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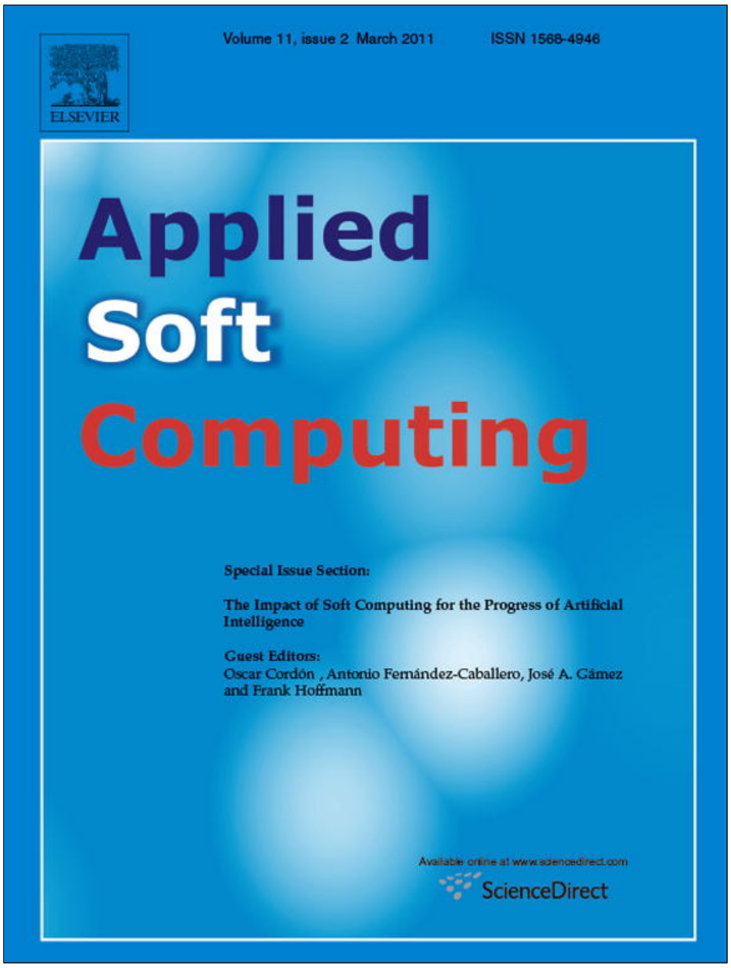
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Application of artificial neural network for predicting weld quality in laser transmission welding of thermoplastics

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ABSTRACT

The present work establishes a correlation between the laser transmission welding parameters and output variables though a nonlinear model, developed by applying artificial neural network (ANN). The process parameters of the model include laser power, welding speed, stand-off distance and clamping pressure; whereas, the output parameters of the model include lap-shear strength and weld-seam width. Experimental data is used to train and test the network. The present neural network model is used to predict the experimental outcome as a function of input parameters within a specified range. Linear regression analyses are performed to compute the correlation coefficients, to measure the relationship between the actual and predicted output values, for checking the adequacy of the ANN model. Further, a sensitivity analysis is performed to determine the parametric influence on the model outputs. Finally, a comparison is made between the ANN and multiple regression models for predicting laser transmission weld quality. The same data set, which are used to develop the ANN model, are also used to develop the multiple regression models. The simulation data obtained from the neural network confirms the feasibility of this model in terms of applicability and shows better agreement with the experimental data, compared to those from the regression models.

1. Introduction

Laser transmission welding is a novel and promising technology for many industries, those involved in joining of plastics. Versatility of laser led to gradual replacement of plastic welding techniques, based on ultrasonic energy, friction, vibration, electric resistance and heated tool. Laser transmission welding of plastic is advantageous in that it is non-contact, non-contaminating, precise, and flexible process, and it is easy to control and automate. In this process, the laser beam penetrates the upper transparent plastic part and is converted into heat by the absorbing lower plastic part. The melt is created only where it is needed, in the joining area of the both partners, to form the weld.

The basic composition of polymer matrix, colorants and additives affect laser energy absorption, reflection and transmission and finally to the mechanical performance of the weld. Presence of reinforcements, mineral fillers, impact modifiers and some heat stabilizers in polymer matrix lower the transmissivity of polymer due to increased scattering effect [1–3]. Thickness of plastic part has also influence in optical properties, especially for semi-crystalline materials. The most important independent process parameters for the laser transmission welding are laser power, welding speed, size of the laser beam spot on the work-piece and clamping pressure [4]. The temperature field inside the weld during welding can be controlled with these process parameters. A number of experimental works have been carried out to study the effects of process parameters on weld quality with various plastic materials and application strategies [1,4–8]. The weld quality can be defined in terms of weld bead geometry, mechanical properties and distortion. In order to get the desired weld quality, a combination of the process parameters should be selected carefully. To define the weld input parameters for new welded products to produce a welded joint with the required specifications is a time consuming trial accompanied by error development effort. An empirical model is therefore needed to be developed that can predict the optimum process parameters to obtain the desired weld quality.

Artificial neural network (ANN) is a powerful empirical modeling tool, suitable for problems which are not amenable to exact analytical solutions, or, where interrelationships between variables are not fully understood but which provide an abundance of data from which ANN can learn and predict. ANNs have gained prominence recently in the field of materials science and manufacturing engineering. Jeng et al. [9] presented the back-propagation and learning vector quantization networks to predict the laser weld-

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Table 1
Experimental results with welding and output parameters.

