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USING MACHINE LEARNING TO PREDICT THE STRESS-STRAIN STATE OF A RING PLATE

Abstract. This article is devoted to the problem of prediction of the stress-strain state of a ring plate using neural networks. The article shows how to train the neural network to estimate the von Mises stress of a ring plate under external uniform pressure.

Machine learning, one of the six disciplines of Artificial Intelligence (AI) without which problems of having machines acting humanly could not be accomplished. Applications of ANNs to engineering structures arise in a variety of industries such as engineering, automotive, space structures, etc. ANNs allow to develop models e.g. for the stress-strain state estimation of some type of solids. Thus, the development of machine learning methods for predicting the behavior of engineering structures is urgent.

The paper describes the scheme for using machine learning in the stress-strain state analysis of a ring plate. Additional input parameters of the data set are the following: outer radius, inner radius, thickness of the plate, Young's modulus, Poison's coefficient, and pressure load. The training set is generated by the finite element method. Initial parameters of the training set have been randomly generated. The artificial neural network merges numerical and one-hot input layers. One hot The developed regression model allows to predict von Mises stresses for a ring plate.

The developed model allows to predict the von Mises stress with 10% of the mean absolute percentage error. The key advantage of an artificial neural network is the speed of prediction. The ANN predicts the von Mises stress almost instantaneously (milliseconds) comparing the finite element method.

Keywords: Machine Learning, Artificial Neural Network, Stress-Strain State, Ring Plate, Prediction, Regression.

1. Introduction

Machine learning, one of the six disciplines of Artificial Intelligence (AI) without which 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].

Neural networks, also known as artificial neural networks, are a subset of machine learning and are at the heart of deep learning algorithms. Their name and structure are inspired by the human brain, mimicking the way that biological neurons signal to one another.

A neural network works similarly to the human brain's neural network. A "neuron" in a neural network is a mathematical function that collects and classifies information according to a specific architecture. The network bears a strong resemblance to statistical methods such as curve fitting and regression analysis.

There are three main components: an input layer, a processing layer, and an output layer. The inputs may be weighted based on various criteria. Within the processing layer, which is hidden from view, there are nodes and connections between these nodes, meant to be analogous to the neurons and synapses in an animal brain (Fig. 1).

Each node, or artificial neuron, connects to another and has an associated weight and threshold. If the output of any individual node is above the specified threshold value, that node is activated, sending data to the next layer of the network. Otherwise, no data is passed along to the next layer of the network.

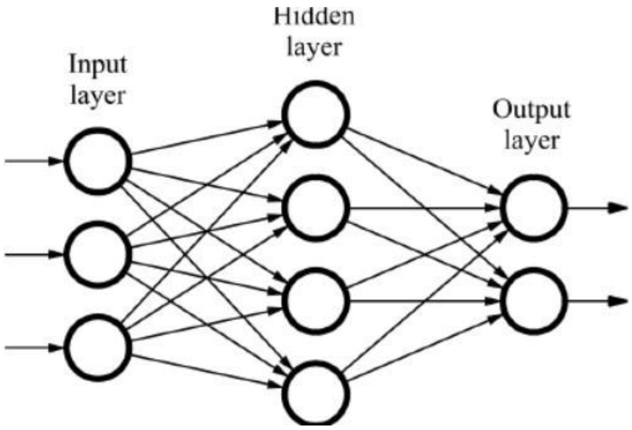

Fig. 1. The common architecture of neural network

In engineering and materials science, the stress-strain analysis uses different mathematical methods to determine strains and stresses in structures subjected to forces. Ring plates are structures widely used in marine vessels and space rockets engineering. A ring plate is a three-dimensional cylindrical solid whose thickness is very small when compared with other dimensions.

Neural networks rely on training data to learn and improve their accuracy over time. However, once these learning algorithms are fine-tuned for accuracy, they are powerful tools in computer science and artificial intelligence, allowing us to classify and cluster data at a high velocity. Tasks in speech recognition or image recognition can take minutes versus hours when compared to the manual identification by human experts.

