Artificial Neural Network Predictive Modelling of Laser Micro-Grooving for Commercial Pure Titanium (CP Ti) Grade 2

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ABSTRACT

Grooving is the process of making a narrow channel on a surface of flat or cylindrical workpiece. Groove is precisely made to parts used in automotive, biomedical, and electronics industries. In automotive industries, groove plays an important role especially on mechanical parts to precisely locate seal (o-ring) to prevent gas/oil leakage between dynamic mating parts. On the other hand, artificial neural network (ANN) has been widely used in developing predictive models of various manufacturing processes to save huge amount of production time and money for industries. Unfortunately, very limited research has been investigated on micro groove quality employing ANN predictive models. Therefore, this research work presents on how the Artificial Neural Network (ANN) predictive model has been established, optimised and utilised

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to predict the laser micro-grooving quality of commercial pure titanium grade 2 material. A 3KW CO_2 laser cutting machine was employed considering laser power, gas pressure, cutting speed, depth of cut and focal distance as the design parameters for modelling. On the other hand, three significant responses namely groove depth, groove width and groove corner radius were investigated. Experimental results were fed to establish the ANN predictive model, which then its parameters were optimized to gain high level prediction accuracy. The predicted results of ANN model presented the mean absolute percentage error for groove depth, groove width and groove corner radius at about 7.29%, 10.93% and 11.96% respectively. The obtained predictive results were found quite promising with the average of mean absolute percentage error (MAPE) for quality predictions which falls between 10 to 15%, concluding the validity of the developed ANN predictive model.

Keywords: *ANN predictive modelling; CO_2 laser cutting; Micro-grooving; Commercial pure titanium (CP Ti)*

Introduction

In today's world of revolutionising industry, most of the mechanical parts are required to be manufactured with tight tolerances without having to go through secondary processes. As such, micro-groove is in demand for super-hard rods in providing precise seats to locate seals, where it is a popular geometric feature especially in the area of precision machining. Micro groove is widely used in critical industries such as automotive, biomedical, aerospace, and microelectronics as sealant sittings, mechanical splitters, rotatable locating rings, micro-sprue actuators, etc. [1]. Gachot et al. [2] revealed that, micro-groove is very helpful in maintaining the performance of lubrication such as in wet sliding conditions to ensure coefficient of friction and wear between the mating parts are maintained. In biomedical field, micro-groove is becoming much crucial for dental implantation ensuring soft tissue formation to prevent the biological adverse effect. Rapidly growing hard-to-machine engineering materials such as titanium is being challenged to be processed by conventional machining. Thus, laser grooving being the non-contact advanced machining process, is mostly preferred by many precision industries as it stands the ability of net production, even for rods with greater length to diameter ratio.

In fact, the superiority of commercial pure (CP) titanium together with micro-groove as initiated by [22] is now in the raise of various applications including dental implants, turbocharger, and valve system. Generally, laser cutting machine which falls under the family of advanced machine tool is capable of cutting almost all kind of materials regardless of material rigidity, flexibility, metallic, non-metallic, malleability, or literally anything under the sky for the matter. Thus, laser cutting is often used as precision machining preference which is also able to produce micro level grooves, holes, and corners with tight tolerances due to its excellent kerf width and narrower heat affected zone [3]. But then, practical applications of the laser advancements by newly exploring industries often spend huge amount of production time and materials which leads into unnecessary money spending before arriving at the final decision of the process parameters setting. In conjunction to that, the machinability investigation of titanium alloy (Ti-6Al-4V) using laser machining has been successfully performed by controlling the material removal rate to attain desired surface roughness [4]. The micro grooving of Ti-6Al-4V alloys conducted by [5] reveals that, a good quality of 8-12 μm groove depth and width was achieved by controlling the pulse frequency, scan speed, and focal length which have direct control over the laser spot size. Taweeporn et al. [6] performed underwater laser micromachining of titanium alloy with different sets of temperatures. It was found that, the effect of laser power, traverse speed and numbers of laser passes are much significant for deep grooving. In fact, to have the laser processing phenomenon be well understood, [7] has modelled the micro-grooving process by employing Artificial Neural Network (ANN).