Experimental information					Results	
Std. order	Welding parameters				Average lap-shear strength (N/mm)	Average weld-seam width (mm)
	Power (W)	Welding speed (mm/min)	Stand-off distance (mm)	Clamp pressure (MPa)		
1	19.00	300.00	28.00	6.30	35.23	2.25
2	25.00	300.00	28.00	6.30	36.97	2.58
3	19.00	420.00	28.00	6.30	36.17	1.92
4	25.00	420.00	28.00	6.30	37.34	2.18
5	19.00	300.00	36.00	6.30	43.80	2.89
6	25.00	300.00	36.00	6.30	56.15	3.15
7	19.00	420.00	36.00	6.30	15.34	2.42
8	25.00	420.00	36.00	6.30	28.63	2.43
9	19.00	300.00	28.00	12.30	37.86	2.24
10	25.00	300.00	28.00	12.30	38.86	2.65
11	19.00	420.00	28.00	12.30	41.74	1.96
12	25.00	420.00	28.00	12.30	38.11	2.22
13	19.00	300.00	36.00	12.30	46.03	2.88
14	25.00	300.00	36.00	12.30	51.00	3.33
15	19.00	420.00	36.00	12.30	19.54	2.46
16	25.00	420.00	36.00	12.30	24.74	2.46
17	22.00	360.00	32.00	9.30	47.43	2.40
18	16.00	360.00	32.00	9.30	41.54	2.21
19	28.00	360.00	32.00	9.30	49.29	2.80
20	22.00	240.00	32.00	9.30	46.57	3.04
21	22.00	480.00	32.00	9.30	21.23	1.84
22	22.00	360.00	24.00	9.30	16.40	2.08
23	22.00	360.00	40.00	9.30	14.10	3.23
24	22.00	360.00	32.00	3.30	44.83	2.35
25	22.00	360.00	32.00	15.30	50.34	2.42
26	22.00	360.00	32.00	9.30	48.11	2.61

ing parameters for butt joints. Nagesh and Datta [10] have used back-propagation neural networks to correlate the welding process variables with the features of the bead geometry and penetration in shielded metal-arc welding process. Zhang et al. [11] have developed a back-propagation neural network model to predict circumferential and longitudinal residual stress profiles in hard turning. Singh et al. [12] have used back-propagation neural network technique to predict the flank wear of high speed steel drill bits for drilling holes on copper workpiece. An ANN model is developed by Okuyucu et al. [13] for analysis and simulation of the correlation between the friction stir welding parameters of aluminium plates and mechanical properties. Aykut et al. [14] have used ANN technique for modeling the effects of machinability on chip removal cutting parameters for face milling of stellite 6 in asymmetric milling processes. Park and Kang [15] have developed back-propagation neural networks to predict the fatigue life of spot welds subjected to various geometric factors and loading conditions. Cevik et al. [16] presents an ANN model for the prediction of ultimate capacity of arc spot welding process characterized by the weld strength, average welding thickness and diameter. Karunakar and Datta [17] have developed an ANN model to predict major casting defects like cracks, misruns, scabs, blowholes and air-locks using back-propagation neural networks. The developed model is found to be capable of predicting the casting defects successfully before the pouring stage of the casting. Hence, this model can be used to prevent the defects in casting process. Pal et al. [18] have developed multiple regression and multilayer neural network models to predict the ultimate tensile stress of pulsed metal inert gas welded plates. The developed ANN model shows better prediction competence when compared with the regression model. Martín et al. [19] proposed an ANN model for reliably predicting the tensile shear load bearing capacity of resistance spot welding joint of 304 austenitic stainless steel. At first, a linear regression model is used to fit the model. But, the residuals analysis reveals nonlinear behavior of the data. Therefore, an ANN model is proposed and found better predictability than that of regression model. Muthukrishnan and Davim [20] have used two modeling techniques namely ANOVA (analysis of variance) and ANN to predict the surface roughness in machining aluminium silicon carbide metal matrix composite. The outcomes of their study show that the ANN is the most effective method compared with ANOVA in terms of prediction potentials.

The literature review demonstrates that ANN is one of the effective and common techniques to map non-linear data set to relevant output parameters. Most of the researchers used ANN for prediction of different process parameters for the desired outputs. Laser transmission welding, being a highly nonlinear process, requires a reliable predictive model to simulate the process. Applications of neural network modeling of laser transmission welding of thermoplastics have not been reported yet. In the present work, an artificial neural network-based model is developed to predict the laser transmission weld quality in terms of lap-shear strength and weld-seam width. Experimental data is used to train and test the network. The predicted outputs based on the ANN model are found to be in good agreement with the unexposed experimental data set.

