Int J Adv Manuf Technol (2008) 39:39–46
DOI 10.1007/s00170-007-1199-1

ORIGINAL ARTICLE

An artificial neural network approach on parametric optimization of laser micro-machining of die-steel

Srijib Kr. Dhara · A. S. Kuar · S. Mitra

Received: 23 April 2007 / Accepted: 7 August 2007 / Published online: 6 September 2007

Abstract In the present research, laser micro machining (LMM) of tungsten-molybdenum general purpose high speed steel (Rex M2) has been studied. Selection of optimum machining parameter combinations for obtaining higher depth of groove and smaller height of recast layer is a challenging task in LMM due to the presence of a large number of process variables. There is no perfect combination of parameters which can simultaneously result in both the highest depth of groove and lowest height of recast layer. This paper presents an attempt to develop a strategy for predicting the optimum machining parameter setting for the generation of the maximum depth of groove with minimum height of recast layer. A feed forward back-propagation neural network has been developed to model the machining process. The model, after proper training, is capable of predicting the response parameters as a function of four different control parameters. Experimental results demonstrate that the machining model is suitable and the optimization strategy satisfies practical requirements. The developed model has been found to be quite unique, powerful and flexible.

Keywords ANN modelling · Depth of groove · Laser micro machining (LMM) · Optimization · Recast layer

1 Introduction

Laser beam machining (LBM) has a great potential in the modern day production scenario. LBM is a high energy density process that works fast on complex shapes, is applicable to any type of material, generates no mechanical stress on work piece, reduces waste, provides ecologically clean technology, and has the ability to do work in the micro range. The low cost of production has made LBM essential in many industries as well as in household applications. The LBM machines range in size from tiny semiconductor devices no bigger than a grain of salt to high-power instruments as large as an average living room. Micromachining is the foundation of the technology to realize miniaturized products. To develop microproducts there must be technological advancement in the field of control, measurement and assembly. In the present research concentration has been given to the control of the factors which affect laser micromachining. Several attempts have also been made to model the LBM process. Although a good number of fundamental research [1–5] have already been done in the area of laser machining technology, very few have been done in the micromachining area. So, further research is still needed in the area of micro-machining for optimal control of machining parameters.

Bachmann [6] developed the process of micro drilling printed circuit board (PCBs) having diameter as small as 10 μm. Riccardi et al. [7] described the fabrication of high-resolution bubble ink jet nozzles having 55 μm diameters with 27° taper using a 300 Hz KrF laser. The material on which the holes were made was 50 μm thick polyimide. Windholz [8] described micro-machining of diamond by micro-second pulse Nd:YAG and nano-second pulse excimer lasers. Schoonderbeek [9] developed high power kW excimer lasers, for simultaneous drilling for huge amount of small holes, e.g. for aerospace applications. Research at the University of Texas and DuPont Electronic Materials [10] has shown the feasibility of the idea to produce nano-particles by illuminating a stream of micro-particles with a

S. K. Dhara · A. S. Kuar (✉) · S. Mitra
Production Engineering Department,
Jadavpur University,
Kolkata 700 032, India
e-mail: arunanshu@rediffmail.com

pulsed excimer laser. A low velocity aerosol stream of 2 μm diameter micro-particles with 10 ns pulses from a 249 nm KrF laser results in nucleation of nano-particles, which are unagglomerated and relatively uniform in size. In the area of 3D micromachining Masuzawa [11] has developed the hole area modulation method using a semitransparent mask, consisting of a series of small holes enabling a continuous variable depth just by oscillating the mask in pre-programmed patterns. Kovalenko [12] reported micro drilling, micro cutting and micro milling of semi-conductors with green laser. The light of copper vapour lasers is more strongly absorbed in metals than that of infra-red laser. This leads to deep holes with a small heat affected zone. Aspect ratios of greater than 40 and surface roughness in the order of 1–2 μm (Ra) are reported by Allen [13]. Elmes et al. [14] conclude that laser micro machining is the preferred technique that corresponds with increased speed and automation in biomedical instrumentation like a pin based picolitre dispenser to take thousands of genetic samples for massive parallel testing. Allen [15] has fabricated inkjet nozzles of metal sheet by three different fabrication technique, i.e micro-EDM, micro-Drilling and copper vapour laser (CVL) machining and evaluated the characteristics of each technique while assessing the differences between. Micro parts of almost any geometry can be produced by mask projection. Drilling holes, however, is the key application in micro fabrication. Excimer laser removes only a thin layer of material and has small penetration depth, allowing precise control of the micro-drilling depth [16].

