Digital Twin for condition based maintenance within a railway infrastructure testing lab

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Abstract

This article presents a digital twin development in a railway case, in order to improve operations and maintenance decisions, aligned with an asset management strategy. A digital framework for the sustainable management of these assets is defined with the purpose of facilitating the implementation on a cloud platform, searching the generation and sharing of the produced models and the evaluation from different perspectives. The developed digital twin allows for the digital representation of railway lines and vehicles, the connection between different entities based on an ontology, the management of data ingestion and storage, and the administration of models for the detection, diagnosis, and prognosis, as well as the representation and control of the level of risk of the assets. When emulation of railway line degradation is searched, different types of data are combined, from on-board sensors in railway vehicles, and physical behaviours, up to machine learning algorithms for estimation. In this way, the degradation behaviour model for the railway line is shown and validated through intelligent models easily replicated in several areas of the railway network, showing risk levels for each one.

1. Introduction

The control of failure risk is one of the main maintenance commitments, not only to preserve the asset function but also to avoid the consequences of a failure (Guillén, Crespo, Macchi, & Gómez, 2016). To continue advancing in the development of solutions that collaborate towards this goal, sophisticated digital maintenance strategies are now required, involving more data, information, and knowledge (Zio, 2022). This is particularly in demand in sectors where not only cost reduction is important, but also control and improvement of safety levels is even more critical, such as in the case of railway infrastructure.

Asset management (AM) has become a key reference for digitalisation thanks to its holistic and global approach of business requirements and their connection with asset performance. According to ISO 55000 (ISO, 2014), Risk Management (RM) has been introduced as a fundamental principle for AM and maintenance throughout the asset life cycle. And for proper risk control, maintenance digitalisation is a must core part of AM, in line with business digitalisation strategies (Márquez et al., 2022). Asset digitalisation modifies maintenance processes positively, whenever this provides sustainable and connected services, which facilitates the use of mature models, previously developed, without advanced knowledge in physical asset behaviours or in Information and Technologies (IT) skills and capabilities (Crespo Marquez, Gomez Fernandez, Martínez-Galán Fernández, & Guillen Lopez, 2020). That is, a digital framework has to require the advanced application of analytical techniques that provide knowledge and control over the processes of infrastructure degradation and digital asset modelling to generate effective maintenance decisions. This integrated system is a challenge in the railway network due to the number of disperse elements and under different environmental and operational conditions (Gómez Fernández & Cre-

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spo Márquez, 2012; Gómez, Fernández, Guillén, & Márquez, 2019).

Consequently, a deep collaboration between different areas of knowledge is necessary to propose complete solutions towards Digital Twin (DT), some based on behaviour patterns and others based on big data and artificial intelligent management. The challenge is how to organise and model the available information to facilitate its interpretation connecting data and models with dynamic maintenance decisions (Fernández, López, Márquez, Fernández, & Marcos, 2022; Ferrero Bermejo, Gómez Fernández, Pino, Crespo Márquez, & Guillén López, n.d.).

In this context, asset digitisation is one of the main challenges. Different references such as BIM (Building Information Modeling), AIM (Asset Information Modeling), AAS (Asset Administration Shell), and a wide variety of DT approaches, have emerged to manage data and provide support to improve the intelligence of asset management and maintenance (Zheng, Lu, & Kiritsis, 2022). In general, digital assets models involve a complete design architecture and data model that generates a virtual entity of connectivity, processing, and digital functionalities, which can model and process data and information, calculate new data using data analysis and simulation tools, optimise equipment performance, and make informed decisions.

For the development of advanced digitisation solutions, architectures and reference models, IIRA - Industrial Internet Reference Architecture, is a reference model developed by the Industrial Internet Consortium (Lin et al., 2019). It provides a framework for designing and implementing industrial internet systems that are interoperable, secure, and reliable. RAMI 4.0 - Reference Architecture Model Industry 4.0, is a reference architecture developed by the Platform Industry 4.0 initiative in Germany. It provides a conceptual model for the digital transformation of industrial production and serves as a guide for the implementation of Industry 4.0 projects. (Aheleroff, Xu, Zhong, & Lu, 2021) adapts the RAMI reference model as a framework for digital twins, proposing extensions to support the design and implementation of digital twin systems. From the IT point of view, platforms such as Azure, Amazon Web, Google Cloud, and other open-source initiatives such as Fiware, provide a ”toolbox” with available modules for integrating and for the development of all the necessary functions and services that a DT may require.

