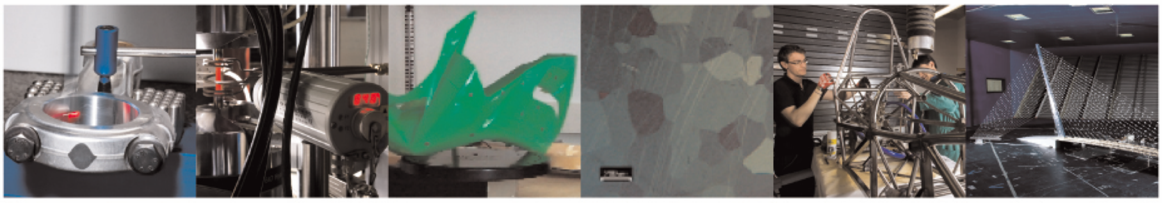
DIPARTIMENTO DI MECCANICA



Condition monitoring of vertical track alignment by bogie acceleration measurements on commercial high-speed vehicles

Ivano La Paglia, Marco Carnevale, Roberto Corradi, Egidio Di Gialleonardo, Alan Facchinetti & Stefano Lisi

This is a post-peer-review, pre-copyedit version of an article published in Mechanical Systems and Signal Processing. The final authenticated version is available online at: http://dx.doi.org/10.1016/j.ymssp.2022.109869

DIPARTIMENTO DI MECCANICA ■ POLITECNICO DI MILANO
via G. La Masa, 1 ■ 20156 Milano ■ EMAIL (PEC): pecmecc@cert.polimi.it
http://www.mecc.polimi.it
Rev. 0

Condition monitoring of vertical track alignment by bogie acceleration measurements on commercial high-speed vehicles

Ivano La Paglia[a], Marco Carnevale[b], Roberto Corradi[a], Egidio Di Gialleonardo[a], Alan Facchinetti[a], Stefano Lisi[c]

[a] Politecnico di Milano, Dipartimento di Meccanica,
Via La Masa 1, 20156 Milano, Italy;

[b] Università degli Studi di Pavia, Dipartimento di Ingegneria Industriale e dell'Informazione,
Via A. Ferrara 5, 27100 Pavia, Italy;

[c] Rete Ferroviaria Italiana S.p.A, Direzione Tecnica,
Piazza della Croce Rossa 1, 00161 Roma, Italy.

Corresponding author: Ivano La Paglia; Politecnico di Milano, Dipartimento di Meccanica, Via La Masa 1, 20156 Milano, Italy; email: ivano.lapaglia@polimi.it; tel: +39 02 2399 8407

Abstract

The paper describes a methodology for condition monitoring of rail track, which exploits acceleration measurements recorded by in-service high-speed vehicles. Estimates of the vertical track alignment are computed from bogie vertical acceleration with suitable linear regression models, relating synthetic RMS indicators representative of vehicle dynamics to track geometry parameters recorded by a diagnostic train. Two different linear models have been introduced, specifically devoted to the investigation of the overall track quality (by means of the RMS of the geometry parameter) and to the identification of isolated defects that may require maintenance intervention (through the track geometry peak value). The proposed solution has been specifically designed for high-speed applications, where trains travel at constant maximum speed for most of the journey. The methodology has been tested and validated against direct measurements taken by a diagnostic train. It allows to correctly reproduce the evolution with time of the railway line defectiveness, both in case of energy content and peak value. This result poses the basis for the development of methodologies for track condition-based maintenance.

Keywords

Condition based maintenance, rolling stock-based diagnostic system, vertical track alignment.

1 Introduction

Rail transport is increasingly becoming a key-player both in the European and worldwide transport policies, especially due to the urgency for a significant reduction of CO_2 emission. Consequently, the traffic growth is leading to a reduction of the time available to carry out inspections of both vehicle and track conditions. This challenge serves as an opportunity for the industry to invest in new technologies. In order to ensure the system safety and reliability, and to efficiently plan maintenance interventions, Condition Monitoring (CM) and

Condition Based Maintenance (CBM) of railway infrastructure are currently becoming desired tools for both railway operators and infrastructure managers.

Up until today, dedicated track recording vehicles (TRV) have been adopted to monitor the quality of the infrastructure, by means of periodic runs along the rail network to gather track geometry parameters by direct and dedicated measurements. This solution has been widely used, being effective in keeping system safety steadily under control. Nonetheless, it is often unable to provide a continuous flow of data to monitor the evolution with time of geometry parameters. Conversely, the development of modern electronics and more compact and robust measuring devices installed on in-service commercial trains would allow to drastically increase data availability. As a matter of fact, new generation trains are usually already equipped with various sensors for vehicle diagnostics that can be usefully adopted also for infrastructure monitoring purposes, integrating the information given by dedicated track recording vehicles. In this respect, the aim of the present research is the design of a system able to provide estimations of track defects' magnitude and evolution from onboard dynamic measurements on the commercial fleet. In this paper the focus is on vertical track alignment for high-speed application.

Several research works have been carried out in recent years for identifying the most appropriate measuring setup to be adopted in the field of infrastructure condition monitoring using in-service vehicle. The layout of the sensors, ranging from carbody to bogie and eventually axlebox-mounted sensors [1], is strictly dependent on the aim of the application, in terms of the wavelength of the track geometry defects of interest: the shorter is the wavelength, the closer the measuring system should be to the wheel/rail interface, since higher frequencies are filtered at every stage of suspension. Axlebox accelerometers can be used to measure short wavelengths' contribution to the vertical track irregularity (i.e. rail corrugation or rail roughness) [2][3], but may suffer of reliability issues as they are subjected to extremely high acceleration (in the range of hundreds of g). As a result, attempts to monitor track irregularity have been carried out by means of bogie-mounted accelerometers [4][5] and pitch and yaw rate gyroscopes as well [6]-[8], with benefits from the primary suspension filtering effect, provided that the attention is devoted to wavelengths longer than the bogie wheelbase. Finally, in the field of track defect identification, attempts to monitor the track irregularity have been made also through accelerometers installed on the carbody [9][10]. However, the possibility to adopt carbody-mounted sensors to estimate the track conditions strictly depends on the defects' wavelength and vehicle speed being considered, due to the filtering effect introduced by the secondary suspension system. With this regard, data measured on the carbody appears suitable mainly for low-speed applications, especially when considering the wavelengths relevant for running safety, i.e. those between 3 and 25 m (addressed as D1 range [11]).

