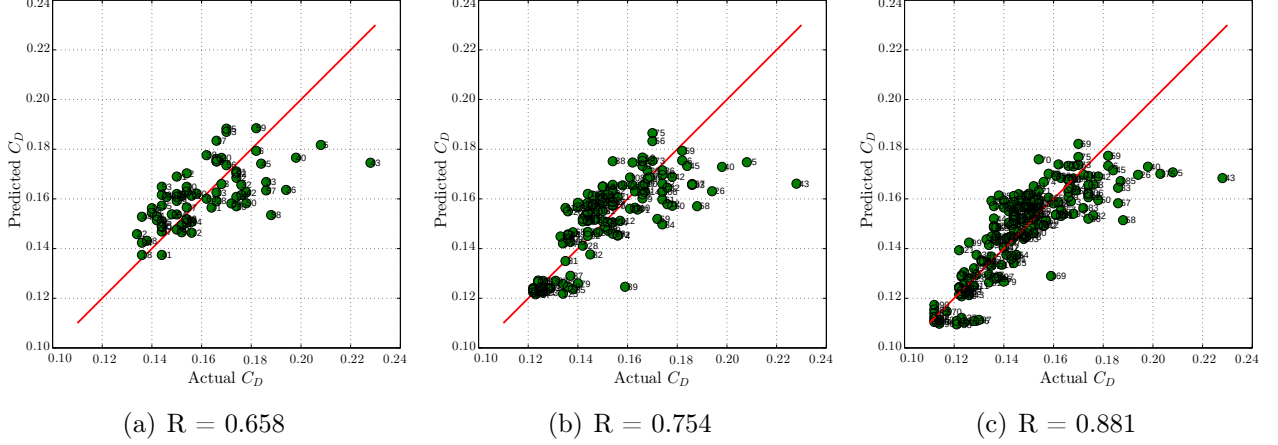


Figure 11: Correlation coefficient obtained from leave-one-out technique for (a) initial DoE; (b) initial DoE + optimization; and (c) initial DoE + optimization + extended DoE + extended optimization.

The proposed geometric parameterization in this paper consists of 25 design variables. Such a general parameterization is proposed with the aim of describing very different train noses that might describe an optimal design in the most demanding train aerodynamic problems. The robustness of the proposed parameterization was shown in fig. 4. However, for a relative simple aerodynamic scenario like front wind and the minimization of aerodynamic drag, it is convenient to evaluate the importance of each design variable in order to detect which design variables have less impact on the objective function. To achieve it, sensitivity computation is commonly used. Here, the analysis of variance (ANOVA) test is used for this purpose. The ANOVA decomposition in MINAMO[®] is a global sensitivity analysis which stands for the global variability of an output over the entire range of the input variables that are of interest, Sainvitu et al. (2013). The Sobol's global indices are the method selected to perform the ANOVA test. This technique is used here not to reduce the curse of dimensionality but to compute which is the effect of each variable. First order sensitivity measures the main effect contribution of each input variable on the output variance, and so on the output response. The sensitivity indices confirm that the main effect corresponds to the design variable b_{HO} , where an increase in relevance is observed from the first optimization to the end of the extended optimization, moving from 54.6% to 72.4%. The influence of the width at the hood cross-section has already been cited as an important variable in Raghunathan et al. (2002), where short train noses with a smaller width at the hood cross-section or larger train noses with a more three-dimensional design present a lower drag. Similar results are observed in Suzuki and Nakade (2013), which are also in concordance with that of Ido et al. (1993).

The train with the minimum drag presented in the optimization has a two-dimensional wedge shape, differing with that of Raghunathan et al. (2002) in the neglecting influence of the nose tip height and so, explaining the change of three-dimensionality with that two-dimensionality mentioned in Suzuki and Nakade (2013). Additionally, in Oh et al. (2018) inward curling edges at both sides of the train nose are observed for the optimal design, confirming the influence of b_{HO} (or any equivalent design variable) on the drag coefficient. To conclude, the influence of b_{HO} is extremely far from the second and third most important ones, which are l_2 and l_1 , respectively. This observation is in agreement with that conclusions from Raghunathan et al. (2002), where the aerodynamic drag does not change for L/W_t values larger than 1.0, where L is the train nose length and W_t the train width, respectively.

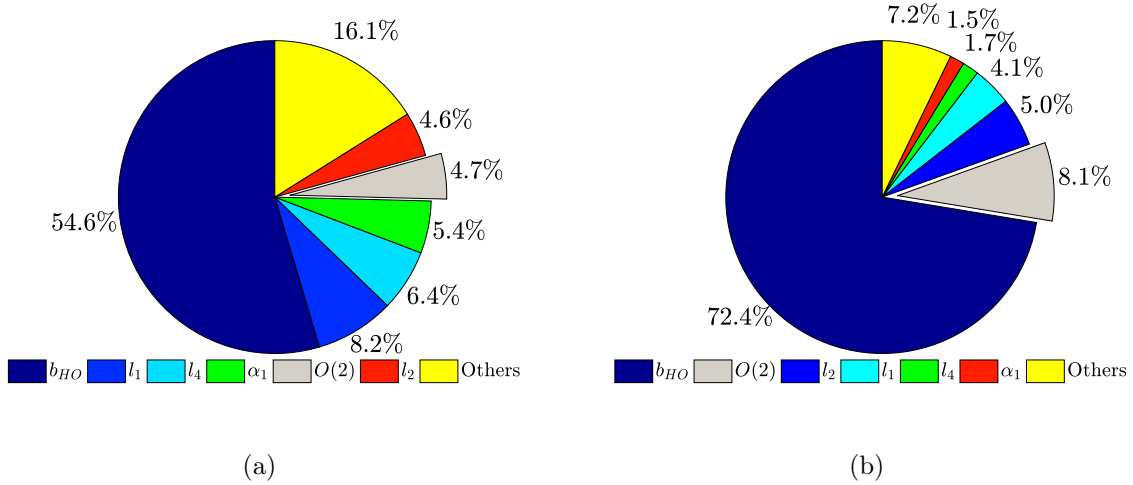


Figure 12: ANOVA test for database size of (a) initial DoE + first optimization; and (b) full database including extended DoE and extended optimization. Second order combination is represented by $O(2)$.

