An Overview of Performance Predictive Models for Railway Track Assets in Europe

Maria José Morais, Hélder S. Sousa, and José C. Matos

Abstract A railway system degrades over time due to several factors such as aging, traffic conditions, usage, environmental conditions, natural and man-made hazards. Moreover, the lack or inadequate maintenance and restoration works may also contribute to the degradation process. In this aspect it is important to understand the performance of transportation infrastructures, the variables influencing its degradation, as well as the necessary actions to minimize the degradation process over time, improve the security of the users, minimize the environment impact as well as the associated costs. Thus, it is crucial to follow structured maintenance plans during the life cycle of the infrastructure supported by the forecasting of the degradation over time. This paper presents a brief description of the variables influencing the degradation of a rail-way system, and the way the performance of the railway track can be measured, within a probabilistic environment. The work developed in other transportation infrastructures, like roadway, is briefly presented for comparison purposes and benchmarking. It also presents an overview of the predictive models being used in railway systems, from the mechanistic to the data-driven models, where the statistical and artificial intelligence models are included.

Keywords Predictive models · Railway · Performance indicators · Probabilistic assessment

1 Introduction

Regular, planned and predetermined inspections and maintenance are essential to control the process of degradation of railway infrastructures and restore the damaged railway sections, thereby guaranteeing the reliability and availability of the railway track, as well as the passenger safety and comfort, not forgetting the cost reduction over the life cycle [1]. The management of railway infrastructures is supported by maintenance plans, that in turn are supported by quality indicators [2]. Just recently, with the aim of simplifying the communication between consultants, operators and

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owners, these indicators started to be called performance indicators [3, 4]. During the 12th Florence Rail Forum on the performance of the railway system, in 2016 [5] it was stressed the need to improve the performance of the European railways. For a more accurate maintenance, the railway track degradation must be predicted by using the appropriate models and methodologies [1] following a risk based approach with the identification of the possible risks and levels of risk. The causes of degradation of the track as well as the factors that could influence this degradation to happen should be known [6]. The aim of this paper is to present the most relevant factors affecting the degradation of the railway track as well as some possible damages, presenting also some relevant aspects to take into account. This will be made in parallel with the analysis of railway track through performance indicators based in railway standards, and the possible improvements that could be adopted from the work developed in other transportation infrastructures, as well as by providing an overview of predictive models being used in the railway system, namely with some operational aspects, possible variables to be used and the most relevant advantages and disadvantages. Special focus is given to the frameworks and management systems based on probabilistic methods.

2 Railway System and the Variables Influencing Its Degradation Over Time

The railway system is divided into railway infrastructure and rolling stock. The railway infrastructure involves the railway track (or simply track), the railway stations, signaling, the catenary system, the drainage system, among others. This paper focus on the first one, particularly in the railway track. The importance of the description of each component, within this paper, is mainly related to the use of Predictive models that are dependent on the component type as they present different deterioration models and patterns. For structural assessment purposes, the track is composed of the superstructure and the substructure [7]. The superstructure corresponds to the top of the track, consisting of rails, fastening system, rail pads and sleepers, while the substructure corresponds to the support and could consist of a ballast system (ballast, sub-ballast and subgrade) or a slab system [6, 8] and may be directly over the soil or crossing bridges, box culvert or tunnels.

Among the most relevant factors affecting the track degradation, the following ones can be highlighted. The track geometry has a heterogeneity along its path, thanks to the existence of straights, curves and crossovers. Besides that, there are discontinuities in the support conditions when the track crosses a bridge deck, a box culvert or a tunnel or when occurs a transition between a slab and a ballasted track [1, 6, 9]. The mentioned heterogeneity is characterized by a variation in the track stiffness [9], that can lead to differential settlements [6], non-uniform dynamic loading, corrugation, wear and fatigue failure of the rail, fatigue failure of the fastening system and cracking of the sleepers [9]. The track is influenced by the environment conditions

[8, 10] such as high temperatures, storm (or similar) with consequent heavy rainfall, and strong wind that can lead to flood, risk of destabilization of earthworks, drainage problems, faller trees or branches (in case they exist close by) and moisture degree of saturation more specifically in the case of the substructure [11].