From the point of view of the methodologies for track condition monitoring, model and signal-based techniques [1] can be adopted, depending on the degree of detail needed and on the admitted effort and complexity. Condition monitoring methodologies can indeed pursue different objectives: at first, the identification of defect existence along the line can be considered. Instrumented vehicles proved to effectively recognise the presence and rise of defects by well distinguished signatures in the measured signals. For instance, wavelet transform has been successfully adopted to identify track corrugation in [12][13]. An application of the wavelet based multi-resolution analysis (MRA) proved to be able to distinguish track irregularity, corrugation and crack contributions to the overall carbody vertical acceleration [14]. In the same field of research, a comparative analysis between Continuous Wavelet Transform (CWT) and the Hilbert-Huang Transform (HHT) showed the latter to be more effective in detecting the presence of track defects [15]. To recognise the presence of a defect along the railway track, a comparative analysis of different features extracted from simulation data and various change-detection techniques has been conducted, showing the energy content of the signal to better reproduce the track variation [16]. However, this methodology showed to be sensitive to vehicle speed uncertainty in [17], where it was considered as a reference to prove the capability of Multiple Vector AutoRegressive Models to detect track deterioration from onboard acceleration data. In a second application, the same authors of [16] investigated the possibility to combine acceleration data gathered by a fleet of light-trains, showing data fusion of carbody acceleration to be suitable for a precise localization of a defect [18]. In any case, all these methodologies may fail to identify defect typologies that haven't been a priori defined and their use to monitor defect evolution can be not straightforward.

A step forward to the development of track condition monitoring techniques would require an estimation of the magnitude of the defects. Synthetic indicators of the geometry parameter of interest can support the assessment of track quality, in particular of its evolution over time, with the possibility to adopt a reduced measuring setup with relatively simple data processing. To this aim, the standard deviation of the track defectiveness can be regarded as a suitable parameter to be monitored. A correlation study between track irregularities and vehicle responses at several location along the vibration transmission path has been carried out in [19], showing a strong correlation between the standard deviation of the wheel-rail vertical force dynamic contribution and the inertia force of the unsprung mass. An attempt to monitor the track geometry degradation on the Malmbanan Swedish heavy haul line has been made in [20], by means of the standard deviation and maximum depth of the longitudinal level. The two research works listed above demonstrate on the one hand the existence of a correlation between inertial measurements on the vehicle and the track geometry [19]; on the other, the possibility to monitor the track condition adopting synthetic indicators computed from the TRV measurements [20]. In the present paper, these two outcomes are combined to provide an estimate of the track conditions from acceleration measurements on a commercial vehicle, adopting synthetic indicators during a long term monitoring campaign.

Finally, more sophisticated techniques to reconstruct the track profile solving inverse problems have been presented, as an example adopting a Kalman filter [21]. Other attempts to reconstruct the track geometry on high-speed Shinkansen trains from axle-box mounted vertical accelerometers have been carried out [14], where the signals have been double integrated and treated with a 10 m versine processing. The validation of the results against measurements taken by a dedicated TRV showed a satisfactory agreement [22]. In [5], a cross entropy method is applied to infer the track longitudinal level that best matches the response of the vehicle at simulation stage. Anyhow it is worth remarking that to improve the quality of the profile reconstruction a wide set of sensors is needed, as recognised in [23] where the combined adoption of carbody, bogie and axle-box mounted sensors allowed an accurate estimation of lateral and cross alignment. The adoption of such complex measuring setup is not compatible with the application on the vehicles of a commercial fleet. Moreover, the implementation of reconstruction methodologies considering an entire fleet would not be straightforward.

Out of the tasks listed above, this paper proposes a methodology for condition monitoring of the vertical track alignment, by means of bogie vertical acceleration measurements recorded by high-speed commercial trains. Specifically, the system is designed to:

a) localise a track defect,

b) estimate the defect magnitude,

c) monitor its evolution over time.

Given the target of the research, a key requirement to be addressed regards the design of a reduced measuring setup and relatively simple data processing, that can be therefore installed on a fleet of vehicles. Thus, the attention has been limited to the design of a methodology to estimate the defect magnitude in terms of synthetic indicators, such as rms and peak values, that are nowadays adopted by the infrastructure managers to schedule maintenance operations [27]. To this aim, suitable linear regression models have been designed, relating synthetic RMS indicators gathered by commercial trains, representative of vehicle dynamics, to track geometry parameters available from TRV runs. The attention has been limited to wavelengths belonging to the D1 range, in between 3 and 25 m. Considering that maintenance operations are typically performed on track sections of few hundred meters, the synthetic parameters are computed on a 100 m window. The proposed solution has been specifically designed for high-speed applications where the vehicle runs at constant speed for most of the service (i.e. 300 km/h in this case). The methodology has been tested and validated by means of acceleration data recorded by a diagnostic train during a reference period of 2 years along the considered high-speed line.

2 Methodology

Nowadays, maintenance operations are scheduled based on railway line geometry measurements periodically performed by special purpose diagnostic trains (at best every few weeks along the same line, depending on the line priority level). As soon as the measured parameter exceeds predetermined thresholds, corresponding signals are recorded in order to trigger the necessary evaluation or operation at specific portion of the line. Even though the time span in between subsequent diagnostic train runs allow to keep track geometry steadily under control, the possibility of relying on commercial trains to continuously monitor the line defectiveness may represent a cornerstone for maintenance management, increasing both the possibility of preventive actions and the effectiveness of maintenance interventions. Furthermore, when installed on an entire train fleet, the system will automatically identify false detections, with benefits in terms of redundancy and consistency of the data.

The peculiarity of a measuring system specifically designed to be installed on a commercial train shall be discussed, taking into account the possible need of instrumenting an already certified vehicle. This issue has a direct impact on the number of sensors to be installed, which should be kept as small as possible in order to comply with the available space and to reduce the impact on risk analysis. Thus, sensor layout results to be a compromise between the compactness of the solution and the capability of the measuring setup to acquire data which are meaningful for vehicle dynamics and suitable for infrastructure monitoring. As a result, accelerometers measuring along both the vertical and lateral direction can be installed at the centre of both bogies of the instrumented coach. A measuring setup permanently installed on a commercial train can be arranged as shown in Figure 1.

