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Methodology of knowledge acquisition for machinery diagnostics[1]

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The paper deals with a comprehensive methodology concerning knowledge acquisition on machinery for the purpose of expert systems suitable for aiding of diagnostic inference. The methodology includes selected methods of diagnostic knowledge representation, methods of knowledge acquisition from domain experts and from preclassified examples, methods of assessment of previously acquired knowledge and a scenario of knowledge acquisition process. All the methods have been implemented in a Knowledge Acquisition System. Moreover, some examples of applications of the elaborated methodology have been given.

Keywords: machinery diagnostics, knowledge acquisition, domain experts, machine learning, assessment of knowledge

1. Introduction

A basic task of machinery diagnostics consists in *diagnosing*, i.e. recognition or identification of a technical state of a given machine that occurs with limited quantity of information. The essence of this activity depends on *diagnostic reasoning* which may be efficiently performed, if: *corresponding data* that constitute premises of the reasoning process have been collected, possible *technical states* attributable to the diagnosed object have been known and the diagnostic system *is equipped with sufficient knowledge* which may be employed in the reasoning.

Recent computerized systems used in common for monitoring of critical machinery collect plenty of data that describe inputs and outputs of the given machine. New datasets are acquired each monitoring cycle. If it is required to follow dynamic changes in the state of the machine (e.g. in real time), then the computer-aided diagnostic reasoning is a right answer. Hence expert systems are ever more and more frequently applied. The modern solutions turn towards real-time (dynamic) expert systems [1]. Whatever the expert system were, a knowledge base would have to be its vital part. Thus the expert system knowledge-based approach requires a comprehensive amount of domain knowledge that may originate from different knowledge sources.

Accessible descriptions of research carried out on acquisition of diagnostic knowledge enabled the author to come into the following conclusions [9]:

- most of them used *ineffective knowledge acquisition methods*,
- there is a lack of a *common method of representation of diagnostic knowledge acquired from different sources*,
- special *computer-aided tools for knowledge acquisition are rare.*

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Moreover, a lack of the *generally acknowledged methodology of diagnostic knowledge acquisition* has been identified.

Therefore the author has undertaken the research whose goal has been to elaborate the *complex methodology of knowledge acquisition for the needs of machinery diagnostics* [9].

The paper is based on the work [9] and is organized as follows. In Section 2 we give a brief description of the problem and outline way of its resolving. Section 3 deals with applied methods of knowledge acquisition and some methods of assessment of knowledge acquired previously. Then in Section 4 we deal with several tools that were included into a knowledge acquisition system *SPWD1*. We also describe some examples of applications of a few methods concerning some frequently occurred problems in rotordynamics (Section 5). The final section contains a brief recapitulation of more important results and conclusions.

2. Problem description

The problem to be solved consists in a selection of suitable methods of *representation of diagnostic data and knowledge*, methods of *knowledge acquisition from domain experts* and *from preclassified examples*, as well as methods and techniques of *assessment and verification of knowledge* acquired previously. The most important criterion of selection of these methods is their adequacy for the needs of the technical diagnostics. A way and order in which the methods would be applied should be defined by an appropriate *scenario of the knowledge acquisition process*.

Prior to solution of such formulated problem a description and analysis of suitable methods and tools of knowledge acquisition have been done. We decided to consider an application of both our own methods and tools and other methods described in the accessible bibliography (see e.g. [7, 13, 14]). Then the selection of the methods most suitable for diagnostics of machinery has been carried out.

To facilitate knowledge acquisition from different sources and make possible hybrid applications of this knowledge (see below) we joined several means and pieces of software into a knowledge acquisition system, whose central element is a *data and knowledge base*. A logical scheme of this base has been called *EMPREL* by the author.

Both the methods applied and means implementing these methods have been verified for typical tasks connected with exemplary yet typical diagnostic problems such that *identification of a malfunction of a rotating machine*. The verification concerned the usefulness of these methods in technical diagnostics estimated by the *efficiency of the classifier(s)* determined by a 'chunk' of knowledge acquired from the given source.

3. Methods applied

We developed and implemented several methods, including *methods of knowledge acquisition*, *methods and techniques of knowledge assessment* and a *scenario of knowledge acquisition process* which is some specific method, too. In the following sections we discuss briefly some groups of methods applied within the described research.

