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Multidisciplinary optimization of a Francis turbine runner

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Abstract. A fully automated multi-disciplinary design optimization procedure for a Francis turbine runner has been developed in a previous task of the Horizon2020-HydroFlex project. The design optimization was limited to blade design, with the goal of improving the hydraulic efficiency and torque, and reducing the harmonic structural stresses. This is to ensure that the turbine is less prone to fatigue, but still performs well hydraulically. Results from the numerical optimization are presented in this paper. From the design optimization, two runner designs are highlighted. One that performs significantly better than a reference design, and one that performs significantly worse. It is observed that small, but significant improvements can be obtained in both torque and efficiency, while at the same time reducing the structural stresses drastically. This shows that there might be previously unknown areas in the design space that can be explored, especially on the structural side.

1. Introduction

The energy mix in the world is changing [1]. Coal and nuclear plants are shutting down, and renewables are gradually becoming more important. This change is one step towards mitigating the climate crisis we observe today [2]. The change to intermittent renewable energy sources, such as wind and solar, increases the need for stable renewable energy sources that can be used as a baseload in the future electrical system. Hydropower can take the role as the renewable baseload in the market. The ability to start and stop production independently of the weather is likely to be highly valuable in the future energy mix and will be an important field of research in the coming years. Lately, some traditional turbine runners have experienced increased stresses due to more variable operation [3, 4]. This could reduce the lifetime of the components in question. It is therefore important to research new ways of designing turbines to facilitate their use in the future. The goal of this paper is to use an automated Francis turbine design procedure, which combines both fluid and structural criteria in an optimization loop. Typically, optimal structural designs will suffer in terms of hydraulic performance. One goal is therefore to investigate if such tradeoff is necessary, and if it is possible to reduce structural stresses without harming the hydraulic performance. The study is limited to looking at turbine designs that will fit into the Francis-99 pit [5], but not perfectly matching the Francis-99 operating conditions, a difference from previous work [6].

2. Methods
The commercial software ANSYS OptiSLang is used to couple together all the procedures outlined in this paper. The procedure is similar to the one explained in [7]. Figure 1 shows an outline of the workflow.

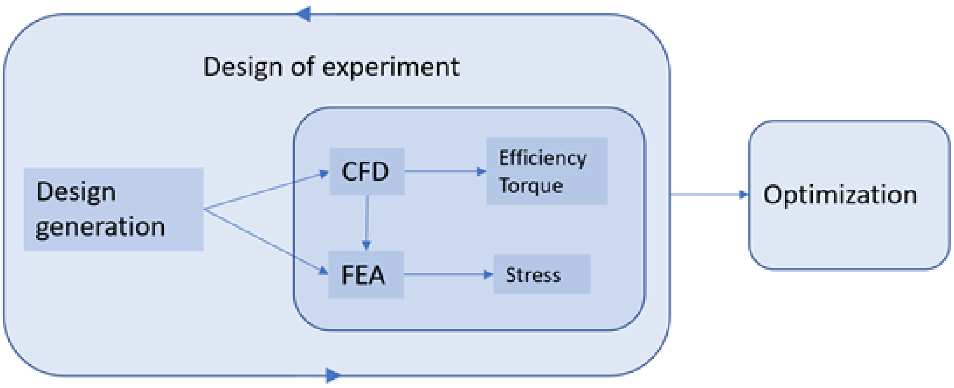


Figure 1. Overview of workflow

2.1. Design generation
In this work, a MATLAB-based design code is used to generate the turbine designs. The code was developed at the Norwegian University of Science and Technology (NTNU), as part of the HydroFlex research project [8]. Please refer to [9, 10] for detailed information regarding the design tool, the parameters and their absolute range, and the theory behind. A brief description of the parameters is given below, note that the notation may differ from previous work.

- $h_{1,2,3,4}$: A Bezier curve with 4 control points that control the shape of the hub curve in the meridional view.
- $TE_{1,2}$: Input to a Bezier curve that controls the location and shape of the trailing edge in the meridional view of the runner.
- PHI: Controls the wrapping angle of the complete blade
- $LEAN_{1,2}$: Leaning of leading and trailing edge respectively
- $DelB_{1,2,3}$: Parameters controlling the outlet blade angle
- Hx: Deviation from design Head
- Qx: Deviation from design Flow
- T:The maximum thickness of the blade.

