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DEVELOPMENT AND APPLICATION OF METAMODELING METHODS FOR ANALYSIS AND OPTIMIZATION OF MECHANICAL SYSTEMS

Summary of Doctoral Thesis

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CONTENTS

THESIS OVERALL REVIEW 4
Relevance of the topic 4
Objective of the thesis 5
Research tasks 5
Thesis scientific novelty 6
The practical value 7
Propositions for the defense 7
The structure and volume 8
Thesis approbation and publications 8
CONTENT OF THE THESIS 8
The first chapter 8
The second chapter 12
The third chapter 14
The fourth chapter 15
The fifth chapter 16
CONCLUSIONS 20
LIST OF PUBLICATIONS 21
REFERENCES 23

Development and Application of Metamodeling Methods for Analysis and Optimization of Mechanical Systems

THESIS OVERALL REVIEW

Relevance of the topic

The rapid progress of computer technologies has facilitated the development of various fields, among them numerical methods and their application for the solution of the mathematical models of complex mechanical systems. As a result, the development of modern engineering solutions is based on the numerical methods implemented in computer simulation software. The design of complex systems, for example, an automobile or a plane, is a highly resource-consuming task that frequently involves several engineering disciplines. An integral part of effective engineer design is optimization which nowadays is based on simulation software. Regardless of the increase of computer calculation power, the complexity of the tasks to be solved and simulation software – for example, finite elements and numerical fluid dynamics software - is increasing as well. For example, the simulation of one car accident takes from 36 to 160 hours. The optimization of two variables requires approximately 50 iterations, and, assuming that each iteration requires a separate simulation, the total computing time would be from 75 days to 11 months.

The doctoral thesis is dedicated to the development of metamodeling methods and their application for the analysis and optimization of various mechanical systems. In order to decrease time necessary for numerical methods, approximation methods are used and models of the mathematical model (metamodels) are created. Such metamodels are being successfully applied for the analysis and optimization of engineering design.

In order to effectively apply metamodeling methods, it is crucial to choose the most appropriate experimental design and the most effective approximation method. The design and approximation of numerical experiments differs considerably from the methods of design and analysis of physical experiments.

In the scientific literature a consensus has been reached that for numerical experiments points should fill the experimental space as uniformly as possible.
To obtain such experimental designs, Latin Hypercube (LH) experimental designs optimized according to a space filling criterion are used. Optimization of experimental designs is a computationally complex and time-consuming task, but once designs are found, they may be published and used repeatedly.

Approximation methods of numerical experiments must be capable of interpolation of experimental points, since, in contrast to physical experiments, mathematic experiments do not possess random error, and furthermore the results of the numerical calculation software frequently have complex response surfaces.

The optimization of engineering designs frequently involves multiobjective optimization with continuous and discrete input factors which must comply with nonlinear constraints. The objective and constraint functions frequently are based on complex mathematical models. Solving such tasks using traditional optimization methods is ineffective. In cases of multidisciplinary optimization, numerical calculations from various engineering fields are used. For the solution of such tasks, approximation models allow significantly decrease the time needed for optimization. Approximation models also allow integrate the results of simulation programs from various disciplines that frequently are based on proprietary and protected data standards. The mixed numerical-physical experimentation approaches are also used for the solution of various problems, for example, the solution of parametric identification tasks.

Metamodeling methods are used in various engineering fields. Among them is the optimization of topology and structure of various composite panels. The research of panel topology or the effectiveness of the form, number and placement of stiffening ribs, is directly connected with the potential weight decrease of the construction, which in turn reduces construction costs and increases the industrial competitiveness of the manufacturer. Such untraditional structural (composite) solutions are used in combination with innovative joining technologies, for example, laser beam welding.

The application of composite unidirectional reinforced laminate materials (particularly in the aviation industry) already has attained nearly 30% of all supporting structure solutions. In the near future it is planned to begin the mass construction of airliners (Airbus 350 and Boeing 787) which are almost completely designed from composite constructions. These constructions are mainly created from thin-wall ribbed panels which, in regard of capacity/weight ratios, are more effective in comparison with the traditional metal alloy predecessors. The successful introduction of such materials and constructive solutions significantly depends on the consistency of mathematical and physical models.

Objective of the thesis

The objective of the doctoral thesis is to develop and improve metamodeling methods and tools for the design, analysis and optimization of engineering elements.

Research tasks

The problems to be solved and the tasks to be completed in this doctoral thesis:

To develop optimization methods for LH-type experimental designs and apply them for the creation of engineering experimental designs.

To create a data base of experimental designs for mechanical design engineering and publish the obtained optimal experimental designs on the Internet.

To develop methods and algorithms for effective application of the kriging method in metamodeling.

To develop methods for the application of non-parametrical approximations in inverse metamodeling.

To test the created methods and software in practical direct and inverse metamodeling and optimization tasks.