ANN multi-objective model was developed to optimize the process parameters of yttrium aluminium garnet (YAG) laser for minimum depth investigation of micro-turning by [8]. ANN model developed by [9] was capable to accurately predict the surface quality of CNC turning processes as compared to Taguchi model. Sathish et al., [10] investigated the ANN predicted of methane yield by different parameters selection and the model was proven to be efficient within the settings of feed forward network (FFN) with one hidden layer was a better approach over other common types for methane content prediction. Ming-Jong [11] has investigated the cut quality measurements of Quad Flat Non-lead (QFN) package which is depth of cutting line, width of heat affected zone, cutting line of epoxy, and copper-compounded using back propagation neural network model. On top of that, four algorithms including broyden fletcher goldfarb shanno quasi-newton (BFG), scaled conjugate gradient (SCG), gradient descent (GD), and lavenberg-marquardt (LM) were also used to simulate the model. Ming-Jong concluded that, LM algorithm is an optimal algorithm which yields much lower error predictions as compared to other optimised algorithms.

On the other hand, optimization of surface roughness has been studied and modelled employing ANN by [12]. The model shows that, 4-7-1 structure predicts best cut quality of surface roughness with properly controlled three design parameters which are cutting speed, power, and assist gas pressure. It has been summarised that, cutting speed plays an important role as compared to other tested parameters. The optimized model of hybrid Taguchi artificial neural network hybrid with genetic algorithm based model was developed by [13] to predict the CO_2 laser cut quality. The model succeeded to predict the cut quality accuracy with the prediction error of not more than 10%. ANN modelling is able to reduce the production cost particularly in precision industries which often waste a lot of experimental time and raw materials to arrive into the optimal settings, especially if it involves new material or new processing [15]. Properly designed ANN model architecture with optimised parameters will be powerful enough to capture the relationship between input and output parameters. The pattern learning ability of ANN makes it a very powerful predictive modelling tool. In other words, artificial neural network can be classified as a black box model which provides information behind the processing physics explicitly [16].

ANN model is often adopted for prediction and optimization of many processes including laser micro-grooving process as it has the ability to compute the very non-linear process phenomenon including laser machining. According to [17], the artificial neural network model can be simplified using mathematical expression as shown in Equation (1).

$$y(k) = F\left(\sum_{i=0}^{m} w_i(k) + b\right) \tag{1}$$

where;

$x_i(k)$ is input value in discrete time k where i goes to 0 to m
$w_i(k)$ is weight value in discrete time k where i goes from 0 to m
b is bias
F is a transfer function
$y_i(k)$ is output value in discrete time k

As to achieve the primary objective of this research which is to predict laser grooving quality of commercial pure titanium grade 2, various critical steps have been performed towards developing a sound ANN model to ensure that the attainable values are within desired values.

Experimental setup and procedures

The aim of this experimental based modelling research is to develop, optimise and validate ANN model to predict and experimentally validate micro-groove quality of laser processed commercial pure (CP) titanium grade 2 rods. The material was selected based on high demand of wide applications in the area of aerospace, architecture, power generation, medical industry, hydro-carbon processing, marine industry and so on [27]. The CP titanium grade 2 is well known for its superior formability, corrosion resistance and strength where, it offers minimum yield strength of 275 MPa as shown in Table 1.

Table 1: Properties and composition of CP titanium grade 2 [14]

Properties	Value
Yield Strength	275 - 410 MPa
Modulus of Elasticity	105 GPa
Density	4.51 g/cc
Specific Heat Capacity	0.523 J/g-°C
Melting Point	Max 1665 °C
Shear Modulus	45 GPa

The specifications of 3-kilowatt carbon dioxide (CO_2) laser cutting machine employed for experimentation in this research are shown in Table 2.

Table 2: Specification of CO_2 laser cutting machine

Laser	Specification
Manufactured by	LVD, Belgium
Brand	LVD Helius
Model	Helius-2513
Maximum laser power	3 kW
Maximum speed	250 mm/s
Envelope	2.50 x1.25 m

On the other hand, Table 3 shows the selected laser machining process parameters. Out of 14 laser processing parameters, five (5) significant ones were selected upon conducting preliminary research. Namely, they are power (P), gas pressure (G), cutting speed (V), depth of cut (d) and focal distance (F).

