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Data-Driven Forecasting of Track Geometry Degradation

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Abstract

This paper presents a methodology to monitor the temporal evolution of the track longitudinal level. It is designed to be integrated into a condition monitoring system installed on in-service vehicles, and it relies on the sequential analysis of degradation time series. To estimate the expected growth of a defect, time-weighted linear regressions with different forgetting factors are computed at each iteration. This way, a probability density function of degradation trajectories is generated. Given predefined threshold amplitudes associated to maintenance interventions, the proposed methodology allows to predict the threshold-crossing times. The application to different defects recorded along the monitored railway line shows that the method captures non-linear degradation trends and progressively refines the forecast of the threshold-crossing time when new data are available. When implemented on in-service vehicles, the proposed strategy can provide useful information to support maintenance decisions.

Keywords: railway track geometry, condition monitoring, vehicle accelerations, longitudinal level, time-series, forgetting factor.

1 Introduction

With the continuous increase of traffic capacity, the time available to conduct inspections and operations necessary to maintain the track in healthy state is progressively being reduced. Therefore, even though track recording vehicles (TRV) are essential to monitor the railway track, in-service vehicles are progressively being instrumented with simple measurement systems suitable for continuous monitoring campaigns [1]. The aim of such monitoring systems should be that of supporting the current maintenance strategies, with daily information provided during every train passage, especially in those lines where TRV inspections are planned every three to four months.

Different strategies have been proposed in this field of research, which implement either data-driven approaches or model-based ones [2]. In the first case, suitable data-processing techniques are used to extract information about the track state, such as rms and peak values, wavelet analysis, band pass filters [3-5]. On the other hand, model-based techniques solve inverse problems: starting from the recorded acceleration data, they are able to reconstruct the input track irregularity. Popular examples are related to the adoption of Kalman filters [6-8].

In previous works, we developed data-driven methodologies that allow estimating the track geometry parameters of interest, combining regression models and vehicle accelerations. For instance, in [9-11] bogie vertical accelerations are used as inputs of simple and multiple regression models to predict the peak value of the longitudinal level. In [12-13], car body accelerations and Gaussian process regression are combined to estimate the peak value of longitudinal level, cross-level and alignment. The working principle of the designed condition monitoring systems can be visually represented by Figure 1a). The recorded vehicle accelerations are processed to compute statistical measures such as rms and peak values over track sections of predefined length (100 m). These are accurately associated to the corresponding track location adopting GNSS data and map-matching techniques [14]. At the training phase of the condition monitoring methodology, these indicators are used to realise the regression models previously mentioned. In the monitoring phase, accelerations recorded by the instrumented vehicle during its operations are used as inputs to the regression models, to provide daily estimations of the track geometry.

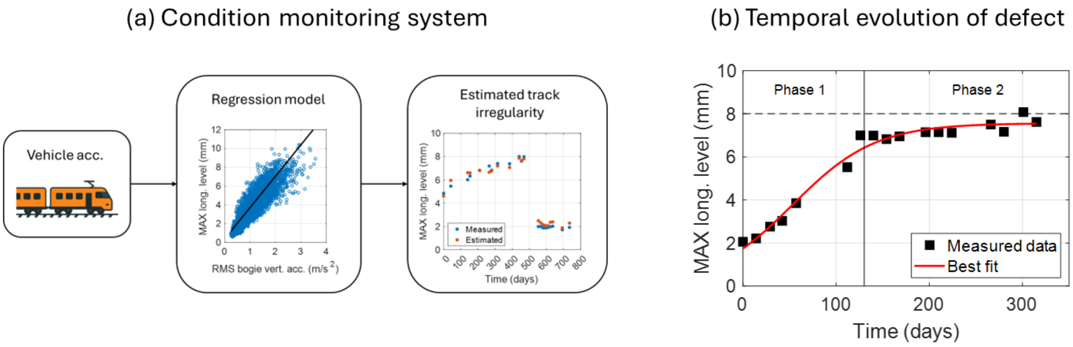

Figure 1: Condition monitoring system. a) working principle of the system, considering bogie vertical accelerations as input; b) non-linear temporal evolution of the peak value of longitudinal level (100 m track section). A vertical line distinguishes different degradation phases.

