Multilevel design optimization of hydraulic turbines based on hierarchical metamodel-assisted evolutionary algorithms

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Abstract. In this paper, an efficient hydraulic optimization procedure is presented and applied to the design of hydraulic turbines. For computationally expensive industrial design optimization problems, an advanced optimization tool (EASY software) and a fast CFD evaluation tool are required. EASY optimization software is a Hierarchical Metamodel-Assisted Evolutionary Algorithm (HMAEA) that can be used in both single- (SOO) and multi-objective optimization (MOO) problems. In order to minimize the CFD solver calls during the optimization design, the MAEA rely on local metamodels, trained on the fly, that are used to identify the most promising members in each population and then only these are to be re-evaluated by the CPU costly CFD solver. For additional economy in the CPU cost, the hierarchical (two-level) optimization scheme is used in this paper, where at each level, a different evaluation tool, a low and a high fidelity specific software, can be linked. The low level utilizes a low-CPU cost and low-accuracy tool to explore the design space with a minimum impact to the wall clock time and the high level, using the high fidelity, high-CPU cost tool is used to exploit the information from the low level. For the applications presented in this paper, the high fidelity model is an incompressible Navier-Stokes equation solver and the low fidelity model is based on the solution of the incompressible Euler equations. In order to optimize the geometry of hydraulic machines, an in-house automatic geometry and mesh generation tool has been integrated in the optimization tool chain. In what follows, 2 three-objective design optimization problems of 3D Francis hydraulic turbines are presented. The optimization objective functions concern the ‘quality’ of the runner outlet velocity profile, the cavitation behavior and efficiency of the runner. The optimization results of the hydraulic turbine components along with the performance of the presented optimization procedure are shown in the paper.

1. Introduction

In real-world engineering applications, such as industrial applications, the optimization for every day design is extensively used, although the computational cost is often quite high. The most known representative method of the global optimization methods is the Evolutionary Algorithms, EAs. The hydraulic design of a hydraulic machine is one of those applications, where the optimization using the EAs can be a non-affordable task for every day design, since the computational cost can be quite high.
after a great number of evaluations that might be needed, in combination also with a high number of design variables.

In order to support and facilitate hydraulic blade designers in their task, an automatic design optimization toolchain is integrated in the design procedure. In this way, the EA design optimization, starting from an existing blade can explore the design space and come up with an optimal blade geometry based on the objective functions and constraints that define the optimization problem. Apart from the requirement of an advanced optimization software (herein the Evolutionary Algorithm System – EASY, [1]), this toolchain consists essentially of a parametric geometry generation tool, a parametric mesh generation tool and an incompressible Computational Fluid Dynamics (CFD) solver. The automatic hydraulic optimization toolchain with its components is schematically presented in figure 1.

For the initiation of the optimization loop, a set of user-defined parameters (design variables) is generated by EASY in order to obtain a set of new candidate solutions. In the hydraulic optimization application, the geometrical parameters consist the design variable set. For each one of these geometries, a numerical grid is created and a CFD simulation is then carried out. The optimization objective functions refer to the hydraulic efficiency of the blade, the cavitation behavior and the quality of the outlet velocity profiles. The values of the objective functions indicate the quality of each candidate solution and are subsequently used by EASY to generate the next generation of candidate solutions. In this way, the optimization searches for the optimal geometries that maximize the hydraulic efficiency and minimize cavitation for a specific outlet velocity profile. In addition to that, due to operational range constraints (i.e. cavitation limitations), the optimal solutions are subject to a number of constraints that can be added in the optimization problem.

In this paper, in order to reduce the CPU optimization cost, the technique of hierarchical search that is supported by EASY was used. Based on this technique, a low (Euler equations’ solver) and a high fidelity model (Navier Stokes equations’ solver) can be used in a multilevel structure in order to speed up the optimization.

Figure 1. The hydraulic optimization toolchain for runner design applications based on the EASY optimization tool.

In what follows, the multilevel technique that is used in the optimization is described in detail and the three-objective optimization design problems of two Francis hydraulic turbines based on the multilevel optimization method are presented.
2. Optimization Platform

Engineering optimization problems can be solved using either stochastic or gradient-based optimization methods. Evolutionary algorithms (EAs) are the most frequently used global search methods. Any analysis software can be accommodated as a black-box tool and reach the optimal solution without being trapped into local optima. The solution of optimization problems associated with a computationally demanding evaluation software, such as CFD codes, becomes expensive. To reach the optimal solution(s), EAs may require a great number of objective function evaluations, increasing, in this way, the CPU cost and making the whole process non-affordable for industrial use.

