Optimizing maintenance decisions in railway wheelsets – Markov Decision Process approach

Joaquim Pedro de Azevedo Peixoto Braga
joaquim.braga@tecnico.ulisboa.pt

Instituto Superior Técnico, Universidade de Lisboa – Portugal
November 2017

Abstract. This paper models the decision problem of maintaining railway wheelsets as a Markov Decision Process (MDP), with the aim to provide a way to support condition-based maintenance for railway wheelsets. A brief background on the railway industry and the role of the railway wheelsets is provided, as well as some background on the technical standards that guide maintenance decisions. A practical example is explored with the estimation of Markov transition matrices (MTMs) for different condition states that depend on the wheelset diameter, its mileage since last turning (or renewal) and damage occurrence. Bearing in mind all the possible maintenance actions, an optimal strategy is achieved, providing a map of best actions depending on the current state of the wheelset.

Keywords: Maintenance optimisation, Train operating companies, Markov Decision Process, Railway wheelsets degradation.

1. Introduction

A former president of the International Union of Railways (UIC) once said, “The railway will be the 21st Century’s preferred mode of transport – if it can survive the 20th Century.” (Nash et al. 2009). In the last 150 years, railway systems have been one of the top chosen means of transport for people, goods and commodities. (Iwnicki 2006).

As the world population grows and the need for energy supply increases, resources are becoming scarcer and with climate change, it has been an imperative guideline to create a strong and effective transport network provision. To face these challenges, it is advisable that the railway sector regains a larger share of transport mode choice, and thus, the railway transport should be in a constant improvement to fulfil the needs of current and future users, and those of society in general. Train operating companies, as well as infrastructure managers, search for the most economic, reliable and efficient processes to make their investments. In a competitive world, railway companies try to conjecture innovative strategic plans to manage their assets, employers and services (Shift2Rail 2015).

In the railway industry, the wheelset is one of the most important components, since it allows the train to curve, keep it on track, while keeping the passenger comfort and avoiding derailment.

On the other hand, it is also one of the top three train components most affected by wear (Jiang, et al. 2017) and worse than that, with serious consequences to the wheel state, by damage (Andrade and Stow 2016). This causes serious implications for the passenger safety and comfort as well as for the wheelset life-cycle itself. Therefore, to avoid performance degradation wheelsets need to go through rigorous inspections and maintenance processes to ensure a high quality level to the railway service.

In what concerns to maintenance procedures, there are mainly two types: corrective or preventive. The former takes place when the process has reached or has gone beyond some thresholds, the latter tries to avoid or delays the process of reaching these thresholds. Balancing these two types of maintenance is the key to avoid unnecessary costs and assets waste.

A wheelset changes its shape due to wear and damage, and so, to conduct its monitoring, it would need a comprehensive model that could predict its shape evolution throughout its life cycle.

An MDP provides a strong condition-based framework to deal with these cases of uncertainty, states prediction and maintenance optimization policies. Although MDP periodic maintenance policy has been used in the rail industry, its use in the field of the wheelsets still sins for scarce. For instance, it common to find in literature, the rail or wheelset wear evolution is usually modelled according to qualitative indexes/degrees of degradation.

Sharma (2016) provides an MDP optimal maintenance policy for the railway track. Here, the wear evolution is modelled (and railway track states are set) based on quality levels of the ability that the railroad track can perform its function and the effect of geo-defects.

Jiang, et al. (2017) optimize the re-profiling policy for train wheels using a semi-Markov decision
process, considering wear in terms of the diameter and flange thickness simultaneously. The problem is formulated in a two-dimensional state space; this space is defined as a combination of the diameter state and the flange thickness state. Nevertheless, they do not consider damaged states, neither include mileage since turning states, which are the contribution of this research work.

Therefore, in this research work, a practical optimal example of railway wheelsets maintenance is explored, using a MDP with the wear evolution and the state space depending on the wheel diameter, its mileage since last turning (or renewal) and damage occurrence.

2. Degradation Inspection and maintenance of railway wheelsets

These three factors – degradation, inspection and maintenance - are symbiotically interconnected in every health condition monitoring engineering system.

Wheelset degradation threatens the railway system safety and well-functioning. Therefore, inspection activities have to periodically take place in order to detect if safety and/or condition parameters/indicators on the wheelset are being met. To put back on track, i.e. recover from those safety/quality/condition levels, it is necessary to act according to maintenance policies that are defined with the help of precise inspections in the structure.

