

# Application of Degradation and Optimization Models for digitization of Maintenance Management in Railway Infrastructures

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**Abstract:** This study presents an innovative methodology to improve the maintenance of railway infrastructures, integrating degradation models and economic optimization. The combination of a degradation model and a semi-Markovian model supported by the Weibull function, calculates the economically optimal degradation, to release the preventive intervention. The development of digital twins of assets and infrastructures makes possible the integration of online data and the incorporation of models that help the maintenance manager in decision-making. Organizations must determine the information to be collected from the assets. Transform the information into inputs for the models and, after their application, would allow them to identify the most economically favorable global maintenance scenarios. This work evolves the decision support on preventive maintenance implementation in the railway sector. From a decision table, used by railway managers, with three levels of risk established subjectively on an experimental basis, it evolves to the objective methodology, designed to determine the optimal degradation. The methodology can be applied to assets by maintenance managers but can also be incorporated into the digital twins. The case study illustrates the practical application of this methodology to the degradation of railway track sections. The research emphasizes the importance of data-driven decision-making for economic maintenance management. However, other priorities such as transportation safety and efficiency could complement the economic one.

**Keywords:** Railway maintenance, Degradation modeling, Economic optimization, Digital twins, Data-driven decision-making

## 1. INTRODUCTION

Rail infrastructure maintenance is crucial to ensure the safety and efficiency of rail transport. Each section of the railway system is subject to any circumstances that cause its deterioration over time. For its study, it is necessary to develop a track degradation model that quantifies the level of defects for each of the sections as a function of time or any other parameter. The track degradation model most commonly used by European Infrastructure Managers was developed in the ECOTRACK project (Rivier, 1998) of the UIC (Union Internationale des Chemins de Fer) in the 1990s. The model describes the level of defects in the geometry, differentiating three stages: (i) An initial settlement stage, of short duration; (ii) A second stage of long duration, where the deterioration is slow and almost linear; (iii) And a third stage where the deterioration increases exponentially and represents an irreversible situation that requires corrective intervention to restore the geometric and mechanical characteristics of the rail tracks.

The ECOTRACK project establishes three levels of deterioration: comfort level, deterioration level, and safety level. Exceeding the comfort level requires preventive interventions to reduce degradation, although it will not return to the initial level. After the level of deterioration, the track section requires corrective intervention. This more costly intervention is intended to prevent degradation from reaching the safety level. The safety level would limit the speed through the section or suspend traffic (EN 13848-5:2017, 2017).

Both preventive and corrective interventions are part of the maintenance policy of a rail infrastructure manager. In addition to considering the safety and efficiency of transport, the manager must establish, for each track section, the economically optimal action strategy based on minimum speed requirements that support the corresponding loads. These facts make it necessary for the manager to study the degradation and find the optimal time to carry out maintenance interventions. The purpose of this article is to help managers identify the most economically optimal degradation for preventive interventions.

The methodology developed combines two models. On the one hand, a degradation model includes a formula to determine the level of risk and develops a degradation function. On the other hand, a second optimization model determines the level of degradation, in an economically optimal way, from which preventive interventions are released. The objective is to provide the manager with the tool to calculate the value of the degradation level that economically optimizes preventive interventions on rail track sections.

The degradation model seeks to establish the Risk Level (RL) indicator based on several factors: degradation speed, condition, traffic, and rail track saturation. Analyzing these factors allows the development of a mathematical formula for the RL that depends on degradation. Later, this formula is used in a semi-Markovian model that values costs based on possible transitions between states: operation, repair, and preventive. The optimization model determines the mathematical formula

that establishes the economically optimal degradation for preventive interventions on the track section.

Three research questions are analyzed in this article. First, how to develop a degradation model that fits the deterioration of the railroad sections. Second, how to adapt the optimization model to use the degradation function obtained in the degradation model. Third, how to incorporate these models into a digital twin, treating their inputs online and generating outputs. These outputs will influence the decision-making of the railway manager about the temporal location of the maintenance interventions for each track section.

Other sections follow this Introduction. Chapter 2 includes a brief review of the literature. Chapter 3 presents the procedure and methodology. The degradation model and the optimization model are included. In Chapter 4, a summary of the use case is exposed. Chapter 5 analyzes and discusses the results obtained. Chapter 6 presents the conclusions.

## 2. BRIEF LITERATURE REVIEW

In recent years, numerous studies have focused on rail infrastructure maintenance digitization. Studies have shown that digital technology integration into rail maintenance practices can improve the decision-making process, causing a positive impact on increasing the reliability and efficiency of this type of transportation. Regarding data processing, availability on demand, standardized accessibility, and interoperability to be used by multiple management or design models. (Platenius-Mohr et al., 2020) state that data about physical objects (devices) must be standardized and added to the asset in such a way that they can be used both inside and outside the organization. These contain the asset information such as its status, service condition, maintenance history, or any additional information used to develop a dynamic risk analysis. In this sense, (Qian et al., 2021) investigate IIoT-based means to monitor railway infrastructure. From them, it is possible to provide individual information to each asset, which can then be used, for example, in a risk model. That article shows how IoT devices can collect countless data to support industrial maintenance decisions. However, it does not fully address the problem of handling and analyzing the data for risk assessment. (De Benedictis et al., 2023) present a conceptual architecture for IIoT anomaly detection based on the digital twin (DT) and autonomic computing (AC) paradigms. They discuss the results using a reference operational scenario of complexity and criticality within the European Rail Traffic Management System. (Djordjević et al., 2024) construct a digital twin of a railway-level crossing to manage risk in the railway sector. The twin simultaneously monitors and visualizes the operation of the level crossing, in real-time, identifying possible faults and equipment failures. On the other hand, (Zhang et al., 2017) offer a risk-based maintenance plan for use in rails. However, because it does not include digitization, the data processing is not as dynamic and continuous as it is processed in digital twins. In our study, we have linked the identity and location of each span with attributes from the design, operation, and asset maintenance. The model's integration allows us to define degradation and find the economically optimal preventive intervention for the asset.