Extending this discussion, we refer to our work published in Munoz-Paniagua et al. (2014), where the optimization of a train entering a tunnel is studied. A simple three-design variables parameterization is used in that case, where the design variables captured the nose bluntness effect, the shrinking effect and the influence of the A-pillar roundness on both the maximum pressure gradient and the drag coefficient. In that reference, it is observed that not only the nose length had a critical impact on the drag coefficient but also the cross-sectional area and the bluntness of the nose played a relevant role, conclusions in good agreement with that from Iida et al. (1996) and Ku et al. (2010). Here, while the cross-sectional area is fixed by the reference cross-section, the bluntness is mainly controlled by design variables α_1 , l_1 and l_2 , as they define the positions of the roof, windshield and hood, and by design variables γ_{WS} and b_{HO} . On the other hand, the A-

pillar roundness is defined by design variables k_{upWS} , k_{upHO} and β_{WS} . The significance of these variables is evidenced here in the ANOVA test of fig. 12 but also in the relationship between the drag coefficient and the design variables presented in fig. 8. The former shows indeed that α_1 , l_1 and l_2 are among the six main contributors to the variance of the drag coefficient. The latter shows that, apart from these design variables, γ_{WS} notably influences the drag coefficient, as a larger value of the design variables leads to a minimization of the objective function. However, there is no evidence of the influence of the design variables related to the A-pillar. This observation is expected and obvious, as this part of the train has a larger importance for crosswind rather than front wind and is mentioned in Krajnovic et al. (2012) and Munoz-Paniagua and Garcia (2019). Finally, it is worth mentioning the relevant role of l_4 . As it is explained in section 2.4, this design variable defines the shape of the lower part of the nose tip, and we expect l_4 to have a major influence on the aerodynamics of the train tail than in the head. This study is left to section 4.

The 25 design variables used for the parameterization of the train nose geometry define the dimensionality of the design space. When dealing with high-dimensional data, Self-Organizing Maps (SOM), Kohonen (1990), arise as an excellent option for reducing the dimensionality and for information visualization, revealing major trends and highlighting correlations between design variables. Indeed, a SOM may be the most compact way to represent a data distribution, translating such high-dimensional data in a two-dimensional map. It is out of scope of this paper an introduction of the theoretical background of SOM, with Kohonen (1990) or Obermayer et al. (2001), among others, as a good choice for this purpose. A SOM is a type of artificial neural network (ANN) that is trained using unsupervised learning to produce a two-dimensional, discretized representation of the input space of the training samples, called a map, and is therefore a method to do dimensionality reduction. This makes SOMs useful for visualization by creating low-dimensional views of high-dimensional data. Here, we take advantage of the implementation of SOM in MINAMO[®] Sainvitu et al. (2013) for a better understanding of the relation between the drag coefficient of the train and the most significant design variables.

Typically, a SOM study involves the creation of multiple heatmaps or visualizations, and then the comparison of these to identify interesting areas on the map, as the individual sample positions do not move from one visualization to another (the map is colored in each case by the corresponding design variable/objective function). More particularly, it is useful to identify any correlation between the design variables and C_D , while the clustering of optimal candidates remains unaltered. Figure 13 shows the SOM visualization of C_D and 8 of the 25 design variables used for the parameterization. The self-organizing map of the drag coefficient show two regions of low-drag (both upper corners). We identify in the first region indices of designs around #190 (#187, #189, #191 or #195), showing that the optimal solutions obtained during the last steps of the optimization are placed in this area. On the other hand, there is a big high-drag region with three poles in the lower right corner, and two discontinuous regions of high drag in the lower side of the

