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Intelligent support system for monitoring machining processes

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Intelligent support system for monitoring machining processes

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Abstract. The intelligent support system for monitoring machining processes was objective of our research. The paper presents process of development of this system which can used in real enterprises. Methodology: to create of the system we use methods of artificial intelligence (neural networks, decision trees and rules, fuzzy logic), using AI methods we created procedures support monitoring machining processes: diagnosis of machining process disturbances using decision rules, control of stability of the machining process based on control card analysis using neural networks, control of surface roughness parameter using neural networks and decision trees and monitoring machine tool through control and compensation of thermal deformations of ball screws of CNC machine tools using neural networks. To optimize of AI models we compared many the models with different structures, chose the best models and used them in intelligent system.

1. Introduction

Support systems using artificial intelligence methods are systems that combine the function of collecting and processing huge amounts of data and the use of increasingly diverse models of intelligent use of collected data and knowledge. Thanks to this, it is possible to analyse data and automatically draw conclusions in a manner similar to human thinking – using uncertain or fuzzy data, analogies and various machine learning algorithms.

The development and use of IT tools in the supervision of machining processes has been the subject of research by scientists from around the world for many years. However, this task has not been solved yet and there is still a lot to be done in this area.

The machining process monitoring includes ongoing measurement and control of parameters related to technological quality, monitoring and forecasting of changes in the value of these parameters [1]. The machining process monitoring support described in the work concerns:

- monitoring the diagnosis of interferences in the machining process; Process interferences may include, for example, poor surface quality, chipping of the workpiece edges, or improper chip disposal; When a specific fault occurs, the operator selects the cause that caused the fault from the list of potential causes, and then the system prompts the operator how to remove the fault. Decision-making rules were used in the expert system. This example is included in the machining process interference analysis,
- monitoring the stability of the machining process based on control charts; sets of points, which indicated the lack of process stability, were determined based on the collected measurements; a system with embedded models in the form of neural networks can monitor process stability and

inform the operator about its absence. This example is included in the workpiece geometry analysis. The shaft diameter was monitored during the grinding process and the roughness parameter Ra for the superfinish process,

- the Ra and Rz surface roughness parameter monitoring; roughness parameters can be monitored by a system containing models in the form of neural networks and decision trees and inform when the norm is exceeded, and thus the need for correction of machining parameters. This example is included in the workpiece diagnostics (surface layer quality),
- monitoring CNC machine tools by controlling and compensating for thermal deformations of ball screws; the system with embedded models in the form of neural networks can monitor current speed and load parameters and based on them predict the elongation of the ball screw of a CNC machine tool. This example is included in the thermal analysis of machine tools.

The machining process monitoring models were developed using neural networks, rules and decision trees. They were developed on actual data from the enterprise. The developed machining process monitoring models have been implemented in the form of an expert system for machining process monitoring with implemented intelligent models of neural networks, rules and decision trees. This will allow solving many different tasks while monitoring the machining process. Such a system, by constantly acquiring new knowledge, will adapt to ever new user requirements. It will imitate the learning of people through self-adaptation, which can be called intelligent action. The research presented in the paper is part of the Industry 4.0 concept developed globally and countrywide, in which very much emphasis is placed on the processing automation and exchange of huge amounts of data and knowledge [2].

2. The state of knowledge in the field of machining process monitoring

In Poland and around the world, research work has been carried out for many years on the use of artificial intelligence methods in the machining process monitoring. The quality of products is influenced by both the course of the machining process and the condition of the machine tools. In the literature, there is a lot of research on process monitoring, i.e. process monitoring and forecasting changes that need to be made for the machining process to run correctly.