2.1.1. The reference design The design code is written so that all parameters are normalized to a range of -1 to 1 [9]. In order to evaluate the performance of the design optimization, a reference design is chosen. For a reference runner design, a natural choice is to use the midpoint for all the design variables, i.e. setting all the design variables to zero. All simulations outputs will be scaled according to this, and any good or bad designs can then be clearly compared with this reference. Figure 2 shows the reference design.

All turbines consists of 17 runner blades and 28 guide vanes. The operating conditions are as for the Francis-99 runner [5], i.e. a specific speed of 0.27, with a flow rate of $0.2m^3/s$, head of 12m and speed of 335 rpm.

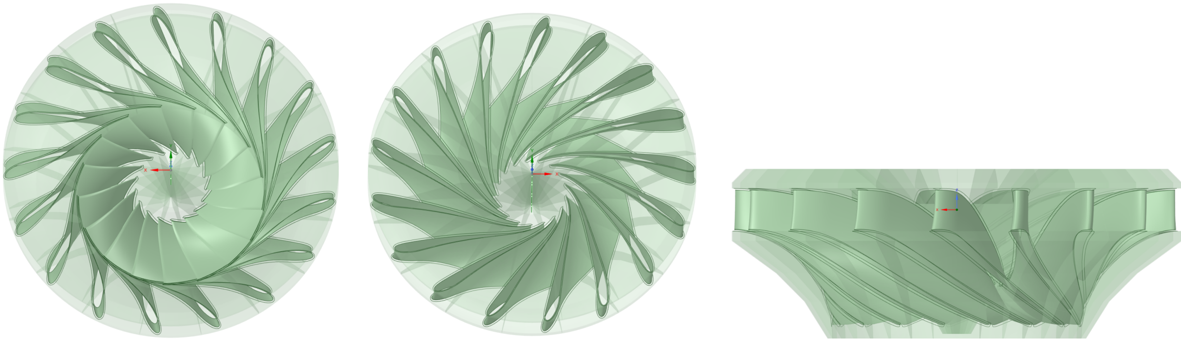
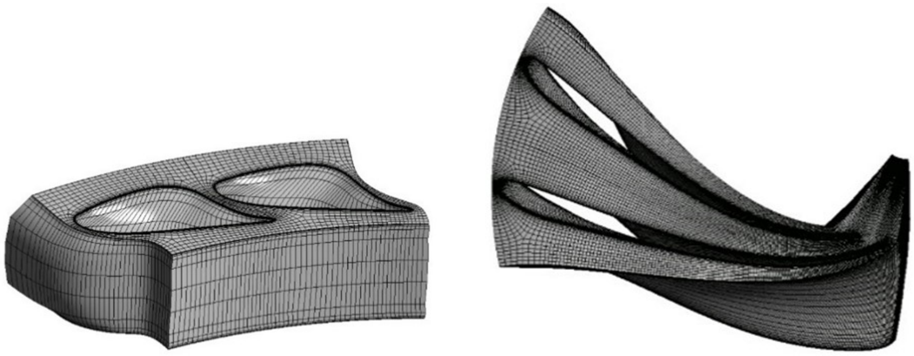


Figure 2. Reference design

2.2. CFD analysis

Computational Fluid Dynamics (CFD) is a trusted way of designing hydro turbines but tends to be very time consuming. There exist methods however, that speed up the process [11]. In this work, a passage modeling technique in ANSYS CFX is used to reduce the computational effort. This process utilizes the rotational symmetry in the geometry, and implements phase-shifted rotational boundary conditions, thus preserving the ability to display global mode shapes in the flow field [12]. The CFD model therefore consists of two passages of a turbine runner, guide vanes, and a cut-off draft tube. Not using a full draft tube is only valid for operating points with no vortex rope, but was chosen here due to computational speed, and the fact that the best efficiency point was the focus. The design optimization is limited to the design of the runner, meaning that the guide vanes and draft tube is keep constant for each of the changes to the runner design. The runner mesh was created in ANSYS Turbogrid, and the refinement was equivalent to 4.25 million nodes in a full 360 model, all hexahedral elements. A typical simulation showed min/max y^+ values of [1.4,48.8]. These mesh settings provided a mesh independent solution. Figure 3 shows a sample design.



