PREDICTION THE EVOLUTION OF TEMPERATURE AND VIBRATIONS ON SPINDLE USING ARTIFICIAL NEURAL NETWORKS AND FUZZY LOGIC

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Rezumat. *Simularea comportamentului arborelui principal din punct de vedere al temperaturilor și vibrațiilor la turații superioare este mult mai economică și mai sigură (evitarea evenimentelor mecanice nedorite) decât încercarea practică. Încercarea practică are un rol important în finalizarea produsului dar pe parcursul desfăşurării încercărilor de prototip este mult mai avantajos economic simularea evoluției parametrilor pe baza unor seturi de date colectate pentru turații critice. În această lucrare este prezentat un mod de analiză hibrid (rețele neuronale artificiale – fuzzy logic) privind predicția evoluției temperaturilor și vibrațiilor la turații superioare pentru care nu au fost efectuate măsurători. Principalul avantaj al metodei il constituie predicția simultană a dinamicii temperaturii și a nivelului vibrațiilor.*

Abstract. *Simulation spindle behavior in terms of temperature and vibration at higher speeds is more economical and more secure (avoid undesirable mechanical events) than testing practice. Testing practice has an important role in finalizing the product but throughout the course of prototype testing is more advantageous economic development simulation parameters based on data sets collected to dangerous speeds. In this paper we present an analysis mode hybrid (artificial neural networks - fuzzy logic) on prediction the evolution of temperatures and vibrations at higher speeds for which no measurements were made. The main advantage of the method is the simultaneous prediction of the dynamics of temperature and vibration levels.*

Keywords: spindle, artificial neural networks, fuzzy logic, ANFIS.

1. Introduction

Thorough knowledge of phenomena generated by the cutting processes and their influence on the life of spindle or spindle has become the key factor in decades in mechanical processing industry [1].

The need to increase productivity led to demand for high-speed machine tools and therefore the development of new bearings, power electronics and control systems and control [2].

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Electro-spindle is one of the most important components of the machine tools taking into account that his properties are closely linked to processing accuracy. Electro-spindle technology is of great importance for research and development of machine tools especially in the high speeds: High Speed Machining - HSM [1, 3].

Technology manufacturing and repair spindle still presents many unknowns generated by work processes and unpredictable situations behavior dynamics, electrical and thermal. The safety and reliability of processing are strongly penalized by the imperfections of dynamic performance and thermal spindle after contact between the tool/chip/track dynamics becoming the main problem for both machine operation and for its qualitative and quantitative [4, 5].

Therefore dynamic performance research, analysis and monitoring of spindle parameters is of great theoretical and practical importance for both the present and especially the future [6, 7, 8].

To determine the effect of heat on the performance of the spindle is necessary to determine the distribution of temperature on the speed of rotation, preload and stiffness throughout the study spindle.

At the same time emphasizing the dynamic character of the spindle is a necessity given the direct impact on the quality of machined surfaces [9].

The purpose of the paper is considering the use of artificial intelligence methods for thermal and dynamic behavior prediction of spindle based on experimental data obtained during rig testing.

2. Research Methodology

Prediction methodology temperature/vibration front and back of spindle bearings presented below using a hybridization of artificial neural networks (ANN) and adaptive neuro-fuzzy network (ANFIS).

The objectives of this research is presented below:

1. Prediction using neural networks of behavior of the spindle assembly to the bearings, the speed characteristic represented by a function of temperature and vibration, the higher speeds were not measured;
2. Objective 1 results form the basis for the analysis of adaptive neuro-fuzzy networks (Adaptive Neuro-Fuzzy Inference System - ANFIS) on Sugeno:
    a) the rules of Fuzzy Inference Systems (FIS) compounding;
    b) analysis of unified 3D surface temperatures and vibration measured and predicted the field.

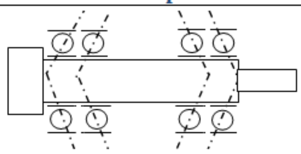
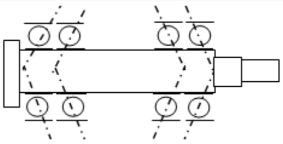
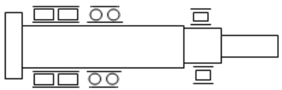
Predicting the behavior spindle assembly at higher speeds allows us to find the limits at which it may be subject and the upper limit of normal.