The main areas of process monitoring include: the course of individual stages or the entire process, finished product diagnostics, product geometry analysis, tool wear monitoring, thermal analysis of machine tools, or vibration diagnostics in machining systems [3]. Machine processes monitoring allows saving data concerning workpieces produced by the same machine tool. Also this monitoring process enables determining deviations and errors from certain conditions (most energetically cost effective conditions, bad machining conditions, or aged machine tools) [4]. Machining errors of thin-walled workpieces are created by deflection of the workpiece or tool caused by cutting forces. In real time in controlling and compensating machining errors, monitoring this failures kinds plays a very important role [5]. The manufacturing industry responsible carbon emission and a big part of energy consumption in the country's economy. We need to describe solutions of energy monitoring in range of energy use. Multi-state modelling of energy efficiency and recurrence analysis of continuous power signals in the machining process were based on a new sensor-based approach and presents in the article [6]. For reduce the downtime of the machine tool and its costs of maintenance and control the quality of the part in machining processes in mass production we need reliable system of tool condition monitoring (TCM) [7]. Polymers, which are reinforced with carbon fibre give many advantages (e.g. resistance of corrosion and weight/strength ratio) in aerospace industry. For increase quality control and productivity we use non-destructive methods for the prediction and detection of surface finishing and occurrence of errors during production and it is very industrially useful [8]. In addition to monitoring, forecasting of changes is a very good solution. Researchers also provided many examples in this regard [9,10]. Decision trees are used for prediction, and above all neural networks [11]. Zaremba presented intelligent manufacturing systems as complex, using AI (expert systems) and computational intelligence (mainly neural networks, fuzzy logic and genetic algorithms) in the design and use of manufacturing systems [12]. Markopoulos et al. describe a series of neuron models created from the prediction of surface roughness in Electrical Discharge Machining [13]. In articles [14,15], research on the control and prediction of Ra, Rz and

Rmax roughness parameters has been presented. The measurements were made on one lathe and the prediction was made using the MLP network. At the network input, cutting depth ap, cutting speed vc and feed speed vf were given. The Ra, Rz and Rmax roughness parameters were at the network output. The results obtained by MLP networks were compared with actual values and gave good results. Other articles provide a process stability assessment using control charts and various IT tools, primarily statistical software and software for various technological operations [16,17]. A lot of work also concerns the thermal analysis of machine tools. The errors, which make up from 40 to 70% of all errors, are caused from the thermal expansion of mechanical components of machine tool [18,19].

Based on the current literature review in the country and the world, it can be concluded that there are examples of using AI methods in the machining process monitoring. The articles described usually present the use of IT techniques to solve individual tasks, such as predicting surface roughness in a selected machining, tool wear monitoring, and thermal analysis of the machine tool. The author also mentioned the application of AI methods to such individual tasks in her article. However, she also went a step further because she proposed a methodology and a prototype of an expert system for the machining process monitoring. According to the author, the reality that surrounds us, also the technical one is very complex and therefore requires a combination of human and machine intelligence into one integrated computer-aided system.

3. Artificial intelligence methods used in the machining process monitoring

In the article I decided to choose specific AI methods by the tasks they are to solve. Neural networks and decision trees are the basic data mining methods that allow discovering knowledge from data and support decision making [20,21]. These methods were used to discover knowledge and support the machining process monitoring. When monitoring the machining process, there is a classification and forecasting problem.

Experiments with various types of neural networks and decision trees were identified and performed. The basic types of neural networks include: unidirectional multilayer, self-organizing and recursive networks. Representatives of these networks were selected to monitor the machining process: unidirectional multilayer networks with backward MLP error propagation, networks with radial base functions RBF, Kohonen (KN) self-organizing networks and Hamming (HN) recursive networks and specific types of decision trees: C4.5, C&RT, CHAID, reinforced trees and random forests. Decision rules are created automatically on the basis of decision trees, which are entered into the expert system. The author analysed the operation of these different types of AI methods for specific tasks of machining process monitoring.

In the machining process monitoring, neural networks were used to: monitor the machining process stability on the basis of control chart analysis, monitor the surface roughness parameter and monitor the machine tool by controlling the compensation of thermal deformation of ball screws of CNC machine tools. Decision trees and forests were used to monitor the surface roughness parameter. Decision rules were used to monitor the diagnosis of machining process interferences. The expert system was also used as a machine operator interface to monitor the machining process.

