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Prediction of Cutting Forces with Neural Network by Milling Functionally Graded Material

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Abstract

Paper shows the general characteristics of graded materials, their previous industrial use and potential use of graded materials in the future. In any case, today the use of graded materials is increasing and moving from the laboratory environment into everyday use. However, the subsequent processing of the graded material remains the big unknown, and represents a major challenge for researchers and industry around the world. It could be said that the study of machinability of these materials is in its infancy and in this area are many unanswered questions. Machinability problem of graded materials was undertaken at the Faculty of Mechanical Engineering in Maribor. After a radical study of the literature and potential machining processes of graded materials, we started with the implementation of cutting processes on the workpiece. This professional paper presents the first results of the analysis, which will be used for further research and machinability study of graded materials. Also prediction of cutting forces with neural network by milling functionally graded material was made. In paper first predicted cutting forces by milling graded material are presented.

Keywords: LENS; functionally graded material; cutting parameters; artificial neural network

1. Introduction

Functionally graded materials (FGM) has been in intensive use for last two decades. The first concepts of graded materials were conceived in 1984 during the development of the Japanese space program. Their main feature is the non-homogeneous microstructure through whole structure, where every layer has its own microstructure and different mechanical properties.

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The most frequently represented scopes of the graded materials are [1, 2, 3]:

- Aerospace
- Military industry
- Medicine
- Optoelectronics

In any case, by reducing manufacturing costs in the future is expected that list of areas where graded materials are used will be much bigger. The greatest advantage of graded materials is their surface functional quality. However the properties of graded materials also depend on the properties of the base material. In most cases, hardness of graded material may vary. Surface layer is the hardest and hardness usually linear fall to the softest zone of material, which is in the region where basic material and graded layer are mixed, shown in Fig. 1 [4, 5].

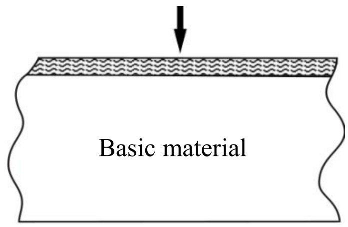

Fig. 1. Schematic view of functionally graded material.

The most common reasons for using graded materials are:

- High surface hardness
- Good surface wear resistance
- Different graded structures dampen vibrations

Special case of graded materials represents partially graded materials that do not have distinct layers with different chemical compositions, but they have a homogeneous chemical composition of the modified microstructure. The mechanical properties of these materials are comparable with the properties of the graded materials with distinct layers with different chemical composition [1, 2].
The largest groups of graded materials are as follows:

- Bioactive graded materials
- Tool steel with C, V, Cr and Ti gradients
- Materials with self-lubricating ability
- Graded materials with high temperature resistant surface layer

2. Properties of functionally graded materials

Graded materials are very innovative product in the field of technology. Also very innovative is their production. The most common methods of manufacture graded materials are as follows:

- The application of thin film coatings (PVD, CVD)
- Powder metallurgy
- Centrifugal method of manufacturing graded material
- Additive fabrication (SLS, LENS, SLM)

The properties of clad layers are classified in three groups (Fig. 2). Some of those properties may be inter-related. The wear resistance can, for instance, be affected by the hardness, the microstructure, the number of cracks and their depth and direction, the bonding between base material and substrate, etc. [1, 5, 6].

