Proactive Maintenance of Railway Switches

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***Abstract*—Railway switches operate in harsh environmental conditions; still, their reliability requirements are high due to safety and economic factors. Once deployed, their maintenance depends on the data collected on their status, and the decisions on due corrective actions. The more regular this data collection and decision cycle is, the better confidence their operator has on effective and proper service. Proactive maintenance, in general, targets exactly this: rather than scheduling maintenance actions based on operating hours or servicing volume, actions should be taken when it is really needed. This requires the effective combination of data collection, analysis, presentation and decision making processes.**

The MANTIS project proposes a reference architecture for proactive maintenance, supported by the concept of cyber-physical systems. Besides suggesting data collection, processing and presentation methods and tools for this, the results were applied in various domains – including production systems, the energy grid, utility vehicles, or railways. The current paper presents data collection, analysis and presentation concepts related to proactive maintenance, applied on railway switches.

I. Introduction

Increasing demands for faster mass transport with high capacity and cycle times create an ever-greater burden on the railway infrastructure. Thus, it is absolutely necessary to monitor the technical equipment of railroad tracks permanently in the best possible way. The earliest possible detection of fatigue wear of the track system (such as broken rails, increased rail wear caused by natural hazards or by excess loading on the track system) can prevent more serious damage with a rapid and correct interpretation and action.

The railway use-case within the MANTIS project [1] is addressing these issues with a proactive maintenance approach of the railway system. This is dedicated to the interlocking system and to the study of possible complications that characterize railway signalling (for example, non-functional and out of control situations).

The main objective of this article is to describe the development of a set of approaches and support tool allowing the continuous status-analysis of specific components within the infrastructure. The continuous analysis aims at determining whether and under which constraints it is possible to make reliable predictions for improving the maintenance process. In particular, identifying anomalies and reducing the emergency maintenance that can be very costly and leads to train delays.

A. State of the Art for Railway Infrastructure Maintenance

Current state-of-the-art maintenance operations within the railway infrastructure are based on the concept of “preventive” or “on-condition” maintenance. However, they only consist of periodical check-ups and substitutions of parts when a failure is detected. These tasks are carried out at given periodical intervals designed to mitigate risk with a considerable safety margin involving having to send maintenance staff to the asset site on a regular basis, exposing them to the usual safety risks of a running railway [11].

Moreover, most modern railways have very low level of capability installed as part of the signalling system. For switches, this usually only comprises of the detection lines which verify that a switch is in the correct end position, locked.

In this context, the development of new maintenance systems, including the integration of heterogeneous monitoring and diagnostic technologies, plays a key role in the improvement of railway safety operations. Existing monitoring solutions show some limitations due to their non-standardized, proprietary nature and very low integration level. Consequently, they are not able to monitor complex asset degradation processes and to detect correlations between them [11].

B. Railway Switch

A railroad switch is a device used by railroads to enable trains to change tracks (see Fig. 1). When a train is destined to run on another path, the switch-man on the locomotive or another employee in the railroad yard will turn the switch to direct the train toward the chosen direction. The railroad switch is activated by moving a long arm from side to side and moving the train tracks to the desired position. While most railroad switch activation is accomplished by hand, some are electronic

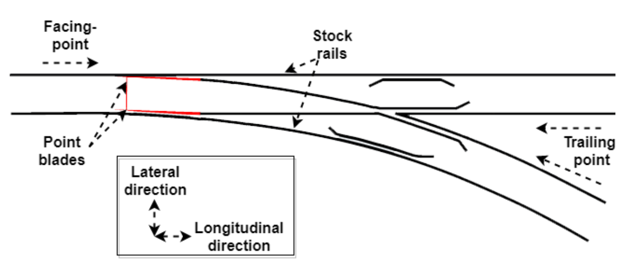

Figure 1: Diagram of simple turnout showing its principal parts. Moving switch blades are shown in red.

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nowadays and can be changed by an employee in an elevated office in the railroad yard.

This paper introduces a real proactive maintenance solution proposed for railway switches. It is based on the concept of Cyber-Physical Systems (CPSs), where a cyber twin of the physical system is modelled, and its status is kept up-to-date through data collection from newly developed on-site physical sensors. The rest of the paper is organized as follows. Section II provides some details on data processing, Section III presents the proactive measurement system, and Section IV describes the process of data visualizations development.

