AGENT APPROACH IN MACHINE DIAGNOSIS

Maciej KLEMM, Maciej TABASZEWSKI

Poznan University of Technology, Poland
ul. Piotrowo 3, 60-965 Poznan, Poland
fax. +48 61 665 2307, email: klemm.maciej@gmail.com, maciej.tabaszewski@put.poznan.pl

Summary

The paper presents a new approach to software development of diagnostic machines. The proposed system is a collection of many independent applications called agents which gain the diagnostic information, process it and inform the user of the system of the occurrence of significant events concerning the operation of the object. This allows a comprehensively support of the operation process by detecting the current condition and forecast a failure. An important feature of the proposed system is the speed, ability to learn through the use of artificial intelligence and openness that allows for any development of the system by adding more new items pursuing new activities or the same action on a different basis (increasing the reliability of inference).

Keywords: condition monitoring, agent system, multisymptom diagnostic, artificial intelligence, data mining.

PODEJŚCIE AGENTOWE W DIAGNOSTYCE MASZYN

Streszczenie

W pracy przedstawiono nowe podejście do tworzenia oprogramowania diagnostycznego maszyn. Zaproponowany system jest zbiorem wielu niezależnych aplikacji nazwanych agentami, które pozyskują informację diagnostyczną, przetwarzają ją i informują użytkownika systemu o wystąpieniu istotnych zdarzeń dotyczących eksploatacji obiektu. Pozwala to kompleksowo wspomagać proces eksploatacji poprzez wykrywanie aktualnego stanu i prognozę do awarii. Istotną cechą zaproponowanego systemu jest szybkość działania, zdolność uczenia się poprzez zastosowanie metod sztucznej inteligencji oraz otwartość pozwalająca na dowolny rozwój systemu poprzez dodawanie kolejnych nowych elementów realizujących nowe działania lub te same działania w oparciu o inne zasady (zwiększanie niezawodności wnioskowania).

Słowa kluczowe: diagnostyka, system agentowy, diagnostyka wielosymptomowa, sztuczna inteligencja, eksploracja danych.

1. INTRODUCTION

Modern machines are characterized by ever greater complexity and requirements for higher reliability. In order to cover the costs associated with maintenance of machines, developed countries need to spend billions of dollars annually [1]. For industrial power plants, refineries, oil-producing and gas plants which perform an important function in the economy an interruption of technological process or a failure of critical equipment can be extremely costly. For example, when designing important objects in the gas industry essential for the functioning of the country an additional construction performing as a reserve in case of unexpected failure (additional gas distribution station, additional compressor station, etc.) is assumed. Despite the additional reserve, inadequately maintained production equipment depletes regularly financial revenue of the company and can cause a very expensive failure. Extending the life of machines and maintaining optimum working conditions through proper maintenance practices is a very important investment to avoid significant costs arising from major accidents. The key to a successful prevention-based monitoring system is the accurate determination of limit values for measured parameters or the construction of learner induction system based on a set of rules. However, mere identification of the current condition is insufficient in case of important objects. Modern surveillance systems should be further equipped with the tools of identification of damage and prognosis of the residual time for its failure. It allows the planning and organization of the repair work resulting in reduced downtime and reduced costs often associated with the unjustified replacement of many items that are in good condition as is often the case with the traditional approach based on a preventive system. In order to accomplish the above tasks, particularly for machines with complex structure where use of traditional diagnostic tools is insufficient, it is reasonable to introduce multisymptom diagnostic machines, artificial intelligence and data mining while maintaining high speed operation of the system (preferably a parallel data processing).

2. AGENT APPROACH IN MACHINE DIAGNOSIS

Since the beginning of the 90s technological solutions based on intelligent software agents are said to be the next revolution in computing. This concerns not only the way they communicate with the computer, but also software development methodologies [2]. An agent can be defined as a unit operating in an environment capable of communicating with the environment including other agents of the system (communication), monitoring their environment (perception), and autonomous decision-making (autonomy) in order to achieve the goals set during the design or operation. Examples of application of agent systems can be found in [3, 4, 5, 6, 7, 8]. Agent software is usually installed on one computer which communicates with another agent via the Internet in order to exchange information and derive a common, optimal decision. A diagnostic system based on the agent approach has been recommended as a result of the work conducted by the authors of this paper. The system is a new solution using the independence and specialization of agents to solve specific diagnostic tasks. The resulting system is a collection of many independent programs working parallelly that acquire the diagnostic information, process it and inform the user of the occurrence of significant events concerning the operation of the plant. This solution makes the system open and flexible. During the operation, substitution of any agent can be made which facilitates the maintenance of the computer without interfering with other agents. In addition, a new agent can be introduced into the system, increasing its capabilities without stopping the data collection and conversion process. The only condition here is adapting the agents or their new versions to the accepted form of databases and knowledge bases. A characteristic feature of the agent approach is the adaptation and learning ability. In particular, the presence of the latter characteristic is desirable for the effective operation of the diagnostic system. In such a system new information must be worked out automatically which helps to improve the system and alerts the user about any problems. Of course this requires interaction with the operation of the system because it is necessary to enter some necessary data related to the confirmation of certain defects or confirmation of the earned value limits, etc. Interacting with the service staff allows the use of heuristic knowledge based on years of experience gained by maintenance services. In order to complete the diagnostic tasks it is necessary to apply artificial intelligence methods and some statistics methods. An important characteristic of agents is independent decisions based on changes in the environment in which they operate.