In order to prepare data in the form of examples of learning files, the data was standardized and coded using fuzzy logic.

4. Case study – An intelligent system for machining process monitoring

4.1. Data Preparation

All data that was used to develop models to monitor machining processes was obtained from real processes in manufacturing companies. The most important data in the machining process monitoring context were selected. Most of the data in databases is raw, incomplete and noisy. To be useful for exploration purposes, these data should go through pre-treatment in the form of cleaning and transformation [22]. Data cleaning consists in record standardization, supplementing missing data or identifying remote points. On the other hand, data transformation involves its standardization or coding. Data standardization was based on the fact that ranges of individual parameters that were very different from each other were scaled to the range of <0.1>. In the first stage of research, min-max standardization was used to scale the raw data [22]. In the second research stage, fuzzy standardization with categories belonging to fuzzy sets was used for greater stability of results. Membership functions take values in the range <0.1>. The standardization was performed using the Fuzzy Logic Toolbox Matlab package.

The data standardization module was performed in the following stages:

- determining the input and output of the standardization module,
- determining the membership function,
- defining the rules (Fig. 1),
- determining the input-output characteristics,
- value standardization.

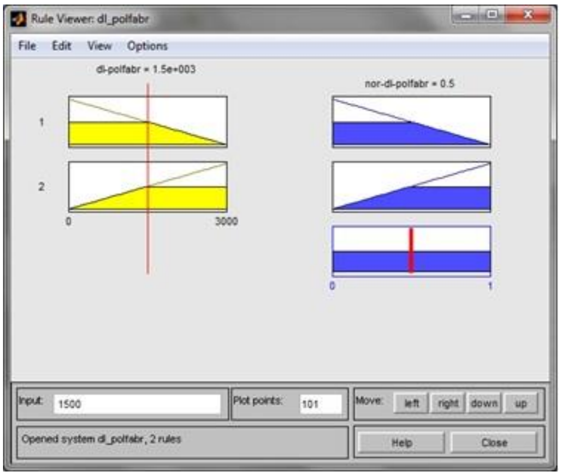

Figure 1. Standardization module rules

Data encoding was used for nominal data. They can have a bistate or multi-state character. In the first stage of research, one-z-N coding was chosen [22]. It involves the use of several numerical variables in the network instead of one nominal. The number of numeric variables is then equal to the number of possible values of the nominal variable. One of these N has a value of 1, the other a value of 0. With such data encoding, the number of network inputs and outputs increases. In the second stage of research, the method of coding nominal values was changed. Nominal values were limited to the range <0.1>. In this way, the number of network inputs and outputs was not increased. This is a big advantage; because problems arise in case of nominal variables with a large number of possible states as the number of numerical variables required for one-z-N encoding is unacceptable due to the very large size of the network, which causes its learning difficulties.

Figure 2 shows the data standardization and coding used in the monitoring process of the Ra and Rz surface roughness parameter. Individual attributes, including groove position (up, down), Ra range and decision (whether decision, whether roughness is normal, whether there is a warning or even operator intervention is required).

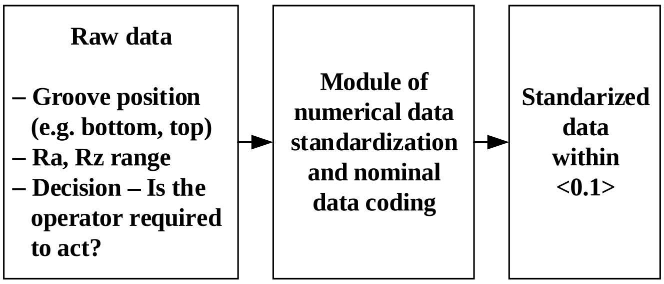

Figure 2. Raw data standardization and coding for Ra or Rz roughness

Sample raw and standardized data for monitoring Ra using the membership function are shown in Table 1.

