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MULTI-OBJECTIVE SURROGATE BASED HULL-FORM OPTIMIZATION USING HIGH-FIDELITY RANS COMPUTATIONS

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Abstract. RANS-based optimization procedures for ship design become increasingly complex and require the development of more efficient optimization techniques. The four phases of the design procedure are: shape parameterization, global sensitivity analysis, multi-objective optimization and design review. The dimensions of the design space can be mitigated by a smart choice for the shape parameterization and by screening and ranking the design variables in the global sensitivity phase. Subsequently, Surrogate Based Global Optimization (SBGO) is used to reduce the cost of the multi-objective optimization phase. For a practical application it is shown that the computational time reduces from two weeks to only a day when using SBGO instead of applying a Multi-Objective Genetic Algorithm (MOGA) directly to the solver. The design review phase is then used to verify and further develop the optimal design. Here, we focus on automatic ship design techniques which comprises the first three steps of the design procedure. Accelerating the ship design process is subject of ongoing research at the Maritime Research Institute Netherlands, making it useful for practical applications with turnaround times of only a few weeks.

1 INTRODUCTION

Automatic RANS-based optimization procedures are becoming increasingly important in practical ship design. However, due to its complexity this type of optimization is very computationally demanding. In order to reduce the computational burden Surrogate Based Optimization (SBO) can be used. A number of studies demonstrated the potential of surrogate acceleration techniques. In [1] surrogates are used to obtain approximate Pareto fronts of a chemical tanker. A number of surrogate techniques were studied including Kriging, universal Kriging and polynomial regression. It was found that the ship design process could be accelerated leading to more efficient ships. In [2] a procedure is discussed that aims to obtain minimum required power and best wake field quality using viscous flow computations. Design of Experiments and generic hull shape variations were used to speed up the optimization process. In [3] the effect of numerous hull form variations and condition variations were studied. Surrogate models were used for each

water depth condition in order to make the final design trade-off.
This contribution aims to make the step to the actual automatic optimization of ships. The previous studies mostly focussed on design space exploration with a clever usage of Design of Experiments. Coupling this to an optimizer can improve the final design and ease the optimization process. To show this an overview of how SBO can be used in practical optimization projects is given. Starting with a base design, four important phases of the design procedure are identified: Shape parameterization: e.g. using generic hull shapes or a set of predefined hull variants (Section 2). Global Sensitivity Analysis: screening of the design space and ranking of the design parameters (Section 3). Multi-Objective Optimization and surrogate acceleration techniques (Section 4). Design review: verify the optimal designs and choose/modify the design if necessary. Although the last step is crucial in the design procedure it is not discussed in this contribution. Here, we will focus on computerized ship design techniques which comprises the first three steps of the design procedure.

2 SHAPE PARAMETERIZATION

For the design space definition we used a B-spline-Merge method [8] for the parametric deformations of the geometry. This method is implemented in the CAD-tool Rhinoceros and is referred to as Rhino-Merge. Rhino-Merge interpolates between some basis hull forms. These basis hull forms span the design space. Figure 1 illustrates how Rhino-Merge can make combinations of the basis hull forms by making linear combinations. Here an example of two basis hull forms is shown of which the average is taken as final shape.

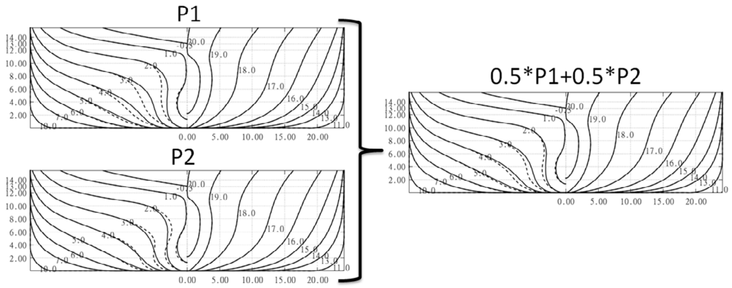

Figure 1: Linear combinations of hull shapes (P1 and P2).

