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The Study of Machine - Tools Dynamic by Using Artificial Intelligence Methods (2-nd Part)

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ABSTRACT

The study of machine-tool dynamic is realised here as "monitoring", meaning checking and improving the functioning of the machine.
In the first part of the paper it is detailed: pattern recognition, with linear classifier; fuzzy methods in pattern recognition; the using of artificial neural networks in pattern recognition .
In this second part of the paper it is detailed: the using of artificial neural networks in pattern recognition, the Kohonen's artificial neural networks and the potential functions method used in pattern recognition; connections between artificial neural networks of the type RBF, Kohonen's networks and fuzzy sets; the classes (tool conditions) for monitoring in turning.
***Keywords**: monitoring, artificial neural networks, pattern recognition, potential functions*

1.Introduction

The study of machine-tool dynamic is realised here as "monitoring", meaning checking and improving the functioning of the machine. Using the ARTIFICIAL INTELLIGENCE METHODS inside monitoring is one of the newest method dedicated to this goal [4].

The state of processing is followed with certain sensors which signs are processed inside the computer, then it takes the decision of monitoring , meaning the identification of a class from the set of classes (process conditions) $c = [c_1, c_2, \dots, c_n]$, according to : if $t_{inf} < x \le t_{sup}$, then $c = c_i$, (1)

where x is the set (vector) of monitoring indices $x = [x_1, x_2, \dots, x_m]$, and t - the admissible limited values .

Example of index : x_2 = the mean value of the cutting force ; class example : c_3 = the tool wear in certain limits .

The monitoring index x_k is bound by the signal y_k of the sensor through :

$$x_k = P(y_k), \qquad (2)$$

where $P(.)$ is an operator who can be dependent of time , non-linear , or even an unanalytical form . So x_k can be even the signal y_k or other value (referring y_k) in the field of time or frequency.

The samples can be registered as in table 1 , in which m is the number of monitoring indices ,

Sam-Ples	*Monitoring indices*						*CLASSES (Process conditions)*
	x_1	x_2	...	x_i	.....	x_m	
x_1	$x(1,1)$	$x(1,2)$	.....	$x(1,i)$	.....	$x(1,m)$	$c(x_1) \in [c_1, c_2, \dots, c_n]$
x_2	$x(2,1)$	$x(2,2)$	.....	$x(2,i)$	.....	$x(2,m)$	$c(x_2) \in [c_1, c_2, \dots, c_n]$
...	...	...	...	...	...	....	.....
x_N	$x(N,1)$	$x(N,2)$	.....	$x(N,i)$	.....	$x(N,m)$	$c(x_N) \in [c_1, c_2, \dots, c_n]$

Table 1 . The order of the samples

n is the number of classes, and N - the number of samples . So $x_k = [x(k,1), x(k,2), \dots, x(k\ m)]^T$ denotes the "k - th vector", and $c(x_k) \in [c_1, c_2, \dots, c_n]$ shows the fact that in this case the result is one of the classes $c_1, c_2, \dots, c_n$.

It can be introduced the function:

$$Q : c \to x \ , \qquad (3)$$

which is "obscure" because on it you cannot do but indirect measurements which are, or you can assume they are bound to the function . If for Q you cannot obtain any theoretical relation, you can use in consequence a method of interpretation of data which involves two phases: **learning** and **classification**. In the learning phase it is formed an empirical relation between x and c for a set of samples in which both x and c are know (a part of data from the table 1). In the classification phase it is used the other part of the table 1, with a view to predicting of c, testing in this way and adjusting the empirical relation. In this way it is done the inversion of function Q :

$$Q^{-1} : x \to c \ . \qquad (4)$$

Now the empirical relation is able to classify **a new sample x** in a certain class c_k .

So Q can have different aspects : an analytical one , an artificial neural network, a pattern recognition, a fuzzy system, etc.

In [4] it was shown the way in which the machine-tools dynamic can be studied by using artificial intelligence (A I) elements (artificial neural networks, pattern recognition, fuzzy systems), which are considerate as being independent methods. We can notice that there are a lot of study methods, but we can't say one is better than the others, in all the applications. So, we must try a few methods and choose the most performant one. Between these methods we can establish coupling bridges, resulting superior study technics (the whole thing being - we know - bigger than the parts sum).

