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Application of a surrogate modeling to the ship structural design

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ABSTRACT

Multi-criteria design of complex engineering systems is methodologically and computationally demanding and time consuming process. Optimization algorithms, problem decomposition, surrogate modeling and methods for decision support are synthesis methods that are usually employed to solve the design problem. The objective of the research presented in this paper was to improve the design process of complex thin-walled ship structures through an application of surrogate modeling on this type of a problem. Methods considered are integrated into interactive computing environment for multi-criteria design in order to enable effective and efficient interaction between designer and design problem within given design timeframe. Surrogate modeling was applied for the approximation of structural responses in order to reduce a number of finite element method (FEM) calculations inside of optimization loop. Applicability of the proposed approach and suitability of different surrogate modeling methods for that purpose is extensively tested on the simple barge example.

1. Introduction

As shown by Zanic et al. (2013), analysis methods for contemporary complex engineering systems, like nonlinear FEM or incremental iterative methods for calculation of hull girder ultimate strength (Andric et al., 2014), can be computationally very demanding and despite of steady advances in computing power, the expense of running many analysis calculations remains nontrivial. Single analysis of one design solution can take from seconds to hours or even much longer for e.g. nonlaminar and non-stationary 3D CFD problems. Therefore, direct use of some analysis methods is not possible in optimization because optimization demands several hundreds or even thousands analysis of different variants. To address such a challenge, surrogate or metamodeling techniques are often used. An application of surrogate modeling as approximations of expensive computer analysis codes can result in significant savings in both number of analysis and total time in which satisfactory optimal solutions are obtained. Due to the wide usage of this approach in many research fields, it can be found under various names like: surrogate (or metamodel) assisted optimization, surrogate (or metamodel) driven design optimization, surrogate (or metamodel) based design optimization, optimization using surrogate models (or metamodels), etc.

As given by Wang and Shan (2007), there are various roles of surrogate modeling in support of design process:

- Model approximation. Approximation of computation-intensive processes across the entire or just a portion of design space is used to reduce computation costs.
- Design space exploration. Surrogates offer insight into the functional relationship between design parameters and design criterions which is one of the obstacles in understanding of numerical models behavior.
- Problem formulation. Based on an enhanced understanding of a design optimization problem, the number and search range of design variables may be reduced; certain ineffective constraints may be removed; a single objective optimization problem may be hanged to a multi-objective optimization problem or vice versa. Metamodel can assist the formulation of an optimization problem that is easier to solve or more accurate than otherwise.
- Optimization support. Industry has various optimization needs, e.g., global optimization, multi-objective optimization, multidisciplinary design optimization, probabilistic optimization, and so on. Each type of optimization has its own challenges. Metamodeling can be applied and integrated to solve various types of optimization problems that involve computation-intensive functions.

Another important aspect of surrogate based optimization that is emerging lately, is easier parallelization of optimization process/ sequence. This property is important due to the characteristics of

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today's computers where computing power increases by increasing the number of CPU or cores. Modern optimization frameworks are under pressure to enable distribution of parallel computation sequences to both standard CPU cores and massive parallel GPU cores. Development of optimization framework that enables effective usage of surrogate assisted optimization on standard multi-core processors, and still substandard GPU cards like nVidia Tesla, makes sense since it can be applied to any type of optimization problem. For some engineering applications where reliable legacy computer codes are used there is actually no practical alternative, since it is practically impossible to rewrite entire computing code in e.g. CUDA to enable usage of nVidia Tesla compute cards.

The design of complex thin-walled structure (e.g. ship, aircraft) falls within the category of large scale problems characterized by several design objectives, hundreds of design variables thousands of design constraints. The objective of the research presented in this paper was to investigate possibilities of improvements of the design process for complex thin-walled ship structures through an application of surrogate-assisted optimization to this type of a problem. More specifically the presented research has investigated possibilities of surrogate modeling of ship structural responses that are inputs for calculation of thin-walled structures adequacy. As explained in detail in Section 4 this challenging task demanded careful consideration of design parameters and extent of each surrogate model in order to reduce the number of surrogate models and experiments necessary for training of those models to applicable level. Since one of the main advantages of surrogate assisted optimization is an efficient solving on multiprocessor or even distributed computer platforms, a special attention is given to the possibilities of parallelization of computations in the optimization loop.

In order to define the terminology and present the theoretical basics of applied techniques, the following section introduces some basic aspects of surrogate modeling, surrogate modeling methods and complex system decomposition. Although complex system decomposition is not a key point of discussion in this paper, the idea of using surrogates for structural response initially came as a result of necessity to have better information about structural response of decomposed ship substructures, as explained in Section 4. Therefore, third section gives a brief introduction to the complex system decomposition/coordination method.

