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TOOL MONITORING SYSTEM - MODULAR STRUCTURE

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Original scientific paper
The main purpose of a tool condition monitoring (TCM) system is to ensure reliable monitoring of the cutting tool edge condition. The system should be simple to configure for different cutting conditions and the obtained results should be interpreted in an unambiguous way. Implementation of monitoring system involves finding solutions to a number of sub-tasks such as selection of the type of signal, definition of sampling rate, selection of patterns, signal filtering, methods for the selection and ranking of features, the process of learning and creation of knowledge base, user friendly procedure for operating TCM, and methods of reacting on established tool condition. Based on these considerations, a modular concept of tool condition monitoring system is proposed. The concept has been tested on machining processes with variable material hardness and cutting depths.

Keywords: *artificial intelligence methods, modular structure of monitoring, multi-sensor approach, tool condition monitoring system*

Nadzor oštrice reznog alata - modularna struktura

Izvorni znanstveni članak
Sustav nadzora reznoga alata treba osigurati pouzdano nadgledanje stanja oštrice reznog alata. On treba biti jednostavan za konfiguriranje za različite uvjete obrade uz nedvosmislenu interpretaciju rezultata. Implementacija sustava nadzora podrazumijeva rješavanje niza podzadataka kao što su odabir tipa signala, definiranje perioda uzorkovanja, postupak odabira uzoraka, filtriranje signala, izbor i rangiranje značajki, odabir tipa neuronske mreže, postupak učenja i stvaranja baze znanja, načini operativnog posluživanja i metode provođenja reakcija. Na osnovi takvih promišljanja u radu je predložen modularan koncept sustava nadzora. Sustav je testiran na procesima s promjenjivom dubinom obrade i materijalima različite tvrdoće.

Ključne riječi: *metode umjetne inteligencije, modularna struktura nadgledanja, nadzor oštrice reznog alata, višeosjetilni pristup*

1 Introduction

The openness of machining processes, constant changes in the field of tool design and in the creation of new materials require the expansion and updating of the current knowledge base. In the machining process, many factors can cause changes in the measured signal, e.g. coolant, structure of materials, tool geometry, machining conditions, etc., so in real conditions, monitoring systems are limited in their range of applications. On the other hand, the influences of individual factors are often unclear and unknown, and one of the greatest challenges is development of algorithms for autonomous, robust and reliable monitoring systems. Often, they are not applicable to other machining systems without a suitable adjustment process. Therefore, the adaptation process of monitoring system for a particular application has to be carried out. However, although numerous studies on tool condition and process monitoring have been done, complying with the requirements for adaptation to conditions in industry, only few have found their application on the market [1]. Due to the development of machine control systems and methods of artificial intelligence, capabilities of monitoring systems are significantly increased. For monitoring of tool wear phenomena, one sensor source cannot satisfy all the requirements of monitoring. A solution to the problem is the use of multiple sensors which combine signals from different sources. Joining sensors for machining process monitoring has recently been intensively investigated [2]. Such an approach results in informations which are more accurate, complete, reliable and robust comparing to single sensor approach. That is why the multi-sensor approach is adopted in the experimental section of this study. Here, neural networks, fuzzy logic and genetic algorithms play a major role and find their wide application in concurrent processing of a larger number of signals. Monitoring models based on the classical concept of fuzzy logic can hardly identify extremely complex dynamic of tool wear if based only on empirical knowledge about the process implemented through the fuzzy rules. Therefore, they should also have the knowledge structuring capacity by learning from data obtained from recorded process signals. It is why a significant contribution of fuzzy logic could be expected in the segment of the hybrid monitoring models [3], which are not considered in this paper. Neural networks (NN) have to be pre-structured (taught) in a number of experiments. If the learning process and adaptation of neural networks are time-consuming and challenging, they can hardly be expected to find wider application in industry. Therefore, there is a strong need to establish a robust and reliable methodology of monitoring as a response to the variable conditions of the process related to the structure of the material and features of machining.

