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Hybrid Modelling Based on Non Homogeneous Poisson Process for Predictive Maintenance

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Abstract

Predictive maintenance requires models that can predict the occurrence of defaults on a network. The method described in this paper overcomes two limitations of classical models. First it also predicts the effect of the maintenance on the lifespan, in a way easy to infer from a dataset. Second it includes inputs from physics models, that reinforce the confidence in extrapolation. This method is based on Non Homogeneous Poisson process and has been tested on squats default occurring on rails in the French railroad network.

Keywords: rail, squats, rolling contact fatigue, machine learning, hybrid model, Poisson process.

1 Introduction

Maintenance of railway networks requires to make decisions to choose where to act, and when. Models that can accurately describe the network are therefore needed. Two main types of models can be used.

On one hand, model from physics can be used to study the assets' behaviour to several constraint. This model, generally based on experimental data, are robust because they are based on equation that have been extensively validated. However, the outputs of these models are generally expressed as "stress" or "effort" [1][2] while asset management requires "lifespan" or "failure rate" [3]. Several hypotheses are thus made to convert physical sizes into risk assessment leading to a result not suited with observation.

On the other hand, the monitoring on the network provides information on the true network, without assumptions [4]. However, these data are more scarce, and it is sometimes difficult to build a model relying solely on this data.

In this work, we propose a method to couple the two approaches in a single pipeline. A model based on Finite Element Method (FEM) is used to predict a fatigue index that describes the effect of rolling contact on the apparition of defects. This index is then used to train a Machine Learning model that allows to predict the failure rate for the whole network. This failure rate is a first step for the management of the network but is not sufficient. Maintenance action should also be described by the model, as managers want to plan them in an optimal way. The proposed Machine Learning model, based on Non Homogeneous Poisson Process, takes this effect into account, and parameters associated to it can be determined from the data.

2 Methods

a. Description of the dataset

This study focuses on the French Railroad network, managed by the SNCF. This network contains around 30 000 kilometres of linear assets. To standardize the measurement, the network has been divided into segments of 108 m that are supposed homogeneous. This choice is motivated by previous work [5]

Several defects are monitored, but this study focuses on squat defects. Squats are crack initiation generated by rolling contact fatigue, that could lead to rail break if it is not treated. They are observed using UltraSonic technology either by walking agent or by measurement train. The detectability threshold is of 5mm. The curative maintenance consists in either cutting the rail around the defect and replace it or grinding it deeper than the defect. Preventive maintenance is also deployed periodically to remove the top layer of the rail and with it, the nucleation that could lead to cracks.

In this study, the date of first observation of a default, and the date of surveillance campaign and grinding have been used. The segments used to train the model must contain more than 5 defects, and more than one grinding on the observation windows which lead to a total of 2 421 data points used in this study.

b. Squat occurrence

A model based on Non Homogeneous Poisson process has been defined [6]. This model gives a simple description of the system that can be easily compared with other models. The model describes the occurrence of default through time at a given point in space. This point represents the 108m segment of rail we considered.

The function $\lambda(t)$ describes the evolution of the failure rate during the asset's lifetime. t denotes the time since the installation (the age) of the assets. This function can lead to different scenario depending on its definition:

- If $\lambda(t)= \lambda$, the failure rate is constant, corresponding to a case without aging. The corresponding survival distribution is then an exponential law **E(λ)**

- If $\lambda(t)= \lambda.t^{b-1}$, the failure rate increases over time, corresponding to a case with aging. The corresponding survival distribution is then a Weibull distribution **W(shape=b, scale=a)**

These two distributions are often used in predictive maintenance and arise in several context related to aging. It can be noted that the scenario without aging is a particular case of the aging scenario, obtained when b=1.

c. Effect of grinding

Grinding, and more generally any reparation or maintenance operation, is expected to influence the lifespan of the asset and its failure rate. These effects can be modelled in several ways, for instance:

- The operation rejuvenates the asset with a fixed effect. The failure rate is then shifted from a factor η : $\lambda_{grinded}(t)= \lambda(t-\eta)$.