Thesis scientific novelty

Within the framework of the doctoral thesis, the algorithm of optimization of Latin Hypercube designs has been developed. The algorithm is based on the coordinate exchange procedure and is combined with the regulated permutation and multiple start global optimization method. Various space filling criteria were compared for the LH experimental designs and the MSE criterion was chosen for the measurement of LH experimental design space uniformity. The continuous MSE design optimization algorithm was modified and adapted to the proposed LH experimental design optimization algorithm. For the optimization of MaxiMin LH experimental designs a criterion was proposed that is based on mean distance that is calculated for all experimental design points in relation with their closest neighboring points, and the standard deviation of the distance of the experimental design points and the nearest neighboring points. This criterion and developed optimization algorithm was used for the optimization of LH experimental designs. LH experimental designs that have been optimized in this way have better MaxiMin criterion value and also values of other space filling criteria, in comparison with the LH experimental designs obtained by other authors that have been optimized according to the MaxiMin criterion.

The doctoral thesis proposes an algorithmic scheme for the speed up of the creation of kriging model in the case of multiple responses. There is no unified approach or methodology for the choice of the covariance function and the values of optimal parameters for kriging method in the scientific literature. Detailed research was conducted regarding various strategies for the determination of covariance function parameters for several test functions and practical tasks.

The promotion thesis proposes an inverse metamodeling method as an alternative to the discrepancy method or as a supplementary instrument for the solution of inverse tasks. The main theoretic and practical problems that must be faced when applying the developed method have been considered. The inverse metamodeling method is applied and compared with the discrepancy method for the identification of carbon-epoxy plate elasticity parameters.

The developed methods of experimental designs and approximation have been used to predict behavior and obtain optimal design variants of metal sandwich panels.

The practical value

The developed optimization algorithm and the obtained and published experimental designs may be used for the practical design of numerical experiments.

The approach for determination of the hyperparameters and speed up of the creation of kriging model may be practically employed in the creation of high-precision metamodels for multidisciplinary analysis and optimization tasks, including the design of engineering elements. On the basis of the obtained results, software tools have been developed for the analysis and optimization of mechanical systems.

The inverse metamodeling method can be employed as an alternative to the discrepancy method or as a supplementary instrument for the solution of identification tasks.

The obtained sandwich panel stiffness, weight and cost optimal solutions may serve as a basis for the acceleration of design processes and improvement of manufacturing effectiveness.

Propositions for the defense

- Metamodeling methods for the design of mechanical systems, which include optimization methods of computer and natural experimental designs, improved nonparametric approximation methods as well as a new inverse metamodeling method.
- Optimization algorithm of Latin Hypercube experimental designs, its application for the obtaining of MSE and MaxiMin optimal experimental designs.
- A method for the determination of kriging covariance function hyperparameters that is based on the cross-validation criterion.
- A scheme for improving the speed of the kriging method in the case of multiple response functions.
- Inverse metamodeling method for the solution of identification tasks.
- Metamodels of various core ribbed sandwich panels for the analysis and optimization of weight, costs and stiffness, as well as practical

recommendations for the finding of optimal panel plate thickness and core stiffener thickness and location.
- Solution of the carbon-epoxy plate elasticity module identification task with the inverse metamodeling method.

The structure and volume

The promotion thesis consists of a preface, 5 chapters, conclusions and literature references. The volume of the thesis is 191 pages, 94 figures, 67 tables and a literature references, containing 261 publication titles.

Thesis approbation and publications

The results of the promotion thesis have been reported and discussed in international conferences and scientific meetings:

- 6th ASMO-UK/ISSMO International Conference on Engineering Design Optimization (Oxford, UK, 2006);
- 9th US National Congress on Computational Mechanics (USNCCM9) (San Francisco, USA, 2007);
- 7*th* World Congress on Structural and Multidisciplinary Optimization *(*WCSMO7) (Seoul, Korea, 21-25 May 2007);
- 14th International Conference on Composites and Nano Engineering (Colorado, USA, 2006);
- RTU 46th and 48th International Scientific Conference (Riga, Latvia, 2005, 2007);
- 5th International DAAAM Baltic Conference (Tallin, Estonia, 2006));
- Combined RTU Institute of Mechanics and LNMK seminars (Riga, Latvia, 3.10.2006, 11.12.2007, 01.04.2008).

The main results of the thesis have been expounded in 14 publications.

CONTENT OF THE THESIS

The first chapter consists of a survey of literature on the role of metamodeling in the design of mechanical systems, the design of numerical experiments, approximation and optimization, as well as inverse problems and methods of their solution, employing physical and numerical experiments.

Development of modern engineering solutions includes extensive use of computer simulation software. The design of complex systems, for example, cars or planes, is a highly complex optimization task that frequently involves various engineering disciplines, several criteria and computationally complex simulation software. In order to simplify the complex numerical models for the last two decades approximation methods or metamodels have been successfully employed.

