CONTEXT DRIVEN MAINTENANCE: AN eMAINTENANCE APPROACH

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Abstract:
All assets necessarily suffer wear and tear during operation. Prognostics can assess the current health of a system and predict its remaining life based on features capturing the gradual degradation of its operational capabilities. Prognostics are critical to improve safety, plan successful work, schedule maintenance, and reduce maintenance costs and down time. Prognosis is a relatively new area but has become an important part of Condition-based Maintenance (CBM) of systems.

As there are many prognostic techniques, usage must be attuned to particular applications. Broadly stated, prognostic methods are either data-driven, rule based, or model-based. Each approach has advantages and disadvantages; consequently, they are often combined in hybrid applications. A hybrid model can combine some or all model types; thus, more complete information can be gathered, leading to more accurate recognition of the fault state.

This approach is especially relevant in systems where the maintainer and operator know some of the failure mechanisms, but the sheer complexity of the assets precludes the development of a complete model-based approach. The paper addresses the process of data aggregation into a contextual awareness hybrid model to get RUL values within logical confidence intervals so that the life cycle of assets can be managed and optimised.

Key words: *Context, time series, hybrid models, symbolic, data driven, prognosis, CMMS, fusión*

INTRODUCTION

Assets are complex mixes of complex systems. Each system is built from components which, over time, may fail. When a component does fail, it is difficult to identify it because the effects or problems that the failure has on the system are often neither obvious in terms of their source nor unique. The ability to automatically diagnose problems that have occurred or will occur in systems has a positive impact on minimising risk for hazard, shutdown and slowdown.

Previous attempts to diagnose problems occurring in systems have been performed by experienced personnel with in-depth training and experience. Typically, these experts use available information recorded in a log. Looking through the log, they use their accumulated expertise to link incidents to the problems that may be causing them. If the incident-problem scenario is simple, this approach works fairly well, but if the incident-problem scenario is complex, it becomes very difficult to diagnose and correct failures associated with the incidents.

Computer-based systems are now being used to automatically diagnose problems to overcome some of the disadvantages associated with relying on experienced personnel. Typically, a computer-based system utilises a mapping between the observed symptoms of the failures and the equipment problems using techniques such as table look ups, symptom-problem matrices, and rules of thumb. These techniques work well for systems with simple mappings between symptoms and problems, but diagnostics seldom have simple correspondences for complex equipment and processes. In addition, not all symptoms are necessarily present if a problem has occurred, making other approaches more cumbersome.

There is a need to be able to quickly and efficiently determine the cause of failures, while minimising the need for human intervention, but the above approaches either take a considerable amount of time before failures are diagnosed, or provide less than reliable results, or are unable to work well in complex systems. the present paper proposes a hybrid approach to asset health assessment. The system is useful for identifying problems and proposing remedial measures to repair or correct them. The result will be helpful in optimising maintenance scheduling and route planning while minimising downtime arising from unexpected breakdowns. Simply stated, it will provide a way of predicting faults and dealing with predicted faults before they occur.

DISPARATE DATA SOURCES FOR ASSET HEALTH ASSESSMENT

Most of the assets have a direct impact on the risk for hazard, shutdown or slowdown of factories, transportation systems or other higher level systems where they are deployed. The condition and maintenance of these assets is critical to the effectiveness, efficiency and security of humans, processes and products [1]. Any improvement in the condition or maintenance management and the technology involved in maintenance tasks can have a substantial influence on the operation and therefore the gotten asset revenue.

There is a need to integrate asset information to get an accurate health assessment of the whole system, i.e. infrastructure, factories, facilities, vehicles etc., and thereby determine the probability of a shutdown or slowdown, [12]. However, for such complex assets, much information needs to be captured and analysed to assess the overall condition of the whole system. Additionally, the development of a variety of condition indicators that can be used for condition monitoring has resulted in a significant amount of new and useful information for maintenance. A great deal of information provided over a large area can quickly lead to information overload and, thus, must be handled carefully.

Moreover, the data collected are often dispersed across independent systems that are difficult to access and not correlated. If the data from these independent systems are combined into a common correlated data source, this rich new set of information could add value to the individual data sources. For example, it is common for most of the facilities to collect work records of where work has been done. Many assets also typically measure their health using CM or NDT techniques as "nowcasting" technologies in order to see where work needs to be done. However, these two datasets can remain in separate and individual systems. By combining the data into a location correlated dataset, i.e. metadata (Figure 1), the quality and/or the effectiveness of the work being performed can be analysed by comparing the "asset health" before and after the work is completed.

Figure 2 shows the systems currently used by the maintainers in factories or facilities. CMMS and CM are the most popular repositories of information in maintenance, where most of the deployed technology is installed and unfortu-

nately isolated information islands are usually created. While using a good version of either technology can assist in reaching the defined maintenance goals, combining the two (CMMS and CM) into one seamless system can have exponentially more positive effects on maintenance and asset performance than either system alone might achieve. The combination of the strengths of a top-notch CMMS (preventive maintenance (PM) scheduling, automatic work order generation, maintenance inventory control, and data integrity) with the capabilities of a leading-edge CM system (multiple-method condition monitoring, trend tracking, and expert system diagnoses) in such a way that work orders are generated automatically based on information provided by CM diagnostic and prognostic capabilities improving dramatically the asset performance, [11]. Just a few years ago, linking CMMS and CM technology was mostly a vision easily dismissed as infeasible or at best too expensive and difficult to warrant much investigation. Now, the available technology in CMMS and CM have made it possible to achieve such a link relatively easily and inexpensively. A top-shelf CMMS can perform a wide variety of functions to improve maintenance performance, [13]. It is the central organizational tool for World-Class Maintenance (WCM). Among many other critical features, a CMMS is primarily designed to facilitate a shift in emphasis from reactive to preventive maintenance.