3.1. Methods of knowledge acquisition

Methods of knowledge acquisition are strongly related to knowledge sources (see Fig. 1). Hence it is reasonable to divide knowledge acquisition methods useful in technical diagnostics into these connected with *human experts* (who may take active or passive part into the knowledge acquisition process) and 'automatic' ones which make possible *knowledge acquisition from databases*. The latter group may be further classified into *supervised* Machine Learning (ML) methods and *unsupervised* methods of Data Mining (DM) and Knowledge Discovery (KD).

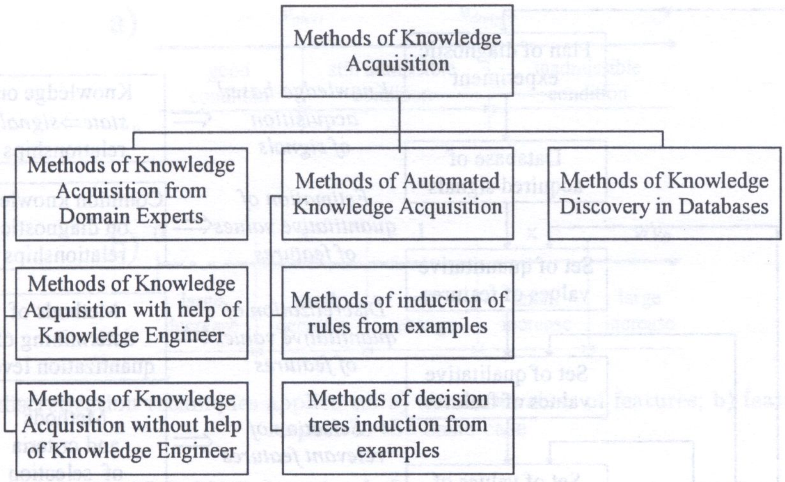

Fig. 1. Taxonomy of applied Knowledge Acquisition methods

Domain experts are very valuable sources of diagnostic knowledge and cannot be omitted through the whole process. Their role is especially important in the introductory phase of this process when a description of the domain is acquired. However, these methods are inefficient if we have to acquire great amount of knowledge counted e.g. in numbers of rules [8]. Therefore it is expedient to apply ML and KD methods that took place through the described research.

3.1.1. Methods of knowledge acquisition from domain experts

We applied the following methods which differ in range of required activity of a knowledge engineer: knowledge acquisition using *paper forms* and using an *electronic form*.

The first method consists in that the expert elicits his/her own knowledge without participation of the knowledge engineer and represents it filling in cells in a special *paper form*. Then the forms *have to be interpreted by the knowledge engineer* who puts down respective records into the knowledge base. This method is suitable for the experts who are unfamiliar with modern software and hardware. However, the influence of the knowledge engineer on final 'chunk' of knowledge is very significant.

The second method is recommended for experts more skilled in modern computer technology. It depends on the use of some specialized software tool which the author called an *electronic form*. This application plays the role of a *knowledge base editor* and corresponds to the second model of the knowledge acquisition process introduced by B. G. Buchanan. Thus the knowledge engineer's role is reduced to an integration and joining of knowledge acquired from different experts and in many cases his/her activity is unnecessary at all.

Both the methods have been implemented using supporting means. These means will be briefly described later.

3.1.2. Methods of knowledge acquisition from databases

We decided to use both *supervised* and *unsupervised* methods. A more comprehensive research concerns an application of the supervised ML methods. They are applicable if we have an access to a database containing *preclassified examples*. The whole process of knowledge acquisition may be carried out within a special diagnostic experiment, either numeric or active one (on the physical object, to whom the measurements of signals apply). This process consists of several steps (see Fig. 2) which will be briefly discussed in the following.

If possible, the *diagnostic experiment shall be conducted according to its plan* which ought to take into account diagnostic knowledge concerning the problem to be solved. The proper plan of the

