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MLP NEURAL NETS IN DESIGN OF TECHNOLOGICAL PROCESS

Izabela Rojek

Summary

This paper proposes MLP neural nets to improve technological process design. The first stage of research concerned the creation of models to selection of machine tools, the second stage pertained the creation of models to selection of tools and the third stage concerned the creation of models to selection of machining parameters. In addition, use of tools is forecasted at various time intervals. The models were created using Statsoft STATISTICA Data Miner. These models were compared in order to obtain the best selection. Based on the models, it is possible to create different scenarios of the design of technological process.

Keywords: neural nets, selection, technological process

Sieci neuronowe MLP w projektowaniu procesu technologicznego

Streszczenie

W artykule przedstawiono opracowanie sieci neuronowych MLP w celu poprawy projektowania procesu technologicznego. Pierwszy etap dotyczył tworzenia modeli wyboru obrabiarek, drugi modeli wyboru narzędzi i trzeci tworzenia modeli do wyboru parametrów obróbki skrawaniem. Dodatkowo w opracowanych modelach uwzględniono prognozowanie użycia narzędzi w różnych przedziałach czasowych. Stosowano program Statsoft STATISTICA Data Miner. Prowadzono analizy wyników dla poszczególnych modeli i opracowano kryteria doboru. Stwierdzono, że wprowadzenie sieci neronowych umożliwia tworzenie różnych scenariuszy projektowania procesu technologicznego.

Słowa kluczowe: sieci neuronowe, dobór, proces technologiczny

1. Introduction

Knowledge management is developing today in many areas, including the design of manufacturing processes and CAPP systems [1]. The combination of knowledge management with CAPP systems provides intelligent CAPP systems.

The primary aim of developing intelligent CAPP systems is to make them reflect expert knowledge and make it available to a system which will use it in solving problems. Integration of artificial intelligence methods can be expected to lead to the creation of better and more accurate methods which could

Address: Izabela ROJEK, PhD, Eng., Kazimierz Wielki University, Institute of Mechanics and Applied Computer Science, Chodkiewicza 30, 85-064 Bydgoszcz, Poland, +48 523257630, corresponding author: e-mail: izarojek@ukw.edu.pl

be used in this area of expertise. The most important function of intelligent systems is drawing conclusions [2].

Contemporary Computer Aided Process Planning (CAPP) systems more and more often use artificial intelligence methods to aid the design of manufacturing processes.

Study of the available literature shows that researchers are more and more often applying the methods of artificial intelligence in the design of manufacturing processes. For example the selection of machining operations is assisted [3], data mining methods are used in manufacturing [4, 5] and neural nets are used in intelligent decision support systems [6]. Article [7] presents application of knowledge based systems in technical preparation of machine parts production and another article [8] shows the binary Petri net as a unified framework for acquisition and representation of knowledge in the scope of machining operations planning.

Moreover, the author developed a set of models with the use of artificial intelligence: neural nets for only selection of tools (linear L, multi-layer net with error back propagation MLP, nets of radial basic functions RBF) [9], hybrid neural nets (hybrid nets: L-MLP; L-RBF, MLP-RBF, L-MLP-RBF) [10].

The present work describes new research concerning the integrated approach. Article discusses neural nets of selection of machines, tools and machining parameters, *i.e.* all elements, which are chosen for each technological operation of technological process. Set of operations creates technological process. In addition, tools are forecasted at various time intervals. For each model tools are made in the form of MLP neural nets for different processes: milling, grinding, turning, etc. The best neural nets, in respect of the quality is selected. Basing on the intelligent models, it is possible to create scenarios for the selection of different components for technological operations. The created models are therefore able to improve the technological processes. The models were tested on real data from an enterprise.

2. Neural nets theories

Neural nets are selected as data mining algorithms. Neural nets are a very good tool for extracting patterns from databases. This advantage enables performance and automation of tasks hitherto reserved for humans. Multi-layer nets with error backpropagation (MLP) are invariably the most widespread and universal neural nets applied to solving different problems. More than 50% of applications using neural nets are multilayer nets trained by the back propagation method [2].

