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Prediction model for determining the optimum operational parameters in laser forming of fiber-reinforced composites

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Abstract Composite materials are widely employed in various industries, such as aerospace, automobile, and sports equipment, owing to their lightweight and strong structure in comparison with conventional materials. Laser material processing is a rapid technique for performing the various processes on composite materials. In particular, laser forming is a flexible and reliable approach for shaping fiber-metal laminates (FMLs), which are widely used in the aerospace industry due to several advantages, such as high strength and light weight. In this study, a prediction model was developed for determining the optimal laser parameters (power and speed) when forming FML composites. Artificial neural networks (ANNs) were applied to estimate the process outputs (temperature and bending angle) as a result of the modeling process. For this purpose, several ANN models were developed using various strategies. Finally, the achieved results demonstrated the advantage of the models for predicting the optimal operational parameters.

Keywords Laser forming (LF) · Fiber-reinforced composite · Fiber-metal laminates (FMLs) · Glass laminate aluminum reinforced epoxy (GLARE) · Artificial neural networks (ANNs)

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1 Introduction

A laser forming (LF) process is a non-conventional method used for material shaping, which can be employed in various industries, such as aerospace and automotive [1, 2]. This technology works based on the generated stresses due to the thermal effect of the laser irritation. The laser heat penetrates through the material surface, and then the cooling process occurs rapidly. This procedure results in a local expansion in the irradiated location and generates thermal stresses and resultant plastic deformation in this area. Laser bending is a class of LF process that can be applied in several manufacturing industries. It can be employed as a rapid prototyping method for deforming metal sheets using a concentrated laser beam [3]. The advantage of this process is the quick, non-contact procedure employed without applying any external force [4]. Nevertheless, it is challenging to apply this process owing to the effects of laser operational parameters on factors including absorption rate, strain hardening and microstructural defects.

Fiber-metal laminates (FMLs) are common and high-performance composite materials with numerous applications in the aerospace and aeronautics industries. They are made of thin layers of metal sheets and a fiber-reinforced polymer, and this combination can provide high toughness and fatigue strength with lightweight properties [5]. Owing to these advantages, FMLs can be used as substitutes for aluminum and magnesium alloys in several metallic products [6]. Airbus A380 is a good example related to the wide application of composite materials. FML composite with glass fibers (glass laminate aluminum reinforced epoxy (GLARE), and Kevlar aramid-reinforced aluminum laminate (ARALL) have been used in the production of this aircraft [7]. Compared with conventional aluminum alloys, GLARE provides up to 30% weight reduction, outstanding fatigue endurance, and excellent impact resistance because of crack bridging and glass fibers. The combination of titanium and graphite polymer (TiGr) is another type of FML with a particular performance, as well as both metal and fibers composite materials [8]. The novel form of hybrid laminates can prevent and arrest crack growth caused by cyclic loading, with high impact and damage tolerance features and low density. Accordingly, this type of composite plays an important role in the aerospace and spacecraft industries [9].

An artificial neural network (ANN) is a data-processing algorithm inspired by natural nervous operations, such as the human brain, with a structure of a countless number of extremely connected processing components (neurons) operating simultaneously. Recently, ANN has been applied as an accurate prediction model for achieving the optimal operational parameters in various fields, such as manufacturing and material processes. For example, Hassani et al. [10] successfully developed an ANN model for predicting the bending angle during LF of steel material. Selvakumar et al. [11] applied ANN modeling for the forming process of Al-Fe composite based on experimental data, and the model could predict the forming parameters, e.g., hydrostatic and axial stresses and the Poisson ratio. Mishra et al. [12] employed a prediction model for estimating the mechanical properties of machined glass-fiber-reinforced plastic laminates, e.g., residual tensile stress using the ANN approach and reported that the model results were in good agreement with the experimental data.

Simulation or modeling techniques can be applied as prediction tools to improve the quality of laser processes by determining the optimum operational parameters [13–17]. This study deals with the LF of FMLs using a high-power diode laser (HPDL). The purpose of this study is to determine the optimum parameters in the LF process using an ANN model. This model uses experimental data, including the laser parameters, as the input, and temperature and bending angle as the output, for training the model. From the results, the model predictions are in good agreement with the experimental data sets, which is provided for the validation of the ANN model.

2 Experimental setup

2.1 Material and equipment

Two types of FMLs composite were used in this study. The first type was called GLARE 1 and consisted of three layers. The first and last layers were made of aluminum alloy (AA7475-T671), and the middle layer was a composite material. Three sheets of GLARE 1 were cut to a size of 1 000 mm × 1 500 mm × 1 mm using a diamond blade under controlled temperature.

