Advanced Optimization Tools for Hydro Turbine Runner Design

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Abstract. The objective of this work is to show how advanced optimization tools can be used for hydraulic turbine design, taking the example of a Francis runner design (new or refurbishment project). The public test case considered corresponds to a R&D turbine model of specific speed Ns = 0.5, originally developed at the Hydraulic Machinery Laboratory (LMH) of École Polytechnique Fédérale de Lausanne (EPFL). Firstly, a standard Computational Fluid Dynamics (CFD) process is used to predict performances, in the form of efficiency and cavitation behaviour. It features structured mesh for distributor (stay vane and guide vane), runner and draft tube. Automatic scripts are created to run computations for several guide vane openings and rotation speeds, covering the whole range of operating conditions, and allowing to obtain numerical hill charts of efficiency and minimum pressure to predict the occurrence of cavitation. Secondly, some operating points are purposefully selected for the optimization and objectives are defined to maximize efficiency while constraints are set for preventing cavitation. To continue with, a parametric blade model is defined: 3D blade shape is obtained from blade to blade sections and a stacking law. Sections are defined by camber and thickness. Finally, a Surrogate Based Optimization (SBO) with Evolutionary Algorithm (EA) is used for searching a global optimum. Design of Experiment (DOE) techniques are employed to efficiently define a database. Dynamic monitoring, data-mining and visualization tools are used; including Leave-One-Out (LOO), Analysis of Variance (ANOVA) and Self-Organizing Maps (SOM), with the objective of facilitating surrogate reliability assessment and a comprehensive understanding of key factors of the problem studied. This methodology is tested iteratively with the Francis Runner Hydraulic design: a first optimization is run, analysed and used to define a second optimization that shows increased benefits in particular for Best Efficiency Point. The results are analysed from a hydraulic point of view to identify the benefits and effects of the last optimization.

1. Introduction

Optimization tools are nowadays often used in the turbomachinery industry, in particular for hydraulic blade runner design, either for new or refurbishment projects. As a matter of fact, the whole optimization process, typically featuring surrogate model and evolutionary algorithms, is usually presented as a black box for the user and designer, with a difficult control and measurement of its correct functioning. In this context, being able to check the performances of the process and analyse the results permits to identify how to improve the optimization process, to further enhance a design and/or shorten the design cycles. This paper describes an optimal runner design project where advanced optimization tools, such as Leave-One-Out Cross-Validation (LOOCV), Analysis of Variance (ANOVA) and Self-Organizing Maps (SOM), are used for surrogate reliability assessment and to facilitate a comprehensive understanding of key factors of the problem studied.

The whole process, from original to final optimized turbine analysis (efficiency hill chart and cavitation behaviour), is applied to the well-known GAMM turbine case developed at the Hydraulic Machinery Laboratory (LMH) of École Polytechnique Fédérale de Lausanne (EPFL) [1]. This public test case
corresponds to an R&D turbine model of specific speed \( N_s = 0.5 \). Geometry (see figure 1) as well as flow conditions are publicly available. Validation data is also provided for some operating points and has been largely used to cross-check accuracy of CFD codes.

![Figure 1. Meridional views of the turbine geometry (distributor and runner, draft tube)](image)

In the presented work, we focus on the optimal design procedure, rather than on validation aspects. The CFD model and design objectives used are representative of a real hydro turbine design project: multipoint optimization is considered with cavitation constraints for the blade. A similar process has already been successfully used for industrial projects of Francis, Diagonal or Kaplan turbines [2, 3].

2. CFD modelling and original results

The commercial package FINE\textsuperscript{TM}/Turbo developed by NUMECA is used for the CFD simulations of this study. Computational domain consists of three blocks: the stay vane and guide vane are meshed together, whereas runner blade passage, as well as the draft tube are in two additional blocks. Interfaces are used to connect the three domains. The meshes are generated with AutoGrid5\textsuperscript{TM} and IGG\textsuperscript{TM} for bladed components and draft tube, respectively. All grids are structured, with matching nodes on the periodic boundaries. Similar grids are generated for every guide vane opening considered. Total cell count is 3.2 Million for each grid. Some views of the computational domain and mesh generated are shown in Figure 2.