In points 2.1, 2.2, and 2.3, this engineering triad (degradation, inspection and maintenance) will be explored for the railway wheelset component.

2.1 Degradation

The wheelset undergoes faults and failures with time, usage and ageing of materials. All the components involved in railway dynamics are subject to complex and concentrated forces due to the high speeds and loads associated with the locomotion. When the vehicle has travelled a certain distance, external factors such as number of trips, distance travelled per day, hot or cold climate conditions, mountainous, dusty or iced roads, heavy stop-and-go cruising also help increasing the natural phenomenon of degradation of the wheelsets and sometimes causing damage.

The wheel-rail contact is a complex system composed by parts of rolling interaction and parts of sliding interaction. In each point of the wheel, there are normal and lateral tangential forces applied in the rolling surface. The rolling mechanism is most of the times limited by the transverse play, with partially sliding surfaces without protection against dust, rain, sand or ballast stones. Both rolling and sliding occur in the contact zone, especially in curves, there can be a large sliding component on the contact as well as larger lateral forces. These sliding frictions, as well as the climate external factors are responsible for changes in shape in some zones in the rolling tread and/or other damage defects that may occur during the wheel’s life-cycle (Iwnicki 2006).

Regarding the wheel profile there are three geometric variables, measured from a tread datum position point (T), that could be indicators to estimate the evolution of the wheelset degradation:

i) The wheel diameter \( D \);
ii) The flange height \( F_h \);
iii) The flange thickness \( F_t \).

Apart from the changes in shape, it can also occur damages in the rolling surface. The most common types of damage detected are: rolling contact fatigue (RCF), cavities and wheel flats (Andrade and Stow 2016).

2.2 Inspection

To assure a high reliability of the system vehicle-wheel-rail wheelset, rigorous inspections have to be made on the wheelset component.

Several thresholds have to be established relatively to the wheelset’s profile, manufacture, service loads, track characteristics, operating temperatures and damage occurrence. These threshold parameters must be preserved with rigorous and recurrent check-ups.

For the scope of this document, the wheelset inspection activities with more interest are the inspections on the wheel profile and the wheelset damage detection techniques. Wheel profile inspections have traditionally been executed through the use of a gauge device, though they have slowly been replaced by laser equipment.

Measurements taken with a laser equipment tend to be faster than with gauge devices. These time savings are easily converted in cost savings and have been the economic justification to adopt laser equipment. Moreover, gauge devices are more prone to human errors, and thus, tend to have a lower precision than the laser equipment. The economic benefits of introducing, such as the increase in precision, are difficult to estimate, especially in the medium/long-term, given a certain maintenance strategy and maintenance yard constraints.

Regarding the detection of damage on the wheelsets there are a few non-destructive testing (NDT) techniques which are commonly executed, such as visual testing (VT), magnetic particle testing (MT) or ultrasonic testing (UT).
2.3 Maintenance

As wheelsets take a critical role concerning the motion of the vehicles and the passenger comfort, their dimension must comply with tight standards for the wheel shape and diameter. On the other hand, due to their use and mileage, it is inherent to the wheel profiles that they wear and damage, and thus, inspection activities should monitor and control the evolution of the main indicators of degradation of a wheelset, and restore them if damage occurs and/or wear is higher than certain limits. The restoration of the shape of a wheelset can be scheduled within the preventive maintenance plan - planned actions - or in the corrective maintenance actions - remedial actions. However, the maintenance actions performed incur in material waste and higher maintenance costs. This problem can be better controlled with an optimized maintenance strategy that could predict the wear evolution and choose the more efficient maintaining actions for each wheelset wear situation.

Concerning the train wheel maintenance process, after an inspection activity being done, two corrective/preventive maintenance situations are possible:

i) The wheel is re-profiled;
ii) The wheel is replaced by a new one.

Bearing these situations in mind, there can be done some interesting maintenance strategies, after a fixed operation period or predetermined mileage, evaluating determined wheel parameters on the shape, such as the wheel tread, flange and damage.

3. A practical example

An MDP is applied to a practical example of wheelset maintenance. Its final objective is to determine an optimal strategy for the maintenance of railway wheelset.

A maintenance policy is derived according to the wheel diameter (D), the mileage since the last turning (or renewal) and damage occurrence, and taking into account three possible maintenance actions. A wheelset state space of 1620 states is defined.

This practical examples uses data from inspections on a single fleet of train (i.e. it only contains trains of one type or class) compiled from December 2006 up to July 2012 used in Andrade and Stow (2016, 2017a, 2017b).