The second composite was called GLARE 2, and comprised of a total of five layers. Three layers were made of aluminum alloys (AA2024-T3), and the composite material was laid in between the aluminum-alloy layers. Additionally, three sheets of GLARE 2 were cut to dimensions of 1 000 mm × 1 500 mm × 2 mm. Both composites were made of a thermoset matrix reinforced with glass fiber, and they were supplied by GTM Advanced Structures Company, Hague, Netherlands.

An HPDL system (Rofin Sinar, DL015 model) with a maximum power of 1 500 W and wavelength of 940 nm was applied for the LF process. The system was applied because of its excellent interaction with aluminum and its low cost. The laser spot was ellipse-shaped with diameters of 1.2 mm and 3.8 mm. Moreover, the laser pass was oriented in the direction of the smaller side during the process.

The bending angles were measured using a Mitutoyo optical projector, while the combination of a thermocouple and thermographic camera was used to measure the temperature outputs. The generated temperature achieved during the laser process was measured using a type K thermocouple (nickel-chromium).

2.2 Experimental procedure

Two steps were followed during this experiment. In the first step, a single laser pass was used for GLARE 1 and GLARE 2 materials to identify the acceptable operational parameters for the bending process. Then, the sequence of laser passes on the surface of the materials was investigated in the second step to obtain the curve profile. Subsequently, the laser paths were designed to perform along an equal distance on the flat laminate surface to determine the desired bending angle. Figure 1 shows a schematic of the experimental process for both GLARE 1 and GLARE 2 composite materials.

As shown in Fig. 1a, the laser beam was irradiated along a straight path at the center of the sheet. Table 1 illustrates the experimental setup for two various composite materials, including 36 and 24 tests for GLARE 1 and GLARE 2, respectively. The results of the primary experimental operation were temperature and bending angle.

The second experimental process was performed based on the initial settings developed from the results of the first experimental analysis. The goal of the second process was to reach the curve profile of FMLs using the parallel lines on the surface of the composite sheet, as shown in Fig. 1b. Table 2 shows the various parameters included in the