In previous works [9-11], we found that the temporal evolution of the defect amplitude can be significantly different depending on the specific track section under analysis.

Linear degradation trends were found in most of the analysed cases, but also non-linear ones were observed. Aa an example, Figure 1b) shows the peak value of the longitudinal level recorded by a TRV during its successive runs along a specific track section 100 m long (although accurate estimations were computed in [10], adopting bogie accelerations as input to the regression model). To better visualize the degradation of the track geometry, data are fitted with a logistic regression, which allows to recognise the non-linear evolution previously mentioned. In particular, a rapid evolution is observed up to day 130, named phase 1 in Figure 1b), after which a linear and slower degradation is observed up to the end of the monitoring period (phase 2).

The data reported in Figure 1b) well follow the theoretical track degradation law described by Guler et al. in [15], where three evolution phases are introduced:

- Phase 1: it occurs after major track operation (like tamping or renewal), and presents a rapid deterioration caused by initial settlement of the track;
- Phase 2: a linear growth rate is observed when the track conditions are stabilised;
- Phase 3: at the end of the lifetime, a final period with exponential deterioration rate is registered.

It is evident that both phases 1 and 2 characterize the defect in Figure 1b), while phase 3 is prevented by the occurrence of a maintenance operation around day 320 (as later shown in Section 3). In fact, these are always scheduled to prevent the track from entering in the final stage of the lifetime, adopting predefined amplitude thresholds. In Figure 1b), this condition is evidenced by the dashed line at 8 mm amplitude, which represents a first warning threshold according to the European Standard [16].

Starting from the experimental evidence provided by Figure 1b), in this paper a methodology to predict when track geometry defects will exceed predefined thresholds is presented. At this stage, longitudinal level measured by the TRV is used to develop the methodology. In the future application, when enough data will be available from the condition monitoring systems installed on in-service vehicles, the methodology will be applied during a continuous monitoring campaign. This way, it will be possible to verify its capabilities towards the implementation of condition-based maintenance strategies.

2 Methods

The example of Figure 1b) clearly shows that non-linear fitting of data available well reproduce the whole degradation of the track geometry. It is worth underlining that this type of analysis is possible given the posterior knowledge of the defect evolution. However, this representation is not suitable in the framework of continuous monitoring: new acceleration data will be available at every train run and should be used to provide daily estimations of the track longitudinal level. Therefore, the monitoring system should be able to identify any changes in the degradation rate as soon as new data are available (and not from the whole observations available a posteriori), to continuously correct the estimation of the threshold exceedance. Therefore, in this section we present the methodology designed to monitor the defect temporal evolution, assuming a progressive increase of data at disposal. It is here anticipated that the proposed strategy relies on a sequential analysis of degradation time series, relying on time-weighted regressions to estimate the expected defect growth.

To present the methodology, reference is made to Figure 2, where the temporal evolution of the peak longitudinal level measured by the TRV along another track section of 100 m is shown. In Figure 2, all data available are reported as a function of the recording time, to represent the posterior knowledge of the defect growth. At first, maintenance events were automatically identified as abrupt reductions of the defect amplitude and confirmed by the infrastructure manager. In this example, two distinct maintenance operations occurred approximately at days 350 and 520, highlighted by vertical red lines. Each period identified by maintenance operations show an evolution belonging to the "phase 2" category (slow linear degradation), even though data are not monotonically increasing. This is likely to be associated to measurement uncertainty (0.5 mm according to [16]). It can be also observed that the second operation proved to be more effective than the first one, since the peak value is restored to very small amplitudes of about 2 mm.