In order to overcome this weakness and reduce the wall-clock time of EA-based optimizations, several techniques have been proposed. These techniques can be divided in those reducing the optimization time by performing concurrent evaluations of the candidate solutions on different processors and in those trying to reduce the number of evaluations needed to reach the optimal solution(s). The most common technique, that aims to reduce the number of evaluations needed, is the use of surrogate evaluation models, the so-called Metamodel-Assisted EAs (MAEAs), [2], [3]. The metamodels are used to inexpensively approximately evaluate the objective function value(s), after being trained on previously-seen evaluated individuals. According to the inexact pre-evaluation approach, with the exception of a few starting generations, all population members are approximately evaluated using local metamodels trained on the fly. Then, a few of them, practically the most promising among them, as indicated by the metamodel, are re-evaluated on the exact model. In this paper, the MAEAs technique and the concurrent evaluation scheme is activated in EASY and used for the runner optimization applications, as in [4], [5], [6], [7], [8].

Additionally, in this paper the technique of hierarchical search (Hierarchical EAs, HEAs, [9], [10]), that is supported by EASY, was used for speeding up the optimization. In HEAs, low and high fidelity models are used with a certain hierarchy according to a multilevel search structure. A different evaluation tool (Multilevel Evaluation), a different search algorithm (Multilevel Search) and/or a different set of design variables (Multilevel Parameterization) can be associated with each level of the multilevel optimization algorithm. In this paper the technique of Multilevel Evaluation is used. At the low level, the low fidelity evaluation tool is assigned with the exploration of the design space, while a search based on the high fidelity model is performed at the high level on migrated promising solutions, coming from the low level. In this way, the low level is responsible for detecting promising solutions at low CPU cost, through low-cost evaluation models, and delivering them to the higher level. There, higher fidelity evaluation models of higher CPU cost are used and the solutions that migrate from the lower level are re-evaluated, making the higher level responsible for delivering the optimal solution(s) of the optimization. A two-way communication between the two levels can be also used. Individuals that migrate from one level to another are automatically re-evaluated using the destination level model. This means that higher level individuals may also move to the low level, so as to stimulate a more exhaustive search in their neighborhood, based on a low-cost evaluation tool. At the low level, evolution terminates, if it consistently fails to provide the upper level with well performing solutions. A multilevel evaluation maintains separate databases at each level. The multilevel technique is described in more detail in [9], [10], [11]. For the multilevel evaluation method that was used, the high level is based on the Navier Stokes equations’ solver and low level is associated with the Euler equations’ solver. The two flow solvers have an average CPU cost ratio of approximately 10:1.

3. Optimization problem: Objective functions

For the definition of the optimization problem, the objective functions of the optimization are presented as follows. Both hydraulic design optimization applications in this paper are concerned with a three-objective runner design optimization. The optimization objective functions that are used refer to

1. \( F_1 \): the quality of the runner outlet velocity profile: the deviation of the circumferential and meridional velocity profiles, at the exit position of the runner, from the target velocity profiles at the outlet, constitutes the first objective function. Since the exit of the runner coincides with
the inlet to the draft-tube, a required mass flow and swirl distribution can be defined as a target, so that the candidate solutions of the optimization try to follow the distributions at the outlet. In this way, the first optimization objective refers to the minimization of this deviation.

2. $F_2$: the maximization of the weighted average efficiency of the runner.

3. $F_3$: the minimization of cavitation which corresponds to the maximization of the minimum pressure observed on the runner surface. In case that there is a cavitation limitation, this can be also used as a constraint.

### 4. Hydraulic Design Optimization Cases

#### 4.1. Case 1

The first application presented in this work is concerned with the three-objective design optimization of a Francis runner. The objectives vector comprises of the three objectives that were presented in Section 3. The optimization is based on a three-operating-point design, including the best efficiency (BE) point and two points at maximum and rated head, respectively. Each objective function is computed for each operating point separately and, then, a weighted sum of the corresponding values for the three operating points, is calculated based on the weights of Table 1. For the first objective, the velocity profiles are based on BE point and the efficiency is the average weighted sum of the three operating points. As far as it concerns cavitation, the objective concerns the maximization of the minimum pressure on the blade among the three operating points.

| Operating Point     | $F_1$ weights | $F_2$ weights |
|---------------------|---------------|---------------|
| Best Efficiency OP  | 1             | 1             |
| Maximum head OP     | 0             | 0.6           |
| Rated head OP       | 0             | 0.3           |

The optimization design variables are based on the runner blade parameterization tool, [6], including 11 and 15 control points for the B-spline curves that describe the spanwise metal angle ($\theta$) distribution at leading (LE) and trailing (TE) edge respectively, 11 and 16 control points for the B-spline curves that correspond to the circumferential positions of the LE and TE ($\theta$) respectively and 11 and 16 control points for the curvature of the mean camber surface for the LE and TE ($\zeta$) respectively. The LE and TE meridional positions are parameterized also with 12 design variables each, reaching a total of 99 design variables, Table 2.