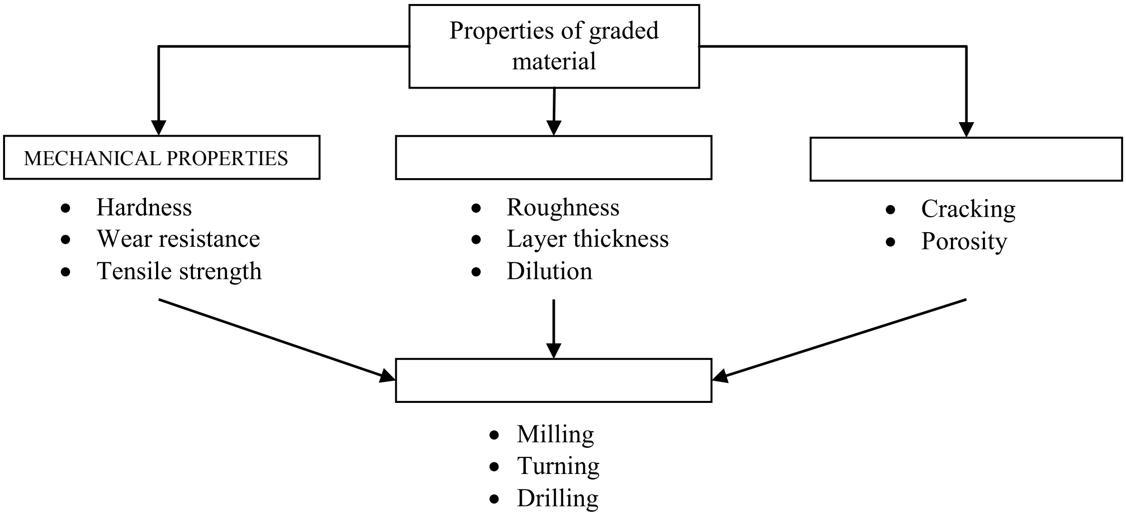

Fig. 2. Properties of graded material.

3. Production of graded material

Laser cladding is used to improve the surface properties of metallic machine parts. A wide variety of commercial metallic or ceramic powders is available. Those powders were developed for the use in plasma and flame spraying. They are also fit for use in laser cladding, because the intended functional properties are the same.

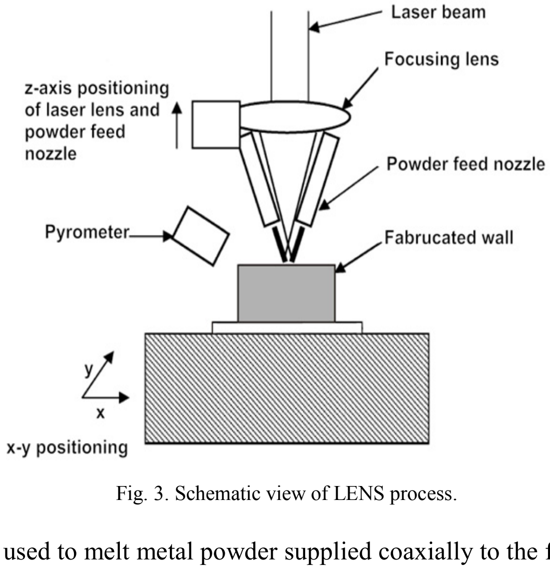

Fig. 3. Schematic view of LENS process.

A high power laser beam is used to melt metal powder supplied coaxially to the focus of the laser beam through a deposition head. The laser beam typically travels through the centre of the head and is focused to a small spot by one or more lenses. The x-y table is moved in raster fashion to fabricate each layer of the object (Fig. 3). The head is moved up vertically as each layer is completed. Metal powders are delivered and distributed around the circumference of the head either by gravity, or by using a pressurized carrier gas. An inert shroud gas is often used to shield the melt pool from atmospheric oxygen for better control of properties, and to promote layer to layer adhesion by providing better surface wetting. Test parts used in the experiment were produced with the machine Optomec LENS 850-R. Operational parameters for the production of test parts on machine Optomec LENS 850-R are shown in Table 1.

Table 1. Operational work settings on LENS machine Optomec LENS 850-R.

Machine settings	Value
Power	580 [W]
Feed rate	10 [mm/s]
Amount of filler material	5.8 [g/m]
Number of layers	4
Spacing between layers	0.4
Mark of filler material	1.3343

4. Artificial neural network (ANN)

The principal characteristic of neural networks is that they are capable of finding the rule that connects output and input parameters, during the process of training. When the neural network is trained, it operates also in situations with which it did not encounter during the process of training [7, 8].

