Multi-fidelity design optimization of Francis turbine runner blades

S Bahrami\textsuperscript{1}, C Tribes\textsuperscript{1}, S von Fellenberg\textsuperscript{2}, T C Vu\textsuperscript{2} and F Guibault\textsuperscript{1}

\textsuperscript{1} École Polytechnique de Montréal, Montreal, Quebec, Canada
\textsuperscript{2} Andritz Hydro Ltd, Pointe-Claire, Quebec, Canada

E-mail: salman.bahrami@polymtl.ca

Abstract. A robust multi-fidelity design algorithm has been developed, focusing to efficiently handle industrial hydraulic runner design considerations. The computational task is split between low- and high-fidelity phases in order to properly balance the CFD cost and required accuracy in different design stages. In the low-fidelity phase, a derivative-free optimization method employs an inviscid flow solver to obtain the major desired characteristics of a good design in a relatively fast iterative process. A limited number of candidates are selected among feasible optimization solutions by a newly developed filtering process. The main function of the filtering process is to select some promising candidates to be sent into the high-fidelity phase, which have significantly different geometries, and also are dominant in their own territories. The high-fidelity phase aims to accurately evaluate those promising candidates in order to select the one which is closest to design targets. A low-head runner case study has shown the ability of this methodology to identify an optimized blade through a relatively low computational effort, which is significantly different from the base geometry.

1. Hydraulic turbine design process

Big changes in global energy demands, increasing environmental concerns, and huge growth potential of cost-efficient hydroelectric energy, have recently resulted in significant changes in the hydropower industry. In this growing international market, there is more need to design hydraulic turbines which are more efficient and durable. As design challenges are getting more complex, runner designers rely more than ever on engineering and simulation tools, especially computational fluid dynamics (CFD), to obtain reliable designs with a competitive time and cost. Although runner designers already employ CFD tools to evaluate their designs, there is a strong need to integrate more tightly CFD analyses in the design chain using efficient optimization methods to obtain more efficient design processes.

A full range of CFD methods has been utilized in the optimization of hydraulic turbine runner blades. Low-fidelity inviscid models (e.g. potential flow) have been employed by some researches such as Holmes and McNab \cite{1}. However, they are not accurate enough in their prediction of flow behavior, mainly due to lack of physics. High-fidelity viscous models have been used to optimize the runner as well (e.g. using turbulent RANS solvers, by Franco-Nava et al. \cite{2} and Pilev et al.\cite{3}); but they are too expensive and slow for iterative industrial runner design processes. To reduce high-fidelity analyses in the optimization loop, surrogate-based optimization approaches have been increasingly employed by hydro researchers, whereby computationally inexpensive approximation models are used in lieu of high-fidelity CFD models. For instance, Artificial neural network was...
applied by Derakhshan et al. [4] to reduce Navier-Stokes solver calls during the optimization of a low-head axial hydro turbine by genetic algorithm. Also, several researchers have used radial basis functions (such as Georgopoulou et al. [5]). Although those approximation models have been used for blade shape optimizations, they still require a large number of high-fidelity viscous evaluations to update the surrogates, and to ensure that they yield reasonably accurate results.

Beside all the aforementioned researches and investigations, industrial runner design process currently relies extensively on the designer’s intuition and experience, using both inviscid and viscous flow analyses, but mostly without using an optimizer. Runner designers can use fast inviscid flow solvers, to carry out most design iterations in early phase of the design process. The high-fidelity analyses are also considered to further assess the design quality and adapt the characteristics searched during the earlier phase. To fulfill industrial design needs, a new practical multi-fidelity design optimization methodology has been developed, which is also a new method from hydraulic research point of view. Based on previous investigations, in this methodology the optimizer employs a computationally-cheap inviscid flow solver in the low-fidelity phase to alleviate cost of high-fidelity CFD evaluations. The low-fidelity optimization problem is corrected by accurate high-fidelity information in an overall design loop. Previous investigations (e.g. by Alexandrov et al. [6], Robinson et al. [7], and by Leifsson and Koziel [8]) indicate that multi-fidelity methods require much fewer high-fidelity viscous evaluations than surrogate models to obtain a given level of accuracy. To comply with runner designers’ approaches, the proposed design framework involves all existing design resources (see Figure 1), adding an automatic optimization loop to decrease designer interactions.