## 3. PROCEDURE AND METHODOLOGY

This study examines how rail maintenance management can be optimized through the digital use of risk analysis and economic analysis.

The digitization of the models would require the model's mathematics and algorithms and the information coming from the state and use of each rail track. With this information, the inputs to the degradation model would be generated. On the other hand, the costs of maintenance interventions and usage income are inputs for the optimization model. A correct distribution of these inputs will require developing the hierarchical structure of the rail network to be digitized and, from there, defining the identification and location codes (for each section), and the attributes related to degradation and costs collected for each track (Figure 1).

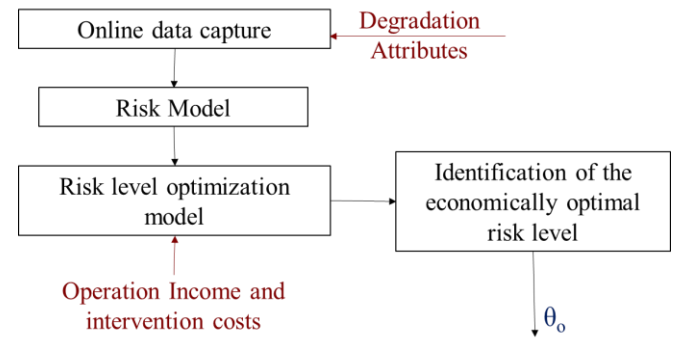


Figure 1. Procedure for obtaining the degradation value that optimizes the launching of the preventive intervention.

This transformation revolves around two models designed to be embedded within digital twins of railway sections, which must be fed with data from the physical asset. The first model represents the degradation of a rail section. The second model represents the evolution of the condition of that section of track and determines the level of degradation.

### 3.1 Degradation Model

We start from the definition track maintenance planning cycle to develop the degradation model. This cycle consists of four activities (ADIF, 2015): knowledge of the track condition through auscultation and inspection; diagnosis, definition, and assessment of maintenance actions; short-term planning and prioritization of maintenance actions (maintenance plan); and execution of maintenance actions. According to this cycle, to execute the maintenance actions, a flow is established where the first stage consists of data collected for the calculation of the basic indicators. The data sources that feed these indicators are railway sections, inventory, incident records, and rail traffic. Its calculation requires a process that includes data extraction, filtering, and elaboration of factors for each indicator. Once the data and basic indicators have been defined and how the attributes are collected have been established, the objective of a railway manager for track management is to calculate the mathematical expression of the Risk Level (RL) for each track section. This expression should help in making decisions about scheduling maintenance tasks. The RL is a

dimensionless indicator that allows to determine the condition of the assets with a double purpose. First, to minimize the risks in the operation of the track (avoiding the implementation of temporary speed limitation or traffic suspension). The second purpose is to maintain the required safety and quality standards. This indicator determines the state of the asset under analysis and is defined as: (ADIF, 2015):

$$RL = C_1 \cdot PR + C_2 \cdot TAC \cdot UF \quad (1)$$

PR is the Potential Risk of an asset, the probability of an asset suffering a failure. UF is the Utilization Factor, it accounts for the impact of a failure on the movement of trains. TAC is the Traffic Affection Constant; it measures the degree of impact on rail traffic that could be caused by an incident depending on the type of system affected. C1 and C2 are coefficients that are dynamically calculated from the PR value.

The PR is an indicator that determines the asset that would need to be renewed based on its condition and level of obsolescence. It is composed of two factors, CF + OF. CF is the Condition Factor and represents the performance of the facilities over the last five years. It is calculated from the facility's Unreliability (UR) and Unavailability (UA) data. OF is the Obsolescence Factor and measures the degree of aging of the system components. It is obtained from the age of the asset (years since its installation). On the other hand, the Utilization Factor (UF) is the indicator that identifies the impact a fault at a given location would have on the movement of trains. It is composed of two other factors, TF + LC. FT is the Traffic Factor, depending on the Average Daily Traffic. LC is the Line Constant and defines and assigns to each type of line its importance.

$$PR = CF + OF \quad (2) \quad UF = TF + LC \quad (3)$$

With the FI and UA data, second-level indicators are elaborated. They constitute the basis on which the first-level indicators detailed above are calculated. These indicators are the Unreliability Factor (URF) and the Unavailability Factor (UAF). The URF is calculated based on the number of failures during the year before the calculation. The URF is calculated from the Unavailability times caused by failures during the year before the calculation. Using Equations (2) and (3), and the factors provided in the text, Equation (1) is updated.

$$RL = C_1 \cdot (CF + OF) + C_2 \cdot TAC \cdot (TF + LC) \quad (4)$$

For decision support, the administrator establishes five scenarios affected by RL indicator values (ADIF, 2015). Three thresholds are defined for risk levels TR1, TR2, and TR3 that will determine in which state (scenario) the assets (track sections) are.