The design optimization is necessary to find the best, or a good engineering solution. During optimization, the best solution from various alternatives is chosen according to a certain criterion. Optimization tasks for engineering problems are frequently complex, since objectives may be nonlinear and design variables have to comply with many constraints. Such global optimization tasks require multiple calculations of objectives or constraints that frequently are based on highly complex and computationally intensive simulations.

Almost all real-life engineering designs should be optimal according to several criteria that frequently are mutually competitive. In such cases a Multiobjective Optimization (MOO) task must be solved

Modern engineering designs involve problems from various engineering disciplines and the MOO task criteria may originate from various engineering fields. For example, during design of an aircraft wing, the optimization task involves both wing structure and aerodynamic calculations. Such analysis and optimization tasks are called Multidisciplinary Optimization tasks (MDO). Often the task of each separate discipline itself may be very complex and computationally-intensive.

Practical engineering solutions should not only be optimal, but they must be robust (with reduced sensitivity) to slight changes in the parameters of the designed system or the characteristics of the environment. In order to estimate the robustness of the designed system Probabilistic Design Optimization and Analysis is used [Wang and Shan (2007)]. The solution of such optimization tasks with local and global (both determined and stochastic) methods is complicated and ineffective. During the last twenty years, global optimization, multiobjective, multidisciplinary robust optimization tasks have been solved employing metamodeling methods [Wang and Shan (2006)]. The main advantages of using metamodeling in optimization are: 1) the reduction of the time necessary for the optimization procedure, using both criteria and constraint approximations, 2) possibility to obtain experimental data in parallel, 3) during the approximation process, knowledge of the significance of the design factors and their influence on the optimal solutions may be obtained, 4) the use of metamodeling allows to work both with continuous and discrete variables.

The Taguchi method and the Response Surface Method [Ramberg and Pignatiello (1991)] have gained popularity and extensive practical use. These two methods have become the basis for several modern engineering design methods, such as the Robust Concept Exploration Method [Simpson (1998)], [Chen et al. (1996)], Variable Complexity Response Surface Modeling [Giunta et al. (1994)], [Giunta et al. (1996)], Concurrent Sub Space Optimization [Renaud and Gabriele (1993)], [Renaud and Gabriele (1994)], Robust Design Simulation [Mavris et al. (1995)] , NORMAN/ DEBORA [Cartuyvels and Dupas 1993], Probabilistic Design System [Fox, E.P. (1996)], etc.

The role of metamodeling in optimization of engineering designs is shown in Fig. 1.

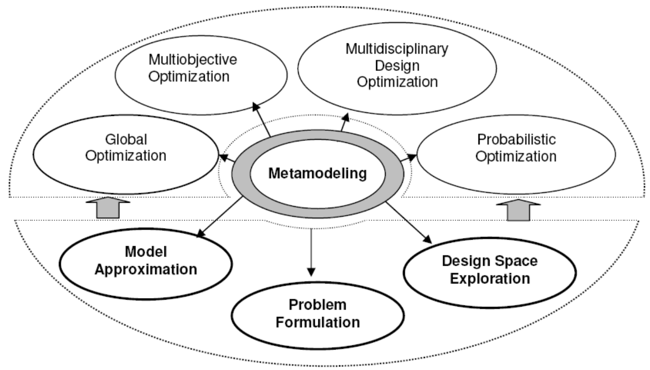

Figure 1. Metamodeling and its role in the optimization of engineering projects

The main advantages of using metamodels are [Jin et al. (2000)] the possibilities:

- To model and understand the mutual relation of input and output parameters.
- To investigate the design variable space, anticipate the design compromises, modify constraints and, if necessary, reformulate the optimization task, visualize the response surfaces.
- Use fast optimization procedures, conduct global, multiobjective optimization.
- Integrate the calculations of various disciplines (that are frequently based on protected standards) and, possibly, distributed and parallel calculations more easily.

The use of metamodels in design optimization usually consists of four stages:

- Choice of effective experimental design.
- Choice of correct mathematical model, in order to be able to approximate experimental data and describe the relation between process input and output.
- Model-fitting.
- Use of approximations for the fast optimization procedure.

Design of experiments is a process that results in the choice of an optimal experimental design. Each experiment (numerical or physical) is related to certain costs. Therefore it is necessary to choose effective experimentation strategy which with minimal costs would allow obtaining the maximum amount of information about interested process. In an effective experimentation strategy, the number of required runs (experimental points) is minimized, and their distribution is such that the information obtained from the experiments is as complete as possible. Computer experiments, in contract to traditional physical experiments, do not have random error since repeated observations with an unchanged input set give identical responses. The design of computer experiments is based on two basic principles, which for the first time were formulated in 1977 by the RTU (then RPI) scientist Vilnis Eglajs:

- Designs do not require more than one observation for a given input set.
- Experimental points must be distributed as uniformly as possible in the experimental region.

