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Hybrid Prognosis for Railway Health Assessment: An Information Fusion Approach for PHM Deployment

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Many railway assets suffer increasing wear and tear during operation. Prognostics can assist diagnosis by assessing the current health of a system and predicting its remaining life based on features that capture the gradual degradation in a system's operational capabilities. Prognostics are critical to improve safety, plan successful work, schedule maintenance, and reduce maintenance costs and down time. Unlike fault diagnosis, prognosis is a relatively new area, but it 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 or model-based. Each has advantages and disadvantages; consequently, they are often combined in hybrid applications. A approach hybrid model can combine some or all model types (data-driven, and phenomenological); thus, more complete information can be gathered, leading to more accurate recognition of the fault state.
This approach is especially relevant in railway systems where the maintainer and operator know some of the failure mechanisms, but the complexity of the infrastructure and rolling stock is huge that there is no way to develop a complete model-based approach. Therefore, hybrid models are extremely useful for accurately estimating the Remaining Useful Life (RUL) of railway systems. The paper addresses the process of data aggregation into a hybrid model to get RUL values within logical confidence intervals so that the life cycle of railway assets can be managed and optimised.

1. Introduction

A railway vehicle is a complex electromechanical vehicle comprised of several complex systems. Each of these systems is built from components which, over time, may fail. When a component does fail, it is difficult to identify the failed component 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 the locomotive systems has a positive impact on minimising locomotive downtime.
Previous attempts to diagnose problems occurring in a locomotive have been performed by experienced personnel with in-depth individual training and experience. Typically, these experts use available information that has been recorded in a log. Looking through the log, they use their accumulated expertise to link incidents in locomotive systems to the problems that may be causing them. If the incident-problem scenario is simple, this approach works fairly well. However, if the incident-problem scenario is complex, it becomes very difficult to diagnose and correct any failures associated with the incidents.
Computer-based systems are now being used to automatically diagnose problems in a locomotive in a bid to overcome some of the disadvantages associated with relying completely 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 production rules. These techniques work well for simplified systems with simple mappings between symptoms and problems. However, complex equipment and process diagnostics seldom have simple correspondences. In addition, not all symptoms are necessarily present if a problem has occurred, thus making other approaches more cumbersome.

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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. There is a need to be able to quickly and efficiently determine the cause of any failures occurring in locomotive systems, while minimising the need for human intervention.

The present paper proposes a hybrid approach to railway vehicle health assessment. The system is useful for identifying problems and proposing remedial measures to repair or correct them. On-board diagnostic systems do not presently communicate with a rail carrier's maintenance or scheduling centres. As a result, those centres do not have direct access to data from remote locomotives which would be helpful in optimising locomotive maintenance scheduling and route planning while minimising locomotive downtime arising from unexpected breakdowns. It is especially desirable to avoid faults resulting in unscheduled shutdowns or slowdowns in vehicle operation, since these are both costly and inconvenient; see Wilmering and Ramesh (2005). It is also desirable to provide a way of predicting faults and dealing with predicted faults before they occur.

The proposed methodology predicts vehicle breakdown using monitoring information from track side (provided by the infrastructure manager) and on-board systems whose data are transmitted from a vehicle to a remote location; it determines whether any of the monitored data are out of a predetermined range; it calculates trends for monitored data determined to be out of range, identifies any system fault, and predicts which, if any, locomotive system(s) must be corrected to avoid vehicle failure and when such system(s) is/are likely to fail unless corrected. The method should predict either operating distance or operating time prior to failure.

2. Disparate data sources for railway health assessment

Railway infrastructure, such as railroads, has a direct impact on the shutdown or slowdown of railway vehicles.. The condition and maintenance of these assets is critical to the effectiveness, efficiency and security of a train. Any improvement in the condition or maintenance management of linear assets and the technology involved in maintenance tasks can have a substantial influence on the operation of the rolling stock that uses this railroad.

There is a need to integrate railroad and rolling stock information to get an accurate health assessment of the vehicles and thereby determine the probability of a shutdown or slowdown; see Camci et al. (2007). However, for railroads and rolling stock, much information needs to be captured and analysed to assess the overall condition of the whole system, i.e. infrastructure plus vehicles. Additionally, the development of a variety of track condition indicators, such as geometry cars, rail defect detection equipment and gage restraint management systems, has resulted in a significant amount of new and useful information for track maintenance. A large amount of information provided over a large area quickly leads to information overload.