Although a large number of research works are reported on laser drilling operation, research work on micro-grooving operation using laser has not been reported so far. In several references, the applicability and superiority of the artificial neural network method of analysis has been reported [17, 18].

The material used for experiments is Rex M2 High speed steel commonly known as die steel. Rex M2 is a tungsten-molybdenum general purpose high speed steel. It is suitable for a wide variety of cutting tools and is often used for metal forming tools such as punches and dies. Rex M2 is a good choice for cutting tools which require moderate feeds

Table 1 Specification details of laser machining set-up

Specification	Description
Laser type	Nd:YAG laser
Wave length	1064 nm
Mode of operation	Q-Switched (pulsed)
Type of Q-switch used	Acousto optic Q-Switch
Mode of laser beam	Fundamental mode (TEM_{00})
Mirror reflectivities	Rear mirror 100%, Front mirror 80%
Beam diameter $1/e^2$	1mm
Laser beam spot diameter	100 μm
Pulse width	120 ns to 150 ns

and speeds. It provides sufficient red hardness along with outstanding toughness for high speed steel. For cold work applications, Rex M2 offers high hardness and wears resistance. Its high attainable hardness provides superior compressive strength for deformation resistance, reducing susceptibility to such problems as peening, denting and edge rollover. Its high tempering temperature and red hardness make it an excellent substrate for most surface treatments. Further, it is found that they are extremely difficult to machine by conventional methods due to their excellent strength property. Different aspects of machining of this alloy have been investigated by several researchers [19]. However, very few comprehensive research works have been reported so far, and thus, no technology tables or charts are available in the field of laser beam machining of this alloy. Therefore it is imperative to develop a suitable technology guideline for optimum and effective machining of die steel.

Selection of optimum machining parameter combinations for obtaining higher depth of groove and smaller height of recast layer is a challenging task in LBM due to the presence of large number of process variables. This paper presents an attempt to develop a strategy for predicting the optimum machining parameter setting for the generation of the maximum depth of groove with minimum height of recast layer. A feed forward back-propagation neural network has been developed to model the machining process. The model, after proper training, is used for predicting the response parameters as a function of

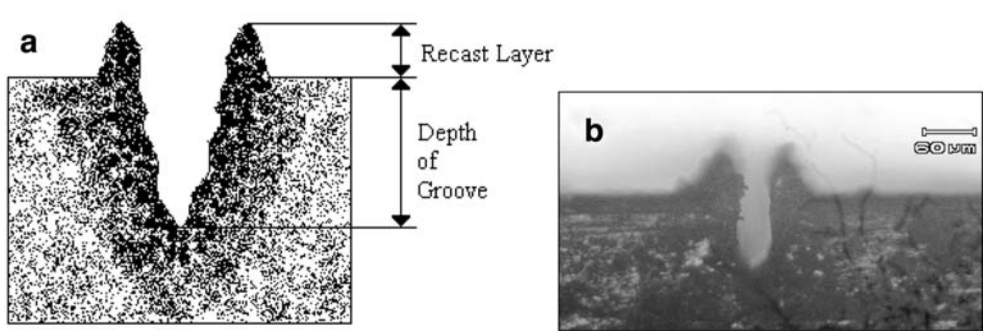

Fig. 1 (**a**) Schematic diagram of machined groove and recast layer and (**b**) Microscopic view of the machined groove and recast layer

Table 2 The machining parameters considered and their levels

Machining parameters	Symbols	Units	Levels		
			L1	L2	L3
Lamp current	A	Amps	16	17	18
Frequency	B	kHz	4	5	6
Pulse width	C	%	4	6	8
Air pressure	D	Kg/cm^2	1	1.5	2

four different control parameters. These predicted values would be used for optimization purposes.