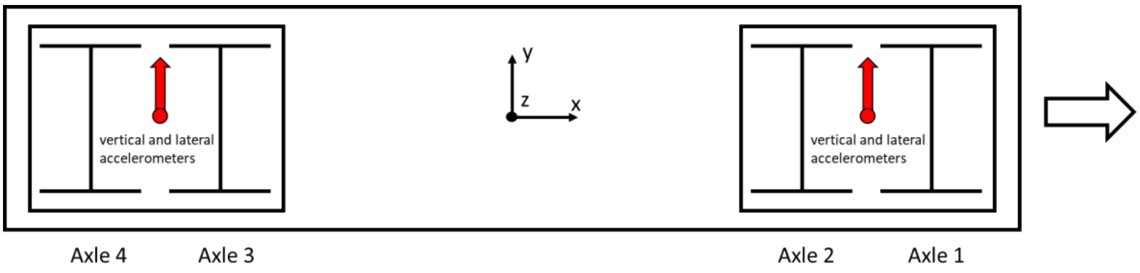


Figure 1. Measuring setup for condition monitoring application installed on commercial train. Vertical and lateral accelerometers installed at the centre of both bogies of the instrumented vehicle.

Once the measuring setup has been designed, a key issue to be addressed concerns with the definition of the dataset to be acquired. In principle, sensors data can be stored in terms of spatial histories, as soon as a proper correlation between time histories and train position along the line is realized. If this is the case, a significant amount of data would then be gathered and transmitted to the ground server for the analysis, so that particular care must be taken to prevent data processing and transmission unit overloads. Alternative strategies consist in the adoption of synthetic indexes representative of vehicle dynamics, which can be computed onboard and then transmitted to the ground server. This latter solution significantly reduces the amount of data to be managed, with benefits in terms of easiness of data transmission and management. Moreover, synthetic indexes extracted in a well specified portion of the line (whose size has to be carefully identified) ease the possibility to perform trend analysis and to monitor the evolution of diagnostic indicators with time, provided that they can be associated to the train position along the track with a reasonable accuracy, typically in the order of meters at worse.

A key requirement for railway infrastructure condition monitoring is represented by the capability of evaluating diagnostic indicators on signal windows triggered at the same milestone positions along the track for subsequent train runs, then associating the diagnostic indicators to the actual position where they are measured. To fulfil this task, enabling the possibility of overlapping and comparing signals coming from different trains' run, a dedicated geo-localization algorithm (based on GPS and odometry signals) has been designed, tested and validated in a high-speed application [24].

If on the one hand the layout of the sensors proposed in Figure 1 could be adopted either for main or high-speed lines, on the other hand diagnostic indicators to be computed onboard must be properly chosen depending on the specific target of the application, selecting the most meaningful indexes, pass-band frequency and window size. With this regard, a reference case has been identified to develop the proposed methodology. The attention is focused on high-speed applications, considering one single train-track system (i.e. a specific high-speed train running along the same line). The benefits resulting from this choice are mainly related to the possibility to design a speed independent methodology: along high-speed lines, during standard passenger service the train will perform runs at the same nominal speed, which is the maximum one allowed along that specific network. The service speed of the considered line is 300 km/h.

As for the rolling stock component, the new Frecciarossa 1000 high-speed train, recently put in service as the result of a shared project between several leading rolling-stock companies, has been identified as a reference case. A condition monitoring system is meant to be installed on this specific commercial train, as part of the work developed by the Joint Research Centre for Transportation established by Fondazione Politecnico di Milano. In light of its designing features, each bogie of the mentioned train has been equipped with a simple measuring setup useful for its running operation, similar to the one shown in Figure 1. Specifically, two different sets of sensors measure the bogie lateral acceleration: on the one hand, the active lateral suspension system requires bogie lateral acceleration to be measured; on the other, they are used as instability detector to ensure running safety. Furthermore, the measuring setup has been realized so as to measure bogie vertical acceleration as well. However, up until today, the results of the research activity have not yet fully been implemented on the commercial fleet, especially for what concerns the part related to the geo-localization system, windows triggering, and continuous data transmission to the ground server.

To cope with the lack of data coming from the commercial fleet, the acceleration measurements considered for the analysis presented in this paper are gathered, without loss of generality, from the same diagnostic train performing the geometry measurements along the considered railway line. In fact, the diagnostic train considered in this study is an out of service high-speed vehicle equipped with a dedicated set of sensors to measure both rail and overhead contact line geometry, as well as vehicle dynamics. In this respect, from vehicle dynamics perspective, there is no difference between the commercial trains of the fleet and this diagnostic train. Furthermore, railway line geometry is expected to be independent on the vehicle performing the measurements, as it is characteristic of the infrastructure itself. Conversely, some benefit rises from the possibility of relying on acceleration data gathered by a diagnostic train: in light of their special purpose aim, they are typically designed with a considerably higher number of sensors (as an example, bogie accelerations are measured in correspondence of each axlebox of the bogie) and they usually store spatial histories that can be processed as desired in order to compute diagnostic indicators of interest. To this aim, with reference to the measuring setup proposed in Figure 1, bogie accelerations acquired in correspondence of each wheelset in vertical and lateral direction have been processed so as to obtain an equivalent acceleration data at the centre of the bogies.

Once a reference case for the analysis has been identified and described, attention can be devoted to the peculiar characteristics of high-speed lines, along which maintenance interventions are often driven by the need to correct vertical track irregularity. Out of several rail geometry features that are periodically monitored by the diagnostic train to plan maintenance operation, specific attention because of its numerousness is devoted to the longitudinal level, which is a parameter defining the unevenness of the track along the top surface of the rails, in accordance with the reference standard EN 13848-1 [11]. In detail, different classification of the

parameter can be registered depending on the defect wavelength of interest. Specifically, longitudinal level in D1 range provides an insight of the rail unevenness for short wavelengths, in between 3 and 25 m.
As an example of the records gathered by diagnostic train, two different 100 m portions of the railway line under analysis are respectively reported in Figure 2a and Figure 2b. The figure shows not only the evolution with time of the longitudinal level measured along the left rail, but also identifies defects whose wavelength is typically in the order of 9-12 m, independently on whether they are distributed or isolated defects.

