Intelligent System Supporting Technological Process Planning for Machining

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Abstract. The aim of the study was to develop a system supporting technological process planning, the functioning of which would resemble the way human experts act in their fields of expertise, one capable of gathering necessary knowledge, analysing data, and drawing conclusions to solve problems. This could be done by utilising artificial intelligence (AI) methods available within such systems. The study proved the usefulness of AI methods, and their significant effectiveness in supporting technological process planning. Technological-process planning based on an expert system is divided into the following stages: the selection of the semi-finished products; the establishing of the technological process structure, and the selection of the workpiece instrumentation, machine tools, tools, and tooling and machining parameters for each technological operation. The system-embedded knowledge takes the form of neural networks, decision trees and facts. The system is presented using the example of a real enterprise. The intelligent expert system is dedicated to process engineers who have not yet gathered sufficient experience in technological-process planning, or who have just begun their work in a given production enterprise, and are not very familiar with its machinery and other means of production..

1 Introduction

For many years, the development and use of IT tools in supporting technological-process planning have been the subject of studies world over. While the potentially greater amount of data should facilitate task and problem solving, in practice it is hardly ever so. Hence, the search continues for increasingly advanced IT tools for data analysis and mining, and, by extension, for the transformation of data into knowledge, as is the case with the intelligent expert system supporting technological-process planning.

The technological process constitutes a core part of the production process, directly entailing changes to shapes, dimensions, and surface quality, as well as the physico-chemical properties of the processed item, or the arrangement of components or assemblies in relation to each other in a product. Starting with the semi-finished product (input) preparation in the technological process, certain technological operations need to be performed. The appropriate operations are selected by the process engineer. Technological-process planning is divided into several stages. The first stage involves selecting the semi-finished products. This is followed by designing the technological-process structure, i.e. the sequence of technological procedures and operations. Then, workpiece instrumentation, machine tools, tooling and machining parameters are selected for each technological procedure and operation. The intelligent expert system is used for technological-process planning based on neural networks and rules.

2 Artificial intelligence methods used in technological process planning

Ciurana et al. [1] presented the integration of technological-process planning with both production planning and steering, based on a shared database. Newman and Nassehi [2] described technological-process planning using an IT system in which machine-tool capabilities play a vital role. An altogether different working technique [3] involved data mining (DM), considered by the author as one of the most beneficial methods utilised in industrial practice, making it possible to acquire knowledge from data and to support decision-making processes. The next stage in IT-tools development entailed the use of artificial intelligence (AI) methods in technological-process planning.
Attempts at increasing the use of artificial intelligence (AI) methods in computer-aided technological-process-planning systems have been made for many years. The use of data-mining methods to acquire the knowledge available in the databases of existing technological processes facilitates the formalisation of the process engineer's inventiveness and experience, taking the form of knowledge included in knowledge bases, and the induction process similar to that which a human expert employs in technological-process planning. Technological knowledge acquired with AI methods, coupled with an intelligent computer aided process planning system(CAPP system), makes it possible to design technological processes that are better aligned with enterprise-specific needs (Table 1).

Table 1. AI methods in CAPP systems.

AI method	Usage
Expert systems (ES)	Expert systems have been widely used in technological-process planning. They are usually made of three core components, i.e. a knowledge base, an induction mechanism, and a user interface[4-8].
Neural networks (NN)	Neural networks facilitate technological-process planning by eliminating the need to search through numerous rules (as in the case of expert systems). The use of a neural network allows the simultaneous consideration of numerous limitations and it is very popular in technical areas [5, 9-14].
Random forests (RF) and decision trees (DT)	Random forests and decision trees represent a basic method of inductive machine learning due to their high effectiveness. This method is based on analysing examples, and is characterised by exceptionally good classification properties. Rule generation based on decision trees makes it possible to formulate rules [15-18].
Fuzzy logic (FL) and fuzzy sets (FS)	A large part of decision making related to process planning can take place in an environment where objectives and limitations are fuzzy, i.e. not fully known. Fuzzy logic can help to achieve this by transforming human knowledge into mathematical models and transposing that knowledge into engineering systems [19,20].