From here on a designer can choose to generate the basis hull forms manually, based on experience or initial CFD calculations. There is also an option to generate basis hull forms in a more generic way. Figure 2 illustrates the set up of the generic hull shapes. The generic hulls shapes are set up in two ways: In order to shift displacement the more widely used Lackenby shift method is used (see [10]), simply by moving the sections with a predefined function. In order to change the local shape of the hull the sections are modified. These modifications can be done in several ways aiming at independent (hence an orthogonal design space) and realistic shape variations; currently we choose Chebyshev mode variations. Note, these modes can be convenient to use for single screw vessels. Other ship types (e.g. prame type ferries, yachts) need different generic functions to result in proper shape variations.

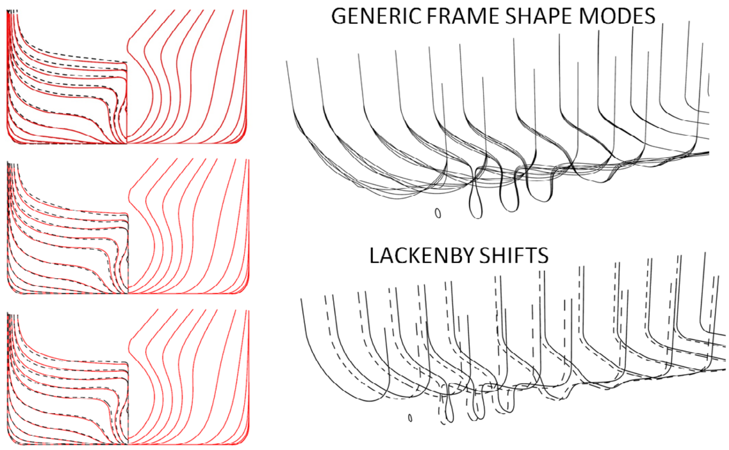

Figure 2: Typical example of generic aft ship section shape variations and Lackenby LCB shifts.

A disadvantage of using generic hull shapes is that the number of basis hull shapes can quickly become too large to handle in combination with an optimizer. With manually designed basis hull shapes this is less of a problem. But, still the curse of dimensionality can set in quite fast when multiple design directions should be looked at. Therefore a sensitivity study is done to detect the most promising generic basis hull shapes.

3 GLOBAL SENSITIVITY ANALYSIS

Global sensitivity analysis is a useful approach to learn about a design problem before an optimization procedure is initiated. One distinguishes between local and global sensitivity analysis. In a local sensitivity study one aims to obtain the partial derivative at a specific point in the design space. This derivative can be computed using an adjoint method or approximated using finite differences. In a global sensitivity study one aims to obtain general trend data over a whole range in the design space. This data is obtained via sampling and regression.

For this study a tanker is taken from the 7th-Framework EU project STREAMLINE. The ships speed is 14 knots, Lpp=94m, B=15.4m, the design draft is 6m and the block coefficient is 0.786. The Froude number is 0.237 and the Reynolds number is $6\text{x}10^8$. More on the optimization of this ship can be found in [2]. The 9-dimensional design space was created by means of generic basis hull forms. Two objectives were chosen: the ship resistance (resistance coefficient) and the wake quality (Wake Object Function) calculated with the structured RANS code PARNASSOS ([13, 14]). In this sense a balance (compromise) can be made between resistance and comfort level. Note, a better objective instead of resistance would be the power. However, because the goal was to test several optimization techniques it was decided to minimize computational effort.

3.1 Partial correlations

An initial Latin Hyper Cube Design of Experiment consisting of 90 PARNASSOS evaluations (10 per dimension) is used to scan the design space. The calculations were performed in parallel and took about 1 day on the MARIN cluster. Dakota ([5]) is used to generate the Latin

Hypercube Design and to automatically obtain the partial rank correlations, see Figure 3. This data is obtained by calculating Spearman's rank correlation coefficients on the Design of Experiment. When an objective is increasing with a design variable the correlation is positive.When the objective and the design variable are related by a monotonic function, Spearman's coefficient becomes equal to one.