II. DATA PROCESSING

Railway switches have been characterized by two sets of time-series data. This section explores the possibilities for forecasting failures, based on these historically available datasets. This information can be categorized into two types:

- **Control data:** data coming from the switch control unit. It includes the commands sent to the switch (i.e. start switching), and some control data collected as a feedback from already existing sensors of the switch. The collected information is coarse grained, with the structure of a log sequence.
- **Physical data:** data coming directly from additional sensors added to some specific switches for a limited amount of time able to measure some physical parameters at a sample rate of at least 1 kHz. The most interesting data used in this analysis are the electric current absorbed during the movement [Ampere], the duration of the movement [second], and the environmental temperature [°C].

Our goal here is to detect anomalies that may result in an eventual maintenance. In particular, we have focused on:

- **Systematic drifts of the profiles:** this can be caused by accumulation of dust on the switch causing an increasing amount of current leading also to a failure of the switch.
- **Deviations from the expected behaviour:** this can be caused by physical obstacles for the movement of the switch that may cause damages to the device.

During data exploration, we have identified five current profiles (see Fig. 2):

- **Profile 1:** This is a very noisy profile that makes the identification of the behaviour difficult and may highlight problems in the data collection. In particular, in the correct positioning of the sensor and/or the presence of sources of noise that may alter the collection.
- **Profile 2:** Similar to Profile 1 but with a limited amount of noise.
- **Profile 3:** Expected profile of a double switch.
- **Profile 4:** Expected profile of a switch.
- **Profile 5:** Profile of a switch with an abnormal behaviour.

The current profile depends on several physical variables that are linked to the mechanical and electrical components used to build the different switches. Therefore, the profiles are linked to the specific model of the switch from which the data are collected. Moreover, environmental factors can also influence the current: temperature, humidity, and dust.

Due to this large variability of the profiles, our main problem is the identification of an approach to define the default correct behaviour. This can be achieved in different ways:

- **Using electro-mechanical equations:** this approach is able to define the physical model of each switch, and it is able to predict the correct behaviour in many different environmental conditions. However, it requires building a model for each kind of switch and tuning the parameters for each installation.
- **Using a statistical approach:** this approach requires the collection of data from a wide set of devices in different operating conditions to define the default behaviours that will be known with some level of uncertainty, but it does not require the manual development of a physical model for each switch. The model can be derived from the data, and can be adapted to different switches collecting additional data.

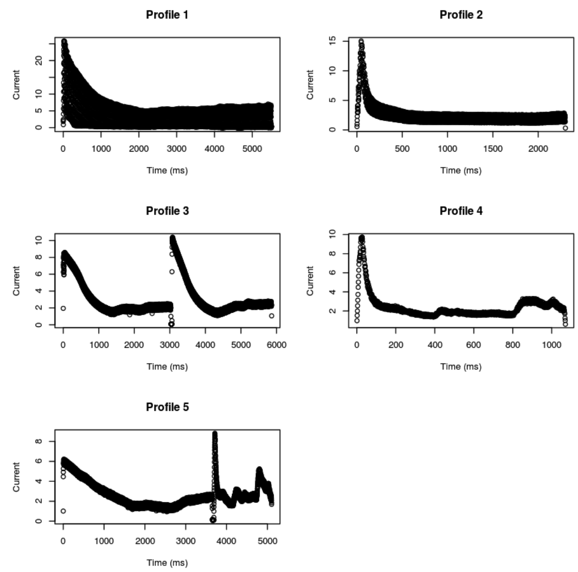

Figure 2: Different profiles of measured

After the investigation of the applicability of these approaches, we decided to explore the statistical one in depth, since it requires less human intervention.

In Fig. 3, we show a statistical features of a specific switch. At this time, the black line is generated calculating the median of the different time series representing the current profiles of hundreds of movements that we know they happened correctly. The other lines define different sets of bands that can be used to understand the behaviour of a specific movement. The blue band defines a range in which the current is considered acceptable during the movement of the switch.

We used threshold detection here. If the current is outside the bands, a warning needs to rise. Therefore, the definition of proper bands is of paramount importance for the detection of an abnormal behaviour. Since the distribution of the samples at each time instant is not normal, we have defined the outliers' bands using the 1st and 3rd quartiles, defined according to the Tukey's range test for outliers [q1-1.5*IRQ; q3+1.5*IRQ] (See Fig. 4).

