Proceedings of the Sixth International Conference on
Railway Technology: Research, Development and Maintenance
Edited by: J. Pombo
Civil-Comp Conferences, Volume 7, Paper 7.14
Civil-Comp Press, Edinburgh, United Kingdom, 2024
ISSN: 2753-3239, doi: 10.4203/ccc.7.7.14

Data-Driven Approach for Condition-Based Maintenance of Freight Train Wheelsets using Markov Decision Process

A. S. Bhadouria[1,2], J. A. P. Braga[2], R. P. Mishra[1] and A. R. Andrade[2]

[1]Mechanical Engineering Department, Birla Institute of Technology and Science Pilani, Rajasthan, India
[2]IDMEC, Instituto Superior Técnico, Universidade de Lisboa Lisboa, Portugal

Abstract

This article presents a data-driven model based on the Markov decision process approach applied to freight train wheelsets to provide a way to support a condition-based maintenance for freight wheelsets. This study analyses observed wear data of freight wheelsets and developed a Markov decision process model. A comparison between key operating variables is also analysed namely the mileage since last maintenance and the gross ton mileage since last maintenance to determine which parameter is more appropriate for developing a two-dimensional state space along with wheel tread diameter. A Markov transition matrices are estimated for various actions, and an optimal strategy is provided, with a decision map for the best actions depending on the current state of the wheelset.

Keywords: railway maintenance, Markov decision process, wheelsets, maintenance modelling, condition-based maintenance, cox proportional hazard model, damage

1 Introduction

The demand for railway transportation has experienced a notable surge over the past decade, propelled by diverse factors such as economic expansion, persistent traffic congestion, and growing environmental considerations[1]. Addressing the growing need for efficient passenger and freight transportation is imperative, with a simultaneous emphasis on reducing dependence on fossil fuels. Railway infrastructure managers are tasked with bolstering reliability and minimizing assets' lifelong costs, mainly by diminishing maintenance expenses. To meet escalating demands, managers must focus on enhancing the reliability of both infrastructure and rolling stock assets, while concurrently reducing the overall life-cycle expenses, primarily through a strategic maintenance approach catering to the needs of passengers and railway companies[2].

The maintenance of the railway industry is a relevant field from both an economic and environmental perspective due to the substantial capital investment required and the lower emission of CO_2[3]. Trains are more environmentally friendly than other modes of transport, and they only emit 1 % of transport emissions including passenger and cargo trains[4]. Hence, the maintenance of the railway industry is necessary to provide an effective mode of transportation for passengers and goods.

The railway wheel plays a pivotal role in modern rail vehicle systems, facilitating smooth navigation around curves, preserving track alignment, and enhancing passenger comfort while mitigating the risk of derailments. Among the various train components, it is particularly susceptible to wear and tear[5].Wheelsets are subjected to re-profiling or replacement to maintain optimal performance due to factors like flange and tread wear, tread peeling, and tread flats, among other criteria. The rail industry commonly employs a periodic maintenance practices, or replace them after a specific operational period or predetermined mileage. However, this approach results in material waste and increased maintenance expenses[6].

A recent survey highlights the significance of attaining higher safety standards while minimizing maintenance expenses. Ongoing research in this field predominantly concentrates on improving preventive and condition-based maintenance strategies, with the existing literature on railway wheels mainly consisting of methodologies related to preventive or condition-based maintenance[7]. Numerous models discussed in current literature can be applied to forecast the degradation of a wheel's profile. Recent methodologies encompass systematic models integrated with vehicle dynamics[8], [9], [10].

Shebani and Iwnicki[11] employ autoregressive models with external input neural networks to predict wheel and rail wear across various contact conditions. The results of experimental tests indicate that artificial neural networks offer more precise wear predictions, achieving 80% and higher model accuracy rates. Recently, a data-driven approach has been adopted to monitor the health and estimate wear of train wheels. Tianli et al.[12] suggested a framework that utilizes group profile data and multi-dimensional health indicators, along with regression techniques such as principal component analysis, hilbert-haung transform, and logistic regression to investigate the health status of high-speed rail wheels. Chi et al.[13] assessed the reliability of high-speed rail wheels by developing multi-state data driven models using actual operational data analysis.

There are ongoing efforts to enhance maintenance strategies for passenger train wheelsets. Lin et al.[14],[15] studied the reliability of locomotive wheelsets using Bayesian survival analysis and explored their degradation with classical and Bayesian approaches. Liu et al.[16] developed a dynamic maintenance strategy for locomotive wheelsets, focusing on system reliability and cost-effective maintenance. However, freight train maintenance research is limited due to inadequate freight data traceability. Zhang et al.[17] analysed the freight wheelset repair data using Weibull and Birnbaum-Saunders distributions, which were performed to study reliability curves and their characteristics. Shi et al.[18] proposed an opportunity-based centralised maintenance strategy based on the wheelsets remaining useful life(RUL) prediction. Hence, improving freight train maintenance strategies is essential to enhance reliability, prolong component lifecycle, and reduce maintenance expenditures. This enhancement is essential as freight trains play a vital role in the EU market, providing efficient bulk transportation of goods at lower costs than air and road alternatives[19].

This study employs a Markov decision process (MDP) approach to provide an optimal strategy with a decision map for the best actions depending on the current state of the wheelset using observed wear data of freight wheelsets. The paper is structured as follows: Section 1 introduces statistical models used in wheelset maintenance and explains the importance of such maintenance for freight trains. Section 2 elaborates on the Markov decision process, whereas Section 3 discusses the application of the Markov decision process in the context of freight trains and presents the problem description; Section 4 presents the optimal policy for freight wheelset maintenance; and the final section provides conclusions and outlines avenues for future research.

