ARCHIVES OF MECHANICAL TECHNOLOGY AND MATERIALS
Vol. 35 2015

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TOOLING SELECTION IN TECHNOLOGICAL PROCESSES USING NEURAL NETWORKS

The idea of the author's research is to develop a system aiding the design of a technological process (a CAPP system), namely a system for creation of a technological process plan, in which the sequence of technological operations is defined and for each operation in the technological process, the appropriate machine, tools, tooling and machining parameters are selected. The article discusses accessory selection in technological processes using neural networks. Tooling selection is a necessary stage in the design of technological processes if a tool that has been selected does not fit the machine. Tooling selection models were prepared using unidirectional multilayer neural networks with back propagation of error (MLP) and a self-organizing Kohonen network. Two completely different neural networks were selected for the selection of the tooling. MLP network represents a network with learning supervision, and network Kohonen network learning without supervision. The training data for the neural networks was prepared at a manufacturing company. The neural networks were made using the Statsoft STATISTICA Data Miner software.

Key words: Tooling (accessory), Technological process, Neural networks

1. INTRODUCTION

The technological process is the main part of the manufacturing process that directly involves changing the shape, dimensions, surface quality, and physico-chemical properties of the workpiece. It is a discrete process in which the condition of the manufactured element changes gradually and usually irreversibly. The technological process can be divided into the machining technological process and the assembly technological process [3].

The design of technological processes has lost its traditional nature as a result of the use of software. Early systems aiding the design of technological processes were expert systems with knowledge bases in the form of decision

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rules. Contemporary systems comprise such artificial intelligence methods as fuzzy logic, neural networks, genetic algorithms, and decision trees. Artificial intelligence makes it possible to record the process engineer's experience in a knowledge base and to conduct inference similar to human reasoning during the design of the technological process.

The idea of the author's research is to develop a system aiding the design of a technological process (a CAPP system), namely a system for creation of a technological process plan, in which the sequence of technological operations is defined and for each operation in the technological process, the appropriate machine, tools, tooling and machining parameters are selected.

The author's previous works discuss research involving the development of systems that aid the selection of tools for technological operations [10,11] and successive articles focus on the selection of machines, tools, and machining parameters for technological operations [12,13]. Moreover, the author has developed models that aid tool use forecasting [14].

One of the stages of the design of the technological process is the selection of technological accessories. This article discusses tooling selection using neural networks. Two completely different neural networks were selected for the selection of the tooling. MLP network represents a network with learning supervision, and network Kohonen network learning without supervision.

The article contains an introduction, characteristic of tooling, the description of used neural networks, and models of tooling selection in the form of chosen neural networks.

2. TOOLING

Tooling, in addition to machines and tools, is one of the elements of the means of production in machining of metals.

Workshop aids are accessories, chucks, and holders; tools and measuring devices, and gauges; and transport devices. In this article, the following definitions were adopted from the literature [1,2,8].

Tooling - a workshop aid that constitutes an extension of the kinematic chain of machines and technological equipment. The function of accessories is to expand the technological capacity of machines or technological equipment. In the case of numerically controlled machines, accessories include turntables, numerically controlled dividing heads, bar feeders, pallet changers, etc.

Chuck - a workshop aid for setting and fixing the workpiece for machining or assembly. Positioning of a workpiece in the chuck is defined as putting the workpiece in a specific position that matches the intended machining. Setting a workpiece in the chuck is defined as putting the workpiece in a specific position in those directions that influence the outcome of the machining, i.e. on achieving the intended machining dimensions and shapes. The purpose of fixing is to make sure that the position of the workpiece achieved with the setting and retaining elements of the chuck does not change in the course of machining.

Tool holder - a workshop aid for setting and fixing machining tools. Examples of holders are reducing sleeves, milling arbors, and clamping holders.

3. NEURAL NETWORKS

Neural networks are selected as data mining algorithms. Neural networks are a very good tool for extracting patterns from databases. This advantage enables performance and automation of tasks hitherto reserved for humans. Multi-layer networks with error backpropagation (MLP) are invariably the most widespread and universal neural networks applied to solving different problems. By teaching the neural MLP networks the iterative BFGS (Broyden-Fletcher-Goldfarb-Shanno) algorithm is used to perform the optimization computing [9]. More than 50% of applications using neural networks are multilayer networks trained by the back propagation method.

