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Application of Deep Learning to Account For Geometric and Material Non-Linearity in Thin Circular Cylindrical Shell Structures

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Abstract
This paper has attempted to abstract out patterns hidden in the complicated non-linear equations governing the behavior of shell structures subjected to large deformations and loads well beyond their elastic limit. 119 thin shell models with varying input parameters were run in ANSYS. The results' validation was done in linear range using MATLAB code as given by [1]. The stress and strain results obtained from ANSYS were then normalized and fed to a neural network containing varying number of hidden layers and trained. 80% of data was used to train the network and remaining 20% to train. The number of hidden layers and number of nodes per layer was changed until the deviation between results given by ANSYS and predicted by neural net was minimized. After training it was found the the network was capable of predicting the results within the margin of 8% as given by ANSYS.

Keywords
ANSYS,MATLAB, Thin Shell, Neural Network, Normalization

1. Introduction

Deep learning is one of the methods of machine learning, where artificial neural networks consisting of multiple layers are used to extract high-level features from large amount of raw data [2]. Various algorithms in Deep Learning like ANN,RNN,GAN,CNN have been quite useful in the image processing world, and thus their usage in structural world has also been popular in health monitoring, crack detection, and damage assessment [3]. The usage has not only been limited to image processing but also in the design and analysis of structures. Kang & Yoon, (1994) applied two layered neural-network to aid simple truss design problems [4]. Adeli & Yeh, (1989) used an artificial neural network (ANN) to design steel beams [5]. Various structural optimization problems have also been solved using deep learning [6, 7]. Neural networks have also been used to represent force-displacement relationships in static structural analysis [8].

One of the major advantages of using a trained neural network over running analysis is that the trained network is capable of providing the ouput results instanteneously. So given sufficient data set for training the network, the results will be instantaneous, and the engineer need not go through the hassle of making the model and running it in any FEA tool like ANSYS or SAP2000. This paper attempts to do the same. By running 119 models in ANSYS, making sure that they reach non linear range, and using the results from ANSYS, the neural network is trained to give output for a given set of inputs.

2. Literature Review

Vanluchene & Sun, (1990) demonstrated that Neural Networks could be used in design and analysis of structures. They also showed that neural network could estimate numerically challenging answers fairly instantly. [9]

For forecasting the residual shear strength of Corroded Reinforced Concrete (CRC) beams at various service durations, Fu et al devised a machine learning (ML)-based technique. In order to accomplish this, they gathered 158 shear tests of CRC beams and used one of the most representative ensemble machine learning algorithms, the gradient boosting regression tree (GBRT), to create a predictive model for the shear strength. [10].

Huang & Burton (2019) investigated using machine learning techniques to classify the in-plane failure modes of infill frames using a data-driven methodology. 114 infill frame specimens from an experimental database were created. Nine structural factors were used as input variables in the implementation and evaluation of six machine learning algorithms for failure-mode categorization. [11].

Tahir & Mandal, (2017) analyzed the buckling load for thin-walled circular cylindrical shells by using two network models with eight and ten neurons used to train, test and validate experimental data [12].

The process of verification in linear range while solving non-linear problems has been motivated by Burad & Angalekar. They used the finite element based program ANSYS to undertake nonlinear analyses of shells. Longitudinal span and radius were chosen as the parameters. The boundary conditions were free on the straight edge and stiff diaphragm on the curved edge, and the loading was self weight, wind load, and seismic load. To ensure that the results obtained were genuine, the elastic zone results were first compared to earlier results [13].

The solution in linear range for shell has been adopted from Mandal & Joshi, [1]. They have developed MATLAB code for the analytical solution of shell problems with rigid diaphragm support in curved edges and free and fixed support in straight edges. Using their code the solution in linear range was verified with the ANSYS model using vertical deflection.

3. Objectives

1. Prediction of maximum Von Mises stress (equivalent stress) and strain in linear and non-linear ranges for a thin circular cylindrical shell using a trained neural net.

2. Validation of the results with analytical solution in linear range.

4. Methodology

119 open thin circular shells with varying parameters as presented below were run in ANSYS. Large deformations were allowed to caputre geometric non linearity and stress-strain curve for aluminium 2023-T3 was provided to capture material non linearity. The output from ANSYS was used to train a neural network, and finally the neural network was used to predict stresses. Validation was done in linear range using analytical solution.