The initiative of the most important agents in the suggested diagnosis system, among other things brings to:

- developing new symptoms on the basis of the existing data,
- developing their limits,
- assessing the ”quality” of the symptom in relation to its usefulness for further tasks,
- selecting the optimal classifier for the purpose of determining the machine condition on the basis of many symptoms,
- optimizing the selection of forecasting model.

3. SCHEME OF AGENT SYSTEM

Figure 1 shows the schematic diagram of the agent system.

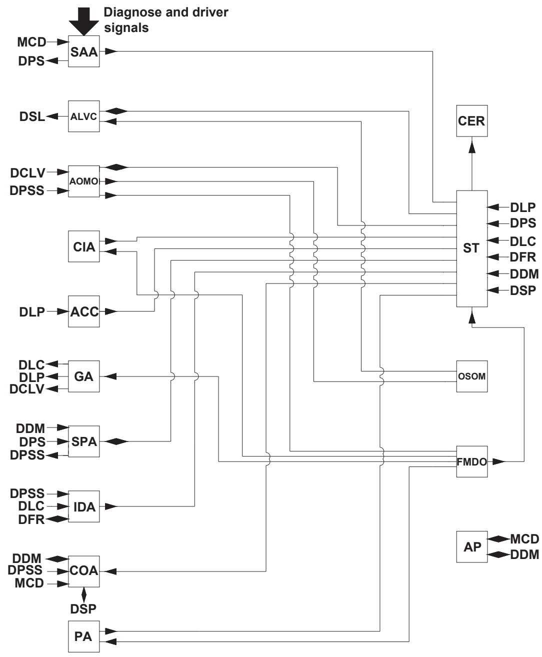

Fig. 1. Simplified diagram of the agent system

Diagnostic agents:

SAA – signal acquisition agent,
ALVC – agent of limit value calculation,
AOMO – agent of observation matrix optimization,
CIA – current inference agent,
ACC – agent of condition class,
GA – genesis agent with the review of current results,
SPA – signal processing agent,
IDA – identify the damage agent,
COA – change observation agent,
PA – prognostic agent.

Databases:

MCD – measurement control database,
DPS – database of primary signals,
DSL – database of suggested limits,
DCLV– database of current limits value,
DPSS – database of primary symptoms and spectrums,
DDM – database of definition measurement,
DLC – database of learner cases,
DLP – database of learning patterns,
DFR – database of fuzzy rules,
DSP – database of spectrum patterns.

Applications and support files:

CER – current events report,
ST – synoptic table,
OSOM – optimized symptom observation matrix,
FMDO – full matrix of diagnostics observation,
AP – administrator programme.

Diagnostic agents are combined with databases and applications which serve to configure the system or to present the results. Technically the various agents were made as 32-bit Windows applications run simultaneously and working „in parallel". The number of processors (cores) supported by the operating system determines the extent of the parallel operation. Applications are written in an object in C++ language. In many cases, applications that perform complex calculations refer to the MATLAB® engine. The MATLAB® engine then performs calculations and returns the results available to the application.
Figure 2 shows a general scheme of co-operation with the application of MATLAB® engine.

