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Design Optimization of Steel and Glass Structures

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Declaration:
Hereby I declare that this doctoral thesis, my original investigation and achievement, submitted for the doctoral degree at Tallinn University of Technology, has not been submitted for any academic degree.

/ Tarmo Velsker /

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TARMO VELSKER

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CONTENTS

LIST OF PUBLICATIONS

The present PhD thesis is based on the following publications referred in the text as "Paper 1", "Paper 2", "Paper 3" and "Paper 4".

Paper 1 ***T. Velsker,*** *J. Majak, M. Eerme, M. Pohlak. Double-curved surface forming process modeling. In: Proceedings of the 7th International Conference of DAAAM Baltic Industrial engineering : 22-24th April 2010, Tallinn, Estonia, p 256 – 262.*

Paper 2 ***T. Velsker,*** *H. Lend, M. Kirs. Design of glass canopy panel. In: Proceedings of the 8th International Conference of DAAAM Baltic Industrial engineering : 19-21th April 2012, Tallinn, Estonia, p 759 – 764.*

Paper 3 *J. Majak, M. Pohlak, M. Eerme,* ***T. Velsker****. Design of car frontal protection system using neural networks and genetic algorithm. In: Mechanika, 2012, 18(4), p 453-460.*

Paper 4 ***T. Velsker****, M. Eerme, J. Majak, M. Pohlak, K. Karjust. Artificial neural networks and evolutionary algorithms in engineering design. In: AMME, 2011, 44(1), p 88-95.*

Author's contribution

The author of the thesis was responsible for collecting and analysis of experimental data, numerical models development and utilization (Paper 1, 2 and 3), in Paper 3 for analysis of the optimality criteria and selection of the strategies. However, contribution of every author should not be underestimated.

ABBREVIATIONS

ANN – Artificial Neural Network
CAD – Computer Aided Design
CAE – Computer Aided Engineering
CSE – Continuous Sensitivity Equation
GA – Genetic Algorithm
DOE – Design of Experiment
EA – Evolutionary Algorithm
EC – Evolutionary Computing
EP – Evolutionary Programming
ES – Evolution Strategies
FE – Finite Element
FEA – Finite Element Analysis
FEM – Finite Element Method
GP – Genetic Programming
HB – Higher-the-Better
HGA – Hybrid Genetic Algorithm
LB – Lower-the-Better
MLP – Multi-Layer Perceptron
NB – Nominal-the-Better
NN – Neural Network
OIMGA – Optimal Individual Monogenetic Algorithm
PMMA – Polymethylmetacrylate
RBF – Radial Based Function
RM – Response Modeling
RMS – Root Mean Square
RS – Response Surface
RSM – Response Surface Method
SN – Signal-to-Noise
SOM – Self Organizing Map

INTRODUCTION

Real world engineering design problems contain several complexities like real, integer and discrete variables, local extremes, and multiple optimality criteria. In the latter case, the conventional design approaches based on traditional gradient techniques fail or perform poorly. Furthermore, other kinds of complexities occur here, such as large plastic deformations, geometric and physical nonlinearities, impact loading, elastic and plastic anisotropy, contact modeling, and handling processes that make the design extremely resource consuming.

The approach proposed in this study is based on integrated use of meta-modeling and global optimization algorithms. Meta-modeling techniques allow us to reduce expensive function evaluations, i.e., overcome complexities related to the cost and time of experiments and/or computations. Global optimization algorithms allow handling several local extremes, mixed integer and discrete variables. Thus, combining of meta-modeling and global optimization techniques together forms prerequisites for successful optimization problem solution.

A number of methods and tools have been developed for building meta-models: regression methods [1, 2], artificial neural network techniques [3-5], kriging models [6 ,7], cubic splines [8, 9] and other tools. The accuracy of the result is a major risk involved in using meta-models to replace actual function evaluation [4, 10]. In the current study the back-propagation artificial neural network methods were selected due to their high accuracy and simplicity.

However, the response modeling techniques can give trustable results only in the cases where the design space is well covered by design data. For that reason extra attention is paid to the design of the experiment. The Taguchi method and full factorial design techniques are employed [11, 12].

The global optimization technique employed in the following is genetic algorithms (GA). During last decades the efficiency of different architectures of evolutionary algorithms (EA) in comparison to other heuristic techniques has been tested in various engineering design problems [13-18]. The evolutionary algorithms emerged as a revolutionary approach compared to classical approaches for solving search and optimization problems involving multiple conflicting objectives. The genetic algorithms are the most widely used EA employed for solving engineering design problems [19].

One of the drawbacks of the traditional GA is also a ratchet effect (crossover cannot introduce new gene values). In order to overcome the drawbacks of the traditional GA numerous improvements are provided including adaptive GA [20], niche GA and hybrid GA [21, 22]. In order to achieve higher accuracy, the real-coded GA operators are used in engineering design instead of traditional binary operators [15, 17, 23, 24]. Development of evolutionary algorithms for multi-objective optimization problems [25, 26] is another topical issue in engineering design. In order to achieve higher accuracy and convergence rate the hybrid GA is employed herein [21 , 22].

The main aim of the current study is to develop a methodology for solving practical engineering design problems with particular focus on sheet metal and glass structures.
Chapter 3 describes only problem formulations and main results, all the details including the solution procedure, results, discussion are described in Papers 1, 2 and 3, supplemented in the Appendix.
The current PhD thesis is based on four academic papers presented in the list of publications and referred to in the text as “Paper 1”, “Paper 2”, “Paper 3”, and “Paper 4”.

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1 THEORETHICAL BACKGROUND

1.1 Design of experiment

Strategies of the design of experiment (DOE) were originally developed for the model fitting of physical experiments, but can also be applied to numerical experiments. The general objective of the DOE is to select the points where the response should be evaluated. Design of an experiment is commonly used to define datasets necessary for composing mathematical models that describe different engineering problems. DOE allows us to investigate simultaneously the effect of a set of variables on a response in a cost effective manner. DOE is superior to the traditional one-variable-at-a-time method that fails to consider possible interaction between the factors.

In the current study the DOE strategies and methods are employed for solving several engineering problems, including a double-curved surface formation, design of a point supported glass canopy panel, and design of a vehicle protection system. DOE strategies are applied for experiment design, but also for dataset design for numerical simulations. We lack a unique DOE technique most suitable for solving different engineering problems. In the following, a short literature review of the DOE techniques is given and the techniques selected for solving the engineering problems considered here are described in more detail.

1.1.1 DOE techniques selection

The DOE based statistical methods are introduced for describing real life problems in the 1920s by R.Fisher (agricultural experiments), followed by G.Box in the 1950s who applied the DOE for modeling chemical experiments [27]. Today's DOE based statistical methods are used widely in various engineering applications, production planning, education and service systems and in other areas.

The main goal of the DOE methods and techniques is to extract as much information as possible from a limited set of experimental study or computer simulations.

A huge number of DOE methods are available in literature and selection of the most suitable method is not the simplest task. However, in order to select an appropriate DOE method and/or technique for a particular problem, some preparatory activities should be performed [11]:

- formulation of the problem to be modeled by the DOE,
- selection of the response variable(s),
- choice of factors (design variables) and determining ranges for these variables.

If this preliminary analysis is a success, it is easier to select the suitable DOE method. Frequently, the selection of the levels of factors is also classified as preliminary work [11].

In the current study the following two DOE methods have been selected and applied in the case studies:

- the Taguchi methods;

– full factorial design.

The first method considered herein (the Taguchi design) allows us to obtain a preliminary robust design with a small number of experiments and it is most often applied at early stages of process development or used as initial design. The second approach is resource consuming, but it leads to more accurate results.

Note that the Taguchi design can be obtained from the full factorial design by omitting certain design points. In addition, there are several approaches based on the full factorial design. For example, central composite design can be obtained from the 2^N full factorial design by including an additional centre and axial points.

An alternate wellknown DOE technique can be outlined as the D-optimality criterion, Latin hypercube, Van Keulen scheme or some other technique. The D-optimality criterion is based on the maximization of the determinant $\left|X^T X\right|$, where X stands for the matrix of the design variables. Application of the D optimality criterion yields a minimum of the maximum variance of predicted responses (the errors of the model parameters are minimized). The Latin hypercube design maximizes the minimum distance between the design points, but requires even spacing of the levels of each factor [12]. The van Keulen's scheme is useful in cases where the model building is to be repeated within an iterative scheme, since it adds points to an existing plan [12].

1.1.2 The Taguchi method

The Taguchi approach is more effective than the traditional design of experiment methods, such as factorial design, which is resource and time consuming. For example, a process with 8 variables, each with 3 states, would require 3^8=6561 experiments to test all variables (full factorial design). However, using Taguchi's orthogonal arrays, only 18 experiments are necessary, or less than 0.3% of the original number of experiments.

It is appropriate here to point out limitations of the Taguchi method. The most critical drawback of the Taguchi method is that it disregards higher order interactions between design parameters. Only main effects and two factor interactions are considered.

Taguchi's methods developed by Dr. Genichi Taguchi are based on the following two ideas:

- quality should be measured by the deviation from a specified target value rather than by conformance to preset tolerance limits;
- quality cannot be ensured through inspection and rework, but must be built in through the appropriate design of the process and product.

In the Taguchi method, two factors, such as the control factor and the noise factor are considered to study the influence of output parameters. The controlling factors are used to select the best conditions for a manufacturing process, whereas the noise factors denote all factors that cause variation. The signal-to-noise (SN) ratio is used to find the best set of design variables. Usually, the SN ratio is calculated to find the individual and combined effect of the factors and the large value is considered as the optimal [28-30]. According to the performance characteristics analysis, the Taguchi approach is classified into three categories:

- Nominal-the-Better (NB),
- Higher-the-Better (HB),
- Lower-the-Better (LB).

Here the Lower-the-Better (LB) approach is employed to minimize the objective functions. The SN ratio is calculated as follows:

$$SN_i = -10\log\left(\sum_{k=1}^{N_i} \frac{y_k^2}{N_i}\right), \tag{1}$$

where i, k, N_i stand for the experiment number, the trial number and the number of trials for the experiment i, respectively.

The results obtained from the Taguchi method can (should) be validated by the confirmation tests. The validation process is performed by conducting the experiments with a specific combination of the factors and levels not considered in initial design data.

1.1.3 Full factorial design

In order to overcome shortcomings of the Taguchi methods the full factorial design can be applied [11]. This approach captures interactions between design variables, including all possible combinations. According to the full factorial design strategy, the design variables are varied together, instead of one at a time. First, the lower and upper bounds of each of the design variables are determined (estimated values used if exact values are unknown). Next, the design space is discretized by selecting level values for each design variable. In the latter case, the experimental design is classified in the following manner [11]:

1. 2^N full factorial design - each design variable is defined at the lower and upper bounds (two levels) only;
2. 3^N full factorial design - each design variable is defined at the lower and upper bounds and also in the midpoints (three levels);

In the case of N=3 the 3^N, full factorial design contains 27 design points shown in Fig. 1 [31].

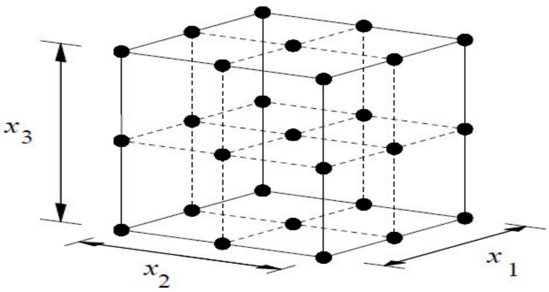


Figure 1 3^N full factorial design [11, 31]

The full factorial design considered includes all possible combinations of design variables and can be presented in the form of general second-order polynomial as

$$y = c_0 + \sum_{i=1}^{N} c_i x_i + \sum_{i=1}^{N} c_{ii} x_i^2 + \sum_{i,j=1; j<i}^{N} c_{ij} x_i x_j \,. \tag{2}$$

In (2) x_i and x_j stand for the design variables and c_i, c_{ij} are model parameters.

It should be noted that the second order polynomial based mathematical model given by formula (2) is just one possibility for response modeling. This model is used widely due to its simplicity. In the current study, the full factorial design is used to determine datasets where the response should be evaluated, but instead of (2) artificial neural networks are employed for response modeling.

Evidently, the number of experiments grows exponentially in the case of 3^N full factorial design (also for 2^N). Thus, such an approach becomes impractical at a large number of design variables. A full factorial design typically is used for five or fewer variables [11].

At a large number of design variables, a fraction of a full factorial design is most commonly used, considering only a few combinations between the variables [11]. The one-third fractions for a 3^3 factorial design are depicted in Fig. 2 [11].

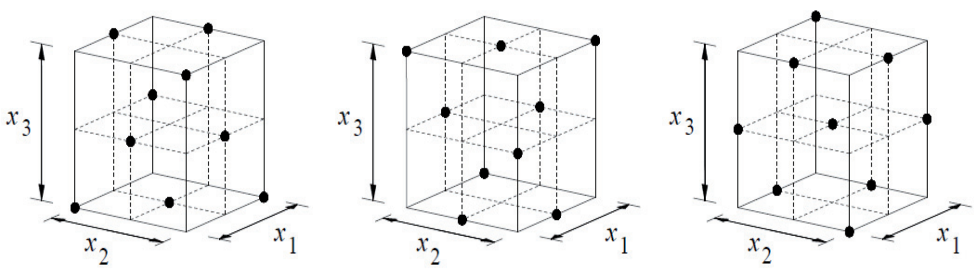


Figure 2 One-third fractions for a 3^3 full factorial design [11, 31]

Thus, in the latter case the number of experiments is reduced to one third in comparison with 3^3 full factorial designs (from 27 to 9). The cost of such an simplification is in the fact that only a few combinations between the variables are considered.

1.2 Response modeling

Response modeling (RM) is a widely used technique in engineering design. Most commonly the response modeling is used to compose a mathematical model describing the relation between the input data and the objective functions. In general, such an approach can be applied in the case of a time consuming and expensive experimental study, but also for modeling complex numerical simulations. The mathematical model is composed on the basis of “learning data” and can be used for evaluating objective function(s) for any set of input data in the design space considered. Some special cases can also be pointed out where it is reasonable to apply response modeling:

- Experimental study is not expensive or time consuming but it cannot be performed in a certain sub-domain of the design space (e.g., technological limitations);
- Numerical simulations are neither expensive nor time consuming but singularities in a certain sub-domain of the design space are the case here.

The RM techniques are used commonly for describing objective functions, but actually can also be applied successfully to describe constraint functions (principally any functions).

In the current study, the RM techniques are applied for modeling:

- FE simulations of the glass canopy panel. The mathematical model is composed for objective functions (maximal deflection, maximal stress, cost).
- Experimental study covering the double-curved surface forming. The precision of the reflector panel reflective surface estimated by the root mean square (RMS) value is evaluated by the response model (objective function).
- FE analysis of the car frontal protection system. Two objective functions are modeled: peak force and difference between the maximal and the minimal force.
- Experimental study covering displacement measurements of the car frontal protection system (in directions perpendicular to the moving direction). Note that this model is composed to describe the constraint function.

A huge number of meta-modeling techniques are available here, from classical to modern, such as regression, splines, higher order polynomials, kriging, neural networks. In the current thesis the artificial neural networks (ANN) techniques have been selected for that purpose. It has been shown in [32, 33] that relatively simple ANN containing one hidden layer can approximate accurately any differentiable function, provided the number of perceptrons in the hidden layer is unlimited. The multiple regression technique has also been tested on some sample problems but ANN is preferred due to the higher accuracy obtained.

Finally, it is appropriate to highlight that in some special situations the use of ANN or other meta-modeling techniques may not be successful:

- Design space is poorly covered by "learning data" (data used in DOE). There are too few results or the results are non-uniformly distributed and some sub-domains are not covered.
- Initial design space is well covered by the DOE data, but there is a need to evaluate functions values outside the initial design space.

In the latter cases the DOE data should be completed in order to obtain trustable results.

1.2.1 Artificial neural networks (ANN)

An Artificial Neural Network (ANN) is an information processing paradigm inspired by the human brain. ANNs consist of a large number of highly interconnected neurons working altogether for solving particular problems. Each particular ANN is designed, configured for solving a certain class of problems like data classification, function approximation, pattern recognition through a learning process. In the current thesis the ANNs designed for function approximation (i.e., response modelling) are considered.

The following historical overview of the ANN is based on [3, 34]. The theoretical concepts of the ANN were introduced in the 1940s and the first neural model was proposed by McCulloch and Pitts in 1943 using a simple neuron (the values of the input, output and weights were restricted to values ± 1, etc). Significant progress in the ANN development was achieved by Rosenblatt who introduced the one-layer perceptron and neurocomputer (Mark I Perceptron) in 1957. A multi-layer perceptron (MLP) model was taken into use in 1960. The learning algorithm (backpropagation algorithm) for the three-layer perceptron was proposed by Werbos in 1974. The MLP becomes popular after 1986 when Rummelhart and Mclelland generalized the backpropagation algorithm for MLP. Radial Basis Function (RBF) networks were first introduced by Broomhead & Lowe in 1988 and Self-Organizing Map (SOM) network model by Kohonen in 1982.

In this thesis the response modeling is performed by use of two-layer (without counting input layer) feedforward neural networks (i.e., forward-only flow is available) and backpropagation learning algorithms. This is the most popular approach in recent engineering design (Eng. Opt. conf.), since it is relatively simple and provides high accuracy. Briefly, the mathematical model of the network can be obtained by:

- summarizing the inputs multiplied by the weights of the input layer, adding bias (for each neuron of the second, i.e., hidden layer);
- applying the transfer function of the hidden layer (for each neuron);
- summarizing the obtained results multiplied by the weights of the hidden layer, adding bias (for each neuron of the output layer);
- applying the transfer function of the third layer (output layer).

The radial bases and linear transfer functions are used, purelin neurons in the hidden and output layers, respectively. The architecture of the ANN considered is shown in Fig. 3.

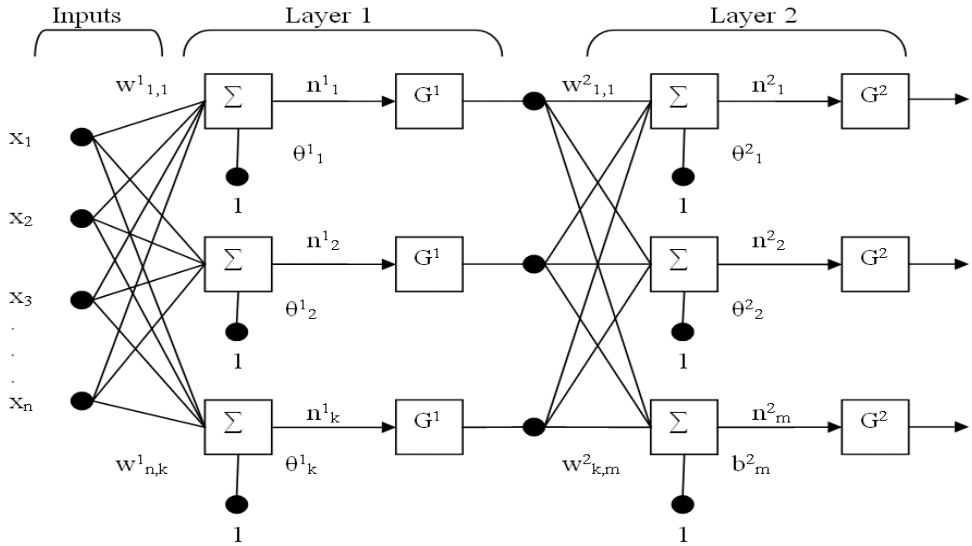


Figure 3 Architecture of the two-layer feedforward neural network

It is appropriate to note that in literature the input layer is commonly not counted and the ANN shown in Fig.3 is considered as a two-layer network (input layer has no transfer function, but input data and weights do).
In the case studies considered in this thesis, the number of neurons in the output layer is 1-2, but the number of neurons in the hidden layer should be determined separately for each particular problem (network configuration).
The most commonly used backpropagation learning algorithm is the steepest descent method (one of the gradient methods). However, the shortcoming of this method is its slow convergence. The Newton method has good convergence rate (quadratic), but it is sensitive with respect to initial data. For that reason, we used the Levenberg–Marquardt learning algorithm, which has second-order convergence rate [35]. The update rule of the Levenberg–Marquardt algorithm is a blend of the simple gradient descent and Gauss-Newton methods and is given as

$$x_{i+1} = x_i - (H + \lambda diag[H])^{-1} \Delta f(x_i) . \tag{3}$$

where H is the Hessian matrix evaluated at x_i, λ and Δf stand for the scaling coefficient and gradient vector, respectively. The Levenberg–Marquardt algorithm is faster than the pure gradient method and is less sensitive with respect to starting point selection than the Gauss-Newton method.

ANNs are widely used for modeling and predicting different processes, optimal design of product parameters and other tasks. Okuyucu et al. [36] modeled the mechanical welding process. In [36] the relation between the FSW parameters of the Al plates and mechanical properties is described by use of the ANN. In [37] an ANN-based model is developed to predict the laser transmission weld quality in

terms of lap-shear strength and weld-seam width. In [38] a knowledge base is established through numerous designs of experiments on beam elements, based on a validated finite element model of a reference vehicle and then ANN is applied to extract the correlation between the beam element features and crash dynamic characteristics. In [39] the ANN is developed in order to predict the flank wear of high speed steel drill bits for drilling holes on a copper work piece.
A workgroup of the Department of Machinery of Tallinn University of Technology (TUT) has successfully applied the ANN technique to solve various engineering design problems. In [9, 40] a numerical algorithm for the modeling of the density of the polymethylmetacrylate (PMMA) powder is developed based on the shape and size property analysis of the milled powder particles. The relation between the density of the filler material and the fractions of the PMMA powder is modeled on the basis of the experimental data. In [41] the response surfaces (RS) are constructed for objective functions (cost and time) for a concurrent set of values of the design variables. However, the latter task is time consuming, since the evaluation of the objective functions includes free size optimization performed by use of the FEA and the optimization package HyperWorks [42]. The main aim of the analysis is to determine optimal thickness distribution of the reinforcement layer. The surface constructed by the use of the ANN technique does not normally contain the given response values (similarity with the least-squares method in this respect).

1.2.2 Sensitivity analysis for ANN models

Impact of the input parameters on the values of the objective functions enables us to evaluate the optimal designs determined. Here the ANN model outputs are used as objective functions of the optimization problem. The sensitivity analysis applied on the trained neural network model allows identifying all relevant and critical parameters from a total set of input parameters. Special attention should be paid to the calculation of sensitivities in the points corresponding to an optimal design.

The output of the above described three-layer perceptron network can be computed as

$$Y = G^2(W_2 G^1(W_1 X + \Theta_1) + \Theta_2)\,, \tag{4}$$

where

$$X = \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix}, Y = \begin{bmatrix} y_1 \\ \vdots \\ y_m \end{bmatrix}, W_1 = \begin{bmatrix} w_{11}^1 & \cdots & w_{n1}^1 \\ \vdots & \ddots & \vdots \\ w_{1k}^1 & \cdots & w_{nk}^1 \end{bmatrix}, W_2 = \begin{bmatrix} w_{11}^2 & \cdots & w_{k1}^2 \\ \vdots & \ddots & \vdots \\ w_{1m}^2 & \cdots & w_{km}^2 \end{bmatrix},$$

$$\Theta_1 = \begin{bmatrix} \theta_1^1 \\ \vdots \\ \theta_k^1 \end{bmatrix}, \Theta_2 = \begin{bmatrix} \theta_1^2 \\ \vdots \\ \theta_m^2 \end{bmatrix}. \tag{5}$$

In (4)-(5) X - input vector, Y - output vector, W_1, W_2 and Θ_1, Θ_2 stand for weight matrices and bias vectors, respectively. The transfer functions of the hidden and output layers are denoted by G_1 and G_2, respectively. Note that layer number 1 corresponds to the hidden layer, 2 – to the output layer (input layer has number 0). In (5) the upper index identifies the number of the layer, the first and the second lower indexes denote the number of the input and the number of the perceptron in each layer, respectively.