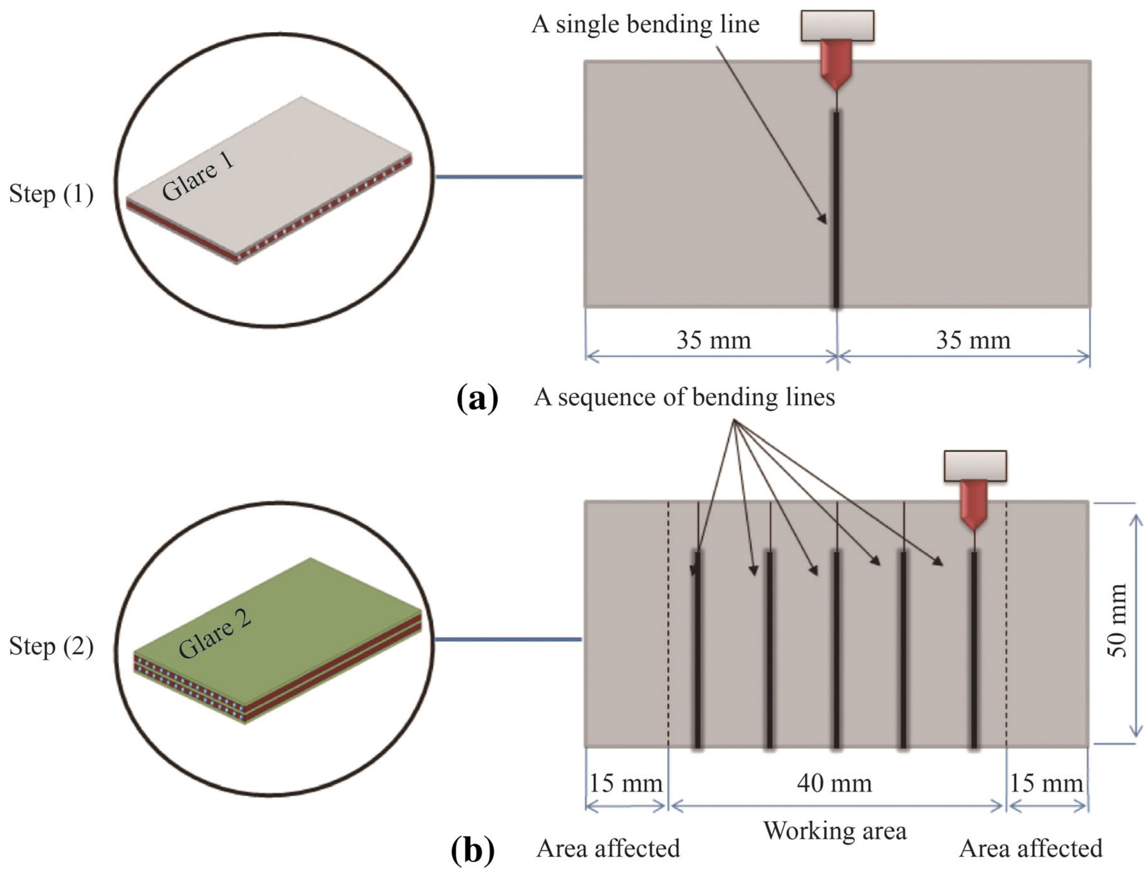

Fig. 1 Experimental set-up **a** for GLARE 1 in the first step and **b** for GLARE 2 in the second step

Table 1 Experimental set-up

	Power/W	Scan speed/(mm·s^{-1})	N pass
GLARE 1	145	10	3
	185	15	6
	225	20	–
GLARE 2	125	10	3
	150	20	6
	175	–	–

Table 2 The second experimental set-up

	Power/W	Scan speed/(mm·s^{-1})	Pitch/mm	N passes	N bending lines
GLARE 1	225	20	3	5	9
				7	7
				8	6
				10	5
GLARE 2	165	20	3	10	5
				13	4

second part of the experiment. The capability of the process and mainly laser bending of FMLs are significantly dependent on the operational parameters and fundamental experiment design. Accordingly, a higher number of bending lines were applied to bend GLARE 1 (up to 9 lines) during the second experiment because of its higher flexibility (a three-layer material). Conversely, a smaller number of bending lines were applied for bending GLARE 2 (up to 5 lines) due to its less flexible structure (five layers and more material). A high-resolution scanner was used to measure the curvature radii (Artec 3D, Artec Space Spider, Luxembourg).

3 ANN setup and progress

The neural network model consisted of two phases including learning and recall. The recall phase function is based on the obtained weight from the learning phase of the data set achieved from the input and output, which is recorded from the real experimental dataset [18]. Several ANN models were investigated using MATLAB 2017 to determine the optimal network. Table 3 presents a summary of the characteristics of the optimal network.

Figure 2 represents the applied neural network model with the application of two hidden layers. As can be seen from Fig. 2, the laser power, scan speed, and numbers of passes were considered as the inputs, whereas the temperature and bending angle were considered as the outputs. To increase the dimension of the input features, the temperature and bending angle attend to the input subset because the temperature and bending angle parameters are interrelated, and it improves the accuracy of the network. In this study, a logsig transfer function was used in a multilayer perceptron (MLP) network as a function approximation in the model structure [19]. In addition, the MLP network was designed and trained with the Levenberg-Marquardt (LM) and adaptive learning rate Back-Propagation (BP) algorithm. Different indexes were used in assessing the ability of each model to evaluate the capability of networks as predictable tools. These indexes are as follows: coefficient of determination (R^2), root mean square error (R_{RMSE}), coefficient of correlation (R).

The best fit between the desired and predicted values would be $R_{\mathrm{RMSE}} = 0$ and $R = 1$.

As mentioned previously, the MLP network was performed using MATLAB. Through the training process, the biases and weights of the ANN model were iteratively adjusted to minimize the errors between the network results and the real outputs. According to the trial study, the primary learning rate was achieved at each epoch with the optimum performance goal [20].

The LM algorithm has been applied as a learning rule in MLP network models to achieve a faster training process, compared to the momentum learning. The LM algorithm is broadly used as a second-order learning algorithm for optimizing problems, and it is usually for small networks due to numerous computations and large memory requirements. The main advantage of the LM algorithm is the minimization of training error, which consequently increases the model accuracy [21]. This algorithm, which was developed by Levenberg [22] and Marquardt [23], is based on a least-square estimation of the nonlinear parameters expressed as [24]

$$\min_{\boldsymbol{x}} \|F(\boldsymbol{x})\|_2^2 = \min_{\boldsymbol{x}} \sum_i F_i^2(\boldsymbol{x}). \tag{1}$$

where vector $\boldsymbol{x}$ is the local minimizer, and the $F(\boldsymbol{x})$ function is the sum of squares.

The BP algorithm is a supervised learning algorithm that contains forwarding computing and backward learning. It was employed in this study to compute the efficiency function derivatives according to the weight and inclination factors of the network and to minimize mapping errors in cooperation with neurons. Further information is provided in Refs. [18, 19, 25] on the BP algorithm.

