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Application of expert systems as an element of sustainable development of educational process

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Abstract. The authors look at the application of neural networks to sustainable business development in the construction industry. The actual work of self-learning neural networks with statistical data tables in construction is studied. The possibilities of managing construction scheduling and material supply requirements from the point of view of work execution with the participation of neural networks are shown. Appropriate statistical indicators can be used in subsequent numerical calculations. Tables above all allow for the systematisation of numerical information. The study of large number of tables by neural networks allows statistical study not only of the collective as a whole, i.e. of the totality of objects and phenomena - macro-units, but also of subdivided collectives, i.e. separate parts of the whole - micro units and complex units (united by one attribute). Therefore the subject of statistical sentence-table may be statistical population as a whole (macro units), aggregate dissected (separate observation units) - micro units and separate aggregate - complex units. This is quite understandable, because statistical judgement can refer to the object of observation at any stage of this process, i.e. as a result of the dissection of the population into micro units, combination of the latter into small populations (complex units) and generalization of micro units and complex units into units of the concept - macro units.According to the results of implementation of the automated control systems based on neural networks the high purity and quality of design solutions based on the automated data processing of production and economic activity of the construction organisation is achieved. Their actual economic efficiency is calculated.

1 Introduction

The use of expert systems in education is a progressing trend in the use of artificial intelligence in an educational environment. These systems are based on the use of artificial intelligence elements and are used in automated educational systems to improve the quality of learning.

The introduction of these technologies ensures the sustainable development of the educational process and contributes to the creation of necessary competences in learners.

The main advantage of expert systems is the ability to accumulate knowledge and preserve it for a long time.

According to Johnson's classification [1], it is a kind of knowledge-based systems. Such systems also include natural language processing systems, which use knowledge in the process, but do not require expert knowledge. Expert systems involve active participation of a human expert and, using mainly the fundamentals of a particular problem domain, solve complex problems not usually solved by non-experts and communicate with the latter in natural language. In teaching university students, this allows them to conceptualise their work and ensure mutual learning and the accumulation of specific competences in the subject area in the process of interaction between the expert system and the student [2-4].

This interaction between the individual and the social environment is carried out as a process of personality formation, a process of social enrichment of individual lifestyle in education and competence acquisition within the framework of higher education. From this we can formulate the basic principles of learning with the help of expert systems

- Objectivity of information; the process itself should be based on objective data obtained through information exchange between the elements directly involved in the educational process and its management bodies. The data requested should be as formalised and easily verifiable as possible. Information provided in the reverse direction should also be specific and useful [3, 5].

- comparability of data. This requirement is due to the fact that tracking the performance of the systeminvolves not only stating its state but also studying the changes that occur in it. Comparability is only possible when the same object is studied, based on the same empirical indicators.

- adequacy; it implies the study of the system taking into account changing external conditions (for compliance with them).

2 Materials and methods

The implementation of this principle involves assessing the impact of various external factors on the implementation of the production process.

- Foresight; it means obtaining data that allows predicting the future of the system, the possible

predictability; in the sense of obtaining data enabling forecasting of the future of the system and possible changes in ways to achieve goals. This principle involves assessing possible trends [2,6].

- Purposefulness, which implies obtaining necessary and sufficient information based on the stated purpose of the activity.

Some features of expert systems in practical use by users are shown in figure 1 (Fig. 1)