4.1 Selection of Input And Output Parameters

Table 1: Input parameters and their range

Geometry	Open Circular Cylinder
Span (L)	100mm to 2560mm
Thickness (t)	1mm to 65.2mm
Half Central Angle	$10^\circ - 34.6^\circ$
Radius (R)	100mm to 715mm
Load Type	UDL 1Mpa to 25.6Mpa

The output parameters under consideration were maximum equivalent stress and maximum equivalent strain.

4.2 Configuration of neural network

The neural network was configured with various number of hidden layers and nodes per layer until the deviation between results predicted by ANSYS and neural network was minimized. Other parameters of the neural network was kept constant. Activation function was Tanh. The network was simple feed forward network with backpropagation algorithm. The learning rate was 0.001, momentum was 0.9 and number of iterations were 100000. All of the coding was done in python using PyTorch module. The number of hidden layers, iterations and learning rate was decided based on the mean squared error loss and maximum deviation in values(stress/strain) predicted by ANSYS and Neural Network. The above configuration gave a reasonable error with good (within 8%) tolerance between predicted and actual output. Much hit and trial was done.

4.2.1 Input And Output Nodes For neural network

Input layer of the network consisted of 5 nodes. Each node for Radius, thickness, load, span and central angle. The output neuron consisted of maximum equivalent stress and maximum equivalent strain.

4.3 Material Input And Boundary Condition

Material Input The material used was Aluminium 2023-T3. Its modulus of elasticity(E) = 72450Mpa and Poisson's ratio = 0.33. As non linear isotropic hardening property the following stress-strain data was provided:

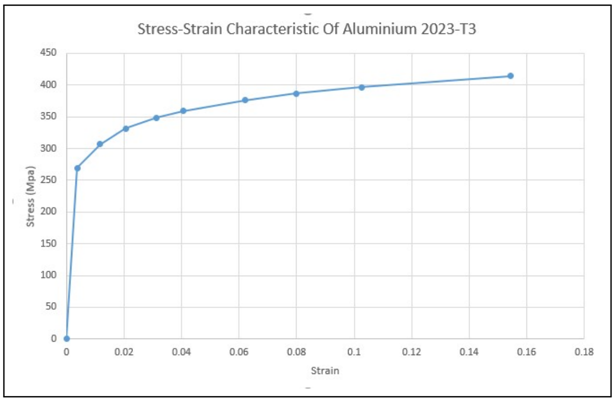

Figure 1: Stress-Strain Curve For Aluminum 2023-T3

Boundary Condition in Models Curved edges on rigid diaphragm (rigid on its own plane only, i.e. v = 0, w = 0, N1 = 0 and M1 = 0) and straight edges clamped (i.e. u = 0, v = 0, w = 0 and $\frac{\partial w}{\partial \theta} = 0$)

4.4 Analytical solution

The solution has been verified solving one of the problems as linear. For verification in linear range, the following equation has been solved in MATLAB by [1].

$$(1+4c^2)\frac{\partial^8 F}{\partial \xi^8} + 4(1+c^2)\frac{\partial^8 F}{\partial \xi^6 \partial \theta^2} + [6+c^2(1-\nu^2)]\frac{\partial^8 F}{\partial \xi^4 \partial \theta^4} + 4\frac{\partial^8 F}{\partial \xi^2 \partial \theta^6} + \frac{\partial^8 F}{\partial \theta^8} + (8-2\nu^2)\frac{\partial^6 F}{\partial \xi^4 \partial \theta^2} + 8\frac{\partial^6 F}{\partial \xi^2 \partial \theta^4} + 2\frac{\partial^6 F}{\partial \theta^6} + (1-\nu^2)(1/c^2+4)\frac{\partial^4 F}{\partial \xi^4} + 4\frac{\partial^4 F}{\partial \xi^2 \partial \theta^2} + \frac{\partial^4 F}{\partial \theta^4} \quad (1)$$