Point 3.1 provides the estimation of the Markov transition matrices (MTMs) for each possible action and point 3.2 discusses the reward/cost functions.

Finally, point 3.3 provides the optimal maintenance policy.

3.1 Estimation of Markov transition matrices

Figure 1 shows that it is not possible to reject that the wear in a wheelset and its change in diameter is statistically independent of its initial state (at least linearly), the diameter of the wheels is a key indicator of the stage in the life-cycle, in which a given wheel is, at a certain period.

Consequently, wheel diameter is a main wheel profile geometric indicator and it is going to be the chosen one that will be studied and modelled in the following estimation of the MTM.

In the sample being analysed, the wheelset diameter (which must be very similar for the right and left side positions) varies from an initial diameter of around 850 mm to a scrap diameter of around 790 mm (below which, it must be renewed).

Bearing in mind the three main chosen differentiator indicators for the wheelset states:

i) wheel diameter (D);
ii) the mileage since the last turning (or renewal) (mst);
iii) damage occurrence;

it is defined a state space composed of 1620 states, where the diameter categories vary between 850 mm and 790 mm and grouped with differences of 1 mm, the mileage since last turning (mst) varies in intervals of 10 thousand miles, from 0 miles up to 250 thousand miles, and a wheelset can be in a state of damage or not. Note that the 60 states with damage are kept at the end of the state space, but without the extension depending on the mileage since last turning, because the transitions from damaged states to non-damaged states are compulsory, since that once the damage is detected it must be removed.

A sub-transition matrix will have to be defined for each possible action. Note that certain
simplifications were adopted as the defined states do not control other parameters such as the flange thickness or height and angle dimensions.

After a wheelset inspection, three actions \( (a = 1, 2, 3) \) can be performed:

- “Do nothing” \( (a = 1) \): the wheelset is ok and it goes back to service in the same state;
- “Renewal” \( (a = 2) \): the corrective or preventive maintenance actions would need to go beyond the scrap diameter, and so the wheel must be replaced by a new one;
- “Turning” \( (a = 3) \): the wheelset goes to a turning lathe for its shape being replaced to values within the standards and it suffers a reduction/loss in its diameter.

“Do nothing” action \( (a = 1) \)

Relatively to the “do nothing” action, since in the transitions analysed, derived solely from states of wear of the wheels, the probability of an increase of diameter size is zero, a transition to a state with higher diameter is considered impossible.

On the other hand, it was verified by the data analysis that the transitions to next states are limited, which means that a transition from a state to another one with a great loss in the diameter due to wear, for example, is very unlikely to happen. Therefore, in what concerns to transitions from one state to the other ones, the probabilities are composed by zeros to states before the current one and zeros for the states very unlikely and not found by the data to happen.

For this work, it is going to be assumed that it is only possible for the wheelset to transit to the state of diameter immediately below with a probability of \( \theta \), as described in Figure 4.1.

![Figure 2: Transitions between states without damage using a probability value \( \theta \) for the “do nothing” action.](image)

Regarding the tread change diameter due to wear, it is possible to predict a mean value \( \Delta D \) for this wearing evolution using a Markovian approach, with time intervals of 10 thousand miles and a MTM:

\[
\Delta D_{\text{ini}} = X_0 p^n \Delta D \tag{1}
\]

By choosing different values for the variable \( \theta \), an average loss of diameter due to wear can be estimated using Equation (4.8) and compared with real data from Andrade and Stow (2016, 2017a, 2017b), as it is shown in Figure 3.

![Figure 3: Change in the tread diameter due to wear \( (\Delta D) \) for wheelsets without damage with mileage since turning, applying the first MTM approach.](image)

In the case of Figure 3, setting 0.15 (upper line in Figure 3) as the probability value for \( \theta \) would be the best approach comparing to the real data.

Now, the transition probabilities to states with damage are going to be considered. The following modelling approach considers only the possibility of a wheelset acquiring damage without change in its diameter, as shown in Figure 4.

![Figure 4: Considered transition probabilities to states with damage.](image)

In Andrade and Stow (2016), the authors used a logistic regression to estimate the probability of occurring damage, given a certain number of explaining variables, namely: i) mileage since last turning and ii) the wheelset diameter. They used the following expression:

\[
p(\text{damage}) = \frac{1}{1 + e^{-(X_i \beta_i + X_{ij})}} \tag{2}
\]

where \( j, \beta_i \) are the slope parameters associated with each covariate \( i \), and \( X_{ij} \) are the values for each covariate \( i \) and wheelset \( j \). Figure 5 estimates the probabilities of occurring damage (here assumed solely as Rolling Contact Fatigue), for the damaged transitions considered in Figure 4, with the evolution of the mileage since last turning.

