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ARTIFICIAL INTELLIGENCE IN THE ENVIRONMENT OF MANUFACTURING

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Abstract. As declared at a number of international forums in the field of production engineering, the next millennium is the era of intelligent manufacturing systems. Many articles have covered this area, but activities are still in the process of development. Most of the problems are connected with knowledge representation, system learning, system configuration, data protocols and data exchange, decision-making strategies, knowledge availability, etc.

Over the recent years, research at the Department of Machinery has concentrated on this problem. The main area of research is connected with the intelligent technological adviser. This paper focuses on the main concept and results in this field: architecture of the system, structure of decision-making modules, description of preliminary results, and discussion.

Key words: intelligent manufacturing, technological decision-making.

1. INTRODUCTION

The modern era is characterized by intensive human activity. An increased development of new products and their quick exchange on the market result in new demands set to the flexibility and quality of production. New forms are needed to organize engineering, and glances of engineers are directed towards the biological world as a perfect and best-organized system. One of the first attempts to use biological world characteristics was *artificial intelligence* (AI). In [1] intelligence is defined as follows:

"The ability of a system to act appropriately in an uncertain environment, where appropriate action is that which increases the probability of success, and success is the achievement of behavior sub-goals that support the system's ultimate goal. Both the criteria of success and the system's ultimate goal are defined external to the intelligent system".

Actions in the field of AI have led to the development of the *expert systems*. Not only must the system model a human expert in its decision-making capability but it must also have the capability of explaining or justifying its conclusions. The task of extracting knowledge from human experts and transmitting it to expert systems is known as *knowledge engineering* [2].

Expert systems mark a paradigm shift in classical AI – a shift from general purpose, knowledge-sparse, weak methods to domain-specific, knowledge-rich techniques in which knowledge is explicitly represented.

A modern engineering system requires many different co-operating knowledge agents and forms of expertise to be fused together to accomplish a common purpose or goal. This data fusion may involve the combining and rectifying of sensor and human information from very diverse sources that can differ in format and level of detail. The reasoning and decision-making components of the system may also be composed of numerous modules that employ various methodologies and computational paradigms.

The "intelligent" CAD/CAM systems are developing in two main directions:

– toward the autonomous "intelligent" systems
– toward the separate "intelligent" modules, for particular design phases, and their integration with conventional CAD/CAM systems via properly designed data structures.

In contrast to the traditional structure of conventional CAD/CAM systems, which means fixed algorithm and data, "intelligent" system means, also, inference of component and knowledge. In the conventional systems, an algorithm unites both control and logic, whereas in "intelligent" systems, an inference component takes control on itself, and logic and data claim knowledge.

Widely spread rule-based expert systems (production systems) are very attractive and user-friendly, but they have an essential disadvantage. While each rule in the system may be very clear, the combined operation and effect of the control program may be relatively opaque. This opacity is rooted in the lack of hierarchy within the set of production rules and dynamic working memory that must be queried to follow the operation of the analysis. The rule base can also lead to inefficiency. Often the addition of more and more rules causes the system to run slower and slower. Another disadvantage is that these systems have a great reliance on human experts for knowledge acquisition. The knowledge acquired from human experts is often of unknown reliability and usability. Probably the most critical failure of most production systems is their inability to learn.

These disadvantages have led to the elaboration of a new generation of expert systems, based on the genetic algorithm, neural networks, and the so-called hybrid intelligent system. But these activities are in a very early phase and only prototypes have been introduced.

Thus, an approach allowing for a decrease in disadvantages of production systems is described in this paper.

2. PARADIGM OF THE INTELLIGENT ADVISORY SYSTEM

Principles of expert systems provide advice to specialists in the related fields. This idea leads to the elaboration of an advisory system.

The main requirements set to the system are as follows:

- information used and supplied by the system has to be compatible with users-modules
- information transfer within modules has to take place using some standard like STEP (Standard for the Exchange of Product Data)
- the system has to function autonomously, as well as in the environment of CAx (Computer Aided activities (Design, Manufacturing, etc.))
- in order to decrease the content of knowledge base, the system has to contain object-oriented (problem) modules
- the system has to consist of two levels: decision-making (advisory) level and information-producing level
- the system has to be based on the principles of AI with opportunities for symbolic equation-solving, "optimizing", and information producing
- information exchange has to take place on the basis of unified product and process model, using the part and feature classification system.