It achieves this shift by allowing a maintenance professional to set up automatic PM work order generation. A CMMS can also provide historical information which is then used to adjust PM system setup over time to minimize unnecessary or redundant maintenance actions or repairs, while still avoiding run-to-failure repairs. PMs for a given piece of equipment can be set up on a calendar schedule or
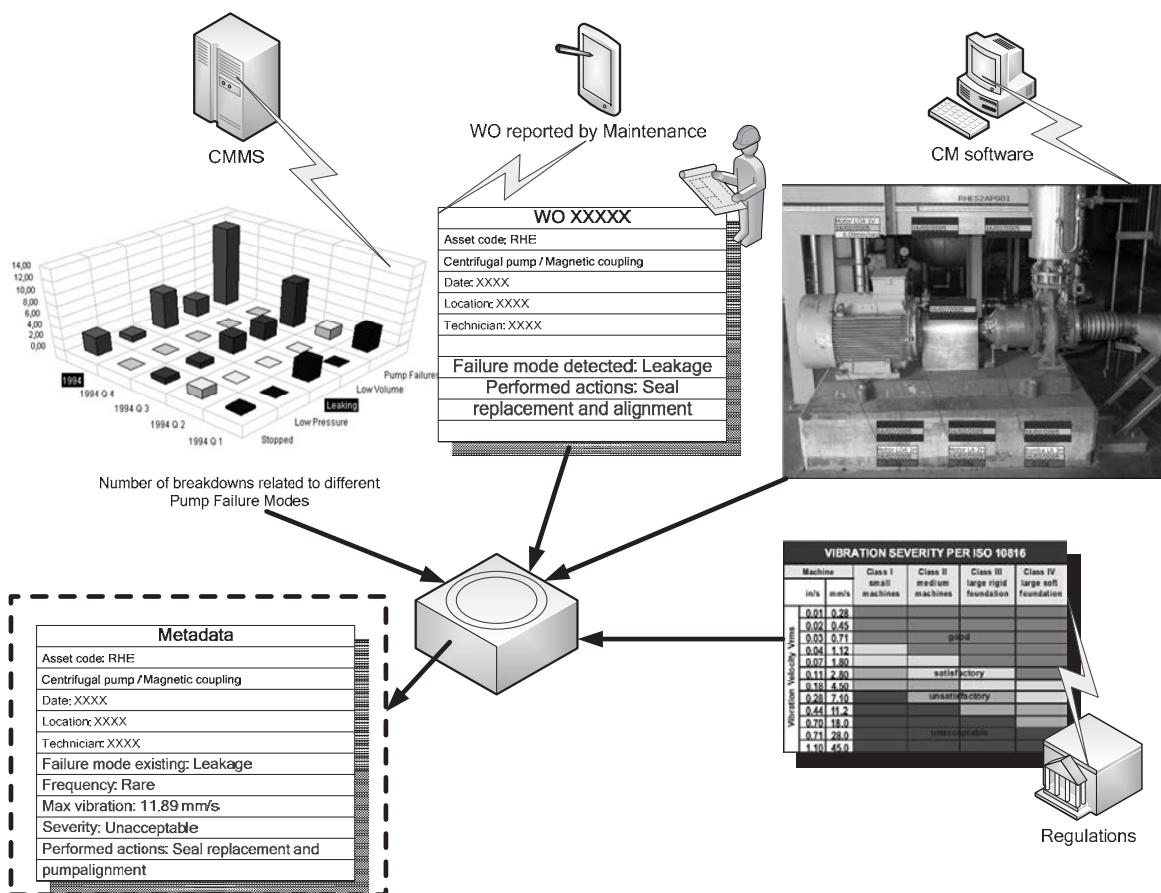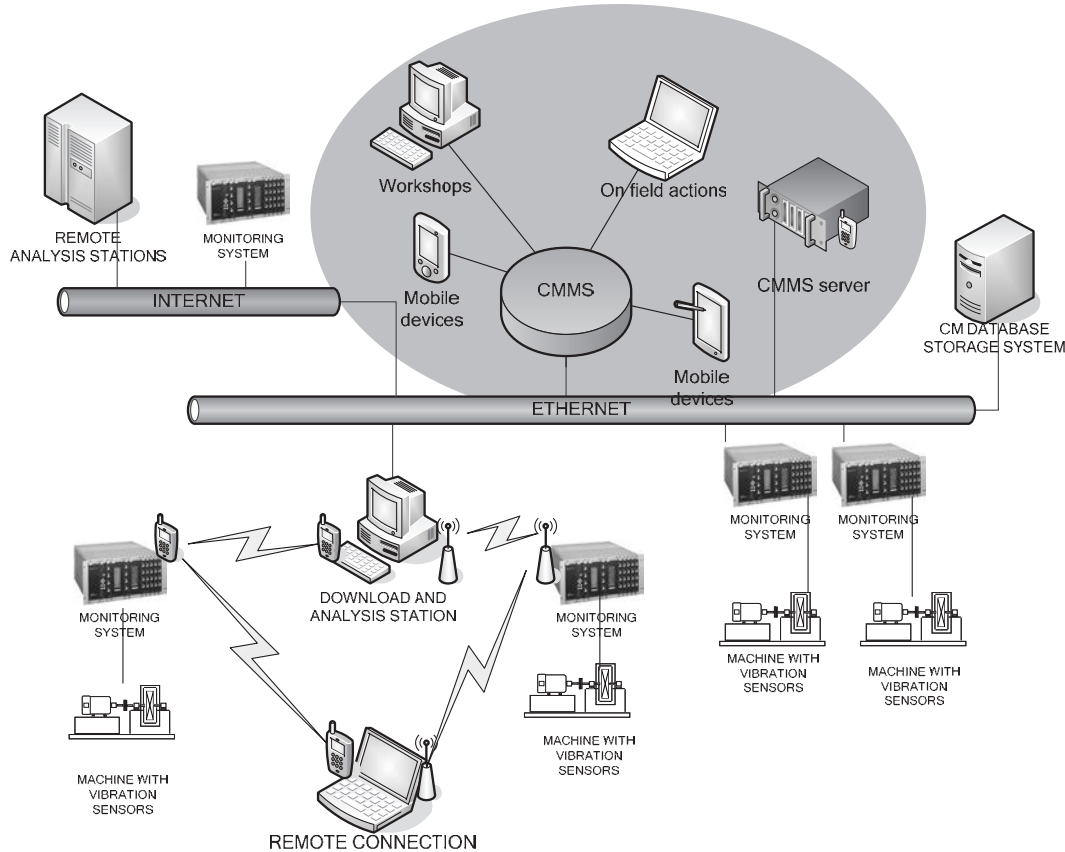