As consequence of loading cycles from the train passage, a plastic differential settlement may occur, that over time can lead to deviations of the original track geometry, as well as breakage and shear deformation of the super and substructure [9]. In consequence an increasing of the acceleration of the train as well as an increasing of the dynamic forces caused by the train may occur [9]. The increasing of forces can speed up the degradation process of the track components, like for example vertical and lateral displacements. Differential lateral movements can compromise the lateral stability of the track and consequently track buckling [9]. In return, this track degradation process can cause the increase of the variation of the interaction between the track and the forces which in turn affects the performance of the track [7, 11].

According to literature, the track condition can be measured through five classes of variables (or parameters) [1, 12] (i) longitudinal level, (ii) alignment, (iii) gauge, (or vertical alignment), (iv) twist and (v) cant (or cross-level, or super elevation) (see Fig. 1). Even if the longitudinal level is considered as the critical factor, it is not realistic to consider only this parameter [1]. Therefore, results are more accurate if the analysis is made taking into consideration the combination between parameters [13].

Taking into account the heterogeneity of the track (in behavior and degradation) the track must be segmented into short length sections (or segment or maintenance units). The methodologies adopted are the division into constant length sections, like 100 or 200 m [1, 12] and the division based on similar structural, environmental, operational and maintenance history characteristics [1] being the last one more effective [1] but more complex.

It should be taken into account, for a realistic representation of the track, the influence of inspections, maintenance and renewal actions, like track accessibility and inspection frequency, rail lubrication, grinding and welding, ballast cleaning, tamping and stone blowing [8, 10]. For example, it is not realistic to assume that the tamping returns the track quality to its original condition [1]. Also, despites it contributes to the improvement of the track geometry condition, its use over the time can lead to the degradation of the ballast and consequently of the track geometry [10, 11].

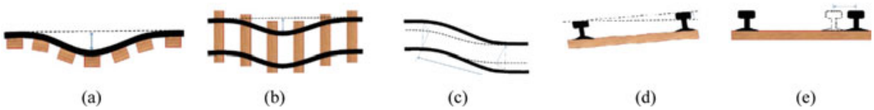

Fig. 1 Railway track quality parameters: **a** longitudinal level, **b** alignment, **c** twist, **d**, cant, **e** gauge (adapted from: [14])

There are other aspects that should be taken into account for legal and ethical aspects, such as reliability, economic loss, social impact, sustainability, not forgetting the implications for human (human injure and loss) [15]. Also, from the environmental and human healthy point of view, there are the pollution, noise and vibration produced during the use of the track.

3 Measurement of the Performance of a Railway Track

Performance indicators (PIs) capture the mechanical and technical properties of a infrastructure and its degradation process over its life cycle, considering also other aspects such as natural aging, quality of the material, serviceability, availability and robustness, sustainability, environmental efficiency (CO_2 foot-print), total life cycle costs and social indicators [3, 16]. PIs can be obtained through visual inspections, non-destructive tests or monitoring systems [2, 4, 16] and numerical and experimental modeling [17, 18]. They can be assessed through condition indices that can be obtained through ratio-based methods, weighted averaging approach, worst-conditioned component approach or qualitative methods [4]. This indices are then transformed into indexes, that are calculated based on the condition of the structural elements and the service provided by the asset, but can also be obtained through probabilistic models which calculates the failure probability [4]. Since PIs do not inform the limit values which indicates a fault or failure condition or what is intended to be obtained from an infrastructure (e.g. to be safe, to be available) performance goals need to be defined that in turn need to have performance criteria and thresholds [3, 4, 19].

Commonly, the railway infrastructure performance follows a RAMS analysis that covers the topics safety (S) and availability (A) that are based on reliability (R) and maintainability (M), more the operation and maintenance [20], taking also into account the Life cycle costs (LCC). These should follow the existing standards, that provide guidance in specifying and achieving these RAMS targets throughout the railway life cycle [21]. Among all the phases of the RAMS life cycle only those concerning the operation and maintenance and modification and retrofit are going to be covered in this paper.