The sensitivity matrix S can be computed as a gradient of the output vector Y as

$$S = \nabla Y = \frac{\partial Y}{\partial X} = \frac{\partial F_2}{\partial Z_2} W_2 \frac{\partial F_1}{\partial Z_1} W_1 \tag{6}$$

where Z_1 and Z_2 stand for arguments of the transfer functions of the hidden and output layers, respectively

$$Z_1 = W_1 X + \Theta_1, \; Z_2 = W_2 G^1(Z_1) + \Theta_2. \tag{7}$$

Obviously, the sensitivity results (6)-(7) given for the three-layer perceptron network can be extended without restrictions to a multiple-layer perceptron (MLP) network with N layers as

$$S_{MLP} = \nabla Y = \frac{\partial Y}{\partial X} = \frac{\partial F_N}{\partial Z_N} W_N \cdots\cdots \frac{\partial F_2}{\partial Z_2} W_2 \frac{\partial F_1}{\partial Z_1} W_1, \tag{8}$$

$$Z_1 = W_1 X + \Theta_1, Z_2 = W_2 G^1(Z_1) + \Theta_2, Z_N = W_N G^{N-1}(Z_{N-1}) + \Theta_N. \tag{9}$$

The matrix notation used allows us to present sensitivity results for a general feedforward MLP neural network in a compact form ((8)-(9)).

The sensitivity analysis showed that the objective functions $F_1(\bar{x})$ (elongation at break) and $F_2(\bar{x})$ (tensile strength) are most sensitive in terms of the mixing ratio of resin and powder.

1.3 Multicriteria optimization

In the following, the multicriteria optimization problem is formulated in a general form covering different particular engineering applications (case studies) considered in the current thesis. Next, some general principles for the analysis of the optimality criteria are proposed by the author and applied for practical engineering problem solution. Finally, the multicriteria optimization techniques and strategies utilized for solving the optimization problems are discussed.

1.3.1 Formulation of the multicriteria optimization problem

Practical engineering problems often include several objectives (strength, stiffness characteristics, cost, time) as well as different technological and geometric constraints and limitations of resources. Thus, the multicriteria optimization problem can be formulated as [18, 43, 44]

$$F(\overline{X}) = \min(F_1(\overline{X}), F_2(\overline{X}),..., F_n(\overline{X})), \tag{10}$$

$$X_i \le X_i^*, \qquad -X_i \le X_{i*}, , \qquad i = 1,...,n, \tag{11}$$

$$G_j(\overline{X}) \le 0, \qquad j = 1,...,m. \tag{12}$$

In (10)-(12) $F_1(\overline{X})$,…, $F_n(\overline{X})$ stand for the objective functions (describing stiffness/strength, electrical properties, cost and other properties) and $\overline{X}$ is a n-dimensional vector of design variables. The upper and lower bounds of the design variables are denoted by X_i^* and X_{i*}, respectively. The functions G_j stand for constraint functions including both linear and nonlinear constraints. Note that the equality constraints can be converted into inequality constraints covered by (11). The n-dimensional design space is defined with lower and upper bounds of the design variables.

It is appropriate to note that the objectives should be given in a normalized form since the magnitudes and the units used to measure the objectives may differ. The objective functions subjected to maximum and minimum can be normalized by Eqs. (13) and (14), respectively [45].

$$f_r(\bar{x}) = \frac{\max F_r(\bar{x}) - F_r(\bar{x})}{\max F_r(\bar{x}) - \min F_r(\bar{x})}, \tag{13}$$

$$f_s(\bar{x}) = \frac{F_s(\bar{x}) - \min F_s(\bar{x})}{\max F_s(\bar{x}) - \min F_s(\bar{x})}. \quad (14)$$

Obviously, after normalization with (13)-(14), both functions should be subjected to minimization. In (13) difference of the maximum and current values of the objective function are minimized, in (14) the difference of the current and minimum values of the objective function are minimized. It should be pointed out that the values of the normalized objective functions are not necessarily in interval [0;1], since the maximal and minimal values of the objective functions used in (13)-(14) are the estimated values. In non-dimensional terms the multicriteria optimization problem can be reformulated as

$$f(\bar{x}) = \min(f_1(\bar{x}), f_2(\bar{x}), ..., f_n(\bar{x})) \quad (15)$$

subjected to constraints

$$x_i \le 1, \qquad x_{i*} \le x_i \;, \qquad i = 1,...,n \;, \quad (16)$$

$$g_j(\bar{x}) \le 0, \qquad\qquad j = 1,...,m \,. \quad (17)$$

In (15)-(17) it is assumed that design variables are normalized so that $x_{i*} = 0$, i.e., the new values are determined in the range [0; 1]. According to an alternate commonly used approach, the new values of the design variables are converted to the range
[-1; 1] i.e. $x_{i*} = -1$.

1.3.2 Analysis of the optimality criteria

Based on the experience gained from solving engineering design problems, the author can conclude that in the case of multi-objective optimization problem:

- an analysis of the optimality criteria is extremely important;
- an analysis of the optimality criteria should be performed before the selection of the solution techniques and strategies for numerical solution of the problem.

These two simple principles remain often without necessary attention. Typical mismatches can be outlined as:

- Underestimated approach.
  The simplest weighted summation technique (or some other technique based on combining of objectives) is applied to conflicting objectives. In this situation the optimal solution is actually not uniquely defined, but such simplifications lead to merely one possible optimal solution. In the case of two objectives, the optimal solutions are determined by the pints of the curve and in the case of n-objectives by an n-dimensional surface.
- Overestimated approach.

Pareto optimality concept is applied to objective functions that are non-conflicting. As result, the Pareto frontier obtained contains merely a single point or several close-located points.

In the current study the optimality criteria have been analyzed for each particular optimization problem before its numerical solution. Basic activities of the analysis can be summarized as follows:

- Finding out objectives to be considered and those that can be omitted in the case of a particular problem. For example, in the case of car frontal protection system design (detailed description in section 5.4), the objective "cost" has been omitted since the cost of the component designed was relatively low and very similar (practically the same) for different configurations of the component.
- Finding out objectives conflicting with each other and those non-conflicting. Preliminary pair-wise comparison – analysis of functions of the objectives. For example, in the case of glass canopy panel design, the two objectives describing mechanical characteristics (maximal deflection and maximal stress) appear to be non-conflicting, both appear to be conflicting with the third objective - the cost of the panel.
- Combining objectives which appear to be non-conflicting with each other. For example, in the case of glass canopy panel, the two objectives describing mechanical characteristics (maximal deflection and maximal stress) were combined into one by use of physical programming techniques.
- Thus, the total number of objectives is reduced.
  Determining weights of the objectives which will be combined into one objective (based on the importance of the objectives in a particular problem).
- Applying the Pareto optimality concept for the remaining conflicting objectives. For example, in the case of glass canopy panel, the Pareto frontier has been composed for combined objectives and cost.

1.3.3 Physical programming

According to the previous section, the solution techniques should be employed after the analysis of the optimality criteria. Furthermore, it was pointed out that in the current study the physical programming techniques will be applied for non-conflicting objectives [46-48].

According to the weighted summation technique, first, the optimality criteria are scaled, then multiplied by weights and summed into the new objective f_{ws} as

$$f_{ws} = \sum_{i=1}^{m} w_i f_i , \tag{18}$$

where m is the number of the optimality criteria used, w_i is the weight of the i-th criterion and

$$\sum_{i=1}^{m} w_i = 1, \qquad 0 < w_i \le 1. \tag{19}$$

In the case of glass canopy panel design, the maximal deflection and maximal stress are combined into one objective, thus $m = 2$. The weighted summation technique cannot cover cases where the criteria transformations are nonlinear. For this reason, the compromise programming technique was introduced.

According to the compromise programming technique, the combined objective is defined as the family of distance functions [49]

$$f_{cp} = \left[\sum_{i=1}^{m} \left(w_i d_i \right)^c \right]^{1/c}, \tag{20}$$

where w_i weighs the importance of the discrepancy between the i-th objective and its ideal value and c reflects the importance of maximal deviation from the ideal solution. Obviously, if $c = 1$, Eq. (20) reduces to Eq. (18), i.e., the compromise programming includes the weighted summation technique as a special case. If $c > 1$, then the larger distances from an ideal solution are penalized more than smaller distances.

Note that there is no unique rule for selecting weights of the objective functions. This is an essential limitation of the physical programming techniques. In the current study the physical programming techniques are employed to design the glass canopy panel (for two selected criteria) and the car frontal protection system. In the case of both of the problems, the distance between optimal and critical values of the objective function is used as a characteristic value for evaluating weights of the objectives.

1.3.4 Pareto optimality concept

As pointed out above, the use of the Pareto optimality concept is justified in the cases when contradictory behavior can be perceived between the objective functions [50-51]. The physical programming techniques discussed above are based on combining multiple objectives into one objective and solving the latter problem as a single objective optimization problem. Independent of the techniques used for combining objectives, some drawbacks exist [52]. For most of the problems, the relative importance of the objectives is unknown and the determination of the weights is complicated. The Pareto optimality concept, according to which all solutions on the Pareto front are optimal, provides an alternate powerful tool for solving optimal design problems. The Pareto front may be continuous (Fig. 4) or discontinuous (Fig. 5).

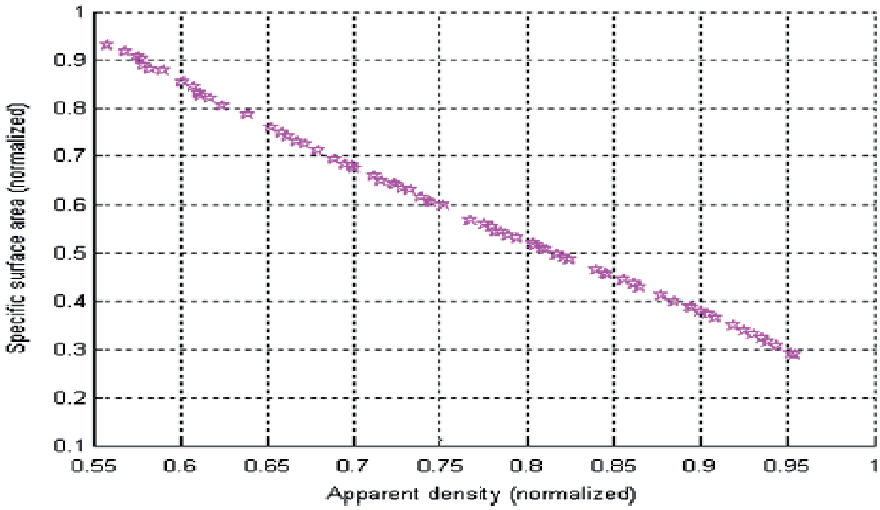


Figure 4 Continuous Pareto front [40]

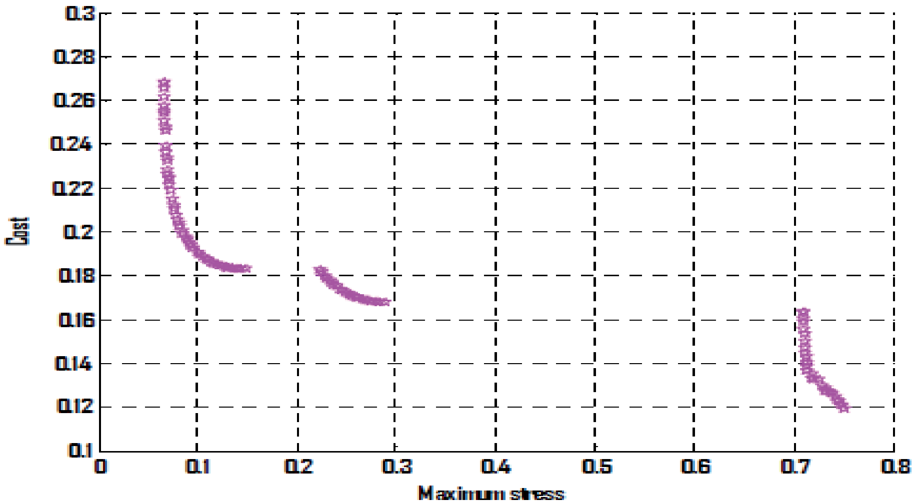


Figure 5 Discontinuous Pareto front [45]

In Fig. 5 the three parts of the Pareto front correspond to sandwich structures with different core materials. Normalization of the objective functions by use of Eqs. (13)-(14) provides that all normalized objectives are subjected to minimization.

The Pareto front of the objective functions provides much more information than the physical programming approaches discussed above. However, the selection of the optimal solution is a complicated task even from the Pareto front and it depends on the particular problem considered [53, 54].

Selecting optimal solutions in the points preceding the rapid ascent of the curve seems reasonable, but not all Pareto curves contain such points (Fig. 4).

2 OPTIMIZATION PROCEDURE

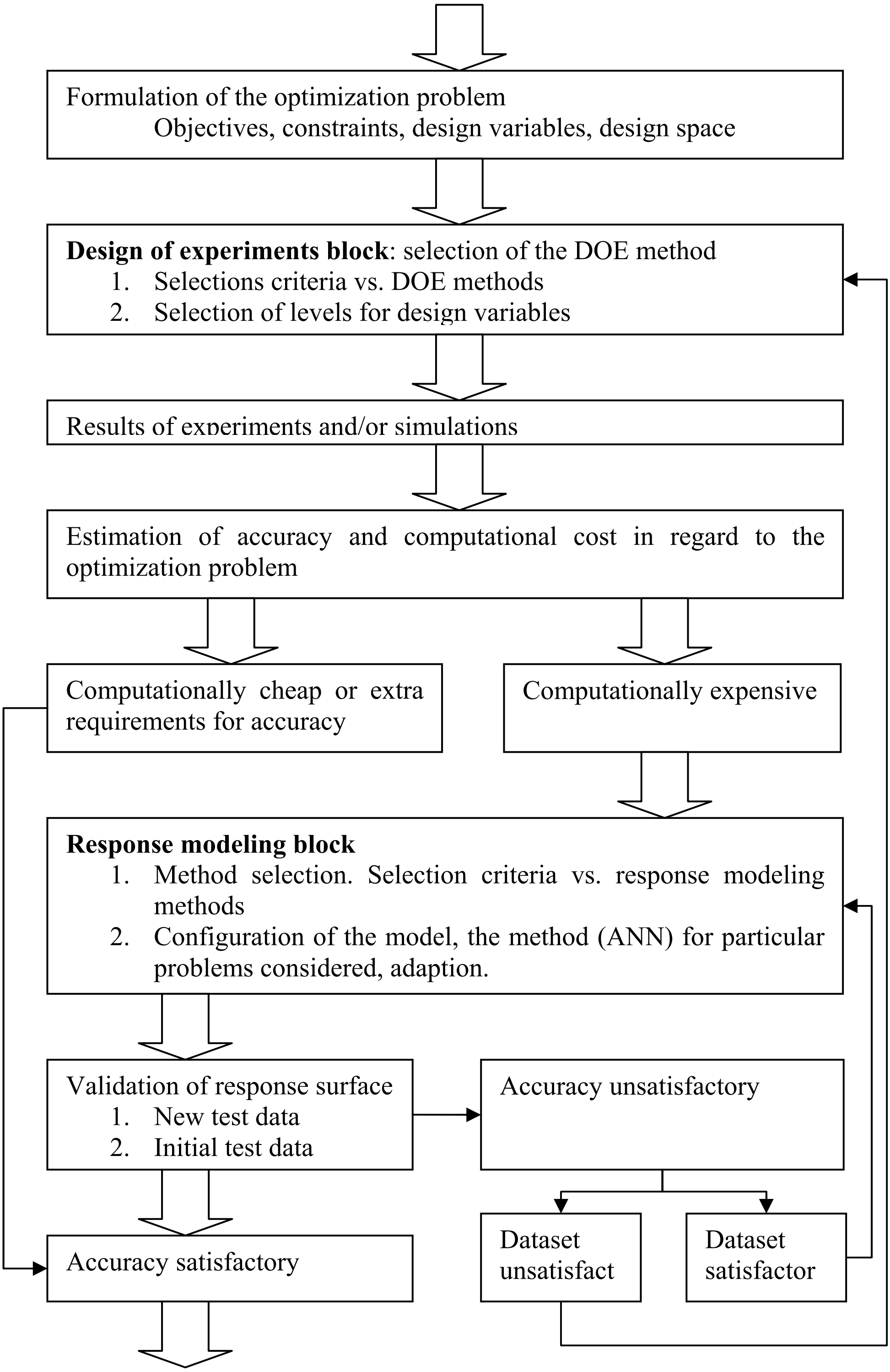
In the following, an optimization procedure is proposed for solving engineering design problems. Main attention is paid to the design of sheet metal and glass structures, at the same time, the algorithm is kept as general as possible.
Modern optimization algorithms are typically iterative (to cover nonlinearity), include a combination of several methods and techniques. In advanced engineering software packages (e.g., LS-DYNA), the optimization algorithms are integrated with response modeling and/or design of experiment methods and techniques. The above features are common also for the optimization procedure proposed in the current thesis. Particularly, the hybrid genetic algorithm, artificial neural networks and the DOE (full factorial design or the Taguchi method) are integrated in an iterative optimization procedure. In the current approach, special attention is paid to preliminary analysis of optimality criteria and constraint functions. Commonly, the latter aspects are not well covered by the optimization algorithms since most of the algorithms are restricted to finding out the extreme value of a single objective. Several multicriteria optimization approaches can be found in literature and a large number of engineering design problems have been successfully solved. However, typically, the number of optimality criteria is limited to 2-3 and the weighted summation technique or the Pareto optimality concept is applied. No general approach to handling optimality criteria seems to be available in literature. This is the main reason why in the current approach focus is on the analysis of the optimality criteria. The optimization approach proposed for solving engineering design problems is based on the following basic steps.

Preliminary analysis of the optimality criteria

1. Conflicting vs. non-conflicting criteria (pairwise analysis)
2. Optimality criteria vs. constraints

Preliminary analysis of the constraints

1. Check for a possibility to reduce the design space, by eliminating certain design variables. These variables can be evaluated after solving reduced order model.
2. Analysis of the optimization problem in regard to decomposition into simpler sub-problems


Formulation of the optimization problem
Objectives, constraints, design variables, design space
Design of experiments block: selection of the DOE method
1. Selections criteria vs. DOE methods
2. Selection of levels for design variables
Results of experiments and/or simulations
Estimation of accuracy and computational cost in regard to the optimization problem
Computationally cheap or extra requirements for accuracy
Computationally expensive
Response modeling block
1. Method selection. Selection criteria vs. response modeling methods
2. Configuration of the model, the method (ANN) for particular problems considered, adaption.
Validation of response surface
1. New test data
2. Initial test data
Accuracy unsatisfactory
Accuracy satisfactory
Dataset unsatisfact
Dataset satisfactor

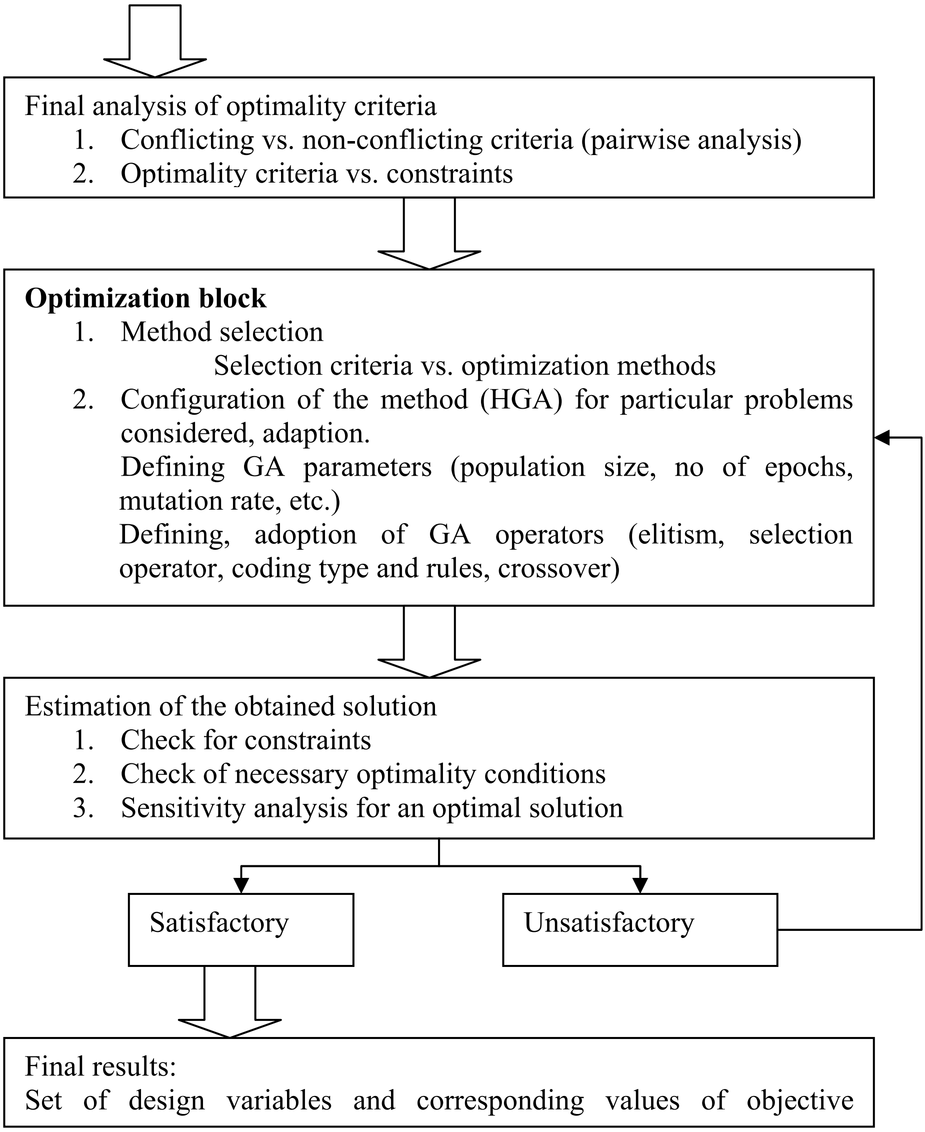


Figure 6 Basic steps of the optimization procedure

Optimization of complex multicriteria engineering design problems can be formulated in several ways. For that reason, the optimality criteria and constraint issues should be clarified. An experience obtained by solving a number of engineering design problems allows us to conclude that the earlier this problem is solved the better. Fixing objective functions and constraints without a preliminary analysis may cause higher complexity of the optimization problem. An analysis of the optimality criteria and constraints according to the principles and rules proposed in section 1.3.2 may lead to a reduced order model with a lower number of objective functions and reduced design space.