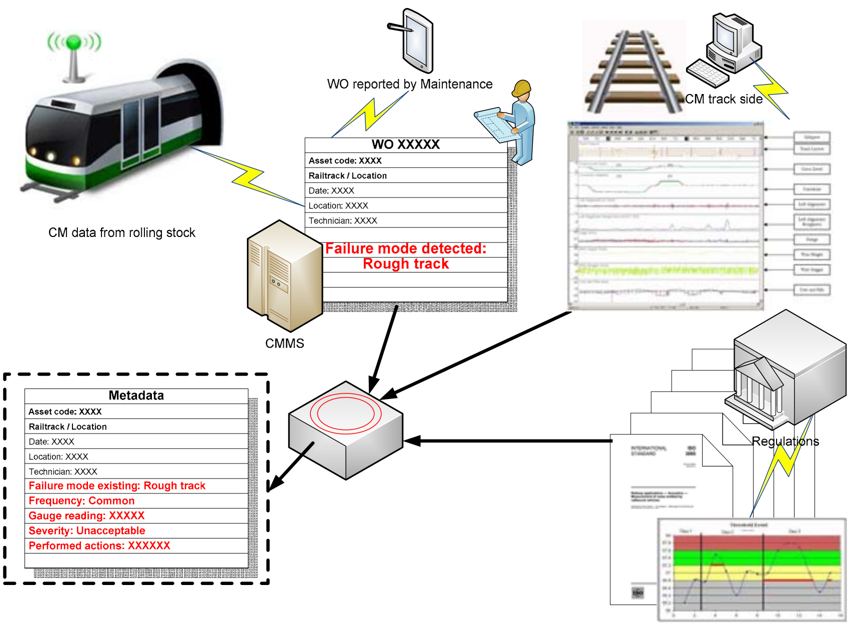

Figure 1: Metadata for maintenance railway knowledge extraction

Moreover, much of the data that is collected about tracks and rolling stock is dispersed across independent systems that are difficult to access and are not correlated. If the data from these independent systems are combined into a common correlated data system, this system could provide a rich new set of information that adds to the value of the individual systems. A simple example is that it is common for facilities like railroads to collect work records of where work has been done. Railroads also typically measure the quality of their tracks to see where work needs to be done. However, these two data sets remain in separate and individual systems. By combining the data into a location correlated data set, i.e. metadata (figure 1), the quality and/or the effectiveness of the work being performed can be analysed by comparing the track quality before and after the work is completed.

3. Information fusion and data mining in railway

Even facilities that have recognised the value of combining data sets to mine useful information must implement expensive and usually inflexible custom software to extract the knowledge that they need; see Galar et al. (2012), making it difficult to experiment with new ideas. The cost and effort involved in the introduction of new analysis tools is often prohibitive and the tools are not built. Accordingly, there is a need for an improved system and method to analyse railway data, namely, a unified perspective on all the relevant data within a single, accurate format. The system should answer such questions as what should be worked on and why? Such a system should equip the user with the knowledge of the infrastructure's and the vehicle´s condition and configuration, so maintenance resources could be targeted to only those areas needing work. The system could also provide the information needed to plan and evaluate opportunities for such things as facility upgrades and expansions. An effective maintenance management system results in direct savings in maintenance programs and capital expenditures.
The proposed methodology provides the tools for analysing railway data from a prognosis point of view; It suggests a unified view and offers a tool for collecting, viewing and analysing a linear asset's and a train´s condition and performance over time. Data are imported from many different independent sources into a correlated data set. The data set may be stored in a database that can store enormous amounts of data on the linear asset and corresponding vehicles.
This integration greatly reduces the efforts and risks in the development of analysis tools.