Predicting the evolution of the speed is performed by software Visual Gene Developer[1] 1.7 - VGD (Build 762 – November 28, 2014, freeware) developed by *Department of Chemical Engineering and Materials Science – University of California-Davis* and it is based on an algorithm with standard backpropagation learning. VGD works with a series of numbers in the range closed [-1, 1], so the values of each parameter of the set of data to be demultiplication so as to obtain a series subunit, and the results are multiplied by the corresponding scaling factor for each parameter of the data set.

3. Experimental data

The experiments were performed on three spindles, write A, B and C.

Table 1. The configuration of the spindles 3

Spindle type	Description	Machine tool
A		Milling
B		Turning
C		Turning

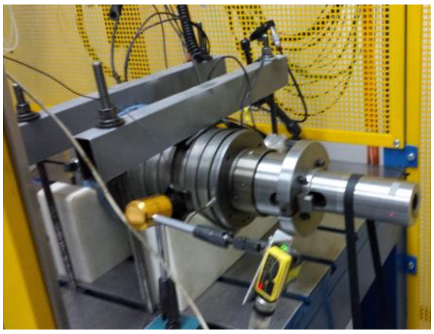


Fig. 1. Experimental device.

All measurements were made on test rig under repair, new bearings and dimensional conditions and geometric surfaces. Parameters measured were temperature, vibration and speed throughout its running of each ensemble. The temperature was monitored by a SKF thermal sensor, vibration speed was

[1]http://visualgenedeveloper.net/index.html

measured by accelerometers 100 mV/g and the equipment NI USB4431, respectively Fastview software, while the speed was monitored by a tachometer laser Banner connected to the same acquisition board NI USB4431.

3.1. Predicting values higher speeds using artificial neural networks with software Gene Visual Developer

VGD build artificial neural network having as an input speed and output variables as training phase for validation temperatures front/back (2 outputs and in the second phase of temperatures and vibration prediction front/back (4 outputs).

VGD for training artificial neural network, were selected for each spindle temperature front/back:

- spindle A – measurements performed to speed 5800 [rpm] – representativeness 28%;
- spindle B – measurements performed to speed 2962-4065 [rpm] – representativeness 31%;
- spindle C – measurements performed to speed 3996 [rpm] – representativeness 29%;

The characteristics of the artificial neural network validation/prediction for the three spindles are presented in Table 2.

Table 2. Characteristics of training neural networks for validation and prediction for the 3 spindles

	spindle A		spindle B		spindle C	
	Training	Predict	Training	Predict	Training	Predict
Topology setting - Parameter						
Number of input variables	1	1	1	1	1	1
Number of output variables	2	4	2	4	2	4
Number of hidden layer	3	3	5	5	5	5
Node# of 1st hidden layer	7	7	10	10	10	10
Node# of 2nd hidden layer	7	7	10	10	10	10
Node# of 3nd hidden layer	7	7	10	10	10	10
Node# of 4th hidden layer	N/A	N/A	10	10	10	10
Node# of 5th t hidden layer	N/A	N/A	10	10	10	10
Training setting - Parameter						
Learning rate	0.01					
Momentan coefficient	0.1					
Transfer function	Hyperbolic tangent					
Maximum # of training cycle	30000		27000		15000	
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	0.004327	0.275929	0.066458	0.394052	0.006542	0.010866
Avg error per output per dataset	0.000103	0.002729	0.001662	0.003397	0.000327	0.000190
Processing time (sec)	15	43	47	57	14	24

You can try different configurations [10, 11, 13, 14], increasing or decreasing:

- the number of neurons in layer (s) intermediate (e) from 1 to 10 neurons / layer;
- the number of hidden layers 1-5;

- learning rate (manifested by vibration: sum of error or average errors per output per dataset);
- number of training cycles between 1 - ... or changing the type of transfer function.

In general, slope of regression coefficient R is considered optimal to: $R_{gen\_optim} = 0{,}93$.

Table 3. Slope of regression coefficient R 4 outputs for the 3 spindles

	spindle A	spindle B	spindle C
OUT 1	0.936087	0.849339	0.947158
OUT 2	0.911447	0.845478	0.933302
OUT 3	0.955672	0.818703	0.975852
OUT 4	0.900045	0.964813	0.990191
Average	0.925813	0.869583	0.961626

The sum of errors at training ranges $e_{temp} = (0.0065 \div 0.0665)$ (temperature) and the prediction interval $e_{temp\_vib} = (0.0109 \div 0.3941)$ (temperature and vibration). The average error output ranges for training $e_{M\_temp} = (0.0002 \div 0.0017)$ (temperature) the prediction interval $e_{M\_temp\_vib} = (0.0002 \div 0.0034)$ (temperature and vibration). It points out that the field two prediction error decreases greatly and are close to as values.