The design of the experiment block contains selection of the DOE methods according to the optimality criteria shown in the following table.

Table 1 DOE methods vs. selection criteria

	Number of experiments needed	Interaction between design variables	Limitations	When used
Taguchi method	Extremely low (L9)	Poorly estimated	Consider poorly nonlinear effect and interactions between variables	At the beginning of a project, initial design (mostly)
Full factorial design	**High 27**	**Well estimated**	**Expensive. Comes impractical for large number of variables (>5)**	**Final design**
Fractional factorial design	Low-Medium (9 1/3 fraction)	Depend on fraction	Smaller fractions –less information	Final design
Central composite design	Medium 15	Relatively well estimated	Expensive	Final design

Table 1 compares the four DOE methods used most commonly in engineering design. Since the engineering design problems considered contain up to five design variables and based on the results in Table 1, the full factorial design was selected to perform the final design. The Taguchi method was selected for initial design as the cheapest in regard to the number of experiments needed. The distribution of the design points in the design space was determined by the DOE method used, but the number of levels for each design variable should be preset (determined for each particular problem, so that the number of experiments remains in a tolerable limit).
The first task in the response modeling block is to select the suitable method. Here the ANN and regression models are compared. The multilevel hierarchical structure and higher accuracy achieved for an equal number of configuration parameters in comparison with the nonlinear regression method are the advantages of the selected ANN method. Furthermore, the ANN method is more flexible where new test data (simulation data) should be included in the model (just additional learning can be performed, no need for rebuilding the model). The second task of the response modeling block is to configure the ANN model, including selection of the number of hidden layers, determination of the number of neurons in the hidden layer(s), selection of the transfer function for each layer. One hidden layer appears sufficient for all the engineering design problems considered. The radial bases and linear transfer functions are used in the hidden and output layers, respectively.
Optimality criteria were analyzed for a second time before the optimization block since the initial analysis may contains some inaccuracies due to limited information

available at the initial stage of the solution procedure. The first task of the optimization block was to select the optimization method. The stochastic optimization methods should be used due to limitations of the traditional gradient based methods (convergence to nearest extreme, cannot handle integer and discrete variables). The GA was selected as the most widely used evolutionary algorithm in engineering design. Table 2 gives a brief comparison of the GA, HGA and gradient methods.

Table 2 Optimization methods

	Traditional gradient methods	GA	HGA
Discrete and integer variables supported	No	Yes	Yes (in general) may not support if GA is combined with gradient method
Convergence to global extreme	Generally convergence to the nearest extreme (which may be local)	Yes, (expected, not guaranteed)	Yes (expected, not guaranteed)
Computational cost	Cheap	Expensive	Medium, expensive in first stage and cheap in second stage
Capability to determine extreme with high accuracy	Yes	No May remain to oscillate near extreme, due to mutations	yes

Obviously, the capabilities of the HGA overperform the corresponding capabilities of the GA and the gradient method. However, no unique approach is available how to generate the HGA method. Most commonly, the GA is combined with the gradient method (if functions are differentiable) or hill climbing / branch and bound, and other algorithms (if functions are non-differentiable). The latter selection can be considered as a configuration of the HGA method for a particular problem. Similarly, HGA adoption, configuration of the GA for a particular problem include the determination of the values of a number of parameters like the mutation rate, the number of epochs, population size as well as defining GA operators (selection rules used, elitism used or not, coding type and rules, crossover).

The obtained solution should be estimated since in the case of nonlinear problems convergence to optimal solutions is not guaranteed. The Karush-Kahn-Trucker optimality conditions hold well if the functions are differentiable. If several ”black box“ type software is used (e.g., FEA), this additional check is justified.

The last step of the procedure – the sensitivity analysis allows us to estimate the influence of the design variables on the objective functions. The optimal solution is ready for practical use if small changes in the design variables do not incur significant changes in the values of objective functions. Also, the most critical design variables can be determined.

3 RESULTS AND DISCUSSION

In the following, the techniques and methods described above are applied to solve different engineering design problems. The optimization procedure is validated by three practical applications considered as case studies.

3.1 Point supported glass canopy panel

The case study is described in detail in Paper 2.

Problem formulation

Main goal of the current case study is to apply an optimization method to determine an optimal configuration of a glass canopy panel. The design parameters are: the thickness of the glass panel, the diameter and the location coordinates of the fixing holes. Among output parameters the deflection and the stresses are considered.
Design of the glass canopy panel is a challenging task because of the material behavior of glass. Additionally, maximum stresses are expected to concentrate around the fixing holes and the only way to analyze stresses satisfactorily is to apply the three-dimensional FEM software. Geometrical nonlinearity is considered since the maximum deflections may exceed the thickness of the glass panel. The length and width of the glass panel are given by the manufacturer (2000 mm and 1700 mm, respectively). Five design variables with four levels each were considered (see Fig. 7).

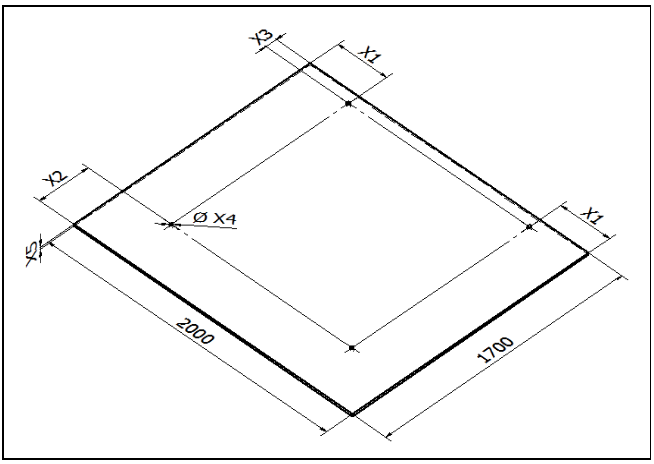


Figure 7 Design variables of the glass panel (X1,...,X5)

Initial values of the design variables were assigned according to manufacturer's suggestions and structural limitations. The Taguchi´s L16 orthogonal array DOE was applied to obtain preliminary results with low computational cost. Later, the full factorial design of experiments was performed to improve the accuracy of the solution. Five design variables with four levels each in the case of the full factorial make a total of 4^5=1024 experiments. To reduce the number of experiments the level of variables was reduced from four to three. This resulted in 3^5=243 simulations.

The FEM simulations (computational experiments) were performed for two load cases. In the first load case the constant pressure was equal to 2 kN/m^2 and the second, with a variable intensity pressure, was loaded by snow. The characteristic of load case two is shown in Fig.8.

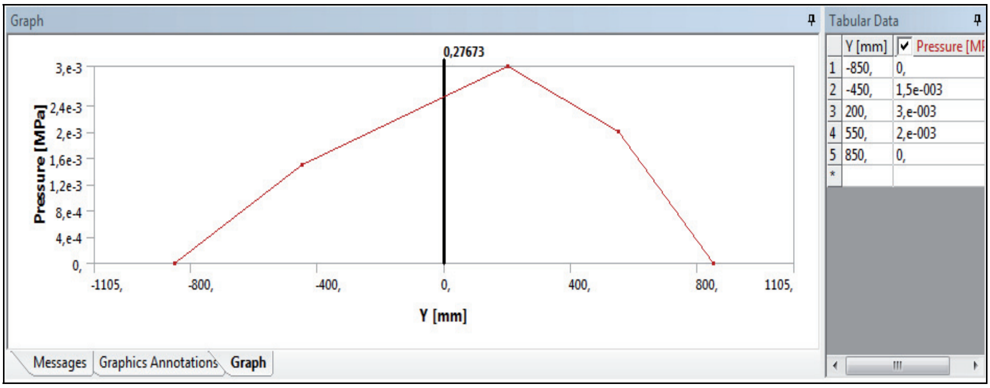


Figure 8 Load case 2 representing loading by snow

For both load cases the gravity was applied.

The above multicriteria optimization problem can be formulated as

$$f(\bar{x}) = \min(f_1(\bar{x}), f_2(\bar{x}), f_3(\bar{x})) , \tag{21}$$

subjected to linear constraints

$$x_i \le x_i^*, \qquad -x_i \le x_{i*}, \ , \qquad i = 1,...,n , \tag{22}$$

In (21) $f_1(\bar{x})$, $f_2(\bar{x})$ and $f_3(\bar{x})$ stand for the normalized maximum stress, deflection and cost of the glass panel, respectively. In (22) x_i^* and x_{i*} stand for the upper and lower limit of the i-th design variable, respectively.

Results and discussion

The structural analysis of the glass canopy panel was performed by employing the FEA software package ANSYS Workbench. Large deflections were considered in the FEA. The computations were performed for both load cases according to the DOE plan, i.e., 16 and 243 simulations for initial robust and final solutions, respectively. The artificial neural networks were used to predict the values of the maximal stresses and deflections.The ANN employed was comprised of three layers: input, hidden and output. The model was trained by use of the Levenberg-Marquardt learning algorithm (combination of Gauss-Newton and gradient methods). The optimization was performed by use of the GA and later improved by use of the hybrid GA (HGA). The GA was combined with the gradient method in the HGA since the design variables contained no integers (in the latter case, for example, the leap frog algorithm can be applied). The optimization process was decomposed into two tasks based on the analysis of the behavior of objective functions. In the first stage, the optimization was performed combining the first two objectives by use of the weighted summation technique and ignoring the cost of the structure as an objective function. In the second, the Pareto optimality concept was applied to the combined objectives and the cost of the structure.

Load case 1: Constant pressure equal to 2 kN/m^2.

As can been seen from Figs. 9 and 10, the maximal stresses occured around the fixing holes and maximal deflections occured in the middle of the panel.

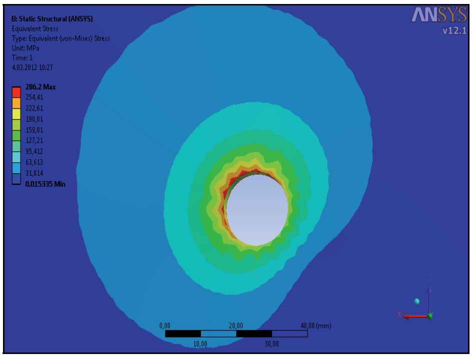


Figure 9 **Equivalent (von-Mises) stress**

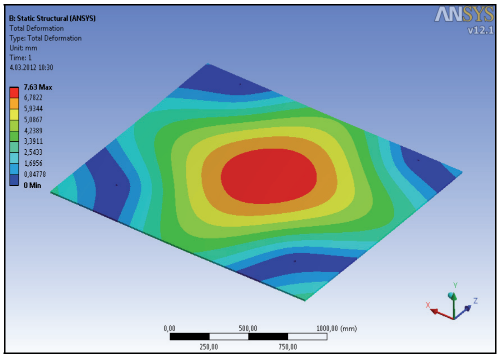


Figure 10 Total deformations

The optimal configuration of the neural network was determined by selecting the number of neurons in the hidden layer. The best results were obtained for 15 neurons. The best validation performance was reached at the 12th epoch (see Fig. 11).

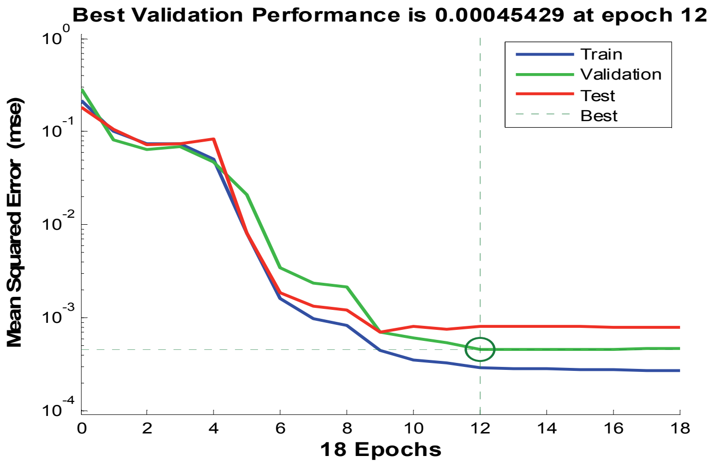


Figure 11 Mean square error of the model vs. number of epoch

Table 3 presents the optimal values of the design variables obtained by applying the GA and the HGA.

Table 3 Optimal values of design variables in non-dimensional terms (load case 1)

	x1	x2	x3	x4	x5
GA:	0.3608	0.9997	0.9989	0.9990	1.0000
HGA (GA + Gradient):	0.3688	1.0000	1.0000	1.0000	1.0000

The results are given in non-dimensional variables and correspond to the first stage of the optimization (the cost is ignored). As can be expected, the solution converges near the optimum but not to the exact optimum in the case of standard GA approach. The HGA approach provides convergence to the optimum and needs less computing time, since the gradient method needs only one function evaluation in each iteration step (in the GA the population size 50 was used). Additionally, four design variables reached an upper limit value.

Load case 2: Variable intensity pressure representing loading by snow.

Similarly to load case 1, the optimal configuration of the neural network appears with 15 neurons in the hidden layer, but the best validation performance was reached with a significantly larger number of epochs (31).

Table 4 presents the optimal values of the design variables obtained by applying the GA and the HGA.

Table 4 Optimal values of design variables in non-dimensional terms (load case 2)

	x1	x2	x3	x4	x5
GA:	0.3640	0.9987	0.9995	0.9989	1.0000
HGA (GA + Gradient):	0.3623	1.0000	1.0000	1.0000	1.0000

Here again, the results are given in non-dimensional variables and correspond to the first stage of the optimization (the cost is ignored). Surprisingly, the results corresponding to load cases 1 and 2 are a quite similar. However, this is good news

since in practice both of the load cases should be considered. Also, it is obvious that without introducing the cost of the panel the thickness reaches the upper limit value in the case of all load cases.
The results based on the analysis of the three optimality criteria in the first stage show contradictiory behavior between the maximal deflection and the cost, the same between the maximal stress and the cost. The maximal deflection and the maximal stress behave similarly.
Resulting from previous conclusions, the maximal deflection and the maximal stress are combined into one objective employing the physical programming technique (weighted summation). The relationship between the two combined criteria and the cost (third criteria) is clarified by use of the Pareto optimality concept (Fig. 12).

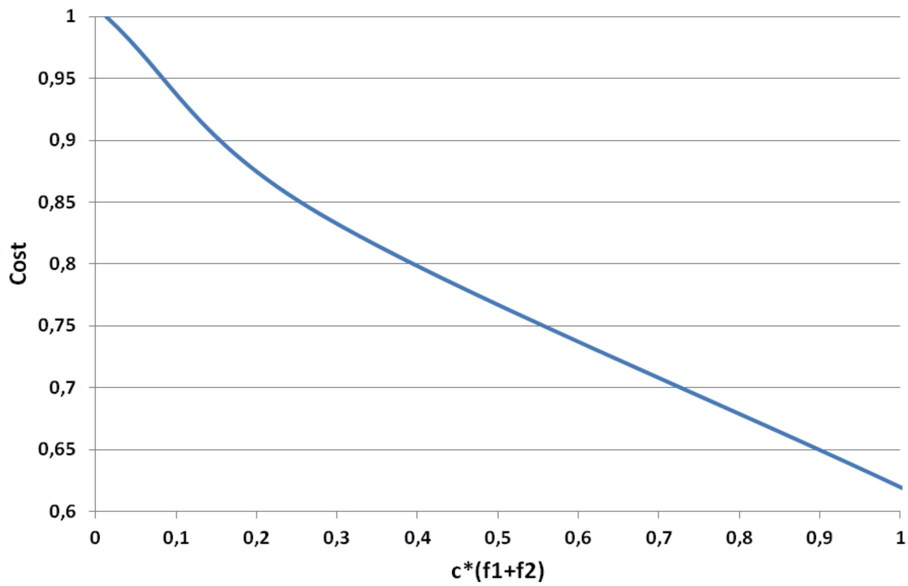


Figure 12 Combined optimality criteria vs. cost

The results given in Fig. 12 correspond to load case 2. All points on the line in Fig. 12 are optimal solutions in terms of Pareto optimality. In practice, the final selection can be made on the basis of financial or some additional considerations.

3.2 Double-curved surface forming

This section reviews the problem formulation and the results. Detailed account of the results and discussion is presented in Paper 1.

Problem formulation

The main goal is to increase the accuracy of the double-curved surface forming. An example of a double-curved surface is depicted in Fig. 13.
The forming method considered in the current application uses a special forming tool which has an adjustable forming surface. This allows the tooling surface to be adjusted in the normal direction on certain locations. Until now adjustment values were determined by a process operator, based on experience and skills. The main problem is that the method has reached the limit and it is not possible to achieve further increase in accuracy.

a) b)

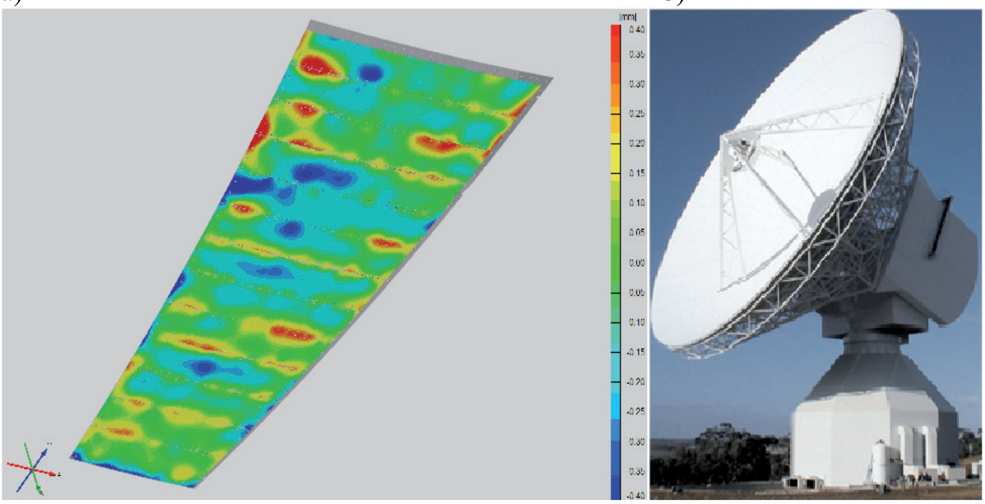


Figure 13 Double-curved surface (a) is a segment of a parabolic antenna reflector (b)

To achieve the main goal, i.e. to increase the accuracy of the forming process the problem should be decomposed into the following simpler subtasks:

a) deviation measuring in the given points
b) response surface modeling
c) computing coordinates corresponding to minimal deviation of the reflective surface
d) coordinate correction for adjustment points

Root mean square (RMS) value is used to characterize the precision of the surface. The RMS of the deviations of the parabolic reflective surface of satellite communication earth-station antenna reflectors is subjected to minimization

$$F = \frac{1}{n}\sum_{i=1}^{n}\left(z_i^m - z_i^0\right)^2 \rightarrow \min \tag{23}$$

where z_i^m and z_i^0 are the values of the coordinates of the reflective surface corresponding to measurement results and zero deviation, respectively.

Results and discussion

In order to increase the accuracy of the double-curved surface forming process the procedure for determining the coordinates of the adjustment points has been developed based on the subtasks introduced in problem formulation section (see Fig. 14).

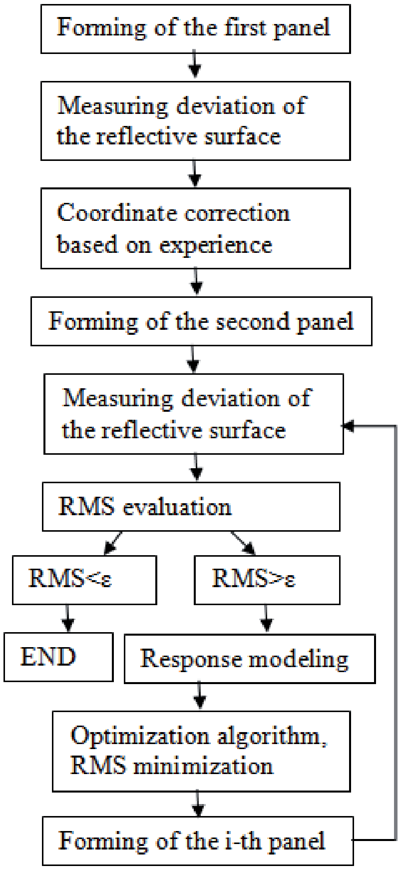


Figure 14 Coordinate correction procedure

This procedure is necessary for each panel formed until the needed accuracy is reached, but also during the whole forming procedure to ensure the stability of accuracy. Because the response model cannot be built on one input and output dataset, operator experience is needed to determine adjustment values. Due to the limited dataset for response modeling at the beginning of the new type panel forming, the problem is regarded as specific. After forming two panels, the dataset is still poor for modeling response between the values of the coordinates of the adjustment points and the deviations of the measuring points, but principally it can be employed. The dataset efficiency for modeling will increase correspondingly the number of the panels formed.

Response surface method (RSM) is employed. The coordinate corrections for adjustment points are treated as input values and the data obtained from the measurement of the deviation of the reflective surface are treated as output values.

In order to determine the minimal value of the objective function (23) the genetic algorithm (GA) was applied.
The deviation of the reflective surface has been minimized. However, zero deviations were not achieved due to measuring, modeling, and other errors. The procedure of the coordinate correction proposed allows us to reduce deviations significantly and the number of experiments performed (panels formed) up to a required accuracy.

3.3 Optimal design of car frontal protection system

The design of the car frontal protection system is described in detail in Paper 3. In the following, the problem formulation and the results are reviewed.

Problem formulation

The main goal of the current case study was to design an extra frontal protection system of a vehicle consisting of tubular parts and the brackets. The frontal protection system is treated as an additional impact energy absorbing element [55-59].
Main attention was paid to the design of the mounting brackets. The stiffness of the brackets is limited by the safety of pedestrians and required structural stiffness of the car accessories. To obtain maximum energy absorption that is smooth enough, an optimal configuration of support components of the structure was searched for. An example of the energy absorbing fastener is given in Fig. 15.
The optimal design problem posed involves several complexities, like large plastic deformations, impact loading, contact modelling. Initial design of the fastener was given by the manufacturer. Thus, the topology was predefined to a certain extent and the main task was to search optimal values of the design variables (a, b, c, d and e) to make maximum energy absorption smooth enough.
The practical objective of the posed problem was to minimize the peak force and also a sudden change in the following forces.