Table 3: Laser processing parameters

Parameters	Unit	Low	Medium	High
Power (*P*)	watt	1500	1650	1800
Gas Pressure (*G*)	bar	170	180	190
Cutting Speed (*V*)	mm/min	700	800	900
Depth of Cut (*d*)	mm	0.25	0.48	0.7
Focal Distance (*F*)	-	-2	-1	0

The specimens used in this experimental work were of the commercially available in the market with 5mm diameter and 130mm in length. Considering five (5) process parameters with three (3) different levels, a total of 32 experiments were designed. For data reliability, three (3) replications were conducted for each experiment which sums into the total 96 experimental runs. The Design of Experiment (DoE) run matrix was established using commercially available statistical package called Minitab employing response surface methodology (RSM) tool by selecting faced cantered central composite design (CCD).

The entire research was carefully design and conducted based on the research methodology established as shown Figure 1. All primary activities were strictly followed accordingly.

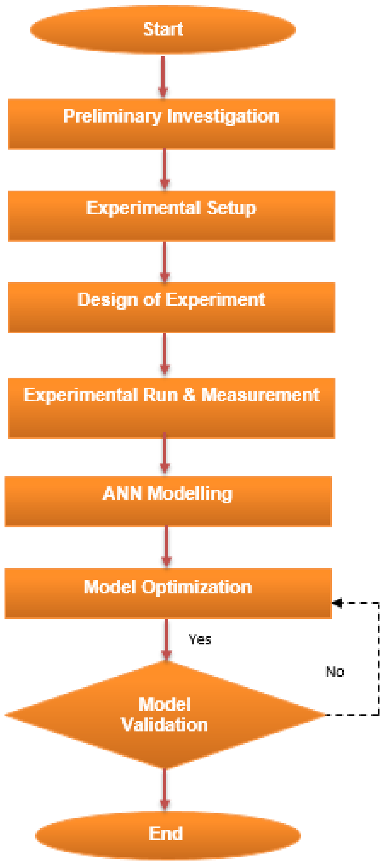

Figure 1: Research methodology flowchart.

The laser grooving process was performed onto the CP titanium grade 2 rod(s) by securing within a three-jaw chuck attached onto a specially designed speed-controlled spinning device. The spinner was properly aligned in the transverse direction laser bean to provide lathe alike interaction. Figure 2 shows how the spinner was mounted and used for laser grooving. The laser machine used in the experimental work was a 2.5 x 1.25 meter flatbed where the interaction of the linearly moving bed axes with spinning speed controllable device enabled the development of a cost effective 3D laser grooving possibility.

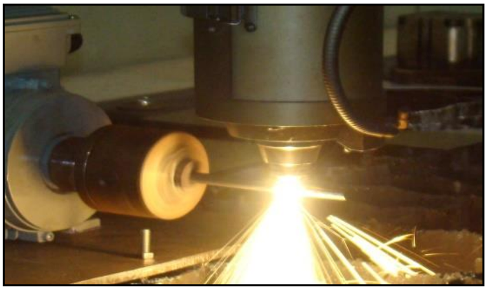

Figure 2: Flatbed Laser with integrated spinner chuck.

The depth, width, and corner radius of the produced micro-groove by laser machine was precisely measured using 20-4600 series model optical comparator made by Scherr-Tumico as shown in Figure 3.

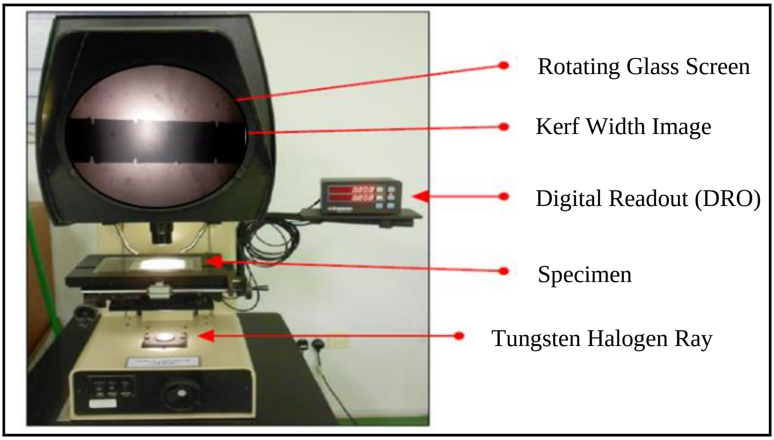

Figure 3: Measuring of micro-groove with optical comparator.

