# PREDICTION OF WELDING RESIDUAL STRESSES USING ARTIFICIAL NEURAL NETWORK

## (Coding Assignment 1)

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#### INTRODUCTION

Residual stress is tension or compression that exists in a material without an external load. It exists as an internal stress in the form of permanent internal strains. Welding is a large contributor to residual stresses; it generally causes tensile residual stresses. Weld locations are significant sources of failure in components. Therefore it is necessary to get values of residual stresses. Artificial intelligence-based predictive techniques like Artificial Neural Networking (ANNs) have seen many applications in recent times. Their ability to learn from different examples make them very flexible and powerful.

ANN model to predict residual stresses during the butt-welding process of two mild steel plates was developed. A multilayer feed forward neural network with backpropagation algorithm has been used to predict the same. A data-driven model was developed from using ANN, this made the procedure of calculating residual stress in weld locations more efficient and less time-consuming. The predicted result was compared with the dataset and the mean square error (mse) was calculated.

The dataset used was obtained from an article "Neuro evolutionary model for weld residual stress prediction" by John Edwin Raja Dhas, Somasundaram Kumanan.

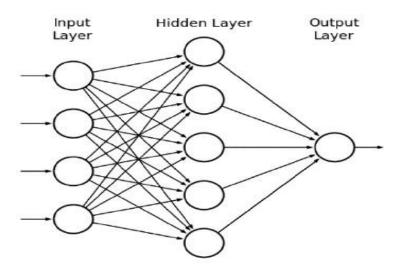
The model developed is fitted with the data collected, wherein the model is trained and is validated using a validation data set (a subset of the original dataset). Hence, the accuracy of the model is calculated.

#### **METHODOLOGY**

The first step of building an effective neural network is understanding the dataset. Knowledge of dependent and independent parameters is essential.

Here the residual stress is the dependent variable and the best input parameters that are selected are arc efficiency, welding current, welding voltage and welding speed.

- Number of input neurons = 4
- Number of output neurons = 1



For obtaining the number of neurons in the hidden layer several iterations were performed with different learning rates(0.1, 0.2, 0.3, 0.5) for different numbers of hidden neurons(5, 6, 7, 8, 9, 10) and it was found that the Mean square error was least with 9 hidden neurons with learning rate of 0.1 and momentum term 0.75 for most of the cases(trial and error), so they are chosen accordingly.

Also using the Empirical formula for optimal hidden neuron

$$M = (L+N)/2 + \sqrt{P}$$

Where L: Number of Inputs

M: Number of Hidden neurons

N: Number of output neurons

P: Number of Training patterns

M can be found using above relation and it comes out to be  $8.82 \approx 9$  hidden neurons

Learning Rate(η)	MSE Train	MSE Test	
0.1	0.000122	0.000383	
0.2	0.000101	0.001566	
0.3	0.000099	0.000677	
0.4	0.000088	0.001727	
0.5	0.000083	0.002324	

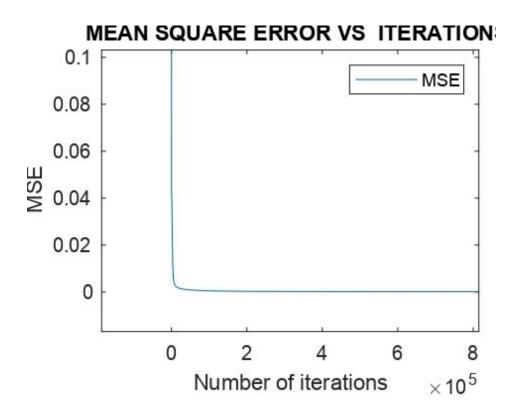
- Number of hidden neurons = 9
- Learning rate = 0.1
- Momentum term = 0.75

From a total of 43 data patterns, 40 of them are used for training and 3 are used as test data. The result obtained for the test set is compared with target values and the error in prediction is given as mean square error. The output of the neural network is stored in a file and a plot is created between the MSE value obtained with different number of iterations during training.

#### **RESULTS**

• A total of 1000000 iterations was performed during training and the mean square error obtained is 0.000122.

The variation of mean square error with the iterations is shown below-



- Using the modified network parameters ,for a total of three test patterns output residual stresses was predicted and the error was calculated as shown
- It must be noted that a small deviation from the results may be seen while running code at different times depending upon the efficiency of the network.

Arc efficiency(%)	Welding speed (mm/s)	Welding Voltage (V)	Welding current (amp)	Experiment al results(resi dual stresses MN/m <sup>2</sup>	ANN result	Absolute Error
0.7	3.3	21	170	162.8	176.59	13.79
0.75	2.5	21	170	64.2	60.97	3.228
0.8	3.3	22	150	115	107.67	7.325

#### • Mean square error for the test set obtained is 0.000383

From the above table it can be seen that the ANN model predicts the residual stresses with significantly lesser error.

#### **CONCLUSION**

- From the above results it can be seen that the ANN model is predicting the residual stresses with a considerable accuracy.
- The input parameters should be chosen with care which influences the output values.
- The MSE decreases very fastly during initial iterations and becomes nearly constant after sufficient iterations.
- Accuracy of model is highly dependent on the number of training patterns.
- It can be noted that the MSE of the test set is always more than the MSE of training data and both of them have very near values when the learning rate is very small.
- Results have small variation due to randomization of initial connection weights.
- Use of momentum rate helps in faster convergence.

### **REFERENCES**

- 1. John Edwin Raja Dhas, Somasundaram Kumanan, "Neuro evolutionary model for weld residual stress prediction". Applied Soft Computing, Volume 14, Part C, January 2014, Pages 461- 468.
- 2. K.A. Kulkarni, Prediction of welding residual stresses using Artificial Neural Network (ANN), Materials Today: Proceedings.