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Expert System Used on Materials Processing

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1. Introduction

Conventional computing programs characterize through an *algorithm* approach as the specialists called it. This approach allows solving a problem by using a preset computing scheme which applies to some structures well-known for input information and produces a result that keep to program operations sequence made within computing scheme. Yet, there is another category of problems whose solving has nothing to do with classic algorithms but supposes a higher volume of specialty knowledge for very strait domains. Such specialty knowledge does not represent the usual "luggage" of a certain human subject, they being on view only for *experts* within the interest domain of the problem. Such problems can treat subjects as automat diagnosis, monitoring, planning, design or technical scientific analysis. Computing programs that solves such problems are known as *expert systems* (ES) and the first development attempts of such programs dates from mid of 1960 – 1970's. Unlike conventional programs, ES are conceived to use, mainly, symbolic sentence, developed through interference. As a branch of *artificial intelligence* (AI), expert systems developed pursuing the study of knowledge processing.

An *expert system* is a program that uses knowledge and interference procedures for solving quite difficult problems, which normally needs the intervention of a human expert to find the solution. Shortly, expert systems are programs that store specialty knowledge inserted by experts.

2. Characteristics of ES

These systems are often used under situations without a clear algorithmic solution. Their main characteristic is the presence of a knowledge base along with a search algorithm proper to the reasoning type. Knowledge base is very large most times, so the way of representing knowledge is very important. Knowledge base of the system must separate from the program, which must be as stable as possible. The most used way of representing knowledge is a multitude of production rules. Operations of these systems are further controlled by a simple procedure whose nature depends on knowledge nature. As in other artificial intelligence programs, when other techniques are not available, search has recourse to. Expert systems built up to date differs from this point of view. The question arises whether there can be written rules as strict as in any situation there is only an applicable solution? And, also, finding all solutions is necessary or it is sufficient only one?

An expert system must have compulsory three main modules that form the so-called *essential system*:

- Knowledge base formed by the assembly of specialized knowledge introduced by human expert. The knowledge stored here is mainly objective descriptions and the relations between them; knowledge base takes part from the cognitive system, knowledge being memorized into a specially organized space; storage form must assure the search of knowledge pieces specified directly through identifying symbols or indirect through associated properties or interferences that start from other knowledge pieces.
- Interference engine represents the novelty of expert system and takes over from knowledge base the fact used for building reasoning. Interference engine pursues a series of major objectives such as control strategy election based on current problem, elaboration of the plan that solves the problem after necessities, switching from a control strategy to another one, execution of the actions preset in solving plan. Although interference mechanism is built from a procedures assembly in the usual meaning of the term, the way in which knowledge are used is not estimated by program but depends on the knowledge it has at command.
- Facts base represents an auxiliary memory that contains all users' data (initial facts that describe the source of the solving problems) and the intermediary results made during reasoning. The content of the facts base is stored generally in volatile memory (RAM) but to user request; it can be stored on hard disk.

2.1 The modules of an ES

Communication module assures specific interfaces for users and for knowledge acquisition. User interface allows the dialogue between user and quasi natural language system. It transmits to interference mechanism user's requests and his results. It facilitates equally the acquisition of the initial problem and result communication.

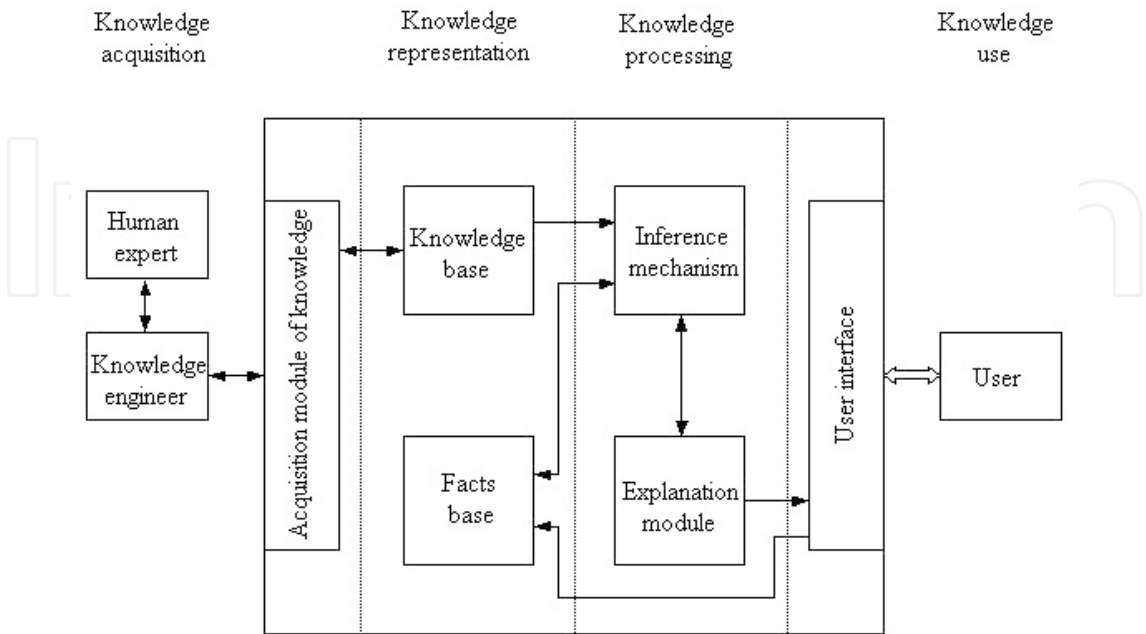


Fig. 1. ES modules

Acquisition module of knowledge takes specialized knowledge given by human expert through the engineer, into a not specific form to intern representation. A series of knowledge can arise as files specific to databases or to other external programs. This module receives the knowledge, verifies their validity and finally generates a coherent knowledge base.

Explaining module allows path tracing followed in reasoning process by resolvent system and explanation issuance for the achieved solution by emphasizing the causes of eventual mistakes or the reason of a failure. It helps the expert to verify the consistency of the knowledge base.

Explanation and updating. In terms of the application that it is built for, the effective structure of an expert system can differ towards the standard structure.

For example, initial data can be acquired from the user and from automatic control equipment

Nevertheless, it is important for expert systems to have two characteristics:

- To explain the reasoning and if it is not possible, human users could not accept it. For this, it must be enough meta-knowledge for explanations and the program must go in intelligible steps.
- To attain new knowledge and to modify the old ones, and usually the only way of introducing knowledge into an expert system is by human expert interaction.

2.2 Development of an ES

The development of an expert system represents design process of the system going from users' demands of implementing testing and finally launching the product onto market for the effective use. Many times, there are distinctions in design stage between physical design and logical one because these stages need different activities and resources both technological nature and human one.