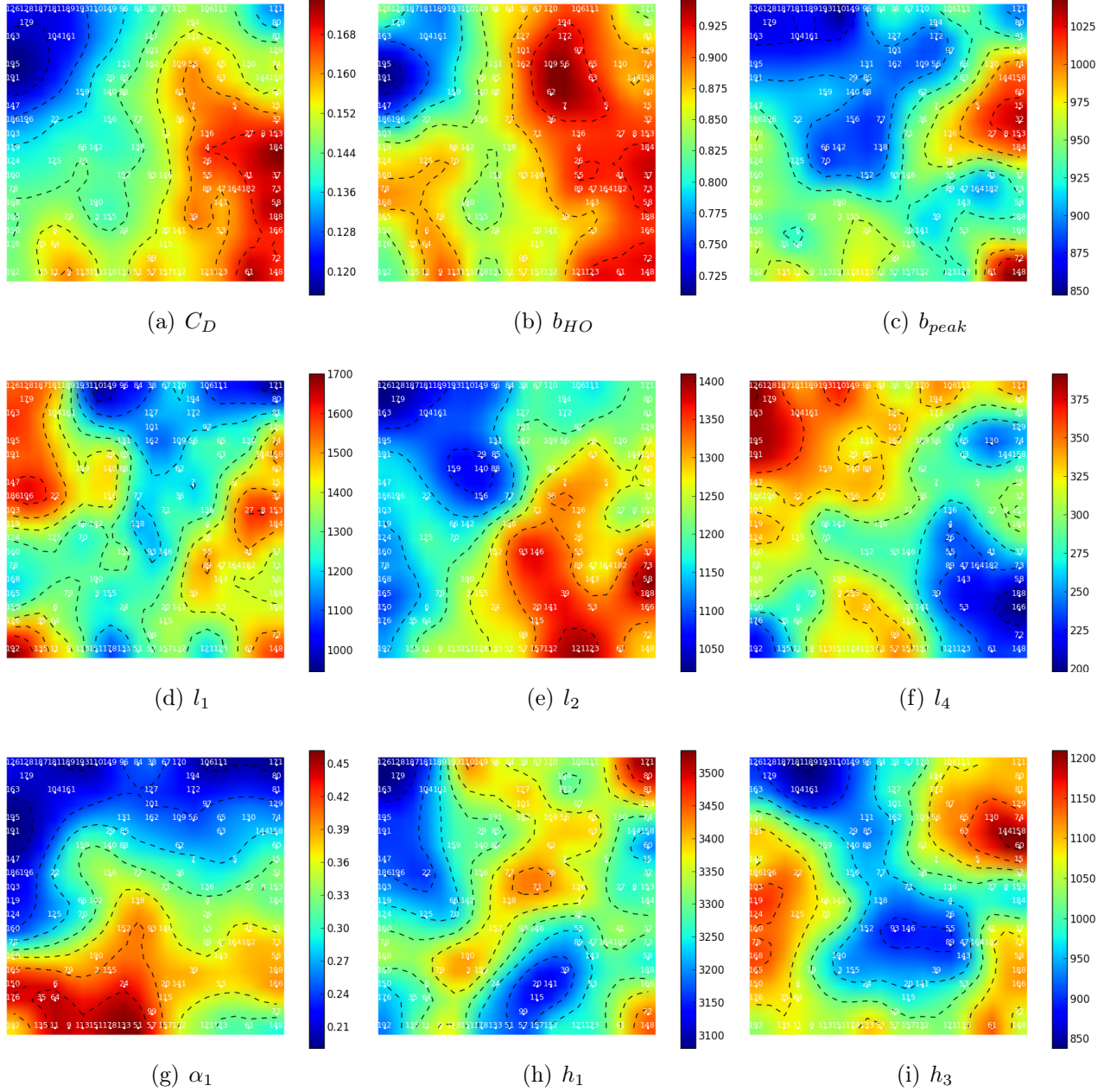


Figure 13: Self-Organizing Map (SOM) visualization of drag coefficient and most significant design variables for the full database.

map. The SOM visualizations of b_{HO} and b_{peak} are those that better correlate with the map of the drag coefficient. Large values of both design variables result into larger drag, but it is the combination of both that lead to lower drag coefficient. In the self-organizing

map of l_1 , it is observed that the region with minimum C_D shows a large value of l_1 , but there are also other regions with large values that, on the contrary, result into high drag. Consequently, it is evidenced the not so strong correlation of this design variable with C_D . On the other hand, it is observed that l_4 presents a negative correlation with C_D , while there is not a significant influence of h_3 on C_D as the correlation is not so strong in this case.

4 Aerodynamic study of the optimal design

4.1 Numerical set-up

The optimization process was based on steady simulations using the $k - \omega$ SST turbulence model. Here, the SAS turbulence model, Menter and Egorov (2010), is used to achieve a more detailed flow description that enhances the aerodynamic analysis of the optimal design. The SST-SAS model is implemented in ANSYS-FLUENT as it is developed from the original $k - \omega$ SST turbulence model, (ANS, 2013). The Semi-Implicit Method for Pressure Linked Equations (SIMPLE) algorithm is chosen for the pressure-velocity coupling, the Bounded Central Difference scheme is used for the momentum equation, and the Least Square Method (LSM) is used for the gradients while the Bounded Second Order Implicit Euler scheme is used for the transient terms. A fixed time step of 10^{-3} s was used for the time integration, which gives a mean CFL value of 1. The number of cells is about 17.9×10^6 . The computational domain is the same as that introduced in section 2.3, with the same boundary conditions. So, the Reynolds number based on the inlet velocity and the train height is kept at $\sim 1.3 \times 10^7$.

4.2 Aerodynamic aspects

Figure 14 presents the flow at the rear part of the ATM and the optimal design. The time-averaged surface flow patterns are visualized using streamlines projected on the train surface. In Osth et al. (2015), the ATM is studied at a $Re_{H_t} = 0.086 \times 10^6$. In that case, the flow separates from the upper edge of the tail surface as the flow along the train body accelerates over the curvature of the tail and the local pressure is decreased. The reattachment line is located in the upper region of the slant surface, and a saddle point is observed at the height of the window as a consequence of the bifurcation of the reattached flow and the reversed flow upwards along the lower part of the train. The foci of the longitudinal vortices are located at a mid height of the train tail surface. A similar flow pattern is depicted in Muld et al. (2013), where the Reynolds number is also of the same order of magnitude. In this paper, a higher Reynolds number is considered, and a slightly different flow pattern is observed in the train tail, closer to that presented in Schulte-Werning et al. (2003), with $Re_D = 12 \times 10^6$ (D refers to an equivalent or hydraulic diameter), although these main features are also detected.

The flow in the slant face is fully attached until it reaches the maximum curvature close to the tail tip, where the flow separates. Meanwhile, the flow from the underbody separates

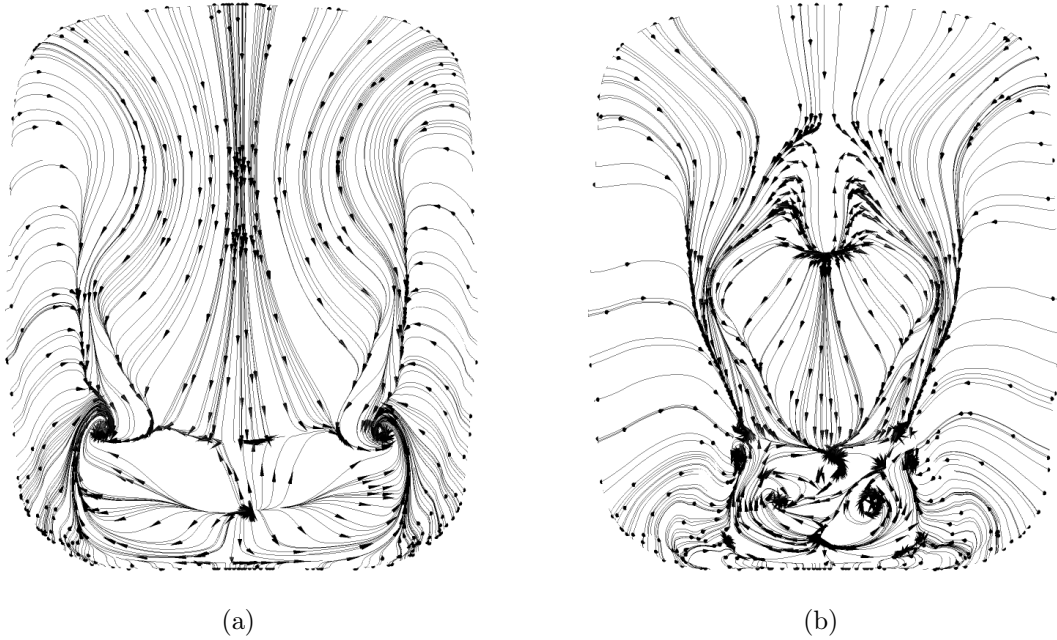


Figure 14: Streamlines projected on the tail surface of (a) ATM and (b) optimal designs.

