EVALUATION OF THE EFFECT OF ND:YVO_4 LASER PARAMETERS ON INTERNAL MICRO-CHANNEL FABRICATION IN POLYCARBONATE

S.M. Karazi and D. Brabazon
School of Mechanical and Manufacturing Engineering,Dublin City University, Dublin, Ireland
shadi.karazi@dcu.ie, dermot.brabazon@dcu.ie

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Abstract: This paper presents the development of Artificial Neural Network (ANN) models for the prediction of laser machined internal micro-channels' dimensions and production costs. In this work, a pulsed Nd:YVO_4 laser was used for machining micro-channels in polycarbonate material. Six ANN multi-layered, feed-forward, back-propagation models are presented which were developed on three different training data sets. The analysed data was obtained from a 3^3 factorial design of experiments (DoE). The controlled parameters were laser power, P; pulse repetition frequency, PRF; and sample translation speed; U. Measured responses were the micro-channel width and the micro-machining operating cost per metre of produced micro-channel. The responses were sufficiently predicted within the set micro-machining parameters limits. Three carefully selected statistical criteria were used for comparing the performance of the ANN predictive models. The comparison showed that model which had the largest amount of training data provided the highest degree of predictability. However, in cases where only a limited amount of ANN training data was available, then training data taken from a Face Centred Cubic (FCC) model design provided the highest level of predictability compared with the other examined training data sets.

1 INTRODUCTION

Laser micro-machining is a materials-processing technique that uses precise laser energy per unit area and per unit time in order to manage the thermal field in the processed material with minimal thermal damage and high precision. The material is in most cases almost instantly brought up to melting temperature and to vaporisation temperatures to create the desired voxelated region of the micro-machined channel. Laser micro-machining processes include the drilling, cutting, milling and engraving of materials with micro-dimensional tolerances.

Various statistical and numerical methodologies have been implemented to predict and optimise several laser manufacturing processes including Artificial Neural Networks (ANN) (Lee et al. 2001); Genetic Algorithms (GA) (Ye, Yuan and Zhou, 2009), Design of Experiments (DoE) (Karazi, Issa and Brabazon, 2009), Finite Element Analysis (FEA) (de Deus and Mazumder, 1996), Ant Colony optimisation (AC) (Wang and Xie, 2005), and Fuzzy Logic (FL) (Shen et al. 2006).

Due to their non-linear, adaptive and learning ability using collected data, ANN models have been successfully applied to a large number of problems in several domain applications. Neural network nodal functions can be evaluated simultaneously, thereby gaining enormous increases in processing speed (Collins and DeLucca, 2008, Neural networks).

The prediction of the dimensions of the laser micro-machining channels is an important requirement for optimisation of the laser control parameters. A Nd:YVO_4 laser micro-machining system was previously used by the current authors for the production of micro-channels (Karazi and Brabazon, 2010) where it was shown that a wide variety of desired geometries can be prepared.

ANN models were constructed and analysed to test their predictive capabilities in this work. These predictive models relate the input laser processing parameters (power, traverse speed and pulse repetition frequency) to the output responses (machined channel width and micro-machining cost). These ANN models may be used to select the process input parameters which are required in order to achieve micro-channel dimensions within a specified budget.

2 EXPERIMENTAL SET-UP

2.1 Experimental Work

In this paper, a 2W Nd:YVO_4 1064 nm wavelength laser system was used for the micro-channel fabrication. These internal micro-channels were created in polycarbonate (PC) sheets of 10 mm thickness. In order to facilitate the measurement of the micro-channels' widths, a 2 mm distance between micro-channels was set. For micro-machining, the PC work pieces were initially positioned on the 3D positioning stage such that the laser spot was focused beyond the sample surface. The laser beam was then fired and the sample moved away from the stationary laser head. This laser micro-machining processing technique enabled creating the internal micro-channel from the back to the front of the sample

2.2 Experimental Design

In order to study the relationship between the main Nd:YVO_4 laser process parameters and the developed micro-channel width and corresponding micro-machining operating cost, an arranged series of information-gathering experiments was designed according to DoE methodology.