Fig. 1 Metadata for maintenance knowledge extraction

Fig. 2 ICT architecture for the integration of CMMS and CM systems in maintenance and asset management

a usage schedule that utilizes meter readings. A fully-featured CMMS also includes inventory tracking, workforce management, purchasing, in a package that stresses database integrity to safeguard vital information. The final result is optimized equipment up-time, lower maintenance costs, and better overall plant efficiency.

On the other hand, a CM system should accurately monitor real-time equipment performance, and alert the maintenance professional to any changes in performance trends. There are a variety of measurements that a CM package might be able to track including vibration, oil condition, temperature, operating and static motor characteristics, pump flow, and pressure output. These measurements are squeezed out of equipment by monitoring tools like ferrographic wear particle analysis, proximity probes, triaxial vibration sensors, accelerometers, lasers, and multi-channel spectrum analyzers. The very best CM systems are expert systems that can analyze measurements like vibration and diagnose machine faults. Expert system analysis like this puts maintenance procedures on hold until absolutely necessary, thus extracting maximum equipment up-time. In addition, the best expert systems offer diagnostic fault trending where individual machine fault severity can be observed over time.

Both CMMS and CM systems have strong advantages that make them indispensable to maintenance operation improvements. CMMS is a great organizational tool, but cannot directly monitor equipment conditions. A CM system excels at monitoring those equipment conditions, but is not suited to organizing your overall maintenance operation. The logical conclusion, then, is to combine the two technologies into a seamless system that avoids catastrophic breakdowns, but eliminates needless repairs to equipment that is running satisfactorily.

## CONTEXT AWARENESS FOR ASSET MAINTENANCE DECISIONS

A context-aware system actively and autonomously adapts and provides the most appropriate services or information to users, taking advantage of people's contextual information while requiring little interaction.

Context-aware systems (Fig. 3), are usually complicated and are responsible for many jobs, such as representation, management, reasoning, and analysis of context information. They require the collaboration of many different components in the systems. There are various types of different context-aware systems, making it hard to generalise a context-aware system process; however, a context-aware system usually follows four steps.

The first step is acquiring context information from sensors. Sensors convert real world context information into computable context data. By using physical and virtual sensors, the system can capture various types of context-aware information. The system then stores the data into its repository. When storing context data, the kind of data model used to represent the context information is very important; context models are diverse, and each has its own unique characteristics. To easily use the stored context data, the system controls the abstraction level of the data by interpreting or aggregating them. Finally, the system uses the abstracted context data for context-aware applications.

The Need For Complex Relations In Contextual Decision Making.

As the key objective of applied fuzzy systems is to transfer ambiguity into value, the main application effort is the translation of vague information from the natural language of experts into the precise and highly interpretable language of fuzzy sets and fuzzy rules. Experts play a leading
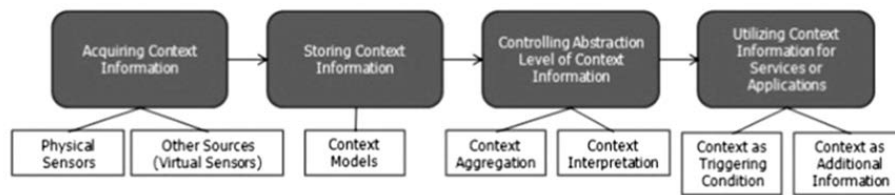
Fig. 3 General Process in Context-Aware Systems

role in this process even in the case of data-driven fuzzy systems; although the rules are automatically discovered by the clustering algorithms, they must be interpreted by the experts [2].