The system architecture is introduced in Fig 1. There is a metasystem to develop system modules. It is a chosen shell or environment for creating expert systems with suitable interface for the field. The user interacts with the control module, consisting of the inference engine and the analyzer, the role of which is to work out via user's interface the search strategy on the basis of initial data given by the user.

The configuration of the first level depends on the user's needs and can be reconfigured any time. On this level, decisions will be made and recommendations will be worked out on the basis of minimum data (i.e., a large DB is not needed). It is meant for human experts working in an interactive way with the system without CAx systems.

The second level of the system is needed in the environment of CAx systems, using related databases.

The described principles will make the system extendible and reconfigurable according to the user's need.

The modules of the system will be: part materials, tool materials, cutting tools, measuring tools, machine tools, process plans, quality engineering, and project management.

The intelligent advisory system introduced in Fig. 1 was planned as a single-technique based system. The production rules based system was used. However, in fact, most of the real world manufacturing problems are not simple. The strengths and capabilities of a single technique cannot effectively solve them. One approach to deal with these complex real world problems is to integrate the use of two or more techniques in order to combine their different strengths. Four types of problem-solving processes are in practical use [3]: information

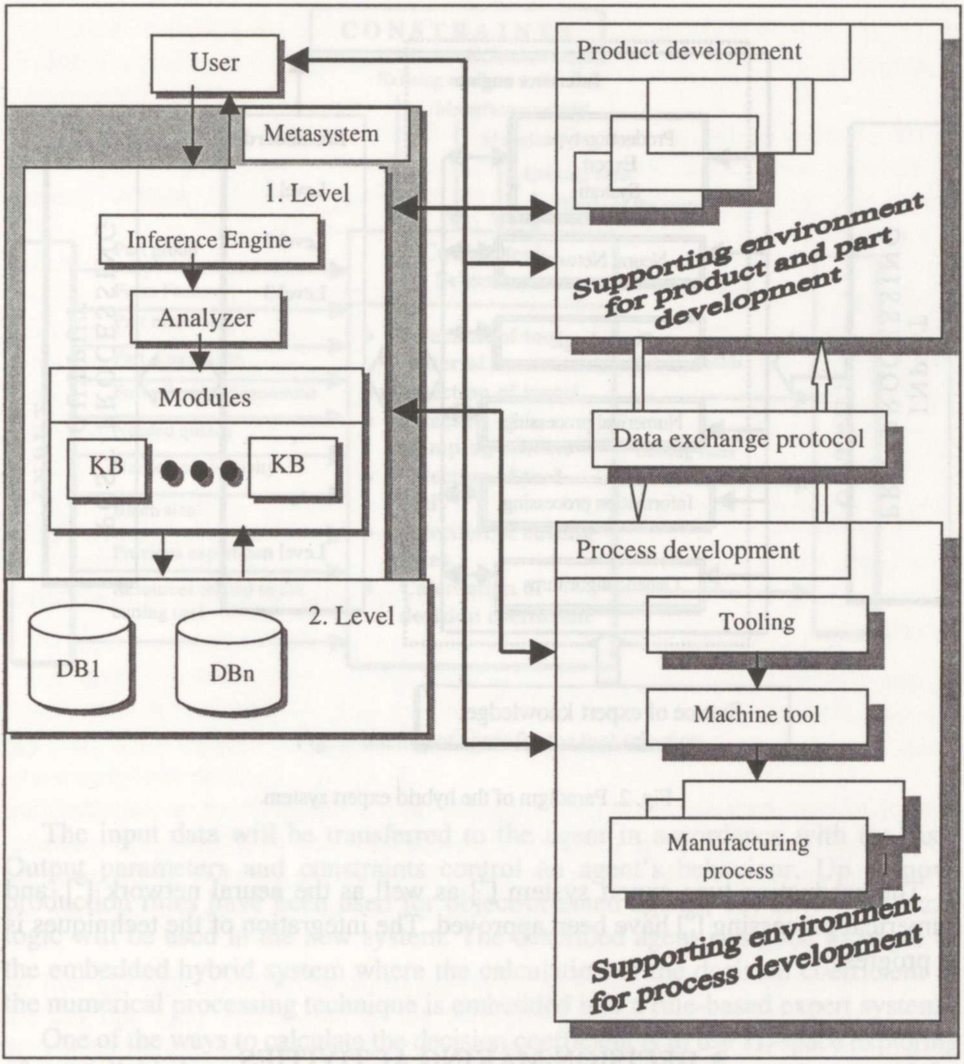

Fig. 1. Architecture of the advisory system.

processing, numerical processing, symbolic processing (production rules based expert systems), and sub-symbolic processing (neural networking). Thus, the hybrid intelligent system would be appropriate. In Fig. 2, the next generation intelligent advisory system is introduced. Input parameters will be pre-processed in accordance with the related module's (or agent's) needs. The different technologies can be embedded or loosely coupled and will share data with each other either directly or through an intermediary mechanism, such as a blackboard system. The planned output with the post-processing needed will finish the task.