**Table 1. Scenarios for states according to the Risk Level (RL)**

RL = 0	Assets with optimal behavior
0 < RL < TR1	Assets with non-optimal behavior but within limits
TR1 < RL < TR2	Assets susceptible to intervention but not prioritized
TR2 < RL < TR3	Assets with priority intervention

TR3 < RL	Assets with urgent intervention
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The intervention decision is subject to the range that delimits each threshold for the TR<sub>i</sub> risk levels. TR<sub>i</sub> levels are established based on the experience of the rail infrastructure manager. These ranges make it easier to make a good decision but do not guarantee the best one.

### 3.2 Semi-Markov optimization model.

A semi-Markovian model that analyzes the evolution of an asset over time has been applied. Three states of the asset are defined, Figure 2.

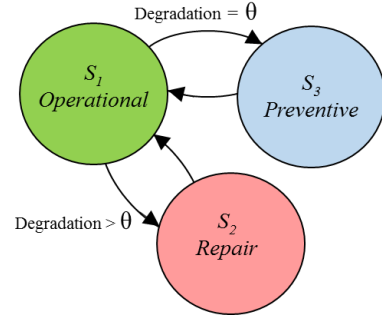


Figure 2. Three states and their possible transitions.

The asset remains in an operating state, when trains are running on the asset. It is in preventive maintenance state when a scheduled intervention to reduce the level of deterioration of the element is being performed. Finally, it is in a state of repair, when any incident has occurred, or the degradation is such that a general repair must be carried out.

Each of these three states has associated income and costs. Income from the use of the asset and costs due to the interventions. Reaching the preventive state will depend on the degradation  $\Theta$ . The model allows finding the optimal degradation level  $\Theta_o$ , economically improving the scenarios proposed in Table 1.

Figure 3 expresses the process to reach the degradation  $\Theta_o$ .

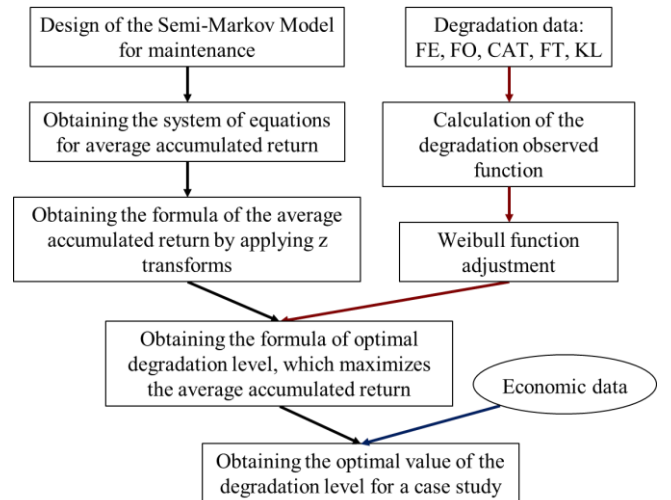


Figure 3. Process for obtaining the optimal degradation value,  $\Theta_o$ .

It starts with the accounting of the returns and revenues associated to the states, transition after transition Figure 4.

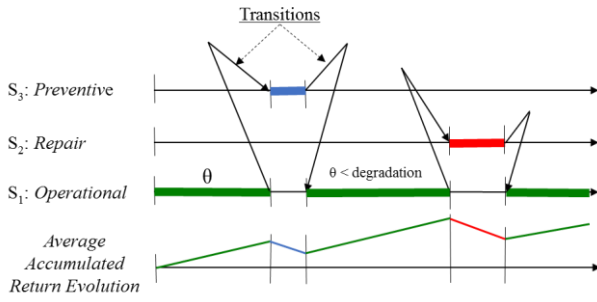


Figure 4. System evolution between states and accumulated returns.

The return variable associated to a transition,  $R(1)$ , is defined and from it the associated return variable in any transition,  $R(m)$ , can be composed. This variable, due to its randomness, cannot be calculated, but it is possible to calculate its average value  $v(m) = E[R(m)]$ , called average cumulative return. The duration of the project will determine the number of transitions to be carried out, i.e. the value of  $m$ .

The variable  $v(m)$  is subject to the starting state of the succession of  $m$  transitions, so the equations of the variables expected accumulated return from state  $i$ ,  $v_i(m)$ , can be defined. The resulting system can be expressed as a system of three difference equations and is solved by applying the  $z$ -transform (Sánchez Herguedas et al., 2022). The value obtained for this variable when the origin of the transitions in the operative state is  $v_1(m)$  in in Equation (5).

$$v_1(m) = \frac{1}{4}[(2m + 1 + (-1)^{m-1})(F(\Theta)(R_{12} - R_{13}) + (R_1\Theta + R_{13})) + (2m - 1 - (-1)^{m-1})(F(\Theta)(R_{21} - R_{31}) + R_{31})] \quad (5)$$

The parameters and variables are shown in Table 2.

Table 2. Parameters and variables of the average accumulated return from the operating state,  $v_1(m)$

$m$	Transition for which calculations are made
$\Theta$	Degradation
$\Theta_o$	Optimal degradation level (ORL = $\Theta_o$ )
$F(\Theta)$	Degradation function
$R_1$	Income associated with time to degradation level $\Theta$
$R_{12}$	Cost of loss of operation of the asset due to repairs
$R_{13}$	Cost of loss of operation of the asset due to preventive interventions
$R_{21}$	Corrective intervention cost
$R_{31}$	Preventive intervention cost

The matrices associated with the calculations to obtain  $v_1(m)$  are the transition probabilities matrix  $P$  and the returns matrix  $R$  associated with the states and transition. Equation ;**Error!**  
No se encuentra el origen de la referencia..

$$P = \begin{pmatrix} 0 & p_{12} & p_{13} \\ p_{21} & 0 & p_{23} \\ p_{31} & p_{32} & 0 \end{pmatrix} = \begin{pmatrix} 0 & F(\theta) & 1 - F(\theta) \\ 1 & 0 & 0 \\ 1 & 0 & 0 \end{pmatrix} \quad (6)$$

$$R = \begin{pmatrix} 0 & R_1\theta + R_{12} & R_1\theta + R_{13} \\ R_{21} & 0 & 0 \\ R_{31} & 0 & 0 \end{pmatrix}$$

To mathematically find the optimal degradation level  $\Theta_o$ , the RL of Equation (1) must be expressed as a degradation function,  $RL \approx F(\Theta)$ , including all factors of that equation.