In this paper, the examined laser process input parameters were laser power, P; pulse repetition frequency, PRF; and sample translation speed; U. Each of these parameters was analysed at the low, middle, and high levels, all of which were determined after initial screening experiments. This 3^3 factorial design of experiments was prepared using Design-Expert V7 software. The design levels of the laser input parameters are shown in Table 1.

Table 1: Design of Experiment set levels of power, pulse repetition frequency and sample speed used, as well as corresponding level coding.

Variables	P (W)	PRF (kHz)	U (mm/sec)
Low	0.5	13	0.5
Mid	1	23	1.74
High	1.5	33	2.98

There are 27 possible combinations of the three process parameters at the three selected levels. The centre point of the design was repeated five additional times, where (P=1 W, PRF=23 kHz, U=1.74 mm/sec), to provide a measure of process stability and inherent variability.

2.3 Micro-channels Width Measurement

The micro-channel width (diameter) for each experiment was measured at three different locations along the produced channel and the average values were determined. Theses dimensional measurements were carried out using Leica optical microscope and OMNIMET image analysis software.

The measurement results of the repeated experiments were averaged to one, bringing the overall number of experiments from 32 to 27 unique experiments. These measurement results (27 for width and 27 for micro-machining cost) provided the data set from which training sets were chosen for the subsequent ANN modelling.

Table 2: Breakdown of estimated micro-machining cost per hour.

Element of cost	Calculations	Cost €/hr
Laser power supply	(800 W) (€0.16/kW hr) (P/2) / 1000	0.064×P
DELL PC Optiplex 170L & monitor	(140 W)(€0.16/kW hr) / 1000	0.0224
CompactRIO - control power	(8.2 W) (€0.16/kW hr) / 1000	0.0013
D-link network switch	(4.5 W) (€0.16/kW hr) / 1000	0.0007
BWD MiniLab - motion power	(43 W) (€0.16/kW hr) / 1000	0.0069
Diode replacement	(€ 11,410 / 10000 hr)	1.141
Maintenance labour	(12 hr/2000 hr operation) (€ 50/hr)	0.3
Total estimated micro-machining cost per hour		1.4723 + 0.064×P

$$\text{Micro-machining cost } [\text{€}/m] = \frac{1.4723+0.064\times P \ \frac{\text{€}}{hr}}{(0.85)\times U\left[\frac{mm}{sec}\right]\left[3600\,\frac{sec}{hr}\right]\left[\frac{m}{1000\,mm}\right]} = \frac{(0.481+0.021\,P)}{U} \quad (1)$$

2.4 Micro-machining Cost Calculation

Processing cost can be approximated as micro-machining cost per length for a specific laser micro-machining operation. In this approach, unplanned maintenances and breakdowns have not been taken into consideration. Furthermore, labour cost was not considered since the Nd:YVO_4 laser was for experimental purposes. Assuming the relationship between the electrical consumption of the laser power supply and the laser power emitted by the laser head is linearly proportional, the total estimated operating cost per hour as a function of the output power can be expressed by $1.4723 + 0.064\times P$.

Table 2 shows a breakdown of estimated micro-machining cost per hour. Assuming 85% utilisation, the total approximated operating cost per unit length (in €/m) is given by the following Equation (1).

2.5 ANN Models' Setup

Three ANN predictive models were developed for the width and another three for micro-machining cost estimation using the three inputs P, U, and PRF. These models were developed in order to examine the influence of changing the number and the selection of training data on the prediction capability of the ANN model. These six models were based on 3 different training data sets as follows:

- Model I: 24 randomly selected experiments (from the total of 27) were used to train the network;
- Model II: 14 experiments, selected according to the Face Centred Cubic (FCC) Design, were used to train the network;
- Model III: 13 experiments, selected according to the Box-Behnken (BB) Design, were used to train the network.