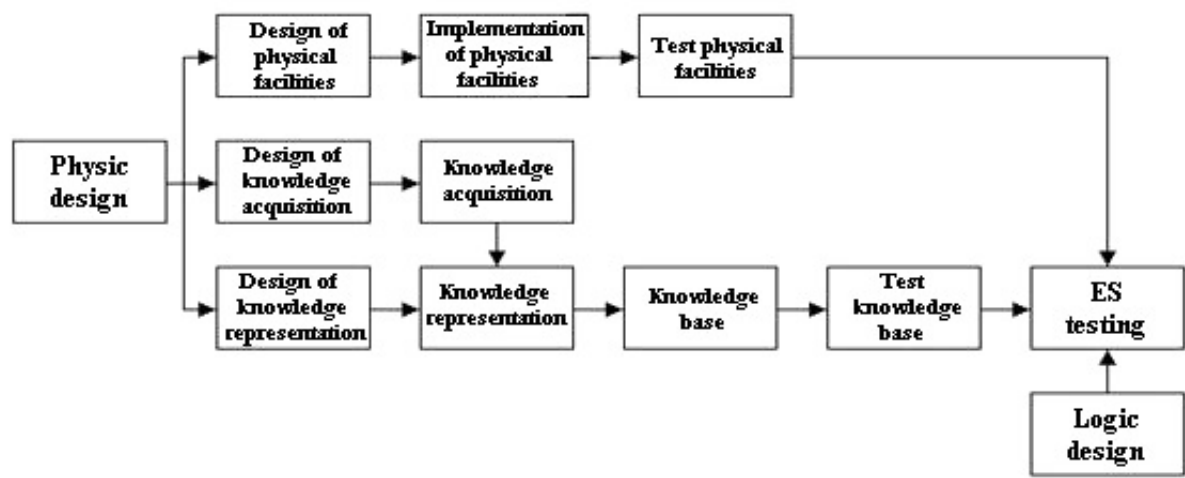


Fig. 2. Physical design.

Physical design includes the design of hardware resources and knowledge base, which includes acquisition components of the knowledge and representation way. When physical part is design sub-systems are appropriate implemented and tested. Only afterwards, they can be tested together with logical part.

Logic design refers to software design and realizes parallel to physical one. First, assembly decisions take such as those linked to the election of a programming language or a shell or a toolkit. Both integration problems of the system and security ones must solve. Then interference engine and interfaces are designed. To program interference engine declarative languages are chosen several times. The design of this part of the system can be seen as an activity of software development, as programming engineering says. The particularity of ES is the importance and development of the knowledge base.

In addition, the exclusive accent is not put on developing interference engine program but on developing the other component such as interfaces.

Each subsystem could need different resources (other programming languages or even other hardware resources) and distinct development techniques.

2.3 ES advantages

- They are valuable collections of information
- They are indispensable without human expertise
- In some situation, they can be cheaper and more effective than human experts can
- They can be faster than human experts can
- If flexible, they can be easily up-dated
- They can be used to instruct new human experts
- At request, they can explain the premises and reasoning line.
- They treat the uncertainty into an explicit manner, which, unlike human experts, can be verified.

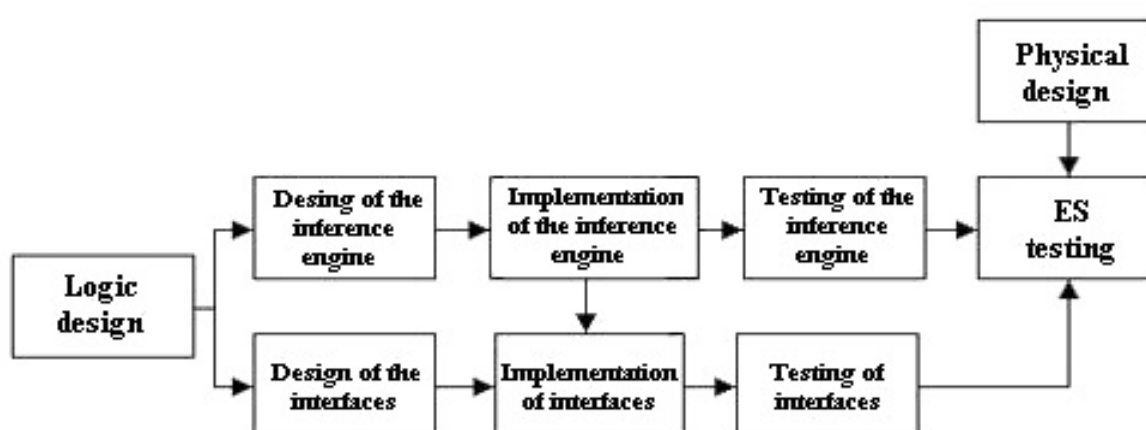


Fig. 3. Logic design.

3. Stages in the design and implementation of an ES

Expert systems are, in fact, particular cases of the *production systems*, which address to some domains with a very strait specialization. In fact, the larger the number of knowledge within a system is the efficient it acts. As human expert, ES has a sphere of competences limited only to a certain domain, usually, very strait, its functionality lying on the human reasoning pattern: starting from certain knowledge or facts, ES develops a series of interferences and reaches to a certain conclusion. Under the context, a synthetic definition of ES would be as follows *programs dedicated usually to a specific domain that try to emulate human experts' behavior*.

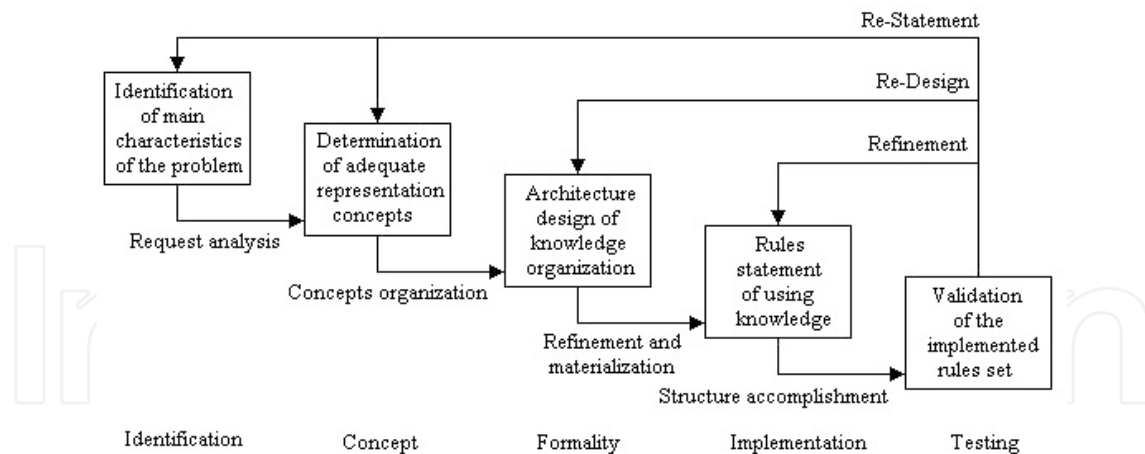


Fig. 4. ES implementation.