2 Modular structure

Creation of the structure of process monitoring is a dynamic process depending on machining conditions, the machine, the process and the tool. Cutting tool condition monitoring can be roughly divided into three independent units: selection of the solution with a similar pattern from the database, creation of a new solution, and *"on-line"* process monitoring [4], Fig. 1.

The first part of modular structure of monitoring contains a database and mechanisms for database search. The second part refers to the method of generation of a new solution, and the third part is the operational part of monitoring that has to ensure quick, good quality and functional data processing and an adequate reaction in real time. In each part the task can be hierarchically divided into a series of simpler sub-tasks, so that the solution of the whole task is achieved by combining the individual results of specialized local sub-systems (experts) and their mutual coordination. A similar approach to problem solving has a modular structure of artificial neural networks [5], which can serve as a useful tool for the development of modular structured tool condition monitoring. Fig. 2 shows the architecture of modular neural network. Modular architecture of NN enables the integration of different neural structures or types of learning, depending on the task.

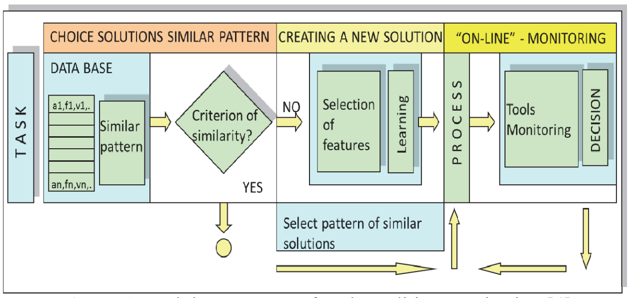

Figure 1 Modular structure of tool condition monitoring [4]

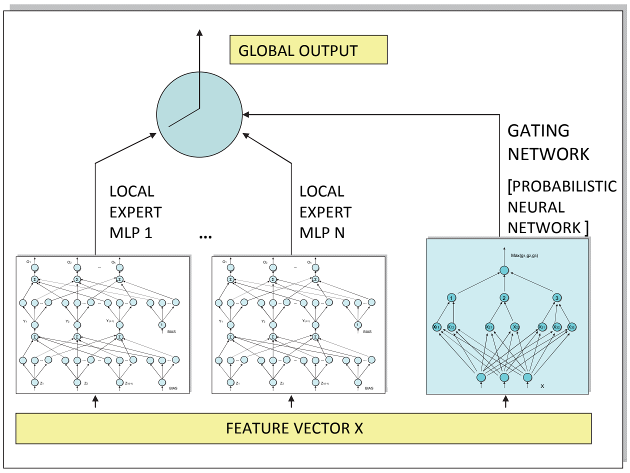

Figure 2 Architecture of modular NN [8]

Some of main advantages of modular neural network are flexibility, incremental learning, robustness, expandability, efficiency and effectiveness [6].

Flexibility. In modular structure, every neural network can be adapted to its task, which means that a new network, which will perform a new sub-task without disturbing the structure of previous learning processes, can be added.

Simple and incremental learning. Local experts can be pre-trained for particular sub-tasks, and then integrated by means of the integration unit.

Robustness. By simplifying a task, i.e. by dividing it into sub-tasks, poor performance of the network and interference can be more easily diagnosed and eliminated without affecting other networks in the structure.

Expandability. Expandability is one of important features of modular neural network. With most neural networks, incremental learning is not possible: if new information is added, the network has to be retrained by means of data used for its original training together with new data. On the other hand, the architecture of modular neural network is suitable for incremental adding of new modules, without disturbing the previously acquired knowledge. Only a gating network is trained for the new class.

Effectiveness. Local networks are simpler and faster. They require smaller computational resources and the time of learning is reduced.

Based on the advantages stated above, features of modular network can be summarized as follows:

- The domain of a local expert is determined by a sub-task,
- Every local expert is functionally independent from other modules,
- Local experts generally have a simpler architecture than the system taken as a whole,
- Every local expert produces a whole output,
- Every local expert can be any type of neural network,
- All local experts have the same number of input and output units,
- Local experts and gating networks have the same inputs, but their outputs are different,
- The gating network output is the probability of local expert selection,
- The number of input units in the gating network is determined by the number of experts in the network,
- When learning is concerned, a local expert does not directly influence other local experts or vice versa.