The type of tasks to be solved has been considered as the principal criterion for AI method selection. Fuzzy logic has been used for normalising and coding facts in the expert system knowledge base, whereas neural networks and decision trees have served the purpose of providing technological insights and assisting process engineers in the course of technological-process planning. The underlying problem in technological-process planning is related to the classification necessary for the proper selection of individual technological-process elements. The results of the study presented in this article relate to identifying, analysing and experimenting with various types of neural networks and decision trees. From among the basic networks (unidirectional multi-layer networks, self-organising neural networks and recurrent networks), the following types were selected: (1) unidirectional multi-layer perceptron (MLP) networks with backward propagation of errors; (2) radial basis function (RBS) networks; (3) self-organising Kohonen networks (KN); and (4) recurrent Hamming networks (HN). Certain types of decision trees, i.e. C4.5, C&RT, CHAID, boosted trees and random forests, were also used in the analysis. Decision rules were developed on the basis of expert trees, and then they were entered into the expert system, following which selected AI methods were analysed in terms of their application to specific tasks related to technological-process planning (Table 2). The expert system was implemented as the process engineer's interface for technological-process planning, using decision rules and neural networks. The rules were generated both traditionally (i.e. manually) and automatically (using decision trees). Data normalisation was performed by means of fuzzy logic to prepare data in the form of individual selection examples.

Table 2. The use of selected AI methods in technological-process planning.

AI methods	Tasks related to technological-process planning
Fuzzy logic	Technological data normalisation and coding in the database
Decision rules	Technological-process structure (operations, procedures) establishment
Neural networks	Selection of: semi-finished products, workpiece instrumentation, machine tools, tools, tooling, machining parameters
Decision trees and forests	Selection of: semi-finished products, workpiece instrumentation, machine tools, tools, tooling, machining parameters

The combination of an expert system, neural networks, and decision trees and rules leads to an intelligent expert system.

3 Case study – An intelligent system for technological-process planning

3.1 Data preparation

Data were collected at the real enterprise providing a wide range of products. Data were collected on semi-finished products, technological-process structures, conventional and CNC machine tools, cutting tools, workpiece instrumentation, and tooling. Technological knowledge was gathered in the form of techno-logical processes which had been developed. The exemplars of technological-process elements comprise a great amount of knowledge, experience, and intuition of process engineers.
The majority of information obtained from databases is raw, incomplete, and noisy. In order for such data to become useful for mining purposes, they need to be cleaned and transformed [21]. Data cleaning entails the unification of records, the supplementation of missing entries, or the identification of extreme points. In turn, data transformation involves normalisation or coding.

Data normalisation

A database is a collection of diverse attributes – features of objects stored in databases. These, in turn, can exhibit various ranges of values. For instance, in the case of machine-tool selection, one of the input parameters, i.e. semi-finished product length, has a range from 0 to 3000, whereas another, i.e. machine-tool power, goes from 0 to 25. As regards some AI methods (e.g. neural networks), such differences will cause input data with a wider range to have an excessive impact on output [21,22]. At the first stage of the study, min-max normalisation was used for data calibration. This involves verifying the extent to which the field value is higher than the nominal value (X), followed by calibrating that difference by the following range (1)

$$X^* = \frac{X - \min(X)}{\max(X) - \min(X)} \tag{1}$$

The normalisation of the semi-finished product length parameter, e.g., for value X = 1500, reached X* = 0.5. At the second stage of the study, fuzzy normalisation with category membership functions was employed with the aim of increasing results stability [23]. The membership functions exhibit values in the range <0,1> (Table 3).

Data coding

The second category of data contains nominal data which can have a bi- or multi-state character. For instance, the machining-type parameter has three states, i.e. roughing, shaping and finishing. At the first stage of the study, the one-of-N coding type was selected, which involves the use of several numerical variables, instead of one nominal variable, within the network structure. For instance, for the machining type parameter, the number of numerical variables is 3, corresponding to the number of the potential values of the nominal variable, i.e. roughing = {1,0,0}, shaping = {0,1,0} and finishing = {0,0,1}. The use of this data-coding method increases the number of network inputs and outputs. At the second stage of the study, the coding method employed in respect of nominal values was modified, i.e. these values were confined to the range <0,1>. For in-stance, for the machining-type parameter, the following values were adopted: roughing = 0.1, shaping = 0.5 and finishing = 0.9. In consequence, the number of network inputs and outputs did not increase, and neither did the structure dimension.

Table 3. Exemplar values for the *semi-finished product length* parameter.

