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Optimization of hydraulic machinery by exploiting previous successful designs.

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Abstract

A design-optimization method for hydraulic machinery is proposed. Optimal designs are obtained using the appropriate CFD evaluation software driven by an evolutionary algorithm which is also assisted by artificial neural networks used as surrogate evaluation models or metamodels. As shown in a previous IAHR paper by the same authors, such an optimization method substantially reduces the CPU cost, since the metamodels can discard numerous non-promising candidate solutions generated during the evolution, at almost negligible CPU cost, without evaluating them by means of the costly CFD tool. The present paper extends the optimization method of the previous paper by making it capable to accommodate and exploit pieces of useful information archived during previous relevant successful designs. So, instead of parameterizing the geometry of the hydraulic machine components, which inevitably leads to many design variables, enough to slow down the design procedure, in the proposed method all new designs are expressed as weighted combinations of the archived ones. The archived designs act as the design space bases. The role of the optimization algorithms is to find the set (or sets, for more than one objectives, where the Pareto front of non-dominated solutions is sought) of weight values, corresponding to the hydraulic machine configuration(s) with optimal performance. Since the number of weights is much less that the number of design variables of the conventional shape parameterization, the design space dimension reduces and the CPU cost of the metamodel-assisted evolutionary algorithm is much lower. The design of a Francis runner is used to demonstrate the capabilities of the proposed method.

Keywords: Design optimization algorithms, Evolutionary Algorithms, Francis runner

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1. Introduction

In the hydropower industry, CFD tools (Euler and Navier-Stokes solvers) combined with modern optimization techniques, such as evolutionary algorithms (EAs) [1], [2] are often used instead of the expensive, in both time and resources, lab tests.

It is well known that the EAs, due to their ability to locate global optima in multi-objective, constrained optimization problems supported by black-box evaluation tools (even commercial software), have gained popularity in design-optimization problems in engineering. Their main disadvantage, though, is the excessive CPU cost when used along with costly evaluation tools, such as the 3D flow analysis software simulating the flow in hydraulic machinery components. To alleviate this drawback, hierarchical schemes and/or low cost surrogate models (often referred to as "metamodels") are used [1], [2]. An efficient way of using metamodels (polynomial response surfaces, artificial neural networks, etc.) within an EA is by assigning the inexpensive/inexact pre-evaluation (IPE, [4], [5], [6]) of the population members to them. More precisely, they act as screening tools distinguishing promising from non-promising individuals in each generation and allowing only the former to be re-evaluated by the expensive and accurate (based on a designer's decision) CFD tool. On the other hand, hierarchical optimization methods employ more than one problem-specific evaluation models, with different modeling accuracy and CPU cost, [7].

It should not escape notice that, when a new hydraulic machinery component (a runner, for instance) is to be designed, there is always a certain amount of useful information (at least in the form of design "directives") included in similar previous successful designs, even if the latter had to operate at (slightly) different conditions. The most evident way to exploit archived designs is by modifying the "closest" one(s) based on human experience. The designer often selects one or more previous designs, corresponding to similar problems, and revises them in order to make them fit to the new problem specifications. This leads to faster response times but the designer is unavoidably biased towards previously designed configurations and, so, she/he might come up with a good, rather than the optimal, design. This paper presents a method which is capable to exploit previous designs within an automated design-optimization procedure by simultaneously reducing the number of design variables (exploiting geometry correlations between successful designs). To demonstrate the new method, the design of a multi-operating-point Francis turbine runner, using the aforementioned method is presented. Through comparison with a standard EA-based design, the efficiency of the proposed method is shown.

2. "Conventional" hydraulic machinery parameterization.