2 Experimental planning

The experiments were performed on a CNC pulsed Nd:YAG laser machining system manufactured by M/s Sahajanand Laser Technology, India. The detailed specification of the experimental setup is listed in Table 1. For each experimental run, the specified input parameter combination was set and the workpiece was machined. The laser beam was allowed to pass across the job for a single time. The workpieces used are rectangular bars of size 2.6×2.6×35 mm^3. For this single pass operation a scratch is formed on the sample. The cross sectional view of the scratch is a V-groove (Fig. 1(a) and (b)). The angle of the groove and other dimensions except the depth of the groove which has been developed by single pass operation of laser beam has not been considered here. The amount of material removal (i.e. depth of groove) for a single pass operation of laser beam on die steel is the main objective of study. When material removal is the main criteria of micro machining then the aim would be to maximize the depth of groove, but when marking operation is going on concentration should be given to minimizing the depth of groove, so minimization or maximization of depth of groove depends on the type of operation to be done. In both the cases the height of recast layer should be as small as possible for the generation of a better surface finish. In the present research analysis of different parameters settings on depth of groove as well as the height of recast layer on die steel in a single pass operation has been carried out through ANN modelling.

Based on literature survey and preliminary investigations, four parameters have been chosen as inputs: lamp current (A), frequency (B), pulse Width (C), air pressure (D). The levels of parameters selected (Table 2) are also based on preliminary experiments and literature survey.

Table 3 Training dataset for the neural network model (the values of the variables are normalized)

Lamp current	Pulse frequency	Pulse width	Air pressure	Depth of groove (mm)	Height of recast layer (mm)
0.88889	0.66667	0.5	0.5	0.0265	0.0385
0.88889	0.66667	0.5	1	0.03175	0.038375
0.88889	0.66667	1	0.5	0.0215	0.038125
0.88889	0.66667	1	1	0.0265	0.033375
0.88889	0.83333	0.75	0.75	0.0278	0.043
0.88889	1	0.5	0.5	0.02175	0.022875
0.88889	1	0.5	1	0.024	0.029375
0.88889	1	1	0.5	0.016	0.02875
0.88889	1	1	1	0.02325	0.02837
0.94444	0.66667	0.75	1	0.023	0.0168
0.94444	0.83333	0.75	0.75	0.02646	0.02928
0.94444	0.83333	1	0.5	0.02866	0.0523
0.94444	1	0.5	0.75	0.02217	0.0188
1	0.66667	0.5	0.5	0.0345	0.04825
1	0.66667	0.5	1	0.035	0.04075
1	0.66667	1	0.5	0.032	0.049125
1	0.66667	1	0.75	0.0268	0.0413
1	0.66667	1	1	0.034	0.041875
1	0.83333	0.5	1	0.0376	0.044
1	1	0.5	0.5	0.03075	0.03475
1	1	0.5	1	0.03125	0.036125
1	1	0.75	0.5	0.0308	0.0598
1	1	1	0.5	0.027	0.038375
1	1	1	1	0.032	0.027375

Table 4 Comparison of the developed model with experimental data and the Errors in prediction (the values of the variables are normalized)

Test Expt. No.	Lamp Current	Pulse Frequency	Pulse Width	Air Pressure	Experimental Depth of groove (mm)	Experimental Height of recast layer (mm)	ANN predicted depth of groove (mm)	ANN predicted height of recast layer (mm)	% Error in prediction of depth of groove	% Error in prediction of height of recast layer
1.	0.8889	0.6667	0.5	0.75	0.0235	0.0385	0.0240	0.0360	2.10	6.51
2.	0.8889	0.6667	0.75	0.75	0.0555	0.0335	0.0563	0.0366	1.48	9.26
3	0.8889	0.8333	1	1	0.0495	0.0365	0.0520	0.0338	4.99	7.50
4.	0.9444	0.6667	0.75	0.5	0.0305	0.0425	0.0294	0.0437	3.57	2.82
5.	0.9444	0.6667	1	0.75	0.0155	0.0225	0.0149	0.0219	3.88	2.72
6.	0.9444	0.8333	0.5	1	0.0285	0.0625	0.0294	0.0614	3.19	1.70
7.	1	0.6667	0.5	0.75	0.0315	0.0465	0.0310	0.0487	1.63	4.74
8.	1	0.6667	0.75	0.5	0.0305	0.0305	0.0291	0.0292	4.44	4.40
9.	1	1	0.75	0.75	0.0245	0.0175	0.0242	0.0188	1.35	7.33
Average % of error									≈2.96	≈5.22
Total average prediction error(%): ≈ 4.09										

Experiments have been carried out using full factorial combinations of these factors and their different levels.