Maintenance engineers and managers face problems in diagnosis and prognosis processes when decisions must be made. Examples of maintenance issues related to quality and quantity of information which justify fuzzy and contextual approaches are listed below.

- vague knowledge must be included in the solution,
- the solution must be interpretable in a form of linguistic rules, i.e. we want to learn about our data/ problem,
- the solution must be easy to implement, use, and understand,
- interpretation is as important as performance.

Information quality and quantity are key parameters in the decision making process when fuzzy and context are used. Even though, there is no fixed order for the design of a fuzzy system, an attempt to define an application sequence for classical expert-based systems is given in Figure 4.
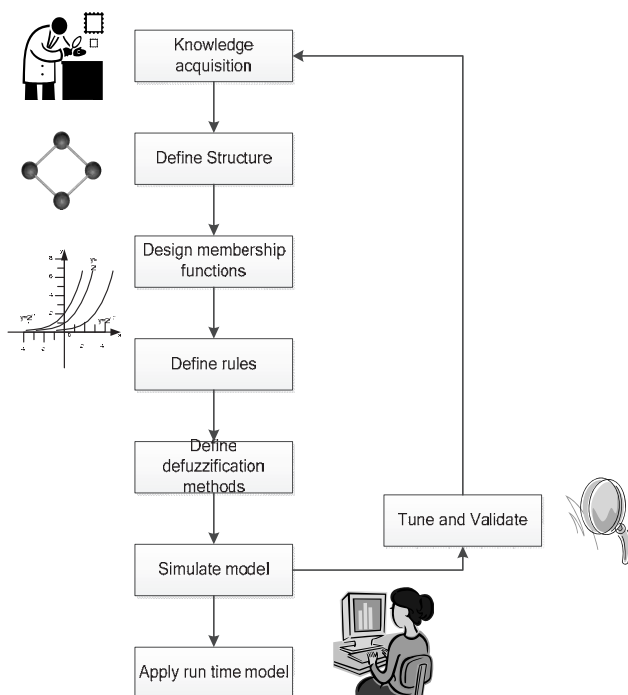
Fig. 4 Application sequence for classical expert-based systems
Source: [3]

Probably 80% of the application success depends on the efficiency and quality of knowledge acquisition. This is the process of extracting useful information from the experts, datasets, known documents and common sense reasoning applied to a specific objective. It includes interviewing the experts and defining key features of the fuzzy system, such as: identifying input and output variables, separating crisp and fuzzy variables, formulating the proto-rules using the

defined variables, ranking the rules according to their importance, identifying operational constraints, and defining expected performance.

Just as the success of expert-based fuzzy systems depends on the quality of knowledge acquisition, so too the success of data-based fuzzy systems is linked to the quality of the available data.

The defined structure at the beginning of the application focuses on data-related issues to select process inputs and outputs from which rules may potentially be derived. Data collection is a critical part of the process; if the data have very narrow ranges and the process behaviour cannot be represented adequately, the chance of discovering appropriate fuzzy rules is very low.

The data processing part of the process includes the discovery of proto-clusters from the data and the definition of the corresponding rules. The most interesting step of the design is determining the size of the granule of the proto-clusters. In principle, the broader the cluster space, the more generic the defined rule. However, some important nonlinear behaviour of the process could be lost. Therefore, the proper size of the fuzzy clusters should be decided together with the domain experts.

The result of the development process is a fuzzy system model based on the generalised rules. There is no difference between either approach in the run-time application [3].

Asset Data Integration Using XML or other standardised file format

New maintenance systems attempt the health assessment of the assets (nowcasting) and prediction for future decisions (prognosis or forecasting) based on all data sources available. In fact, as mentioned above one big issue is that the ICT aspects related to maintenance are more and more complex with a real need of harmonized solutions. Indeed the ICT issues have received the popular name of eMaintenance when disparate maintenance information sources (on and off line, with different granularity, locations and nature) are involved. For that purpose, eMaintenance architectures flexible enough are needed to be deployed in any facility in order to be integrated as a support system gathering data in automatic way. The proposed architecture for collecting and integrating data from disparate data sources based on standardised file format and web services is in Figure 5.