The method to calculate  $\Theta_o$  consists of finding the mathematical equation expressing the value of  $\Theta_o$  for any transition  $m$ . For this, it is necessary to derive  $v_1(m)$  for  $\Theta$  and equal to zero,  $\frac{dv_1(m)}{d\Theta} = 0$ . From this expression, in some of the cases, it is possible to obtain the equation defining  $\Theta_o(m)$ . One such case is when the degradation function is a Weibull function. The Weibull function has the facility of being able to adapt to degradation scenarios by simply varying one of its three parameters. In this case, the third parameter is zero. To apply this procedure, the Risk Level must be converted into a distribution function (path between 0 and 1 for values of  $\Theta$ ). This is achieved by applying, for example, the Median Rank Method (MRM). From the distribution function observed by MRM, a table of values of the degradation  $\Theta$  and its probability of occurrence of that degradation  $F(\Theta)$  is constructed. The logarithmic method (Sánchez-Herguedas et al., 2022) is applied to these data to obtain the parameters of the Weibull function that best fits the observed function.

When the Weibull function [ $W(\alpha, \beta)$ , with  $\alpha$  = shape,  $\beta$  = scale] found is introduced in equation the value of  $\Theta_o(m)$  can be found (Sánchez-Herguedas et al., 2021) using Equation (7).

$$\theta_o(m) = \left( \frac{\beta^\alpha}{\alpha} \cdot \frac{(R_{21} - R_{31})(2m - 1 - (-1)^{m-1})}{(R_{12} - R_{13})(2m + 1 + (-1)^{m-1})} \right)^{\frac{1}{\alpha-1}} \quad (7)$$

This expression determines the degradation for which the execution of the preventive intervention is economically optimal. The railway manager will carry out it, considering other conditioning circumstances such as operability, security, logistics, etc.

Another method could also be applied to find  $\Theta_o$ . For example, using a numerical method such as Nelder Mead. This procedure should be repeated for each transition  $m$ . However, as the cycle of transitions in the model is closed every two steps, it would be sufficient to calculate for any  $m$  with an even value since they all present the same result for  $\Theta_o$ . In cases where the project duration implies an odd  $m$  value, the calculation would have to be performed for that  $m$  value. The application of this method is time-consuming and not as easy.

#### 4. STUDY CASE

This case study analyzes the degradation of a rail section to determine the degradation point at which preventive intervention on the asset becomes economically optimal. The proposed degradation model considers five factors and two coefficients that vary with one of them. Each of them (CF, OF, TAC, TF, LC, C1, and C2) adds degradation to the track section, and from the values collected, the RL can be

determined. The rail manager has determined that a value of 10 of RL prohibits movement on the section. Therefore, it will coincide with the value 1 (maximum value) of the degradation function  $F(\Theta)$ . Experimentally, the degradation for level 10 is 19,800 degradation units for the track section. The minimum measurable degradation is 0.005 which is matched to level 1 and the zero value of  $F(\Theta)$ . Next, the degradation is calculated for levels 2 to 9. For this, the amplitude of the logarithm of the degradation is divided by 9 ( $\ln 19,800 - \ln 0.005$ )/9 = 0.92, distributing each intermediate level separately by the value 0.92. The  $F(\Theta)$  values for each RL are shown in column two of Table 3. We refer to the resulting distribution as the observed distribution. In this case, it is not necessary to determine the observed distribution using the median rank method because we have not started from a point cloud but from an experimental function formed by field data. Starting from pairs of values (degradation and probability of that degradation) of the observed distribution (e.g., ten distributed probability values), the logarithmic scales are applied. Respectively  $\ln \Theta$ ; and,  $\ln (\ln (1/(1-F(\Theta))))$  (Table 3).

**Table 3. Data for the representation of the Weibull function**

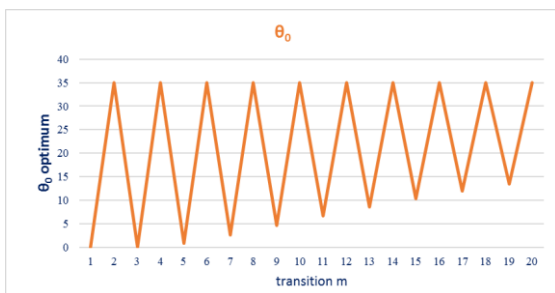
Degradación $\Theta$	$F(\Theta)$	$\ln \Theta$	$\ln (\ln (1/(1-F(\Theta))))$
0.005	0.00025	-5.298	-8.29392463
0.013	0.00063	-4.374	-7.36947566
0.032	0.00158	-3.455	-6.44953991
0.080	0.004	-2.526	-5.51945758
0.200	0.01	-1.609	-4.60014923
0.500	0.025	-0.693	-3.67624726
1.260	0.063	0.231	-2.73226098
3.160	0.158	1.151	-1.76040462
8.000	0.4	2.079	-0.67172699
19.800	0.99	2.986	1.52717963

The data in Table 3 generate a Weibull show in Table 4.