2.The using of artificial neural networks (A N N) in pattern recognition (P R)

In [5] it is shown that an A N N with 3 layers can form a decision surface as those formed by a classifier who uses the *k - N N rule* . In [8] it is demonstrated that any A N N totally connected , with feedforward , is asymptotically equivalent with an optimal Bayes'classifier [6].

The classical ANN are limited in their performance on difficult problems in PR , their results being sometimes poorer than those of Bayesian classifiers , which attempt to optimise the decision surfaces .

2.1.The Kohonen's A N N

These ANN are differing from classical networks in the first way that only the reference weight vector closest to the input is modified .

The general Kohonen's ANN is simplified since it does not comprise the interconnections between the neurones . Each input is connected to all neurones . It is preferable to have a number of active outputs for one class rather than just one , and the number of neurones is significantly higher than the number of classes , so that several neurones can be associated with one class .

The supervised learning algorithm for P R

For each neurone i , W_i is the vector of weights of connections coming from the input signal : $W_i = [\, w_{i1}, \dots, w_{in} \,]^T$.

The algorithm is :

- each class is assigned a number of neurones , proportional with the *apriori* probability of this class in the learning group ;
- the weight vectors are initialised with the values of one input vector from the group of neurones above mentioned ;
- a new input vector X is compared with all the weight vectors and one vector W_c, (the closest to X) is chosen . The weights are modified by :

$$W_c(t+1) = W_c(t) \pm K(t)[\,X(t) - W_c(t)\,], \qquad (5)$$

the sign is "+" if X and neurone c belong to the same class (to make W_c closer to X), else we put the sign "-" (the weight W_c is altered to be more distant from X).

For the other neurones the weights remain unchanged .

The factor $K(t)$ is named *the learnig rate* and is a positive function, which decrease with increasing t, one might use: $K(t) = a - b\,t \geq 0$. In [7] it is shown that the optimum situation is realised if $K(t) \in [0, 1]$.

In the classification phase , a vector X presented to the network causes it to search for the neurone with the closest weight vector ; this neurone then represents the class to which the vector X belongs .

Results obtained with this method are very close to results from Bayesian classifier [6].

In [7] this algorithm is modified by replacing the weighting vector W_c from (5) with a prototype vector, representative for a class.

There are n classes , each with M_i , ($i = 1, \dots, n$) vectors from the learning group: $X = x_i^{(j)}$, ($i = 1, \dots, M_i$; $j = 1, \dots, n$). For each class on determine a number of np_i vectors prototype : $Z = z_i^{(j)}$, ($i = 1, \dots, np_i$; $j = 1, \dots, n$) . When to the network on present the vector $x_i^{(j)}$, on determine :

$$\min_{i,k}\{\|x_i^{(j)} - z_i^{(k)}\|\}_{i=1,\dots,np_k,\ k=1,\dots,n} \qquad (6)$$

If the minimum is attend for $k = j$ (that means the prototype belongs to class j) , then the prototype is adjusted by the relation:

$$z_c(t+1) = z_c(t) + K(t)\cdot[\,x_i^{(j)}(t) - z_i^{(k)}(t)\,] \quad (7)$$

and if $k \neq j$, the sign "+" in front of K is replaced with "-".

This adjusting is made for each prototype be as representative as it can for a form group, the prototype being *initiated* with vectors from the respective class of the learning group.

In the classification stage on evaluate the criterion: $C_K(x) = \min\limits_{\substack{i=1,\dots,np_j \\ j=1,\dots,n}} \{\|x - z_i^{(j)}\|\}$, (8)

the form x being attributed to the class which belongs the prototype which minimises the criterion (8).

2.2.The fuzzy - Kohonen algorithm

In many applications it is necessary to know the membership degree of a form to a class ; that is realised by the help of he fuzzy - Kohonen algorithm .

We consider two classes c_i which contain M_i vectors ($i = 1,2$). In the fuzzy approach , to a vector from c_1 it is attributed membership degrees both to class c_1 and to class c_2. The prototypes are adjusted with a relation as to (7):

$$z(t+1) = z(t) \pm K(t)\,|\,\mu_1(x) - \mu_2(x)|\,[x(t) - z(t)] \;, \qquad (9)$$

where x is the form which is presented to the algorithm , z - the prototype which is adjusted, $\mu_i(x)$ - the membership degree of x to c_i ($i = 1, 2$) ; the sign "+" is put if the prototype and the form belong to the same class , and contrarily it take the sign "-" .