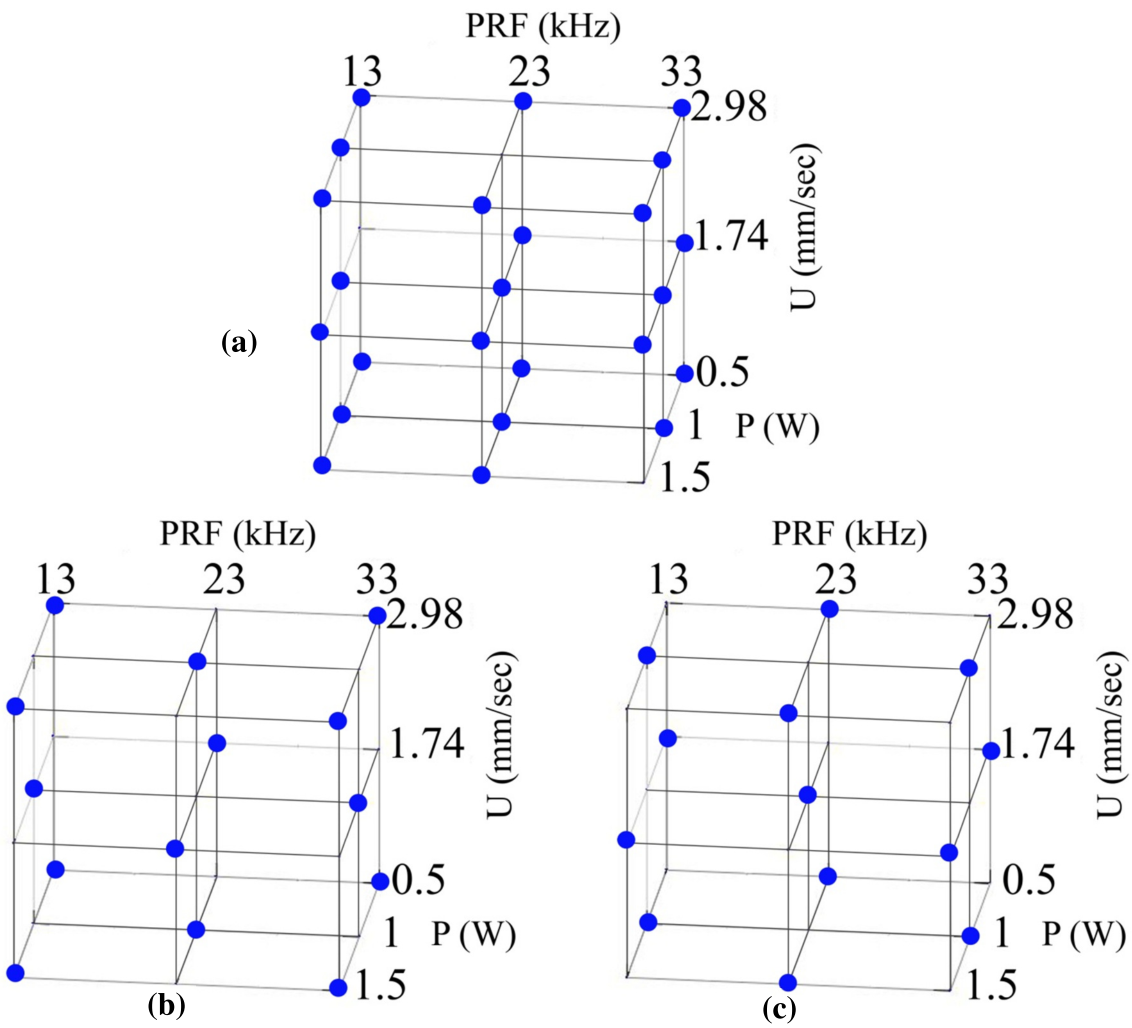

Figure 1: Schematic representation of the training data for (a) model I, (b) model II, and (c) model III.

Each of these three models was used for two models, one for the width prediction and another for the operating cost per metre prediction. All 27 experimental data were employed for verification purposes in order to locate the best ANN structure within the various possible architectures for each model. Figure 1 shows a representation of the training data distribution in 3D space (a) for model I, (b) for model II, and (c) for model III. The training set of models II & III were selected according to two popular designs; FCC Design and BB Design respectively. These two designs were selected in order to investigate which design should be chosen in case only a limited number of experiments could be performed. This scenario could occur when for example carrying out the experiments is time consuming, expensive, or dangerous.

