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Artificial neural network modelling for polyethylene FSSW parameters

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KEYWORDS
Friction Stir Spot Welding (FSSW);
High density polyethylene (HDPE);
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Optimization.

Abstract. In a Friction Stir Spot Welding (FSSW) process, welding parameters (the tool rotational speed, tool plunge depth, and stirring time) affect the nugget formation in high-density polyethylene (HDPE) sheets. The size and microstructure of the nugget determine the resistance of the joint to outer forces. The optimization of these parameters is vital to obtaining high-quality welds. Feed forward back-propagation artificial neural network models are developed to optimize the FSSW parameters for HDPE sheets. Input variables of these models include tool rotation speed (rpm), the plunge depth (mm), and the stirring time (s) that affect lap-shear fracture load (N) output. Prediction performances of 6 models in different specifications are compared. These models differ in terms of the training dataset used (80%-100%) and the number of neurons (5-10-20) in a hidden layer. The best prediction performances are obtained using 20 neurons in a hidden layer in both training dataset. There is good agreement between developed models' predictions and the experimental data.

1. Introduction

In the automotive industry, aluminium alloys and aluminium composite parts are widely used in the body structure of cars accounting for 20% of the total weight of the vehicle [1]. The automotive industry invented the Friction Stir Spot Welding (FSSW) process in 2001 to join aluminium parts together [1]. This welding process was successfully applied to thermoplastic sheets [2]. The FSSW process is applied to thermoplastic sheets in four stages: (1) plunging, (2) stirring, (3) solidifying, and (4) retracting [3-5]. At the end of the operation, a nugget forms which joins the workpieces together. The tool rotation speed, its plunged depth, and stirring time determine the size, characteristics of the nugget, and the mechanical properties of weld joints [4,5].

Recently, in the field of joining materials, computer-aided Artificial Neural Network (ANN) modelling has gained increasing importance. Controlling the welding parameters and mechanical properties of welds are important problems in welding processes [6]. ANN models have a wide range of applications regarding optimization of welding parameters and analysis of quality control specifications [7-12]. Based on the literature examinations, there are very few number of studies on optimization of welding parameters of FSSW thermoplastic sheets. There are 2 applications of the Taguchi method [13,14] and an ANN application [15]. In this ANN-based paper, only two welding parameters were studied. The present study makes an attempt to use ANN modelling to optimize FSSW parameters of HDPE sheets.

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2. Materials and methods

HDPE sheets with 4 mm thickness were used in this study. A semi-automatic milling machine was used to weld the sheets. The lap-shear test is the most common weld test for spot welds. Therefore, lap-shear test specimens were produced by the milling machine. In lap-shear tests, fracture loads were identified. The fracture load determines the weld quality of a spot weld. A high fracture load indicates that a high-quality spot weld has been produced in the joining operation. Table 1 displays how the welding parameters vary in this research. In each welding operation, the stirring tool immerged into the weld area with a 3.3 mm/s plunging rate. The deviation limits of the plunging depth varied within ± 0.01 mm. All the welds were produced without preheating. In each welding, 50-second constant dwell time was used. Moreover, 192 welds were produced with 64 different welding parameters. By each welding parameter, 3 welds were produced. The tests were planned to determine the effects of tool plunge depth, rotation speed, and stirring time on polyethylene FSSW lap-shear fracture load. The lap-shear tests were done on an Instron machine at a constant crosshead speed of 5 mm/s. For each of welding parameters, 3 tests were done and the arithmetic average was calculated.

3. Results and discussion

The relations between FSSW parameters (welding stirring time, plunge depth, and tool rotational speed) and lap-shear fracture load of HDPE welds are shown in Figures 1, 2, and 3, respectively. The graphics were drawn by using the calculated arithmetic averages of the lap-shear fracture loads. Each point on the graph represents the average fracture load of three welds produced with the same welding parameters. The effects of welding parameters on the lap-shear fracture load are not explained in this paper, because other authors have already investigated them in detail [3,4].