From the comparison of relations (7, 9) we notice that for the fuzzy - Kohonen algorithm the learning rate depends on the membership degrees too , so the prototypes will be more attracted from the forms with bigger fuzzy degrees .

2. 3.The fuzzy approach of P R with Kohonen's ANN

In the section 2.1 the affiliation of forms is <u>not</u> correlated to the form position in the class domain from the forms space , it means it is <u>not</u> in view if the form is situated in the centre of class , or on its outskirts . By the fuzzy approach on specify the membership degree of forms to the respective classes , beginning with the further moment of establishment the prototypes , in number of p_j , ($j = 1, 2$) , while it is unfurled the algorithm from the section 1.1 .

We define the prototypes fuzzy degrees of the two classes $\{\mu^k_{ij}\}$, ($i = 1, 2$; $j = 1, 2, \dots, np_i$; $k = 1, 2$) , with the relation :

$$\mu^1_{ij} = 1 - \frac{\|p^i_j - mp^1\|}{\|p^i_j - mp^1\| + \|p^i_j - mp^2\|} \;, (1 = 1,2 \;;\; j = 1,2,\dots,np_i) ,$$

$$\mu^2_{ij} = 1 - \frac{\|p^i_j - mp^1\|}{\|p^i_j - mp^1\| + \|p^i_j - mp^2\|} \;, (1 = 1,2 \;;\; j = 1,2,\dots,np_2) \;, \qquad (10)$$

in which : p^i_j , ($j = 1, 2, \dots, np_i$) are the prototypes of class i; mp^i - *the medium prototype* of class i , ($i = 1, 2$) ; $\|\;.\;\|$ - the Euclid's distance .

It is noticed the following aspect : as p^1_j is closer to mp^1 , as the distance $\|p^1_j - mp^1\|$ is smaller , μ^1_{1j} tends to the value 1 , and μ^1_{2j} to 0 . This thing is in concord with the fact that the prototypes p^1_j belong more to class 1 than to class 2 .

To classify a form x , we calculate the membership degrees to classes c_1 and c_2 , with the relations:

$$\mu_1(x) = \frac{\mu_{1p^1_q}\dfrac{1}{\|x - p^1_q\|^{2/(m-1)}} + \mu_{1p^2_r}\dfrac{1}{\|x - p^2_r\|^{2/(m-1)}}}{\dfrac{1}{\|x - p^1_q\|^{2/(m-1)}} + \dfrac{1}{\|x - p^2_r\|^{2/(m-1)}}} \;,$$

$$\mu_2(x) = \frac{\mu_{2p^1_q}\dfrac{1}{\|x - p^1_q\|^{2/(m-1)}} + \mu_{2p^2_r}\dfrac{1}{\|x - p^2_r\|^{2/(m-1)}}}{\dfrac{1}{\|x - p^1_q\|^{2/(m-1)}} + \dfrac{1}{\|x - p^2_r\|^{2/(m-1)}}} \;, \qquad (11)$$

where :

p^1_q = the prototype of class 1 the nearest to form x ;

p^2_r = the prototype of class 2 the nearest to form x ;

$\mu_{1p^1_q}$ = the membership degree of the prototype p^1_q to class 1 ;

$\mu_{1p^2_r}$ = the membership degree of the prototype p^1_r to class 1 ;

$\mu_{2p^1_q}$ = the membership degree of the prototype p^1_q to class 2 ;

$\mu_{2p^2_r}$ = the membership degree of the prototype p^1_r to class 2 ;

m = a parameter which controls the distances weight (the usual values are 3 and 5) .

The form x will belong to the class for which there is $\max\{\mu_1(x), \mu_2(x)\}$.

3.The Kohonen's ANN and the potential functions method used in PR

It is known that the discriminate function , that uses the potential functions method , is obtained with a correction algorithm that sometimes doesn't classify correct all forms , in the testing stage . This difficulty is eliminated by using Kohonen's ANN , which determine the nucleus p_k of the potential functions .