In this paper, the most commonly used technique; the feed-forward back-propagation neural network is adapted for the prediction of cutting forces in milling operation. It consists of an input layer (where the inputs of the problem are received), hidden layers (where the relationships between the inputs and outputs are determined) and an output layer (which emits the output of the problem).

The input parameters for the neural network were depth of cut (a_p) and feed rate (f), which is shown in Fig. 4. The input parameters influenced most on the size of cutting force, which is an output parameter of ANN [9, 10].

4.1. Topology of neural network

The number of neurons in the input layer is defined by the number of input parameters; the input layer includes two neurons. The number of neurons in the output layer is the same as the number of output parameters. In our case this 3 or 1 output parameters. Output parameters shown in Fig. 4 and Fig. 5 in our case are:

- components of cutting forces in all three directions of the coordinate system (F_x, F_y, F_z)
- main cutting force R [11]

In our case two neural networks with different number of hidden layers were made. Fig. 4 shows the topology of first neural network in which output parameters were the components of cutting force (F_x, F_y, F_z) in the directions of the coordinate system used by the CNC machine. Feed-forward back-propagation neural network with 4 hidden layers was used [12, 13, 14].

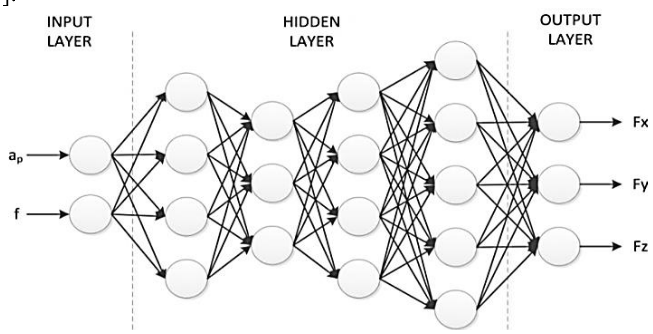

Fig. 4. Feed-forward back-propagation neural network with 4 hidden layers and 3 outputs.

Fig. 5 shows the topology of second neural network that was used to predict the main cutting force *R*. Feed-forward back-propagation neural network with 4 hidden layers was used.

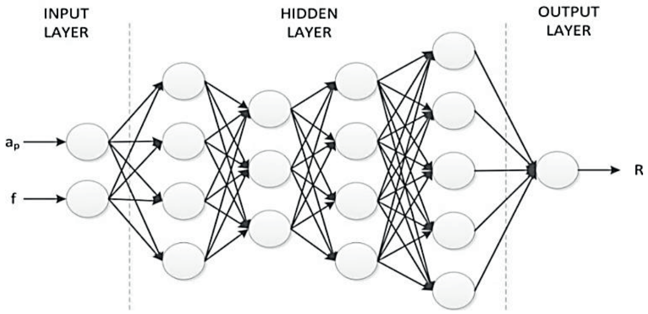

Fig. 5. Feed-forward back-propagation neural network with 4 hidden layers and 1 output.

5. Experiment realization

Milling of workpieces made of graded material was on CNC milling machine Heller BEA 01. Material GGG70 (hardness 23 HRC) was used as the basic material (Fig. 1), while the mixture of the basic material and the feed material S-6-5-2 (hardness 65 HRC) was used for the making of the graded layer which was 2.5 mm thick.

Cutting parameters used in experiment were: spindle speed n = 3000 rpm, feed rate f = 200 mm/min and cutting depth a_p = 0.5 mm. An example of the measured cutting forces F_x, F_y and F_z by milling graded material are shown in Table 2.

