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HYBRID EARLY WARNING SYSTEMS

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ABSTRACT

New tools are needed to reach high goals for uptime and availability in industrial processes. Early warning of developing faults is one part of the strategy to reach these goals. A single method rarely meets all requirements, but combining methods and techniques in a hybrid system offers advantages and can overcome limitations in the individual approaches. Methods considered are physical models, artificial neural networks, and case-based reasoning. The paper discusses the pros and cons, strengths and weaknesses of the three methods and three combinations of hybrid solutions in order to assist in select a suitable combination for a specific early warning challenge ahead.

Keywords: Early Warning Systems, Intelligent Agents, Case-Based Reasoning, Artificial Neural Networks, Physical Models.

1. INTRODUCTION

Most of the productive equipment in industrial processes are subject to degradation and requires maintenance. Indication on when a machine is deviating from normal behaviour may be provided by an early warning system. Traditionally a maintenance engineer uses her/his senses such as hearing/smell/touch/vision together with additional sensor readings available. This is in many situations sufficient and may even surpass any available automatic system. Unfortunately in many industrial applications there are a number of factors making human monitoring as the main vehicle for early warnings less suitable. Some examples of factors are: 1) a missed early warning leading to breakdown is very costly (production line etc.), 2) monitoring to costly in terms of hours, 3) to fast processes, actions sometimes need to be taken within milliseconds, seconds or minutes to prevent serious faults, 4) relationship between sensor readings and warning is to complex.

Monitoring and early warning systems are efficient means of preventing avoidable and costly maintenance, or to increase the time between detection of a fault and planning and performing maintenance actions. In order to be cost effective, early warning is often applied to only a part of the domain in a process or machine - that which has the greatest impact on maintenance costs. When deciding methods and techniques for such a system the main factors to consider are: 1) Knowledge available of the part to monitor, 2) Historical data available on the part to monitor, 3) Experience available of the part to monitor, 4) On-line data available on the part to monitor, 5) Quality of the measurements.

The ideal situation is if so much data is available that the monitored part can be simulated on a level where all faults can be simulated and predicted. This is rarely the case in real world problems, but they exist. If parts can be simulated simulations may be used to improve the early warning systems performance. Historical data is valuable in a variety of ways, how long is the mean time between failure (MTBF) for different parts, if available, how are sensor signals before a fault, any indications of the fault embedded in the sensor readings? Experience may be experience from the part to monitor, e.g. a if a wooden plank is overloaded it starts to make a cracking sound. On line data may be from sensors already available in the equipment used for control (so called sensorless monitoring) or sensors with the purpose to enable early warning, sensors such as sound, vibration, temperature, smell, purity (of oil/water), acceleration, tension/deformation etc. Initially these data can be used for collecting experience in the form of a correlation between sensor readings and particular problems and later on for more accurate warnings. The quality of sensor measurement is also important, are there missing measurements and faulty measurements? The process itself may degenerate due to for example fouling, this also need to be considered to keep up the long term robustness of the system. A diagnostic system that is robust to degeneration has been proposed [1].

Recent advances in artificial intelligence opens up for new application of early warning systems. In this paper we will shortly describe a number of methods and techniques from artificial intelligence that can be used in an early warning system and how a hybrid approach further can improve the results.

2. IDENTIFICATION OF FAULTS, METHODS AND TECHNIQUESLUBRICATION MANAGEMENT

We will shortly introduce a number of common early warning techniques which in principle are fault identification techniques used in both predictive and corrective maintenance and also briefly list their strengths and weaknesses.

2.1. Artificial Neural Networks

The following is introductions to artificial neural networks (ANN), for more in depth reading on ANN in maintenance see [2]. An ANN is a mathematical construction that can be used for modelling multidimensional systems, i.e. mapping of many inputs onto many outputs. Among their most common applications are pattern recognition and multi-dimensional non-linear regression [3].

There are different types of neural networks. The type of network depends on factors such as their architecture, the paradigm used to train them, and the direction in which the data flows through them, among others. During the training, the ANN learns the internal representations for the training data, and once the training is over, it can make predictions for new input patterns. An ANN with generalization capability is expected to perform well in a real case application for the system for which it has been trained if the data used for training is representative of the system.

The strength of the ANN is that it got low computational requirement and a parallel structure that make the ANNs suitable for on-line applications. It can represent non-linear relations without any knowledge other than sensor measurement data. Dependency on data is also the weak point. Data from real sensors may contain errors that need to be filtered, which is a tedious task and require domain expert.