The standard way of parameterizing hydraulic machinery shapes (such as blades, the hub and shroud generatrices, etc.) is by means of Bezier curves and/or B-Splines. Without loss in generality, in a design-optimization algorithm, the blade shape can be modeled by superimposing a parameterized thickness distribution on a parameterized mean camber surface. Figs. 1 to 7 demonstrate the basic features of such a parameterization and introduce (some of) the design variables. For instance, fig. 1 shows typical spanwise distributions of the mean camber surface angles at the leading (LE) and trailing (TE) edges. The circumferential position of the blade LE and TE, in the spanwise direction, are shown in fig. 2. Finally, fig. 3 shows how the mean camber surface curvature can be defined by the so-called ζ angle distributions (more details are beyond the scope of this paper) for the LE and TE. In all these curves, the coordinates of all or some of the control points are the design variables.

The contours of the LE/TE and the hub/shroud generatrices on the meridional plane are parameterized by means of Bezier curves with 4 (LE and TE) and 14 (hub and shroud) control points each, as in fig. 6. The so-defined mean camber surface, a number of dimensionless chordwise thickness distributions for the suction and pressure sides (blade profiles, as in fig. 4) and the spanwise thickness distributions for the two blade sides (fig. 5), together define the blade shape, such as the one shown in fig.7.

To summarize, based on the previous discussion and the relevant figures, a turbine runner (stator, rotor and casing) design often yields more than 300 design variables. This will be referred to as the "conventional" parameterization which could be (and has been) used along with an EA for designing a new optimal shape. However, even by using the advanced EA variants (such as a metamodel-assisted EA or MAEA and/or hierarchical search), the CPU cost is still high. This paper aims at further reducing this cost and, for this reason, previous designs are exploited, leading to just a few design variables to cope with.

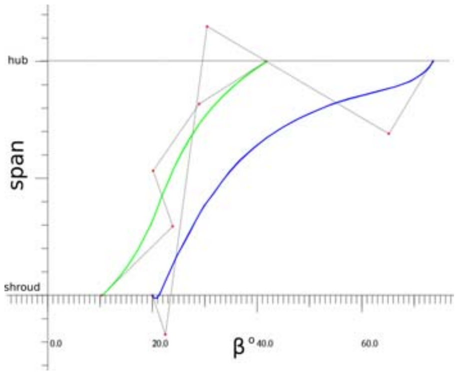

Figure 1: Spanwise distributions of mean camber surface angle β at the LE (blue) and TE (green); both are parameterized using Bezier curves with 5 control points each.

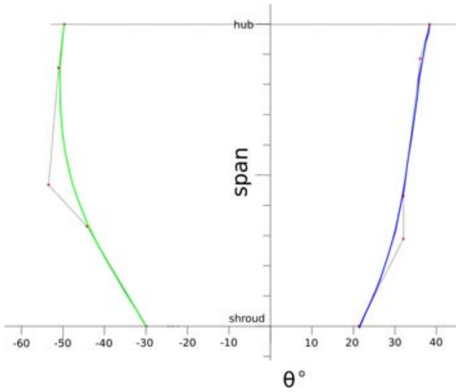

Figure 2: Circumferential position of the LE (blue) and TE (green) of the blades, in the spanwise direction; both are parameterized using Bezier curves with 5 control points each.

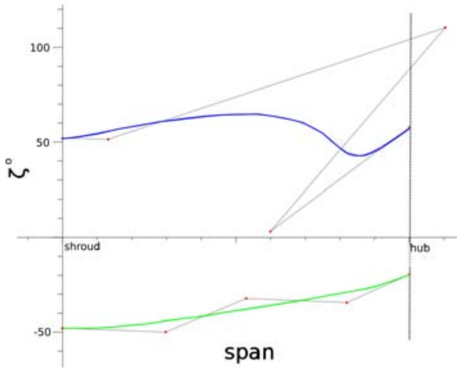

Figure 3: Spanwise distributions of the mean camber surface curvature (represented by the so-called ζ angle) at the LE (blue) and TE (green); parameterization as in figs. 1 and 2.

