

# Constrained Multi-Objective Design Optimization of Hydraulic Components Using a Hierarchical Metamodel Assisted Evolutionary Algorithm. Part 2: Applications

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## Abstract

In the companion paper, hierarchical metamodel-assisted evolutionary algorithms (HMAEAs) that are capable to efficiently solve costly optimization problems, were presented and demonstrated in design problems associate with a single operating point. In the present paper, the same optimization procedure is adapted to the design of optimal blades of Francis runners, in a multi-objective, multi-operating point way. At first, the industrial viewpoint of the design problem is presented, focusing on its main difficulties and possible approaches to solve it. The optimization targets, such as cavitation safety and desired load distributions along the blade from the leading to the trailing edge, are defined and brought in the form of objective functions. During the design, several geometrical and flow related constraints, concerning the pressure, mass and swirl profiles at the runner outlet, must be met. Emphasis is laid on the problem formulation of Francis and Kaplan runner blades, followed by comments on possible extension to Pelton turbines. A two-level optimization scheme is then set up and solved by employing a two-level HMAEA. On the low level, a low CPU cost exploration of the search space is carried out on a less accurate CFD tool, i.e. an Euler equations' solver running on coarse grids. The high level utilizes a more accurate and CPU demanding simulation process, by focusing on the best performing areas of the design space identified and communicated by the low level.

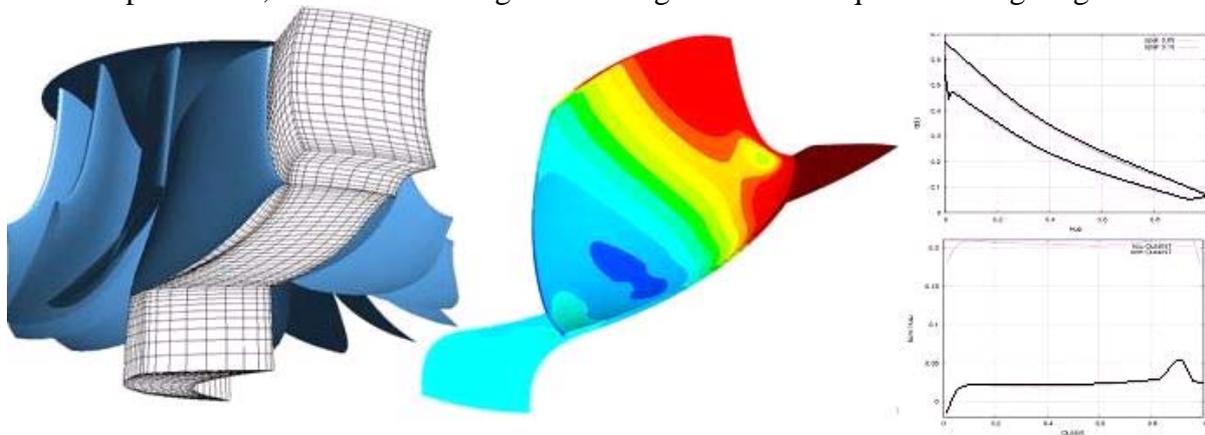
Keywords: design of Francis/Kaplan/Pelton runners; optimization algorithms; evolutionary algorithms; metamodels.

## FROM MANUAL TO AUTOMATED DESIGN PROCESSES

Manual design processes, which are still in industrial use, rely on a series of refinements of existing designs but can easily be trapped into local optimal solutions. For this reason, the outcome of a manual process is often an improved, rather than the optimal, design. The need for using global optimization algorithms, which are able to deal with complex engineering problems with many objectives (related even to different disciplines) and/or constraints, is clear. Among them, evolutionary algorithms (EAs), have already become quite popular. As mentioned in the companion paper [1], their conventional variant is costly and, nowadays, more and more attempts are made to speed up EA-based design processes.