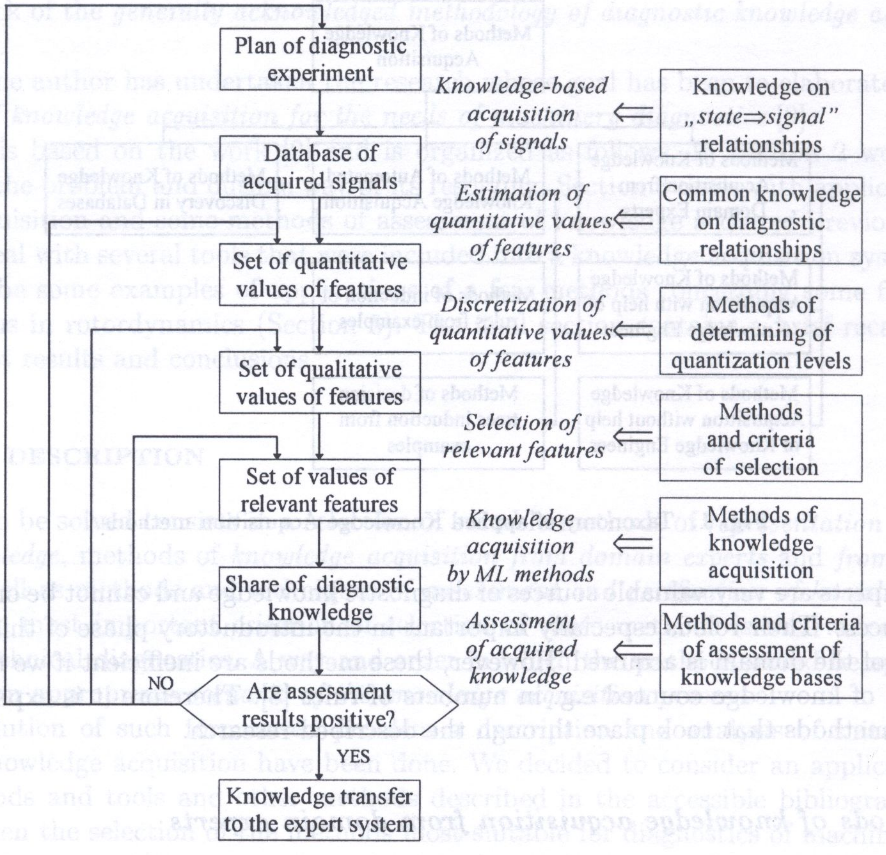

Fig. 2. Methodology of supervised knowledge acquisition using ML methods

experiment is crucial for the success of the whole process. During the experiment we are able to acquire *signals that carry information on machinery malfunctions.* If the experiment is numeric, then signals are generated using *model-based approach. Active diagnostic experiments* require measurements of needed diagnostic signals. It is reasonable to *store realizations of signals into the database.* Hence we are able to extract *qualitative features* containing essential information on the condition of the diagnosed machine. Two solutions are possible here (Fig. 3): application of absolute values of features or relative ones compared with reference values of features of some basic example which represents features of the object whose technical condition is considered to be good. Then each example is represented by a record in the dataset whose fields contain several values of *conditional attributes* and, since we have to deal with the supervised process, value(s) of at least one *decision attribute* denoting the class(es) where the classified example belongs. Each example is considered as *positive* for some concept that corresponds to some given technical state (malfunction) and as *negative* (counterexample) for all other classes.

It is preferred to use *qualitative values of conditional attributes.* Hence respective *discretization of quantitative values* of signal features is necessary. The author's attempt to the discretization of quantitative attributes takes into consideration experts' knowledge on the machine to be diagnosed using knowledge acquired from the examples (see also [6]). The discretization process requires some *set of threshold values* (*levels of discretization*) that partition the domain of a given signal feature. The selection of these values is vital for the whole process of automatic knowledge acquisition, too. We prefer such methods which give only *few levels of discretization.* Some original solution suggested by the author is shown in Fig. 3.b. Following the ISO 2372 Standard it has been assumed that the difference between classes of technical states is constant and may be used for rough estimation of discretization levels. The value of this quotient is constant for neighboring discretization levels v_k, v_{k+1}:

$$x = v_{k+1}/v_k \tag{1}$$

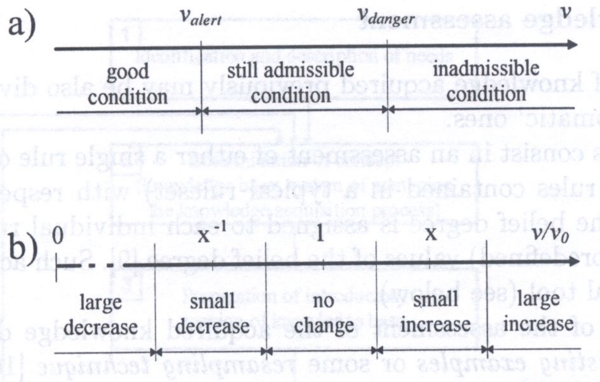

Fig. 3. Two discretization techniques applied to: a) absolute values of features; b) feature values with respect to the basic case

and is set to $x = 2.5$ in the ISO 2372 Standard. In our research we use some optimization method which makes possible to define values of x individually for each measuring point (which in case of our last research concerning the turbine generator is justified by different properties of stages of the turbine and, as a consequence, differing admissible vibration levels that are lower for High-Pressure stage and higher for Low-Pressure stage) and for physical quantity observed by means of diagnostic signals. In our research we typically apply values $x \in \langle 1.2, 2.8 \rangle$ finding optimal ones during several iterations. Since we use only a few qualitative values for one variable, easy interpretation of the resulting qualitative values is possible, particularly if we assign each discrete value (after discretization) to some linguistic value understandable by the untrained user (see Fig. 3).