at the end of the flat side (we recall that the underbody geometry of the train has been dramatically simplified and no details underneath the train have been considered), so that the two shear layers roll up into two recirculatory flow regions, as it is typically observed in the vertical flat base of the Ahmed body, Ahmed et al. (1984). Here, the lower vortex is more intense than the upper one. The axes of these vortices are perpendicular to the streamwise direction. Besides, the symmetrical flow pattern exhibits two counter-rotating longitudinal vortices which emerge from each of the nose shoulders. Each stable focus is fed by three lines of strong streamline convergence or negative bifurcation lines: one where converge the streamlines from the lateral side and the slant face, one from the underbody and lateral side streamlines, and one more from the separation line corresponding to the upper vortex detached at the base (and central streamlines).

A different flow pattern is observed for the optimal design when compared to the ATM. Now, a simple U-shaped separation is detected in the windshield region of the train tail, Détery (2001); Peake and Tobak (1980). The separated flow quickly reattaches at the beginning of the hood, creating a small recirculation bubble, evinced in fig. 15. Topologically, this results into a free-slip critical point above the line of symmetry, and a node of attachment or stagnation point from which a large number of wall streamlines arise, as it is observed in fig. 14(b). The pattern of the streamlines emerging from this node is influenced by the shape of the train end (the more slender shape of the optimal design makes the A-pillars to converge to the nose tip rather than keeping them

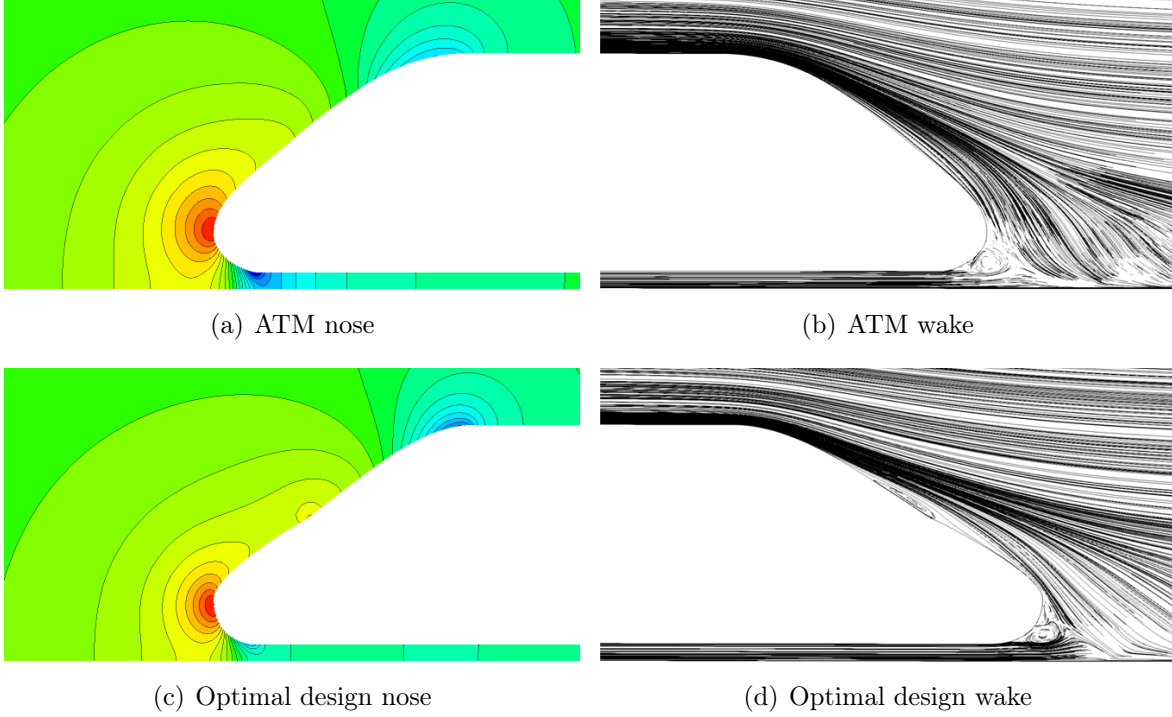


Figure 15: Pressure coefficient field (left) and pathlines (right) in the symmetry plane at the nose and tail regions, respectively, for the reference (ATM) and optimal design.

parallel like in the ATM case) and the resulting separation line from the saddle point. This negative bifurcation line is fed by the streamlines coming from the roof and the A-pillars, narrowing the U-shaped separation region. In Bell et al. (2017), a separation and reattachment is also observed at the train tail for a geometry with a slant angle of 30 degrees (defined with respect to the horizontal) studied at $Re_{W_t} = 0.7 \times 10^6$, although it is not mentioned such flow topology description for their predominantly two-dimensional train model. Here, the slant angle of the optimal design is ~ 35.6 degrees (defined by the slope of a line, connecting control points $\mathbf{P}_2$ and $\mathbf{P}_3$, with respect to the horizontal, fig. 10), justifying the similar behavior to the flow topology observed in Bell et al. (2017) aforementioned.