The optical comparator allows precise measurements to be captured with the ability of magnifying the image up to 50X larger with high degree of accuracy even for a very tiny part or groove in this matter. The measurements were taken at three different points along the circumference with 120˚ each point. The average of these three readings was considered as the values of the micro-groove profile. The measurement and observation of the grooves were performed based on ISO 5346 standard. Figure 4 shows the schematic drawing of how the groove depth, width and corner radius were observed as per ISO 5346 standard.

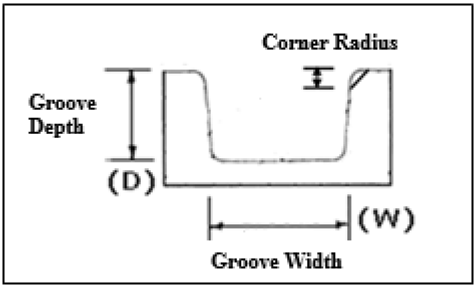

Figure 4: Schematic diagram of groove observations.

ANN Modelling of Micro Grooving

In this model, a three layer ANN network architecture consists of input layer, hidden layer, and output layer as shown in Figure 5 was utilised. The input layer of the architecture consists of five (5) neurons indicating the number of input process parameters. On the other hand, the output layer consists of three neurons, which are also the predictive responses namely, groove depth, groove width and groove corner radius. In the middle of the architecture there is a hidden layer with number of neurons which are considered as crucial element to determine the prediction. Therefore, the appropriate selection of neuron numbers is very important in order to establish excellent predictions with minimal number of iterations in ensuring the network processing speed and accuracy. Every model is evaluated based on how accurate can the predictions be made. Means, smaller the prediction error value, more accurate and robust the model is to be. The prediction error can be calculated or defined based on Equation (2).

$$\textit{Prediction error (\%) = Exp. results – Pred. results / Exp. result x 100\%} \qquad (2)$$

After a serious study, a feed forward back-propagation network was finalised for the ANN model development. The training and testing of datasets have been performed using neural network algorithms under commercially available Mat lab software. From the total of 96 experimental datasets, 85% of them were used for training and the rest were used for the testing of ANN network.

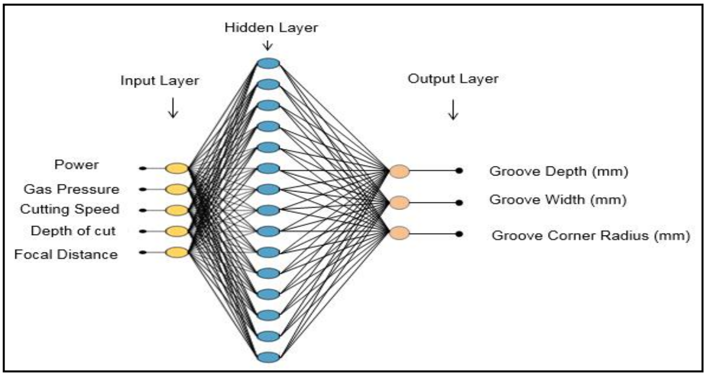

Figure 5: ANN 5-15-3 architecture with 5 inputs, 1 hidden layer and 3 outputs.

Through a thorough investigation, the neuron numbers of hidden layers were determined as in the ANN architecture. The predicted results of ANN model were evaluated by considering the minimum percentage of prediction error. There are six (6) design parameters of ANN that was considered for modelling which are namely; network algorithm, training function, transfer function and adaption learning, hidden layers, error goal and neuron numbers. In order to obtain precise predictions without having to go through trial-and-error methods, the established ANN model was optimized for its attributes and parameters within as shown in Table 4.

Table 4: ANN Attributes and optimized parameters.