We consider the case of the binary classification , the classes c_j contain M_j forms and np_j prototypes (notation p^j_k , $k = 1, 2, \dots, np_j$ and determined with the Kohonen ' s algorithm) , ($j = 1, 2$) .

The discriminate function is defined by the relation :

$$D(x)=\sum_{k=1}^{np1}\Psi(x,p_k^1)-\sum_{k=1}^{np2}\Psi(x,p_k^2), \qquad (12)$$

in which we notice that the prototypes (inferred from the learning group) become the nucleus of the potential functions.

The function from (8) is used in the correction algorithm (37) from the first part of this paper.

4. Connections between ANN of the type RBF, Kohonen's networks and fuzzy sets

4.1. Radial basis functions (RBF) networks

An another approach of ANN , different from the "BackProp" algorithm is the following : we consider the learning problem as one of approximation the curves in a multidimensional space. In this case the learning process is equivalent with finding that surface which "matches" the best with the lot of learning data. The hidden levels from ANN has the part to produce a lot of functions to represent the input vectors , the respective space being formed by the functions named **RBF** .

The usefulness of RBF networks results from [2]: "a complex problem of classification can be solved better, in the sense of separability, in a more dimensional space than in a reduced dimension one". So that we have N vectors n-dimensional $x \in X$, for each of these we define a vector

$\Phi(x)=[\Phi_1(x), \Phi_2(x), \ldots, \Phi_m(x)]^T$.

The function Φ sinks the vectors of the input space in a new space m-dimensional ($m > n$) . The structure of a RBF network is shown in the figure 1. These networks are realised just

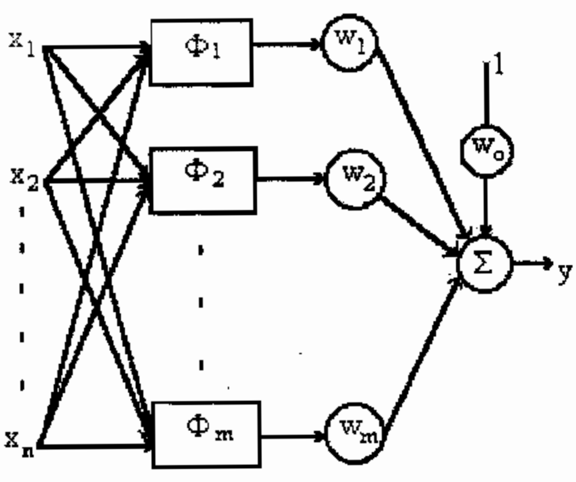

Fig . 1 , A RBF network

The network implements a function :

with one only hidden level , no matter the problem complexity.

$$y=f(x)=\sum_{j=1}^{m} w_j\ \Phi_j(x,\gamma_j)+w_o, \qquad (13)$$

where the function

$\Phi_j(x,\gamma_j)=\Phi_j(\|x-\gamma_j\|)=\Phi_j(r)$ (14)

is a **radial function** , nelinear as a rule , for which we can use one of the following expressions : $\Phi(r)=r \rightarrow$ linear radial;

$\Phi(r)=r^2 \rightarrow$ square;

$\Phi(r)=exp[-r^2/(2\sigma^2)]$, with $\sigma>0$, $r \geq 0 \rightarrow$ gaussian;

$\Phi(r)=r^2 \log(r) \rightarrow$ plate spline . (15)

The most used function is the Gauss's one, which presents a symmetry radial around the average, what explains the name of *radial function.*

The known vectors $\gamma_j \in R^n$, $j=1, 2, \ldots, N$ are named **the centres** of the radial function.

The learning of the RBF network consists in establishing the centres γ_j and determining the weights w_j , objectives which are realised by minimalizing the square error, using a gradient method.

The square error for each pair of vectors $\{x_k, y_k\}$ applied , respectively , by input and output of the network, is:

$$E=\left(\sum_{j=1}^{m} w_j\ \Phi_j(x_k,\gamma_k)+w_o-y_k\right)^2,$$

$$\forall\ k=1,2,\ldots,n_l, \qquad (16)$$

where n_l is the number of vectors from the learning lot.

