Spetals verk

Francis turbine runners

Surrogate- model approach

- optimaliserer med trinnløs teknologi

Design of Francis turbine runners based on a surrogate-model approach

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Abstract

This paper will demonstrate the use of a surrogate-model based approach for Francis turbine runners design. Spetals Verk has taken the benefit from a new parametric definition of the Francis turbine runner blade in combination with extensive and systematic CFD and FEM simulations, and thereby implemented a surrogate-model approach in the Francis turbine design process. This enables evaluating a large range of factors simultaneously, tuning the surrogate-models to mimic the turbine runner responses over the complete design space. The surrogate-model is a useful way to gain insight into the global behavior of various turbine blade designs. A complete new design series of Francis runners have been developed based on this approach. It has also given new knowledge about important factors in Francis turbine overall performance.

Introduction

One of the major challenges in hydro turbine design is to ensure a globally optimized turbine design, taking into account the many responses of the turbine design such as performance at various operating points, cavitation, operating stresses, pressure pulsations, weight, size, fatigue life, vibration and manufacturability. Also hydraulic interaction between turbine components needs to be addressed to ensure a globally optimized turbine design. Not only are there a large number of responses, the designer needs to consider these responses simultaneously. For example, the designer typically wants to increase the efficiency without increasing on operating stresses. Optimal settings of the design parameters for one response may be far from optimal or even physically impossible for another response. In addition, the runner blades are geometrically complex and its shape typically controlled by a large number of design parameters.

Traditionally, the optimization of a turbine design involves setting the design parameters so that the result becomes as good as possible. Often this is done by changing one design parameter at a time until no further improvement is achieved. This approach is normally denoted as the COST approach (Changing One Separate parameter at a Time) and is recognized to be very time-consuming, even for an experienced designer. Focusing on few responses and/or design parameters at the time could also prevent insight into possible relations between the various responses and design parameters. This approach could thus lead to a sub-optimized turbine design, or in the worse situation, a turbine failing to meet its expectation at site.

Recent trends

Currently, hydro turbine designers are mainly relying on simplified CFD solvers (typically 3D Euler or potential flow solvers) to reduce the CPU time needed for the optimization. These codes typically lack some accuracy in terms of performance predictions compared to fully 3D Navier-Stokes solvers, especially far from best efficiency operation. Fully 3D Navier-Stokes solvers are mainly used in the final stage of the optimization for fine-tuning and verification. The optimization process is also mainly manually driven, meaning that the designer is changing the geometry based on the previous simulation results. The final turbine design is therefore, to a large extent, reflecting the specific designer’s personal experience.

During the last decade the dramatic increase in computational force has been experienced. Even complex simulations can now be performed on personal computers which only few years ago were only realistic on specialized, and expensive, simulation computers. Also the communication between various commercial CFD/FEM software, meshing codes and CAD software has been improved.

These improvements imply that more automated computational design approaches are getting more realistic for industrial application. Still, however, a full Francis runner optimization would imply that typically 100 design parameters had to be optimized, which currently is too ambiguous. Simplifications are therefore currently needed to enable solving the optimization problem – however the difficult question is *which* simplification strategy to use to ensure a fast, precise and accurate design process.

Different approaches have been presented to reduce the overall CPU time by focusing on the different factors related to an automated hydro turbine design optimization approach. A multi-level CFD technique was described in (1). Other optimization algorithms have been presented in (2), (3), (4), (5) and (6).

The Surrogate-model approach

A surrogate-model is an explicit model of the relations between responses and design parameters. The approach can also be seen as a way to build a structured experience database, building functional relations between responses and design parameters in the design space. It is a systematic approach, using design of experiments (DOE) to reduce the necessary number of runs and to populate the design space. A flowchart describing the surrogate-model approach can be seen in Figure 1.

Except a surrogate-model based optimization process for a draft tube (7), little literature is available on surrogate-model approaches for hydro-turbine component developments. The approach is, however, well recognized in other simulation driven engineering industries like gas-turbine, automotive and aviation industries ((8) and (9)).