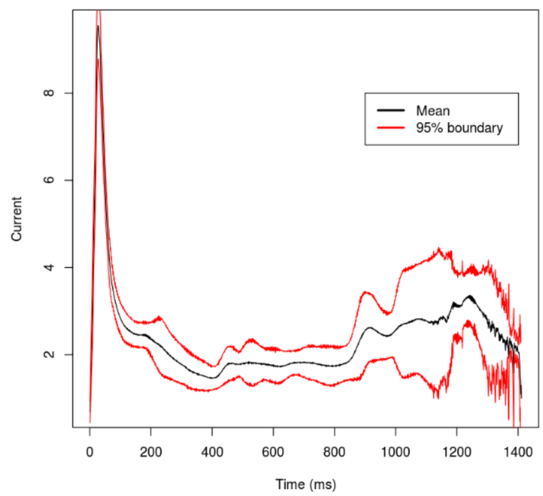

Figure 3: Initial statistical model

Looking at the diagrams, we have noticed a quite large range, especially at the end of the movement. After a deeper investigation, we have found that this behaviour is due to the fact that the analyzed single set of data was hiding two different data sets. In fact, the behaviour of the switch is different in the summer

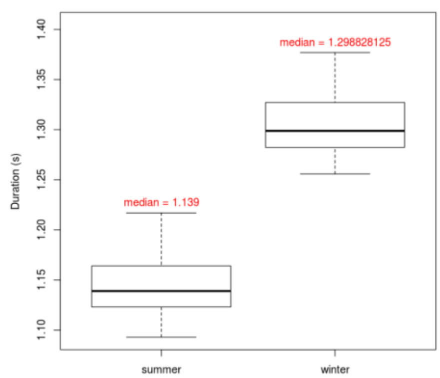

Figure 5: Movement durations in summer and winter

compared to the winter due to the temperature sensitiveness. In particular, there are several aspects that are connected to the temperature, such as the duration of the movements (Fig. 5) and the current peaks (higher in winter).

For these reasons, it is not sensible to define a statistical model without considering the season (actually the temperature of the environment). To address this problem, we have performed the same analysis dividing the dataset into two sets based on the time of the year of the data.

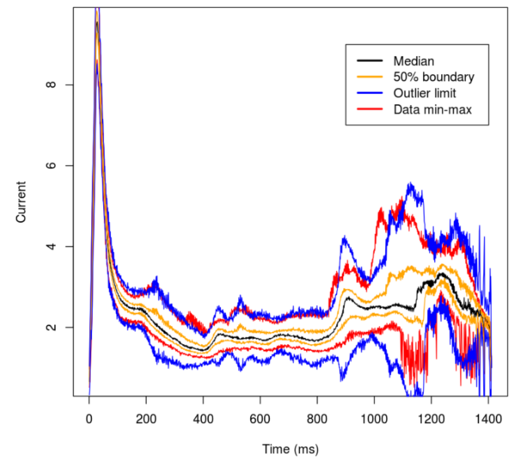

Figure 4: Identification of bands for quartiles and outliers

To validate the model, we have used a bootstrap approach building the model using a random subset of correct movements in the same season and verifying it with the rest of the data. Fig. 4 shows the number of outliers when the model is trained with a specific number of random movements. From the diagram, it is clear that the more movements are considered in the model the better the model becomes. However, after about 25 movements, the performance is not improving much and the number of outliers is below 2% of the samples.

This analysis is very helpful for defining the statistically correct behaviour of a switch using data coming from the field and tuning a model without any specific knowledge of the internal structure of the switch. In this way, the model can be easily adapted to different switches working in different conditions. However, due to the temperature sensitiveness, the model must be tuned using data in the different seasons.

This data can be analysed using log analysis approaches. However, due to the coarse grain and the lack of a sufficient amount of information from the field (including tagged data describing anomalies) resulted in an analysis that is not able to build a relevant model that can actually be used.

The aim for analysing such data by applying those different statistical approaches is to determine a model of the default behaviour of the switch, and to identify anomalies in the behaviour. Among various purposes of diagnosis and prognosis [2], this can be used for failure prediction [3], and other proactive maintenance purposes [4], including root cause analysis and the calculation of remaining useful life.

III. Measurement System for Proactive Maintenance of Railway Switches

Since historical data are inadequate for predicting failures and diagnostics, new approaches had to be applied. In order to collect data with the required precision and regularity, a new data collecting system had to be planned and built. This included the development of a new, low cost but non-invasive measurement system that can be attached in retrofit to operational switches. This system is implemented to measure new factors that affect the life expectancy of the railway infrastructure.