In this model, it is understood that the data collected from disparate sources are converted into a common format using, for instance, XML. For data from disparate data sources to be collected and used in a single system, a configuration database or other integrated configuration system must be provided. In addition, an explorer type display or hierarchy should be provided to allow the manipulation, organisation and use of the collected data, making it available to various applications.
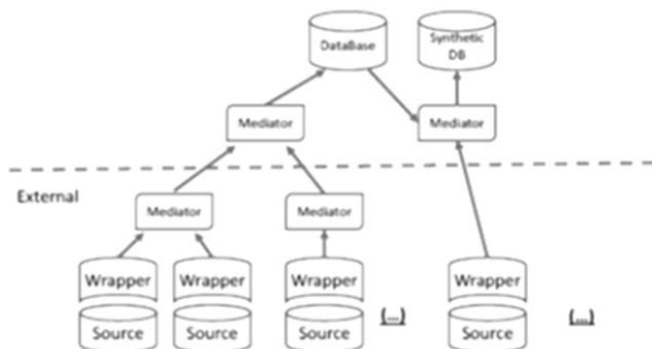
Fig. 5 Integration of disparate data sources

Figure 5 illustrates an architectural overview of a system which collects data from disparate data sources. Generally, the system may include several systems, such as a maintenance management system CMMS, condition monitoring system for both infrastructure and rolling stock, traffic planning and scheduling system, as well as other systems connected by a LAN, the Internet, etc. XML can be used as a transaction server, sending XML wrapped data to the web services indicative of the data. XML wrapped data are read and written from/to the data base via web services.

The web services must include a series of web service listeners which listen for or subscribe to certain data from other data sources and provide these data to the subscribing applications. The web listening services (which may be part of the data collection and distribution system) may listen for and redistribute alarms and events data, process condition monitoring data, and equipment condition monitoring data. Interfaces for this data are used to convert the data to a standard format or protocol, such as the Fieldbus or to XML, as desired.

The web services will be in contact with and receive data from other external data sources via web servers. These external sources may include vibration monitoring data sources, real-time optimisation data sources, expert system analysis data sources, predictive maintenance data sources, loop monitoring data sources, or other data sources.

Finally, a configuration database is used to store and organise the data, including any data from the remote data sources, such as data measurements of forces and load, wheel profiles, flat wheel detectors, hot box detectors, and data from the external web servers.

CONTEXT-DRIVEN MAINTENANCE

Once connectivity is sorted out then sense making becomes the real challenge for data sets. It is therefore time for migrating concepts from e(lectronic) Maintenance to i(ntelligent) Maintenance, [15]. Maintainers must deal many different data sources. In this paper, we use a system framework supporting the integration of various data sources which could have different formats and natures. To handle those differences, the system framework should provide facilities for data wrapping and mediation between different data formats, along with interfaces for external data wrappers and mediators.

The system should also be able to add new sources and mediation procedures and handle the necessary data validation and consistency checking. From the operation point of view, different data spaces must be managed at different levels of the system.

At the data management data space, the following agents and databases must be managed and merged for:
- database, containing the database baseline,
- synthetic database, containing derived calculations from the database or from external sources not included in the database,
- information on managing the databases,
- information on managing wrappers and mediators,
- archived data.

An example of typical data and their relation for transportation facilities can be seen in Figure 6.

1. Prognosis: Achilles heel of health assessment

Beside safety hazards, there are two basic risks associated with assets: shutdowns and slowdowns. These risks materialise in economic loss, [14]. The only way to save money is to perform a proper prognosis, not just a diagnosis. There are three basic ways to model how faults develop: symbolic models, data-driven models, and physics of failure models based on physical principles and mathematical formulations.

1.1 Symbolic models

A symbolic model uses empirical relationships described in words (and sometimes numbers as well) rather than in mathematical or statistical relationships. For example, a semantic description may be a rule for determining whether a fault exists under a certain set of conditions.

Words are a basic form of data for much social science research because they are the usual medium of social exchange. For many purposes, insight into meanings can be obtained by examining profiles of ideas and contextual information contained in text. By "text" we mean a transcript of naturally occurring verbal material, including conversations, written documents such as diaries or organisation reports, books, written or taped responses to open-ended questions, media recordings, and verbal descriptions of observations. Ultimately, the transcript consists of a computerised file of conventional words and sentences for one or more cases.

Clearly, methodologies for directly, systematically and efficiently handling textual data are needed. Traditionally, trained coders are utilised but serious validity, reliability, and practical problems are often encountered.

An example can be a fuzzy rule for how a degradation parameter depends on other parameters, as for example:

IF curvature IS high AND sleeperType IS concrete AND nominalTrackSpeed is low THEN b IS ...

Here, curvature, nominalTrackSpeed and parameter b, the deterioration rate, become linguistic variables, while high and low are linguistic labels, whose semantic meaning is given by fuzzy sets defined over the domains of the respective parameters.

The models found in work orders and maintenance reports, handwritten by maintenance crews, are good for general descriptions of causal relationships, but verbal descriptions are not effective for detailed descriptions of complicated dependencies and time varying behaviour.

