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A Comparison Study Between Modeling The Heat Affected Zone (Haz) For The Laser Cutting Of Ti-6al-4v Sheets By Using The Artificial Neural Network Method And Multi Regression Method

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ABSTRACT

This research presents an attempt to study the influence of laser cutting parameters such as thickness, Lens Focal Length, Beam Power, Cutting Speed and Gas Pressure on the Heat Affected Zone (HAZ) width. Two predictive models were developed using Artificial Neural Network (ANN) and multi regression modeling method. The relative importance of laser cutting parameters on (HAZ) width was determined based on (ANN) neuron weights and (ANOVA) method. The comparison between the experimental data and the predicted data indicates that the (ANN) model has attain an accuracy for predicting (HAZ) more than the multi regression model with a coefficient of determination of (R^2)=85.02%.

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دراسة مقارنة بين نمذجة المنطقة المتأثرة بالحرارة (HAZ) لتقطيع صفائح TI-6AL-4V بالليزر باستخدام طريقة الشبكة العصبية الصناعية وطريقة الانحدار المتعدد

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الكلمات المفتاحية:

الشبكة العصبية الصناعية
المنطقة المتأثرة بالحرارة
ليزر ثاني أوكسيد الكاربون
تحليل الانحدار المتعدد

الـــخُـــلاصـــة

يمثل هذا البحث محاولة لدراسة تأثير عوامل القطع بالليزر التي تشمل السمك ، البعد البؤري للعدسة ، طاقة الشعاع ، سرعة القطع وضغط الغاز على عامل عرض المنطقة المتأثرة بالحرارة (HAZ). تم تطوير نموذجين تنبؤيين باستخدام الشبكة العصبية الصناعية (ANN) وطريقة نمذجة الانحدار المتعدد. تم تحديد الأهمية النسبية لعوامل القطع بالليزر على العرض (HAZ) بناءً على أوزان الخلايا العصبية (ANN) وطريقة (ANOVA). تشير المقارنة بين البيانات التجريبية مع البيانات المتوقعة إلى أن نموذج (ANN) قد حقق دقة توقع (HAZ) أعلى من نموذج الانحدار المتعدد بمعامل تحديد R^2 = 85.02 ٪.

1. INTRODUCTION

At the present time, the development of advanced manufacturing processes has a significant deal of attention. Specialists have developed many techniques for the purpose of processing various types, sizes, and shapes of materials (complex and simple), as well as taking into account the environmental conservation while reducing time, efforts and costs [1]. Due to their effective properties, titanium and its alloys have high demand in various industries. The classic cutting procedures face difficulties in cutting these types of alloys due to many reasons namely, low elastic modulus, their poor thermal conductivity, and high chemical affinity at raising temperatures. The laser cutting methods have proper control of various process parameters, so it is widly used for obtaining a quality cut process [2]. The laser cutting technique is summarized by focusing the laser beam onto the workpiece surface for the purpose of melting or evaporating the material with the high temperature. This technology enables cutting very tiny workpiece within the micro range and gives productions with free of mechanical pressure distortions compared to the other techniques [3]. As a result of the high temperature, which generated by the focus of the laser beam on the surface of the material, the areas which are surrounding the cutting region are affected and many unwanted phenomena may occur. This includes decline in weldability, surface cracking, deformation, embrittlement, and fatigue resistance. This area of the material which has microstructure and mechanical features were influenced by the heat generated during laser cutting process called heat affected zone (HAZ) [4]. An investigative study was presented by [5] to determine the effect of the laser cutting parameters on the heat affected zone in CO_2 laser cutting of AISI 304 stainless steel, the technique of artificial neural network was used to create the relationship between these parameters. A hybrid approach of genetic algorithm and artificial neural network has been suggested and applied by [6] for the data obtained from L_{27} orthogonal array experiments in order to optimize different quality characteristics for the kerf taper and surface roughness. Biswas et al., 2010 [7] has developed a feed-forward back-propagation artificial neural network (ANN) model for laser micro drilling of titanium nitride-alumina composite to generate the maximum circularity process at the entry and the exit as well as minimum hole taper. Tamilarasan and Rajamani, 2017 [8] suggested a multi-response optimization methodology for the Nd: YAG laser cutting parameters of titanium alloy sheet (Ti-6Al-4V), regression models to the process parameters were developed, and the estimated values match with the experimental values. Hu et al., 2019 [9] established the regression equation based on response surface technique in order to analyze the influence of the laser processing parameters. Lazov et al., 2018[10] has determined the optimal laser cutting parameters by using support vector regression method to reach the minimization of average surface roughness. In this work, the 32 sets of six cutting parameters of CO_2 laser (with assist pressure of Nitrogen gas) were taken to build two predict models (the ANN and multiple regression) in order to predict the HAZ width [11]. Laser cutting parameters include, material thickness, cutting speed, laser beam power, assist gas pressure, lens focal length percentage and heat affected zone measurements. For the purpose of determining which models are stronger in the prediction among other, a comparison between results of ANN and multiple regression has been done to find the closeness of predicted values with the experimental data.