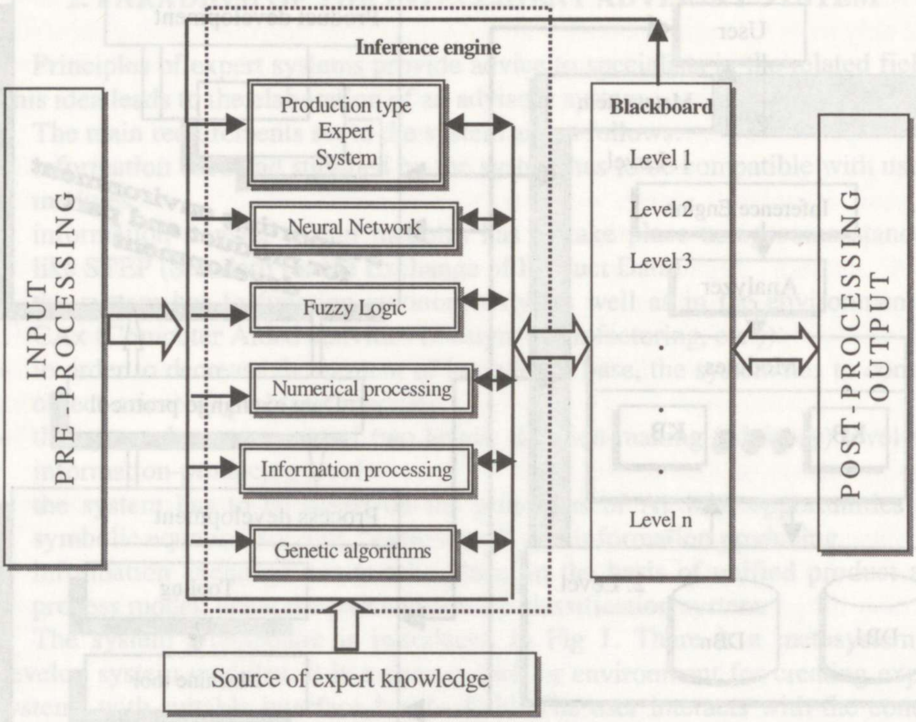

Fig. 2. Paradigm of the hybrid expert system.

The production type expert system [4] as well as the neural network [5], and numerical processing [6] have been approved. The integration of the techniques is in progress.

3. DECISION-MAKING ACTIVITIES

Decision-making has an essential role in an advising process. It can be done on the basis of heuristic knowledge (fuzzy environment and related techniques) as well as using numerical processing to calculate the decision coefficient.

The new term "intelligent agent" is in use. For instance, according to [7], the concept of agent means an independent, intelligent and virtual entity with defined degrees of freedom, able to collect and process data, which are the basis for creating a model of the surrounding environment and taking decisions. In Fig. 3, the intelligent tool selection agent is introduced. In our sense, two types of agents are in use: object-oriented and implementation-oriented. An object-oriented agent is for solving the subtasks (selection of tool material, selection of insert, etc.), and an implementation-oriented agent is for solving the practical complex problems (tool selection, process planning, inspection, etc.).