ANN Attributes	Optimized parameters
Network algorithm	Feed-forward BP
Training function	Levenberg–Marquardt
Transfer function	Hyperbolic tangent
Number of hidden layer	One (1)
Error goal	0.0001
Number of neuron	15

Results and Discussion

The entire experimental results gained for the total number of 96 experimental runs against their respective responses are as shown in Table 5.

Table 5: Experiment results – responses over the experimental runs

No.	GD (mm)	GW (mm)	CR (mm)	No.	GD (mm)	GW (mm)	CR (mm)
1	0.16	0.34	0.12	49	0.65	0.16	0.22
2	0.39	0.20	0.15	50	0.45	0.18	0.17
3	0.66	0.18	0.26	51	0.42	0.17	0.18
4	0.41	0.18	0.23	52	0.72	0.24	0.27
5	0.12	0.15	0.12	53	0.25	0.32	0.10
6	0.43	0.20	0.15	54	0.49	0.19	0.15
7	0.44	0.14	0.14	55	0.64	0.09	0.19
8	0.44	0.15	0.28	56	0.26	0.28	0.08
9	0.45	0.16	0.11	57	0.72	0.17	0.19
10	0.69	0.15	0.13	58	0.59	0.20	0.10
11	0.23	0.24	0.14	59	0.61	0.24	0.13
12	0.73	0.20	0.27	60	0.63	0.21	0.22
13	0.48	0.18	0.17	61	0.22	0.27	0.08
14	0.20	0.24	0.06	62	0.20	0.23	0.15
15	0.68	0.08	0.14	63	0.23	0.29	0.17
16	0.24	0.26	0.19	64	0.48	0.17	0.12
17	0.49	0.14	0.16	66	0.49	0.21	0.12
18	0.66	0.13	0.29	66	0.24	0.26	0.11
19	0.46	0.18	0.17	67	0.64	0.14	0.14
20	0.13	0.29	0.15	68	0.48	0.20	0.15
21	0.39	0.22	0.19	69	0.51	0.20	0.16
22	0.35	0.25	0.17	70	0.30	0.29	0.08
23	0.44	0.21	0.20	71	0.69	0.22	0.16
24	0.20	0.33	0.11	72	0.41	0.21	0.12
25	0.13	0.30	0.12	73	0.16	0.28	0.07
26	0.51	0.19	0.18	74	0.23	0.23	0.10
27	0.52	0.17	0.13	75	0.25	0.27	0.09
28	0.18	0.29	0.13	76	0.64	0.13	0.19
29	0.46	0.18	0.15	77	0.21	0.26	0.08
30	0.71	0.21	0.23	78	0.66	0.16	0.14

31	0.73	0.14	0.24	79	0.67	0.12	0.18
32	0.44	0.21	0.15	80	0.20	0.25	0.08
33	0.41	0.22	0.12	81	0.48	0.23	0.10
34	0.21	0.31	0.10	82	0.49	0.24	0.11
35	0.15	0.27	0.14	83	0.49	0.20	0.12
36	0.40	0.13	0.15	84	0.23	0.26	0.10
37	0.22	0.37	0.15	85	0.17	0.21	0.10
38	0.72	0.12	0.14	86	0.7	0.17	0.16
39	0.37	0.19	0.17	87	0.66	0.15	0.14
40	0.61	0.18	0.24	88	0.52	0.16	0.15
41	0.22	0.35	0.15	89	0.50	0.23	0.19
42	0.38	0.26	0.16	90	0.71	0.14	0.16
43	0.43	0.19	0.22	91	0.48	0.19	0.13
44	0.58	0.14	0.16	92	0.44	0.20	0.10
45	0.43	0.19	0.14	93	0.65	0.20	0.13
46	0.40	0.19	0.13	94	0.47	0.22	0.14
47	0.48	0.22	0.14	95	0.49	0.17	0.15
48	0.47	0.21	0.16	96	0.60	0.15	0.16

Based on the experimental results, ANN model with multiple outputs has been developed. Various architectures were designed, optimised and tested where in this case, 5-15-3 architecture was seen to be fitting best and therefore it is selected for this modelling process. Table 6 shows the optimised neural network parameters within the 5-15-3 network architecture.