The influencing parameters and RAMS formulas are given in the EN 50126-1 [21]. RAM mathematical formulas can be found in the EN 61703. Dedicated to the definitions and measurement for the technical, administrative and managerial areas of maintenance, it is worth to mention the EN 13306. The EN 15341, not dedicated exclusively to the railway system, gives the formulas and possible influencing factors, proposing a classification of PIs into groups. Figure 2 presents possible influencing parameters, as well as the RAMS and formulas according to the mentioned standards. Besides these, it is fundamental to consider also the Life cycle costs of the railway track and the influence of the track use for the environment, not directly addressed on the previous standards. According to the work presented by the Committee on Technical Cooperation in the Development of the Rail Transport System in 2016 concerning the RAMS and LCC [21], it should be followed the inspection, preventive maintenance, corrective maintenance, overhaul and cleaning costs for maintenance proposes, presenting some formulas that are shown in Fig. 3.

It is important to understand what is being done in other transport sectors, like roadway, with the aim of improving what is being done in the railway system. Looking at the work developed in the roadway sector, under COST-Action TU1406, the PIs for bridge assessment were clustered into five groups. (i) Reliability, (ii) Availability, (iii) Safety, (iv) Economy, and (v) Environment [2, 18]. This clustering was taken into account and can be adapted to the railway, particularly in the case of the PIs related with costs and environment.

4 Overview of the Predictive Models

Predictive models (or degradation models) are algorithms that analyse a set of data, identifying patterns and estimating the time until PIs reach limit values and by this way predicting the future condition of the track. This will contribute for an optimized management, allowing more efficient and integrated maintenance plans, regular inspections and monitoring.

From literature, the existing approaches to build a predictive model can be classified into (see Fig. 4), (i) Mechanistic (or Physical) and (ii) Data-driven Models existing also the (iii) Empirical Mechanistic Models [1, 24]. The Data-driven Models can be dived into Statistical and Artificial Intelligence Models [7, 11]. Each one of these approaches can be divided into various categories that in turn can be divided into various sub-categories [11].

These models need the definition, among other aspects, of the input and output variables. The first ones are the independent (or predictor) variables that are used to predict (or forecast) the second ones that are the dependent (or predicted) variables. The definition of these varies, not only according to data available and the results to be obtained, but also according to the type of model. A bigger number of independent variables can improve the accuracy and efficiency of prediction, the same way as a limited number of dependent variables [7]. Figure 5 presents, according to the literature [1, 7, 11, 25], the possible variables organized into groups.

4.1 Mechanistic and Empirical Mechanistic Approaches

In Mechanistic Models the properties of both track and train are based on laboratory experimental data, being also possible to take into consideration all the possible variables influencing the track degradation. This way the relation between the track and the vehicle can be properly clarified [1, 7]. However, these models do not deal well with the uncertainty of the behaviour of the track caused by the heterogeneity of the track, being also time consuming and complicated to have all the measurements

RAMS quantification		
Reliability	Description	Possibility of the track to perform a required function under given conditions and time interval.
	Parameters	λ(x); MUT; MTTF; MTBF; F(t); R(t)
	Formulas	$MTBF = \frac{TBF}{number\ of\ failures} = \frac{\Sigma(downtime\ start - uptime\ start)}{number\ of\ failures}$ $\lambda(x) = \sum \frac{1000000000\ hours}{MTBF}$ (FIT)
Availability	Description	Possibility of the track be in conditions to perform a required function under given conditions and time interval.
	Parameters	A; Ai; Ao; FA; SA
	Formulas	$A = \frac{MTBF}{(MTBF+MDT)}$ $MDT = \frac{\Sigma(Start\ up\ time - start\ of\ downtime)}{number\ of\ failures}$
Maintainability	Description	Possibility of a maintenance action be carried out at a track item under given conditions and time interval.
	Parameters	MDT; MTBM; MTBM(c); MTBM(p); MTTM; MTTM(c); MTTM(p); MTTR; MRT; FC; RC
	Formulas	$MTTR = \frac{\Sigma(end\ Corrective\ action - start\ Corrective\ action)}{number\ of\ Corrective\ action}$
Safety	Description	Freedom from unacceptable risk of harm.
	Parameters	h(t); pWSF; Active time to return to safe state
	Formulas	SIL = risk analysis where the risk associated with the hazards is calculated