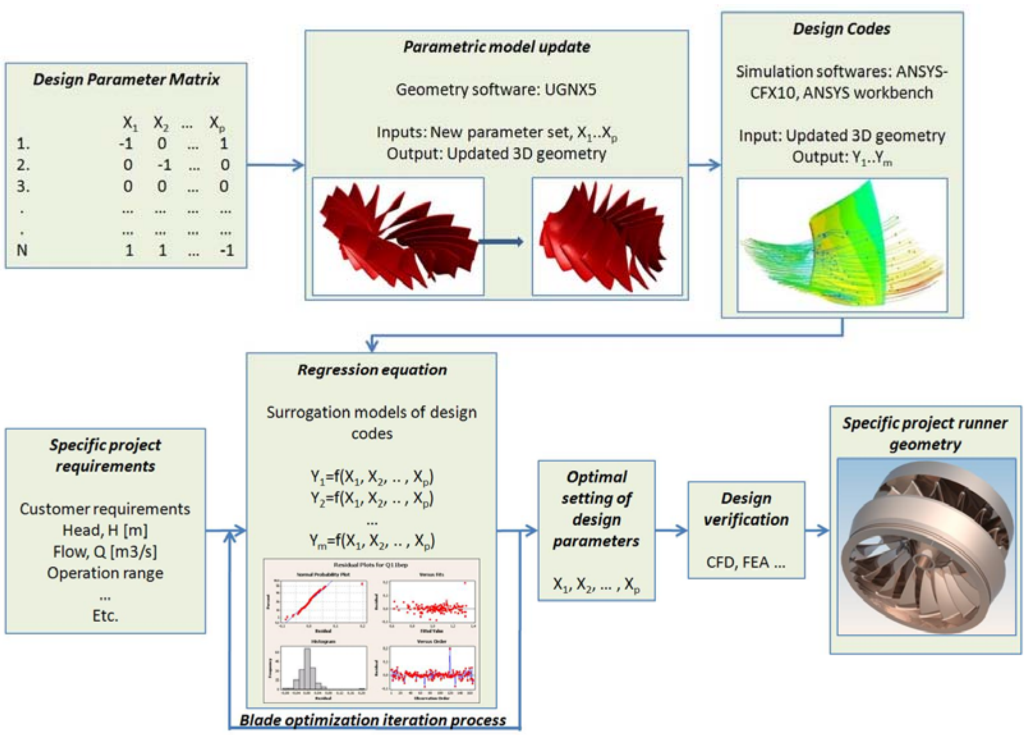

Figure 1 : Flowchart for surrogate-model design method

The surrogate-models can be used to give the designer insight into the relations between design parameters and responses within the design space. It also enables evaluating a large range of responses and design parameters simultaneously, tuning the surrogate-models to mimic the turbine responses over the complete design space.

Some distinction can be made between previous mentioned approaches and of the surrogate-model approach:

- The previous mentioned approaches search towards a global optimum. Once the optimum is found the intermediate designs used on the process are normally discarded.
- In the surrogate-model approach one is not only interested in finding the optimal parameter vector but also to gain insight into the parameter and response sensitivity of the turbine design. Here the surrogate is tuned to mimic the underlying design codes as closely as needed over the complete design space.
- By also focusing on parameter sensitivity, a sound basis for a robust turbine design is gained.
- When a sound surrogate-model is established, it could replace expensive and time-demanding CFD and FEM simulations in specific turbine design developments in order to provide a faster and more effective exploration of the design and solution space. Further optimization can still occur as a post processing step.
- The objective function, typically reflecting the customer voice in a specific project, can then easily change from project to project without implying heavy project specific simulations in most situations.