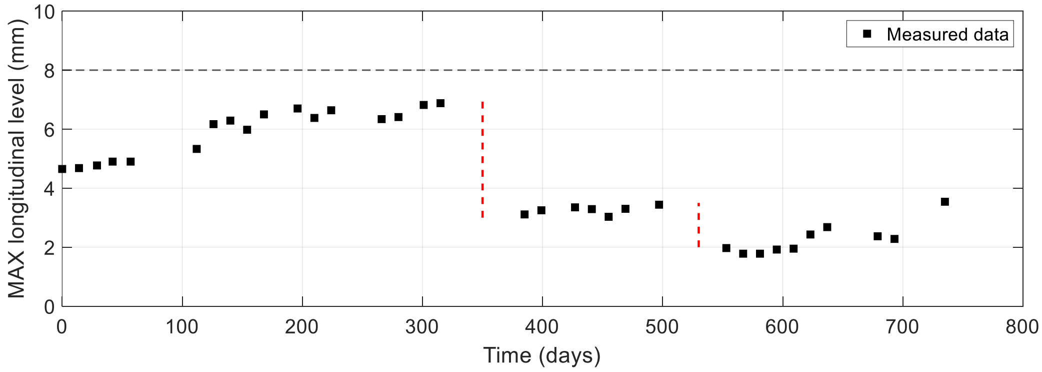

Figure 2: temporal evolution of the peak value of longitudinal level along 100 m window. Two maintenance operations registered at days 350 and 520 (shown as red dashed lines).

Each maintenance interval must be analysed independently to avoid mixing different degradation regimes. Hereafter, the first monitoring period (before maintenance operation at day 350) is considered, where a significant evolution of the defect is observed, from 4.5 up to 7 mm. In the considered interval, defect growth was modelled using a linear regression as follows:

$$d(t) = p_1\, t + p_2 \tag{1}$$

where $d(t)$ represents the defect amplitude at time t, p_1 is the slope of the regression line and p_2 the intercept.

At the beginning of the maintenance interval, an initial estimate of the degradation trend is provided considering a subset of the available measurements. A simple linear regression is performed, which provides a baseline estimate of the defect evolution.

This step of the methodology is represented in Figure 3a), where black markers identify the considered initial subset, while grey markers are used to report "future observations". The blue line represents the best fitting line, and dashed style is used to project the evolution up to the threshold value of 8 mm, providing a first estimate of the threshold-crossing time. In this study, 30% of the observations belonging to the interval are used as initial subset, which represents a reasonable dataset available at the early stage of monitoring. In a real case application, a monitoring period of 3 months could be considered to initialise the methodology.