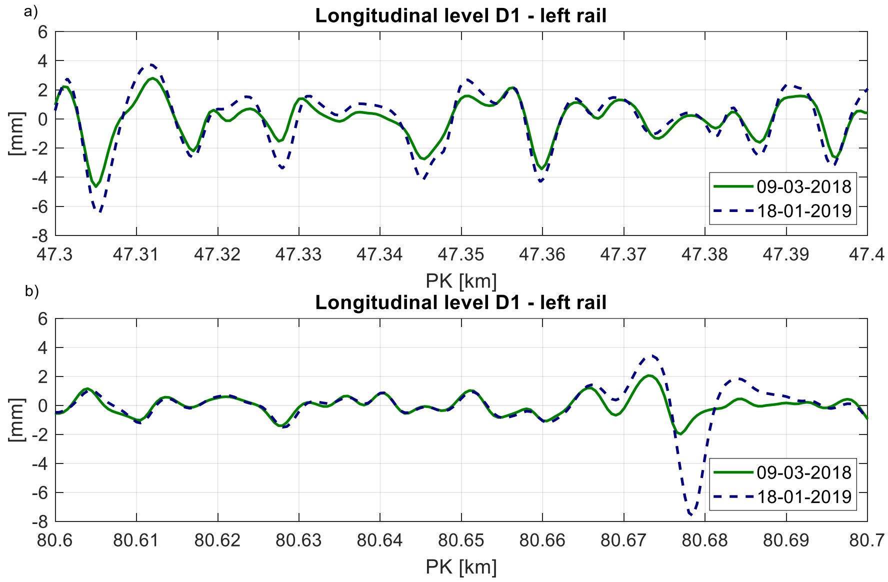


Figure 2. Spatial histories of the longitudinal level in D1 range (3-25 m) recorded on the left rail of the track, two portions of 100 m length. a) Examples of a distributed defect, b) example of an isolated defect.

It is worth mentioning that the results shown in Figure 2 have been obtained by properly geo-referencing the acquired data at the post-processing stage, so as to allow the comparison of the acquired signals. Odometry signal stored by the train is indeed insufficient for a precise geo-localization of data, as it suffers from drifts during braking and acceleration phases [24].

Once the geometry parameter of interest has been identified, synthetic indexes representative of the track quality can be finally defined. Specifically, given the measurements on both left and right rails, the mean longitudinal level has been computed at first, to provide an aggregate information of the line defectiveness. Secondly, the choice of the window size for the index calculation has been addressed. In light of the characteristic wavelengths of the longitudinal level in the D1 range (3-25 m) and the results highlighted in Figure 2 (9-12 m), a spatial window of 100 m has been selected for the analysis, the size being a trade-off between the need to guarantee to catch the defect inside the window itself, and to reduce the amount of data to be transmitted and processed as well. Finally, the root mean square (RMS) of the mean longitudinal level has been computed along the entire railway line, on each 100 m segment.
With the aim of identifying the most adequate acceleration parameter to be continuously monitored from the in-service train, the RMS of the track geometry indicator has been related to the RMS of the vertical and lateral bogie accelerations (along the same spatial window of 100 m) measured at the corresponding mileage position of the line. For the sake of clarity, notice that acceleration measurements have been considered in the low

frequency range of 0-40 Hz to be consistent with the defects' wavelength considered by the longitudinal level (3-25 m) at the target speed of the train.

Figure 3 shows the results of the comparison on a 10 km section of the railway line: the top diagram shows the RMS of the mean longitudinal level in the D1 range, while in the middle and bottom diagrams the RMS of the bogie vertical and lateral acceleration are respectively shown.

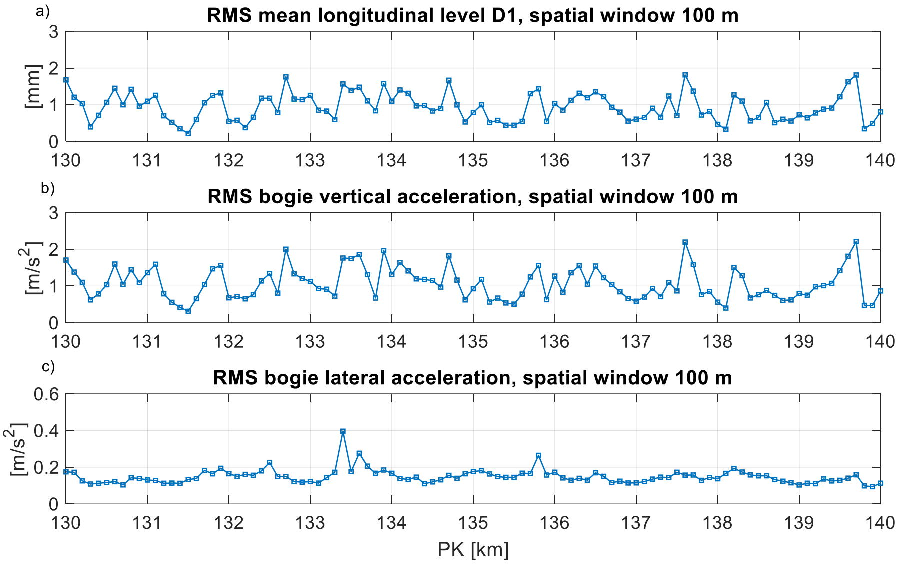


Figure 3. Synthetic indexes computed on a spatial window of 100 m as a function of milestone position. a) RMS of mean longitudinal level in D1 range (3-25 m); b) RMS of bogie vertical acceleration; c) RMS of bogie lateral acceleration.