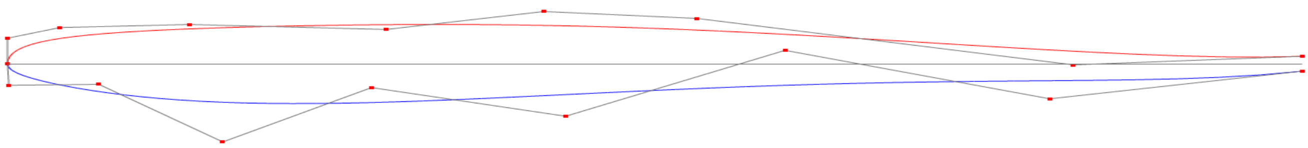

Figure 4: Dimensionless chord-wise thickness distributions for the suction (red) and pressure (blue) sides; both are parameterized using Bezier curves with 9 control points each.

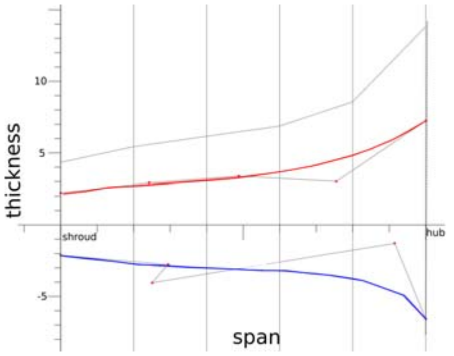

Figure 5: Spanwise absolute thickness distributions for pressure (red) and suction (blue) side; parameterization as in figs. 1 and 2.

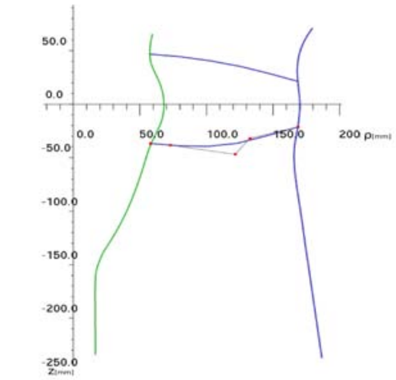

Figure 6: Parameterized meridional contour.

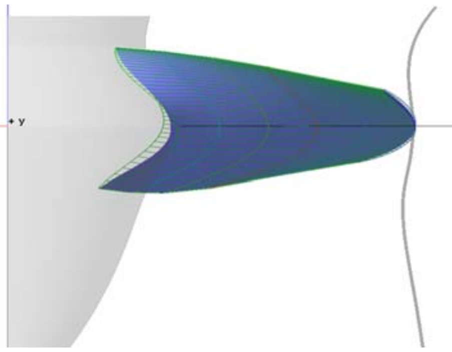

Figure7: Mean camber surface (blue) and the superimposed thickness profiles (green) generate the 3D blade.

3. Designing a new component based on archived designs

Let us assume that a small number of previous designs are available. These designs must have been performed for similar problems and archived with respect to all design variables, in conformity with the same parameterization. Let us denote by $GEO_i = (b_1^i, b_2^i, ..., b_n^i)$, i=1,m the m archived designs. Let b_j (j=1,n) denote the "conventional" design variables as described in Section 2. It is a simple matter to assume that any new design b_j^{new} (j=1,n) may result from the combination of m archived designs, by means of weights w_i (i=1,m). This is, in fact, equivalent to a multi-linear interpolation scheme, namely

$$b_j^{new} = \sum_{i=1}^{m} w_i b_j^i \Big/ \sum_{i=1}^{m} w_i \tag{1}$$

Without loss in generality, we may assume that $w_i \in [0,1]$. Setting up an optimization method merely based on eq. 1 leads to a parsimonious set of unknowns (or design variables, namely the m values of w_i ;recall that m is a quite small number compared to n). However, since (a) m is small and (b) a multi-linear interpolation with the same weight for all variables comprising the same archived design is used, the flexibility and effectiveness of such a method is questionable.