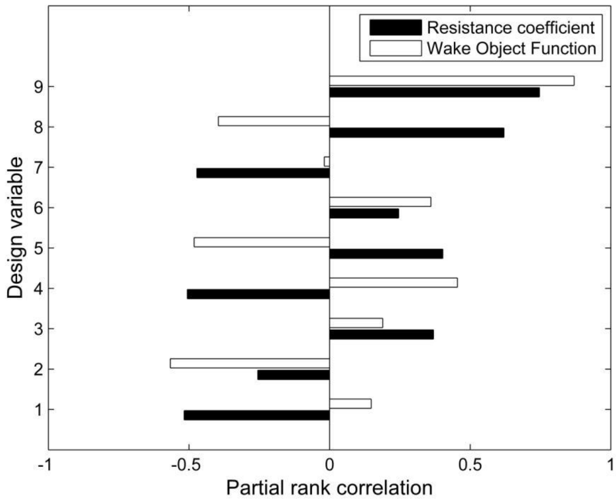

Figure 3: Partial rank correlations

Looking at Figure 3 we can now distinguish between design variables that result in conflicting/non-conflicting objectives or have only a limited effect on the objectives. For example, design variable nine shows a strong positive correlation with both resistance coefficient and Wake Object Function. This is an indication that the variable can be ignored in the optimization study which leads to dimensionality reduction.

3.2 Scatter plots

Scatter plots help to interpret the correlations from Figure 3 by visualizing the data along with the trends. Figure 4 shows a scatter plot of the two objectives: Resistance coefficient (Obj1) and Wake Object Function (Obj2). Note that the slopes of the trends correspond to the correlations in Figure 3.

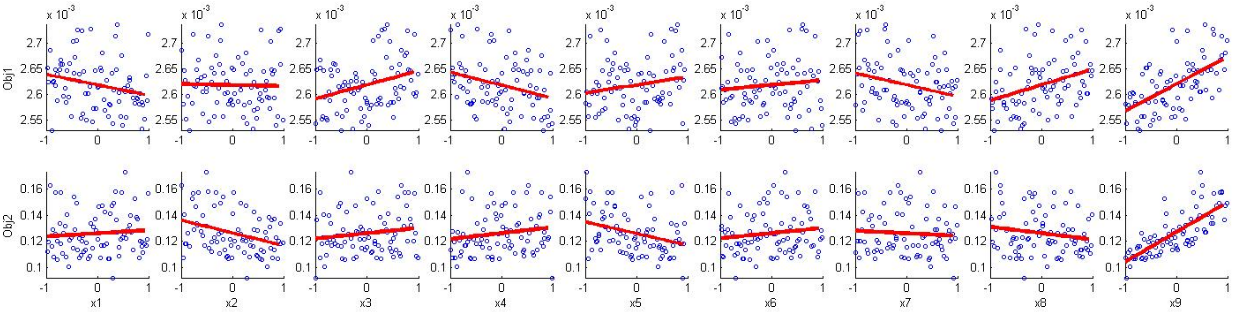

Figure 4: Scatter plots and partial linear trends. The slopes correspond to the correlations in Figure 3.

If design parameters have a strong interaction, scatter plots and partial correlations can be deceptive. In this case interaction detection methods are required such as variance based decomposition to reduce the dimensions of the optimization problem, see [9]. However, the interactions are usually small when the mode shapes are geometrically orthogonal. This is the case for the Chebyshev mode variations used in this contribution.

4 MULTI-OBJECTIVE OPTIMIZATION AND SURROGATE ACCELERATION TECHNIQUES

Multi-objective optimization arises naturally in ship design problems since multiple objectives need to be optimized that may or may not conflict with each other. A classical example is the optimization of the wave resistance defined at several conditions that approximate a ship's operational profile, see [11].