Table 6: ANN parameters for 5-15-3 architecture

ANN Parameter	Value
Network Architecture	5-15-3
Training/Testing Data	83/13
Network	Feed forward back Propagation
Performance	MSE
Training Function	Trainlm
Transfer Function	Tansig/Tansig
Learning Function	LearnGDM

Figure 6 shows the performance simulation of the developed model for training environment. The ANN model training performance was determined based on the lowest Mean Square Error (MSE) gained. The training curve mean square error (MSE) was seen decreasing with the increase of the epoch number till it reaches 12. If the test curve increases significantly before the validation curve increased, it is then possible that some over-fitting to have occurred. At this point, the curve remained constant and therefore the value of 0.00079511 is considered best for training, and model validation performance was observed to be epoch number 6.

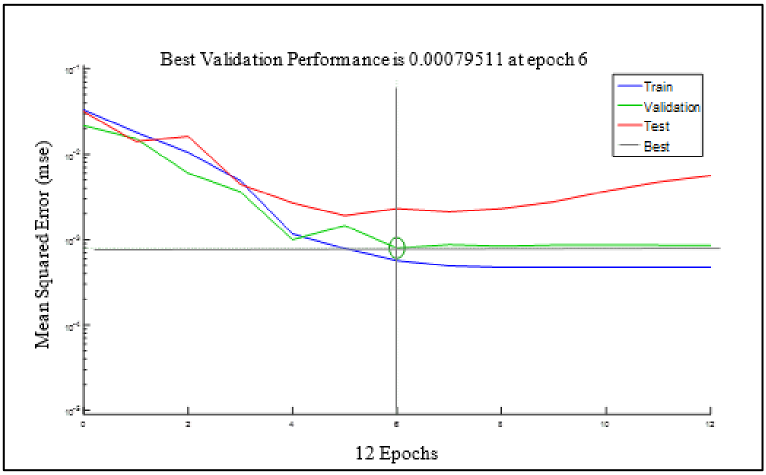

Figure 6: Performance simulation plot of 5-15-3 network.

The decreasing of training mean square error indicates that the training was almost perfect. The validation and test curves gained shows similarity in performance trend of the work performed by [18], which proves the model development coherence between both types of research work.

As for the ANN architecture validation, regression analysis was established in order to analyse the ANN model network outputs and the targets. Figure 7(a) shows the correlation of regression coefficients for training pattern with 0.98981 being the regression value. On the other hand, Figure 7(b) and Figure 7(c) show the regression correlation for validation and testing pattern with 0.98977 and 0.95605 of their respective regression values. The correlation coefficient of regression for total corresponding response is observed to be 0.98469 as shown in Figure 7(d).

Thus, the value of regression coefficient is very close to one which indicates the established and optimised ANN model predictions matches very well as compared to experimental results.