Similar to the ATM, negative and positive bifurcation lines are detected in the side edges of the train tail. The width of the region at which these streamlines extend is of the same order for both train models. However, those from the ATM develop parallel to the streamwise direction while for the optimal design the streamlines present a spanwise component that bends these to the symmetry plane, particularly the inward negative bifurcation lines. Indeed, these streamlines converge to a stable node, as it is depicted in fig. 14(b). It is also detected a pair of vortices in the base of the optimal design. It is

well known that the strength of the lower vortex depends (in the first instance) upon the flow conditions in the ground clearance gap Ahmed et al. (1984). As this is kept constant for both the ATM and optimal design, there is not a very significant difference between them. However, it is yet observed that the geometry of the optimal design increases the curvature of the region where the cattle-guard or spoiler should be placed (see fig. 3 or table 2), which results in a weaker vortex when compared to the ATM. The results presented in Jakubek and Wagner (2012) are in good agreement with this observation, as their adjoint-based optimization led to a smoothly curved design in the lower part of the nose tip for the drag minimization objective, which is directly related to the size and magnitude of the base vortices, Oh et al. (2018). Meanwhile, the strength of the upper vortex is dependent upon the strength of the longitudinal vortices. Figure 14 shows that this upper vortex is of a lesser strength when compared to the ATM.

Figure 16 presents instantaneous flow structures at the train wake, visualized by iso-surfaces of positive values of the second invariant of the velocity gradient tensor Q , such that $Q = 1.0 \times 10^3$. The iso-surfaces are colored by the streamwise velocity component. As it has been mentioned before, two longitudinal vortices are formed on the side edges of the slant face. For both the ATM and the optimal design, these vortices occur close to the ground, as is also pointed out in Baker (2010). The strength of the pair of counter-rotating longitudinal vortices is the main source of the induced drag. In this sense, it is observed for the ATM how these vortices are stronger than those formed in the optimal design, containing more energy, as it is shown in fig. 16. Their footprint on the train surface is a strong localized low pressure on the sides of the slant face of the ATM, see fig. 19. The downwash induced by such strong vortices ensures that the central flow coming from the roof remains attached down to the maximum curvature of the nose tip. Hucho (1998) remarks that this attached flow is not an indication of low drag. Quite to the contrary, the negative pressures induced on the slant by the vortices result into a higher drag force.

The objective of an aerodynamic shape optimization has been precisely to attenuate the strength of these streamwise wake vortices. Mair (1978) suggests that boat-tailing (i.e. slendering the rear part) is the most effective way of reducing axisymmetric bluff body drag, with an optimal boat-tail angle of 22° (with respect to the streamwise direction). This value is in good agreement with the one obtained for the optimal design (see fig. 16), leading to a more slender conical shape of the train nose, as it is also proposed in Grosche and Meier (2001) to diminish these vortices. Such an effect is achieved here with the Bézier curves for the cross-sectional, but also by enlarging the nose shape. Indeed, the former is directly influenced by the design variables l_1 and l_2 , which define the nose length. In Niu et al. (2018), an increase of the train nose length from 8 m to 12 m (i.e. $2.35W_t$ to $3.5W_t$) resulted into a decrease of total C_D of about 10%, while in Raghunathan et al. (2002) not only the nose length but also the slenderness are considered to reduce the drag coefficient, reaching similar conclusions. This geometry feature influences the direction of the longitudinal vortices and so the distance between them. In fact, as it

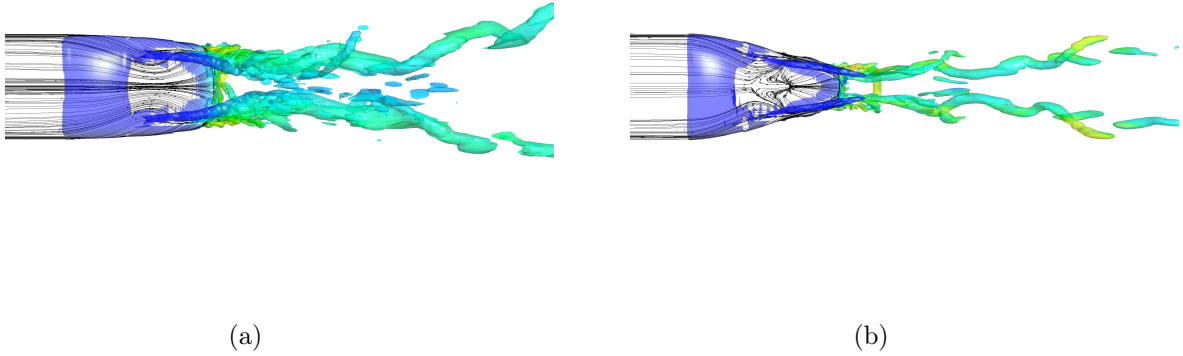


Figure 16: Instantaneous flow structures at the train wake for (a) ATM and (b) optimal design. Iso-surface of $Q = 1.0 \times 10^3$, colored by the RMSE of u , which varies between 0.002 and 18 m s^{-1} .

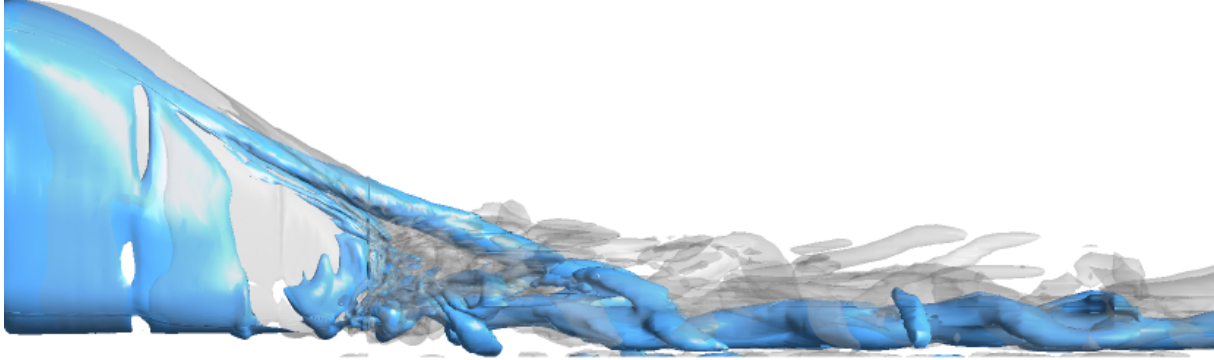


Figure 17: Comparison of wake vortices visualized by iso-surfaces of $Q = 0.01$ for the ATM (grey) and the optimal design (blue).

is reported in Duriez et al. (2009), the drag is decreased when the distance between the two longitudinal vortices is reduced. Figure 16 clearly shows how the distance between the longitudinal axis of these vortices is lower for the optimal design when compared to the ATM. Besides, fig. 17 puts in evidence that the vertical thickness of the shed vortex wakes in the optimal case is significantly lesser than in the ATM one. This observation has also been noted in Oh et al. (2018) to result into a lower drag.