Among other, the set of the archived solutions reveals the statistical distribution of each design variable and, consequently, this can also be used to set the bounds of the design space. In place of eq. 1, the nonlinear equations

$$b_j^{new} = \Phi_j^{-1}\left[\sum_{i=1}^{m} w_i \Phi_j\left(b_j^i\right) \Big/ \sum_{i=1}^{m} w_i\right] \tag{2}$$

can be used to define each new design. In eq. 2, Φ_j are appropriate nonlinear functions. Based on the assumption that the archived designs (which will otherwise be referred to as *design bases*) correspond to operating conditions correlated to the new ones, the new design should conform to a normal distribution. Should this be the case, the sigmoid cumulative distribution function could be used for Φ_j [10].

$$\Phi_{\mu,\sigma^2}(x) = \frac{1}{\sigma\sqrt{2\pi}} \int_{-\infty}^{x} \exp\left(\frac{-(u-\mu)^2}{2\sigma^2}\right) du, x \in \Re \tag{3}$$

where μ (mean) and σ (standard deviation) are calculated for each "conventional" design variable (j); schematically:

$$\begin{bmatrix} b_1^1 \\ \vdots \\ b_n^1 \end{bmatrix} \begin{bmatrix} b_1^i \\ \vdots \\ b_n^i \end{bmatrix} \begin{bmatrix} b_1^m \\ \vdots \\ b_n^m \end{bmatrix} \rightarrow \begin{bmatrix} \mu_1 \\ \vdots \\ \mu_n \end{bmatrix} \begin{bmatrix} \sigma_1 \\ \vdots \\ \sigma_n \end{bmatrix}$$

The use of the cumulative distribution function, eq. 3, practically confines b_i within $\mu_i \pm 3\sigma_i$. To overcome this limitation, a single extrapolation variable Ψ which multiplies all computed (based on the archived designs) σ values and, thus, extends the search space, is introduced. Ψ is used as follows,

$$\begin{bmatrix} \sigma_1 \\ \vdots \\ \sigma_n \end{bmatrix} = \Psi \begin{bmatrix} \sigma_1^{computed} \\ \vdots \\ \sigma_n^{computed} \end{bmatrix} \quad ,\Psi \geq 1 \tag{4}$$

With either eq. 1 or eq. 2, an optimization problem with m weights (the number m of design bases is considered to be small) as unknowns is neither effective nor flexible. Such a method may overcome the curse of dimensionality (since the number of design variables is no more depending on n) but may lead to sub-optimal solutions. For this reason, the grouping of design variables that correlate with each other must also be used. Correlated design variables such as, for instance, those defining the mean camber surface angle at LE, etc, are grouped together. After forming these groups, different weights are associated with each one of them. This is why the new weights are denoted by $w_{i,k}$, where the first index corresponds to the i^{th} design basis and the second one to the k^{th} group of design variables (which b_i belongs to). In conclusion, in place of either eq. 1 or eq. 2, the following equation

$$b_j^{new} = \Phi_j^{-1}\left[\sum_{i=1}^{m} w_{i,k}\Phi_j\left(b^i\right) \Big/ \sum_{i=1}^{m} w_{i,k}\right] \tag{5}$$

is used.

Based on eq. 5, an optimization problem with m·K unknowns (or m·K+1, to also account for Ψ), where K is the number of design variable groups, is set up. Search methods, such as EA (or MAEA), with the proposed parameterization may locate the global optimum, much more efficiently than an EA (or MAEA) based on the conventional parameterization. In this paper, the MAEA of the EASY optimization software developed and brought to market by NTUA, [8], is used. Locally valid, on-line (i.e. during the evolution) trained metamodels (radial basis function networks) are used to approximately pre-evaluate the population members by overcoming the evaluation of non-promising individuals. In the so-called IPE (Inexact Pre-Evaluation, ([4], [5], [6], [7]) technique of the EASY optimization platform, [8], only a small percentage of the population in each generation is evaluated by the exact and costly evaluation tool. The exactly evaluated individuals, in all but a few starting generations (in which the metamodels cannot be used since the database of previously evaluated individuals does not contain enough information for training the metamodels), are all pinpointed by the metamodels.

4 Application: Design of a Francis runner

A multi-objective, multi-operating-point design-optimization of a Francis turbine runner is presented as proof of concept. The quality of a Francis runner is evaluated by considering the pressure coefficient C_p distribution over the blade as well as the outlet velocity profile distributions. Herein, the target is to design the entire runner (including the meridional hub and shroud contours) and, based on the conventional parameterization, an excessive number of designs variables (as many as 336!) would have been used.