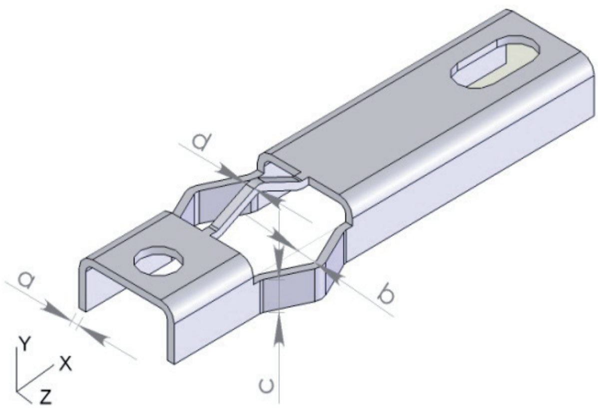


Figure 15 Energy absorbing structure

The corresponding multicriteria optimization problem is formulated as

$$\min\left(F_1(\bar{x}), F_2(\bar{x})\right), \tag{24}$$

where $F_1(\bar{x})$ and $F_2(\bar{x})$ stand for peak force and difference between the maximal and the minimal force, respectively

$$F_1(\bar{x}) = \max_t F(t,\bar{x}),\ F_2(\bar{x}) = \max_t F(t,\bar{x}) - \min_t F(t,\bar{x}). \tag{25}$$

In (25) t and $\bar{x} = (x_1, x_2, ..., x_n)$ stand for time and a vector of independent design variables, respectively. The design variables and displacements are subjected to the constraints

$$x_i \le x_i^*,\quad -x_i \le -x_i^{**},\quad \sqrt{u_2^2 + u_3^2} \le u^*,\ (i = 1,...n) \tag{26}$$

In (26) u_2 and u_3 in stand for the displacements in the y and z direction, respectively, u^* is a given limit value. These values of the displacements u_2 and u_3 were measured experimentally. Actually, the constraint on stiffness is described by means of displacements in the $y-z$ plane. The protection system of a vehicle designed should satisfy two requirements simultaneously:

- must be a good energy absorber,
- must have high stiffness characteristics in the directions perpendicular to the moving direction.

The first goal is achieved by the minimization of objective functions and the second by satisfying the constraints (26).

Results and discussion

The finite element analysis was performed using the software package LS-DYNA and fully integrated shell elements. Two kinds of the FEA were realized:

- dynamic analysis - crash simulation,
- static analysis - stiffness evaluation.

The FEA model was validated against the results obtained from the experimental study. The brackets with different configurations were tested. Changes in the topology of the bracket may change also the number of design variables (from 4 up to 8). The compression tests performed allowed us to obtain initial values of the force components and deformation modes. The sensitivity of the reaction force appears to be highest with respect to thickness and lowest with respect to the upper fold.

The results of the FEA and experimental tests are shown in Fig. 16, where *a=1.6*mm, *b=12*mm, *c=6*mm and *d=10*mm. Note that it is assumed here that the shape of the fold is triangular and the bend angle is used instead of the design parameter e.

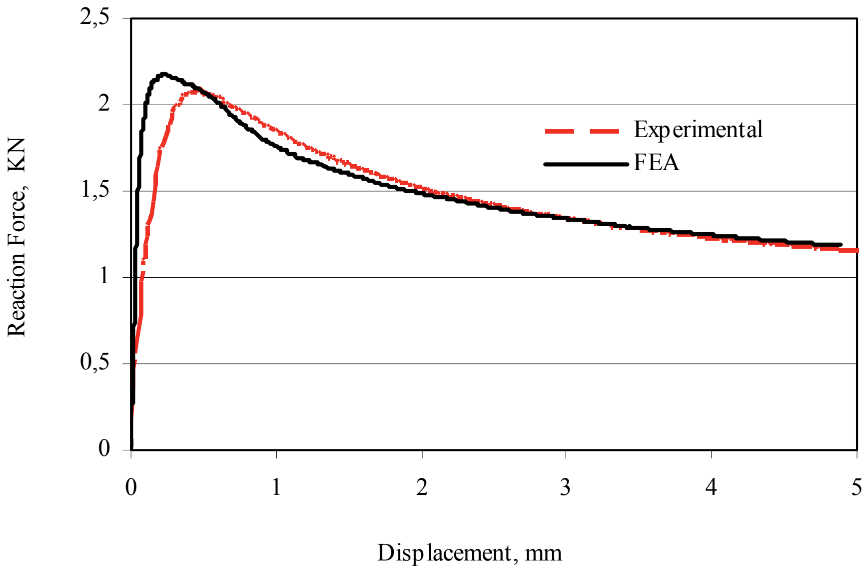


Figure 16 Load-displacement relation: FEA vs. experimental study

It can be seen from Fig. 16 that the results of the FEA and the experimental study are in good agreement. The optimization of the bracket was performed by use of the hybrid genetic algorithm. The two objective functions used are non-conflicting, therefore it is not necessary to apply the Pareto front. The reaction force appears to be the most critical in terms of pedestrian safety. The reaction force versus time relation is given in Fig. 17. The solid and dashed lines in the figure correspond to the initial and optimal solutions, respectively. The stiffness of the bracket with an optimal design in the moving direction of the vehicle is much lower than that of the reference bracket with initial design.

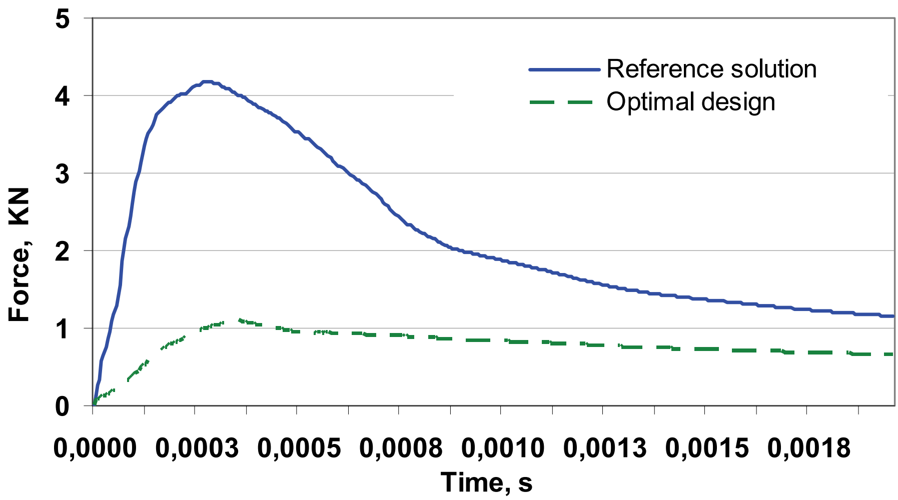


Figure 17 Reaction force vs. time for initial and optimal solution

The solution of the posed optimization problem allows reducing the value of the reaction force more than four times in comparison with the reference value.
The current study shows that changes in design parameters and the topology of the bracket affect the reaction force significantly. Therefore, the optimization methodology developed and applied has been successful to solve the current engineering problem. Additionally, the final design of the bracket is simple to fabricate and has low fabrication costs.

CONCLUSIONS

The following conclusions apply to all case studies.
General conclusions:

1. The methodology proposed for solving engineering design problems is based on adaptation, tuning of the optimization procedure (chapter 2) for particular problems and appears suitable for solving real world engineering design problems containing several complexities like real, integer and discrete variables, local extremes and multiple optimality criteria, geometrical nonlinearity, large plastic deformations and other complexities..
2. Main features of the optimization procedure developed:
   2.1 Multicriteria optimization algorithms, DOE and response modeling are integrated into a unique iterative procedure.
   2.2 Special attention was paid to the analysis of the optimality criteria. Commonly the weighted summation or the Pareto optimality concept is applied for solving multicriteria engineering design problems. According to the current approach, the rules/principles for handling optimality criteria are proposed (see details in section 1.3.2).
   2.3 Special attention was paid to the analysis of constraints. Equality constraints were analyzed and if possible, some design variables were eliminated (analytically, symbolic computation may be used).
3. An analysis of the optimality criteria and constraints performed may lead to reduced order model (lower number of optimality criteria or design variables), i.e., reduce complexity of the engineering design problem.
4. The methodology proposed for the design of sheet metal and glass structures can be extended for solving a wider class of engineering design problems, since the optimization procedure does not contain specific limitations. However, validation should be performed with corresponding case studies and some improvements may be needed.
5. The performance of global optimization techniques can be improved substantially by introducing hybrid algorithms (e.g., combining the GA with the gradient method or hill climbing),
6. ANN and global optimization techniques need certain tuning for each particular engineering design problem (in classical techniques not required).

The conclusions concerning each of the three particular case studies can be outlined as:

Point supported glass canopy panel:

- Contradictiory behavior can be perceived between the maximal deflection and the cost.
- Contradictiory behavior can be perceived between the maximal stress and the cost.

- The maximal deflection and the maximal stress behave similarly. These two objectives are combined into one using a weighted summation technique. Thus, the initial problem is simplified significantly.

Double-curved surface forming:
- The problem considered is specific due to the limited dataset for response modeling at the beginning of the new type panel forming.
- The procedure developed allows reducing deviations significantly, the required accuracy has been achieved, the zero deviations cannot be achieved due to measuring, modeling and other. errors.

Optimal design of the car frontal protection system:
- The two objective functions used are non-conflicting and can be combined into one by use of a weighted summation technique. Thus, the initial problem is simplified significantly.
- The sensitivity of the reaction force appears to be highest with respect to thickness and lowest with respect to the upper fold.
- The values of the reaction force may change several times due to changes in the design parameters and the topology of the bracket.
- The nonlinear constraint (26) deploys substantial restrictions on the original design space.
- The bracket designed is characterized by its low cost and simplicity of fabrication.

Finally, the proposed optimization procedure has been successfully implemented in the case of all three practical engineering design problems.

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Abstract

The PhD thesis is based on the published articles. The main aim of the current study is to develop a methodology for solving practical engineering design problems with particular focus on sheet metal and glass structures.

To validate the proposed methodology real world engineering design problems were solved. Such problems contain often several complexities like mixed integer and/or discrete variables, a number of local extremes, multiple optimality criteria. In the latter case the traditional design approaches based on traditional gradient based techniques fail or perform poorly.

The methodology proposed in this study is based on an integrated use of metamodeling and global optimization algorithms. In the following, the basic steps of the practical solution procedure are outlined. First, the initial mathematical formulation of the engineering design problem is given. Next, the optimality criteria are analyzed and non-conflicting criteria are combined into one criterion. In the following steps, the DOE is performed, followed by the structural analysis (FEM), response modeling (ANN), model validation and optimization (GA). Finally, the sensitivity analysis is performed. The basic steps of the solution procedure may be repeated iteratively starting from the DOE if the accuracy achieved is not high enough. The response modeling may be executed on the results obtained from the experimental study and/or computer simulations.

The key results of the thesis are:

- The methodology proposed for solving engineering design problems covering sheet metal and glass structures.
    - The optimization procedure proposed is based on an integrated use of the DOE, ANN and GA (chapter 2),
    - Rules and suggestions for handling multiple optimality criteria are proposed (section 1.3.2)
- An analysis of the optimality criteria and constraints performed may lead to reduced order model (lower number of optimality criteria or design variables), i.e., reduced complexity of the engineering design problem.
- Solution of three real world engineering design problems as case studies:
    - design of a point supported glass canopy panel,
    - improving the forming process of double-curved surface forming,
    - design of the car frontal protection system according to the requirements of the Directive 2005/66/EC of the European Parliament and of the Council.

The results of the thesis have been presented in three international conferences and published in four scientific papers, one of them in journal indexed by ISI WEB of Science.

Kokkuvõte

Käesolev doktoritöö on esitatud kokkuvõtva ülevaateartiklina, mis on ühtse kogumina vormistatud publikatsioonide seeriana.

Eesmärgiks on välja arendada metoodika teatud kindlate lehtmetallist ja klaasist konstruktsioonide analüüsiks ja optimeerimiseks.

Töö fookuseks on praktiliste insenerirakenduste realiseerimine. Vaadeldakse ülesandeid, mis sisaldavad optimaalset projekteerimist. Selliste insenerirakendustega kaasnevad enamasti ka teatud keerukused, nagu täisarvuliste ja/või diskreetsete väärtustega muutujate kasutamine, mitmed lokaalsed ekstreemumid ja hulk optimaalsuse kriteeriume. Traditsioonilised gradiendi kasutamisel põhinevad algoritmid üldjuhul selliste ülesannete lahendamiseks ei sobi.

Käesolevas töös väljapakutud lähenemine põhineb vastavusepindade ja globaalse optimeerimise tehnikate kombineerimises. Järgnevalt on lühidalt välja toodud praktilise lahendusalgoritmi peamised etapid. Kõigepealt teisendatakse praktiline insenerirakendus matemaatilisele kujule ehk esitatakse optimeerimisülesande esialgne matemaatiline püstitus. Järgnevalt analüüsitakse optimaalsuse kriteeriume ja kombineeritakse mittevastuolulised kriteeriumid üheks liitkriteeriumiks. Järelejäänud vastuolulistele kriteeriumidele rakendatakse Pareto optimaalsuse kontseptsiooni. Seejärel teostatakse katsete planeerimine, millele järgneb struktuurianalüüs (lõplike elementide meetodi abil), vastavusepinna koostamine (tehisnärvivõrkude abil), mudeli valideerimine ja optimeerimine (geneetilisi algoritme kasutades). Lahendusalgoritmi põhisamme võib läbida iteratiivselt alustades katsete planeerimisest, juhul kui eelnevalt ei saavutatud piisavat täpsust. Vastavusepinna koostamisel võivad olla lähteandmeteks kas eksperimentide ja/või numbriliste simulatsioonide tulemused.

Töö põhitulemused:

1. Praktiliste inseneriülesannete lahendamiseks väljatöötatud metodoloogia, mis on fokuseeritud peamiselt metall- ja klaaskonstruktsioonidele ning põhineb peatükis 2 toodud optimeerimisprotseduuri realiseerimisel.
2. Koostatud optimeerimisprotseduuri peamised iseärasused on järgmised:
   2.1. multikriteriaalse optimeerimise algoritmid, katsete plaaneerimine ja vastavuse pinna modelleerimine on integreeritud terviklikuks iteratiivseks protseduuriks;
   2.2. enne probleemi lahendama asumist teostatakse optimeerimiskriteeriumide detailne analüüs;
   2.3. töös on pakutud välja reeglid/printsiibid optimeerimiskriteeriumide käsitlemiseks.
3. Teostatud optimeerimiskriteeriumide ja kitsenduste analüüs võivad viia lihtsustatud mudelini, mis sisaldab vähem sihifunktsioone või muutujaid.
4. Töös arendatud metodoloogiat võib laiendada erinevate insenerirakendustes sisalduvate optimeerimisülesannete lahendamiseks, kuna kasutatud protseduur ei sisalda otseselt probleemispetsiifilisi mooduleid. Samas on kindlasti vajalik metoodika valideerimine konkreetsele üleanneteklassile vastavate praktiliste näidetega ning võimalik, et ka täiustamine.

Töös lahendatud praktilised inseneriülesanded:

1. Klaaspaneeli optimaalne projekteerimine:
   1.1. optimeerimise kriteeriumid: maksimaalsed pinged ja läbipaine ning maksumus;
   1.2. optimeerimise parameetrid: paneeli paksus, kinnitusavade asukoha koordinaadid ning ava läbimõõt, kokku viis parameetrit;
   1.3. tulemused/järeldused: maksimaalsed pinged koonduvad kinnitusava servadel, maksimaalne läbipaine paneeli keskosas; optimaalsuse kriteeriumitest maksimaalne pinge ja läbipaine käituvad sarnaselt, kuid maksumus on mõlemaga vastuolus; viimase lahendamiseks on esiteks pinged ja läbipaine kombineeritud üheks kriteeriumiks, kasutades kaalude summeerimise tehnikat, ning teiseks on rakendatud Pareto optimaalsuse printsiipi leidmaks optimum kombineeritud kriteeriumi ning maksumuse vahel.
2. Topeltkumerusega pindade vormimisprotsessi täiustamine:
   2.1. optimeerimise kriteeriumid: satelliitsidemaajaama antenni reflektorpaneeli peegelpinna täpsus;
   2.2. optimeerimise parameetrid: reflektorpaneeli vormimisprotsessis kasutatava spetsiaalse reguleeritava vormi pinna reguleerimise väärtuste suurused;
   2.3. tulemused/järeldused: välja töötatud meetod, mis võimaldab paneeli peegelpinna kõrvalekallet märgatavalt vähendada ning nõutud täpsust saavutada; ülesande muudab eriliseks uut tüüpi paneeli vormimise alustamisel vastavusepinna modelleerimine limiteeritud andmete hulgaga.
3. Auto kaitseraua optimaalne projekteerimine:
   3.1. optimeerimise kriteeriumid: kronsteinile mõjuv reaktsioonijõud ning selle järsk muutus;
   3.2. optimeerimise parameetrid: kronsteini mõõtmed, erinevate variantide puhul 4 kuni 8 parameetrit;
   3.3. tulemused/järeldused: projekteeritud kronsteini saab kirjeldada madala hinna ning valmistamise lihtsusega; reaktsioonijõu väärtus võib muutuda kordades tulenevalt parameetrite ning topoloogia muutusest, antud ülesande puhul väheneb optimeerimise meetodi rakendamise tulemusena esialgne reaktsioonijõud neli korda.

Väljatöötatud optimeerimisprotseduur osutus sobivaks kõigi kolme praktilise inseneriülesande lahendamiseks.
Käesolev doktoritöö on üles ehitatud järgnevalt. Töö koosneb kahest peatükist ning kokkuvõttest.
Esimene peatükk sisaldab teooria ülevaadet. Kolmes alapeatükis antakse lühiülevaade katsete planeerimise tehnikatest (DOE), vastavusepinna modelleerimise tehnikatest ning mitmekriteriaalse optimeerimise strateegiatest. Antud alapeatükid on fokusseeritud tehnikate ja strateegiate valiku kirjeldusele ning tehtud valikute põhjendustele. Katsete planeerimise meetoditest leiavad käsitlust Taguchi meetod ja täisarvuline katsete planeerimine. Vastavusepinna modelleerimise meetoditest on lühiülevaade antud tehisnärvivõrkude meetodist (ANN) ning käsitletud on ka antud mudelite tundlikkuse analüüsi. Mitmekriteriaalse optimeerimise strateegiate puhul on kirjeldatud optimeerimisülesande püstitust, optimeerimise kriteeriumite analüüsi, mitme funktsiooni kombineerimise meetodeid (Physical programming) ning

Pareto optimaalsuse meetodit. Kusjuures alapeatükk 1.3.2 optimeerimise kriteeriumite analüüs sisaldab peamiselt antud töö autori analüüsi ja järeldusi.
Teine peatükk sisaldab üldist lahendusalgoritmi, mis on esitatud protseduuri kujul, ja praktiliste inseneriülesannete lahendusi. Kirjeldatakse juba eespool nimetatud kolme praktilise inseneriülesande tulemusi, mida kasutatakse töös esitatud metoodika valideerimiseks. Töö viimases osas on toodud peamised järeldused.
Töö tulemused on esitatud kolmel rahvusvahelisel konverentsil ja avaldatud neljas ajakirjas, millest üks on indekseeritud ISI WEB Science poolt ja kaks ISI WEB of Proceedings poolt. Publikatsioonid on esitatud antud töö lisades.

APPENDIX A

Publications

PAPER 1

T. Velsker, *J. Majak, M. Eerme, M. Pohlak. Double-curved surface forming process modeling. In: Proceedings of the 7th International Conference of DAAAM Baltic Industrial engineering : 22-24th April 2010, Tallinn, Estonia, p 256 – 262.*

7th International DAAAM Baltic Conference
"INDUSTRIAL ENGINEERING"
22-24 April 2010, Tallinn, Estonia

DOUBLE-CURVED SURFACE FORMING PROCESS MODELING

Velsker, T.; Majak, J.; Eerme, M.; Pohlak, M.

Abstract: *The forming process of earth-station antennas reflector panel is studied. The paper is focused on improvement of the accuracy of panels formed in order to meet the increasing quality requirements. The coordinate correction procedure, based on use of response modelling and optimisation, has been developed. The numerical algorithm has been implemented in MATLAB code.*

Key words: satellite antennas, surface forming, response modelling, optimisation.

1. INTRODUCTION

There are several industries where increasingly higher surface accuracy requirements are posed for double-curved surfaces. One industrial application is satellitecommunication earth-station antennas.(see Fig.1)

Fig. 1. 35m diameter antenna [1].

The main goal of the current study is to increase an accuracy of the double-curved surface forming process. The forming method considered below is based on use of the adjustable forming surface which supports reflective surface. Adjustments of the surface are available in fixed set of points and in directions normal to the surface only.

The response surface method (RSM) is employed in order to model relation between input and output data. In the current paper, the generalized regression neural networks (NN) are used for the surface fitting. An approach proposed is based on the use of the MATLAB neural network toolbox.

The deviation of the reflective surface has been minimized by use of hybrid genetic algorithm. Traditional gradient based optimization methods have a trend to converge to the nearest optimum (which may appear to be local), also computation of the first order derivatives of the objective function $f(\bar{x})$ and the constraints function $g(\bar{x})$ with respect to the design variables $\bar{x}$ is necessary. In that reason a genetic algorithm is employed for solving the optimization problem posed. The advantages of the GA over traditional gradient based techniques can be outlined as follows:

- in general, the convergence to global extreme can be expected;
- integer type design parameters can be used;

- computation of derivatives of objective and constraints functions is not required.
-

However, there are also some disadvantages common to GA:

- convergence to the solution close to global optimum (not exactly optimum);
- relatively long computing time.

In order to overcome the above mentioned drawbacks, several refined GA approaches are proposed in literature [2-3] Henz et al. (2007) present a global–local approach for the optimization of injection gate locations in liquid composite molding process simulations [2]. The hybrid approach used provides a global search with the GA and was subsequently further refined with a gradient-based search via the CSE (continuous sensitivity equations). In [3] stochastic hybrid genetic algorithm is developed for survivable resilient networks design. The specialized crossover and local search operators are introduced in the GA algorithm. In Zhu et al. 2007 a novel GA, particularly suited to hardware implementation, is introduced. The optimal individual monogenetic algorithm (OIMGA) is treated, which includes global and local searches that interact in a hierarchical manner.

In [4-6] a similar two layer network was applied by the authors for modeling different engineering problems (design of large composite parts, design of car protection system, modeling new composite material etc.).

2. PROBLEM FORMULATION

In order to achieve the main goal- increase an accuracy of the double-curved surface forming process the procedure for determining the coordinates of the adjustment points has been developed. The two main subtasks of the procedure can be outlines as:

a) deviation measuring in given points,
b) response surface modelling,
c) computing coordinates corresponding to minimal deviation of reflective surface,
d) coordinate correction for adjustment points. (see Fig. 2)

Root mean square (RMS) value is used in order to characterise the precision of the surface. Irrespective of measuring method a certain number of measuring points deviation on the surface is needed for calculating RMS.

In real adjustment process the coordinates in normal directions are considered as input data and the deviations of the reflective surface points as output data (results).

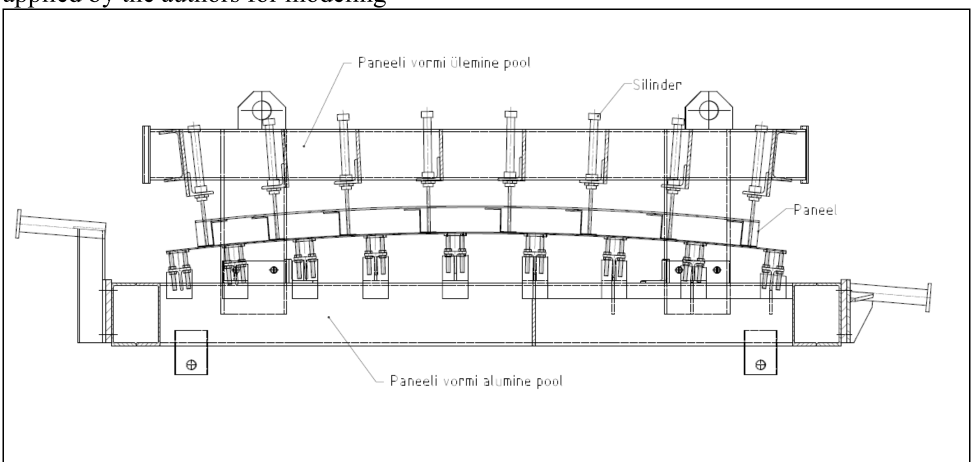

Fig. 2. Forming tool with adjustable surface [7].