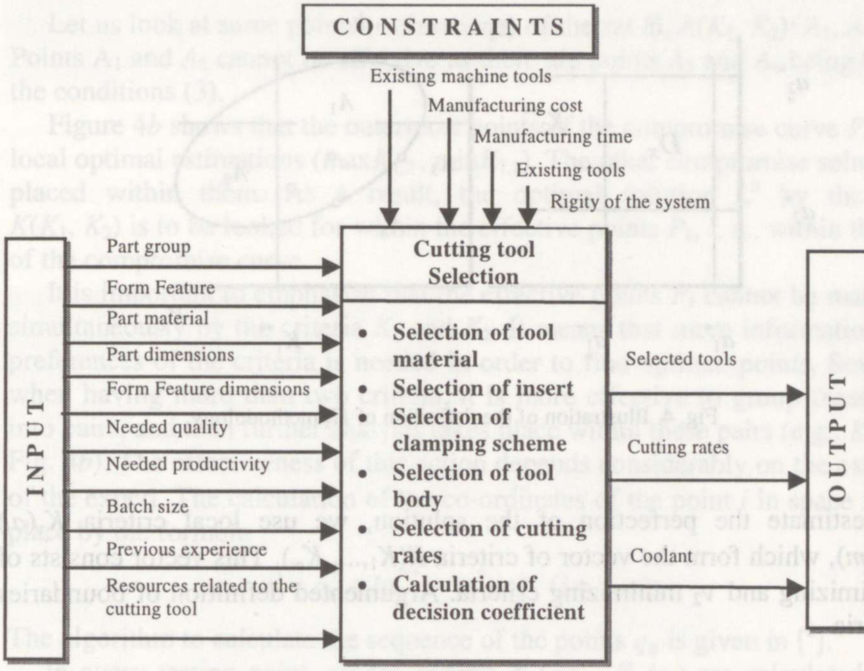

Fig. 3. Intelligent agent for the tool selection.

The input data will be transferred to the agent in accordance with the task. Output parameters and constraints control an agent's behaviour. Up to now, production rules have been used for object-oriented agents, but obviously fuzzy logic will be used in the new system. The described agent is a good example of the embedded hybrid system where the calculation of the decision coefficient as the numerical processing technique is embedded into a rule-based expert system.

One of the ways to calculate the decision coefficient is to use Π_τ-space exploring of even-divided sequences point to point. According to [8], the preference of the method is that voluntary selection of test points in a multidimensional space is not effective enough, as a human being lacks the intuition of multidimensional space, and the dialogue between an expert and a computer takes place in the understandable language and categories. The decision-making coefficient will be calculate by the methodology described below.

A set of constructional, geometrical, and technological parameters a_j ($j = 1, n$) performs the vector $A(a_1,..., a_n)$, the parametric constraints of which

$$a_j^* \le a_j \le a_j^{**} \tag{1}$$

are selected with the help of recommendations, experience or intuition. Constraint (1) forms the subspace D_x in the n-dimensional space (Fig. 4a). The limited space is defined by criteria restrictions.

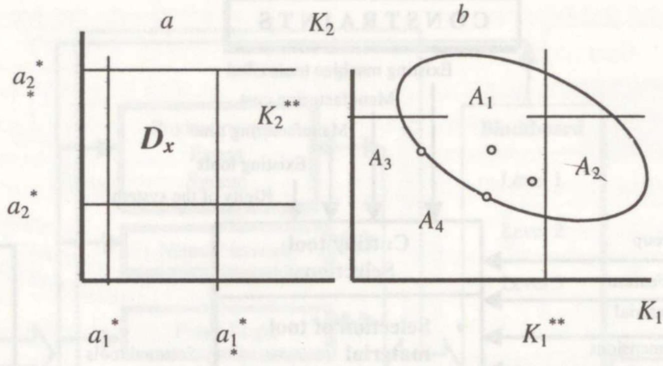

Fig. 4. Illustration of the definition of Π_τ methodology.

To estimate the perfection of the solution, we use local criteria $K_\nu(a_j)$ ($\nu = 1, m$), which form the vector of criteria $K(K_1,..., K_m)$. This vector consists of ν_1 maximizing and ν_2 minimizing criteria. Argumented definition of boundaries by criteria

$$K_\nu(a_j) \geq K_\nu^{\max}, \forall \nu \in \nu_1$$
$$K_\nu(a_j) \leq K_\nu^{\min}, \forall \nu \in \nu_2 \quad (2)$$

cannot always succeed before the process, and so these have to be specified during the dialogue. Thus, as most of the criteria are functional, the pseudo-criteria in the form of $K_i = f_i\,(a_j)$ in order to make the process of the solution easier, are practical for use. Then, the restrictions in the form $K_i\,(A) \leq K_i^{**}$ or $K_i\,(A) \geq K_i^*$ take place.