2 Markov Decision Process

An MDP is a mathematical framework that model decision-making in discrete, stochastic, and sequential environments. States, actions, transition probabilities, rewards and a discount factor characterize it[20].

A stochastic process, denoted by a sequence of states $\{X_n = 0,1,\dots,N\}$, forms a Markov chain with transition probabilities $p_{i,j}$. In each state i, a selection is made from the potential set of states $s \in \{s_1, s_2, \dots, s_N\}$; and an action is chosen form the optimal set of actions $a \in \{a_1, a_2, \dots, a_M\}$ and a set of decision epochs $t \in \{1,2,\dots,T\}$. For a given current state $X_n = i$ and an action $a_n = a$, then Markov property can be expressed by equation (1) as follows:

$$P(X_{n+1} = j | X_n = i, a_n = a) = p_{i,j}(a) \tag{1}$$

According to Markovian property, the transition probabilities depend only on the present state and action. They are non-negative, and within a range of $0 \leq p_{i,j} \leq 1$, with the sum of probabilities for all possible transitions must be 1, and it is shown by equation (2) that is,

$$\sum_{j=0}^{s_N} p_{i,j}(a) = 1, \quad i = 0,1,\dots,s_N \tag{2}$$

For a specific action a ,the transition matrix denoted as $P(a)$.The n-step transition probabilities matrix for a given action can be easily computed by raising the matrix $P(a)$ to the power of n is expressed by equation (3) as follows:

$$X_n = X_0 \times P^n(a) \quad (3)$$

In an MDP framework, the key objective is to find actions that optimize the total or average reward/ cost across feasible solutions for each state. This leads to optimal policy[20].The optimal expected discounted cost for state i is represented by equation (4) is as follows:

$$v(i) = \min_{a\in\{a_0,\dots,a_M\}} \left\{ c(i,a) + \sum_{j\in S} \gamma \times v(j) \times p(j|i,a) \right\}, \forall i \in s, \quad (4)$$

Where $v(i)$ represents the optimum expected discounted costs incurred from epoch n onwards for the current state i. The predicted cost incurred for state i under action a is denoted by $c(i,a)$. The discount factor $\gamma \in [0,1]$, representing the discounting extent. Additionally, $p(j|i,a)$ denotes the probability of transitioning to a new state j given the current state i under the action a.

3 MDP Application to Freight Railways Wheelsets

This section illustrates the application of the Markov decision process to freight railway wheelsets. Section 3.1 explains the problem and its related assumption, while section 3.2 outlines the parameter selection. In section 3.3 the state space of the Markov transition matrix is defined, and finally, section 3.4 explains the calculation of the Markov transition matrix using wheel wear data.

3.1 Problem Description and Assumptions

The dataset under analysis was gathered from December 2015 to April 2023 (i.e., a 7-year interval) from a fleet of wagons. The dataset contains different numbers of wagons, each equipped with four wheelsets.

The present work operates under the assumption that all observations yield reliable estimates of the true states of the system and all maintenance actions yield consistent outcomes. Markov decision process model encompasses the following considerations:

I. The wheel tread diameter (D), is a primary indicator of wheel profile for determining the lifecycle stage for a given wheel at a certain epoch(n);
II. The occurrence of wheel damage, including rolling contact fatigue (RCF), flats or cavities, poses a significant risk to the lifecycle of railway wheelsets;
III. The Mileage since last maintenance (M) operation of each wheelset;
IV. The Gross Ton Mileage since last maintenance (GTM) and it is measured in Million Gross ton km (MGT.km);
V. The three potential maintenance actions $(a = 1,2,3)$;

- Do nothing $(a = 1)$: wheelset is ok and is returned to service in the same state;

- Renewal ($a = 2$):the maintenance actions, whether corrective or preventive, must extend beyond the scrap diameter. Consequently, the wheel necessitates replacement with a new one;
- Turning ($a = 3$): The wheelset undergoes turning on a lathe to align its shape with standard specifications, leading to a decrease or loss in diameter.

Previous studies utilized wheel tread diameter (D) and Mileage since last maintenance (M) as key parameters to construct a state space and Markov Transition Matrices [21], [22]. In the context of freight railways, we examine the Gross Ton Mileage since last maintenance (GTM) and compared it with the Mileage since last maintenance (M) to investigate that which parameter affect the wheel tread diameter (D) the most. Following the comparison, we select the most appropriate parameter along with wheel tread diameter (D) and defined the state space, the MTM and the MDP model for supporting maintenance/turning decisions in freight railway wheelsets. The next subsection defined the selection of parameter.

