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PREDICTING THE MECHANICAL SYSTEM OUTPUT PARAMETERS BY APPLYING THE ARTIFICIAL NEURAL NETWORK METHOD

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Abstract: *The paper aims to simplify the experimental research activity of the mechanical systems behavior and to perform a prediction of the output parameters of the system, in case of a stable behavior of the system, with the preservation of data known as input parameters. The prediction will be valid for at least two output variables that are interdependent. The proposed algorithm is: setting the characteristics of the ANN network: no. of layers, no. the nodes, the transfer function, the number of training cycles; validation of the ANN architecture; the prediction of two output parameters in interdependence.*

Keywords: *Artificial Neural Network, prediction of parameters, regression coefficient.*

1. INTRODUCTION

In the literature, the explanation of the functioning of a network of neurons was first given by W. McCulloch (neurophysiologist) and W. Pitts (mathematician). D. Hebb on a later research has reported that two nerves that trigger the connection between them simultaneously are improving themselves [1].

A particular problem in *Artificial Neural Network* (ANN) development was the error management: a problem solved by the error-recognition pattern that is distributed throughout the network, and using minimum two layers; a model now is called ANN with back propagation networks. The error recognition model is constructed so that the final output nodes are connected with the previous nodes, having the characteristics of a highly nonlinear feedback system [2].

Using ANN method, the predictions could be made in many areas: searching for trends, ordering, object recognition problems, understanding of vision and speech, etc.

The optimal number of hidden layers and hidden neurons / layers are difficult to specify without significant experience [3].

There are certain estimation, such as those of Kolmogorov (1957), which state that for the approximation of a function of n variables, it would be necessary $n \cdot (2 \cdot n + 1)$ neurons in the first hidden layer and, in the case of the use of two hidden layers ($2n$ + 1) neurons. More recent research has shown that these estimations do not always lead to an optimal solution [4].

The neurons of hidden structures have the role of detecting the traits, the laws, the regularities contained in the training patterns.

A large number of hidden neurons/layer negatively influences the generalization capacity of ANN. It also leads to an increase in the volume of data to be processed and thus, to an increased duration for the training phase. A too small number of neurons is not enough to form an internal representation of the appropriate data and can lead to a large square error during training periods and consequently to a large error corresponding not only to test data but also to training data.

The optimal number of hidden neurons will be determined experimentally. A special import into the ANN algorithm is the simple linear regression which estimates scores for a variable according to a second variable [5], with a very strong correlation between the two variables [6].

The correlation coefficient r is directly related to the determination coefficient r^2. The higher value of the coefficient of determination is closer to the maximum value 1, the more variation of the response could be explained by the explanatory variables, the difference being allocated to unknown variables or correlations [7–10].

The linear regression model Theil-Sen proposes to calculate the median of the slopes of all lines by pairs of two-dimensional sample points. In comparison with the smallest squares estimator, the Theil-Sen (TS) estimator is robust against extreme values. It has a decomposition point of about 29.3% in the case of a linear linear regression, which means it can tolerate arbitrary data up to 29.3% in the case of bidimensional problem [11, 12].

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2. RESEARCH METHODOLOGY

In this paper we take into consideration a mechanical system consisting in a rotating table having a single CNC axis to be controlled and using an electrical drive motor (EM).

The measured parameters are presented in Table 1 and characteristics of the experiment in Table 2.

The selected input data sets (no. of measurements), for each rotating table weight, are using a one-degree resolution. The data acquisition system produced two measurements between 13 and 1750 for two successive grades. The number of measurements between two consecutive degrees depends on the system stability represented by the weight of the rotry table.

For prediction, is using the software Visual Gene Developer 1.7 (VGD) – ANN with backpropagation (ANN-BP) [13].

The data sets selected for the three rotating table weights are used as input and output variables for the ANN input and output layer respectively. We want to determine the degree of generalization of a certain ANN architecture for prediction. For example, we want to find out if a specific ANN architecture for a rotating table balance 0 [gr] in the field [0^0, -20^0] is also valid for [-20^0, 0^0] as well as extending to the other weights of the rotating table 500 [gr] and 4.500 [gr].

