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HYBRID DECISION-MAKING SYSTEM

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Summary. The paper presents a hybrid decision-making system oriented at the diagnosing of working machines on the basis of the knowledge acquired during laboratory and operational tests. Rule-based inference combined with procedural diagnosing enabled to make a precise diagnosis of the machines examined in the study.

Key words: hybrid system, expert system, diagnostics, knowledge base, inference strategies

INTRODUCTION

The fact that modern working machines are equipped with electronic systems enabling automatic control over working processes makes it necessary to apply complex diagnostic systems supporting these processes. Modern computational (information) systems, in contrast to the traditional ones, are characterized by parallel data processing, the use of software capable of learning:

– supervised learning, which consists in adaptation changes in the values of the weights of a neural network,
– unsupervised learning, which consists in the classification of input signals,

and creation of if-then rule bases of quantitative knowledge in fuzzy systems.

Intelligent information systems are also referred to as expert systems, in which fuzzy logic is used for the inference process, and knowledge is represented in the symbolic (rule-based) and non-symbolic (numerical) form by means of neural networks and genetic algorithms, or defined with individualized inference procedures. It follows that an essential element of the intelligent expert system is the hybrid inference process [McGarry and MacIntyre 2000], based on both symbolic and non-symbolic knowledge. The above concepts of diagnostic inference were employed to build a Hybrid Diagnostic Inference System (HDI), composed of the following knowledge bases:

– if-then rule base,
– base of individualized damage detection procedures,
– help base – providing support and hints to system users.

The Hybrid Diagnostic Inference System allows to generate a diagnosis using various ways of diagnostic knowledge representation, promoting user-friendly cooperation, even if the user is not an expert in a given branch of knowledge.

STRUCTURE AND FUNCTIONS OF THE HYBRID DIAGNOSTIC INFERENCE SYSTEM

The Hybrid Diagnostic Inference System comprises four interrelated modules: knowledge acquisition module, knowledge representation module (rule-based and procedural knowledge), inference module and dialogue with the user module (Fig. 1).
This system combines, on a cooperative basis, two methods of knowledge representation:
– rules concerning general knowledge,
– procedures based on the identification of individualized values of the attributes of the object examined.

The modules of knowledge acquisition, inference and dialogue with the user are discussed in detail in references [Michalski and Rychlik 2000, 2001, Michalski *et al*. 2001].