(a) (b)

Figure 3. Sample mesh of guide vane (a) and runner (b)

The fluid was modelled as incompressible water and turbulent using the k-omega SST model. At the inlet of the guide vanes, a total pressure of 12 m head was defined with a flow direction corresponding to the stay vanes outflow. At the outlet, a static, atmospheric pressure was defined. This setup replicates what is done in a previous study [6]. Unsteady simulations [13] were done for a total of 15 blade passing periods with 30 timesteps per period (about 0.7 degree rotation per timestep), with a steady state solution as the initial condition. The pressure field in the runner was decomposed using a Fourier series, extracted and passed on to a subsequent structural analysis. The direct outputs from the CFD simulations used in the optimization loop are the runner torque (T) and efficiency (η).

$$T = \int p \cdot r dA \tag{1}$$

$$\eta = \frac{T \cdot \omega}{Q(p_{t1} - p_{t2})} \tag{2}$$

Where p, r, ω, p_t, Q denotes the fluid pressure, radius from rotational axis, angular velocity, total pressure at inlet/outlet and flow rate, respectively.

2.3. FEA analysis

To assess the structural performance of the runner, Finite Element Analyses (FEA) were performed using Ansys Mechanical. Specifically, a static analysis and a harmonic analysis were done for each design. The effects of the surrounding water were captured by using acoustic elements. Similar as for the CFD analysis, circular symmetry has been used to reduce computational expense, in essence reducing the geometric model to a sector representing 1/17th of the actual size, see Figure 4. The 3D modeling software ANSYS SpaceClaim was used to generate the structural geometry, and imported in ANSYS Mechanical for meshing, as described in [7]. A typical sector mesh consisted of approximately 600 000 nodes, which is equivalent to 10 million nodes in the full 360 geometry, see Figure 4 for example.

The material model is defined as isotropic elastic material, with a young modulus of 118GPa and a Poisson's ratio of 0.3. The Fourier coefficients from CFD analysis, (A_0 for the static analysis, A_1, B_1 for the harmonic acoustic analysis) are mapped as pressure loads on the runner using ANSYS Parametric Design Language (APDL). Note that even though the CFD analyses are performed on a cyclic symmetric model, the resulting pressure field on the runner may be asymmetric. The spatial variation of the asymmetric pressure field is accounted for and preserved through the mapping process, giving a behavior representative of a full 360-degree model. The shaft connection is fixed in the analysis.

Typically, areas prone to fatigue failure in a Francis turbine runner are the fillets at the trailing edge near the hub [14, 15]. The fillets near the trailing edge on the suction side were found to be high stress areas, both near the hub and the shroud. These areas are therefore used to evaluate the stress in the turbine, see figure 4. Stress results are extracted from these two areas, and the static von Mises stress, σ , harmonic principal stress amplitude, $\Delta S1$, and the corrected harmonic principal stress amplitude, S, are calculated. For each area, the maximum of the corrected harmonic principal stress amplitudes are exported as optimization output:

$$S_n = max\Big(\frac{\Delta S1}{1 - \frac{\sigma_{eqv}}{UTS}}\Big) \tag{3}$$

Where the possible subscripts h, s, denotes the hub and shroud location respectively, and UTS denotes the ultimate tensile strength equal to 300MPa.

2.4. Design of experiments

The first step of an optimization analysis is a Design of experiments. In this procedure the goal is to get as much understanding of the design space, and corresponding solution space, as possible. The traditional way of doing this is to perform a sampling of the design space. This can be done in different ways; in this paper the Latin Hypercube method [16] was used for the