- The operation rejuvenates the asset based on its age. The failure rate is then shifted from a factor η multiplied by the age A of the assets when the operation is performed: $\lambda_{grinded}(t)= \lambda(t-\eta.A)$. This method can model classical effect of maintenance:

    - If η=0, the asset is « as bad as old » after the operation
    - If η=1, the asset is « as good as new » after the operation

  However, this method is difficult to define in the case of repeated operation and require a long history of measurement to infer the parameters values. The main problem is the choice of the "age", which can be the true age or the remaining age before the previous operation.

- The operation modifies the later aging of the asset. In this case, parameters λ or **b** are modified. This effect is also difficult to infer and require experimental data, to be able to identify which parameters is modified and how.

The different method can be combined, but the estimation of parameters then requires a large dataset. This is particularly problematic given that the observation period for the network (since the digitization of data acquisition processes) is short compared to the age of the rail. In this work, we therefore chose to keep the model simple and use a fixed effect of the grinding.

d. Parameters estimation

Three parameters, **λ**, **b** and **η** must be inferred from our dataset, for each segment. λ defines the failure rate, b characterizes how this rate evolves with aging, and η quantifies the rejuvenation effect of maintenance by reducing the asset's effective age. The values have been found by using a genetic algorithm. This algorithm follows three steps:

- A list of 100 candidate parameters set ***(λ, b, η)*** is sampled from a prior distribution
- For each set, the likelihood of the data is computed
- The 10 best parameters sets are used as to build the prior distribution for the next iteration, by adding a gaussian noise to each parameter.

This method is not new, but the model can encompass two modifications to better adapt to the dataset.
First the likelihood is computed based on the number of new defaults in each time interval. Therefore, the observations do not need to be regular, and the interval can be of different length without difficulties.
Second the model can take into account the accuracy of the observer. It is possible to add coefficients that modify the likelihood based on a false positive rate or a false negative rate. These two rates will increase or decrease the numbers of expected observations from the model. These parameters need to be estimated separately and have been disregarded in this study.

3 Results

The previously presented model can be applied to the French railways network. The procedure is composed of three steps:

a. Estimation of the parameters ***(λ, b, η)*** of the Poisson process

The parameters have been estimated for the 2 421 available datapoints. The distribution found in the data are consistent with Weibull distribution. This type of distributions is expected in reliability model. An example of the fit of the model is given on figure 1a. For the location that has been grinded, the effect of the operation has been estimated. This effect led to a shift of the distribution, which is consistent with the data used in this study. This type of observations and the associated model are given on figure 1b.

When a grinding operation is planned, the associated survival function is not a Weibull anymore. This function is presented on figure 2. It can be noticed that the grinding expands the expected lifespan with no defaults of the assets.

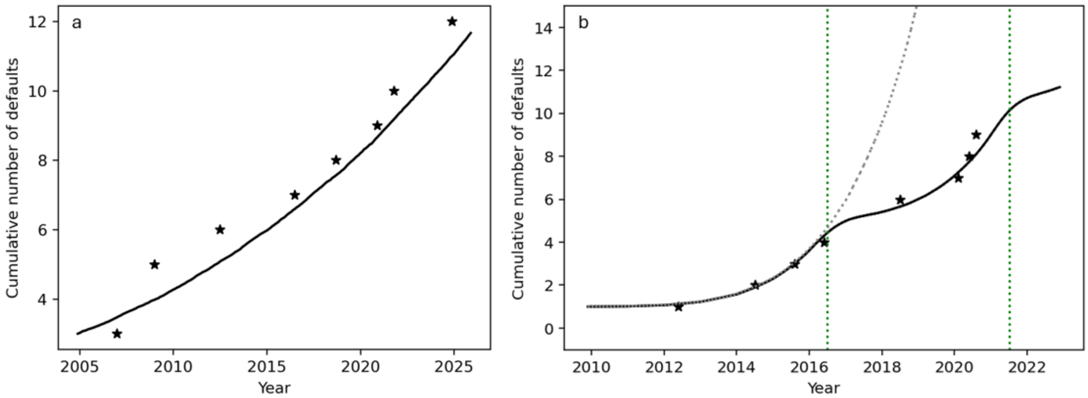

Figure 1: Two examples of fit between the model and the data. Stars indicate the numbers of default observed in the dataset for the different campaigns, the black curves indicate the expected number of defaults predicted by the model. On panel a, no grinding operation is performed, on panel b. grinding operation are performed at the date indicated by the green lines. The dotted grey lines indicate the expected number of default if no grinding had been performed