The development of digitalisation solutions for maintenance becomes much more complex. It involves the physical view of the asset and the knowledge and use of digital capabilities. Both must be managed together with a very high level of integration. To achieve this goal, this project has involved a joint effort of specialists in track degradation modelling and monitoring, asset management and maintenance, and cloud/IoT technologies. The result is a fully functioning laboratory for the investigation of DT solutions. This paper presents a description of a proper framework for digital asset management according to advanced IT cloud strategies and its application on the maintenance of railway tracks. Section 2 presents the track degradation problem and the monitoring techniques that motivate the design and construction of the railway lab, which will be modelled in the digital asset framework proposed and analysed in Section 3. Finally, the paper concludes with a section on track operations and maintenance management issues and conclusion.

2. CONDITION BASED DIGITAL MODEL FOR TRACK DEGRADATION FAILURE MODE

This section presents the practical case of the University of Seville, which was used to experimentally validate the impact of maintenance activities on track degradation through irregularities in its track geometry.

Accurate knowledge of the geometry of the track is essential to guarantee the safety of the rolling stock. Measurement of track irregularities and evaluation of track state are not straightforward. Manual measuring trolleys or sophisticated laboratory vehicles equipped with different sensors are normally required to estimate track irregularities. The use of any of these methods imply not just an important investment of time, but also a large amount of money, interrupting the regular traffic during those periods. The current trend in the railway industry points to the development of new computational models that allow a fast and reliable measurement of irregularities on the track and evaluation of safety during regular vehicle operation. To that end, fast and precise computational models are required that allow, in Real-Time (RT) execution, the measurement of the track irregularities.

2.1. Track Degradation Condition Monitoring Review

The use of a computational model based on several sensors at different locations in the infrastructure and in the vehicle represents an automatic way to obtain track irregularities and vehicle safety state. However, obtaining precise results through this sophisticated model usually requires a large computational cost, which can compromise the investment in real-time performance models. In recent years, many works have been published in this line, exploring different approaches, such as the use of Kalman filters, the measurement of the vertical acceleration of the car body, and the application of artificial intelligence to obtain lateral track irregularity (Tsunashima, Naganuma, & Kobayashi, 2014) (Karis et al., 2018) (Rosa et al., 2021) (Kraft, Causse, & Martinez, 2019).

The Department of Mechanical and Manufacturing Engineering of the University of Seville has demonstrated the potential of this type of testing infrastructure for the experimental validation of computational models of railway vehicles and the measurement of track irregularities. However, formulating

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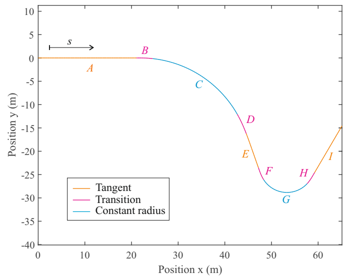
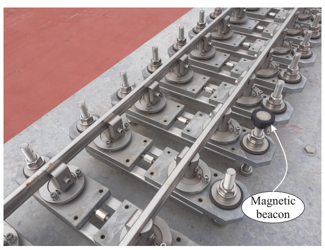


(b)

Figure 1. View (a) and diagram (b) of the testing track.



(a)

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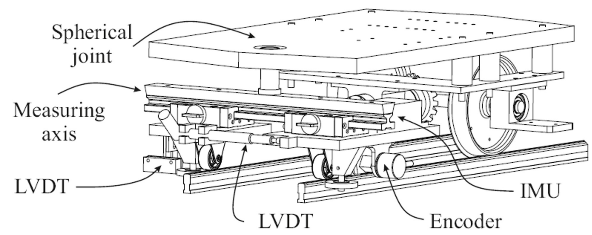
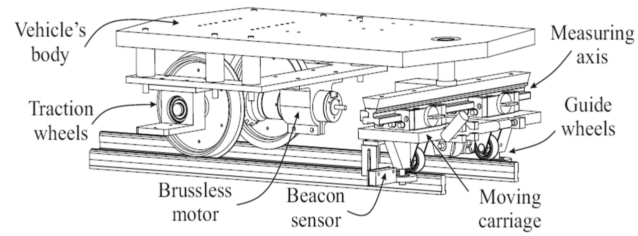
Figure 2. (a) Track sleepers. (b) Track overall view



(a)



(b)

Figure 3. Views of automated inspection vehicles.

such computational models represents a significant challenge due to the strong nonlinearity of the system, requiring complex field tests to validate their performance. This implies difficulties in accessing a railway vehicle and its infrastructure, which can be costly and complicated (Urda, Aceituno, Muñoz, & Escalona, 2021); (Muñoz, Urda, & Escalona, 2022).