Initial considerations

To ensure a successful implementation of the surrogate-model approach, carefully considerations of the following factors were necessary:

- **Number of parameters to solve:** The computational cost of an optimization problem is highly influenced by the number of design parameters. Hence, there is much to gain in finding a minimum amount of relevant design parameters as possible. A high parameter number may increase the shape manipulation complexity, where a low number may provide a poor and a limited range of feasible solutions.
- **Complexity and sample selection of surrogate-model to apply:** The surrogate-model approach is sound as long as the model can sufficiently estimate the design code. Initial knowledge about typical complexity and behavior of every response is therefore necessary for a successful implementation.
- **Range for all design parameters which defines the design space extent:** Based on the previous point the design space was established to comply with the surrogate-model complexity.

Geometric parameterization

Based on the experience from the previous section, a significant effort was necessary to develop an efficient runner geometry parameterization with a minimum number of design parameters, as well as design space constraints. Functional dependencies between design parameters were used to reduce the total number of design parameters. Also classical theory (10) was used to constrain some design parameters and thereby limit the design space. UGNX5 parametric environment was utilized to generate the parametric geometry.

Based on these considerations, including extensive flexibility and robustness testing, a parametric blade defined by 10 free design parameters was developed. Examples of blades based on this definition can be seen from Figure 2.

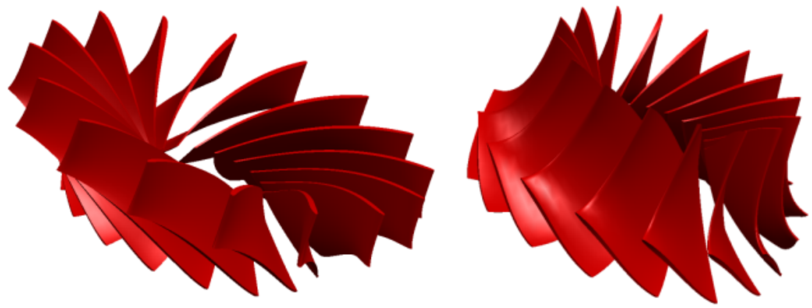

Figure 2: Flexibility and robustness: A number of 10 free design parameters were found sufficient to describe a large range of blade shapes. Speed number Ω*=0.3 to the left. Speed number Ω*=0.9 to the right.

Three different types of design parameters were defined:

- The free design parameters which are to be systematically investigated and optimized during the optimization process
- The dependent design parameters, which are functionally dependent on one or more of the free design parameters.
- The fixed design parameters, which are kept constant during optimization.

One of the free design parameters was the speed number, *Ω, enabling the blade shape to change continuously with the speed number. From this parameter, several dependent parameters are defined, in ex. Parameters that are defining the shroud and band contours. A summary of the design parameters can be found in Table 1.

Table 1 : Summary or design parameters for the parametric blade

	Design parameters = 93		
	Free parameters to optimize	Dependent parameters	Fixed parameters
Blade shape	10	31	5
Blade thickness distribution		10	10
Blade inlet/outlet profiling		4	8
Shroud/band contour		11	4
Total=	10	56	27

The design space was thus populated with a relatively large range of runner designs, covering from speed number 0.3 to 0.9 where all free design parameters were changed systematically.

Experimental design

A design space defined by 10 parameters that are changed in 3 levels simultaneously would imply that approx 59.000 runner designs had to be evaluated. This would take several years of computational effort with the current computational force and fully 3D NS-stokes solvers. Based on expected complexity of the responses a Box-Behnken design with 10 degrees of freedom was chosen to statistically populate the design space with a structured set of data points. A total of 170 runner designs were necessary to construct the surrogate-models.

Surrogate-models

Surrogate-models for each response were constructed based on a second-order response surface. A response surface model for k input variables can be stated as

$$y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{\substack{i=1,\, j=2 \\ i<j}}^{k} \beta_{ij} x_i x_j + \sum_{i=1}^{k} \beta_{ii} x_i^2$$

Where y is the response variable, x_i, are the design parameters, and β's are the coefficients to be estimated.