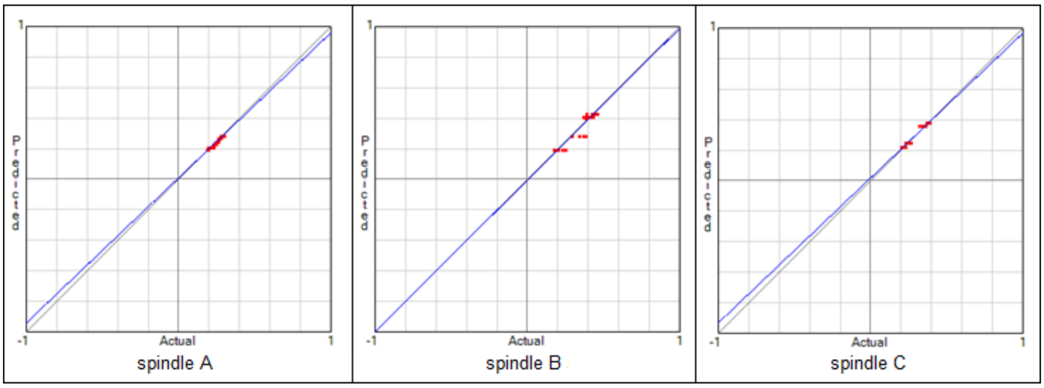


Fig. 2. Representation of the slope of the regression R for the 3 spindles.

In our case: $R_{B\_optim} = 0{,}87 < R_{A\_optim} = 0{,}93 < R_{A\_optim} = 0{,}96$.

This inequality shows that the slope of the regression results are obtained:

a) *unsatisfactory* for grouping dataset into multiple poles on field (R_B);

b) *good* for grouping data set evenly distributed field (R_A);

c) *very good* for grouping data set to the extreme poles of the field (R_C).

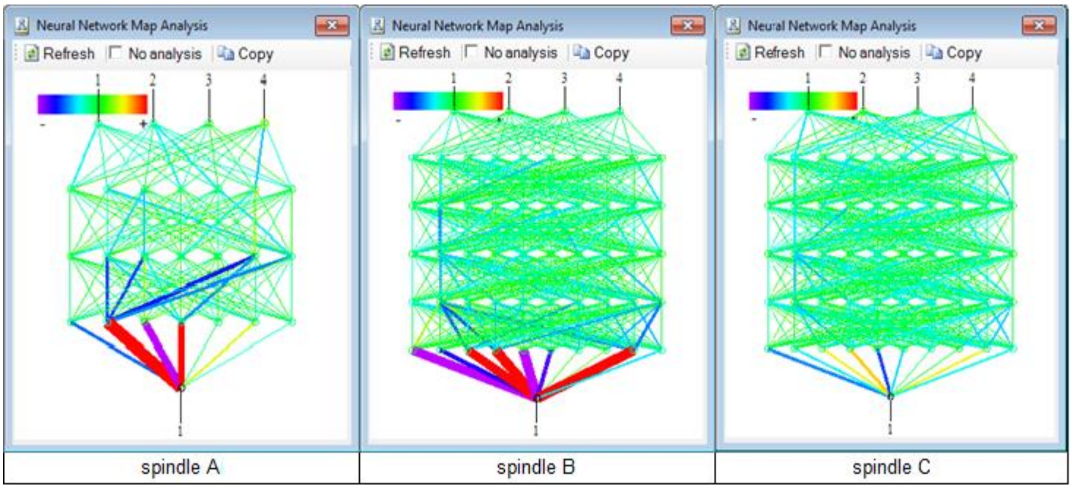


Fig. 3. Information flow through ANN for the 3 spindles.

In Fig. 3 red line corresponds to positive numbers which tend to (+1), and negative numbers purple line that tend to (-1). If A and B spindle information flow to the first hidden layer is dominated by extremes numbers of the field, ie ((-1) and (1)) when the spindle centered at C numbers (-0.5) and (+0.5).

For upper most hidden layers of information flow is focused on the colors green and blue, so around ± 0. Line width is proportional to the weight factor (importance) amounting absolutely or the threshold value.

From prediction is noted that the spindle C temperatures will be much higher than the spindle A and B, so the whole spindle-bearings-housing is very tight being created conditions for growth:

- heat flow over 23%;
- vibration amplitude over 65%;

Graphs temperature/vibration front/back for the 3 spindles, are represented in Fig. 4, highlighting fields measurement, validation and prediction ANN.