When calculating the MLP networks the transition (activation) functions used for the neurons on the hidden layer are optionally hyperbolic tangent, linear, logarithmic and exponential and the functions used for the neuron on the output layer are hyperbolic tangent, linear or softmax. The error functions used in the teaching runs are optionally the sum of the squares function (SOS) and the cross entropy.

Kohonen networks are one of the basic types of self-organizing nets. Thanks to their ability of self-organization, they open up completely new possibilities, one of which is the adaptation to previously unknown input data. Self-organizing maps, also referred to as Kohonen networks, are neural networks which are associated with their coordinates defined on a straight line, a plane, or in any n-dimensional space. Kohonen networks are usually one-way nets in which each neuron is connected with all components of the N-dimensional input vector x.

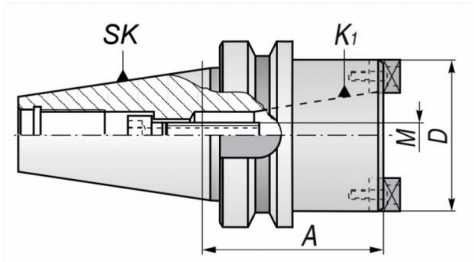
A detailed description of neural networks is presented in [4,15,16]. In the next chapters, experiments will be conducted using models of the MLP, and Kohonen artificial neural networks.

4. TOOLING SELECTION

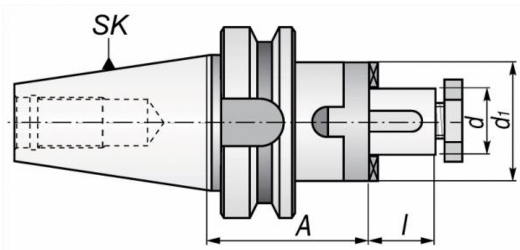
4.1. Tool holders

Tooling selection takes place after the machine and the tool have been selected, once the decision has been made that the selection is required.

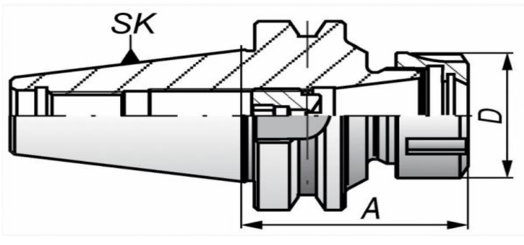
In this research study, the accessories have been limited to the tool holder. Examples of holders are reducing sleeves (a), milling arbors (b), and clamping holders (c) (fig. 1).



a) Reducing sleeves for tools with the SKBT-ISO grip | TYPE 1660 [5]



b) Universal milling arbors for milling cutters with locking grooves or drive grooves DIN 138BT-DC | TYPE 7361 [6]



c) Clamping holders (for ER DIN 6499 sleeves) for tools with cylinder grips BT-ER | TYPE 7626 [7]

Fig. 1. Examples of tool holders

Data on accessories has been collected at a manufacturing plant where the accessories are used with specific machines and tools. The detailed data has been taken from the manufacturer's web site [5,6,7].

Coordination of the machine-tool-holder assembly can mitigate the continued tendency to shorten the machining time, while meeting the very high requirements pertaining to the accuracy of manufacturing and reliability of the manufacturing process.

Position of the tooling selection is shown in Fig. 2. After the selection of a machine and tool, system verifies that the tool fits on the machine. If it does not match then the tooling selection occurs. The next step is the selection of manufacturing parameters. Information about the machine, tool, tooling and machining parameters are stored and system selects another technology operation. The technological process is presented in the form of a report after the selection of all technological operations.

4.2. Preparation of data for tooling selection

In order to prepare the training data for the formation of neural networks, an analysis of the technological processes has been conducted in relation to the selection of tooling for selected machines and tools in a manufacturing company.