The system was developed through close collaboration with industry experts. The choice of the appropriate attributes is based on expert knowledge since the different types of switches are not equally affected by these impacts.

This system is based on the MANTIS platform [5] and complies with the architecture of the platform in full extent. Therefore, this system is a concrete instantiation example, and consists of the following modules (Fig. 6):

- Standalone data gathering edge device;
- Edge broker implementing MQTT;
- The MIMOSA database using Microsoft SQL Server;
- Data analytic modules; and
- The MANTIS Human-Machine Interface (HMI).

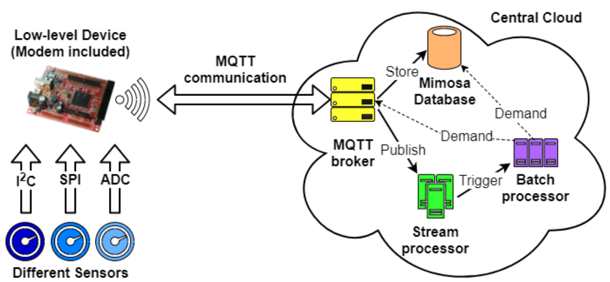

Figure 6: Architectural setup for the measurement system

The so-called edge device here – which is the embedded subsystem deployed with the railway switch – is not only responsible for gathering new data but pre-processing and forwarding it to the cloud in an appropriate, MANTIS-enabled message format.

The heart of this device is an STM32F4 series MCU (Microcontroller Unit) which employs a single ARM-Cortex-M4 core. It is capable of collecting, storing and pre-processing the information, while also handing the messaging tasks as well. It offers numerous communication interfaces – including UART, SPI, I2C –, and 12-bit analogue-to-digital converts; thus both analogue and digital sensors can be used.

In this case, this system includes (i) one digital integrated humidity and ambient temperature sensor, (ii) one digital temperature sensor and (iv) four analogue displacement sensors.

A. New Factors Collected

The system measures several factors that can affect the wear of the railway switch over time. These expert-identified factors can be divided into two groups:

- **Operational factors:** These parameters are directly related to the operation of switches – that is why they have a significant impact on condition deterioration. In our implementation, we measure lateral and longitudinal displacement of point blades. These point blades direct trains to one of the possible paths, i.e., they are the moving parts of a switch.
- **Environmental factors:** These parameters are well-known to affect almost every physical system. The most significant one is temperature. More precisely, here the ambient temperature and the temperature of the rails are measured. The latter value can cause dilation of rails thus it affects the operation of switches indirectly. Another environmental quantity is humidity, which plays a lead role in corrosion.

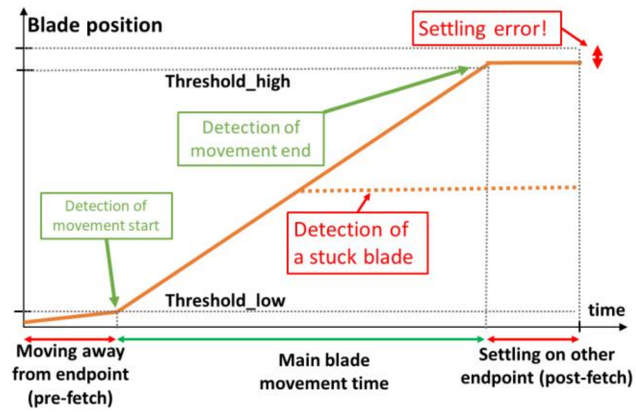

Figure 7: Displacements of switch's point blades

Since the ambient parameters are changing slowly, reading the values periodically, every half an hour provides appropriate accuracy and resolution for this use-case.

Measuring operational quantities is also possible with this system. In our case it includes the displacements of switch's point blades, as Fig. 7 shows. Here, the excepted resolution is higher than in the other case and we are interested in gathering data only during switching sequences.