Analyzing Fig. 4 draw the following conclusions for spindle:

- A - to temperature it is slightly higher than the back and higher vibrations on the back than the front.
- B - balancing temperature differences tend to follow each other and the vibration is manifested by large imbalance between the front and back;
- C – temperature is higher than the front and back vibration higher on the back than the front, two variable components keeping a constant difference each other, watching each other.

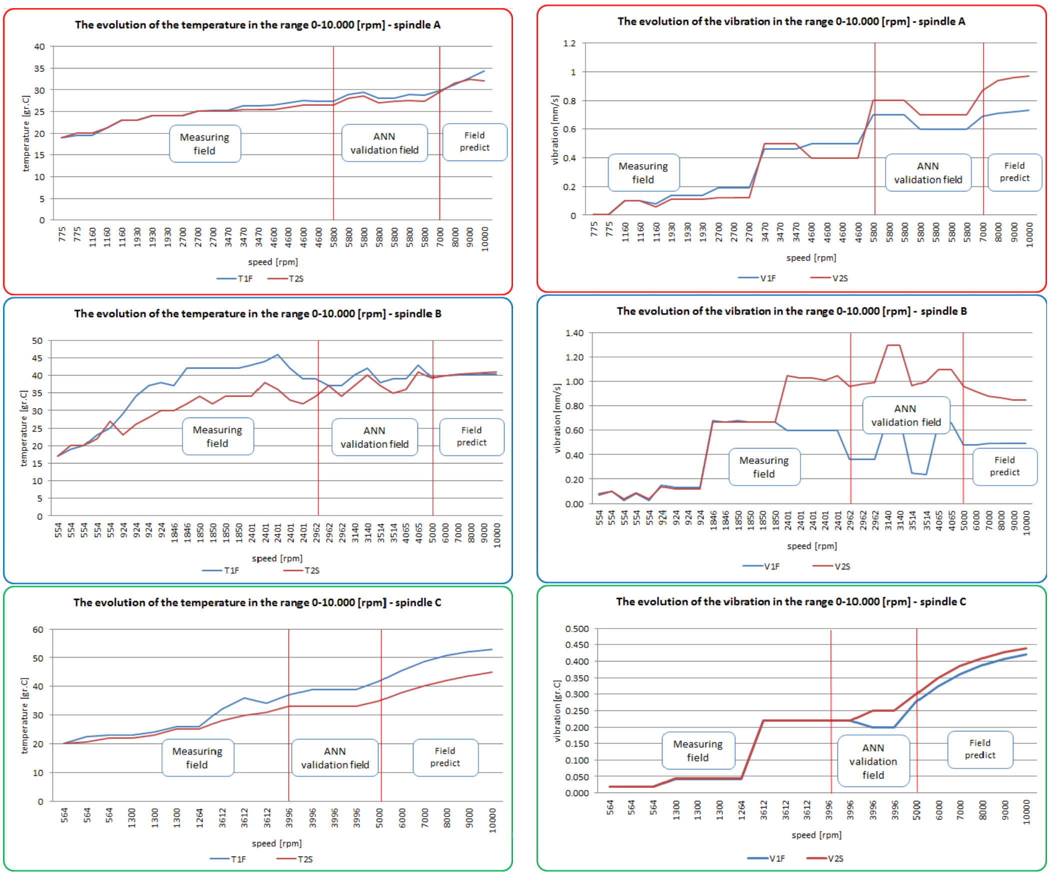


Fig. 4. Charts for the 3 spindles in the fields of measurement, validation, prediction
a. Temperature; **b.** Vibration.

The differences in values for temperature/vibration front/back are determined by:

- bearing configuration;
- preload conditions;
- geometrical surfaces condition.

To interpret the data correctly predicted must take into consideration the evolution percentage of average temperature/vibration front/back between training and prediction for the 3 spindle (Table 5) with the following notations:

- T1P – temperature predicted in front; T1T – temperature training in front;
- T2P – temperature predicted back; T2T – temperature training back;
- V1P – vibration prediction in front; V1T – vibration training in front;
- V2P – vibration prediction back; V2T – vibration training back;

Table 4 Evolution of the temperature and vibration for the 3 spindles

		T1P/T1T	T2P/T2T	V1P/V1T	V2P/V2T
		[gr.C]	[gr.C]	mm/s	mm/s
spindle A	Average Training	28.5	27.6	0.633	0.733
	Average Prediction	32.06	31.36	0.71	0.94
	Evolution [%]	**12.49%**	**13.62%**	**12.16%**	**28.24%**
spindle B	Average Training	39.33	36.78	0.48	1.08
	Average Prediction	40	40.3	0.49	0.89
	Evolution [%]	**1.70%**	**9.57%**	**2.08%**	**-17.59%**
spindle C	Average Training	38.5	33	0.21	0.235
	Average Prediction	48.6	40.6	0.36	0.39
	Evolution [%]	**26.23%**	**23.03%**	**71.43%**	**65.96%**