Table 3 Characteristics of selected network

Parameter	Characteristic
Activation function	Logsig-Logsig
Number of layers	2
Number of neurons	20–20
Data davison percentage	70–15–15
Number of epochs	1 000
Type of learning rule	Levenberg-Marquardt, Back-Propagation
Type of code	MATLAB code
Software requirement	MATLAB

4 Results and discussion

The experimental results were collected from a previously published study [5], which investigated the effect of laser parameters (including laser power and velocity, and number of passes) on the formability of FMLs. In this study, a multiple scanning method was introduced to achieve the final structure. Therefore, this section directly discusses the results of the modeling process. This ANN model was used to present a predictable tool for estimating two relevant targets: temperature and bending angle. The MLP neural network was employed with the application of LM and BP algorithms for modeling the experimental data, including both the inputs and outputs, and all the results were obtained based on the coefficient of determination (R^2) value. The coefficient of determination is a generally applied statistical approach used for presenting data on the strength of the linear correlation connecting the observed and the calculated values. Figure 3 depicts the comparison between the measured and the predicted temperatures for GLARE 1 in the training and testing phases. These graphs show the best fitting line between the calculated and desired output data set with respect to the temperature data for various learning rates and the number of hidden layers.

Table 4 shows the statistical reports of linear regression for the temperature parameter related to GLARE 1. The minimum values for the total observed data were achieved, and the lowest R^2 value for the training and testing phases were 0.999 86 and 0.978 45, respectively. Moreover, the coefficient of determination of these models for the testing temperature set was close to 1. Therefore, the correlation of determination for the testing set demonstrates the output accuracy, which is due to the capability of the LM algorithm for predicting laboratory outputs.