![Figure 2. Computational domain and B2B mesh of distributor and runner (with one repetition)](image)

3D Navier-Stokes simulations are carried out on these grids, using Spalart-Allmaras turbulence model [4], with rotating blocks for the runner and the following boundary conditions set: total pressure and flow direction at inlet, periodic boundaries, mixing plane rotor/stator interface and static pressure at outlet.
A total of 60 computations are run, for 10 guide vane openings (GV 15° to GV 37.5°) and 6 rotational speeds (from 387 to 581 RPM), to create a numerical efficiency hill chart. Efficiency is calculated as per International Electrotechnical Commission (IEC) code formulas [5], extracting torque and mass flow from the simulations. Minimum values for static pressure on different blade surfaces (Leading Edge, Pressure and Suction Sides) are also extracted from the 3D field to assess cavitation risk on the operating space. Static pressure value corresponding to cavitation inception has been defined with IEC code formulas and a Sigma value of 0.35 that was defined from existing hydropower project specifications [6]. Figures 3 and 4 show the results obtained for original geometry as 2D contour plots on energy (Ψ) versus mass flow (Φ) coefficient space. On Figure 3, 3 operating points have been marked that will be used in the optimal design objectives. For cavitation occurrence, negative values in red report existence of static pressure values lower than vapor pressure, while positive values in green are cavitation-free.

![Figure 3. Numerical efficiency hill chart for original GAMM geometry](image)

![Figure 4. Cavitation occurrence chart for LE and SS for Sigma = 0.35.](image)

The numerical results show a BEP in agreement to experimental data, and retrieve correctly the double peak shape of efficiency hill chart, characteristic of this configuration [1]. Regarding cavitation occurrence, there is no experimental data available, yet numerical results for the arbitrary value of Sigma = 0.35 report LE cavitation for a large area at high energy (Ψ) and mass flow (Φ) coefficients.

3. Optimization procedure and tools

3.1. Software tools
The optimization process has been performed using NUMECA software FINE™/Design3D, which has multiple techniques available based on the concept of function approximation [7]. It features a blade
parametric modeller AutoBlade™ and an advanced optimization package MINAMO™, recently integrated from CENAERO developments. This optimization and post-processing kernel uses cutting-edge genetic algorithms, design of experiments techniques and efficient non-linear surrogate modelling. It also includes post-processing and data-mining capabilities (LOOCV, ANOVA, SOM). These tools are integrated in a compact all-in-one graphical user interface.

3.2. Optimization method
The approach features the use of an approximate or surrogate model and genetic or evolutionary algorithms to find an optimum. The purpose of the approximate model is to have a fast method able to mimic the real blade performance predicted by the accurate model (i.e. the CFD simulations). This method requires the existence of a database containing several blade geometries and their associated hydraulic performances. These database samples are used to construct the approximate model.

As a first step in a runner hydraulic optimization process, a blade parametric model is defined where a set of parameters corresponds to a particular geometry. Then, to complete the information to obtain a valid sample, an accurate evaluation must be performed with several CFD runs. In this project, hydraulic information (efficiency, cavitation behaviour based on blade minimum pressure) is wanted for 3 operating points, therefore 3 different sets of meshing, running and post-processing tasks need to be performed for each geometry. Due to the large number of tasks, these steps are automated and run in batch. Before launching the optimization, an objective function must be defined as a sum of penalties with proper weights, each penalty being a scaled difference from the desired result (for example maximum efficiency, or a minimum pressure on the blade above vapor pressure). Finally, the optimization algorithm selects samples maximizing the objective function, and is run iteratively, so that every new sample is used to enlarge the database, improving the surrogate model predictions near the optimum.

3.3. Advanced optimization tools

3.3.1. Design of Experiments (DoE)
The Design of Experiments, which is the sampling plan in the design parameter space, is a crucial ingredient of the optimization procedure, especially when the function evaluations are expensive, because it must concentrate as much information as possible. Indeed, the quality of surrogate models are mainly related to the good choice of the initial sample points. The challenge resides in the definition of an experimental set that will maximize the ratio of the model accuracy to the number of experiments, as the latter is severely limited by the computational cost of each sample point evaluation. Evaluation of the target function is carried out separately in the following step; DoE exclusively focus on the generation of uniformly distributed sample points, without any information on the corresponding target function values. Of all DoE techniques offered by MINAMO [8], in this project we used the default choice of Latinized Centroidal Voronoi Tessellations (LCVT) [9].