Semi-finished product length (mm)	
Raw data	Normalised data
65	0.029
100	0.033
1000	0.163
1500	0.500
2900	0.967

3.2 Intelligent system schematic

Following the analysis of the construction documentation, production volume, and the availability of means of production, technological-process planning begins with semi-finishedproduct selection. Data should be entered as inputs, and then processed by a neural-network model, resulting in semi-finished product selection. This is followed by establishing the technological-process structure, i.e. the sequence of technological operations and procedures using decision trees. In the case of every technological operation and procedure, input data are entered with a view to selecting workpiece instrumentation using a neural-network system. In consequence, a symbol of the processed item chuck is obtained.

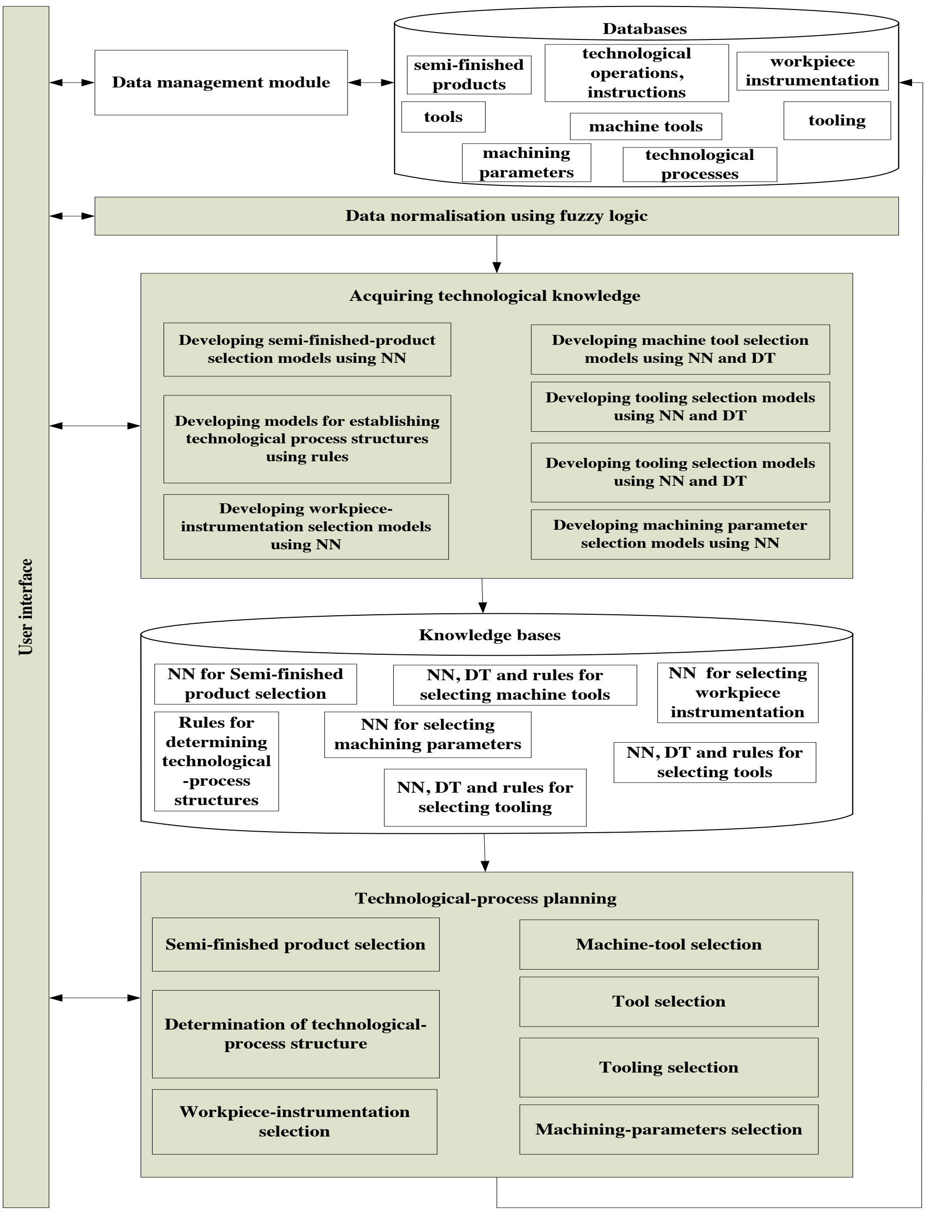

Fig. 1. An intelligent expert system for technological-process planning; NN – neural networks, DT – decision trees.