4. Developed artificial neural network models

In this study, 6 ANN models are developed including three input variables: tool rotation speed (rpm), plunge depth (mm), and dwell time (s), which affect the Lap-shear fracture load (N) output. Feed forward back-propagation ANN models are used to predict the Lap-

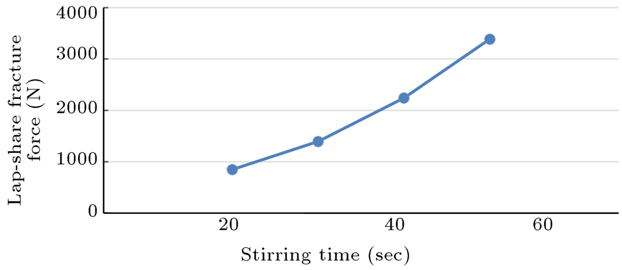

Figure 1. The effect of stirring time on lap-shear tensile fracture load.

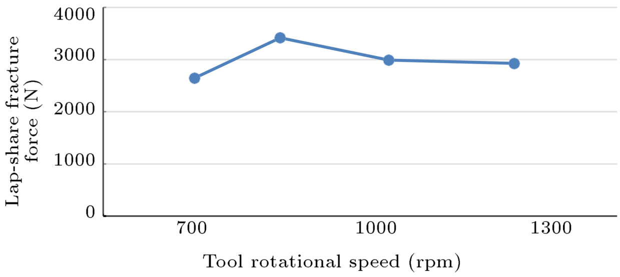

Figure 2. The effect of tool rotational speed on lap-shear tensile fracture load.

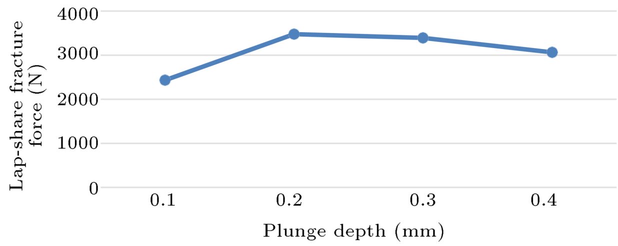

Figure 3. The effect of plunged depth on lap-shear tensile fracture load.

shear fracture load. A sample dataset of laboratory experiments is shown in Table 2. The input-output data can be actual or normalized. It is obvious that using normalized data leads to better results. Dataset is normalized using Eq. (1):

$$X = (Xi - X\min)/(X\max - X\min)$$

X = Normalized data

Xi = Actual data

$X\min$ = Minimum value of actual data

$X\max$ = Maximum value of actual data (1)

Table 1. Welding parameters and their ranges.

Welding parameters	Units	Ranges
Tool plunge depth	Millimeter (mm)	0.1 - 0.2 - 0.3 - 0.4
Tool rotation speed	Round per minute (rpm)	560 - 710 - 900 - 1200
Stirring time	Seconds (s)	15 - 25 - 35 - 45

Table 2. Sample dataset from laboratory experiments.

Data No.	Inputs			Outputs		
	Tool rotation speed	Plunge depth	Dwell time	Lap-shear fracture load		
				Experiment 1	Experiment 2	Experiment 3
1	560	0.1	25	400	500	450
2	560	0.3	25	800	800	900
3	710	0.1	45	2198	2306	2434
4	900	0.2	35	2459	2824	2300
5	900	0.4	15	1000	900	780
6	1120	0.2	25	2330	2600	2560
7	560	0.1	35	715	785	850
8	1120	0.1	25	900	1200	1350
9	710	0.4	35	2210	1923	2100
...	...	...	...	...	...	...
64	900	0.4	45	2760	2838	2976

Table 3. Normalized dataset sample of laboratory experiments.