3.2 Parameter Selection

The key parameter of developing a state space, the MTM and the MDP model; wheel diameter (D) is the essential variable, and for selection of another variable, we developed a two different linear models using a simple linear regression approach considering variables diameter of wear ($|\Delta D_w|$), the Mileage since last maintenance (M) and the Gross Ton Mileage since last maintenance (GTM). The linear models are defined by equation (5) and (6) is defined as:

$$\text{M1: } |\Delta D_w| = \beta_0 + \beta_1 \times M \quad (5)$$

$$\text{M2: } |\Delta D_w| = \beta_0 + \beta_1 \times GTM \quad (6)$$

Upon comparing both models, the following results shown in Table 1, which are as follows:

Model	Regression coefficient	Estimates	P value	R-squared	Residual Standard error (σ)
M1	β_0	-1.210	0.259	0.563	4.411
	β_1	5.395×10^{-5}	1.841×10^{-11}		
M2	β_0	-2.650	0.003	0.731	3.436
	β_1	1.118×10^{-6}	$< 2\times10^{-16}$		

Table 1: Summary of Linear Model M1 and M2

The results indicate that both models based on their independent variable is statistically significant. Model M2 exhibits higher R-squared values compared to M1, suggesting that variable gross ton mileage since last maintenance (GTM) has greater impact on the wheel tread diameter (D). Consequently, for developing MDP models, the state space and estimation of MTM’s involves the variables wheel tread diameter (D) and gross ton mileage since last maintenance (GTM).

3.3 State Space

The state space is determined by key indicators of the wheelset states: wheel diameter (D) and gross ton mileage since last maintenance (GTM). Wheel diameter ranges from an initial diameter (D_i) of 920 mm to a scrap diameter (D_f) of 850 mm, divided into 1 mm intervals (i.e.,70 different levels). Simultaneously, the gross ton mileage since the last maintenance ranges from 0 to 25 million Gross Ton-km [MGT.km] in 0.5 million Gross Ton-km [MGT.km] intervals yielding 51 discrete levels or epochs. Finally, a wheelset can be damaged or not in 70 states with damage, which are kept at the end of the state space. Transitions from damaged to non-damaged states are compulsory because they must be removed once the damage is detected. Hence, damage states have not had an extension depending on the gross ton mileage since last maintenance. Therefore, there are 3640 different states, denoted as s $\in \{s_{1,\ldots,}s_{3640}\}$.

3.4 Estimation of MTM's

The assumption that the wear of a wheelset ($|\Delta D_w|$), as indicated by its diameter change, is statistically independent of its initial diameter (D_i) as shown in Figure1, is reasonable because the independence hypothesis cannot be rejected at a significance level of 0.05.

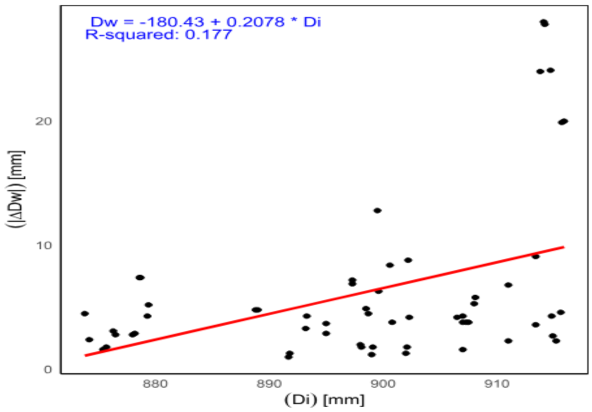

Figure 1: Diameter loss due to wear ($|\Delta D_w|$) across various diameters (D_i)

An MTM has been specified for every distinct actions. This section is partitioned into three subsections explaining the estimation of the Do-nothing MTM (P_1), the Renewal MTM (P_2), and the Turning MTM (P_3).

3.4.1 Do-nothing action

According to the Do-nothing strategy, increasing a wheel's diameter is only possible through replacement. Data indicates that significant decreases in diameter due to wear are highly improbable. Hence, simplifying it's assumed that the only feasible transitions from one state to another involve a decrease in diameter with a probability θ, or the wheelset stays in its current state with a probability $(1-\theta)$, as depicted in Figure 2.

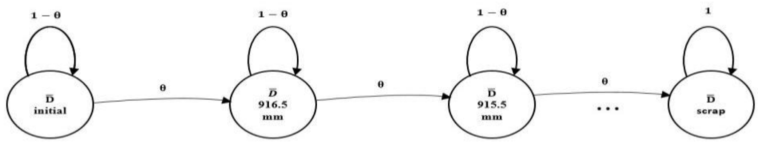

Figure 2: Transitions between states due to linear wear depending on parameter θ for the Do-nothing action.

Regarding the reduction in diameter caused by wear, the Markovian approach enables the prediction of the average value ($|\Delta\overline{\mathrm{D}}_{\mathrm{w}}|$) at 0.5 (MGT.km) intervals as illustrated by equation (7).

$$|\Delta\overline{\mathrm{D}}_{\mathrm{w(n)}}| = \mathrm{X}_0 \mathrm{P}^{\mathrm{n}} \mathrm{D}_{\mathrm{w}} \tag{7}$$

To calculate the average scalar values, we examined the varying wheel diameters across different wear conditions is indicated by equation (8).

$$|\Delta\mathrm{D}_{\mathrm{w}}| = [0\ 1\ 2\ \dots\dots 69]^{\mathrm{T}}\quad (\mathrm{mm}) \tag{8}$$

The possible variations in wheelset diameter, based on the diameter values represented in the sample, ranging from an initial diameter (D_{i}) of 920 mm to scrap diameter (D_{f}) of 850 mm and the initial state of the wheelset is illustrated by equation (9) is as follows:

$$\mathrm{X}_0 = [\mathrm{P}(\Delta\mathrm{D}_{\mathrm{w}} = 0)\ \ \mathrm{P}(\Delta\mathrm{D}_{\mathrm{w}} = 1)\ \ \cdots \mathrm{P}(\Delta\mathrm{D}_{\mathrm{w}} = 69)] = [1\ \ 0\ \cdots\ \ 0] \tag{9}$$