By comparing the RMS of the geometry indicator to the RMS of bogie accelerations, a significantly high degree of correlation can be observed when considering the vertical acceleration. As an example, refer to the milestone position at 137-138 km, where a remarkable agreement between these two indexes can be highlighted. Even though a contribution of the lateral acceleration in correspondence of significant geometry RMS can be identified as well, as an example at the 133.4 km, no clear evidence of a systematic correlation seems to exist. As a result of this preliminary discussion, the RMS of bogie vertical acceleration has been considered as the only parameter representative of the quality of the rail track with reference to longitudinal level. Conversely, as already mentioned in [25], a direct correlation is not achievable when considering the bogie lateral acceleration and the rail alignment.

A necessary condition for track monitoring by means of acceleration measurements consists in the capability of the index to correctly reproduce the evolution with time, allowing trend analysis of the index itself. In order to verify whether the diagnostic indicator identified for the monitoring activity satisfies this requirement, Figure 4 shows the evolution with time of the RMS of the track geometry index (top diagram) together with the RMS of the bogie vertical acceleration (bottom diagram). Both indexes have been computed on a spatial window of 100 m, along a 5 km portion of the considered line travelled at the train maximum speed, in a time period of approximately 6 months.

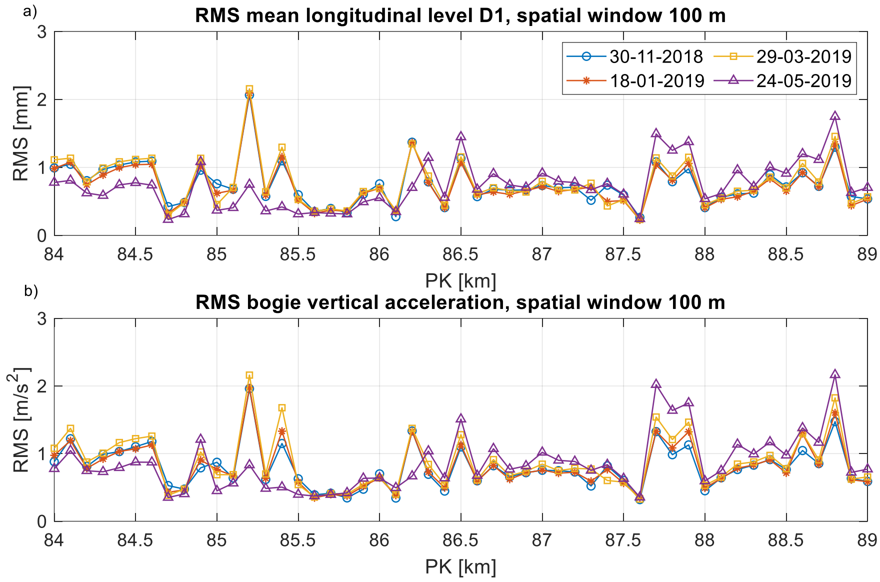


Figure 4. Evolution with time of the synthetic indexes chosen for the analysis as a function of line mileage position. a) RMS of the mean longitudinal level in D1 range (spatial window of 100 m); b) RMS of the bogie vertical acceleration (spatial window of 100 m).

At first, the strong correlation between track geometry and bogie vertical acceleration recorded at the same time can be highlighted by comparing Figure 4a and Figure 4b. These outcomes further confirm the results achieved in Figure 3, along a different portion of the same railway line. As an example, considering the milestone position 87.5-88 km, a significant increase of the RMS of both track irregularities and bogie vertical acceleration is observed in approximately 6 months of monitoring activity. Furthermore, maintenance operation can be observed at km 85-85.5, where the track irregularities show a remarkable reduction from 2 to 0.8 mm. Correspondingly, a drastic reduction of the bogie acceleration RMS is registered along the same mileage portion. The described outcomes clarify that, in principle, the evolution with time of the infrastructure status can be effectively monitored by means of acceleration measurements, as far as this set of data can be properly related to the corresponding defectiveness of the line, in order to assess whether the acceleration is approaching a corresponding threshold value for the rail geometry.

The significant correlation observed in Figure 3 and Figure 4 can be explained considering the Frequency Response Function (FRF) between the vertical track alignment and the bogie vertical acceleration. To this aim, a simplified linear model of the vehicle is adopted (Figure 5a) considering the DoFs corresponding to the vertical and pitch motions of the carbody, the vertical motions of the bogies and the vertical track alignment as an imposed displacement to the lower extremities of primary suspensions, taking into account the phase shift between the excitations to the two bogies. Both secondary and primary suspensions are represented as spring-damper elements, the dampers being introduced as Maxwell elements, accounting for the stiffness of the end mountings. Figure 5b shows the Bode diagram of the obtained FRF, considering the vertical track alignment as input (angular frequency $\Omega = 2\pi\, V/\lambda$, with V corresponding to the vehicle speed and λ to the irregularity wavelength) and the vertical acceleration of the front bogie as output. The dashed lines delimit the D1 range (λ=3-25 m) considering the reference speed of 300 km/h. For comparison, an experimental estimate of the frequency response function made up using the same experimental data (before pre-processing them to compute the synthetic indexes) is also provided. The estimated values are reported using red star markers for frequencies consistent with D1 range and only when the corresponding coherence function is larger than 0.9. It is apparent that the FRF gain is almost constant in the frequency range of interest, except for the small portion at the lower frequencies (corresponding to the longer wavelengths) affected by the resonance of the bogie on the primary suspension, where a certain attenuation occurs. In fact, the zeros in the origin corresponding to the double derivation introduced by the acceleration measurement are compensating the second order filtering action introduced by the primary suspension. Conversely, the contribution of the low frequency outside the range of interest is considerably attenuated, the overall system acting as a high-pass filter.

