10th International Research/Expert Conference
”Trends in the Development of Machinery and Associated Technology”
TMT 2006, Barcelona-Lloret de Mar, Spain, 11-15 September, 2006

THE LASER CUTTING OPTIMIZATION BY NEURAL NETWORKS

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ABSTRACT
Aim of this contribution is to present the optimization of the laser cutting process by artificial neural networks. NeuroSolution for Excel 1.02 was used in order to interpret complicated dependencies between technological characteristics of laser cutting and output parameters. Multilayer feed forward neural networks are utilized for modelling and prediction of input parameters of laser cutting machine. The experimental results were processed, evaluated and graphically interpreted.
Keywords: laser, cutting, artificial neural networks, optimization

1. INTRODUCTION
The cost of laser technology is still extremely high, though it is constantly falling, and consequently its usage is justified only if the quality of the final product is significantly better and if the process becomes more reliable. Laser applications in plastic materials cutting and micro-machining have grown considerably in many industries since it is now possible to achieve a superior quality finished product along with greater process reliability [1].
In the last two decades many studies to examine laser cutting process has been published. Ivarson et al. [2] studied oxidation dynamics and striation formation in laser gas assisted cutting process. They showed that cyclic cutting events were associated with the temporal behaviour of oxidation reactions. Laser cutting of polymeric materials was examined by Fenoughty et al. [3]. They indicated that the laser could be effectively used in high speed cutting of thin laminates. Grum and Zulijan [4] investigated heat affected zone in laser cutting process. They indicated that the heat transfer rates in the cutting front influenced the quality of cut. Yilbas [5] investigated laser cutting process in details. He indicated that the end product quality depended on the laser, workpiece parameters and the proper selection of the parameters.
Parameters of laser cutting and laser micro-machining are a key factor for final product quality and properties. Aim of this paper is to present application of artificial neural network for prediction of laser machine parameters.

2. MULTILAYER FEED FORWARD NEURAL NETWORKS
Artificial neural networks (ANNs) can be defined as massive parallel computational system, which has ability to store and process information. The most important property of ANNs – ability to generalize is caused by their topology. Neural network is nothing more than the connection of large number of units – neurons. Various configurations of ANNs are possible for different applications. This study is focused on multilayer feed forward network (MFFNN), which is one of the most popular

architectures. This type of ANN was developed from the Rosenblatt's perceptron network so that it is often also called as a multilayer perceptron (MLP).
In the MFFNN the information flows between the neurons only in the forward direction i.e. towards the output end. Neurons of each layer can have inputs from any neurons of the earlier layer. Each neuron is characterized by the generally nonlinear transfer function *S* and by the threshold value *b*. The neuron sums the weighted inputs and the threshold, and passes the result through its characteristic transfer function. The transfer function is usually same for all neurons from the layer.
Weights are commonly labelled $w_{\text{number of layer}}$(source neuron, target neuron), thresholds likewise. Values can be arranged into matrixes and the function of the three-layer neural network can be written:

$$\boldsymbol{y}_{out} = S_3\left(\boldsymbol{b}_3 + \boldsymbol{W}_3 \cdot \boldsymbol{x}_2\right) \tag{1}$$

$$\boldsymbol{x}_2 = S_2\left(\boldsymbol{b}_2 + \boldsymbol{W}_2 \cdot \boldsymbol{x}_1\right) \tag{2}$$

$$\boldsymbol{x}_1 = S_1\left(\boldsymbol{b}_1 + \boldsymbol{W}_1 \cdot \boldsymbol{u}_{in}\right) \tag{3}$$

where $\boldsymbol{y}_{out}$ is output vector of the MFFNN, S_i is transfer function of the $\boldsymbol{i}$-th layer, $\boldsymbol{b}_i$ is bias vector of the $\boldsymbol{i}$-th layer, $\boldsymbol{W}_i$ is weighting matrix of the $\boldsymbol{i}$-th layer, $\boldsymbol{x}_i$ is output vector of the $\boldsymbol{i}$-th layer and $\boldsymbol{u}_{in}$ is input vector of the MFFNN.

3. METHODOLOGY

In order to interpret complicated dependencies between technological characteristic of laser cutting and output parameters NeuroSolution for Excel 1.02 was used.
Experimental results were used for training of an artificial neural network with the aim of developing the laser micro-machining component model. The three values of laser cutting output were measured. Specimens of PMMA material was used for tests. The experiments were carried out for all combinations of the chosen parameters, which are thickness of specimen from PMMA, cutting speed and power of laser, other parameters are kept constant.
The used MFFNN had one four-neuron hidden layer with hyperbolic tangent transfer function. The output layer consisted of three neurons with hyperbolic tangent transfer function (Figure 1).