2. Materials and Methods:

2.1 ANOVA analysis

The analysis of variance (ANOVA) was conducted by using the MINITAB17.1.0

program for the experimental results in order to determine the contribution of each parameter of the laser cutting process. According to this analysis, the p-value for Thickness (T), Lens Focal Length (LFL), and Cutting Speed (CS) are less than 0.05. Consequently, the effect of these parameters on HAZ is significant but for the parameters of Beam Power and Gas Pressure (GP) the p-value are greater than 0.05, therefore the effect of these parameters on HAZ is insignificant, Table. 1.

Table 1. ANOVA analysis results

Source	*DF*	*Seq SS*	*Adj SS*	*Adj MS*	*F-Value*	*P-Value*	*Contribution (%)*
Thickness (mm)	1	0.000367	0.000367	0.000367	86.41	0.000	42.53
Lens focal length %	1	0.000026	0.000026	0.000026	6.00	0.021	2.95
Beam power (KW)	1	0.000012	0.000012	0.000012	2.84	0.104	1.40
Cutting speed (m/min)	1	0.000343	0.000343	0.000343	80.67	0.000	39.71
Gas pressure (bar)	1	0.000005	0.000005	0.000005	1.24	0.275	0.61
Error	26	0.000111	0.000111	0.000004			12.8
Total	31	0.000864					100.00

3. Artificial neural network model

3.1 Division of data

The 32 datasets of laser cutting parameter were divided into two sets randomly (learning and validation). Generally, 80% of the total data is used for learning and 20% is used for validation. The learning dataset was divided into 30% for the testing set and 70% of the training set. The distribution of data for each dataset based on that they are statistically consistent and thus represent the convergent statistical population, Table. 2.

Table 2. Division of laser cutting parameters data.

No.	*HAZ (µm)*	*Thickness (mm)*	*Lens focal length %*	*Beam power (KW)*	*Cutting speed (m/min)*	*Gas pressure (bar)*
Training Data	401	6.35	80	3	0.5	18
	347	6.35	30	3	0.5	18
	342	6.35	80	4	0.5	14
	320	1	80	4	0.5	14
	302	6.35	80	3	1	14
	302	6.35	80	4	1	14
	288	1	80	4	0.5	18
	285	1	30	4	0.5	14
	261	1	30	3	0.5	18
	272	1	30	4	0.5	18
	271	6.35	80	3	1	18
	258	1	80	3	0.5	18
	242	1	30	4	1	14
	238	1	80	3	1	14
	232	1	30	3	1	14
	225	1	30	4	1	18
	206	1	30	3	1	18
	213	1	80	3	1	18
[illegible]	398	6.35	80	3	0.5	14

