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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.

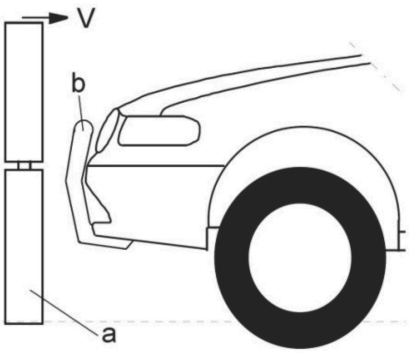

Fig. 1. Lower legform impact testing (a - Legform impactor, b - Frontal protection system, V - velocity of impactor)

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.

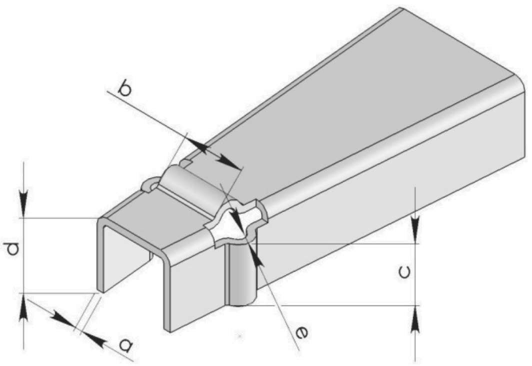

Fig. 2. Energy absorbing component (a, b, c, d and e are design variables)

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, $\bar{x} = (x_1, x_2, ..., x_n)$ 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.

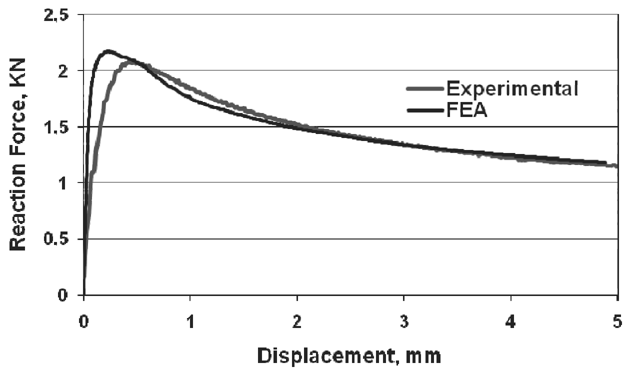

Fig. 3. Load-displacement curves: experimental and FEA

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.

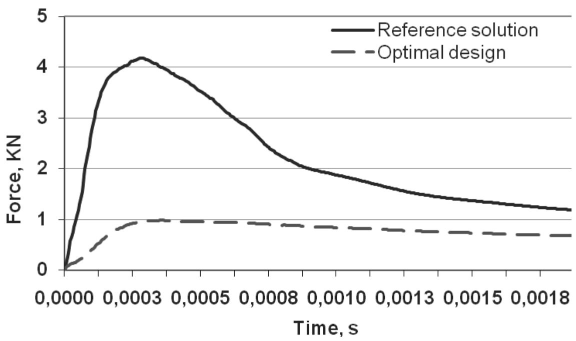

Fig. 4. Force - time diagram: reference solution and the optimal design

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.

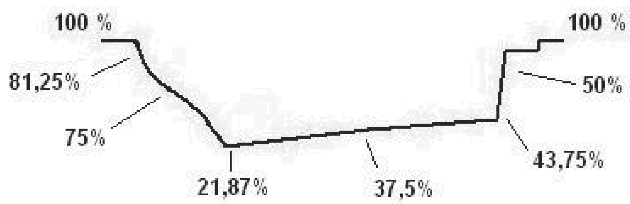

Fig. 6. Wall thickness reduction in a 3.2 mm thick blank

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:

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

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.

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

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

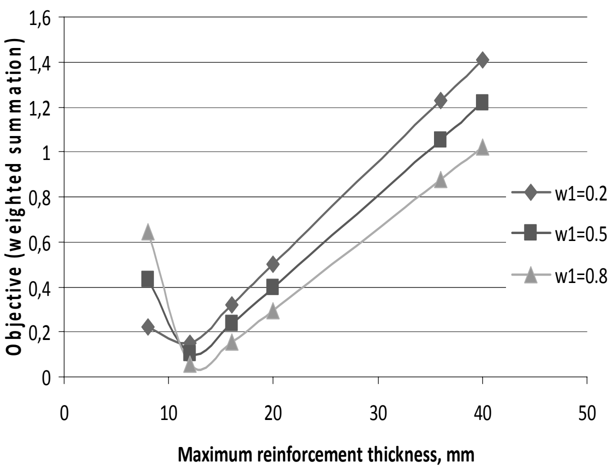

Fig. 7. Objective function (weighted summation) vs. maximum thickness of the reinforcement layer

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.

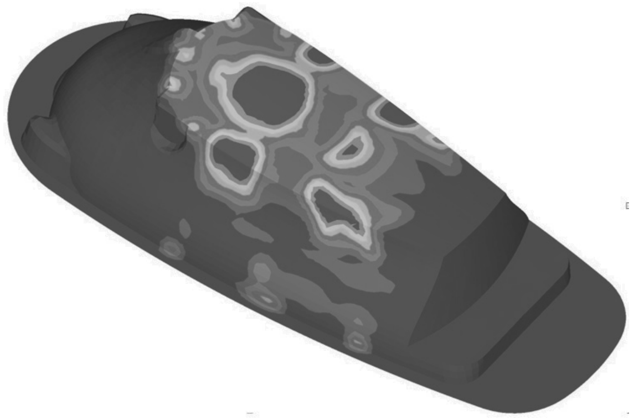

Fig. 8. The optimal thickness distribution of reinforcement

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

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

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.

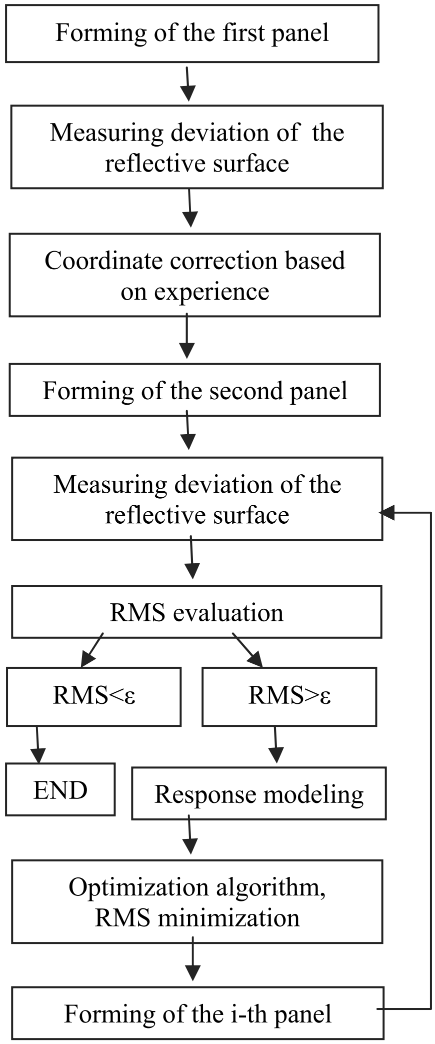

Fig. 9. Coordinate corrections procedure

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.

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.

Acknowledgements

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