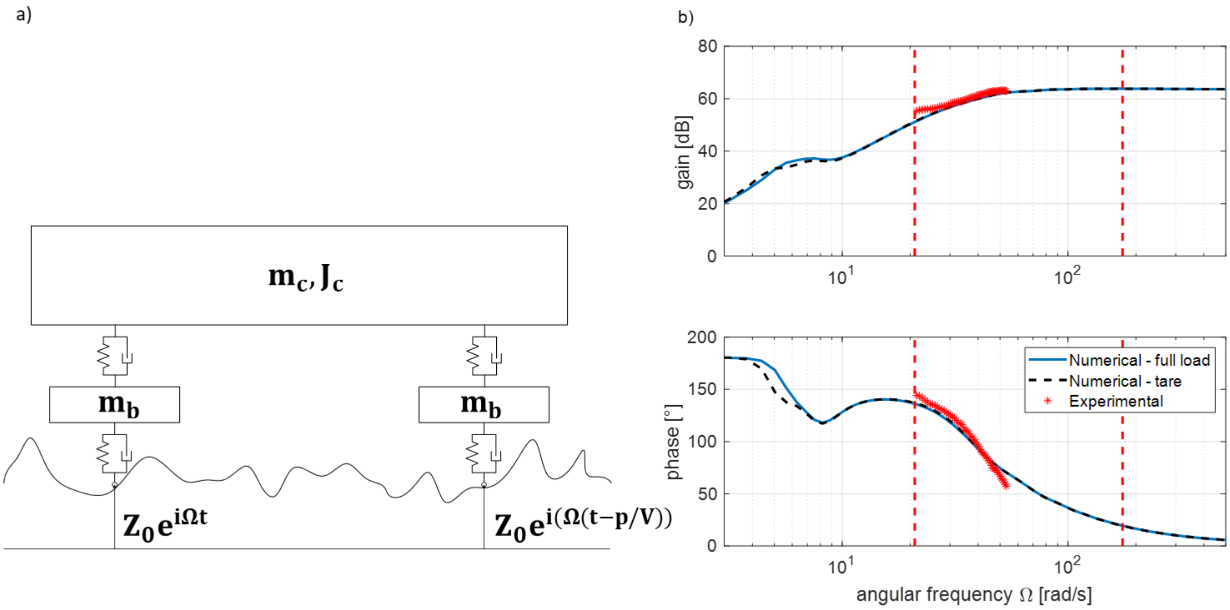


Figure 5. Frequency Response Function between the vertical track alignment and the vertical bogie acceleration. a) Reference model for the FRF evaluation. b) Bode diagram of the FRF between vertical track alignment and vertical acceleration of the front bogie. Solid and dashed lines refer to the full load and tare vehicle configurations; star markers refer to experimental data.

It is worth mentioning that the effect of the vehicle load on the considered FRF is negligible, at least in the frequency range of interest, as shown in Figure 5b. This is very important when considering the application to a commercial vehicle, since the load condition may vary from tare to full load. Moreover, the observed behaviour is common to different vehicles, considering that the design is usually very similar in terms of natural frequencies associated with carbody and bogie bouncing. On the contrary the running speed has a key role: when reducing the speed, the range of interest is moving to lower frequencies and the attenuation portion inside the range is becoming wider. Thus, the result is significant for high-speed application (300 km/h) at constant speed.

In light of these results and discussion, reported in Figure 3 to 5, the methodology proposed in this paper relies on the definition of linear regression models relating the RMS of the acceleration data and a geometry parameter computed from the longitudinal level acquired by the diagnostic train. Although a simple modelling strategy has been adopted, it retains the direct correspondence between acceleration data gathered from a railway vehicle and the track geometry conditions measured along the line.

For the sake of consistency, both synthetic indexes have been computed along the same spatial window of 100 m at the corresponding mileage position. In order for the models to be statistically relevant and representative of several operative conditions (new and worn wheel profile as well as rail track), data acquired during a significant time period along the considered line should be gathered. In addition, it is worth reminding that high-speed lines are travelled at the maximum allowed speed for the entire trip, exception made for the acceleration and braking phases required to approach and leave railway stations. For this reason, the linear regression models have been realized considering all the data at disposal during the period in between March 2018 and August 2019 along the considered high-speed line (200 km approximately), as detailed in Table 1. Figure 6 shows an example of regression line between the RMS of the mean longitudinal level and the RMS of bogie vertical acceleration. Note that the obtained regression line is characteristic of the considered train-track system. For instance, a new linear model should be introduced when considering a different trainset running along the same high-speed line. Similarly, in case the train is running on others high-speed lines with different nominal characteristics (or at different target speed), new models should be accounted for.

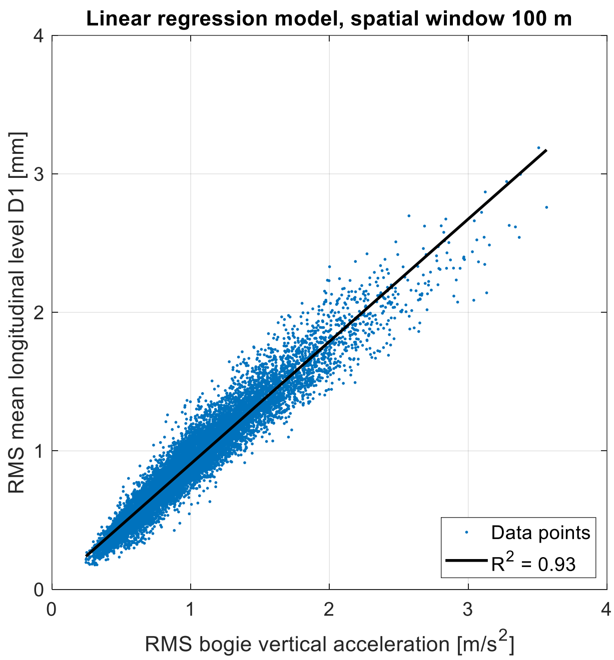


Figure 6. Linear regression model for railway line geometry estimation: RMS of mean longitudinal level in D1 range as a function of the RMS of bogie vertical acceleration (spatial window of 100 m). Data gathered along the entire railway line at the maximum speed (300 km/h) during the monitoring period in between March 2018 and August 2019 (training phase).

The linear model shown in Figure 6 presents a remarkably high degree of correlation between the considered data, as testified by the R^2 coefficient of determination of 0.93 and by the reduced dispersion of the data around the best fitting line. This leads to relevant implications for the exploitability of the methodology proposed:

when the measuring system will be installed and running onboard of commercial trains, the RMS of bogie vertical acceleration, recorded daily along a specific railway line, could be used as the input for the linear regression model to get an estimation of the railway line geometry. All data gathered from the fleet at the target speed could be considered; conversely in case a specific train was running at a different speed along the considered portions of the line, data could be discarded. Even in the latter case, compared to the direct geometry measurements periodically recorded (monthly/fortnight) by dedicated track recording vehicles, a continuous flow of data for track monitoring may then be achieved, thus enabling a remarkable improvement in the management of railway infrastructure.