Cutting forces were measured with the system shown in Fig. 6. Main parts of the cutting force measuring system are:

- CNC machine with CNC controller
- Dynamometer
- Charge amplifier
- Data acquisition
- Software for optimization

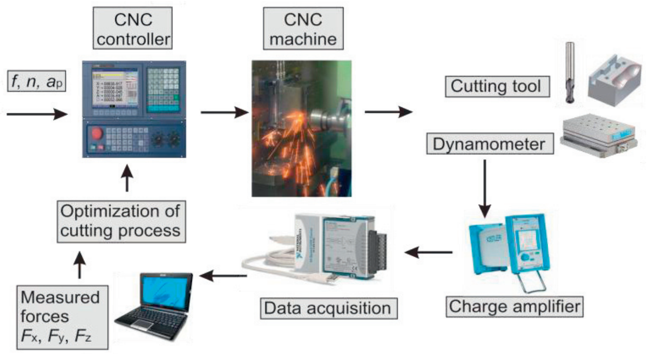

Fig. 6. Cutting force measuring system.

Measured cutting forces by milling functionally graded material were further used to build a neural network which is shown in Fig. 4 and Fig. 5.

Milling on workpieces was performed with carbide ball-end mill cutters and end mill cutters manufactured by Sandvik Coromant. The geometry of the cutters used in our experiments is shown in Fig. 7.

By milling graded materials, advantageous, short and broken chips were produced (Fig. 7). Large tool wear have negatively influence on the quality of the machined surface. After 25 minutes of machine treatment on the CNC machine, the cutting edge breakage on both cutters appeared.

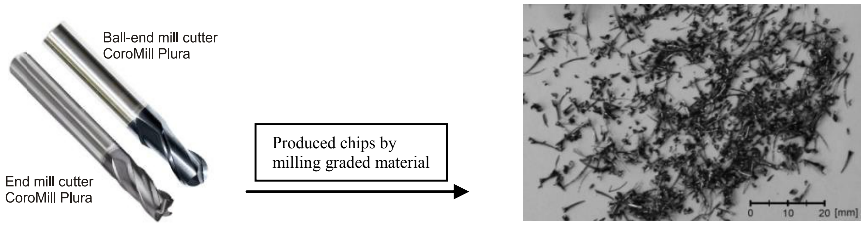

Fig. 7. Used cutters and chips by milling graded material.

6. Neural network training and results

For neural network learning, data shown in Table 2 were used; but 4 samples which were used for testing ANN were eliminated. For the purpose of testing the learning effectiveness of ANN experiments under the serial number 8, 15, 27 and 32 were eliminated.

Table 2. Depth of cut, feed rate and measured forces F_x, F_y, F_z, R.

Exp. No.	a_p [mm]	f [mm/min]	F_x [N]	F_y [N]	F_z [N]	R [N]
1	0.25	10	545.30	148.60	51.30	567.51
2	0.25	15	561.70	173.10	62.50	591.08
3	0.25	25	583.90	196.70	69.70	620.07
4	0.25	50	628.80	211.40	77.90	667.94
5	0.25	75	694.50	255.70	87.70	745.25
6	0.25	100	765.10	302.20	98.60	828.51
7	0.50	10	841.60	305.90	117.50	903.15
8	0.50	15	893.60	308.60	134.90	954.96
9	0.50	25	962.00	315.10	156.40	1024.30
10	0.50	50	1081.00	323.30	180.80	1142.70
11	0.50	75	1187.40	352.10	207.50	1255.77
12	0.50	100	1243.60	398.40	267.80	1333.03
13	0.75	10	1303.70	428.60	302.70	1405.33
14	0.75	15	1394.70	489.30	365.70	1522.61
15	0.75	25	1472.20	536.70	403.40	1618.07
16	0.75	50	1568.80	595.50	443.30	1735.59
17	0.75	75	1652.90	653.40	521.60	1852.32
18	0.75	100	1742.80	774.30	615.20	2003.84
19	1.00	10	1814.20	832.40	705.80	2117.16
20	1.00	15	1879.30	889.10	794.60	2225.68
21	1.00	25	1987.20	952.30	856.40	2364.16
22	1.00	50	1973.80	1023.60	901.30	2399.16
23	1.00	75	2087.60	1068.70	968.70	2537.43
24	1.00	100	2165.10	1102.70	1009.10	2630.95
25	1.50	10	2224.00	1153.60	1085.30	2730.36
26	1.50	15	2301.80	1204.50	1145.70	2839.32
27	1.50	25	2397.30	1247.30	1214.30	2962.66
28	1.50	50	2461.10	1284.30	1287.60	3060.12
29	1.50	75	2533.90	1311.30	1352.00	3157.22
30	1.50	100	2642.60	1374.60	1448.40	3312.21
31	2.00	10	2812.50	1437.20	1584.90	3533.78
32	2.00	15	3001.80	1489.70	1712.30	3763.24
33	2.00	25	3138.60	1533.40	1842.70	3949.39
34	2.00	50	3314.30	1573.60	1958.60	4158.96
35	2.00	75	3522.40	1638.40	2040.00	4387.85
36	2.00	100	3785.20	1745.80	2115.60	4674.54