- They cannot reason based on intuition or common sense because they cannot be easily representable
- They are limited to a restrained domain; knowledge from other domains cannot be easily integrated nor cannot generalize convincingly
- Learning process is not automate; in order to up-date knowledge it is needed human intervention
- Nowadays, they cannot reason based on theories and analyses
- The knowledge stored in knowledge base depend very much on the human expert that express and articulate them

As a component of *production systems*, ES is one of the most used patterns for representing and control of knowledge. Within this terminology, the word *production* must not be confounded with which happens in factories and plants. Its significance can be translated according to the definition as the *production* of new facts added into knowledge base due to the appliance of these rules. A possible definition of the production system including ES referring to their structure could comprise the following elements:

- A set of rules, each rule has two components such as component *condition* that determines when the rule applies and component *consequence* that describes the action, which results by applying the rule. This set of rules form *rules base*.
- One or many databases contain the information describing the analyzed problem. This database contains initial information where new facts add resulted by applying the rules. This set of information forms *facts base*.
- A control mechanism or rules interpreter frequently named interference engine, which assures the stability of rules appliance order for the existent database. The selection of the rule that applies and solve the appeared conflicts when many rules can be applied simultaneously.
- Communication between operator and ES accomplishes by a specialized interface that assures the efficient exploitation and development of the ES. This interface allows the achievement of two important functions such as:
 - a. On one hand, at human operator demand ES can explain the reasoning it achieved. This is necessary because as complex and “praised” ES is, human operator cannot always accept “blindly” the solution proposed by ES but he wants to pursue and analyze the reasoning machine made.
 - b. On the other hand, in order ES develop by gathering experience it is necessary the modification of the old knowledge and addition of new ones into knowledge base.

The first two components form the so-called *knowledge base*. Representation and organization of knowledge base are two essential aspects for the correct functioning of ES. If it is desired for a ES to develop it is absolutely necessary that knowledge base is completely separated by the rest of the program that uses it (communication interface with the operator and interference engine). The interaction between human operator and ES is synthetic described in figure 5.

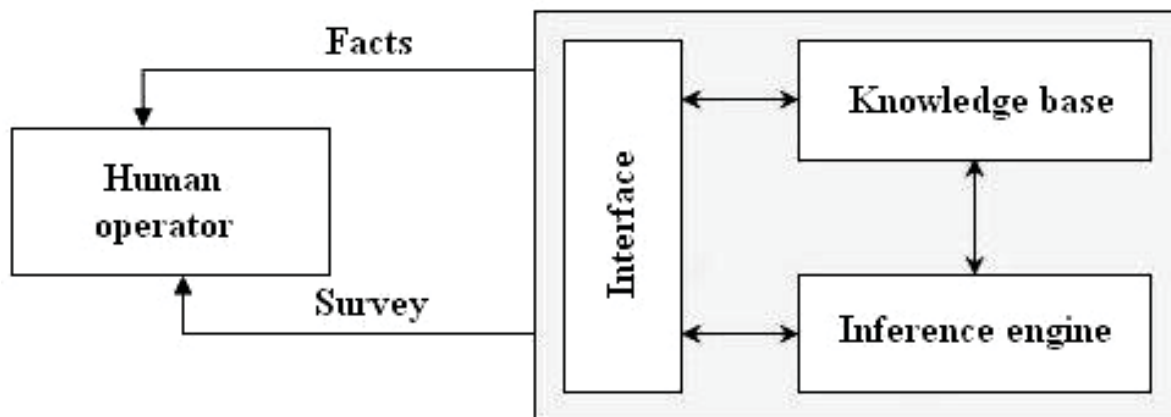


Fig. 5. Communication between human operator and expert system

Under the context of considering ES as formalism of the AI, this organization presents two big advantages such as:

- On one hand it represents a really inspired simulation of the intelligent processes with a dominant nature on information processing,
- On the other hand, it assures the possibility of adding new rules without disturbing the system in assembly, property that responds very well to the statement according to which no intelligent system is definitive.

Summarizing the above definition, ES characterizes by the following attributes:

- Necessary knowledge refers to a relative strait domain and they are well specified.
- ES are underlying less on algorithm techniques and more on an important volume of knowledge from a specific domain.
- An ES can be built only with the help of a human expert open to spend an appreciable time to transfer its own expertise to the program. This knowledge transfer makes gradually by frequent interactions between human expert and program.
- The volume of necessary knowledge depends on problem. There can be situations when several dozens of rules and other situations are necessary to establish thousands of rules.
- The selection of the control structure for a particular ES depends on the specific of the problem.
- Knowledge is represented under declarative form by using usually a structure type IF...THEN... As a result, the majority of expert systems use *rules bases*.
- Knowledge base is clearly separated by the control mechanism of knowledge handling (inference engine).
- Communication with human operator makes through a relative complex interface, which assures the integration, communication, explanation and delivery of knowledge.
- In most cases, the interface consists in a specialized module meant for the modification of the existent knowledge and the acquisition of new knowledge for ES development.

The general structure of an ES that reflects these attributes is described in figure 6.

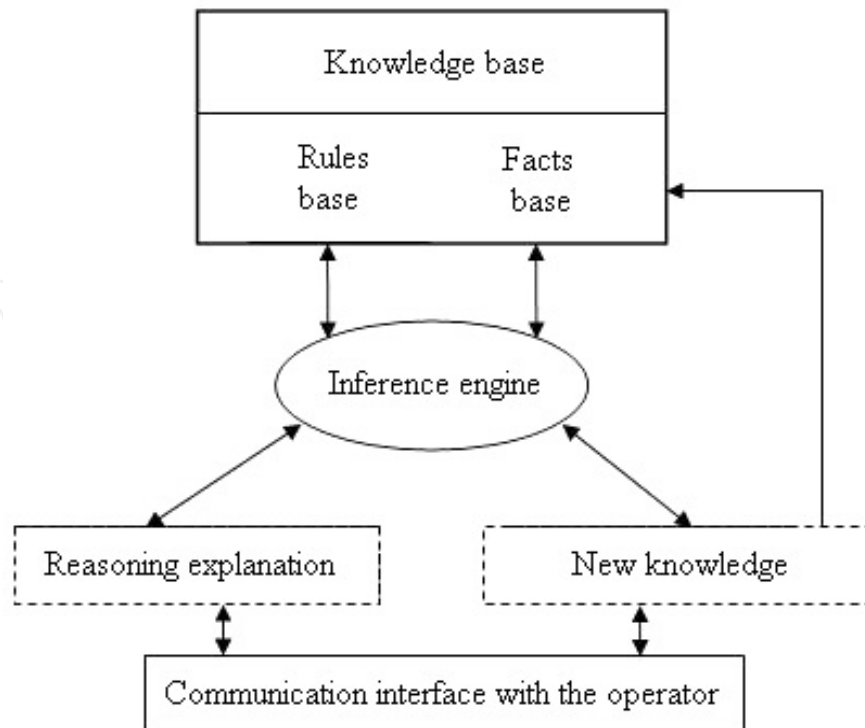


Fig. 6. General structure of an ES.

As for the proper functioning of an ES, the specific mechanism that underlies reasoning realized by program is inference. According to DEX definition, inference is a logic operation that passes from a statement to another one and where the last statement is deduces from the first one. Yet, many times ES are used in parallel with the interface and search techniques, where, at every turn, from the multitude of the rules defined at system level apply only one and once in a while two or most three rules.

Thus, the inference is equivalent to a deduction process that starts from the initial or final conditions, and, by the sequential appliance of some rules, it gets into desired state. Fortunately, in many situations building a set of rules that allow the appliance of pure inference is not possible and, as a result, reasoning row used by ES transforms into a search process. In consequence, intelligent search techniques represent all-important elements in ES functioning.