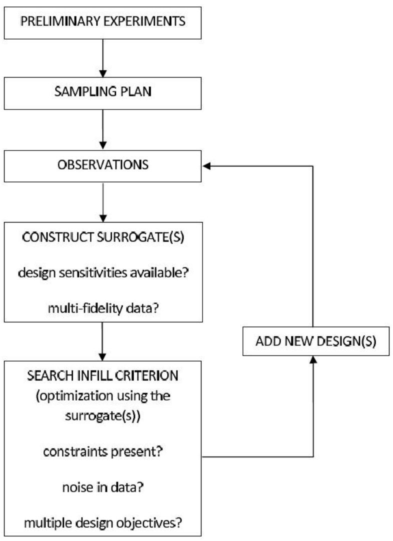

Figure 5: Surrogate acceleration method from [4].

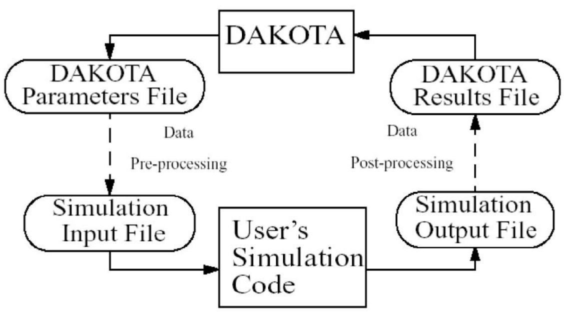

Figure 6: Dakota interface, see [5].

The increasing computational complexity of practical optimization problems results in high dimensional design spaces that cannot always be reduced by dimension reduction techniques. When the dimensions are not too high, surrogate based acceleration techniques can be used to mitigate the computational effort of the optimization, see for example the acceleration scheme shown in Figure 5. This algorithm is implemented in Sandia's optimization toolkit Dakota ([5]) and can be used once the interface between the in-house simulations code ReFRESCO or PARNASSOS is established, see Figure 6. ReFRESCO is an unstructured state-of-the-art viscous-flow RANS code while PARNASSOS is a structured steady viscous-flow RANS code. The choice of the solver depends on the application and budget of the design project. If the optimization is a pure trade-off of (conflicting) objectives that do not depend on other optimizations it is named a single level optimization. This is the topic of Section 4.1. For some practical problems, e.g. hull-propeller optimization, two or more levels of optimization exist. These so called multi-level optimization problems often require an extreme number of expensive code simulations. Reducing the computational effort of such problems with surrogate acceleration is a challange. This is the topic of Section 4.2.

4.1 Single-level optimization

In this section we study the single-level optimization problem defined in Section 3. The objective functions that need to be minimised are the resistance coefficient and the Wake Object Function obtained from the "streamline" tanker sailing at a speed of 14 knots (Fn = 0.237). First, a direct Multi-Objective Genetic Algorithm (MOGA) is used on the simulation code PARNASSOS in order to obtain the true Pareto front. Second, two strategies are used to obtain approximate Pareto fronts: surrogate based optimization on the initial surrogate (without adding new designs) and surrogate optimization on updated surrogates (adding new designs).

4.1.1 Direct Multi-Objective Genetic Algorithm

The results of the MOGA are shown in figure 7. The optimization progresses towards the onset of the true Pareto front. However, after 2 weeks (and over 300 PARNASSOS evaluations) the process stopped due to time constraints. Note, these evaluations cannot fully be done in parallel because all evaluations of a MOGA population should finish before evaluations of the next population can start.

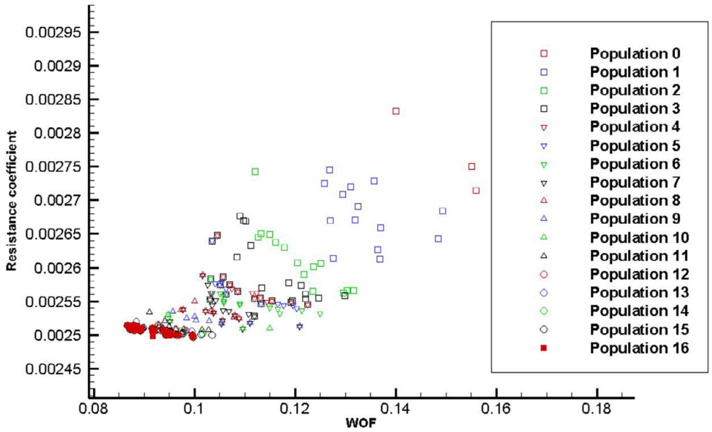

Figure 7: Pareto plot for resistance versus wake quality (Wake Object Function, WOF) for a direct MOGA.

