THE USE OF EXPERT SYSTEM FOR MARINE DIESEL ENGINE DIAGNOSIS

WYKORZYSTANIE SYSTEMU EKSPERTOWEGO DO DIAGNOZOWANIA OKRĘTOWEGO SILNIKA TŁOKOWEGO

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Abstract: The paper presents a diagnostic system for marine diesel engine based on an expert system model. The research relevant to knowledge acquisition for this system was done, knowledge data set was built and general structures of the expert system was proposed. Basic sources of knowledge which can be used for construction of knowledge data set are also identified. The basic knowledge related to the diesel diagnostic was undertaken from experts and diagnostic data base. The paper questionnaire was used to the knowledge acquisition from experts. The basic knowledge related to the marine diesel exploitation was undertaken. The rule induction algorithms was used to knowledge acquisition from data base. During the experiment efficiency of LEM induction algorithms was compared to new MODLEM and EXPLORE algorithms. Training and test data were acquired from experiment on marine engine Sulzer 3AL 25/30.

Keywords: technical diagnostic, expert system, marine diesel engines

Streszczenie: W artykule przedstawiono koncepcję systemu diagnostycznego okrętowego silnika tłokowego opartą na modelu systemu ekspertowego. Zrealizowano pozyskiwanie wiedzy diagnostycznej, opracowano bazę wiedzy oraz zaproponowano ogólną strukturę systemu. Wiedza dla ekspertowego systemu diagnozowania silnika okrętowego została pozyskana od ekspertów (specjalistów w dziedzinie eksploatacji) oraz z diagnostycznych baz danych. Do pozyskiwania wiedzy od ekspertów zastosowano wywiad kwestionariuszowy. Podjęto próbę pozyskania podstawowej wiedzy z dziedziny eksploatacji silników umożliwiającą ocenę ich stanu technicznego. Pozyskiwanie wiedzy z baz danych przeprowadzono z wykorzystaniem indukcyjnych metod uczenia maszynowego. Dane uczące dla algorytmów indukcji zostały zgromadzone w wyniku realizacji eksperymentu czynnego na silniku Sulzer 3Al 25/30.

Słowa kluczowe: diagnostyka techniczna, system ekspertowy, silniki spalinowe

1. Introduction

The development of diagnostic systems for marine diesel engines is vital for both ship safety and economic reasons. Nowadays, many diagnostic systems have been created by both research laboratories and engine producers. Typical disadvantage of most systems is their completeness. This means that diagnostic algorithms of technical conditions, adopted during system creation, cannot be updated or modified during later operation.

The solution to the problem could be an expert system in ship engine diagnosis. Module system structure, and above all, the separation of database from remaining program, enables creation of diagnostic system of open type, where diagnostic knowledge can be updated and cumulated.

This paper presents diagnostic system concept, for marine diesel engine, basing on expert system model. The relevant knowledge database was created with use of collected diagnostic data.

Diagnostic data were collected from experts (ship engine professionals) and diagnostic databases.

2. Collecting knowledge from experts

The survey was to collect declarative opinions, useful in technical analysis of engine condition. Collection was made in a fashion where knowledge database programmer played a vital role [1]. The programmer was responsible for the interpretation and aggregation of collected expert opinions.

The survey was to obtain operational knowledge information in the form of diagnostic relations, like “damage – damage symptoms”. Along with operational knowledge, collected information included basic appliance instructions, necessary for storage format of diagnostic report. Basic knowledge included dictionaries of object names, object property names, as well as, terms indispensable for data storage.

Expert data were collected during Questionnaire Interviews [2]. The questionnaire questions were tabled. Malfunction listing was created on the basis of problems addressed in professional literature [3, 4]. Questionnaire used open questions with an option of entering new malfunction names by the respondent. Survey experts were chosen on the basis of having at least second mechanic license with 2 years occupational experience. 36 experts took part in the survey.