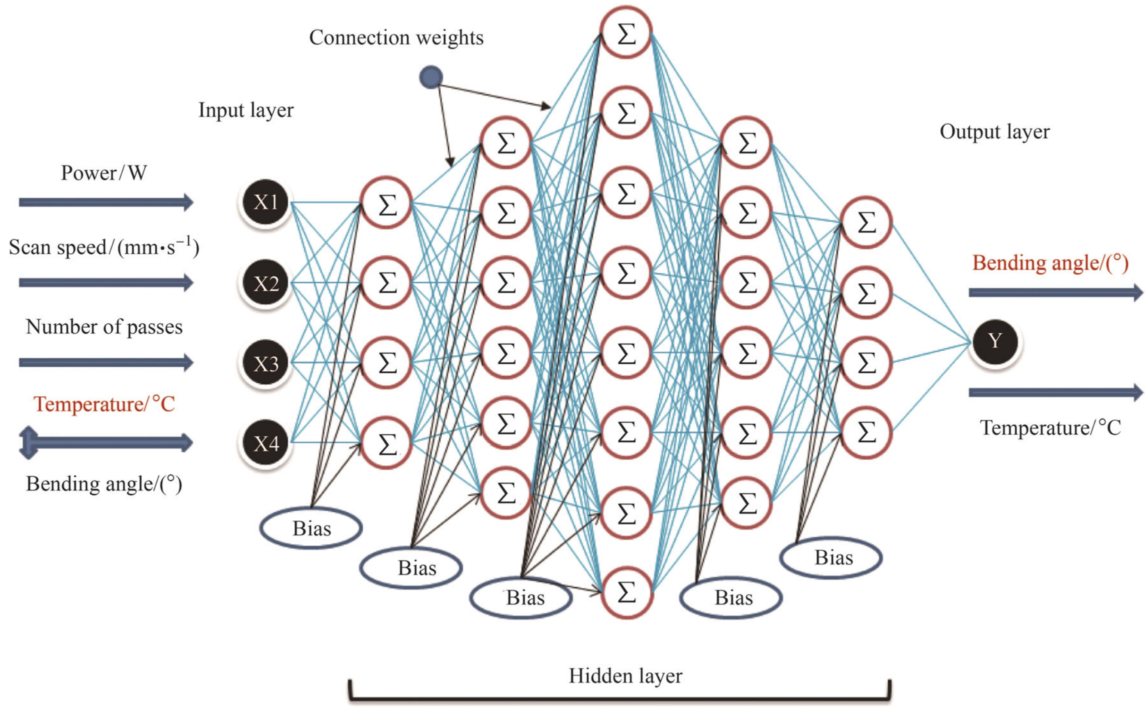

Fig. 2 Schematic of the neural network model

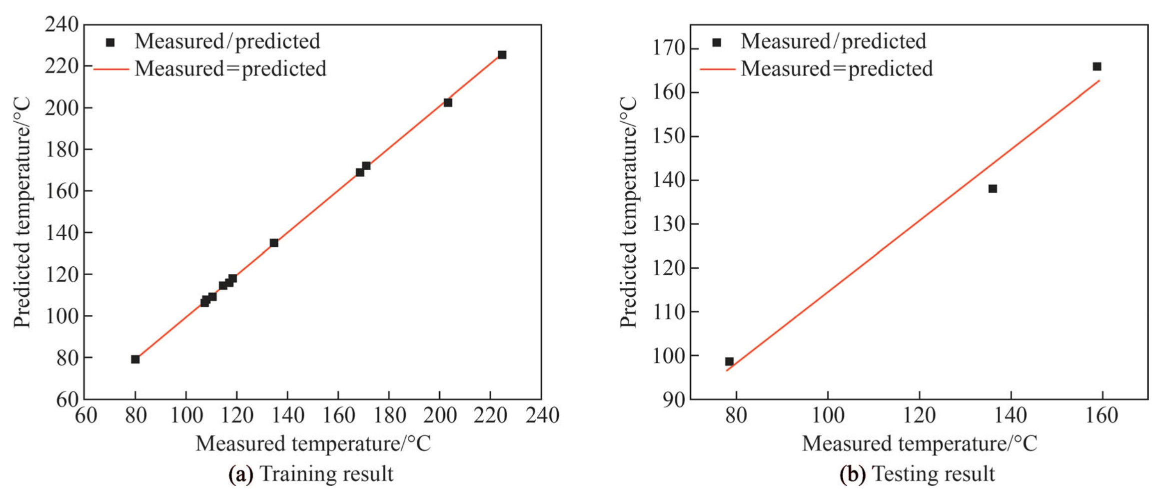

Fig. 3 Comparison between the measured and the predicted temperatures in the training/testing phase (GLARE 1)

Table 4 Statistical report of linear regression in the training and testing phase (temperature)

Statistical parameters	Training	Testing
Residual sum of squares	2.985 57	49.397 10
Pearson's ratio	0.999 93	0.989 17
Coefficient of determination (R^2)	0.999 86	0.978 45
Adj. R-square	0.999 85	0.956 91

The same model was employed for predicting the bending angle for GLARE 1. Linear regression analyses were also applied to estimate the correlation of determination for the ANN model. Figure 4 shows the relationship between the real and the predicted output data and, it can be observed that the value of R^2 is close to unity, which proves the capability of the modified model. According to Table 5, the R^2 value is 0.980 6 for the training and 0.963 2 for the testing of the bending angle. The MLP model provides an excellent fitting for each of the two bending phases with the experimental results.

As mentioned previously, the prediction model that was applied for the GLARE 1 yielded excellent results, and the network could be used to predict any experimental results related to the temperature and bending angle accomplished through the LF process. Accordingly, the same model was applied to investigate GLARE 2 using similar connection weights and bias. Figure 5 displays the trend of the experimental data and a regression model of the correlation between the real and the predicted temperature output values for GLARE 2. Table 6 shows that the achieved results have an excellent performance and can be used to accurately predict the temperature of the LF process with an average predicting error of less than 5%.

Figure 6 shows the comparison of the measured and predicted bending angles for GLARE 2. From the obtained results, which are listed in Table 7, the predicted data show good agreement with the measured bending results. Furthermore, these results demonstrate that the proposed approach is an accurate and reliable model for precisely predicting the forming under variable parameters and conditions.

The ANN data processing can be improved by increasing the size of the databases of effective parameters, expanding the number of recorded datasets in the laboratory, or both [26]. The strategy of increasing the number of data was applied in this study through data mining, which was a combination of the GLARE 1 and GLARE 2 data sets. Figure 7 shows the network performance results of the training and testing phases of the temperature process of the GLARE 1 and GLARE 2 materials. As can be seen from Fig. 7, the coefficient of determination (R^2) for the temperature increased from 0.978 4 for GLARE 1 to 0.981 1 for GLARE 1 + GLARE 2 based on the new method, as listed in Table 8.