2.2. Experimental Lab for Track Degradation Testing

Consequently, this university department has been working in recent years on the development of a unique in Europe scaled railway infrastructure (Chamorro, Aceituno, Urda, del Pozo, & Escalona, 2022), running any new computational model on scaled vehicles over a 1:10 scaled track, analysing the dynamics behaviours without compromising the safety of real vehicles and tracks or passengers.

The experimental scaled track is an open end 90-meter-long track,installed on the roof of the Engineering School of Seville University, built with a sequence of tangent, transition, and constant-curvature sections. Fig.1 (a) shows an aerial view of the building and the track, and Fig.1 (b) highlights the different sections of the track. The rails and slabs have been manufactured in stainless steel and rest on a set of metallic benches distributed along the roof of the building as shown in Fig.2. The rail heads are a scaled reproduction of a standardised UIC-50 rail profile, while the body of the rail has been modified to allow its installation on the slabs. Track slabs have been designed to allow the manual introduction of track irregularities through a series of bolts and nuts that allow the variation of the track gauge, the cant angle, and the relative high between both rails on every single track slab.

This department relies on an automated inspection vehicle Fig. 3 that, combined with the total station and the measurement of the sensors installed on it, allows for a fast and accurate measurement of track irregularities. This vehicle has two main parts: the body of the vehicle and the measuring axis. Both parts are connected by a spherical joint that isolates the rotation of the vehicle body and the measuring axis. The body of the vehicle includes the traction system consisting of a rigid set of wheels powered by a brushless electric motor and a direct gear transmission. The wheels are a scaled reproduction of a real wheel profile that guarantees self-centering of the axis on the track. The master piece of this inspection vehicle is its measuring axis. It includes a linear guide and two moving carriages. The measuring axis is instrumented with a precision encoder and an inductive sensor, which allows for the exact location of the vehicle on the track. It has an Inertial Measurement Unit (IMU) and an inclinometer on the left carriage, and a LVDT between both carriages that allows for the direct measurement of the track gauge variation. A set of guide wheels and a traction spring connect both carriages, guaranteeing the minimum distance between them during vehicle operation. The vehicle is also equipped with a NImyRIO- 1900 and a mini PC with 3G connection to control the vehicle and acquire all sensor signals.

3. CODITION BASED DIGITAL FRAMEWORK FOR TRACK DEGRADATION

In order to obtain a digital twin of this asset for condition-based track degradation detection, diagnosis, and prognosis,

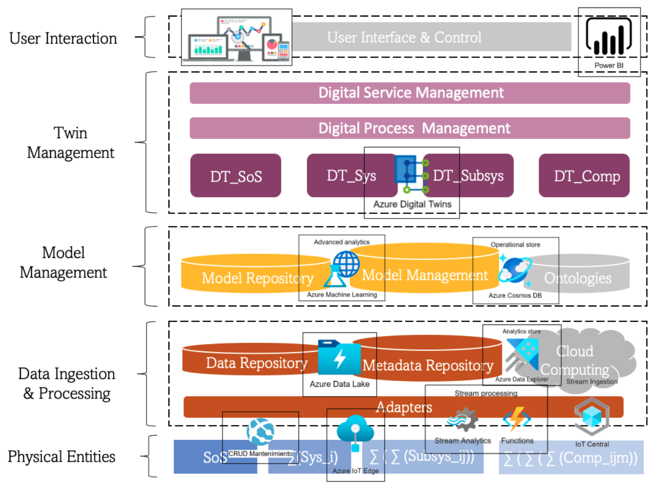


Figure 4. Condition-Based Digital Architecture for Digital Asset Modelling

different existing solutions of DT are reviewed on the market. These cloud solutions have a high potential and flexibility, to cover different studies, however, this converses them in a set of modules which can be linked instead of providing suitable unique guidance for preparing Prognostics and Health Asset Management projects. Searching for a suitable template for practical implementation that outlining general guidelines to follow, the study is based on Microsoft Azure which stands out for offering the right platform for asset-based projects, allowing different cloud-based components to be connected, compounding flexible architectures for asset management.

