

VERIFICATION OF NEURAL NETWORK MODEL OF LASER MICRO-MACHINING

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ABSTRACT

In the paper the experimental data from laser micro-machining process were processed and modeled by artificial neural network. The laser micro-machining technique is highly complex and industrial laser machines combine a lot input parameters. Thus, white box modeling using mathematical equations is not suitable. The purpose of the neural model is to predict optimal settings for laser machine.

Keywords: artificial neural network, laser, micro-machining

1. INTRODUCTION

The task of the laser micro-machining has very extensive usage in industrial applications. The system development and introduction of these technologies is very attractive. Micro-machining belongs to the group of production processes, in which undersized products are made. Production specifications trend to continual minimization of product's dimensions [1]. The laser is optimal tool for its features in this development. Results of the laser micro-machining – surface quality of product and his utility in specific application – depend on the laser parameters and the polymer material type [2]. In order to interpret complicated dependencies between technological characteristics of laser micro-cutting and output parameters artificial neural networks (ANNs) were used.

Compared to traditional computing methods the ANNs are robust and global [3]. Because of this, ANNs are widely used for system modeling, function optimization, image processing, and intelligent control. ANNs give an implicit relationship between the input(s) and output(s) by learning from a data set that represents the behavior of a system. ANNs consist of a large number of processing elements, called neurons that operate in parallel. Computing with neural networks is non-algorithmic. They are trained through examples rather than programmed by software.

2. METHODOLOGY

In order to develop the laser micro-cutting component model, experimental results were used. The three parameters of laser micro-cutting output were measured. Material PMMA was used for tests. The experiments were carried out for all combinations of the chosen parameters, which are cutting depth, feed rate and laser power, other parameters are kept constant.

All simulations were done using Matlab 6.5 with Neural Network Toolbox. As can be seen from the figure 1, the three-layer feed forward ANN was used. The first and second layer had fifteen and ten

neurons with the hyperbolic tangent transfer function. On the contrary, the third layer had only two neurons with the linear transfer function.

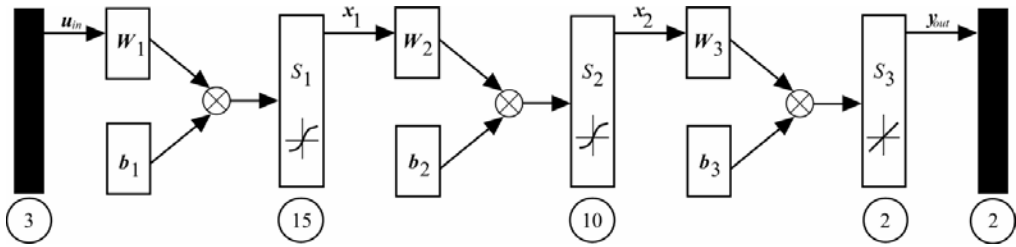


Figure 1. Schema of the artificial neural network based model

2.1. Procedure

1. Preparation of training data for the ANN

- Input data contained vectors [depth, Ra, Rz]. Where Ra and Rz are the surface roughness characteristics (see also table 1)

2. Creation of the ANN

3. Training of the ANN

- Levenberg-Marquart algorithm was used

4. Testing of the ANN

- Testing data were chosen for standard Ra and variety of depth (see table 2, 3, 4)

Table 1. Training set of input and output parameters

Input parameters		Output parameters		
Power (%)	Feed (%)	Depth (μm)	Ra (μm)	Rz (μm)
30	70	15	7,2	36,9
40	70	39	7	45,9
50	70	51	7,2	45,1
60	70	116	7,9	54,5
70	70	146	8,8	57,7
80	70	160	7,3	46
30	100	8	8,1	38,2
40	100	25	4,8	29,7
50	100	31	10	48
60	100	37	9,7	52,3
70	100	47	8,1	48,5
80	100	63	11,2	59,8

Table 2. Testing set of input parameters Ra=1,6 μm , Rz=10 μm and different depth in μm

depth (μm)	50	55	60	65	70	75	80	85	90	95	100
Ra (μm)	1,6	1,6	1,6	1,6	1,6	1,6	1,6	1,6	1,6	1,6	1,6
Rz (μm)	10	10	10	10	10	10	10	10	10	10	10
power (%)	57,03	57,03	57,48	59,98	65,68	72,16	75,70	76,67	76,60	76,26	75,93
feed (%)	85,05	83,63	82,07	81,07	80,70	80,22	79,33	78,37	77,58	77,00	76,60