The reference value (θ) for the transition probabilities was calculated by regression approach, considering a subset of the original data where no action (turning/renewal) was taken. A simple linear regression without an intercept was considered. According to ordinary least squares (OLS) criterion, the resulting regression line is represented in black (Figure 3), by setting the value of θ = 0.44 in equation (8), equation (7) can be solved to determine the n-step transition probabilities (i.e. the probability that process in state i will be in state j after n additional transitions). The value of θ = 0.44 produced the best fit line, as illustrated by Figure 3. The data points (shown as black crosses) represent a loss in wheel diameter ($|\Delta\mathrm{D}_{\mathrm{w}}|$) due to wear and are categorized by the variable “gross ton mileage since last maintenance”.

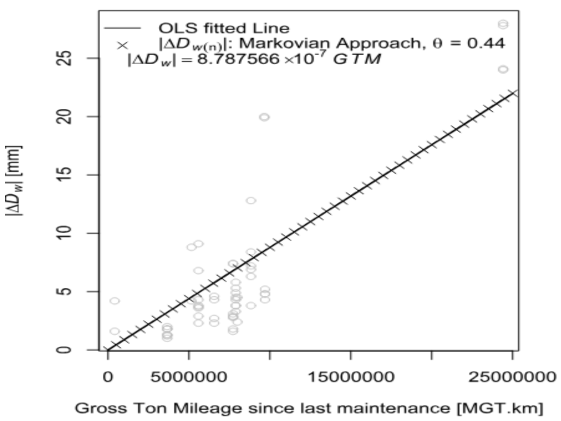

Figure 3: Diameter loss ($|\Delta\mathrm{D}_{\mathrm{w}}|$) for wheelsets with Gross Ton Mileage since last maintenance

Further, it is necessary to derive the probabilities of a wheel transitioning to a damaged state. The fundamental assumption is that once a wheel is detected as damaged, it cannot continue to be in service until the wheel is to be replaced or reprofiled. Consequently, the transitions form an undamaged wheel to a damaged one are depicted in Figure 4.

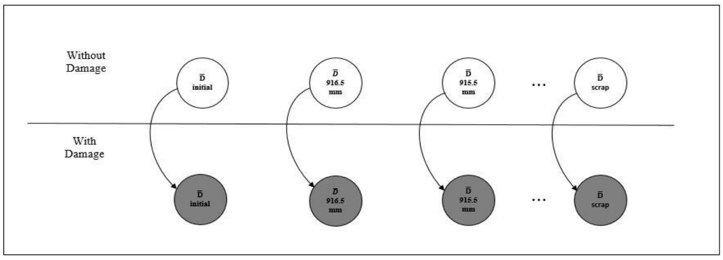

Figure 4: Transition Probabilities to state with damage

For the estimation of damage probabilities, a Cox proportional-hazard model (CPHM) is implemented[23], [24]. A CPHM model derived by Costa et al. [22] is to be adopted to derived a new CPHM model. Hazard rates are calculated using the CPHM, displayed in Figure 5. The probability of occurring damage in a wheel at a given diameter at a specific GTM is taken by the discretized values of hazard curves, as shown in figure 5.

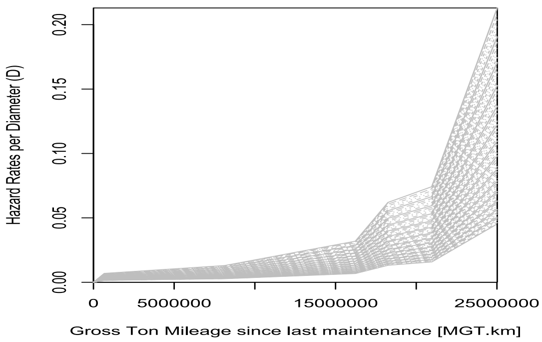

Figure 5: Survival probabilities estimated per diameter group, with representative values gross ton mileage since last maintenance.

The damage probabilities are considered independent of wear probabilities. Hence, the joint transition probabilities of damage and wear is equal to the product of the marginal transition probabilities, as follows:

$$\mathrm{P}(\mathrm{wear} \cap \mathrm{damage}) = \mathrm{P}(\mathrm{wear}) . \mathrm{P}\ (\mathrm{damage}) \qquad (10)$$

After obtaining the transition probabilities and damage probabilities value, the Markov transition matrices for ‘Do nothing’ action (P_1), is a 3640 by 3640 matrices composed by the sub-transition matrices in a diagonal block form, is illustrated by as equation (11) is as follows:

$$
P_1 = [P^1_{i,j}] = \begin{array}{c}
\begin{array}{ccccc} \underline{\overset{0}{\text{MGT.km}}} & \underline{\overset{10}{\text{MGT.km}}} & \underline{\cdots} & \underline{\overset{25}{\text{MGT.km}}} & \underline{\overset{states}{with\ damage}} \end{array} \\
\begin{bmatrix}
0 & P_W^{(70\times70)} & 0 & 0 & \\
0 & \ddots & P_W^{(70\times70)} & 0 & \\
0 & 0 & \ddots & \ddots & P_D^{(3570\times70)} \\
0 & 0 & 0 & P_W^{(70\times70)} & \\
\vdots & \ddots & 0 & 0 & \\
0 & 0 & \cdots & \cdots & I^{(70\times70)}
\end{bmatrix}^{(3640\times3640)}
\end{array}
\begin{array}{l} \text{0 MGT.km} \\ \text{10 MGT.km} \\ \vdots \\ \text{25 MGT.km} \\ \text{States with} \\ \text{damage} \end{array} \tag{11}
$$