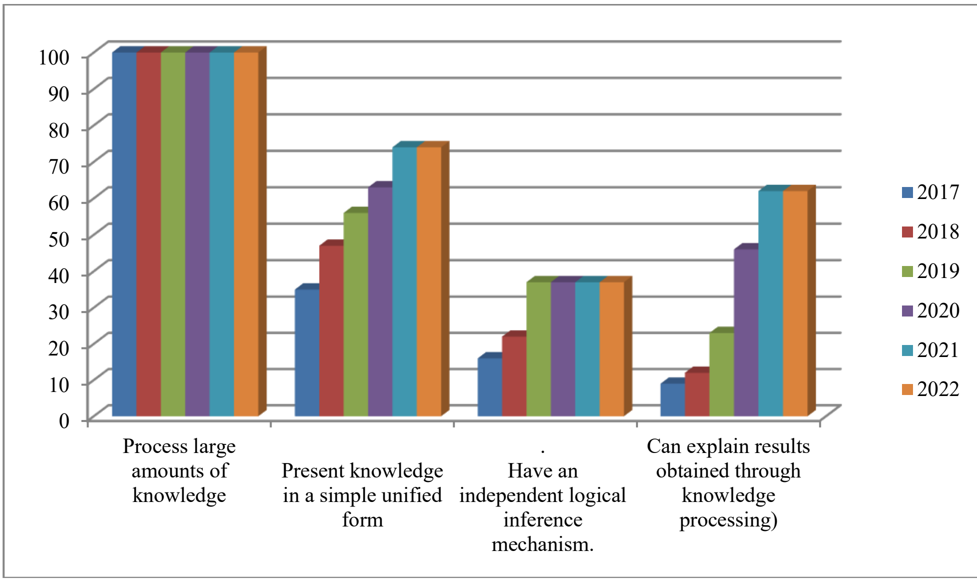

Fig. 1. Use of expert systems according to survey participants (data obtained by the authors).

When considering the effectiveness of expert systems, it is convenient to highlight their practical and methodological value.

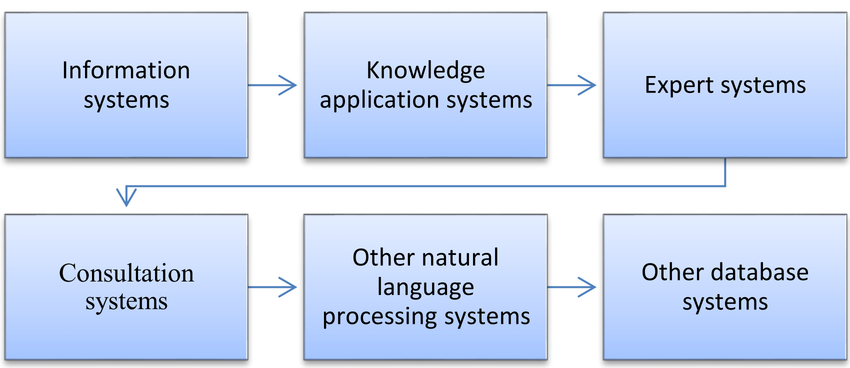

Fig. 2. Classification of expert systems with a focus on knowledge application systems (compiled by the authors).

There are now many known publications on research in medical diagnostics, computer software design, fine arts, etc. These are all studies of how the specialist solves complex fuzzy problems, how to describe the difference between the specialist and the novice. However, the question of who is better able to process and use knowledge has not yet been answered, apart from a few hints [3, 8-11].

As can be seen from the examples above, the methodological value of off-the-shelf systems is that they offer new research topics and methods. At the same time, knowledge extraction methods for building expert systems as an alternative to the known variety of methods for "getting at what humans know" are expected to enrich methodology through the combined application of all these methods.

Knowledge sources can generally be thought of as the expert, the system developer and the user. In practice, the same person can play several roles. Sources of knowledge for expert systems are intellectual products: textbooks, reference books, materials of specific research in the problem area, etc. In addition, the developers of the system themselves already have knowledge in the relevant area and teach the system the correct algorithm for extracting knowledge [9].

In the relatively early stages of research, the expert system did not have a qualitative distinction between differentiated but biased knowledge and expert judgement. Nowadays, such a distinction can be attributed to the difference in training and education time for the expert, which reaches five thousand hours in length. The implication was that it was easier to understand the characteristics of the expert as an object of comparison by contrasting examples than to study only his outstanding ability in a particular field. In particular, the prevailing view was that a novice was the same expert without content knowledge and it was hypothesized that an expert could be made into a novice if the latter was given the missing knowledge. Nowadays, there is an analogous opinion that an expert system with an empty knowledge base is a rookie system that will become a real expert system if it is filled with knowledge modules, such as product rules [12].

In the process of learning to work with expert systems, students themselves learn to extract and apply knowledge, including from areas previously unknown to them and new methods and algorithms created independently [13].

Regardless of the knowledge extraction methods chosen, experts in the construction of expert systems will transfer knowledge to them in the hope of gaining it from the experts. If the functions of the system have already been defined, then of course the most important thing is to obtain the rules of inference that are needed to implement these functions [14, 15].

1. basic structure. It is very important to list the objects, concepts and attributes that form the basic structure of the problem domain and to know the properties of the domain. The relationship between objects, concepts and attributes is organised through inference rules. Consequently, by addressing questions to the expert about what the system should advise, which blocks constitute the system, and which blocks these blocks consist of, it is possible to specify a language for describing rules, such as those similar to the rules embedded in the system.

2. Reasonableness criteria. Why does the expert solve a certain problem in this particular way? Maybe this way has a high heuristic value, or maybe it has been prepared for failure? What kind of support does this method need?