One of the most often used networks in the chip-forming machining, according to [7], is a feedforward static neural network i.e. a multilayer perceptron (MLP). In the experimental section of this paper, the modular neural network consisted of a series of local experts and gating network, was used. Local experts have the MLP structure of network, while for the gating network, which selects a local expert, a probabilistic neural network (PNN) is used.

3 Experimental planning

The experiments were carried out on three-axis machining centre AG 755VT with a Heidenhain TNC 426 control unit. The open structure of the control unit enables the extraction of current signals of the main drive into a separate database. For measuring a particular variable, one sensor source for that variable cannot satisfy all the requirements of monitoring. A solution to the problem is the use of multiple sensors which combine signals from different sources [9]. Joining sensors for machining process monitoring was thoroughly investigated in [2]. Research was focused on the creation of reconfigurable multi-sensor monitoring systems equipped with sensors for measuring cutting forces, vibrations, acoustic emissions (AE), current, etc., to be applied in different machining processes.

3.1 Measuring equipment

The aim of the experiment is to verify the proposed concept of modular tool condition monitoring. The measuring configuration consists of force and acoustic sensor together with a module for receiving and preprocessing of signals, Fig. 3.

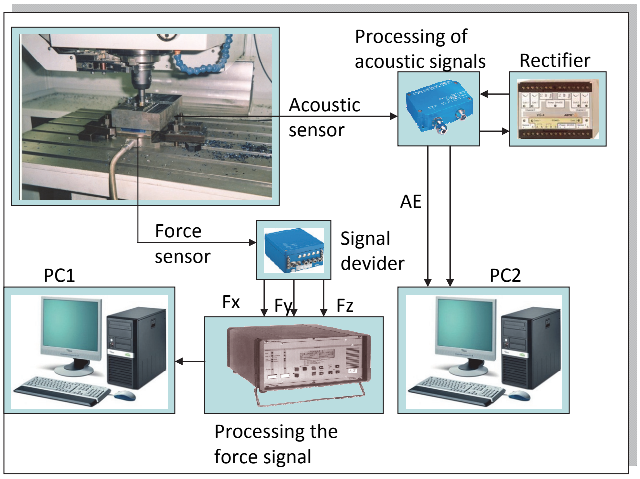

Figure 3 Measuring equipment [8]

Table 1 Conditions and regimes of experiments

EXPERIMENT A					Machining parameters		
Type of experiment	Tool	Material / Type insert	Workpiece material / Hardness	Number of experiment	Speed v /m/min/ min-1	Feed f /mm/min/ f_z /mm/z	Depth a_p /mm
A1.	R390-016A16 11L	R390-11 T3-08M-PM 4030	42CrMo4	1	220/4377	1313/0,15	2
				2	175/3491	768/0,11	1
			20 HRc	3	140/2785	446/0,08	0,5
A2.	R390-016A16 11L	R390-11 T3-08M-PM 4030	42CrMo4	1	185/3680	1104/0,15	2
				2	149/2964	652/0,11	1
			25,6 HRc	3	120/2387	382/0,08	0,5
A3.	R390-016A16 11L	R390-11 T3-08M-PM 4030	42CrMo4	1	160/3183	955/0,15	2
				2	126/2516	554/0,11	1
			32,5 HRc	3	100/1989	318/0,08	0,5
EXPERIMENT B					Machining parameters		
Type of experiment	Tool	Material / Type insert	Workpiece material / Hardness	Number of experiment	Speed v /m/min/ min-1	Feed f /mm/min/ f_z /mm/z	Depth a_p /mm
B1.	R390-016A16 11L	R390-11 T3-08M-PM 4030	42CrMo4	1	160/3183	955/0,15	0,5
				2	126/2516	554/0,11	
			32,5 HRc	3	100/1989	318/0,08	
B2.	R390-016A16 11L	R390-11 T3-08M-PM 4030	42CrMo4	1	160/3183	955/0,15	1
				2	126/2516	554/0,11	
			32,5 HRc	3	100/1989	318/0,08	
B3.	R390-016A16 11L	R390-11 T3-08M-PM 4030	42CrMo4	1	160/3183	955/0,15	1,5
				2	126/2516	554/0,11	
			32,5 HRc	3	100/1989	318/0,08	
B4.	R390-016A16 11L	R390-11 T3-08M-PM 4030	42CrMo4	1	160/3183	955/0,15	2
				2	126/2516	554/0,11	
			32,5 HRc	3	100/1989	318/0,08	