To make the whole process computationally effective we select a subset of relevant attributes. There are several methods of selection, e.g. based on minimal reducts using rough-sets approach [13] or the *PROMISE 2* method [4]. Having done this we have the database of examples prepared for knowledge acquisition using supervised ML methods.

To acquire knowledge from databases of examples we apply the following very well-known ML methods:

1. *induction of rules* using:
   (a) *star general covering* methodology [7],
   (b) *rough sets* approach [13, 3],
2. *induction of decision trees* [14].

The assessment of the acquired knowledge depends on the application of either *special set of testing examples* or some *resampling technique* and then calculation of *classification errors*. The very convenient and frequently used criterion concerns the *overall empirical error rate* (see next section). If we obtain the error rate that is unacceptable we have to repeat the process iteratively. There are some possibilities (see Fig. 2):

1. *new subset of relevant attributes* which can be obtained using other method of features selection;
2. *new set of quantization levels* and repeated quantization of continuous attributes;
3. application of *other signal features* which are more sensitive to the considered malfunctions and can better distinguish different states;
4. modification of the *plan of diagnostic experiment* in order to collect new signals whose feature values will supplement the set of learning examples.

This iterative process will be continued until the stop criterion (e.g. concerning the overall empirical error rate) will be satisfied.

The author and J. M. Żytkow have also begun a research on applications of KD methods which have given very promising results briefly reported in [12].

3.2. Methods of knowledge assessment

Methods of assessment of knowledge acquired previously may be also divided into those applied by human experts and 'automatic' ones.

Expert-based methods consist in an assessment of either a single rule or the whole ruleset (which is rare because of many rules contained in a typical ruleset) with respect to its/their substantial correctness. A value of the belief degree is assigned to each individual rule being assessed. We use only several qualitative (predefined) values of the belief degree [9]. Such activity of the human expert may be aided by a special tool (see below).

'Automatic' methods of the assessment of the acquired knowledge depend on the application of either *special set of testing examples* or some *resampling technique* [16] and then calculation of *classification errors*. Here the *overall empirical error rate* $\widehat{\epsilon}_{ov}$ is often used, defined as:

$$\widehat{\epsilon}_{ov} = \frac{n_{err}}{n_t} \tag{2}$$

where n_{err} denotes number of classification errors and n_t is the total number of testing examples.

With regard to the number of examples contained in the specific datasets we apply either *k-fold cross validation* or *random subsampling* techniques [16]. Because we are often faced with uneven distribution of examples between classes, we introduced some *weighted error rates* [9], where the most widely used *weighted overall empirical error rate* $\widehat{\epsilon}^{w}_{ov}$ is defined as:

$$\widehat{\epsilon}^{w}_{ov} = \frac{1}{K} \sum_{k=1}^{K} \frac{n_{err|k}}{n_{t,k}} \tag{3}$$

where $n_{err|k}$ denotes number of classification errors for examples belonging to the class number k and $n_{t,k}$ is the number of testing examples of this class.

Moreover, we proposed *hybrid couples of methods of knowledge acquisition and subsequent assessment of this knowledge base.* There are two 'cross-like' possibilities: knowledge acquired from domain expert may be verified using a set of testing examples, or knowledge acquired by ML methods may be assessed by human experts. The former pair is particularly interesting since it makes possible to assess quality of a dataset of examples using a *set of generally acknowledged rules* [9]. These rules may be acquired e.g. from very much experienced and widely recognized domain experts.

3.3. Scenario of knowledge acquisition process

The knowledge acquisition process can be modeled using a *scenario* which may be interpreted as a program of proceeding (a kind of a method). This model contains the following stages [9] (see Fig. 4):

1. *elaboration of a concept* including an identification and description of needs and determination of the concept of the solution of the particular knowledge acquisition problem (steps 1, 2 in Fig. 4),
2. *elaboration of a prototype* concerning a pilot version of the knowledge base and verification of the concept (steps 3, 4 in Fig. 4),
3. *elaboration of the full version of the knowledge base* including its verification and preparation of a documentation (steps 5, 6 in Fig. 4),
4. *usage of the knowledge base and authors' supervision* including the delivery of the knowledge base to the user and its commissioning by the user (steps 7, 8 in Fig. 4).