3.1. Basic Cloud Framework for track degradation

The basic cloud architecture for asset management could be represented according to the hierarchical levels of organisation defined by RAMI 4.0 - Reference Architecture Model Industry 4.0 in the Azure Cloud Architecture, with the aim of providing a fundamental framework for structuring, planning, and controlling the Digital Twins Cloud Solution over resilient and scalable Azure modules. From the point of view of information technologies, the hierarchical levels for asset management based on Azure are described as follows:

- At the bottom (level 0), the physical assets and processes are included, being managed and operated by sensors, actuators, and devices. There are different types of data transmissions in sensors and devices depending on the supplier; and different types of connection with them (PLC, fieldbus, and distributed systems or servers); then it is needed to operate all of them in an integral view and communicate data, commands, and events to the upper level. In our architecture, this level is based mainly on the Central Internet of Things and stream processing functions, where a collection of devices are connected, monitored, and controlled. A big data streaming and event ingestion service is implemented to receive and process millions of events per second. In addition, AZURE IoT EDGE is used as a container of sensors and devices to communicate data in real time to the network. Data at this level can be sent to an event hub to be transformed and stored with any real-time analytics provider.
- In level 1, called Data Ingestion and Processing, data processing and control are executed, both mainly in real time. This level requires a large amount of computing, storage, and routing capacity, so specific servers or mainframes are used to enforce systems, data warehouse, and data mining on all of the asset information. Centralisation is the objective at this level. In the proposed architecture, data are captured in real time by an Azure Data Lake Storage instance for long-term retention or microbatch processing by an Azure Data Explorer instance for short-term preservation. In addition to cold storage, Azure Data Lake Storage Gen2 is used by a set of capabilities dedicated to big data analytics, through low-cost tiered storage of raw files with high availability and disaster recovery capabilities over a long period of time. The Azure Data Explorer provides an end-to-end solution for data ingestion, query, visualisation, and is managed as a high-performance big data analytics platform that makes it easy to analyse large volumes of data in near real time.
- Level 2 is characterised by the Model Management, it is the kernel of the asset knowledge where real and predicted behavioural asset models are developed. This level is crucial in the sustainability of the solution, where the different behavioural models are managed as a service-orientated vision, facilitating their replication even in different assets. This is developed in our architecture mainly on two modules, Azure machine learning and Cosmos DataBase. Advanced Analytics develops sophisticated and definable statistical models to gain insight that drive better products, streamlined operations, reduced costs, and innovative customer experiences. The built models are stored in Cosmos DB to be provided to the next level with the purpose of developing Digital Twins.
- Then, based on previous models, on the Twin Management level, number 3, digital entities are defined to represent twins of assets, places, and objects in the physical environment. These Digital Twin entities are defined based on the JSON-like language called the Digital Twin Definition Language (DTDL) by Microsoft, allowing the construction of their state properties, telemetry events, commands, components, and relationships. From a asset perspective, level 3 avoids 'analysis silos' that could obstruct future developments and improvements. This level seeks an integrated vision for real-

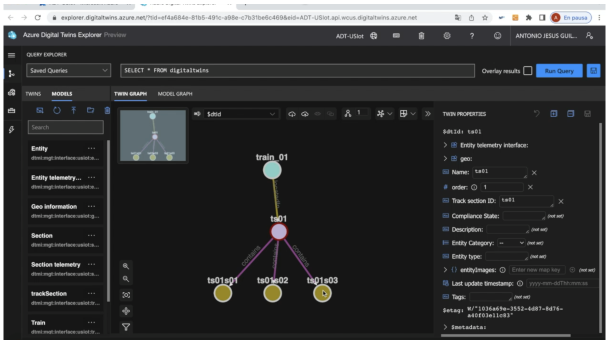


Figure 5. Representation of the DT for CBM: Entity Ontology.

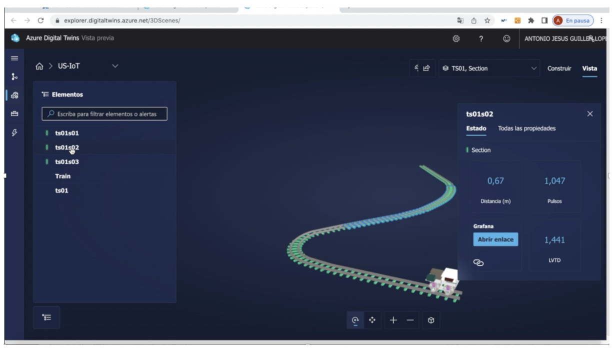


Figure 6. Representation of the DT for CBM: 3D model

time visibility and traceability, which facilitates diagnostic, prognostic analysis, and expert decision making. Thanks to these DTDL models the collected asset information is analysed and converted into useful knowledge and recognised and user-friendly information about the asset. Once the Azure Digital Twins model has been created, the models/interface is implemented mixing reality, and autonomous systems; it is considered an event producer that updates the properties of the digital twin.

- And finally, level 4 is focused on facilitating user interaction in order to make it more productive, reliable, environmentally friendly, safer, and less risky. A simple and basic interface for decision making is defined based on Power BI custom reports in real time for different types of decision, strategic, tactical, and operational.