There are other factors that can be expected to have an effect on the measure of performance. In order to minimize their effects, these parameters are held constant: the traverse speed (10 mm/sec), type of assisted gas (air). The focusing of the laser beam has been done manually with the help of the charge-coupled device (CCD) camera and CCTV closed-circuit television (CCTV).

The grooving performance of LBM is measured by the depth of the groove and height of recast layer developed on the groove. Artificial neural network (ANN) has been used to model the LBM process. The validity and accuracy of the developed model has been examined properly. Optimization of multiple responses with the help of predicted responses of ANN model has been done.

Four input parameters with three levels could have a total 3^4 combinations of experiments for full factorial design. A total of 33 experiments have been done to get the responses. The responses considered here are the depth of groove and height of recast layer. Some of the responses (24) are set as target while training of the network is going on (Table 3). Out of all the training algorithms, the Levenberg Marquadt (LM) algorithm is the fastest and least memory consuming one [17]. In the present research, the LM algorithm is used for training the network. Neural network toolbox of MATLAB software has been used. After proper training of the network when the desired goal (the goal has been set as the network output is at least 10^{-6} decimal point close to the target value) has been achieved, the network is simulated with other input parameters combinations and the network responses are compared with experimental responses (Table 4). Thus validation of the developed model has been checked. Optimum parameter setting for the desired responses is then found out by using the responses of the network model.

The depth of the groove and height of recast layer were measured by Optical Measuring Microscope (Olympus STM6) at 10X magnification.

3 ANN modelling of laser micro machining process

Artificial neural networks can be used to model complex relationships between inputs and outputs or to find patterns in data. In essence, a neural network can be viewed as a function that maps input vectors to output vectors. The knowledge is presented by the interconnection weight, which is adjusted during the learning stage using the back-

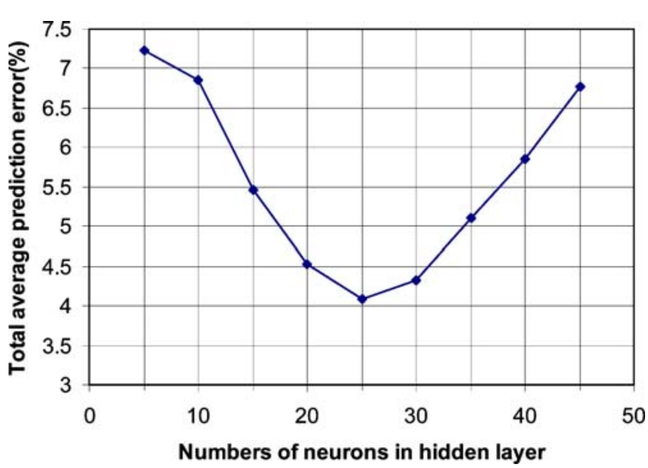

Fig. 2 Plot for determining the number of neurons in hidden layer

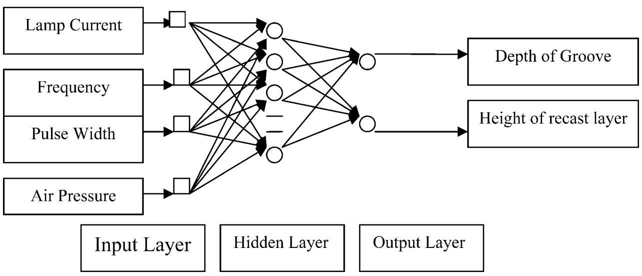

Fig. 3 Configuration of the neural Network

propagation learning algorithm that uses a gradient search technique to minimize the mean square error between the actual output pattern of the network and the desired output pattern.

Before training the neural network, the architecture of the network has been decided; i.e. the number of hidden layers and the number of neurons in each layer. As there are 4 inputs and two outputs, the number of neurons in the input and output layer has to be set to 4 and 2, respectively. According to Fausett [17] the back-propagation architecture with one hidden layer is enough for the majority of applications. Hence, only one hidden layer has been adopted. A trial and error procedure was employed to optimize the number of neurons in the hidden layer in which the prediction error is minimum. Prediction error and total average prediction error have been defined as follows:

$$\text{Prediction error}\,\% = \left|\frac{(\text{Experimental result} - \text{Predicted result})\times 100}{\text{Experimental result}}\right| \tag{1}$$

$$\begin{array}{c}\text{Total average}\\ \text{prediction error}\end{array} = \frac{(\text{avg. pred. error in depth}) + (\text{avg. pred. error in recast layer})}{2} \tag{2}$$

