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Prediction of Bending Angle for Laser Forming of Tailor Machined Blanks by Neural Network

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Abstract: Tailor-made blanks are sheet metal assemblies with different thicknesses and/or materials and/or surface coatings. A monolithic sheet can be machined to make the required thickness variations referred to as tailor machined blanks. Due to the thickness variation in tailor machined blanks, laser bending of these blanks is more complicated than that of monolithic plates. In this article, an artificial neural network (ANN) will be configured to predict the bending angle of laser formed tailor machined blanks. The input parameters of neural network are selected as the start point of scan path, laser irradiating method, laser beam diameter, laser output power and the number of radiation passes. The results show that a 5×8×1 trained neural network can predict the bending angle with acceptable accuracy. Comparison of the randomly selected tests with experimental results shows 1.1% error in the prediction of bending angle by trained artificial neural network.

Keywords: Tailor machined blank, Laser forming, Artificial neural network, Bending angle.

1. Introduction

By developing the laser technology, a non-traditional manufacturing process called "laser forming" is developed. The laser beam is used as a tool. The contactless tool can form the sheet in the desired shape by controlling the intensity of laser beam power and movement speed. Laser bending is developed by using laser technology to bend the sheet to the specified curvature. The thermal gradient along the scanning path of laser beam leads to beam bending [1]. The bending of single layer sheets by laser forming had been studied by different researchers [2-6]. Fetene et al. [3] studied the effects of process parameters (power, thickness, width, number of passes, scan speed and laser beam diameter) on laser bending of AH36 steel strips. Due to the laser source travel, asymmetry in the formed samples will happen. Maji et al. [4] used surface response methodology to find the effect of the process parameters on bending angle. Wang et al. [7] used ANSYS software for the simulation of laser bending by FEM software. Some researchers proposed special scanning patterns to form complicated shapes by laser forming. Wang et al. [8] proposed a scanning planning for the fabrication of a curved tube. Chakraborty et al. [9] proposed a new approach for laser forming of a bowl-shaped surface by irradiating the center of a flat circular blank. The investigations show that the laser beam diameter has a significant effect on the bending pattern. The blanks bent towards the laser beam for smaller laser beam diameters and the reverse happened for larger spot diameters (~10 times of the sheet thickness).

The designers always try to reduce the weight of structure by modifying the material distribution. Tailor Machined Blanks (TMB) and Tailor Welded Blanks (TWB) are two concepts that have been developed by researchers to improve the stress distribution in the parts. The tailor welded blanks consist of two or more parts with different thicknesses that have been assembled and welded together. Kreimeyer et al. [10] used laser beam to weld aluminum to titanium blanks with different thicknesses. The tailor

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machined blanks are prepared by eliminating the material through mechanization and reduction of thickness in the sheet sections. The TMBs have more structural integrity than TWBs. The TMBs are used as structural parts in the aviation and automotive industries. The main shortcoming of the tailor machined blanks is the difficulties of forming. The thickness varies in different locations of the sheet. Merklein et al. [11] have published a review paper on different manufacturing processes associated by tailored blanks. Zadpoor et al. [12] studied the effect of the machining process and thickness ratio on tailor machined blanks. The investigation shows that both the machining process and the thickness difference have a significant impact on the forming behavior and failure mechanism of the specimens. Bending to a specified curvature radius is a forming process that depends on the thickness of the sheet. Therefore, different bending angles and curvature radii will be obtained in various sections of the blank, and laser bending of tailor machined blanks is more difficult than that of monolithic sheets [13, 14].

Recently, the artificial intelligence is employed for modeling, prediction and decision making in the manufacturing processes. Among different artificial intelligence tools, the artificial neural network (ANN) is the most interesting for the researchers due to its powerful prediction of complex systems. The neural network can be used in nonlinear systems to predict the output with considerable accuracy [15-21]. The neural network consists of three layers, input layer, hidden layers and output layer. The input layer consists of nodes associated with the process parameters, and the output layer determines the predicted parameter. The hidden layers find the relation between the input and the output by finding the optimum set of coefficients in the training progress of ANN. Averett et al. [15] used ANN to predict the residual mechanical properties and fatigue life. Han et al. [16] established an adaptive fuzzy-neural network model for material property prediction during high temperature deformation by less than 10% error. Sabokpa et al. [17] used a feed-forward back propagation ANN to predict the high temperature flow behavior of an AZ81 magnesium alloy. The results showed that the trained ANN is more efficient and accurate to predict the hot compressive behavior of cast AZ81 magnesium alloy than the constitutive equations. Haghdadi et al. [18] carried out a similar study to predict the materials flow behavior at high temperature in cast A356 aluminum alloy. In 2013, Abbassi et al. [19] employed the finite element coupled with ANN to identify the parameters of damage model in ductile materials. The neural network tool has been implemented in laser forming by some researchers in recent years. Cheng and Lin [20] employed the neural network in order to estimate the bending angle in laser forming. The input layer nodes were forming parameters including spot diameter, scan speed, laser power, and workpiece dimensions (thickness and length of the sheet). The results showed that using radial basis function for neural network model can predict the bending angle precisely. In 2011, Gisario et al. [21] predicted and controlled the springback phenomenon in sheet metal bending by laser-assisted bending using neural network.

