

Application of an Artificial Neural Network in friction stir welding

Abstract:

The artificial neural network (ANN) can be used as a model for friction stir welding (FSW), predicting the correlation between FSW parameters and weld properties. ANN for predicting properties of welded plates by FSW is explained and previous works in this field are reviewed. Furthermore, some examples of applications of ANN in FSW are presented. The development of sound joints between materials is of great importance in FSW. One of the most challenging problems is choosing appropriate welding parameters in order to produce a sound joint. Traditionally, a time-consuming trial and error development was carried out to determine welding parameters. Additionally, an optimized welding parameters combination was not achieved, because welds can be fabricated with very different ideal welding parameters. Different optimization techniques can be employed to determine the optimized output parameters by specifying the relation between the input and output variables. Applications of optimization methods in FSW are explained, and basic principles of these methods, such as Taguchi, genetic optimization, and multi-objective optimization methods are described

Methodology:

In this section, an ANN model is developed to simulate the correlation between the FSW parameters and mechanical properties of a butt joint, as a function of weld and rotational speeds. The summary of experimental results is presented in table. As shown in the table, the inputs are the rotational speed and the traverse speed, and the output is hardness.

Traverse Speed	Rotational Speed	Hardness
20	1400	92.3
20	1200	94.2
20	900	93.7
20	700	96.7
20	565	97.9
36	1400	90.23
36	1200	92.1
36	900	94.1
36	700	95.25
36	565	97.3
63	1400	89
63	1200	90.1
63	900	91
63	700	90.9
63	565	95.2
96	1400	87.21
96	1200	88.23
96	900	90.1
96	700	91.67
96	565	92.89

Results obtained:

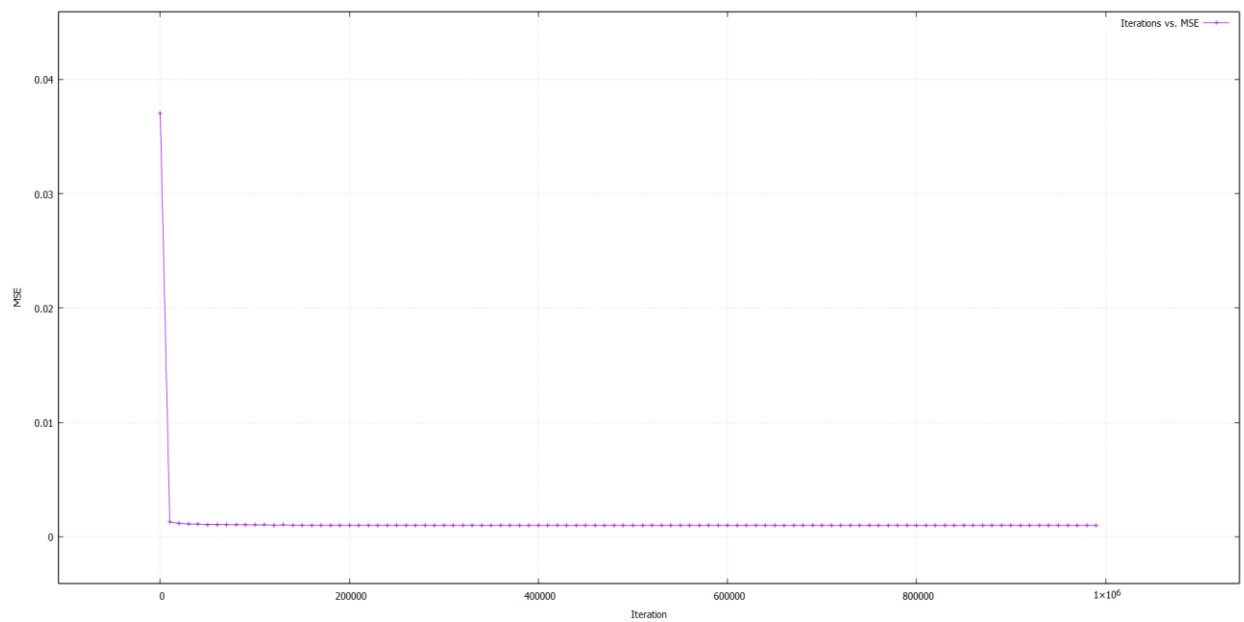
<i>Pattern</i>	<i>Input-1</i>	<i>Input-2</i>	<i>Target value</i>	<i>Output value</i>
1	20.000000	1400.000000	92.300000	92.660195
2	20.000000	1200.000000	94.200000	93.463885
3	20.000000	900.000000	93.700000	94.553956
4	20.000000	700.000000	96.700000	96.791142
5	20.000000	565.000000	97.900000	97.709624
6	36.000000	1400.000000	90.230000	91.152492
7	36.000000	1200.000000	92.100000	91.961583
8	36.000000	900.000000	94.100000	93.378754
9	36.000000	700.000000	95.250000	95.125998
10	36.000000	565.000000	97.300000	97.535878
11	63.000000	1400.000000	89.000000	88.894383
12	63.000000	1200.000000	90.100000	89.417191
13	63.000000	900.000000	91.000000	90.770963
14	63.000000	700.000000	90.900000	91.886453
15	63.000000	565.000000	95.200000	95.172705
16	96.000000	1400.000000	87.210000	87.872754
17	96.000000	1200.000000	88.230000	88.046611

The table represents the training pattern followed to train the ANN.

After training, the ANN is tested on 3 more patterns as followed:

<i>Pattern</i>	<i>Input-1</i>	<i>Input-2</i>	<i>Target value</i>	<i>Output value</i>	<i>Error in prediction</i>
18	96.000000	900.000000	90.100000	90.106252	0.006252
19	96.000000	700.000000	91.670000	92.404469	0.734469
20	96.000000	565.000000	92.890000	92.877978	0.012022

The variation of Mean Squared Error (MSE) with the number of iteration is depicted below:



Observation & conclusion:

The optimum number of training patterns is calculated using the formula:

$$N_h = \frac{N_s}{\alpha * (N_i + N_o)}$$

Where, N_h is the optimal number of hidden neurons,

N_i is the number of input neurons,

N_o is the number of output patterns,

α is arbitrary scaling factor ranging from 2 to 10

The error in prediction (MSE) turned out to be 0.049494 during the testing phase.

The optimal number of hidden neurons turned out to be 2 and it was implemented in the code of the aforesaid Neural Network's training.