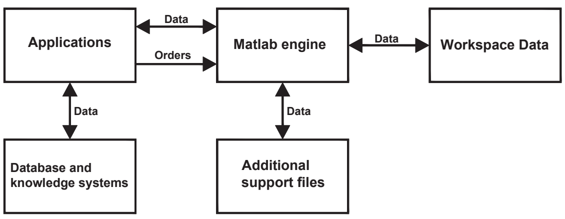

Fig. 2. General scheme of co-operation with the application of MATLAB® engine

This approach allows the implementation of even very complex algorithms. Most of the agents require no user interface so they work in the background. Specialized applications such as program administrator for configuring the system or synoptic table are responsible for the interaction with the user. Data necessary to realize the applications are read and written directly by the applications themselves. Thus, only applications have a direct contact with the database or knowledge base. Whereas, triggered scripts realized by the MATLAB® engine collect and store, if necessary, the data from and to the auxiliary configuration files. In order to test the proper operation of algorithms, simulated data validating the predictable results were introduced. In order for the, simulated data to be close to the actual data random interferences were implemented. Additionally, some tests were carried out based on measurement data. The tests helped determine the correctness of the procedures by individual agents and the proper operation of the system as a whole.

4. DESCRIPTION OF DIAGNOSTIC AGENT

<u>Signal Acquisition Agent (SAA)</u> - reads signal transducers and / or diagnosed machine control system in accordance with the configuration preset in the administrator program (AP) by the user of the system. Signal acquisition takes place without the nonstationary conditions. In addition, when the machine stops, the agent's task is to stop the acquisition process to prevent erroneous results to be entered into the database. The current agent is to stop the data stream when the other agents do not keep up with its processing (queue overflow detection).

<u>Signal Processing Agent (SPA)</u> - Its task is to define measures of the signal point in the frequency bands given by the user and worked out by the system and to calculate the signal amplitude spectrum. The agent samples the data from the queue waiting to be processed and removes them from the queue. As soon as signal measurement values are set, they are recorded in the corresponding table also containing information about the values of operating parameters of the measurement time and measurement uncertainty The agent sets out the following useful diagnostic measures:

- root mean square (RMS),
- peak,
- kurtosis,
- peak factor,
- clearance factor,
- impulse factor.

<u>Change Observation Agent (COA)</u> - The task of this agent is to identify changes in the signal and to generate new frequency bands for measurement in which the change is significant. This is done by detecting changes in the current spectral image and comparing it with the reference spectrum obtained at the earliest possible stage of machine life. The spectrum of a model is created for each combination of operating parameters thus the reference standard may occur later than at the beginning of the operations. New frequency bands are stored in an appropriate database which is interpreted by the signal processing agent (SPA). It should be noted that the newly generated frequencies are not removed from the database, even if for some reason there are no more changes of the effective value of the signal in the band

or even in case of a return to the initial baseline (recorded for the reference spectrum). In other words, once found changes-sensitive band is saved in the database.

Agent of Observation Matrix Optimization (AOMO) - The task of the agent is to assess individual symptoms in terms of their suitability for diagnostic tasks. In addition, this agent assesses the symptom sensitivity. The Signal Processing Agent (SPA) evaluates the measurement uncertainty associated with that measure. Quality assessment of symptoms (no recognized power of the trend), the numerical value of sensitivity and measurement uncertainty are recorded in the database. In this way, none of the defined symptoms is removed from the processing queue; at the most, it will be ignored by successive agents if it is rated "insufficient".
The agent distinguishes the following types of curves of life:
- no trend (fluctuation around a constant value),
- linear trend,
- trend of an average dynamics describable with a second-degree polynomial,
- stronger trend, growing rapidly.

Another task of the agent is to include in the observation additional information about generalized symptom which by definition must carry information about the overall condition of the machine. This symptom is developed on the basis of PCA distribution [9].

Agent of Limit Value Calculation (ALVC) – Agent of limit value calculation is based on the method of symptom reliability [10, 11, 12, 13, 14, 15, 16, 17, 18, 19]. Having collected several measurements (for a given combination of operating parameters), and having taken into account suggestions as to the curve of life (in the absence of a significant limit value trend is not determined), the agent sets the empirical distribution of the symptom and chooses the best model of symptom reliability. The dependence is determined by the designated limit symptom. Information about the limit value is added to the table representing the optimized observation matrix. Independent limits value may be defined by the user. The first measurement being taken, the values are set at the level larger by 16dB than the value of the measurement. The user of the system decides if the obtained limit value is to replace the existing one (the initial value or the user-defined one).

Identify the Damage Agent (IDA) - The main goal of the agent is signal observation (additional and independent from the observation done by CIA) to detect characteristic components (combinations of components) that are associated with certain defects [20, 21]. A fuzzy classifier has been used here which conditions not only the type of damage but also classifies the contractual rate on the basis of the rules. The choice of location, width and shape of the corresponding fuzzy sets are of paramount importance, so that the user is notified only of the essential problems, i.e. those where individual damages are fully traceable. In addition to defining the fuzzy rules, it also requires defining stage adaptation of specific sets of signals available immediately after booting a new machine or after repairs. It is the only agent in which expertise is required during the system startup. After the startup, the agent makes it possible to correct the fuzzy sets as soon as specific examples of measurements with the identified defects appear.