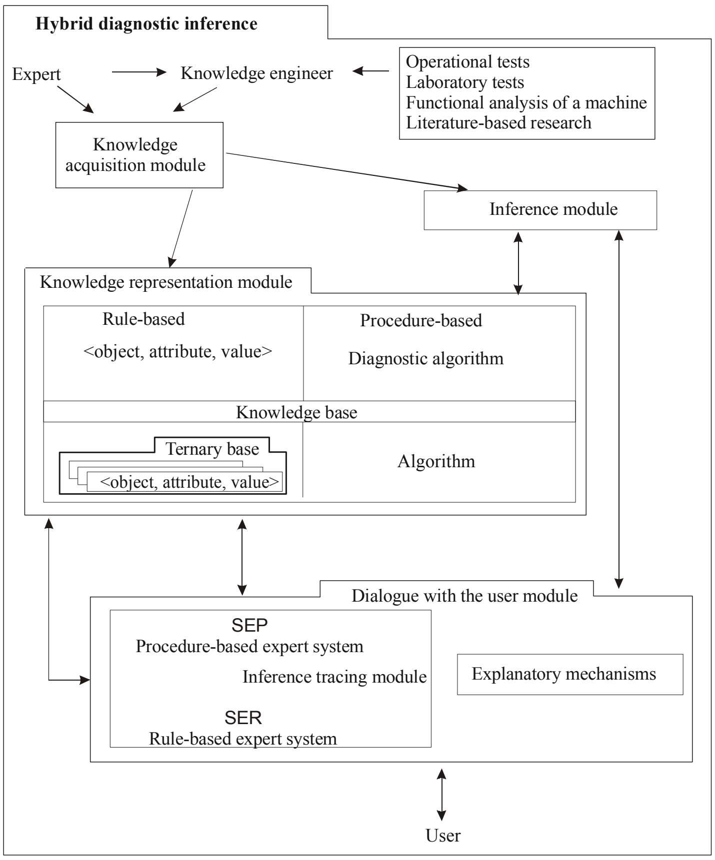

Fig 1. Structure of the Hybrid Diagnostic Inference System

RULE-BASED DIAGNOSING

The method of rule-based diagnosing was developed using a structural model in the form of the Diagnostic Knowledge Matrix (DKM), according to the relation:

Diagnostic symptom – state $(X \Rightarrow SD)$,

X – set of diagnostic symptoms,
SD – set of unserviceability (unfit) states.

In this method, the diagnosing process is carried out according to the following procedure:

1) For times t and Θ (working life of the machine), the symptom vector $\overline{SD_j^n}(t,\Theta)$ with elements $sd_j(t, \Theta)$ is created, where:
   - n – number of successive inspections made according to the specified procedure of information set ordering, taking into account the criteria applied to control the condition of a machine and localize damage, defect or failure, i.e. the criteria of the greatest information increment, ease and possibility of check, probability (certainty) of the occurrence of unserviceability states,
   - j – SD number,
   - sd_j – element of the symptom vector, which assumes the following values:
     0 – if the admissible value of the signal has not been exceeded,
     1 – if the admissible value of the signal has been exceeded.
2) The vector $\overline{SD_j^n}(t,\Theta))$ is compared with the set of standard vectors $\{\overline{SD_w}\}$, created by DKM columns. The vector $\overline{SD_i}$ (included in the set $\overline{SD_j^n}(t,\Theta)$) is the vector of the i-th unserviceability state, i.e. $X_i \equiv \overline{SD_i}$. The general form of the Diagnostic Knowledge Matrix is given in Table 1.

Table 1. Form of the Diagnostic Knowledge matrix (DKM)

i j	$X_1 \equiv \overline{SD_1}$	$X_2 \equiv \overline{SD_2}$	……………	$X_i \equiv \overline{SD_i}$
sd_1	$a_{1,1}$	$a_{2,1}$	………..	$a_{I,1}$
sd_2	$a_{1,2}$	$a_{2,2}$	………..	$a_{I,2}$
………..	………..	………..	………..	………..
sd_J	$a_{1,J}$	$a_{2,J}$	………..	$a_{I,J}$

The vectors are compared according to the following rule:
In DKM, $a_{i,j}$ denote its elements, where:

$i = \overline{1,I}$ – numbers of unserviceability states in DKM,

$j = \overline{1,J}$ – numbers of symptoms recorded in DKM.

$a_{i,j} = \begin{cases} 0 \\ 1 \end{cases}$, elements of the matrix assume the value of 0 if there is no correlation between the i-th unserviceability state and the j-th symptom (CF = 0), where as $a_{i,j}$ = l if there exists such a correlation (CF ≠ O).

3) If $\overline{SD_j^n}(t,\Theta) \cap \left(\overline{SD_w}\right) = \varnothing$, the n+1 step is taken to verify signals, which allows to create another vector $\overline{SD_j^{n+1}}(t,\Theta)$.
4) If $\overline{SD_j^n}(t,\Theta) \cap \left(\overline{SD_w}\right) = \overline{SD_i}$, it means that the i-th unserviceability state X_i. has occurred.
5) If all symptoms recorded in DKM have been verified and the following relationship has taken place $\overline{SD_j^{n=1,J}}\ (t,\Theta) \cap \left\{\overline{SD_w}\right\} = \varnothing \wedge \bigvee_{j=1,J} sd_j = 1$,

it means that the unserviceability state cannot be identified explicitly on the basis of diagnostic inference, and that at least one symptom of this state has been observed. Thus, at the end of the diagnosing process it is necessary to enumerate all unserviceability states whose vectors contain the maximum number of elements assuming the value of l corresponding to the vector $\overline{SD_j^{n=1,J}}\ (t,\Theta)$.