Then, based on the input data which have been entered, and in line with the neural-network model, the machine-tool and tools are selected, respectively. The next stage involves verifying whether the tools match the machine tool (based on the dimensions of the former). If the dimensions are non-compliant, tooling selection needs to be performed, i.e. on entering the machine-tool and tools symbols, the neural-network model selects the appropriate tooling symbol. The last stage involves determining the process parameters, where the machine-tool and tool symbols, along with the remaining data, are entered as inputs to the neural net-work, and on that basis the machining parameters are determined. Technological-process planning ends with selections for the operations and procedures included in the previously developed technological-process structure. This unique methodology was then employed to develop a schematic of an intelligent expert system for technological-process planning (see Fig. 1). It is made up of (1) a user interface, and modules for (2) data management, (3) data normalisation using fuzzy logic, (4) technological-knowledge acquisition, and (5) technological-process planning.

3.3 Knowledge sources for the system on the example of models of semi-finished product selection

Technological-process planning support was developed using artificial-intelligence methods.
Semi-finished product selection was performed using unidirectional multi-layer perceptron (MLP) networks with backward propagation of errors, radial-basis function (RBS) networks, and Kohonen and Hamming networks. Figure 2 presents an exemplar structure of MLP and RBF neural networks for semi-finished product selection.
Table 4 features a comparison of MLP, RBF, Kohonen and Hamming networks for the selection of semi-finished products, taking into account effectiveness expressed in percentage terms. Moreover, neural-network models were established with various conditions regarding the network-learning process completion, i.e. the number of error-function epochs and values. Figure 3 outlines the learning, testing, and validation errors of the most suitable MLP, RBF, Kohonen and Hamming networks. In the course of the neural networks analysis, their effectiveness was found to depend on the following parameters: in the case of MLP and RBF networks, on the number of neurons in the hidden lay-er, the number of training cycles according to a specific learning algorithm, the values of the error function and the function of activation in the hidden and out-put layer; and in the case of the Kohonen networks, on the network topology, the number of training cycles, and the error function.

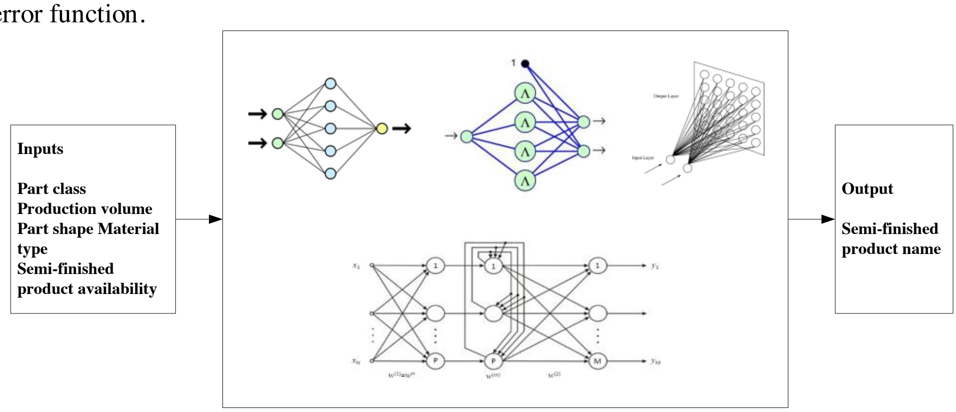

Fig. 2. Selection semi-finished product by MLP, RBF, Kohonen, and Hamming neural-network structure.

Table 4. The parameters of the most suitable neural networks in terms of semi-finished product selection.

NN name	MLP 5-10-1	MLP 5-15-1	RBF 5-46-1	RBF 5-60-1	SOM 6-30	SOM 6-100	H 5-M-1
E [%]	99.27	100.00	97.82	99.09	99.82	100.00	100.00
LA	BFGS	BFGS	RBFT	RBFT	K	K	---
NE	100	100	100	100	100	100	1000
EF	Ent	Ent	SOS	Ent	Ent	Ent	MSE
AFinHL	L	Tanh	G	G	---	---	---
AFinOL	S	Tanh	Lin	S	---	---	---

Where: H – Hamming, M – MAXNET, E – effectiveness, LA – learning algorithm, NE – number of epochs, EF – error function, AFinHL - activation function in the hidden layer, AFinOL - activation function in the output layer, K – Kohonen, Ent – entropy, L – logistic, S – Softmax, G – Gaussian, Lin - Linear

The MLP 5-10-1 symbol refers to the number of network inputs (5) – the number of neurons in the hidden layer (10) – the number of network outputs (1); Kohonen 6-30 refers to the number of network outputs (6) – network topology (5x6); and Hamming 5-MAXNET-1 refers to the number of network outputs (5) – the MAXNET hidden layer in which all neurons are connected to each another – the number of network outputs (1).