Inputs			Outputs
Tool rotation speed	Plunge depth	Dwell time	Lap-shear fracture load
0.001779359	0.125	0.125	0.002976190
0.268683274	0.875	0.375	0.389880952
0.606761566	0.625	0.625	0.671130952
0.998220641	0.625	0.125	0.122023810
0.001779359	0.125	0.875	0.406547619
0.268683274	0.375	0.125	0.251190476
0.606761566	0.625	0.625	0.627976190
0.998220641	0.625	0.625	0.583333333
0.268683274	0.625	0.125	0.235119048
0.606761566	0.375	0.875	0.913095238
0.998220641	0.625	0.125	0.190476190

Six ANN models, including different properties, are developed in this study, and their prediction performances are compared. Three of the developed ANN models respectively include 5-10 and 20 neurons in the hidden layer; 80% of this dataset is used for training data and the other 20% for validation. In the other three developed ANN models, 5-10 and 20 neurons in the hidden layer are trained with 100% of dataset and validated with the same dataset used in the first three ANN models. The normalized training and testing dataset samples of laboratory experiments are shown in Table 3; testing dataset is shown in bold.

In this study, feed forward back-propagation ANN model is preferred, which has been used herein for multi-layered ANNs due to being a global approximator and the best performed ANN model under current values.

Levenberg Marquardt is used as a training algorithm in the developed feed forward back-propagation ANN model. Gradient Descent with Momentum (GDM) learning algorithm is applied to the learning algorithm in Matlab software. Variables are normalized between 0-1; therefore, LOGSIG (Log- sigmoid) transfer function is preferred for the developed ANN model. Six different ANN models are developed with different properties as mentioned above (percentage of training dataset and the number of neurons in the hidden layer). As a result of tests and analyses, network's optimum topology has been obtained with specific iteration. The developed ANN model consists of 3-neuron-input layers that represent inputs, hidden layers made of 5-10 and 20 neurons, and the output layer made of a neuron. Structures representing ANN's input, output, and hidden layers are shown in Figure 4. Then, the developed ANN models have been run 6 times with the mentioned properties.

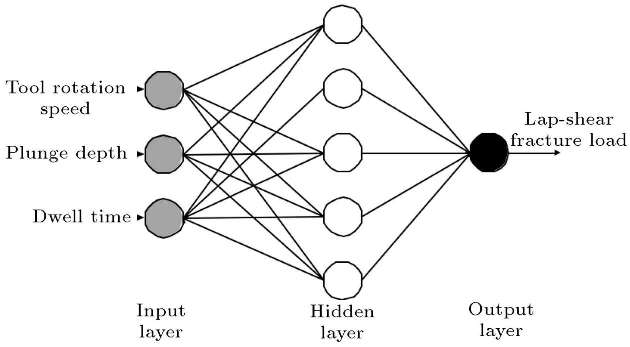

Figure 4. Structure of developed ANN models.

5. Conclusion

In this study, six different developed models were compared with actual data, as illustrated in Figure 5. Outputs of these ANN models were compared with the actual values listed in the chart below after training completion. Then, MAE (Mean Absolute Error) and MAPE (Mean Absolute Percentage Error) were selected as types of error by means of Eqs. (2) and (3) to validate the developed ANN models given in Table 4. The best prediction performance was obtained with 100% training set and 20 neurons in the hidden layer as shown in bold in Table 4:

