

POLSKA AKADEMIA NAUK Instytut Badań Systemowych

ZASTOSOWANIA INFORMATYKI W NAUCE, TECHNICE I ZARZĄDZANIU

> Redakcja: Jan Studziński Ludosław Drelichowski Olgierd Hryniewicz



Polska Akademia Nauk • Instytut Badań Systemowych Seria: BADANIA SYSTEMOWE Tom 41

Redaktor naukowy: **Prof. dr hab. Jakub Gutenbaum**

Warszawa 2005

ZASTOSOWANIA INFORMATYKI W NAUCE, TECHNICE I ZARZĄDZANIU

Redakcja: Jan Studziński Ludosław Drelichowski Olgierd Hryniewicz Książka wydana dzięki dotacji KOMITETU BADAŃ NAUKOWYCH

Książka zawiera wybór artykułów poświęconych omówieniu aktualnego stanu badań w kraju, w zakresie rozwoju modeli, technik i systemów informatycznych oraz ich zastosowań w różnych dziedzinach gospodarki. Kilka artykułów omawia aplikacyjne wyniki projektów badawczych i celowych Ministerstwa Nauki i Informatyzacji.

Recenzenci artykułów:

Dr inż. Lucyna Bogdan Prof. dr hab. inż. Ludosław Drelichowski Prof. dr hab. inż. Olgierd Hryniewicz Dr inż. Edward Michalewski Dr inż. Grażyna Petriczek Prof. dr hab. inż. Andrzej Straszak Dr inż. Jan Studziński

Komputerowa edycja tekstu: Anna Gostyńska

Copyright © Instytut Badań Systemowych PAN, Warszawa 2005

Instytut Badań Systemowych PAN ul. Newelska 6, 01-447 Warszawa

Sekcja Informacji Naukowej i Wydawnictw e-mail: biblioteka@ibspan.waw.pl

ISBN 83-89475-03-0 ISSN 0208-8029

APPLICATION OF ARTIFICIAL INTELLIGENCE METHODS IN KNOWLEDGE MANAGEMENT IN THE INTELLIGENT DATABASE ENVIRONMENT

Izabela ROJEK

Institute of Environmental Mechanics and Applied Computer Science, Kazimierz Wielki University <izarojek@ab.edu.pl>

In knowledge management, application of artificial intelligence methods was presented by example of an intelligent database for computer-aided process planning. Due to the process planning demands, the intelligent database (IBD_PT) was defined as a hybrid system combining a relational database, knowledge base, knowledge acquisition module, expert system, simulator of neural network and user interface. The quintessence of knowledge management is subtraction, classification and manifestation of knowledge, information and experience. IBD_PT includes knowledge and experience of expert process engineers in the area of process planning and mechanisms of applying rules, models, facts and proper inference in order to design such process planning which would meet specific conditions.

Keywords: Knowledge management, neural network, expert system, process planning.

1. Introduction

6

Artificial intelligence (AI) methods present a scientific research area, which is applied more and more frequently in knowledge management.

The quintessence of knowledge management is subtraction, classification and manifestation of knowledge, information and experience. At present, the most difficult problem is to "mine" knowledge and experience i.e. obtain it from workers (Bennett, Gabriel, 1999). That is because the workers do not want to share their knowledge. In accordance with the definition, the process of knowledge management is divided into the following sub-processes: acquisition, identification, organisation, collection and utilisation of knowledge (Demarest, 1997).

Among the most essential knowledge management tools we can distinguish such systems as: document management, workflow, groupware, intranet, corporate portals, data warehouses, computer-aided decision systems and expert systems.

In AI methods, four most common methodological standards were defined, namely: expert systems, neural networks, genetic algorithms and fuzzy logic theory.

Recently, a new category of AI tools has appeared – the so-called hybrid systems. They combine traditional expert systems, learning systems, neural networks and genetic algorithms. Hybrid systems integrate AI techniques and have many complementary features and properties. Therefore, these systems give us hope to create better and more efficient methods of problem solution. Learning systems capable of improving their performance on the basis of gathered experience could be an essential achievement with regard to traditional expert systems which are based solely on acquiring knowledge from expert people. It is particularly essential in situations when this knowledge is not accessible, presents formalization problems, is incomplete or ambiguous.