![Figure 5: Probability of damage with mileage since last turning.](image)
A sub-transition matrix for the probability values of the different 1560 states without damage to the different 60 states with damage in the following way:

\[
P_A = [p_{ij}]
\]

The addition of damage to the problem causes some particular alterations in the transition probability values for the sub-transition matrices between states without damage, since now these probability values also have to guarantee that damage has not occurred. For these cases, it is assumed the independence between wear and damage occurrence and the joint probability of two independent events factorizes into their marginal probabilities (Puterman 2014):

\[
P(\text{wear} \cap \text{damage}) = P(\text{wear}) \cdot P(\text{damage})
\]

Therefore, the sub-transition matrix for the wear situation becomes as follows:

\[
P_A = [p_{ij}]
\]

Adding now the effect of damage to the state space considered, the non-zero probability transition values of the MTM if the “do nothing” action is chosen (\(a = 1\)) would be the following:

\[
\begin{align*}
p_{1,1} &= 0.5P(\text{damage}) + 0.5P(\text{no damage}) \\
p_{1,2} &= 0.5P(\text{damage}) + 0.5P(\text{no damage}) \\
p_{1,3} &= 0.5P(\text{damage}) + 0.5P(\text{no damage}) \\
p_{1,4} &= 0.5P(\text{damage}) + 0.5P(\text{no damage}) \\
p_{1,5} &= 0.5P(\text{damage}) + 0.5P(\text{no damage}) \\
p_{1,6} &= 0.5P(\text{damage}) + 0.5P(\text{no damage}) \\
p_{1,7} &= 0.5P(\text{damage}) + 0.5P(\text{no damage}) \\
p_{1,8} &= 0.5P(\text{damage}) + 0.5P(\text{no damage}) \\
p_{1,9} &= 0.5P(\text{damage}) + 0.5P(\text{no damage}) \\
p_{1,10} &= 0.5P(\text{damage}) + 0.5P(\text{no damage})
\end{align*}
\]

In a matrix form, the final MTM for the “do nothing” situation \((P_1)\), composed by the sub-transition matrices of Equations (4.12) and (4.14) in a diagonal block form, is as follows:

\[
P = [p_{ij}] =
\]

- “Renewal” action \((a = 2)\):

Relatively to the renewal action, independently of the current state of the wheel (damaged or undamaged), it is certain that it goes to the initial state, as described in Figure 4.6.

\[
\text{Figure 6: Transitions between states for the “renewal” action.}
\]

Therefore, the MTM for the “renewal” situation \((P_2)\) is a 1620 by 1620 matrix as follows:

\[
P_2 = [p_{ij}] =
\]

- “Turning” action \((a = 3)\):

For the “turning” action, a distinct loss in the diameter due to turning (re-profiling of the wheel) is achieved if damage has occurred or not. In case it has occurred, the diameter loss tends to be significantly larger on average and with an higher dispersion as depicted in Figure 7.
Figure 7: Histograms of the loss in diameter due to turning ($\Delta D_{\text{turn}}$) in a wheelset: (a) with damage and (b) without damage.

Figure 7 was built using the relative frequency from past samples as an approximation of the transition probabilities, i.e. (Sharma 2016):

$$p(\text{turning}) = \frac{n_j}{N} \quad (8)$$

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.

These transitions for the “turning” action in theory are schematically represented in Figure 8.

![Figure 8: Transitions between states for the “turning” action if the wheel is in a state of $D_{\text{initial}}$.](image)

The construction of the MTM for the “turning action” is built up in diagonal expansions Figure 8, the transitions to next states are limited, which means that a transition from a state to another one with a great loss in the diameter does not happen at some point (according to Figure 7, it is defined 30 mm as the maximum loss in diameter possible). Therefore, regarding transitions from one state to the other ones, the probabilities are composed by zeros to states before the current one and zeros for states after the current one that the “turning action” “cannot reach”.

When a wheelset is turned, it goes back to a state where mileage since last turning ($\text{mst}$) is zero, and if it has damage it goes to a state without damage, since once the damage is detected it must be removed.