In order to summarise the proposed methodology a flow-chart is provided in Figure 7. Two steps are envisaged; the first is the training phase, previously described, that combines acceleration data from commercial trains with track geometry recorded from the diagnostic train in order to develop the linear regression model; the second takes advantage of this predictive model to perform the track condition monitoring. Table 1 summarises the data considered for both the training and validation phases in terms of reference periods and number of train runs available.

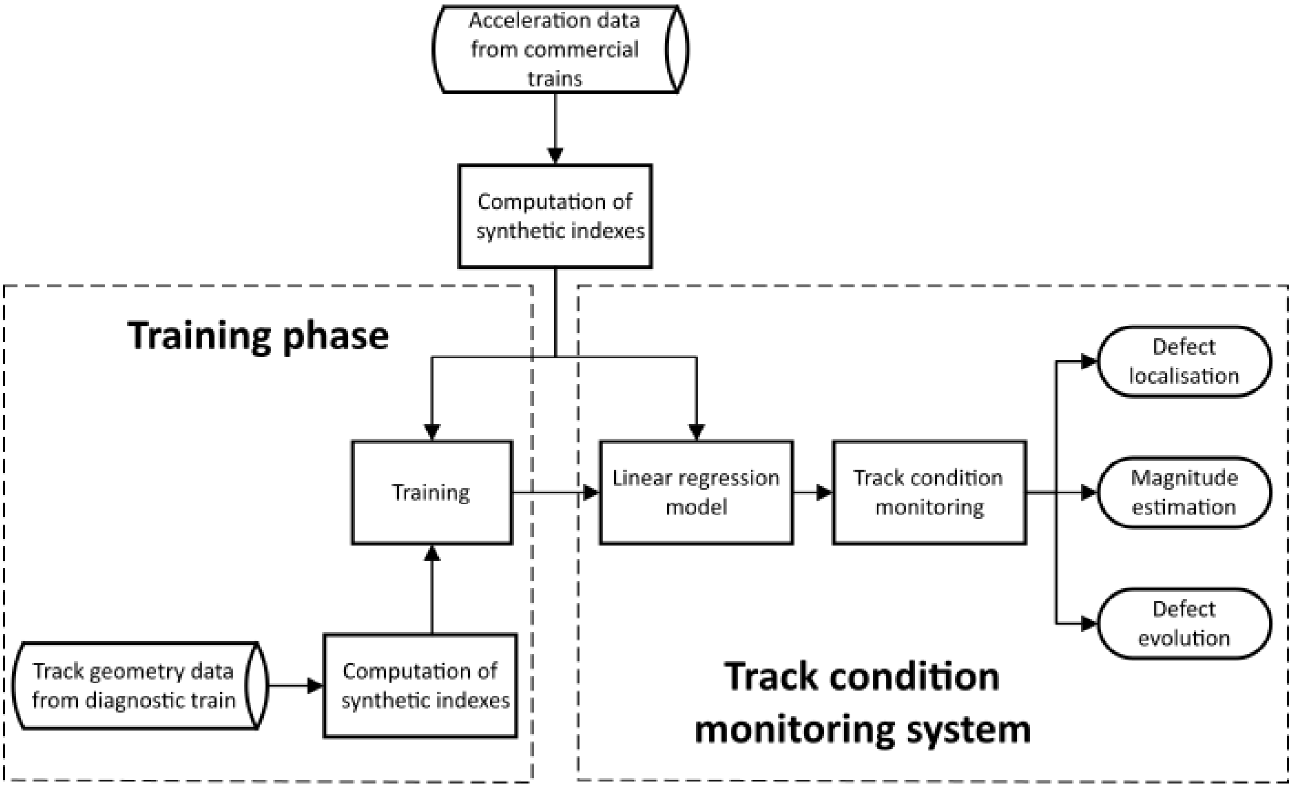


Figure 7. Flowchart of the proposed track condition monitoring system.

	Reference period	**Number of train runs**
Training phase	March 2018 – August 2019	12
Validation phase	September 2019 – March 2020	10

Table 1. Summary of the data distribution along the training and validation dataset. All acceleration data gathered at the train maximum speed of 300 km/h.

With reference to Table 1, a remark can be made regarding the data stored in the two phases. Notice that a similar number of train runs defines the two periods (12 and 10 respectively), despite the training phase being significantly longer. This is a consequence of the data coming from the track recording vehicle: more geometry than acceleration data are actually at disposal since all available geometry data could be exploited, whereas only acceleration data at the maximum train speed have been considered, being the vehicle dynamics and the relationship between geometry and acceleration strictly dependent on speed.
The performances of the designed tool will be evaluated in the next section.

3 Model validation and results discussion

This section investigates the capability of linear regression models to estimate the railway line geometry and to predict its evolution with time, only based on the acceleration data recorded. By exploiting the acceleration data in combination with a pre-built linear model like the one shown in Figure 6, an estimation of the track geometry can be computed. Two different analyses are proposed. The former (Section 3.1), relying on the linear model described in Section 2, considers the RMS of the railway line vertical alignment to provide information in terms of the overall line defectiveness. The latter (Section 3.2) focuses instead on local defects along the line, by considering the peak value of the longitudinal level (MAX in the following). In the current standard EN 13848-6 [26] and related adopted procedures, this value is exploited to drive maintenance interventions when predefined threshold values are exceeded.
The model outputs are then compared to the direct measurements of track geometry performed by the dedicated track recording vehicle, to verify to what extent and with which degree of accuracy the proposed methodology can be used to monitor track evolution. For the sake of clarity, it is worth mentioning that the proposed methodology can be extended to different combination of synthetic indexes and various spatial windows for index calculation (25 m in the following) as well.