Table 5 Statistical report of linear regression in the training and testing phase (bending angle)

Statistical parameters	Training	Testing
Residual sum of squares	5.136 46	1.594 42
Pearson's ratio	0.995 22	0.981 21
Coefficient of determination (R^2)	0.980 65	0.963 24
Adj. R-square	0.977 72	0.896 49

Linear regression was used to compare the predicted data of temperature and bending angle. Figure 8 shows the best fitting performance of the training and testing phases of the bending angle from the combined data of GLARE 1 and GLARE 2. The statistical parameters, such as coefficient of determination, increased significantly from 0.963 2 for GLARE 1 to 0.987 6 for GLARE 1 + GLARE 2, as shown in Table 9. The results prove that a relationship between the value of the data and the accuracy of the network model exists.

Table 10 compares the statistical reports obtained from linear regression fitting curves for the training and testing phase of GLARE 1 versus GLARE 1 + GLARE 2 data sets for temperature and bending angle, respectively. The correlation between the training and testing phases of the bending angle for GLARE 1 and GLARE 1 + GLARE 2 is close to 1. Therefore, the obtained results prove the database modification effect in increasing the value of data inside the database, as well as the ability of the implemented model to predict the experimental values of temperature and bending angle. Furthermore, it is confirmed that the improved MLP model with the LM algorithm is reliable and suitable for the LF of FMLs. From the results, it can be observed that one of the applicable techniques is

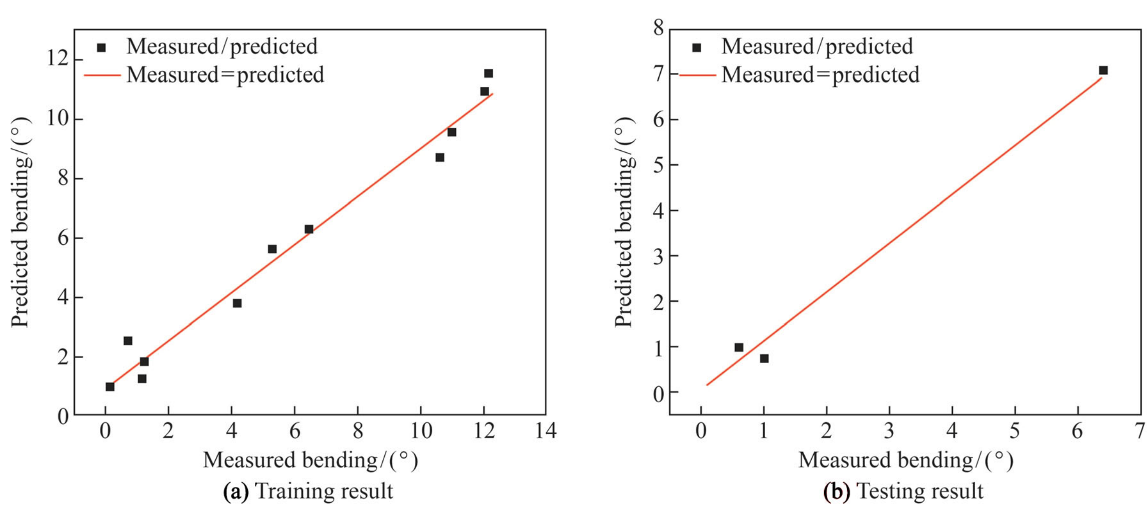

Fig. 4 Comparisons between measured bending and predicted bending in the training/testing phase (GLARE 1)

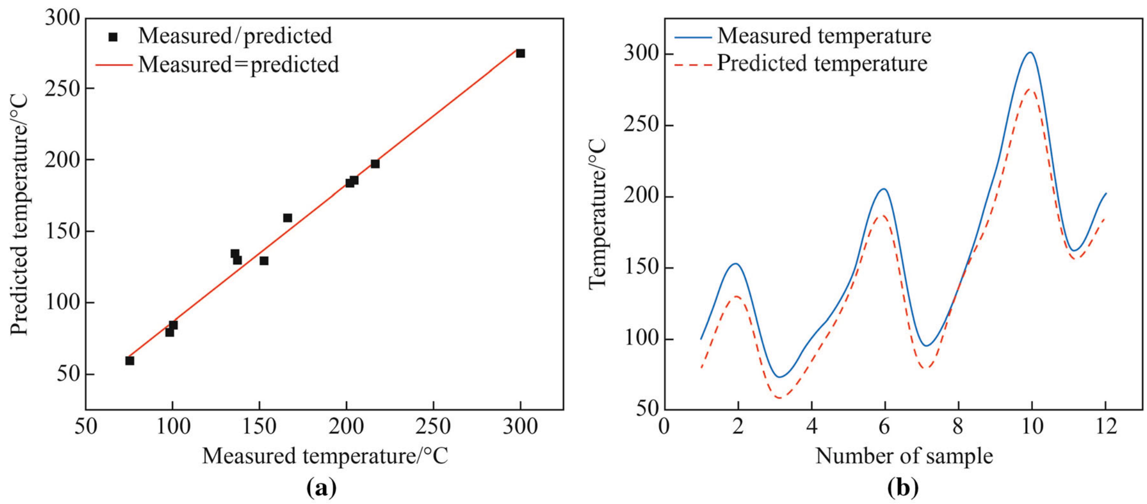

Fig. 5 Comparisons between measured and predicted temperature (GLARE 2)