According to these levels and using minimal number of Azure modules, it is facilitated the development of Digital Twin of different assets, as in our case of track degradation replicating the developments for a complete railway network.

3.2. Condition-Based Analysis for track failure mode control

Digital Twin (DT) have two fundamental representations within the platform and solution used. In 5, the basic ontology is depicted. In this case, the railway line is divided

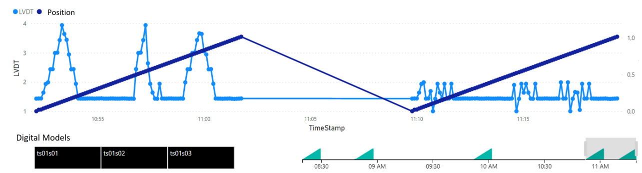


Figure 7. LVDT values in two-route tests for the three sections

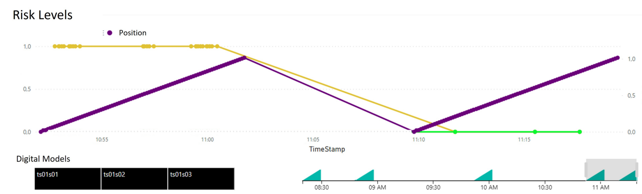


Figure 8. Risk Levels for Degradation Detection

into three sections, and both the entire line and each of the sections have their respective DTs, as well as the DT for the monitored vehicle. 6 shows the 3D model of the track, where it is also possible to access and select each individual DT. In the case of the scale track, the assets to be managed are the three sections into which it is divided (Sections 1, 2, and 3 in Fig. 5).

The DT model for CBM focusses on the representation of failure modes, which are defined as properties of entities (assets). These failure modes have associated input signals from the auscultating vehicle. These raw input signals are transformed into descriptors, whose interpretation generates results that can be related to detection, diagnosis, or prognosis, always for specific failure modes of the track sections. Finally, the different information from the interpretation of the descriptors is used to define the risk levels for the failed mode analysed (following the method detailed in (Fernández et al., 2022)).

The geometry of the scale track is evaluated with a forward velocity of the vehicle of 2.5 m / s, which is equivalent to 90 Km/h according to the scale.

The input signal is obtained from the LVDT, and the failure modes are all those that present the deviation of the LVDT measurement as a symptom. It is important to note that the deviation from the track gauge measurement provided by the LVDT is actually a symptom. Different failure modes of rails, fastenings, sleepers, or even infrastructure elements may be behind this symptom. The system reacts by detecting the problem, precisely locating it within the section, and associating this detection not only with one failure mode, but with all the potential failure modes related to that symptom. Therefore, this is a detection case and for a diagnosis more information is needed to discriminate between different failure modes with precision.

Fig. 7 and 8 show the results obtained. In the left-bottom part of the figure, there are three black boxes indicating the three different track sections. The route of the vehicle is shown in Fig. 7 as a dark blue line that increases with the relative distance (between 0 and 1) according to the secondary axis. When the dark-blue line decreases, it is the return route to the origin. Thus, the LVDT is measured with a blue line on the primary axis, indicating high values on the first route over the three sections, and normal values on the second route, with the idea of introducing the behaviour of risk levels for this detection case. 8 presents this risk level, where on the first vehicle route due to LVDT values the risk level is medium (yellow) and on the second route the risk level is green due to normal values. 8 also has both routes with a purple line on a secondary axis for relative distance. In both figures, in the right-bottom part is the TimeStamp of the testing, with a grey shadow to indicate the time window.

For a future prognosis case, we have prepared the framework deploying local and cloud environments using the ONNX standard that facilitate the exchange format using the Python SDK, and a Jupyter Notebook for the creation and implementation of the necessary computing resources.

4. CONCLUSION

This paper explains a basic Digital Twin framework based on Microsoft Azure Solution to CBM strategies based on the failure mode track risk using geometry irregularities measurement. Different levels in the architecture are defined for sustainability and with simple relations among the modules used. Thus, from a service-orientated perspective, the definition and replication of Digital Twins are facilitated. Managed measurement from sensors and their processing are funnelled towards the detection and prediction algorithms. In this case, the kinematic behaviour was particularly evaluated when a vehicle moves along a scaled three-section track, providing high accuracy and using commercial sensors of the railway sector. The used developments not only to detect geometry irregularities, but also in the right time and location, crucial for optimal repair activities, and for safety decisions based on the produced risk levels in case of critical values. In the future, more complex models for prognosis will be included.

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