Apart from the aforementioned shape modifications, which mainly result into a more slender design, an increase in the nose length (without any further modification) will decrease the roof angle in the nose/tail to train body transition, and so influence on the

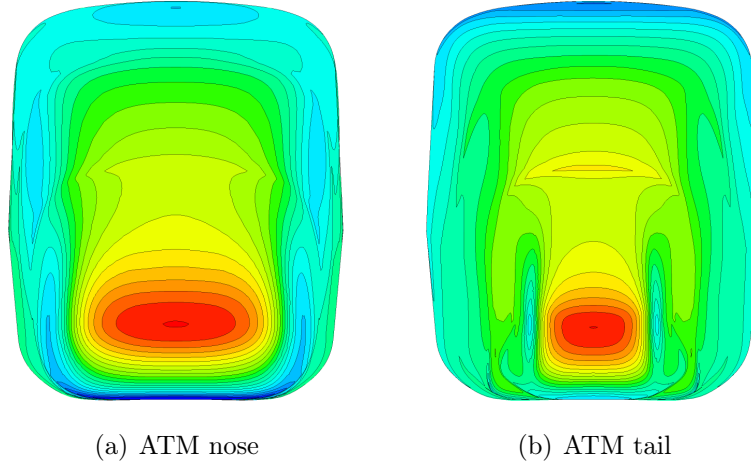


Figure 18: Pressure coefficient C_p distribution over nose surfaces for (left) ATM and (right) optimal design. Values are ranged between -1.0 and 1.0.

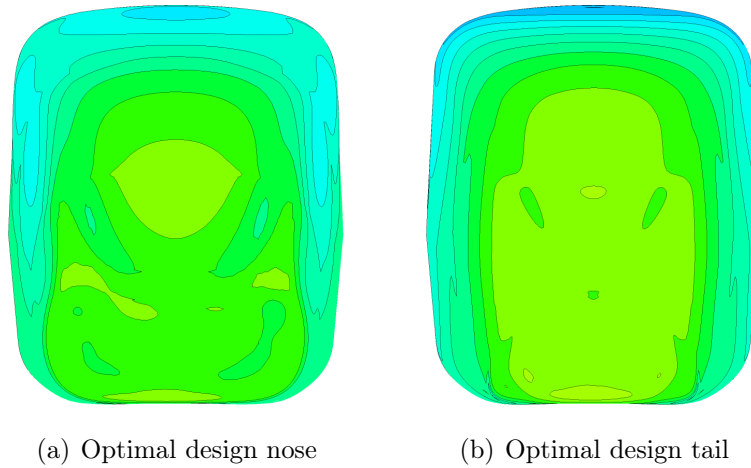


Figure 19: Pressure coefficient C_p distribution over tail surfaces for (left) ATM and (right) optimal design. Values are ranged between -1.0 and 1.0.

aerodynamic drag. In fig. 19, it is observed how in this region a significant low-pressure
 zone occurring just beyond the carbody-tail transition, being sharper for the optimal
 design than for the ATM. Latter, the pressure recovery appears much more effective
 for the optimal design, and the adverse pressure gradient leads to the flow separation.
 However, the counter-rotating vortices cause a much higher drag than the separation
 bubble, and so this explains the lower drag of the optimal design in spite of such small

recirculation bubble. Indeed, similarly to what is indicated in Choi et al. (2014), a strong near-wall momentum after flow reattachment delays the main separation to the nose tip, which results in significant drag reduction.

5 Conclusions

We have presented in this paper a whole description of the optimization process of the nose shape of a high-speed train to minimize its drag coefficient.

- For this purpose, we use a GA as the optimization method as they are able to deal with constraints and multimodal problems, not smooth (even discontinuous) topologies and domains in which the data is noisy.
- GA requires a geometric parameterization for each optimal candidate. This is achieved by considering a 25-design-variables parameterization, accurate enough to reproduce the shape of the reference model (ATM) while is robust and flexible to be applied to other nose shapes, introducing a notable variability in the design space. Indeed, this feature has proved to be basic for a notable reduction of the drag coefficient.
- GA also requires a surrogate model to support the search of the optimal solution. The surrogate model has been built using MINAMO[®], which also automatize the online optimization process and controls all the software calls required in the workflow. The computational cost of the numerical simulations included in the design of experiments and used for the set-up of the surrogate model is significantly reduced if an online rather than an offline scheme is considered.
- An ANOVA test is used here not to reduce the curse of dimensionality but to compute which is the effect of each design variable. First order sensitivity measures the main effect contribution of each input variable on the output variance, and so on the output response. The sensitivity indices confirm that the main effect corresponds to the design variable b_{HO} , with l_1 , l_2 and l_4 also playing a relevant role.
- The optimal solutions obtained in successive iterations converge to a drag coefficient which result into a reduction of about $\sim 32.5\%$ with respect to the ATM. This convergence is evinced also in the SOM plots, obtained with MINAMO[®].
- The final correlation coefficient obtained from leave-one-out technique of the surrogate model increases up to 88.1%, showing also a good capability of prediction.
- Two accurate evaluations are considered at the end of the paper. The reference model and the optimal design are simulated using the SAS turbulence model.

6 Acknowledgement

We acknowledge Cenaero Research Center, and in particular Dr. Ingrid Lepot and Dr. Caroline Sainvitu, for their support with the MINAMO[®] license and assistance/advice in the optimization approach set-up.