Table 1. Sample raw and standardized data for monitoring the surface roughness parameter Ra

Neural network input	Sample data	
Parameters	**Raw data**	**Standardized data**
Groove position	top	1
Ra range	1.056-1.600	0.9
Decision – whether operator action required	intervention	0.75

In order to prepare learning data, an analysis of actual parameters measured during the machining process was performed. Using specific parameters, proper learning files were prepared to develop models in the form of neural networks and decision trees. All cases were divided into a learning file (75%); a test file (15% of records) and a validation file (10% of records). The neural network was taught using a learning file, tested with a test file and additionally its operation was checked with a validation file. The validation file is the answer to neural network overfitting. In case of decision trees, the file with examples was divided into a learning and test file.

In the same way, the data was prepared to create models for monitoring:

- the machining process stability on the basis of control chart analysis using neural networks,
- surface roughness parameter using neural networks and decision trees,
- machine tools by controlling and compensating for thermal deformations of ball screws of CNC machine tools using neural networks.

An exemplary structure of MLP and RBF neural networks for machine tool monitoring by controlling and compensating for thermal deformations of ball screws of CNC machine tools is shown in Figure 3.

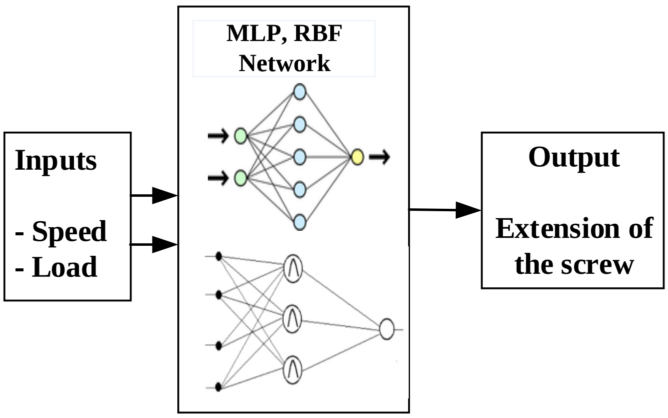

Figure 3. Structure of MLP and RBF neural networks

Decision rules were created in case of the machining process monitoring interferences. An analysis of interference in machining processes was performed. Decision rules were prepared that allow defining scenarios of removing interferences in machining processes using the data on machining interferences and the criteria for defining interferences, diagnosing their causes and ways of removing them, following the generally accepted principles from the literature and the principles developed in the company.

4.2. Machining process monitoring models

Machining process interference monitoring - Examples of diagnosing interference in the machining process and suggestions for their removal, broken down into individual technological operations, are presented in many machining guides, e.g. of GARANT company. Table 2 was the starting point for the module development.

Table 2. Causes of interferences and ways to remove them for milling

	Interference	Possible causes
1	Incorrect surface quality	Cutting edge wear, cutter runout
2	Chipping of the workpiece edge	Incorrect cutting conditions, improper cutting edge shape
3	Non-parallel or uneven surface	Low rigidity of the cutter or workpiece
4	Extreme flank wear	
5	Extreme groove wear	
6	Fracture and breakage due to thermal shock	Incorrect cutting conditions, improper cutting edge shape
7	Creation of built-up edge	
8	Incorrect chip removal, chip block	
9	Vibrations, chatter	Difficult cutting conditions, incorrect workpiece clamping
10	Shank cutter fracture	Incorrect cutting conditions, length of cutter overhang

1	2	3	4	5	6	7	8	9	10	How to remove the interference
■			■	■						Choose a tougher cutting insert grade
					■					Choose a cutting insert grade that is more resistant to dynamic loads
					■					Choose a cutting insert grade that is more resistant to high temperatures
■						■				Choose a cutting insert grade that is more resistant to adhesion
■						■	■			Increase cutting speed
			■	■				■		Reduce cutting speed
						■	■			Increase feed
■	■	■		■	■		■	■	■	Reduce the feed
■	■	■		■	■			■	■	Reduce cutting depth
							■	■	■	Change cutter diameter and cutting width
■			■	■		■	■			Check the use of the coolant
	■	■	■	■	■	■	■	■		Increase the clearance angle
	■			■	■					Increase the tool angle
■	■	■	■		■					Change the shape of the auxiliary tool
		■			■					Change the accuracy of the cutter rotary movement
	■	■			■			■	■	Change cutter stiffness, overhang length (L / D ratio)
	■	■			■			■		Use a machine tool with higher power and rigidity

