Boosting Holistic Railway Infrastructure Monitoring and Health Prediction by Integrated Data Sets and Analysis

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Abstract. The digitalization and automatization of railway infrastructure health diagnostics using various kinds of embedded wayside and onboard sensors in combination with common monitoring and inspection motivates a more and more integrated health analysis for all the relevant asset components such as rails, ballast, switches and crossings, point machines, and others. In this context, the present contribution discusses how an integrated research data set – as currently being collected by partners within the Europe's Rail project IAM4Rail – is going to stimulate new research and developments as well as innovative solutions with regard to several use cases from the field of railway infrastructure maintenance. This includes the application of modern data fusion techniques based on artificial intelligence as well as physical and hybrid modelling approaches.

Keywords: Holistic PHM, Data Fusion, Data Analytics, Digital Twin.

1 Introduction

The railway infrastructure is a complex combination of various components such as rails, ballast, switches and crossings (S&C), point machines (PMs), catenary, interlocking etc., all having their own fault options and therefore often being maintained separately in practice. However, components often do not operate independently, and also their health condition and degradation may depend on each other. Holistic railway infrastructure monitoring thus aims at explicitly taking such dependencies into account for the purpose of enhanced diagnostics and health prediction including considering the connections to train operations. As for advancing digitalization and AI (= Artificial Intelligence) research, this requires systematic and synchronized data covering all relevant components including manual and automatic inspection data and maintenance reports as well as structured data from embedded sensors together with information about environmental conditions.

Partners from the Europe's Rail research project IAM4Rail has been collecting such a comprehensive data set for a 22 kilometers long main line with mixed traffic on four parallel tracks and about 40 switches between Amsterdam and Utrecht in the Netherlands. A short overview of the data and measurement technologies used is given in Section 2. Based on that, Section 3 discusses several use cases and examples that has been or will be addressed in more detail using these data. The paper concludes with a short summary in Section 4.

2 Data and technologies

Intending to foster the development of enhanced tools for integrated health monitoring and fault diagnostics via (simulation-oriented) physical models and/or modern data-driven approaches, various kinds of train-borne data are collected via the so-called LEONARDO platform (cf. Section 2.1). All this is accompanied by current curve (incl. control circuit) and sometimes also power supply measurements for the PMs together with environmental data such as temperature (cf. Section 2.2). For a dedicated switch, also sleeper displacements (per axle) and blade positions via inductive sensing are going to be measured. In addition to that, by using different modelling techniques and simulation frameworks, synthetic data sets will be generated by means of virtual sensors to complement the data obtained by means of real sensors in field test campaigns. Synchronized maintenance and manual inspection reports will help to validate and interpret the automatically generated measurements as well as the results that are going to be derived from them algorithmically.

2.1 The LEONARDO platform in a nutshell

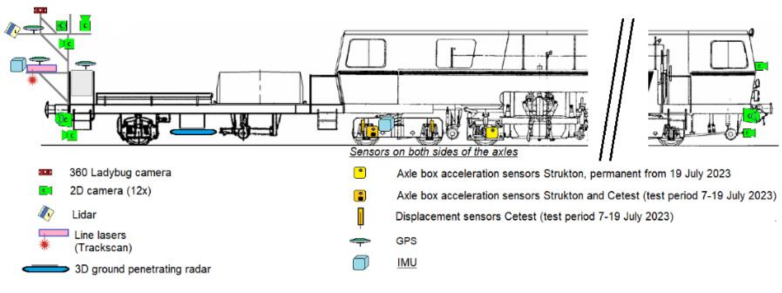

Fig. 1. Overview of the sensors mounted on the LEONARDO platform.