In this paper, a prediction model using RNA-BP is proposed, and the following steps are used:

1. Establishing variable input to the input layer.
2. Determination of variable output to the output layer prediction.
3. Establishment of ANN-BP features: number of hidden layers, number of nodes per hidden layer, learning rate, transfer function, number of training cycles (to be achieved by experimentation).
4. Training and validation of the ANN-BP architecture.
5. Using the ANN-BP architecture validated for parameter prediction of the other two weights of the table 500 [gr] and 4.500 [gr].

Table 1

Measured parameters

Name	Symbol	UM
time	t	[ms]
speed	n	[rot/min]
position	α	[°]
torque	M	[Nm]
power consumed	P	[kW]
tension	U	[V]
frequency	f	[Hz]
ME temperature	T	[°C]

Table 2

Characteristics of the experiment

Nr. of measurements	Time	Rotating table weight	Selected nr. of measurements	Nr. of oscillations [-20, 20] of the rotary table
	[ms]	[gr]		
12891	51560	0	160	2
11786	47140	500	161	2
12275	49096	4500	189	2.5

3. APPLICATION OF ANN-BP IN THE CASE OF PREDICTION OF OUTPUT PARAMETERS OF A ROTARY TABLE

An experimental stand is consisting in a rotating table assembly. The components are provided by Siemens: 1FK7042-5AF71-1FH0 electrical motor, the SINAMICS S120 6SL3040-1LA01-0AA0 converter, the SITOP PSU200M 6EP1333-3BA10 and various fuses [14]. The material for rotary table assembly was aluminum alloy, and it together with the electric motor weights a total of 35 [kg]. The mobile part of the rotating table has 11.5 [kg]. Figure 1 shows the experimental stand on which the research was made.

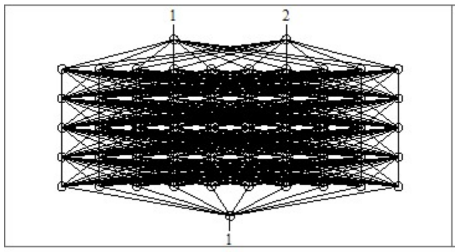
Position sequences α are following:

a) α for the table 0 [gr]: -1_-20_0_20_0_-20_0_20_0;
b) α for the table 500 [gr]: 0_-20_0_20_0_-20_0_20_0;
c) α for the table 4.500 [gr]: -9_-20_0_20_0_-20_0_20_0_-18_-6_-13;

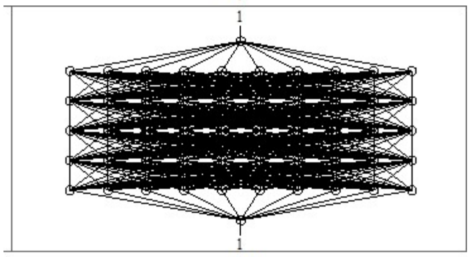
The prediction is done with the following ANN architectures (Fig. 2):

A. an input variable and two output variables (a);
B. an input variable and an output variable (b).

Fig. 1. The experimental system using a rotary table.



a)



b)

Fig. 2. The prediction experiment using ANN-BP architecture.

Table 3

The ANN-BP characteristics for which the best predictive precision was obtained

	Predictive experiment	
	A	B
Topology setting - parameter		
Number of input variables	1	1
Number of output variables	2	1
Number of hidden layer	5	
Node # of 1st hidden layer	10	
Node # of 2nd hidden layer	10	
Node # of 3rd hidden layer	10	
Node # of 4th hidden layer	10	
Node # of 5th hidden layer	10	
Training setting - parameter		
Learning rate	0.01	
Nomentum coefficient	0.1	
Transfer function	Hyperbolic tangent	
Maximum # of training cycle	175,000	300,000
Target Error	0.00001	
Initialization method of threshold	Random	
Initialization method of weight factor	Random	
Analysis update interval (cycles)	500	
Training status - parameter		
Sum of error	0,00332859	0.00047000
Avg error per outputper dataset	0,00008321	0.00002350
Processing time (sec)	232	873

3.1. Prediction of two output variables with an input variable

The input data set (Table 4) is the measured values for the consumed power parameter and for the supply voltage of the electric motor and torque we want to find the prediction. ANN-BP training is done for the left-hand data set.

The input and training data set corresponds to a shift of the rotating table position $\alpha = [0,\ldots,-20]$, and the prediction is made for a displacement of the rotating table position $\alpha = [-20,\ldots.,0]$.