The questionnaire included malfunctions of the following engine components:

- Fuel system
- Crank-piston system
- Combustion chamber
- Turbocharging system
- Starting-reversing system
- Cooling system
- Lubrication system

Each expert was to name malfunction symptoms in relevant blank space of his questionnaire form.

Results made up 35 diagnostic rules. The rules included combined premises concluding on technical conditions of particular engine system.

Below presented is an example of such a rule:

Rule R1 system : injection detail: injector

Damage: injector nozzle seizing (injector open)

Symptoms:

- a) Mean effective pressure - drop*
- b) Max. combustion pressure - drop*
- c) Fumes colour change – smoking*
- d) Combustion gases temperature in remaining cylinders - growing*
- e) Max. injection pressure - drop*

Obtained sets of rules were verified in compliance with the procedures proposed by W. Moczulski [1]. Single rules were verified by experts, by ranking them with degree of conviction on their validity.

3. Collecting knowledge from database

The target of the survey was to obtain rules enabling diagnostic of technical conditions of a marine diesel engine on the basis of exploitation information, available in database.

Each set of rules was determined with automatic induction method. LEM2 [5] classical algorithm results were compared with MODLEM [5] and EXPLORE [5] algorithms results.

The assessment of rule induction algorithms was made with the use of data obtained in active experiment on a laboratory engine.

The engine tested was a four stroke Sulzer 3A1 25/30, of nominal power $N_n=408\text{kW}$ and $n=750$ rpm revolution. The engine was fitted with a measurement system enabling reading of basic operational parameters, like

pressure and temperature of combustion gases, charged air, coolant and lubricator. Additionally, taken were fast-changing pressure measurements in engine cylinders and fuel lines. All parameters were automatically saved in a database integrated into measurement system.

The research program was conducted according to active experiment principles. During the experiment, each time, one level of particular malfunction was simulated and all parameters were measured, with engine working within 50 to 250 kW range. The experiment excluded simultaneous presence of multiple malfunctions, as well as, different ranges of particular malfunction.

The following malfunctions were taken into account:

- Air compressor efficiency drop
- Turbocharger filter contamination
- Air charger cooler contamination
- Exhaust duct contamination
- Injection pump leakage
- Diminished injector opening pressure
- Clogged injector nozzle
- Badly calibrated injector nozzle
- Leaky cylinder head

Measurement results were saved in the database and converted to a decision table. Such a form of data presentation is required by adopted rule-induction algorithms. In such a situation, instructing examples are presented in the tabled verses, together with a set of attributes. One of the attributes is decisive, and qualifies a particular example to particular class of decisiveness [5].

The obtained table includes 454 instructing examples, where each of them is represented with 43 numerical attributes. Examples related to 9 simulated engine malfunctions.

Because algorithms LEM2 and EXPLORE should not be applied directly to numerical data, initial discretization was employed.

Investigated induction algorithms were applied both to non-discretized and discretized data.

Survey software, named ROSE2 was prepared Institute of Intelligent Systems of Decision Support at Poznan College of Technology [6, 7].

Evaluation of rule sets was made with regard to classification. It means that verified classifier was each time created basing on rules. Presented in table 1 are the rules and right classification choices obtained with *10-fold cross*

validation technique for investigated rule-induction algorithms. The results of classification are presented in table 1.

Table. 1. Classification results obtained with different algorithms

No	Initial discretization	Induction Algorithm	Number of obtained rules	Percentage of correctly classified examples [%]	Percentage of incorrectly classified examples [%]	Percentage of non-classified examples [%]
1.	None	LEM2	178	24	32	44
2.		MODLEM	35	87	2	11
3.		EXPLORE	5	21	76	3
4.	Local Method	LEM2	56	91	9	0
5.		MODLEM	46	91	9	0
6.		EXPLORE	300	74	26	0

Obtained results indicate high efficiency of MODLEM algorithm in case of non-discretized data. The obtained classification accurateness, estimated with *10-fold cross validation* technique, was 87 %. Classification accuracy obtained with LEM2 algorithm was, in this case, 24 %, while in case of EXPLORE algorithm, in 21 %. In the case of initial digitalization conducted with help of LEM2 and MODLEM algorithms, identical results were obtained. The lowest accuracy was obtained with EXPLORE algorithm.