The LEONARDO platform [1] uses a retrofitted tamping machine which has been transformed into an advanced rail measurement train for gathering comprehensive and accurate data on both the rail condition and the environment (cf. Fig. 1). Its "Trackscan" laser measurement system is employed to measure the railway tracks while a LIDAR (= Light Imaging, Detection And Ranging) sensor is utilized to map the surrounding environment alongside the tracks. Both the railway tracks and the surroundings are captured through an optical camera system which gathers detailed visual information. The LEONARDO also incorporates 3-dimensional ground penetrating radar (GPR) to measure ballast and ground layers, providing valuable data regarding the stability and consistency of the rail infrastructure. Additionally, axle-mounted acceleration and displacement sensors are integrated to record vibration patterns and measure the elongation of primary suspensions, aiding in the assessment of overall rail performance and safety including estimating relevant track geometry parameters.

2.2 The POSS® System in a nutshell

POSS® [2] is a condition monitoring system for assets in the railway and power industry. It consists of local dataloggers and sensors that collect measurements and send the data to a central server where it is visualized in a User Interface. The main focus of POSS® is the monitoring of PMs which includes measuring the consumed current during a throw, as well as the state of some related relays and the ambient temperature. When anomalies are found in these measurements (e.g., through the exceedance of predefined thresholds), the system triggers a warning or alarm, indicating to a team of maintenance experts that the behavior of the switch deviates from the expected patterns. The maintenance experts then go on to further analyze the data to see if any maintenance or repair activities are required.

3 Use Cases and Examples

3.1 Enhanced monitoring of plain line tracks via data fusion

The automated detection and diagnosis of rail surface defects (e.g., rail corrugation, squats) and track geometry defects is important for the efficient maintenance of plain line tracks. While anomalies can already be detected quite well using suitable algorithms for analyzing the information from vehicle-borne sensors (cf. [3]), a comprehensive defect diagnosis, i.e., the automatic identification of the type of defect and the understanding of its underlying cause, is still a big challenge. Here, the algorithmic combination of camera data and measurements of the dynamic vehicle-track interaction from axle-mounted accelerometers in terms of data fusion based on multi-sensor systems (multi-purpose-vehicles) is expected to increase the accuracy of automated defect classification. Furthermore, combining established methods for monitoring the track geometry (e.g., longitudinal profile) using vehicle-borne accelerometers with insights into the ballast and ground layer derived from GPR data will provide unprecedented information on the underlying cause of geometry defects.

3.2 Enhanced fault diagnostics for point machines

Recent fault diagnostics for (electro-mechanical) PMs often relies on current curve measurements (cf. Section 2.2) which are then interpreted by maintenance practitioners for triggering suitable maintenance actions. Modern approaches for automatically detecting anomalous current curves and identifying the underlying primary faults based on AI and ML (= Machine Learning) can help to make this process more effective while reducing the manual effort (cf. [4]).

In this context, the integration with onboard and wayside sensor data correlated to ballast quality and track geometry, for instance, is expected to allow for even better results when accelerated degradation or misalignment of movement-related switch components such as rods or rollers are just a secondary effect of bad track geometry or ballast conditions. Therefore, GPR and train-borne acceleration data (cf. Section 2.1) together with wayside measurements of displacements and/or blade position can be used for better parameterizing existing diagnostic models (cf. Fig. 2) which are mainly based on current curve analysis so far. Note that this might also include or require optimizing the models' structure in view of causal inference (cf. [5]).

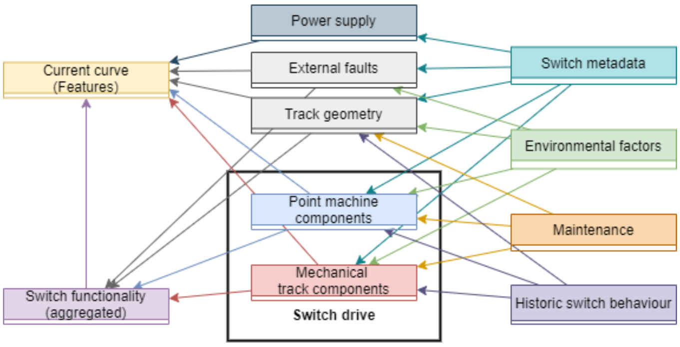

Fig. 2. Simplified Bayesian network model for holistic PM diagnostics [6]. Note that track geometry and switch drive components, for instance, are conditionally dependent here given the current curve as evidence. Thus, knowing track geometry is expected to immediately affect the inferred fault probabilities of the switch drive components.