Using event-driven measurement cycles is the chosen and effective solution, but it has disadvantages as well: the trigger signal can be noisy. For example, if a train crosses the junction it shakes the whole equipment, so the point blades and that shake will trigger a fake measurement. Moreover, if the device starts a

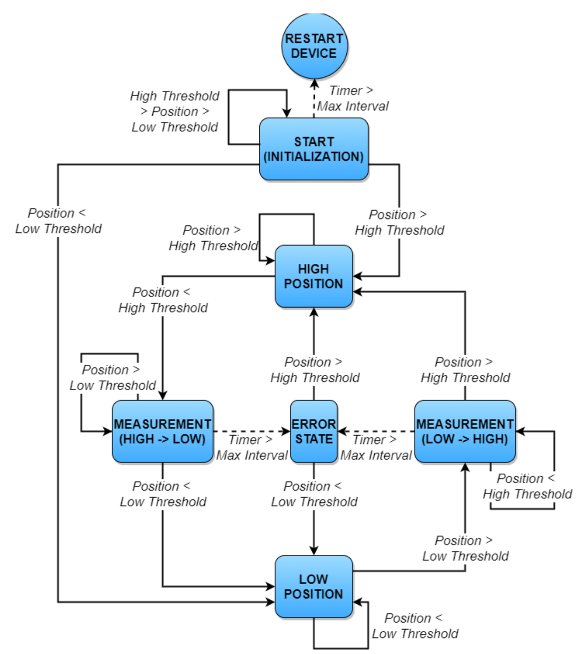

Figure 8: Measurement states

measurement and the actual position does not reach the end position – just nearly approaches it –, the measurement cycle will not stop. Another option could be to trigger when the actual position of point blades crosses a predefined threshold level and stop the measurement if it crosses another threshold level. In this case all information about the movement between the real end positions and the threshold levels would be lost.

The state-transitions of the measurement are presented by Fig. 8. In the case when the measurement takes longer than a predefined (expected) interval, the measurement stops and triggers the device to send a warning message to the central cloud. This function indicates an error, which means that the point blades cannot reach their end position – so the switching operation failed.

There is another, different error state, which is related to the settings of threshold level. After starting, the device checks the actual position of point blades, and if its value is between the two threshold levels, the device will restart and wait for resetting the threshold values. The reason is that if the actual position is between the thresholds, that means the switching operation failed. Still, it's unlikely to install – or maintain – the measurement system while the switch is out of order due to a malfunction.

B. Platform Level

The gathered information is placed into an interoperable JSON-based message format developed by the MANTIS project [1], based on the MIMOSA [6] domain ontology. The messages contain not only the results of measurements, but additional information: (i) exact timestamp, (ii) duration of the measurement, (iii) identifier of the edge device instance and (iv) additional values that help the re-assembly of the message at broker side.

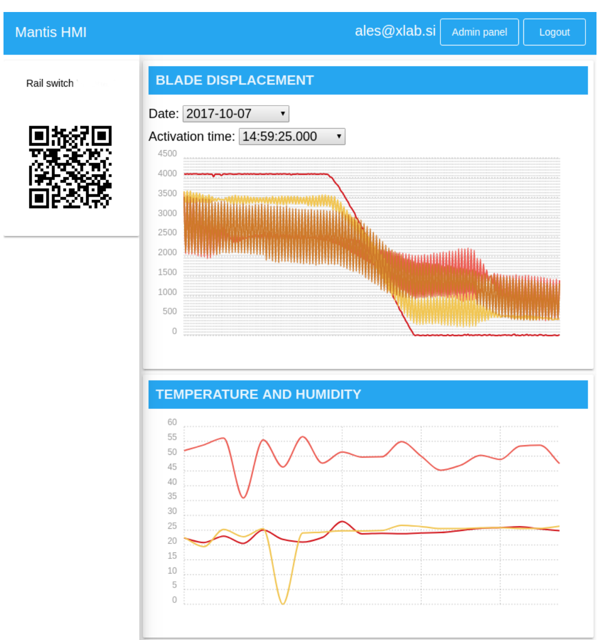

Figure 9: A dashboard for monitoring a switch

The messages are transmitted via MQTT protocol over TCP/IP. The wireless connection between the edge device and the central cloud is provided by a SIM-800 based GPRS modem which is attached to the MCU via serial line. The central cloud contains an MQTT Edge Broker, which handles the messaging, while both the Low-level Device and the cloud implement an MQTT client each.

In the central cloud, the message is received by a Mosquitto MQTT broker [7] with specialized MANTIS developed parser client. The information is then stored into a MIMOSA OSA-CBM database, which is a standard architecture for condition-based maintenance systems.

The parsed datasets will be processed offline by data mining and analysing tools. Future works include that the incoming message can be analysed online, automatically by a stream processor. This will enable an automated alerting and forecasting system to be developed.

The processed and analysed information is stored in the database, thus the central cloud can provide relevant information to different parts of the MANTIS architecture, for example for the Human-Machine Interfaces.