Measurement data from real sensors do not represent the full operation range of the process or machine, because it is a risk to run the machine to its limits. In practice the model can be run within the space it has been trained on, but not outside. Outside this space there is no control of the size of the model estimation error. Data-driven models such as ANN experience increasing model error if the domain they model is slowly changing due to e.g. fouling and ageing. Retraining a new model to the new set of parameters incorporates filtering of real measurement data.

2.2. Physical models

Physical models are derived from physical experiments. The equations that describe the relation between input and output are well founded in a theoretical framework and thereby transparent to the user. The theories used are simplifications of the real world and a dataset is needed to tune factors in the equations. By tuning factors the model reproduces data closer to the measurements.

Benefit of the physical model is that internal properties of a machine or process can be estimated without being measured and few data are needed to tune the model to reproduce output data from input data. With this knowledge simulations can be performed to produce artificial data that represents the machine behaviour for the full operating range. In addition knowledge of how different errors affect the machine, failures can be simulated and the behaviour of the machine analysed.

Drawbacks are that domain experts are needed to build and tune models, and for complex processes the models may not be able to execute fast enough for on-line applications. They often inherit iterative procedure to compute outputs, and therefore it is difficult to estimate the computation time. To develop physical models there must be rigid knowledge available for the domain to be modelled, which is not always the case.

2.3. Case-Based Reasoning

Engineers often reason about specific cases and use past experience in solving a current situation. Case-based reasoning (CBR) is derived from instance-based learning [4] and is inspired by human reasoning. It offers a method to implement experience based diagnosis systems for real-world applications [5] and it can offer decision support in the area of fault diagnosis [6].

Motivated by the doctrine that similar situations lead to similar outcomes; CBR uses a database containing cases (experienced symptoms, diagnosis, action taken and outcome) and use these case to solve new problems of a similar nature [7]. A CBR system has the ability to display adequate performance even with a sparsely populated case library as it does not require a complete case library for functioning properly from the beginning. The case retrieval can provide intermediate results that are user-friendly and may be used in decision support for technicians. The system improves its base of experience when the new cases are added to the case library. Also it fosters experience reuse and experience sharing in the sense that classified cases from different sources can be added to a common library.

3. HYBRID SYSTEMS

Ideally one of the techniques/methods meets the needs for the task, but with increasing requirements in industrial production rarely one single technique and method meets the needs. The fortunate situation in the presented approaches are that different techniques have different weakness and strengths and may be combined in such a way that the combination has a better performance than can be achieved with any of the included techniques themselves. We will here present and discuss a number of combinations and their properties. In addition to the methods we also consider the concepts of agents and information fusion.

The identified methods and techniques are presented in different combinations and discussed from the aspect of the five main factors to consider listed in the introduction: 1) Knowledge available of the part to monitor, 2) Historical data available on the part to monitor, 3) Experience available of the part to monitor, 4) On line data available on the part to monitor, 5) Quality of the measurements.

The following sections discuss a number of interesting hybrids and also discuss agents as model of thinking when exploring hybrid systems.

3.1. ANN-CBR

A neural network classifier can be derived from a CBR system to be used as an alternative approach to CBR classification [8]. The neural network can represent a compilation of selected domain knowledge from the case library and it can act as decision support in response to its input. The approach is to compile domain knowledge from the CBR system using attributes from previously stored cases. This approach requires enough knowledge available of the part to monitor to be already stored in the case library.
The neural network can act as a small and simple classifier that use only a selected part of the knowledge stored in the CBR system. If additional information about a classification result is wanted, similar cases storing additional historical data and experience can be retrieved from the original CBR system. Once successfully trained, a neural network classifier can be directly applied to on-line data and due to the inherent robustness of a properly configured and trained neural network classifier it has the ability to gracefully handle failing quality of sensor measurements such as noisy, missing and faulty measurements and sensor degradation.