Artificial neural networks are used in various areas related to information processing. For example, in such areas as: pattern recognition, optimization problems, control theory, engineering design problems, extrapolation and forecasting. There is a large amount of software that uses the capabilities of artificial neural network technology. In modern production, computer-aided design systems have become widespread, which allow the design of technological processes with less time and money, with increasing accuracy of the designed processes and processing programs.

Neural networks are often used for statistical analysis and data modeling, in which their role is perceived as an alternative to standard nonlinear regression or cluster analysis techniques. Thus, they are typically used in problems that may be couched in terms of classification, or forecasting. Some examples include image and speech recognition, textual character recognition, and domains of human expertise such as medical diagnosis, geological survey for oil, and financial market indicator prediction.

2. Methods

The rapid development of computer technologies led to the fact that a significant part of computing work was entrusted to computers. Due to the high speed of calculations, their low cost and sufficient accuracy for many applied problems, it became possible to use methods "heavy" in terms of computations and time expenditures for solving mathematical problems. Examples include enumeration methods, iterative, methods using large amounts of statistical data). However, along with the previously created solution methods and algorithms, new ones began to appear, the existence of which apart from the computer is difficult to imagine.

2.1 Literature review

The increasing popularity of artificial neural networks leads to an increasing number of researches devoted to the development of ANN models for modeling various fields. Modelling of solids, the stress-strain state is also a possible domain of ANNs applications.

In the early 2000s, the development of deep learning of convolutional networks based on training with a teacher. In [33], the application of the inverse error propagation algorithm for learning a deep neural network with an architecture similar to the neocognitron and cresceptron, consisting of convolution and maximal selection layers, was described for the first time. This architecture of neural networks is actively used to this day [31, 32].

The paper [4] 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 randomly 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.

Nowadays, a large number of software systems for learning deep neural networks have been created [26, 28, 27]. Among the most popular of these are Caffe, Theano, TensorFlow, Torch and CNTK. TensorFlow [24] was created by Google in 2015 and includes systems for efficient work with tensors and streaming data processing on the graph. In addition to the systems described above, we can also mention the Keras library [26], which provides a user-friendly and easy-to-use software interface for learning deep neural networks. Keras is not a standalone system, but runs on top of Theano, TensorFlow or CNTK. In 2016, Keras joined TensorFlow.

The work [29], devoted to the use of neural network extrapolation methods in the calculation and design of structures, in addition to the source information uses useful information about additional information and completes the network based on new data, then once performed neural network extrapolation. To solve the problems of mechanics, the theory of plates and shells, step neural network technologies are used with additional modeling, but without changing its structure [30].

In [10], the proposed strategy demonstrates the effectiveness of machine learning to reduce experimental efforts for damage characterization in composites. 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. The article [15] deals with the use of a neural network technology for researching the wave damping effect of a solid foundation plate in the closed system "building – foundation – ground" under vibratory impact on the ground. For this purpose, the solutions of direct and inverse forecasting problems are studied on the basis of the developed practical method of step neuronet forecasting. The last has been successfully tested on the model problems of mathematics, the theory of elasticity and plasticity as well as static problems of structural mechanics and building structures. The article [16] formulates the efficiency suppositions of using neuronet approaches to construction engineering problems. It enumerates some results obtained by examples of the problems of the theory of elasticity and plasticity, structural mechanics and engineering structures in the field of control, optimization and forecasting. Machine learning and deep learning have become increasingly more widespread in computational mechanics and mechanical analysis [19-21]. For instance, in [22] authors developed a deep learning model to directly estimate the stress distributions of the aorta. In addition, in [23], they also used machine learning to estimate the zero-pressure geometry for two given pressurized geometries of the same patient at two different blood pressure levels for the human thoracic aorta. In [20] approximated the large deformations of a nonlinear, muscle actuated beam by using a deep-autoencoder to simulate soft tissue biomechanics. The article [24] demonstrated that machine learning can be used as a supplement to the finite element analysis of physical system modeling, and it can efficiently address some corresponding problems. Moreover, neural network algorithms have also been used to replace the conventional constitutive material model to improve finite element analysis [25]. Machine learning and neural networks also perform well in other civil and geotechnical engineering research areas, such as the prediction and classification of rockburst [26, 27].

