AN ARTIFICIAL NEURAL NETWORK FOR DIMENSIONS AND COST MODELLING OF INTERNAL MICRO-CHANNELS FABRICATED IN PMMA USING ND:YVO_4 LASER

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ABSTRACT

For micro-channel fabrication using laser micro-machining process, estimation techniques are normally employed to develop an approach for system behaviour evaluation. Artificial Neural Network (ANN) is one of the numerical methodologies that can be utilised as an estimation technique for these processes. This technique is used in this paper in order to develop predictive models that are capable of finding a set of laser processing parameters that provides the required micro-channel dimensions with the least possible cost. In this work, an integrated methodology is presented in which the ANN training data sets were obtained by Design of Experiments (DoE) methodology. A 3^3 factorial design of experiments (DoE) was used to get the experimental data set. Laser power, P; pulse repetition frequency, PRF; and sample translation speed; U were the ANN inputs. The channel width and the produced micro-channel operating cost per metre were the measured responses. Eight ANN predictive models were developed on four different training data sets for internal micro-fabrication in PMMA using a Nd:YVO_4 laser. These models were varied in terms of the selection and the quantity of training data and constructed using a multi-layered, feed-forward structure with a the back-propagation algorithm. The responses were adequately estimated by the ANN models 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 that had the largest number of training data was the best. However, when only limited number of training data should be used, the model that used Face-Centred Cubic (FCC) Design for selecting the training data proven to be the most successful.

Keywords: pulsed Nd:YVO_4 laser; ANN; factorial DoE; predictive models; channel dimensions; PMMA.

1 INTRODUCTION

Laser micro-machining is a materials-processing technique that uses lasers to make managed thermal alterations to provide required micro-scale geometrical shape and dimensional ablations. Laser micro-machining processes include the drilling, cutting, milling and engraving of materials with micro-dimensional tolerances. In spite of the fact that laser micro-machining is a technically complex manufacturing process, research work has made the production of accurate, regular, and defect-free parts possible at high rate [1]. Laser micro-machining is employed in many micro-machining applications in the domains of telecommunications, glass cutting, micro-sensors; micro-via, ink jet printer nozzles, biomedical catheter drilling, thin-film scribing; micro-fluidic channels for blood/protein analysis; optical vibration sensors; three-dimensional binary data storage; and novelty fabrications [2-5].

To get a set of laser operating parameters that provides the required micro-channel dimensions for a specific application under certain processing restrictions, predictive models can be used. Various statistical and numerical methodologies have been implemented to predict and optimise several laser manufacturing processes including Artificial Neural Networks (ANN) [6]; genetic algorithms [7], design of experiments [8], finite elements analysis [9], ant colony optimisation [10], and fuzzy logic [11].

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. Many researchers have for example applied DoE, evolutional algorithms and ANN techniques in the area of laser welding [12].

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 used by the current authors for the production of micro-channels [13].

ANN predictive models were constructed, utilised and analysed for significance 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). The ANN models may be used to select the input parameters for required output dimensions or to predict the dimensions of the channels based on set inputs.

2 EXPERIMENTAL SET-UP

2.1 Experimental work

In this paper, a Nd:YVO_4 laser system of 2 W maximum power and 1064 nm wavelength was used for the micro-channel fabrication. These internal micro-channels were created in polymethyl methacrylate (PMMA) sheets of 10 mm thickness. In order to facilitate the measurement of the micro-channels' widths, a 2 mm distance between each two micro-channels was set. The PMMA sample work piece was positioned at the beginning of each experiment on the 3D positioning stage such that the laser spot is focused beyond its back surface. Afterwards, the laser source was turned on and the sample moved away from the stationary laser head. Figure 1 shows optical components setup and the work piece. This laser micro-machining processing technique enabled creating the internal micro-channel from the back to the front of the sample Instead of creating the micro-channel on the surface of polymers' samples with the difficult and rather fragile subsequent bonding.

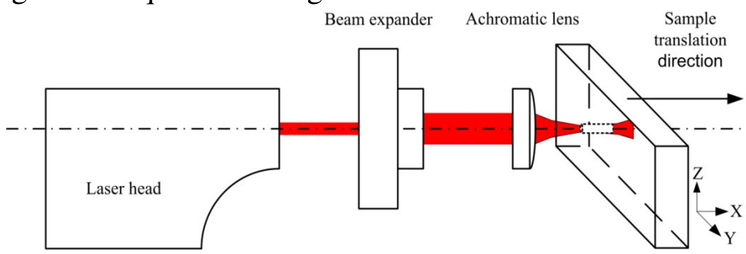

Figure 1: Laser micro-machining optical components arrangement.

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 strategy.

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 low level is represented by -1, the middle by 0, and the high level by 1. The actual and coded experimental 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	Actual			Coded		
	Low	Mid	High	Low	Mid	High
P (W)	0.5	1.0	1.5	-1	0	1
PRF (kHz)	13	23	33	-1	0	1
U (mm/sec)	0.50	1.74	2.98	-1	0	1

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. So that the total number of conducted experiments was 32. Two measured responses were carried out namely: the channel width and the micro-machining operating cost per metre of produced micro-channel.

2.3 Micro-channel 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 point pair, between which the width was measured, was picked using the cursors and by looking at all views of the channel.

The measurement results of the repeated experiments were averaged with the original experiment reducing the overall number of results 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.

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. However, labour cost should be considered when dealing with operational systems.