In the next section, the multi-fidelity optimization algorithm is presented which is based on this design framework.

2. Multi-fidelity design optimization methodology

2.1. Low-Fidelity phase
The main iterative computations are carried out in the low-fidelity phase which contains the low-fidelity optimization loop (Figure 2). It aims to approach the major design characteristics via thousands of fast and computationally inexpensive low-fidelity (i.e. inviscid flow) evaluations within an optimization loop. This loop starts with a low-fidelity parameterized model (i.e. a few design variables) representing the initial geometry. Inviscid flow field calculations produce the required information, such as velocity and pressure distributions on the blade, to evaluate objective functions and constraints. An optimizer selects new design variable values, based on the improvement or deterioration in the objective and constraint values. The low-fidelity optimization phase focuses on meeting specific target flow characteristics that are indirectly associated with low energy losses.
(equivalently high machine efficiency). In this project, a potential flow solver has been chosen as the inviscid flow solver.

A derivative free optimization algorithm has been selected to handle the problem at hand. NOMAD (Non-smooth Optimization by Mesh Adaptive Direct Search) [9] is an open source [10] C++ implementation of the Mesh Adaptive Direct Search algorithm [11].

![Multi-fidelity design optimization algorithm](image)

2.2. Filtering process

Based on the number of objectives, the dominant solution or a set of them (i.e. Pareto optimal solutions) can be identified after the low-fidelity optimization. However, differences between low-fidelity optimization results and high-fidelity Navier-Stokes results are expected, which is due to assumptions of inviscid flow evaluations. Preliminary investigations have approved that other feasible optimization solutions that are not too far from dominant solutions can also bring high efficiency in Navier-Stokes evaluations. Therefore, a versatile filtering algorithm (filtering unit in Figure 2) has been developed to select a few promising candidates which are geometrically different and dominant in their own territories. These candidates are transferred to the high-fidelity phase for Navier-Stokes evaluations.

The filtering process contains the following parts:

- Filtering feasible optimization solutions.
- Mapping the design space into a distributing standard hypercube.
- Distributing those solutions into small unit-length hypercubes.
- Selecting one dominant candidate from each unit-length hypercube.
- Selecting a few geometrically-different candidates out of all selected candidates via a clustering method.

The details of proposed filtering processes are available in a previous publication [12].

2.3. High-fidelity phase

In the high-fidelity phase (see Figure 2), a viscous flow solver is used to accurately evaluate selected candidates. It aims to choose the best design candidate which has a good efficiency at the right operating condition, and minimum cavitation. This design candidate may be transferred into the low-fidelity phase as a new initial design for the next optimization step, or selected as the final design based on certain convergence criteria or computational budget limit. The number of design variables of the best candidate may be increased when it is transferred, mainly in order to give more flexibility to the optimizer to satisfy real constraints in the next step. By analyzing the results of the high-fidelity phase, it is possible to recalibrate the objectives and constraints, in order to obtain the desired results and expected final goals in the high-fidelity phase.
Due to rotational periodic conditions, the viscous flow analysis is performed only for a single passage of the runner flow. This domain is usually discretized using approximately 200,000 structured cells. The commercial Navier-Stokes code ANSYS-CFX has been employed for the flow field simulations using the standard two-equation k-ԑ RANS turbulence model. Details of the methodology, integrated tools and validations can be found in the references [13-15].