Current Inference Agent (CIA) - The algorithm of the agent reads the new data and compare the current value of the symptom to its limits. The task of the agent to respond to the emergence of new data in the system, to compare the obtained readings of symptom values with the limits and the technical assessment based on the results of these comparisons as well as to inform the user about the occurrence of exceedances by means of a synoptic chart.

Agent of Condition Class (ACC) - Agent of status classification is based on the classification of distance and "k nearest neighbors" method [22]. This allows to run the classifier on the relatively small number of observations learners. Based on the collected examples learners, the agent allows to distinguish between two conditions: fit and unfit. The proposed method is a supervised method which means that it requires the existence of many examples of classes of learners to describe both conditions. This undoubtedly represents a significant problem. Therefore, it is assumed that initially a major role in determining the status of the class will be played the Current Inference Agent. But with the influx of cases related to both learners: the system operation as well as archival data, or data obtained from other machines of the same type, given by the service, the classifier will be able to suggest the resulting class status for specific data (recognition), as well as to run a testing phase and define a classifier error.

Genesis Agent with the review of current results (GA) - The current agent allows the user to enter some information about events and the identification of operating symptoms which probably correspond to the change in status. The latter possibility stems from the fact that the exclusion of an object and the statement of its unavailability may occur after the fact of failure. For example, a spindle bearing failure may be detected through the analysis of the deficiencies that arise as a result of grinding. The user must associate the information about the damage with the observation of trends in symptoms. In some cases it may be very simple (e.g. crack identification manifested with a sudden jump in symptom), but sometimes, if there is a slow upward trend, determination of transition time into an unfit condition will be done only with some approximation.

Prognostic Agent (PA) - The task of the agent is to develop estimates of the residual time to failure based on a variety of symptoms [23]. It should be noted that the final estimate of the residual time to failure based on the number of independent measurements is not easy. This is due to the fact that each symptom may indicate a different value of the residual time. It is important to eliminate the symptoms that are not sufficiently sensitive (no reaction to wear) from the process of multisymptom forecast construction, hence the need for the selection of symptoms. The selection of an adequate predictive model is also of paramount importance. Forecasts built on outdated models will lead to significant errors. A separate forecast based on the best (of the group considered) model is developed for each symptom. In the next step generated information is used to estimate the residual time. The limit values of symptoms are determined using the Border Designation Value Agent (BDVA).

5. SUMMARY OF THE SYSTEM AS A WHOLE

The final version of multiagent diagnostic system allows the implementation of the following diagnostic tasks:
- acquisition of diagnostics signals,
- processing and analysis of diagnostic signals,
- evaluation of the symptoms,
- detecting changes in the signal and searching for sensitive frequency bands, changing significantly with the severity of the operation time,
- comparison of symptoms with the limits,
- independent classification based on multiple symptoms,
- implementation of fuzzy decision rules,
- evaluation of symptom forecasting models,
- setting limits by method of reliable symptoms,
- visualization of results,
- system configuration.

6. CONCLUSIONS

The developed system enables a comprehensive service to assist the maintenance process by detecting the current condition and forecast the time to change it. This is essential for critical machinery, the sudden failure could result in large financial losses resulting from the interruption process, or a sharp object injury, which can endanger human life and health. The proposed system is unique and although it has been tested at various levels, it is a prototype solution. A significant feature of the proposed system is its openness allowing any development of a system by adding more new items pursuing new activities, or the same action under different rules (to increase the reliability of inference). The system was tested at different levels, from the testing algorithms used by testing the implementation of individual agents, finishing all tests based on the test stand. Made every effort to ensure that the proposed system was quite reliable. It is, however, important to realize that, as is the case with everyone, even much simpler programs, such a complex system may have some imperfections and errors undetected. Thus, as is the case in all programs, the system must be further developed and bugs must be removed as they are identified.

ACKNOWLEDGMENT

The paper was written partly due to financial support of Ministry of Science and Higher Education of Poland, grant No 1751/B/T02/2009/37 and project 4.R.09 financed by the Ministry of Science and Higher Education of Poland and coordinated by the Central Institute for Labour Protection - National Institute.