The use of new forming technology based on non-traditional tools is increasing in the new world. Among the 21st century technologies, the laser beam technology can have an outstanding position. The authors have done several researches in the field of laser forming [13, 14, 22, 23]. The laser beam is a powerful tool and complicated shapes can be fabricated by controlling the process parameters. In this way, an engineering attitude can help the researchers to utilize the full capability of the laser beam technology. One of the main problems in using laser beam technology in forming is the local effect on the sheet forming. Despite the mechanical forming technology that apply the load or pressure on the wide area of the blank, local forming by laser can lead to distortion, wrapping or lack of geometrical dimensioning and tolerancing. These undesirable effects can be restricted by using predictive tools. The literature survey shows that few researches have been carried out in the application of neural network to model laser forming process. All of laser forming, tailor machined blanks and neural network have been introduced recently, and based on the author's knowledge, there are not any reported researches on the application of neural network to model the laser bending of tailor machined blanks.

As it was mentioned above, the existence of two different thicknesses in one single assembly leads to different forming behaviors such as different bending angles and curvatures in various sections of the blank. Therefore, in this work, an artificial neural network (ANN) will be configured to predict the bending angle of laser formed tailor machined blanks.

2. Laser Bending and Network Training

In this section, firstly, the laser forming specification will be introduced, and then the neural network configuration will be explained.

2.1. Laser forming process

Tailor Machined Blanks (TMBs) are blanks with different thicknesses; the difference is due to different machining processes. In this work, the samples were prepared from mild steel with 200mm (length) × 200mm (width) × 2mm (thickness) dimensions. The thickness of half of the blank was decreased to 1 mm through the milling operation to prepare tailor machined blanks. Having machined the blank, it was located and fixed in its position by clamps. Fig.1 shows the schematic illustration of the sample and the irradiation path of the laser beam. The top surface of the blank was darkened with graphite coating to increase the laser beam absorption of the specimen. A continuous CO_2 was used for laser forming of the tailor machined blank. After passing the laser beam with specified speed and irradiation, the blanks bent due to the localized heating. The speed of beam travel is important and researches show different irradiation methods for laser processing [13]. Three main proposed irradiating methods are Equal Speed Method (ESM), Proportional Speed Method (PSM) and Improved Speed Method (ISM). In the ESM, the speed of travel is equal in both sections, while in PSM the speed is twice in the thinner section (proportional to the ratio of thick/thin thickness). The third method, ISM, needs running a series of numerical simulations. The graph for the variation of bending angle versus the irradiation speed should be obtained and plotted for each thickness separately. The decision on the speed in the thin section is made according to the equal bending angle for both sections. A detailed discussion can be found in [13].

After laser processing of the TMBs, the bending angles of the samples were measured using a coordinate measuring machine (CMM) at 11 locations along the scanning path. Fig.2 shows the bent tailor machined blank after the irradiation of laser beam and the consequent bending.