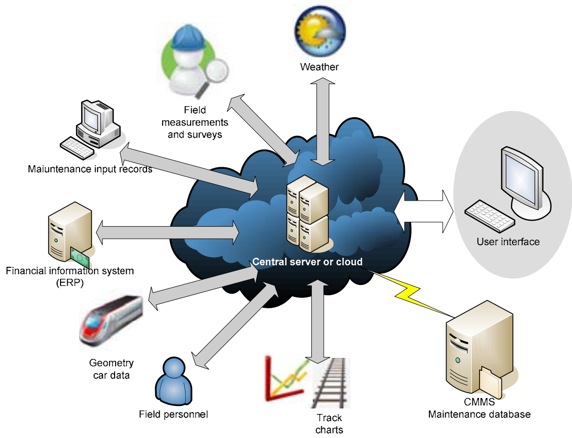

Figure 2: Existing interfaces to collect relevant information for data mining

The developed mining system can provide and collect information. A central data store can integrate information on the railroad and vehicle. For a railroad, the database can integrate railway information encompassing the following areas: Layout-Configuration of rail line elements along a rail route; Condition-Location and date of track condition information; Maintenance; Traffic-Accounting; and Analysis Geometry.
As Figure 2 shows, the central data store is derived from a variety of data sources and provides information to multiple system users. The central data store may also be enhanced to dynamically interact with other information servers (e.g., through client-server database standards, middleware, or multi-tier architecture).The interaction relies on information fusion with rolling stock. Meanwhile, most of the information collected in the server or "cloud" is off-line and corresponds to interventions, track condition etc.; the rolling stock generates online data which is sent to the cloud where it is fused with track side data, potentially warning the operator about imminent shutdowns or slowdowns.
These warnings must be presented using a user interface which can integrate all the data about track conditions and weather with the rolling stock condition (provided by on board systems). This should produce a prognosis about shutdowns or potential slowdowns with risk consequences in terms of costs.

This integration should also have the ability to optimise maintenance management in both vehicles and infrastructure by proposing proper corrective actions as a result of rule extraction provided by the data mining of the cloud; see Létourneau et al. (2005).

4. Prognosis: Achilles heel in health assessment

There are two basic risks in railway systems: shutdowns and slowdowns. These risks materialise in economical loss. 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: using symbols, using data, and using mathematical formulations based on physical principles.

4.1 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. The models that can be 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 systems, Ashraf (2004); 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. The integration of work orders from both rolling stock and infrastructure is essential to reproduce the exact scenarios where the shutdown can occur and predict it beforehand to perform preventive actions.

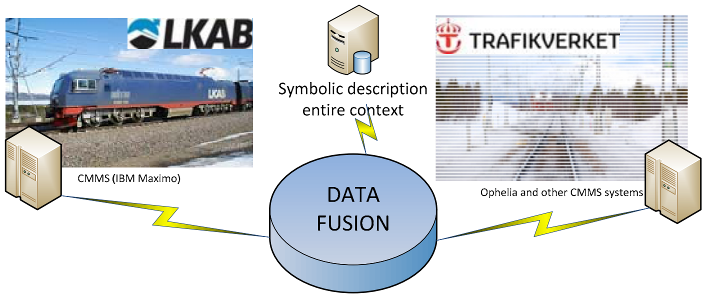

Figure 3: Integration of symbolic data sources from both rolling stock and infrastructure

4.2 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. 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 for monitoring and fault diagnosis of 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 signal processing and a variety of classification techniques. Sensor fusion has been used for fault diagnosis by combining different data sources to improve accuracy; see Schwabacher (2005). 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 railway condition monitoring rely on data-driven techniques. In fact, with feature extraction to obtain track quality factors or the degradation stage of the bearings in the vehicles, the health of both track side and rolling stock can be assessed using mathematical tools based just on the experience and variability of condition indicators. This is especially relevant in complex systems like railways and has been successfully applied in aircraft industry as well; see Brown et al. (2007)

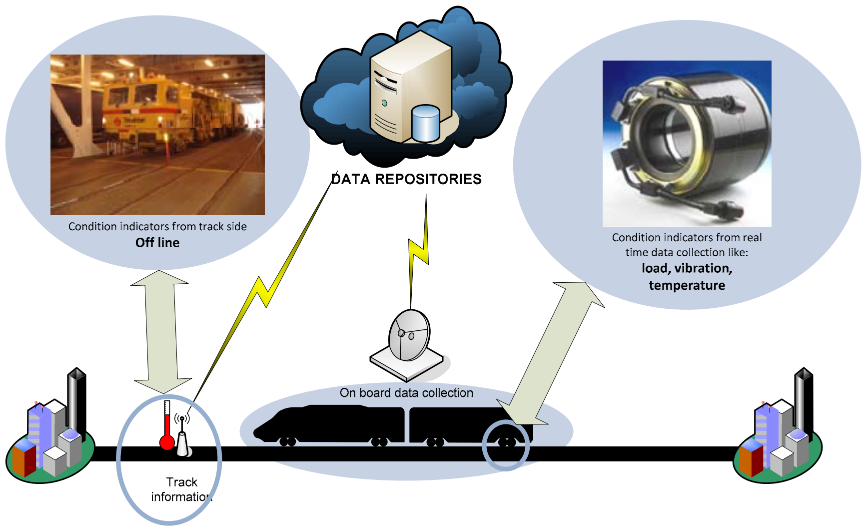

Figure 4: Integration of data driven sources (condition indicators) from both rolling stock and infrastructure