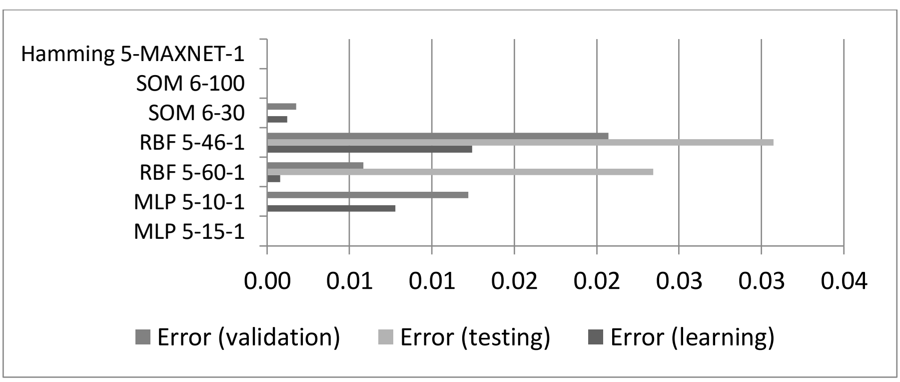

Fig. 3. The learning, testing and validation errors of the most suitable MLP, RBF, Kohonen and Hamming networks.

Neural-network outputs were also analysed. In the course of the analysis of all the neural-network models developed, the MLP (5-15-1), Kohonen (6-100) and Hamming network models proved the most effective for semi-finished product selection (100.00% effectiveness). Therefore, the simplest network (MLP) could be used for their selection. The assessments also covered the operational-network accuracy on the basis of the new data, and the degree of certainty defining the relationship of the new input data with specific template classes. Both parameters influence neural-network effectiveness, and the higher the accuracy and degree of certainty the better the ability to classify neural networks. The same model-development method was used for establishing neural-network and decision trees models in the process of selecting workpiece-instrumentation, tool chucks,

machine tools, tools, tooling and machining, parameters. Whereas, the framework technological process was created using decision-making rules.
The use of the system for selection of semi-finished product is shown in Fig. 4. The process engineer first enters the relevant input data, including the product name and production volume, and then selects the appropriate semi-finished product.

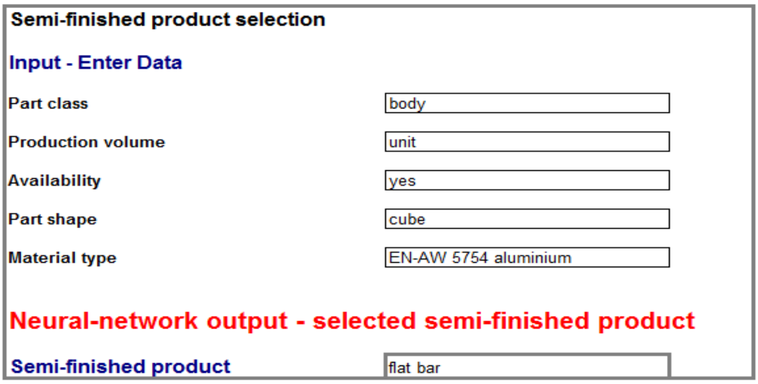

Fig. 4. Semi-finished product selection.

Next, the process engineer establishes further elements of the technological process. All the results obtained from the expert system were verified and recognised as correct by process engineers, which can be considered as confirming the usefulness of this kind of IT tools in industrial practice.

4 Summary

The aim of the study was to develop an intelligent expert system supporting technological process planning, the functioning of which would resemble the way human experts act in their fields of expertise, one capable of gathering necessary knowledge, analysing data, and drawing conclusions to solve problems. This could be achieved by employing AI methods. The study proved the usefulness of AI methods (neural networks and decision trees), and their high effectiveness in supporting technological-process design.
The intelligent expert system is dedicated to process engineers who have not yet gathered sufficient experience in technological-process planning, or who have just begun their work in a given production enterprise, and are not very familiar with its machinery and other means of production. It should be stressed that such a system plays an advisory role, and the final decision always belongs to the process engineer. The expert system's functioning was described using the example of a real enterprise.
Our further studies focus on systematic development and implementation of AI within Industry 4.0, i.e. next generation of industrial systems, and real impact of the novel technologies such as additive manufacturing and internet of things.

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