Inferences development parallel to search processes is controlled by inference engine that assures information handling from knowledge base by realizing four types of actions as follows

- Overlying of the rules base over facts base to identify the applicable rules;
- Selection of the applied rules;
- Rules appliance;
- Verification of stop criterion.

Inference engines can use two types of inference such as *foreword chaining* (from initial state towards final state) or *backward chaining* (from final state towards initial state). In case of foreword chaining, inference engine controls the production/adding of new facts into facts base and in case of back ward chaining – it verifies certain hypothetical information established during the process of backward chaining.

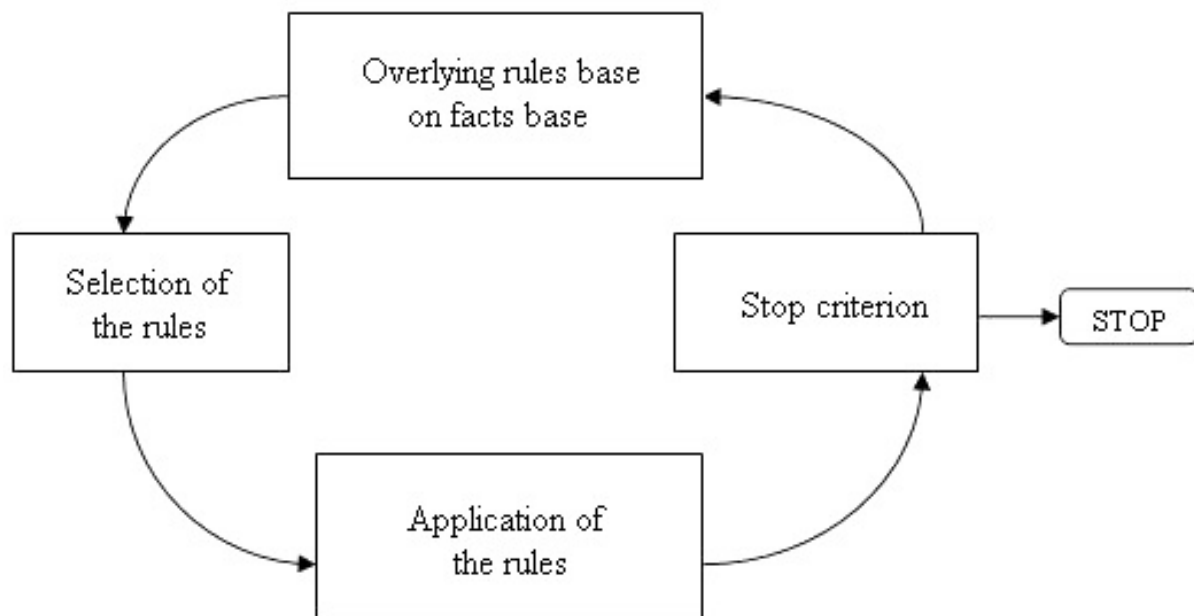


Fig. 7. Functioning of inference engine.

Between the processes controlled by inference engine one of the most important and sensitive is the selection of rules that will be applied. Difficulty of this process lies in the fact that, at a certain moment, the database can contain facts that simultaneously satisfy the conditions of multiple rules; the decision to take is which rules will be applied. Inference engine functioning according to those four actions that it controls is described in figure 7.

4. Neural networks (NN)

Artificial neural networks (ANN) called sometimes simply neural networks (NN) are formed from groups of artificial neurons, interconnected between them, which based on an algorithm process the received information.

Practically networks are work instruments that make a regression analysis on the data from a database.

Neurons, nodes of the network are connected together their connections having specific ponderosities based on the transmitted information. Each node has many inputs, each with its ponderosity. The output is and input for other neurons presented sometimes as vectors or data matrixes. Connection ponderosities between neuron must not be known prior, they are determined with the aid of learning algorithm of the system. The ponderosity modifies the iteration so that input vector is closer as value to the preset, real vector for each input. Once taught neuron network can solve similar problems. Interpolation is made with fuzzy logic system achieving hybrid system.

These neural networks are used especially in solving technical problem, when data are not complete, the correlation between parameters are not linear, the decisions made by humans are based on intuition or the problems are quite complex and estimators' matrix is ill-defined.

ANN advantage consists in the fact that the network function without asking for detailed information about the system. Another major advantage of ANN is that it learns relatively easy the correlations between inputs and outputs and it even learns to simulate the relations between input and output parameters.

5. The analysis of expert systems

The analysis of expert systems – ES shows us that not the special module is connected with the knowledge of the domain. Knowledge implies both explicit knowledge and intrinsic (implicit) knowledge. Explicit knowledge are embodied in documentations, codes, standards, transferable or accessible procedures. Intrinsic knowledge implies both a professional culture and a constitutional one. They are found «hidden» inside man’s mind, in its reasoning. These are harder to encode, communicate or free for access. Accordingly, in order to approach diagnosis or analysis problems of the different Thermal Systems (TS) built artificial intelligence systems. The *comparison* between these three approach groups allows us the selection of the most appropriate work method.

Comparison elements	Case-based reasoning (RBC)	Neural Network (NN)	Rule-based reasoning (RBR)
Module of data building, their representation	Data regain for similar problems	Recognition of some valid models and standards	Rules type if-then
Module of data achievement	Old solved cases	Learning according to the learning algorithm. Input data ponderosity	According to human experience and to experts’ ideas within domain
Expert’s procedure in solving the problem	Extraction of similarity cases from database	Recognition of the correlation cases between input-output measures and it learns the network	Step-by-step, logically
Construction of the analysis system	Easy to build but it needs time	Black box. No need for detailed knowledge in the domain	Difficulties in knowledge acquisition (data, standards, codes etc.)
Data renewal	Handy	By learning in a trained manner	Handy
Their understanding	Hard	Acceptable	Easy

Table 1. Comparison elements.

The last researches bring light that the best approach is the accomplishment of a hybrid expert system where the modules can be built separately based on a proper inference engine.

6. Existent expert systems

6.1 The QuenchMiner

The ES was realized, several years ago, at the Center of excellence for heat treatments at Worcester Polytechnic Institute, USA. It was meant to help the specialists that make heat treatments. ES tries to give an answer to user’s questions regarding the functional parameters in a heat treatment cycle, especially when material cools down. In figure 8 presents the structure of an expert system.

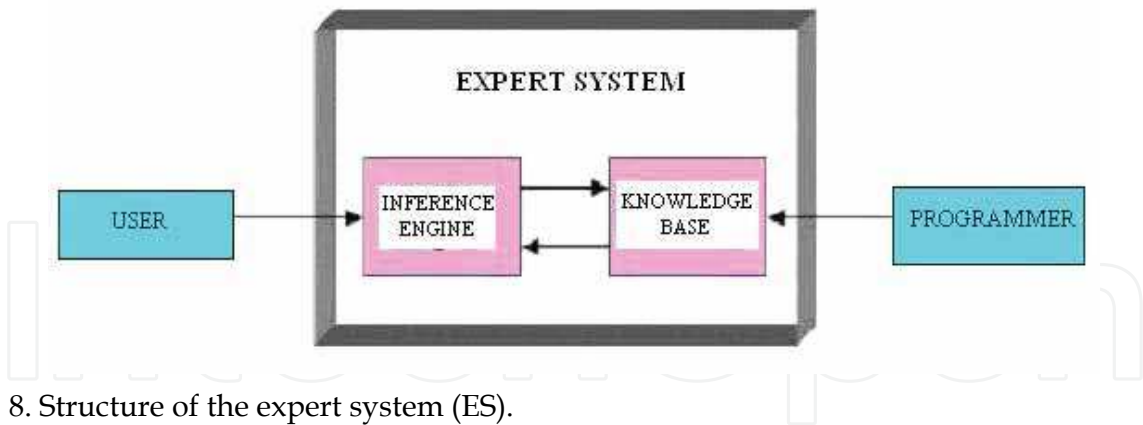


Fig. 8. Structure of the expert system (ES).

