DESIGN OF GLASS CANOPY PANEL

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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 evolutionary 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 $X_1$, $X_2$, $X_3$, $X_4$ and $X_5$ (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 ($X_1$, $X_2$, $X_3$, $X_4$ and $X_5$ are design variables).

Thus, $X_1$, $X_2$ and $X_3$ stand for coordinates of the holes, $X_4$ is diameter of the hole and $X_5$ 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.

<table>
<thead>
<tr>
<th>Independent variable</th>
<th>Levels</th>
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<tr>
<td>$X_1$</td>
<td>1 300 2 350 3 400 4 450</td>
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<tr>
<td>$X_2$</td>
<td>1 300 2 350 3 400 4 450</td>
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<tr>
<td>$X_3$</td>
<td>1 65 2 75 3 80 4 85</td>
</tr>
<tr>
<td>$X_4$</td>
<td>1 18 2 24 3 30 4 36</td>
</tr>
<tr>
<td>$X_5$</td>
<td>1 12 2 14 3 16 4 20</td>
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Table 1. Levels of design variables
Table 2. Taguchi DOE, L16 orthogonal array

<table>
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<tr>
<th>N</th>
<th>X1</th>
<th>X2</th>
<th>X3</th>
<th>X4</th>
<th>X5</th>
<th>Max. Str., Mpa</th>
<th>Max. Def., mm</th>
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<td>300</td>
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</tr>
</tbody>
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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. 4. Max. stress distribution around fixing hole](image)

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](image)

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.
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

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

(3)

where \(H\) is the Hessian matrix evaluated at \(x_i\), \(\lambda\) and \(\Delta\) stand for the scaling coefficient and gradient vector, respectively. the Levenberg–Marquardt algorithm is faster than pure gradient 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

\[ f(x) = \min(f_1(x), f_2(x)), \]  

(4)

subjected to linear constraints

\[ x_i \leq x_i^*, -x_i \leq x_i, \quad i = 1,\ldots, n, \]  

(5)

In (4) \(f_1(x)\) and \(f_2(x)\) 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 and 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

\[ f_s = \sum_{i=1}^{m} w_i f_i. \]  

(6)

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

\[ \sum_{i=1}^{m} w_i = 1, \quad 0 < w_i \leq 1. \]  

(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.

8. ACKNOWLEDGEMENTS

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9. REFERENCES


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