Conclusion 1:

a) the error between the measured and predicted voltage (Table 5)is of 5.08%.

b) the error for the torque parameter between measured and predicted (Table 5) is 8.69% .

The coefficient of quantification is r^2 and it is always a positive number and varies between 0 and 1. As the value of the coefficient of determination is closer to the maximum value 1, the variance of the response variable can be explained by explanatory variables, the difference being attributed to unknown variables and inherent correlations (Table 6).

The trend of the voltage parameter is characterized by the oscillation of one side of the trend measured with the tendency to obtain values deviated from those measured by the peaks.

The trend of the torque parameter is highlighted by approximately constant hold over the predicted range.

On the whole, by looking at Figs. 3 and 4, it is noted that the predicted values for the two parameters are very close to the measured ones, so the ratio between the predicted and the measured parameter is roughly the same.

The regression coefficients for the two parameters have values above 0.92, which indicates that variation of the response could be explained by the precision of 92%. It is noted that the regression coefficient for the torque has a value close to 1.

Conclusion 2: making a comparison between errors and the regression coefficient, the following situation is observed:

a) voltage: error 5 % with a regression coefficient of 0.92;

b) torque: error 8.6 % with a regression coefficient of 0.99.

Table 4

Input and training data set

Consumed Power [kW]	Voltage [V]	Torque [Nm]	Consumed Power [kW]
0.00000000	0.00000000	-0.00036905	0.03425755
0.00099230	0.06328006	-0.03128152	0.02786221
0.00121498	0.05120925	-0.03313291	0.02665282
0.00356930	0.08037100	-0.05088685	0.02119440
0.00527461	0.06824102	-0.06642690	0.01504110
0.00631492	0.06855066	-0.07572371	0.01780396
0.00923714	0.08535340	-0.09858611	0.01440219
0.01455119	0.10388416	-0.11737162	0.01045006
0.01462487	0.08717130	-0.12936966	0.01334459
0.01738447	0.10607197	-0.14048848	0.00677833
0.01744896	0.10320084	-0.14552225	0.00976990
0.01517768	0.09230233	-0.13326703	0.00324468
0.02514975	0.12621210	-0.16965181	0.00493979
0.02508267	0.11777279	-0.17351912	0.00123903
0.03309459	0.13318257	-0.20274467	0.00302142
0.03103888	0.12940058	-0.19771177	0.00004840
0.04294271	0.16116758	-0.23547153	0.00102315
0.03566536	0.13826797	-0.20900552	-0.0000728

Table 5

Comparison of the measured and predicted data set

Measured		Prediction	
Tension	Torque	Tension	Torque
[V]	[Nm]	[V]	[Nm]
0.134066	-0.212067	0.134489	-0.202501
0.120079	-0.189134	0.122700	-0.180983
0.120977	-0.181048	0.120483	-0.176648
0.115145	-0.161574	0.110484	-0.155619
0.093379	-0.138491	0.098307	-0.127471
0.101379	-0.151713	0.104041	-0.140883
0.108755	-0.136701	0.096875	-0.124143
0.079872	-0.113673	0.086525	-0.101105
0.093904	-0.124415	0.094383	-0.118414
0.074862	-0.085062	0.073200	-0.074743
0.084545	-0.102189	0.084391	-0.096634
0.061025	-0.057589	0.054827	-0.043197
0.082670	-0.073983	0.064467	-0.059192
0.045589	-0.034513	0.041093	-0.021979
0.058479	-0.052878	0.053429	-0.040962
0.043454	-0.009432	0.031597	-0.008117
0.061913	-0.030280	0.039450	-0.019539
0.034408	0.008359	0.030571	-0.006650
0.967556	**-1.408816**	**0.968287**	**-1.327767**
Average			

Table 6

Characteristics of the regression coefficient for 0 [gr]

Category	Ouput Variable	Regr. Coeff (r^2)	Slope	y-intercept
Training	voltage	0.923	0.938249	0.00409611
Training	torque	0.996	1.010523	0.00473886

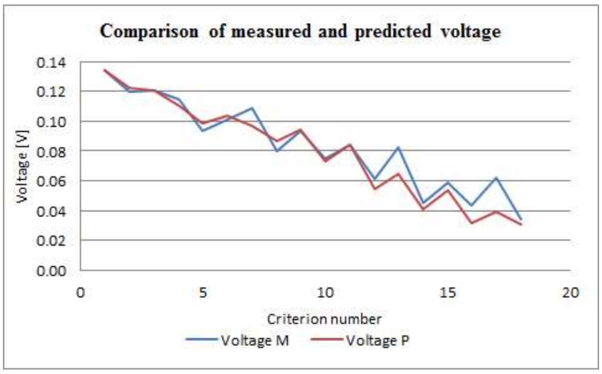


Fig. 3. Comparison of measured and predicted voltage.