To ensure performance stability, the runner to be designed is desirable to yield optimal performance at three operating points (peak point H=40m, part load H=33m and full load H = 48.4m). The three-operating-point design is handled as an optimization problem with two objectives, i.e. a Pareto front is sought. The first objective quantifies the outlet swirl and mass-flow distributions and the second is related to the quality of the C_p plots at the three operating points. In specific:

• *Objective 1* (F_1): minimization of the weighted sum of two quantities, namely (a) the deviation of the outlet swirl distribution from the target one and (b) the deviation of the outlet mass-flow distribution from the target one (see, for instance, fig. 12).

• *Objective 2* (F_2): minimization of the standard deviation of the load along the chordwise direction, by considering the computed C_p distributions along a number (herein, 11) of spanwise equally distributed blade profiles (fig. 13).

The value of each objective function is computed for each operating point separately and, then, the “overall” value F_i is set equal to the weighted sum of the corresponding values for the three operating points.

In the sake of safety against cavitation, inequality constrains are imposed on the σ-histogram. For all operating points, the σ-histogram should be less or equal than a safety-factor times plant σ_{begin}, where σ_{begin} is the value of σ that cavitation starts for the specific plant. Note that the σ-histogram is an approximation to σ, [9],

$$\sigma = \frac{P_\infty - P_{min}}{\frac{1}{2}\rho U_\infty^2} \; \frac{P_\infty - P_{histogram}}{\frac{1}{2}\rho U_\infty^2} = \sigma_{histogram} \tag{6}$$

In the present study, three previous successful designs are used as design bases. The “conventional” design parameters were clustered to form 6 groups: leading and trailing edge relative circumferential position (fig. 2), leading and trailing edge angles (fig. 1), pressure and suction side thickness distributions (fig. 5), meridional contour and profiles (figs. 4 and 6). Based on this grouping, 6 weights per design basis are introduced. Including the extrapolation variable Ψ, 3x6+1=19 optimization variables in total (much less than the >300 design variables of the "conventional" parameterization) are, finally, used.

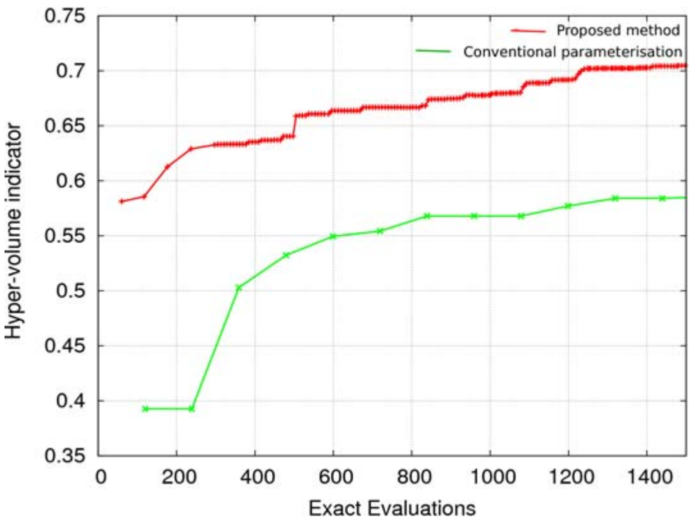

Figure 8: Hypervolume indicator plots for the computed fronts of non-dominated solutions. The horizontal axis corresponds, practically, to CPU cost.