In above equation F is expressed as follows to satisfy the boundary condition:

$$F = \sum_{m=1}^{\infty} f_m(\theta) sin\lambda\xi = \sum_{m=1}^{\infty} Ae^{\alpha\theta} sin\lambda_m \xi \quad (2)$$

α is obtained by substituting equation 2 in equation 1. The constants **A** are obtained by satisfying boundary condition in the straight edges. Particular solution are obtained by expressing u,v, and w as follows:

$$\begin{aligned} u_o &= \sum_{m=1}^{\infty} A_{0m} cos\theta cos\lambda_m \xi \\ v_o &= \sum_{m=1}^{\infty} B_{0m} sin\theta sin\lambda_m \xi \\ w_o &= \sum_{m=1}^{\infty} C_{0m} cos\theta sin\lambda_m \xi \end{aligned} \quad (3)$$

5. FEM solution in ANSYS

In ANSYS Shell181 element with 6DOF per node was used to analyse the shell structure. The mesh size was kept at 50mm for larger models and 5mm for smaller ones and quadratic element order was used.

6. Results

6.1 Analytical solution And Validation

For validation open cylindrical shell with properties given below was used. The validation was done based on vertical deflection i.e w. Table shows data from ANSYS and analytical solution:

Radius	715mm
Thickness	62.5mm
Half Central Angle	34.6^o
Span	2560mm

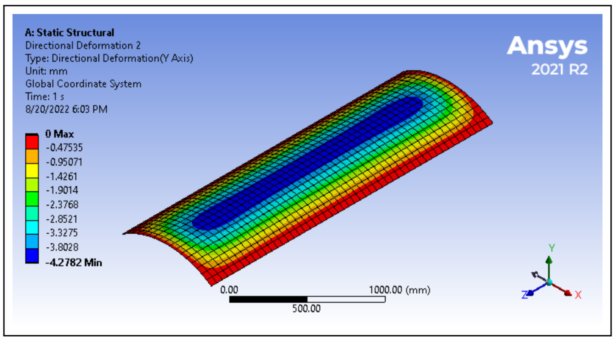

Figure 2: Deflection

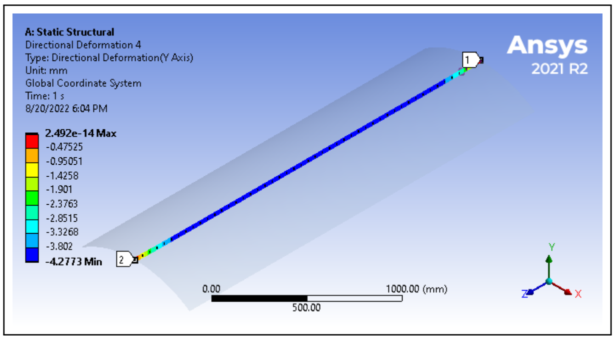

Figure 3: Deflection along mid

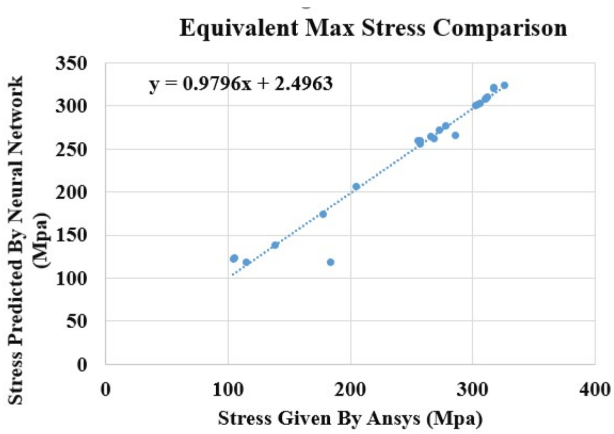

Figure 4: Stress Comparison for 5-20-2

Table 2: Analytical solution and ANSYS solution for vetical deflection

Distance(mm)	ANSYS(mm)	Analytical Solution(mm)
1120	4.167	4.165
1280	4.165	4.164
1440	4.167	4.165
1600	4.174	4.173
1760	4.195	4.197
1920	4.242	4.245
2080	4.277	4.275

All data are for center i.e $\theta = 0^o$.