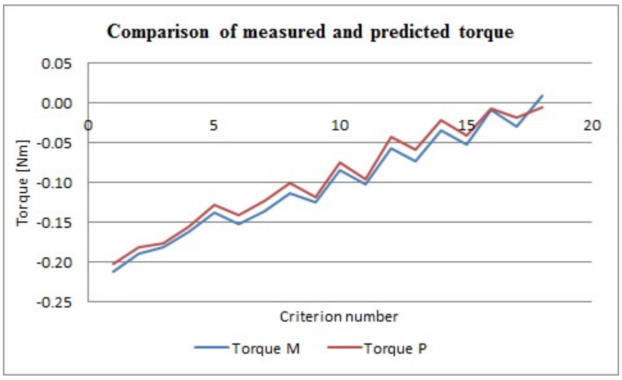


Fig. 4. Comparison of measured and predicted torque.

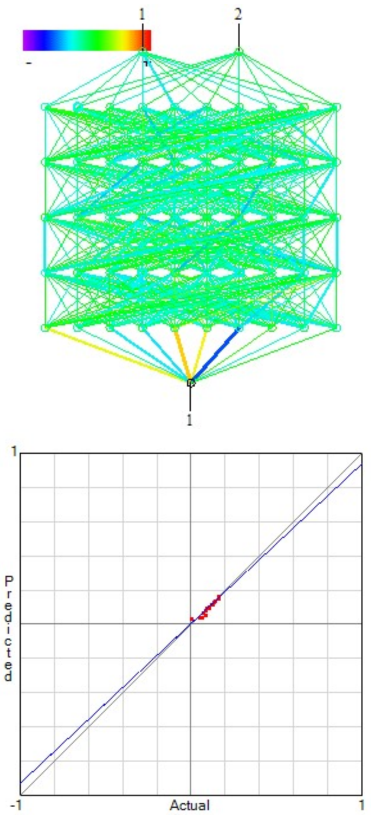


Fig. 5. ANN-BP architecture, the input-output data stream and the predicted data set layout on the regression slope for 0 [gr].

ANN-BP uses a data stream comprised between approximately ± 0.75, (−0.75 – negative flow highlighted in blue and 0.75 – positive flow outlined in orange).

Conclusion 3: for predicting two variables for an oscillation angle $\alpha = [0,...,-20,...0]$ of the rotating table results with an accuracy of over 90% (error below 10%).

We continue to use this ANN-BP architecture with 175,000 training cycles for predicting tension and torque for tables 500 [gr] (Table 7, Fig 6).and 4.500 [gr] (Table 8, Fig 7). for the same oscillation, respectively $\alpha = [0,...,-20,...0]$

Conclusion 4:

a) the error between the measured and predicted voltage is of 12 %.
b) the error for the torque parameter between measured and predicted is about 8.5 %.

Conclusion 5:

a) the error between the measured and predicted voltage is very low (less than 0.01%).
b) the error for the torque parameter between measured and predicted values is about 1.6 %.

Table 7

Characteristics of the regression coefficient for 500 [gr]

Category	Ouput Variable	Regr. Coeff (r^2)	Slope	y-intercept
Training	voltage	0.923	0.938249	0.00409611
Training	torque	0.996	1.010523	0.00473886

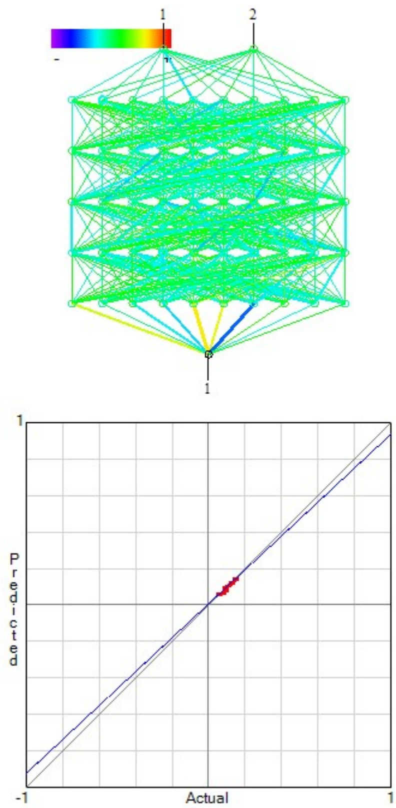


Fig. 6. ANN-BP architecture, the input-output data stream and the predicted data set layout on the regression slope for 500 [gr].