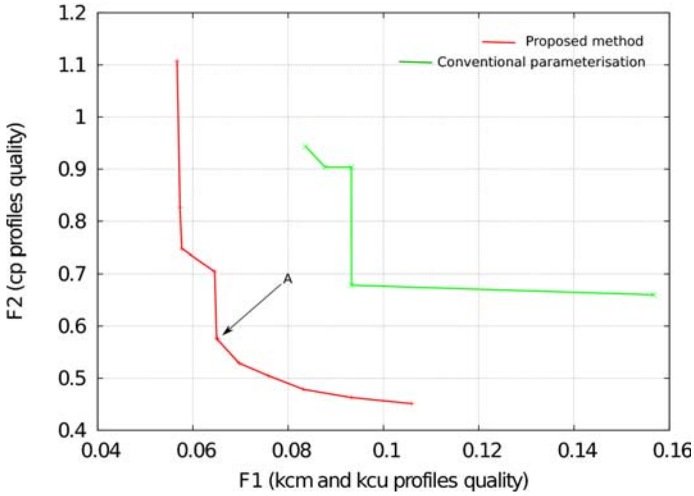

Figure 9: Fronts of non-dominated solutions computed at the cost of 1500 evaluations.

Comparisons between the performance of MAEAs using the "conventional" Francis runner parameterization (336 design variables) and that of the proposed method (19 design variables) are displayed in figs. 8 and 9. In fig. 8, the two optimizations carried out are compared in terms of the hypervolume indicator, characterizing the quality of the computed Pareto fronts. The hypervolume indicator quantifies the part of the design space which is dominated by the Pareto front members; higher values correspond to better fronts of non-dominated solutions. As shown in fig. 8, an extra advantage of using the method proposed in this paper is that it substantially facilitates the use of the artificial neural networks, acting as metamodels. Using metamodels that replace, as much as possible, the number of costly problem-specific (i.e. CFD-based) evaluations, it is possible to overcome difficulties related to their training or the deterioration of their predictive abilities due to the increased number of input parameters. The final fronts of non-dominated solutions are presented in fig. 9. From the front computed using the new parameterization, a single design (point "A" on fig. 9) was selected and used in some other figures, for the purpose of comparison. For the same purpose, the three geometry bases (previous successful designs) are also presented, all of them at the peak load point.

5 Conclusions.

An optimization platform that combines evolutionary algorithms with the ability to exploit information contained in previous successful designs, in order to reduce the computational burden, is used to design a Francis runner. New designs are defined as combinations of the previous successful designs, after clustering similar design variables into groups and associating one weight per group of variables and archived design. This leads to a reasonably small number of design variables, even by an order of magnitude smaller than that of "conventional" parameterizations, and reduces the optimization cost of the evolutionary algorithm. This cost can be reduced even more by using metamodels (artificial neural networks) to screen out non-promising solutions during the evolution, at low cost. The artificial neural networks used profit also of the reduction of the design space dimension, since they become much more dependable.

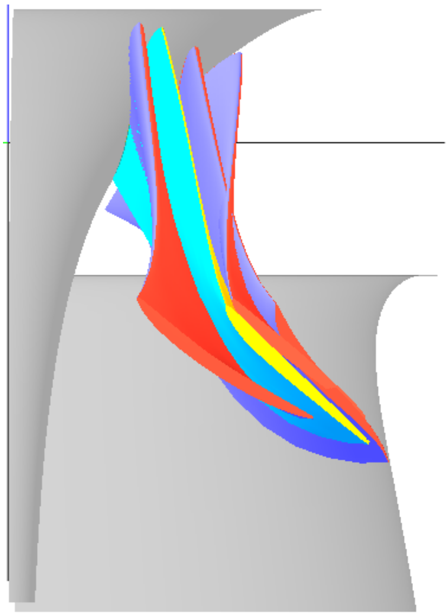

Figure 10: Design "A" (yellow: pressure side, light blue: suction side) in comparison with the geometry bases (red: pressure side, blue: suction side).

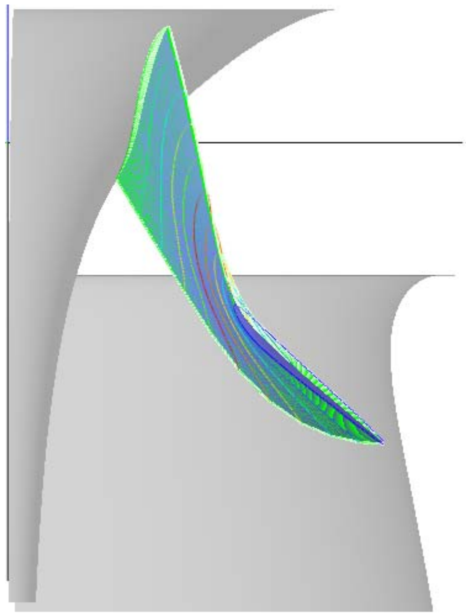

Figure 11: Optimal blade "A" ; mean camber surface and absolute thickness profiles.