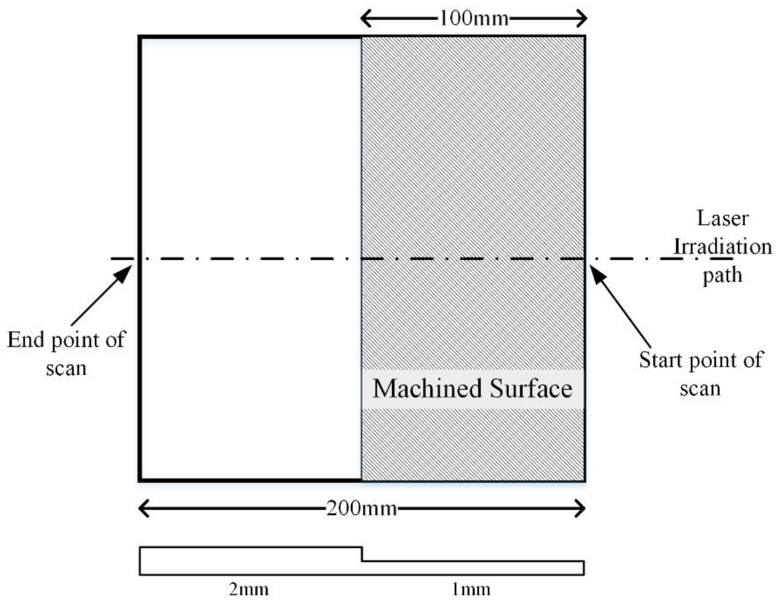

Fig.1. The blank dimensions and irradiating path.

Fig. 2. The tailor machined blank after laser forming.

2.2. Neural network configuration

Artificial neural network is developed to predict the nonlinear behavior of the phenomenon. The neural network consists of three different layers including input layer, hidden layer and output layer. The neurons of the input and output layers are equal to the number of input parameters and output parameters respectively. The hidden layer may be one or more layer and finding the relation between the inputs and outputs is its main job. The hidden layer multiplies different weight coefficients into the inputs to obtain the value of the output; however, finding the appropriate coefficients is not straightforward. These coefficients are found in a superior procedure called "training of network". In the current study, a neural network is constructed in the MATLAB neural network toolbox. The input layer has 5 neurons corresponding to the "Start point of scan", "Irradiating method", "Laser beam diameter", "Laser output power" and "Number of radiation passes". The desire of neural network prediction is the "Bending angle" (1 neuron in output layer). The training function is selected as "TRAINLM" function and the transfer function of ANN is selected as "TANSIG" function (hyperbolic TANgent SIGmoid function). Moreover, the adaption learning function is selected as "LEARNGDM" function. The TRAINLM function is a network training function that updates weight and bias values according to Levenberg-Marquardt optimization. It is often the fastest backpropagation algorithm in the MATLAB toolbox and is highly recommended as a first-choice supervised algorithm. Different levels were defined for input parameters according to the laser processing features and 18 experiments were designed for implementation. Each experiment was repeated 3 times and a total of 54 datasets were prepared for neural network configuration. 20% of the data (9 data experiments) was selected randomly among the total of 54 datasets and excluded from the datasets. These 9 data will be used for the examination of the trained network. The training of network includes entering the selected 45 datasets and the corresponding output to the network and letting the ANN algorithm find the proper coefficients by repeated epochs. Fig. 3 shows the regression results of network training and examination by the MATLAB software.

Table 1 shows the list of 54 experiments which were implemented experimentally. The subsequent bending angle obtained after laser processing is also showed in Table 1. It should be noted that the start point of laser beam scanning and the irradiation method are discrete quantitative values and the corresponding level of the parameters are showed by integer numbers according to the definition of Table 2. Table 3 shows the experimental test plannings implemented in this study. The test planning was carried out based on the orthogonal array method.