Table 8

Characteristics of the regression coefficient for 4.500 [gr]

Category	Ouput Variable	Regr. Coeff (r^2)	Slope	y-intercept
Training	voltage	0.5323	0.41752	0.03875933
Training	torque	0.1704	0.13223	-0.02502337

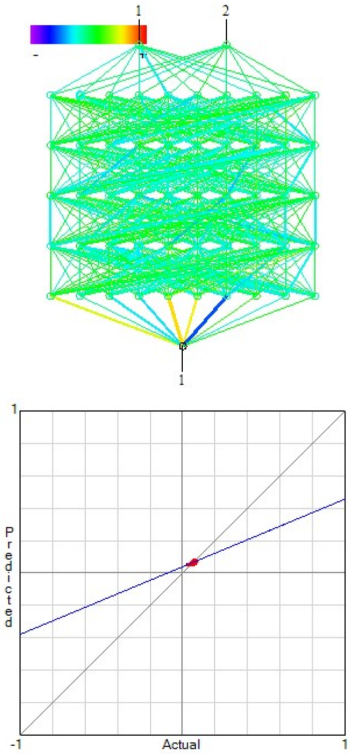


Fig. 7. The ANN-BP architecture, the input-output data stream and the predicted data set layout on the regression slope for 4500 [gr].

General concluding A:

a) the error between the measured and predicted voltage is in the range 0.01–12 [%].
b) the error for the torque parameter between measured and predicted values is in the range 1.6–8.6 [%].

We can use the same ANN-BP architecture to predict supply voltage and torque for a rotating table weighting between 0 and 4500 [gr] for an oscillation angle $\alpha = [0,\ldots,-20,\ldots0]$.

From the point of view of the information flow that starts from the input layer to the first hidden layer it has the same characteristics in all three cases analyzed, namely the data set size is in the range ± 0.75.

If the prediction of the values on the regression slope in the first two cases is evenly distributed along it, for the mass of 4500 [gr] it is distributed which leads to the highest precision of the prediction.

In all three cases the predicted values are positioned on the regression slope in quadrant 1.

3.2. Predicting an output with an variable input

In this case, from the two parameters we give up the voltage parameter and we use the ANN-BP architecture in Fig. 2,*b*) with the characteristics presented by Table 3, experiment B.

Conclusion 6: the error for the torque parameter between measured and predicted values is 4.6%, for a regression coefficient $r^2 = 0.99$ (Table 9, Fig. 8).

Table 9

Regression coefficient for weight 0 [gr]

Category	Ouput Variable	Regr. Coeff (r^2)	Slope	y-intercept
Training	torque	0.9957	0.995629	-0.000566475

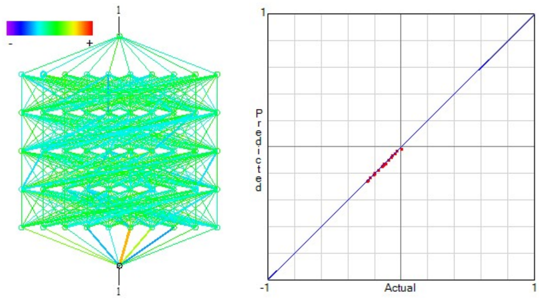


Fig. 8. The ANN-BP architecture, the input-output data stream and the predicted data set layout on the regression slope for 0 [gr].