Thus, the analysis of recent studies and publications allows us to conclude that problems of developing models based on neural networks for predictions of the stress-strain state are urgent. The neural network for the stress-strain state analysis might be used as a module of CAD that provides fast predictions to the designer.

2.2 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 us 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.

2.3 Purpose

The purpose of this analysis is to make a prediction model using neural networks which are able to predict the stress-strain state of a ring plate. Using this model, we can make predictions of maximum deflection and the intensity of stresses of the ring plate. A plate with outer radius $\boldsymbol{radius_o}$, inner radius $\boldsymbol{radius_i}$, uniform thickness $\boldsymbol{h}$, Young's modulus $\boldsymbol{E}$, Poisson's ratio $\boldsymbol{\vartheta}$. A plate is loaded transversely by a distributed load $\boldsymbol{q}$ per unit area. Both inner and outer edge of a plate may be clamped (deflection and rotation are disabled), supported (deflection is disabled, rotation is enabled), fixed rotationally (deflection is enabled, rotation is disabled), or free (deflection and rotation are enabled).

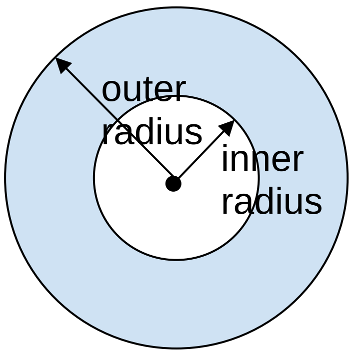

Fig. 2. The model of the ring plate

3. Research Methods

A dataset is generated using the finite element method. Radiuses of the plate might be of an arbitrary length but $\boldsymbol{radius_i < radius_o}$. Other input parameters of the data set are selected to include mechanical properties of metals. Parameters of a plate are randomly generated with following restrictions:

$radius_o \in (0.1; 5)(meters)$;
$radius_i \in [0.2; 0.8] \cdot radius_o$ $(meters)$;
$h \in [(radius_o)/100; (\,radius_o)/20]$ $(meters)$ [116];
$E \in [50000;\ 300000]$ (MPa);
$\vartheta \in [0;\ 0,45]$;
$q \in [0.001;\ 0.1]$ (MPa).

The parameters of the plate are generated randomly. The data generation algorithm is shown below:

algorithm *generation_ring_plate*
input:
  n (the number of values in the dataset)
output:
  S (dataset for study)
begin
  $S \leftarrow \emptyset$
  for $i \leftarrow 1$ **to** n **do**
  begin
    $radius\_o \leftarrow random\ (0.1{,}5)$
    $radius\_i \leftarrow random(0.2; 0.8) \cdot radius_o)$
    $h \leftarrow random((radius_o)/100; (\,radius_o)/20)$
    $q \leftarrow random(0{,}001; 0{,}1)$
    $E \leftarrow random(50000; 300000)$
    $\vartheta \leftarrow random(0; 0{,}45)$
    $S \leftarrow S \cup (radius\_o, radius\_i, h, E, \vartheta, q)$
  end
end

The artificial neural network is divided into two branches: the numerical branch and the categorical branch. Numerical data includes 6 parameters of the plate – $radius_o$, $radius_i$, h, E, q, ϑ. The categorical branch covers 12 possible combinations of boundary conditions. Hence this input layer has 6 neurons of numerical branch and 12 neurons of categorical branch. Numerical branch has 4 inner hidden layers of 30 neurons each, the categorical branch includes 2 inner layers of 60 neurons each. After merging, the network includes 4 inner layers of 90 neurons in each. The outer layer includes 1 neuron to determine the intensity of stresses σ_max (Fig. 3).

The correlation graph for input and output values of the plate is shown at Fig. 4.

As a result of a computational experiment conducted from 1000 epochs, we obtained the root mean square error (Fig. 5), as well as the values of stress intensity (Fig. 6).

In the experiment, we compared analytical and predicted by the neural network values of the von Mises varying the outer radius (Fig. 6).

4. Conclusion

This article proposes neural network models for predicting the stress-strain state of a ring plate. The algorithm for data generation for plates has been developed. Computational experiments with basic neural network architectures were performed.