As it is not possible to turn a wheelset beyond the scrap diameter, when the wheelset is in a scrap diameter state, at some point of its mileage since last turning ($\text{mst}$), and the histograms of Figure 4.7 indicate diameter losses that go beyond the scrap diameter for that final state, what happens is that the probabilities of the remaining transitions are summed up becoming the probability value for the wheelset to stay at the final state, i.e. the scrap diameter.

Using the probability values withdrawn from Figure 7a, it is possible to compose the sub-transition matrix for the “turning” action from states without damage:

$$P_{\text{initial}} = \begin{bmatrix}
\vdots & \vdots & \vdots & \vdots & \vdots \\
0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 \\
\vdots & \vdots & \vdots & \vdots & \vdots \\
0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 \\
\end{bmatrix} \quad (9)$$

In the same way, using now the probability values withdrawn from Figure 7b, it is possible to compose the sub-transition matrix for the “turning” action from states with damage:

$$P_{\text{with damage}} = \begin{bmatrix}
\vdots & \vdots & \vdots & \vdots & \vdots \\
0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 \\
\vdots & \vdots & \vdots & \vdots & \vdots \\
0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 \\
\end{bmatrix} \quad (10)$$

Finally, applying to the state space of Equation (4.3), the MTM when the “turning” action is chosen ($P_3$) is composed as follows:

$$P_3 = \begin{bmatrix}
P_{\text{initial}} & P_{\text{with damage}} \\
P_{\text{with damage}} & P_{\text{initial}} \\
\end{bmatrix}$$

3.2 Reward/cost function

The MATLAB® Toolbox program chosen to solve this problem used a reward maximization function to derive the expected total discounted value rewards. Therefore, the values used to represent the costs of the maintenance operations must be negative (Chadès et al. 2014).

To derive the rewards/costs function, a reward vector for each action chosen ($a = 1, 2, 3$) must be specified in a similar way of Equation (2.9).

The “do nothing” action ($a = 1$) does not hold any operational cost. However, it is important to guarantee, due to the state space constraints adopted, that when the wheelset reaches states of scrap diameter, mileage since last turning (mst) of 250 thousand miles or damaged states, other option
different from “do nothing” is chosen. This is done by giving, to these critical states, cost values larger than the ones used in the remaining actions. For these states, it was assumed that values of -10 thousand monetary units should be assigned, as represented as follows:

Based on the values presented in Andrade and Stow (2017b), it was considered for the “renewal” action (\(a = 2\)) an average value of -8000 monetary units, regardless of the state a wheelset is, and hence, the reward vector is as follows:

\[
q_1^2 = \begin{bmatrix}
q_1^2(s_1) \\
\vdots \\
q_1^2(s_{1620})
\end{bmatrix} = \begin{bmatrix}
-8000 \\
\vdots \\
-8000
\end{bmatrix} \quad (13)
\]

Moreover, and having in mind the values reported in Andrade and Stow (2017b), it was chosen a value of -400 monetary units to turn a wheel, independently of the wheelset state. However, similar to the case of the “do nothing” action, there are some critical states where a “renewal” action is needed, those are the cases when the scrap diameter is reached. And, therefore, for the “turning” action (\(a = 3\)) the reward vector is as follows:

\[
q_1^3 = \begin{bmatrix}
q_1^3(s_1) \\
\vdots \\
q_1^3(s_{1620})
\end{bmatrix} = \begin{bmatrix}
-400 \\
\vdots \\
-400
\end{bmatrix} \quad (14)
\]

### 3.3 Optimal policy

The MATLAB® Toolbox program derives the policy for this process in a decision vector as the one of Equation (2.14). Organizing the decision process in a graphic table for the damage and undamaged states with the evolution of the mileage since last turning (\(mst\)), it is possible to map a decision graphical table as represented in Figure 4.9.

By analysing Figure 9, one can see that the transition probability methods adopted in section 3.1 and reward values chosen in section 3.2 resulted in actions that were intended: i) for the damaged wheelsets, only actions of “turning” or “renewal” are assigned, being the “renewal” actions left over for the last states where the “turning” action would go beyond the scrap diameter; ii) for the undamaged wheelsets, at states with a mileage of 250 thousand miles an action of “turning” or “renewal” is chosen, so the variable \(mst\) returns to zero, and “renewal” action is chosen for scrap diameter states and states where “turning” would go beyond it.

Figure 9 can then serve as a guideline for condition-based maintenance, i.e. depending on the diameter (\(D\)), mileage since last turning (\(mst\)) and whether or not damaged has occurred; it provides the optimal action that maximizes the total rewards (minimizes the total costs) for each defined wheelset state.
4. Conclusion and future research

This final chapter provides the conclusions of the research, identifies some limitations and points out further steps of improvements and enhancements for the research here conducted.