Section 5 explains some special considerations on incorporation of surrogate modeling into object oriented architecture of environment for decision support OCTOPUS Designer (OCTOPUS, 2011).

Application and validation of considered methods and the proposed approach on simple barge structure is given in Section 6. It presents elaborative study on the accuracy of different applied surrogate modeling techniques for metamodeling of structural responses and application of surrogate modeling for surrogate assisted optimization of a simple barge structure.

2. Surrogate modeling

As given in introduction, surrogate/approximation/metamodeling, is the key to surrogate assisted optimization. It can be stated that surrogate modeling actually evolves from classical Design of Experiments (DOE) theory, in which polynomial functions are used as response surfaces, or surrogate models. One of the most cited handbooks with detail overview of DOE for classical (physical) experiments is Montgomery (2001), while the overview of surrogate modeling for deterministic computer experiments (DACE – design and analysis of computer experiments) can be found in e.g. Fang et al. (2006a, 2006b) or Simpson et al. (2001a, 2001b).

The main difference between “classical” and computer experiments is nonexistence of random error for deterministic computer experiments, which according to Sacks et al. (1989) leads to the conclusion that surrogate model adequacy is determined solely by systematic bias and that the classical notions of experimental blocking, replication and randomization are irrelevant. In depth review of surrogate modeling for computer based engineering design can be found in Refs. Simpson et al. (2001a, 2001b) and Wang and Shan (2007).

Steps necessary for generation of surrogate models includes: planning of experiments or sampling (Fig. 1), execution of simulations with original analysis methods, generation or creation of selected surrogate model and validation of surrogate model adequacy.

After selecting an appropriate experimental design according to appropriate criteria (Goel et al., 2008; Viana et al., 2010) and performing the necessary computer runs, the next step is to choose a surrogate model type and corresponding fitting method. Many alternative models and methods exist, and there is no clear answer which is better. The selection of appropriate surrogate model depends mostly on characteristic of physical phenomenon that is approximated. Some of widely used surrogate models in engineering include: Response Surfaces – RS (Fang et al., 2006a, 2006b; Kaufman et al., 1996; Montgomery, 2001; Roux et al., 1996), Kriging (Koch et al., 2002; Martin and Simpson, 2005; Simpson et al., 2001a, 2001b), Radial basis functions – RBF (Fang et al., 2006a, 2006b; Powell, 1992; Regis and Shoemaker, 2007), Artificial Neural Network – ANN (Miralbes and Castejon, 2012; Park et al., 2013; Patnaik et al., 2005), Support Vector Machine – SVM (Collobert and Bengio, 2001; Rivas-Perea et al., 2013), Multivariate Adaptive Regression Splines – MARS (Friedman, 1991).

Generally, the value of a target criteria response y at some location $\boldsymbol{x}$ can be written as

$$y(\mathbf{x}) = \hat{y}(\mathbf{x}) + \varepsilon_b \tag{1}$$

where $\hat{y}(\mathbf{x})$ is surrogate model of response y, while ε_b is a surrogate model error or bias. As already stated, one of the characteristics of deterministic computer experiments is nonexistence of random error ε_r, and that is the reason why it is not included in expression (1).

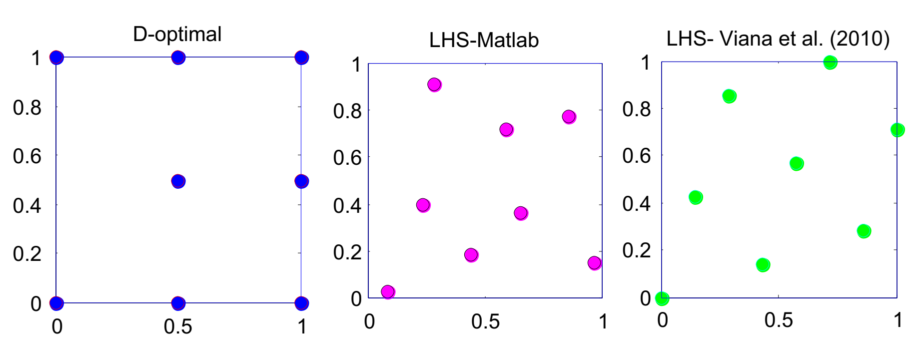

Fig. 1. Preview of D-optimal design and two different space filling LHS designs.