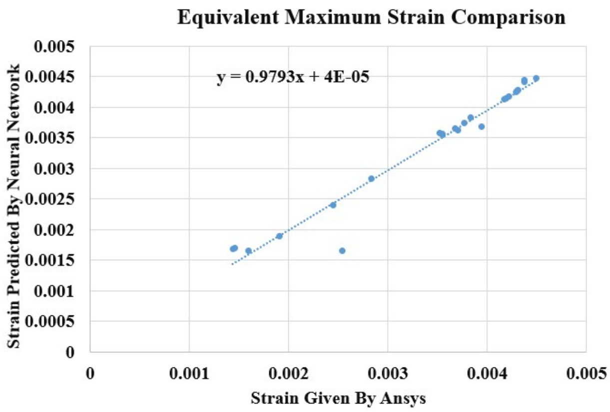

Figure 5: Strain Comparison for 5-20-2

For 5-20-2, the mean squared error loss was found to be 0.0228. The max stress deviation was 35.5% and max strain deviation was 34.7%. The neural network at this point is learning but not quite effectively. So we increase the number of hidden layers.

7. Neural Network Outputs

The neural network was trained with varying number of hidden layers to find the optimum number such that the maximum deviation between predicted and ANSYS values was minimized. The figures below show how the values predicted provided by ANSYS and neural net differ for different number of hidden layers and different nodes per layer in the hidden layers.

Notation: The notation of 5-10-2 means that there is input layer with 5 nodes, then there is one hidden layer with 10 nodes and final output layer with 2 nodes.

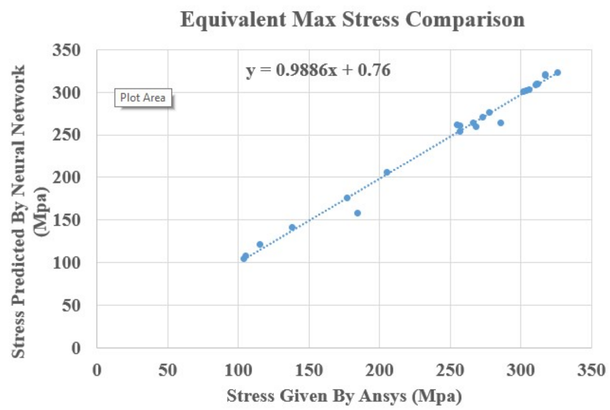

Figure 6: Stress Comparison for 5-10-10-10-2

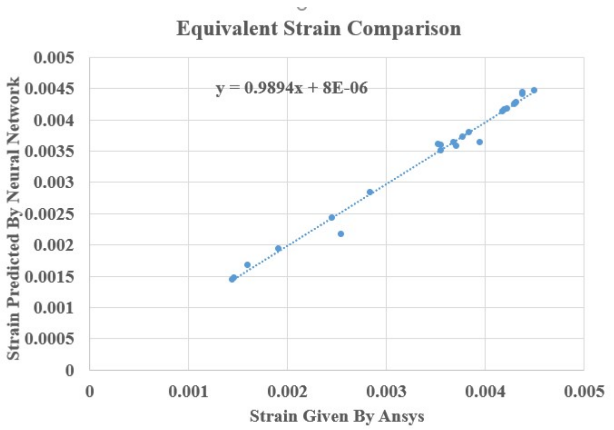

Figure 7: Strain Comparison for 5-10-10-10-2

For 5-10-10-10-2, the mean squared error loss was 0.0126. The max deviation in maximum equivalent stress was 14.1% and in maximum equivalent strain was 14.5%. At this point the neural network seems to be learning as inprovement in the prediction can be observed.