The number of neurons in the hidden layer is changed and the total average prediction error is calculated for each case. The number of neurons in the hidden layer is 25, for

Table 5 The machining parameters considered divided in five levels

Machining parameters	Symbols	Units	Levels L1	L2	L3	L4	L5
Lamp current	A	amps	16	16.5	17	17.5	18
Frequency	B	kHz	4	4.5	5	5.5	6
Pulse width	C	%	4	5	6	7	8
Air pressure	D	Kg/ cm^2	1	1.25	1.5	1.75	2

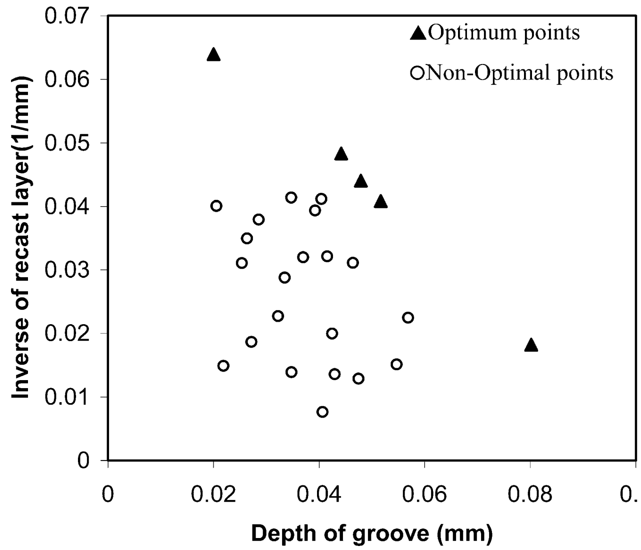

Fig. 4 Search for optimal combinations

which the total average prediction error is minimum. The procedure for determining the number of neurons in the hidden layer is shown graphically in Fig. 2. The input parameters were normalized to lie between 0 and 1. The model developed is a cascade forward back-propagation network having 25 neurons in the hidden layer. So, 4-25-2 is the most suitable network for the task. The developed model is shown schematically in Fig. 3.

The experimental results as shown in Table 3 are used to train the neural network. The parameters displayed in Table 3 are presented in normalized value. Properly trained back-propagation networks tend to give reasonable answers when presented with inputs that the network has never fed before. Typically, a new input leads to an output being presented. In back-propagation it is important to be able to calculate the derivatives of any transfer functions used.

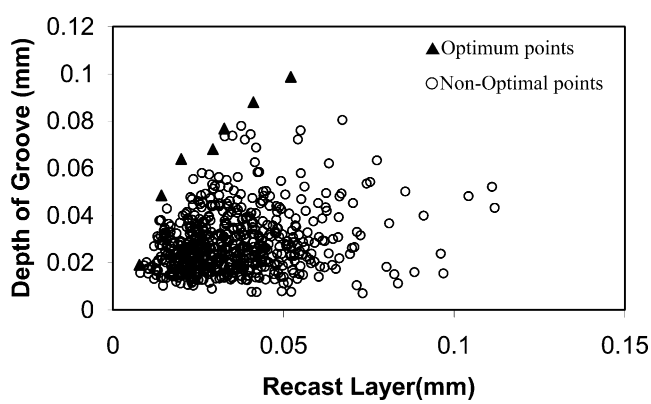

Fig. 5 Machining performance prediction of the ANN model for all 625 combinations

Table 6 Technology guideline for optimal machining of Rex M2 HSS material

Sl. No.	Input parameters				Responses	
	Lamp current (amp)	Pulse frequency (k Hz)	Pulse width (%)	Air pressure (Kg/cm^2)	Depth of groove (mm)	Height of recast layer (mm)
1	16.5	4.5	8	1.75	0.07688	0.03263
2	17	4	7	2.00	0.04854	0.01421
3	17	4	8	2.00	0.06396	0.02000
4	17	5.5	4	1.25	0.01907	0.00776
5	17.5	4	8	2.00	0.06807	0.02927
6	18	5	7	2.00	0.08798	0.04118
7	18	5	8	2.00	0.09878	0.05213

There are many algorithms available for training of multilayer network.