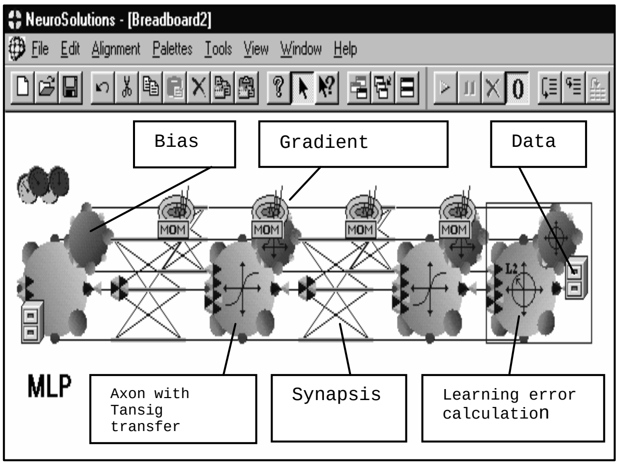

Figure 1. Schema of the multilayer feed forward neural network used for the prediction

4. NETWORK TRAINING AND RESULTS

The thickness of cutting specimen of PMMA, the cutting speed and the power of the laser were chosen as a set of input parameters. The surface roughness in place of cut, the depth of cut and the tensile strength were chosen as a set of output parameters (Table 1).
The network training involved the process of interactively adjusting the interconnection weights in such a way that the prediction errors on the training set are minimized. The back-propagation algorithm was applied to each pattern set, input and target, for all pattern sets in the training set. Since

the learning process was iterative, the entire training set had to be presented to the network over and over again, until global error reached a minimum acceptable value. (Figure 2)

Table 1. Training set of input and output parameters

Input parameters			Output parameters		
Thickness (mm)	Speed (m/min)	Power (W)	Ra (mm)	Depth of cut (mm)	Rm (MPa)
3	0,10	800	0,3	1,15	64
6	1,00	400	0,4	1,22	71
2	3,00	400	0,4	0,98	63
20	0,10	800	0,2	1,11	51
10	0,42	350	7,2	1,22	32
10	0,50	400	0,3	1,05	66
10	2,00	400	0,2	0,98	48
6	3,00	400	0,3	0,95	60
6	0,60	350	3,3	1,05	37
10	1,00	400	0,3	1,00	62
3	0,90	350	6,5	1,02	46
6	0,90	350	5,2	1,11	27
2	1,00	400	0,5	1,12	53
3	0,50	800	0,4	1,00	60
3	1,00	800	0,3	0,98	52
6	0,48	350	2,7	1,25	46
3	3,00	800	0,3	0,81	50
10	0,24	350	5,4	1,35	45
10	0,48	350	5,2	1,20	30

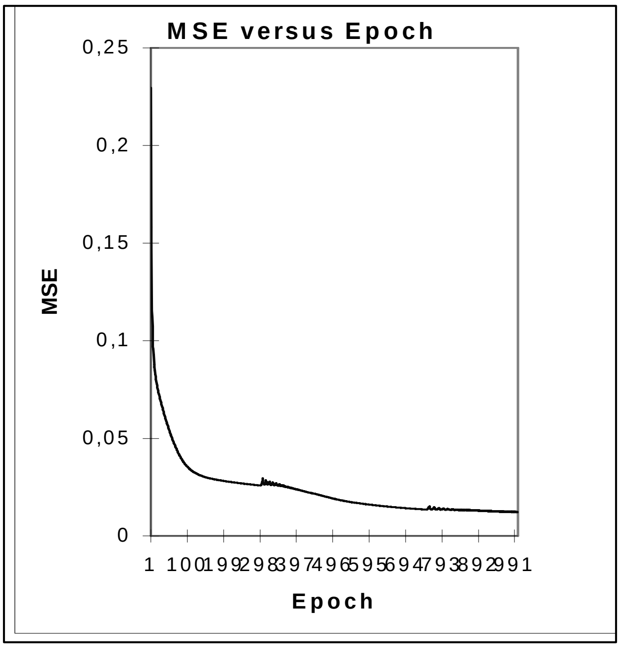

Figure 2. Global error minimization during training of network

An extensive number of tests were done on the laser machine to confirm the neural model with different cutting parameters. Following figures present the results of experiments and the comparison and analysis of results between the experimental and ANN model depending on the cutting parameters. The results and the values of the surface roughness, the depth of cut and the tensile strength are graphically presented (Figure 3 and 4). By comparison of the results predicted by ANN and the results of experiments the following was determined: the values from prediction coincide well with the values from experiments and, in addition, the processes of the change of the cutting parameters are well. Table 2 shows the comparison of the predicted values and the measured values.