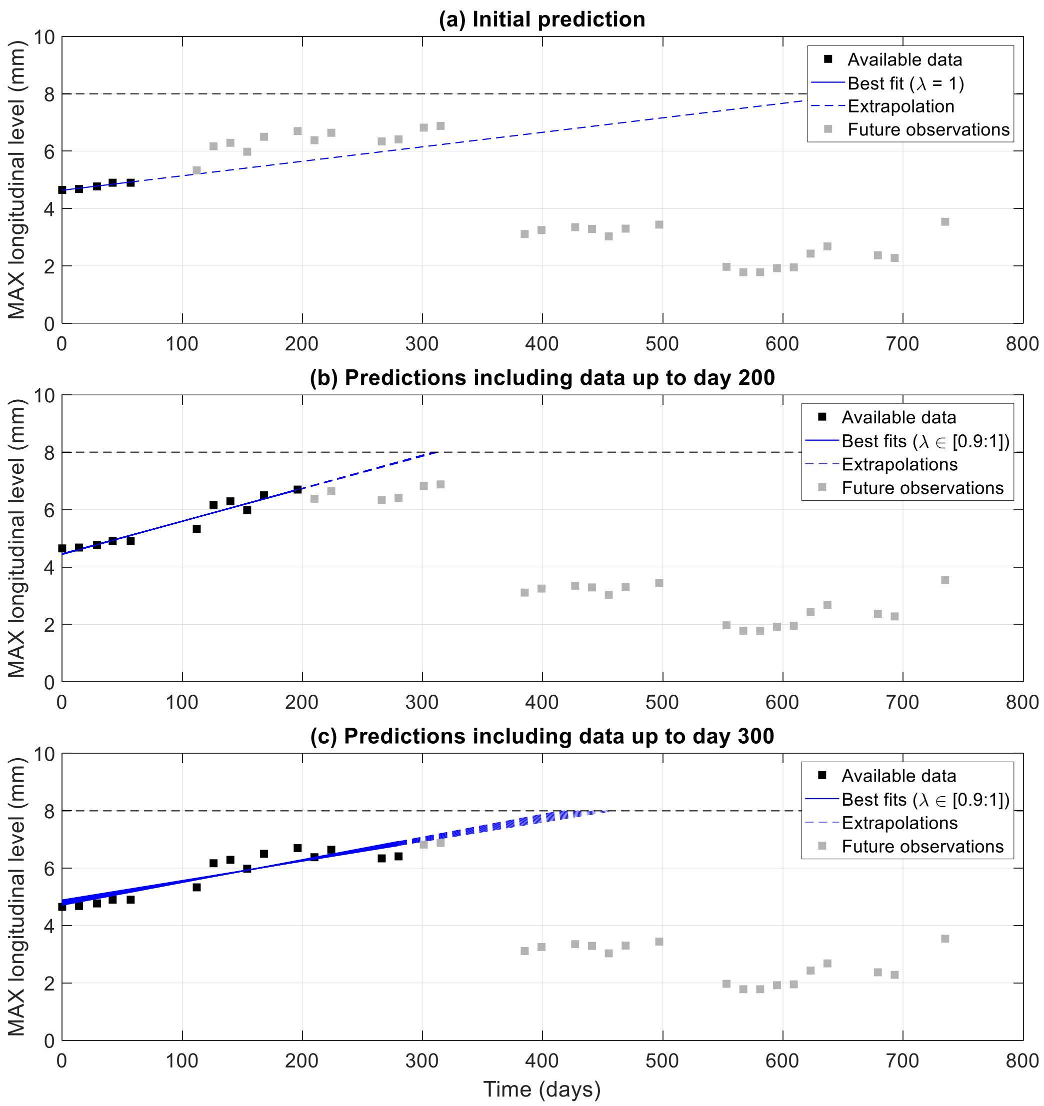

Figure 3: methodology for sequential analysis of degradation time series. a) initial subset, 30% of available data; time-weighted regressions considering b) data up to day 200; c) data up to day 300.

As additional measurements become available, the regression model is updated sequentially. At this step, a suitable strategy to account for possible changes in degradation is introduced, that relies on weighted regressions implementing the concept of forgetting factor λ. This parameter assigns higher importance to recent observations, while retaining information from earlier measurements. Therefore, the weighted linear regression was defined using exponentially decaying weights, defined as

$$w_i = \lambda^{N-i} \tag{2}$$

where λ is the user-defined forgetting factor, N is the number of available observations and i stands for the considered measurement. To exemplify, for $\lambda = 1$ all data equally contribute to the regression, which leads to a standard least-squares regression (as in case of the initial subset); for $\lambda < 1$, the influence of older data decreases exponentially. In this work, different values of forgetting factor λ were used to generate a distribution of degradation rates $p_1(\lambda, n)$ for every new measurement n available. In particular, λ varies between 0.9 and 1, with a step increase of 0.01. This way, the evolution of the degradation rate can be monitored over time introducing the uncertainty associated to different weights. This modelling choice is expected to effectively capture significant changes in the temporal evolution of the defect, supporting the scheduling of maintenance operations.

A first examples of forgetting factor application is presented in Figure 3b), where all data available up to day 200 are considered (black markers). Although hardly visible, eleven fitting lines are reported in Figure 3b), each one associated to a specific λ value. For the considered case, negligible differences are thus observed. A second example is proposed in Figure 3c) where all data up to day 300 are included. It is now evident that different forgetting factors λ produce different best fitting lines, and corresponding threshold-crossing times.

Once the basic principles of the developed iterative procedure have been presented, Figure 4 proposes the final result of the analysis. In particular, in Figure 4a), the time at which the fitted degradation line intersects the threshold of 8 mm are represented as coloured markers. Each marker corresponds to one regression obtained with a specific set of available data and a given forgetting factor. This data representation shows how the expected threshold-crossing time evolves as additional data become available. In fact, predictions based on earlier measurements are reported in blue, whereas predictions obtained from more recent data gradually shift towards yellow. In addition, just to ease the visualization, Figure 4a) also reports three fitting lines associated to the initial subset (blue line), data up to day 200 (in green) and data up to day 300 (in yellow), considering $\lambda = 1$.