References

- (2006). *TSI-Technical Specification for Interoperability of the trans-European high-speed rail system*. Official Journal of the European Communities.
- (2009). *EN14067 - 4:2005 +A1. Railway Applications - Aerodynamics - Part 4: Requirements and test procedures for aerodynamics on open track*.
- (2013). *ANSYS Fluent User's Guide. Release 15.0*. ANSYS, Inc., Canonsburg, PA.
- Ahmed, S. R., Ramm, G., and Faltin, G. (1984). Some salient features of the time-averaged ground vehicle wake. *SAE Transactions*, pages 473–503.
- Baker, C. J. (2010). The flow around high-speed trains. *Journal of Wind Engineering and Industrial Aerodynamics*, 98 (6):277–298.
- Baker, C. J., Quinn, A., Sima, M., Hoefener, L., and Licciardello, R. (2012). Full scale measurement and analysis of train slipstreams and wake. part 1: ensemble averages. *Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit*, 98:277–298.
- Bell, J. R., Burton, D., Thompson, M., Herbst, A., and Sheridan, J. (2014). Wind tunnel analysis of the slipstream and wake of a high-speed train. *Journal of Wind Engineering and Industrial Aerodynamics*, 134:122–138.
- Bell, J. R., Burton, D., Thompson, M. C., Herbst, A. H., and Sheridan, J. (2017). The effect of tail geometry on the slipstream and unsteady wake structure of high-speed trains. *Experimental Thermal and Fluid Science*, 83:215–230.
- Choi, H., Lee, J., and Park, H. (2014). Aerodynamics of heavy vehicles. *Annual Review of Fluid Mechanics*, 46:441–468.
- Délery, J. M. (2001). Robert Legendre and Henri Werlé: Toward the elucidation of three-dimensional separation. *Annual Review of Fluid Mechanics*, 33:129–154.
- Duriez, T., Aider, J. L., Masson, E., and Wesfreid, J. E. (2009). Qualitative investigation of the main flow features over a TGV. In *EUROMECH Colloquium 509. Vehicle Aerodynamics: External Aerodynamics of Railway Vehicles, Trucks, Buses and Cars*, pages 1–6, Berlin, Germany.

- Farin, G. (1993). *Curves and Surfaces for Computer-Aided Geometric Design. A Practical Guide*. Academic Press Professional, 3rd edition.
- García, J., Munoz-Paniagua, J., and Crespo, A. (2017). Numerical study of the aerodynamics of a full-scale train under turbulent wind conditions, including surface roughness effects. *Journal of Fluids and Structures*, 74:1–18.
- Garcia, J., Munoz-Paniagua, J., Jimenez, A., Migoya, E., and Crespo, A. (2015). Numerical study of the influence of synthetic turbulence inflow conditions on the aerodynamics of a train. *Journal of Fluids and*, 56:134–151.
- Goldberg, D. E. (1989). *Genetic Algorithms in Search, Optimization and Machine Learning*. Addison-Wesley Publishing Company, 2nd edition.
- Grosche, F. R. and Meier, G. E. A. (2001). Research at DLR Gottingen on bluff body aerodynamics, drag reduction by wake ventilation and active flow control. *Journal of Wind Engineering and Industrial Aerodynamics*, 89:1201–1218.
- Hemida, H., Baker, C. J., and Gao, G. (2014). The calculation of train slipstreams using Large-Eddy Simulation. *Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit*, 228(1):25–36.
- Holland, J. H. (1975). *Adaptation in Natural and Artificial Systems*. The University of Michigan Press, 1st edition.
- Hucho, W.-H. (1998). *Aerodynamics of Road Vehicles*, chapter Aerodynamic Drag of Passenger Cars, pages 131–237. SAE International.
- Ido, A., Iida, M., and Maeda, T. (1993). Wind tunnel test for nose and tail of train. *RTRI Report*, 7(7):59–66. (in Japanese).
- Iida, M., Matsumura, T., Nakatani, K., Fukuda, T., and Maeda, T. (1996). Optimum nose shape for reducing tunnel sonic boom. *In IMECHE Conference Transactions, Mechanical Engineering Publications*, 8:271–282.
- Jakubek, D. and Wagner, C. (2012). Shape optimization of train head cars using adjoint-based computational fluid dynamics. *International Journal of Railway Technology*, 1(2):67–88.
- Kikuchi, K., Iida, M., and Fukuda, T. (2011). Optimization of train nose shape for reducing micro-pressure wave radiated from tunnel exit. *Journal of Low Frequency Noise, Vibration and Active Control*, 30(1):1–19.
- Kohonen, T. (1990). The Self-Organizing Maps. In *Proceedings of the IEEE*, volume 78, pages 1464–1480. Springer.

- Krajnovic, S. (2009). Shape optimization of high-speed trains for improved aerodynamic performance. In *Proceedings of the Institution of Mechanical Engineers. Part F: Journal of Rail and Rapid Transit*, volume 223, pages 439–452.
- Krajnovic, S., Helgason, E., and Hafsteinsson, H. E. (2012). Aerodynamic shape optimization of high-speed trains. In *Proc. of the First International Conference on Railway Technology: Research, Development and Maintenance*.
- Ku, Y.-C., Rho, J.-H., Yun, S.-H., Kwak, M.-H., Kim, K.-H., Kwon, H.-B., and Lee, D.-H. (2010). Optimal cross-sectional area distribution of a high-speed train nose to minimize the tunnel micro-pressure wave. *Structural Multidisciplinary Optimization*, 42:965–976.
- Kwon, H.-B., Jang, K.-H., Kim, Y.-S., Yee, K.-J., and Lee, D.-H. (2001). Nose shape optimization of high-speed train for minimization of tunnel sonic boom. *JSME International Journal Series C*, 44(3):890–899.
- Lee, J. and Kim, J. (2008). Approximate optimization of high-speed train nose shape for reducing micropressure wave. *Structural and Multidisciplinary Optimization*, 35(1):79–87.
- Li, R., Xu, P., and Ji, P. (2016). Multi-objective optimization of a high-speed train head based on the FFD method. *Journal of Wind Engineering and Industrial Aerodynamics*, 152:41–49.
- Mair, W. A. (1978). *Aerodynamic Drag Mechanisms of Bluff Bodies and Road Vehicles*, chapter Drag-reducing techniques for axi-symmetric bluff bodies, pages 161–187. Springer.
- Menter, F. R. and Egorov, Y. (2010). The Scale-Adaptive Simulation method for unsteady turbulent flow predictions. Part 1: Theory and model description. *Flow, Turbulence and Combustion*, 85(1):113–138.
- Muld, T. W., Efraimsson, G., and Henningson, D. S. (2012). Flow structures around a high-speed train extracted using Proper Orthogonal Decomposition and Dynamic Node Decomposition. *Computers and Fluids*, 57:87–97.
- Muld, T. W., Efraimsson, G., and Henningson, D. S. (2013). Mode decomposition and slipstream velocities in the wake of two high-speed trains. *International Journal of Railway Technology*, 2(1):1–38.
- Munoz-Paniagua, J. and Garcia, J. (2019). Aerodynamic surrogate-based optimization of the nose shape of a high-speed train for crosswind and passing-by scenarios. *Journal of Wind Engineering and Industrial Aerodynamics*, 184:139–152.