The system proposes a module for diagnosing interferences in a situation where the machining process is carried out incorrectly. A practical example has been illustrated for milling operations. When an interference occurs in the production process, the machine operator using this module knows how to remove the interference, and then the operator can pass the information about the changes to the process engineer for implementation into the process so that such interference does not appear in the future. This module improves the quality of the technological process. Based on the table 2 and knowledge of the process engineer, decision rules have been developed that can assist the machine operator in diagnosing and removing interference.

For example, an interference of poor surface quality may be caused by wear to the cutting edges or by cutter runout. Such interference can be removed in several ways by: choosing a harder type of cutting insert, choosing a cutter insert grade resistant to adhesion, increasing cutting speed, feed reduction,

reduction of cutting depth, checking the use of a cooling lubricant. It is up to the process engineer's experience to prioritize these remedies.

The machining process stability monitoring on the basis of control chart analysis using neural networks - Another practical example concerns control charts of the machining process. The control chart is a document recording the results of testing samples taken systematically from current production during process control. The chart observation comes down to noticing the characteristic arrangement of points, which signals the loss of process stability. These systems are sets of points, but are also visualize the condition of the process. The task of the quality engineer was to indicate which point systems for a given process are symptoms of stability loss. Such signals for the average value chart can be: shifts, trend and run, mixtures, cycles, fluctuations and stratification [23,24]. From each process (grinding and superfinishing) 504 samples of 5- and 10-element samples were collected. It is a set of stability patterns and its lack. The learning file at the input of the neural network contains process condition images. The image shows a set of 5 or 10 measurements. At the output we decide whether the set of 5 or 10 measurements indicates whether the quality of the process is in the norm (standard) or not (Ascending run - RR, Descending run - RM, Ascending trend - TR, Descending trend - TM, Top offset - SU, Bottom Offset - SD, Mixture - MIX, Fluctuation - FLK, Stratification - STR).

Figure 4 shows the best models of neural networks for assessing process stability and the operator. The effectiveness of neural networks and machine operator is given in [%]. The percentage of correct operator classifications was compared to the results.

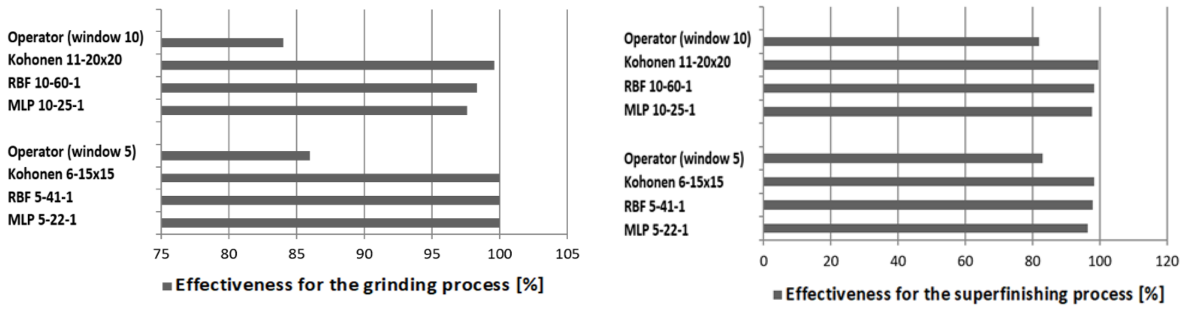

Figure 4. Effectiveness of process stability assessment tools for the grinding and superfinishing process

Recognition of the process quality image by neural networks is a great achievement compared to the recognition of this image by the operator. Unfortunately, the operator coped much worse with pattern recognition and process quality control. Analysing the operator's work and neural networks, it is concluded that the image length has no significant effect on the quality of recognition.