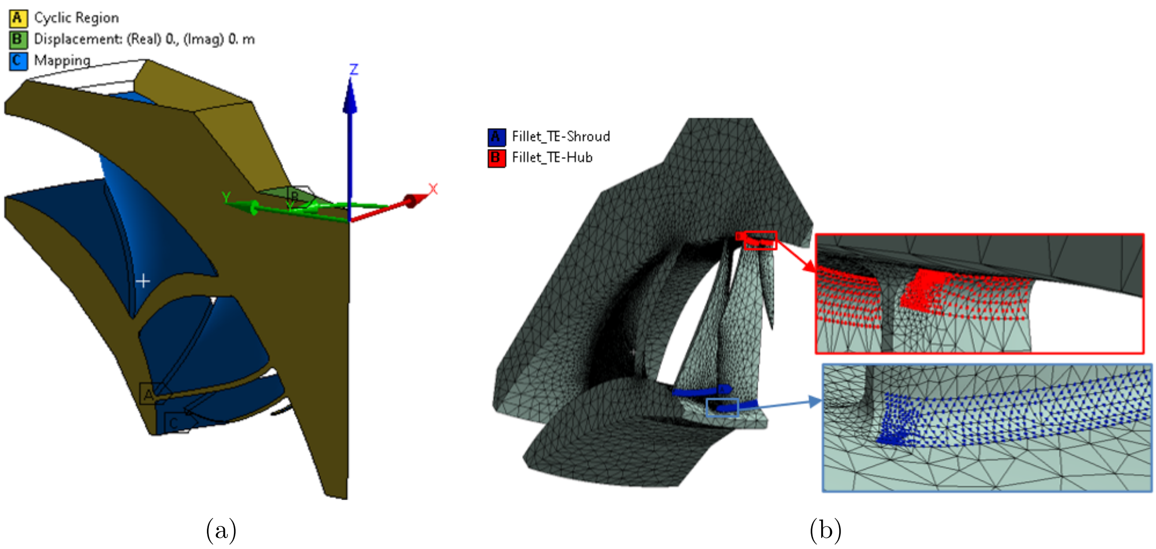


Figure 4. Applied boundary conditions on cyclic model (a), typical mesh for structural domain with node selection for regions of interest (b). Acoustic bodies are hidden

15 input design parameters with a range of [-1;1], see chapter 2.1. The Design of experiments created a total of 67 successful designs.

2.4.1. Metamodel of optimal prognosis When the sampling is done, the relation between the input and output needs to be modelled. This can be done using a variety of interpolation and regression methods. In ANSYS OptiSLang there exist a method that scans the possible methods and finds the optimal procedure. In practice, for each model, a measure of predictive quality, Coefficient of Prognosis (CoP) [17], is extracted. The best model for explaining that specific input/output relation is then the Metamodel of Optimal Prognosis (MOP). The resulting model is a hyperspace representation of the results and can be visualized as a Response Surface in three dimensions.

2.5. Optimization

The Design of experiments procedure aims to cover the complete design and solution space, optimization focuses on narrowing the design space down to one or more optimal designs. There exist two different procedures, MOP-optimization where the metamodels generated in the design of experiments are basis for optimization, and optimization using the underlying solver directly. Due to dramatic speedup, the MOP-optimization procedure will be used in this paper.

2.5.1. MOP optimization The metamodels generated in the design of experiments are lightweight, mathematical, and reduced order models of the solution space. A very important thing to consider when performing MOP-optimization is that the metamodel predicts the actual underlying behavior of the system. This is of outmost importance, as the procedure is decoupled from the underlying solver. When deciding if the metamodel quality is good enough, CoP is used as an indicator [17]. The higher this value is for the given metamodel, the better, but as a rule of thumb, CoP 80% is used.

2.5.2. Optimization strategy There is no optimization procedure that is best in all applications, it depends on the intended use [18]. In this paper more than one optimization goal will be defined, and therefore Nature Inspired methods tend to perform best [19]. These are global methods, which means that the risk of getting stuck in a local optimum is low. One of the overall goals of this work is to perform multi-objective optimization. This means that more than one optimization target is specified, e.g., high efficiency and low stress, and find the design that best fulfils both these objectives. In this paper, a good design will be found by minimizing stresses, while preserving the efficiency. Similarly, a bad design will be found by maximizing the stresses. Recall that all outputs are scaled to the reference design.

3. Results

3.1. Design of experiments

The CoP Matrix in Figure 5 shows the breakdown of the metamodels describing the four simulation outputs, as well as the total model predictability. The metamodels are good, with CoP values of more than 80% for all selected outputs