- Munoz-Paniagua, J., Garcia, J., and Crespo, A. (2014). Genetically aerodynamic optimization of the nose shape of a high-speed train entering a tunnel. *Journal of Wind Engineering and Industrial Aerodynamics*, 130:48–61.
- Munoz-Paniagua, J., Garcia, J., Crespo, A., and Laspougeas, F. (2015). Aerodynamic optimization of the nose of a high-speed train using the adjoint method. *Journal of Applied Fluid Mechanics*, 8(3):601–612.
- Munoz-Paniagua, J., Garcia, J., and Lehugeur, B. (2017). Evaluation of RANS, SAS and IDDES models for the simulation of the flow around a high-speed train subjected to crosswind. *Journal of Wind Engineering and Industrial Aerodynamics*, 171:50–66.
- Niu, J., Wang, Y., Zhang, L., and Yuan, Y. (2018). Numerical analysis of aerodynamic characteristics of high-speed train with different train nose lengths. *International Journal of Heat and Mass Transfer*, 127:188–199.
- Obermayer, K., Sejnowski, T. J., and Poggio, T. A. (2001). *Self-Organizing Maps formation: foundations of neural computation*. MIT Press.
- Oh, S., Jiang, C.-H., Jiang, C., and Marcus, P. S. (2018). Finding the optimal shape of the leading-and-trailing car of a high-speed train using design-by-morphing. *Computational Mechanics*, 62:23–45.
- Orellano, A. (2010). Aeroefficient - optimized train. In *modeFRONTIER International Users Meeting 2010*, Trieste, Italy.
- Orellano, A. and Schober, M. (2006). Aerodynamic performance of a typical high-speed train. In *4th WSEAS International Conference on Fluid Mechanics and Aerodynamics*, pages 18–25, Elounda, Greece.
- Osth, J., Kaiser, E., Krajnovic, S., and Noack, B. R. (2015). Cluster-based reduced-order modeling of the flow in the wake of a high speed train. *Journal of Wind Engineering and Industrial Aerodynamics*, 145:327–338.
- Osth, J. and Krajnovic, S. (2014). A study of the aerodynamics of a generic container freight wagon using Large-Eddy Simulation. *Journal of Wind Engineering and Industrial Aerodynamics*, 44:31–51.
- Peake, D. J. and Tobak, M. (1980). Three-dimensional interactions and vortical flows with emphasis on high speeds. Technical report, Advisory Group for Aerospace Research and Development, Neuilly-Sur-Seine, France.
- Raghunathan, R. R., Kim, H., and Setoguchi, T. (2002). Aerodynamics of high-speed railway train. *Progress in Aerospace Sciences*, 38:469–514.

- Rho, J., Ku, Y.-C., Kee, J.-D., and Lee, D.-H. (2009). Development of a vehicle modeling function for three-dimensional shape optimization. *Journal of Mechanical Design*, 131:1–10.
- Sainvitu, C., Beauthier, C., Dumeunier, C., and Guenot, M. (2013). *MINAMO User Manual*. Cnraero.
- Saka, Y., Gunzburger, M., and Burkardt, J. (2007). Latinized, improved LHS and CVT point sets in hypercubes. *International Journal of Numerical Analysis and Modeling*, 4(3–4):729–743.
- Samareh, J. A. (2001). Survey of shape parameterization techniques for high-fidelity multidisciplinary shape optimization. *AIAA Journal*, 39(5):877–884.
- Schetz, J. A. (2001). Aerodynamics of high-speed trains. *Annual Review of Fluid Mechanics*, 33:371–414.
- Schulte-Werning, B., Heine, C., and Matschke, G. (2003). Unsteady wake flow characteristics of high-speed trains. In *Proc. of Appl. Math. Mech.*, volume 2, pages 332–333.
- Shuanbao, Y., Dilong, G., Zhenxu, S., Guowei, Y., and Dawei, C. (2014). Optimization design for aerodynamic elements of high speed trains. *Computers and Fluids*, 95:56–73.
- Simpson, T. W. and Peplinski, J. D. (2001). Metamodels for computer-based engineering design. Survey and recommendations. *Engineering with Computers*, 17(2):129–150.
- Suzuki, M. and Nakade, K. (2013). Multi-objective design optimization of high-speed train nose. *Journal of Mechanical Systems for Transportation and Logistics*, 6:54–64.
- Vytla, V. V., Huang, P. G., and Penmetsa, R. C. (2010). Multi-objective aerodynamic shape optimization of high speed train nose using adaptive surrogate model. In *28th AIAA Applied Aerodynamics Conference*, number AIAA 2010-4383, Chicago, IL.
- Wang, S., Bell, J. R., Burton, D., Herbst, A. H., Sheridan, J., and Thompson, M. C. (2017). The performance of different turbulence models (URANS, SAS and DES) for predicting high-speed train slipstream. *Journal of Wind Engineering and Industrial Aerodynamics*, 165:46–57.