2. Experimental description

The laser used is the Coherent FAP-diode laser system with a 3-axes CNC work table, coordinated with the motion system and computer interface. The maximum optical power of the system is 30 W and has an output wavelength of 809.40 nm. The FAP-System optical radiation is delivered via a SMA 905 connector, which mates to an 800-μm diameter transport fiber. The imaging module attached to the distal end of SMA 905 connector consists of two lenses mounted in cylindrical stainless steel housing. The first lens in the optical assembly collimates the output of the fiber end and the second lens re-images the fiber end. The natu-

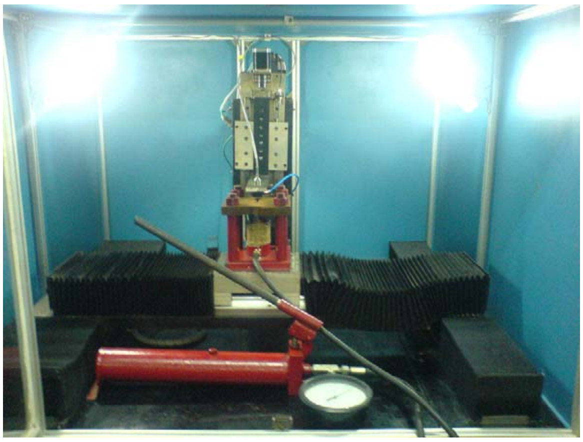

Fig. 1. Photographic view of experimental setup.

ral and opaque (containing 0.2% wt. carbon black) acrylics plaques of dimensions 80 mm × 35 mm × 4 mm of each, cut from injection molded acrylic sheets, are used as the work materials. A welding fixture is used for repeating work, to maintain the lapping area constant, 20 mm × 35mm for every run and to prevent misalignment between the parts to be welded in lap joint geometry. Hydraulic clamp pressure is applied in between the workpieces to ensure the intimate contact between them. The configuration of contour welding is adopted for this study. Fig. 1 shows photographic view of experimental setup.

All the welded specimens are tested for their relative strengths under tension using a microprocessor-controlled Instron universal tester. The lap-shear strength is calculated as the maximum load to failure per unit length of the weld. The weld-seam width for each specimen is measured using a Mitutoyo Tool maker's microscope. The weld-seam width for each of the specimens is measured at the center of the weld-seam length. The experimental results furnished in Table 1, are presented previously [8].

3. Back-propagation artificial neural network (BP-ANN)

BP-ANN is a widely used supervised learning algorithm which consists of forward and backward passes [21]. It is constructed by three layers, namely, input layer, hidden layer and output layer. Using back-propagation, the weights and biases, associated with the neurons, are adapted to minimize the mapping error (i.e. the training set classification error). After repeated presentation of the training data patterns to the BP-ANN, the weights and biases of the architecture become stabilized and the ANN is said to be trained. The classification or prediction of new data patterns is accomplished by propagating the new pattern through the neural network (i.e. multiplying by weights, adding biases, and applying the non-linear transfer function). The aim of this network is to train the net to achieve a balance between the ability to respond correctly to the input patterns that are used for training and the ability to provide good responses to the new inputs within a specified range. Artificial neural network, developed in the present study, is presented in Section 4.

4. Model development

Four input variables, namely: power (W), welding speed (mm/min), stand-off distance (mm), and clamp pressure (MPa) and two output variables namely: lap-shear strength (N/mm) and weld-seam width (mm) are used in a single network to establish the logical relationship between inputs and outputs. A multilayer feed-forward neural network with back-propagation algorithm is used to model the laser transmission welding process. In this study, the back-propagation is used with a network having an input layer with four neurons, one/two hidden layer(s) having varying number of neurons in each of the hidden layer and an output layer with two neurons. The performance of neural network depends on the number of hidden layer and the number of neurons in the hidden layer. Thus, several combinations are tried out to choose an optimal combination as presented in Table 2.

Table 2
Performance of neural network with different architectures.

Sl. no.	Network architecture	Mean prediction error (%)	Maximum prediction error (%)	Minimum prediction error (%)
1	4-4-2	9.45	36.24	0.67
2	4-5-2	8.70	30.07	0.17
3	4-6-2	7.66	26.64	0.26
4	4-7-2	5.37	17.58	0.45
5	4-8-2	6.52	24.01	0.51
6	4-9-2	19.20	47.24	0.76
7	4-10-2	6.04	25.62	0.43
8	4-11-2	9.26	39.36	0.73
9	4-12-2	7.71	19.04	0.43
10	4-13-2	10.85	25.39	0.64
11	4-14-2	13.44	38.47	0.77
12	4-15-2	13.17	40.85	0.68
13	4-16-2	13.27	49.48	0.67
14	4-17-2	9.38	27.33	0.77
15	4-18-2	11.47	35.57	0.29
16	4-19-2	12.22	28.24	0.77
17	4-20-2	11.26	30.50	0.71
18	4-4-3-2	9.47	29.97	0.69
19	4-4-4-2	6.95	16.30	0.71
20	**4-4-5-2**	**4.82**	**15.59**	**0.11**
21	4-5-4-2	11.99	49.13	0.57
22	4-5-7-2	10.08	29.28	0.78
23	4-6-3-2	7.94	26.83	0.42
24	4-6-4-2	11.48	35.02	0.07
25	4-6-5-2	14.32	63.68	0.67
26	4-7-5-2	6.51	23.60	0.20
27	4-7-7-2	10.29	18.02	0.65
28	4-7-9-2	9.80	36.14	0.71
29	4-7-10-2	13.69	61.27	0.80
30	4-8-4-2	10.55	36.80	0.19
31	4-9-7-2	10.23	35.12	0.27
32	4-9-10-2	12.32	28.26	0.08
33	4-10-6-2	16.62	38.49	0.74
34	4-10-10-2	14.29	39.08	0.77
35	4-12-10-2	5.85	23.15	0.73
36	4-12-12-2	9.33	27.44	0.75
37	4-15-6-2	8.25	21.51	0.75
38	4-15-10-2	8.24	17.95	0.65
39	4-16-4-2	15.59	49.74	0.04
40	4-16-5-2	8.93	30.38	0.74
41	4-16-6-2	7.58	26.00	0.76
42	4-16-7-2	9.89	21.03	0.67
43	4-16-10-2	10.83	32.43	0.73
44	4-16-14-2	9.25	23.99	0.78
45	4-17-5-2	7.67	16.93	0.27
46	4-17-8-2	7.25	14.87	0.44
47	4-17-10-2	12.05	42.18	0.67
48	4-18-10-2	12.78	33.84	0.67
49	4-20-10-2	12.85	47.00	0.75
50	4-20-20-2	9.46	34.15	0.76

The selected model architecture is marked in bold.