4.1.2 Surrogate based optimization on the initial surrogate

As a next step surrogates were obtained from the initial Latin Hyper Cube design used in Section 3.1. The surrogates were constructed using a quadratic polynomial fit and universal Kriging with quadratic trend. Subsequently, MOGA was used on the quadratic polynomial fit to obtain an approximate Pareto front. Figure 8 shows the populations of this simulation in the objective space. Like for the direct MOGA the populations steadily progress towards a Pareto front.

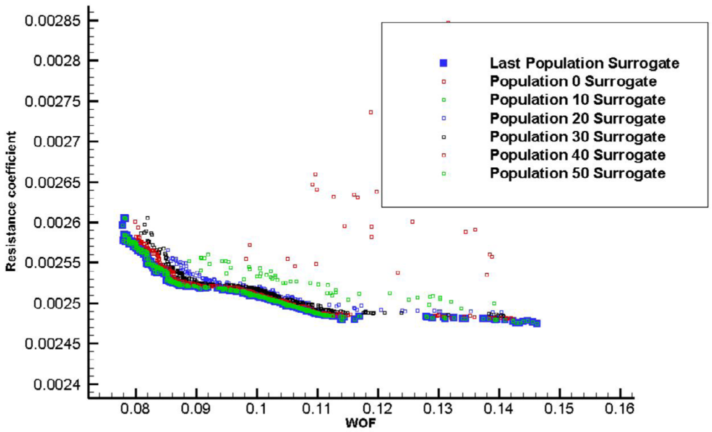

Figure 8: Pareto plot for resistance versus wake quality (Wake Object Function, WOF) for a MOGA on an initial response surface.

Figure 9 shows the comparison between the Pareto front from the direct MOGA approach and that from the approximate Pareto fronts using the quadratic polynomial and universal Kriging. Clearly the way the surrogate is built influences the approximate Pareto front. Still, both approximations are close to the true MOGA front while they were computed in only a day as apposed to the two weeks required by the direct MOGA approach.

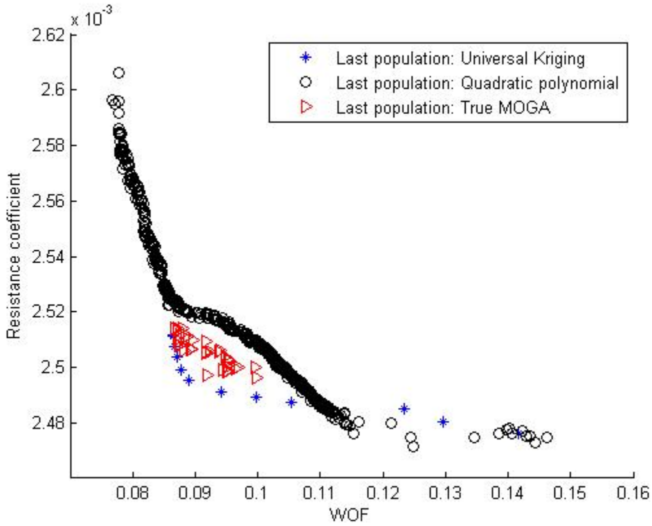

Figure 9: Pareto plot for resistance versus wake quality (Wake Object Function, WOF) for a direct MOGA, a MOGA on a quadratic response surface, and a MOGA on a universal kriging response surface.

The question arises whether the surrogate can be updated with new designs in order to improve its quality. This leads to Surrogate Based Global Optimization (SBGO) on updated surrogates as discussed next.