Table 6 Statistical report of linear regression in the prediction phase (temperature)

Statistical parameters	ANN result
Residual sum of squares	49.397 14
Pearson's ratio	0.989 17
Coefficient of determination (R^2)	0.978 45
Adj. R-square	0.956 91

Table 7 Statistical report of linear regression in the prediction phase (bending angle)

Statistical parameters	ANN result
Residual sum of squares	1.594 42
Pearson's ratio	0.981 21
Coefficient of determination (R^2)	0.963 24
Adj. R-square	0.896 49

to enhance the model accuracy by compiling a database with recorded data from several laboratories and employing the training and testing phases of the prediction.

5 Conclusions

This paper presents a prediction model for the LF of two different types of FML composite materials using several neural network models. The prediction tool was applied as a reliable method to determine the temperature and bending

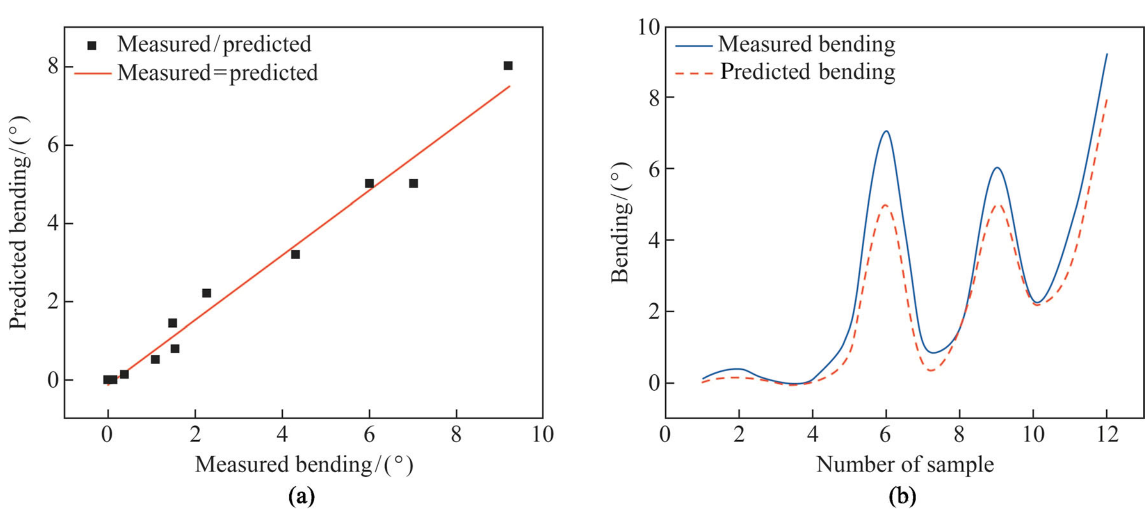

Fig. 6 Comparisons between measured and predicted bending angle (GLARE 2)