4 Testing of the developed model

An experimental approach was adopted, which involves testing of the trained neural network against another set of experimental data, illustrated in Table 4, which are drawn randomly from the full factorial data set. All the parameters shown in Table 4 are normalized. The errors in prediction are also presented in Table 4. However, the set of combinations is different from those used for training the network [20]. It can also be seen from Table 4 that the model predicted data follows the experimental data very closely. As the maximum error in prediction for depth of groove is below 5% (actually 4.98%) and for height of recast layer it is below 10% (actually 9.25%) it can be said that the error is within the tolerable limit. The average error in the prediction for depth of groove is 2.96% and for the height of recast layer 5.22 %, which are very small indeed. The total average prediction error of the network (which helps in determining the number of neurons in hidden layer) is calculated as 4.09%.

5 Strategy for parametric optimization through ANN model

The developed ANN model has been used to predict the response parameters, i.e. depth of groove and height of recast layer for all combinations of input factors. For better optimization, all of the input parameters have been divided into five levels within their working range as illustrated in Table 5. This helps in generating more predictions (5^4=625). Thus more optimal combinations were found as the searching was not confined within a small number of predictions.

The ANN model was used to predict the depth of groove and height of recast layer for all possible combinations of factors, i.e. 625 combinations. Figure 4 shows all of these 625 responses corresponding to those input parametric combinations. Each point in the graph corresponds to a particular input parameter setting. From Fig. 4 it is observed that the general trend is that a higher depth of cut is associated with higher height of recast layer. Further from all these predictions, it was observed that within the given parametric range, depth of groove varies between 0.007 to 0.098 mm and height of recast layer varies between 0.008 to 0.112 mm which are wide range as micro-machining is concerned.

Table 7 Final verification experiment and comparison with the optimum result

Test Expt. No. of Table 6	Lamp Current	Pulse Frequency	Pulse Width	Air Pressure	Experimental Depth of groove (mm)	Experimental Height of recast layer (mm)	ANN predicted depth of groove (mm)	ANN predicted height of recast layer (mm)	% Error in prediction of depth of groove	% Error in prediction of height of recast layer
1	16.5	4.5	8	1.75	0.0785	0.0315	0.07688	0.03263	2.07	3.57
4	17.0	5.5	4	1.25	0.0185	0.0075	0.01907	0.00776	3.06	3.42
7	18.0	5.0	8	2.00	0.0975	0.0525	0.09878	0.05213	1.32	0.71
Average % of error									2.15	2.57
Total average prediction error(%): ≈ 4.72										

To illustrate the optimization strategy graphically, predictions were plotted in Fig. 4. Instead of 625 predictions, only a few have been plotted in so that the philosophy of optimization can be understood more explicitly. Our target is to get the maximum depth of groove while keeping the height of recast layer as small as possible. For convenience, depth of groove and inverse of height of recast layer was considered as the x- and y- axis, respectively. Here the target is to maximize both the depth of groove and the inverse of height of recast layer. However, these two targets are conflicting, and there cannot be any such single combination that will simultaneously maximize them. Hence, there will be several optimal combinations instead of a single optimal combination, and it is truly a multi-objective optimization problem. The optimization search should be for a set of combinations that will give superior output. This set of points corresponds to the optimum points in the plot. Here, superior output means that it is better than any other output at least with respect to one of the process criteria, i.e. depth of groove or inverse of height of recast layer. If one parameter combination yields a better result in both the process criteria, or if it is higher with respect to at least one process criterion and is equal with respect to the other compared to a second parametric combination, then the second combination should never be selected in preference to the first. In other words, graphically, a point is not optimal if there is any other point that is above and right to the first point. If both the points have the same coordinates, both will be considered. Now it is quite clear why some points situated at the boundary were referred to as optimum points in Fig. 5. Certainly, all points outside this set of optimum points are not desirable. The parameter setting for which these optimum results can be obtained is shown in Table 6 along with predicted responses. To further verify the proposed model another set of experiments have been carried out and compared with the predicted optimum results. For this purpose parameter settings corresponding to serial number 1, 4 and 7 of Table 6 have been arbitrarily selected for the final verification experiment and also compared with the result shown in Table 6. It was observed that predicted value is quite close to the experimental result. The experimental result and the predicted optimum result along with the corresponding prediction error have been shown in Table 7.