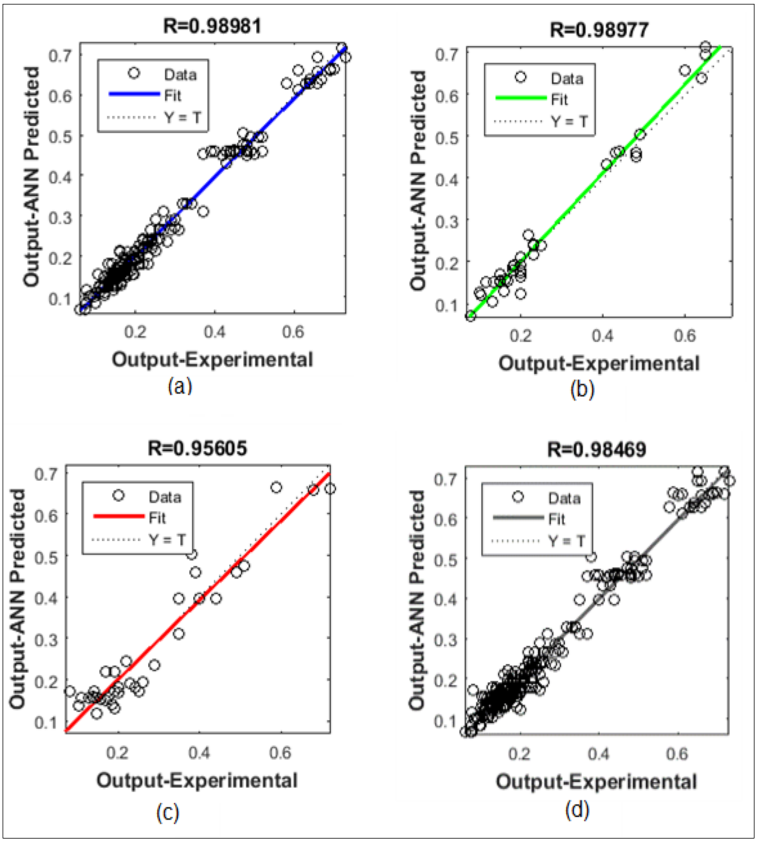

Figure 7: Regression coefficient of 5-15-3 ANN model: (a) training (b) validation (c) testing, and (d) overall data sets.

Table 7 shows the mean absolute percentage error (MAPE) of neural network training for 5-15-3 network architecture which was the main measure of model efficiency. The overall percentage of prediction error for 5-15-3 model architecture is 10.06% which indicates that, the data training for 5-15-3 architecture possesses good model training which yields the accuracy beyond 85% (15% error). In this context, the predictions made by the established ANN model can be considered highly accurate based on MAPE prediction categories made by [19]. He mentioned that the predictions can be classified into four different categories namely, below 10% as highly accurate prediction, 10-20% as good prediction, and 20-50% as reasonable prediction and 50% and above is inaccurate prediction.

Table 7: MAPE error of 5-15-3 architecture

Response	MAPE (%)	Average MAPE (%)
Groove Depth	7.29	
Groove Width	10.93	10.06
Groove Corner Radius	11.96	

The predictions by the ANN model were then experimentally validated for selected sets or runs. The comparative scatter plot of 5-15-3 architecture between experimental and predicted for groove depth, groove width and groove corner radius are shown in Figure 8, Figure 9, and Figure 10, respectively.

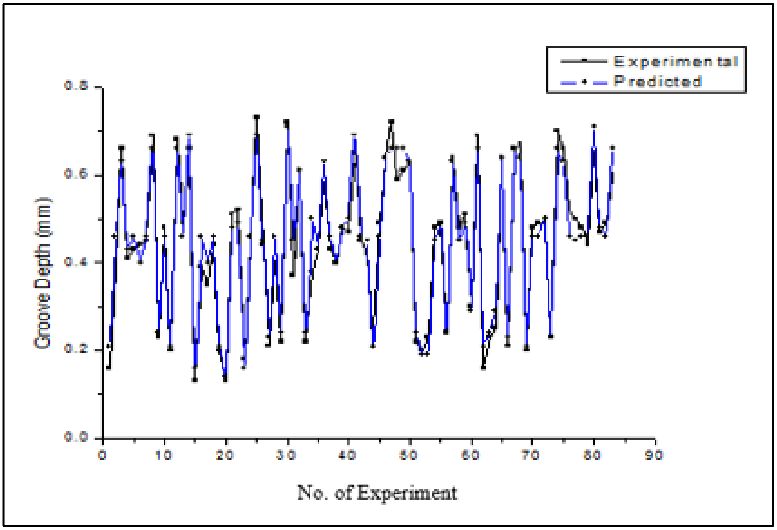

Figure 8: ANN predicted versus experimental for groove depth.

It is very clear that, the comparative scatter plot between experimental and predicted by the established ANN model with 5-15-3 architecture for groove depth, width and radius provided very promising results. Similar work on ANN modelling has been conducted by [20, 21] and the researchers found that, the ANN model utilised in their research has successfully made close predictions to the experimental results where the error was within 15%.