**Table 4. Degradation data and costs associated with transitions**

Weibull ( $\alpha, \beta$ )		Returns			
$\alpha$	$\beta$	R12	R13	R21	R31
1.11	11.31	-5.5	-1.0	-1.50	-2.00

We take from (Table 4) the cost data associated with preventive and corrective interventions. The optimal location of the preventive intervention should be when the degradation reaches  $\Theta = 35$ . Other optimal degradation values are shown in Figure 5. Performing preventive interventions when degradation  $\Theta = 35$  will yield a higher economic return.



**Figure 5. Values obtained for the optimum degradation for each transition m.**

## 5. ANALYSIS, RESULTS AND DISCUSSION

The case study investigates the optimal choice of preventive intervention for a section of track. The section belongs to a class and occupies a position in the hierarchical structure of the railway network and is therefore determined by its identification and location codes. Its graphical representation can be generated from these two codes.

The attributes of the asset are developed around these two codes. The attributes are essential for the physical asset digitization, generating the digital asset, since they make it possible for the digital asset to simulate the behavior of the physical asset (twinning). The attributes, therefore, must be associated with the model in which they will be used. It is essential to generate an attribute structure for each model. In some cases, an attribute can be used by several models, which can lead to errors. In the digitization process, priority is given to model development and their attributes, establishing from a second model the possible relationships between the models and the shared attributes.

If the relationships of the models and attributes are defined, new assets can be easily incorporated into the digitization as long as their class is defined. Otherwise, the class and class attributes must be defined for each of the models that are part of the digitization. The new models incorporated require the definition of their attribute structure for each asset to which the new model will be applied.

The information related to the variables and parameters collected for the variables in Equation (4) and Table 2 are the attributes that must be associated with each asset so that their values can be used in the digital asset representation. From there, both models can be run. Figure 6 shows the relationships between assets, codes, and attributes before (blue) and after (red) digitization.

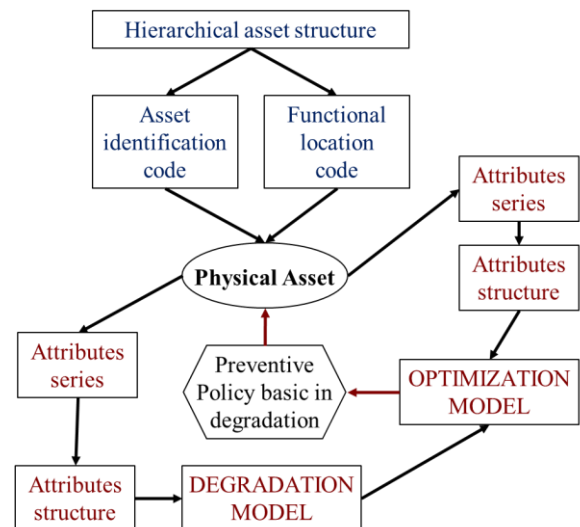


Figure 6. Structures, coding, and attributes asset. Before (blue) and after (red) digitization process.

Before the appearance of digital twins, the hierarchical structure of the asset was established around the asset, allowing a correct codification of each of its elements. From the operation and maintenance of the asset, attributes emerged that could be used in models to aid decision-making. When digitization is developed, the models and data of the specific physical asset are integrated into the digital asset. This forces the establishment of an attribute structure for each model. In digitization, these structures and the relationships between them must be included. This concept encompasses the idea of data structure since it allows relationships between structures designed for automatic model execution, together with the hierarchical structure of the physical asset.

## 6. CONCLUSIONS

The study proposes a comprehensive methodology for optimizing rail infrastructure maintenance through degradation modeling and economic optimization. The combination of a degradation model, which evaluates the degradation of an asset as a function of various factors, and a semi-Markovian optimization model, which determines the economically optimal time for preventive interventions, provides efficient decision support for railway maintenance.

The case study addresses the optimal selection of preventive interventions on a railway track section. From the degradation data, the costs of maintenance interventions and the income from the use of the assets, the value of the degradation that economically optimizes the releasing of the preventive intervention is provided.

The methodology underlines the importance of data-driven decision-making for optimal economic maintenance management. The research points out the relevance of digitization and mathematical models in the execution of strategies to ensure the lifetime and sustainable performance of the railway infrastructure. In the application to determine the optimal degradation, the adaptability of the Weibull function to different degradation scenarios stands out.

The possible limitations in the application of this methodology are related to the acquisition and processing of information to prepare the model inputs. Many organizations lack this information and others, although they have it, still do not manage it efficiently. Few organizations are making progress in this regard by developing digital twins that integrate information and inputs on the one hand and mathematical models on the other. In the future, these organizations will have these tools and will be able to optimize the management of their infrastructure maintenance in an integrated manner. Other priorities, such as transport safety and efficiency, could complement the economic one.