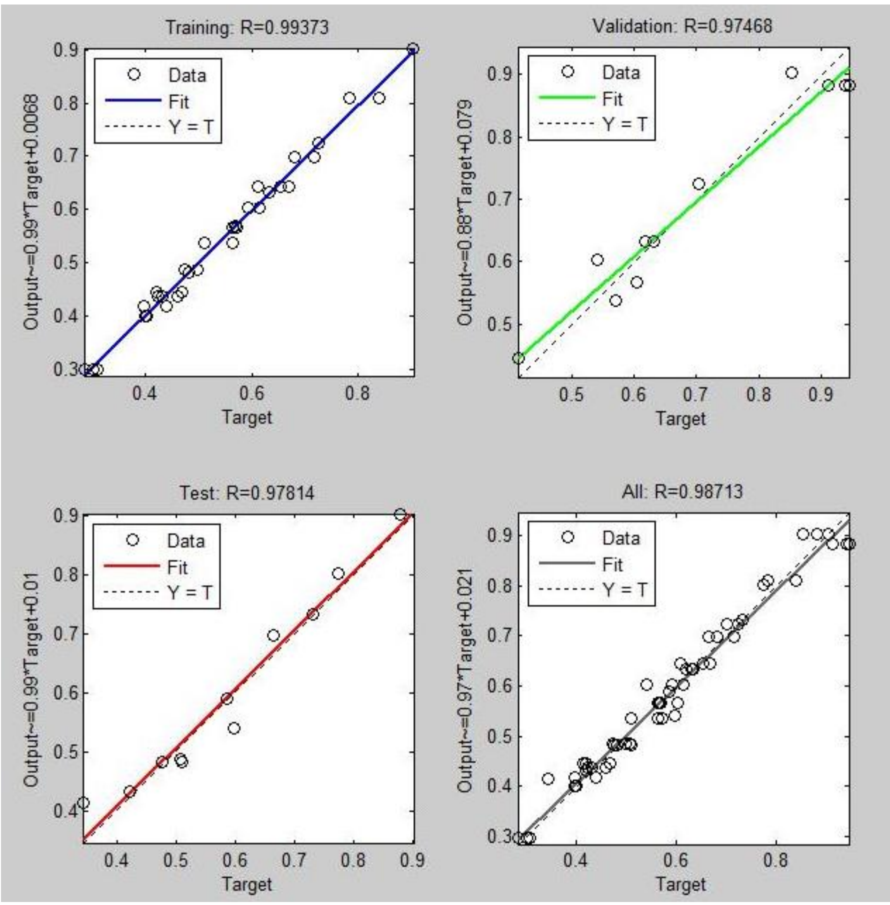

Fig. 3. The regression results of neural network training and examination.

Table 1. The experimental test planning and subsequent bending angle.

#	Start point of scan	Irradiating method	Laser beam diameter (mm)	Laser output power (W)	Number of radiation passes	Bending angle (Exp.)
1	1	1	6	500	3	0.9438
2	1	1	5	400	2	0.6687
3	1	1	4	300	1	0.423
4	1	2	6	500	2	0.8534
5	1	2	5	400	1	0.598
6	1	2	4	300	3	0.477
7	1	3	6	400	3	0.5633
8	1	3	5	300	2	0.31
9	1	3	4	500	1	0.4222
10	2	1	6	300	1	0.633
11	2	1	5	500	3	0.7753
12	2	1	4	400	2	0.5932
13	2	2	6	400	1	0.732
14	2	2	5	300	3	0.5633
15	2	2	4	500	2	0.6639
16	2	3	6	300	2	0.4394

Table 1 Continued.

19	1	1	6	500	3	0.939
20	1	1	5	400	2	0.6532
19	1	1	6	500	3	0.939
20	1	1	5	400	2	0.6532
21	1	1	4	300	1	0.431
22	1	2	6	500	2	0.8803
23	1	2	5	400	1	0.604
24	1	2	4	300	3	0.483
25	1	3	6	400	3	0.5872
26	1	3	5	300	2	0.302
27	1	3	4	500	1	0.414
28	2	1	6	300	1	0.6189
29	2	1	5	500	3	0.782
30	2	1	4	400	2	0.6145
31	2	2	6	400	1	0.7244
32	2	2	5	300	3	0.5112
33	2	2	4	500	2	0.6804
34	2	3	6	300	2	0.4218
35	2	3	5	500	1	0.5083
36	2	3	4	400	3	0.3987
37	1	1	6	500	3	0.9102
38	1	1	5	400	2	0.6101
39	1	1	4	300	1	0.46
40	1	2	6	500	2	0.9033
41	1	2	5	400	1	0.568
42	1	2	4	300	3	0.51
43	1	3	6	400	3	0.5708
44	1	3	5	300	2	0.285
45	1	3	4	500	1	0.4688
46	2	1	6	300	1	0.6312
47	2	1	5	500	3	0.8388
48	2	1	4	400	2	0.5404
49	2	2	6	400	1	0.7027
50	2	2	5	300	3	0.5716
51	2	2	4	500	2	0.7158
52	2	3	6	300	2	0.3979
53	2	3	5	500	1	0.4988
54	2	3	4	400	3	0.3448

Table 2. Level of parameters definition and corresponding coded value definition.

Level of parameter	Start point of scan	Irradiating method
1	Thick (coded value=0)	Improved Speed Method (coded value=0)
2	Thin (coded value=1)	Proportional Speed Method (coded value=0.5)
3		Equal Speed Method (coded value=1)

Table 3. Experiments test planning.