Application of AI methods in knowledge management will be presented based on an example of intelligent database application supporting process planning.

Research into the application of an intelligent database supporting the production process design has begun as a part of the author's doctoral studies in this area. Initial groundwork focused on the creation of production databases, as well as definition of selection algorithms with regard to tools, machine tools and cutting parameters. The resulting application – a database supporting the production process design – was implemented and tested in a selected enterprise which manufactures injection moulds.

Further research confirmed the need to employ an expert system and a neural network to manage production knowledge, in order to gain independence from expert engineers. Addition of these methods allowed for the creation of a hybrid system, consisting of both a traditional and knowledge database, expert system and a neural network. Testing the system with artificial intelligence (AI) methods proved successful in the area of knowledge acquisition, in particular in knowledge management. The results obtained were also verified in the enterprise.

Now, the research will aim at the application of machine learning, focusing on the induction of decision trees for the acquisition of production knowledge due to the possibility of representing knowledge in its symbolic form.

2. Intelligent database characteristics

An intelligent database (IBD_PT) aids process planning. IBD_PT environment is characterised by diversity and similarity to the natural environment of a process engineer's work. The way IBD_PT works is similar to an expert process engineer's reasoning.

Due to the process planning demands, the intelligent database was defined as a hybrid system combining a relational database, knowledge base, knowledge acquisition module, expert system, simulator of neural network and user interface. IBD_PT includes knowledge and experience of expert process engineers in the area of process planning and mechanisms of applying rules, models, facts and proper inference in order to design such process planning which would meet specific conditions. Detailed description of IBD_PT is included in Ph. D. thesis (Rojek-Mikołajczak, 2000).

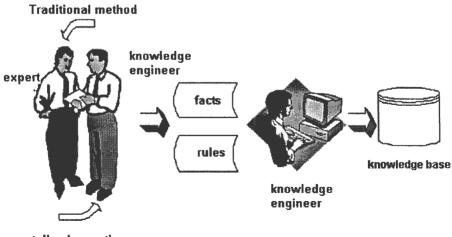
In an intelligent database application, we can distinguish the following stages of knowledge management: acquisition, identification, organisation, collection and utilisation of knowledge.

3. Knowledge management stages in IBD_PT environment with implementation of AI methods

3.1 Traditional method of knowledge acquisition

Data and knowledge for intelligent database was acquired both by means of traditional and formalized methods (Rojek-Mikołajczak, 2003). The data concerning materials and production means were acquired from standard's specifications, catalogues, literature, enterprise documentation and databases already present in the enterprise.

Traditional method of knowledge acquisition depended on observing process engineers and talking with them (Fig. 1). In many situations, it is a knowledge engineer who makes the acquisition process possible. The engineer uses the following methods: observation of an expert during problem solving, knowledge analysis based on the instructions given by the expert, case study of real-life solutions previously developed by the expert, and knowledge gathered on the basis of analogy.



talk, observation

Figure 1. Traditional method of knowledge acquisition

3.2 Formalized method of knowledge aacquisition

The use of neural networks for knowledge acquisition is a very interesting research area. The process of neural network design comprises of several steps, namely: initial data processing (pre-processing), selection of a neural network model, identification of structure and parameters of the chosen model, as well as the model verification.

Pre-processing plays an important role in both learning and testing processes of neural networks. At this stage, it is necessary to address such problems as proper attribute choices, their selection or picking relevant examples (Rutkowska et. al., 1997).

Choosing proper variables generates some additional issues which act to restrict the selection of an optimal variable set. They include the following problems: the so-called "curse of dimensionality", data correlations or interdependencies. Another problem related to pre-processing is the representation of symbolic (non-numeric) data by a neural network. The network can process only numeric data. Therefore, the network which has been used in the construction of the model supports some classification and encoding applications. The latter uses the one-of-N encoding (example shown in tab.1).

Machining Type	Roughing	Finishing
Roughing	1	0
Finishing	0	1

Table 1. Example of one-of-N encoding for the input parameter: machining type.

Because of the change of symbolic values into numeric ones, the number of inputs and outputs of the neural network increases. The above example of the machining type shows that as a result, one input becomes two.