Rule-based knowledge is represented by a set of facts and rules in the ternary form <O,A,W> , including:

<Object, Attribute, Value>,

where facts are governed by rules by means of logical conjunctions (and, or, etc,), and the inference module is based on backward inference strategies [Michalik 2003].

PROCEDURE-BASED DIAGNOSING

Procedural knowledge is a result of certain checking and verifying steps (procedures), enabling to estimate the technical condition of a given object or working processes taking place within this object. In this case the diagnosing procedure may be developed on the basis of analytical, laboratory and operational tests, which provided the basis for determining inference algorithms. The algorithms obtained for logical and rule-based knowledge may be then processed into computer programs in the form of diagnostic procedures applicable to various mechanical assemblies of working machines.

The use of procedural knowledge in the aspect of the functioning of HDI enables to:

– forecast and diagnose changes in the state/condition,
– determine the reasons for the existing state/condition,
– optimize the structure and operational parameters of the object.

The main function of the hybrid diagnostic inference system is to identify the unserviceability state of machines on the basis of the symptoms observed. The functional, process- and information-related complexity of the diagnosing problem may be presented in its general form, as information flow control (Fig. 2).

The HDI system may be considered as two independent, intersecting planes representing diagnostic inference. The intersection edge of the planes represents their cooperation, with independent functioning (Fig. 3).