To support maintenance-oriented interpretation of the results, the probability density function (PDF) was obtained from all the predicted threshold-crossing times (represented by the coloured markers). The resulting PDF is shown in Figure 4a) as a solid black line, in correspondence of the 8 mm threshold. The realised PDF provides a synthetic representation of the time when the defect is expected to reach the maintenance limit, given a certain amount of data.

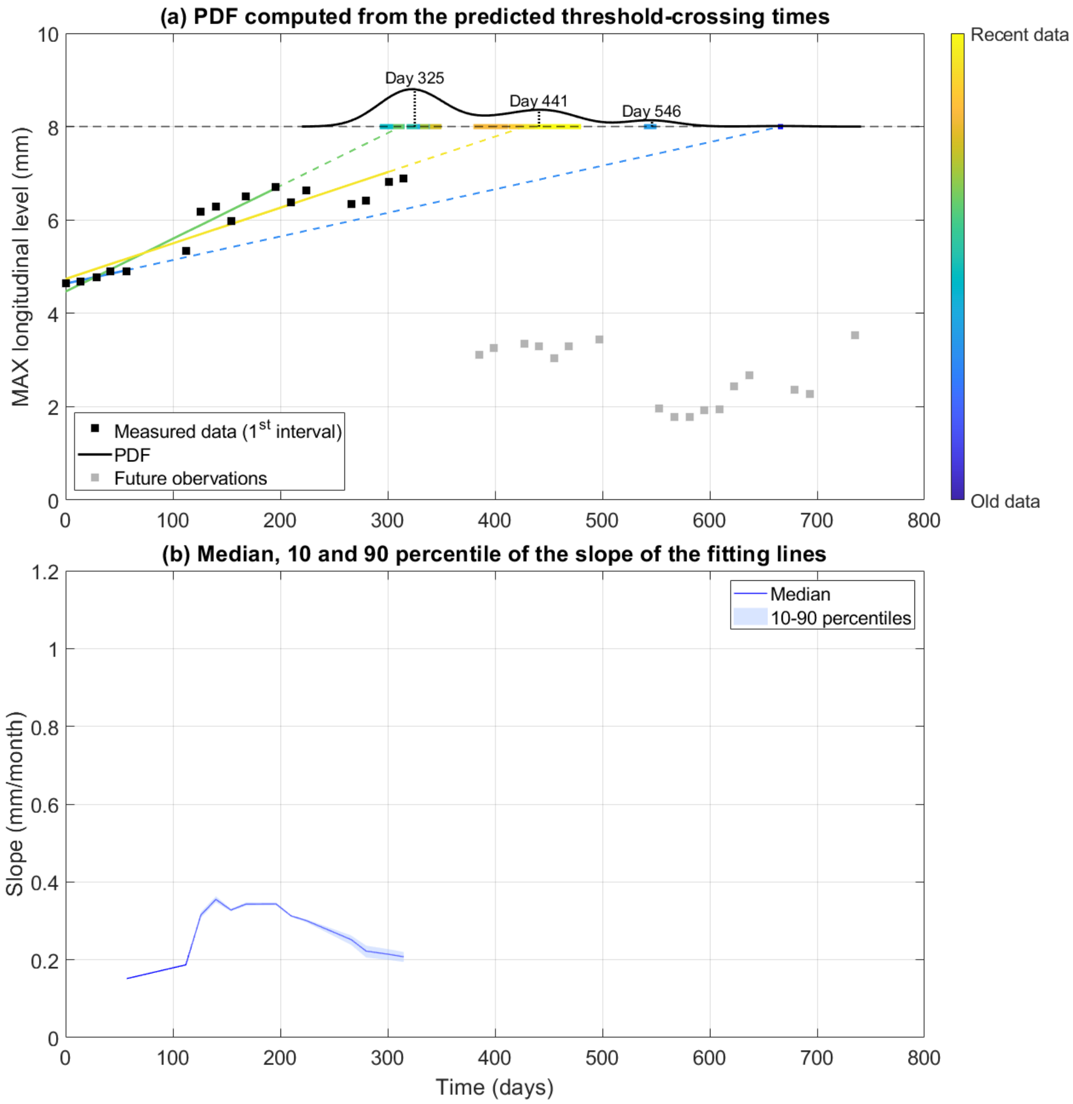

Figure 4: sequential analysis of degradation time series for defect 1. a) PDF computed from the predicted threshold-crossing times; b) temporal evolution of the degradation trend: median, 10 and 90 percentile of the slope of the fitting lines.

In the case under analysis, the PDF shows three local maxima, corresponding to different clusters of predictions, which are generated at different stages of the monitoring campaign. In fact, early predictions produce a peak far in time (day 546, associated to predictions reported in blue), given an initial slow evolution of the defect. Additional data show an increase in the degradation rate; as a result, the expected threshold-crossing time shift leftwards (day 325, green colour), generating a second local peak in the PDF. Finally, the most recent data provide the latest predictions of crossing the 8 mm threshold at day 441. To summarize, the presence of multiple local maxima is to some extent expected, as it reflects the progressive refinement of the prediction as soon as more recent data are available.