	105	110	115	120	125	130	135	140	145	150	155	160
	1,6	1,6	1,6	1,6	1,6	1,6	1,6	1,6	1,6	1,6	1,6	1,6
	10	10	10	10	10	10	10	10	10	10	10	10
	75,66	75,46	75,32	75,22	75,16	75,12	75,10	75,10	75,10	75,10	75,11	75,12
	76,313	76,12	75,98	75,88	75,81	75,76	75,73	75,70	75,68	75,67	75,66	75,66

Training and testing: network training involves the process of interactively adjusting the interconnection weights in such a way that the prediction errors on the training set are minimized. The Levenberg-Marquart algorithm is applied to each pattern set, input and target, for all pattern sets in the training set. Since the learning process is iterative, the entire training set will have to be presented to the network over and over again, until global error reaches a minimum acceptable value. Value of input characteristics (power and feed) are stated as a percents from maximal power ($P_{max}=30W$) and maximal feed ($f_{max}=1066\text{ mms}^{-1}$).

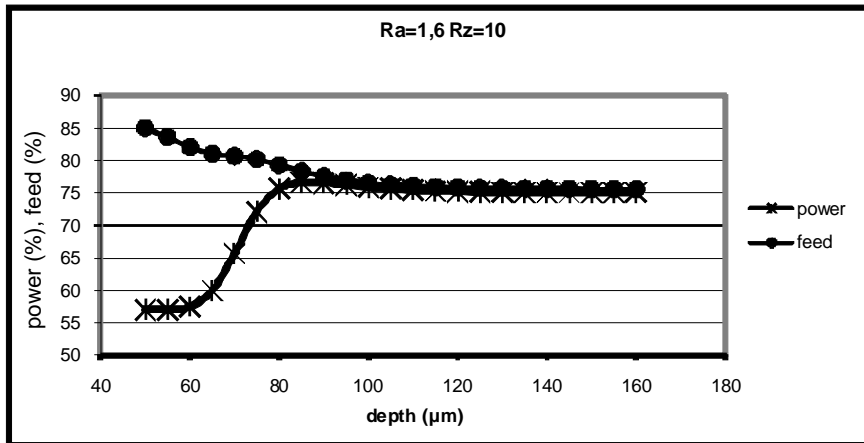


Figure 2. Network response for $Ra=1,6\mu\text{m}$ and $Rz=10\mu\text{m}$

Table 3. Testing set of input parameters $Ra=1,6\mu\text{m}$, $Rz=10\mu\text{m}$ and different depth in μm

depth (µm)	50	55	60	65	70	75	80	85	90	95	100
Ra (µm)	3,2	3,2	3,2	3,2	3,2	3,2	3,2	3,2	3,2	3,2	3,2
Rz (µm)	20	20	20	20	20	20	20	20	20	20	20
power (%)	61,76	62,30	62,45	62,33	61,74	60,16	58,81	62,60	68,33	71,58	72,93
feed (%)	74,38	73,67	72,95	72,31	71,66	70,74	70,21	72,17	74,40	75,33	75,61

105	110	115	120	125	130	135	140	145	150	155	160
3,2	3,2	3,2	3,2	3,2	3,2	3,2	3,2	3,2	3,2	3,2	3,2
20	20	20	20	20	20	20	20	20	20	20	20
73,50	73,78	73,96	74,11	74,24	74,35	74,46	74,55	74,64	74,71	74,78	74,84
75,67	75,67	75,65	75,64	75,63	75,63	75,62	75,62	75,62	75,62	75,62	75,63

Table 4. Testing set of input parameters $Ra=6,3\mu\text{m}$, $Rz=30\mu\text{m}$ and different depth in μm

depth (µm)	50	55	60	65	70	75	80	85	90	95	100
Ra (µm)	6,3	6,3	6,3	6,3	6,3	6,3	6,3	6,3	6,3	6,3	6,3
Rz (µm)	30	30	30	30	30	30	30	30	30	30	30
power (%)	70,293	62,156	62,203	62,42	62,659	63,082	64,103	66,629	71,455	76,575	79,6
feed (%)	78,904	71,796	71,508	71,381	71,288	71,206	71,098	70,907	70,608	70,322	70,159