3 Results

The means used by the assessor depend on these criteria. Hypnograms used by the sleep disorders expert, decision-making models used by the decision-making expert, etc. - all these tools are only available to the assessor, they are like an extension of the assessor's hand. One of the goals of implementing expert systems is to facilitate the use of such tools by non-experts, so it is desirable to gain knowledge on their use from experts.

The literature on building expert systems discusses knowledge extraction methods that highlight the advantages of choosing one approach or another for system development. We look at three approaches: long-term working group, rapid prototyping, and the "emphasis on knowledge analysis" approach, and consider briefly one of the current knowledge extraction methods used in the project.

Long-term working group. Experts and knowledge engineers organise a long-term group to collaboratively build models and problem-solving programmes.

Operational prototyping. In this approach, a proactive group of experts is formed, and after the knowledge engineers assimilate initial knowledge of the problem domain, the experts are questioned in detail and, within a short time frame, complete the program, which is considered a prototype.

The work of assessing and modifying the resulting expert system will then be essentially carried out. In this approach, a blueprint of the system will be created, so to speak, and it will sometimes be necessary to reject everything if necessary. The prototype will be developed as a kind of testing ground which will generate sufficient interest and enthusiasm amongst the student experts for the construction of the expert system.

Particular attention is paid to knowledge analysis. This approach is based on as detailed a preliminary analysis of knowledge and problem-solving methods in the problem domain as possible. The system will only be designed and implemented after a comprehensive knowledge analysis.

The purpose of the analysis is to reduce the risk and cost of building the expert system. It is difficult to specify the functions of the system in detail if the design and implementation ideas are not taken into consideration, so in order to confirm the capability, usefulness and feasibility of the system, information is gathered to clarify the constraints of important design decisions without creating any prototype system. Such decisions relate, for example, to the depth and form of knowledge representation.

Another incentive for serious knowledge analysis is related to the fact that it is usually very difficult to keep the experts interested for a long time. If critical information is gathered and analysed in advance, it is often possible to make design and implementation decisions on the basis of the information gathered, without already liaising with the experts.

All these approaches do not contradict each other, but differ in emphasis. At present it is difficult to answer the question of which approach is optimal. However, as expert systems become technically better and more widespread, the criteria for comparing approaches will change, and it is possible that the boundaries for classifying and selecting them will become fuzzy.

In practice, it is convenient for students to break down the process of knowledge analysis into two broad stages. The purpose of the first stage is to determine the roles to be played by the designed expert system and the user. Consequently, here it is necessary to analyse the problem domain, define the tasks to be solved and collect information about the working environment of the experts and the expert system.

4 Discussion

The aim of the second step is to specify in detail the work to be performed by the expert system, provided that the functions of the human-machine system, consisting of the system itself and the user, have been defined. This specification will also include the knowledge for the realisation of the expert capability and the rules for logical deduction.

When the definition of functions is complete, an interpretive model is created to interpret the data obtained during knowledge extraction. Now the information from the experts and other sources can be described in terms of the interpretation model.

. The outside world is the world of system users, or in other words, the world in which we live. The use of terms close to those in the external world is not only convenient for users when communicating with the system, but also contributes to a real representation of the subject area. But this requires a transformation between external (natural language, image, etc.) and internal (knowledge representation language) languages. As said above, if the internal knowledge correctly reflects and represents the structures of the external domain as models, then it can be assumed that the result of the partitioning into modules in hierarchical worlds is consistent with the semantic structure of the external language. Furthermore, the dialogue with the external world is only conducted in the worlds associated with the theme of the dialogue. Consequently, if the interface is represented as a model of worlds, unambiguously corresponding to the hierarchical worlds, if the correspondence is successful, a lot of conveniences can be obtained in case of using natural language as an external language of the system, which will be discussed further. The model is called a multihierarchical model, the interface unit is called a language domain, and the internal knowledge unit is called a concept domain.

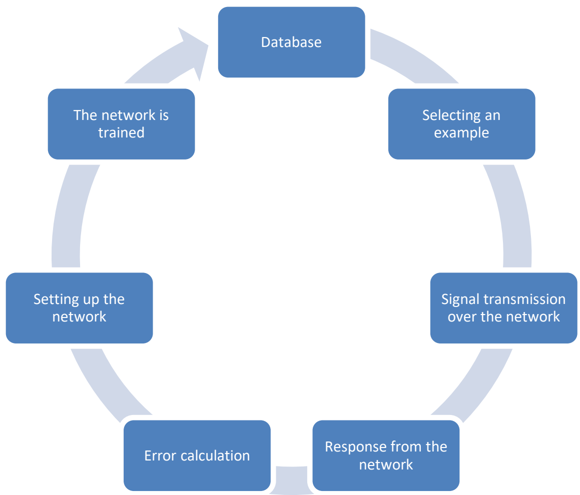

Fig. 3. The process of training a neural network to search for knowledge (compiled by the authors).