Where:
λ(x) - Failure rate [1/time, 1/distance, 1/cycle]
TBF - Time Between Failures [time]
MTBF - Mean Time Between Failures (for repairable items) [time (distance, cycle)]
MTTF - Mean Time to Failure (for non-repairable items) [time (distance, cycle)]
MTTR - Mean Time to Repair [time] (for constant λ(x), constant repair rate and no preventative maintenance: MTTR=MDT
MDT - Mean Down Time [time (distance, cycle)]
MUT - Mean Up Time [time (distance, cycle)]
MTBM - Mean Time Between Maintenance [time (distance, cycle)]
MTBM(c), MTBM(p) - MTBM (corrective or preventive) [time]
MTTM - MTBM (corrective or preventive) [time]
MTTM(c), MTTM(p) - MTTM (corrective or preventive) [time]
MTTR - Mean Time to Maintain [time]
MRT - Mean Repair Time Fault [time]
FC - Fault Coverage Repair [dimensionless]
RC - Repair Coverage [dimensionless]
F(t) - Failure Probability [dimensionless]
R(t) - Reliability (Success Probability) [dimensionless]
Uptime - moment after an action on the previous failure
Downtime - moment of initiation of a failure
FIT - Failure in time
Active time to return to safe state [time]
A; Ai; Ao - Availability, inherent and operational [dimensionless]
FA - Fleet Availability [dimensionless]
SA - Schedule Adherence [dimensionless]
SIL - Safety Integrity Level
h(t) - Hazard rate [1/time, 1/distance, 1/cycle]
pWSF - Probability of wrong-side failure [dimension-less]

Fig. 2 RAMS quantification according to EN 50126-1 (adapted from: [9, 21]) and the terminologies according to the EN 13306 (adapted from: [22, 23])

of all the variables along all the track. This way, these models are considered suitable only for particular sections (and not for several sections) [1, 7, 11, 24]. Taking into account the mentioned disadvantages these models are rarely being used during the last years [7].

An alternative to these conventional Mechanistic Models are the Empirical Mechanistic Models, which are a combination of the mechanistic and the statistical models, being based on the behaviour of the system's components coupled with measurements, data records and observations. The advantage of these models compared to the conventional ones, is their ability to model the entire rail track.

Costs quantification		
Preventive maintenance costs	Formulas	$CY\_MP = \sum_{i=1}^{x} (No\_MP_i \cdot QT_i \cdot (CM\_MP_i + MH\_MP_i \cdot CMH))$
Corrective maintenance costs	Formulas	$CY\_MC = \sum_{i=1}^{x} (No\_MC_i \cdot QT_i \cdot (CM\_MC_i + MH\_MC_i \cdot CMH))$ $\quad No\_MC_i = IN\_FA_i \cdot OT$

Where:
QT = Total quantity of item
i = Maintenance action per item and failure mode
CMH = Costs per working-hour
IN_FAI = Failure rate
OT = Operating time or operating distance per life cycle (depending on the unit of the failure rate)
CY_MP = Preventive maintenance costs
CY_MP = Corrective maintenance costs

No_MP = Number of preventive maintenance actions per life cycle
No_MC = Number of corrective maintenance actions per life cycle
MH_MP = Working-hours per preventive action
MH_MC = Working-hours per corrective action
CM_MP = Average costs of material per preventive action
CM_MC = Average costs of material per corrective action

Fig. 3 Cost quantification according to committee on technical cooperation in the development of the rail transport system in 2016 concerning the RAMS and LCC (adapted from: [21–23])