3. Optimization arrangement
The optimization problem is formulated as:

Minimizing \( f(y) \)

Subject to \( g_j(y) \leq 0 \); \( y_l < y < y_u \)

Where \( y \) is the N-dimensional vector of design variables, and \( y_l \) and \( y_u \) are respectively the lower and upper bounds of design variables. One objective and three constraints have been defined in this project.

3.1. Objectives
Previous investigations in Andritz Hydro and École Polytechnique de Montréal have indicated that the blade length can affect directly or indirectly most blade design criteria, such as proper pressure distribution and blade loading, and minimum pressure drop. Therefore, minimizing the length of the blade has been chosen as the optimization objective. The objective function is calculated from the average of the camber line lengths on specific blade sections.

3.2. Constraints
Three constraints control important design criteria addressing minimum losses and maximum efficiency at the right operating condition:

- **Velocity constraint:** To control the losses in the draft tube, it is necessary that the runner delivers an appropriate tangential velocity profile at the draft-tube inlet [16, 17]. Therefore, this velocity component has been determined to be similar to a targeted profile within a safe bound, which is based on designers’ experiences.
- **Blade loading:** one constraint prevents negative blade loading on all blade sections.
- **Cavitation:** one constraint has been defined to limit the minimum allowed pressure for all blade sections, in order to address cavitation issues during the optimization.

4. Test case
A low-head Francis turbine runner has been chosen. The goal is to design a runner such that on a given efficiency curve (speed coefficient; \( N_{ed} \) equal to 0.407) it provides the peak position at a given flow coefficient; \( P_{ed} \) equal to 0.294. This turbine contains 13 runner blades and 20 guide vanes.

4.1. Initial geometry and design variables
Figure 3(a) shows blade edges and runner inner/outer contours, projected in the meridional plane. Figure 3(b) illustrates the simple geometry of the initial blade. Figure 3(c) shows the aggregated fluid flow domain considered in the computational analyses. Inlet and outlet boundaries are illustrated on the top and bottom of the blade respectively. Figure 3(d) illustrates the whole runner considering rotational periodicity of the flow domain.
Blade geometries are parameterized through an in-house software developed by Andritz Hydro Ltd. [18]. The software allows changing the number of parameters representing the geometry, modifying each of them, and visualizing the geometrical model.

Table 1 shows the main geometrical parameters and design variables. Curvature of the blade is governed by the beta angle parameter on nodes along streamline sections from the leading edge to the trailing edge. Blade length is defined by the camber line length in each section. The lean of the leading edge is represented by theta points on a 2D projected curve from band to crown. Delta beta, delta length, and delta theta are three different types of design variables which are used in the optimization to control variations of beta, length and theta respectively. The band-side contour is optimized using cylindrical coordinates (i.e. r and z) of two points located downstream of the leading edge on the band. Proper bounds of variations are defined for each four types of design variables. Seventeen design variables have been employed during the optimization. The initial geometry is a poor hydraulic blade shape (see Figure 3(b)). Its thickness has been created using a NACA blade thickness profile (see Figure 4).

Table 1. Number of independent parameters & design variables

|                         | Initial model parameters | Optimization design variables |
|-------------------------|--------------------------|------------------------------|
| Blade curvature         | 9                        | 9                            |
| Blade length            | 11                       | 2                            |
| Blade leading edge      | 11                       | 1                            |
| Band contour            | 20                       | 4                            |
| Crown contour           | 43                       | Fixed                        |
| Blade thickness         | 80                       | Fixed                        |
| Number of blades        | 13                       | Fixed                        |

4.2. Results

40,000 potential flow evaluations were carried out in the low-fidelity optimization loop. Then the filtering unit connected the two design phases by selecting four promising candidates out of all
feasible solutions, and sending them for high-fidelity analyses (see Figure 5). These candidates are as different as possible in the design space. For instance, Figure 6 shows that those selected candidates have been located in different mapped hypercubes, which have been presented in this figure from different design variable perspectives in two 2D mapped design spaces. As it is obvious in this figure, the bounds of all design variables have been divided into four equal sections by the filtering unit.