There are some feedbacks that make possible introduction of corrections and changes into the database under construction (see Fig. 4).

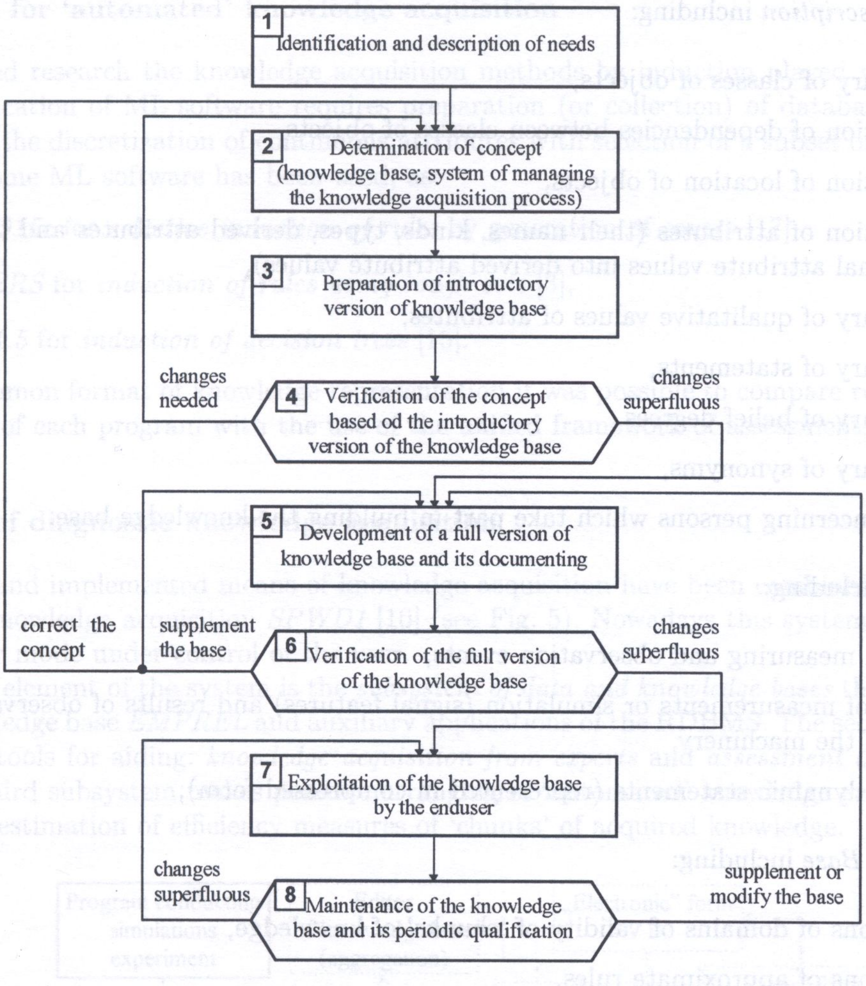

Fig. 4. Scenario of knowledge acquisition process [9]

4. Means for aiding of knowledge acquisition process

We wanted to verify correctness of the methods and their usability for technical diagnostics. This verification required the implementation of the previously described methods in the form of some corresponding means which are briefly described in the following subsections.

4.1. Data and knowledge base *EMPREL*

Taking into account the need of a unified knowledge representation format, the author has proposed a logical scheme called *EMPREL* of the relational database which was applied as the data and knowledge base [9]. This base plays the integrating role in the whole project. We assumed that all considered objects and concepts belong to the *closed world* which contains a denumerable quantity of different states. Thus it was possible to apply dictionaries of objects, object classes, attributes and their values, etc. The author's remark was that both the database and knowledge base use the same dictionaries and thus in order to avoid redundancy it is reasonable to bind both these bases together. This base has been implemented into a relational database management system (RDBMS).