For MLP nets, the experiments connected with the creation of neural net 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 5 to 30, while the second parameter, namely the number of teaching runs, assumed values from 5 to 50. For each condition of the end of the teaching process, an error function (entropy and SOS function) was verified. After the completion of each experiment, tests were performed in order to provide information on incorrectly classified decisions. The quality of a net's operation as well as its RMS error were compared in the experiments. In classifying nets, quality was calculated as a ratio of correctly classified cases compared with all cases in the set.

When analyzing neural nets, 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 influences on MLP net.

The neural net was taught using the teaching file and tested using the test file; also, its operation was verified using the validation file. The validation file is the answer to overteaching of neural nets.

The neural nets were created using Statsoft STATISTICA Data Miner.

3. Manufacturing knowledge management

Manufacturing knowledge comes from many sources. Data from catalogs and databases can be obtained in a simple manner. However, if one wishes to acquire the knowledge, preferences and experience of the process engineer, simple information tools are not enough. It is necessary to create such models and tools that will enable that knowledge to be contained in a computer system. Therefore the method of machine learning was used (Fig. 1).

In the past, a process engineer used catalogs, often in a paper form. For the accurate design of technological process, one should add preference models for the intelligent support system. In such a system there can be accumulated the knowledge and experience of many experts and engineers.

The preferences of the process engineer are included in the system in the form of decision rules, which are used by the engineer in the design of the technological process. It is assumed that the basis for the selection of machine tools and tools is the order of ranking of the machine tools and tools, based primarily on the frequency of machine tools and tools selection by the engineer. The highest priority is assigned to the tools most frequently selected by the engineer.

The choice of machine tools, tools and machining parameters is influenced by many factors that the process engineer must take into account, including: volume of production, type of processing, workpiece material, the type of machine, the type and accuracy of processing, and the shape of the machined surface.