2.6 Configuration of ANN Models

In this work, all the studied ANN models were of feed-forward structure and back-propagation algorithm. Moreover, they were designed and executed using the aNETka software. Due to the lack of a quantifiable procedure for theoretical appraisal of the best ANN architecture, exhaustive trial-and-error study was performed to find the best ANN configuration for each model. Two ASCII text input files were prepared for each model. The first one contained the training data inputs and corresponding outputs for the training stage. The second one contained all 27 experimental data inputs and their corresponding outputs for the verification stage. In order to find the best ANN model, the number of hidden layers was changed up to four and the number of neurons in each hidden layer was varied up to 100 neurons. A diagrammatic description of the examined ANN architectures is shown in Figure 2.

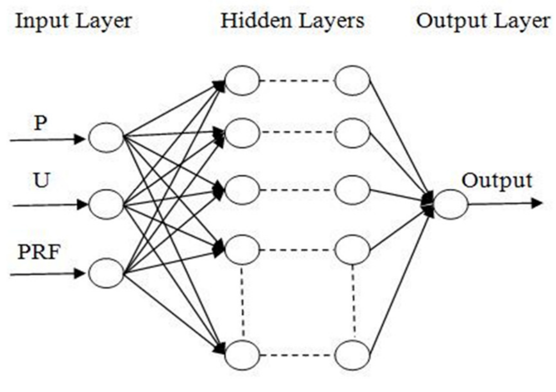

Figure 2: Architecture of feed-forward ANN schema developed with three inputs and one output.

Due to its good generalisation capability, a transfer sigmoid function was used in all investigated ANN architectures. Since the learning rate value controls the magnitude of weight and bias updates, the choice of this value meaningfully influences ANN schemas training time. Empirically the learning rate value was manually varied between 0.0001 and 6 depending on the progress of the aNETka execution during training process.

To avoid and reduce the probability of the training runs being stuck in local optima, the momentum parameter was utilised and fixed at a medium value of 0.8 for all ANN training runs.

In the ANN program used the training data was iteratively passed one by one through the ANN structure and the weights were automatically adjusted after each iteration. Part of the training data was randomly selected and set aside by the aNETka software in order to be used as a validation set and a criterion to decide when to stop the training. In an effort to minimise the training error and avoid over training, the training process was supervised during the ANN model formulation. The training part of the aNETka software provided the user with a graphical chart of the past and current RMS error value. This graphical chart was ceaselessly supervised so that ANN configurations with the highest prediction capability could be obtained for each model. Configurations for which the RMS errors raised significantly and continuously during training were dropped. Afterwards, the process of ANN structure formation was restarted and only structures with RMS error value below 0.001% were accepted.

3 RESULTS

3.1 Final ANN Structures

In this work and after trying a wide variety of hidden layer diversifications, it was discovered that the best ANN schemas were obtained with one or two hidden layers. Table 3 shows the number of neurons in the hidden layers that achieved best predictions of width and cost for models I, II, and III.

Table 3: Number of neurons in the hidden layers for width and depth in I, II, and III models.

Model	Hidden layers	width	cost
I	**1st**	6	4
II	**1st**	3	4
	2nd	3	-
III	**1st**	8	4

3.2 ANN Predictive Models' Comparison

Comparison criteria are needed in order to quantify the difference between values produced by a model and the actual values. After a profound search in statistics, three statistical estimators were found to be the best criterions that together can do the required work. These statistical estimators are MSE (Mean Squared Error), R2 (The coefficient of determination), and MAPE (Mean Absolute Percentage Error). These estimators were employed to provide a measure of how well future outcomes are likely to be predicted by the investigated model. Table 4 shows a side by side comparison between models I, II, and III in terms of the three chosen estimators.

The Mean Squared Errors (MSE), the coefficients of determination (R^2), and the Mean Absolute Percentage Errors (MAPE) for width and depth in I, II, and III models are shown in Table 4. Lower values of MSE and MAPE and higher values of R^2 indicate better model fit.