During the experiment, current signals of the feed drive unit and the main drive, signals of cutting forces and acoustic emissions (AE) were collected. In each stage of the experiment, the cutting tool flank wear (VB) was measured. After the data had been collected, the patterns for computing were selected and prepared. Due to a large number of parameters in interaction, it is very difficult to identify and extract particular impacts, i.e. there is no unambiguous answer about the quality or the number of features which would enable a satisfactory level of reliability of a monitoring system. It is necessary for each single case to weight and classify the wear features. Selection of machining parameters is related to the workpiece material, the tool and cutting conditions. The possibility of applicability of modular structure of the NN, in case of significant changes in cutting depth and the workpiece material hardness was tested. The influence of material hardness on the behavior of monitoring system was tested on 42CrMo4, quenched and tempered steel, at three hardness values (20-26-32 HRC), while the cutting depth is changed in the range 0,5 ÷ 2 mm on the material 42CrMo4 with hardness value of 32,5 HRC. Cutting regimes (cutting speed, feed, depth of cut) were selected in accordance with the tool manufacturer's recommendations for a given tool and workpiece material. Tab. 1 summarizes all the conditions of experiments. The first group of conditions (experiment A) refers to the testing of the impact of a change in workpiece hardness on the structure of signals of force, current and AE in different conditions of the cutting tool state. The other group of experiments (experiment B) refers to the testing of the impact of a change in cutting depth on the measured signals. All experiments were done without the use of cooling agent.

3.2 Definition of the patterns

Every signal of force, current, and acoustic emission is divided in five patterns, which were further used for learning, testing and validation of artificial neural network, Fig. 4. The patterns were selected from the middle part of signal, in the area where there are no transition processes such as tool entry and tool exit.

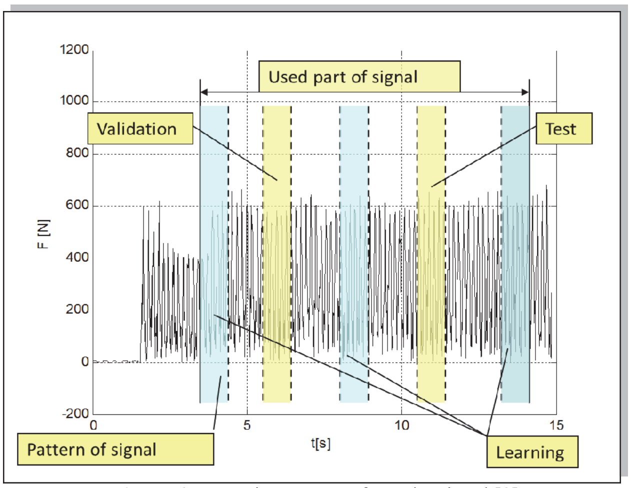

Figure 4 Extracting patterns from the signal [8]

Since the majority of wear features are distorted or are insensitive to cutting conditions, selection of features is of outmost importance for monitoring system. Application of large number of features is not practical since it increases noise at decision making and it demands considerable computing resources. Therefore it is necessary to perform feature ranking. Numerous methods could be used for feature ranking, but there is no generally accepted method. Various researchers plaid for various, or its own, method, depending on available equipment and applied experimental conditions. In the frame of this research, for testing phase the dominant features were used which were previously extracted and ranked by correlation coefficients [4]. In each experimental phase, wear parameter on flank face (VB), was measured as output value. For classification purpose, the three classes of tool wear are defined (class _1 [0÷0,1] mm; class _2 [0,1÷0,2] mm; class _3 [0,2>] mm).