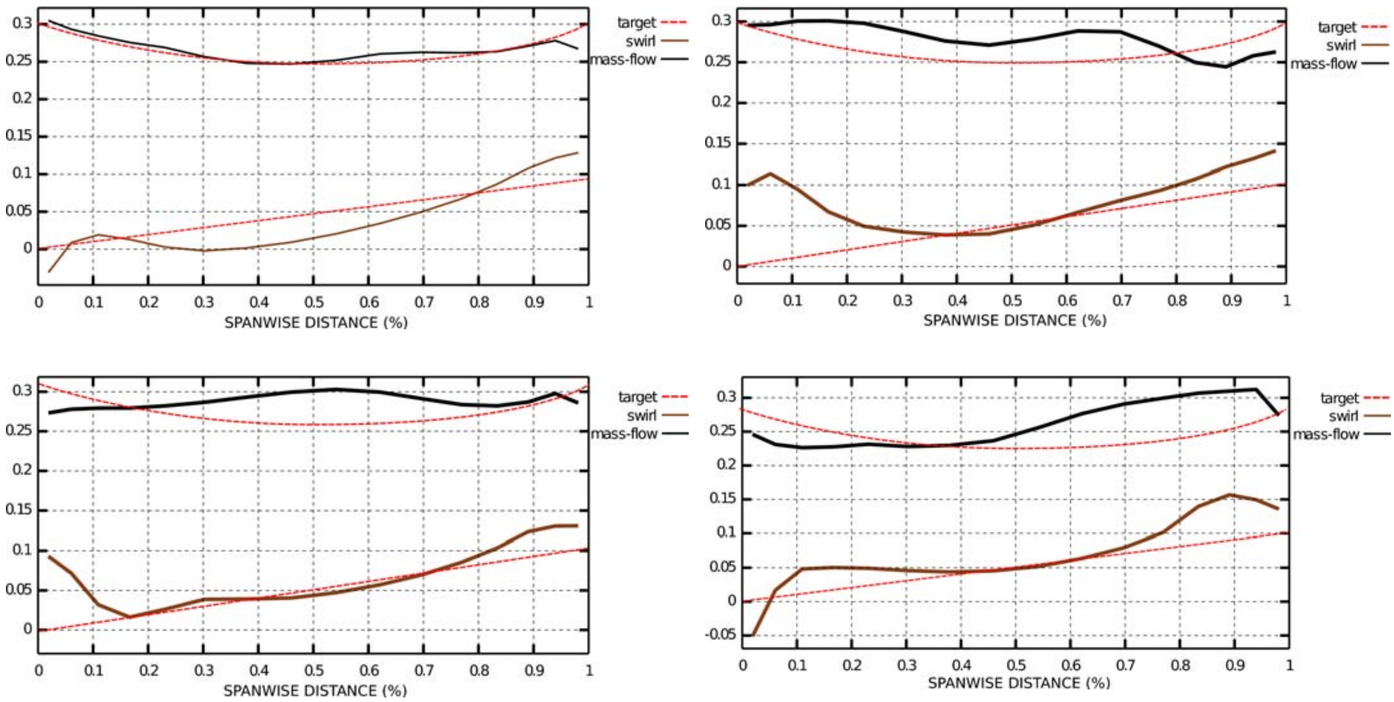

Figure 12 : Swirl and mass distributions (contributing to F_2) for the optimal solution "A" (top-left), the three bases. Target curves are shown in red. Design "A" is by far closer to the target distribution than any of the bases.