3. COORDINATE CORRECTION PROCEDURE

First note, that the coordinate correction procedure is time consuming, since besides numerical algorithm it contains also earth-station antennas reflector panel forming process. The coordinate corrections are necessary for each panel formed until needed accuracy have been reached. However, at the beginning of the forming process of a new type of panel there is not preliminary model data (measurement results) for predicting the coordinates of the adjustment points. First measurement data are obtained after forming first panel of a given type. The corrections done before forming second panel are based on experience of operators, because the response model cannot be built on one input and output dataset. After forming two panels of a given type the dataset is still poor for modelling response between values of the coordinates of adjustment points and deviations of measuring points, but principally the coordinate correction module can be employed. Two main subtasks of the coordinate correction module are the response modelling and optimisation. Detailed scheme of the coordinate corrections procedure is given in Fig.3

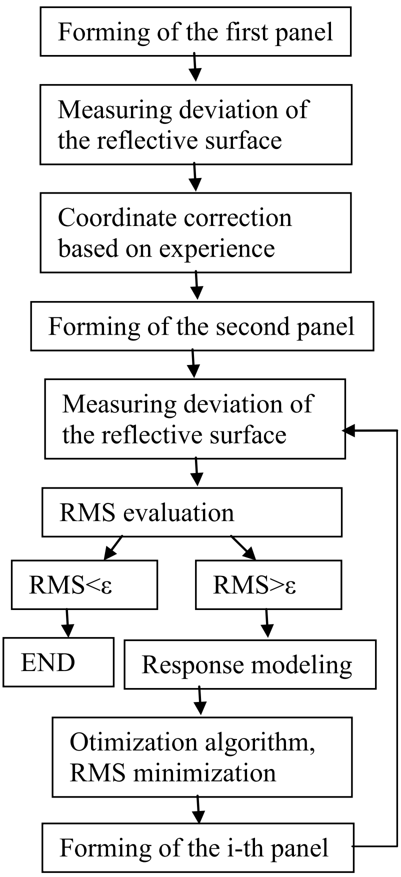

Fig 3. Coordinate corrections procedure

Note that the coordinate corrections less than given constant (0.08 mm) are omitted due to fact that the errors, caused by performing coordinate changes, may exceed the correction value.

Let us assume that after forming n-th panel the required accuracy has been achieved (RMS<ε) and here is no need for coordinate correction. However, the measurement of the deviation of reflective surface and RMS evaluation should be continued in order to guarantee the quality of the product. It may appear that after forming certain number of panels, the accuracy requirement will be violated in some local region or globally (different affectors). In latter case the coordinate correction procedure should by "switched on".

4. RESPONSE SURFACE MODELING

Using surrogate models for the approximation of the objective and constraint functions is a common technique for reducing computational cost of engineering design problems. In the following, the coordinate corrections for adjustment points are treated as input values and the data obtained from measurement of the deviation of reflective surface are treated as output values. In order to characterize the precision of the surface the root mean square value has been computed (response).

The generalized regression neural networks (NNs) are used for the surface fitting. The surface constructed by the use of NNs does not normally contain the given response values (similarity with the least-squares method in this respect). An approach proposed in this paper is based on the use of the MATLAB neural network toolbox. A two-layer network is generated. General scheme of the multilayer NN can be found in [8]. In Fig. 4 the architecture of two layer NN is given, where $\boldsymbol{p}$, $\boldsymbol{a}$, $\boldsymbol{w}$, $\boldsymbol{b}$ and $\boldsymbol{f}$ stand for input vector, output vector, weight matrix (SxR), bias vector and transfer functions, respectively. The first layer has radbas neurons and the second layer has purelin neurons. The dimensions of the weight matrix S and R are determined by number of elements in input (layer) vector and number of neurons in layer.
The neural network architecture, depicted in Fig. 4, is covered by a quite simple mathematical formula

$$a^2 = f^2[LW^{2,1}f^1(IW^{1,1}p + b^1)], \qquad (1)$$

where $IW^{1,1}$ and $LW^{2,1}$ stand for wieght matrices of the input and second layer, respectively, f^1 is a linear and f^2 radial bases function. The neural network model, built in MATLAB, can be exported to different computing environments using the relation (1).
In order to calculate outputs for a concurrent set of values of the design variables, a network simulation function **sim** was used.

5. MINIMIZATION OF THE DEVIATION OF REFLECTIVE SURFACE

The root mean square value of the deviations of the parabolic reflective surface of satellite communication earth-station antennas reflectors is subjected to minimization

$$F = \frac{1}{n}\sum_{i=1}^{n}[(z]_i^m - z_i^0)^2 \rightarrow min \quad , \qquad (2)$$

where z_i^m and z_i^0 are the values of the coordinates of reflective surface corresponding to measurement results and zero deviation, respectively. As described above, each value of the function F corresponds to one panel formed. Thus, the experimental data, gathered at the beginning of the forming process of new

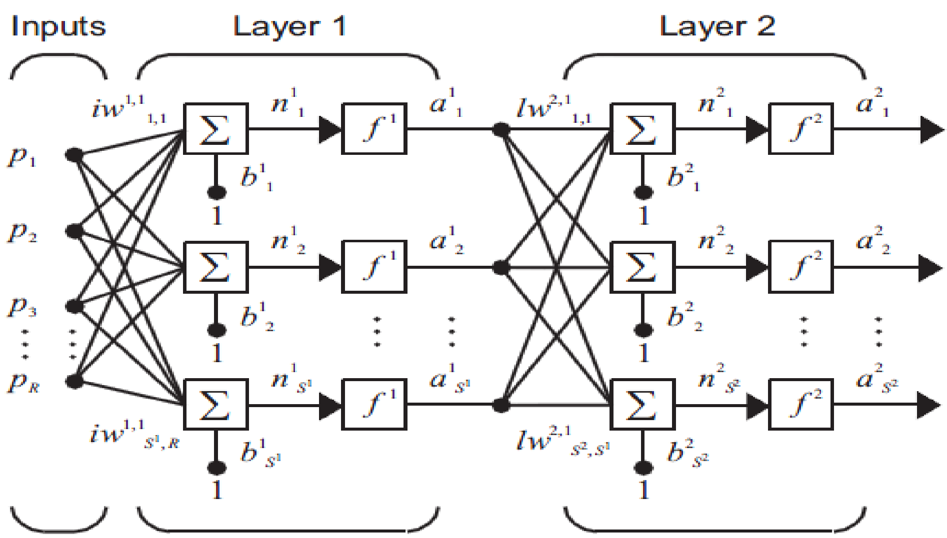

Fig. 4. Architecture of the two layer feedforward neural network.

type of panels is limited and response modeling necessary.
Let us proceed from the surface modeled by the use of neural networks (see section 4). In order to determine the minimal value of the objective function (2) the genetic algorithm has been applied. In order to achieve higher accuracy the real-coded approach of the genetic algorithm is considered. As it can be expected, optimization via genetic algorithms (GA) uses natural selection as a tool of search for the optimal solution in the global domain, the computed solution is not the global extreme, and rather it is a value close to it. Thus, further refinement of the design is still necessary. An approach considered for design improvement herein is employing hybrid GA. This algorithm consists from a global search and one or more local searches. The global search is performed by the GA, but the steepest decent method is applied for the local search using the following domain

$$\begin{gathered} lb[i] = x_i^g - \delta_i, \\ ub[i] = x_i^g + \delta_i, \\ (i = 1, \dots, n), \end{gathered} \tag{3}$$

where x_i^g stands for the value of the design variable obtained from the global search and δ_i is a given deviation for the $i-$th variable. The hybrid GA converges faster in comparison with GA and results higher accuracy.

6. RESULTS

The deviation of the reflective surface has been minimized. However, the zero deviations are not achieved due to measuring, modeling, etc. errors. Employ-ing the coordinate correction algorithm proposed, allows to reduce the number of experiments performed (panels formed) up to required accuracy has been achieved. The problem considered is specific due to limited dataset for response modeling at the beginning of the new type panel forming.

7. CONCLUSION

The main goal of the current study has been achieved, the accuracy of the double-curved surface forming process has been improved. The artificial neural networks and global optimization techniques are combined for solving the engineering problem posed above.

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PAPER 2

T. Velsker, *H. Lend, M. Kirs. Design of glass canopy panel. In: Proceedings of the 8th International Conference of DAAAM Baltic Industrial engineering: 19-21th April 2012, Tallinn, Estonia, p 759 – 764.*

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"INDUSTRIAL ENGINEERING"
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DESIGN OF GLASS CANOPY PANEL

Velsker, T. Lend, H. Maarjus, Kirs.

Abstract: *The main objective of the current study is to design point supported glass panel with prescribed stiffness/ strength properties.The maximal deflection of glass panel and maximum stress around fixing holes are two objectives considered above.*
Structural analysis of the point supported glass panel is performed by applying FEM (geometrically nonlinear plate theory). Based on FEA results the mathematical model is composed using artificial neural networks (ANN). Optimal set of design variables is determined by employing evolotionary algorithms.
Key words: design of glass canopy, Taguchi DOE, FEA, evolutionary algorithms.

1. INTRODUCTION

Over a last couple of decades, glass as a building material has undergone a transformation from being used as a building envelope to also being used as part of the load-carrying structure and elements [1-2]. For example glass floors, roofs, canopies etc. Application of the point supported glass and FEM analysis have been the main reason of the rapid progress in this area. Safety, failure issues of the concerning glass panel structures are studied in [3-5].
The point supported glass canopy panel design considered involve large and relatively thin lites of glass with certain amount of bolt holes. The critical problems are high stresses around fixing holes and large deflection of the panel. In the current study behaviour of these quantities is characterised by introducing ANN based mathematical model.
Artificial neural network (ANN) modeling is inspired by the biological nerve system and is being used to solve a wide variety engineering problems. [6,7].
ANN approach is known as a successful analytical tool for response modeling and is used by many researchers to predict the mechanical, thermal and electrical properties of materials and structures [8-10].
The main goal of the current study is to determine optimal canopy panel thickness and also locations and dimensions of the fixing holes to minimize maximal deflection and maximum stress. The posed problem can be solved by use of multi-criteria optimization approach described in [11-13]. An analysis of the objective functions has been performed and based on In order to manage local extremes and the design variables with discrete values the hybrid genetic algorithm is applied [14-15].

2. PROBLEM FORMULATION

The current paper is concentrated on design of point supported glass panel for canopy (see Figure 1). Designing of glass constructions is a special challenge because of the material behavior of glass. Main criteria considered herein are maximum stress around fixing holes and deflection of glass panel. These criteria are depending on the glass panel thickness, fixing holes location and diameter.

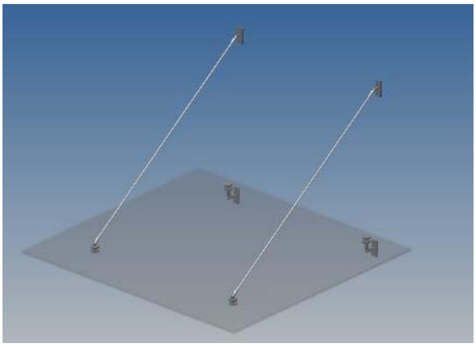

Fig. 1. Glass canopy with four point supports.

Width and length of the panel are given by the manufacturer, which are 1700 mm and 2000 mm accordingly. Main task is to search for an optimal set of design variables X1, X2, X3, X4 and X5 (see Figure 2) determining geometry of the supports. Panel is made of structural glass. In the current study it is assumed to be monolithic solid glass panel.

Panel is loaded by gravity and design load caused by snow (up to 2 kN/m^2).

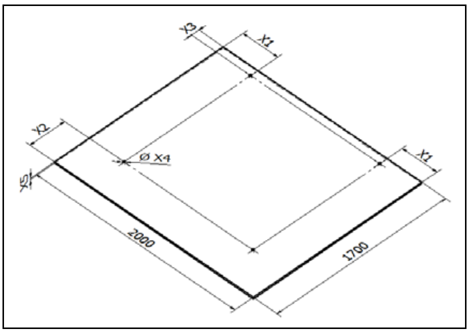

Fig. 2. Glass panel (X1, X2, X3, X4 and X5 are design variables).

Thus, X1,X2 and X3 stand for coordinates of the holes, X4 is diameter of the hole and X5 is thickness of the panel.

3. FINITE ELEMENT ANALYSIS

The only way to analyse a glass plate with point-bearings in a satisfying manner is by means of a threedimensional-FEM software system [1]. When glass panel subjected to the snow or wind load, it usually deforms more than its thickness. Under this situation, its behavior cannot be modeled accurately by linear theory[2]. Therefore a non-linear plate theory is employed.The stress-strain state of the glass panel is analysed by use of FEA (ANSYS). The FEA model with solid elements for analysis of the glass lite has been developed.

Because of the glass panel relatively large dimensions FE model general mesh elements size is 20 mm to avoid long calculation time. Maximum stresses are concentrated around the fixing holes. Therefore to get precise results of maximum stresses in mentioned locations, elements size is reduced to 3 mm. This is applied in 40 mm diameter sphere around the holes (see Figure 3).

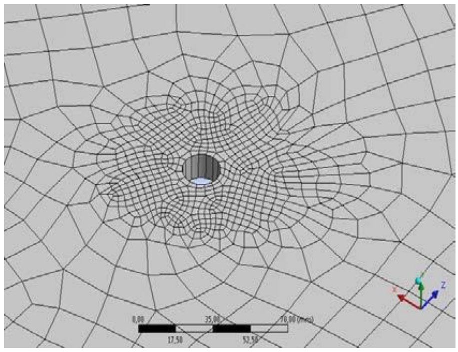

Fig. 3. FE mesh in hole region

Five design variables have been used for analysis of the panel. In order to reduce the computational cost the design of experiment (DOE) is performed.

First values for every variable were assigned according to manufacturing and structural limitations (see Table 1). Four level for each variable are considered.

Independent variable	Levels			
	1	2	3	4
X1	300	350	400	450
X2	300	350	400	450
X3	65	75	80	85
X4	18	24	30	36
X5	12	14	16	20

Table. 1. Levels of design variables

N	Design variable values					Results	
	X1	X2	X3	X4	X5	Max. Str., Mpa	Max. Def., mm
1	300	300	65	18	12	286,2	7,6
2	300	350	75	24	14	156,3	3,3
3	300	400	80	30	16	102,6	1,6
4	300	450	85	36	20	110,2	1,4
5	350	300	75	30	20	161,0	4,4
6	350	350	65	36	16	160,8	4,4
7	350	400	85	18	14	78,3	1,0
8	350	450	80	24	12	117,6	2,6
9	400	300	80	36	14	100,9	2,7
10	400	350	85	30	12	82,7	1,5
11	400	400	65	24	20	147,5	4,2
12	400	450	75	18	16	92,2	2,3
13	450	300	85	24	16	59,1	1,4
14	450	350	80	18	20	78,6	2,4
15	450	400	75	36	12	105,8	3,0
16	450	450	65	30	14	118,8	4,0

Table. 2. Taguchi DOE, L16 orthogonal array

Parametrical model according to variables (X1, X2, X3, X4 and X5) was created in ANSYS Workbench.
The Taguchi's design of experiments (DOE) is applied in order to reduce the number of computational experiments (computational time). Taguchi's L16 ortogonal array is employed and corrsponding values of the design variables as well as objective functions considered are given in Table 2.
The distribution of the maximal stress near fixing hole is depicted in Figure 4.

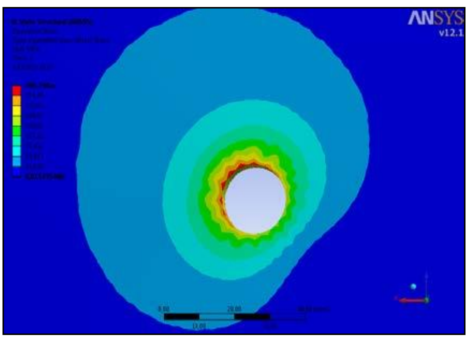

Fig. 4. Max. stress distribution around fixing hole

In can be seen from Figure 4 that the maximal stress near fixing hole is not symmetric and has values up to 300 Mpa.
The distribution of the deflection of glass panel is depicted in Figure 5.

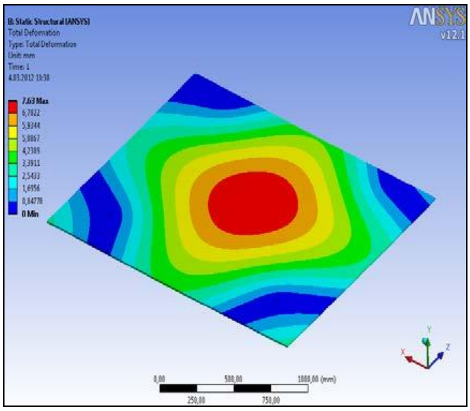

Fig. 5. Distribution of the deflection of glass panel

It can be seen from Figure 5, that the distribution of the deflection can be characterized by symmetry and has values up to 8mm.

4. MATHEMATICAL MODEL

In the current study, the artificial neural networks (ANN) technique was used for prediction the values of the maximal deflection and maximum stress. The inputs to the network are geometrical parameters describing locations of the fixing holes, holes diameter and thickness of the panel. The output data sets of the ANN are formed using values of the maximal deflection and maximum stress obtained from series of FEA simulations (structural analysis of the panel).
Data pre-processing has been applied for both input and output data of the ANN model since the range and unit in one sequence may differ from the others. The original input and output sequences can be normalized by use of formulas (1) and (2), respectively.

$$x_i = \frac{X_i - \min X_i}{\max X_i - \min X_i}, \qquad i = 1,...,n, \ (1)$$

$$f_j(\bar{x}) = \frac{F_j(\bar{x}) - \min F_j(\bar{x})}{\max F_j(\bar{x}) - \min F_j(\bar{x})}, \quad j = 1,...,k. \ (2)$$

In (1) X_i and x_i stand for original and normalised input sequences (design variables), respectively. In (2) $F_j(x)$ and $f_j(x)$ stand for original and normalised output sequences (objective functions), respectively and $\bar{x}$ is vector of input variables. As result the values of the both, both input and output sequences remains in interval [0,1]. The ANN employed comprise of three layers: input, hidden and output layers. The number of neurons in hidden layer is determined from simulation results. The transfer functions applied in hidden and output layers are radial basis and linear functions, respectively. The back propagation learning-algorithm is used. The model was trained with Levenberg–Marquardt learning algorithm which has second-order converging speed [18]. The update rule of the Levenberg–Marquardt algorithm is a blend of the simple gradient descent and Gauss-Newton methods and is given as

$$x_{i+1} = x_i - (H + \lambda diag[H])^{-1} \Delta f(x_i). \qquad (3)$$

where H is the Hessian matrix evaluated at x_i, λ and Δ stand for the scaling coe-ficient and gradient vector, respectively. the Levenberg–Marquardt algorithm is faster than pure gardient method and is less sensitive with respect to starting point selection in comparison with Gauss-Newton method.

5. MULTICRITERIA OPTIMISATION

For above posed multicriteria optimisation problem can be formulated as

$$f(\bar{x}) = \min(f_1(\bar{x}), f_2(\bar{x})), \qquad (4)$$

subjected to linear constraints

$$x_i \le x_i^*, \qquad -x_i \le x_{i*}, \ , \qquad i = 1,...,n, \qquad (5)$$

In (4) $f_1(\bar{x})$ and $f_2(\bar{x})$ stand for the normalised maximum stress and deflection of glass panel, respectively (see formula (2)). In (5) x_i^* and x_{i*} stand for the upper nad lower limit of the i-th design variable, respectively.

In the case of multicriteria optimization problem with conflicting objectives the Pareto optimality concept can be considered as one of the most powerful and general approach. However, an analysis performed in the case of posed problem shows that the objectives considered are not conflicting. Such an result is not surprising, since both objectives are related to stiffness/strength of the structure [12-13].

As result, the use of the simpler multicriteria optimisation strategy is reasonable. Mostly these strategies are based on combining objectives into one objective function and solving latter problem as a single criterion optimization problem.

In the following the weighted summation technique is employed. According to this technique the optimality criteria given by (2) are multiplied by weights and summed into general objective f_s as

$$f_s = \sum_{i=1}^{m} w_i f_i \,. \qquad (6)$$

where m is the number of optimality criteria used, w_i is weight of the i-th criteria and

$$\sum_{i=1}^{m} w_i = 1, \qquad 0 < w_i \le 1. \qquad (7)$$

The constrained optimization problem has been solved by use of hybrid GA algorithm [14-15]. An advantage of the hybrid GA with respect to GA is higher convergence speed and reduced computing time [19].

6. DISCUSSION

The main conclusions can be outlined as

- The objectives considered are not conflicting, thus use of physical programming techniques is justified;
- In the case of considered objective functions the optimal thickness of the plate is equal to upper limit and can be fixed (not considered as a design variable). The situation will be changed when problem formulation is completed with third objective function – cost of the panel (planned as future study).
- The initial robust optimal design is determined by row of Taguchi dataset with best value of the objective function (6)
- The initial robust optimal design can be improved in range of 20-30% (decrease of objective function) depending on design space used.
- Larger data set is needed in order to improve ANN model (future study). The dataset based on Taguchi's DOE technique does not consider complex interactions between design variables.

7. CONCLUSION

The Taguchi's DOE method has been applied for design of data sets for structural analysis of the glass canopy panel. Based on FEA results the mathematical model for prediction of the values of objective functions is developed. The artificial neural network and evolutionary algorithms are employed for response modeling and search for optimal design. Finally, the sensitivity analysis has been performed. The objective function (6) appears most sensitive with respect to the thickness of the glass panel. However, in the case of objective function (6) the thickness corresponding to optimal solution reaches the upper value (boundary of the design domain) and thus can be fixed. This result can be expected, since glass panel with maximal thickness has highest stiffness/ strength properties. As mentioned in section 6, the situation can be changed by introducing new additional objective – cost of the panel.

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PAPER 3

J. Majak, M. Pohlak, M. Eerme, ***T. Velsker****. Design of car frontal protection system using neural networks and genetic algorithm. In: Mechanika, 2012, 18(4), p 453 – 460.*

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Design of car frontal protection system using neural networks and genetic algorithm

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1. Introduction

In general, the car frontal protection systems are designed with an aim to protect vehicles. However, the use of traditional vehicle protection systems may cause certain risk to pedestrian safety. There are two principally different types of the car frontal protection systems: original equipment and separate technical units.

The aim of this study is to design separate technical units of a vehicle which basic components include tubular parts and the brackets. The final product designed had to satisfy the requirements of the Directive 2005/66/EC of the European Parliament and of the Council [1]. In the following, the car frontal protection system is considered as a complementary energy absorbing structure.