No.	HAZ (μm)	Thickness (mm)	Lens focal length %	Beam power (KW)	Cutting speed (m/min)	Gas pressure (bar)
	358	6.35	30	4	0.5	18
	361	6.35	80	4	0.5	18
	290	6.35	80	4	1	18
	278	6.35	30	4	1	18
	275	1	80	4	1	18
	262	1	30	3	0.5	14
	262	6.35	30	3	1	14
Validating Data	383	6.35	30	4	0.5	14
	319	1	80	3	0.5	14
	315	6.35	30	3	0.5	14
	289	6.35	30	3	1	18
	281	6.35	30	4	1	14
	220	1	80	4	1	14
Max.	401	6.35	80	4	1	14
Min.	206	1	30	3	0.5	10

3.2 Test for divisions

To examine the normal distribution of dataset divisions and assess whether the means of these compared groups of the training, testing and validation are statistically different from each other, T-test was carried out. The results of test showed that the dataset divisions had met the normal distribution requirements, Table. 3.

Table 3. T-test results for the ANN input and output parameters.

Data set	*Mean*	*Variance*	*T-Value*	*T-Critical*	*Situation*
Gas pressure (bar)					
Training	278.06	2650.29	-0.94	2.07	Accept
Validating	301.17	2869.77			
Thickness (mm)					
Training	2.78	6.73	-1.44	2.07	Accept
Validating	4.57	7.63			
Lens focal length %					
Training	57.78	653.59	0.92	2.07	Accept
Validating	46.67	666.67			
Beam power (KW)					
Training	3.44	0.26	-0.23	2.07	Accept
Validating	3.50	0.30			
Cutting speed (m/min)					
Training	0.75	0.07	0.00	2.07	Accept
Validating	0.75	0.08			
HAZ (μm) Argon					
Training	16.22	4.18	1.68	2.07	Accept
Validating	14.67	2.67			

3.3 Scaling of data

In order to ensure that all the parameters of the laser cutting process receive the same attention during stage of learning, a simple scaling was conducted by using maximum and minimum values for each parameter as in Eq. 1.

The scaling process eliminates parameter values (Xn) by arranging it between (0 and 1).

$$X_n = \frac{X - X_{min.}}{X_{max.} - X_{min.}} \qquad (1)$$

3.4 ANN model setup

The idea of developing ANN was energized by mimicking the biological neural system. Today, this technique is independent of pre-established basics or models and become an alternative computing pattern closer to reality [12]. The presence of the many variables (input and output parameters) makes the task of building ANN model highly difficult. Therefore, this resorted the author(s) to use trial and error in determining the optimum parameters. Accordingly, it should outline the architecture of the ANN model as a three layers only, input, hidden, and output layer, Fig. 1. According to previous recommendations of the previous studies, chosen one hidden layer can approximate any continues function [13]. Input layer includes five neurons, each neuron for one of the input laser cutting parameters (thickness (T), lens focal length (LFL), beam power (BP), cutting speed (CS), and assist gas pressure (GP)). Output layer includes one neuron for output parameter (HAZ). The hidden layer has two neurons only, that were determined according to the minimum (RMSE), (ME) and maximum (R), Fig. 2. Also, it was found that the ANN model gives the best predict for data when the momentum rate, and learning rate were equal to 0.1 and 0.3, respectively, Figs. 3 and 4. The number of iterations was equal to 100000, because of no further progress in the performance of the ANN model after this number. In the same way, the selection of the type of transfer function was based according to the performance of ANN model, the optimum prediction was met with used sigmoid, sigmoid, and tangent transfer function for input, hidden, and output layer, respectively, Fig. 5.