Computer analysis

A hybrid mesh from ANSYS-Icem was selected for the simulations in view of its ability to make associative meshes for the relatively large range of geometries. A structured mesh is recognized as more accurate, however they are more difficult to obtain for such large geometric variance of geometries, and control parameters are necessary. The mesh used (see Figure 3) had approximate 1.4 million elements.

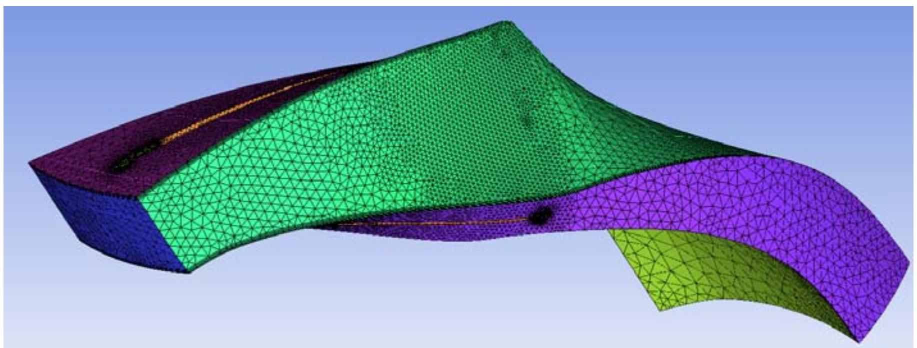

Figure 3 : Hybrid mesh used in the runner domain. 30<y+<400

The performance of each design was estimated by running CFD and FEM simulations in various operating points. Due to the importance of having high accuracy surrogate-models, a full 3D Navier-Stokes solver from ANSYS-CFX 10 was utilized for all simulations.

Objective function definition

There is no unique definition of an optimum turbine design. It will be a result of the design engineer philosophy, which is a combination of a set of requirements (like acceptable operating stress levels) and emphasized responses of the design (in example weighing of efficiency at different operating points).

The objective function is a measure of how well the design parameter settings have satisfied the combined goal for all the responses. The objective function has a range of zero to one. One represents the ideal case and zero indicates that one or more responses are outside their acceptable limits.

The parameter definitions used in the objective function can be found in Table 2.

Table 2 : Objective function parameter definitions

y_i	Predicted value of i^{th} response
T_i	Target value for i^{th} response
L_i	Lower acceptable limit for i^{th} response
U_i	Upper acceptable limit for i^{th} response
d_i	Desirability for i^{th} response
D	Objective function value for the combined response desirabilities
r_i	Weight of desirability function of i^{th} response
w_i	Importance of i^{th} response
W	Σw_i

The desirability for each response is calculated according to the following system:

Table 3 : Desirability is calculated as follows: To maximize a response to the left, to minimize a response in the middle and to target a response to the right

$d_i = 0$	$y_i < L_i$	$d_i = 0$	$y_i > U_i$	$d_i = \left(\frac{y_i - L_i}{T_i - L_i}\right)^{r_i}$	$L_i \le y_i \le T_i$
$d_i = \left(\frac{y_i - L_i}{T_i - L_i}\right)^{r_i}$	$L_i \le y_i \le T_i$	$d_i = \left(\frac{U_i - y_i}{U_i - T_i}\right)^{r_i}$	$T_i \le y_i \le U_i$	$d_i = \left(\frac{U_i - y_i}{U_i - T_i}\right)^{r_i}$	$T_i \le y_i \le U_i$
$d_i = 1$	$y_i > T_i$	$d_i = 1$	$y_i < T_i$	$d_i = 0$	$y_i \in \langle L_i, U_i \rangle$

The objective function is the geometric mean of the individual desirability. The formula for the objective function is hence:

$$D = \left[\prod\left(d_i^{w_i}\right)\right]^{1/w}$$

Design exploration

Results

Conclusions

By this methodology, one can in a large extent replace the expensive CFD model with a surrogate-model in the optimizations phase, in order to provide a faster and more effective exploration of the design and solution space. In addition it ensures a better insight into the relationship between design parameters and the various responses.

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