Using Machine Learning to Predict the Stress-strain State of a Rectangular Plate with a Circular Cut-out

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Abstract. The paper describes the scheme of machine learning using for the stress-strain state analysis of a rectangular plate with a circular cut-out. The plate might be of arbitrary sizes and the cut-out might be of an arbitrary radius. Each side of the plate is supposed to be free, supported or fixed. Additional input parameters of the data set are following: size of plate's side, thickness of the plate, Young's modulus, Poison's coefficient, and pressure load. Initial parameters have been random generated. The training set is generated by the finite element method. The artificial neural network merges numerical and one-hot input layers. The developed regression model allows to predict von Mises stresses for a rectangular plate with a circular cut-out.

Keywords: Machine Learning, Artificial Neural Network, Stress-Strain State, Plate, Pre-diction, Regression.

1 Introduction

Machine learning, one of the six disciplines of Artificial Intelligence (AI) without which the problems of having machines acting humanly could not be accomplished. Machine learning allows us to 'teach' computers how to perform problems providing examples of how they should be done [1]. Machine learning is a useful tool for abundant data (also called examples or patterns) explaining a certain phenomenon. The world is quietly being reshaped by machine learning, the Artificial Neural Network (also referred in this manuscript as ANN or neural net) being its oldest [2] and most powerful [3] technique. ANNs also lead the number of practical applications, virtually covering any field of knowledge [4].

Applications of ANNs to engineering structures arises in a variety of industries such as construction, automotive, space structures, etc. ANNs allow to develop models e.g. for the stress-train state estimation of some type of solids. Thus, the development of machine learning methods for predicting the behavior of engineering structures is urgent.

In aviation engineering and shipbuilding, the use of prismatic solids with a cut-out in which one size (thickness) is much smaller than the other two is widespread. Such solids could be modeled by plates. Models based on artificial neuron networks should take into account the geometric and mechanical parameters of the body, as well as boundary conditions.

1.1 Analysis of recent research and publications

The increasing popularity of artificial neural networks leads to an increasing amount of researches devoted to the development of ANN models for modeling various fields. Modelling of solids the stress-train state is also possible domain of ANNs applications. For example, [5–7] explores the possibilities of machine learning to solve the problems of fracture mechanics. Particularly, in [5], the data of 64 computational experiments and 3 full-scale experiments are used for the training of the neural network to predict possible zones of beam destruction. In [6], a neural network based on the Kalman filter is employed to predict the collapse of a highway on a bridge processing temperature and oscillation data. In [7], a model based on the self-organizing map of Kohonen is developed to detect the fracture using vibration data. In [8], the possibilities of neural networks in the prediction the maximum displacements in rail beams are investigated. The neural network model is constructed as a function of two variables: the frictional parameter and load speed. 663 points are used for training, which allowed to get maximum the finite element model error in 5.4%. In [9] a combination of principal component analysis (PCA) and convolutional neural networks (CNN) are used to predict the entire stress-strain behavior of binary composites evauated over the entire failure path, motivated by the significantly faster inference speed of empirical models. The authors show that PCA transforms the stress-strain curves into an effective latent space by visualizing the eigenbasis of PCA. Despite having a dataset of only 10-27% of possible microstructure configurations, the mean absolute error of the prediction is <10% of the range of values in the dataset, when measuring model performance based on derived material descriptors, such as modulus, strength, and toughness. Their study demonstrates the potential to use machine learning to accelerate material design, characterization, and optimization. In [10] the proposed strategy demonstrates the effectiveness of machine learning to reduce experimental efforts for damage characterization in composites.

Thus, the analysis of last researches and publications allows to conclude that problems of developing models based on neural networks for predictions stress-stain state are actual.

1.2 The Problem Statement

Computer-aided design requires the development of methods and software for stress components fast estimation. The classical methods of mathematical modeling (e.g. the finite element method) allow to evaluate the stress-strain state with a good accuracy. Moreover, the preparation of adequate mathematical models and the corresponding computational experiments could be time-consuming. A possible alternative is machine learning methods. Artificial neural networks (ANN) are frequently used in machine learning. ANN could be trained over a data set of an object states and then employed as interactive assistants in the design process.

The problem of predicting the parameters of the state of an object by its geometric and mechanical parameters could be classified as a regression problem.

1.3 Purpose

The purpose of this analysis is to make a prediction model which be able to predict the stress-strain state of a rectangular isotropic plate with a circular cut out. A plate with width w , height h , radius of cut out r, the center of a circle (x_0, y_0) , uniform thickness h, Young's modulus E, Poisson's ratio ϑ . A plate is loaded transversely by a distributed load q per unit area. Edges of a plate may be clamped, simply supported, or free.

Research objectives such as:

1. Develop an algorithm for training and testing models.
2. Explore the capabilities of ANN for prediction of maximum plate deflection.
3. Develop a neural network to predict the maximum deflection of the plate.

2 Research methods

The plate might be of arbitrary sizes and the cut-out might be of an arbitrary radius. Each side of the plate is supposed to be free, supported or fixed. Additional input parameters of the data set are following: size of plate's side, thickness of the plate, Young's modulus, Poison's coefficient, and pressure load.

A dataset is generated using the finite element method. Parameters of a plate are randomly generated with following restrictions:

$w \in [0.1; 10]$ (meters);

$h \in [0.1; 10]$ (meters);

$r \in [3s; \frac{1}{2}a - 3s]$ (meters), where s is a size of a background cell in a meshing routine (for an uniform mesh we could use $s = \frac{\max(w,h)}{n}$, n^2 is a number of cells in the mesh), $a = \min\,(w, h)$;

$x_0 \in [0; \frac{1}{2}a - r - 3s]$ (meters);

$y_0 \in [\frac{1}{2a} - r - 3s]$ (meters);

$h \in [\frac{1}{80}a\,; \frac{1}{5}a]$ (meters);

$E \in [50000; 300000]$ (MPa);

$\vartheta \in [0; 0{,}45]$;

$q \in [0{,}01; 0{,}1]$ (MPa).