3.3 Extraction and selection of features

There are numerous techniques and methods for the processing of machining signals (extraction, selection and final processing of features) and for the integration of features (decision making) developed in laboratories worldwide, and most of them are really efficient in machining processes. However, they require adaptation for each set of specific conditions of machining and therefore they can hardly find wider application in industry. Due to a large number of parameters in interaction which influence the cutting tool condition, it is very difficult to identify and extract particular impacts. This means that there is no unambiguous answer about the quality or the number of features which would enable a satisfactory level of reliability of a monitoring system to be achieved. It has to be decided for each single case which signals are the best at detecting the cutting tool condition and at identifying the best method of signal analysis for a targeted function of monitoring. Features can be divided into three basic domains: time domain, frequency domain and time- frequency domain.

Time domain is the original signal level. In dynamic processes it is not very practical to store raw signals; therefore, they have to be summarized. One of methods to summarize data in time domain is the use of statistical features of signals. The most important statistical features are: statistical mean values and correlation functions, strengths of signals, envelopes of peak amplitudes, crest factor, signal ratios, trends, etc. In addition to statistical features, deterministic expressions can be used to describe the process in time domain. The description of random processes by means of mathematical functions is very complex.

Frequency domain. Most signals consist of periodic components, transition phenomena and stochastic elements that can be connected with the monitored value. Time-dependent complex wave functions can be easily presented in the frequency domain as a harmonic series. Frequency components precisely define the information content by their amplitudes, frequencies and phases. Spectral analysis assumes the stationary signal and therefore ignores transient processes or non stationary signal characteristics. It is suitable for machining processes with continuous engagement of tool and workpiece (e.g. turning), i.e. in situation where appearance time of certain signal component is not important, but just the fact that it exists in basic signal. It is also assumed that the frequencies connected with tool wear influence and change the structure of basic signal, and that it is possible establish unambiguous relation between wear and change in signal structure. As frequency areas (bands) containing the information on tool wear are not known in advance, there is necessity and problem of their estimation.

Time-frequency domain. Traditional spectral analysis assumes a stationary signal, and ignores non-stationary processes or non-stationary features of the signal. Time-frequency analysis (wavelet) is increasingly more frequently used for the monitoring of non-stationary processes. This analysis enables the signal to be presented both in the frequency and the time domain. Wavelet method transforms the signal by applying various band pass and various resolutions. The signal is decomposed in rough approximation and detailed information. Signal decomposition in various frequency bands is achieved by continual signal filtering with high pass and low pass filters in time domain. Low pass frequency area defines the base of the signal (signal approximation), while the high frequency areas are the source of signal details. Frequency area (frequency band) for approximation and for details of level m is [10]:

$$\left[0, \frac{1}{2} f_s 2^{-m}\right] \text{ i } \left[\frac{1}{2} f_s 2^{-m}, \frac{1}{2} f_s 2^{-(m-1)}\right],$$

where f_s is the frequency of signal sampling. Result of wavelet transform is the series of coefficients belonging to various frequency bands (approximation coefficients and detail coefficients). At low frequencies, good resolution in frequency domain and poor resolution in time domain are obtained, and at high frequencies, the situation is reversed. In lower frequency signals (of force, current), there is a larger share of features from the time domain, while in high frequency signals, such as AE and vibration, features from the frequency domain come to the fore, and lately they are followed by features from the time-frequency domain [11].

Collection of a sufficient amount of data that precisely describe the monitored process is related to the sampling time, which is in turn related to the character of the signal and the used equipment. As the sampling time increases, it is possible to miss the phenomena relevant for the estimation of cutting tool condition. On the other hand, as the sampling time decreases, the amount of data increases, which makes the analysis and processing of signals more difficult.

3.4 Evaluation of the feature selection

The evaluation of acquired knowledge is a significant component of process data analysis. The basic idea for evaluation of classification models is the concept of fault. The usual methods for evaluation of success of sample classification are learning curve, confusion matrix, receiver operating characteristic (ROC) curve, etc. Quality assessment of the monitoring system performance depends on the characteristics of the considered problem. In this study, confusion matrix is used for evaluation of the process classification. A confusion matrix shows the number of correct and incorrect predictions made by the classification model compared to the actual outcomes (target value) in the data.