The knowledge base consists in basic rules and knowledge on the heat treatment (quenching) introduced by the expert in this domain. The database contains statements on quenching ways with details on the experimental conditions. The rules introduced into the database were achieved through "Data Mining" technique applied to the knowledge base. The data achieved from technical literature and reports regarding the experiences connected with materials quenching. The architecture of the expert system is shown in figure 9.

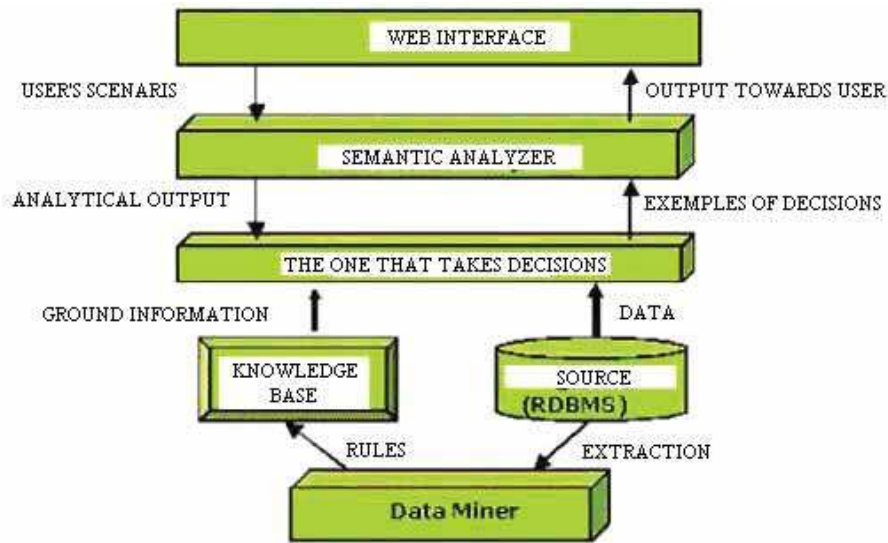


Fig. 9. Architecture of expert system ES.

The basic components are *knowledge base* and *inference engine* (decision engine). The decision engine uses as work technique the system based on rules and the examination technique *forward chaining*. The user introduces the data of the problem through a dialogue interface. The data are undertaken and processed into semantic analysis module and sent to inference Engine. This realizes a set of decisions by using the data stored into RDBMS module and the reasoning rules from knowledge base. Outputs from decision module reach again to the user by passing through semantic analysis module. Quench Miner helps the user to optimize the process of heat treatment. ES offers to the expert in heat treatment a technical support for his decisions.

Input parameters, which ES use, depend and select according to the problem that need to be analyzed. Quench Miner is focused on the analysis of the following problems from the process of heat treatment:

- Orientation of the material in coolant vertical or transversal and depends on material geometry.
- Cooling speed depends on viscosity of the coolant, its agitation speed the oxides layer from the surface of the material. It classifies in rapid, moderate or slow.
- Uniformity of cooling process such as uniform or non-uniform.
- Global coefficient of heat transfer depends on cooling speed, material density and specific heat and geometric factors. It classifies in high, average and low.
- Residual tensions in the material after heat treatment depend on material history and the entire cycle of heat treatment, the material supported. It classifies in negligible, moderate or high.
- Hardness of the material after treatment is influenced by cooling speed, carbon content and type of the coolant. It classifies in high, average and low.
- Deformation tendency of the material depends on cooling speed, nature of the coolant and residual stresses within material. It classifies in small, average and high.
- Cracking probability is influenced by the same parameters as deformation is.
- Input variables of the expert system.

List of the input variables is exhaustive, but between these, only those that influence the problem analyzed by the expert system are chosen.

- Coolant water, oil, polymer
- Temperature of the coolant high, average, low
- Agitation speed for coolant insufficient, moderate or excessive,
- Viscosity of the coolant big, average, small
- Agitation type that defines the way agitation realizes through pump, adjustment or compressor
- Circulation speed of the coolant
- Type of the coolant old or new
- Degradation of the polymer as coolant
- Material that must be treated, steel mark
- Material geometry
- Material surface and its section
- Material volume big, small
- Material density high, low
- Specific heat high, low
- Oxide layer from material surface,
- Material roughness rough or smooth
- Orientation of the material in the coolant
- Carbon content within material
- Grains structure of the material
- Plastic deformation of the material,

Output parameters for ES:

- Orientation of the material in the coolant
- Cooling speed,
- Uniformity of cooling process,
- Global heat transfer coefficient,
- Residual stresses in material,
- Hardness of the material,
- Cracking probability.

The user can select as output parameter one or more variables from those itemized above. We consider cooling speed as output parameter.

Input parameters:

- coolant: water
- temperature: high
- agitation speed: insufficient
- viscosity
- circulation speed of the coolant
- material
 - section: thin
 - volume:
 - oxide layer: thick
 - surface roughness: rough

We notice that the user must not complete all the lines. Certain fields are determined automate by inference engine ES processes input data and presents on the display the result of the analysis: rapid in our case.

Inference engine can also present intermediary reasoning based on rules from knowledge base such as:

- a coolant with small viscosity (water) implies a rapid cooling,
- an insufficient agitation implies a slower cooling
- the areas with thin walls implies a rapid cooling
- a thick oxide layer implies a slower cooling
- a rough surface implies a rapid cooling,
- high temperature of the coolant implies a slower cooling

Per total cooling is rapid.

The program is written using Java Expert System Shell, so-called JESS. Jess uses for program progress Forward Chaining examination technique. Inference rules apply directly to the knowledge base. Input data are stored in working memory. At every turn, the program gives a set of rules that satisfy the data from working memory. In order to “map” (fit) the rules with data from the database Jess uses RETE algorithm.

Rules apply or eliminate taking into account their specificity, the conflict between them and ponderosity.

Decisions that QuenchMiner expert system takes are actually estimations based on empiric relations experimentally ascertained and validated in practice. These are a support for the user in taking appropriate decisions.

Decisions taken into inference Engine base on the analysis of input data and output variables, ES identifies the dependences between variables based on cause-effect relations.

The ponderosity of each input variable is determined by analyzing the impact or in output variable. In addition, it is analyzed influence tendency of each variable on cooling speed taking into account its ponderosity and compares between them these tendencies in order to model the final answer.

6.2 Expert system based on anterior cases RBC (Case-Based Reasoning)

Expert system based on anterior cases is, in fact, the process of solving new problems based on given solutions of some similar anterior problems. RBC lies on prototype theory explored in human cognitive sciences. RBC depends on the intuitive fact that new problems are often similar to those met anterior and their solutions will be similar to those given in the past. RBC does not offer concrete solutions, sure conclusions to the current problem.