The data of machines, tools and tooling were collected in a real production company. Examples of tooling selection have been prepared in cooperation with technologists. Selection criteria concern the tooling dimensions (length, diameter) to fit into the machine and tools.

Based on the tooling data and the selection criteria, a training file was prepared. The classification cases were prepared in the following manner. Qualitative predictors were identified. At the input the neural network has the code of a machine and the code of a tool, and at the output - the tooling code.

All the cases of tooling selection in the database (532 records) were divided into a training file (75% of the records), a test file (15% of the records), and a validation file (10% of the records). The neural network was taught using the trianing file and tested using the test file; in addition, its operation was verified using the validation file. The validation file is used to address the problem of overfitting of neural networks. Table 1 shows a part of the training file.

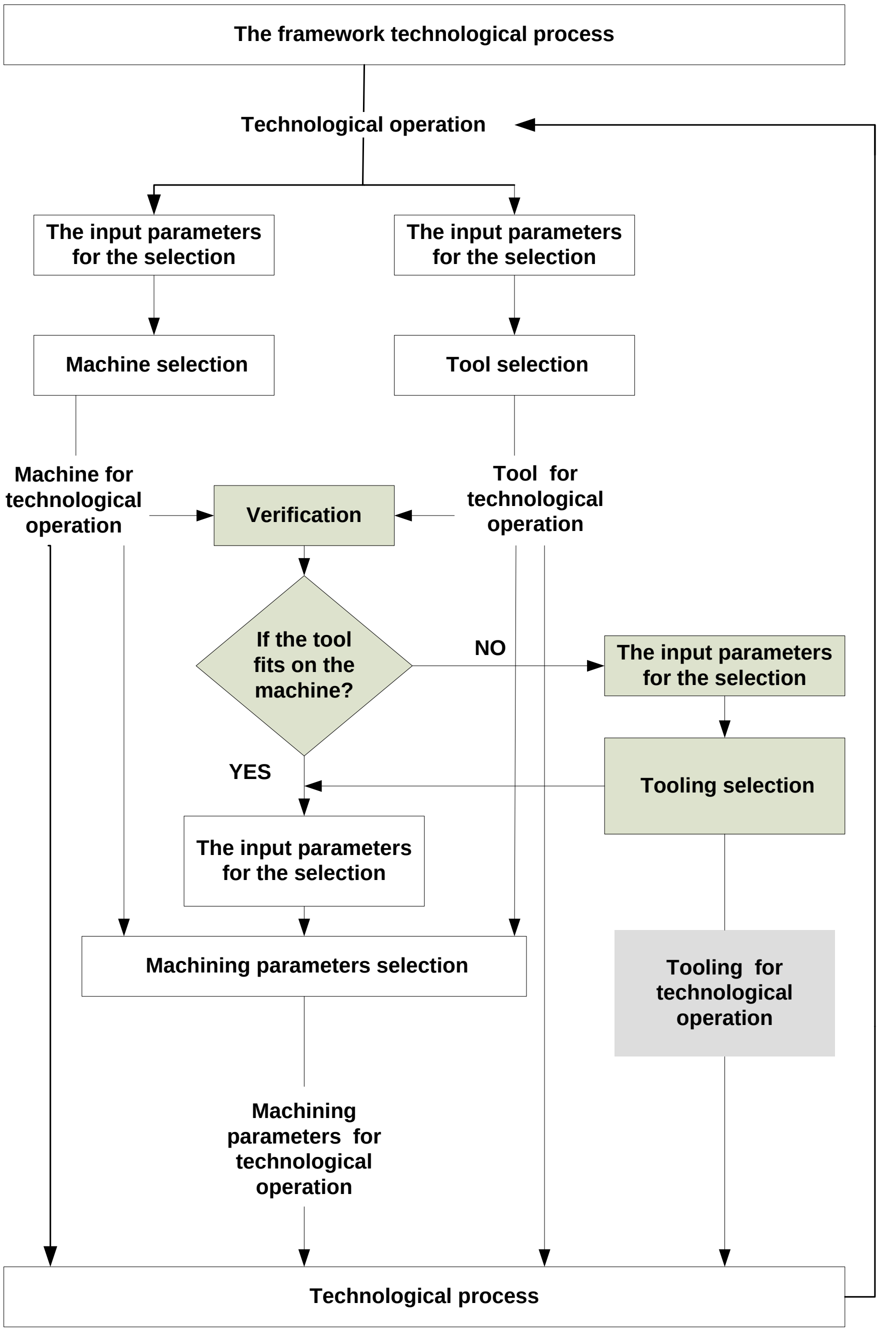


Fig. 2. Position of the tooling selection in the design of the technological process