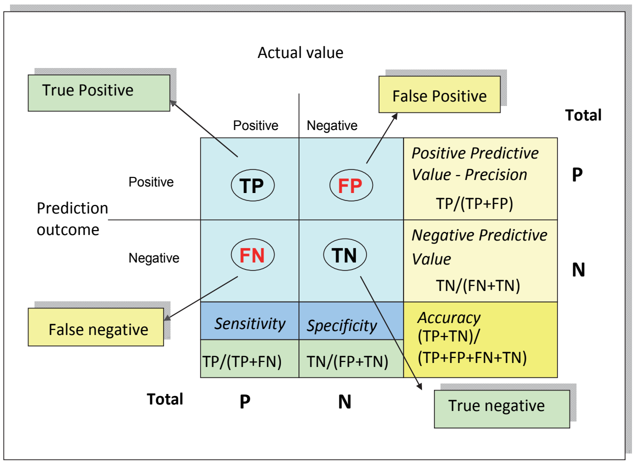

Figure 5 Confusion matrix

The matrix is $N \times N$, where N is the number of target values (classes). The following table displays a 2×2 confusion matrix for two classes (Positive and Negative), Fig. 5.

This matrix shows the percentage of the accurate and the inaccurate classification of the output variables. It is also possible to determine different types of parameters and to give additional information about the quality of classification. Namely, in majority of practical situations, i.e. when there are more classes, it is important to differentiate the particular types of parameters:

- *Accuracy:* the proportion of the total number of predictions that were correct,
- *Positive Predictive Value or Precision:* the proportion of positive cases that were correctly classified,
- *Negative Predictive Value:* the proportion of negative cases that were correctly classified,
- *Sensitivity or Recall:* the proportion of actual positive cases which are correctly classified,
- *Specificity:* the proportion of actual negative cases which are correctly classified.

4 Analysis

Since machining processes are in most cases subjected to stochastic changes in workpiece material hardness and cutting depth, particularly in the first cut (forging, cast, welded joint), several types of experiments were carried out. In each experiment, the influence of combinations of signal features (multi-sensor approach) is tested. In the first series of experiments, the behavior of the classification system quality is tested in the cases when a set of data for the same material but of different hardness values comes as an input which exceeds the limits of the trained knowledge. Machining parameters, dominant features for each signal and their combination were used for learning, testing and verification. Comparison procedure was carried out for different combinations of features of the same type of signals. In Tab. 2 the comparative results of classification are given for different materials hardness. Classification accuracy is expressed in percentages.

Table 2 Results of classification by using NN

Material : 42CrMo4		RESULTS OF CLASSIFICATION /%								
Learning: hardness /HRc		20			26			32.5		
Testing: hardness /HRc		20	26	32,5	20	26	32,5	20	26	32,5
No.	Combination									
1	*Fx*	83,3	36,7	30,0	40,0	86,7	26,7	26,7	36,7	96,7
2	*Fy*	90,0	30,0	40,0	83,3	93,3	23,3	40,0	33,3	93,3
3	*Fz*	100,0	23,3	56,7	33,3	100,0	43,3	46,7	43,3	73,3
4	*Fr*	80,0	33,3	30,0	56,7	93,3	56,7	40,0	50,0	93,3
5	*Fx,Fy*	90,0	46,7	36,7	50,0	83,3	36,7	50,0	20,0	86,7
6	*Fx,Fz*	80,0	30,0	50,0	16,7	100,0	50,0	43,3	40,0	83,3
7	*Fy,Fz*	100,0	20,0	26,7	40,0	96,7	23,3	10,0	50,0	93,3
8	*Fx,Fy,Fz*	96,7	23,3	30,0	33,3	100,0	36,7	36,7	53,3	86,7
9	*Ix*	86,7	50,0	30,0	30,0	93,3	50,0	50,0	40,0	60,0
10	*Iy*	86,7	36,7	46,7	33,3	90,0	33,3	56,7	60,0	60,0
11	*Is*	76,7	36,7	26,7	20,0	83,3	46,7	40,0	23,3	40,0
12	*Ix,Iy*	83,3	36,7	36,7	43,3	90,0	26,7	33,3	53,3	76,7
13	*Ix,Is*	86,7	63,3	46,7	46,7	90,0	36,7	36,7	33,3	76,7
14	*Iy,Is*	93,3	40,0	16,7	50,0	100,0	16,7	50,0	60,0	56,7
15	*Ix,Iy,Is*	80,0	26,7	20,0	30,0	96,7	33,3	40,0	33,3	76,7
16	AE	86,7	16,7	43,3	26,7	76,7	40,0	23,3	33,3	66,7