Surface roughness parameter using neural networks and decision trees - An important parameter of surface quality control is the roughness of the processed surface determined by Ra (average arithmetic deviation of the profile from the average line) and Rz (the highest profile height) (PN-EN ISO 4287: 1999). However, Rz measurement was made with an older generation device (roughness height according to ten profile points), which was in accordance with the withdrawn PN-M-04256-02: 1987 standard. Experiments were performed to monitor the Ra and Rz parameter, in which artificial intelligence methods were used. The developed models can be used to signal whether the roughness parameter is normal or not. In case of exceeding the acceptable range, a system with models of neural networks or decision trees may signal the need to correct cutting parameters. The tests were carried out on several machine tools, which may also indicate which machine was the best in terms of obtaining the best quality machined surface [25].

Roughness assessment models were made using decision trees created according to the C4.5 algorithm. The learning file looked identical to the one for neural network teaching. It was important to choose the right parameters for the classifier: the stop criterion (the parameter of the minimum number of examples forming the leaf of the tree) and the parameter for cutting the tree. The best tree in terms of classification was selected, where the alloy criterion included 2 examples and without the option of cutting the tree. Rules were generated based on the trees, which were then introduced into the prototype expert system (Fig. 5).

```
rules

  0014 : decision = "warning" if        // (12.0)
         range_Ra = "0,822-0,939";

  0015 : decision = "norm" if           // (10.0)
         range_Ra = "0,881-1,026";

  0016 : decision = "warning" if        // (7.0)
         range_Ra = "0,940-1,055";

  0017 : decision = "warning" if        // (5.0)
         range_Ra = "1,027-1,173";

  0018 : decision = "norm" if           // (3.0)
         range_Ra = "Below 0";

  0019 : decision = "intervention" if   // (2.0)
         range_Ra = "1,056-1,600";
```

```
rules

  0012 : decision = "warning" if        // (6.0)
         range_Rz = "4,107-4,693";

  0013 : decision = "norm" if           // (3.0)
         range_Rz = "0,587-1,173";

  0014 : decision = "norm" if           // (3.0)
         range_Rz = "3,521-4,106";

  0015 : decision = "norm" if           // (3.0)
         range_Rz = "0,000-0,732";

  0016 : decision = "intervention" if   // (2.0)
         range_Rz = "6,600-10,000";
```

Figure 5. Sample decision rules for expert system

Machine tool monitoring by controlling and compensating for thermal deformations of ball screws of CNC machine tools using neural networks - The last example of machining process monitoring concerns machine tool monitoring by controlling and compensating for thermal deformations of ball screws of CNC machine tools. Analysing the issue of dissipated energy in the screw-nut assembly and bearing assemblies due to friction, one can assume a simplifying assumption that the amount of dispersed energy depends on the design of the servo drive as well as its operating conditions. The essence of the compensation method of thermal deformations of ball screws consists in the use of information from the machine control and drive system regarding the current value of rotational speed and torque. This information, due to the sufficient frequency of measurements, will form the basis for building a predictive thermal compensation model of ball screws based on artificial neural networks [26,27]. The method assumes that by analyzing the instantaneous torque value and instantaneous engine speed value, it is possible to determine with some approximation the amount of energy dissipated in the screw, which determines its elongation. This process is carried out frequently enough, especially in small machine tools, which are characterized by high dynamics of positioning error changes due to the phenomenon of thermal expansion of the ball screw [27].

A fragment of the collected experimental data is shown in Table 3. These data include speed, load and screw elongation. The speed range varies from 25 to 300 in step 25.