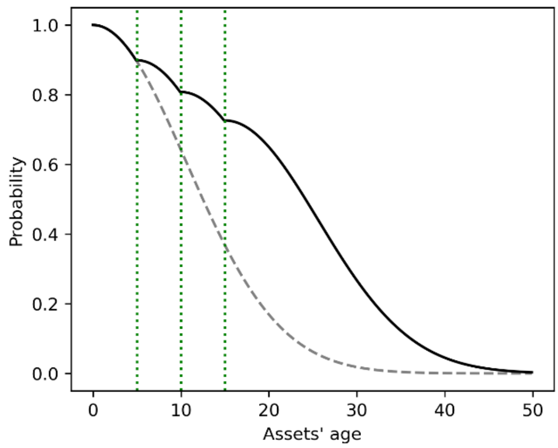

Figure 2: Survival function with and without grinding. The grey curves indicate the evolution of the survival function, i.e. the probability that the first default appear before the age x. The black curve indicated the survival function with grinding operation every five years. Green lines indicate the moment where grinding is performed.

b. Clustering based on computed fatigue index

Different groups of assets have been created, based on the median age at which a default appears. These groups are based on several variables, including the fatigue index, computed with FEM model [7]. The use of variables based on physic allow to reduce the number of variables. The weight of the trains and the curvatures or the track are now already summed up within the fatigue index.

c. Extrapolation to the network.

The extrapolation is performed using a kriging method [8]. This method extrapolates the parameters values for a given segment using the average of the close segment weighted by the distance. this method is easy to compute and allows to quickly extrapolate to the whole network. This method has been modified to consider the clustering done in step 2: the segment used to determine the values of a new one are weighted based on their distance, but also their cluster. If they belong to the same cluster, the weight is 1, if they belong to a different one the weight is 0.5. this method can be refined in order to account for more distance between groups.

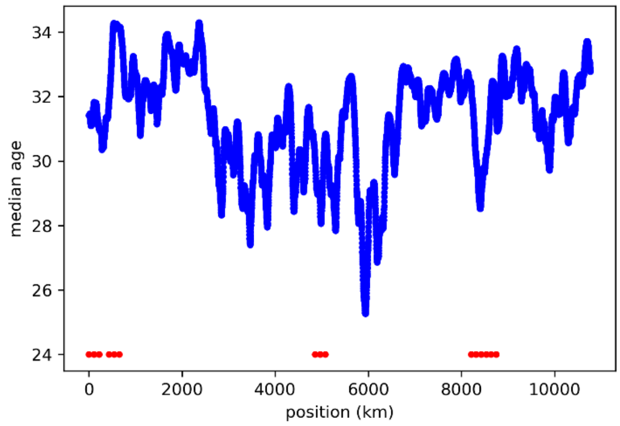

Figure 3: An example of profile of defaults occurrence obtained for a line of the French Railways Network. The blue lines indicate the median age at which the first default occurs along this line. The red lines indicate the segment where data where available. The profile is then completed using kriging and fatigue index.

4 Conclusions and Contributions

In this work we proposed a method that allows to compute the occurrence of defaults on a railways network. This method uses Non Homogeneous Poisson Process to model this process. It then led to Weibull distribution, as found in many maintenance studies, when no maintenance operations are planned; but led to more complex distributions when maintenance is performed. A simple fixed effect has been estimated with the dataset used in this study, due to narrow window of observations. However, the model we proposed could be more complex, and give a general version of the classic “as-good-as-new” vs “as-bad-as-old” effects.

The second addition is a coupling with fatigue index computed with FEM model. The use of physic model is an efficient way to reduce the number of variables used in Machine Learning model. Moreover, it ensures that the relationship between variables make sense from a theoretical point of view. This coherence between variables makes the user more confident in the extrapolation performed via machine learning methods. This coupling has been performed with a minimal number of adaptations, by using a classical kriging method. More advance methods could be used to increase the predictive power of the model and reinforce the coupling between simulation and machine learning.

The results of this study will be used to assess the efficiency of the maintenance operation on the network. Once the model is built, it is then easy to use even on a large scale, and it is possible to perform simulation of different scenario using the Poisson process.

This study also show that the efficiency of grinding can be different between different segments of rail. These differences have already been studied [9][10]. The effect of grinding could be better estimated by adding another physic model to the Poisson Process.

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