Experimental data are used to train the network. Among the 26 experimental results, 20 input–output data sets are chosen for training the network, while rest of the 6 results is used as test data. All the input–output variables are normalized between 0 and 1. Neurons in the input layer do not have transfer function, while a log-sigmoid transfer function is used in the other layers as the outputs are ranging between 0 and 1.

MATLAB 7.0 application tool is used in all the stages of model development including training and testing of the network. The

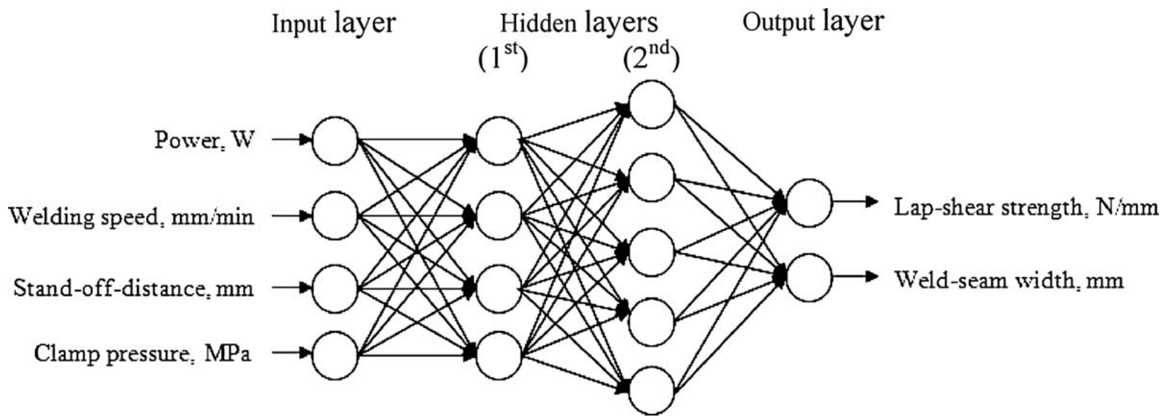

Fig. 2. Back-propagation neural network used for predicting lap-shear strength and weld-seam width.

feed-forward network is created using the MATLAB function newff. This command creates the network object and also initializes the weights and the biases of the network. During training, the weights and biases of the network are iteratively adjusted to minimize the performance function mean squared error – the average squared error between the network outputs and the actual outputs. The adaptive learning rate is used for training the network using MATLAB function 'traingda'. With an initial learning rate of 0.05, lr_dec of 0.7, lr_inc of 1.05, max_perf_inc of 1.04 and a performance goal of 0.0001, the networks are trained for a maximum of 200,000 iterations. Trial study is performed to find out the best initial learning rate value. To determine the initial learning rate, other parameters are kept constant and the initial learning rate is varied over a selected range. The best initial learning rate value is chosen at which the model gives least mean squared error. It is observed during the trial study that the initial learning rate has hardly an impact on the performance of the network, as the learning rate is changing at each epoch, according to the adaptive rates, to achieve the performance goal. The adaptive rates are taken as the typical values of MATLAB function 'traingda' [22]. The training is stopped when given number of epochs elapse or when the error reaches the performance goal. For testing the predictability of the developed neural network model, mean prediction errors (%) are calculated for each of the network architecture as follows:

$$\text{mean prediction error (\%)} = \frac{1}{p}\sum_{1}^{p}\left(\frac{|\text{actual value} - \text{predicted value}|}{\text{actual value}} \times 100\right) \quad (1)$$

Mean prediction error (%) is calculated by averaging all the individual percentage prediction errors for all the test data sets.

5. Evaluation of results and discussion

The model with two hidden layers having four neurons in the first hidden layer and five neurons in the second hidden layer (4-4-5-2 as shown in Fig. 2) is found to be the most suitable network architecture with lowest mean prediction error (%). The mean, maximum and minimum prediction errors for this network are 4.82%, 15.59% and 0.11% respectively. This network predicts more accurate results than other networks, tested for new data set. This network is trained for 200,000 iterations and reaches a performance mean squared error of 0.0005 as connection weights increase or decrease to minimize the mean squared error between the predicted outputs and actual outputs at each epoch. Fig. 3 shows the performance mean squared error of this neural network model at the end of training. The prediction error (%), obtained by the selected back-propagation neural network model for all the test samples in predicting the lap-shear strength and weld-seam width, are presented in Tables 3 and 4, respectively. The comparisons of actual and predicted values are presented in Figs. 4 and 5 for lap-shear strength and weld-seam width test data sets, respectively. It is clear from the results, that the neural network prediction of laser transmission welding parameters follow the experimental results very closely.