Modern design of computer experiments often is conducted using Latin Hypercube (LH) designs that are optimized according to some space filling criteria. As of this moment, the literature does not present results that conclusively prove the superiority of any single criterion. However many authors believe that the maximum entropy and distance-based criteria give the best results [Jin et al. (2001)], [Santner et al. (2003)], [Bursztyn and Steinberg (2006)]. Popular space filling criteria that are not based on a previous assumption of the input-output functional form are the MaxiMin, MSE, Discrepancy, Entropy and Eglajs criteria. A significant amount of literature exists on the optimization of experimental designs without constraints on levels according to the MaxiMin and MSE criteria, while the LH design optimization algorithms have received significantly less attention.

Regression analysis employs two different approaches [Härdle (1990)]: parametric approximation and nonparametric approximation. Computer experiments, in contrast to traditional physical experiments, do not have random error, therefore approximation of computer experiments should employ methods that interpolate experimental data. The most popular methods for computer experiment approximation are Gaussian process regression (GPR) or kriging (see [Barton (1998)], [Booker (1998)], [Currin 1991], [Sacks (1989)], [Rassmussen and Williams (2006)]), Locally Weighted Polynomial approximations or Moving Least Squares (see [Cleveland (1979)], [Levin (1998)], [Fan and Gijbels (1996)] etc.), Radial Basis Functions [Dyn (1986)], [Powell (1987)], Neuron Networks (see [Cheng and Titterington 1994], [Haykin 1994], Smith and Mistree (1993)], Support Vector Regression [Clarke et al. (2005)], etc. In practice, approximations of numerical experiments do not always go directly through the experimental points. Frequently Response Surface Methods (RSM), are employed although from the point of view of statistics this approach is not completely correct.

Kriging is a popular computer experiment approximation method. Kriging is based on the Bayesian approach in statistics and is well suited to the processing of determined computer experiments for an average number of input factors. The kriging method generates all possible Gaussian process realizations with a given

mean value and covariance function. The realizations that do not correspond to experimental data are discarded [Rasmussen and Williams (2006)].

To employ kriging method in practice, the parameters of the covariance function must be determined. The scientific literature considers two methods: Cross-Validation (CV) and the Maximum Likelihood Method (MLL), the most frequently used method for hyperparameter determination is the MLL method.

Despite the vast amount of various approximation methods, there is no consensus in the scientific literature on which of the methods is the best. Recommendations are given in some studies depending on the problem scope, response non-linearity and amount of experiments.

Inverse engineering problems are solved in cases when model parameters are to be determined on the basis of data obtained in experiments. In practice, such tasks are solved, using the Mixed Numerical–Experimental Techniques (MNET). In this method, the solutions of the inverse task are the model parameters for which the least difference exists between the physical and the numerical experiment. In the engineering practice of the last two decades, MNET methods have been used for parameter identification tasks in various fields: engineering mechanics, to identify heat conductivity [Trujillo et al. (1997)], determine acoustic [Panneton et al. (2003)], damping [De Visscher (1995)], [Tudor (2003)], plasticity [Furukwaw and Yagawa (1998)], [Yoshida (2003)] properties, in civil engineering, to identify soil permeability [Javadi et al (1999)] and elasticity properties [Hikawa et al. (2004)], in electrical engineering to identify piezoelectric properties [Ferin G. (2004)], in biomedicine to determine the mechanical properties of skin [Hendriks et al. (2003)] and liver [Kauer (2001)]. The basic problems that have to be solved when employing the MNET approach are: the inaccuracies of the mathematical model and the existence of several alternative solutions.

In the end of this chapter, the dissertation thesis objectives and tasks are formulated.

The second chapter proposes an optimization algorithm for Latin Hypercube experimental designs. Its application for LH experiment optimization is described. Figure 2 shows the block diagram for the proposed LH experimental design optimization algorithm.

The experimental design optimization algorithm was used for LH experiment optimization according to the MSE and MaxiMin criteria.

For the optimization of experimental designs without LH constraint according to the MSE criterion, the so-called NTLBG algorithm exists, which allows optimization process to converge to the local minimum. In order to optimize LH experimental designs according to the MSE criterion, the NTLBG algorithm was modified so that for each cyclic coordinate change it was checked whether by reducing the level of a given factor for two runs, the distance from the experimental points to the mean value of the supporting point group for each experimental point was reduced.