Table 10

Regression coefficient for 500 [gr]

Category	Ouput Variable	Regr. Coeff (r^2)	Slope	y-intercept
Training	torque	0.9960	1.001503	0.001661217

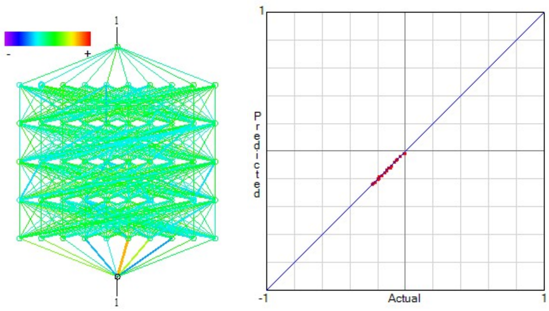


Fig. 9. The ANN-BP architecture, the input-output data stream and the predicted data set layout on the regression slope for 500 [gr].

Conclusion 7: the error for the torque parameter between measured and predicted is 8.6%, for a regression coefficient $r^2 = 0.99$ (Table 10, Fig. 9).

In the first two cases for a regression coefficient above 0.9957, predictive errors of up to 10% are obtained.

It can be seen that the information flow in the first two cases, which departs from the input layer to the first hidden layer, has approximately the same characteristics as the ones in the previous sub-paragraph, namely the data set size is in the range ± 0.75.

Predictive values are evenly distributed along the regression slope with the observation that they are in quadrant 3.

Conclusion 8: the error for the torque parameter between measured and predicted values is 254% for a regression coefficient $r^2 = 0.17$ (Table 11, Fig. 10).

A large error occurs in prediction is also reinforced by a very low regression coefficient (r^2 = 0.17), which points out that the variance of the response variable can't be explained by explanatory variables that is attributed to unknown variables and correlations.

Table 11

Characteristics of the regression coefficient for 4500 [gr]

Category	Ouput Variable	Regr. Coeff (r^2)	Slope	y-intercept
Training	torque	0.1720	0.16727	-0.008497994

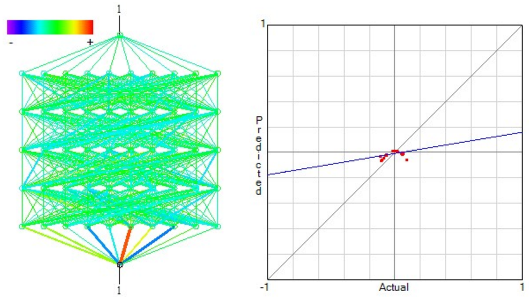


Fig. 10. ANN-BP architecture, the input-output data stream and the predicted data set layout on the regression slope for 4500 [gr].

In this case, the ANN-BP, while using the information flow between the input layer and the first hidden layer, uses the ± 1 value range, it does not succeed in training to identify the algorithm characteristic of the input data set.

This is also evidenced by the predicted values that are distributed in semicircle curve in all four quadrants on the regression slope.

Explanation of the error: The error is due to the fact that ANN-BP was applied to α = -9_-20_0_20_0_-20_0_20_0_-18_-6_-13 (4500 [gr]) so at the second oscillation and not at the first oscillation. Note that position α (4500 [gr]) leave from (−9) and not from 0, reason why the second oscillation was selected for α = 0_-20_0.

The error is supported by the regression coefficient that has an extremely low value (0.17) and the final set-up of the values on the regression slope (the semicircle form of the line as normal). In the first case the use of two output parameters (prediction) managed to "draw" the prediction to the real values.

General concluding B: The error for the torque parameter between measured and predicted values is situated in the range of 4.6–8.6 [%] for a rotating table weight of 0 [gr] and 500 [gr], so we can use the same ANN-BP to predict supply voltage and torque for a rotating table weighing between 0 and 500 [gr] for oscillation $\alpha = [0,...,-20,...0]$.

4. CONCLUSIONS

Case study presented in the paper shows that for ANN model and, in general, for the prediction data models, the selecting of the data set to be analyzed must be done by researchers with a large experience in statistical and data processing. They have to understand the interdependencies between the parameters and how they influence each other so that when there are big errors in the data analysis, they know the reason for the occurrence (uncorrelation for roughly identical situations) and eliminate them from the model.

The ANN-BP case study for the prediction of 1 or 2 parameters has demonstrated that the same architecture and features for data sets with close values for the same rotation position and different weights of the rotating table can be used.

The error obtained in this study is about 10% and a regression coefficient in the most cases is over 0.92. There are cases when the use of a certain output parameter (prediction) extracted from a set of parameters in a very strong interdependence leads to gross errors as presented in the example above.

It is emphasized that in the case of using two output parameters, the prediction is strongly influenced by correlation of the outputs.

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