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×P. Assuming 85% utilisation, and transforming all the variables to SI units, the total approximated operating cost per unit length (in €/m) is given by the following Equation (1).

$$\text{Micro-machining cost [€/m]} = \frac{(0.481 + 0.21P)}{U} \qquad (1)$$

2.5 Artificial neural network models' setup

Four ANN predictive models were developed for the width and another four 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 eight models were based on four 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 Design, were used to train the network.
- Model IV: 14 randomly selected experiments were used to train the network.

Each of these four 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.

In this work, the percentage of training data to overall data was set to a low level for models II, III and IV compared to model I. This percentage of models II, III and IV is much less than would normally be used for the generating of ANN predictive models. The training set of models II & III were selected according to two popular designs; FCC Design & Box-Behnken Design respectively. These two designs along with model IV were selected in order to investigate which design should be chosen in case very limited number of experiments is allowed. This scenario could be when carrying out the experiments is lengthy, expensive, difficult, or dangerous.

2.6 Configuration of ANN

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 three and the number of neurons in each hidden layer was varied up to 100 neurons.

Due to its good generalisation capability, a transfer sigmoid function was used in all investigated 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. The programme repetitively presented the training data one by one to the ANN structure being developed, and the weights were automatically adjusted after each iteration. 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 error raised 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

It was discovered that the best ANN schemas were obtained with one or two hidden layers. This was anticipated since only models of extremely complex nature need multiple hidden layers. Table 2 shows the number of neurons in the hidden layers that achieved best predictions of width and cost for models I, II, III and IV.

Table 2: Number of neurons in the hidden layers for width and depth in I, II, III, and IV models.

Model	Hidden layers	Micro-channel width	Micro-machining cost
I	1^{st}	6	4
II	1^{st}	5	4
III	1^{st}	8	4
IV	1^{st}	4	5
	2^{nd}	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), R^2 (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. Practically these three estimators were used for the selection of the best ANN schemas for each model in the first place. Table 3 shows a side by side comparison between models I, II, III and IV in terms of the three chosen estimators.

Table 3: Comparison criteria for width and depth models in I, II, III, and IV models.

Estimator	Width				Estimator	Cost			
	I	II	III	IV		I	II	III	IV
MSE	21.5	77.3	87.5	112.2	MSE	0.01×10^{-8}	9×10^{-8}	270×10^{-8}	3300×10^{-8}
R^2	0.98	0.94	0.92	0.92	R^2	0.99	0.99	0.99	0.99
MAPE	0.6	1.7	2.3	2.2	MAPE	0.03×10^{-3}	0.4×10^{-3}	1×10^{-3}	12×10^{-3}

It can be seen from the comparison drawn in Table 3 that model I was the best, II was the second best, and IV was the worst in terms of MSE, R^2, and MAPE for both width and cost outcomes. The capability of the models to predict the whole data set signifies the generalisation ability of the models since part of experimental data set were never presented to the predictive models in the training stage. The generalisation of model I can be found to be better than other models in that it has predicted the actual channels' widths and productions' cost more precisely.

4 DISCUSSION

Factorial DoE designed experiments were used to develop eight ANN predictive models of four different training data sets. ANN trials were performed using multilayered feed-forward structure and back-propagation algorithm. These trials were carried out in order to construct ANN predictive models that predict laser machined micro-channel geometrical and economic parameters. The ANN architecture that achieved the lowest MSE and MAPE and the highest R^2 for the whole data set was selected for each ANN predictive model, see Table 2. This selection was feasible by using aNETka software to get the outcomes predictions for whole data set for all studied architectures and then selecting the best in terms of the three statistical criteria. The estimated outcomes from the eight ANN predictive models were compared with the actual experimental data in terms of the three statistical criteria.

Over time, the developed ANN predictive models may not predict as correct as when they were first developed as a result of the equipments' deterioration. In this case, a simple re-training for the best ANN configuration with a re-captured experimental data using aNETka software is needed.

Regarding the capability and limitations, ANN predicting models are productive in estimating the investigated micro-machining outcomes in addition to selecting micro-machining input values for a desired process outcome. However, these predictive models can be applied only to the examined laser and material, and within the studied ranges [14].

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. This was established in other researchers' works [15].

Ranking the models (I, II, III, and IV) 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 IV, 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.

When limited number of training data is used, model II was the best, model III was the second best, and model IV came last, even though all 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 Box-Behnken 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. On the other hand, model IV the worst prediction might be due to the fact that the selection of training data set for this model was entirely arbitrary. Even though all experimental data available are provided using DoE methodology, the last point illustrates the significance of carefully selecting the training data set rather than at random.

It can be seen clearly from Table 3 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”.

Another notice from Table 3 that all statistical estimators came to an agreement, model I was the best, model II the second, and model IV 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.

Currently, modelling laser micro-machining process by traditional numerical or analytical techniques is not feasible. Practically, trial-and-error approach is employed to set the process control parameters when starting a new laser micro-machining operation with specific dimension. This approach can be lengthy and expensive particularly for small lot production or prototyping, and generally does not guarantee best process control parameters’ selection for required manufacturing purposes [14]. Models presented in this work enabled the selection of laser control parameters for particular dimension within the investigated range of dimensions and with the least production cost.

5 CONCLUSION

DoE was used to design an arranged series of information-gathering experiments to characterise micro-channel formation using 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), R^2 (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 for the two studied responses. On the other hand, when an average number of training data is to be used, model II was the most excellent, model III was the second best, and model IV came last. 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 Box-Behnken 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. Furthermore, outcomes illustrated the significance of carefully selecting the training data set rather than at random, despite the fact that all experimental data available are provided using DoE. 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 may demand producing micro-channels with exact dimensions and optimum (least) production cost. It was established in this work that the developed ANN predictive models are efficient at satisfying these demands and using ANN can be utilised as an effective predictive tool for laser micro-machining parameters' selection.

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