MSE, R^2, and MAPE were calculated according to the Formulas below:

$$\mathrm{MSE} = \frac{1}{n}\sum_{\mathrm{i}=1}^{n}((\mathrm{y_i} - \hat{\mathrm{y}}_\mathrm{i})^2) \quad (2)$$

$$\mathrm{R}^2 = \frac{\sum_{\mathrm{i}=1}^{n}((\hat{\mathrm{y}}_\mathrm{i} - \bar{y})^2)}{\sum_{\mathrm{i}=1}^{n}((\mathrm{y_i} - \bar{y})^2)} \quad (3)$$

$$\mathrm{MAPE} = \frac{1}{n}\sum_{\mathrm{i}=1}^{n}\left|\frac{\mathrm{y}_i - \hat{\mathrm{y}}_\mathrm{i}}{\mathrm{y_i}}\right| \quad (4)$$

Where n is the number of experiments, y is the actual value, and $\hat{y}$ is the predicted value, $\bar{y}$ is the mean of actual values.

Practically these three estimators were used for the selection of the best ANN schemas for each model in the first place. Moreover, they were used to compare the models I, II, and III.

4 DISCUSSION

In this work, factorial DoE assisted in the selection of training data sets for the ANN predictive models. Furthermore, it was found that ANN predictive models have inherent capability to effectively re-produce the outcomes of a nonlinear, complex and dynamic system, like a laser micro-machining system.

Ranking the models (I, II, and III) according to the three statistical estimators, model I was the best for width and cost responses. This might be attributed to the great number of training data used in this model (24 out of 27 available data). This was the largest amount of training data compared to the other models (14 for model II and 13 for model III). This enabled model I to predict the whole experimental data width and operating cost with a small margin of error.

Model II was next best and better than model III, even though both having almost the same number of training data but different training data set. This might be due to the fact that the training data set in model II was chosen according to FCC Design which covers all the corner points from the experimental data space. While the rather worse prediction of model IIIs that used BB Design, can be comprehended when the absence of the eight experimental data space corner points from the training set is taken into account. So due to the lack of these influential points, the estimation within the data ranges will not be adequately exact from this model.

It can be seen clearly from Table 4 that statistical estimators for cost prediction are a lot better than their counterparts for width prediction. This can be attributed to the fact that production cost is proportional to its inputs and it was originally estimated using Equation (1). Furthermore, this demonstrates the ability to utilise ANN as an arbitrary function estimation technique that uses experimentally observed data to "learn".

Table 4: Comparison criteria for width and depth models in I, II, and III models.

Estimator	Width			Estimator	Cost		
	I	II	III		I	II	III
MSE	24.8	192.7	206.8	MSE	8×10^{-11}	9065×10^{-11}	273253×10^{-11}
R^2	0.99	0.95	0.95	R^2	0.99	0.99	0.99
MAPE	1.2 %	6.0%	7.2 %	MAPE	0.003 %	0.038 %	0.100 %

Another notice from Table 4 that all statistical estimators came to an agreement, model I was the best, model II the second, and model III the worst with regards to both predictions, width and cost. This indicates that these estimators work together in harmony and have been well chosen. These results empirically establish their use as criteria for selecting both the best ANN configuration for a developed model and the best model that describes a system or a problem.

5 CONCLUSION

DoE was used to design an arranged series of information-gathering experiments to characterise micro-channel formation using a Nd:YVO_4 laser. The relationship between the main laser process parameters and the developed micro-channel width and corresponding micro-machining operating cost was examined using feed-forward, back-propagation ANN predictive models. The influence of changing the number and the selection of training data on the prediction capability of the developed ANN predictive model was investigated. MSE (Mean Squared Error), R2 (The coefficient of determination), and MAPE (Mean Absolute Percentage Error) were utilised as a basis for comparison between the developed ANN predictive models.

The comparison showed that model I (which has the highest number of training data) was the best. Moreover, model II is better than model III (both have almost the same number of training data but different training data set). This indicates that the more training data employed the better model fit acquired. However, when limited number of experiments (training data) is allowed, the outcomes of this work favoured using FCC Design over BB design for the selection of training data. This result indicates that using FCC design for training data selection was found more efficient in predicting width and micro-machining cost and highlighted the importance of including all experimental data space corner points in any training data set. Moreover, this comparison showed that the ANN modelling technique can be smoothly employed to predict the laser machined micro-channel dimensions and production cost precisely.

Automated systems control can allow the use of the models presented in this paper in order to produce optimised micro-channels with high dimensional precision and least production cost.

It was established in this work that the developed ANN predictive models were efficient at satisfying these demands and were effective for the prediction of the most appropriate laser micro-machining parameters.

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