Table 1

Training file structure

Machine code	Milling cutter code	Tooling code
LG800	DIN 326-D10 HSS	BT40.A45.MK1FV
PRO3210S	DIN 326-D50 HSS-E	BT50.A75.MK5FV
HCMC15/18	DIN 326-D10 HSS-E	BT50.A45.MK1FV
FEMCO_WBMC-100	DIN 326-D36 HSS- Golden Line	BT50.A75.MK4FV
LG800	DIN 326-D25 HSS- Golden Line	BT40.A70.MK3S
FEMCO_WBMC-100	DIN 326-D16 HSS-E	BT50.A65.MK3S
HCMC15/18	DIN 326-D25 HSS-E	BT50.A90.MK4S
FEMCO_WBMC-100	DIN 326-D56 HSS-E	BT50.A120.MK5S
LG800	DIN 345 NWKC 5	BT40.A50.MK1P
PRO3210S	DIN 345 NWKC 7	BT50.A120.MK1P
HCMC15/18	DIN 345 NWKC 43	BT50.A180.MK4P
FEMCO_WBMC-100	DIN 345 NWKC 60	BT50.A215.MK5P
PRO3210S	DIN 69871	BT50.A80.ISO40
FEMCO_WBMC-100	DIN 69871	BT50.A80.ISO40
LG800	Milling Head FI100	BT40.A52.D32S

4.3. Accessory selection using neural networks

This article presents in detail the models for the milling operation. Models were prepared in the form of different neural networks: MLP, and Kohonen network. The model parameters were changed for each type of network,.

In the case of the MLP networks, the experiments were connected with the creation of neural network models with one hidden layer that included two parameters: the number of neurons in the hidden layer and the number of teaching runs. The neurons in the hidden layer were selected experimentally. In the experiment, the parameter defining the number of neurons in the hidden layer assumed values from 10 to 60 (for MLP), while the second parameter, namely the number of teaching runs, assumed values from 10 to 100.

In the case of the Kohonen network (SOFM network), the topology of the network (5x6, 10x10, 15x15, 20x20, 25x25) and the number of the teaching cycles changed.

An error function (entropy and SOS function) was verified for each condition of the end of learning process. After the completion of each experiment, tests were performed in order to provide information on incorrectly classified decisions. The quality of a network's operation as well as its RMS error were compared in the experiments. In classifying networks, quality was calculated as a ratio of correctly classified cases compared with all cases in the set.

Table 2 shows a summary of the best neural networks for the tooling selection. The BFGS algorithm was used for the purpose of teaching MLP networks. For example, BFGS 21 means that the optimum solution was found in 21 steps. In the case of the Kohonen network, network teaching was performed using the Kohonen method, which consisted in assigning cluster centers to the radial neuron layer. The overall evaluation of a network was the classification quality measure given in percentage values. The table shows the network effectiveness of selection of the tooling expressed in % with the error function (entropy), the error value with the teaching algorithm (BFGS), the function of activation in the hidden layer (only for MLP – Tanh function), and the function of activation in the output layer (only for MLP – softmax function).

When analyzing neural networks (MLP, Kohonen), one must note the fact that their effectiveness was influenced by the number of neurons in the hidden layer, the number of the teaching cycles and the error function. In addition, the activation function in the hidden and output layer influence on MLP network.

The structure of neural networks is much more complex due to its qualitative attributes. Kohonen networks handled accessory selection much better.

Having analyzed various neural networks models, Kohonen network model (3-625) was chosen as the most effective for tooling selection (network effectiveness 99.76%).