![Figure 5](image1)

**Figure 5.** Objective function value versus iteration number of feasible solutions.

![Figure 6](image2)

**Figure 6.** Distribution of selected solutions in the mapped design space.

High-fidelity Navier-Stokes analyses indicate that the 38173rd solution of the optimization is the best selected candidate, which has the efficiency curve peak at the targeted power coefficient with less than 1% error (see Figure 7), while it has satisfied all constraints. The optimized blade is much shorter with a complex pattern of blade curvature with about 8 degree modification of the leading edge lean. Using length objective with three well-defined constraints has led to energy loss minimization and large efficiency enhancement (about 5.5%) at the right operating condition.
Satisfaction of tangential velocity constraint has significantly improved the tangential velocity profile at the runner outlet on the targeted operating condition, which plays an important role to minimize energy losses and to maximize the efficiency. Comparison of Figure 8 and 9 shows the improvement of low-fidelity pressure curves along the blade to satisfy the cavitation constraint on the targeted operating condition. Pressure coefficients have been normalized with the minimum and the maximum coefficients of the optimized blade. These pressure curves are relatively consistent with high-fidelity results. The proper arrangement of pressure curves along the optimized blade sections has led to an appropriate blade loading and negative load prevention. As Figure 10 shows, no negative blade loading is seen in low-fidelity evaluation results of the optimized blade, and the load is distributed monotonically along different sections.

![Figure 7](image7.png)

**Figure 7.** Efficiency improvement of the optimized blade versus normalized power coefficient.

![Figure 8](image8.png)

**Figure 8.** Normalized pressure coefficient along the initial blade sections.
The results indicate that no more design step is needed, since:
- All defined constraints have been satisfied in the first step.
- No relaxed constraint has been used in the optimization; so there is no need to increase the number of design variables to achieve feasibility of real constraints.
- High-fidelity evaluations have indicated that the main optimization target (i.e. right peak position) has been achieved properly, with a good efficiency. Therefore, no target correction is needed.

However, if there was a significant deviation from the targeted peak position in all high-fidelity assessments of the selected candidates, the linear correction could be applied to the operating condition which could be used in the next optimization step.

The optimized blade may be employed by designers as a good starting point to do very fine tunings and manipulations to obtain very detailed characteristics of a desired design. This final design step cannot be carried out within the optimization mainly due to the necessity of using a lot of geometrical parameters.

5. Conclusion
A robust multi-fidelity design optimization methodology has been developed to integrate advantages of high- and low-fidelity analyses, aiming to help designers to reach efficient turbine runners in reasonable computational time and cost. In the low-fidelity phase an automatic derivative-free optimization loop is in charge of providing a lot of solutions using fast low-fidelity inviscid flow
evaluations. Considering important challenges of the design environment (such as non-linear non-convex design spaces and noisy inviscid flow solvers) an open source optimizer, NOMAD, has been chosen. Since the low-fidelity solver used in the optimization is not accurate enough and the efficiency is not directly reachable, a filtering unit selects a limited number of geometrically different candidates which are dominant in their own neighborhoods. The expensive high-fidelity phase is responsible for evaluating those candidates and choosing the best. These accurate results are valuable as well to calibrate low-fidelity optimization.

The developed methodology demonstrated its advantages by designing a low-head Francis runner through a relatively low computational cost. Although the initial geometry was quite poor, all design targets was met in the first optimization step without any optimization tuning. This test case indicated that by proper definitions of optimization features (e.g. design variables, objectives and constraints) an optimized geometry is achievable which is geometrically different from the initial one.

In future investigations, other effective parameters should be studied to define appropriate objectives and constraints, to address other important aspects of a good design in the high-fidelity phase, such as the flatness of the efficiency curve and designing based on several operating points.

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