(A. Aamodt and E. Plaza, 1994), proposed that case-based reasoning need to be described in four steps:

1. Recovery of the similar cases from the past. A case consists in a problem and its solution and the observations how it reached to this solution;
2. The use all over again of the solutions. It analyzes the connection between the anterior case and the current problem. It identifies the resemblances and differences between the two cases and adapts the solution to the current case;
3. Review of the solution. The new adapted solution tests and if necessary modifies;
4. Retain of the solution. The solution adapted to the new case is stored as a new case into memory.

Each task from those four steps divides in other tasks. Thus, to recover anterior cases we need to accomplish the following stages:

- *Cases identification, their search, initial match and selection of the most accurate case.*
- To use all over again the solution we must realize the next steps such as solution copying, its matching and modification. The task regarding review of the solution implies its evaluation (by learning and simulation) and defects repair.
- *Retain of the solution implies its integration by its continuation, knowledge updating, the adequate index of the solution and the extraction of the main descriptors by justifying them for the found solution.*

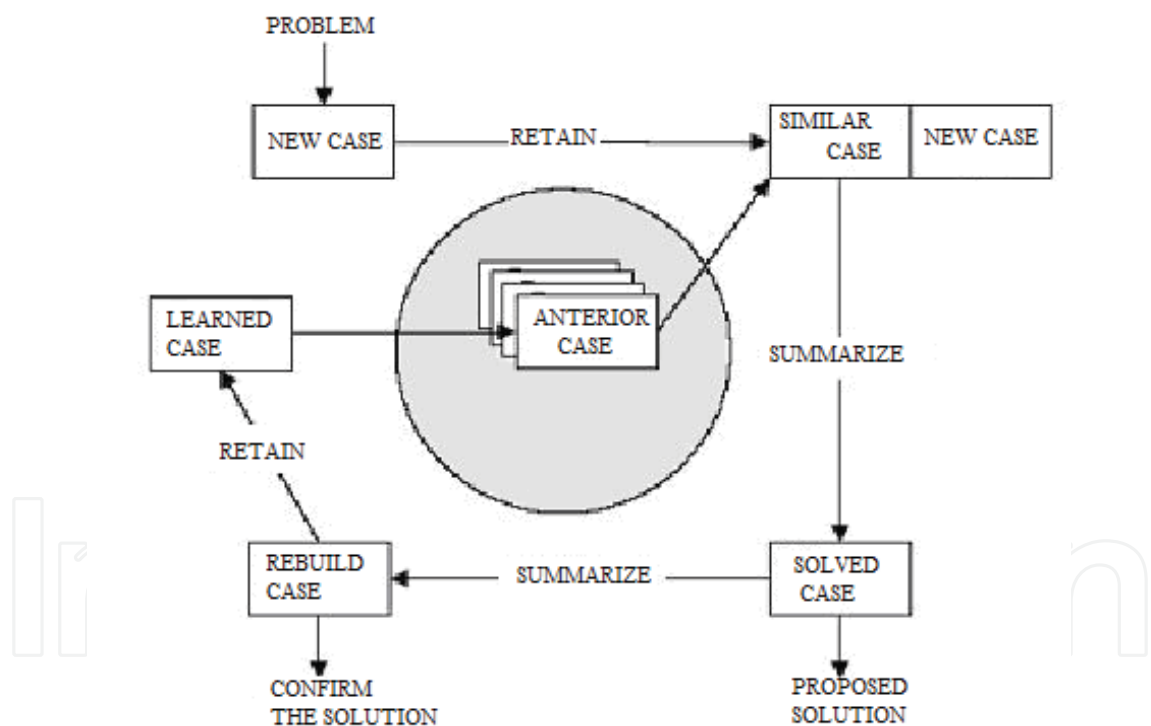


Fig. 10. Case-Based Reasoning general model.

Re-establish mechanism of the similar cases from the past is very important in method case. For this, the method of the closest neighbors is used. In this method considers that all the characteristics of the case are as much important, which practically does not confirm. Accordingly, it proposed to give different ponderosities for the most important characteristics based on the information they carry.

(Shin et al., 2000) proposed a hybrid method to regain knowledge made of CBR and neural networks technique. The system is adequate especially when the characteristics of the case

are numerical expressed. A distance type normalized Euclidean measures the similarity of the characteristic features (Kwang and Sang, 2006). If X is the past case with the characteristics x_1, x_2, \dots, x_n and takes part from class x_c and q the vector of the current problem with the characteristics q_f , then the difference between the two vectors defines through the relation

$$d(x, q) = \left(\|x_f - q_f\|^2 \right) \quad (1)$$

by introducing value barriers, certain features can be considered similar between the two cases. If we introduce ponderosities for the characteristics of the case based on their importance then the distance between the two cases defines through the following relation

$$D(x, q) = \sqrt{\sum w_f^2 \times \text{difference}(x_f, q_f)^2} \quad (2)$$

where:

$$|x_f - q_f|, \text{ if } f \text{ is characterized numeric}$$

$$\text{difference}(x_f, q_f) = |x_f - q_f|, \text{ if } f \text{ has numerical value, or} \quad (3)$$

$$\text{difference}(x_f, q_f) = 0, \text{ if } f \text{ has symbolic value and } x_f = q_f, \text{ or} \quad (4)$$

$$\text{difference}(x_f, q_f) = 1, \text{ for other cases} \quad (5)$$

If the characteristic features have symbolic or unsorted values that the featured that match can be numbered for the simple cases and it determines a similarity based on similar characteristics.

For the complex cases proposed a more complicated metric. Stanfill and Waltz proposed as measure "value difference metric" (VDM) that takes into account the similarity of characteristics value.

We consider two cases X and Y , which have N characteristic features x_i , respectively y_i . We suppose n - number of classes and f_i declared features and g characteristic class where c_l is a possible one. Under these conditions, VDM defines by the set of relations:

$$\begin{aligned} \Delta(X, Y) &= \sum_{i=1}^N \delta(x_i, y_i) \\ \delta(x_i, y_i) &= d(x_i, y_i) w(x_i, y_i) \\ d(x_i, y_i) &= \sum_{l=1}^n \left| \frac{D(f_i = x_i \cap g = c_l)}{D(f_i = x_i)} - \frac{D(f_i = y_i \cap g = c_l)}{D(f_i = y_i)} \right|^k \\ w(x_i, y_i) &= \sqrt{\sum_{l=1}^n \left(\frac{D(f_i = x_i \cap g = c_l)}{D(f_i = x_i)} \right)^2} \end{aligned} \quad (6)$$

D is the number of examples in a data set for learning that satisfies the requested condition.

$D(x_i, y_i)$ is a measure of similarity between the characteristics of X and Y .

$D(f_i = x_i \cap g = c_i) / D(f_i = x_i)$ represents the probability for a case with features x_i is classified in class c_i .

$w(x_i, y_i)$ represents the ponderosity with which x_i feature imposes the class.