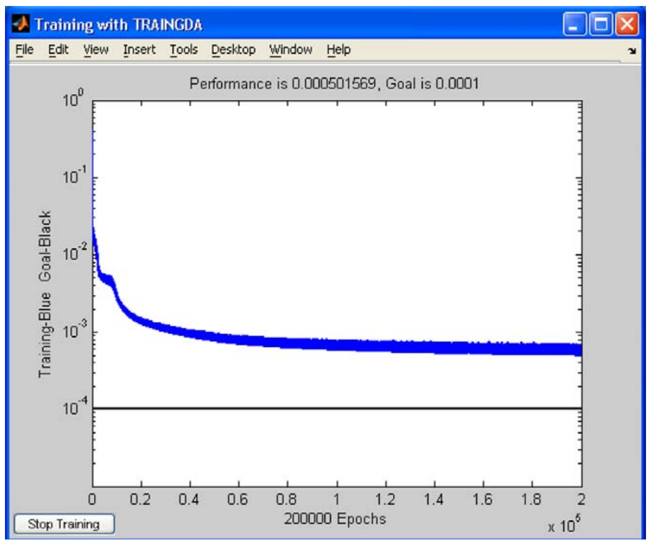

Fig. 3. Mean squared error of the network to predict lap-shear strength and weld-seam width.

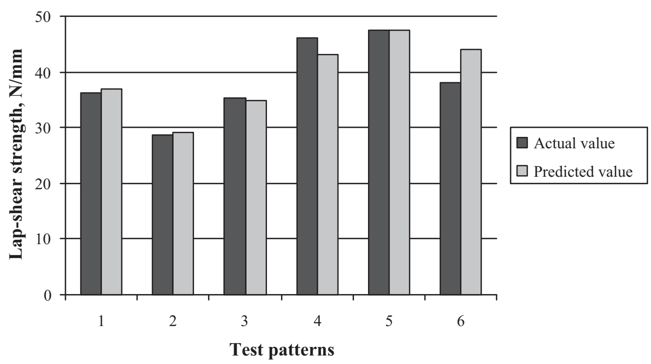

Fig. 4. Actual and ANN predictions of lap-shear strength.

Table 3
Comparison of actual and predicted outputs for test data of lap-shear strength.

Sl. no.	Welding parameters				Lap-shear strength (N/mm)			
	Power (W)	Welding speed (mm/min)	Stand-off distance (mm)	Clamp pressure (MPa)	Actual	ANN output	|Error|	% |Error|
1	19	420	28	6.3	36.17	36.91	0.74	2.05
2	25	420	36	6.3	28.63	29.14	0.51	1.77
3	19	300	28	6.3	35.23	34.91	0.32	0.92
4	19	300	36	12.3	46.03	43.17	2.86	6.21
5	22	360	32	9.3	47.43	47.38	0.05	0.11
6	25	420	28	12.3	38.11	44.05	5.94	15.59

Table 4
Comparison of actual and predicted outputs for test data of weld-seam width.

Sl. no.	Welding parameters				Weld-seam width (mm)			
	Power (W)	Welding speed (mm/min)	Stand-off distance (mm)	Clamp pressure (MPa)	Actual	ANN output	|Error|	% |Error|
1	19	420	28	6.3	1.92	1.94	0.02	1.15
2	25	420	36	6.3	2.43	2.58	0.15	6.27
3	19	300	28	6.3	2.25	2.04	0.21	9.12
4	19	300	36	12.3	2.88	3.03	0.15	5.30
5	22	360	32	9.3	2.40	2.51	0.11	4.54
6	25	420	28	12.3	2.22	2.11	0.11	4.79

Linear regression analyses are performed to compute the correlation coefficient for the ANN model. The correlation coefficient is used to measure the relationship between the actual and predicted output values. A correlation coefficient (R^2) of 0.997 is obtained for the training patterns while predicting both, lap-shear strength and weld-seam width, as shown in Figs. 6 and 7, respectively. The correlation coefficient of 0.835 and 0.907 are obtained for the test patterns as shown in Figs. 8 and 9, respectively. In both the cases, the values of R^2 are close to unity, which indicate the adequacy of the developed model. Therefore, this neural network model can be used for predicting the outputs of laser transmission welding process with significant accuracy.

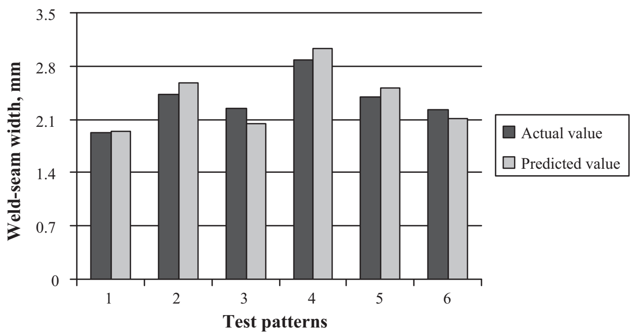

Fig. 5. Actual and ANN predictions of weld-seam width.

5.1. Sensitivity analysis

Sensitivity analysis is performed to identify the critical parameters and their tendencies, which is vital for model validation where the aim is to compare the predicted outputs to the experimental results. This study can find out the order of importance of the parameters on the model output. Sensitivity analysis yields the information about the parameter which must be measured most accurately and the effect of any small increment and decrement of that parameter on the overall design objectives.