REFERENCES

[1] W.Q. Wang, M.F. Golnaraghi and F. Ismail, *Prognosis of machine health condition using neuro-fuzzy systems*, Mechanical Systems and Signal Processing 18 (2004) 813-831.
[2] Kamil Żarów, *Przewidywanie awarii*, Inżynieria i Utrzymanie Ruchu Zakładów Przemysłowych, czerwiec 2009.
[3] Stranjak A., Ebden M., Rogers A., *A Multi-Agent Simulation System for Prediction and Scheduling of Aero Engine Overhaul*, Proc. of 7th Int. Conf. on Autonomous Agents and Multiagent Systems (AAMAS 2008). May, 12-16., 2008, Estoril, Portugal.
[4] McArthur S.D.J., E. Davidson M., Hossack J.A., McDonald J.R., *Automating Power System Fault Diagnosis through Multi-Agent System Technology*, Proceedings of the 37th Hawaii International Conference on System Sciences – 2004
[5] S. D. J. McArthur S.D.J., Davidson E.M., *Multi-Agent Systems for Diagnostic and Condition Monitoring Applications*, Internet publication: http://www.emse.fr/~boissier/enseignement/sma06/ exposes/01372751.pdf, availability: September 2011
[6] Rouff C.A., Hinchey M., Rash J., Truszkowski W., Gordon-Spears D., *Agent Technology from a Formal Perspective*, Springer-Verlag London Limited 2006
[7] Chiung-Hon Leon Lee, Wen-Shang Tseng, Chin-Mu Chen, Alan Liu, Syuan-Ming Huang, Huang-Bin Huang, *Designing an Intelligent Agent for Information Appliances*, Journal of Computers Vol.18, No.1, April 2007.

[8] Savarimuthu B. T. R., Purvis M., Fleurke M., *Monitoring and controlling of a multi - agent based workflow system*, Australasian Workshop on Data Mining and Web Intelligence (DMWI 2004), Dunedin. Conferences in Research and Practice in Information Technology, Vol. 32.
[9] Kornacki J., Ćwik J., *Statystyczne systemy uczące się,* Warszawa, WNT 2005
[10] Cempel C., *Pareto Law of Damage Evolution in Application to Vibration*, Condition Monitoring. Bulletin of the Polish Academy of Sciences, vol. 39, No 4, 1991, str. 573-588
[11] Cempel C., *Passive Diagnostic Experiment, Symptom Reliability and Their Applications in Vibration Condition Monitoring*, Zagadnienia eksploatacji maszyn, Zeszyt 2-3 (82-83), 1990.
[12] Papoulis A., Probability, *Random Variables, Stochastic Processes*, McGraw Hill, New York 1965.
[13] Cempel C., Natke H.G, Yao J.P.T., *Symptom - Based Reliability for Critical Operating Systems*, Intern. Workshop on Damage Assessment, Pescara - Italy, May 1995.
[14] Tomaszewski F., Cempel C., *An Attempt to Diagnose a Locomotive Combustion Engine by Utilizing Vibroacoustic Processes*. The Archives of Transport , No 1, 1991.
[15] Cempel C., *Pre-Breakdown Symptom Value for Vibration Condition Monitoring*, Bulletin of The Polish Academy of Sciences, Technical Sciences Vol. 37, No 7-12, 1989.
[16] Cempel C., Natke H. G., Tabaszewski M., *A Passive Diagnostic Experiment with Ergodic Properites*, Mechanical Systems and Signal Processing, 1997, vol. 11, s. 107 – 117.
[17] Cempel C., *Damage Initiation and Evolution and Operating Mechanical Systems*, Bulletin of The Polish Academy of Sciences, Technical Sciences, 1992, vol. 40, no. 3, s. 201 – 214.
[18] Cempel C., Natke H. G., *System Life Cycle – System Life: The Model Based Technical Diagnostics*, A View on Holistic Modeling, System Research, 1993, 10 (1), s. 53 – 62.
[19] Cempel C., *Theory of Energy Transforming System and their Application in Diagnostics of the Operating Systems*, Applied Mathematics and Computer Science, 1993, vol. 3, no. 3, s. 533 – 548.
[20] Białko M., *Sztuczna inteligencja i elementy hybrydowych systemów ekspertowych*, Koszalin, Wydawnictwo Uczelnianie Politechniki Koszalińskiej 2005.
[21] Łachwa A., *Rozmyty świat zbiorów, liczb, realizacji, faktów, reguł i decyzji*, Warszawa, Akademicka Oficyna Wydawnicza EXIT 2001.
[22] Larose D. T., *Odkrywanie wiedzy z danych*. Wprowadzenie do eksploracji danych, Warszawa, PWN 2006.
[23] Tabaszewski M., *Wielosymptomowa prognoza stanu i czasu do awarii z wykorzystaniem sieci neuronowych*, Diagnostyka, 2007, vol. 2 (42), s. 43 – 48.