3.4.2 Renewal action

In context of Renewal action, whether the wheel is currently damaged or undamaged, transitions to the initial state are considered certain, as illustrated in Figure 6. Hence, the Markov transition matrices for ‘Renewal’ action (P_2) is a 3640 by 3640 matrices, structured in equation (12) as follows:

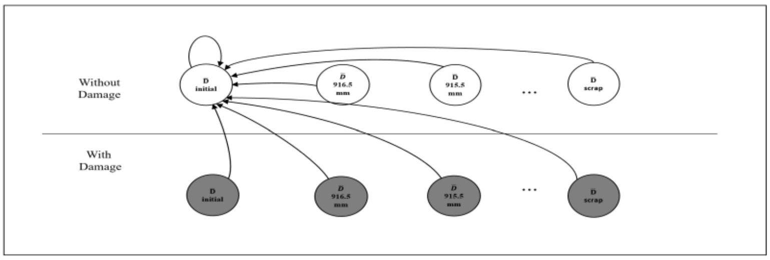

Figure 6: Transitions between states for the Renewal action

$$
P_2 = [P^2_{i,j}] = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ 1 & 0 & \cdots & 0 \\ \vdots & \cdots & \cdots & \vdots \\ 1 & 0 & \cdots & 0 \end{bmatrix}^{(3640\times3640)} \tag{12}
$$

3.4.3 Turning action $(\mathbf{a = 3})$

Relative to the Turning action transition between states are schematically showed in Figure 7. There is a feasible reduction in diameter resulting from the re-profiling of the wheel, whether damage has been occurred or not.

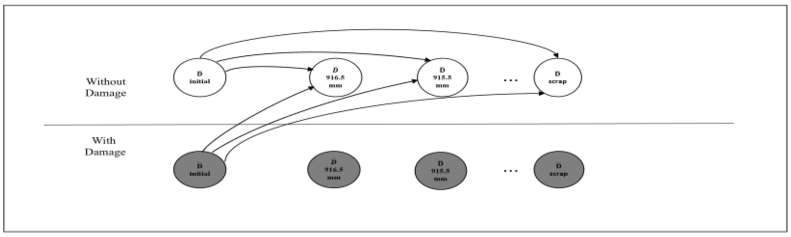

Figure 7: Transitions between states for the Turning action

The database used by the Portuguese train operating company does not differentiate between turning situations that involve damage and those that do not. As a result, the probability distributions for diameter loss due to turning (ΔD_T) for both damaged and undamaged wheels were assumed to be the same, based on the data from Braga and Andrade[21].The probabilities were calculated by using the relative frequency from turning data of wheelsets as an approximation of the transition probabilities, that is shown by equation (13) and Figure 8:

$$P(\text{turning}) = \frac{n_j}{N} \tag{13}$$

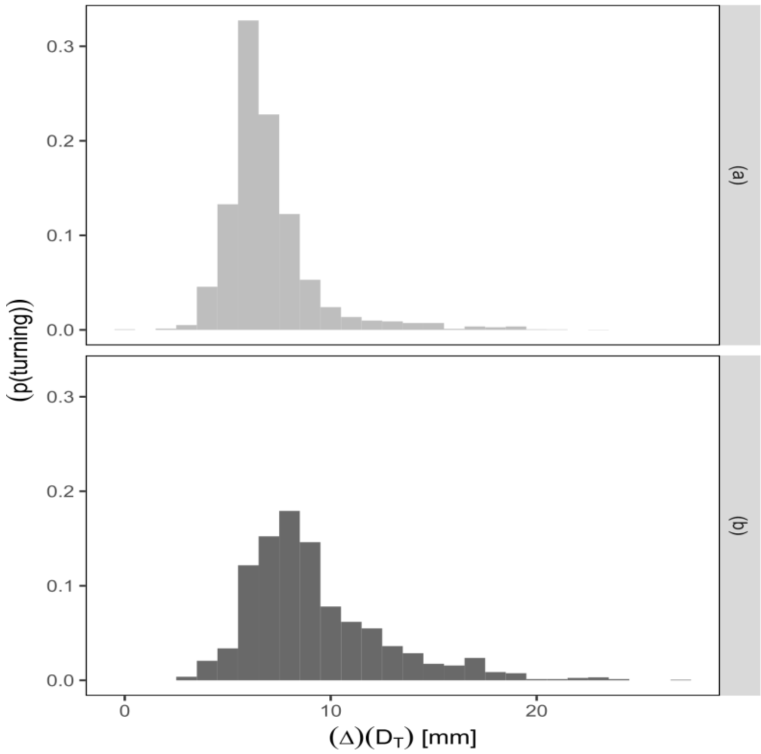

Figure 8: Histogram of the Diameter Loss due to Turning (ΔD_T) in a wheelset

In which n_j is the number of wheelsets that transit to a class j of diameter loss and N is the total number of wheelsets.