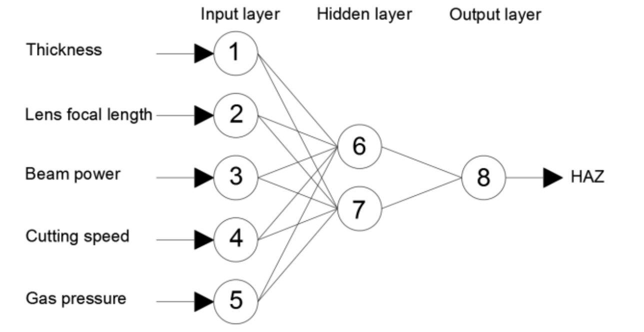

Fig. 1. Architecture of ANN model

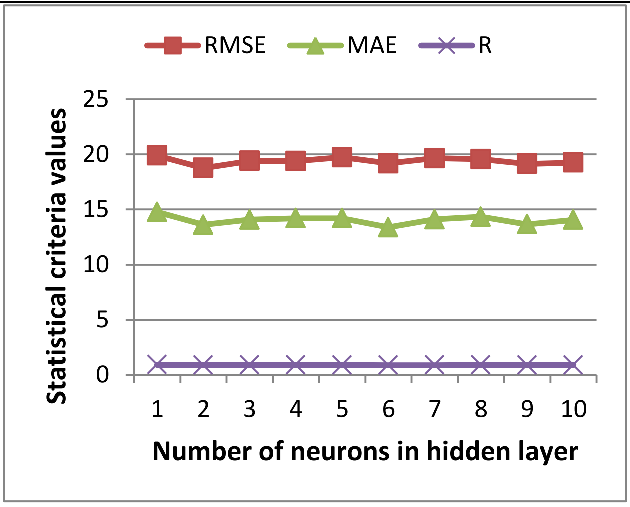

Fig. 2. Performance of the ANN model with different hidden layer neurons (Learning rate = 0.1 and Momentum rate = 0.3).

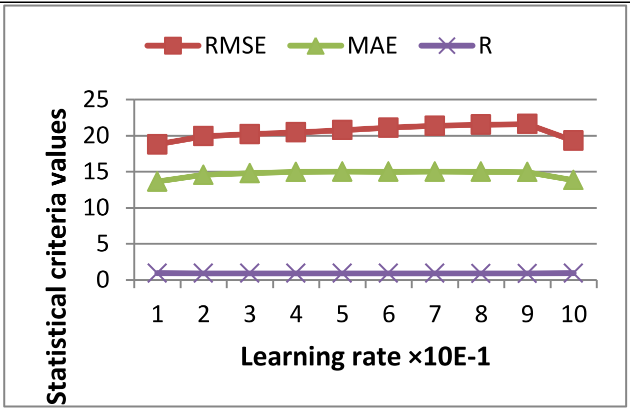

Fig. 3. Performance of the ANN model with different Learning rate (Momentum rate = 0.3 and hidden layer neurons = 2).

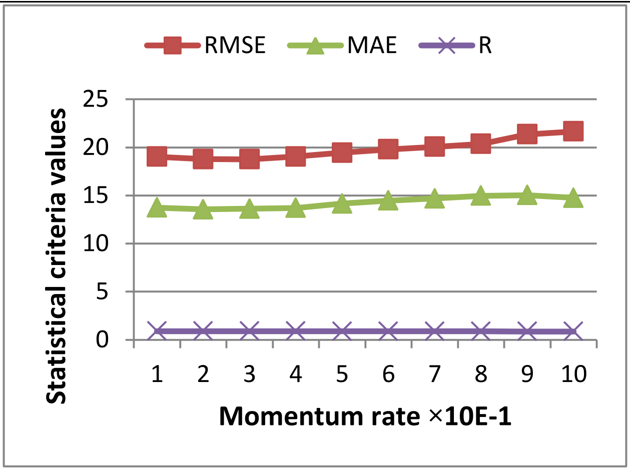

Fig. 4. Performance of the ANN model with different Momentum rate (Learning rate = 0.1 and hidden layer neurons = 2).