Developed ANN allows to predict the von Mises stress of a ring plate loaded transversely by a distributed load. The Fig. 5 shows that training has a good convergence. The mean error of ANN predictions is approximately 10%. Prospects for further studies are associated with genetic algorithms used in ANN optimization.

The key advantage of an artificial neural network is the speed of prediction. The ANN predicts the von Mises stress almost instantaneously (milliseconds) comparing the finite element method. The von Mises stress is typically used in the strength analysis. So, pretrained artificial neural networks might be used as an interactive assistant in CAE or CAD software.

Further research is related to the development of artificial neural networks that will predict the stress-strain state according to the drawing or image of shell structures using machine vision and classification algorithms.

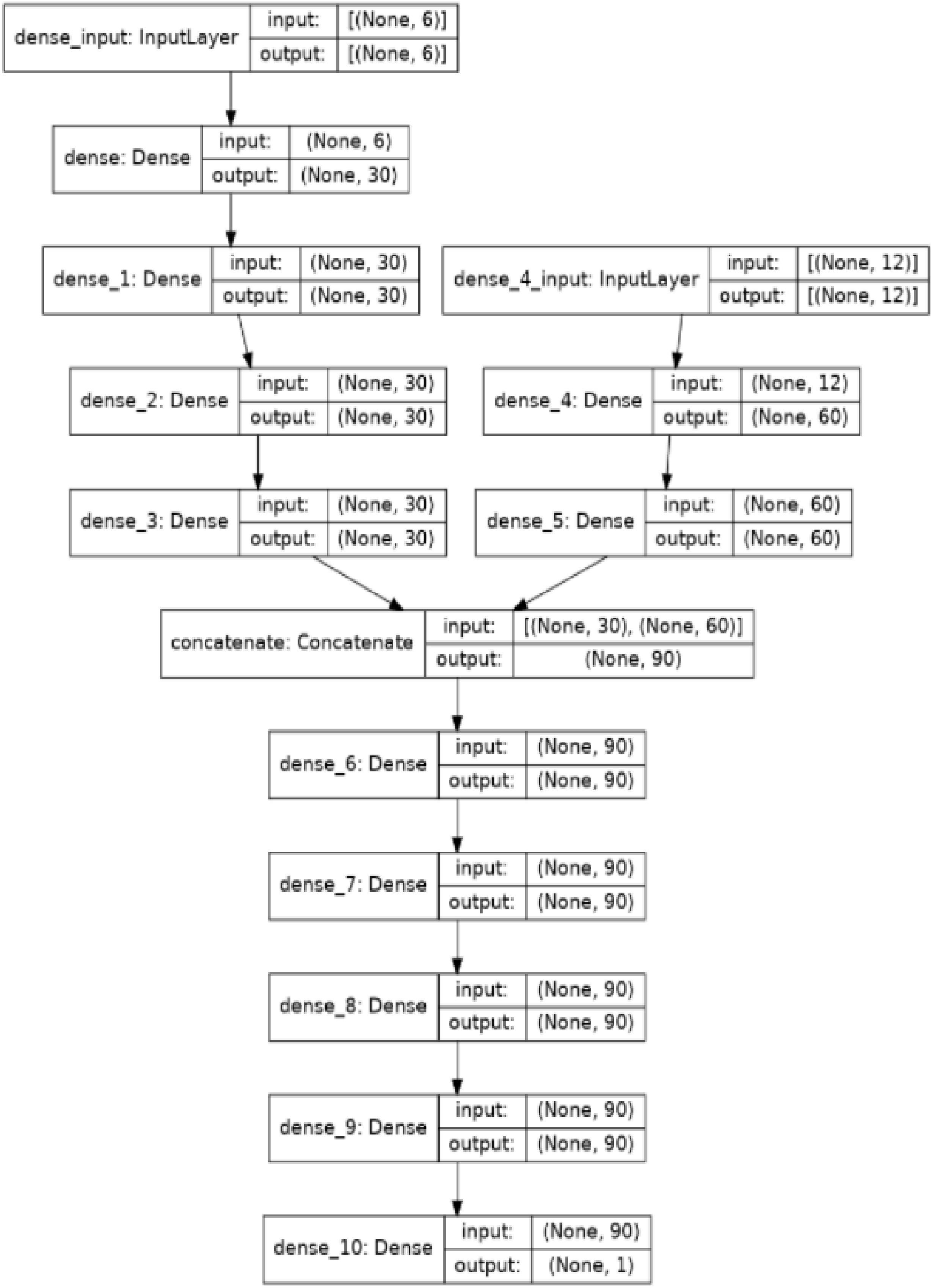

Fig. 3. The best scheme of neural network model for determining the maximum deflection of the ring plate