The manual design loop of hydraulic turbine blades uses a fully parametric blade representation based on Bezier curves and B-Splines. All parameters have a geometric and hydraulic motivated meaning, such as the leading or trailing edge angles, the relative circumferential position of the edges, the thickness distribution from hub to shroud and so on

(see [2] for more details). In our applications, a typical design has between 50 and 60 degrees of freedom but there is no limitation concerning either the parameterization or the tool. Integrated in this tool is an Euler equations' solver to numerically predict the inviscid flow field on a single block grid of about 11.000 cells [3,4]. In general, the user does not need to enter data other than a file with the operating points under consideration, as defined once at the beginning of each project. Either the mesh generation or the flow solver and the post-processing tool call for no additional input; they are using "fixed" data files which reflect the experience from previous successful designs. A typical simulation at a single operating point on a modern PC, including mesh generation and post-processing, takes no more than 60 CPU sec, depending mainly on the convergence criterion. So, for instance, working with EAs in the framework of an automated design process, it suffices to have an estimate of the number of evaluations required to get the optimal solution(s) and the number of operating points in order to predict the overall CPU cost. On a cluster of processors, the wall clock time can be noticeably reduced by assigning all the independent evaluations within a generation to different processors, while maintaining the convergence of the sequential design algorithm.



**Figure 1.** Typical view of a mesh created for a Francis runner flow channel. Pressure field, blade load and swirl distribution are also shown.

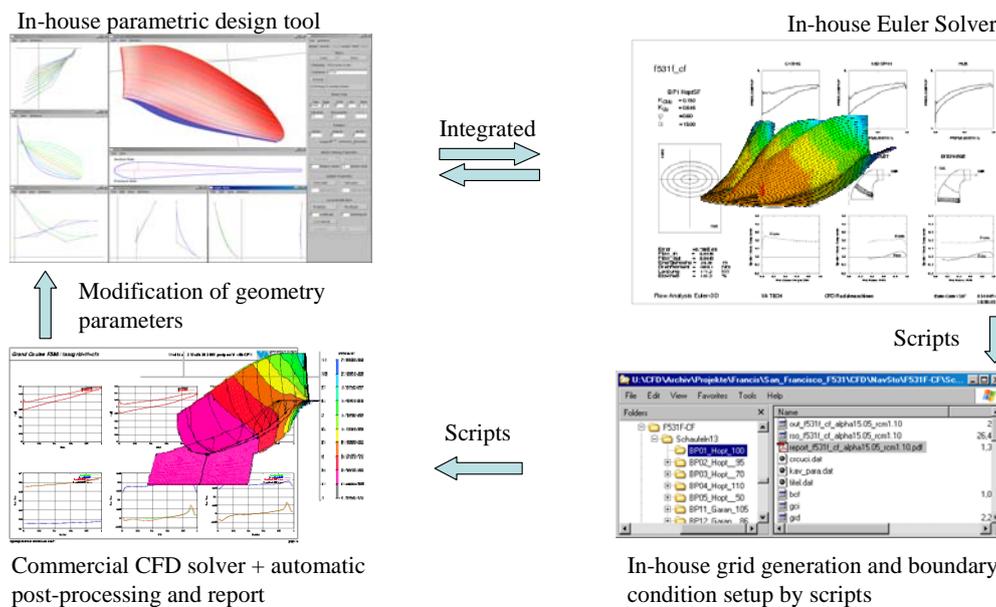
The post-processing provides information regarding flow and pressure fields, in full or condensed form, via diagrams. The designer works, for several loops, with these two tools only, investigating the performance of designs at different operating points. If there is a promising design, then a finer multi-block grid is created and either an Euler (on a finer mesh) [3,4] or a Navier-Stokes (on the appropriate mesh) simulation is carried out. For the finer simulations, typical grid sizes are about 100.000 cells (Euler equations) and 250.000 cells (Navier-Stokes equations). In all cases, the flow domain normally covers only one channel, figure 1, and sometimes includes the guide vanes. The grid generation program may need adaption by tuning some of its parameters (in the data template) at the beginning of the project but, then, works without user-interaction. The obtained flow results provide 'ideas' on how to modify the design parameters and, thus, the blade; this process is illustrated in figure 2. During the design project, the work is shifted more and more from the Euler equations based loop to Navier-Stokes simulations. This shift indicates that the design converges and that the first phase (which, in general, is adequate for the purpose of dimensioning) switches to fine-tuning. Among the decisions to be made during the manual design process, we mention two of them:

(a) Decisions on how to modify the current geometry, by interpreting the results of the flow simulations (either on coarse or fine grids).