$$\text{MAE} = \tfrac{1}{n}\sum_{t=1}^{n} |At - Ft| \tag{2}$$

$$\text{MAPE} = {}^{100\%}\sum_{t=1}^{n} |At - Ft| nAt, \tag{3}$$

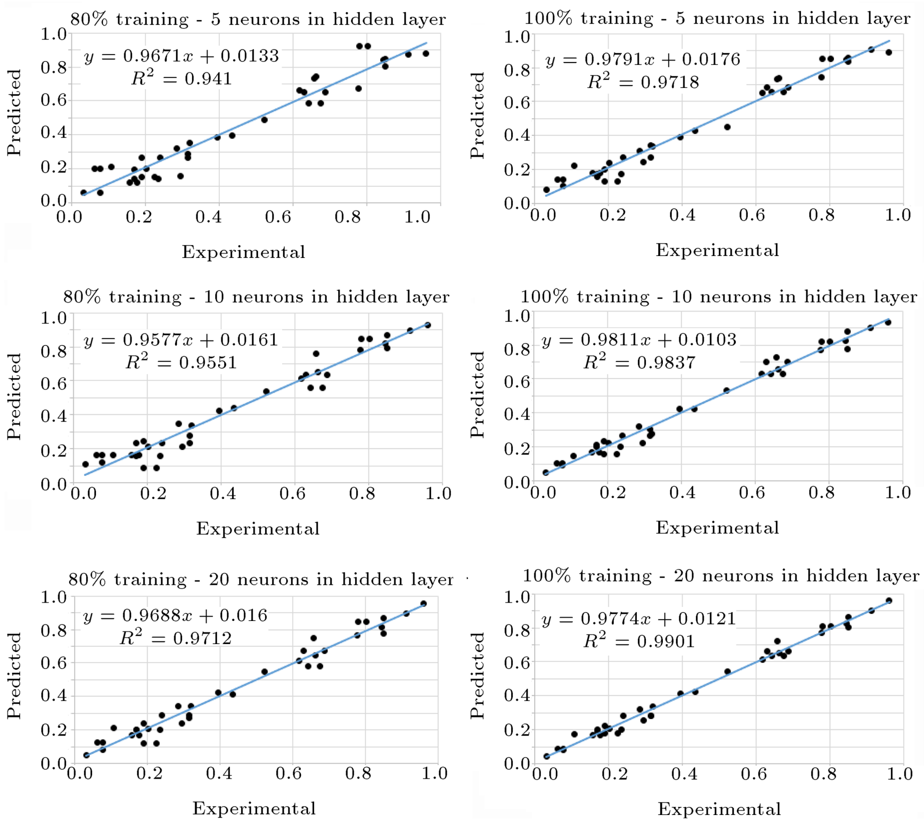

Figure 5. Regression analysis results of 6 developed ANN models.

Table 4. MAE and MAPE values of 6 developed ANN models.

Ratio of training dataset		80%			100%	
Number of neurons in hidden layer	5	10	20	5	10	20
MAE	0.0567	0.0475	0.0392	0.0384	0.0305	0.0233
MAPE (%)	27.462	27.645	17.606	21.417	13.381	10.035

Table 5. Regression equation and MSE values of developed ANN model.

Ratio of training dataset (%)	Number of neurons in hidden layer	Regression equation	R^2
80	5	$y = 0.9671x + 0.0133$	0.9410
80	10	$y = 0.9577x + 0.0161$	0.9551
80	20	$y = 0.9688x + 0.016$	0.9712
100	5	$y = 0.9791x + 0.0176$	0.9718
100	20	$y = 0.9774x + 0.0121$	0.9901

where At is actual data, Ft is forecast at time t, and n is the number of samples.

Figure 4 shows the comparison between experimental and predicted values of the output variable by using 6 developed ANN models. Comparison results (regression equations and MSE values) of all developed ANN models are concisely given in Table 5.

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Biographies

Memduh Kurtulmuş obtained his MSc degree in Metal working field in 1994 at Marmara University, Istanbul, Turkey. He finished MSc study in 1998 and PhD program in 2005 at Marmara University. Both of his theses were in welding technology field. He obtained Level 3 certificates about Non-Destructive Testing Processes at the Turkish Standarts Institute in 2003. He received a BSc degree in Mechanical Engineering at Istanbul Newport University. He became an International Welding Engineer at Romanian Welding Institute in 2006. He worked at Marmara University Technical Engineering Faculty as a Research Assistant in the years of 1994-2006. He became an Assistant

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Alper Kiraz was born in 1985. He graduated in 2007 from the Department of Industrial Engineering at Sakarya University, where he started his undergraduate studies in 2003. He started his master's degree in Industrial Engineering at Sakarya University in 2007 and started his career as a Research Assistant at Sakarya University Faculty of Engineering Department of Industrial Engineering at the beginning of the year. He completed his master's thesis titled "Virtual Laboratory Design with Artificial Neural Networks" and started his PhD in January 2010. He is currently an Assistant Professor of Industrial Engineering at Sakarya University.