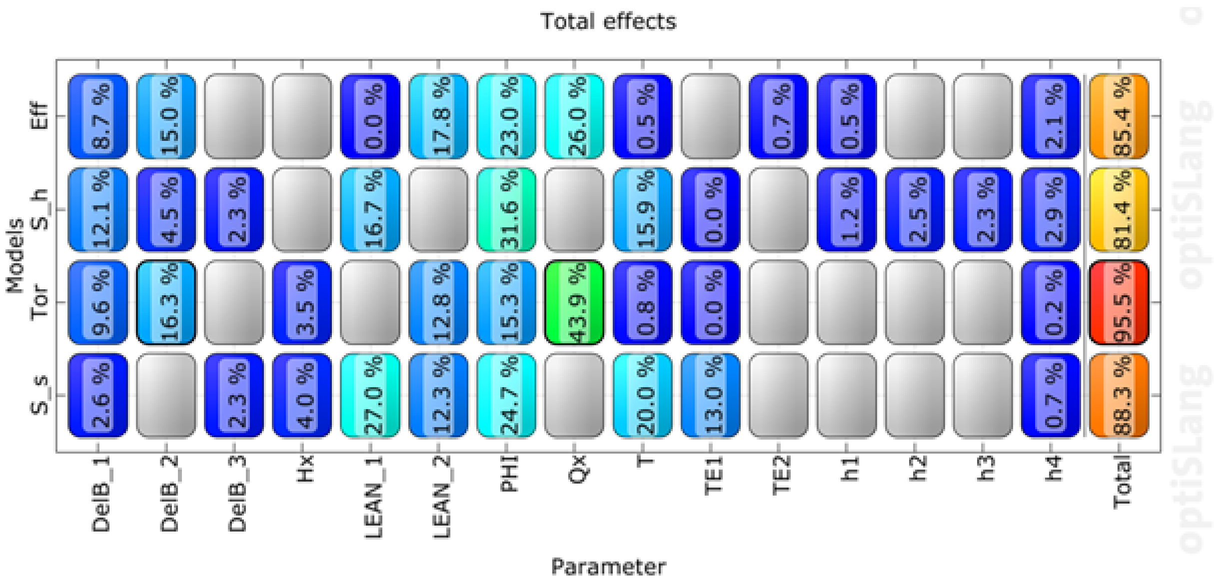


Figure 5. CoP Matrix of the simulation outputs

Figure 6 shows the metamodel for S_s as a function of two of its most influential design variables. All other design variables are given a reference value in the plots, which is why the samples appear scattered. The true model is hyper-dimensional, and not possible to visualize in three dimensions. These metamodels are the basis for the subsequent optimization.

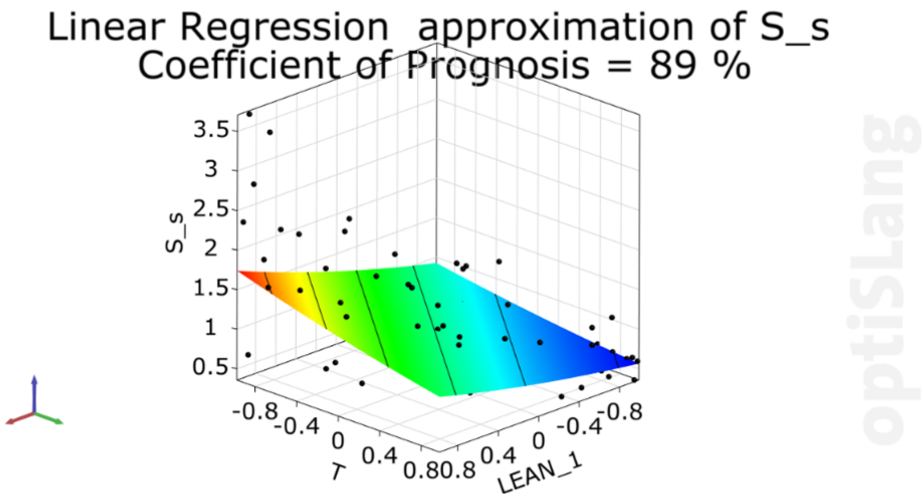


Figure 6. Response surface 3D plot for Ss

3.2. Optimization

The optimization procedure was applied to the MOP's to find both a good and a bad design. A verification of these designs using the above CFD and FEA procedure was then performed. Table 1 shows the results from the optimization, compared with the reference design. Two columns are included for each design, where MOP refers to the MOP approximation, and Simulation refers to the CFD and FEA verification. This shows that the Metamodel approximation is very similar to the full simulations. It is also clear that the best design performs a lot better than the reference in the structural domain, and similarly worse for the bad design.