One doubtless advantage of MODLEM algorithm, comparing with LEM2, is direct numeric data use, without the need for employing initial discretization. On one hand it simplifies the process of data gathering, on the other, improves readability and interpretation of the created rules. In such a situation, the Expert System user previews parameter values included in rule reasoning. Additional advantage of MODLEM algorithm, in spite of its slightly lower classification effectiveness, is low percentage of incorrectly classified examples (in case of initially non-digitalized data). Doubtful examples are then dropped without any classification.

Classifier verification techniques, like *10-fold cross validation* or *leave one out*, enable effective assessment of classification effectiveness of the rule bundle, obtained through induction. However, we must keep in mind the natural shortages of automatic machine-learning methods. During learning process, usually all available attributes describing object operation are used. Learning algorithms enable effective selection of so called relevant attributes, which bear diagnostic information. Such selection takes into account information quantity, necessary for differentiating of classified objects. What is missing, is the opportunity of automatic accountability for

real cause-consequence relations of symptom type, like disqualification criteria. During the learning process, there is a danger of taking into account attributes which bear no diagnostic information but result from operational conditions of the object or randomly occurring disturbances.

Due to above reasons, essential rule-analysis attempt was made on the rules obtained during automatic induction process. There is no reason in analyzing adopted limits of clauses in rule reasoning, because these result from opportunity of differentiating of particular conditions and it would be difficult to find logical justification for them, however, we can attempt to justify the influence of a particular condition (of simulated malfunction) based on the attributes included in rule reasoning.

To identify the reason for air compressor efficiency drop, four rules were created. Below presented are the rules in ROSE2 format:

rule 8. $(a22 < 145.625) \ \& \ (a35 \geq 506.25) \Rightarrow (Dec = 1);$

rule 9. $(a22 < 103.125) \ \& \ (a37 \geq 387.45) \Rightarrow (Dec = 1);$

rule 10. $(a4 \geq 8.75) \ \& \ (a22 < 75) \Rightarrow (Dec = 1);$

rule 11. $(a34 \geq 517.2) \Rightarrow (Dec = 1);$

- a4 – Maximum combustion pressure - cylinder 3
- a22 – Charging air pressure;
- a34 – Combustion gases temperature behind cylinder 1
- a35 – Combustion gases temperature behind cylinder 2
- a37 – Combustion gases temperature prior to turbocharger

The reasoning in rule no. 8 addresses two basic conditions. They relate to attributes of a22 (charged air pressure) and a35 (combustion gases temperature, measured behind cylinder 2). The symptom of simulated efficiency drop in air compressor should appear in the form of charging pressure change. It is a diagnostic parameter that should react to any malfunction of this component. Charging pressure drop results in lower air quantity entering cylinder, as well as, in operational process disturbances. In result of such disturbances, temperature values taken behind cylinders could drop or rise.

Therefore, the reasoning of rule 8 should be considered valid. Similar justification is valid for rules 9 and 11, whose reasoning relates to combustion temperature values, measured behind cylinders, as well as, charging air pressure. In the reasoning of rule no. 10, additionally, maximal combustion pressure in cylinder 3 is also taken into account. It can be reasonably assumed that the change in the parameter is a symptom of

combustion process disturbance, resulting from a smaller amount of charged air.

The presented essential analysis was made for all obtained diagnostic rules. Taking into account the results presented in the above chapter, the final induction of rules was made with help of MODLEM algorithm in ROSE2 environment. With such induction, 35 rules were obtained with combined reasoning premises enabling identification of engine conditions which were simulated during the experiment.