3.2. Use of Adaptive Neuro-Fuzzy Inference System for prediction Sugeno 3D surface temperatures and vibration of the speed with Matlab software

We use data set on which were built the graphs in Fig. 4 for building Adaptive Neuro-Fuzzy Inference System (ANFIS) Sugeno.
ANN configuration for the 3 spindles is:

- ✓ two input variables - temperature/vibration front/back;
- ✓ output variable - speed;
- ✓ Membership function for input variables - triangular;
- ✓ Membership function for variable output - linear (Takagi-Sugeno-Kang);
- ✓ training method - Hybrid;
- ✓ tolerance error – 0;
- ✓ epochs – temperature (A-30, B-10, C-135), vibration (A-20, B-20, C-10).

The 8 or 9 output membership functions are aggregated to a single output.

In Fig. 5 are represented in diagrams temperature/vibration front/back of the speed for the 3 spindles subject to experiment with the data sets: A – 29, B – 35 and C – 20.

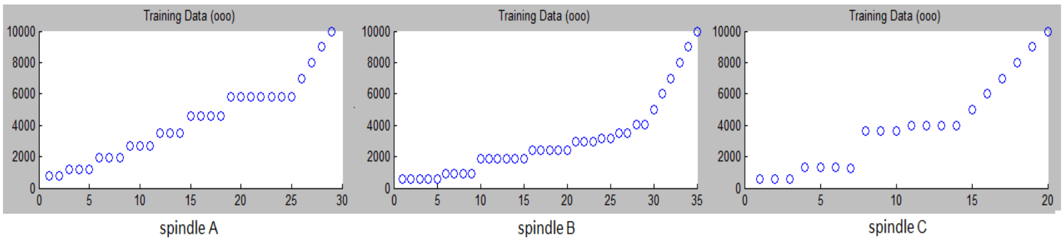


Fig. 5. Training charts temperature/vibration of the speed to the 3 spindles.

The errors of the speed of temperature in Fig. 6 confirmed regression slopes Fig. 2 and related comment. Thus it is observed that the greatest amount of error is characteristic spindle B - 736 with stabilization in 4 epochs, followed by spindle A - 286 with stabilization in 15 epochs and the best results spindle C - 117 with stabilization 122 epochs.

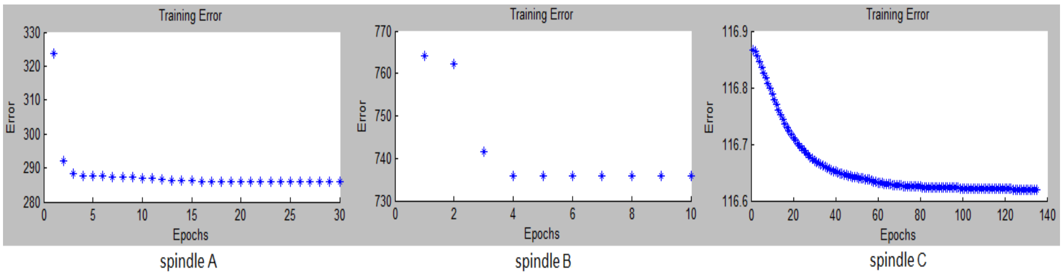


Fig. 6. Charts for training errors for temperatures of the speed to the 3 spindles.

In the case vibration training errors of the speed (Fig. 7) observed that after a few errors epochs stabilizes.

For the 3 spindles have the following error sizes: A - 18 with stabilization in an epoch, B - 132 with stabilization epochs 14 and C - 94 with stabilization in 3 epochs.

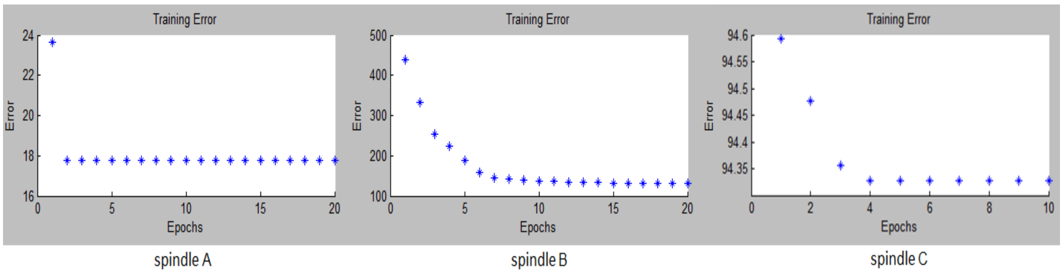


Fig. 7. Charts for training errors for vibration depending on the speed of the 3 spindles.