4.1 Conclusion

Wheelset maintenance is a procedure where wheelsets undergo a maintenance schedule to prevent wheelsets from failing when in service. Introducing condition-based planning and management using a MDP approach can be achieved, providing a more efficient method of managing the wheelsets assets than the traditional rules-based methods.

During this dissertation, the main problems were explained, improvements and procedures of the wheelsets inspection, degradation and maintenance. It was introduced the importance of the wheelset maintenance and inspection in the global context of the railway industry, presenting the main components of a wheelset, namely the ones that are more important for the inspection and consequently maintenance activities. The occurrence and evolution of the wheelsets degradation was explained and also a key factor for its comprehension was mentioned – the occurrence of damage.

Among all the possible approaches to model and solve this maintenance problem, it was chosen a data-driven model of decision and optimization based on the Markov Decision Problem (MDP). Its initial premises, basic elements, structural blocks and chain developments were presented.

This MDP model was then applied to a practical case of wheelset maintenance decision. It was defined the diameter change, the occurrence of damage and the mileage since last turning (or renewal) as the main indicators to control the process of maintenance and degradation of the wheelsets. The state space was divided into 1620 states according to the previous indicators and a set of three actions were defined: i) “do nothing”, ii) “renewal” and iii) “turning”. The decision process then was derived with the support of the MATLAB® MDP Toolbox (Chadès, 2014) and a useful map of decisions to support the decision-maker to take the best maintenance choice for each wheelset state was made.

Going into detail at the map of decisions of Figure 4.9 it is possible to conclude that an action of preventive maintenance (turning) would be advisable for railway wheelsets with a mileage since last turning between 210 and 240 thousand miles and a wheel diameter between 799 and 801 mm. In the remaining cases, the wheelset should run until the 250 thousand miles are completed between maintenance intervals or a damage has occurred.

4.2 Limitations

Several limitations can be identified during the process that led to the present dissertation. First of all, the proposed modelling approach could not adopt the wheelset historical data from a Portuguese train operating company in useful time. This limitation was overcome by the use of past data and useful information from published papers (Andrade and Stow 2016, 2017a, 2017b).

Secondly, though the state space was sufficiently large to describe different diameters, mileage since turning and the occurrence of damage, it did not control for the evolution of the flange thickness and height as well as the angle inclination. Such limitations were not considered severe to the aim of the present thesis, but for further steps they would have to be included as the current standard limits these additional parameters. Nevertheless, most of turning decisions are currently made based on mileage and/or the occurrence of damage and not due to these additional dimensions, and thus it is reasonable to argue that they might not affect to a great extent the optimal map that was made (Figure 4.9).

Moreover, an important limitation of the MDP approach is the estimation of the MTM and thus, the fact that such empirical approach is mainly data-driven, which represents an alternative way to vehicle dynamic simulations. Therefore, the conclusions drawn might be only applied to the data that was analysed and not immediately transferable to other case studies. In other words, the conclusions might be case specific and the MTM would have to be re-estimated (using Survival statistical models, for example) to feed this new case study applied to the Portuguese train operating company.

Finally, the proposed analysis did not take into account the uncertainty associated with inspection activities themselves, in particular using laser or human-based inspection procedures. The analysis of historical data would have to take this into account, i.e. condition data was collected with different precisions over time.

4.3 Future Research

Future research would have to overcome the points identified above as limitations of the present work. As MDPs provide a powerful framework for the solution of problems of maintenance and inspection, and the optimization of these processes has received considerable attention along the years, there are some extensions of the MDPs, such as Latent or Hidden Markov Decision Processes (Madanat 1993...
and Madanat and Ben-Akiva 1994) or Partially Observable Markov Decision Processes (POMDP) (Papakonstantinou and Shinozuka 2014b and Young 2013) that might provide useful steps for further research. These approaches consider hidden observation variables or belief states, since they assume that it is not possible to know exactly the real state/condition of a wheelset because of the uncertainty of the equipment used in the inspections. Therefore, the value functions of these optimization processes deal with the uncertainty and these are more flexible processes. To accomplish that, observability matrices that contaminate with noise the current MTMs would have to be estimated, using the different precisions of the inspection equipment. Ideally, one would assess the optimal value of the MDP with human-based inspection and the optimal value with laser inspection and compare them to estimate the economic benefits of introducing laser inspection.

5. References