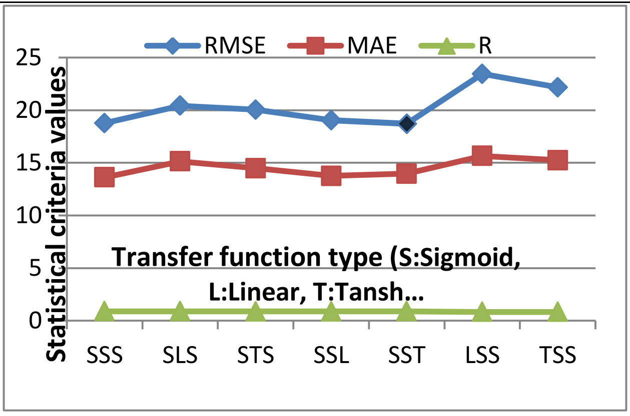

Fig. 5. Performance of the ANN model with different Transfer Function (Learning rate = 0.1, Momentum rate=0.3, and hidden layer neurons = 2).

3.5 Sensitivity analysis

Laser cutting parameters differ from each other in amplitude of affect the cutting process. In order to identify which of these parameters has the most significant impact, a sensitivity analysis was carried out by using Garson method [14] based on connection network weights of the ANN model, Fig. 6.

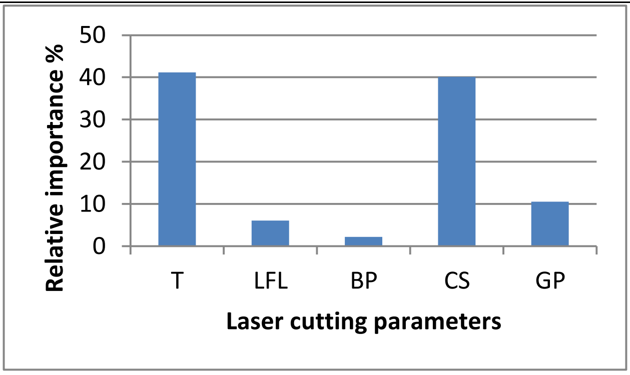

Fig. 6. Sensitivity analysis results for laser cutting parameters.

The results illustrated that the thickness (T), cutting speed (CS), and gas pressure (GP) parameters had the most weighty effect on the predicted HAZ with a relative importance of 41.15% and 40.08%, 10.51%, respectively, while the parameters of lens focal length (LFL) and beam power (BP) had a relative importance of 6.08% and 2.16%, respectively.

3.6 Multiple Regression analysis

The multiple regression model for predicting HAZ has been developed by using the MINITAB17.1.0 program as shown in Eq. 2.

$$HAZ(\mu m) = \frac{1}{(-0.05721+0.001267T(mm)+0.000036LFL(\%)+0.001228BP(KW)-0.01310CS(m.min^{-1})-0.000203GP(bar))^2} \quad (2)$$

3.7 Comparison of the results

The results of experiments, multiple Regression model and ANN model were listed in Table. 4 and represented graphically in Fig. 7 in order to compare between result values.

Table 4. Experimental, multiple regression, and ANN results of HAZ width.

Experiment number	*Thickness (mm)*	*Lens focal length %*	*Beam power (KW)*	*Cutting speed (m/min)*	*Gas pressure (bar)*	*Experimental HAZ (mm)*	*Regression HAZ (mm)*	*(ANN) HAZ (mm)*
1	1	30	3	0.5	14	262	285.755	283.181
2	6.35	30	3	0.5	14	315	364.894	360.800
3	1	80	3	0.5	14	319	299.987	302.808
4	6.35	80	3	0.5	14	398	374.796	380.615
5	1	30	4	0.5	14	285	290.392	286.381
6	6.35	30	4	0.5	14	383	368.327	345.542
7	1	80	4	0.5	14	320	304.775	300.777
8	6.35	80	4	0.5	14	342	377.741	364.369
9	1	30	3	1	14	232	224.698	233.480
10	6.35	30	3	1	14	262	285.922	282.690
11	1	80	3	1	14	238	231.878	240.037
12	6.35	80	3	1	14	302	300.161	298.202
13	1	30	4	1	14	242	226.933	251.568
14	6.35	30	4	1	14	281	290.561	284.336
15	1	80	4	1	14	220	234.527	256.263
16	6.35	80	4	1	14	302	304.949	295.6677
17	1	30	3	0.5	18	261	266.108	255.610
18	6.35	30	3	0.5	18	347	347.534	352.487
19	1	80	3	0.5	18	258	279.091	278.029
20	6.35	80	3	0.5	18	401	359.557	375.392
21	1	30	4	0.5	18	272	270.270	269.469
22	6.35	30	4	0.5	18	358	351.649	340.548
23	1	80	4	0.5	18	288	283.600	285.362
24	6.35	80	4	0.5	18	361	363.223	361.352
25	1	30	3	1	18	206	216.125	201.044
26	6.35	30	3	1	18	289	266.256	261.916
27	1	80	3	1	18	213	221.638	207.172
28	6.35	80	3	1	18	271	279.252	279.155
29	1	30	4	1	18	225	217.834	231.796
30	6.35	30	4	1	18	278	270.423	272.030
31	1	80	4	1	18	275	223.689	236.183
32	6.35	80	4	1	18	290	283.766	284.312