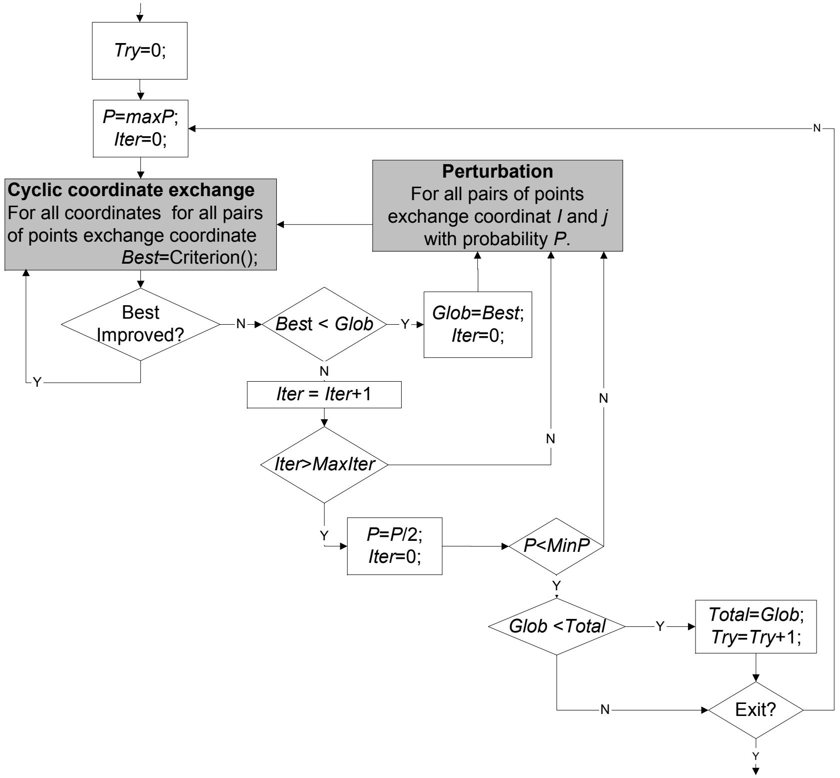

Figure 2. Block diagram of LH optimization algorithm

To obtain the so called Maximal-minimum distance (MaxiMin) optimal LH experimental designs, a new criterion ϕ was introduced and used

$$\phi = Mmd - kStd \quad (1)$$

where

$$Mmd = \frac{1}{n}\sum_{i=1}^{n} \min_{j=1..n,\, j\neq i} \left\| x_i - x_j \right\| , \quad (2)$$

$$Std = \sqrt{\frac{\sum_{i=1}^{n}\left(Mmd - \min_{j\neq i}\left\| x_i - x_j \right\| \right)^2}{n-1}} . \quad (3)$$

Coefficient k was taken from interval [0, 1].

Optimizing designs according to the ϕ criterion, and accepting designs that have better MaxiMin criterion value lead to a fast optimization procedure for the

obtaining of LH experimental designs optimized according to the MaxiMin criterion. Such optimized designs have also better values for other space filling criteria.

For LH design optimization, scientific literature describes several space filling criteria. To evaluate the effectiveness of space filling criteria, a test function was used and the linear correlation of various space filling criteria and the test function approximation error was compared. It was concluded that the MSE criterion has the largest correlation with the approximation error of the given test function. It was therefore concluded that LH experimental designs that are optimized according to the MSE criterion can be effectively employed for design of computer experiments.

A data base has been developed and the obtained space filling experimental designs have been published on the Internet (www.mmd.rtu.lv).

The third chapter considers problems and solutions that are to be faced for practical application of the kriging method for computer experiment approximation. The main problems are computation-intensive model development which includes the computation of the inverse matrix of the covariance matrix and the finding of the optimal covariance function parameters (hyperparameters). The thesis proposes an algorithmic computational scheme which allows to decrease the time necessary for the kriging model creation in the case of several response functions. This scheme is based on the fact that the covariance matrix depends on the experimental design, the covariance function and the hyperparameters of the covariance function, but does not directly depend on the data of the response function. This scheme was complemented with steps for the improvement of the calculation speed of MLL and CV criterions in the case of several response functions.

Additionally questions were considered relating the choice of the covariance function, the choice of the covariance hyperparameters and their optimal settings. From the literature survey, it was concluded that a unified approach to the choice of the covariance function and the number of its hyperparameters does not exist. In this chapter, CV and MLL criteria were compared for the covariance function hyperparameter optimization for several one and two-factor tasks. It was empirically determined that it is possible to effectively solve these optimization tasks, using the quasi-Newton method by choosing the initial point θ_i=1. In cases when the quality of the obtained approximation was unsatisfactory, the optimization process was repeated, using other initial points θ_i=0.1 and θ_i=5, as well as using the Particle Swarm global optimization method.

The second part of the third chapter proposes an inverse metamodeling method (see Figure 3) for the solution of inverse tasks.

Several problems have to be faced when solving identification problems using approach of inverse metamodeling. First, it is possible to approximate the inverse relation only in cases when the inverse model exists. If the inverse model does not exist or the inverse relation is not unique, its approximation usually has low accuracy and therefore the method may give bad solutions. For many tasks, the number of responses can be increased, and it is shown that the ambiguousness disappears even if each of the responses individually is nonlinear with non unique inverse relation. In practice, it is often possible to increase the number of the measured responses (greater than the number of identifiable parameters), therefore there is reason to believe that this drawback of inverse metamodeling is not particularly significant for most practical tasks. Ambiguous inverse relation may indicate an error in measurements, in the mathematical model or a possibility that the problem may exist in the formulation of the task.