In the database three main subbases may be identified:

1. *Domain description* including:
   (a) dictionary of classes of objects,
   (b) description of dependencies between classes of objects,
   (c) description of location of objects,
   (d) description of attributes (their names, kinds, types, derived attributes and transformations of original attribute values into derived attribute values),
   (e) dictionary of qualitative values of attributes,
   (f) dictionary of statements,
   (g) dictionary of belief degrees,
   (h) dictionary of synonyms,
   (i) data concerning persons which take part in building the knowledge base;
2. *Database* including:
   (a) data on measuring and observation events,
   (b) results of measurements or simulation (signal features) and results of observations made by users of the machinery,
   (c) base of dynamic statements (represented in compressed form);
3. *Knowledge Base* including:
   (a) definitions of domains of validity of 'chunks' of knowledge,
   (b) definitions of approximate rules,
   (c) descriptions of rule sources (as persons or ML software),
   (d) scores of rules (formulated by independent experts during assessments of individual rules.

The data- and knowledge base *EMPREL* is accessible in a Local Area Network with the use of Client/Server technology. The unified format of knowledge representation makes possible integration of several software tools that give the opportunity to apply optimal ML methods and to join results of knowledge acquisition from both the human experts and databases. The more comprehensive description of the base *EMPREL* contains [9, 10].

4.2. Tools aiding knowledge acquisition from experts

Two groups of means have been developed: for *acquisition of intrinsically new knowledge* and for *assessment of knowledge acquired previously.* For experts that prefer traditional methods some *paper forms* for acquisition of new knowledge and assessment of previously acquired knowledge have been prepared. For experts skilled in modern computer technology the author suggested a specific software tool called *electronic form* (more information on this application called *EMPREG* in [11, 18]).

The latter tool is some application of the RDBMS whose database has the logical scheme conforming with the *EMPREL* format. The database is accessed using the ODBC (*Open DataBase Connectivity*) technique. Results of expert's operation are written down into a working knowledge base and may be subsequently subject to further processing (e.g. by the Knowledge Engineer) and finally attached to and integrated with the developed knowledge base.

4.3. Software for 'automated' knowledge acquisition

In the described research the knowledge acquisition methods by induction played very significant role. The application of ML software requires preparation (or collection) of database of examples which involves the discretization of continuous attributes with selection of a subset of relevant ones.

Moreover some ML software has been used, as:

- program *AQ15c* for *selective induction of rules* by generation of covers [17],
- program *LERS* for *induction of rules using rough sets* [3],
- program *C4.5* for *induction of decision trees* [15].

Due to the common format of knowledge representation it was possible to compare results of induction by means of each program with the use of the unified framework of assessment.

4.4. System of diagnostic knowledge acquisition

All developed and implemented means of knowledge acquisition have been combined into a system of diagnostic knowledge acquisition *SPWD1* [10] (see Fig. 5). Nowadays this system is operated in semi-automatic mode under control of the user.

The central element of the system is the *subsystem of data and knowledge bases* that includes the data and knowledge base *EMPREL* and auxiliary applications of the RDBMS. The second subsystem form software tools for aiding: *knowledge acquisition from experts* and *assessment of knowledge by experts*. The third subsystem makes possible arranging of 'automated' knowledge acquisition using induction and estimation of efficiency measures of 'chunks' of acquired knowledge.