A large number of papers covering different impact energy absorbing problems can be found in literature [2-6]. Al Galib et al. 2004 [2] have studied experimentally and numerically the energy absorption in axially loaded circular aluminium tubes (compressive loading). Static and dynamic analysis of the circular thin-walled tubes with various mass and impact velocity has been performed. FE analysis results are found to be in good agreement with test results. Alghamdi 2001 [3] has studied different deformation modes (axial crushing, lateral indentation) of energy absorbing structures such as circular and square tubes, honeycombs, sandwich plates, etc. Gupta 2001 [4] has studied the applicability of structural foam in car protection system design. The potential areas where the steel structures can be replaced with structural foam were found out. An aim of such replacement is to provide light weight design and advanced energy absorption properties. The frontal crash of vehicles is studied by Griškevičius et al. 2003 [5]. Dependence of energy absorption capabilities on age of the vehicle has been detected. It is pointed out that modern AVC longeron columns may absorb several times more energy than corroded longeron columns in old vehicles. De Kanter 2006 [6] has performed experimental and numerical analysis of energy absorbing structures designed using multi-materials. The crushing behaviour of the metallic and plastic cylinders has been analysed. It has been observed that both metallic and composite characteristics are common to the multi-material elements in the crashing behaviour. The techniques for integrating metal and polymer materials were discussed.

Due to new regulations (more strict requirements constituted by the Directive 2005/66/EC) the frontal protection systems of a vehicle should be redesigned in order to improve their energy absorption (softer) in the case of car-pedestrian accidents [7-10]. Du Bois et al. 2004 [7] provide an overview of the vehicle design safety problems. In [8] the brake assist system is analysed and its advantages are pointed out. In Matsui [9] the lower extremity injury is investigated. The influence of some key factors - vehicle bumper height and impact velocity is discussed. It appears that in the case of impact velocity in range 20-30 km/h the basic injury is knee ligament, but in the case of impact velocity near 40 km/h the injury is a fracture of the lower extremities. The cushioning methods and new trends in bumper design (lower stiffeners, beam face features, etc) are reviewed by Schuster 2006 [10]. In [10] special attention is paid to techniques allowing reducing the lower limb impacts of pedestrian.

The design of frontal protection system of a vehicle is commonly based on application of optimisation techniques [11, 12]. In [11] the crashworthiness analysis is performed by use of software package LS-OPT. In order to save recourses the meta-modelling techniques are employed.

Optimal design of a crash box is investigated by Wang [12] considering the difference between maximum and minimum force values as objective function. Such an approach allows obtaining more smooth distribution of the force values. Main attention is paid to shape optimization of a crash box.

This paper studies the possibilities of increasing the safety of pedestrians in the case of traffic accidents. The frontal protection system, consisting of tubular parts and the brackets, is clamped to a vehicle. Latter amplification is performed without structural changes of the vehicle. Thus, the energy absorbing structures of the vehicle holds good. The study is focused to the design of the brackets. The key factors need to be considered in design of the brackets are the safety of the pedestrians and mechanical properties of the car accessories. There are two opposite kind of constraints on design of the brackets. Firstly, the car protection system must be flexible enough in order to evade extreme accelerations of human body in case of the traffic accident. Secondly, the car protection system must be stiff enough in order to withstand to the accelerations of the car. This allows using extra lights fastened to car protection system.

The size, shape and topology of the fastening components are subjected to optimization in order to achieve maximum energy absorption. The optimal design problem posed involves several complexities, like large plastic deformations, geometric and physical nonlinearities (studied by the authors in [13, 14]), impact loading, contact modelling and quite strict limitations on the design space accrue from the geometry of the brackets (small dimensions), the requirements set by the manufacturer and the EU directive [1].

In this study the FE software package LS-DYNA is used for the car-pedestrian crash situation analysis. The approximation of the objective and constraint functions is modelled by use of a neural network and search for an optimal design is accomplished by applying genetic algorithm. The real-coded genetic algorithm is employed, which allows to provide higher accuracy. However, in a standard formulation the genetic algorithm may converge close to an optimal solution. The refined algorithms are proposed for design improvement. The function approximation and optimization modules are realized in MATLAB and C++ programming environment.

Due to high safety requirements (safety of pedestrian) two alternate solutions are developed and compared (first approach is introduced in [15], where the solution is treated by the use of optimization software package LS-OPT). A theoretical estimate on the deformation energy is given.

2. Estimate on deformation energy

In the following it is assumed that the velocity v_0 of the legform coincide with that of the car protection system. In the case of simplified model the kinetic energy can be given as

$$E_B = m\frac{v_0^2}{2}, \quad E_D = \left(M+m\right)\frac{v_0^2}{2} \tag{1}$$

where the indexes E_B and E_D correspond to the kinetic energy before and during crash and v_0 is initial velocity of the legform. The masses of the legform and the car protection system are denoted by m and M, respectively. The formula of the deformation energy of the bracket D_D can be expressed as

$$D_D = E_B - E_D \tag{2}$$

Computing the deformation energy as an integral of the

$$E_D = \int F ds \quad \text{or} \quad E_D = \int F dt \tag{3}$$

Latter formulas describe dependence of the reaction force F on the velocity v.

3. Testing procedures

The Directive 2005/66/EC defines several different tests for the frontal protection system (Directive 2005). The tubular accessories fastened to the front of the car may worse considerably the situation for a pedestrian in case of an accident, so only minimum requirements can be met without adding sophisticated systems (like airbags, etc). A minimum test is the lower legform impact test. The car frontal protection systems with a height of over 500 mm need for the upper legform impact test.

In the current study, the height of the car frontal protection system is limited up to 500 mm and the safety requirements corresponding to upper legform test can be omitted (Fig. 1).

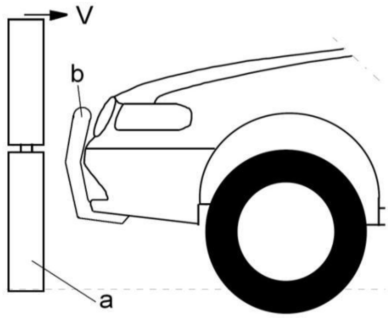

Fig. 1 Lower legform impact test

The legform 'a' was shot at the speed v at the car frontal protection system 'b' (v = 11.1 m/s). The following sensors were installed in legform impact or: an acceleration sensor; a bending angle sensor; shear displacement sensor. The directive 2005/66/EC [1] requires that

$$\alpha \le 21°, \gamma \le 6 \text{ mm}, a_{ut} \le 200g, \left(g = 9.81\frac{\text{m}}{\text{s}^2}\right) \tag{4}$$

where α, γ and a_{ut} stand for the maximum dynamic knee bending angle, maximum dynamic knee shearing displacement and the acceleration measured at the upper end of the tibia, respectively. The constraints (4) hold good for the vehicles with total permissible mass less than 2500 kg. For more weighty vehicles the values of the parameters α, γ and a_{ut} are 26.0°, 7.5 mm and 250 g, respectively. The most complicated task is handling of the constraint subjected to acceleration.

An overview on energy absorbing structures including laminates, honeycombs and rings is given in [3, 6, 16]. Various materials (solid metals, composites, multi-materials) are utilized in these structures. The energy absorption structures can be categorized into two main types characterized by (Fig. 2):

– high peak of reaction force (type I);
– flat load-displacement curve (type II).

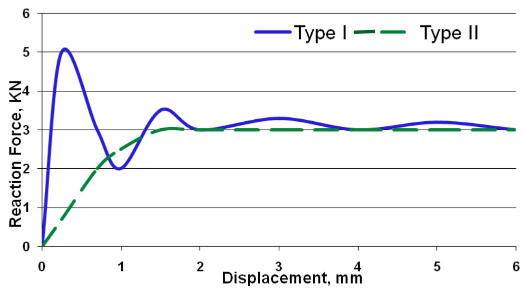

Fig. 2 Force-displacement relationship: 2 types of energy absorbing structures

Obviously, it is desirable that the reaction force will increase steadily to certain given level and then remain unchanged [16]. In this study the energy absorbing structure of type I (bracket) was redesigned by changing the geometry, adding cutouts, folds and performing parameter design. The resulting bracket belongs to the energy absorbing structure of type II.

The acceleration can be decreased by employing optimal design techniques for determining optimal configuration of the frontal protection system. Let us return to the lower legform impact test described in Fig. 1. Corresponding acceleration distribution is depicted in Fig. 3. Obviously, the constraints imposed on the acceleration are not satisfied in the case of tubular parts and the bracket used by the producer originally (Fig. 3). Thus, it can be concluded that the car frontal protection system in its original configuration is too stiff.

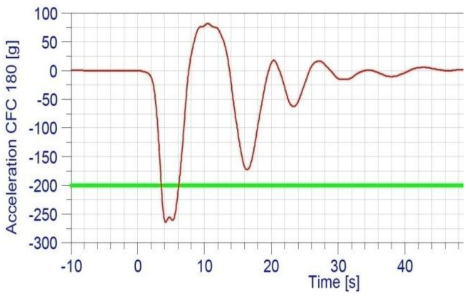

Fig. 3 Acceleration diagram: lower legform impact test

In the current study the main attention is paid to design of the fastening components as energy absorbers. In Fig. 4 is shown initial design of the bracket suggested by the manufacturer. The main aim is to determine the optimal values of the design variables *a*, *b*, *c*, *d* and *e* shown in Fig. 4. Initial topology of the bracket is given by manufacturer, but certain changes in topology are allowed (the fold: form, location; etc.).

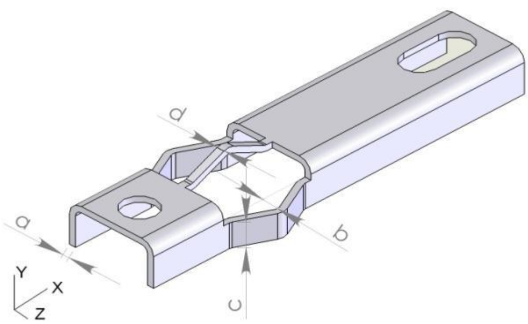

Fig. 4 Energy absorbing structure

The properties of the tubular components were determined by applying robust design and technological constraints.

4. Objective and constraint functions

Obviously, one of the most realistic and practical objective for posed problem is minimization of the peak force (acceleration). However, not only the first peak force, but also a sudden change in the force (following unloading) constitutes a potential risk for the pedestrian. For that reason the above posed problem is considered as multicriteria optimization problem and formulated as

$$min\left(F_1\left(\bar{x}\right), F_2\left(\bar{x}\right)\right) \tag{5}$$

Subjected to linear and nonlinear constraints given as

$$x_i \le x_i^*, \quad -x_i \le -x_i^{**}, \quad u_c = \sqrt{u_2^2 + u_3^2} \le u^*, \; (i = 1,..n) \tag{6}$$

In Eq. (5) $\bar{x} = (x_1, x_2, \ldots, x_n)$ is a vector of independent design variables. The objectives $F_1(\bar{x})$ and $F_2(\bar{x})$ stand for peak force and difference between the maximal and the minimal force, respectively

$$\left.\begin{aligned} F_1\left(\bar{x}\right) &= \max_t F\left(t, \bar{x}\right) \\ F_2\left(\bar{x}\right) &= \max_t F\left(t, \bar{x}\right) - \min_t F\left(t, \bar{x}\right) \end{aligned}\right\} \tag{7}$$

In Eq. (7) $F(t, \bar{x})$ stands for axial (frontal) force component and t is a time. Nonlinear constraint (6) is set on the displacements in the $y - z$ plane. The protection system of a vehicle designed should satisfy two requirements simultaneously:

– must be a good energy absorber;
– must have high stiffness characteristics in the directions perpendicular to the moving direction.

The weight of the car frontal protection system is assumed as an acting load. The stiffness of the car frontal protection system as a whole is determined experimentally by measuring the displacements in the y and z direction denoted by u_2 and u_3 in Eq. (6), respectively. The constraint on stiffness is described by Eq. (6), where u^* is a given limit value. Thus, in normal car exploitation conditions the Eq. (6) must be satisfied.

5. Solution algorithm

The weighted summation is the simplest and most commonly used technique employed for solving multi-objective optimization problems. The Pareto optimality concept can be considered as a most general approach for solving multicriteria optimization problems. However, an analysis done for the current problem allows to conclude that the objectives considered are not in contradiction. Thus, there is no reason to apply the Pareto optimality based approach. The two optimization techniques considered in the following are: the weighted summation, compromise programming.

The approaches used for the Genetic algorithms (GA) improvement: two stage GA and the hybrid GA. These techniques are discussed in more detail above (design improvement). Basic steps of the design procedure proposed are given in Fig. 5. The experimental validation of the computer simulation is included in the algorithm in order to describe the full design process. Actually, the impact tests are performed in TÜV Rheinland (Germany). The static compression tests of the fastening components are executed in TUT (Tallinn University of Technology). The topology of the bracket has been modified based on experimental data.

The major modules of the algorithm are described in detail in the following sections.

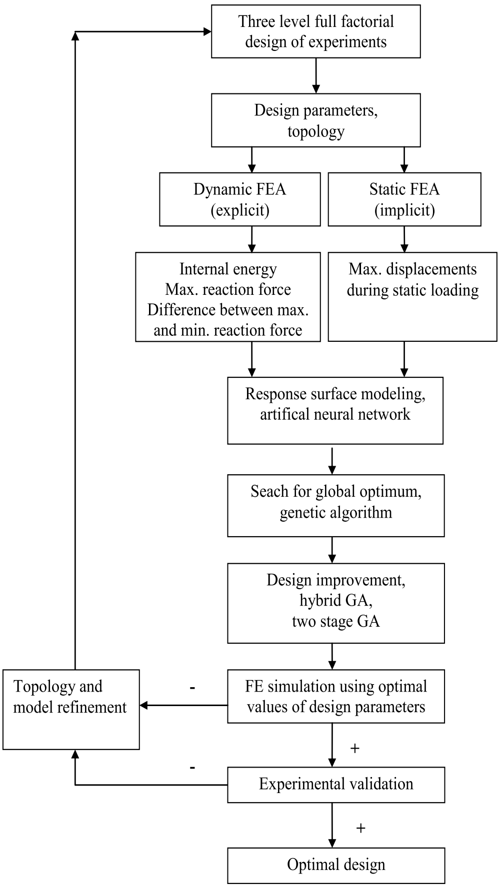

Fig. 5 Basic steps of the design procedure

6. Numerical analysis

In the following the finite element analysis software package LS-DYNA is employed and fully integrated shell elements are considered [17]. The multi-linear relationship is assumed for describing the stress-strain behavior. The plastic anisotropy is modeled by use Hill's yield criterion. Two kind of FEA is realized:

– dynamic analysis - crash simulation;
– static analysis - stiffness evaluation.

It can be seen from Fig. 5 that the values of the input data for FEM analysis (i.e. the design variables shown in Fig. 4) are determined by design of experiment and the values of the output data obtained (i.e. maximal reaction force, difference between maximal and minimal reaction force, maximal displacements during static loading) are utilized for response modeling.

The FEA model proposed is validated against results obtained from experimental study. The brackets with different configurations were tested. Changes in topology of the bracket may change also the number of design variables (from 4 up to 8). The compression tests performed allows obtaining initial values of the force components and deformation modes. The results of the FEA and experimental tests are shown in Fig. 6, where $a = 1.6$ mm, $b = 12$ mm, $c = 6$ mm and $d = 10$ mm. Note that here is assumed that the shape of the fold is triangular and the design parameter e is omitted (bend angle is used instead of design parameter e).

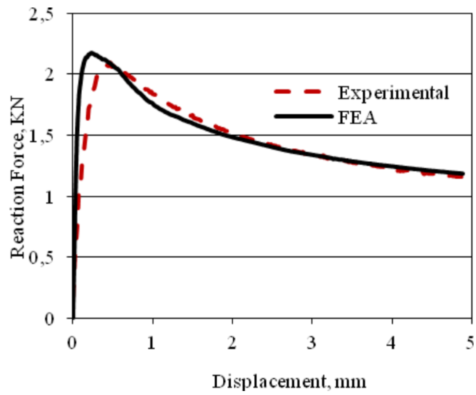

Fig. 6 Load-displacement relation

The FEA results appear to be close to corresponding experimental results (see Fig. 6). Remarkable differences in values of the reaction force are observed in the case of brackets with inner folds, where the folded parts of the bracket move into contact. Actually here take place sliding between the contacting surfaces. Occurrence of the sliding can be confirmed experimentally, since the symmetry conditions are not fulfilled ideally in an experimental test, but not numerically. Even in this exceptional case, good agreement between numerical and experimental results can be found in the range of small deformations corresponding to peak force. Remarkable differences in the values of reaction force can be observed in the case of large deformations (caused by contact between the folded surfaces). Obviously, the first peak of reaction force is the most significant in regard to pedestrian safety.

The dependence of the reaction force on design parameters *a*, *b*, *c*, *e* is illustrated in Fig. 7.

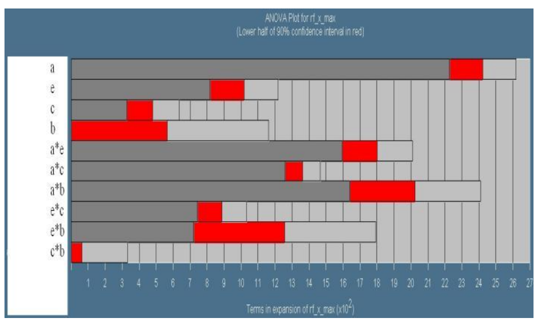

Fig. 7 The influence of design parameters *a*, *b*, *c*, *e* and their interactions on the value of the reaction force

The sensitivity of the reaction force is highest with respect to thickness and lowest with respect to the upper fold. Note that the results given in Fig. 7 depend on the selection of the design space. The values of the reaction force may change more than 10 times due to changes in design parameters and the topology of the bracket. Also, the nonlinear constraint Eq. (6) deploys substantial restrictions on original design space.

7. Surrogate models

The evaluation of the objective and constraint functions described above includes time consuming FE simulations.

In the following the FE analysis results are used as response values, corresponding to the data set of design variables. The artificial neural networks (ANN) are used for the response modeling. The ANN based approximation of the objective and constraint functions is realized by the authors in software package MATLAB and C++ programming environment. Levenberg-Marquardt algorithm was used to train the ANN model. It is a compromise between the gradient descent and Gauss-Newton optimization methods used widely in engineering applications 20]. In the first and second layer of the ANN the radial bases and linear transfer functions are employed, respectively. In [15] the posed optimization problem is realized by use of software packages LS-OPT (combined with LS-DYNA). The solution is analogous to the current approach.

8. Optimization

In this section, the optimization modules are discussed in detail.

8.1. Why GA?

GA were first developed by Holland [18]. Traditional gradient based optimization methods have a trend to converge to the nearest optimum (which may appear to be local), also here is need for computation of the derivatives of the objective and constraint functions with respect to the design variables. In the following, a genetic algorithm is employed for solving the optimization problem posed. The GA has the following advantages over traditional gradient based techniques:

- in general, the convergence to global extreme can be expected;
- integer type design parameters can be used;
- computation of derivatives of objective and constraints functions is not required.

However, there are also some disadvantages common to GA:

- convergence to the solution close to global optimum (not exactly optimum);
- relatively long computing time.

In order to overcome the above mentioned drawbacks, several refined GA approaches are proposed in literature [19]. Henz et al. [19] studied optimization of injection gate locations in liquid composite molding process and presented a global–local search approach. The hybrid search approach used include a global search performed by use of GA and was improved with a gradient search (continuous sensitivity equations). In [20-22] multilevel optimization strategy has been developed and validated by solving different engineering design problems (design of large composite structures, design of sandwich panels, etc). In [23] a novel GA, particularly suited to hardware implementation, is introduced. The optimal individual monogenetic algorithm (OIMGA) is treated, which includes global and local searches with hierarchical structure.

8.2. Search for an optimal solution

As mentioned above the objectives considered are not in contradiction and the Pareto optimality concept is not employed. First the two objectives given by Eq. (7) are normalized

$$\left.\begin{aligned} f_1(x) &= \frac{F_1(x) - min\,F_1(x)}{max\,F_1(x) - min\,F_1(x)} \\ f_2(x) &= \frac{F_2(x) - min\,F_2(x)}{max\,F_2(x) - min\,F_2(x)} \end{aligned}\right\} \tag{8}$$

Next the following multicriteria optimization techniques are employed:

- weighted summation (Eq. (9));
- compromise programming (Eq. (10)).

$$f_{ws} = \sum_{i=1}^{m} w_i f_i \tag{9}$$

$$f_{cp} = \left[\sum_{i=1}^{m} \left(w_i f_i \right)^p \right]^{1/p} \tag{10}$$

In Eqs. (9) and (10) m stand for the number of objectives ($m = 2$) and w_i for weights of the objectives. The combined objective function has been minimized by use of genetic algorithm.

In optimization algorithm the values of the reaction force in moving direction and the $y-z$ displacement are determined from corresponding response surfaces introduced above. The response surfaces built by use of ANN are given by analytical formulas. Thus, the evaluation of the objective function in optimization algorithm is computationally relatively cheap operation. In this study the MATLAB Genetic algorithm and Direct Search Toolbox is employed for minimization of the objectives (9) and (10). In order to achieve higher accuracy the real-coded approach of the genetic algorithm is considered. It was not surprising that combined use of ANN and standard GA lead to the solution close to global extreme, but does not provide convergence to global extreme (remains to bend near global extreme). Thus, certain improvement of the algorithm seems reasonable.

In [15] the leap-frog algorithm is applied and the solution of the optimization problem is realized by the use of software package LS-OPT. In the following different approach is used.

8.3. Design improvement (refined algorithm)

As mentioned above, two different approaches are considered for design improvement – the two stage GA and the hybrid GA. Both algorithms consist from a global search and one or more local searches. In the case of the two stage GA, the genetic algorithm is employed for search in both levels (global and local). The domain for the local search is given as

$$x_i^g - \delta_i \le x_i \le x_i^g + \delta_i\,, \quad \left(i = 1,\dots,n\right) \tag{11}$$

where x_i^g is a value of the design variable corresponding to global search and δ_i describes the deviation. The lower and upper bound vectors of the design variables are redefined as

$$lb[i] = x_i^g - \delta_i, \quad ub[i] = x_i^g + \delta_i, \quad (i = 1,...,n) \qquad (12)$$

Obviously, the numerical results obtained using sub sequential runs of the GA code may differ, since the GA is based on a stochastic search method. Furthermore, if several equal or close minimal values of the fitness function exist in the global design space, then the optimal solutions corresponding to different subsequent runs of the code may differ significantly (i.e. the values of design variables differ significantly, but the corresponding values of the fitness function are close). In the latter case the design space (11) should be specified and the local search performed for a set of solutions is obtained by applying the global search. The solutions are given in matrix population and the corresponding values of the fitness function in array scores.

The hybrid GA considered herein, include GA and the steepest decent methods applied in global and local level of the optimization algorithm, respectively. The best individual of the population generated by the GA is used as an initial value of the gradient method. In the cases where elite population (set of solutions obtained by fitness-based selection rule) contains individuals, which chromosomes (parameters) differ substantially, it is reasonable to perform local search for all these individuals. Thus, the number of local searches necessary depends on the result of the global search. The local search may be interpreted as a design improvement. To reach the final solution the results of all local searches are to be compared (selection is based on the value of the fitness function). Note that the 2D array population should be sorted using the values of the fitness function given in array scores before the selection of the elite population (initially not sorted).

It was observed that the hybrid GA converges faster and exactly to the extreme value of the objective function in comparison with two stage GA. However, the two stage GA may appear more effective in particular cases when several extreme values of the objective function are expected in the local search domain.