The multilevel evaluation method was used for the optimization, where the high level is based on the N/S solver and the low level is associated with the Euler solver, with a CPU cost ratio of 10:1. In Table 3, the multilevel optimization settings are presented. The first interlevel migration takes place before the first generation of the high level and after 10 generations of the low level. In this way, the low level provides better solutions, due to the higher number of generations. The CPU cost, after any migration, which means after $e_1$ evaluations with the N/S solver and $e_2$ with the Euler solver, is equal to $e_1 + e_2/10$ CFD evaluation cost units. At this first migration, 20 elite individuals migrate to the high level, where they are once again evaluated with the N/S solver this time. At the same time, the low level receives 5 elites from the high level, in order to perform a more detailed search in their neighborhood, based on the low-cost evaluation tool. The optimization problem was studied with $\mu=15$ parents and $\lambda=30$ offspring for the high level and $\lambda=50$ offspring for the low level, since each evaluation of the low level is based on a low cost evaluation tool.

| Table 1. Weights used for $F_1$ and $F_2$. |
|-------------------------------------------|
| Operating Point     | $F_1$ weights | $F_2$ weights |
|---------------------|---------------|---------------|
| Best Efficiency OP  | 1             | 1             |
| Maximum head OP     | 0             | 0.6           |
| Rated head OP       | 0             | 0.3           |

| Table 2. Design variables number and their description. |
|---------------------------------------------------------|
| # design variables | design variables                        |
|---------------------|-----------------------------------------|
|                     | Spanwise distributions of $\theta$      |
|                     | 27                                       |
|                     | Spanwise distributions of $\zeta$       |
|                     | 22                                       |
|                     | Spanwise distributions of $\beta$       |
|                     | 26                                       |
|                     | LE and TE                               |
|                     | 24                                       |
At the cost of 820 CFD evaluation cost units, the computed Pareto front of non-dominated solutions based on the multilevel evaluation mode (HMAEA) can be seen in figure 2. The 820 cost units refer to 540 (18 generations) and 280 (55 generations) cost units of the high level and low level, respectively. 9 inter-level migrations were performed during the optimization and in 6 out of 9, a number of elites that migrated from the low level were included in the Pareto front of the high level. In figure 2, the initial solution, which is imposed as a candidate design in the population of the first generation, is also plotted and an optimal design is selected from the two-level optimization pareto front. The optimal geometry outperforms the initial one in both deviation from target velocity distributions and cavitation by keeping the efficiency almost at the same level.

Table 3. The multilevel optimization settings for the high and low level.

| Parameter                              | High Level | Low Level |
|----------------------------------------|------------|-----------|
| Offspring Population Size              | 30         | 50        |
| Parent Population Size                 | 15         | 15        |
| Elite Population Size                  | 50         | 50        |
| Generation of First Migration          | 1          | 10        |
| Elites Imported on First Migration     | 20         | 5         |
| Migration frequency (generations number)| 1          | 5         |
| Elites Imported                        | 15         | 5         |

A comparison between the optimal and initial design objectives can be seen in figure 3. The outlet velocity profiles of the optimal design are in high agreement with the target distributions, both at the circumferential and meridional plane, which is important for the draft-tube feeding. This can be seen in figure 3, on the right, where the deviation between target-optimum is lower than the target-initial one. As for the cavitation behavior of the runner blade, the pressure distribution at the shroud is presented also in figure 3 for the initial and optimal blade geometry, for the operating point with the worst cavitation behavior. As it can be seen, the minimum pressure at the LE has been increased giving a cavitation free operating point. The pressure distribution is also plotted on the blade for the initial and optimal blade geometry in figure 4, showing also the small differences in the blade shape.

In terms of comparison, an optimization is also performed based on a single-level evaluation with the N/S solver, using the same configuration as the high level of the multilevel optimization. In order to evaluate the contribution of the Euler low level to the multilevel optimization, a comparison between the single (classic MAEA) and two-level (HMAEA) optimization is shown in figure 5 for the first generations at the cost of 135 CFD evaluation cost units. Performing a fair comparison, 60 cost units (2 generations) of the high level and 75 cost units (15 generations) of the low level are compared with 120 cost units (4 generations) of the single-level optimization. For F1 and F3 objectives, the multilevel front outperforms the single-level from the first generations, as it can be better seen in close up view in figure 5.

In figure 6, a comparison between the multilevel (HMAEA) and single-level (MAEA) approach for a three objective optimization with the same configuration but for one operating point this time, the BE one, is presented for generation 22 and 47 of HMAEA and generations 33 and 68 of MAEA for equal cost units. In this case, where the Euler solver focuses on the improvement of the cavitation behavior on one operating point, the advantage of using the multilevel algorithm can be seen more clearly, since it outperforms the single-level and reaches a better non-dominated solutions front at the same cost units, or, it can reach the same front as a single-level optimization at lower CPU cost.
Figure 2. Pareto front of non-dominated solutions based on the multilevel evaluation (HMAEA) at the approximate cost of 820 CFD evaluation cost units. The initial and the optimal design are also included, showing that the optimal design is significantly better in $F_1$, $F_3$ and slightly better in $F_2$. For the $F_1$, $F_3$ pareto front, a close-up view of the pareto front is also plotted.