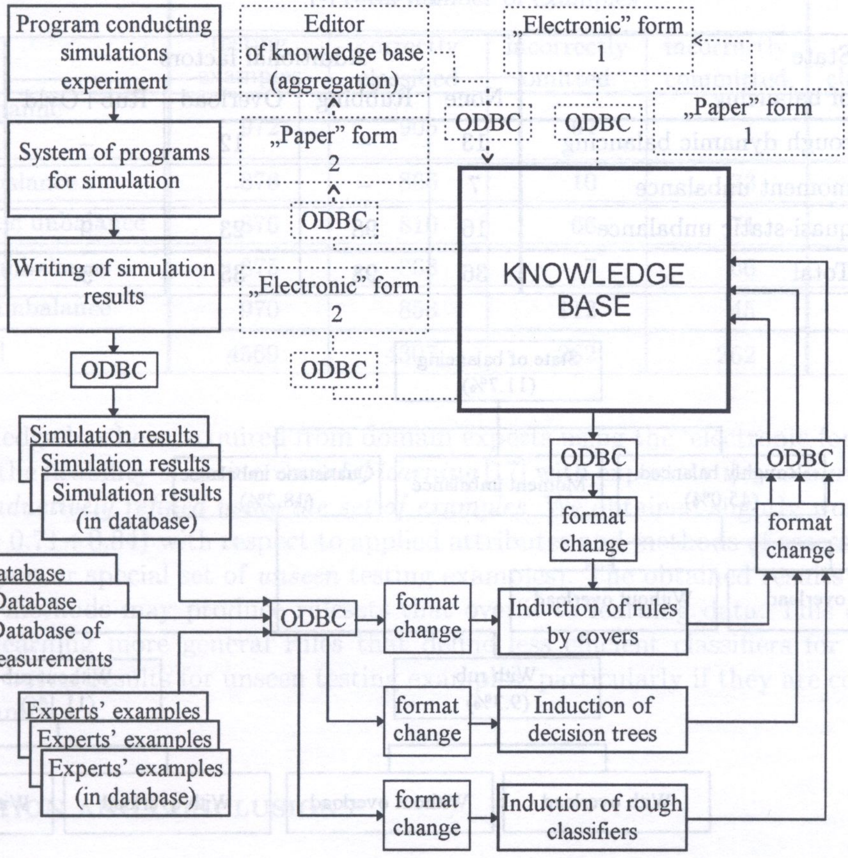

Fig. 5. System of diagnostic knowledge acquisition *SPWD1* [9]

The *SPWD1* system has been employed in verification of usefulness of the methods and tools. We give some examples of applications of the system's components in the next section.

5. EXAMPLES OF APPLICATIONS

Exemplary applications of the described methods and means have been presented in [9, 10]. These examples concerned rotordynamic problems related to diagnosing of some technical states of a rotating machine. The investigations were carried out using a *material model of a rotating machine* (so-called *Rotor Kit*). In addition we prepared a dataset performing a *numerical experiment* by means of a simulations software system *MESWIR* [2].

5.1. Data acquired within active experiment

The investigations concerning the material model have been performed in an *active experiment conditions*. Within the experiment we considered relationships between rotor vibrations and such their causes as: *unbalance*, *rubbing* and *overload*, which occurred by several rotating speeds of the rotor (subcritical, critical and overcritical speeds). Numbers of observations concerning several combinations of considered elementary technical states are shown in Table 1 [9]. Measurements and signal processing have been carried out by P. Kostka [5].

Since combinations of these factors caused *complex technical states* of the object, common ML methods gave poor results yielding the overall efficiency $\widehat{\eta}_{ov} = 1 - \widehat{\epsilon}_{ov}$ of the classifier amounting to 65 percent (see [5]). Therefore the author elaborated a novel attempt consisting in a *decomposition*

Table 1. Numbers of observations for different combinations of factors considered in the active experiment [9]

State of balancing	Additional factors				Total
	None	Rubbing	Overload	Rub+Ovld	
rough dynamic balancing	13	–	12	–	25
moment unbalance	7	–	–	–	7
quasi-static unbalance	16	98	23	9	146
Total	36	98	35	9	178