One can see that the worst results of cclassification are shown for the features of AE and main spindle current (Is). The force features show the best classification results, and slightly worse the features of motor current of feed drives. It can be noticed that the rank of features of individual signals change with the significant change of the process parameters. Analogous procedure was carried out for different cutting depths (0,5 ÷ 2 mm). From this set of experiments one can conclude that networks are not suitable for the classification of phenomena in processes with big deflections from the referential set of data for learning, or, in other words, the set for learning should encompass a large aspect of the phenomenon. Widening the application area of neural network requires setting up a new structure of the neural network (global neural network), the implementation of the learning process with an expanded data set, and re-optimization of the system. On the other hand, modular neural network is suitable for widening of application area by adding the new modulus (local experts) without disturbing the previously acquired knowledge. The question is whether the accuracy of the modular network is higher or lower than the accuracy of global neural network. Answer to this question was obtained in a second series of experiments, where the task of both approaches, local experts and global neural network (both of MLP type), was to classify resultant tool wear into one of three classes. The results of classification of modular and global NN are presented in Tab. 3.

Table 3 Average results of classification

Material	RESULTS OF CLASSIFICATION		
42CrMo4	Type of neural networks	Modular	Global
Hardness / HRc	20	87,5	85,6
	26	92,1	82,7
	32	76,3	79,8
	Average accuracy / %	85,3	82,7
Depth / mm	0,5	84,8	73,7
	1	71,9	69,8
	1,5	83,8	75,4
	2	79,8	75,2
	Average accuracy / %	80,1	73,5

Comparison between the modular and the global neural network is made for different combinations of features of the same type of signal. One can see from the table that the modular network for the same experiment conditions shows better results of tool condition classification for different levels of workpiece material hardness and different cutting depths. It shows that, comparing with global network, modular network achieves about 3 % better average quality classification for materials with different hardness levels, and 7 % better average quality classification for varying cutting depths. The global network learns by the whole set for learning every time a new task is added, while the modular network is expanded by a local expert for a single field and learns only the characteristic vector. Based on these considerations it can be concluded that it is better to take smaller fields of operation of a single local expert and to build them into the already achieved level of knowledge.

5 Conclusion

Through an experiment carried out, the research shows that the classification quality is variable and that it depends on the selected combination of features. Also, special attention has to be devoted to the selection of features of different signals in order to ensure their compatibility in the case when the multi-sensor approach to monitoring is applied. Machining parameters must be included in the case of changeable conditions of input variables. Features from time-frequency domain are dominant. It is shown that the best classification results, in most cases, are obtained by combinations of features of the same type of signal. Based on the research it can be concluded that the global neural networks are not suitable for classification of phenomena in processes with large deviations from the reference data set for learning, i.e. in this case the learning set should be expanded. Expanding the learning set requires the large network structures, and that can slow the learning process and make it impractical in actual industrial applications. In contrast, the proposed modular structure of NN, maintains the existing level of knowledge and learns only that part which is emerging as a new, i.e. train the local expert for a specific area. In addition, the global network shows slightly worse results than the modular network. Based on the results of the experiments, research indicates that it is desirable to develop a modular platform of the monitoring system, which will be provided by the development and improvement of local experts, and upgrading knowledge base without disrupting the existing structure of attainment knowledge. Additionally, the concept of modular structured monitoring which is proposed in the paper can serve as a good basis to build transferable knowledge base, required for different configurations of machine tools and processes. It should be pointed out that this principle can be applied in cases where a complex task can be divided into a series of simpler sub-tasks, i.e., the application of modularity implies the existence of substantial and visible functional or structural division of the task.

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