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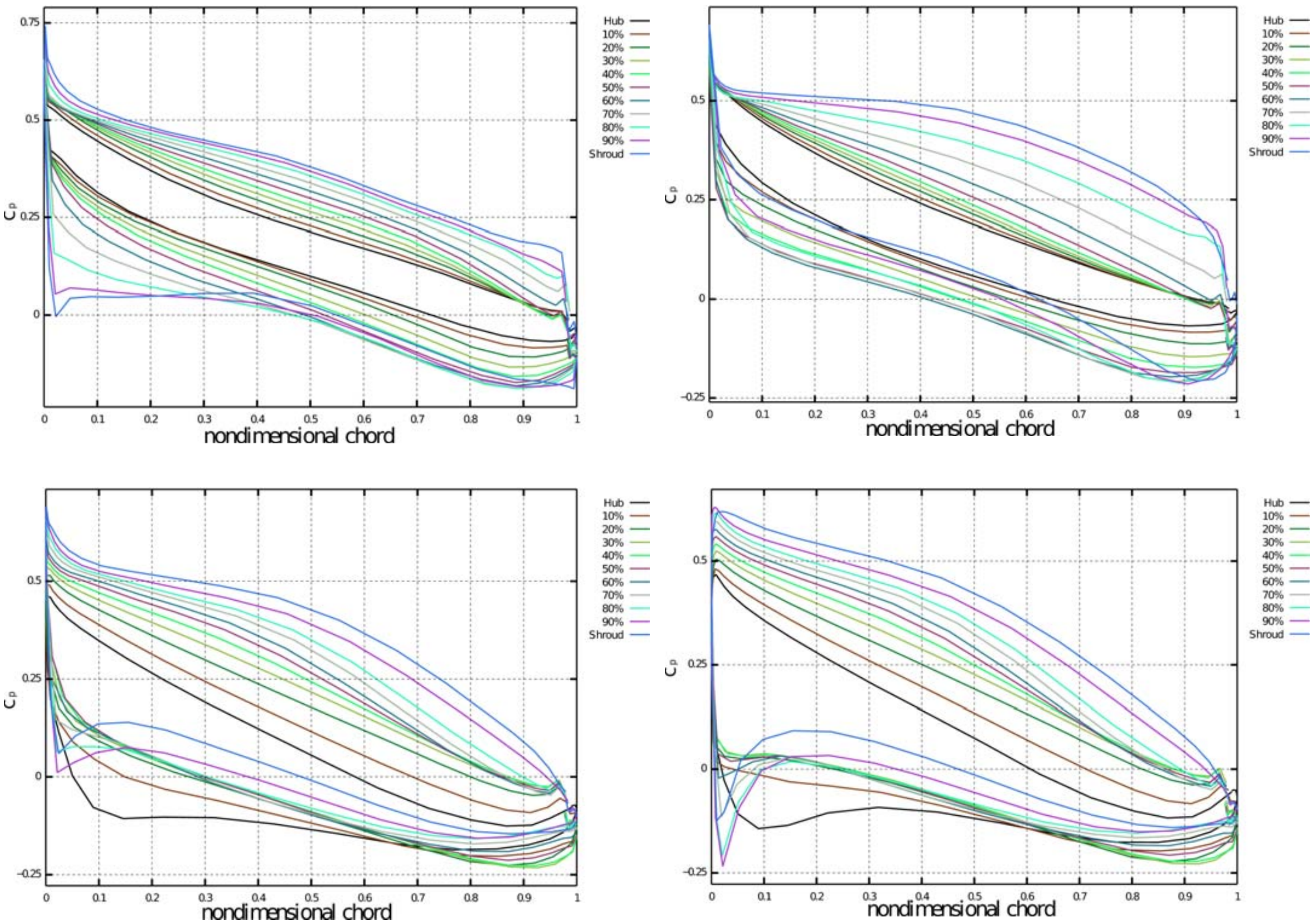

Figure 13: Cp profiles (contributing to F_1) for the optimal solution "A" (top-left), the three bases. The chordwise load stability of "A", compared to the bases, is absolutely clear.