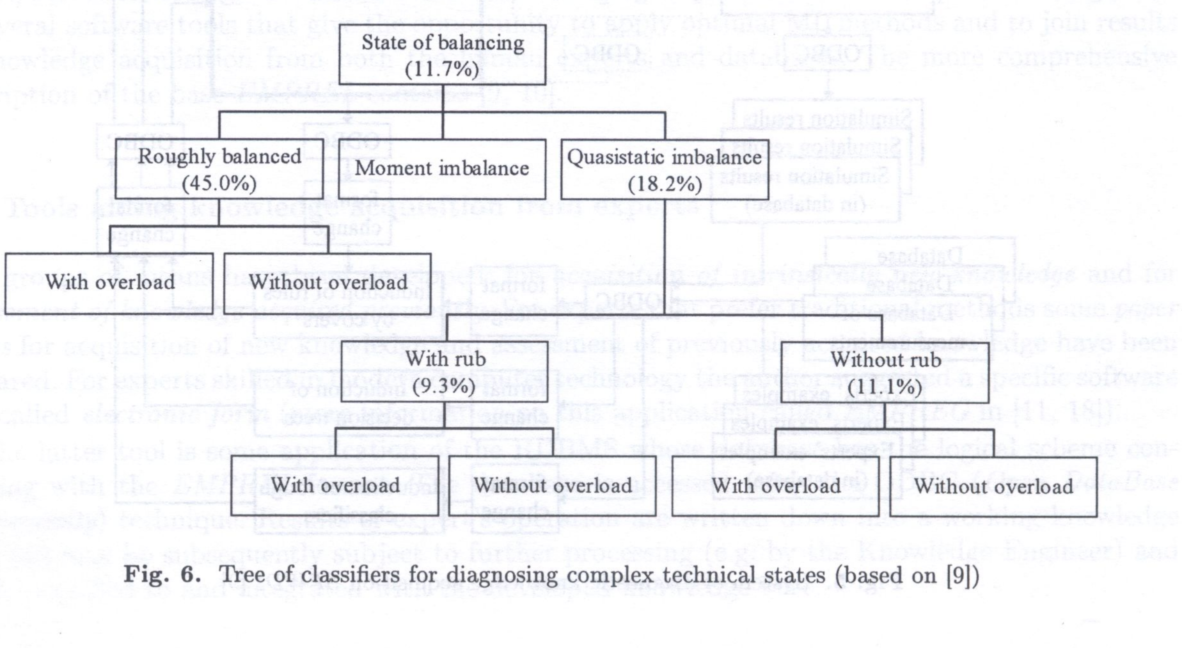

Fig. 6. Tree of classifiers for diagnosing complex technical states (based on [9])

of the set of examples according to the structure of the set of considered technical states [9]. The best tree is shown in Fig. 6 (figures in the blocks represent classification errors $\hat{\epsilon}_{ov}$ for each classifier).

The efficiency of several classifiers determined by the 'chunk' of knowledge obtained using the new method has been essentially increased, that proved the usability of this method in typical diagnostic tasks where complex technical states are commonly observed. However, significant errors are encountered if we observe overload. They may be caused by too small overload magnitudes applied during the experiment, which did not cause vibration response that is typical in case of such malfunction.

5.2. Data acquired within numerical experiment

The *numerical experiment* has been performed according to less complex plan where only elementary states of balancing and closed numbers of examples for each considered class have been taken into account. Because we decided to represent data and knowledge using qualitative attribute values, an interesting problem was identified consisting in the need of discretization of continuous (quantitative) attribute values. The author suggested a *method of optimal selection of quantization levels with respect to minimum classification errors.* We applied only a few qualitative values which may easily be represented by linguistic values. This makes the interpretation of knowledge easy to understand for human experts.

We obtained very high efficiency of classifiers (about 95 percent – see Table 2) determined by knowledge portions acquired by means of all ML methods applied.

Table 2. Summary of results of estimation of the classification performance [9]

Class No.	Name of technical state	Total number of examples				Fraction of examples
		testing examples	correctly classified	incorrectly omitted	incorrectly committed	correctly classified [%]
1	rough dynamic balancing	972	905	67	7	93.1
2	static unbalance	876	866	10	73	98.9
3	quasi-static unbalance	876	810	66	71	92.5
4	moment unbalance	875	868	7	66	99.2
5	dynamic unbalance	970	858	112	45	88.5
Total		4569	4307	262	262	94.3

Moreover knowledge has been acquired from domain experts using the 'electronic form'. Thus we were able to verify the usability of an *incremental learning* [17] with experts' rules as *input hypotheses* which were then *inductively refined using the set of examples.* We obtained slightly worse efficiency of classifiers ($\widehat{\eta}_{ov} = 0.71 \div 0.84$) with respect to applied attributes and methods of assessment (either resampling techniques or special set of *unseen* testing examples). The obtained results enable us to conclude that ML methods may produce rulesets that overfit to learning data. This effect should be minimized by learning more general rules that define less efficient classifiers for the training examples, but give better results for unseen testing examples, particularly if they are collected from other source of examples.

6. Recapitulation and conclusions

Within the conducted research we elaborated the *comprehensive methodology of diagnostic knowledge acquisition* which includes many *methods of knowledge acquisition* from the most important sources of diagnostic knowledge and *methods of knowledge assessment*. These methods were implemented in several applications subsequently joined in the *integral knowledge acquisition system*. This system gives intrinsically new opportunities in efficient acquisition of diagnostic knowledge from different sources and in hybrid attempt to evaluation of knowledge.

The research confirmed that the applied methods and tools make possible to efficiently carry out the knowledge acquisition process with the use of the most valuable sources of diagnostic knowledge concerning typical tasks of rotordynamics of machinery. The process is effective enough even in case of complex technical states of the object(s). Due to the common knowledge representation format the hybrid approach to the whole process of knowledge acquisition and assessment is possible.

However, all the developed methodology needs further verification. An interesting opportunity becomes recently carried-out research concerning knowledge acquisition of large industrial turbine sets where we are faced with more complicated problems as: nonlinear phenomena, compound technical states, many attributes of objects, complex problem of optimal data quantization connected with the selection of relevant attributes, etc. This research has been recently initiated by the author in the Department of Fundamentals of Machine Design, Silesian Technical University of Gliwice. Some problems concerning this research subject are discussed in [6].

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