Sensitivity analysis is carried out to examine the contribution of an input variable to the outputs using training data sets. Fig. 10

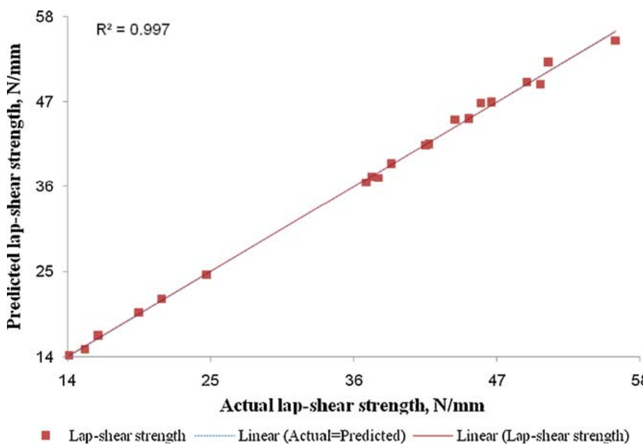

Fig. 6. Scatter diagram with best fit of ANN prediction vs. actual lap-shear strength for training patterns.

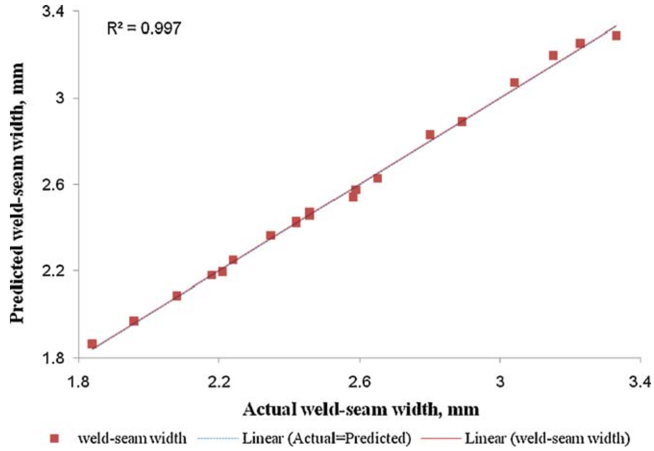

Fig. 7. Scatter diagram with best fit of ANN prediction vs. actual weld-seam width for training patterns.

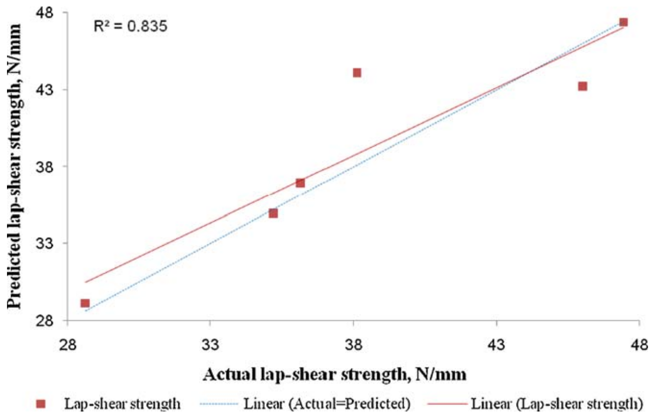

Fig. 8. Scatter diagram with best fit of ANN prediction vs. actual lap-shear strength for test patterns.

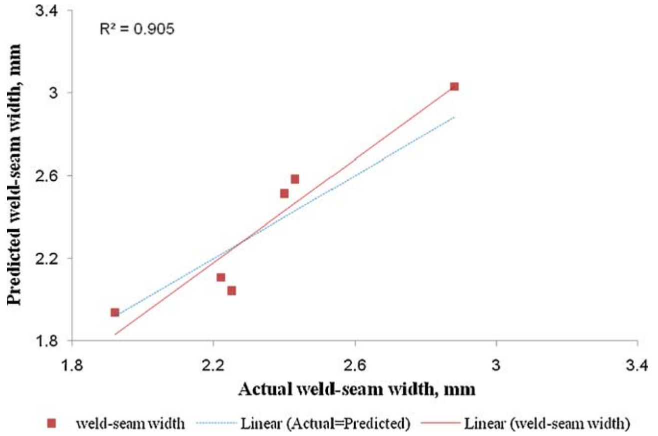

Fig. 9. Scatter diagram with best fit of ANN prediction vs. actual weld-seam width for test patterns.

shows the sensitivity of power on lap-shear strength and weld-seam width is positive, which indicates an increase in the value of the outputs with an increasing value of the power. It is noticed from the above figure, that lap-shear strength and weld-seam width are more sensitive in the low power region than high power region. In Fig. 11, the negative value of welding speed sensitivity of lap-shear strength and weld-seam width indicate a decrease in the value of the outputs with increase of welding speed. It is seen that power and welding speed sensitivity of lap-shear strength is

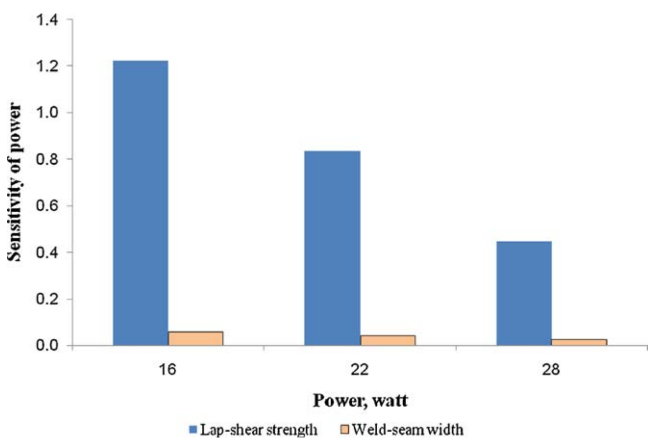

Fig. 10. Sensitivity anlysis results of power (Constant parameters: welding speed at 360 mm/min, stand-off distance at 32 mm, clamp pressure at 9.3 MPa).