Choosing a neural network model

A neural network is used for approximation of multiple dependencies within machine tool selections. The chosen network is feedforward, multilayered, and employing the backward error propagation method in the learning process. Its operational characteristics are relatively simple and well-known. The structure of a feedforward network is operationally stable and reliable. Task analysis (i.e. tool selection) has not implied the necessity of using a recurrent network. Process operation planning employs fixed rules (laws) to select machine tools. However, in addition to the rules, each process engineer chooses specific tools on the basis of personal experience. This experience has been included in process operation examples used in the network's learning process. Identifying structure and parameters of the chosen network model
Identification of the model's structure answers the following questions:

- How many layers does the neural network consist of (whether hidden layers are required?)
- How many neurons does each layer contain?
- Is it necessary to include an extra neuron to ensure a better network stability during the learning process (bias)?
- How to refine learning parameters of the network (learning rate, momentum factor etc.)?

Identification of the model's parameters consists of the refinement of interneuron connection weights. Connection weights are being ever adjusted until the Root Mean Square variable reaches its minimum, which in turns allows for the termination of the learning process.

The number of hidden layers as well as the number of neurons in these layers seriously influences the operational quality of a layered network. Most often, the number of hidden neurons is determined on an experimental basis. The problem here is quite complicated: too few hidden neurons prevent the network from acquiring sufficient knowledge on the problem to be solved; whereas an overly complex architecture results in the so-called "handicap" i.e. generalisation (the network memorises the training set too precisely, creating generalisation problems with regard to cases not included in the learning process).

The above predicament is usually solved through experimental means. Multiple recurrences of the learning process allow for designing networks which are large enough to "learn" the given problem, and at the same time small enough to generalise correctly.

Verifying the neural network model

Verification consists of testing, verification and adjustment of the neural network model. Model testing examines the network's operation on data included in a test file. Model verification allows for ensuring that the network selects correct output parameters for new input variables. Model adjustment consists of a change in the number of neurons in the network, extension of the learning process if the network is over-trained or a change in the number of hidden layers.

In order to assess the quality of knowledge acquired by the network during learning, three factors have been used: Root-Mean-Square Error (RMS), learning (training) tolerance and testing tolerance. The user can trace the above factors, and as a result determine the moment of termination of the learning process. RMS Error is the standard error, calculated as the sum of squared deviations of the actual and desired values, divided subsequently by the number of words. Drawback of this standard lies in the fact that it does not reflect an error of a single network output. However, it allows for the definition of the mean deviation in the training set presentation period ("epoch"). Therefore, a tolerance factor is checked as well, defining an acceptable error of a single network output. Tolerance factor correlates with sets outside tolerance, and shows the number of sets included in a group outside the current tolerance variable for the network's outputs.

Example of knowledge acquisition for selecting machine tools

A neural network has been trained to select cutting tools for a production process. A tool is chosen by means of a feedforward multilayer back-propagation network. Network inputs consist of production requisites for tool selection. Outputs comprise a set of values defining results which are obtained when selecting tools for the given requisites.

For a milling operation, the neural network's input variables include: milling type, work surface type, type and hardness of material, required surface roughness, construction and clamping type, milling diameter, number of cutting edges as well as the overall length of the milling cutter. The network's output variable is milling cutter symbol (Fig. 2).

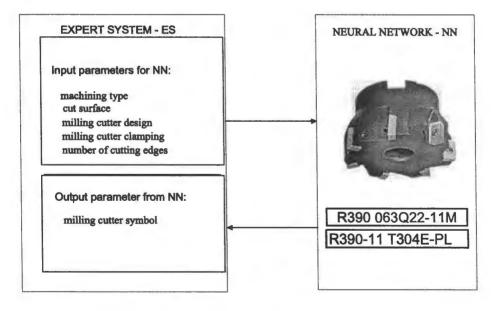


Figure 2. Knowledge acquisition using a neural network

The neural network has been trained on 300 examples of milling cutter's selection. The number of layers and neurons in the hidden layer has been refined through experimental means.