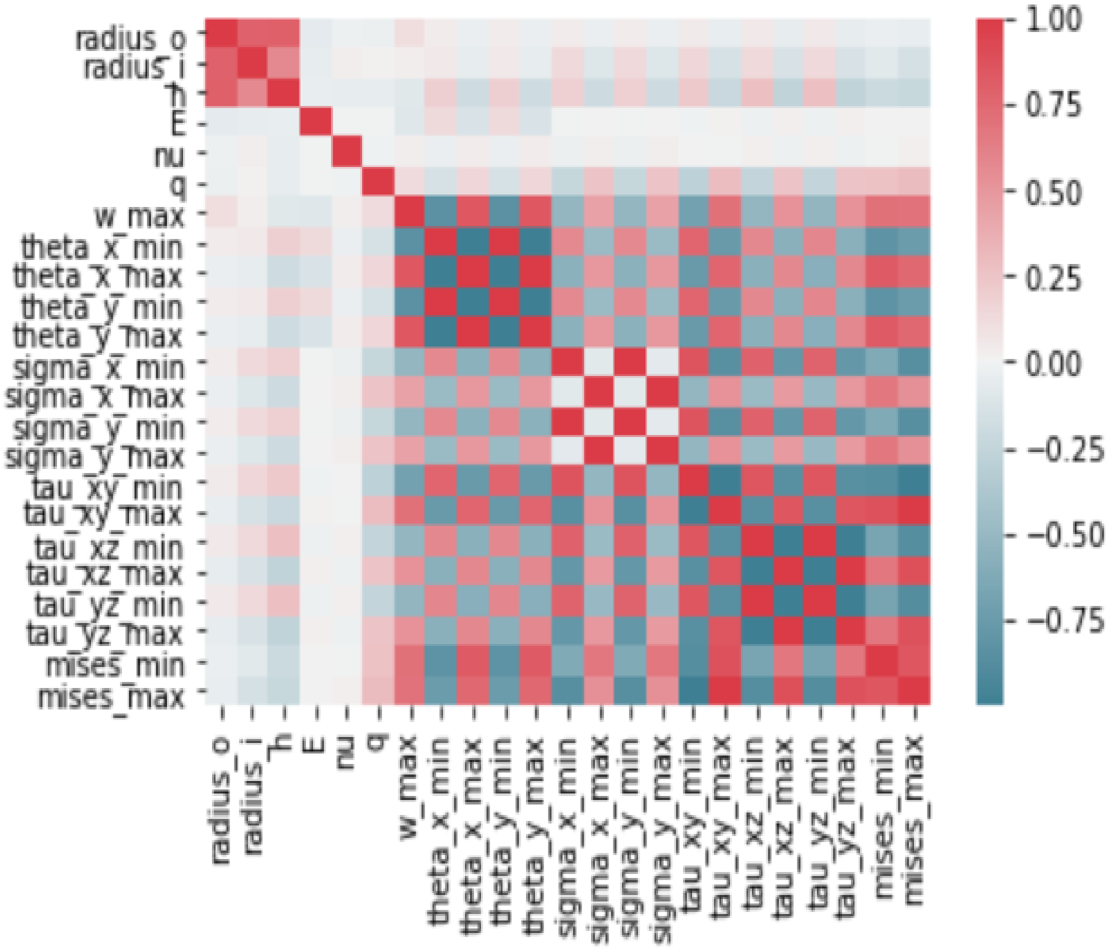

Fig. 4. The correlation graph of the ring plate

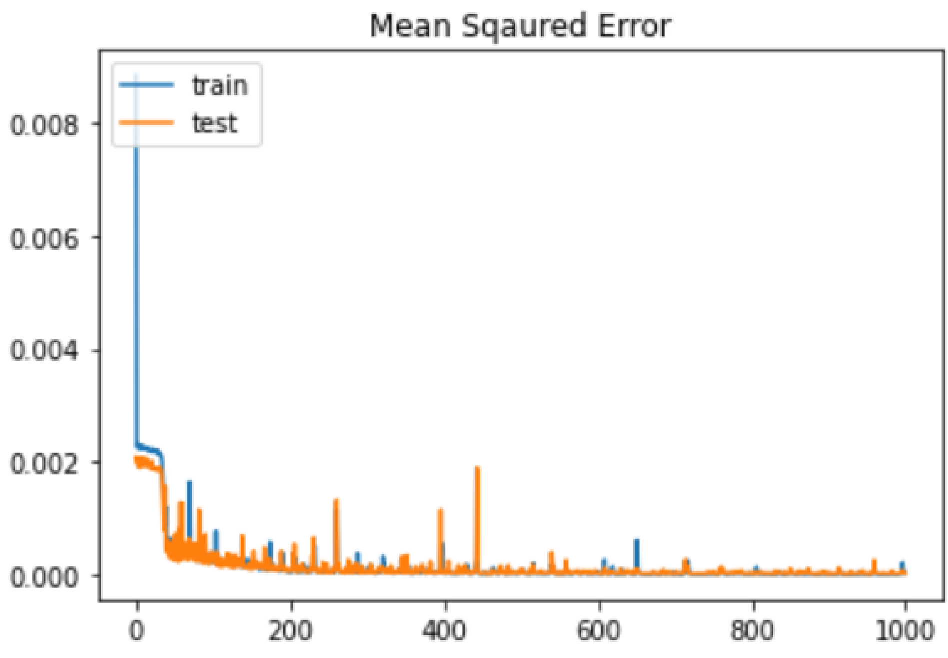

Fig. 5. Neural network model for determining the maximum deflection of the ring plate