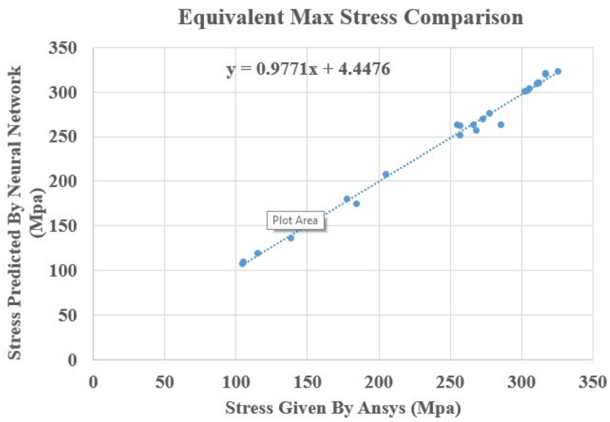

Figure 8: Stress Comparison for 5-10-30-10-2

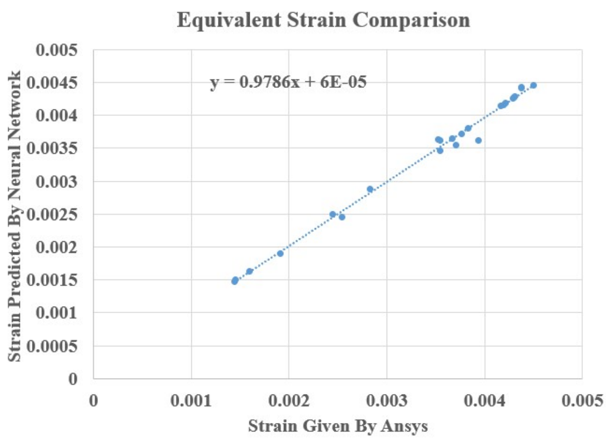

Figure 9: Strain Comparison for 5-10-30-10-2

For 5-10-30-10-2, the mean squared error loss was 0.0113. The maximum deviation in maximum equivalent stress was 7.8% and in maximum strain was 7.9%. We are still observing some improvement in the learning process.

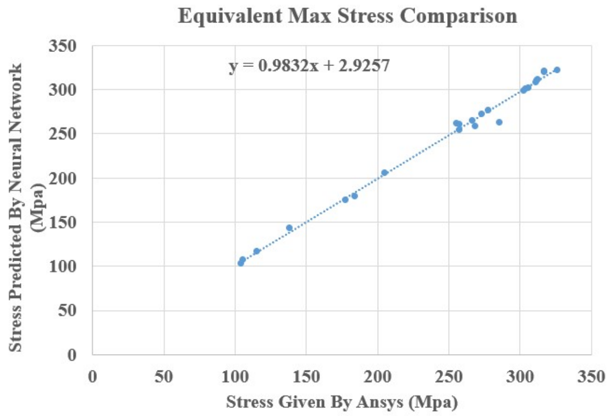

Figure 10: Stress Comparison for 5-10-50-10-2

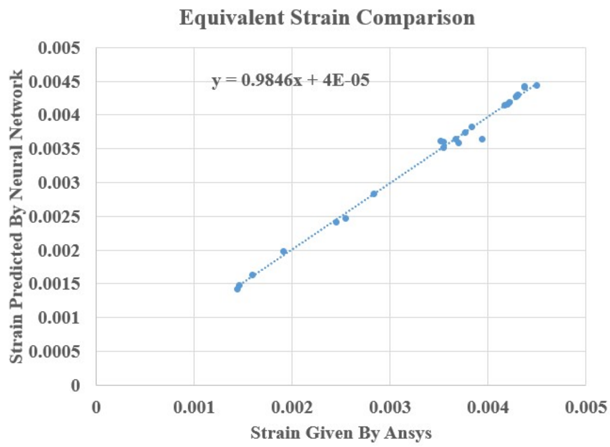

Figure 11: Strain Comparison for 5-10-50-10-2

For 5-10-50-10-2, the mean squared error loss was 0.0105 , and the maximum deviation in maximum equivalent stress was found to be 7.7% and for strain was found to be 7.6%.