(b) Decisions on whether a design should be investigated further using more accurate and expensive tools. Practically, this is equivalent to a decision on whether or not it is worth paying additional time and cost on the current design.

Practically, an automated process does the same without the interference of the engineer. In the automated process, the aforementioned decisions are taken by the optimization program. And that is exactly what the HMAEA is doing. Therefore, from a technical point of view, the manual process matches perfectly the automated hierarchical process. The designer’s skill and experience is replaced by a heuristic learning algorithm, at higher CPU cost. Whether the outcome of the optimization process meets our expectations or not depends strongly on the definition of the objective function which is, thus, of great importance.

Practically, in many industrial design applications, defining the optimization objectives may become complicated, since this is more than just looking for the highest efficiency or the minimum loss at one operating point. In what follows, objectives and constraints for use in the design of Francis and Kaplan runner blade design problems are presented. HMAEAs are adjusted to the problem in hand and a fully automated optimization process, with the minimum CPU requirements, is used. Extension on Pelton turbines is also discussed. Finally, the aforementioned tools are implemented in the optimization of a Francis runner blade.



**Figure 2.** Schematic presentation of a “manual” design optimization approach. The engineer begins from an initial design and proceeds by applying small modifications based on experience. If the new design appears to be promising, after being evaluated on an Euler equations solver running on a coarse grid at low CPU cost, it is re-evaluated using more computationally demanding CFD solvers. If the last evaluation reveals a better design than the initial one, the latter is displaced by the new one. The process goes on until the engineer reaches the desired improvement, as judged by the post-processed results (pressure, swirl distributions etc).

## PROBLEM FORMULATION – OBJECTIVE FUNCTIONS AND CONSTRAINTS

In hydraulic machinery optimization problems, a set of criteria-requirements related to pressure and velocity component profiles, either across the blade–height or the streamlines,

determine the fitness of a candidate design and the constraints to be met. The most important of them are:

- Requirements for constant pressure coefficient ( $C_p$ ) profile from the inlet to outlet. Francis runner blades are designed to carry out small flowrates and operate in high head differences, on which work production is mostly based. Thus, the desired pressure distribution along the blade (from the inlet to the outlet) must decrease monotonically, for constant load. On the other hand, Kaplan runners are mostly used in cases of small height differences and great flowrates, the latter being most important in work production. Thus, the required  $C_p$  profiles for Kaplan runners decrease less while moving from the inlet to the outlet, compared to Francis ones, figure 3.

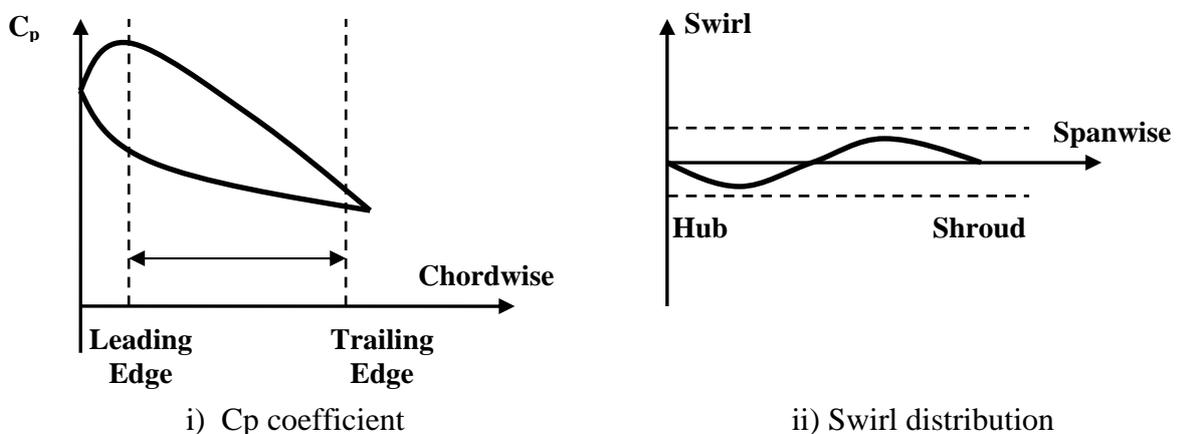
- Requirement for constant meridional velocity distribution along the blade from hub to shroud.