The next step is testing the FIS. In this sequence error is tested against ANN input data.

Analysing the Fig. 8 and Fig. 9 notes that in terms of training error temperature/vibration occur 3 cases (Table 6): overlapping, around (vicinity of the values underlying the analysis speed) and outside.

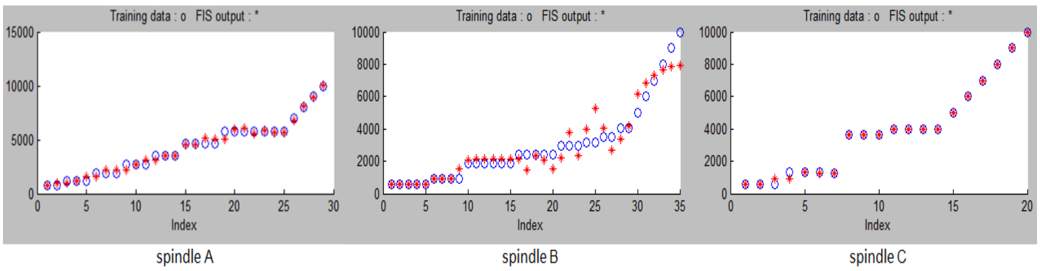


Fig. 8. Charts and data error for the training set temperature to the 3 spindles.

Average weights percentage of spindle C (fitness - 82.5%, around - 17.5%) is best centered around the values speed and the biggest errors in the weighted average percentage we have for spindle B (fitness - 57.14% around - 17.14% and on the outside - 25.71%).

Table 5 Percentage share of the 3 situations to the 3 spindles

		spindle A		spindle B		spindle C	
		Points	[%]	Points	[%]	Points	[%]
Temperature	Fitness	13	44.8%	9	25.7%	18	90.0%
	Arond	15	51.7%	10	28.6%	2	10.0%
	On the outside	1	3.4%	16	45.7%	0	0.0%
Vibration	Fitness	27	93.1%	31	88.6%	15	75.0%
	Arond	2	6.9%	2	5.7%	5	25.0%
	On the outside	0	0%	2	5.7%	0	0.0%
Average	Fitness		68.97%		57.14%		82.50%
	Arond		29.31%		17.14%		17.50%
	On the outside		1.72%		25.71%		0.00%

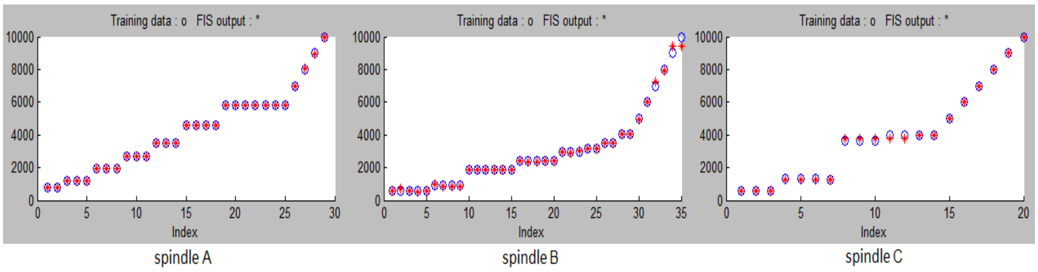


Fig. 9. Charts training data set and vibration error to the 3 spindles.

From the pairs of data (A - 29 B - 35 C - 20) ANFIS Sugeno [12] is carried 8 or 9, the basic rules are shown in Fig. 10 for the speed and temperature according to Fig. 11 speed vibration function for the 3 spindles.