**Funding.** Grant PID2022-137748OB-C32 funded by MCIN/AEI/ 10.13039/501100011033.

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10:00 - 10:30

Coffee break

10:30 - 12:30

Digital Twins for maintenance applications		Chair: Marco Macchi Co-chair: Mauricio Rodriguez	Maintenance strategies, simulation and optimisation of complex systems		Chair: Giacomo Barbieri Co-chair: Roberto Sala
38	Application of Digital Twin Technology for the Digitization of Railway Maintenance Services in Compliance with European Regulation EU 779/2019	Antonio Guillen*, Antonio Sánchez, Mauricio Rodríguez Hernández	22	Towards a Business Intelligence Application for Evidence-Based Maintenance	Giacomo Barbieri*, Juliana Laserna, Luis Mario Mateus
40	Integrating maintenance and energy problems through a Digital Twin-based decision support framework under the guidance of Asset Management	Edoardo Palmiessa*, Angelo Premoli, Irene Roda, Marco Macchi	29	Maintenance Lifecycle Cost Analysis through Agent-Based Simulation	Roberto Sala*, Fabiana Pirola, Veronica Arioli, Emanuele Dovero
41	Ontology-Based Digital Twin for Maintenance Decisions in Manufacturing Systems: An Application at Laboratory Scale	Sofia Zappa*, Chiara Franciosi, Adalberto Polenghi, Alexandre Voisin	58	A Methodology to Support the Strategic Implementation of Smart Maintenance	David Sanchez-Londono*, Irene Roda, Giacomo Barbieri
43	Digital Twins Based on Integrated Models: Supporting Joint Decisions on Maintenance and Production Planning	Chiara Cimino, Laila El Warraqi*, Elisa Negri	64	Supply Chain Demands and Cooperation Maintenance for Resilience in Manufacturing in Post-COVID Era - a Literature Review	Justyna Palalas-Maliszewska*, Marcin Topczak, Malgorzata Szmoda
46	Digital Model of a Wind Turbine Oriented to Broken Tooth Analysis	Deiver Jiménez-Santín, Mariela Cerrada*, Josué Enriquez-Zárate, Diego Cabrera, René-Vinicio Sánchez	73	An optimal maintenance strategy for machining system considering production rates	El Mehdi Guendouli*, Lahcen Mifdal, Sofiene Dellagi, El Mehdi Kibbou, Abdelhadi Mouki
93	Physics-Enhanced Digital Twin Based Solution to Control Process State in a Steel Manufacturing Plant	Kisan Sarda, Carmen Del Vecchio, Fabio Fruggiero*, Francesco Mancusi, Fernando Menchetti, Creste Riccardo Natale	94	Maintenance Optimisation of Heating, Ventilation and Air Conditioning Systems to Improve Indoor Air Quality	Alena Puchkova*, Jorge Merino, Ajith Kumar Parlikad

12:30 - 13:45

Lunch

13:45 - 15:45

Artificial Intelligence for maintenance, asset, and product lifecycle management (1)		Chair: Alexandre Voisin Co-chair: Katarzyna Antosz	Reliability, dependability, and risk-based approaches		Chair: Manuel Herrera Co-chair: Alessandra Cantini
13	Extending Asset Lifespan through Data Augmentation-Assisted Quality Control	Ruben Alonso, Guido Nole, Vincenzo Cutrona, Diego Reforgiato Recupero*	17	A Model for Dependability Analysis of a Complex System	Virag Wasnik*, Ayeley, Philippe Tchanganli, Carmen Martin, Francois Péris
18	Perspectives for the Application of Reinforcement Learning for the Integrated Order-Dispatching and Maintenance Scheduling	Djonathan Quadras, Marina Meireles Pereira, Lúcio Galvão Mendes, Lynceio Falavigna Braghirolli, Enzo Morosini Frazzon*	26	Alarm Webs: A Framework for Decoding RAN Alarm Dynamics	Anandapur Mukherjee*, Manuel Herrera, Hanu Priya Indrian, Luning Li, Henry Brice, Arjun Parekh, Ajith Kumar Parlikad
25	A Novel Semi-Supervised Contrastive Learning Approach for Rotating Machinery Fault Diagnosis with Limited Labeled and Class-Imbalanced Data	Qin Zhao*, Zhixing Wei, Tianhao Li	37	Hydrogen in Glass Sector: A Comparison between Risk-Based Maintenance and Time-Based Maintenance Approaches	Giulia Collina*, Alessandra Cantini, Leonardo Leoni, Saverio Ferraro, Filippo De Carlo, Maria Bucelli, Nicola Faltrinieri
36	Digital Twin Enhanced Multitask Learning Framework for Fault Diagnosis of Electromechanical Coupling System	Laila Tao*, Xuanxuan Su, Jin Kaixin, Li Shangyu, Zhengduo Zhao, Qixuan Huang	78	Application of Degradation and Optimization Models for Digitization of Maintenance Management in Railway Infrastructures	Mauricio Rodriguez Hernández, Vicente Gonzalez-Prida, Antonio J. Sanchez Herguedas*, Adolfo Crespo Marquez
57	Evaluation and Comparison of Selected Machine Learning Methods for Improving Maintenance Processes	Katarzyna Antosz*, Monika Kulisz, Jozef Husár	104	Contribution of Maintenance to Reconfigurable Manufacturing Systems: State of the Art and Challenges	Huu-Truong Le, Chiara Franciosi*, Phuc DO, Alexandre Voisin
100	Predicting Defect Rates of Printed Circuit Board Assemblies: Towards Zero Defect Manufacturing and Zero-Maintenance Strategies	Emiel Miedema, Hendri Kortman, Christos Emmanouilidis*	87	A Reliability-Based Methodology for Resilient Spare Parts Planning and Control	Gabriele Sirti*, Riccardo Accorsi, Giorgia Bartolotti, Riccardo Manzini, Michele Ronzoni