- Criteria related to the swirl distribution from hub to shroud, at the outlet position. For the sake of efficiency and blade stability, we expect that the average swirl at discharge is almost zero or, at least, varies slightly around zero and that the mass distributions from hub to shroud, at blade outlet and discharge, are constant. These criteria are illustrated for Francis and Kaplan turbines in figure 3.

- Designs with reduced cavitation phenomena, [5]. As described in the companion paper, the cavitation effect is quantified by counting down the number of grid regions where pressure falls below the vapor one; alternatively, the cavitation criterion can be expressed in terms of the minimum pressure value on the blade which must be maximized; the application presented in this paper makes use of the latter criterion.

The first criterion represents the “quality” of the  $C_p$  distribution and is our first objective function. The fourth criterion quantifies the behaviour of the turbine with respect to cavitation, is in general contradictory to the previous ones, and constitutes our second objective function. The second and third criteria are often treated as constraints.

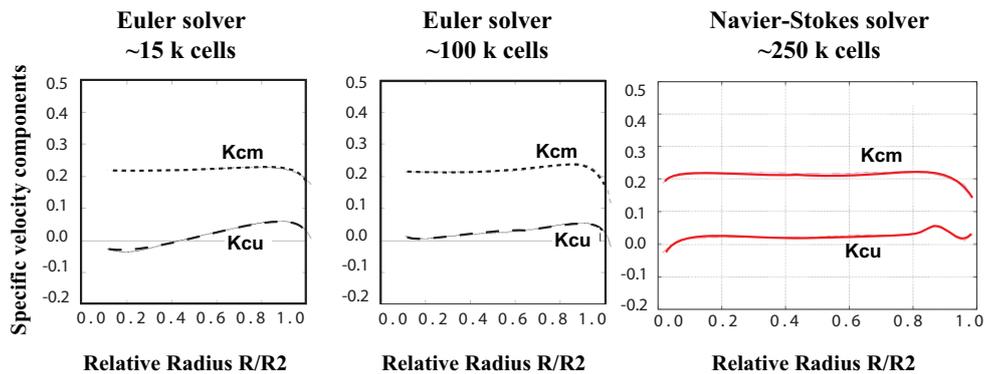
Moreover, in this paper, a multi-operating point optimization policy is proposed. According to this, the cost function is the weighted average of the cost function vectors computed for the design flow conditions and two other operating points close to the design one. This is expressed by  $\vec{f}_i(\vec{x}) = \sum_{j=1}^{N_{op}} w_{ij} \vec{f}_{ij}(\vec{x})$  and ensures the robustness of the obtained solution. Through such an objective function, runners that perform equally well in a range of operating points around the nominal one, can be designed.



**Figure 3.** Recommended constant pressure coefficient ( $C_p$ , left) and peripheral velocity component (right) distributions for Francis runners. Arrows and dashed lines indicate the empirical rules for the desired features of monotonicity of the  $C_p$  profile and zero swirl.