4.3 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 damage mechanisms) based on first principles, or an empirically derived relationship. Many investigations into damage 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, and fouling. Specific damage 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 damage model is to develop appropriate constitutive relationships for the energy lost during damage accumulation and to observe the complementary variables that characterise the relationship. 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 vibrations which produce flat wheels and tremendous economical loses is a well-known case of a successfully applied physical model; see Palo et al. (2012). Similarly, there are many track degradation methods based on material sciences which predict the condition of the track according to environmental aspects, stress, traffic, axle tons etc..

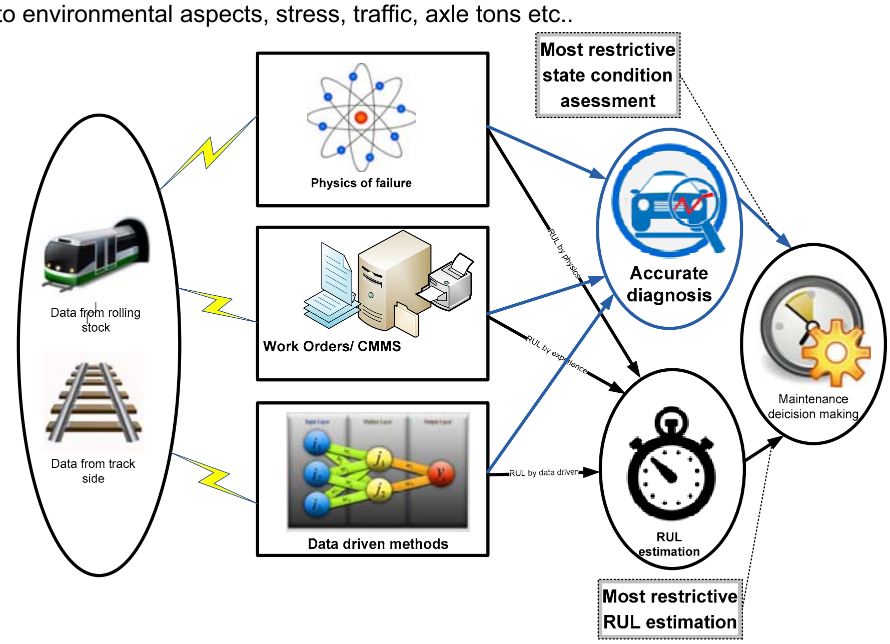

Figure 5: Hybrid prognosis approach to railway assets.

4.4 Hybrid models

A hybrid model combines some or all three model types (symbolic, data-driven, and phenomenological), so that more complete information allows for more accurate recognition of the fault state; see Galar et al. (2012). While most models incorporate some prior knowledge, little work has been done on explicit hybrid modelling for fault diagnostics and maintenance decision making. The goal for system reliability (indeed, any classification exercise) is to minimise Bayes risk, that is, to choose the lowest risk option based on the observed system outputs and conditional probabilities of what state the system is in, given the observed data. Minimum Bayes Risk decision making relies on conditional probabilities, which rely on a posteriori probabilities and prior probabilities of states of the system (in this case, fault modes). Since risks to the railway operation include not only shutdown or slowdown but also safety hazards and environmental impacts, research is required to develop risk expressions that include these considerations in maintenance decision making.

5. Conclusions

In summary, a Hybrid Model-Based Approach to Dynamic System Modelling with Damage Accumulation Phenomenological modelling and data-driven models have been successfully combined to relate process features to damage accumulation in time-varying railway equipment. New approaches have been developed for modelling damage mechanisms, for classes of faults that occur in components and systems, and the approach is tested on existing systems that are critical to the safe and reliable operation of current railway assets.

In the new approach, process modelling is combined with damage modelling. Constitutive relationships are based on physical phenomena and are found using standard system identification methods. Alternatively, if physics are not well understood or the process is not completely observable, an empirical relationship can be derived using data-driven methods.

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