6 Conclusion

In the present research, laser beam machining (LBM) of Rex M2 high speed steal has been carried out, and an advanced optimization strategy has been used to determine the optimal combination of control parameters. The method used is also capable of optimizing the depth of groove while maintaining the height of recast layer within specified limits. A cascade forward back-propagation neural network is used to construct the LBM process model. It has been found that among several neural configurations, a cascade forward back-propagation ANN of type 4-25-2, one hidden layer with 25 neurons can provide a best prediction. The validation experiments for the developed model were conducted and it was found that prediction accuracy of the model is quite good. A graphical method has been used to search out the optimal combinations of parameters from the set of all possible combination of parameters setting, i.e. 625 predictions. Seven optimum parametric combinations were identified out of 625 combinations, which will act as technology guideline for effective machining of the material. Through this optimization strategy, one can obtain more optimal parametric combinations, which will lead to efficient utilization of laser beam machining in practice. This approach has high potential to be used in other machining processes.

References

1. Chen TC, Darling RB (2005) Parametric studies on pulsed near ultraviolet frequency tripled Nd:YAG laser micromachining of sapphire and silicon. J Mater Process Technol 169(2):214–218
2. Li Q, Zheng Y, Wang Z, Zuo T (2005) A novel high-peak power double AO Q-switches pulse Nd:YAG laser for drilling. Opt Laser Technol 37:357–362
3. Wei Y, Zhang G, Huang C, Huang L, Wei M (2006) High power single wavelength 1338 nm Nd:YAG laser. Opt Laser Technol 38 (3):173–176, April
4. Sun Z, Li R, Bi Y, Hu C, Kong Y, Wang G, Zhang H, Xu Z (2005) Experimental study of high-power pulse side-pumped Nd:YAG laser. Opt Laser Technol 37:163–166
5. Kuar AS, Doloi B, Bhattacharyya B (2006) Modeling and analysis of pulsed Nd:YAG laser machining characteristics during micro-drilling of Zirconia (ZrO_2). Int J Mach Tools Manuf 46(12–13):1301–1310
6. Bachmann FG (1990) Industrial laser applications. Appl Surf Sci 46:254–263
7. Riccardi G, Cantello M, Mariotti F, Giacosa P (1998) Micro-machining with excimer laser. CIRP Ann 47/1:145–148
8. Windholz, R, Molian P (1997) Nanosecond pulsed excimer laser machining of CVD diamond and HOPG graphite. J Mater Sci 32:4295–4301
9. Schoonderbeek A, Biesheuvel CA, Hofstra RM, Boller K-J, Meijer J (2002) High speed drilling of metals with a long pulse XeCl excimer laser. Proc SPIE 4760 High –Power Laser Ablation IV
10. Burgress DS (2001) Laser ablation generates nano-particles. Photonics spectra, pp 26–29, July
11. Masuzawa T, Olde Bennker J, Eindhoven JJC (2000) A new method for three dimensional excimer laser micromachining by Hole area Modulation (HAM). CIRP Ann 49/1:139–142

12. Kovalenko V, Anyakin M, Uno Y (2000) Modelling and optimisation of Laser Semiconductor cutting. Proc ICALEO, vol. 90, Laser Micro-Fabrication, pp D82–D92
13. Allen D, Almond H, Logan P (2000) A technical comparison of micro-electro-discharge machining, micro drilling and copper vapour laser machining for the fabrication of ink jet nozzles. Proc SPIE 4019:531–540
14. Elmes S et al (2001) Laser machining of micro reservoir pins for gene analysis and high throughput screening. ICALEO Laser Micro fabrication Conference M303, ISBN 0-912035-73-0
15. Allen DM, Almond HJA, Bhogal JS, Green AA, Logan P, Huang XX (1999) Typical metrology of Micro-hole arrays made in stainless steel foils by two stage EDM. CIRP Ann 48/1:127–130
16. Ready JF (2001) LIA handbook of laser materials processing. Magnolia, Orlando, FL, pp 491
17. Fausett L (1994) Fundamentals of neural networks: architectures, algorithms and applications. Prentice–Hall, New York
18. Haykin S (2002) Neural networks: a comprehensive foundation. Pearson Publication, Harlow
19. Puri AB, Bhattacharya B (2003) An analysis & optimisation of the geometrical inaccuracy due to wire lag phenomenon in WEDM. Int J Mach Tools Manuf 43:151–159
20. Sarkar S, Mitra S, Bhattacharyya B (2005) Parametric optimisation of wire electrical discharge machining of γ titanium aluminide alloy through an artificial neural network model. Int J Adv Manuf Technol 7(2/3/4):207–223