3.3.2. Leave-One-Out Cross-Validation (LOOCV)
The LOOCV procedure is a way to estimate the accuracy of a surrogate model without the need of an external dataset for validation. The method uses a single sample point from the original data set as the validation data, and the remaining sample points as the training data. This is repeated so that each sample point in the database is used once as validation data. Finally, one obtains a set of estimated outputs (with LOOCV) and one of real outputs for each response. These output sets can be statistically analysed for error estimation by computing a correlation coefficient. From this analysis, a user can select the best surrogate model for each design problem and eventually decide to increase and improve its database. Figure 5 presents two different cases of correlation coefficients, satisfactory or not.
Figure 5. Plot of actual vs. predicted values: example of satisfactory or not correlation coefficients.

3.3.3. **Analysis of Variance (ANOVA)**

The ANOVA decomposition in MINAMO is a global sensitivity analysis i.e. the global variability of an output over the entire range of the input variables of interest. ANOVA allows to quantify the notion that some variables and interactions are much more important than others by computing the Sobol's global indices [10]. Figure 6 shows a typical pie chart used to define most important parameters of a response (for example efficiency).

Figure 6. ANOVA displays of a response (OP1 and OP2 efficiency).

3.3.4. **Self-Organizing Maps (SOM)**

The idea of SOM is to project high-dimensional data onto a low-dimensional (typically two-dimensional) map. For doing so, they use a neighbourhood function to preserve the topological properties of the input space, therefore similar data items will be mapped to nearby locations on the map. SOM allow the user to identify "clusters" and may reveal which features the members of a cluster have in common. These visual inspection tools are useful for revealing major trends and discovering correlations and anti-correlations among parameters and/ or responses.

Figure 7. Self-organizing maps for two antagonist responses (OP1 and OP2 efficiency).
4. Blade parametric model
A model of 5 stacked sections has been defined to generate the 3D blade. A camber curve and its thickness addition define each section, and stacking is done on the leading edge (Figure 8):
- Camber curve is defined by 3 angles: inlet, camber and outlet angle.
- The thickness of the blade section is defined by a Bezier curve of 10 parameters.
- Stacking is done on the leading edge along a sweep (Z, R plane) and a lean (span,θ) curve.

Using this topology, a fitting process is performed for the runner to retrieve the geometrical parameters corresponding to the existing 3D shape. A set of initial parameters is thus obtained.

5. Optimal design objectives
The objectives for optimal design have been defined arbitrarily, but in an analogue way as for other industrial design projects:
- Move and increase Best Efficiency Point (BEP) towards OP1;
- Maintain efficiency level for two other operating points (OP2 and OP3), so that we avoid a peak-shaped hill chart;
- Reduce or remove cavitation occurrence on the runner blades. For this constraint, the same arbitrary and challenging sigma value as before (0.35) has been considered.

The operating points selected are shown on the efficiency hill chart of original geometry (Figure 3).

6. First optimization
6.1. Database and optimization
To define a design space large enough to reach a global optimum, the variable parameters of the blade parametric model and their bounds are to be carefully defined. In this project, the LE shape (lean and sweep) as well as all sections camber curves angles were freed, while band, crown and profiles thickness were fixed. A total of 21 parameters were thus defined as variable. For the bounds, some manual testing can be done initially to ensure notable changes of geometry and a simple a posteriori check is performed to avoid that any parameter reaches its minimum or maximum bound.

Usually, the number of database samples should be 2 to 3 times the number of free parameters; in our project about 100 samples were run, in order to cope with potential incorrect elements (geometry, mesh or computation failures).