An important characteristic of CBR is its correlation with learning process. This needs a set of techniques for extracting relevant knowledge from experience, to integrate the case into existent knowledge and to index the case to assimilate it with the similar cases. Learning can be:

- inductive,
- rapid,
- learning based on explanations through:
 - learning the most general rules;
 - learning of the rules more often used;
 - resignation of the unused rules so the learning system is not delayed.

6.3 Expert systems based on neural networks for the control of hardening control through induction of the material

The surface hardening of the material by induction heating followed by a heat treatment made of quenching and annealing is an old procedure often used in industry. The hardness prediction of the material after such a heat treatment is hard to achieve due to non-linear phenomena that take place and to their difficulty in simulation. More, the problem of process control proves to be very difficult. The use of artificial intelligence proves to be of good omen. At Southern-Illinois University, Technologies Department designed and realized an ES based on neural network for this purpose.

The furnace for induction heat treatment is made of a coil with a big diameter that makes a tunnel where the material for heat treatment passes through. The coil is supplied with high frequency currents. The material is transported through this tunnel with a certain speed given by an engine depending on the necessary time for heat treatment at a certain temperature.

Variables parameters:

- shifting speed of the material given by pulling speed of the engine,
- height of the trembler coil,
- temperature of the material at the furnace exit,
- time made by the material from furnace exit until it drops into a coolant for quenching.

All the parameters are expressed in distances.

Material hardness is determined by material speed in the furnace and temperature at furnace exit. The correlation between hardness and pulling speed of the engine and material temperature using a linear regression equation proved to be very weak. Correlation coefficient in R^2 is of 18.7%. In order to control the entire hardening process through induction, it was designed a neural network, which is capable to make predictions on hardness and functional parameters.

The system consists in two neural networks type "backpropagation" with a supervised learning module. Input parameters are pulling engine speed and material temperature.

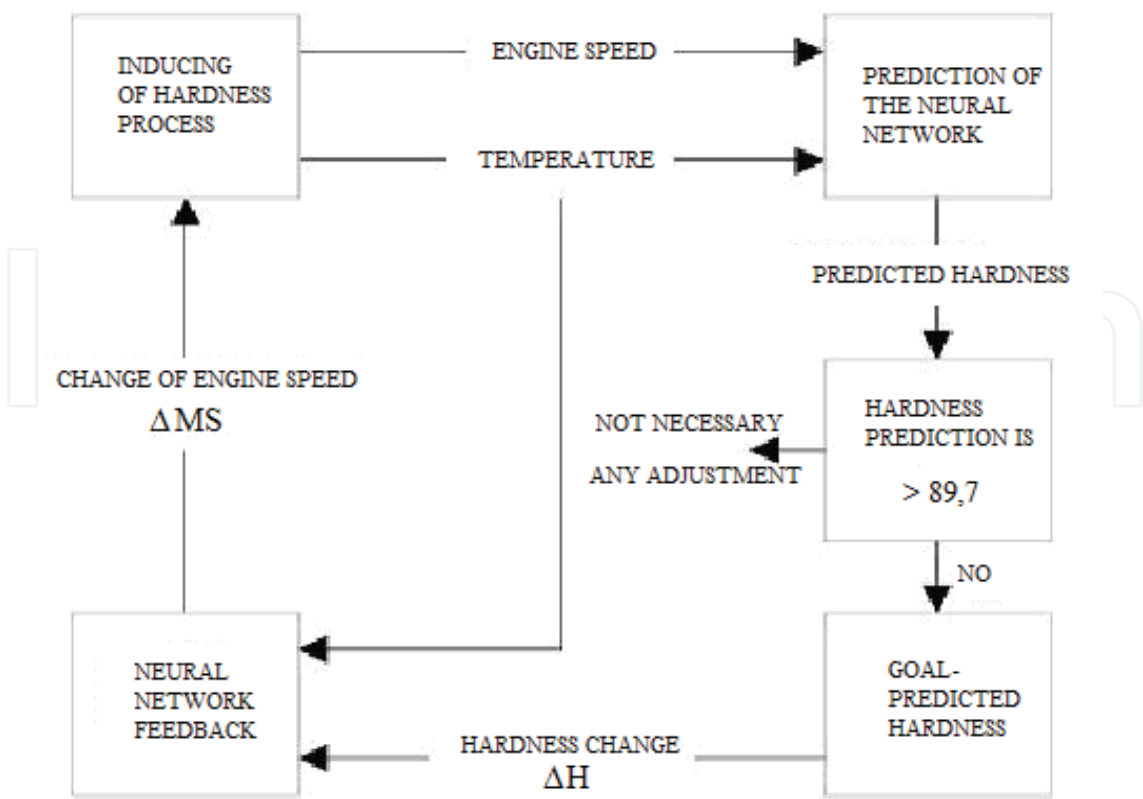


Fig. 11. Control system with an artificial neural network of the hardening process.

The first neural network was designed to predict on material hardness according to input parameters. The network consists in two input layers, three hidden layers and one output layer. For training, 30 set of data used and for tests 15 set of data used. The network was taught by admitting an error of 5% on the entire value range of the hardness. The value of the precise hardness in proportion to real hardness both at learning and at test is given in figures 12 and 13.

The sum of the square errors decreased considerably in relation to a linear regression anterior determined from 15.68 to 2.53.

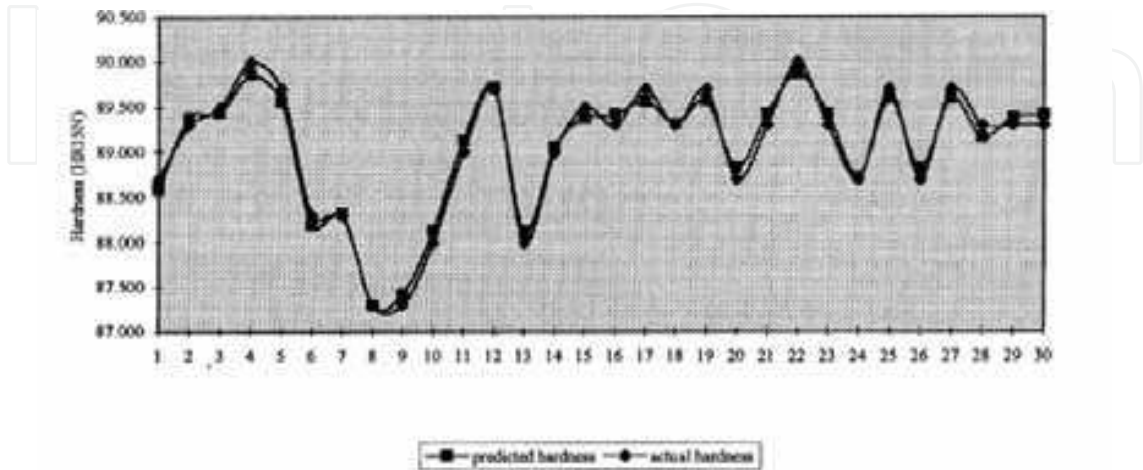


Fig. 12. Prediction of RN network for data used for learning: real hardness towards predicted hardness.