## ADAPTING HMAEAs TO THE PROBLEM IN HAND

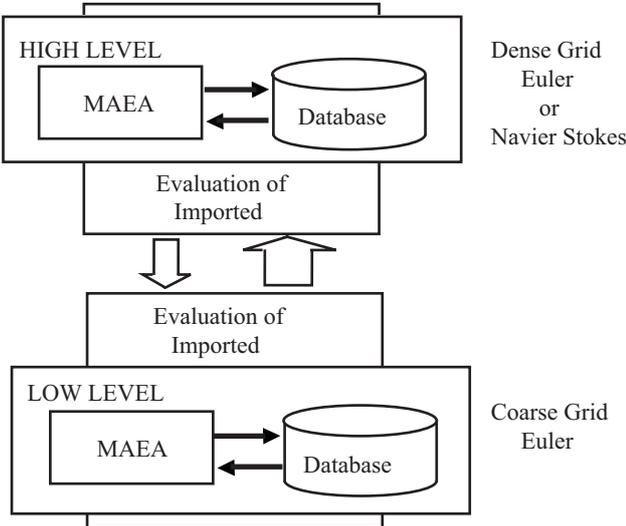
In this section, the adaptation of the HMAEA algorithm, described in the companion paper [1], into the previously defined multiobjective, multi-operating point optimization of runner blades is presented. A two-level optimization structure (HMAEA) is set up: on the low level, a MAEA that uses an Euler equations' solver running on coarse grids to evaluate candidate solutions is in use. The high level utilizes also a MAEA with either the same Euler solver running on a fine grids or a Navier-Stokes solver. The outcomes of Navier-Stokes and coarse- and fine-grid Euler calculations on the same Francis turbine are compared in figure 5; in the same figure, the grid sizes used are clearly marked. On either level, each candidate solution is evaluated at three operating points and the weighted average of the score vector is computed, as described before. Thus, three calls to the CFD solver are needed per individual and level. Since, on the low level, the evaluation of a candidate design involves three calls to a coarse-grid Euler solver and considering that a single point calculation costs around one minute on a PC, the evaluation of a low level candidate solution takes approximately 3 minutes. The ratio of CPU evaluation costs on the high and low levels is about 3 to 1. So, it is reasonable to retain the inverse proportion for the MAEA populations on the two levels. For instance, if the offspring population size on the high level is equal to 50, the corresponding size on the low level should be around 150 offspring. Of course, this is nothing more than a rule of the thumb and different values can be used with likely better performance. Figure 5 illustrates the flowchart of the proposed method. The migration of individuals among the two levels is controlled by user-defined parameters.



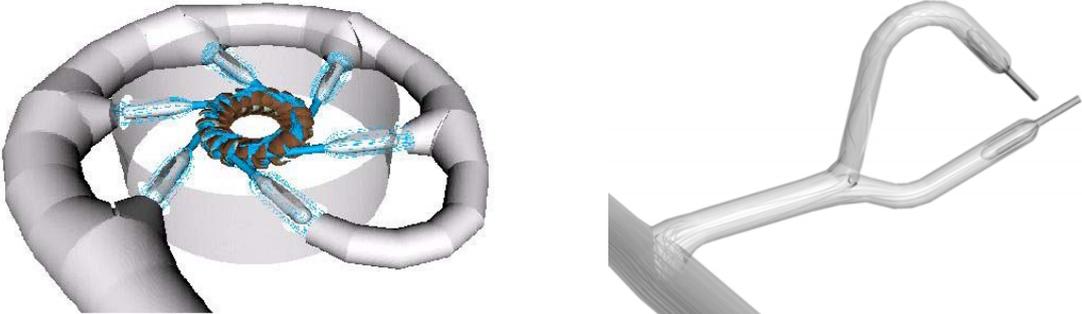
**Figure 4.** Comparison of the coarse- (left) and fine-grid (middle) Euler equations solutions and a Navier-Stokes one (right) on a candidate runner. The specific velocity component distributions at discharge positions are shown.

This methodology is used for the design of a Francis runner. For Kaplan turbines, similar CPU costs are expected. However, for Pelton turbines, the situation is somehow different. In a Pelton distributor, for instance, figure 6 (left), the influence of the quality of water jets on the design is now absolutely clear and this has a direct impact on the turbine efficiency [6]. The jet quality depends on a combination of various parameters including the shape of the jet (as induced by secondary structures; consider, for instance, the case of a two-jet turbine with strong curvature in figure 6 right), its dispersion and turbulence intensity. “Cost” parameters, such as number of segments, weight, and welding length among others, must be taken into account. Indeed, the overall size of the distributor is a key cost parameter of the Pelton plant. Up to now, the optimization of distributors was carried out manually, based on intuition and/or experience, using a combination of qualitative/quantitative parameters. Furthermore, only RANS simulations are applied to predict the flow in the distributors, as viscous effects are critical when simulating flow detachment and jet patterns. The simulation processes are