Finally, to complement the analysis, Figure 4b) shows the slope of the fitting lines $p_1(\lambda)$, expressed in mm/months. For each cluster of data, the median value is reported as a solid line, while the 10-90 percentiles are reported as shaded areas. Note that no percentiles are available in correspondence of the initial subset, since a single regression was evaluated. In the considered case, as already declared, no substantial variations in the evolution rate are observed, with p_1 ranging between 0.2 and 0.4 mm/months. On the other hand, the proposed methodology is showing consistency managing the uncertainty associated to early forecasts.

3 Results

In this section, the proposed methodology is applied to the same defect presented in Figure 1b). The obtained results are reported in Figure 5, where the first maintenance interval up to day 350 is considered. In fact, during the whole monitoring campaign, maintenance operation was carried out, as visible by the significant reduction of the defect amplitude (red dashed line, day 350).

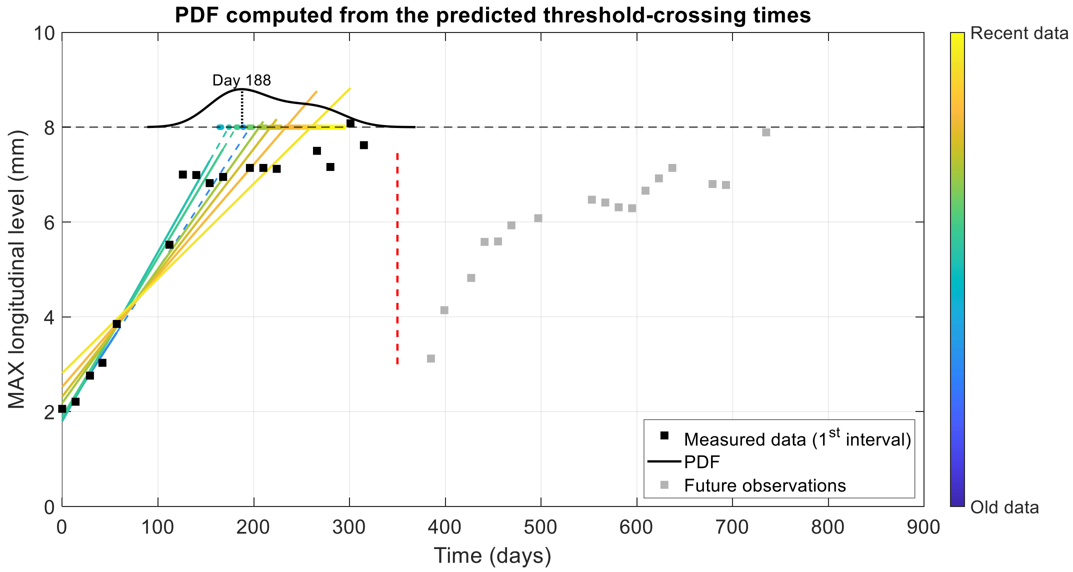

Figure 5: sequential analysis of degradation time series for defect 2, before maintenance operation carried out at day 350. PDF computed from the predicted threshold-crossing times.