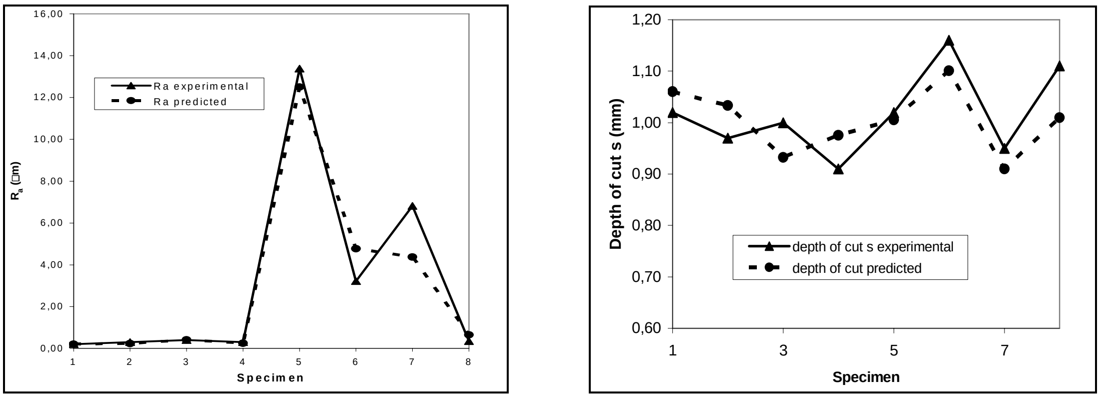

Figure 3. Comparison of predicted results and measured data - surface roughness and depth of cut

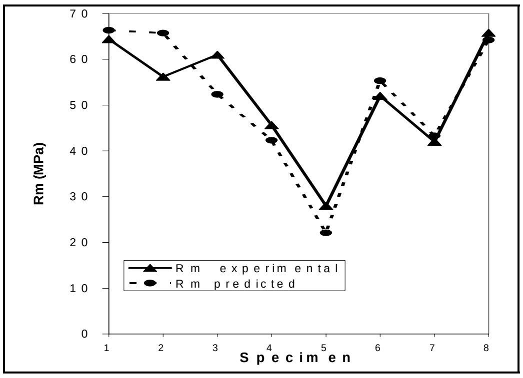

Figure 4. Comparison of predicted results and measured data - tensile strength

Table 2. Comparison of predicted and measured data

Measured data						Predicted data - MFFNN		
Thickness (mm)	Speed (m/min)	Power (W)	Ra (mm)	Depth of cut (mm)	Rm (MPa)	Ra (mm)	Depth of cut (mm)	Rm (MPa)
6	2,00	400	0,20	1,02	64	0,20	1,06	66
3	1,50	800	0,30	0,97	56	0,23	1,03	66
2	6,00	400	0,40	1,00	61	0,41	0,93	52
20	1,00	800	0,30	0,91	46	0,25	0,98	42
6	0,72	350	13,38	1,02	28	12,50	1,01	22
3	0,60	350	3,22	1,16	52	4,77	1,10	55
3	1,50	350	6,81	0,95	42	4,37	0,91	43
10	0,10	800	0,35	1,11	66	0,65	1,01	64

5. CONCLUSION

In conclusion, it is possible to state that supervised neural networks can be successfully used to estimate the output parameters developed during the laser cutting process. The comparison between the predicted cutting parameters and measured cutting parameters was done. It can be claimed that the comparison of the results obtained from the neural model and the experimental results confirms the efficiency and accuracy of the model for predicting the optimization. By using a multilayer feed forward neural network with back propagation training method, the neural network was trained to an accuracy of ±2% error for all three parameters.

6. ACKNOLEDGEMENT

This work was supported by the Ministry of Education, Youth and Sports of the Czech Republic under grant MSM 7088352102. This support is very gratefully acknowledged.

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