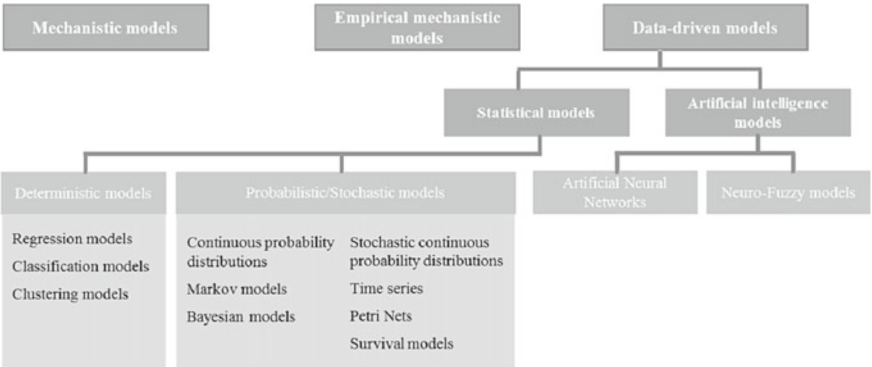

Fig. 4 Predictive model approaches (adapted from: [1, 7, 11, 25])

4.2 Statistical Approach

Unlike Mechanistic Models, Statistical (or empirical) Models do not consider the mechanical component of the track [11] and its interaction with the influencing factors [1], what can be seen as disadvantage. However, they are based in real data, what is considered an advantage, and in addition, they can work with a big quantity of data (both input and output), making them more accurate [1]. Soleimanmeigouni et al. [1] proposes the combination between Mechanistic and Statistical modeling. In these models the relationship between the factors influencing the track degradation, such as traffic, track components and maintenance variables, and its condition is obtained through the relation between the input variables (or descriptive factors) and output variables [1]. Statistical Models can be divided into Deterministic, Probabilistic and Stochastic Models [7, 11].

Influencing Variables	Predictive Models					
	MM	EMM	DM	PM	SM	AIM
Track Geometry	x	x	x	x	x	
Longitudinal level, alignment, gauge, cant and twist Breakage of the rail and settlement of the track						
Track Structure					x	
Type of rails, sleepers and fastening system Support and drainage system						
Track Quality Index		x		x		
Track Geometry Index + Track Structure Index						
Track Operations		x	x			
Train speed and track limit speed, traffic volume Axle weight and accumulated tonnage						
Environmental conditions				x		x
Temperature, snow and flood Soil type, falling rock, landslide						
Maintenance parameters		x	x	x	x	x
Time of inspection and renewal, Number of interventions, speed restrictions and track closures Maintenance actions as rail lubrification, grinding and welding, ballast cleaning, tamping and stone blowing						
Time		x			x	x

Notes:
MM - Mechanistic, EMM - Empirical mechanistic,
DM - Deterministic, PM - Probabilistic, SM - Stochastic and AIM - Artificial Intelligence models

Fig. 5 Main variables (or factors or parameters) influencing the track degradation, according to the type of predictive model (adapted from: [1, 7, 11, 25])

4.2.1 Deterministic Models

The Deterministic Models describes the variables inputs and outputs on an exact way, not involving any randomness or uncertainty. This does not allow to take into account possible errors and changes that can happen during measurements, as well as the variability in track performance (two similar track sections with the same type of use and maintenance may have different behaviours) [10]. This can lead to uncertainty in prediction. Besides that, these models do not apply in the same way the degradation rate on used tracks and maintained tracks, even if these different tracks are under the same loads [7]. Also, the interaction that could occur between degraded components of the infrastructure is not considered [26].

The Regression Models are a type of Deterministic Model that are generally used due to their simplicity in representing the underlying degradation path. However, they require a big quantity of measurement data to achieve an acceptable accuracy. Besides that, these models cannot be updated with new data and are independent of previous observations [1].

4.2.2 Probabilistic Models

Contrary to the Deterministic Models, Probabilistic ones involve randomness, i.e. the uncertainty is inherent to these models, and they consider the current condition state of the assets [26]. The heterogeneous degradation is represented by using a random effect for each section [1]. These models take use of distribution patterns to represent the probability of an event (e.g. failure) during an interval time [11]. The most used models are the Markov models and Bayesian Models.