This information is usually off-line information recorded in the CMMS system; it gives important hints to create the context or scenario where the fault is developing, allowing us to identify the real fault and distinguish it from false alarms.
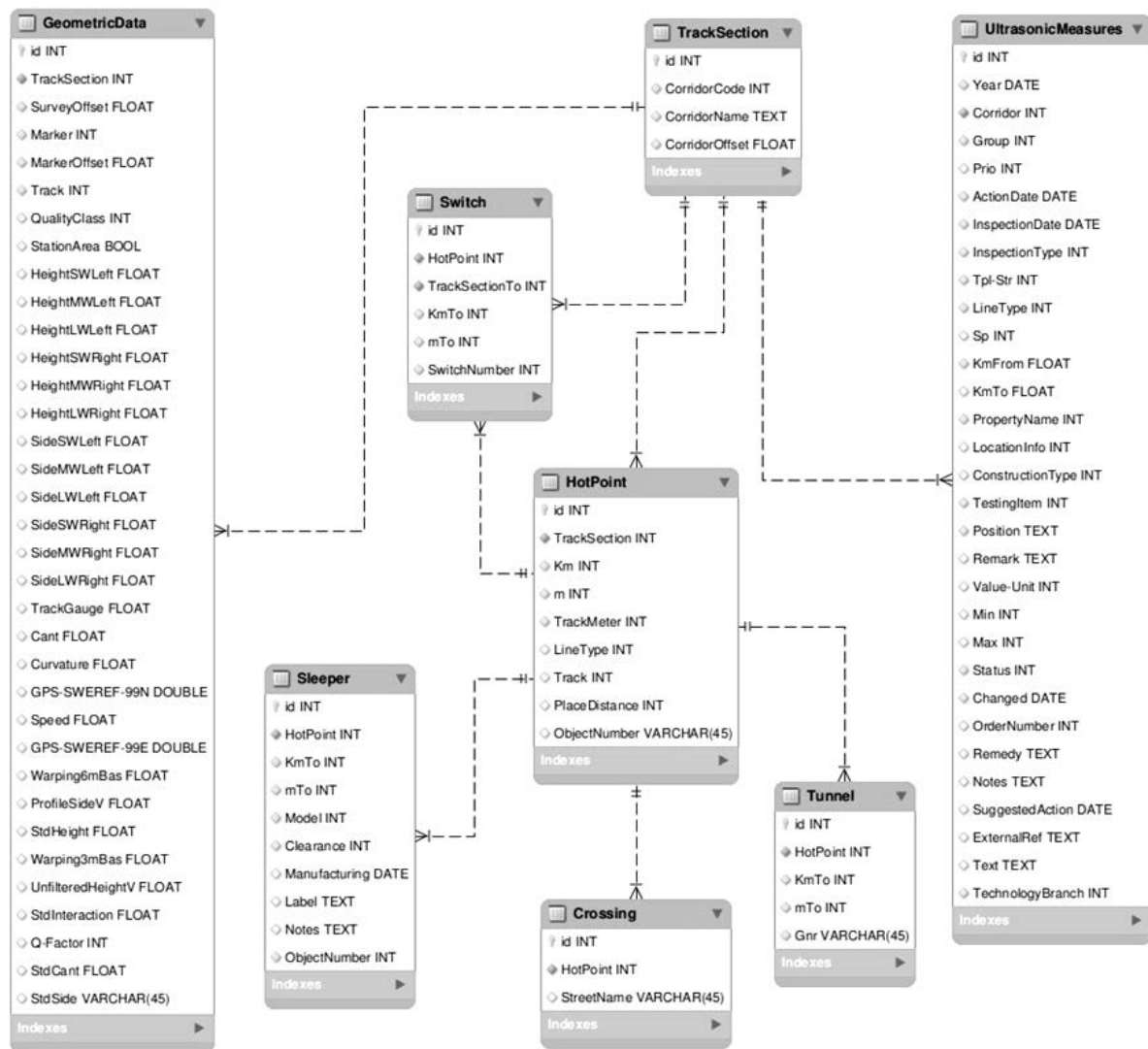
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Fig. 6 Database design for Sweden case study (OPTIRAIL project)

1.2 Data-driven models

A data-driven model relies on relationships derived from training data gathered from the system. Condition monitoring systems typically use thresholds for features in time series data, spectral band thresholds (usually from vibration signals), temperatures, lubricant analyses, and other observable condition indicators, under the assumption of steady-state operating conditions, being the first one i.e time series very popular to solve CM issues, [10]. A data-driven approach considers a condition indicator signal to be a set of random variables from a stochastic process represented by probability distributions. Numerous methods have been developed to monitor and diagnosis faults in equipment components and process equipment, using a combination of process measurements and indirect measurements related to faults (such as vibrations and lubricant analysis features), extracting and ranking features with signal processing and a variety of classification techniques. Sensor fusion has been used for fault diagnosis by combining several data sources to improve accuracy [4]. A system that includes the ability to detect, isolate and identify faults is called a fault diagnosis and isolation system (FDI). Almost all successful data-driven FDI models are for systems that can be considered time invariant; i.e., the dynamics of the system and the damage accumulation rate do not vary with time.

Many methods used in condition monitoring rely on data-driven techniques for both factories and facilities. In fact, transportation systems and health care facilities like hospital are becoming extremely popular as monitored assets where context seems to be a feasible solution. Figure 7 shows an example where a work order seems to be missing what proved the real need of combining information sources for context creation.
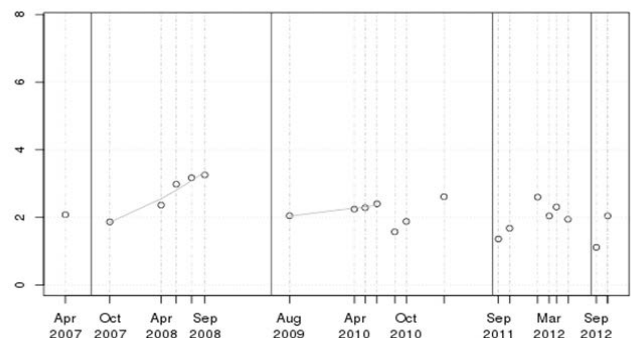