As described in Section 1, the considered defect is characterized by a significant non-linear degradation trend, that was well represented (a posteriori) by a logistic regression. In Figure 5, to give evidence of the significant variation of the evolution, more fitting lines are reported (considering dataset with 50 days increase) relying on the same colour-bar previously introduced.

The PDF computed from the predicted threshold-crossing times shows a first peak at day 188, which is strongly affected by the early stage of the monitoring campaign, where a fast degradation is observed (phase 1 of Figure 1b)). Starting from day 130, more recent data clearly evidence a reduction in deterioration rate (phase 2), so that the predictions are shifted later in time.

On the one hand, the analysis confirms the capability of the methodology to adapt to sudden changes of defect growth. On the other, in this specific case, it is possible to observe that even stronger forgetting capabilities could be necessary to better trace the temporal evolution. Therefore, in the prosecution of this research activity, adaptive strategies to choose the range of variation of λ can be implemented, considering the most recent information about degradation rate. Finally, it can be observed that one datapoint is actually above the threshold of 8 mm (day 300), that is likely to be the reason for the maintenance operation later registered.

To complete the analysis, the second period ranging from day 350 to 800 is considered and reported in Figure 6a), together with the one previously analysed for comparison. Note that the same blue-yellow transition applies to each monitoring period, since they are individually analysed. The evolution of the defect during the second maintenance period resembles the previous one; however, the change in degradation rate seems to manifest earlier in time (already 50 days after the initial measurement of day 380). Correspondingly, the PDF computed considering $\lambda \in [0.9\ 1]$ is able to capture two maxima respectively at day 542 (associated to early predictions), and at day 723 (driven by more recent data). It is interesting to note that the last measurement available (black marker close to the 8 mm threshold) it is very close to the predicted crossing time.

Finally, Figure 6b) collects the temporal evolution of the degradation rate, with median and 10-90 percentiles, for both monitoring periods. Compared to the defect presented in Figure 4, a significantly higher degradation rate is here observed, that reaches values larger than 1 mm/month in the initial stages of the evolution, both before and after maintenance. This behaviour is coherent with the phase 1 evolution of track defects. Note that the non-monotonic increase of the degradation rate in the first period (days up to 120 of Figure 6b)) is likely to be associated to the initialization of the methodology. Conversely, the increase in the 10-90 band around days 200-300 can be associated to the larger dispersion of the measured data.

Finally, the two curves in Figure 6b) share similar trends before and after maintenance: if we consider days 150-300 and 450-550, the decrease in deterioration rate follows a similar reduction. This can be associated to the specific characteristics of the considered track section, in terms of ballast, subgrade, and morphology. After day 550 the deterioration rate tends to assume a constant value, which is characteristic of phase 2 (linear deterioration). In the considered case, values around 0.3 mm/month are observed, which are in agreement also with the defect analysed in Figure 4.