3.2. Physical Model - ANN

In this proposed combination the physical model is the generator of data to build the ANN used for early warning. The main feature of the combination is to utilise the calculation speed of the ANN for on-line early warning and the physical model to generate training data for the ANN.
Assume that we got a physical model that mimics the thermodynamic behaviour in for example a gas turbine or compressor. The historical is often limited due to many reasons, for example if the machine is new (no historical), sensor failure corrupt the dataset or the machine have been operating at only steady-state. The ANN is fed training data generated from physical model simulations that cover complete operation range. Thereby the cumbersome task to choose and filter training data from a real process is avoided. Data from simulator can be automatically generated and do not need any pre-treatment. The simulated data got the same accuracy as the physical model, which may not be accurate enough to capture deviations for early warning. The final adaptation of the early warning system to real behaviour is done when ANN is trained on real data together with the artificial data. The need for real data is limited to small calibration dataset representing one operating point. The calibration dataset need to be free from outliers or sensor faults.
Most machines and processes are subject to slow change such as fouling and wear, and more abrupt changes such as replacement of components, [2](Karlsson, 2008b). These changes are in this combination handled by iteratively calculating the slow change included in the model, and the more abrupt changes are estimated and compensated for in model parameters, the final calibration of the early warning is done by choosing a calibration dataset after the machine is in operation and retrain the ANN together with the new artificial dataset. Now we got a combination of a physical model that can generate training data to an ANN to be used for on-line early warning. The ANN detection levels are very low and are not achievable using thresholds on single measurement devices. Combining methods instead of integrating them opens up for system built of modules where the components; physical model and ANN, are easily exchanged as better are developed.
When using early warning together with a maintenance strategy an important issue is that maintenance decisions are not solely influenced by the plant owner, the maintenance instructions of the equipment manufacturer are very important. The insurance company that insures the equipment and other stakeholders must be convinced of the benefits and robustness of early warning and the impact on reliability before such a system may be used where there is risk for equipment damage if detection of a fault is missed.

3.3. Physical Model – CBR

A case library of pre-classified sensor signals can be assembled in order to automate fault diagnosis using the CBR methodology. A sparsely populated case library may be extended by incorporating model-based reasoning if adequate knowledge of the part to monitor is available. Using adequately specified physical models and pre-classified sensor signals from the model simulation, normal behaviour and faults can be simulated and predicted and additional information such as historical data and experience can be retrieved from similar, previously stored cases in the case library.

On-line data with early warning capabilities such as gear vibrations [9] can be extracted from a simulated physical model and correlated with real measurements of sensor signals stored in the case library. It requires suitable diagnostic parameters that can be projected from model simulation results onto real measurements of sensor signals and it may also require adequate quality of sensor measurements.

3.4. Agents

Agents are a popular approach in artificial intelligence. Agents can be implemented in any of the mentioned techniques and methods and it is not uncommon that agents are implemented with a number of different methods and techniques able to handle a variety of different situations. When building an early warning system definition of agents and the way of thinking when designing the system. Russell and Norvig [10] state that, "an agent is anything that can be viewed as perceiving its environment through sensors and acting upon that environment through effectors". A pure reactive system like a thermostat would meet this basic definition, but most definition also includes social skills (communication) and some "intelligent" behaviour, e.g. ability to pro-activeness, learning and predicting. An agent's goals or desires may be to monitor machinery and keep maintenance costs low without reducing reliability and life expectancy. Agents are computer systems that have properties such as: autonomy, social abilities, reactivity and pro-activeness. All the desirable properties when building an early warning system is described in [11,12,13] and we suggest it is also a powerful context of thinking when building a hybrid early warning system independent of implementation choices.

4. CONCLUSIONS

Combination of methods into hybrids for early warning can if properly done benefit from the strengths of two or more methods, and at the same time cover for the weaknesses. The result is an efficient hybrid with features not possible to reach with single method. From various basis regarding the prerequisites in knowledge, data, experience and measurements, three combinations have been proposed that can provide early warning to be used for example for maintenance decisions. The examples show the strengths of the chosen methods and the combination of them as hybrid system.

A hybrid system using an extended case library by incorporating physical model simulation in combination with additional information such as historical data and experience previously stored as cases in the case library may provide a more complete approach to early warning. The case retrieval may provide more accurate classification results and experience from past cases are available as decision support. The hybrid for early warning combining physical model and ANN show how the real world problem of attaining representative, error free data is partly covered by simulation of physical model to produce ANN training data. The final ANN is generated from a mix of calibrated dataset from real data and the dataset from simulations. The ANN low requirement on computational power is utilised for on-line early warning. A hybrid approach combining a CBR system and a neural network classifier may be used when a small and robust classifier is wanted using only a selected part of the knowledge stored in the CBR system. If properly configured and trained, a neural network classifier has the ability to gracefully handle failing quality of sensor measurements and if additional information about a classification result is wanted similar cases storing additional historical data and experience can be retrieved from the original

CBR system. Agents are autonomous, reactive and pro-active. All these properties are desirable when building an early warning system and we suggest it also as powerful context of thinking when building a hybrid early warning system independent of implementation choices.
Considering the large potential in hybrid systems we propose to explore hybrids for industrial applications and developing guidelines to simplify the process when choosing suitable solution for early warning systems.

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