After generating the database, the LOOCV tool was used to assess the surrogate model: after comparing the results for various techniques available, Kriging method was selected, as it was offering the highest correlation coefficients for efficiency and cavitation response, and optimization was launched for 30 iterations. Figure 9 presents a history plot of this optimization.
6.2. CPU costs
Although the number of simulations to perform is quite high (3 operating points per sample for 135 elements for a total of more than 400 CFD runs), CPU costs are reasonable: the full process can be run in a week on a 24 cores workstation (equipped with an Intel Xeon® CPU ES-2697 v2 @ 2.70 GHz).

| Process                  | CPU time (CPU.h) | Clock time          |
|--------------------------|------------------|---------------------|
| Mesh generation          | < 5 min          |                     |
| CFD run (per OP)         | 8 h              | < 1 h (12 procs)    |
| Post-processing          | < 5 min          |                     |
| Hill Chart (60 OP)       | 500 h            | 1 day (24 procs)    |
| Database (100 samples, 3 OP) | 2500 h         | 5 days (24 procs)   |
| Optimization (30 iterations) | 720 h         | 1.5 day (24 procs)  |

Table 1. CPU costs of the various processes

6.3. Results analysis
The results of the first optimization in terms of efficiency are shown in Table 1. Some improvements are obtained in particular for OP1 and BEP, that are now very close in the hill chart. The optimization also respects the cavitation constraints.

|       | BEP     | OP1     | OP2     | OP3     |
|-------|---------|---------|---------|---------|
| ORI   | 90.6 %  | 89.6%   | 88.3%   | 85.5%   |
| OPT1  | 92.0%   | 91.8%   | 86.5%   | 86.3%   |

Table 2. Efficiency values for used operating points of original (ORI) and optimal design (OPT1)

Besides hydraulic results, optimization tools ANOVA and SOM are used to find out potential improvement of the process.

Figure 9. Scatter plot: OP1 efficiency for database (blue) and optimization (orange) samples
ANOVA indicates that parameters with the most significative influence on efficiency are located at the shroud sections (camber parameters of last 2 sections). It is therefore recommended to refine the blade parametric model locally.

SOM analysis shows that OP1 and OP3 responses are correlated, meaning that OP3 could be left out of the optimization procedure, therefore reducing the computing time by one-third. On the other hand, OP1 and OP2 responses appear to be antagonist (Figure 7). That is why optimal design will be a compromise between increasing OP1 efficiency while not excessively decreasing that of OP2. Similar observation may apply for the cavitation constraint.

7. Second optimization

Based on previous results a new optimization is performed:

- Parametric model is modified by refining the sections distribution, reducing the distance to the shroud;
- Initial design is set now to be OPT1, by resetting initial parameter values to the ones of OPT1.

Thanks to the affordable CPU costs of the process, the same number of samples and iterations are employed for this second optimization.

Results of this optimization are given in Table 3 and the full set of simulations (10 GV openings and 6 rotation speeds) is performed to obtain the numerical efficiency hill chart and cavitation occurrence plots. The BEP point moves as wanted, with an increase in efficiency of about 2%, and cavitation behaviour is improved by reducing the risk for a wide range of operating conditions (Figures 10 and 11). A visual comparison of the geometry obtained and the original design is presented in Figure 12.

|         | BEP  | OP1  | OP2  | OP3  |
|---------|------|------|------|------|
| ORI     | 90.6%| 89.6%| 88.3%| 85.5%|
| OPT2    | 92.7%| 92.4%| 86.9%| 87.0%|

Table 3. Efficiency values for main operating points of original (ORI) and optimal design (OPT2)

Figure 10. Numerical efficiency hill chart for optimal design OPT2
8. Conclusions

A hydraulic optimal design of the GAMM turbine runner has been presented, where advanced optimization tools were used to improve the capabilities of the optimization. After characterising the hydraulic performance of the runner using an efficient CFD model, a first optimization has been done to move and improve BEP value, while removing cavitation risks. This optimization has been analysed using advanced tools: including Leave-One-Out Cross-Validation (LOOCV), Analysis of Variance (ANOVA) and Self-Organizing Maps (SOM); some ways of improvement of the whole procedure have been identified and implemented. A second optimization has been run to achieve further benefits: final runner has a BEP efficiency of about 2% higher than original design, and cavitation risks were significantly reduced.

Thanks to the advanced tools used, optimal design procedure is made comprehensive, key parameters can be identified, and computational cost can be reduced to the minimum, leading to better results overall, and opening the door to more complex optimizations, by introducing a more complete simulation system, or increasing the number of parameters to achieve even more innovative designs.
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