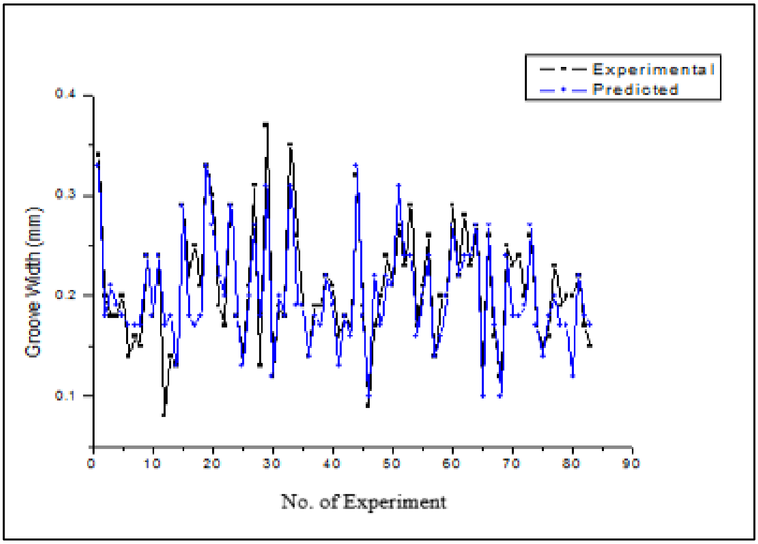

Figure 9: ANN predicted versus experimental for groove width.

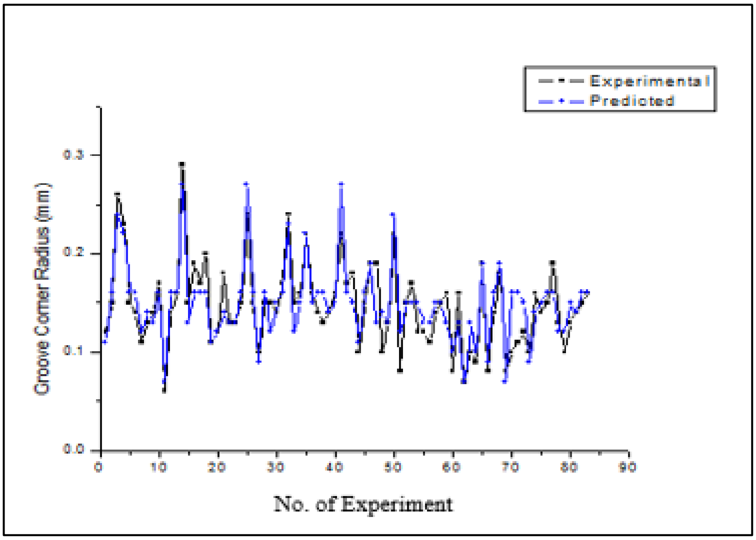

Figure 10: ANN predicted versus experimental for groove corner radius.

The exact overlapping of almost 85% of the signature graph spikes between experimental and predicted values proves that, a properly designed and optimised ANN model is capable of capturing the pattern and processing behaviour of even a complex and non-linear parametric relationship, in this case even for non-linear laser machining process.

Conclusions

Developing an artificial intelligence neural network model to understand the phenomena of a complex and non-linear laser processing to predict micro-grooving quality of CP Titanium Grade 2 has been successfully conducted besides attaining efficient predictions. Perhaps, a flatbed laser machine was modified by integrating a controllable spinning device to perform laser micro-grooving on a cylindrical part. Transforming the flat to 3D machining is primary contribution of this work where, it would be a cost effective solution for most precision metal machining industries. Secondly, the developed and optimised ANN model with 5-15-3 architecture was able to precisely predict the machining accuracy and cut geometry quality. The model stands to contribute in terms of cost and time saving to most industries employing laser lathing as their primary businesses. As to improve the parameter selection of laser cutting accuracy, an effective ANN model selection has been developed in this research to model the experiment before bringing it into actual environment. The results show that, the ANN model was able to predict the desired responses; groove depth, groove width, and corner radius. The achieved mean absolute percentage error (MAPE) for groove depth, width and corner radius was about 10% in average, where each of them yields with 7.29%, 10.93% and 11.96% respectively. This indicates the model robustness allowing the predictions to achieve as high as 90% in accuracy. As overall, the development of ANN model and the validation between predictive model and experiment shows an excellent agreement. To move forward and explore ahead within the field and further enhance the prediction accuracy, it is strongly recommended to develop Adapted Neuro-Fuzzy Inference System (ANFIS) predictive model where the attained results can be directly compared with the attained results.

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