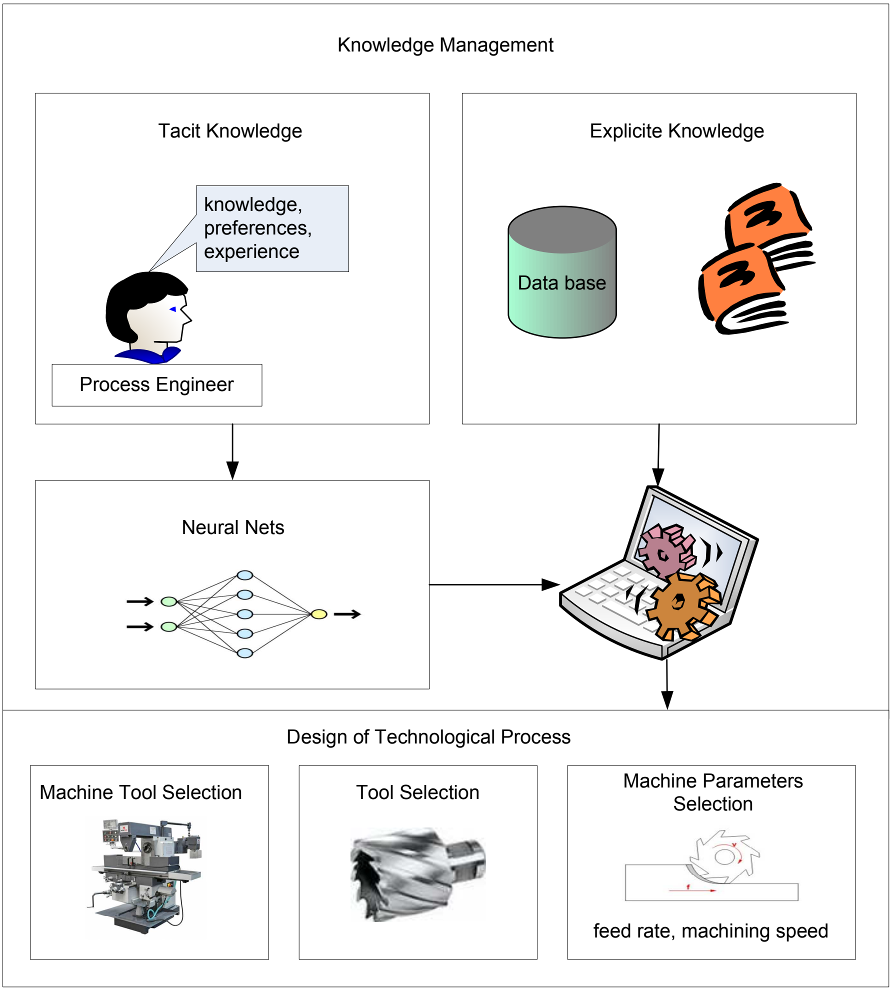

Fig. 1. Knowledge management for design of a technological process

Experiments were performed for selected technological operations. This article presents in detail the models for the milling operation. Models were prepared in the form of MLP neural nets.

4. Neural nets in design of technological process

4.1. Selection of tools for technological operations

4.1.1. Structure of teaching file

In order to prepare the teaching data for neutral nets, an analysis was performed of chosen enterprise's tools, which were divided into drills, milling cutters, lathe tools, and grinding wheels. The tools were selected separately for each technological operation.

Based on the tool data and the selection criteria, a teaching file was prepared for MLP neural nets for milling. The following data was fed at the input of the neural net: type of operation; type of machined surface; type of machined material; roughness; type connect; type of milling cutter mounting; diameter of the milling cutter [mm]; shape of the milling cutter; number of blades; total length of the milling cutter [mm], milling speed vc [m/min.]; milling depth ap [mm], feed rate [mm/min.]; cost of operation; and milling width [mm]. At the output of the neural net, the milling cutter symbol was obtained.

All the cases (553 records) were divided into a teaching file (75% of the records), a test file (15% of the records), and a validation file (10% of the records).

4.1.2. Neural nets supporting tool selection

Table 1 shows a summary of the neural nets for the milling cutter selection. The overall evaluation of a net was the classification quality measure given in percentage values.

Having analyzed various neural nets models, MLP net models (15-27-1, 15-15-1, 15-23-1) were chosen as the most effective for machine tool selection (net effectiveness 100%). This effectiveness was achieved with a different number of teaching cycles (according to the order of mentioned above net: 24, 37, 42) and with various system functions (error function, function of activation in the hidden layer, function of activation in the output layer).

Table 1. Parameters of the best MLP nets for tool selection

MLP Net	**Effectiveness %**	**Error (teaching)**	**Error (testing)**	**Error (validation)**	**Function of activation in the hidden layer**	**Function of activation in the output layer**
15-27-1	100.00	0.0000	0.0000	0.0000	Tanh	Softmax
15-15-1	100.00	0.0000	0.0000	0.0000	Tanh	Softmax
15-23-1	100.00	0.0000	0.0000	0.0000	Logarithmic	Softmax

Designation: x-x-x = number of neurons in the input layer – number of neurons in the hidden layer – number of neurons in the output layer

4.2. Selection of machine tools for technological operations

In order to prepare the teaching data for neural nets, an analysis of the machinery used at chosen enterprise has been performed, in particular in relation to the CNC machines: mills, mill-drills, grinders, and turning lathes. The machine tool was selected separately for each technological operation.

Based on the machine tool data and the selection criteria, a teaching file was prepared for the MLP nets. The following data is fed at the input of the neural net: type of operation, product length/width/diameter (X,Y,Z), mm, size of the working space (X,Y,Z), mm, max. diameter of the tool, mm, length of the tool, mm, cost of operation of the machine tool, PLN/h, min. and max. rotational speed, rpm, max. working range f, mm/min., and machine tool power, kW. The machine tool symbol is obtained at the output of the neural net.

All the cases (521 records) were divided into a teaching file (75% of the records), a test file (15% of the records), and a validation file (10% of the records).

Having analyzed various neural nets models, MLP net models (14-19-1, 14-8-1, 14-30-1, 14-15-1) were chosen as the most effective for machine tool selection (net effectiveness 100%). This effectiveness was achieved with a different number of teaching cycles (according to the order of mentioned above net: 5, 19, 13, 10) and with various set of functions (error function, function of activation in the hidden layer, function of activation in the output layer).

4.3. Selection of machining parameters for technological operations

In order to prepare the teaching data for the neural nets, an analysis of the technological processes with regard to selection of the machining parameters for specific machines and tools was performed. The machining parameters were selected separately for each technological operation.