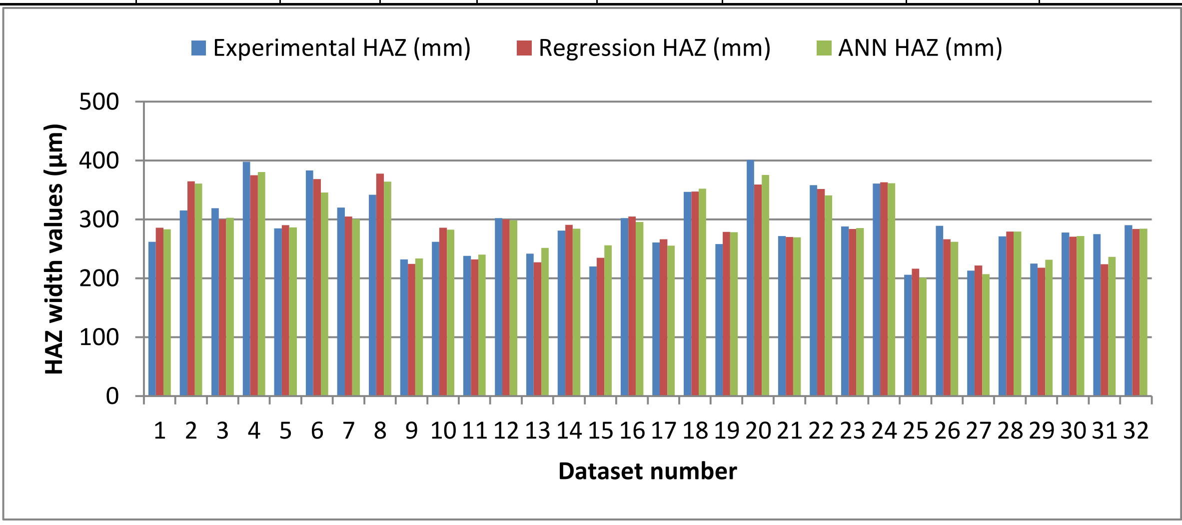

Fig. 7. Comparison between results of HAZ width for experimental, multiple regression, and ANN models.

4. Results and Discussion

A database of experimental results was used to develop two prediction models (the multiple regression and the ANN). For the ANN model, Feed-forward multi-layer perceptions (MLPs) were implemented and trained with the algorithm of back-propagation, as they have a high ability of data mapping. The results of T-test showed no significant difference between training, testing, and validation groups from a statistical point of view [15]. As it can be noticed from Figs. 2, 3, and 5, there was a significant harmonious of RMSE and MAE for whole neurons. From all figures, the value of correlation coefficient (R) remains approximately constant in all cases, this positive value refers to a strong uphill linear relationship [16]. The comparison between ANOVA and ANN relative of importance results indicated that there was a reasonable converge, therefore, this agreement ensures the size of contribution of each parameter in laser cutting process. The results of running ANN model indicate the higher prediction accuracy of the HAZ width values than the multiple regression model within the scope of laser cutting parameters, Figs. 8 and 9. Also, the final results indicate the important role of pre-processed input and output laser cutting parameter data (training, testing, and validation) for improving the performance of the ANN model [17].