4.1.3 Surrogate Based Global Optimization on updated surrogates

A more elaborate SBGO takes the resulting Pareto front, determines the new designs to be evaluated, and adds those results to the dataset in order to update the surrogate. On the new surrogate a MOGA is done to determine an updated Pareto front. This process is visualized in Figure 10 showing the initial Design of Experiment, the front obtained on the initial surrogate, true values of the new designs that are selected from the initial surrogate front, the front obtained on the updated surrogate and finally the true front obtained with direct MOGA. All results are obtained using the quadratic polynomial fit.

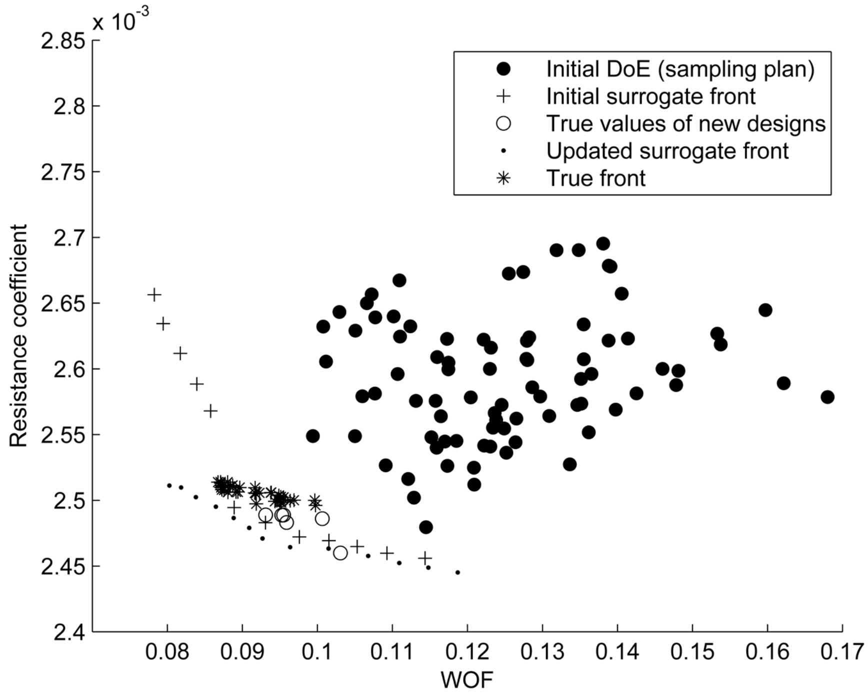

Figure 10: Pareto plot for resistance versus wake quality (Wake Object Function, WOF) using SBGO on updates surrogates.

Note that the true values of the new designs that are selected from the initial surrogate are already quite close to the true front, as expected. The resistance coefficients of the new designs are a bit smaller than the true values and this leads to an updated surrogate front with slightly lower resistance coefficients. The new front is more compact (all resistance coefficients smaller than $2.55 \cdot 10^{-3}$) and more aligned with the true front at the cost of only a few additional calculations. Since the true values of the new designs are already slightly better than the values of the true front obtained with MOGA it is suspected that the latter was not entirely converged when it reached its maximum number of evaluations.

A practical issue with these type of optimizations is the importance of failure capturing and its effect on simulation robustness. The failure capture techniques available in Dakota are abort, retry, recover and continuation. The recover method returns a dummy value to Dakota in case of failure and the continuation method searches for nearby parameters that do not fail. Since surrogates can be sensitive to outliers, these methods are sometimes not satisfactory and manual intervention is required to obtain the desired results. Knowledge of the simulation robustness is therefore critical for the success of (automatic) surrogate based optimization methods.

4.2 Bilevel optimization

Bilevel optimization is a branch of optimization, which contains a nested inner optimization problem within the constraints of an outer optimization. These inner and outer optimization problems are also called the upper level and lower level respectively. In naval ship design such problems arise naturally from sub-systems that interact with and influence each other, see [6]. Due to the complexity of these type of optimization problems surrogates are often used to mitigate the computational effort. Depending on the type of interaction between the sub-systems one can replace either the lower level objectives, upper level objectives or all objectives by surrogates, see [7]. Here we consider the optimization of the shape of a twin screw open shaft vessel and propeller, the upper and lower optimization level respectively, see Figure 11.