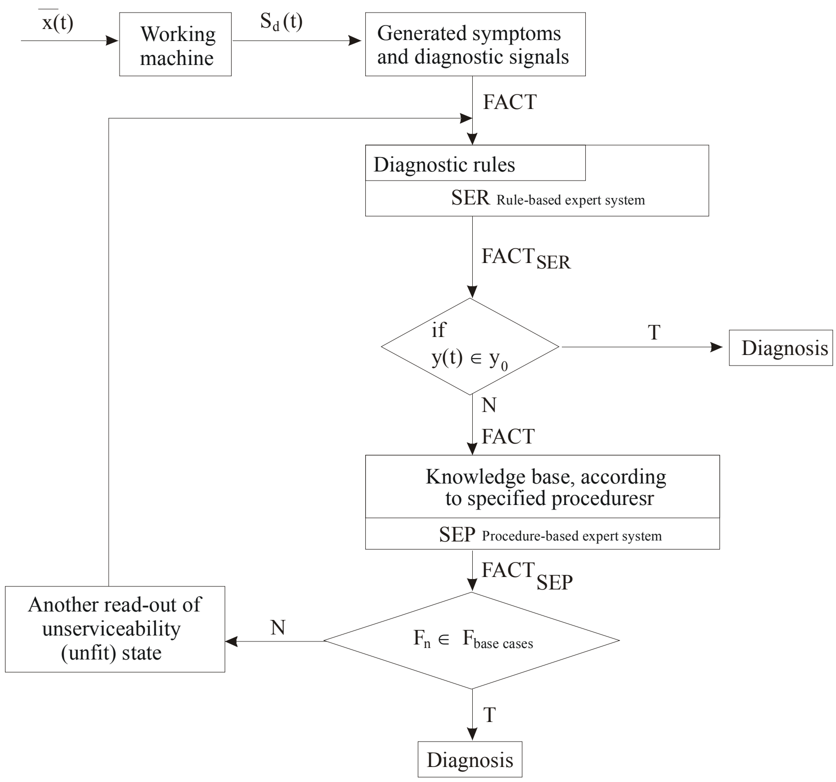

Fig. 2. Illustration of machine diagnosing using HDI

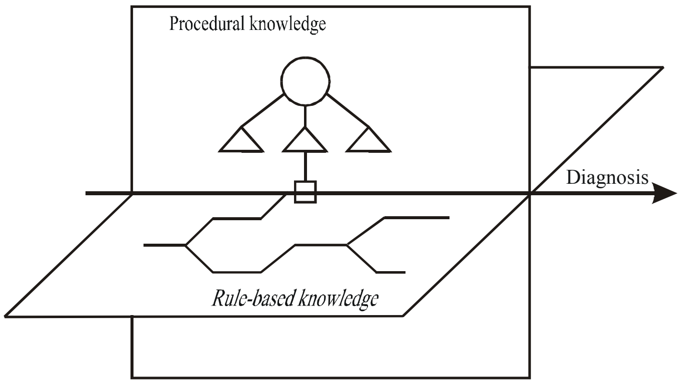

Fig. 3. Module-based structure of Hybrid Diagnostic Inference

The module-based structure of the HDI system enables independent functioning of all modules, whose cooperation takes place by way of data exchange, according to user's needs and requirements.

EXAMPLE OF HYBRID DIAGNOSTIC INFERENCE

In the example given below, the hybrid diagnostic inference system was created using the PC-Shell program [Michalik 2003], to represent rule-based knowledge, and the environment Delhpi, to develop procedures of diagnostic inference concerning the technical condition of the hydraulic system of a combine-harvester. The rule-based knowledge was recorded in the form of facts and rules. The knowledge base was divided into five blocks, i.e. source of knowledge, attributes, rules, facts, control and check. Procedural knowledge is represented in the „Oscillogram" program. This program enables to visualize and analyze oscillograms of transients in the cycle of pressure measurement as a function of time of the lifting mechanism in the hydraulic system. It also identifies dynamic indices determined on the basis of transients.

In the case of the hydraulic system of a Bizon Z058 combine-harvester, Hybrid Diagnostic Inference was aimed at identifying its unserviceability on the basis of symptoms recorded in the diagnostic knowledge matrix and analysis of pressure change oscillograms. The user can define and identify the problem during the dialogue with the system. This discussion can be led at two levels – rule-based knowledge and procedural knowledge. Figure 4 presents a view of model windows of the HDI system, applications of PC-Shell and „Oscillogram".

a) b)

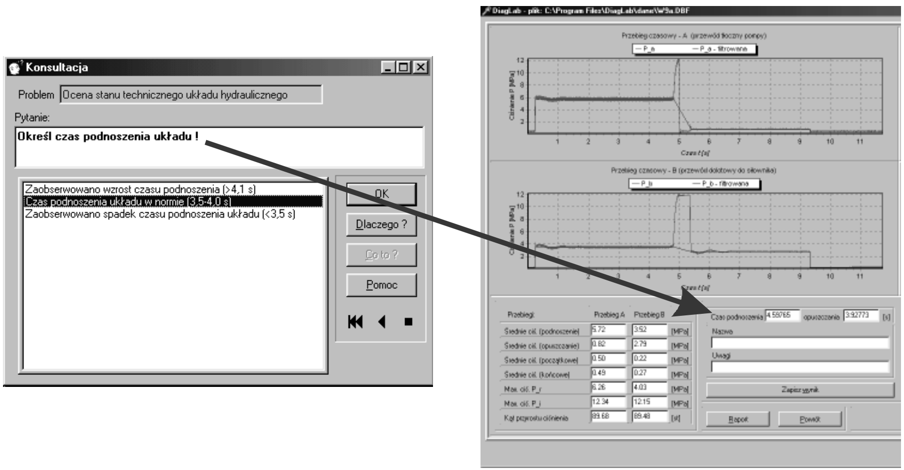

Fig. 4. A window of the HDI system for the hydraulic system of a combine-harvester, a) dialogue box of rule-based knowledge, b) view of the „Oscillogram" program with identified characteristics of a diagnostic signal

Having initialized the rule-based module, the user has to answer the questions asked by the system. If the user cannot answer them, he can search for information in the procedural knowledge resources. He can acquire the necessary knowledge by analysis of the oscillogram recorded in the „Oscillogram" program, where the values of the signal characteristics are identified, so that they can be used by the rule-based module during the diagnosing process. The user-system communication allows to generate a diagnosis. An example of a diagnosis generated by the system is presented in Fig. 5.