Based on the machining parameter data and the selection criteria, a teaching file was prepared for the MLP nets. The following data was fed at the input of the neural net: type of operation, type of machined material, symbol of selected tool, roughness, machining depth ap, mm, milling width, mm, target depth, mm, and machine symbol. At the output of the neural net, a set of parameters to be set on the machine was obtained: feed rate, mm/min., machining speed, m/min., duration, min., and tool service life, min.

All the cases (617 records) were divided into a teaching file (75% of the records), a test file (15% of the records), and a validation file (10% of the records).

Having analyzed various neural nets models, MLP net model (8-10-1) was chosen as the most effective for machine tool selection (net effectiveness 98.04%). This effectiveness was achieved with a number of teaching cycles (49) and with set of functions (error function – Entropy, function of activation in the hidden layer – Tanh, function of activation in the output layer – Softmax).

4.4. Forecasting models of tool use in different intervals of time

4.4.1. Structure of teaching file

Nowadays, the use of tools in enterprises is controlled on the general level. The number and condition of tools is checked in tool-houses according to a predefined time schedule. However the worked out models will permit to forecast requirements for particular tools in different temporary intervals and react more quickly to the lacks of tools in an enterprise, which will prevent the standstills of production and also the increase of production costs. Prediction models were worked out for forecast use of tools in different temporary intervals, such as: hours, days, weeks and months. The models were taught correct forecasting on the basis of real data in the form of examples of tool use. Every model was tested for the correct prediction.

Knowing the model of the facility, the reaction to various input violations should be analyzed. It is interesting to defining the future state of the facility for the time $t+n$, where n is the prediction horizon, t contains the input changes history up to the present. The prediction horizon n = 1 marks e.g. 1 day. In order to construct time sequences which are later used in the forecasting model, the values of flow before the moment t (t-1, t-2, …, t-7) as neural net input and after the moment t (t+7) as neural net output were added.

All the cases (650 records) were divided into a teaching file (75% of the records), a test file (15% of the records), and a validation file (10% of the records).

4.4.2. Neural nets supporting forecasting of tool use

Table 2 shows a summary of the neural nets for the forecasting of tool use. The overall evaluation of a net was the classification quality measure given in percentage values.

Having analyzed various neural nets models, MLP net models (7-10-8, 7-19-8, 7-29-1) were chosen as the most effective for machine tool selection (net effectiveness 100%). This effectiveness was achieved with a different number of teaching cycles (according to the order of mentioned above net: 25, 27, 32) and with various system functions (error function, function of activation in the hidden layer, function of activation in the output layer).

Table 2. Parameters of the best MLP nets for the forecasting of tool use

MLP Net	Effectiveness, %	Error (teaching)	Error (testing)	Error (validation)	Function of activation in the hidden layer	Function of activation in the output layer
7-10-8	100.00	0.0000	0.0000	0.0000	Tanh	Softmax
7-19-8	100.00	0.0000	0.0000	0.0000	Tanh	Softmax
7-29-8	100.00	0.0000	0.0000	0.0000	Logarithmic	Softmax

Conclusions

Analysis of the neural net models showed that the neural net is a very good method of decision classification for design of technological process.

The data were taken from a real enterprise. Using neural nets as classification models, an application intended to aid a process engineer in the design of technological process was implemented. The application for the design of technological process, in a dialog form, queries the process engineer about input attributes and provides answers in the form of machine tool symbols, tool symbols and machine parameters.

The author's earlier works focused on the creation of intelligent models for milling operations for only toll selection. In this article, research concerning design of technological process is presented in the following form: machine tool selection, tool selection and machine parameters selection. In addition, tools are forecasted at various time intervals. It has been shown that the same methods of machine learning can be used to develop intelligent models for CAPP systems.

The application of intelligent models to aid process planning, introduced a new quality to the CAPP systems and can serve as a foundation for the algorithmization of new "intelligent" systems.

Application of artificial intelligence methods enables the creation of a support system which collects knowledge automatically and has adaptation skills. This is particularly important when developing a system for complex real systems, in which continuous changes occur and where one process depends on another, many factors are interdependent and every change triggers more changes.

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