4. System concept

The following general assumptions were adopted in relation to the manner of operation of Expert Diagnostic System for ship engine:

- System user (ship mechanic) feeds data into a computer in form of answers to system-generated questions.
- System may also use data from ship database automatically.
- System generates diagnosis statements on engine qualification to the class of particular conditions.

Basic role of Expert System is to produce statement diagnosis while taking into account input data (fed directly by user or taken automatically from database).

Adopted architecture of the system is of module type. This enables, among other things, easy system updating by adding new elements and making multiple configurations. The system comprises of the following main modules:

- Database (changeable and constant data)
- Knowledge database
- Knowledge obtaining module
- Conclusion module
- Interface module

The structure of the system is presented in figure 1.

Fig. 1. The general structure of Expert System

The most important detail of the whole system is Conclusion Module. It is responsible for the reasoning process and choosing relevant diagnosis. Conclusion Module and Interface Control use CLIPS language. CLIPS enables building basic system elements in homogenous environment. Conclusion Machine, Interface Control and Knowledge Database perform their duties in CLIPS environment.

4.1. Knowledge management module

Most of modern tools for expert systems, including CLIPS environment, lack dedicated software for database management. Database is typically included in a system in the form of a text file saved in the format accepted by particular expert system. During our system development, the necessity arose to create dedicated software for diagnostic information management. The application was created in DELPHI environment and, as an independent module, is included in applications making up Expert System of Combustion Engine Diagnosis.

Knowledge Management Module performs the following actions:

- Installing and editing attribute name dictionaries, objects and malfunctions
- Updating, tracing and editing rules already saved in database
- Assessing rules saved in database
- Importing rules into database from ROSE2 environment
- Exporting database to CLIPS environment format

4.2. Knowledge database

In knowledge database, saved is the basic information on application sector and operational instructions enabling engine diagnosis. Basic information includes object description and object classes, object attribute description, as well as, term dictionaries (of objects, attributes, malfunctions and symptoms).

Operational knowledge is included in rules, enabling assessments of engine conditions. Operational knowledge comprises two sub-bases. This is due to the different methods of recording expert information and automatically generated information. Expert information is of quality type. While collecting data from experts, it was found that they tend to use expressions like "high temperature of combustion gases" or "low pressure of charged air". However, they have problems when it comes to expressing quantitative values of such attributes. In case of data obtained with inductive methods, existent rules relate to quantitative values of attributes. The decision to divide the database in order to convert it to uniform representations, was made for the following reasons:

- Quality information from experts, converted to quantity relations, would demand determining nominal engine and quantitative definition of terms like "high temperature" and "low pressure". The second part seems to be particularly difficult. The definition of "high temperature" may assume different meanings for different experts, and it may strongly depend on the kind of diagnosed engine.
- Quality relations seem to be the most suitable for recording general diagnostic relations and useful for diagnosing various kinds of engines. What is more, this kind of representation enables easy information update, because it intuitively corresponds with the reasoning shown by experts.
- It is generally possible to obtain quality information in an inductive way with the use of initial digitalization, however, it substantially complicates the process of the automatic information collecting. Discretization also diminishes readability of thus obtained rules and makes the dialogue with user difficult.

Taking into account the above difficulties of uniform representation of expert-obtained information and inductively obtained one, each source was stored independently. Expert-obtained information, of general nature, was presented in the form of qualitative rules. Inductively obtained information was saved in the form of quantitative rules (strict).

Quality information was obtained in expert interviews. The database includes 36 rules enabling diagnosing of chosen engine systems.

All rules, saved in qualitative database, were assessed by experts. The detection of malfunctions in the said engine systems with use of these rules is possible at expert-determined certainty level.

Another independent information database of Expert System makes the base with automatically obtained data. Here MODLEM algorithm was used. The rules saved in the base are quantitative in nature (strict). The database contains 35 rules enabling detection of chosen malfunctions of injection system, serviceable parts changing system and combustion chamber system.