Fig. 7 Work order missing in 2010; odd deterioration in 2011

1.3 Physics of failure models

A model based on the physics of failure allows prediction of system behaviour using either an analytical formulation of system processes (including degradation mechanisms) based on known principles or an empirically derived

relationship. Many investigations into degradation mechanisms have been conducted, producing important empirical damage models that are valid in a fairly narrow range of conditions, such as wear, fatigue cracking, corrosion etc. Specific degradation mechanisms are generally studied and characterised under standard test conditions. Physics-based models are highly useful for describing the dynamics of time-varying systems, including different operating modes, transients, and variability in environmental stressors, but at the expense of the effort required to develop and validate the model.

The key challenge for a physics-based degradation model is to develop appropriate constitutive relationships for the condition decrease during degradation accumulation and to observe the complementary variables that characterise the relationship.

Following the example above, in the railway field, there are many physical models already validated which characterise the degradation of both track and rolling stock. For instance, the degradation of the wheel profile according to lateral forces and the degradation of track when running with flat wheels causing tremendous economical loses are well-known cases of a successfully applied physical model [5]. Similarly, many track degradation methods based on material sciences can predict the condition of the track according to traffic volume, number of trains/wheels, gross tonnes, axle load environmental aspects etc..

The deterioration of track quality is often assumed to be proportional to the current quality [7, 8]. In this sense, a track in good condition deteriorates more slowly than a track in bad condition. This is usually modelled with the differential equation

$$Q(t) = Q_0 * e^{bt}$$

Here, Q_0 is the track quality at time t=0 and the b parameter Is the deterioration rate characterising the behaviour in time. That is, the quality measure evolves according to an exponential model. This information provided by the physical models is extremely valuable in order to speed up

the prediction of the degradation supported by a deep knowledge of failure mechanisms, main weakness of data driven systems which need high number of observation with high granularity to extract the desired knowledge.

The following figures show some examples. Figure 8 shows an example where no interventions are registered throughout the whole period in consideration. We see that the track is slowly deteriorating.
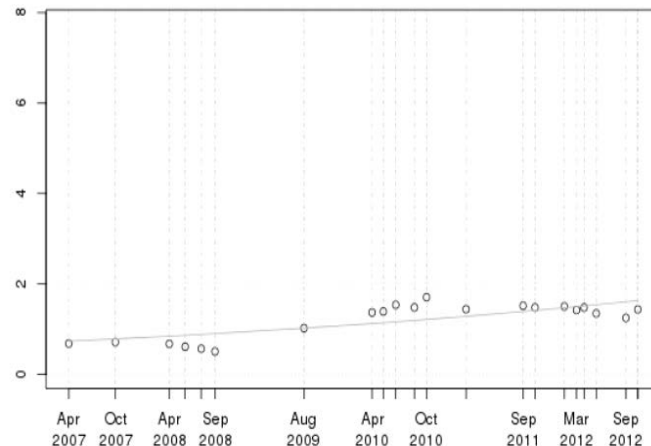

Fig. 8 No registered work with slow deterioration of track

1.4 Hybrid models

A hybrid model combines some or all three model types (symbolic, data-driven, and physical); more complete information allows more accurate recognition of the fault state [6] (Fig. 9).

These hybrid approaches use a data-driven model to find and confirm a physical based deterioration model for an asset based on historical data from CM measurements and work orders. This model is used to predict the future asset health and the time to when a maintenance operation has to be performed; see Figure 10.
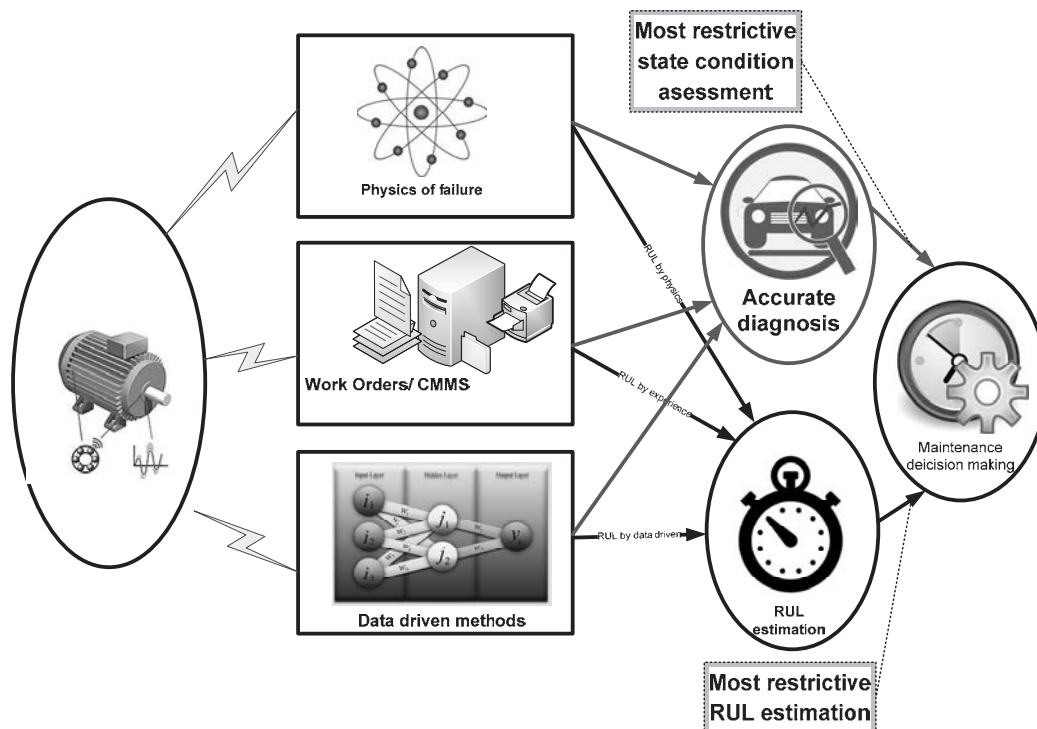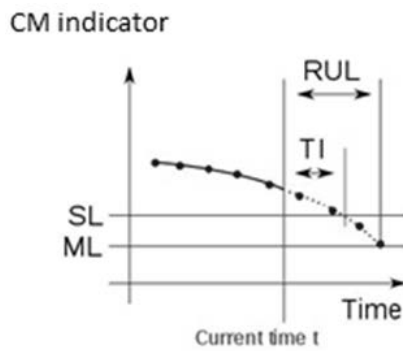