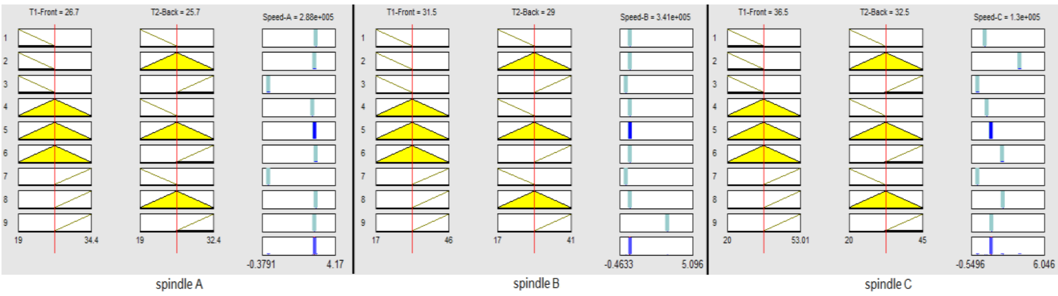


Fig. 10 FIS Sugeno fuzzy logic rules temperature of the speed to the 3 spindles

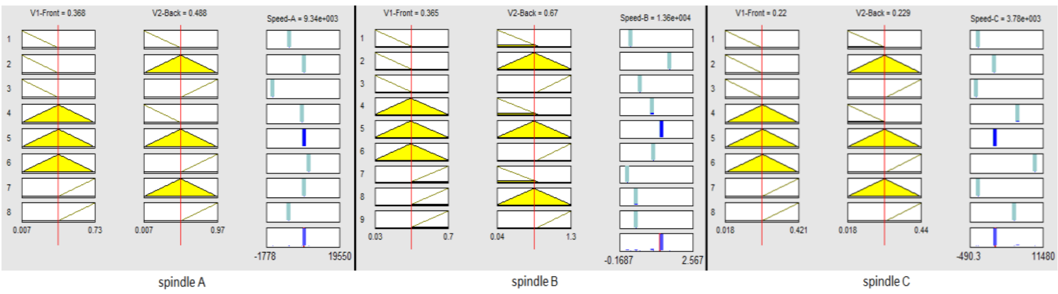


Fig. 11. FIS Sugeno fuzzy logic rules to vibration of the speed to the 3 spindles.

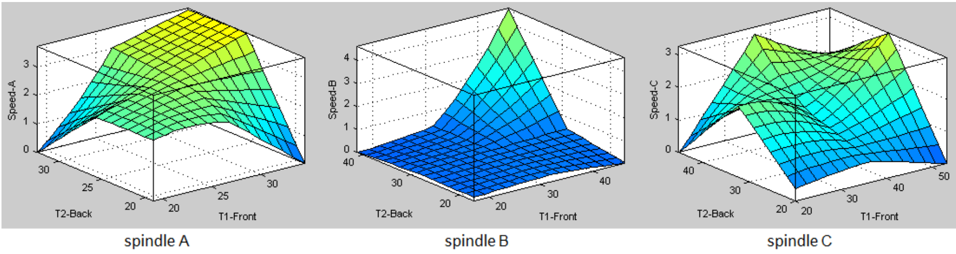


Fig. 12. 3D charts of temperature depending on the speed of the 3 spindles.

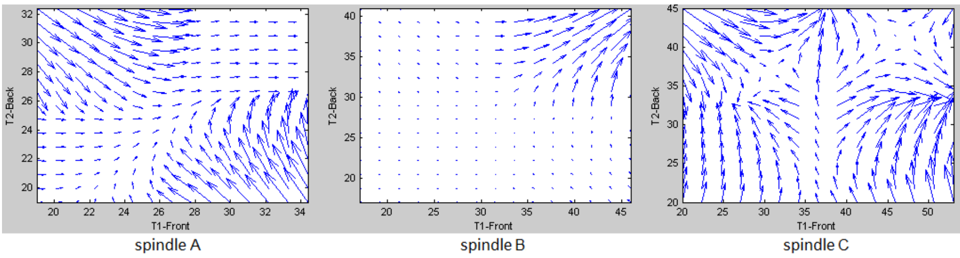


Fig. 13. Quiver temperatures depending on the speed of the 3 spindles.

3D speed characteristics depending on the temperature front/back:

- spindle A – continuous linear increase of the temperature front simultaneously with increasing speed and back of temperature increases abruptly in the range 20^0-24^0 [C] followed by slow growth with trend capping at higher speeds (Fig. 12). In terms of the quiver of temperature trends can be observed that the decrease in maximum temperatures are curved and directed towards their growth at higher speeds and the first landing follows a linear trajectory towards higher speeds (Fig. 13);
- spindle B – continuous linear increase of the temperature front simultaneously with increasing speed and back of temperature increases abruptly in the range 17^0-30^0 [C] followed by a steep decline towards higher speeds (Fig. 12). Quiver by focusing speeds higher temperatures (Fig. 13);
- spindle C – uneven of the temperature variation front characterized by 3 peaks and a slow increase in temperature back within 20^0-35^0 [C] followed by a steeper increase to higher speeds (Fig. 12) and temperatures quiver is focused towards these peaks (Fig. 13);