8.4. Freeware based solution

Obviously, the FEA performed above is a problem specific, but the approximations of the objective (constraint) functions as well as optimization are the tasks of more general character. Thus, the solution algorithm treated to solve the latter problems can be applied to solve wider class of similar optimization problems.

For that reason a freeware based solution covering function approximation and optimization tasks in C++ code is developed. Another consideration for the development of C++ code was the fact that the MATLAB GA toolbox has been developed in parallel with the solution of the posed optimization problem (first versions of MATLAB GA algorithm does not support the constrained optimization).

Due to the similar main algorithms used, the numerical results obtained by the use of freeware and MATLAB based solutions coincide or are close.

The main advantages of the commercial software MATLAB based solution in comparison with the freeware based solution is the presence of advanced tools for graphics.

9. Numerical and experimental results

Satisfaction of the constraints imposed on acceleration is most complicated task. Furthermore, huge acceleration (or corresponding reaction force) is most critical also in terms of pedestrian safety. Thus, the objective f_1 in Eqs. (9) and (10) has higher priority in comparison with objective f_2. The solution of the posed optimization problem allows reducing the value of the reaction force more than 4 times in comparison with the reference value. The reference solution was chosen with a reserve since the predicting of the value of the *y-z* displacement u_c (constraint) corresponding to a certain set of design variables is extremely complicated (detailed description is given in section 5). The reaction force versus time relation is given in Fig. 8. The solid and dashed lines in Fig. 8 correspond to the initial and optimal solutions, respectively. The constraints (6) are satisfied in the case of both solutions. The stiffness of the bracket with initial design in the moving direction of the vehicle is much higher than that of optimized bracket. Thus, the total energy absorption is higher in the case of reference solution.

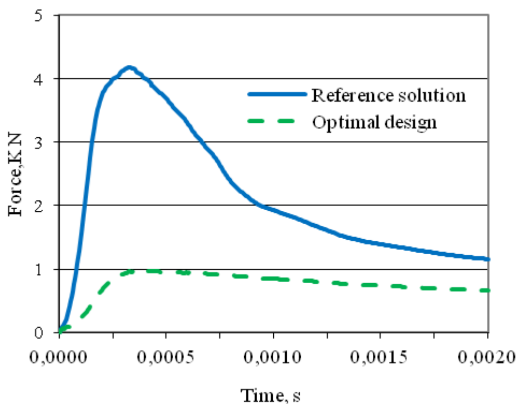

Fig. 8 Force vs. time diagram: reference solution and the optimal design

Obviously, the character of the reaction force curve corresponding to the optimal solution and the character of the curve corresponding to the energy absorber of type II, shown in Fig. 2, are close (Fig. 8). In Table the optimal values of the reaction force components, thicknesses of the metal sheet and also nonlinear constraints corresponding to the optimization algorithms introduced in the current paper and in [15] are compared.

Based on results shown in Table, it can be concluded that the values of the reaction force corresponding to GA, the two stage GA and the hybrid GA algorithms are close to each other. However, certain differences between the latter solutions and the solution, obtained by applying software package LS-OPT [15], can be observed. It should be noted that in the case of first three methods the response surface is considered to be “static” i.e. it is not modified

Table

The values of the frontal force components, thicknesses and nonlinear constraints correspond to the optimization algorithms introduced in the current paper and in [15]

Optimization algorithm	GA	Two stage GA	Hybrid GA	LS-OPT
Frontal force component, N	1157	1134	1125	1067
Thickness of the sheet, mm	1.74	1.72	1.71	1.7
Nonlinear constraint, mm	0.007	0.0073	0.0073	0.0073

during optimization process. In the case of forth solution method (LS-OPT based) the response surface is considered to be dynamic i.e. it is updated in each iteration step. Since the software packages LS-DYNA and LS-OPT are compatible, the sequential executing of explicit and implicit solvers can be realized by introducing a special user defined script. Combining MATLAB with FE solvers is more cumbersome (several restrictions exist on what kind of standalone executable MATLAB code can be compiled with the MATLAB compiler).

The nonlinear constraints have an inequality form in the case of simple GA algorithm and turn to an equality form in the case of all other methods. The optimal design appears most sensitive with respect to the thickness of the bracket (discussed in more detail in section 6). The number of function calls performed by the GA method (global and local level) depends on random values and is not determined uniquely. However, approximately 10-100 times more function calls were observed in the case of the proposed optimization algorithm in comparison with the gradient method.

The two stage GA and the hybrid GA algorithms are discussed above, the solution treated by the use of software package LS-OPT is described in detail in [15]. It is correct to note that the numerical methods used in the software package LS-OPT for optimization differ from those used in the MATLAB and C++ algorithms described above. The LS-OPT version 3.1 features Monte Carlo based point selection schemes. The sub-problem is optimized by the dynamic leap-frog method.

10. Conclusions

1. The design procedure for optimization of the frontal protection system of a vehicle has been proposed. The results obtained in the current study are compared with the results given in [15].

2. The results obtained from experimental study and FE simulations were found to be close to each other (see section 6 for details). The influences of the different design parameters on the final results are estimated. A simple theoretical estimate on deformation energy is given.

3. The energy absorbing component (bracket) designed is characterized by its low cost and simplicity of fabrication.

4. The frontal protection system has been designed according to the Directive 2005/66/EC. As a result, the EU patent application no 07108163 “Mounting bracket for frontal protection system” was submitted. Nine products have passed through the type improvement test.

Acknowledgements

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AUTOMOBILIO PRIEKIO APSAUGOS SISTEMOS PROJEKTAVIMAS NAUDOJANT NEURONINĮ TINKLĄ IR GENETINĮ ALGORITMĄ

R e z i u m ė

Sudarytas optimalus automobilio priekio apsaugos sistemos projektas. Šis straipsnis yra skirtas jungiamųjų komponentų projektavimui aprašyti. Automobilio ir pėsčiojo susidūrimo situacija buvo analizuojama naudojant tikslų sprendinį LS-DYNA. Tikslo ir jėgų ryšio funkcijoms modeliuoti panaudotas dirbtinis neuroninis tinklas, o optimalus variantas nustatytas naudojant genetinį algoritmą. Gauti skaitiniai rezultatai patvirtinti eksperimentiškai.

J. Majak, M. Pohlak, M. Eerme, T. Velsker

DESIGN OF CAR FRONTAL PROTECTION SYSTEM USING NEURAL NETWORK AND GENETIC ALGORITHM

S u m m a r y

Optimal design of the frontal protection system of a car is considered. The study is focused on design of the fastening components. A simple theoretical estimate on deformation energy is given. The car-pedestrian collision situation is analyzed by use of the LS-DYNA explicit solver. Corresponding stiffness analysis is performed by use of the LS-DYNA implicit solver. The approximation of the objective and constraint functions is modeled by use of artificial neural network (NN) and search for an optimal design is performed by use of a genetic algorithm (GA). The obtained numerical results are validated against experimental test results.

Keywords: design, car frontal protection system, neural network, genetic algorithm.

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PAPER 4

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Artificial neural networks and evolutionary algorithms in engineering design

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Analysis and modelling

ABSTRACT

Purpose: Purpose of this paper is investigation of optimization strategies eligible for solving complex engineering design problems. An aim is to develop numerical algorithms for solving optimal design problems which may contain real and integer variables, a number of local extremes, linear- and non-linear constraints and multiple optimality criteria.
Design/methodology/approach: The methodology proposed for solving optimal design problems is based on integrated use of meta-modeling techniques and global optimization algorithms. Design of the complex and safety critical products is validated experimentally.
Findings: Hierarchically decomposed multistage optimization strategy for solving complex engineering design problems is developed. A number of different non-gradient methods and meta-modeling techniques has been evaluated and compared for certain class of engineering design problems. The developed optimization algorithms allows to predict the performance of the product (structure) for different design and configurations parameters as well as loading conditions.
Research limitations/implications: The results obtained can be applied for solving certain class of engineering design problems. The nano- and microstructure design of materials is not considered in current approach.
Practical implications: The methodology proposed is employed successfully for solving a number of practical problems arising from Estonian industry: design of car frontal protection system, double-curved surface forming process modeling, fixings for frameless glazed structures, optimal design of composite bathtub (large composite plastics), etc.
Originality/value: Developed numerical algorithms can be utilised for solving a wide class of complex optimization problems.
Keywords: Global optimization techniques; Response surface modeling; FEA

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1. Introduction

Engineering product (structure) optimization process consists of three major supportive components:

- fast CAD tools for creation of geometry proposals,
- effective CAE tools for fast and accurate structural analysis and improvement of assessments,
- standards for geometry and process technology with the objective to transfer knowledge and experiences from the older projects to new projects.

The problems of product optimization discussed below could be summarized under term structural optimization and classified into topology, shape and sizing optimization [1,2].

Multilevel strategies and their variants address the multidiscipli-nary design optimization through a formal treatment of interdisciplinary couplings [3,4]. However, these techniques are issues of intensive research, the problems of convergence and effective application are yet not fully resolved. Haftka [5] proposed a quasi-separable bi-level optimization approach. The objective function in this approach of a system level is a synthesis or a composition of the optimal subsystem responses. Important task of subsystems in such an approach is the representation of optimal subsystem responses at the system level by surrogate models.

In the case of the several contradictionary objectives the most general approach is application of the Pareto optimality concept, according to which all solutions on the Pareto front are optimal (the Pareto front represents the set of all "non-dominated" points). The shape of the Pareto front provides valuable information. However, the selection of an optimal solution is still complicated and depends on a number of factors, like the specific problem considered, additional information available, etc. [6-8].

An alternate approach for solving multiple criteria analysis problems are physical programming techniques, according to which multiple objectives are combined into one objective and latter problem is solved as single objective optimization problem. Independent on methodology how the objective functions are combined into one objective (weighted summation, compromise programming, etc.), such an approach has some drawbacks. Namely, the relative importance of the objectives is not known in most of cases and the evaluation of the weights is complicated.

Current study is focused on solving engineering optimization problems, which contain often real and integer variables, a number of local extremes, multiple optimality criteria. In latter case, the conventional approaches based on traditional gradient technique fail or perform poorly. In the following, an optimization approach that integrates meta-modeling and evolutionary algorithms is developed.

Evolutionary algorithms are population-based stochastic search techniques simulating mechanisms of natural selection, genetics and evolution. The literature overview on evolutionary computing (EC) techniques in structural engineering can be found in [9-12], where different features of evolutionary algorithms (EA-s) are discussed and historical perspectives of EC are outlined. Historically, the GA-s, evolution strategies (ES) and evolutionary programming (EP) are three developed general approaches. The approaches differ in the types of generation - to - generation alterations and on computer representation of population. The fourth general approach - genetic programming (GP) is a method for automated creating of a computer program [9]. GP represents individuals as executable trees of code.

The engineering design problems as rule contain finding the global optimum in the space with many local optima. Evolutionary algorithms including GA have property to escape the local extreme and have a better global perspective than the traditional gradient based methods [10]. A certain class of optimal design problems contains multiple global extremes i.e several solutions correspond to the same value of the objective function. Desirably all or as many as possible global extremes should be found. Obviously, in latter case the algorithms manipulating with population instead of single solution are preferred.

However, manipulating with population instead of single solution has also some drawback - numerous evaluations of candidate solutions are necessary. For complex engineering problems, such evaluations are time consuming (capacious FEA, tests, etc.). The latter problem is solved most commonly by using meta-models. Various techniques including regression and interpolation tools (splines, least square regression, artificial neural network, kriging, etc) can be utilized for building surrogate models [13,14]. An accuracy and computational cost are basic characteristics, which must be considered in selection of the appropriate meta-models [14].

GA-s have been developed rapidly during last decades as an effective and simple optimization technique. One of the drawbacks of the traditional GA is also a ratchet effect (crossover cannot introduce new gene values). In order to overcome the drawbacks of the traditional GA a large number of improvements is provided (CHC GA, adaptive GA [15], niche GA and hybrid GA [16-17], etc.). In order to achieve higher accuracy, the real-coded GA operators are used in engineering design instead of traditional binary operators (more efficient for operating with real numbers, the chromosome is implemented by a vector of floating-point numbers) [18-19]. The development of evolutionary algorithms for multi-objective optimization problems [20-21] is another actual topic in engineering design.

In the current study Artificial Neural Networks (ANN) and real-coded GA are used for performing meta-modeling and search for a global extreme, respectively. Thus, the number of function evaluations is reduced and convergence to the global extreme can be expected. In order to speed up algorithm, the real-coded GA is combined with gradient method (steepest descent). In this hybrid GA the global search is performed by the use of real-coded GA and local search by the use of gradient method. Some modifications to hybrid GA are mode depending on the character of particular optimization problem solved. The structural analysis of the car frontal protection system (case study 1) and composite bathtub (case study 2) is performed by the use of FEM software packages LS-DYNA and HyperWorks, respectively. The multistage optimization procedure has been developed. In the case of first problem considered (design of car frontal protection system) an alternative numerical approach is developed by the use of finite element optimization package LS-OPT and the obtained numerical results are validated against experimental test results [8,22].

2. Multi stage optimization model

In general the considered engineering optimization problems can be divided into the following subtasks (stages):

- evaluation of the objective functions for given vector of design variables x (includes FEA);
- response surface modeling (meta-modeling);
- global optimization using multiple criteria analysis techniques discussed in details below.

Note, that the first stage: evaluation of the objective functions may include structural analysis and optimization, topology, shape and size optimization, etc. For example in the case of composite bathtub, the first stage contains free-size optimization for a given set of input data.

In response surface method (RSM) the design surface is fitted to the response values using regression analysis. Least squares approximations are used for this purpose most commonly. In the current paper, the generalized regression neural networks (NN) are used for the surface fitting. In the case of car frontal protection system and composite bathtub the output data obtained from FE analysis are treated as response values, since in the case of double-curved surface forming process modeling the response values for meta-model are obtained from experiments. Let us proceed from the predetermined set of designs. The surface constructed by the use of NN does not normally contain the given response values (similarity with least-squares method in this respect). An approach proposed is based on the use of the MATLAB neural network toolbox and authors written C++ code. A generated two-layer network has radial basis transfer function neurons in the first and the linear transfer function neurons in the second layer. Similar two-layer (one hidden layer) network is generated also in FE software package LS-OPT for composing response surface. The response surface values are generated simultaneously for all response quantities.

Note that in the current study the meta-modeling technique is applied not only for building objective (fitness) functions, but also for building some constraint functions (needed to be evaluated from FEA or experiments). It should also be mentioned that the implementation of the neural network based model was much simpler and more flexible than the alternative solution based on use of B-splines.

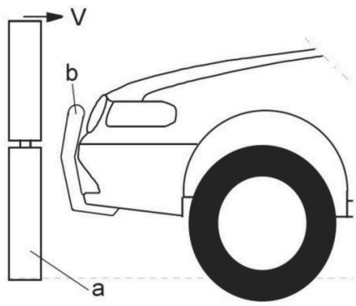

Fig. 1. Lower legform impact testing (a - Legform impactor, b - Frontal protection system, V - velocity of impactor)

Let us proceed form surface modeled by the use of neural networks. In order to determine the minimum value of the objective function the hybrid GA containing local and global level search has been treated. The global and local level search has been performed by the use of GA and steepest descent methods, respectively. In order to achieve higher accuracy the real-coded algorithm is used. The best individual (solution) of the population generated by GA is used as an initial value of the gradient method (local level search). In the cases where elite population (set of solutions obtained by fitness-based selection rule) contains individuals, whose chromosomes differ substantially, it is reasonable to perform local search for all these individuals. Thus, the number local searches necessary depend on a result of the global search. The local search may be considered as design improvement, since the global search realized by the use of GA may converge to solution close to global optimum (exact optimum is not achieved), also the gradient method is less time consuming. The final solution is determined by comparison of the results of all local searches performed (selection is based on value of objective function). The nonlinear constraints are considered through penalty terms.

The solution is implemented in MATLAB code. Note that the 2D array population should be sorted using the values of the fitness function given in array scores before selection of the elite population (initially unsorted).

An alternative solution of the problem 1 (design of car frontal protection system) is realized by the use of FE software package LS-OPT [23]. The latter solution is based on the use of leap-frog algorithm.

3. Case study 1: optimal design of car frontal protection system

Main attention is paid to optimal design of brackets. Preliminary configuration of the bracket is given by the manufacturer. The solution method proposed for considered optimization problem is based on the use of FEA system. An analysis of car-pedestrian collision situation is performed by the use of LS-DYNA explicit solver and the stiffness analysis with LS-DYNA implicit solver.

3.1. Problem formulation

The directive 2005/66/EC defines several different tests for frontal protection system. As it can be seen, the tubular extra accessories that are mounted to the front of vehicle will worsen considerably the situation for pedestrian in case of accident, so only minimum requirements can be met without adding sophisticated systems (like airbags, etc). Minimum test is lower legform impact test. Upper legform test is required for systems with height over 500mm. In the current study, it is assumed that the height of the designed car frontal protection system is less than 500 mm and main attention is paid to the safety requirements proceeding from lower legform test (see Figure 1).

In the test the impactor (a in Figure 1) has been shot at the speed of 11.1 m/s at the frontal protection system of the vehicle. There are three types of sensors mounted inside the impactor: acceleration sensor, bending angle sensor and shear displacement sensor. According to the directive 2005/66/EC (Directive 2005):

- the maximum dynamic knee bending angle shall not exceed 21.0°;
- the maximum dynamic knee shearing displacement shall not exceed 6.0 mm;
- the acceleration measured at the upper end of the tibia shall not exceed 200 g.

It is assumed above that the total permissible mass of the vehicle is less than 2500 kg. In the case where the total permissible mass of the vehicle exceeds 2500 kg, the corresponding maximum values of the knee bending angle, knee shearing displacement and acceleration measured at the upper end of the tibia are 26.0°, 7.5 mm and 250 g, respectively.

With bending angle and shear displacement it is easier to fit between the limits, with acceleration limit the situation is more complicated.

In the literature, different kinds of energy absorbing structures (rings, laminates, honeycombs, etc.) can be found, materials vary from solid metals to composites and cellular materials [24-26]. Unfortunately, most of structures absorb energy in an unstable manner. The two principal different types of energy absorbing structures are classified as follows: type I structure with a flat-topped load-displacement curve and type II structure with a high peak of reaction force when impact loading starts followed by smaller peaks or more constant level of reaction forces. More desirable situation would be if the reaction force increased steadily to some predefined level and would remain constant on this level [26]. In the current study the energy absorbing structure of type I (bracket) has been redesigned by changing geometry, adding cutouts, folds and performing parameters design. The resulting bracket belongs to energy absorbing structure of type II. In order to decrease the acceleration, optimal design of tubular parts and brackets has to be addressed.

The current study is focused on the design of brackets located between the vehicle bamper and the tubular extra accessories that are mounted to the front of vehicle. The model proposed consider the car frontal protection system and applied forces only. The bracket is designed as main energy absorbing component (see Figure 2). Initial design of the energy absorbing component depicted in Figure 2 is given by the manufacturer. Thus, the topology is predefined ro a certain extent by the manufacturer and main task is to search for an optimal set of design variables a, b, c, d and e (see Figure 2). However, some corrections in topology are available (for example the fold: form, location; etc.). The properties of the tubes are selected as appropriate as technologically possible (light structure, thin walls, etc), detailed design of tubes is omitted.

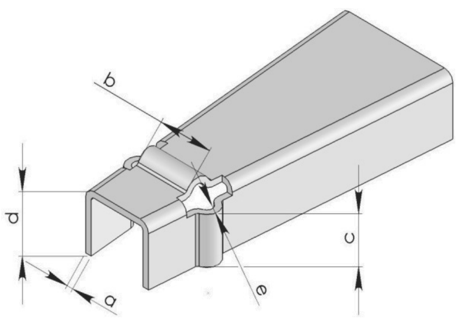

Fig. 2. Energy absorbing component (a, b, c, d and e are design variables)

In the following, two different optimality criteria are discussed. The objective functions corresponding to these criteria can be expressed as

a) minimization of the peak force F (peak acceleration)

$$f_1(\bar{x}) = \max_t F(t,\bar{x})\,; \tag{1}$$

b) minimization of the difference between maximal and minimal force

$$f_2(\bar{x}) = \max_t F(t,\bar{x}) - \min_t F(t,\bar{x})\,. \tag{2}$$

In (1)-(2) t stands for time, $\bar{x} = (x_1, x_2, \ldots, x_n)$ is a vector of independent design variables and $F(t,\bar{x})$ stands for axial (frontal) force component.

In order to cover both criteria the multi-criteria optimization problem is formulated and solved applying the weighted summation and compromise programming analysis techniques.

3.2. Finite element analysis

LS-DYNA software was utilized for numerical analysis. Fully integrated shell elements are considered. The stress-strain behaviour is modeled with multi-linear approximation. In order to consider plastic anisotropy the Hill's second order yield criterion is employed. The FEA is performed separately for crash simulation and stiffness analysis. The total number of simulations depends on number of design variables and on grid density, fixed in the stage of simulation data design. The dynamic and static analysis is performed with the same sets of the simulation data in order to get complete set of output data. The output data used in further optimization procedure contains extreme values of the frontal force component and displacements in y-z plane obtained from the dynamic and static FE analysis, respectively.

In order to validate the FEA models the experimental study was carried out. Several versions of the component shown in Figure 2 were tested (the number of design variables used in the case of different approaches was from 4 up to 8). The preliminary estimates of the force components and deformation modes are obtained from the compression tests of the brackets performed on universal testing equipment. In Figure 3 the load displacement curves obtained from experimental tests and FEA are compared. The design parameters values are taken as a=1.6 mm, b=12 mm, c=6 mm and d=10 mm (see Figure 2). The folds with triangular shape (instead of convex arc) are considered and instead of the design parameter e given in Figure 2 the bend angle with the value 5 degrees is used.

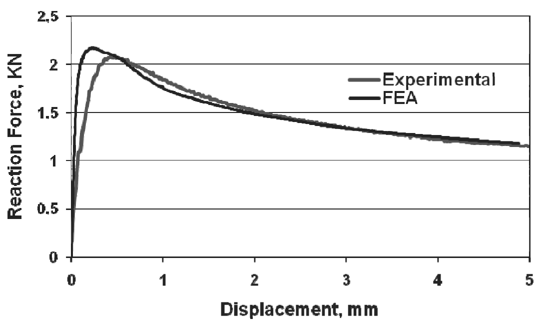

Fig. 3. Load-displacement curves: experimental and FEA

It can be seen from Figure 6 that the experimental and FEA results are found to be in good agreement, the peak values of the reaction force and also the shapes of the curves are close.

3.3. Numerical and experimental results

The limitation on acceleration (or corresponding force component) appears to be the most critical. For that reason the force component f_1 is considered as a dominating term in an optimality criterion. As the result of design process, the maximum value of the frontal force component f_1 is reduced more than 4 times in comparison with reference solution. The reference solution was chosen with reserve since the predicting of the value of y-z displacement (constraint) corresponding to a certain set of design variables is extremely complicated. In Figure 4 the frontal force component f_1, corresponding to initial (reference) and optimal sets of design variables, is given, respectively. All constraints are fulfilled in the case of both designs. Note that energy absorption is twice higher in the case of initial design. The latter fact can be explained with reduced dimensions of the component.