Main cutting force R shown in Table 2 is calculated as:

$$R = \sqrt{F_x^{\ 2} + F_y^{\ 2} + F_z^{\ 2}} \tag{1}$$

Best validation performance of ANN, which will be used to predict cutting forces in different directions of the coordinate system of the CNC machine is shown in Fig. 8. Feed-forward back-propagation neural network with 10 hidden layers was used to predict cutting forces in x, y and z directions.

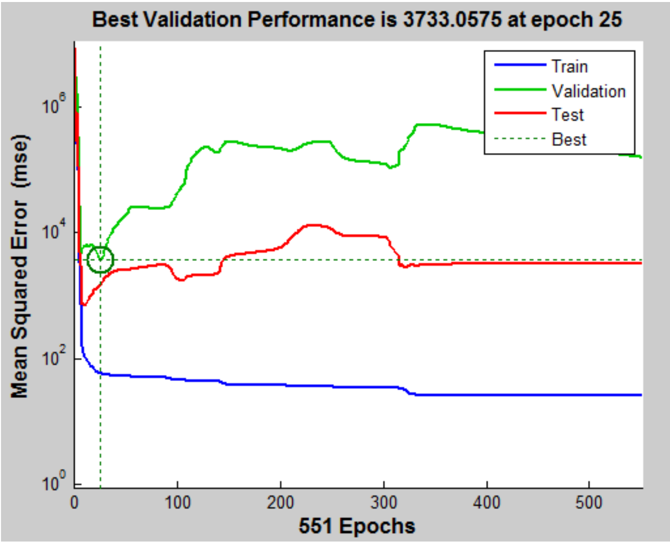

Fig. 8. Results of ANN for predicting F_x, F_y, F_z.

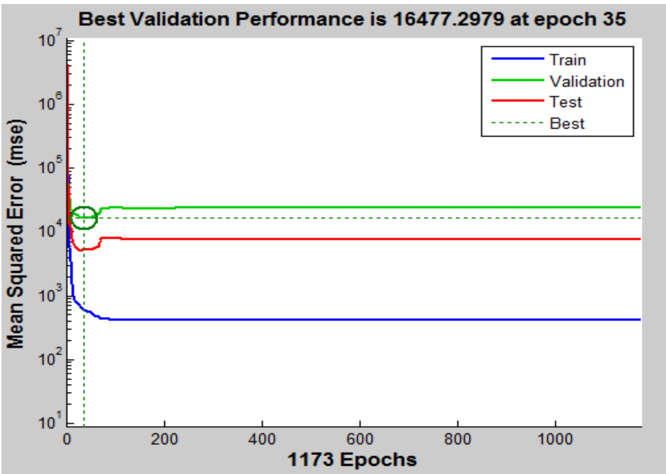

Fig. 9. Results of ANN for predicting main cutting force R.

Table 3 shows the testing results of ANN; where maximum learning error of neural network is 21 %. This is actually negligible error; it means that the difference between actual and predicted force is round 50 N by experiment 1. In experiments from 25 to 36 much higher forces appears; (in comparison with experiments from 1 to 24) the maximum learning error of ANN in this cases is less than 4 %.