105	110	115	120	125	130	135	140	145	150	155	160
6,3	6,3	6,3	6,3	6,3	6,3	6,3	6,3	6,3	6,3	6,3	6,3
30	30	30	30	30	30	30	30	30	30	30	30
80,951	81,528	81,704	81,405	80,086	77,172	74,614	74,252	74,433	74,569	74,667	74,745
70,082	70,037	69,982	69,862	69,592	69,413	70,816	73,367	74,813	75,35	75,53	75,59

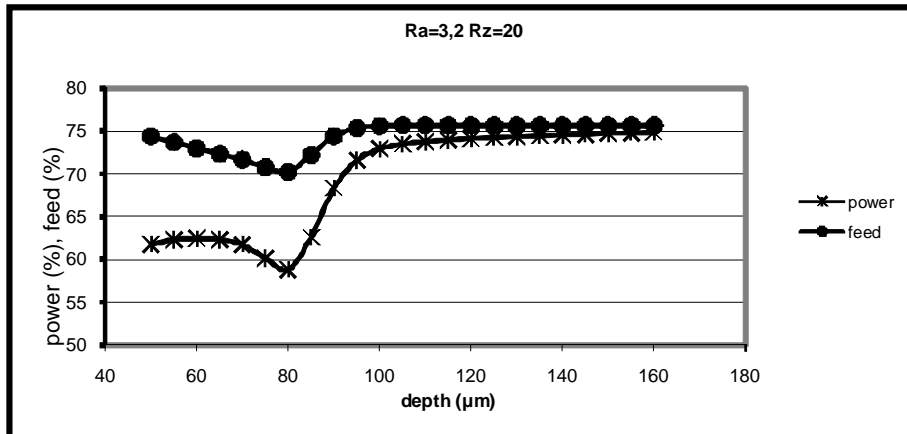


Figure 3. Network output for $Ra=3,2\mu m$ and $Rz=20\mu m$

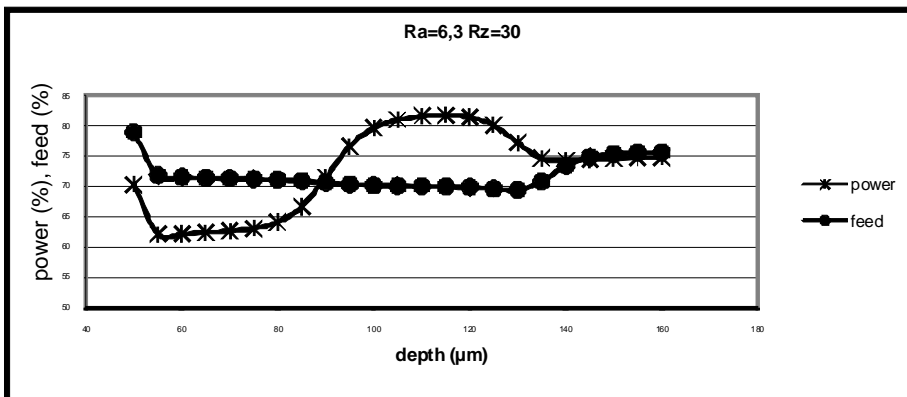


Figure 4. Network output for $Ra=6,3\mu m$ and $Rz=30\mu m$

3. CONCLUSION

At the conclusion it is possible to state that feed forward artificial neural networks are used to successfully estimation the output parameters developed during the laser cutting process. The depth and surface quality are contrary, therefore it is difficult to find optimal setting for these two parameters. There are many satisfactory combinations. Thus, it is necessary to define an economical factor. This will be the subject of further research.

4. ACKNOWLEDGEMENT

This work has been supported by the Ministry of Education, Youth and Sports of the Czech Republic under grant MSM 7088352102 and by the Grant Agency of the Czech Republic under grant 102/07/P137. This support is greatly acknowledged.

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