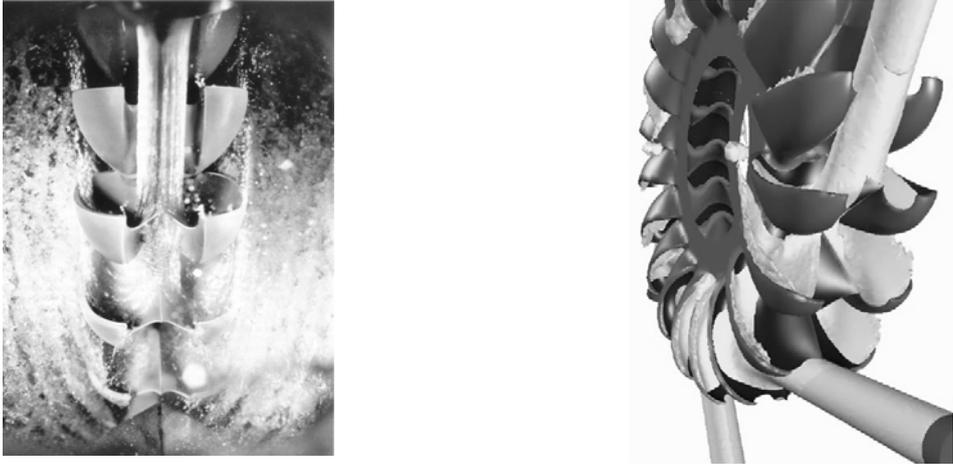
well established and produce results with proper accuracy. Consequently, with the (high) costs of RANS simulations for such components, automatic (EA-based) optimal design processes for Pelton distributors cannot routinely be applied, as for the design-optimization of blades. However, this may serve as a “learning” methodology to identify the influence of specific design parameters and classify their relative influences. This allows reducing the number of the free parameters in a design session and spending more effort on the most sensitive among them.



**Figure 5.** The proposed two-level optimization platform for hydro turbine blades.



**Figure 6.** A Pelton turbine with six jets and vertical shaft (left). Visualization of flow patterns and jet in a two-jet Pelton turbine (right).



**Figure 7.** Flow patterns in a Pelton runner (visualization of water sheets).

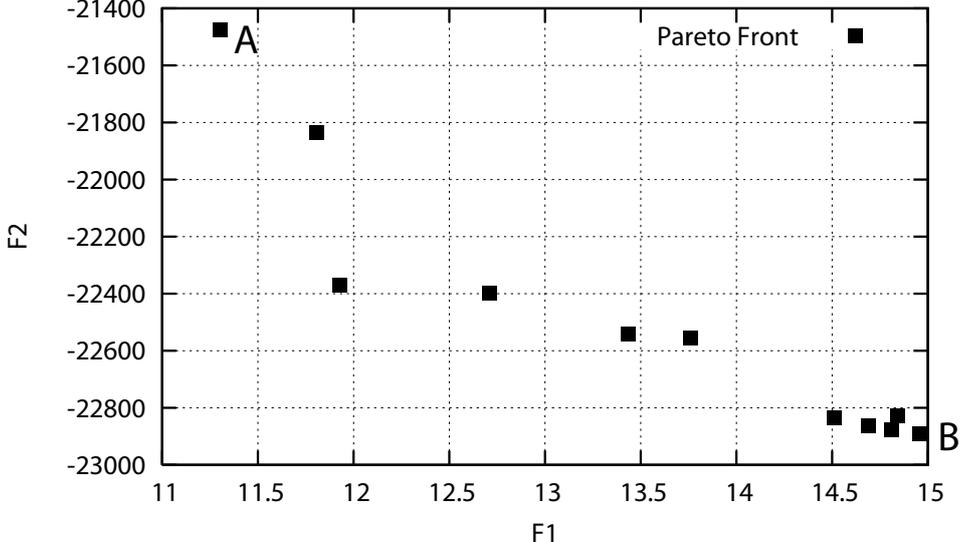
A remaining issue is how to weigh and normalize mathematically the various quality parameters to allow convergence to a “good” design. The complexity is even higher in the case of multi-jet turbines as it appears that the relative importance of these parameters depends on the nozzle under consideration. An analogy can be made with spiral casings in turbine operation where the logarithmic behavior of the flow is well established only after a fair portion of the circumference. The creation of proper objectives functions is handled through a combination of CFD and experimental analyses, which all lead to better understanding of the flow behavior within the Pelton distributors. It is, hence, a worthwhile approach at least from this point of view.