The wheel diameter could not be decrease by more than 30 mm at any point as shown in the histogram. Therefore, any states preceding the current one or those too distant for the Turning action to accomplish have transition probabilities set to zero. When a wheelset undergoes turning, it goes back to state where the gross ton mileage since last maintenance (GTM), and if damage has occurred, it goes back to a state without damage, since once the damage is detected, it must be replaced. The histogram of Figure 8 (a) indicates that diameter losses surpassing the scrap diameter in the final state. The probabilities of further transitions are combined to determine the likelihood of the wheelset remaining at the final state (i.e., the scrap diameter). Thus, it's possible to create the sub transition matrices for the "Turning" action from states without considering damage. In the same manner, using the probability values from Figure 8 (b), it is possible to compose the subtransition matrices for the "Turning" action from states with damage. Hence, the Markov transition matrices for the Turning action (P_3) is composed in the following manner which shows by equation (14).

$$P_3 = [p^3_{i,j}] = \begin{array}{c} \\ \left[\begin{array}{ccccc} \underline{\text{0 MGT.km}} & \underline{\text{10 MGT.km}} & \cdots & \underline{\text{25 MGT.km}} & \underline{\text{states with damage}} \\ p_T^{(70\times70)} & 0 & & 0 & 0 \\ p_T^{(70\times70)} & 0 & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ p_T^{(70\times70)} & 0 & 0 & 0 & 0 \\ p_T^{(70\times70)} & 0 & 0 & 0 & 0 \end{array}\right]^{(3640\times3640)} \end{array} \begin{array}{l} \\ \text{0 MGT.km} \\ \text{10 MGT.km} \\ \vdots \\ \\ \text{25 MGT.km} \\ \text{States with damage} \end{array} \tag{14}$$

3.5 Reward Function

The MDP Toolbox (MATLAB software) is selected to address the issue to employs a reward maximization approach to calculate the expected total discounted value rewards is assigned for all maintenance actions is to be negative [25].To construct the reward function, we define a reward vector (q) for the actions Do-nothing, Renewal, Turning.

The assumption for the Do-nothing action (a = 1) operates no operational cost, for Renewal action (a = 2) a fixed monetary unit (mu) 800 is assigned irrespective of the wheelset current state and the last action which is Turning a value of 50 mu for the wheel, without concerning the current state of the wheelset and a cost of correcting the damaged wheelset is 150 mu. However, for the critical states of the wheelsets for Do-nothing and Turning action a value of 10,000 mu is to be assigned. Hence, the reward vector for all actions (a = 1,2,3) is as defined by equation (15), (16) and (17) is as follows:

$$q_i^1 = \begin{bmatrix} 0 \\ \vdots \\ q_{70}^1(s_{70}) \\ 0 \\ \vdots \\ q_{3640}^1(s_{3640}) \end{bmatrix} = \begin{bmatrix} 0 \\ \vdots \\ 10000 \\ 0 \\ \vdots \\ 10000 \end{bmatrix} \begin{array}{l} \\ \rightarrow \text{scrap diameter} \\ \\ \\ \rightarrow \text{scrap diameter} \\ \\ \end{array} \tag{15}$$

$$q_i^2 = \begin{bmatrix} q_1^2(s_1) \\ \cdots \\ q_{3640}^2(s_{3640}) \end{bmatrix} = \begin{bmatrix} 800 \\ \cdots \\ 800 \end{bmatrix} \tag{16}$$

$$q_i^3 = \begin{bmatrix} q_1^2(s_1) \\ \vdots \\ q_{70}^1(s_{70}) \\ q_{71}^2(s_{71}) \\ q_{3571}^1(s_{3571}) \\ \vdots \\ q_{3640}^1(s_{3640}) \end{bmatrix} = \begin{bmatrix} 50 \\ \vdots \\ 10000 \\ 50 \\ 150 \\ \vdots \\ 150 \end{bmatrix} \begin{array}{l} \\ \\ \rightarrow \text{scrap diameter} \\ \\ \\ \text{damage} \\ \\ \end{array} \tag{17}$$

4 Optimal Policy

The MDP Toolbox within MATLAB software is employed to calculate the optimal policy for railway wheelset maintenance. The optimal policy is presented in a decision map based on the gross ton mileage since last maintenance (GTM), represented as shown in Figure 9.

The techniques for determining transition probabilities and choosing reward values in the "Reward/cost function" section have resulted in customised actions for the undamaged and damaged wheelsets. Figure 9 (b) highlights the actions of damaged wheelsets; only turning and renewal actions is to be assigned. The renewal actions are recommended for the last states where the "Turning" action would surpass the scrap diameter. For the undamaged wheelsets, Figure 9 (a) indicates the recommended actions based on gross ton mileage since last maintenance (GTM) and wheelset diameter(D). It provides the critical point let us assume the point G^* where the turning action is recommended (G^* = 12 MGT.km and D = 867 mm). The grey pattern on the right side of the map, suggests that turning action should be performed earlier as the diameter decreases. This relationship holds approximately until the point G^*. The diameters below (867 mm or closer to scrap diameter), this strategy permits more shifts to GTM. For diameters below 860 mm, the best strategy is not to perform turning at all and let the wheelset wear out until the scrap diameter.