Parameters	Levels of parameters
Start point of scan	Thick blank
	Thin blank
Irradiating method	Improved Speed Method
	Proportional Speed Method
	Equal Speed Method
Laser beam diameter (mm)	4, 5, 6
Laser output power (W)	300, 400, 500
Number of radiation passes	1, 2, 3

The values in Table 1 must be coded to be recognized by the neural network. Equation 1 shows the coding relation for all values of Table 1. Besides, the coded value of the start point of laser beam scanning and irradiation method parameters have been shown in Table 2.

$$X_{coded}=\frac{X-X_{\min}}{X_{\max}-X_{\min}} \tag{1}$$

The neural network configuration consists of three main steps: selecting proper number of neurons and hidden layers, training procedure and examination of the trained network. The number of neurons in hidden layer are absolutely dependent on the complexity of the problem, and there is no straight way to determine the required number of neurons. The number of neurons and the number of hidden layers are usually determined by trial and error method. Therefore, different neural networks are configured. The number of neurons in hidden layer varies from 4 neurons to 12 neurons and the number of hidden layers varies from 2 layers to 6 layers. The proper network will be selected according to the average error of examination data. The examination of the trained network was done by selecting nine experiments which had been randomly selected from Table 1 and were excluded from the data which had used for the training of the neural network. Table 4 shows the selected experiments for network examination procedure.

Table 4. The selected experiments for network examination.

#	Start point of scan	Irradiating method	Laser beam diameter (mm)	Laser output power (W)	Number of radiation passes	Bending angle (Exp.)
2	1	1	5	400	2	0.6687
7	1	3	6	400	3	0.5633
15	2	2	4	500	2	0.6639
21	1	1	4	300	1	0.431
28	2	1	6	300	1	0.6189
35	2	3	5	500	1	0.5083
41	1	2	5	400	1	0.568
48	2	1	4	400	2	0.5404
52	2	3	6	300	2	0.3979

3. Results and Discussion

Configured neural networks with different numbers of neurons in hidden layer were trained, and average error was calculated between the predicted value with ANN and the measured value of bending angle for a randomly selected data set. Fig. 4 shows the average of mean square error (MSE) for examination data. The results show that minimum error will be obtained for network with three hidden layers and 8 neurons in each layer. Table 5 shows the detail of examination data and comparison of the predicted value by artificial neural network and experimentally measured bending angle. The number of neurons in hidden layer equals 8. Fig. 5 shows the configuration of final trained neural network. Figure 3 shows the configuration of artificial neural network according to the obtained results of the current work.

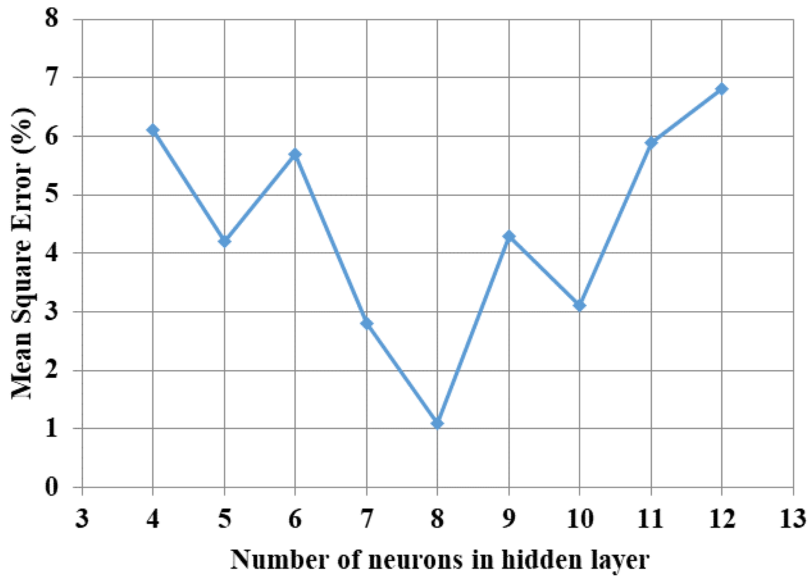

Fig. 4. Average of mean square error obtained for different number of neurons in hidden layer.

Table 5. Comparison of bending angle predicted by ANN and measured value (8 neurons in hidden layer).