The results obtained allowed for the conclusion that the smallest Root Mean Square Error (RMS) (0.0161) occurred for a three-layer neural network with a 22-50-39 structure (the network consisted of 22 neurons in the input layer, 50 neurons in the hidden layer and 39 neurons in the output layer). The error also decreased with the increasing number of "epochs" (with the smallest error value for 100,000 "epochs"). Identification of the model's parameters consists of the refinement of interneuron connection weights. Connection weights are being ever adjusted until the occurrence of the stopping condition for the learning process. In this case, the stopping condition has been defined as the number of "epochs" with the value of 100,000. Neuron network model has been tested on data included in a test file. Model verification has allowed for ensuring the proper network operation with regard to new input variables. Tooling data acquired through the operations of a neural network are fed into the expert system, which in turn is used by a process engineer to define cutting and adjustable parameters of a machine tool.

3.3 Identification of manufacturing knowledge

Manufacturing knowledge includes facts and rules. The former occur as production data, whereas the latter result from experience of the production engineer who designs the manufacturing process.

In an enterprise, production data focus on three main groups of entities: orders, products, production means.

Data of time deadlines and quantities of manufactured products are assigned to the "orders".

"Products" include all data describing the product i.e. structure, geometry, material, manufacturing data, manufacturing process and data on the product's life cycle.

"Means of production" contain data describing production potential of the enterprise (machine tools, tooling, tools).

Rules of knowledge bases describe activities during the manufacturing process design (selection of a framework process, selection of the machine tool, selection of manufacturing parameters) and a production engineer's experience.

Fig. 3. shows an example of a decision tree for selecting type and order of operations in case of an injection mould plate. On the basis of this tree rules were created in the knowledge base.

On the other hand, a neural network contains knowledge on the selection of cutting tools in the form of neural combinations.

3.4 Organisation of Manufacturing Knowledge

In the intelligent database, a mixed representation was selected, to include the following:

- Declarative knowledge containing descriptions of products and production descriptions, which are essential for process planning; descriptions must be complete and unambiguous. Declarative knowledge occurs in the form of a relational database.
- Procedural knowledge of planning including: activity algorithms, selection of framework processes, selection of tools, selection of the machine tool and selection of machining parameters; in the case of selecting production means, order of tasks is very important; for example, selection of a tool can be made after the selection of operations. In the IBD_PT, knowledge occurs in the form of rules of inference and actions.

Moreover, declarative-procedural knowledge includes manufacturing processes already designed as examples.

3.5 Collection of Manufacturing Knowledge

Relational database is a source of data and a platform of data exchange between modules of an intelligent database.

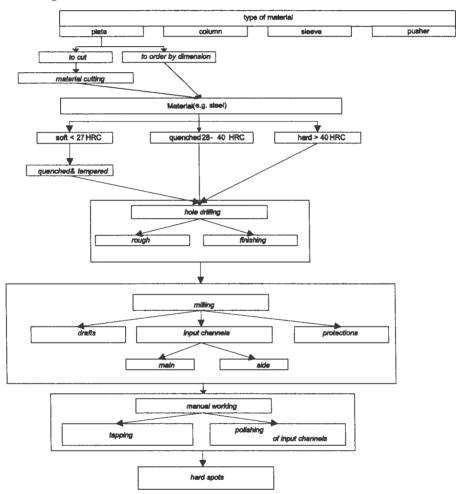
Using a relational manufacturing database, IBD_PT utilises the potential of data and knowledge already existing in the designed manufacturing processes in the enterprise.

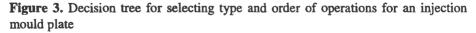
Knowledge base was created with the use of a computer-aided knowledge engineering system "CAKE". The base consists of several heterogeneous knowledge sources.

Each of these sources stores knowledge to solve a different secondary problem (sub-problem). In the intelligent database, knowledge occurs in the form of expert knowledge base of selecting framework processes, machine tools, machining parameters; neural network for the selection of tools and base of explanations and metaphors to explain the made-up decision.

3.6 Searching for Manufacturing Knowledge

Using IBD_PT, a production engineer designs the manufacturing process according to the semi-generative method of manufacturing process planning. In the preliminary stage of IBD_PT operations, design data is transferred from a CAD system to the database. Viewing design documentation and a part list, the process engineer can begin the process of creating the manufacturing documentation. On the basis of the part list, material orders are created. One by one for each specific part, and using an expert system, the process engineer prepares a manufacturing process framework. Having approved the framework, the engineer selects machine tools for each operation, taking into consideration size of the treated item and precision of machining.