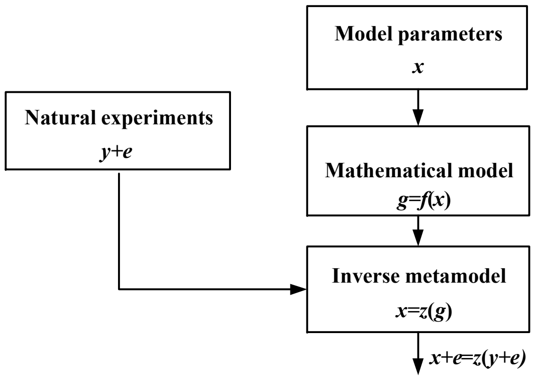

Figure 3. Scheme for the inverse metamodeling method

Second, it is impossible to plan the calculated responses, therefore when creating inverse metamodels the experimental points do not uniformly cover the research region. For this reason, one must deal with singular matrices, by using polynomials for approximation whose coefficients are determined with the least squares method. For this case the quasi-inversed matrix approach with Singular Value Decomposition method is recommended.

The inverse metamodeling method, in contrast to the discrepancy method, allows directly evaluate the quality of the solution by determining the accuracy of the metamodel, using the cross-validation. The estimation of the quality of inverse solutions is very significant in practical tasks. The second main advantage of inverse metamodeling is the fact that, using polynomial approximations, it is possible to directly evaluate the influence (significance) of the various outputs on the inputs.

The fourth chapter tests the proposed experimental design and approximation methods, using various 2, 3 and 5 factor test tasks for various numbers of experimental points. Test functions described in the literature were used to compare the effectiveness of the CV and MLL criteria for the determination of covariance function hyperparameters. Approximations for all test functions were made using both the CV and the MLL method. The

covariance function parameters were determined in two ways. In the first approach, m+1 (m – number of factors) hyperparameters were determined: one power hyperparameter and m distance deviation hyperparameters (distance deviation hyperparameters that correspond to each input factor). In the second approach, two hyperparameters were determined: power hyperparameter p and one distance deviation hyperparameter that is common to all the input factors. For almost all of the test tasks, the best approximation accuracy was obtained using the CV criterion and determining m distance deviation hyperparameters.

In this chapter, the accuracy of kriging approximations was compared for two, three and 5 factor test tasks with first and second order polynomial and locally weighted first and second order polynomial approximations. For the kriging covariance function, m+1 hyperparameters were determined using the CV criterion. It was concluded that in the majority of two factor tasks and in all of the considered three and 5 factor test tasks the kriging method gives higher approximation accuracy (see Figure 4).

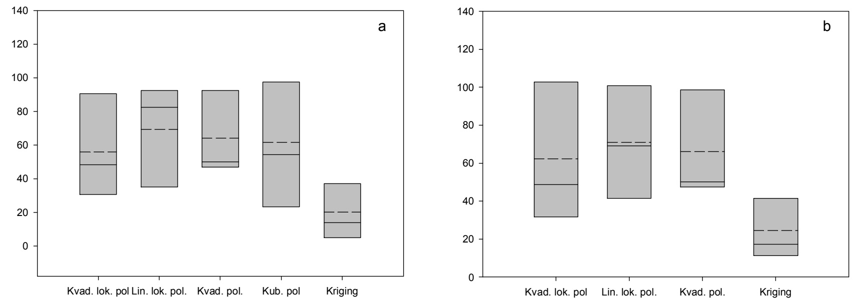

Figure 4. Comparison of test function approximations, using various methods and various numbers of points (figure a – 3 factor test tasks, figure b – 5 factor test tasks)

In the fifth chapter, the developed methods of design of experiments, approximation and software were applied for the solution of practical engineering design problems – optimization of sandwich panels and the identification of elasticity parameters for thin-wall composite construction elements.

The first of the considered practical problems is the approximation and optimization of the strength calculations of metal I, C, O, Oc, Z and V type core sandwich panels (see Figure 5).