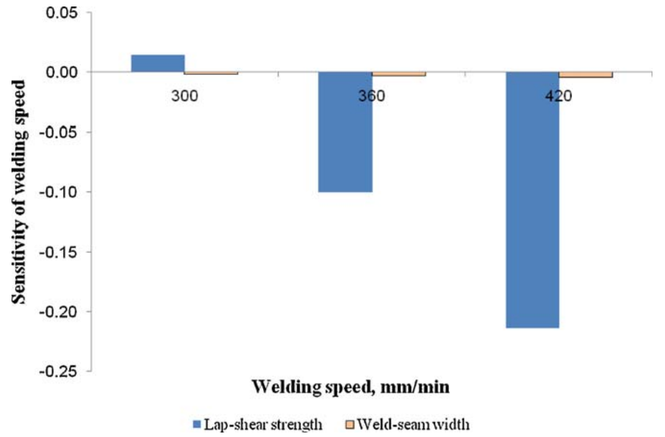

Fig. 11. Sensitivity anlysis results of welding speed (constant parameters: power at 22 W, stand-off distance at 32 mm, clamp pressure at 9.3 MPa).

superior to weld-seam width. It implies that the variation of power and welding speed causes a little change of weld-seam width and greater change of lap-shear strength. Fig. 12 presents the stands-off distance sensitivity results of lap-shear strength and weld-seam width. The stands-off distance sensitivity on weld-seam width is much less than on lap-shear strength and, thus, it is difficult to plot the two with a common primary vertical axis. Therefore, the stands-off distance sensitivity of weld-seam width is plotted with primary vertical axis and the same for lap-shear strength is plotted with secondary vertical axis. The trend of stands-off distance sensitivity of weld-seam width is negative. The stands-off distance sensitivity of lap-shear strength is quite interesting as it is positive with lower stands-off distance values and negative with the higher value of stands-off distances. The sensitivity of clamp pressure on lap-shear strength and weld-seam width is positive, as shown in Fig. 13. The lap-shear strength is more sensitive in the low clamp pressure region but sensitivity of weld-seam width increases in the high clamp pressure region.

5.2. Comparative study of ANN and multiple regression models

The performances of ANN and multiple regression models are compared in terms of mean prediction error (%), for predicting the laser transmission weld quality. Linear and 2nd order polynomial models, for lap-sear strength and weld-seam width, are developed using multiple regression analysis (MRA). Twenty experimental data sets, which are used to develop the ANN model, are

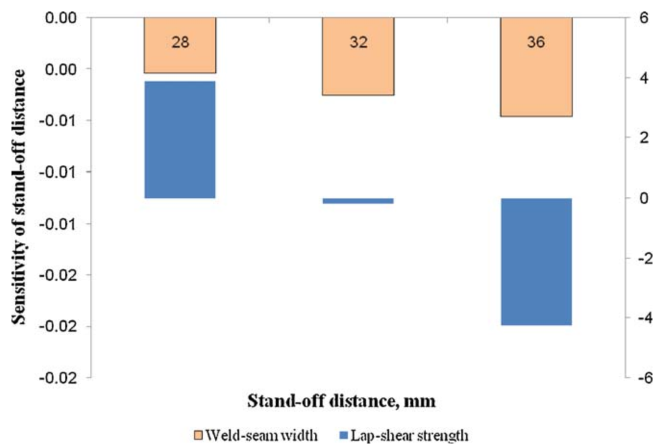

Fig. 12. Sensitivity anlysis results of stand-off distance (constant parameters: power at 22 W, welding speed at 360 mm/min, clamp pressure at 9.3 MPa).

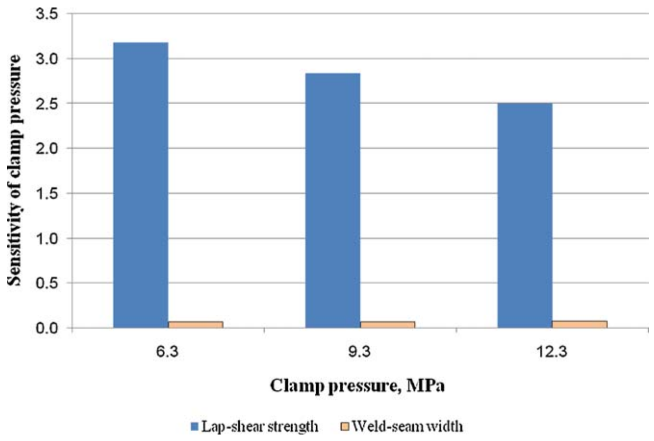

Fig. 13. Sensitivity anlysis results of clamp pressure (constant parameters: power at 22 W, welding speed at 360 mm/min, stand-off distance at 32 mm).