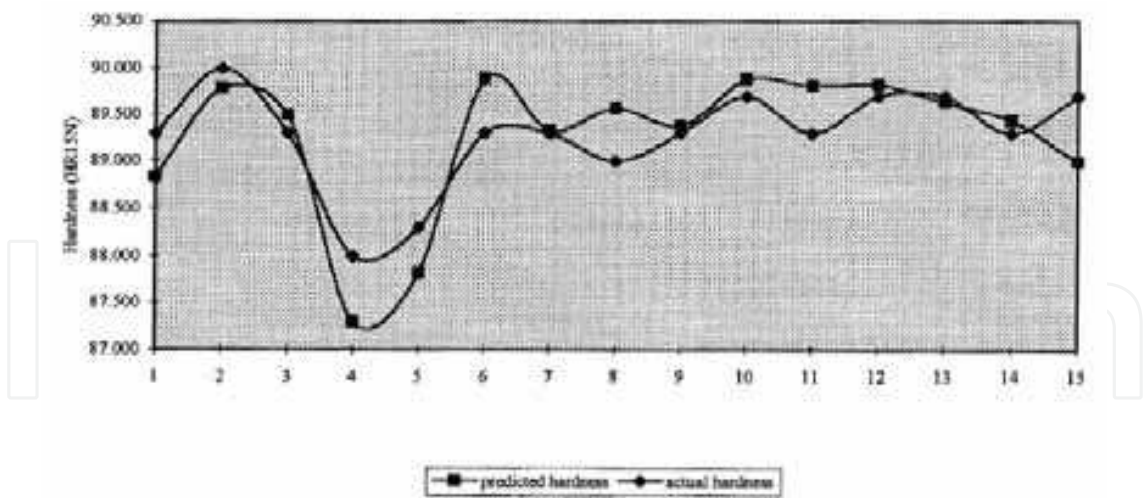


Fig. 13. Prediction of the network for test data: real hardness towards predicted hardness.

For the network that acts as feedback the same type of network adopted (backpropagation, supervised). The architecture is a little bit different meaning that the layer of intermediary neural has four layers. In a case the set of data for training is 14 and for tests 9 set of 3 data used. The network was taught with a tolerance of 5% on hardness range. The speed of pulling engine varies depending on the difference between predicted hardness and real hardness of the material. This difference is an input variable of the first layer of the network. The other input is made of material temperature.

7. Validity of expert system

The prediction of the neural network was tested with 32 set of real data. Each set contains two inputs speed of the engine and material temperature. The exit from the model is material hardness. In feedback neural network, input variables represent the difference between the value predicted by network and the real one and material temperature. Depending on this value, the pulling engine speed of the material through the furnace modifies so that the difference is smaller and the calculated value is closer to the real one. The compared results are given in table 2 and are graphically presented in figure 14.

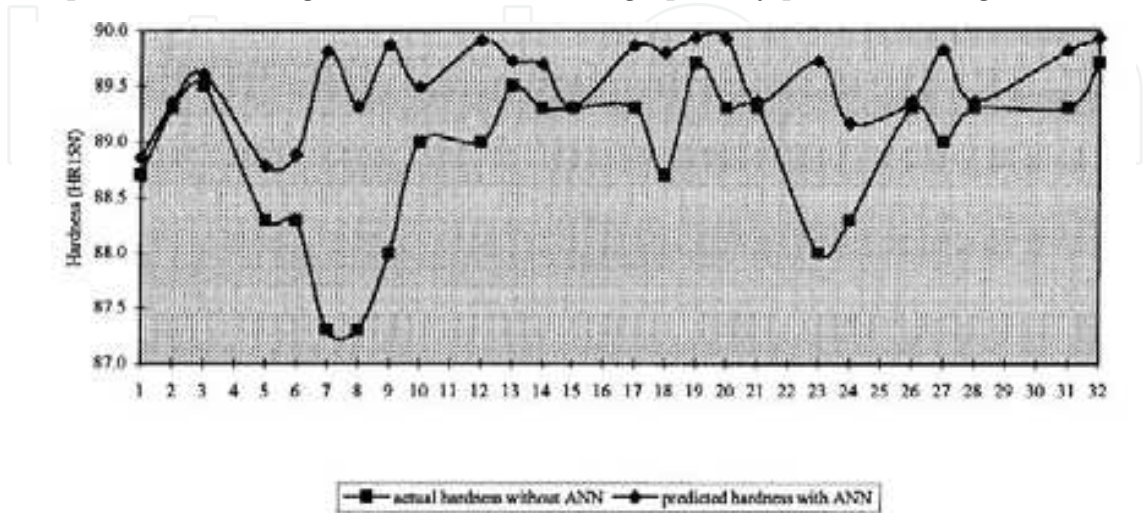


Fig. 14. Values of hardness without RNA in proportion to hardness values with RNA.

No.	Hardness without RNA (HR15N)	Hardness with RNA (HR15N)	Hardness modification (HR15N)
1	88.7	88.852	0.152
2	89.3	89.354	0.054
3	89.5	89.608	0.108
4	-	Adjusted	Necessary
5	88.3	88.780	0.480
6	88.3	88.890	0.590
7	87.3	89.817	2.517
8	87.3	89.314	2.014
9	88.0	89.871	1.871
10	89.0	89.495	0.495
11	-	Adjusted	Necessary
12	89.0	89.917	0.917
13	89.5	89.732	0.232
14	89.3	89.701	0.401
15	89.3	89.306	0.006
16	-	Adjusted	Necessary
17	89.3	89.865	0.565
18	88.7	89.807	1.107
19	88.7	89.941	0.241
20	89.3	89.933	0.633
21	89.3	89.354	0.054
22	-	Adjusted	Necessary
23	88.0	89.724	1.724
24	88.3	89.165	0.865
25	-	Adjusted	Necessary
26	89.3	89.366	0.066
27	89.0	89.821	0.821
28	89.3	89.354	0.054
29	-	Adjusted	Necessary
30	-	Adjusted	Necessary
31	89.3	89.825	0.525
32	89.7	89.929	0.229
inferior	88.8800	89.5488	
Standard deviation	0.6880	0.3587	

Table 2. Comparison between hardness without RNA and with RNA.

8. Conclusions and perspectives of expert systems

Even though, at the beginning, the followers of artificial intelligence promotion (AI) through expert systems hoped to develop some systems that would exceed through their performances the human experts, this desire did not fulfill, at least not now. This happened because knowledge acquisition within an ES is not a very simple process, as it may seem at a

first glance. Why this process would be so complicated? Probably the easiest answer is that human expert gains, in time, not only knowledge but also *experience*. Knowledge itself allows the development of some reasoning based on rules (as in ES case). On another hand, *experience* allows the development of some *subliminal* reasoning (not accessible yet by computing programs), which in day-to-day life would translate by *instinct* or *inspiration*. Due to this, the majority of ES developed so far limited to relative tight domains that can be quantified in a rigorous and direct manner.

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The ability to create intelligent machines has intrigued humans since ancient times, and today with the advent of the computer and 50 years of research into AI programming techniques, the dream of smart machines is becoming a reality. The concept of human-computer interfaces has been undergoing changes over the years. In carrying out the most important tasks is the lack of formalized application methods, mathematical models and advanced computer support. The evolution of biological systems to adapt to their environment has fascinated and challenged scientists to increase their level of understanding of the functional characteristics of such systems. This book has 19 chapters and explain that the expert systems are products of the artificial intelligence, branch of computer science that seeks to develop intelligent programs for human, materials and automation.

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