4.2. PR with RBF networks , in determinisitic approach

In case we have n classes c_k , each class contains M_k forms, ($k = 1, 2, \ldots, n$), we use the RBF network from figure 2. The learning group is formed in this way: if $[x_1, \ldots, x_p]^T \in c_j$, then $y_j = 1$ and the other outputs are nulls.

After the learning of network , for the input vector $[x_1, \ldots, x_p]^T \in c_k$ the output y_k must be the biggest of the outputs.

4.3. Classifier with RBF networks, fuzzy sets and the Kohonen's algorithm

From above we deduce that by using Kohonen's algorithm we can determine the radial functions *centres* , and the network weights are calculated in function with the membership degrees of the prototypes to the classes.

To form the classifier (in case we have *2* classes c_j, the learning group contains M_j forms, ($j = 1, 2$) we cover the following steps:

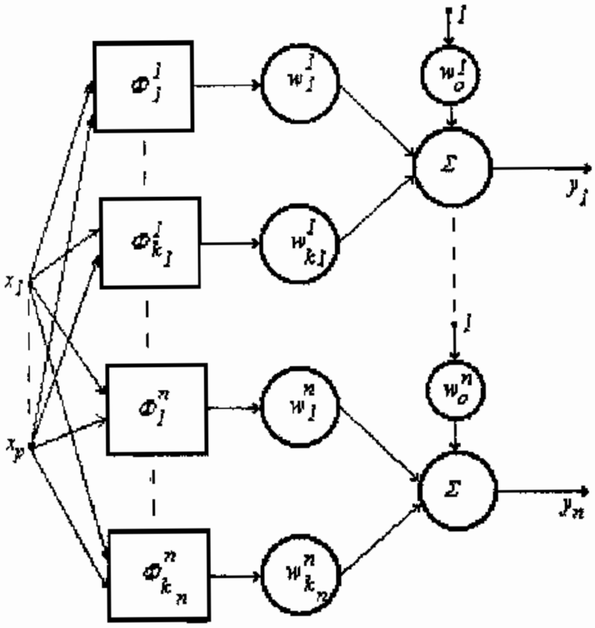

Fig . 2 , **RBF network for PR**

1°- By using Kohonen's algorithm we determine the prototypes , their number is np_1 and np_2 , associated to the 2 classes. These prototypes are considered the centres γ_j of functions Φ_j $(\| x - \gamma_j \|)$. We determine the functions in this way:

$\{ \Phi^1_j \ (\| x - \gamma^1_j \|) \}_{j=1,2,\ldots,np}$

and $\{ \Phi^2_j \ (\| x - \gamma^2_j \|) \}_{j=1,2,\ldots,np}$.

2°- The weights of the RBF network (analogous with that one from the figure 2 , but in which there are two inputs (x_1 , x_2), two outputs (y_1 , y_2), $k_1 = np_1$, $k_n = np_2$, , $w^1_0 = w^2_0 = 0.5$), we calculate by using fuzzy sets:

$w^1_j = \mu^1 (1, j) - \mu^1 (2, j), (j = 1, 2, \ldots, np_1);$

$w^2_j = \mu^2 (2, j) - \mu^2 (1, j), (j = 1, 2, \ldots, np_2)$,

where the membership degrees of the prototypes to classes are determined with the relations (10).

A new form $[x_1 , x_2]$ is classified in the class where it is realised the $max \{ y_1 , y_2 \}$.

If after the cover of these steps , there are more forms from the learning group which can not be classify , that means

$$| y_1 - y_2 | \le \varepsilon , \qquad (17)$$

ε being a parameter by which it is imposed a safety reserve, then we correct the weights with the formula:

$$w_j^k = w_j^{k-1} - e(k) | \mu_1 (x) - \mu_2 (x) | . \Phi. (y_x - y_{\bar{x}}) , \qquad (18)$$

where :

x = the form which couldn't be classified ;

y_x = the input adequate to the class to which it belongs ;

$y_{\bar{x}}$ = the input adequate to the class to which it doesn't belongs ;

$e(k)$ = the learning rate ;

$\mu_1 (x)$ = the fuzzy degree of form x to class 1;

$\mu_2 (x)$ = the fuzzy degree of form x to class 2.

After a correction step , it is determine unclassified forms again . The adjusting stops when the RBF network classify correctly all the forms from the learning group .