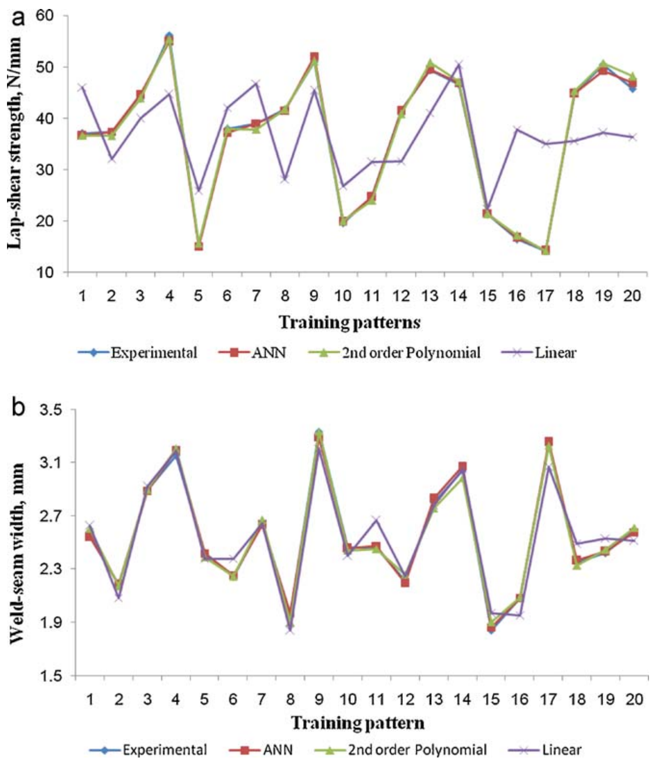

Fig. 14. Comparison between ANN and MRA models for prediction of (a) lap-shear strength and (b) weld-seam width, using training patterns.

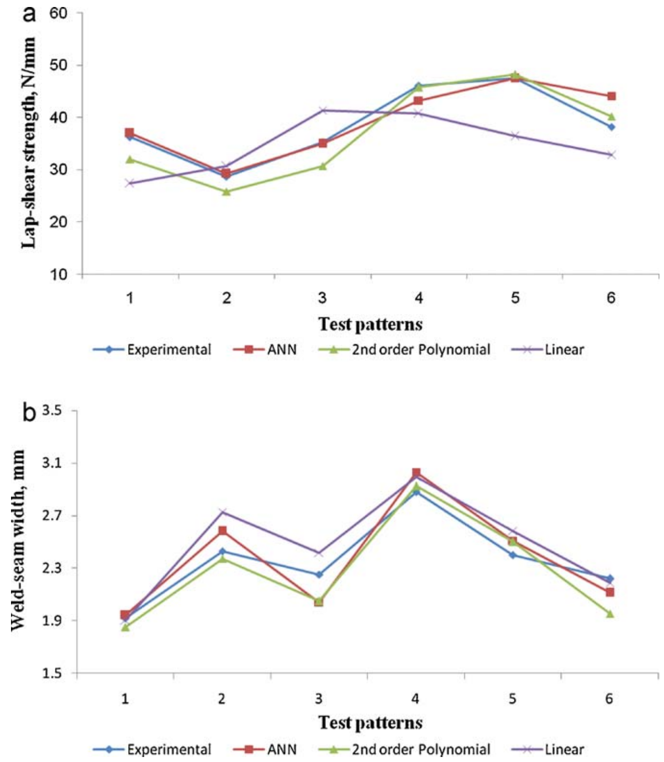

Fig. 15. Comparison between ANN and MRA models for prediction of (a) lap-shear strength and (b) weld-seam width, using test patterns.

also used to develop the MRA models. The remaining 6 data sets are used for testing the developed models. The comparison plots of the experimental data and prediction data of the lap-sear strength and weld-seam width for the MRA and ANN models are shown in Figs. 14 and 15, respectively. It can be observed from these figures that the results obtained by ANN model are in closer agreement with the experimental results for training and testing samples than those for MRA models. In Tables 5 and 6, the ability of the models to predict the test data is furnished. ANN model shows a good prediction rate as compared to the traditional predictive models and, thus, the ANN model can be readily employed to predict the laser transmission welding outputs.

Table 5
Comparison of performance between ANN and MRA models for predicting lap-shear strength.

Model	Mean prediction error (%)	Maximum prediction error (%)	Minimum prediction error (%)
ANN	4.4401	15.5865	0.1054
2nd order polynomial	7.0613	13.0114	0.7820
Linear	16.2643	24.5189	6.8477

Table 6
Comparison of performance between ANN and MRA models for predicting weld-seam width.

Model	Mean prediction error (%)	Maximum prediction error (%)	Minimum prediction error (%)
ANN	5.2157	9.3333	1.0417
2nd order polynomial	5.4832	12.0601	1.5557
Linear	5.6201	12.1625	0.9753

6. Conclusions

The aim of this paper is to show the possibility of the use of neural networks for the determination of the weld quality in terms of weld strength and weld dimensions for laser transmission welded thermoplastic sheets. Results show that, the neural network can be used as an alternative way in these systems. The neural network model is proposed to estimate the lap-shear strength and weld-seam width, using the process variables. The validation of the model is evaluated quantitatively, using the mean prediction error (%). The best architecture, obtained for the present work, is 4-4-5-

2, using back-propagation algorithm with adaptive learning rate. The correlation coefficients (R^2) for training and test patterns for lap-shear strength and weld-seam width are close to unity, which indicate excellent agreement between experimental data and predicted values. Furthermore, a comparison is made between MRA and ANN models for prediction of laser transmission welding outputs. ANN model shows a better prediction rate as compared to the MRA models.

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at doi:10.1016/j.asoc.2010.10.005.

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