15:45 - 16:15

Coffee break

16:15 - 18:35

Artificial Intelligence for maintenance, asset, and product lifecycle management (2)		Chair: Vibhor Pandhare Co-chair: Mariela Cerrada	Industry 5.0, human factors, education, and skills in maintenance		Chair: Christos Emmanouilidis Co-chair: Luca Fumagalli
66	The Use of Decision Trees to Identify the Causes of Failures in a Medical Enterprise - a Case Study	Malgorzata Jasulewicz-Kaczmarek, Mariusz Piechowski*, Izabella Rojek, Dariusz Mikolajewski	85	Building and Sustaining Competence in Maintenance: A Prescriptive Training Model	Valentina Di Pasquale*, Salvatore Digiesi, Ivan Ferretti, Antonio Padovano
75	Anomaly Detection Using Electrical Signature Analysis and Machine Learning: Application to a CNC Mill	Paola Cocca*, Gökan May, Valerio Pesenti Campagnoni, Elena Stefana, Ruggero Bortolani, Davide Romagnoli	92	Empowering Operator 5.0: human-centric design of an augmented reality tool for a learning factory	Antonio Padovano*, Martina Cardamone, John Klaess
79	Deriving Inferences through Natural Language from Structured Datasets for Asset Lifecycle Management	Sanchit Singla, Soumyabrata Bhattacharjee*, Vibhor Pandhare	97	A Decision Support System Tailored to the Maintenance Activities of Industry 5.0 Operators	Ludovica Maria Oliveri, Ferdinando Chiacchio*, Francesco Facchini, Giorgio Mossa
89	Diagnostic Method for Hydropower Plant Condition-Based Maintenance Combining Autoencoder with Clustering Algorithms	Samy Jad*, Xavier Destorges, Kamal Medjaher	103	Asset Criticality and Risk Prediction Via Machine Learning in Wind Farms: Problem-Based Educational Activities in a Smart Industry Operations Course	Christos Emmanouilidis*, Ype Wijnia
60	Fault Classification in Reciprocating Compressors: A Comparison of Machine Learning and Deep Learning Approaches	René-Vinicio Sánchez*, Jean Carlo Macanella, Diego Cabrera, Mariela Cerrada	99	Transformation of the Product Lifecycle Value Chain towards Industry 5.0	Hanbing Xia, Jiahong Li, Milisavjevic Syed Jelena, Konstantinos Salonitis*
33	AI in Assessing Industry 4.0 Adoption in Colombia: A Case Study Approach	Luis Alberto Cruz Salazar*, Santiago Gil, Germán Dario Rueda Carvajal, Gabriel Jaime Sánchez-Zuluaga, German Dario Zapata-Madrigal	44	From OEE to OSEE: How to Reinforce Production and Maintenance Management Indicator Systems for Sustainability?	Theresa Madreiter*, Fazel Ansari
7	Optimizing 'Explore' Rose Production Data with SVM in Smart Agriculture	Vicente D. Herrera, Estefani Lucero, David I. Iñis, Jessica Carmelina Mora, Cristian Paul Chuchico Arcos, Kevin A. Espinel, Michelle Herrera, Juan Escobar, Marcelo Vladimir Garcia*	39	Experience on Centralizing the Asset Management and Maintenance Engineering Function in an Italian Multi-Utility Company	Irene Roda, Adalberto Polenghi*, Marco Macchi, Ilaria Marini, Bartolomeo Greco, Lorenzo Benevento, Paolo Parenti, Andrea Pegoianni

19:30

WELCOME RECEPTION

## 6th IFAC International Workshop on Advanced Maintenance Engineering, Services and Technology



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[amest2024@unica.it](mailto:amest2024@unica.it)

### Maintenance and Asset Lifecycle Management for Sustainable and Resilient Systems

Thursday (June 13<sup>th</sup>)

08:30 – 10:15

Panel

Interoperability in maintenance

Keynote Prof. Birgit Vogel-Heuser

Modular and adaptive field level automation architectures to support predictive maintenance

Keynote Prof. Dimitris Kyritsis

Ontology based asset information modeling for predictive maintenance

10:15 - 10:30

Coffee break

10:30 - 12:30

Digitalisation for asset and product lifecycle management		Chair: Adolfo Crespo Co-chair: Mario Caterino	Prognostics and health management, condition-based maintenance and condition monitoring		Chair: Alessandro Guzzini Co-chair: Janusz Szpytko
27	Asset Digitalization Strategy Using IoT Platforms and Asset Health Model	Eduardo Candon*, Adolfo Crespo Marquez, Antonio Guillen	15	Adaptive Ensemble Learning for Machine Tool Prognostics from Meta-Feature-Based Context Information	Simon Leohold*, Michael Freilang
31	Application of Digitalisation in Regulated Environments for Predictive Failure Modelling	Frank Doyle*, Samuel Carvalho, Zsolt Kovacs, John Cosgrove	42	A Transfer Learning Approach for Anomaly Detection within a Collaborative Prognostic Framework for Advanced Maintenance Services	Melissa Negri, Luca Pavan, Adalberto Polenghi*, Marco Macchi, Alessandro Ruberti
52	Improving the Efficiency of Greasing Operations with the Lubrication Management Support System - a Case Study	Mariusz Piechowski*, Ryszard Wyczółkowski, Waldemar Paszkowski, Artur Meller	49	Data-Driven Fault Detection in Reciprocating Compressors: A Method Based on PCA and GLRT	Mauricio Cabrera*, Diego Cabrera, Mariela Cerrada, René-Vinicio Sánchez
53	An investigation into connection between BIM and Digital Twins technologies	Sergey Sychev*, Andre Balako, Thanh Trung Nguyen, Anthony Xavier, Katarzyna Ambasz, José Machado	74	Experimental Measurements of the New Gas Smart Meters' Current Discharges to Suggest Improvement Solutions for Power Supply Battery Life Extension	Alessandro Guzzini*, Cesare Saccani, Marco Pellegri, Marcello Bondesan
63	OPC-UA in Interoperability – a Performance Comparative Testing	Luís Freitas, Filipe Pereira, Helena Lopes, Ana Lima, Pedro Marujo, Erika Ottaviano, José Machado*	82	State-Of-Art of Heavy Machinery Monitoring System, Perú Case Study	Cecilia Cuadros, Renzo Vidaurre Moreno, Janusz Szpytko*
72	Cyber Physical Systems: A Brief Survey and an Application of a MIR (Mobile Industrial Robot) for Inspection	Pielugi Rea, Maurizio Ruggiu, Piero Ponchielli, Erika Ottaviano*, Angel G. Gonzalez Rodriguez	96	Enhancing Feature Extraction in Sensor Fault Detection through Canonical Correlation Analysis	Natalia Trapani*, Leonardo Longo