Table 1. Performance of selected designs

Indicator	**Reference design**		**Good design**		**Bad design**	
	MOP	Simulation	MOP	Simulation	MOP	Simulation
Efficiency	0.999	1.000	1.003	0.996	0.994	0.995
Torque	0.999	1.000	1.039	1.022	0.978	0.975
S_s	1.010	1.000	0.416	0.381	3.408	3.710
S_h	1.110	1.000	0.252	0.341	3.373	3.477

Figure 7 shows the reference design, good design and bad design as 3D geometries. Note the differences in the blade geometry. Figure 8 shows a spider plot of the design variables when finding the best and worst design, respectively. The reference design would show as a circle with constant radius at the midpoint of each variable. There are clearly clusters of design variables that affect the performance of the runner. Finally, Table 2 lists the design variables, for reference.

Table 2. Design parameters for presented designs

	$DelB_1$	$DelB_2$	$DelB_3$	Hx	$LEAN_1$	$LEAN_2$	PHI	Qx	T	TE1	TE2	h1	h2	h3	h4
Ref	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Good	0.73	0.97	0.75	-0.94	-0.97	0.98	0.92	0.97	0.68	0.64	0.77	0.89	0.20	-0.55	0.27
Bad	-0.926	-0.67	-0.37	0.65	0.92	0.19	-0.92	-0.94	-0.93	-0.99	0.73	-0.82	-0.68	0.51	0.34

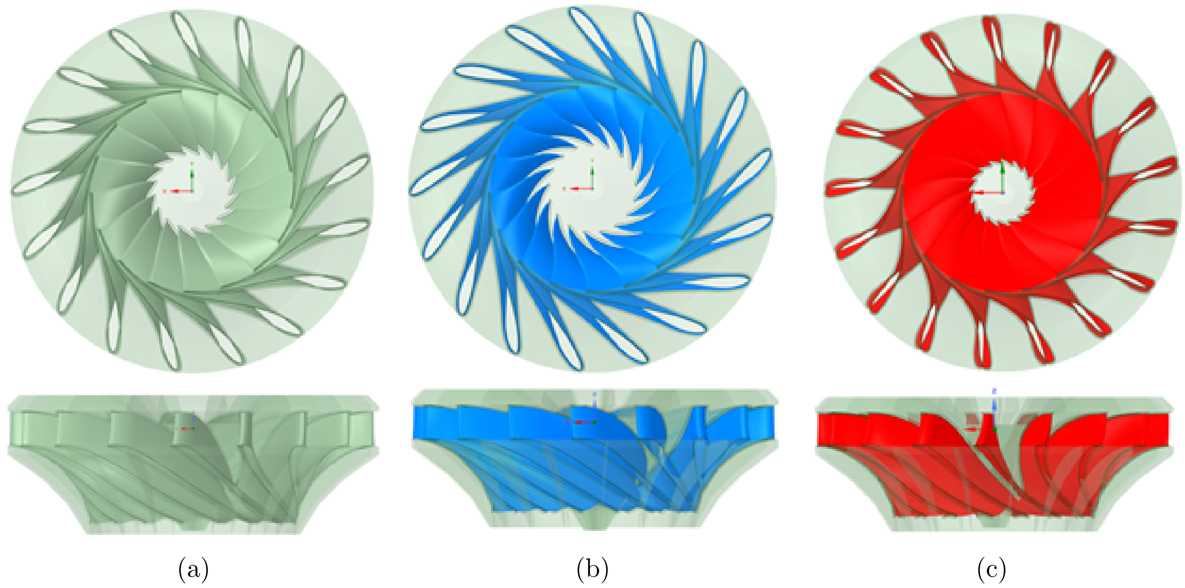


Figure 7. Reference design geometry (a) the good design (b) the bad design (c)