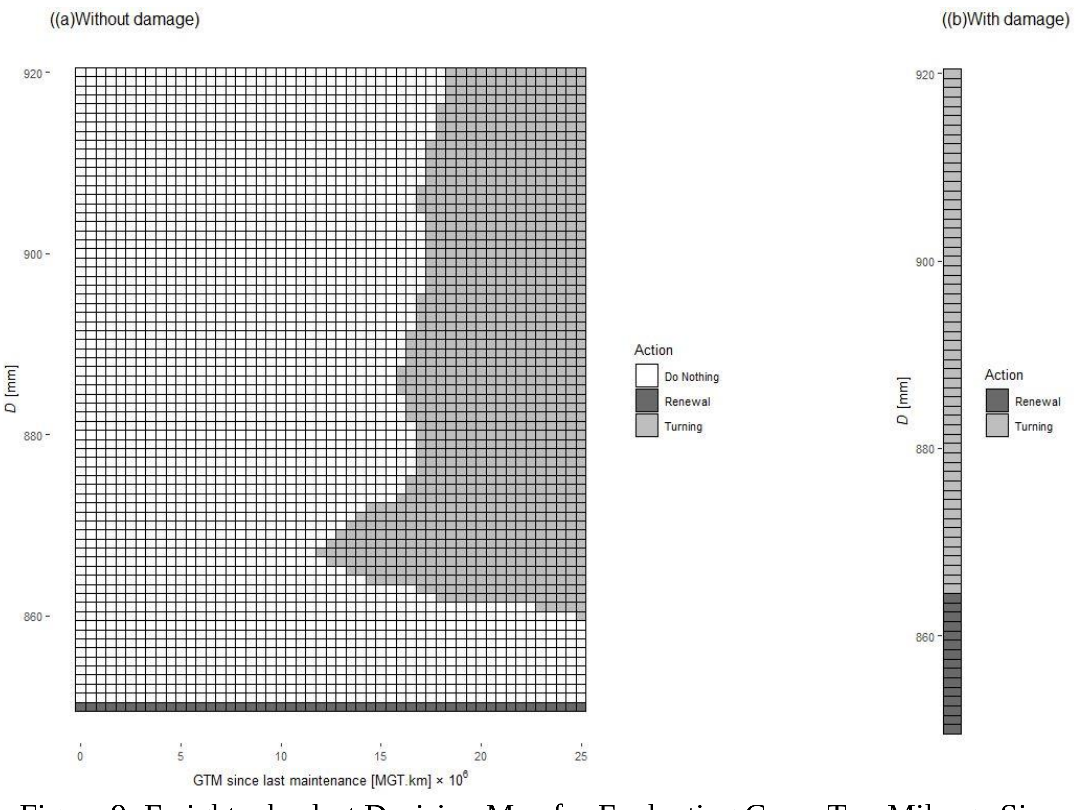

Figure 9: Freight wheelset Decision Map for Evaluating Gross Ton Mileage Since Last Maintenance

5 Conclusions and Contributions

A data-driven model-based approach is applied to maintain the freight train wheelsets and provide a better decision process in terms of the turning of wheelsets and replacement policy. The main result of this study is the creation of decision maps, that guide the following: For freight wheelsets up to a critical point G^* (located at 11.5MGT. km and a wheel diameter of approximately 865 mm), predictive turning actions are more important in terms of exceeding the wheelset lifecycle. However, after reaching this critical point, predictive turning gradually loses importance in the wheelset reprofiling policy. The decision map also shows that if the diameter of a wheelset is below 860 mm; the best strategy is not to perform turning and allow the wheelset wear out until it reaches the scrap diameter.

Acknowledgements

The authors would like to thank the support of the Medway Transport and Logistics operating company, namely Engineer Paulo Alves for providing the details of the freight trains. This work is supported by the Foundation for Science and Technology (FCT) through IDMEC, under LAETA, project UIDB/50022/2020. The authors would also like to thank FCT for the support in project PMO- RAIL 2022. 01738.PTDC. (DOI: http://dx.doi.org/10.54499/2022.01738.PTDC). This work was also developed within the Smart-Wagons project (C644940527-00000048), financed by NextGenerationEU, PRR.

References

[1] K. Lyu *et al.*, “Analysis on the features and potential causes of wheel surface damage for heavy-haul locomotives,” *Eng. Fail. Anal.*, vol. 109, no. November 2019, p. 104292, 2020, doi: 10.1016/j.engfailanal.2019.104292.

[2] R. F. Abenoza, O. Cats, and Y. O. Susilo, “Travel satisfaction with public transport: Determinants, user classes, regional disparities and their evolution,” *Transp. Res. Part A Policy Pract.*, vol. 95, pp. 64–84, 2017, doi: 10.1016/j.tra.2016.11.011.

[3] European Environment Agency Report No 02/2022, “Decarbonising road transport - the role of vehicles, fuels and transport demand,” *Transport and environment report 2021*, no. 02. pp. 1–92, 2022.

[4] H. Ritchie, M. Roser, and P. Rosado, “CO_2 and greenhouse gas emissions,” *Our world in data 2020, May 11*. 2020.

[5] Z. Jiang, D. Banjevic, E. M. Mingcheng, and B. Li, “Optimizing the re-profiling policy regarding metropolitan train wheels based on a semi-Markov decision process,” *Proc. Inst. Mech. Eng. Part O J. Risk Reliab.*, vol. 231, no. 5, pp. 495–507, 2017, doi: 10.1177/1748006X17710816.