The same discussion applies to Pelton buckets, as shown in figure 7, using experimental and CFD studies, with higher degree of complexity from both numerical and physical point of view [7]. On one hand, the cost for simulating the flow in a Pelton runner is by an order of magnitude higher than that of a distributor. On the other hand, with respect to the high performance level of new generation buckets, the necessary accuracy of CFD must remain below 0.3%, as on model test rigs, to allow design convergence in the optimization loop. This further increases the costs of simulations. Various approaches are under consideration to reduce/eliminate this limitation but this is beyond the scope of this paper.

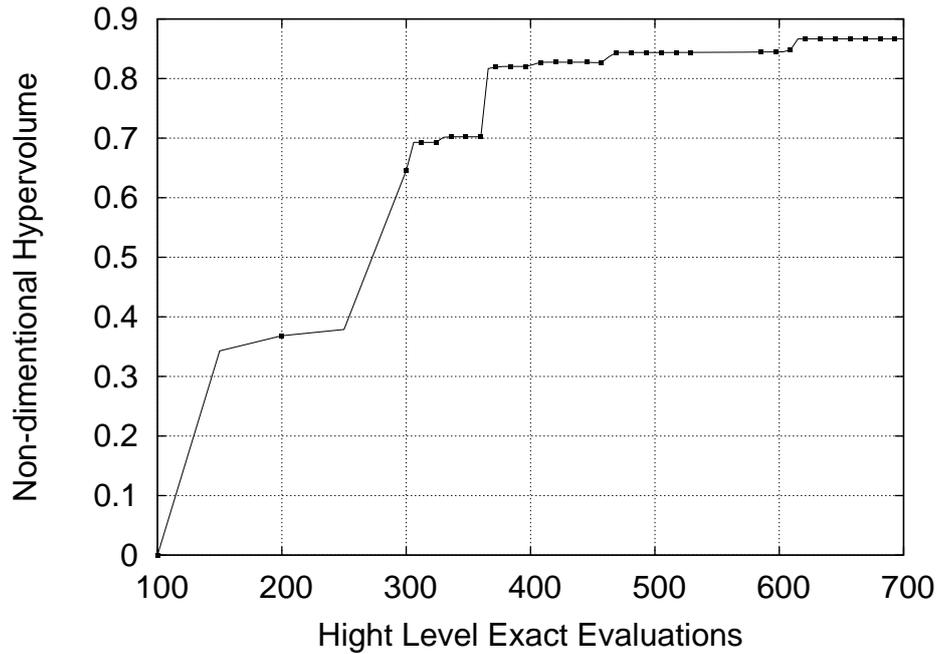
**HMAEA APPLICATION – FRANCIS RUNNER OPTIMIZATION**

The proposed HMAEA is used to design Francis runner blades at three operating points with head [m] and volume rate [m<sup>3</sup>/s] equal to (40, 0.30), (40, 0.38) (design point) and (40, 0.42), respectively. The runner has 17 blades and an external diameter of 0.34 m. The optimization targets are: a) achieving optimal C<sub>p</sub> profiles (F<sub>1</sub>) at casing, median span and hub, with the less possible monotony changes, i.e. constant or at least constantly decreasing load along the blade and b) minimization of the cavitation effect (F<sub>2</sub>), by increasing the minimum pressure value on the blade.

The parameterization was the same used in the “manual” approach and relies on Bezier polynomial curves to generate the 3D blade shape. The control points of these curves constitute the design variables, being free to vary between user-defined bounds. Any candidate solution is forced to respect the list of constraints described in the problem formulation section.