Figure 3. On the left, the pressure distributions of the initial and optimal design at shroud location. For the initial design, cavitation is observed at the LE, while the optimal one is free of cavitation. On the right, the deviation of the initial and optimal design velocity profiles from the target ones at the outlet. Higher agreement between target-optimum outlet velocity profiles than target-initial, for both circumferential ($k_{cu}$) and meridional ($k_{cm}$) positions.
Figure 4. The pressure distribution on the blade of the initial (left) and optimal (right) design is plotted. The minimum pressure observed for the initial design at LE at the shroud location (dark blue area) has been increased through the optimization giving raise to the optimal design, as it can be seen also in figure 3. The pressure distribution of the optimal design is above zero (light blue color).

Figure 5. A comparison between the multilevel (HMAEA) and single-level (MAEA) approach is presented for generations 2 and 4 of the HMAEA and MAEA, respectively, for equal cost units, showing the contribution of the low level in the optimization.
Figure 6. A comparison between the multilevel (HMAEA) and single-level (MAEA) approach for a three objective optimization for one operating point, the BE one, is presented for generations 22 and 47 of the HMAEA and generations 33 and 68 of MAEA for equal cost units.

4.2. Case 2
The second application represents the three objective design optimization of a Francis runner based on three operating points, the best efficiency (BE), full-load (FL) and part-load (PL) point, as before. This application concerns the same objectives as in the previous case and the weights used for the weighted average efficiency are 0.85, 0.05 and 0.15, respectively, since more focus is put on increasing the efficiency of the BE point and cavitation of the other two. A total of 41 design variables were selected in order to parameterize the blade, including 11 control points for each one of the beta, theta and zeta distributions at LE and TE edge, and 8 control points for the LE meridional positions. The multilevel evaluation method was used also for this case with \( \mu=15 \) parents and \( \lambda=30 \) offspring for the high level and \( \lambda=50 \) offspring for the low level.

The Pareto front of non-dominated solutions, that was acquired after 1375 CFD evaluation cost units, is presented in figure 7. The 1375 cost units refer to 930 (31 generations) and 445 (89 generations) cost units of the high level and low level, respectively. The optimal geometry selected from the Pareto front, figure 7, has an increase in hydraulic efficiency (0.15% for BE, 0.5% for FL and 0.1% for PL), as well as a gain in terms of deviation from the target velocity profiles, keeping the minimum pressure on the blade almost at the same level as the initial design. The streamlines at the pressure side of the initial and optimal blade for the BE point, shown in figure 8, indicate also the differences in blade shape that concluded in a higher efficiency blade. In figure 9, the differences in shape can be more clearly seen comparing the initial to the optimal blade geometry.

In both cases shown in this paper, the high level is selected to be initialized by the elites of the low level at the first migration. This means that the first population of the high level will include elites migrating from the low level, which will be re-evaluated with the N/S solver and included in the first generation (generation 0) in case they are better than the initial one. In this case, the high level waits the low level for 10 generations, to finish in order to start its evaluations. In figure 7, generation 0 is also plotted. A comparison between generation 0 and the initial design indicates the good performance of the low level, since all four elites of generation 0 have migrated from the Euler level and are included in the first generation, giving a boost in the optimization right from the beginning.
Figure 7. Pareto front of non-dominated solutions based on the multilevel evaluation (HMAEA) at generation 31 and generation 0, along with the initial and optimal design. The four elites of generation 0 of the high level have migrated from the low level and are successfully integrated in the first generation, indicating that the low level has detected promising solutions at low CPU cost.

Figure 8. The streamlines for the BE point at the pressure side of the initial (left) and the optimal (right) blade, with the latter to have a significantly higher efficiency and a gain in terms of deviation from the target velocity profiles, keeping the minimum pressure on the blade almost at the same level as the initial design.

Figure 9. Differences between the initial (gray) and optimal (blue) blade.
5. Conclusion
In this paper, for additional economy in the optimization CPU cost, a hierarchical (two-level) optimization scheme, that is supported by the EASY optimization software, was used for the runner design optimization. The Euler equations’ solver was used in this two-level optimization as the low cost evaluation tool for the low level, next to the N/S solver for the high level, contributing to the speed up of the optimization. One- and three- objective optimization problems for three operating points have been examined, giving rise to optimal designs, that can be used by the designers either as a better starting geometry to continue on with designing or for further optimization, by adapting once again the design parameters, objectives and constraints.

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