- The **Markov Process** can be classified according to the nature of the time parameter and the state space. Taking into account the first one, a Markov process can be a discrete-time Markov process or a continuous-time Markov process. Relatively to the second one a Markov process can be discrete-state Markov process (also called Markov chain) or continuous-state Markov process [27]. The Markov chain consists of a set of transitions from one condition state for another, determined by a current state vector and a probability distribution, represented by a transition matrix. The current state vector, a N*1 matrix, corresponds to the possibility of starting at each one of the N possible states. The probability distribution is represented by a transition matrix N*N, where N is the number of possible conditions states (every possible state appears once in the rows and once on the columns), with each cell (i, j) corresponding to the probability of transitioning from state i to state j. This matrix satisfy the Markov property [28] (or memory-less property of the Markov process), i.e., the prediction of the future condition state is based only in the current state and not on the past state or the way the current state was achieved [11, 25, 26, 28], what does not represent the reality. The transition probabilities depend only of the current state, being independent of the age of the asset and its effects on the evolution of its degradation. This means that two assets, even if they have different ages, if they in the same current state, are going to have the same probability of changing to the next condition state [29]. Also, the transition probabilities need to be updated every time that new data is collected from a new inspection and or maintenance action what can be time consuming [26]. According [26], transition probabilities assume that the condition can keep the same or get worst, to avoid the difficulty in estimating the transition probability of assets where were performed conservation actions. These models have as limitation the fact that the transition between condition states must occur at a constant rate [7, 10]. Besides that, they do not consider in an efficiently way the effects caused by the interaction between different components with degradation [26] being limited to small track models [7].
- **Bayesian Models** (BN), like Hidden Markov Models (a particular case of Markov Models), are probabilistic graphical models, being composed of nodes and arcs (or edges or links). Here, the first one represents the random variables (or a set of variables) and the second one represents the conditional probabilistic relation between nodes. However, while in the Hidden Markov Models the arcs can go in both directions creating a cycle, in the BN the arcs can only go in one direction, not being possible to have a cycle, being this way named directed acyclic graph [29].

BN take use of the Bayes's Theorem, where the parameters, assumed as random variables, are quantified by a prior distribution (or previous distribution) combined with the likelihood to achieve the posterior distribution of the parameters. The prior distribution represents the "people beliefs" about the parameters before observing the data and the likelihood distribution represents the information given by that the observed data [11]. Hierarchical Bayesian Models (HBM) are a specific case of BN, formed by multiple sub-BN (or levels) integrated (or combined) in a hierarchical way to reach the posterior distribution by using the Bayes's Theorem, where the uncertainties in each sub-model are propagated from one level to the next. The implementation of the computational Method Markov Chain Monte Carlo (MCMC) allows to perform over and over the Bayes's Theorem [7, 11, 30], allowing the data to be updated over the time [11]. Markov Chain Monte Carlo is the application of the Monte Carlo (MC) Method by using the Markov Chain. The MC use the process of repeated random sampling to make numerical estimations of unknown parameters, being, this way, modelled the likelihoods of outcomes, which helps understanding the impact of risk and uncertainty in prediction and forecasting models. BN have the advantage of using and combining collected data (e.g. from inspections) with expert knowledge regarding variables on which no data exists. However, collecting and organizing expert knowledge (based in their belief) in a way that can be converted into probabilistic distributions can be difficult [31]. Another advantage of BN is the fact that, if some variables have a known state, it is possible to update the state of the remaining variables through an inference algorithm taking use of the Bayes' Theorem [32].

4.2.3 Stochastic Models

Stochastic Models, in opposite to deterministic ones and such as the probabilistic ones, involve randomness. The same set of input variables and initial conditions can result in different set of outputs, once it takes use of a probability distribution function [7, 11]. They aim in understanding the distribution of the degradation of the track over the time [7]. While the deterministic models are easier to use, the Stochastic ones are considered more realistic [11]. It is fundamental to consider the effect of the heterogeneity of the degradation along the track over the time due to the heterogeneity of the track in consequence of the variation in geometry, materials, traffic, environment and maintenance actions. In the following are briefly mentioned two of the different models according to [11] Time Series, Petri Nets and Survival Models.

- **Time Series** are a sequence of observations (or data collected) taken sequentially and at equally periods of time (e.g. monthly, annually), where the dependent variable is obtained in function of time, not existing an obvious independent variable. This allows to analyse the variable changes over time, being possible to analyse the past, monitor the present and predict the future [11]. According to the frequency of data different patterns can be observed and can be used to do the forecasting.