3.3 Enhanced modelling of crossing degradation

Digital twin frameworks can be very helpful for analyzing the health condition of crossings [7] and for optimizing the design of related sensor systems. For this purpose, MBS (= Multi Body Simulation) and FEM (= Finite Element Method) models are going to be used for simulating the vehicle-track interaction at different running conditions. On the one hand, MBS simulations allow for calculating the contact patches between wheels and the turnout. On the other hand, FEM models are necessary to study medium and high-frequency domain accelerations. Processing these synthetic accelerations then reveals the most relevant KPIs (= Key Performance Indicators) for defining the degradation level of the assessed turnout within a degradation trend. Moreover, knowing the set of most relevant KPIs also helps to reduce the number of required sensors and to choose suitable ranges and sampling rates for real world applications.

Fig. 3 shows a flowchart of the approach using both MBS and FEM models. From simulations at different degradation levels and running conditions, a degradation database (DDBB) is going to be generated to eventually define the health conditions with real measurements, such as those described in Section 2 by means of sensors installed in the S&C. Although previous field tests are required to validate the models, the leverage of this methodology is the simulation of faulty conditions and degraded scenarios [8].

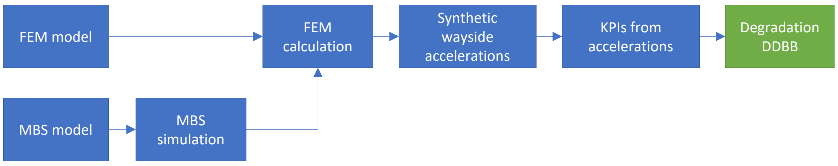

Fig. 3. Flowchart to obtain degradation databases for a specific turnout.

3.4 Optimized sensor selection and positioning

Parallel measurements for the same infrastructure asset or the same track element using various wayside and/or onboard sensors (cf. Section 2) are likely to contain redundant information about the respective health conditions. While data fusion (cf. Section 3.1) can help then to increase the reliability of the estimated health states, the data at the same time allow for analyzing which sensors or combinations of sensors (together with their positioning) are the most informative ones or, on the contrary, could be dropped from the overall sensor layout without too much loss of information. Even more, transferring knowledge as obtained from a few highly equipped and comprehensively monitored infrastructure assets could reduce the sensor needs for the large rest of similar assets in the rail network. As a result, sensors can be selected and positioned in a more optimal way considering both statistical power of the data and cost efficiency.

3.5 Train operations and asset criticality analysis

Train operations are not only important as influencing factor for the physical degradation of infrastructure assets (cf. Section 3.3), but also determine or affect the criticality of relevant assets (e.g., S&C) in the network because of a possibly limited availability of bypass options in the case of failure (cf. [9]). Combining such a criticality perspective with information about the respective assets' current or predicted health conditions (as obtained by methods like mentioned in previous sections) can help to optimize maintenance decisions not only on the asset level, but also on the network level while systematically reducing the total amount of delay and disturbances in train operations from a holistic perspective.

4 Conclusion

Comprehensive and systematic real-world data sets based on various kinds of sensors in parallel for a dedicated track section or pool of fixed assets as described in Section 2 are still rarely available in practice, but have the large potential of pushing research and development forward with regard to many use cases of infrastructure monitoring and maintenance (cf. Section 3). The proposed holistic approach is expected to provide further insights into the relations between the different infrastructure or track components by means of data analytics and modelling. By that, it promotes a more integrated view on the health management of railway infrastructures, possibly even including analyzing asset criticality from the perspective of train operations.

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