IV. Data Visualization

In order to use the measurements gathered from the sensors and the results of the analysis, data have to be visualized [8] in a way suitable for the needs of railway switch maintenance service. This requires the design and implementation of an intelligent and efficient user interface to monitor the railway switch (see Fig. 9), and to assist the maintenance team in performing the necessary maintenance work (as an example, see Fig. 10). Following the methodology proposed by the MANTIS project, the scenario-based design approach has been used in the process of the interface design [9]. Use-case scenarios, providing detailed description of the context of use, as well as intended users and devices have been identified and refined in several iterations. These pointed out where the user interface requirements could have been specified according to the IEEE 830 standard [10]. There were five main human roles identified, ranging from the maintenance technician to the business manager. For each of those roles a suitable device was identified. Resulting human-machine interface needs to be developed both for personal computer as well as for mobile devices. Basic requirements, derived from the scenarios, include:

- Monitoring the parameters given by the measurement box;
- Displaying the alarms that indicate the abnormal movement of the railway switch; and
- Displaying the task schedule for the maintenance service.

To provide the maximum assistance to the maintenance team, several context-aware features have been proposed, mostly based on the user role and location. Such features proved to be most useful in performing the maintenance actions on the field. Information shown to the maintenance team, varies depending on whether the team is located at the company's headquarters, on their way to perform the maintenance action, or on the spot of the maintenance task. Another such example is a personalised suggestion. When a user performs the maintenance work, the interface suggests the next step to the user, based on the history of their interaction. The users are thus provided with the right information when they need it.

In the MANTIS project, guidelines and recommendations concerning both technical details of different interface types as well as interface design have been proposed. Guidelines have been studied and successfully applied to the railways use case. As a result, first mock-ups have already been designed and are currently under the usability evaluation. In this early design stage, inspection-based formative evaluation is being performed. In this form of usability evaluation, the users are not involved yet. Mock-ups are being evaluated by the usability specialists with reference to established guidelines and principles to eliminate major issues before user testing and to incrementally validate users' requirements. Without going into implementation details, formative evaluation is trying to establish to what extent the developed solution:

- Supports user tasks within a goal, in terms of functions;
- Allows navigation from screen to screen and within;
- Allows the user to identify relevant information, etc.

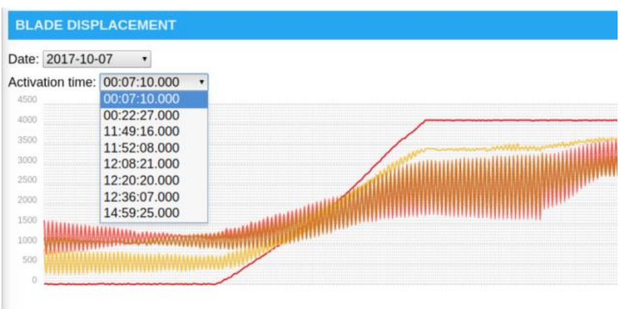

Figure 10: An HMI widget displaying high-frequency displacements measured during a single activation

Currently, qualitative data is being collected to refine the current design. If needed, formative evaluation will be repeated until satisfactory result.

Once the formative evaluation is done, enhanced HMI solutions resulting in working prototype should conform to the established guidelines and standards. Performed assessment test will be used to evaluate how well a user can actually perform full-blown realistic tasks and to identify specific usability deficiencies in the product. Important point in this stage of evaluation is the selection of representative users and appropriate tasks. Since context-awareness is implicitly involved in the functionality of the maintenance system, it should be included in the scenarios employed in all stages of usability evaluation.

When the prototype is refined and enhanced to a final HMI solution, verification and validation tests will be performed. A verification test has the objective to ensure that usability issues identified in earlier tests have been addressed and corrected appropriately. On the other hand, a validation test is used to evaluate the performance of the solution in terms of efficiency and effectiveness, or how well and how fast the user can perform various tasks and operations.

V. Conclusion

Along with the evolution of Industrial Internet of Things, the concept of Cyber-Physical Systems and the industrial initiatives, such as Industrie4.0, proactive maintenance solutions for industrial systems are starting to appear. Besides providing a general architecture to tackle the corresponding challenges, the MANTIS project suggests toolsets for data collection, processing and presentation. This paper presented tangible results, where the MANTIS concepts were applied to the use-case of railway switches. These included the measurement method and its physical manifestation; the analysis of the measured data – and based on that profiling and modelling of the physical behaviour of the switch; and the result presentation HMI tailored for various types of contexts and users – ranging from the maintenance technician to the business manager.

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