12:30 - 13:45

Lunch

13:45 - 15:30

End of life management of complex systems		Chair: Maria Holgado Co-chair: Foivos Psarromatis	Product-service systems for maintenance and asset management		Chair: Fabiana Pirola Co-chair: Marko Simic
45	End-of-life Management of Consumer Products and Industrial Assets: A State of the Art Analysis of Decision-Making Approaches and Methodologies	Irene Roda*, Maria Holgado	54	Designing Smart Product-Service Systems: The SEEM-Smart Methodology and Its Application in the Electrical Industrial Sector	Vanessa Zani, Vicente Gonzalez-Prida Diaz, Veronica Arioli*, Roberto Sala, Fabiana Pirola, Adolfo Crespo
28	Do Obsolescence and Shortages have an impact on Reliability, Maintainability and Availability?	Sahar Karaani*, Mariem Besbes, Marc Zolghadri, Claude Baron, Maher Barkallah, Mohamed Haddad	81	Smartphone As a Tool in Remote Maintenance of Healthcare and Laboratory Equipment	Janusz Szpytko*, Pawel de Sternberg Stojalowski
19	Understanding Obsolescence and Shortage in French Industry: An Empirical Analysis	Mariem Besbes*, Marc Zolghadri	98	Predictive Maintenance Servitisation Pathways	Jiahong Li, Milisavljevic Syed Jelena, Konstantinos Salonitis*
48	Circular Product Design for Allowing Re-Using and Re-Purposing of Products and Components: A Conceptual Framework for Circularity	Foivos Psarromatis*, Victor Azamfirei, John David Lindström	76	A preliminary investigation on DDPSS requirements to provide process quality as a service: example on laboratory scale	Lorenzo Ghedini*, Adalberto Polenghi, Irene Roda, Marko Simic, Denis Janković, Niko Herakovic (Italy)
51	Resilience Strategies and Techniques to Extend the Lifespan of Complex Systems Dealing with Obsolescence	Imen Ben Brahim*, Marc Zolghadri, Christophe Theillet, François Dechamp	90	Preliminary investigation of the state of the art on digital servitization for Industrial Asset Lifecycle Management	Lorenzo Ghedini*, Irene Roda, Marco Macchi, Alessandro Pozzetti

15:30 - 15:45

Coffee break

15:45 - 17:45

Resilience and sustainability		Chair: Chiara Franciosi Co-chair: Robert Meissner	Maintenance, product and asset lifecycle management		Chair: Ajith Parlikad Co-chair: Adalberto Polenghi
59	A Discrete Event Simulator to Support Maintenance Decision-Making Considering Economic and Environmental Sustainability	Carlos Torres, Giacomo Barbieri*, Mariela Muñoz	23	Evaluating Investment in Condition Monitoring for Fleet Maintenance	Adolfo Crespo del Castillo*, Ajith Kumar Parlikad
11	Hydrogen-based aircraft auxiliary power generation: Economic and ecological comparative assessment of preventive maintenance implications	Robert Meissner*, Antonia Rahn, Anne Oestreicher, Kai Wicke, Gerko Wende	86	Asset Performance Management: current status and future development	Marco Macchi, David Sanchez-Londono*, Alejandro Martinez, Adalberto Polenghi, Irene Roda, Alessandro Pozzetti, Cristóbal Barriga
35	System Resilience of a Liquid Hydrogen Terminal During Loading and Unloading Operations	Lucas Claussner*, Federico Ustolin	61	Management of Spare Parts for Efficient Maintenance: A Case Study in the Dairy Sector	Beatrice Marchi*, Caterina Galati, Simone Zanon
55	Resilience and Sustainability Plants Improvement through Maintenance 4.0: IoT, Digital Twin and CPS Framework and Implementation Roadmap	Federico Briatore*, Mattia Braggio	67	Organizational Value Framework for Asset Management Decision-Making	Giacomo Barbieri*, Ana Maria Benavides, Esteves Luis Alfredo, Camilo Olaya, Freddy Zapata
77	Decentralised Persistent Identification - an Emerging Technology for Sustainability Maintenance and Knowledge-Driven Processes	Andrey Vukolov*, Erik van Winkle, Vyacheslav Tikhonov	30	Exploring MBSE for Asset Digitalisation in the Energy Sector: a Battery Energy Storage System Design Study	Celia Martínez Sillero*, Antonio Guillen, José López Domínguez, Vicente González-Prida Díaz, Juan F. Gomez Fernandez
			95	Predicting Road Condition Using Linear Hierarchical Modelling	Maharshi Harshadthai Dhada*, Georgios M. Hadjilametriou

18:00 - 19:00

AMEST Working Group meeting

20:00

CLOSING CEREMONY & GALA DINNER

Friday (June 14<sup>th</sup>)

09:00 - 13:00

Technical and Social activities