*Fig. 9 Hybrid prognosis approach to assets*
Source: [6]

Fig. 10 RUL estimation based on existing and predicted CM indicator

If no maintenance operations are performed, the CM indicator is continuously decreasing, as the asset health degenerates, until it reaches the service level (SL) or the maintenance level (ML) threshold. As maintenance operations are continuously performed the CM indicator will not be a smooth decaying function but will also represent the maintenance actions performed, so that the graph will have upward jumps. If historical work order data are available, we can correlate the geometric measurement data to the work orders; we will typically find a situation like that shown in Figure 11, where the work order can be used to identify jumps and cut the time series into pieces, the so-called deterioration branches.
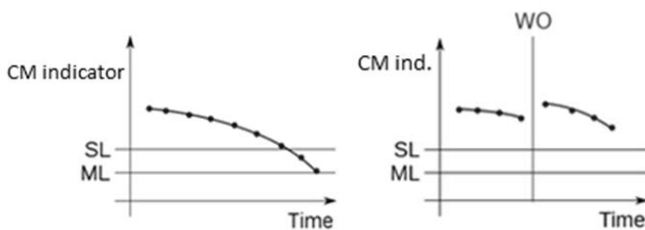
Fig. 11 Influence of performed maintenance on CM indicator

In Figure 12, the work orders and adjusted models explain the data well. Degradation adjusted according to exponential distribution (physical knowledge) can be seen between work orders (redlines). These time series concept implies a fusion of management data and condition monitoring data. Indeed the right interpretation of such data can be only understood via hybrid where symbolic (maintenance expertise) and degradation (physical and data driven) are taken into consideration.
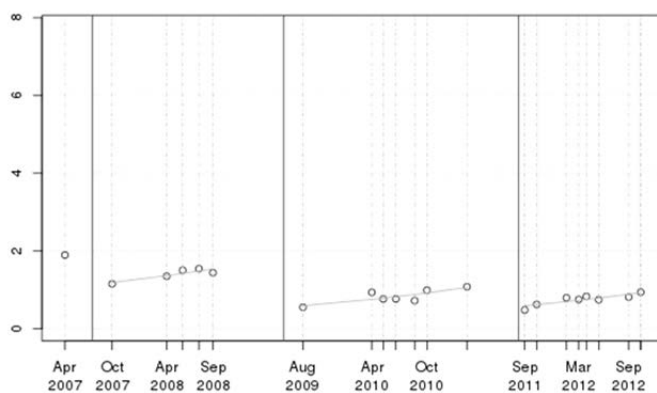
Fig. 12 Good fit of work orders and adjusted exponential model

In this way, the multi-criteria RUL predictions based on experience based data, context data, and degradation model are combined with a multi-objective economic optimisation, giving the maintenance planners a tool for better planning [9].

CONCLUSIONS

In summary, the article proposes a hybrid model-based maintenance decision system where operating conditions are related to degradation accumulation in a system. It develops new approaches to modelling degradation mechanisms for classes of faults occurring in components and systems. The new approach combines information from the expertise of the maintenance workers (symbolic models), physical models of degradation based on known damage mechanisms and finally the data driven models which get all gathered info together and try to extract new information not visible a t a glance without this integration.

The symbolic information is integrated using fuzzy approaches since experience based knowledge cannot be easily translated into equations. On the other hand previous knowledge of damages and failures help data driven methods to click and flow up this deterioration and perform a proper forecasting even though the data set may not be complete. Indeed hybrid overcomes the problem of incomplete data sets where unknown states are filled and replaces by previous knowledge (symbolic or physic).

Finally, the different nature of data requires a data wrapping with several levels and categories in order to produce meaningful relations. For that purpose context awareness has demonstrated to be a suitable technology to build thee relations and perform the desired forecasting according to the established data links.

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