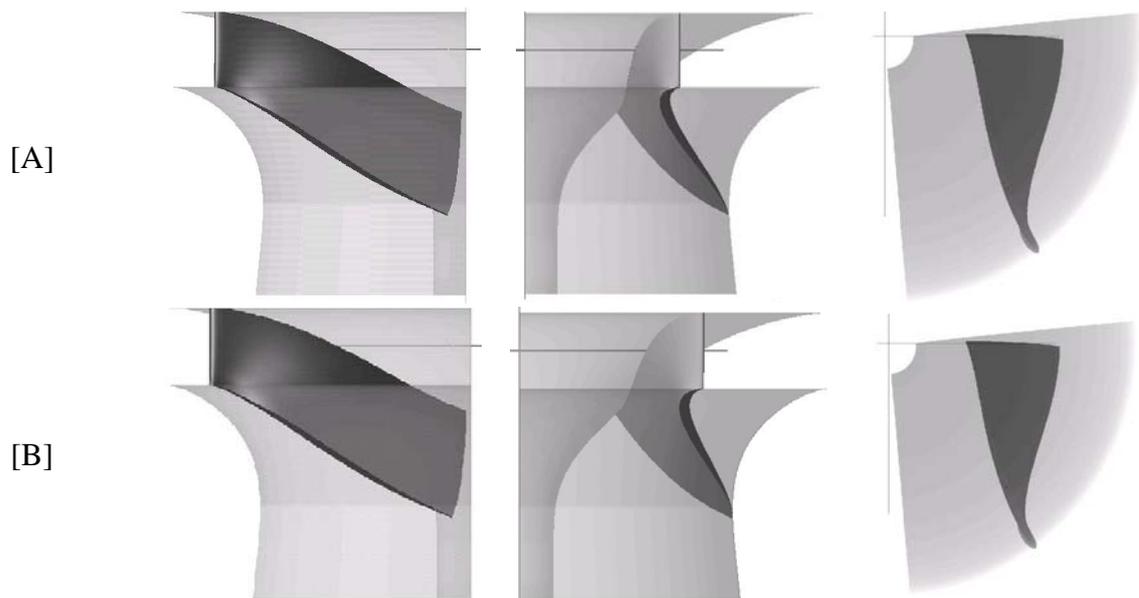
**Figure 8.** Non-dominated fronts, i.e. the approximated Pareto front computed after 700 high level exact evaluations. Note that both (F<sub>1</sub>, F<sub>2</sub>) must be minimized.



**Figure 9.** Convergence of the Pareto front approximation. The abscissa corresponds to exact evaluations on the high level. The ordinate gives a measure of the non-dimensionalized hypervolume indicator of the Pareto front approximation; we recall that this is a scalar quantity that measures the hypervolume (herein area) of the part of the objective space which is dominated by the current front; a user-defined reference point  $(F_{1,REF}, F_{2,REF})$  determines the upper-right corner, on the  $(F_1, F_2)$  plane, figure 8, of the dominated area. In the present figure, filled rectangles indicate the migration of promising low level individuals to the high level.

The optimization is carried out using a  $(50, 14, 50; 6)$  MAEA with a dense grid (100.000 cells) Euler solver as the exact evaluation tool on the high level and a  $(100, 35, 50; 10)$  MAEA with a coarse grid Euler solver (15.000 cells) on the low level. Metamodels start being used upon completion of the fourth high level generation and the second low level one. As soon as the phase of Inexact Pre-Evaluations starts and metamodels take over, only six (high level) and ten (low level) members of the current generation on each level undergo exact evaluations. Every two high level generations, the ten current best individuals migrate from the low to the high level. The same number of elite individuals migrate from the high level to the low one, every three low level generations. Immigrants to the any level undergo evaluations using the destination level tool.

Figure 8 presents the Pareto front approximation consisting of the non-dominated fronts after 700 exact high level evaluations. In figure 9, the evolution of the Pareto front approximation on the high level is illustrated by also showing the interference of migrations to the high level (shown as filled rectangles). The plotted quantity is the so called hypervolume indicator and quantifies the part of the objective space that is dominated by the current front. A reference point on the objective space must be defined, as explained in the figure caption.



**Figure 10.** Blade shapes corresponding to the two solutions at the edges of the approximated Pareto front. With respect to figure 8, the blade marked with [A] is the one with the best  $C_p$  distribution, according to our expectations and the corresponding objective function ( $F_1$ ). The blade marked with [B] stands for the shape that gives the best performance with respect to cavitation.

## CONCLUSIONS

This paper discussed, from the industrial point of view, manual and automated design processes for hydraulic machine runners. The discussion presented above demonstrates that an automated process (a hierarchical method, in specific) practically mimics the process of manually designing the blade, in the sense that the initial dimensioning process is followed by refinement (this time, without interventions by the engineer). Discussions focus on the design of Francis runners. The method is expected to perform equally well in the design of Kaplan runners but the extension to Pelton turbines is not that straightforward; the reasons for the latter have been exposed in detail. Thus, the hierarchical metamodel-assisted evolutionary algorithm is used for the design of a Francis runner at three operating points and with properly defined objective functions.

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