The expert system suggests a machine tool to be used and justifies its choice. The next stage is the selection of tools. The engineer selects tools using the neural network. Information regarding the chosen tools is passed on to the expert system, which calculates appropriate settings of the machine tool. Having accepted tools, cutting parameters and machine adjustments, the process engineer generates a stepby-step instruction (process card) for the manufacturing process in question and finishes work with the application.

Figure 4 shows stages of knowledge search needed for planning a manufacturing process with the use of AI methods.

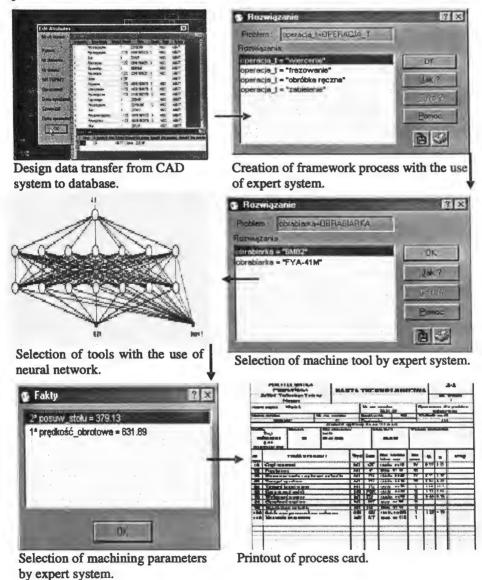


Figure 4. Application of AI methods for knowledge search

4. Conclusions

The surrounding world is a world of constant changes. Therefore, knowledge is a factor conditioning our abilities to react briskly to market alterations. Application of AI methods in knowledge management allows us to obtain a much stronger competitive advantage than the use of traditional methods. Also, it makes it possible to design manufacturing processes more efficiently.

An intelligent database uses two AI methods, namely an expert system and a neural network which improved management of manufacturing knowledge in the enterprise. IBD_PT makes it possible to obtain selected, condensed and analysed information and facilitates making up a decision. As such, IBD_PT can be included among systems which aid decision making, and in turn are considered one of the most essential tools of knowledge management.

References

- Bennett R., Gabriel H. (1999) Organisational factors and knowledge management within large marketing departments: an empirical study. *Journal of Knowledge Management*, 3, 3, 212-225.
- Demarest M. (1997) Understending knowledge management. Long Range Planning, 30, 3, 374-384.
- Rojek-Mikołajczak I. (2000) Methodology of design of intelligent database for computeraided process planning, Ph. D. thesis, Poznan University of Technology, Poznań. Poland (in Polish).
- Rojek-Mikołajczak I. (2003) Knowledge management in intelligent database aided process planning, article in the Computer Integrated Management publication, WNT, Warszawa, II, 324-331 (in Polish).
- Rutkowska D., Piliński M., Rutkowski L. (1997) Neural Networks, Genethic Alghoritms and Fuzzy Systems. WN PWN, Warszawa (in Polish).

Jan Studziński, Ludosław Drelichowski, Olgierd Hryniewicz (Redakcja)

ZASTOSOWANIA INFORMATYKI W NAUCE, TECHNICE I ZARZĄDZANIU

Monografia zawiera wybór artykułów dotyczących informatyzacji procesów zarządzania, prezentując bieżący stan rozwoju informatyki stosowanej w Polsce i na świecie. Zamieszczone artykuły opisują metody, algorytmy i techniki obliczeniowe stosowane do rozwiązywania złożonych problemów zarządzania, a także omawiają konkretne zastosowania informatyki w różnych sektorach gospodarki. Kilka prac przedstawia wyniki projektów badawczych Ministerstwa Nauki i Informatyzacji, dotyczących rozwoju metod informatycznych i ich zastosowań.

ISBN 83-89475-03-0 ISSN 0208-8029

W celu uzyskania bliższych informacji i zakupu dodatkowych egzemplarzy prosimy o kontakt z Instytutem Badań Systemowych PAN ul. Newelska 6, 01-447 Warszawa tel. 837-35-78 w. 241 e-mail: biblioteka@ibspan.waw.pl