Table 2

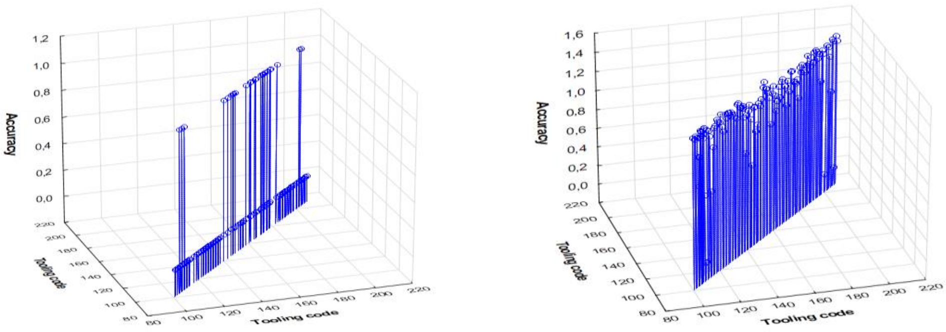
Summary of the best neural networks for the tooling selection

Network name	Effectiveness [%]	Error value	The number of learning cycles
MLP 2-36-1	**77.19**	**0.22808**	**24**
MLP 2-56-1	77.10	0.22897	51
MLP 2-19-1	75.99	0.24011	21
Kohonen 3-25	98.37	0.01630	100
Kohonen 3-225	99.29	0.00711	100
Kohonen 3-625	**99.76**	**0.00241**	**100**

Symbols MLP 2-36-1 means number of neurons in input layer (2)– number of neurons in hidden layer (36) – number of neurons in output layer (1) and Kohonen 3-625 means number of neurons in input layer (3) – network topology (25x25).

The accuracy of neural networks was assessed, too. The accuracy shows the operation of the network for new data. This parameter depends on the effectiveness of classification of neural network. The accuracy is greater, when the neural network has a higher quality classification.

Figure 3 shows the accuracy of the best MLP network and Kohonen network depending on the tooling code. The accuracy of Kohonen network is better.



MLP 2-36-1 Kohonen 3-625

Fig. 3. Accuracy of the best MLP and Kohonen neural networks

The neural networks were created using Statsoft STATISTICA Data Miner.

5. CONCLUSION

Tooling selection is one of the stages of the design of the technological process. It is necessary if a tool does not fit the machine.

An analysis of neural network models demonstrated that Kohonen networks turned out to be better models for the selection of accessories. This can be explained by the unique characteristics of these networks, which have the ability to learn without a teacher. What also affected this outcome was the fact that the training file contained only qualitative data.

Accessory selection supplements the selection of the machine, the tools, and the machining parameters, which together allow us to design a technological process.

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DOBÓR OPRZYRZĄDOWANIA NARZĘDZIOWEGO W PROCESIE TECHNOLOGICZNYM PRZY UŻYCIU SIECI NEURONOWYCH

S t r e s z c z e n i e

Ideą badań autorki jest opracowanie systemu wspomagania projektowania procesu technologicznego (systemu CAPP), czyli systemu, w którym kolejność operacji technologicznych jest zdefiniowana, a dla każdej operacji następuje odpowiedni dobór obrabiarek, narzędzi, oprzyrządowania oraz parametrów obróbki. W artykule przedstawiono dobór oprzyrządowania narzędziowego przy użyciu sieci neuronowych. Dobór ten jest niezbędnym etapem projektowania procesu w przypadku, gdy dobrane narzędzie nie pasuje na obrabiarkę. Zostały wykonane modele doboru oprzyrządowania przy zastosowaniu sieci neuronowych jednokierunkowych wielowarstwowych ze wsteczną propagacją błędu (MLP) oraz samoorganizującej się sieci Kohonena. Dane do nauczenia sieci neuronowych zostały przygotowane w przedsiębiorstwie produkcyjnym. Sieci neuronowe zostały wykonane przy użyciu oprogramowania Statsoft STATISTICA Data Miner.

Słowa kluczowe: oprzyrządowanie, proces technologiczny, sieci neuronowe