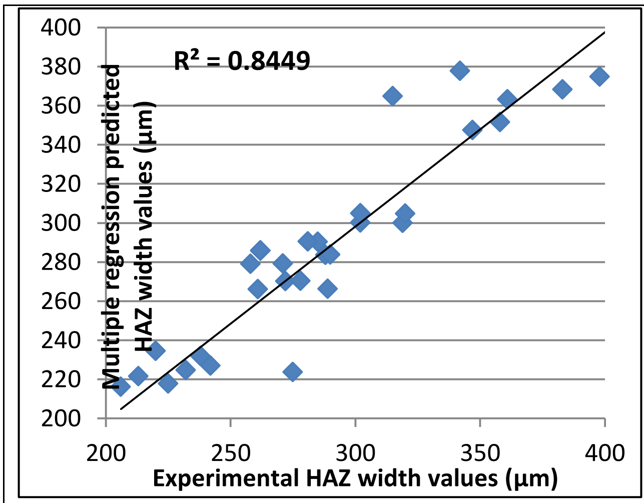

Fig. 8. Comparison between experimental and multiple regression HAZ results.

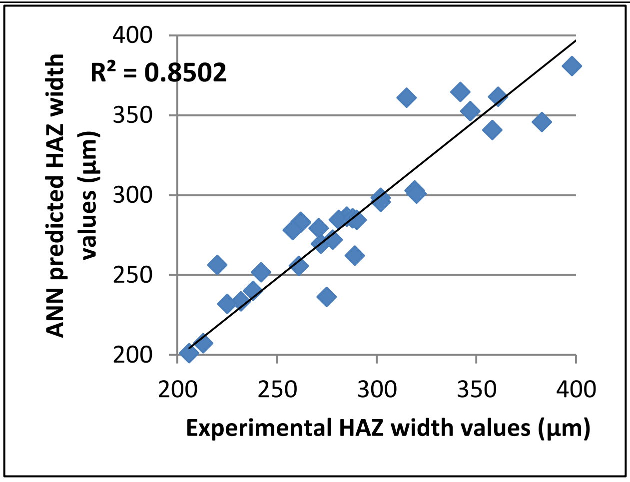

Fig. 9. Comparison between experimental and (ANN) HAZ results.

5. Conclusions

The analysis of the effect of laser cutting parameters was conducted for TI-6AL-4V Sheets. Two prediction models (the ANN and multiple regression) were built in order to predict the HAZ width based on 32 sets of six cutting parameters of CO_2 laser (with assist pressure of Nitrogen gas). The cutting parameters selected during analysis were material thickness, cutting speed, laser beam power, assist gas pressure, lens focal length percentage and heat affected zone measurements. For ANN model, the best effective transfer function type in the hidden layers was the sigmoid function. Both ANOVA analysis and the ANN model indicated that the laser cutting process were highly sensitive to thickness (T), cutting speed (CS), and assist gas pressure (GP) parameters and less sensitive to the parameters of beam power (BP) and lens focal length (LFL). To check the ability of the developed models, the percentage errors were computed from Table. 4 for the differences between the experimental and predicted values. The results show that the mean, minimum and maximum percentage errors in regression model were 5.064 %, 0.153 % and 18.658 %, respectively. However, the ANN model errors were 4.769 %, 0.097 % and 16.483 %, respectively. From the comparison between the models (Multi regression and ANN) for accuracy regarding the coefficient of determination (R^2), it can be concluded that the ANN model predicts the HAZ width with higher accuracy than the multiple regression model with (R^2) equal to 84.49% and 85.02% for multiple regression and ANN, respectively.

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