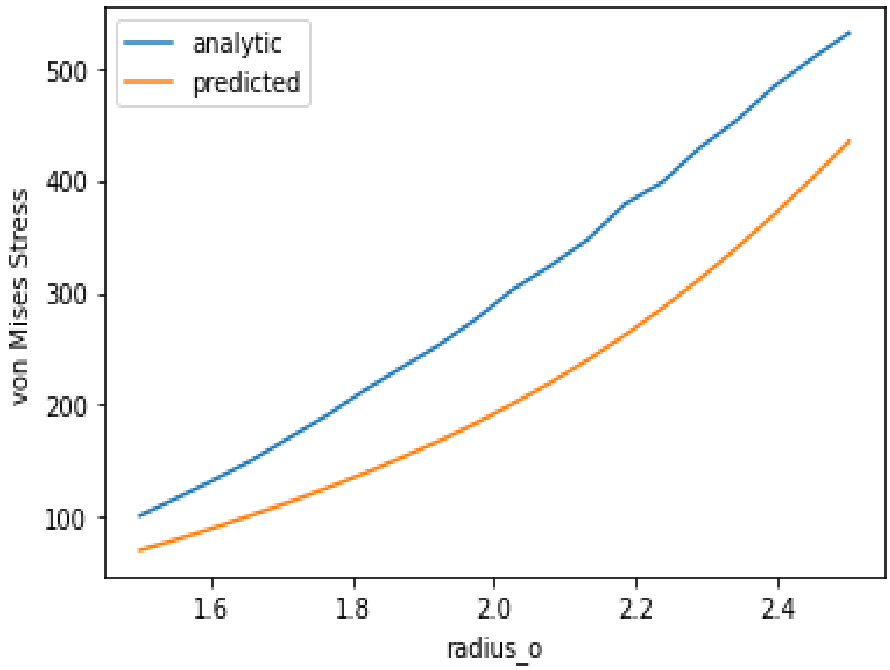

Fig. 6. Neural network model for determining the von Mises Stress of the ring plate

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