The presented database is open. It can be developed and modified in any way.

5. System verificaiton

During the verification of the proposed expert system, the assessment concerned the information saved in system database, as well as, operative value of the system itself (procedures of reasoning and concluding, as well as, interface control).

Expert-obtained rules were verified for their subject-matter properties. Such arrangement resulted in feedback, which in turn enabled the verification of the adopted terminology and applying the method for interpretation by programmer on one hand, and on the other hand, the verification of essential correctness of the rules themselves.

Information assessment made by experts was conducted by means of choosing particular certainty level, ranking the rule correctness [8].

Automatically obtained diagnostic rules were verified with regard to efficiency in diagnosing specific engine conditions, as well as for their subject-matter qualities.

The assessment of system operation took into account the abilities of interface dialogue and the process of correct reasoning.

5. Summary

Complex diagnostic systems for marine diesel engine diagnosis face limited application in ships, particularly due to their high cost. Ship engines are

fitted with assorted indicators and measurement tools enabling control of many operational parameters, as well as, storing such measurements in databases. Technical condition verdict is however still the responsibility of the engine operator, and here comes the room for IT systems, which could facilitate such processes.

The expert system application may substantially enhance abilities of monitoring systems presently existent in power rooms, in respect of ship engine diagnosis. Such system enables saving valuable, operational knowledge for later use. Additional advantage, represents the opportunity of automatic collection of diagnostic information with machine learning methods. The usefulness of such methods for creation of diagnostic rules was proved on the basis of examples stored in database.

The expert system enables integration within a single frame of both information collected from experts and automatically collected one. A doubtless advantage of expert system is the opportunity of updating and developing the content recorded in the database. Due to this feature, the effectiveness of the system may grow during engine operation and facilitate gaining new experience.

References

- [1] Moczulski, W., *Metody pozyskiwania wiedzy dla potrzeb diagnostyki maszyn*, ZN Pol. Śląskiej nr 1382, Seria: Mechanika z. 130, Gliwice 1997.
- [2] Sobocki, M., *Wprowadzenie do metodologii badań pedagogicznych*, Oficyna Wydawnicza IMPULS, Kraków 2001.
- [3] Grzywaczewski, Z., *Niezawodność statków*, Wydawnictwa Przemysłu maszynowego WEMA, Warszawa 1988.
- [4] Żółtowski, B., Cempel, Cz., *Inżyniera Diagnostyki Maszyn*, Polskie Towarzystwo Diagnostyki Technicznej, Instytut Technologii Eksploatacji PIB Radom, Warszawa, Bydgoszcz, Radom 2004.
- [5] Stefanowski, J., *Algorytmy indukcji reguł decyzyjnych w odkrywaniu wiedzy*, Wydawnictwo Politechniki Poznańskiej, Rozprawy nr 361, Poznań 2001.
- [6] Predki, B., Slowinski, R., Stefanowski, J., Susmaga, R., Wilk, Sz., ROSE - *Software Implementation of the Rough Set Theory*, In., L.Polkowski, A.Skowron, eds. *Rough Sets and Current Trends in Computing*, Lecture Notes in Artificial Intelligence, vol. 1424. Springer-Verlag, Berlin (1998), 605-608.
- [7] Predki, B., Wilk, Sz., *Rough Set Based Data Exploration Using ROSE System*. In., Z.W.Ras, A. Skowron, eds. *Foundations of Intelligent*

- Systems, Lecture Notes in Artificial Intelligence, vol. 1609. Springer-Verlag, Berlin (1999), 172-180.
- [8] Cholewa, W., *Diagnostyczny system doradczy DT3D100. Organizacja procesu wnioskowania*, Raport częściowy nr DT6D131 z realizacji projektu PBZ-038-06, KPKM Pol. Śląskiej, Gliwice.

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