[6] J. De Arizon, O. Verlinden, and P. Dehombreux, “Prediction of wheel wear in urban railway transport: Comparison of existing models,” *User Model. User-adapt. Interact.*, vol. 45, no. 9, pp. 849–866, 2007, doi:

10.1080/00423110601149335.
[7] F. Ghofrani, Q. He, R. M. P. Goverde, and X. Liu, “Recent applications of big data analytics in railway transportation systems: A survey,” *Transp. Res. Part C Emerg. Technol.*, vol. 90, no. September 2017, pp. 226–246, 2018, doi: 10.1016/j.trc.2018.03.010.
[8] S. Pradhan, A. K. Samantaray, and R. Bhattacharyya, “Prediction of railway wheel wear and its influence on the vehicle dynamics in a specific operating sector of Indian railways network,” *Wear*, vol. 406–407, no. April, pp. 92–104, 2018, doi: 10.1016/j.wear.2018.03.020.
[9] G. Tao, Z. Wen, X. Zhao, and X. Jin, “Effects of wheel–rail contact modelling on wheel wear simulation,” *Wear*, vol. 366–367, pp. 146–156, 2016, doi: 10.1016/j.wear.2016.05.010.
[10] Y. Muhamedsalih, J. Stow, and A. Bevan, “Use of railway wheel wear and damage prediction tools to improve maintenance efficiency through the use of economic tyre turning,” *Proc. Inst. Mech. Eng. Part F J. Rail Rapid Transit*, vol. 233, no. 1, pp. 103–117, 2019, doi: 10.1177/0954409718781127.
[11] A. Shebani and S. Iwnicki, “Prediction of wheel and rail wear under different contact conditions using artificial neural networks,” *Wear*, vol. 406–407, no. March 2017, pp. 173–184, 2018, doi: 10.1016/j.wear.2018.01.007.
[12] T. Men, Y. F. Li, Y. Ji, X. Zhang, and P. Liu, “Health assessment of high-speed train wheels based on group-profile data,” *Reliab. Eng. Syst. Saf.*, vol. 223, no. August 2021, p. 108496, 2022, doi: 10.1016/j.ress.2022.108496.
[13] Z. Chi, R. Chen, S. Huang, Y. F. Li, B. Zhou, and W. Zhang, “Multi-State System Modeling and Reliability Assessment for Groups of High-speed Train Wheels,” *Reliab. Eng. Syst. Saf.*, vol. 202, no. December 2019, p. 107026, 2020, doi: 10.1016/j.ress.2020.107026.
[14] J. Lin, M. Asplunda, and A. Paridaa, “Reliability analysis for degradation of locomotive wheels using parametric bayesian approach,” *Qual. Reliab. Eng. Int.*, vol. 30, no. 5, pp. 657–667, 2014, doi: 10.1002/qre.1518.
[15] J. Lin, J. Pulido, and M. Asplund, “Reliability analysis for preventive maintenance based on classical and Bayesian semi-parametric degradation approaches using locomotive wheel-sets as a case study,” *Reliab. Eng. Syst. Saf.*, vol. 134, pp. 143–156, 2015, doi: 10.1016/j.ress.2014.10.011.
[16] B. Liu, J. Lin, L. Zhang, and M. Xie, “A Dynamic Maintenance Strategy for Prognostics and Health Management of Degrading Systems: Application in Locomotive Wheel-sets,” *2018 IEEE Int. Conf. Progn. Heal. Manag. ICPHM 2018*, pp. 1–5, 2018, doi: 10.1109/ICPHM.2018.8448740.
[17] Y. Zhang, Z. An, M. Lu, and Q. Meng, “Reliability analysis of railway freight car wheelset based on Birnbaunm-Saunders fatigue life distribution,” *Vibroengineering Procedia*, vol. 35, pp. 88–93, 2020, doi: 10.21595/vp.2020.21797.
[18] H. Shi, J. Yang, and J. Si, “Optimization of Wheel Maintenance Strategy for Railway Freight Train Based on Remaining Useful Life Prediction,” *Proc. - 2020 Progn. Heal. Manag. Conf. PHM-Besancon 2020*, pp. 79–88, 2020, doi: 10.1109/PHM-Besancon49106.2020.00020.
[19] A. Kwilinski, O. Lyulyov, and T. Pimonenko, “Environmental Sustainability

within Attaining Sustainable Development Goals: The Role of Digitalization and the Transport Sector," *Sustainability*, vol. 15, no. 14, p. 11282, 2023.

[20] M. L. Puterman, *Markov decision processes: discrete stochastic dynamic programming*. John Wiley & Sons, 2014.

[21] J. A. P. Braga and A. R. Andrade, "Optimizing maintenance decisions in railway wheelsets: A Markov decision process approach," *Proc. Inst. Mech. Eng. Part O J. Risk Reliab.*, vol. 233, no. 2, pp. 285–300, 2019, doi: 10.1177/1748006X18783403.

[22] M. de Almeida Costa, J. P. de Azevedo Peixoto Braga, and A. Ramos Andrade, "A data-driven maintenance policy for railway wheelset based on survival analysis and Markov decision process," *Qual. Reliab. Eng. Int.*, vol. 37, no. 1, pp. 176–198, 2021, doi: 10.1002/qre.2729.

[23] D. R. Cox, "Regression models and life-tables," *J. R. Stat. Soc. Ser. B*, vol. 34, no. 2, pp. 187–202, 1972.

[24] D. R. Cox, *Analysis of survival data*. Chapman and Hall/CRC, 2018.

[25] I. Chadès, G. Chapron, M. J. Cros, F. Garcia, and R. Sabbadin, "MDPtoolbox: A multi-platform toolbox to solve stochastic dynamic programming problems," *Ecography (Cop.)*., vol. 37, no. 9, pp. 916–920, 2014, doi: 10.1111/ecog.00888.