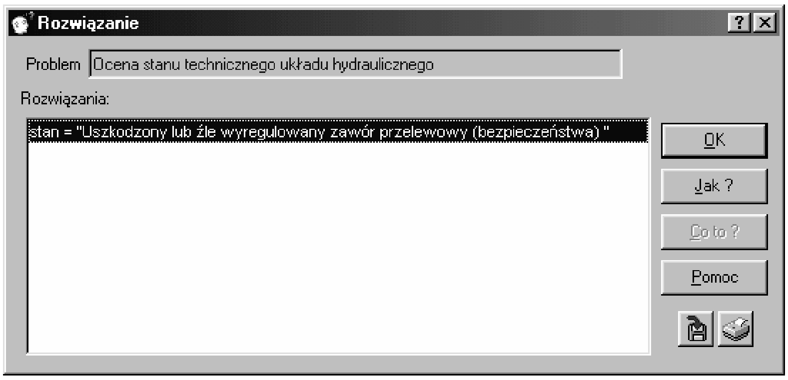

Fig. 5. Diagnosis generated by rule-based knowledge in the PC-Shell program

The PC-Shell program also provides tools explaining the diagnosis made. The conclusion and premises that enabled to arrive at a given diagnosis are shown in the dialogue box „How". A view of this dialogue box is presented in Fig. 6.

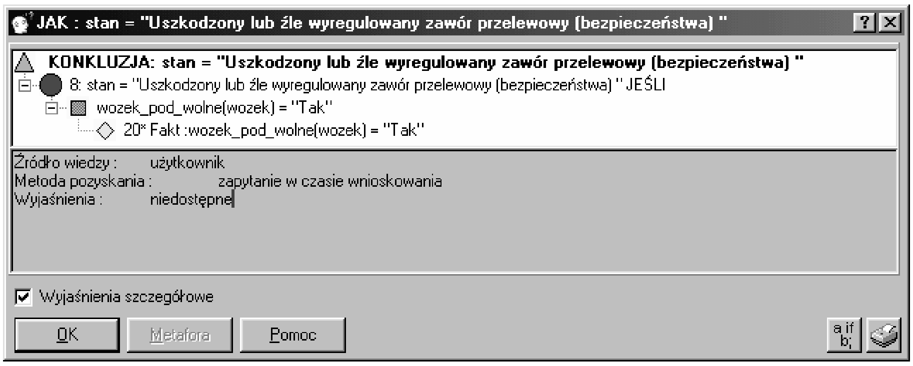

Fig. 6.Dialogue box providing explanation to the diagnosis made in the PC-Shell program

The „Oscillogram" program identifies the main characteristics of a diagnostic signal. In the procedure considered it is the pressure in the hydraulic system of a Bizon Z058 combine-harvester. In addition, the program identifies the key dynamic indices determined on the basis of transients.

CONCLUSIONS

The Hybrid Diagnostic Inference system described in the paper, oriented at diagnosing unserviceability, was developed on the basis of knowledge gained during laboratory and operational tests on the studied object. The knowledge acquired and introduced into the system, in the form of rules and diagnostic procedures, allows to obtain a greater „intellectual" potential of the system, i.e. to select the most appropriate diagnosis. Due to the combination of the two methods of knowledge representation, this system is referred to as „hybrid'.

Hybrid systems oriented at determining the technical condition of machines are characterized by dynamic development aimed at performing the following functions: control over the state/condition, forecasting the state/condition, damage localization. In order to make the so called „intelligent systems" fulfill the above functions, it is indispensable to apply tools for learning, which still is the major obstacle to their large-scale development and implementation.

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