Table 3. Causes of interferences and ways to remove them for milling

Parameter	**Value**		
Speed [mm/s]		F-25 mm/s	
Load [Nm]	0.3593	1.1141	1.4959
Elongation [um]	1.0767	1.2000	1.6200
Speed [mm/s]		F-50 mm/s	
Load [Nm]	0.4539	1.2025	1.5608
Elongation [um]	1.9333	1.7800	1.9143

Models for predictive deformation compensation were created using MLP, RBF and Kohonen neural networks. The network inputs include speed and load. The network output indicates the screw elongation for MLP and RBF networks. MLP networks had a short learning time and were the least effective. RBF networks showed better performance, but the hidden layer had more neurons in each network, which increased network complexity and increased learning time. Kohonen networks proved to be the best, but they had a much more complex structure and the longest learning time. Figure 6 presents the screen of a prototype expert system that is used to predict thermal deformation (elongation) of ball screws of CNC machine tools using neural networks. After entering the speed and load values, the operator obtains a system reply in the form of a potential screw deformation value (elongation value).

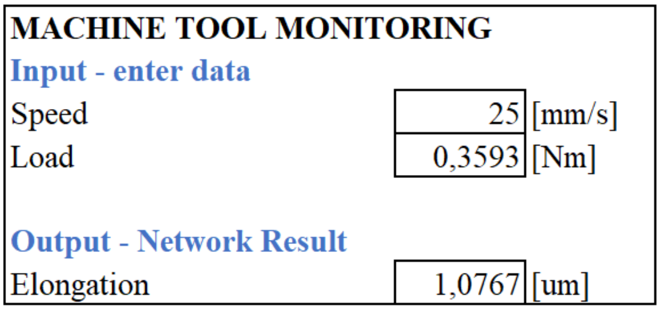

Figure 6. Example of an expert system operation

4.3. Methodology for developing an intelligent system for monitoring the machining process

The support for monitoring the machining process was developed using artificial intelligence methods. Even the best-developed technological processes [28,29] must be corrected after receiving information from production, where during a product manufacture, the machining processes show deviations from previously designed technological processes. Therefore, it is necessary to monitor machining processes and make adjustments to ensure the product quality. Based on the definition of monitoring according to [1], the developed methodology includes measuring the current value of specific quantities characterizing the technological quality of the workpiece, monitoring the course of the machining process and forecasting changes in the value of these quantities.

The machining process monitoring should begin with the measurement of selected quantities to be monitored. The measured quantity is monitored, whether it is normal or not. If it is not normal, the machine operator should receive a message about exceeding the norm. In the event of exceeding the norm, the next forecasting module should prompt the machine operator how he should react. In this way, different quantities can be monitored that can be distinguished during the machining process. The correction of the monitored quantities and information whether the machining process is carried out in accordance with the previously developed technological process can be used to evaluate the technological process.

The developed methodology was then used to develop the intelligent support system for monitoring the machining process. Figure 7 shows a diagram of the support system for monitoring the machining process. Before obtaining knowledge to monitor the machining process in the form of models, the data normalization process was carried out. On the basis of data collected in databases, knowledge is acquired in the form of monitoring models of selected quantities of the machining monitoring process. These models are remembered in the knowledge base in the form of neural networks, rules and decision trees. Then, through the user interface, the machine operator can monitor the machining process using developed models.