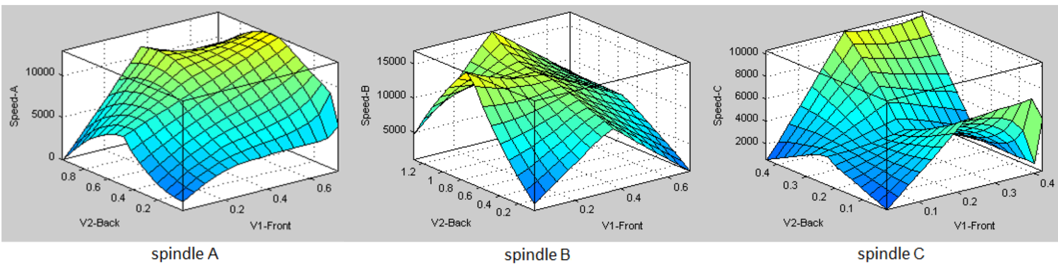


Fig. 14. 3D diagrams of the speed of vibration to the 3 spindles.

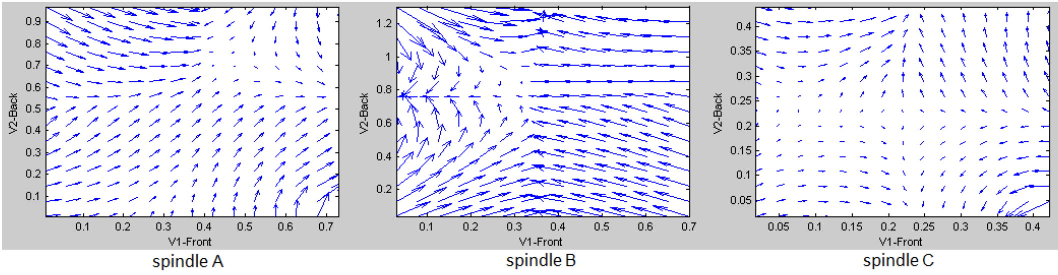


Fig. 15. Quiver vibration of the speed to the 3 spindles.

3D features vibration function of speed in front / back:

- spindle A – linear growth and continuous vibration front and rear vibration linear growth capping ceiling at 10,000 rpm [rpm] (Fig. 14). From the point of view of the quiver of the vibration tendencies are similar to those of temperature (Fig. 15);
- spindle B – vibration are perpendicular to front and back, forming two peaks (Fig. 14). Developments of the two vibrations is identical, namely: steep increase in the first half, followed by a short landing and continued stabilization of the steep rise higher speeds. Also quiver vibration and converge the two peaks (Fig. 15);
- spindle C – variation uneven vibration. Vibration back is characterized by two extremes of stabilization. One which corresponds to vibration and other vibration levels at high speed front the top (Fig. 14). The quiver vibration converges to the top quadrant of the quadrants I and II and IV quadrant to the lower edge of the quadrants III and IV (Fig. 15).

Conclusions

This study presents a method of analysis hybrid type ANN-ANFIS using ANN environment VGD for prediction of parameters that were measured and use the results to study the behavior of 3D speed according to the temperature/vibration front/back Sugeno ANFIS, Matlab. (1).

ANN prediction parameters, environment VGD, was conducted in two stages. The first step was to validate the measured values of temperature front/back by training network to obtain the best regression slope (*R*). The result obtained was used to predict vibration front/back. Mentioning that direct prediction of the four output variables is not correct because large errors. Soft reset at each necessary training for reducing errors due to remaining memory of previous training. (2).

Making full measurement on a spindle fixed to determine if it falls within the initial parameters is a lengthy process (over 8 hours), inefficient economically, which led to the use of ANN to predict, based on a set low measurements performed in a few hours. (3).

When using Sugeno ANFIS, Matlab, it was necessary correction of the parameter field Input/Output membership functions to be consistent with the measured and predicted. (4).

3D visualization of surface temperatures/vibration front/back depending on the speed and the quiver of these parameters leads to a correct interpretation of the results and make the necessary corrections to the whole (bearing configuration, conditions preload and geometrical surfaces condition). (5)

The introduction of genetic algorithms in modeling datasets type Multi-Input-Multi-Output (MIMO) further processed with ANN and FL are subject to further research.

Acknowledgment

This work was partially supported by the Sectorial Operational Program Human Resources Development 2007-2013 of the Ministry of Education and Scientific Research, Romania, co-financed by the European Social Fund through the projects POSDRU/187/1.5/S/155420 and POSDRU/159/1.5/S/134197.

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