The subset of the parameters a_j, satisfying the conditions (1) and (2) will be called below as a permitted or alternative set of parameters $\{a_a\}$ and the set $\{L(a_a)\}$ as the set of permitted solutions. In fact, within the permitted set of solutions, the set of effective solutions L_e is present. The solution is effective when at the points defined by the set $\{A\}$, there is no other such solution a_A' where the inequalities $a_A' < a_A^e$ or $a_A' > a_A^e$ are not valid, and inequalities

$$K_\nu(a_A') < K_\nu(a_A^e)$$
$$K_\nu(a_A') > K_\nu(a_A^e) \quad (3)$$

are valid. One of these conditions has to be strong (> or <).

Let us now look at the process of solution if we have two boundaries $K(K_1, K_2)$. If the set of effective parameters $\{a_A^e\}$ in the domain D_x denominates as P_x (named as the compromise curve), then on the plain K_1, K_2 the set of effective solutions L_x^e corresponds to the points P_x. Such a situation is illustrated in Fig. 4b.

Let us look at some points (estimations) of the set $D_x A(K_1, K_2)$: A_1, A_2, A_3, A_4. Points A_1 and A_2 cannot be effective as there are points A_3 and A_4 being better by the conditions (3).

Figure 4*b* shows that the outermost points of the compromise curve P_k are the local optimal estimations ($\max K_{1,2}$, $\min K_{1,2}$). The other compromise solutions are placed within them. As a result, the optimal solution L^o by the criteria $K(K_1, K_2)$ is to be looked for within the effective points P_k, i. e., within the points of the compromise curve.

It is important to emphasize that the effective points P_k cannot be made better simultaneously by the criteria K_1 and K_2. It means that more information on the preferences of the criteria is needed in order to find optimal points. Sometimes, when having more than two criteria, it is more effective to group these criteria into pairs, and then further analysis takes place within these pairs (e.g., $K_1 - K_2$ in Fig. 4*b*). The effectiveness of this action depends considerably on the experience of the expert. The calculation of the co-ordinates of the point i in space Π_τ takes place by the formula

$$x_j^i = a_j^{\,*} + (a_j^{\,**} - a_j^{\,*})q_{ij} \quad (j = 1, n). \tag{4}$$

The algorithm to calculate the sequence of the points q_{ij} is given in [8].

In every testing point, all the criteria $K_1(a_j),\ldots,K_k(a_j)$ are calculated and for every criterion, a table is created. The number of the testing point is in the table as well. This method is realized, using the programming language *Visual Basic*. An example is presented in Fig. 5.

Selection or specification of the boundaries takes place during the inspection of the testing tables. It is important to know that if the selected boundary K^{**} is too small, then the set of allowed points can be empty. The emptiness of the set D is checked by the inequalities

$$K_\nu(a_{ij}) \le K_\nu^{\;**} \quad (\nu = 1, 2, \ldots, k). \tag{5}$$

If s values corresponding to the selected boundaries K_1^{**} are in the testing table so that

$$K_1(a_{i1}) \le \ldots \le K_1(a_{im}) \le K_1^{\;**} \tag{6}$$

is valid, then testing takes place by looking on all boundaries in the points $a_{i1},\ldots, a_{is}$. After that, when the set D of the allowed points is found, the optimal solution will be looked for. The determining evaluation criterion $K(A)$ is selected and the solution of point A is expressed as

$$K(A) = \min K(A)\,. \tag{7}$$

Then the co-ordinates of the point A are optimal.