5.The monitoring in turning

For monitoring in turning, in [4] it is shown the classes (tool conditions), define like in Table 2. Tool breakage was identified by a chip on the tool inserts bigger than $0.05\ mm^2$. Chatter is identified by the high frequency noise and the chatter marks on the machined surface. Transient cutting (or intermittent cutting) is produced by machining a workpiece that has a slot along the feed direction.

We shall work on the conditions from the table 1 in order to co-ordinate them with [9, 10] where from we quote: "The usual criteria for the wear of the rapid steel knifes and of the knifes with hard - cutting alloy plates are (fig . 3):

- the medium breadth of the wear by the separation from the main back edge in B zone is $VB_B = 0.3\ mm$ if this has a regular form; - the maximum breadth of the same wear $VB_{B\,max} = 0.6\ mm$, if this has a irregular form ."

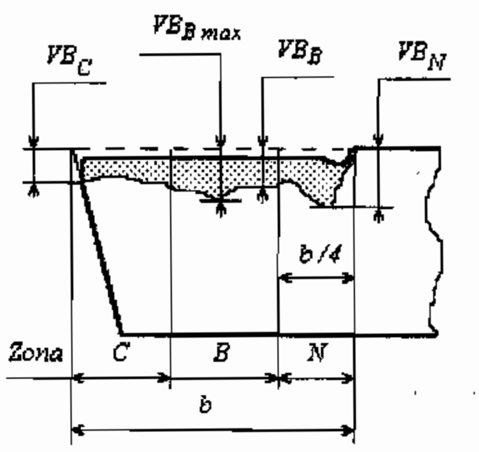

Fig . 3 , The wear of knife

We shall adapt the classes c_1 , c_3 , c_4 and c_5 (from the table 2) in accordance with these prescriptions and us shall *rearrange* the classes as in table 3 . In connection with class c_2 (from the table 3), in [10] it is shown that "the advanced (catastrophic) deterioration means the intense deterioration of the edges of the knife after a period of normal cutting, under the combined action of all the factors that are involving in the processing". For the quantitative evaluation of this state, we propose an overtaking with more than $0.1\ mm$ of the wear criteria, and the overtaking till $0.1\ mm$ showing a *severe wear*.

In conclusion, the $n = 8$ classes referring to the working conditions are those from the table 3, in which **to the first three classes the working conditions are *normal* and the other ones are *unnormal***.

In order to obtain the monitoring indices you have to use sensors which measure the three components of the cutting force ($\mathbf{F}_x$ - the force on the direction of advance, $\mathbf{F}_y$ - the repelling force, $\mathbf{F}_z$ - the main force), the accelerations of cutter holder vibrations (a_x, a_y, a_z) and the power given by the electric engine (P). The signs of the sensors are registered simultaneously and they are sampled.

Class	Tool conditions	Identification on cutter	Identification on workpiece	Number of samples
c_1	Normal	wear < 0 . 1 mm	---------	$M_1 = 144$
c_2	Tool breakage	chipping > 0.05 mm^2	---------	$M_2 = 49$
c_3	Slight wear	0.11 < wear < 0.15 mm	---------	$M_3 = 114$
c_4	Medium wear	0.16 < wear < 0.30 mm	---------	$M_4 = 114$
c_5	Severe wear	0.31 mm < wear	---------	$M_5 = 114$
c_6	Chatter	Fresh tool	Chatter marks	$M_6 = 61$
c_7	Transient cutting	Fresh tool	An axial slot	$M_7 = 15$
c_8	Air cutting	---------	---------	$M_8 = 13$

Table 2 , The classes for monitoring in turning

Class	Tool conditions	Identification on cutter	Identification on workpiece
c_1	Normal	V B < 0,1 mm , or V B$_{max}$ < 0,2 mm	---------
c_2	Slight wear	0,11 < V B < 0,2 mm , or 0,21 < V B$_{max}$ < 0,4 mm	---------
c_3	Medium wear	0,21 < V B < 0,3 mm , or 0,41 < V B$_{max}$ < 0,6 mm	---------
c_4	Severe wear	0,31 < V B < 0,4 mm , or 0,61 < VB$_{max}$ < 0,7 mm	---------
c_5	Tool breakage	V B > 0,41 mm , or V B$_{max}$ > 0,71mm	---------
c_6	Chatter	Fresh tool	Chatter marks
c_7	Transient cutting	Fresh tool	An axial slot
c_8	Air cutting	---------	---------