Boundary conditions are also randomly generated. These values are categorical data. Possible boundary conditions are following: a free edge, a supported edge, a clamped (fixed) edge. Any combination of boundary conditions is possible excluding situations with four free edges or one supported edge and three free edges. Denote boundary conditions at the edge $x = -\frac{w}{2}$ by c_0, at the edge $y = -\frac{h}{2}$ by c_1, at the edge $x = \frac{w}{2}$ by c_2, at the edge $y = \frac{h}{2}$ by c_3. If we also enumerate a free edge by 0, a supported edge by 1, a clamped edge by 2, then we get the following restriction:

$$c_1 + c_2 + c_3 + c_4 \geq 2$$

Categorical data one hot encoded by vector of 76 values.
The randomly generated dataset includes approximately 11000 records. Approximately 7500 records are left after data cleaning because the maximum deflection must be greater than 10^{-5} meters and less 0.2 of the plate thickness.

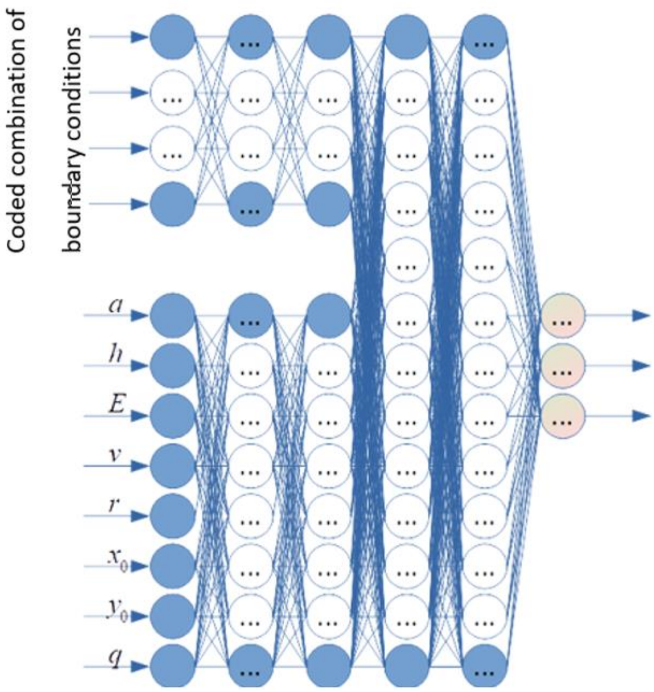

Fig. 1. The layers of neurons in the model.

The model of an artificial neural network is developed. This model includes few dense layers of neurons (see Fig. 1). Separate input layers are used for numerical and categorical data. Each input layer is connected with hidden dense layers. Then the

dense layer merges the output the hidden layers for numerical and categorical data processing. The last layer is connected with the additional hidden dense layer. Finally, the output layer is connected with the last hidden layer.
For machine learning, the original set of values is divided into two parts: training and test. The training part contains the values of the input parameters of the results, which use an algorithm for constructing trees. The test part is usually less than the training part, its values are used to test (in the case of regression analysis) the accuracy of training. The accuracy of the regression analysis is evaluated by calculating the root mean square deviation of the values calculated for the test part as a result of machine learning from the original values.

Input and hidden layers use hyperbolic tangent function as activation. The output layer uses the linear activation.

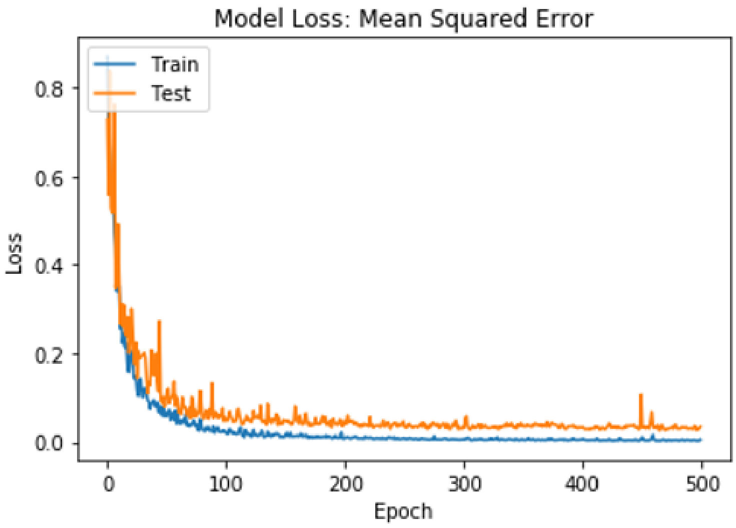

Fig. 2. Mean square deviation

The number of neurons in the input layers are the same as the number of elements in input arrays. I.e. 8 neurons are used to process float data and 76 neurons are used to process categorical data. A number of neurons in hidden layers is variated to get the minimum of the loss function. The mean squared error is employed is a loss function. The Fig. 2 shows loss functions for both train and test sets. The mean absolute percentage error of the model is approximately 20%.

3 Conclusion

Developed ANN allows to predict the maximum deflection of a rectangular plate with a circular cutout loaded transversely by a distributed load. The Fig. 2 shows that training has a good convergence. The mean error of ANN predictions is approximately

20%. Prospects for further studies are associated with genetic algorithms using in ANN optimization.

The key advantage of an artificial neural network is the speed of prediction: the plate deflection is predicted almost instantaneously (milliseconds) comparing the finite element method. So, pretrained artificial neural networks could be employed as interactive assistances in computer-aided design.

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