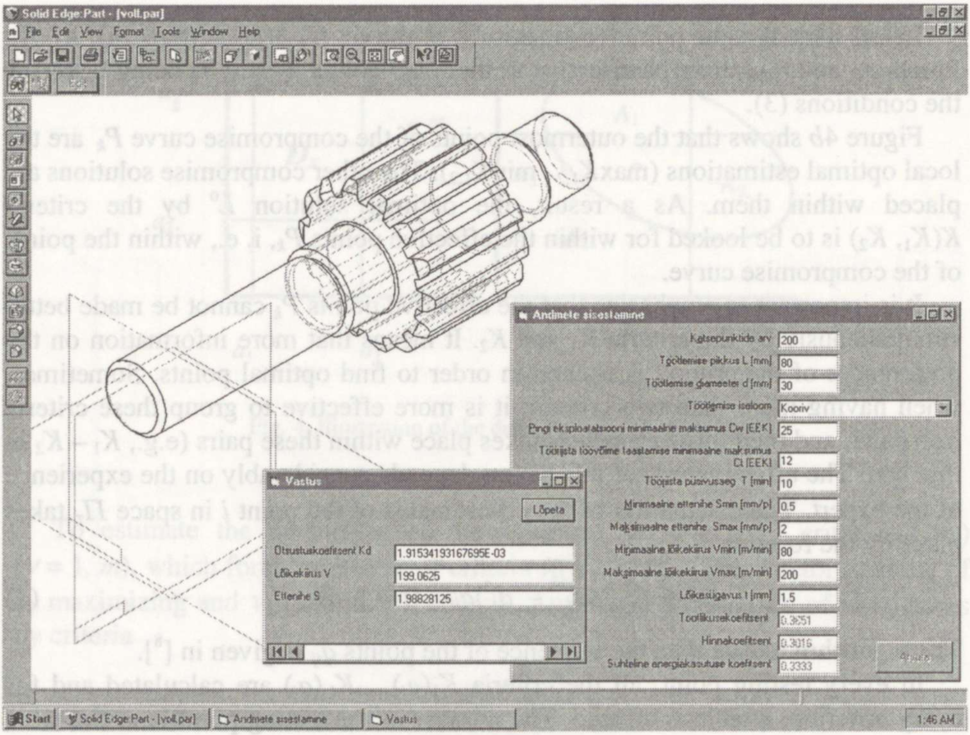

Fig. 5. Example of interrelation within modules (agents).

The problem here lies in the selection of the evaluation criterion, which is crucial. It is possible to select one determining criterion or several ones. In the case of one determining criterion or target function, the selection has to be done within the $K_1,...,K_k$. Generally, it is rather difficult to do. By solving the technological problems, it would be suitable to select a complex evaluation criterion (decision coefficient) as a function of all the criteria in the form

$$K_D = \sum \alpha_\nu K_\nu(A), \quad \nu = 1,..., k, \tag{8}$$

where α_ν is a coefficient of relative importance (CRI), and the conditions $\alpha_\nu \neq 0$ and $\alpha_1 + ... + \alpha_k = 1$ have to be fulfilled. To calculate the CRI, the method of comparing parameters' (objects') pairs and the statistical treatment of these results are used. The case with several determining evaluation criteria suits better in a design situation, and it is a special topic for discussion.

Thus, the evaluation criterion $K(A_l)$ has to be calculated in all points in the optimization block. It seems to be practical to use normalized criteria related to the best criteria of the maximum value or as the weighted mean.

In the first case, if $K_v^{**} = K_v(A_1)$ is the criterion with the maximum value, the normalized criteria are

$$\lambda_v(A_j) = K_v(A_j)/K_v^{**} \tag{9}$$

and in the testing tables, the row (7) is substituted by

$$1 \geq \lambda_v(A_{12}) \geq \ldots \geq \lambda_v(A_{1N}) \,. \tag{10}$$

Figure 5 demonstrates the use of the described methodology. In order to manufacture the shaft, the cutting rates are needed. Activating the surface on the shaft, the related data will be prepared for transfer to the needed module. After activating the most right icon on the main toolbar (Fig. 5), the data will be transferred to the module (agent) of the cutting rates. The larger window on the display is for the initial data and the smaller one for the selected cutting rates. As criteria, the productivity, cost, and energy consumption are used.

The methodology described is also used to select the cutting tools for the surfaces.

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TEHISINTELLEKTI VÕIMALUSTE KASUTAMINE TÖÖTLEVAS KESKKONNAS

Jüri PAPSTEL

Viimase aja rahvusvahelistel teadusfoorumitel on deklareeritud, et järgmine aastasada on intelligentse töötlemise ajajärk, pidades silmas tehisintellekti laialdast kasutamist tootmises. Hoolimata mitmetest sellealastest töödest on tehisintellekti kasutamine alles prototüüpide tasemel. Põhiprobleemid on seotud teadmuste esitamise, süsteemi õpivõime, süsteemi konfigureerimise, andmeprotokollide ja andmevahetuse, otsustuste tegemise strateegia, teadmuste kogumise ja muuga.

Aastate jooksul on nimetatud teemat käsitletud ka Tallinna Tehnikaülikooli masinaehituse instituudis. Põhiline uurimisvaldkond on olnud seotud intellektuaalse tehnoloogilise nõustajaga. Artiklis on käsitletud intelligentse nõustamissüsteemi põhikontseptsiooni ja selle praktilist rakendamist.