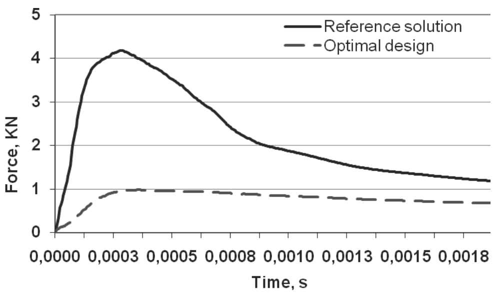

Fig. 4. Force - time diagram: reference solution and the optimal design

Fig. 5. The final assembled product

It can be seen from Figure 4 that the shape of the force curve corresponding to the optimal design is quite similar with the shape of a curve corresponding to energy absorber of type II, described above.

4. Case study 2: optimal design of composite bathtub

The objective is the optimization of structure and manufacturing processes of the composite plastic bathtub. The structural analysis of the product is performed with FEA. The optimal thickness distribution is determined with free size optimization. The final properties of the part are determined by minimizing the cost and production time simultaneously.

4.1. Problem statement

The current paper is concentrated on design of derivative products. For finding out optimal technology route we have to cut down the structure of the technology process into different process segments, meaning that we have to solve different sub systems, like finding out the optimal vacuum forming technology, the technology for post-forming operations (trimming, drilling the slots and cut-outs into the part, decoration, printing, etc), strengthening (reinforcing) and assembly. The bathtub is produced in two stages - in the first stage the shell is produced by vacuum forming, and in the second stage the shell is strengthened by adding glass-fiber-epoxy layer on the one side. Current study is focused on strengthening of the shell by adding glass-fiber-epoxy layer and the first stage -vacuum forming process is described briefly.

The vacuum forming part thinning process has been analyzed with different materials like ABS, PMMA white 2000BM 1516, polycarbonate ICE (UV) and acrylic FF0013 plexiglass. In the following, the acrylic FF0013 plexiglass formed at the temperature 320-340˚C is considered (heating time 6 min and cooling time 2 min). The sample of the final assembled product is shown in Figure 5.

In vacuum forming the thinning is a natural consequence of the deformation conditions. The thickness variations are potentially large for a part. Therefore, it is often important to control the thickness variations in order to meet functional requirements of the part. The values of thinning of the plastic sheet in the forming operations can be determined from experience, special tests or simulations. The experimental tests have been performed in order to analyze the wall thickness reduction in certain materials. The results of analysis for plexiglass are given in Figure 6.

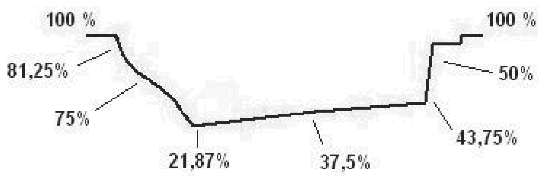

Fig. 6. Wall thickness reduction in a 3.2 mm thick blank

It can be seen from Figure 6 that the thickness reduction is maximal in bottom area. Obviously, the strengthening of the shell is necessary and it can be performed in both stages of manufacturing process. In the following the detailed attention is paid to reinforcement of the shell (adding glass-fiber-epoxy layer) since the stiffness of the reinforcement layer is significantly higher than acrylic layer.

The reinforcement problem of the bathtub shell can be formulated as a multi-objective optimization problem and expressed in mathematical forms as:

$$\begin{aligned} &\min F(x) = \{F_1(x), F_2(x)\}, \\ &F_1(x) = C(x_1, x_2, \dots, x_n), \\ &F_2(x) = T(x_1, x_2, \dots, x_n). \end{aligned} \quad (3)$$

subjected to linear and nonlinear constraints. In (3) $C(x)$ and $T(x)$ are cost of the glass-fiber-epoxy layer and manufacturing time, respectively and x is a vector of design variables. The linear and nonlinear constraints proceed from technological (maximum layer thickness), exploitation (displacement limit) and safety (stress limit) considerations. Since the units used to measure the objectives $F_1(x)$ and $F_2(x)$ are different (cost and time), it is reasonable to represent the objectives in terms of relative deviation i.e.

$$f_1(x) = \frac{\max F_1(x) - F_1(x)}{\max F_1(x) - \min F_1(x)}, \; f_2(x) = \frac{\max F_2(x) - F_2(x)}{\max F_2(x) - \min F_2(x)}. \quad (4)$$

Obviously, the objective functions $f_1(x)$ and $f_2(x)$ are defined in interval [0,1].

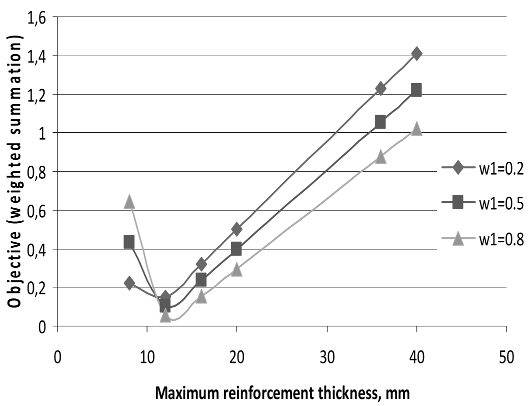

Fig. 7. Objective function (weighted summation) vs. maximum thickness of the reinforcement layer

4.2. Results and discussion

The values of the objective function corresponding to weighted summation technique are pointed out in Figure 7, where dependence on maximum thickness of the reinforcement layer is shown. The values of the weight w_1 corresponding to the first criterion (cost) are varied from 0.2 to 0.8. As it can be seen from Figure 7, the shape of the curves describing objective function depend on the values of the weights, but the extreme value of the objective is reached in the case of same value of the maximum thickness of the reinforcement layer. The objective decreases in same range where the material volume decreases, after that the material volume approaches to constant value, but the objective increases significantly. The latter fact is caused due to additional drying expenses (layer-wise covering technology is used due to technological limits on maximum layer thickness in one-time layer setup, thus, larger total thickness means that larger number of sub-layers should be used). Similar values of the objective function are obtained in the case of compromise programming technique (omitted for conciseness sake).

The bathtub with optimal thickness distribution of reinforcement layer corresponding to extreme value of the objective function (compromise programming and weighted summation technologies) is shown in Figure 8.

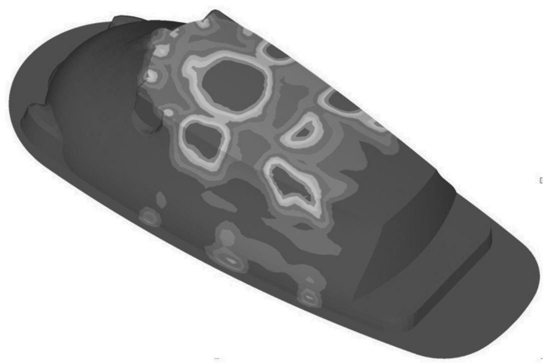

Fig. 8. The optimal thickness distribution of reinforcement

It appears that the reinforcement layer is the thickest in areas where the local loading is applied (at the middle of the bottom area) and bottom-wall transitional areas (see Figure 8).

5. Case study 3: double-curved surface forming process modeling

There are several industries where increasingly higher surface accuracy requirements are posed for double-curved surfaces. One industrial application is parabolic reflective surface of satellite communication earth-station antennas reflectors. The forming method considered below is based on use of the adjustable forming surface which supports reflective surface. Adjustments of the surface are available in fixed set of points and in directions normal to the surface only.

5.1. Problem statement

In order to achieve the main goal- increase an accuracy of the double-curved surface forming process the procedure for determining the coordinates of the adjustment points has been developed.

The main subtasks of the procedure can be outlines as:

- deviation measuring in given points,
- response surface modeling,
- computing coordinates corresponding to minimum deviation of reflective surface,
- coordinate correction for adjustment points.

In real adjustment process the coordinates in normal directions are considered as input data and the deviations of the reflective surface points as output data (results).

The root mean square (RMS) value of the deviations of the parabolic reflective surface of satellite communication earth-station antennas reflectors is subjected to minimization

$$F = \frac{1}{n}\sum_{i=1}^{n}(z_i^m - z_i^0)^2 \rightarrow min, \qquad (5)$$

where z_i^m and z_i^0 are the values of the coordinates of reflective surface corresponding to measurement results and zero deviation, respectively. As described above, each value of the function F corresponds to one panel formed. Thus, the experimental data, gathered at the beginning of the forming process of new type of panels is limited and response modelling necessary.

5.2. Results and discussion

The deviation of the reflective surface has been minimized. However, the zero deviations are not achieved due to measuring, modelling, etc. errors. The developed coordinate correction algorithm is shown in Figure 9.

Employing the proposed coordinate correction algorithm, allows to reduce the number of experiments performed (panels formed) up to required accuracy has been achieved. The problem considered is specific due to limited dataset for response modelling at the beginning of the new type panel forming.

6. Case study 4: design of fixings for frameless glazed structures

Attaching the glass to the structures using bolted fittings directly connected through holes in the glass is used widely, since it allows to improve transparency of the connection. The point supported structural glass designs considered involve large and relatively thin lites of glass. The stress-strain state of the glass lite is analysed by use of FEA (ANSYS). Non-linear plate theory is employed, because the deflections of the glass lite may exceed half of its thickness.

The following sub goals are considered in optimal design of fixings:

- determination of optimal locations and dimensions of the fixing holes (topology optimization),
- optimal design of fixing element (to guarantee elastic behaviour of the fixing element in certain loading conditions; rigid behaviour of the fixing element may cause failure of the glass lite).

The FEA model for analysis of the fixing element and glass lite structure has been developed. However, solving optimal design tasks described above is currently in progress.

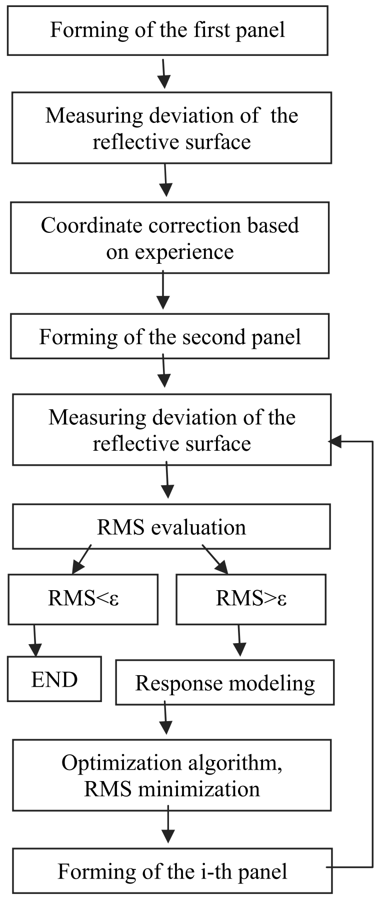

Fig. 9. Coordinate corrections procedure

7. Conclusions

The artificial neural networks and hybrid genetic algorithm are used together for solving a number of quite different engineering design problems including design of car frontal protection system, design of composite bathtub, design of double-curved surface forming process modeling, design of fixings for frameless glazed structures. It can be concluded that the optimization algorithm proposed has been shown good performance with respect to convergence to global extreme (responsibility of the global level search, GA) and accuracy (responsibility of the local level search, gradient method). Certain adaption of the algorithm was necessary depending on character of particular optimization problem considered (GA operators used, constraint handling, parameters tuning). The algorithm has been implemented in MATLAB and C++ code.

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APPENDIX B

Curriculum Vitae

1. Personal data

Name	Tarmo Velsker
Date and place of birth	15^{th} of November 1981, Paide, Estonia
Nationality	Estonian

2. Contact information

Address	Anna küla, Paide vald, Järvamaa, 72601, Estonia
Phone	+372 5042340
E-mail	tarmovelsker@hotmail.com

3. Education

Educational institution	Graduation year	Education (field of study/degree)
Tallinn University of Technology	2008	Product Development and Production Engineering / MSc
Tallinn Collage of Engineering	2005	Machine Building / Diploma

4. Language competence/skills (fluent; average, basic skills)

Language	Level
Estonian	Native
English	Fluent
Russian	Average

5. Professional Employment

Period	Organisation	Position
September 2006-…	Vertex Estonia AS	Chief Designer
February 2006 – September 2006	Vertex Estonia AS	Mechanical Designer
September 2004- September 2005	Konesko AS	Liaison of Manufacturing
January 2004- September 2004	Sumar AS	Mechanical Designer

6. Scientific work

Papers

I. Velsker, T., Eerme, M., Majak, J., Pohlak, M., Karjust, K. 2011. Artificial neural networks and evolutionary algorithms in engineering design. *In:* AMME, 44(1), p 88-95.

II. Majak, J., Pohlak, M., Eerme, M., Velsker, T. 2012. Design of car frontal protection system using neural networks and genetic algorithm. *In:* Mechanika, 18(4), p 453-460.

III. Velsker, T., Lend, H., Kirs, M. 2012. Design of glass canopy panel. *In:* Proceedings of the 8th International Conference of DAAAM Baltic Industrial engineering : 19-21th April 2012, Tallinn, Estonia.

IV. Velsker, T., Majak, J., Eerme, M., Pohlak, M. 2010. Double-curved surface forming process modeling. *In:* Proceedings of the 7th International Conference of DAAAM Baltic Industrial engineering : 22-24th April 2010, Tallinn, Estonia.

7. Defended theses

Parabolic antennas reflector panels, MSc, Tallinn University of Technology, 2008

8. Main areas of scientific work/Current research topics

Design of sheet metal and glass structures, structural analysis and optimization (CAD,FEA), design of experiment, response modelling.

9. Other research projects

01.01.2011 - 31.12.2013	ETF grant ETF8485. Design of Materials and Structures with elastic and/or plastic anisotropy.
01.01.2012 - 31.12.2014	SF0140035s12. Optimal design of composite and functional material structures, products and manufacturing processes.

Elulookirjeldus

1. Isikuandmed

Ees- ja perekonnanimi	Tarmo Velsker
Sünniaeg ja -koht	15. november 1981, Paide, Eesti
Kodakondsus	Eesti

2. Kontaktandmed

Aadress	Anna küla, Paide vald, Järvamaa, 72601, Eesti
Telefon	+372 50 42 340
E-posti aadress	tarmovelsker@hotmail.com

3. Hariduskäik

Õppeasutus (nimetus lõpetamise ajal)	Lõpetamise aeg	Haridus (eriala/kraad)
Tallinna Tehnikaülikool	2008	Tootearendus ja tootmistehnika / Magister
Tallinna Tehnikakõrgkool	2005	Masinaehitus / Diplom

4. Keelteoskus (alg-, kesk- või kõrgtase)

Keel	Tase
Eesti keel	emakeel
Inglise keel	kõrgtase
Vene keel	kesktase

5. Teenistuskäik

Töötamise aeg	Tööandja nimetus	Ametikoht
September 2006-…	Vertex Estonia AS	Juhtkonstruktor
Veebruar 2006-September 2006	Vertex Estonia AS	Konstrueerimis-insener
September 2004-September 2005	Konesko AS	Tootmise koordinaator
Jaanuar 2004-September 2004	Sumar AS	Konstruktor

7. Teadustegevus

Teadusartiklite loetelu on toodud inglisekeelse elulookirjelduse juures.

8. Kaitstud lõputööd

Paraboolantennide reflektorpaneelid, Magister, Tallinna Tehnikaülikool, 2008.

9. Teadustöö põhisuunad

Metall- ja klaaskonstruktsioonide projekteerimine, konstruktsioonide analüüs ja optimeerimine (CAD, FEM). Katsete planeerimine, vastavuspinna modelleerimine.

10. Teised uurimisprojektid

01.01.2011 - 31.12.2013	ETF grant ETF8485. Materjalide ja konstruktsioonide optimeerimine arvestades elastset ja/või plastset anisotroopiat.
01.01.2012 - 31.12.2014	SF0140035s12. Komposiit- ja funktsionaalsetest materjalidest konstruktsioonide, toodete ja tootmisprotsesside optimaalne projekteerimine.

DISSERTATIONS DEFENDED AT TALLINN UNIVERSITY OF TECHNOLOGY ON *MECHANICAL AND INSTRUMENTAL ENGINEERING*

1. **Jakob Kübarsepp**. Steel-Bonded Hardmetals. 1992.

2. **Jakub Kõo**. Determination of Residual Stresses in Coatings &Coated Parts. 1994.

3. **Mart Tamre**. Tribocharacteristics of Journal Bearings Unlocated Axis. 1995.

4. **Paul Kallas**. Abrasive Erosion of Powder Materials. 1996.

5. **Jüri Pirso**. Titanium and Chromium Carbide Based Cermets. 1996.

6. **Heinrich Reshetnyak**. Hard Metals Serviceability in Sheet Metal Forming Operations. 1996.

7. **Arvi Kruusing**. Magnetic Microdevices and Their Fabrication methods. 1997.

8. **Roberto Carmona Davila**. Some Contributions to the Quality Control in Motor Car Industry. 1999.

9. **Harri Annuka**. Characterization and Application of TiC-Based Iron Alloys Bonded Cermets. 1999.

10. **Irina Hussainova**. Investigation of Particle-Wall Collision and Erosion Prediction. 1999.

11. **Edi Kulderknup**. Reliability and Uncertainty of Quality Measurement. 2000.

12. **Vitali Podgurski**. Laser Ablation and Thermal Evaporation of Thin Films and Structures. 2001.

13. **Igor Penkov**. Strength Investigation of Threaded Joints Under Static and Dynamic Loading. 2001.

14. **Martin Eerme**. Structural Modelling of Engineering Products and Realisation of Computer-Based Environment for Product Development. 2001.

15. **Toivo Tähemaa**. Assurance of Synergy and Competitive Dependability at Non-Safety-Critical Mechatronics Systems design. 2002.

16. **Jüri Resev**. Virtual Differential as Torque Distribution Control Unit in Automotive Propulsion Systems. 2002.

17. **Toomas Pihl**. Powder Coatings for Abrasive Wear. 2002.

18. **Sergei Letunovitš**. Tribology of Fine-Grained Cermets. 2003.

19. **Tatyana Karaulova**. Development of the Modelling Tool for the Analysis of the Production Process and its Entities for the SME. 2004.

20. **Grigori Nekrassov**. Development of an Intelligent Integrated Environment for Computer. 2004.

21. **Sergei Zimakov**. Novel Wear Resistant WC-Based Thermal Sprayed Coatings. 2004.

22. **Irina Preis**. Fatigue Performance and Mechanical Reliability of Cemented Carbides. 2004.

23. **Medhat Hussainov**. Effect of Solid Particles on Turbulence of Gas in Two-Phase Flows. 2005.

24. **Frid Kaljas**. Synergy-Based Approach to Design of the Interdisciplinary Systems. 2005.

25. **Dmitri Neshumayev**. Experimental and Numerical Investigation of Combined Heat Transfer Enhancement Technique in Gas-Heated Channels. 2005.

26. **Renno Veinthal**. Characterization and Modelling of Erosion Wear of Powder Composite Materials and Coatings. 2005.

27. **Sergei Tisler**. Deposition of Solid Particles from Aerosol Flow in Laminar Flat-Plate Boundary Layer. 2006.

28. **Tauno Otto**. Models for Monitoring of Technological Processes and Production Systems. 2006.

29. **Maksim Antonov**. Assessment of Cermets Performance in Aggressive Media. 2006.

30. **Tatjana Barashkova**. Research of the Effect of Correlation at the Measurement of Alternating Voltage. 2006.

31. **Jaan Kers**. Recycling of Composite Plastics. 2006.

32. **Raivo Sell**. Model Based Mechatronic Systems Modeling Methodology in Conceptual Design Stage. 2007.

33. **Hans Rämmal**. Experimental Methods for Sound Propagation Studies in Automotive Duct Systems. 2007.

34. **Meelis Pohlak**. Rapid Prototyping of Sheet Metal Components with Incremental Sheet Forming Technology. 2007.

35. **Priidu Peetsalu**. Microstructural Aspects of Thermal Sprayed WC-Co Coatings and Ni-Cr Coated Steels. 2007.

36. **Lauri Kollo**. Sinter/HIP Technology of TiC-Based Cermets. 2007.

37. **Andrei Dedov**. Assessment of Metal Condition and Remaining Life of In-service Power Plant Components Operating at High Temperature. 2007.

38. **Fjodor Sergejev**. Investigation of the Fatigue Mechanics Aspects of PM Hardmetals and Cermets. 2007.

39. **Eduard Ševtšenko**. Intelligent Decision Support System for the Network of Collaborative SME-s. 2007.

40. **Rünno Lumiste**. Networks and Innovation in Machinery and Electronics Industry and Enterprises (Estonian Case Studies). 2008.

41. **Kristo Karjust**. Integrated Product Development and Production Technology of Large Composite Plastic Products. 2008.

42. **Mart Saarna**. Fatigue Characteristics of PM Steels. 2008.

43. **Eduard Kimmari**. Exothermically Synthesized B_4C-Al Composites for Dry Sliding. 2008.

44. **Indrek Abiline**. Calibration Methods of Coating Thickness Gauges. 2008.

45. **Tiit Hindreus**. Synergy-Based Approach to Quality Assurance. 2009.

46. **Karl Raba**. Uncertainty Focused Product Improvement Models. 2009.

47. **Riho Tarbe**. Abrasive Impact Wear: Tester, Wear and Grindability Studies. 2009.

48. **Kristjan Juhani**. Reactive Sintered Chromium and Titanium Carbide-Based Cermets. 2009.

49. **Nadežda Dementjeva**. Energy Planning Model Analysis and Their Adaptability for Estonian Energy Sector. 2009.

50. **Igor Krupenski**. Numerical Simulation of Two-Phase Turbulent Flows in Ash Circulating Fluidized Bed. 2010.

51. **Aleksandr Hlebnikov**. The Analysis of Efficiency and Optimization of District Heating Networks in Estonia. 2010.

52. **Andres Petritšenko**. Vibration of Ladder Frames. 2010.

53. **Renee Joost**. Novel Methods for Hardmetal Production and Recycling. 2010.

54. **Andre Gregor**. Hard PVD Coatings for Tooling. 2010.

55. **Tõnu Roosaar**. Wear Performance of WC- and TiC-Based Ceramic-Metallic Composites. 2010.

56. **Alina Sivitski**. Sliding Wear of PVD Hard Coatings: Fatigue and Measurement Aspects. 2010.

57. **Sergei Kramanenko**. Fractal Approach for Multiple Project Management in Manufacturing Enterprises. 2010.

58. **Eduard Latõsov**. Model for the Analysis of Combined Heat and Power Production. 2011.

59. **Jürgen Riim**. Calibration Methods of Coating Thickness Standards. 2011.

60. **Andrei Surzhenkov**. Duplex Treatment of Steel Surface. 2011.

61. **Steffen Dahms**. Diffusion Welding of Different Materials. 2011.

62. **Birthe Matsi**. Research of Innovation Capasity Monitoring Methodology for Engineering Industry. 2011.

63. **Peeter Ross**. Data Sharing and Shared Workflow in Medical Imaging. 2011.

64. **Siim Link**. Reactivity of Woody and Herbaceous Biomass Chars. 2011.

65. **Kristjan Plamus**. The Impact of Oil Shale Calorific Value on CFB Boiler Thermal Efficiency and Environment. 2012.

66. **Aleksei Tšinjan**. Performance of Tool Materials in Blanking. 2012.

67. **Martinš Sarkans**. Synergy Deployment at Early Evaluation of Modularity of the Multi-Agent Production Systems. 2012.

68. **Sven Seiler**. Laboratory as a Service – A Holistic Framework for Remote and Virtual Labs. 2012.