To describe such a multihierarchical model, it is convenient to choose a logical language for the following five reasons.

1. Logic languages by their purpose are languages for modelling human logical inference process, so they provide a more natural representation of knowledge than other programming languages.

2. Logical languages represent theses expressed in natural language as first order predicate logic statements, therefore they provide better consistency with natural languages than other languages.

3. The representation of statements is simple and unified, so it is possible to describe in the same format knowledge defined within worlds, knowledge that forms the structure of worlds, and metacognitions that use knowledge in statements as objects. And this means that logical languages have a flexible structure as languages for describing knowledge.

4. Nowadays it is easy for a student to acquire a Prolog processing system in a logical language and anyone can learn it.

It is called

The advantages of Boolean languages are the reason for its successful use nowadays as a knowledge description language, in spite of some disadvantages, say, low efficiency of the brute force procedure with returns.

By learning specific linguistic knowledge, the student's understanding of such a phenomenon as language is enhanced when working with expert systems.

The language domain is a unit for performing mutual transformations between concepts from the domain of concepts and natural language, so two functions are needed here: a transformation function between concepts and natural language semantics and a function to either synthesise sentences from simple words according to natural language grammar or to parse sentences. The world of grammar on the upper level of the language domain includes the grammatical knowledge necessary for sentence synthesis or parsing and the knowledge of words shared across all worlds: for example, English prepositions, most of the function words, Japanese auxiliary verbs and adjectives and other grammatical forms. The language domain worlds below the grammar world are word and concept transformation units, i.e. they are the vocabulary worlds. Dividing the vocabulary according to the object worlds has the following merits.

1. The number of dictionary objects can be reduced to the number of objects in the concept area, which provides good processing efficiency.
2. In the object domain, the semantic range of multi-valued words is limited, so it is easy to identify their meaning. For example, a frame in the world of knowledge representation means Minsky's frame model, in the world of computer-assisted learning means a sequential display learning model
3. As synonyms (parameters and arguments) can be defined in pairs, which rules out misunderstanding.

As already mentioned, multivalued words usually express different concepts, so they often belong to different worlds in the field of language. In the multihierarchical model, the worlds serving as the topic of conversation inherit the necessary knowledge from the higher-level worlds and through unification define word concepts, which plays an essential role in identification.

The hierarchical organization of worlds is also effective for processing fuzzy sentences.

Student's knowledge acquisition in expert intelligent information systems can be broken down into two stages: the system generation stage and the knowledge addition stage in the finished system. Knowledge input in natural language dialogue during system generation seems to be the most interesting research topic of the knowledge acquisition process, but technical methods for knowledge input into systems have not yet been mastered. It is proposed to enter knowledge into the vocabulary and concept domain through dialog editors, in the form of figures, tables, etc. It is possible to consider knowledge acquisition by existing systems.

1. Clarification of fuzzy knowledge. As mentioned above, when there is insufficient knowledge in the system, it is difficult to correctly identify fuzzy input sentences in natural language. By acquiring correct knowledge in a dialogue with the user, the system provides such identification, if, of course, the knowledge in the system is consistent. Attention should also be paid to the fact that insufficient reliability of the user model reduces the reliability of the system.
2. Completeness of knowledge, and detection and processing of inconsistent knowledge. During execution of programs in logical languages identifying meaning in the domain of concepts, failures are possible in two cases, namely: when knowledge does not include the rules corresponding to the notation of predicates of some goal or subgoal, and when, despite the presence of such rules, parameter inconsistency or inconsistent conditions occur. Failure in the first case is overcome by identification with the new knowledge, but failure in the second case already requires identification of its causes. In case of redundant knowledge, i.e. when identification of an input sentence in the domain of concepts is successfully completed and in a natural language dialogue the answer "yes" is given to this sentence but the user receives a sentence with the same meaning, system knowledge correction is not necessary.

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5 Conclusion

Globally, there has been a steady increase in interest in the sustainability of the industry in the new digital economy, reducing costs and improving production efficiency. According to the results of the implementation of the automated control systems based on neural networks the high purity and quality of design solutions based on the automated data processing of production and economic activity of the construction organization is achieved. Their actual economic efficiency is calculated and financial incentives are provided to participants in the development and implementation of design solutions depending on the resulting savings, which ensures the motivation and sustainable development of industry processes in the construction business and the construction business itself.

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