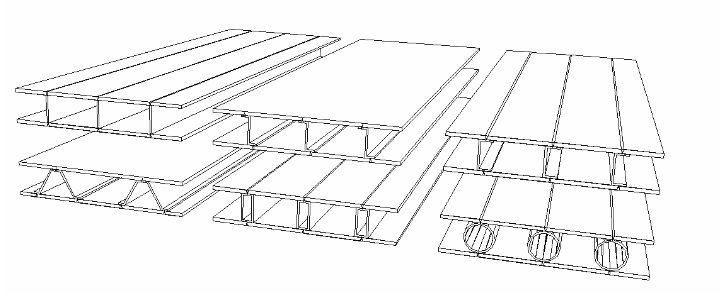

Figure 5. Schemes of metal sandwich panels of various core types

For the design of numerical experiments, a 6 factor LH experimental design was employed that was optimized according to the MSE criterion, using the algorithm proposed in the second chapter. For the creation of the metamodel, 250 experimental points were used and other 250 experimental points were used for the validation of the obtained metamodels. The numerical experiments for all profile type sandwich panels were conducted in cooperation with the leading researcher of the RTU Institute of Materials and Constructions Kaspars Kalnins, creating the finite element model using the ANSYS software (see Figure 6). The panels were loaded with a uniformly distributed 3 kPa load, supplementing it with concentrated 1kN force in the center of the panel.

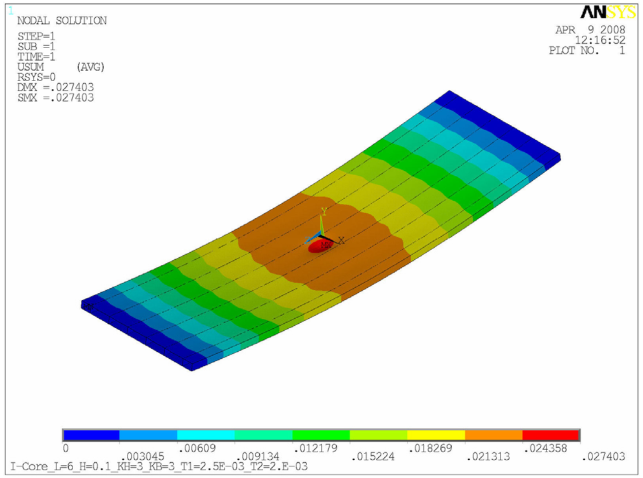

Figure 6. I core sandwich panel deformation

In this thesis, 7 responses were measured and approximated. For the approximation of sandwich panel calculation, the kriging method turned out to be the most effective, determining the covariance function distance deviation

hyperparameters for each factor and using the CV criterion for the evaluation of the accuracy of approximation prediction (see Figure 7).

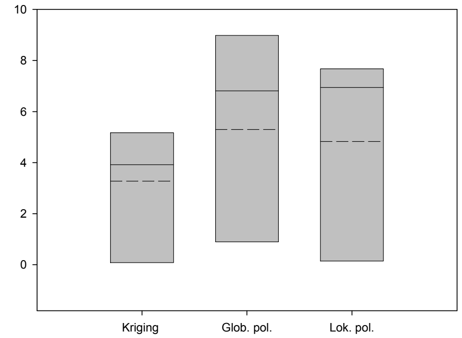

Figure 7. Approximation error for various responses for the I core panel in 250 test points, using kriging, polynomial and locally weighted polynomial approximations

It was determined that the quality of approximation of the sandwich panel plate deformations could be improved by introducing an additional variable that is inverse proportional to the second moment of inertia of the panel cross-section.

The created metamodels were used to find optimal I core panel variants. During the optimization process, three discrete parameters and one continuous parameter were varied. The panel length and width were fixed, assuming that they were given from the design specification. The boundaries used in the optimization procedure were chosen on the basis of the guidelines of the certifying organization Det Norske Veritas [DNV Technical report (2003)] for the certification of ship deck panels. For the finding of Pareto optimums, three criterion functions were chosen: panel mass, relation of panel length to bottom plate deflection and the panel production costs that were obtained with the formula

$$C = 0.7 y_7 + n\left(5\times10^5 (t_1 + t_2) - 500(t_1 + t_2) + 4\right)L\,, \qquad (5)$$

where y_7 – panel mass, n – number of ribs, t_1 – thickness of top and bottom plate, t_2 – core support thickness, L – panel length [Farkas (2003)].

Figure 8 shows the obtained Pareto optimal points.

The obtained Pareto optimal solutions were validated with the FE calculation model and it was concluded that the metamodels have sufficiently high accuracy in the optimum points. For example, the relative error of panel deformation is 2.61%.

It was concluded that the developed methods of design of experiments and approximation may be applied for the creation of high-accuracy metamodels and approximation of FE calculations of various core type metal sandwich panels. The obtained solutions may serve as a basis for the acceleration of design processes and improvement of manufacturing effectiveness