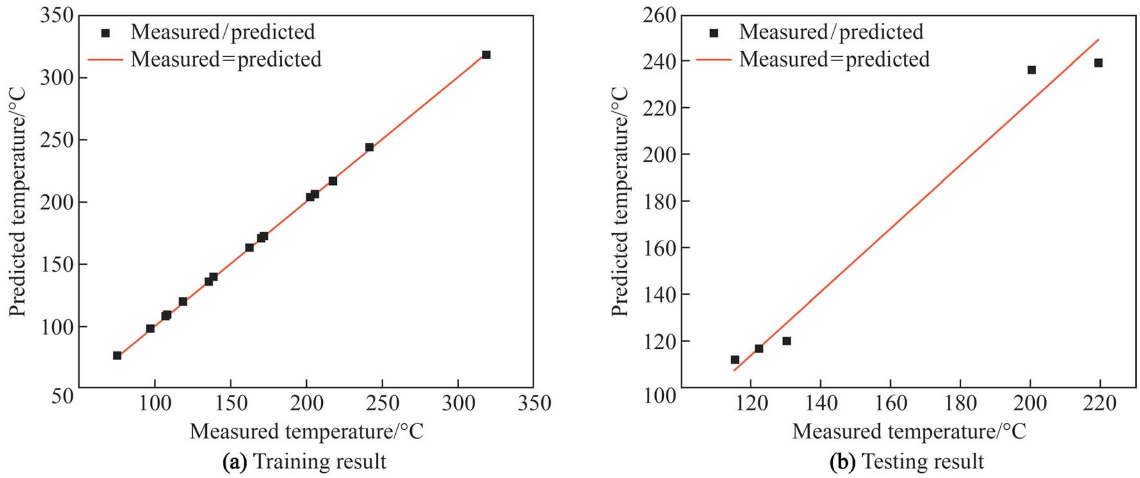

Fig. 7 Training and testing results of the GLARE 1 and GLARE 2 model for temperature

Table 8 Statistical report of linear regression in the training and testing phase (temperature)

Statistical parameters	Training	Testing
Residual sum of square	4.854 09	337.389 00
Pearson's ratio	0.999 96	0.990 52
Coefficient of determination (R^2)	0.999 92	0.981 12
Adj. R-square	0.999 91	0.974 83

Table 9 Statistical report of linear regression in the training and testing phase (bending angle)

Statistical parameters	Training	Testing
Residual sum of squares	2.272 57	0.403 07
Pearson's ratio	0.995 46	0.993 81
Coefficient of determination (R^2)	0.990 95	0.987 64
Adj. R-square	0.990 45	0.983 52

angle during the LF process based on the operational parameters (laser power and scan speed). In this study, an MLP model was employed by applying the LM algorithm for the simulation of the process variables. From the results of the study, the following conclusions can be drawn.

(i) The ANN model was proposed to estimate the temperature and bending angle based on the process inputs, including laser power and scan speed. The validation of the model was evaluated quantitatively using a mean prediction error based on the coefficient of determination (R^2).

(ii) The correlation of coefficients (R^2) for the training and testing patterns for the bending angle and temperature are close to unity, which demonstrates excellent agreement between the experimental data and predicted values.

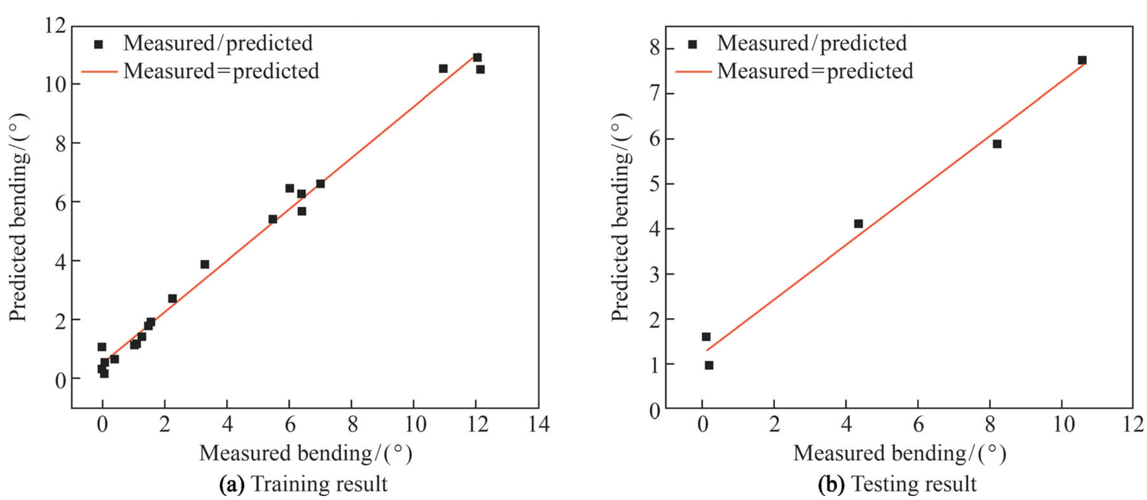

Fig. 8 Training and testing results of the GLARE 1 and GLARE 2 model for bending angle

Table 10 Comparison of the coefficients of determination for GLARE 1 and GLARE 1 + GLARE 2 (temperature and bending)

Phases	Coefficient of determination (R^2)	
	GLARE 1	GLARE 1 + GLARE 2
Training temperature	0.999 86	0.999 92
Testing temperature	0.978 45	0.981 12
Training bending angle	0.980 65	0.990 95
Testing bending angle	0.963 24	0.987 64

(iii) The ANN model can be applied as a production tool for optimizing the LF of FMLs. The neural network solution can be a powerful tool for predicting, controlling, and managing laser processing and an adequate alternative to analytical and numerical models.

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