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A Bayesian model to assess rail track geometry degradation through its life-cycle

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ABSTRACT

One of the major drawbacks in rail track investments is the high level of uncertainty in maintenance, renewal and unavailability costs for the Infrastructure Managers (IM) during the life-cycle of the infrastructure. Above all, rail track geometry degradation is responsible for the greatest part of railway infrastructure maintenance costs. Some approaches have been tried to control the uncertainty associated with rail track geometry degradation at the design stage, though little progress has improved the investors' confidence. Moreover, many studies on rail track life-cycle cost modelling tend to forget the dynamic perspective in uncertainty assessments and do not quantify the expected reduction of the uncertainty associated with degradation parameters as more inspection data is collected after operation starts.

In this paper, a Bayesian model to assess rail track geometry degradation is put forward, building up a framework to update the uncertainty in rail track geometry degradation throughout its life-cycle. Using inspection data from Lisbon-Oporto line, prior probability distributions are fitted to the model parameters quantifying the associated uncertainty at the design stage, and then they are sequentially updated as more inspection data becomes available when operation starts. Uncertainty reduction in geometry degradation parameters is then assessed by computing their posterior probability distributions each time an inspection takes place.

Finally, the results show that at the design stage, the uncertainty associated with degradation rates is very high, but it reduces drastically as more inspection data is collected. Significant impacts on the definition of maintenance cost allocation inside railway business models are discussed, especially for the case of Public and Private Partnerships. Moreover, potential impacts of this methodology in maintenance contracts are highlighted. For the case of a new infrastructure, it is proposed that maintenance costs assessments related to track geometry degradation are no longer assessed at the design stage based only on the prior probability distributions of the degradation model parameters, but renegotiated instead after a 'warm-up' period of operation based on their posterior probability distributions.

1. Introduction

A recent European research project (INNOTRACK) while conducting a survey to Infrastructure Managers (IM) concluded that risk analysis is not widely considered in life-cycle cost calculations and identified it as an area of improvement in life-cycle cost calculations (INNOTRACK, 2007). Moreover, several Best Practice Studies conducted by the Office of Rail Regulation (ORR) consisting of international visits to IM reported an expected decrease of existing maintenance costs in the order of 20–30% through the development of a risk-based approach to infrastructure maintenance (ORR, 2008). Considering that maintenance costs for rail track subsystem may represent 55% of total maintenance costs in the case of high-speed line system (López-Pita, Teixeira, Casas, Bachiller, & Ferreira, 2008), more research concerning rail track degradation may bring more cost-effective tools and ideas in rail track management, increasing ultimately railway transport competitiveness.

Previous research works have focused in maintenance strategies to optimize ballast tamping and renewal actions from a life-cycle cost perspective (Zhao, Chan, Roberts, & Stirling, 2006), without focussing on the uncertainty in degradation model parameters. A recent work included uncertainty aspects in life-cycle cost estimations for the rail component assigning probability distributions to reliability parameters (Patra, Söderholm, & Kumar, 2009). In terms of track geometry degradation, some studies tried to predict deterioration rates at the design stage based on the infrastructure features and operating conditions through multiple linear regression or other

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data mining technique, though no reasonable model was achieved (Esveld, 2001 on the work carried out by the Office for Research and Experiments (ORE) committee D 161).

Having said that, this paper puts forward a Bayesian model for rail track geometry degradation in order to assess the evolution of uncertainty through the life-cycle of the infrastructure. The model is run using inspection data from the main Portuguese rail line (Lisbon-Oporto line).

The Lisbon-Oporto line has a total length of 337 km, and it has been under a renewal process since 1996. The renewal works performed included a thorough improvement of the track bed bearing capacity and a complete renewal of track superstructure, incorporating monoblock concrete sleepers spaced by 60 cm each, rail UIC 60 and Vossloh fastening system with plastic railpads ZW 687 (vertical stiffness 450 kN/mm). The sample analyzed in the present study includes a series of inspection data of 1725 renewed track sections (200 m long). Unfortunately, reliable inspection data is only available from 2001 up to now. In terms of inspection conditions, it is conducted four times a year and in terms of operating conditions, this line has passenger train-sets running at a maximum speed of 220 km/h and freight train-sets running at 80 km/h. Information on infrastructure features such as the location of switches, bridges, stations and plain track, layout percentages in the track section (curves, spiral and tangent), curve radius and cant were collected for each track section.

2. Bayesian idea

Before the late 1980s, Bayesian approaches were only considered as interesting alternatives to the 'classical' statistical theory in stochastic modelling. However, as more powerful computers became widely accessible and as statisticians (re)discovered Markov Chain Monte Carlo (MCMC) methods in the early 1990s, Bayesian statistics suddenly became the latest fashion in modelling throughout all areas of science.