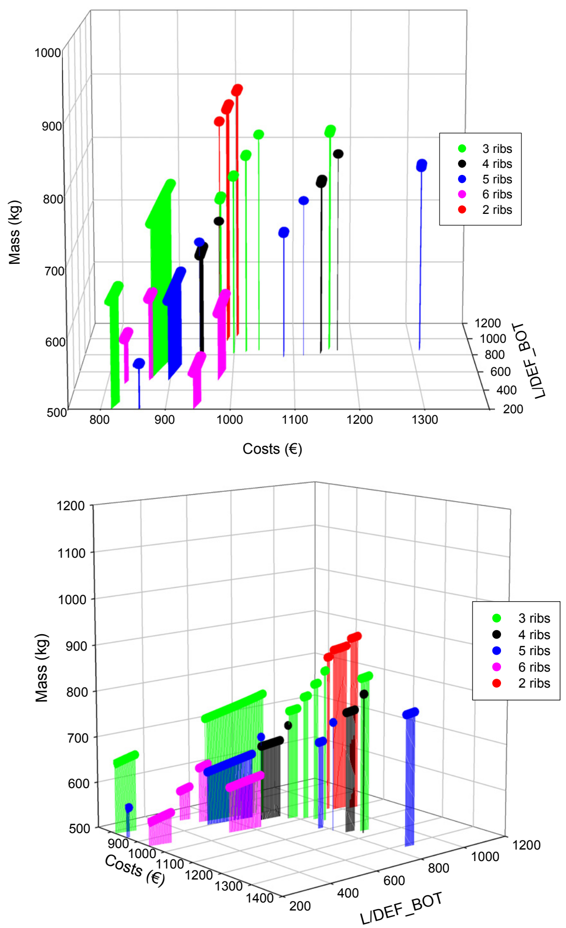

Figure 8. Pareto points for I core sandwich panel

In the second section of the fifth chapter, the inverse metamodeling method proposed in the third chapter was used for the identification of elasticity properties of a ribbed carbon-epoxy plate. The obtained results were compared with the results of the discrepancy method.

In this task, FE element calculations were used. The transverse, axial and shear modules of elasticity were used as the inputs of FE model and eigenfrequencies as outputs. In the identification task, the first 7 physically measured resonant frequencies were used to identify three elasticity modules. The inverse metamodels were obtained with a low CV error and the inverse metamodeling method gave similar results in comparison with the results of the discrepancy method. It was concluded that the inverse metamodeling method may be used both as an alternative of the discrepancy method, and as a supplementary tool. In further tasks, it is recommended to use both methods to increase and control the accuracy of identification. The inverse metamodeling method allows to identify the significance of parameters and to determine eigenfrequencies that influence the identifiable parameters the most. The question of frequency choice is still to be studied, and in further experimental measurements it is necessary to eliminate the influence of external factors as much as possible. In the given task, it is also necessary to increase the number of natural experiment measurements, in order to be able to evaluate the dispersion of the frequency measurements.

Development and Application of Metamodeling Methods for Analysis and Optimization of Mechanical Systems

CONCLUSIONS

1. In the promotion thesis, an exhaustive literature analysis has been conducted on the metamodeling of mechanical systems, including design of experiments, analysis and optimization.
2. Metamodeling methods have been developed for the design of mechanical systems that include optimization of designs of computer and natural experiments, improved non-parametrical result approximation methods as well as a new inverse metamodeling method.
3. For the optimization of designs of computer experiments, a coordinate exchange algorithm is proposed in combination with regulated permutation and multiple start global optimization method. The proposed optimization algorithm has been implemented in computer software. Internet database of experimental designs has been created, where the obtained experimental designs have been published.
4. It has been shown that space-filling experimental designs that are optimized according to the MSE criterion are effective for the creation of metamodels of mechanical systems.
5. In the dissertation thesis, kriging hyperparameter determination method has been developed using the cross-validation criterion that increases the accuracy of metamodels. An algorithm is proposed for the effective application of the kriging method in the case of several responses.
6. The higher prediction accuracy of the kriging method has been experimentally proven, in comparison with other parametrical and non-parametrical approximation methods.

7. An inverse metamodeling method is proposed that allows to solve inverse engineering design tasks, including parametric identification, as well as evaluate the adequateness of the solutions.
8. The effectiveness of the developed algorithms, methods and software has been proven in generally accepted analytical test tasks and practical tasks of optimal construction design and parametric identification.
9. Future work directions – improvement of inverse metamodeling, development of sequential experimental designs and multiobjective experimental optimization methods.

LIST OF PUBLICATIONS OF J. JANUŠEVSKIS

1. Auzins, J., Janusevskis, J., Janushevskis, A. (2007). Optimization of Experimental Designs for Metamodeling. *Proceedings of the 9th US National Congress on Computational Mechanics,* San Francisco, CA, July 22 – 26, CD-ed, 1 page.
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CONFIRMATION

I confirm that I have developed this Doctoral Thesis that has been submitted to review in Riga Technical University for the acquisition of the doctor's degree in engineering sciences. This thesis has not been submitted to any other university for the acquisition of a scientific degree.

Jānis Januševskis.............................(signature)

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The promotion thesis consists of a preface, 5 chapters, conclusions and literature references. The volume of the thesis is 191 pages, 94 figures, 67 tables and a literature references, containing 261 publication titles.