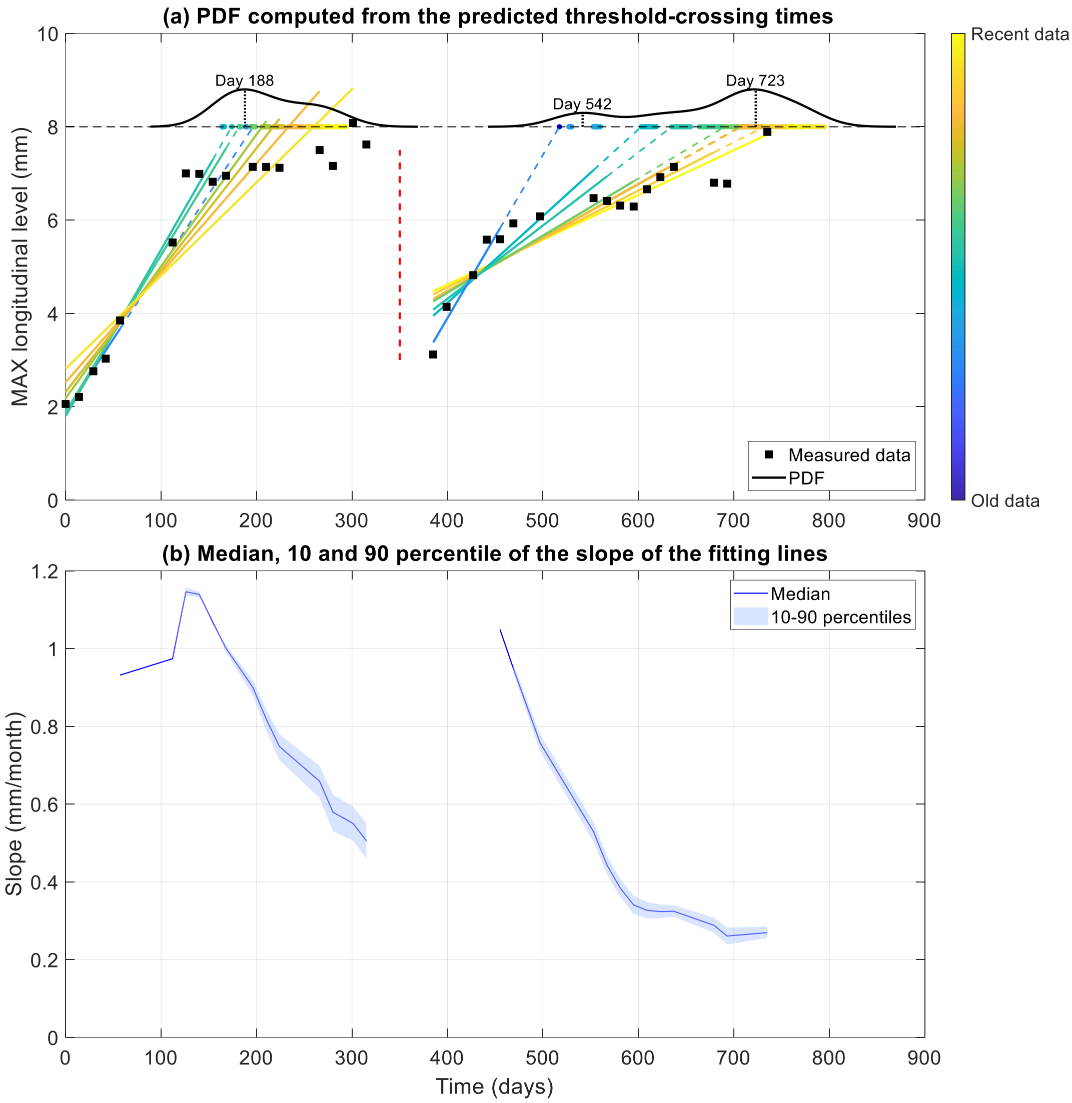

Figure 6: sequential analysis of degradation time series for defect 2, considering the whole monitoring period. a) PDF computed from the predicted threshold-crossing times; b) temporal evolution of the degradation trend: median, 10 and 90 percentile of the slope of the fitting lines.

4 Conclusions and Contributions

In this paper, a methodology to monitor the temporal evolution of the track longitudinal level is presented, which relies on the sequential analysis of degradation time series. Time-weighted linear regressions with different forgetting factors are computed at each iteration of the methodology, which allows to estimate the expected growth of a defect. Starting from the predicted threshold-crossing times, the probability density function of degradation trajectories is generated, which defines the probability to reach the predefined threshold amplitudes associated to maintenance interventions, given new data available during the monitoring period.

The methodology was applied to two different longitudinal level defects recorded along the considered railway line. In the first case, a defect characterized by an almost linear degradation trend was analysed. The methodology progressively refines the forecast of the threshold-crossing time when new data are available. When applied to the second defect, the method was able to capture its non-linear temporal evolution. In the end, when implemented on in-service vehicles, the proposed strategy can provide useful information to support maintenance decisions.

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