Table 2 , The classes for monitoring in turning , rearranged

Looking on this sizes in [4] are proposed *m = 11* monitoring indices: x_1' - the mean values of the resultant cutting force ($\overline{\mathbf{F}} = \sqrt{\overline{F}_x^2 + \overline{F}_y^2 + \overline{F}_z^2}$, where $\overline{\mathbf{F}}$ is the mean value); x_2' = the crest factor of the force $\mathbf{F}_x$ (C_F = [max ($\mathbf{F}_x$) - min ($\mathbf{F}_x$)] / $\overline{F}_x$); x_3' - the mean ratio of the cutting forces ($\overline{F}_t / \overline{F}_r = \overline{F}_z / \sqrt{\overline{F}_x^2 + \overline{F}_y^2}$); x_4' - the mean crossing rate of the force $\mathbf{F}_x$ (the number of times that the force signal crosses its mean value in the sampling period); x_5' - the power of the force $\mathbf{F}_x$ in frequency band 1- 125 Hz; x_6' - the power of $\mathbf{F}_x$ in band 126 - 250 Hz; x_7' - the power of $\mathbf{F}_x$ in band 251 - 500 Hz; x_8' – the power of the vibration on x - direction, in band 0 - 125 Hz; x_9' - the same power in band 126 - 250 Hz; x_{10}' - the same power in band 252 - 500 Hz; x_{11}' - the R M S of the cutting power .It is to be observed that the 8 indices depend on the force or vibration on the direction of advance x.

Taking into account that: - the force F_y brings about the distortion Δ y which influences directly the dimensional precision and the cylindrical form;

- the force F_z it is not significant because the distortion Δ z spreads only in little measure and is conversely proportional withhe diameter of the piece;

-the force F_x depends , mainly , of the speed of the longitudinal advance , being possible the omission of this component , if it is working with small advances , we shall **improve** the above indices, considering F_y instead F_x and instead of vibration on x - direction (measured by accelerometer a_x placed on the cutter holder) - the relative displacement tool - piece on the y – direction.

6. Conclusions

In the future we plan to realise the experiment and to try a few of above methods , to choose the most performant one (for the case of monitoring in turning).

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Studiul dinamicii masinilor – unelte utilizand metodele inteligentei artificiale (Partea a 2-a)

Rezumat

Studiul dinamicii masinilor – unelte se realizeaza in sensul "monitorizarii", adica verificarea si ameliorarea functionarii masinii.
In prima parte a lucrarii s-au detaliat: recunoasterea formelor, cu clasificator liniar; metode fuzzy in recunoasterea formelor; utilizarea retelelor neuronale artificiale in recunoasterea formelor.
In aceasta parte a 2-a a lucrarii se prezinta: utilizarea retelelor neuronale artificiale in recunoasterea formelor, retelele neuronale artificiale ale lui Kohonen si metoda functiilor de potential utilizate in recunoasterea formelor; conexiuni intre retele neuronale artificiale de tip RBF, retele Kohonen si multimi fuzzy; clasele (starile sculei) pentru monitorizarea strunjirii.

L'étude de la machine - outils dynamiques en employant des méthodes d'intelligence artificielle (2-ème partie)

Résume

L'étude de la machine-outil dynamique est réalisée ici en sense de „monitorisation ', signifiant le chèque et l'amélioration du fonctionnement de la machine.
Dans la première partie de l'ouvrage c'est détaillé: la reconnaissance des échantillons, avec linéaire classifier; des méthodes fuzzy dans la reconnaissance des échantillons; l'utilisation des réseaux neuronaux artificielles dans la reconnaissance des échantillons.
Dans ce second partie de l'ouvrage c'est détaillé: l'utilisation des réseaux neuronaux artificielles dans la reconnaissance des échantillons, les réseaux neuronaux artificielles de Kohonen et les méthodes des fonctions de potentielle utilisée dans la reconnaissance des échantillons; des rapports entre les réseaux neuronaux artificielles de l'espèce RBF, les réseaux de Kohonen et les ensembles fuzzy; les classes (les conditions d'outil) pour monitorisation dans tournage.