- **Petri Nets** are graphical-mathematical models composed of places and transitions, connected by arcs. Places, represented graphically by circles, simulates states, conditions or resources within the system to be modelled. Transitions, represented graphically by bars, simulates the events that occur in the system and may cause change in the condition of the system. Arcs connects places and transitions, and could be input and output arcs [11].
- **Survival models** (or failure time models) analyse the expected time until the occurrence of an event (e.g. damage, failure), having associated with the hazard function and the survival function, that analyse the probability of failure of the event (or asset) [11].

4.3 Artificial Intelligence Approach

Artificial Intelligence Models, take use of the knowledge of human brain behaviour [11], showing high accuracy compared to the mechanical and statistical approaches [7]. The models are trained with a bid quantity of data and them tested with another quantity of data, what has an impact in the accuracy of the model [7]. Once these models are recent, there is a lack of literature, what is considered as a disadvantage. Another disadvantage is that they lack the transparency that models like the mechanical or statistical ones have. These models can also present some difficulties in the calibration of the model parameters [7]. In the following are briefly mentioned two of the different models according to the literature, Artificial Neural Networks (ANNs) and Neuro-fuzzy Models (ANFIS) [7, 11].

- The **ANNs** consist in a neural network (group of independent neurons) that communicate with each other through weighted connections (synaptic weights). This network is trained, by attributing and changing the weight to the connections between the neurons until get closer to the desired outputs [14, 25].
- The **ANFIS** are a combination of ANNs with Fuzzy Inference System (FIS), integrating this way the neural networks and the Fuzzy Logic. The Fuzzy Logic uses the human decision making, working with all the possibilities between yes and no, in opposition to the conventional computer's logic, which simply uses the options of true and false that corresponds to the human's yes and no. The Fuzzy sets and the Fuzzy membership functions are the parameters of these models.

5 Conclusions

To predict the degradation of the railway track it is important to understand what influences its degradation, so it is possible to select the most appropriated performance indicators. This work can be improved by the experience gained in other infrastructures fields.

Besides that, it is important to understand which possible predictive models exists, their advantages and disadvantages, so this way, according to the available data and what is intended to predict, select the most appropriated model, so it can be possible to develop accurate maintenance plans.

It is fundamental to consider the effect of the heterogeneity of the degradation along the track over the time due to the heterogeneity of the track in consequence of the variation in geometry, materials, traffic, environment and maintenance actions. This is possible if Probabilistic and Stochastic Models are used. Using the Deterministic ones, it is not possible to consider this heterogeneity nor even measurement errors that could occur. Figure 5 shows the most important advantages and disadvantages, as well as the influencing parameters of the presented Predictive Models, as well as the most important Performance Indicators.

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Predictive Models	Advantages	Disadvantages	Influencing Parameters
Mechanistic	- Use of few geometrical data - Based on the mechanical behaviour of the system's components	- Non-consideration of the uncertainty of the track behavior due to the heterogeneity of the track - Difficulty in quantifying the track and vehicle properties - Difficulty in understanding the interaction between the track components and properties	- Track Geometry
Statistical	- Capacity to work with a big quantity of data - Based in real data - Takes use of the distribution pattern to represent the probability of failure or disruption in a time interval	- Not based on the mechanical behaviour of the system's components	
Deterministic	- Easier to use	- Non-consideration of the randomness or uncertainty - Non-consideration of the possible interaction between degraded components	- Track Geometry - Track Operations - Maintenance parameters
Probabilistic / Stochastic	- Involve randomness - Non-consideration of the uncertainty of the track behavior due to the heterogeneity of the track - Consideration of the current state of the assets - More realistic	- Need for more statistical and computational ability	- Track Geometry - Environmental conditions - Track Geometry Index + Track Structure Index - Maintenance parameters
Artificial intelligence	- Models trained and tested with a bid quantity of data	- Lack of information, since AI models are recent - Difficulty in calibrating the model parameters	- Environmental conditions - Maintenance parameters

Fig. 5 Advantages, disadvantages and parameters to take into consideration for predictive models

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