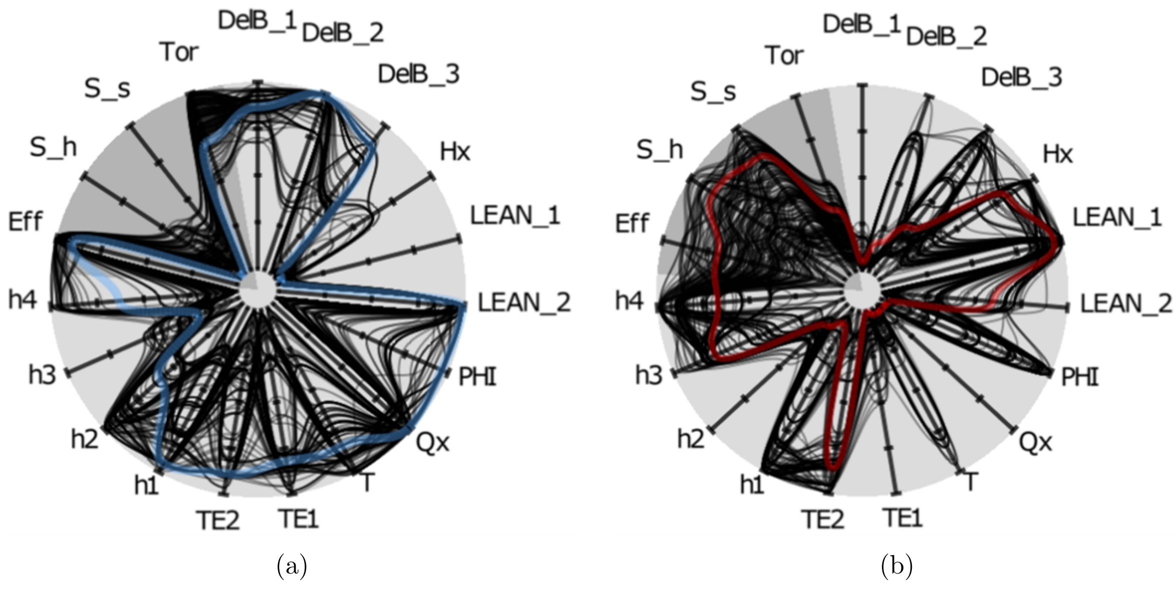


Figure 8. Spider plot of good designs with the selected good design in blue (a) all bad designs with the selected bad design in red (b)

4. Discussion and further work

When generating the metamodels for the different outputs, it is apparent that a small subset of the variables accounts for most of the variation in the results. Moreover, the variables affecting the CFD and FEA domain are not necessarily the same. These learnings should be considered when designing future hydraulic equipment. Specifically, it shows that a single objective optimization, i.e. for efficiency, is inherently risky, as the variables governing the structural performance are deemed not important and left out of any optimization procedures. One of the goals of the paper was to investigate if it was possible to get large improvements in structural integrity, without lowering the hydraulic performance. From Table 1 we see that both the good and the bad design was within 1% from the reference in terms of efficiency, but a factor of 3 better/worse in terms of stresses. This means that the bad design had 10 times larger stresses than the good design, at similar hydraulic outputs. There are drawbacks to the procedure presented here. The flow rate through the runner is not explicitly fixed, something that can explain some of the variation above. However, an inspection of the presented designs show that the flow rate varies less than 5% from that of the reference design. Another drawback; due to the process being fully automated, any failed steps, geometry generation, meshing or simulation, will be tagged as a failed design. That design is then left out of the metamodeling and optimization. A failed design, however, is not necessarily the same as a bad design. This can skew the results towards a range in the design space where the numerical process had fewest failed designs. Examples of this include; errors when building the structural geometry, failures in the CFD and FEA simulations, mesh, and more. Additionally, in automated processes it is harder to make sure that the numerical simulations have reached sufficient and similar convergence levels. This is one reason why it is important to always perform a controlled verification of the designs selected in the optimization process. As future work, constraints could be implemented. Typically, a constraint would be imposed on the stresses, the argument being that it does not matter what the stresses are, as long as it is below a certain value, then optimize hydraulics. There also exist different outputs from the CFD and FEA that can be used, but this is left to the user to decide. Another topic for further work would be to include several design points, guide vane openings, and even rotational speeds. This can find designs more suited for variable speed operation, a flexibility that could be a requirement of the future electricity market. For this, it may also be important to find a design suited for the start/stop of the turbine, and implementation of simplified tests for this should be considered.

5. Conclusion

A Francis runner design tool has been implemented in an optimization loop. Outputs from both the fluid and structural domain was used to make sure that the selected designs would not let the structural integrity suffer at the expense of hydraulic performance. From the available design space, two interesting designs were highlighted, one good and one bad. Interestingly, it was possible to find a design that performed much better than the reference in structural terms, without reduction in the hydraulic outputs. This dispels the notion that there must be a tradeoff between the structural and fluid performance. A similarly bad design was also found, which highlights the sensitivity in the runner designs. The metamodels created from the Design of Experiments shows that not all design variables affect the performance. Additionally, different design variables were important in the fluid and structural domain, respectively. This indicates that one should do multi-objective optimization in order not to miss out on important design features.

Acknowledgement

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