Best validation performance of ANN used for predicting main cutting force R is shown in Fig. 9. In this case Feed-forward back-propagation neural network with 4 hidden layers shown in Fig. 5 was used.

Training results of ANN for predicting main cutting force R are shown in Table 4. Maximum learning error of neural network is less than 9 %, which is actually negligible, it means that the difference between actual and predicted cutting force is less than 100 N.

In experiments from 25 to 36 much higher forces appears (in comparison with experiments from 1 to 24) the maximum learning error of ANN in this cases is less than 8 %. It was actually found out that this prediction does not have influence on our CNC machine and milling process.

Table 3. Measured and predicted values of cutting forces F_x, F_y, and F_z by using ANN.

Exp. No.	Measured values			Predicted values using ANN			% Error		
	F_x [N]	F_y [N]	F_z [N]	F_x [N]	F_y [N]	F_z [N]			
1	545.30	148.60	51.30	539.36	179.83	45.64	1.09	21.02	11.03
2	561.70	173.10	62.50	558.87	179.12	57.49	0.50	3.48	8.02
3	583.90	196.70	69.70	588.70	184.33	68.39	0.82	6.29	1.88
4	628.80	211.40	77.90	625.94	210.79	76.95	0.46	0.29	1.22
5	694.50	255.70	87.70	695.14	252.47	87.58	0.09	1.26	0.14
6	765.10	302.20	98.60	765.14	304.24	96.60	0.01	0.68	2.02
7	841.60	305.90	117.50	849.00	290.38	128.17	0.88	5.07	9.08
9	962.00	315.10	156.40	962.56	293.99	159.29	0.06	6.70	1.85
10	1081.00	323.30	180.80	1083.92	333.49	187.82	0.27	3.15	3.88
11	1187.40	352.10	207.50	1210.66	376.98	221.24	1.96	7.07	6.62
12	1243.60	398.40	267.80	1187.96	415.80	227.72	4.47	4.37	14.97
13	1303.70	428.60	302.70	1301.12	437.34	300.84	0.20	2.04	0.61
14	1394.70	489.30	365.70	1391.14	491.65	350.03	0.26	0.48	4.29
16	1568.80	595.50	443.30	1466.33	565.28	426.53	6.53	5.08	3.78
17	1652.90	653.40	521.60	1649.98	659.07	528.14	0.18	0.87	1.25
18	1742.80	774.30	615.20	1743.68	765.70	618.17	0.05	1.11	0.48
19	1814.20	832.40	705.80	1819.23	857.71	741.13	0.28	3.04	5.01
20	1879.30	889.10	794.60	1885.37	884.08	794.02	0.32	0.57	0.07
21	1987.20	952.30	856.40	1981.11	959.32	865.33	0.31	0.74	1.04
22	1973.80	1023.60	901.30	1972.20	1018.66	903.60	0.08	0.48	0.26
23	2087.60	1068.70	968.70	2092.14	1058.34	961.86	0.22	0.97	0.71
24	2165.10	1102.70	1009.10	2163.96	1112.23	1008.62	0.05	0.86	0.05
25	2224.00	1153.60	1085.30	2188.63	1160.11	1081.05	1.59	0.56	0.39
26	2301.80	1204.50	1145.70	2253.53	1173.15	1132.62	2.10	2.60	1.14
28	2461.10	1284.30	1287.60	2462.55	1278.98	1292.92	0.06	0.41	0.41
29	2533.90	1311.30	1352.00	2532.13	1321.45	1344.88	0.07	0.77	0.53
30	2642.60	1374.60	1448.40	2641.77	1373.83	1447.84	0.03	0.06	0.04
31	2812.50	1437.20	1584.90	2924.67	1469.79	1657.64	3.99	2.27	4.59
33	3138.60	1533.40	1842.70	3144.98	1523.56	1832.03	0.20	0.64	0.58
34	3314.30	1573.60	1958.60	3304.83	1578.51	1960.72	0.29	0.31	0.11
35	3522.40	1638.40	2040.00	3404.13	1690.78	2060.85	3.36	3.20	1.02
36	3785.20	1745.80	2115.60	3739.45	1808.50	2195.87	1.21	3.59	3.79

Table 4. Measured and predicted values of main cutting force R by using ANN.