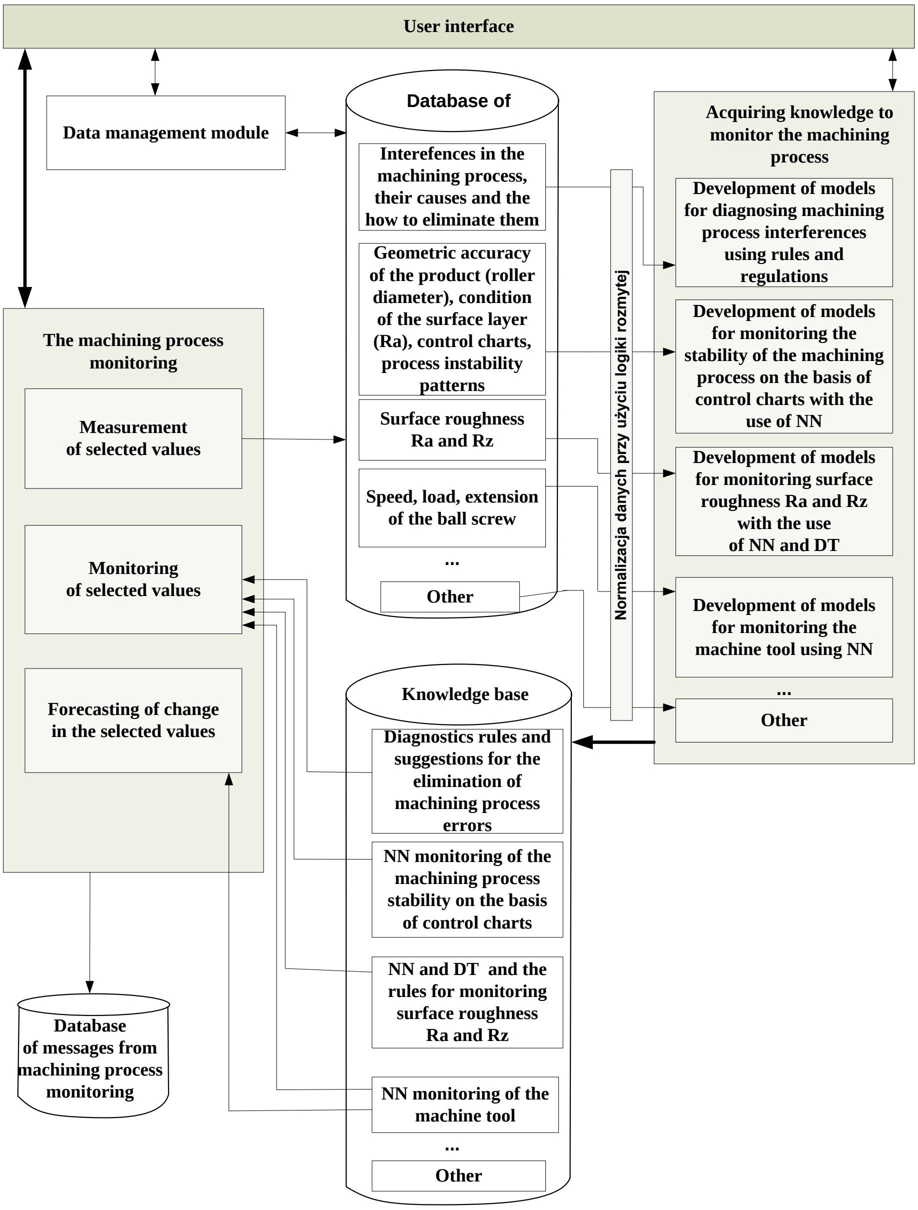

Figure 7. Diagram of the support system for monitoring machining processes (NN - neural networks, DT - decision trees)

5. Conclusion

The article presents an intelligent system for monitoring machining processes. The research showed the usefulness of AI methods (neural networks, trees and decision-making rules) and their high efficiency to support selected elements of the machining process monitoring. A number of neural networks models and decision trees were made, differing in type, structure and parameters of the learning and testing process. Comparison of models gave interesting research conclusions and allowed to choose the most effective models. The article presents neural networks and decision trees intentionally. The author's intention was to show the solution of the problem by completely different approaches. The neural network gives us results in the form of a "black box" without explaining how to get a specific result. However, the use of decision trees allows us to automatically generate decision rules that explain the result in an intuitive way. The created models of neural networks and decision trees were tested on data from a production company. It should also be emphasized that the process of collecting actual data to develop learning sample files for neural networks or decision trees is a very labor-intensive process and requires a lot of consultation with machine operators. Data standardization and coding had to be carried out. Fuzzy logic was used for this purpose.

Summing up selected the methods of artificial intelligence (neural networks and decision trees), it is important to emphasize their great advantages and the need to use these methods that mimic human reasoning.

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