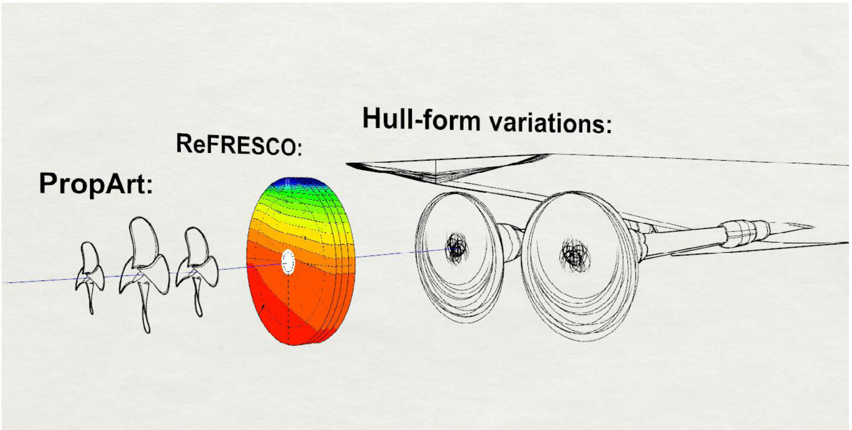

Figure 11: From right to left (downstream): Variations of the hull shape, shaft orientation, and propeller diameter. Nominal wakefields calculated for each hull form with the RANS solver ReFRESCO. Lower level: propeller optimization using PropArt with the nominal wakefields as input.

The overall goal is to find the orientation and shape of the hull/propeller combination that corresponds to minimum required power for propulsion and maximum comfort within the operational profile. Each optimization problem can be driven by its own dedicated software. We use the optimization toolkit Dakota ([5]) to drive the upper level optimization problem on the CFD code ReFRESCO [1] and an in-house optimization tool called PROPART ([12]) for the lower level optimization problem on the simulation code PROCAL ([16]). The nominal wakefield that results from an upper level evaluation acts as an input to the lower level propeller optimization. Finally, two-way coupling is used between ReFRESCO and PROCAL (with the optimized propeller) in order to take into acount interaction effects. Surrogate acceleration techniques as discussed in Section 4.1.2 and 4.1.3 are used to reduce the upper level evaluations of the optimization. This study is part of ongoing research at MARIN. New results will be published in future publications.

[1]ReFRESCO (www.refresco.org) is a community based open-usage CFD code for the Maritime World. It solves multiphase (unsteady) incompressible viscous flows using the Navier-Stokes equations, complemented with turbulence models, cavitation models and volume-fraction transport equations for different phases ([15]).

5 CONCLUSIONS

Four important phases of a ship design procedure are identified: shape parameterization, global sensitivity analysis, multi-objective optimization and design review. The first three phases comprise automatic ship design methods. Acceleration of these techniques will increase their practical applicability.

The shape parametrization can be defined by linear combination of predefined hull shapes or by using generic hull shapes. It is found that the number of required generic hull shapes quickly becomes too large which motivates the use of global sensitivity analysis and dimension reduction techniques.

Partial correlations and scatter plots can be obtained by sampling and regression. When interactions are not too strong this data can be used to reduce the dimensions of the design-space. This is usually the case when geometrically orthogonal hull shapes are used in the shape parameterization.

The complexity of present RANS-based multi-objective optimization problems calls for optimization techniques that reduce the required computational effort. Surrogate Based Global Optimization (SBGO) is a promising approach to mitigate the computational burden that results from high dimensional design spaces and/or multi-level (nested) optimization problems that arise naturally in naval ship design. For a practical application we showed that SBGO reduces the required computational time from two weeks to only a day when compared with a direct Multi-Objective Genetic Algorithm. It is however crucial to have knowledge about the robustness of the simulation code and to properly capture simulation failures during the SBGO process.

This knowledge and experience is currently acquired in several ongoing projects at the Maritime Research Institute Netherlands.

6 Acknowledgement

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