Exp. No.	Measured values R [N]	Predicted values using ANN R [N]	% Error
1	567.51	567.02	0.09
2	591.08	582.66	1.42
3	620.07	613.65	1.04
4	667.94	689.83	3.28
5	745.25	765.04	2.66
6	828.51	840.25	1.42
7	903.15	939.36	4.01
9	1024.30	1008.18	1.57
10	1142.70	1119.54	2.03
11	1255.77	1227.38	2.26
12	1333.03	1332.36	0.05
13	1405.33	1525.04	8.52
14	1522.61	1553.62	2.04
16	1735.59	1742.74	0.41
17	1852.32	1866.37	0.76
18	2003.84	1980.95	1.14
19	2117.16	2174.88	2.73
20	2225.68	2205.63	0.90
21	2364.16	2265.29	4.18
22	2399.16	2403.59	0.18
23	2537.43	2526.47	0.43
24	2630.95	2634.44	0.13
25	2730.36	2794.75	2.36
26	2839.32	2826.89	0.44
28	3060.12	3042.73	0.57
29	3157.22	3184.61	0.87
30	3312.21	3314.22	0.06
31	3533.78	3801.58	7.58
33	3949.39	3935.32	0.36
34	4158.96	4167.69	0.21
35	4387.85	4409.60	0.50
36	4674.54	4657.97	0.35

The quality of learning ANN was tested with data that were excluded from the learning base. Table 5 shows the data that were used to test and verify the quality of the trained ANN. In the table measured values for control of predicted data and the calculation of the percentage error are shown. The maximum error in the prediction of individual components of the cutting forces is less than 9 % and the total cutting force error is less than 3 %, which is certainly under acceptable limit, that was set as a goal before our experiments were implemented.

Table 5. Parameters that were used to test and verify the quality of the trained ANN.

Exp. No.	a_p [mm]	f [mm/min]	Measured values				Predicted values using ANN				% Error			
			F_x [N]	F_y [N]	F_z [N]	R [N]	F_x [N]	F_y [N]	F_z [N]	R [N]	F_x	F_y	F_z	R
8	0.50	15	893.60	308.60	134.90	954.96	895.99	294.40	146.05	962.48	0.27	4.60	8.27	0.79
15	0.75	25	1472.20	536.70	403.40	1618.07	1472.91	548.97	394.30	1609.61	0.05	2.29	2.26	0.52
27	1.50	25	2397.30	1247.30	1214.30	2962.66	2346.14	1194.04	1206.59	2890.30	2.13	4.27	0.64	2.44
32	2.00	15	3001.80	1489.70	1712.30	3763.24	2996.60	1487.61	1714.53	3845.65	0.17	0.14	0.13	2.19

7. Conclusion

The first results of milling very hard material such as graded material shows us that the machining of such materials is possible. In any case, in the future will be even more important to focus on the correct geometry of the cutting tool to reduce the size of the cutting forces in all three directions of the coordinate system which are at the moment very large.

On the other hand, the prediction of the cutting forces proved to be very reliable; the error in predicting cutting forces was smaller than 10 %. This is a very reliable prediction for the planned cutting force, which allows us to operate the machine in a safe area.

Our wish for the future is to find the suitable cutting parameters (cutting speed, feed rate, cutting depth...) for optimal milling of graded material. With this optimal cutting parameters we want fully displace the grinding of graded material with milling, where material removal is greater.

In any case simulations, optimizations, predicting of cutting parameters and cutting experiments of graded materials are wished to be performed. Our goal is to introduce milling of graded material into daily production and replace grinding with more productive cutting process.

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