#	Start point of scan	Irradiating method	Laser beam diameter (mm)	Laser output power (W)	Number of radiation passes	Bending angle (Exp.)	Bending angle (ANN)	Mean Square Error (%)
1	1	1	5	400	2	0.6687	0.65	2.796471
2	1	3	6	400	3	0.5633	0.57	1.189419
3	2	2	4	500	2	0.6639	0.667	0.466938
4	1	1	4	300	1	0.431	0.44	2.088167
5	2	1	6	300	1	0.6189	0.609	1.599612
6	2	3	5	500	1	0.5083	0.51	0.334448
7	1	2	5	400	1	0.568	0.57	0.352113
8	2	1	4	400	2	0.5404	0.537	0.629164
9	2	3	6	300	2	0.3979	0.4	0.527771
							Average Error	1.109345

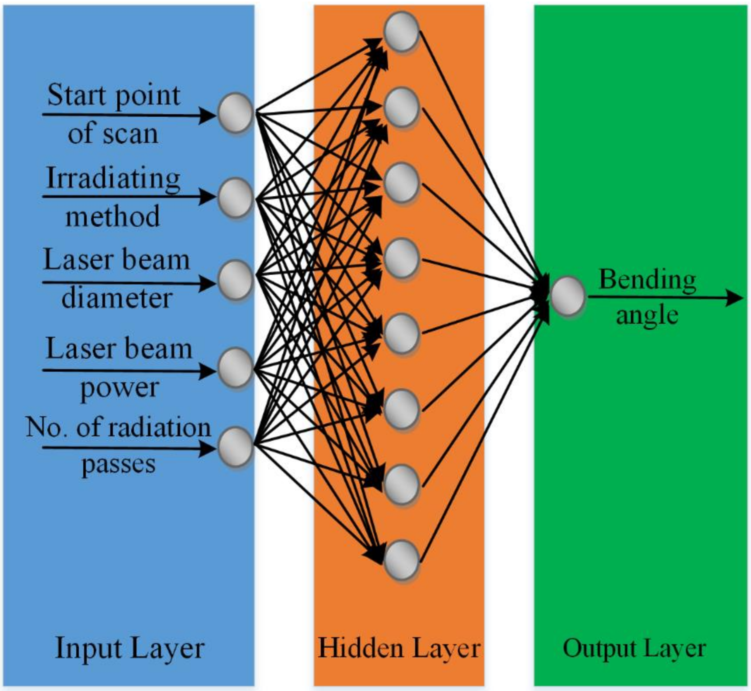

Fig. 5. Artificial neural network configuration.

4. Conclusion

In this article, an artificial neural network has been configured to predict the bending angle in the laser formed tailor machined blanks. Main parameters are selected and coded to be defined in the neural network. A set of experiments including 54 data sets have been carried out experimentally and the bending angle of the tailor machined blanks have been measured after laser processing20% of the results are selected randomly, after using the training of the neural network for network assessment. Average of mean square error shows that neural network with 8 neurons and three hidden layers can predict the bending angle by a considerably low error (1.1%).

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پیش بینی زاویه خمش برای شکل دهی با لیزر ورقهای ترکیبی ماشینکاری شده به کمک شبکه عصبی

مهدی صفری و جلال جودکی

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چکیده: ورقهای ترکیبی، ورقهای فلزی با ضخامت های مختلف و/یا مواد و/یا پوشش های سطحی مختلف می باشند. یک ورق یکپارچه جهت ایجاد ضخامت های متغیر می تواند ماشینکاری شود که به آن ورق ترکیبی ماشینکاری شده می گویند. به خاطر وجود ضخامت های مختلف در ورقهای ترکیبی ماشینکاری شده، خمکاری با لیزر این ورقها پیچیده تر از ورقهای یکپارچه می باشد. در این مقاله، یک شبکه عصبی مصنوعی جهت پیش بینی زاویه خمش ورقهای ترکیبی ماشینکاری شده که به وسیله لیزر شکل دهی شده اند پیکربندی خواهد شد. پارامترهای ورودی شبکه عصبی شامل نقطه شروع مسیر تابش دهی، الگوی تابش دهی با لیزر، قطر پرتوی لیزر، توان خروجی لیزر و تعداد پاسهای تابش دهی انتخاب می شوند. نتایج نشان می دهند که یک شبکه عصبی $5\times8\times1$ می تواند زاویه خمش را با دقت قابل قبولی پیش بینی نماید. مقایسه آزمایش های انتخاب شده تصادفی با نتایج تجربی نشان می دهد که در پیش بینی زاویه خمش با شبکه عصبی مصنوعی آموزش داده شده، 1/1 درصد خطا وجود دارد.

واژه های کلیدی: ورق های ترکیبی ماشین کاری شده، شکل دهی با لیزر، شبکه عصبی، زاویه خمش.