In fact, MCMC methods brought the generalization needed in the calculation of the posterior distribution, in particular for cases with non conjugate priors in which asymptotic methods do not apply. Physicists were familiar with MCMC methodology from the 1950s, at first through Metropolis, Rosenbluth, Rosenbluth, Teller, and Teller (1953) and later by Geman and Geman (1984). Nevertheless, the realization that Markov Chains could bring this generalization in Bayesian statistics only came with Gelfand and Smith (1990) and in more practical terms when a dedicated BUGS software (Bayesian Using Gibbs Sampling) became available (Lunn, Thomas, Best, & Spiegelhalter, 2000). For more details on the history of MCMC please see Robert and Casella (2008).

In short terms, Bayesian approaches diverge from classical statistical theory in the fact that they consider parameters as random variables that follow a prior distribution. This prior distribution is then combined with the traditional likelihood to obtain the posterior distribution of the parameters of interest. This combination of prior and data information is processed using the so-called Bayes' rule, providing a probabilistic mechanism of learning from data. Therefore, the calculation of the posterior distribution $f(\theta|x)$ of the parameters θ given the observed data x can be computed as:

$$f(\theta|x) = \frac{f(x|\theta)\cdot f(\theta)}{f(x)} \propto f(x|\theta)\cdot f(\theta) \tag{2.1}$$

The posterior distribution combines the prior distribution $f(\theta)$ of the parameters θ and the likelihood $f(x|\theta)$. The denominator in the expression above is the marginal distribution of the data $f(x)$ and it can be computed by integrating the numerator in the parametric space Θ:

$$f(x) = \int_{\Theta} f(x|\theta')f(\theta')d\theta' \tag{2.2}$$

Usually the target posterior distribution is not analytically tractable, though in some special cases (where priors are conjugate distributions for the likelihood) the resulting posterior distribution belongs to the same distributional family of the prior. In such cases, the parameters that define the posterior distribution can be easily calculated based on the prior parameters and some statistics from the data. In the general case (for non conjugate priors) we need MCMC simulation to assess the posterior distribution.

We can assess the posterior distribution $f(\theta|x)$ by sampling from a target distribution that is equal to $f(x|\theta)\cdot f(\theta)$ up to a normalizing constant $f(x)$. MCMC method is the appropriate algorithm to generate samples while exploring the parametric space Θ. Although for finite parametric spaces, the idea to introduce Markov Chains may seem intuitive, for continuous parametric spaces this idea implies the definition of a Kernel function to represent the conditional density of $\theta^{(i+1)}$ given the value of $\theta^{(i)}$. The idea is to build and simulate a Markov Chain $\{\theta^{(j)}, j = 1, 2, \ldots, N\}$ in a way that it converges in distribution to the posterior distribution $f(\theta|x)$, meaning that the equilibrium distribution of the selected Markov Chain is the posterior distribution. Many MCMC algorithms have been developed to perform in such a way: the two most popular MCMC methods are the Metropolis-Hastings algorithm (Metropolis et al., 1953) and the Gibbs sampling (Geman & Geman, 1984). We will not cover them in detail and redirect the reader to Andrieu, Freitas, Doucet, & Jordan (2003), Bernardo (2003) or any introductory Bayesian statistical book (Paulino, Turkman, & Murteira, 2003), or alternatively to a practical insight in WinBUGS (Ntzoufras 2009).

Having introduced the Bayesian idea, we may divide the Bayesian approach into four stages: model building or specification, calculation of the posterior distribution (with the appropriate method of computation), analysis of the posterior distribution and conclusions (inference concerning the problem under consideration). Note that in the first stage (model building), we need to identify the main variable of the problem, find a distribution that adequately describes it (while including other variables that may influence it) and specify the prior distribution and the likelihood of the model. Moreover, a very important step is specifying the prior distribution using a noninformative (or vague prior) or incorporating preceding known information, using old samples from problems under the same boundary conditions or from expert judgement. This process is usually called elicitation of the priors. In the next sections, we will follow as strict as possible, the four stages mentioned above to describe the Bayesian approach, but let us first discuss rail track geometry phenomenon.

3. Rail track geometry degradation

Track geometry degradation is usually quantified by five track defects: the longitudinal levelling defects, the horizontal alignment defects, the cant defects, the gauge deviations and the track twist. Although many infrastructure managers tend to sum up all these defects into a track quality index which is typically function of the standard deviations of each defect and train permissible speed (as reported in El-Sibaie & Zhang (2004) or Zhao et al. (2006)), the standard deviation for the short wavelength (3–25 m) of longitudinal levelling defects is still regarded as the crucial parameter for planned maintenance decisions as it is confirmed by a recent guide on best practices for optimum track geometry durability (UIC, 2008). Longitudinal levelling defects are defined as the geometrical error in the vertical plane, measured in millimetres from the