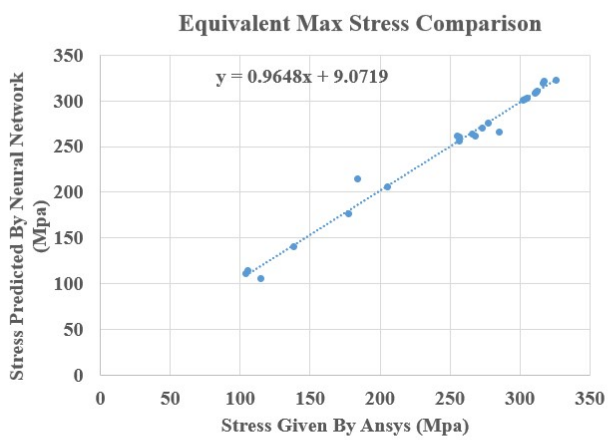

Figure 12: Stress Comparison for 5-10-30-50-30-10-2

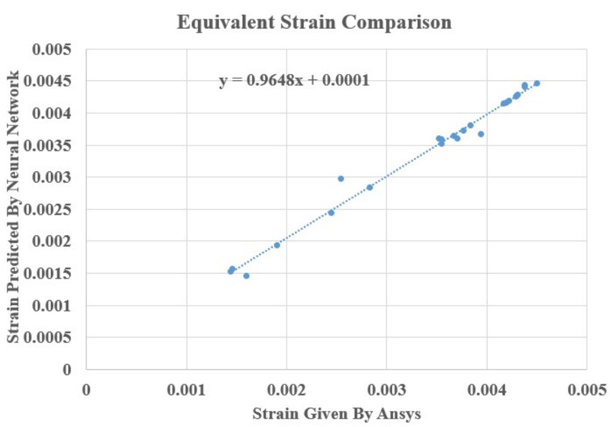

Figure 13: Strain Comparison for 5-10-30-50-30-10-2

For 5-10-30-50-30-10-2, the mean squared error was 0.007, and the maximum deviation for maximum equivalent stress was found to be 16.7% and for strain it was 16.8%. The data has been overfitted at this point.

8. Discussion

In this paper,119 thin shell models with rigid diaphragm support in curved edges and clamped in straight edges were analysed in ANSYS turning on large deflections to accomodate geometric non-linearity and complete stress strain curve of aluminium 2023-T3 was provided to account for material non-linearity. To make sure that the results were genuine, validation has been done in linear range of the analysis or considering linear effect only. After analysis the data from the models i.e. maximum equivalent stress and maximum equivalent strain were used to train the neural network. For training the neural network data was split into 80% training set and 20% testing set. Various configuration of neural network were tried to get best possible output. Figures 5 to 11 display the variation in results provided by ANSYS and neural network as the number of hidden layers and nodes per layer was increased. What is being expected here is a straight line $y = x$ i.e. line with slope of 1 and intercept of 0 and all points fall on that line, which implies that the neural network perfectly agrees with ANSYS, but since the feat cannot be achieved practically, we want to see slope close to 1 and intercept close to 0. Moving from 5, we start with slope of 0.9796 and intercept of 2.4963. The slope and intercept are quite close to what is being expected but we can clearly see one of the points is way off the line i.e. that particular point if responsible for maximum deviation of 35.5% which is way large deviation. So at this point we increase the number of hidden layers. Most of the work performed in this paper is based on hit and trial. So huge number of trials have been performed to achieve the mentioned results.

As we increase the nodes per layer and number of hidden layers, we may see that the slope of 0.983 and intercept of 2.92 has been achieved in figure 11. One may observe that the intercept has increased but the significant matter of concern is the maximum deviation in the maximum equivalent stress and strain among all the test data has to be minimized, which in this case is only 7.7% and 7.6%. Increasing the number of hidden layers again has caused overfitting and the network has performed poorly as given in figure 13.

9. Conclusion

Following conclusions can be drawn from this paper. The conclusions do meet the objectives set previously in this paper.

1. For linear range, the analytical solution from MATLAB agreed quite well with the model from ANSYS. The deformations agreed within 1% as given by exact analytical tools.

2. Even a simple feed forward neural network utilizing back propagation algorithm was able to learn the patterns behind the complicated equations governing non-linearity in shell structures. From multiple hit and trail a maximum deviation of 7.7% in maximum

equivalent stress and 7.6% in equivalent strain was achieved. This percentage can be reduced by running larger samples in wider range of values. This paper doesn't claim to have produced a working neural network model that can predict stresses for any given input as the number of sample was limited. It can however predict stresses in the range it has been trained in. But the main conclusion is that increasing the model numbers and range of input data, any reasonable input could be provided to obtain the stress output. The result might not still be used for engineering use, but it can sure give reasonable estimate within seconds without doing any analysis in FEM tools like ANSYS.

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