3.1 Evaluation of RMS of track mean longitudinal level through RMS of bogie vertical acceleration

Out of the indexes proposed, attention has been devoted at first to the energy content of the considered diagnostic indicators, by relating the RMS of the bogie vertical acceleration to the RMS of the railway line geometry. Provided that the mean value of the considered signal is considerably small, the analysis can be regarded as an indication of the standard deviation of the railway line geometry. In accordance with the methodology presented in Section 2, a linear regression model realized on spatial windows of 100 m has been considered for the analysis.
The proposed methodology has been tested on specific portions of the railway line. In order to select them out of the entire railway line, milestone positions with high level of vertical bogie acceleration RMS and a significant evolution with time have been considered. As an example, Figure 8a reports the RMS of bogie vertical acceleration evaluated in 6 spatial windows of 100 m. The RMS of the mean longitudinal level evaluated at the same mileage position is reported in Figure 8b. For visualization purposes, only geometry data

with corresponding acceleration measurements have been shown out of the records of the whole monitoring period, as reported in the legend. A significant evolution with time is identified in the increase at milestone position 47.3 km both in the acceleration RMS of Figure 8a and in the corresponding railway line geometry of Figure 8b. It is worth reminding that the high repeatability of the results and the strict correspondence between peaks is enabled by the application of a precise geo-localization algorithm.

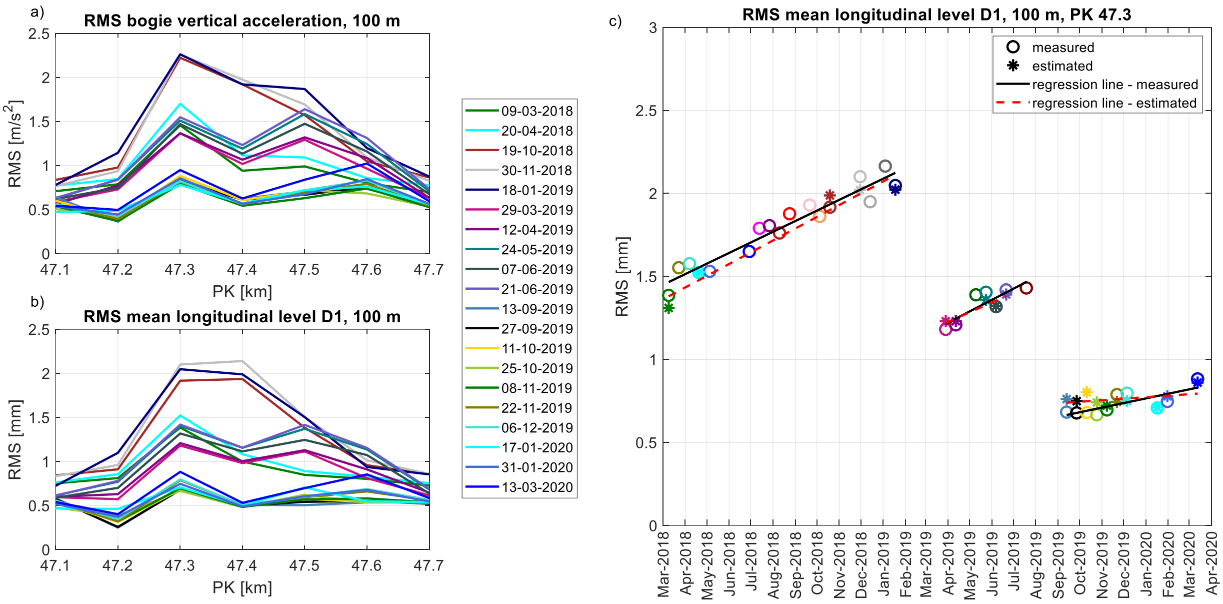


Figure 8. Results of the linear regression model relating RMS of bogie vertical acceleration to RMS of mean longitudinal level D1, spatial window 100 m, distributed defect. a) Measured RMS of bogie vertical acceleration. b) Measured RMS of mean longitudinal level in D1 range. c) Comparison of time trends measured by the diagnostic train and estimated by means of the proposed linear regression model.

In the envisaged application, once a portion of interest with high acceleration RMS values has been identified, the values related to this specific window can be used for estimating the rail line geometry. To exemplify and validate this procedure, the acceleration RMS data corresponding to milestone position at km 47.3 are exploited as an input for the linear model regression equation of Figure 6, obtaining as an output the estimated RMS values of track mean longitudinal level. These values are represented with star markers in Figure 8c. Circle markers on the same Figure 8c represent, on the other hand, the RMS of the direct geometry measurements of Figure 8b, which are in very good agreements with the estimated ones.

Both the directly measured and estimated data clearly highlight the evolution of track geometry with time. To give evidence of the degradation rate, two regression lines are computed as the best-fit of the estimated (dashed line) and measured RMS data (solid line). As their slopes are very close, they point out the very same degradation trend.

Three different zones can be identified in the considered time period, with a clear drop of RMS values corresponding to the maintenance interventions registered in January 2019 and in September 2019. After the first intervention (January 2019) the value of track RMS of about 1.25 mm is restored, and the degradation rates evidenced by the regression lines before and after the maintenance operation seem to be unchanged. This is clearly inferred by the estimated RMS too, and by the related regression lines. Also in the case of the second maintenance intervention registered in September 2019, the estimated RMS clearly highlight the variation in the track quality. Even smaller values of the RMS and lower degradation rates are observed, proving the effectiveness of the second track intervention.

As a conclusion of the above discussion, an extremely accurate correspondence between estimated and measured data is achieved throughout the entire monitoring period. With this regard, it is worth reminding that data belonging to both training (up to August 2019) and validation sets are shown in Figure 8c. Similar results in terms of accuracy can be observed, independently on the data considered, proving the capability of the methodology to predict the track conditions. Maintenance operations are correctly identified both in terms of time record and amplitude decrease. When comparing the degradation trends identified by the slopes of the regression line evaluated with the measured and the estimated RMS, a further confirmation of the accuracy of the methodology can be pointed out.

A final remark can be made regarding data availability. As already mentioned, more geometry than acceleration data are currently at disposal, on account of the dependency of the vehicle dynamics on train speed and in accordance with Table 1. Conversely, when the system will be fully operational onboard of a commercial train, a remarkably higher set of acceleration data will be available and considered to monitor track evolution, while the lower number of periodic direct geometry measurements could be of use to verify the effective degradation trend as predicted by the model.

In conclusion, the results of Figure 8c proved the methodology to be extremely accurate in geometry estimation adopting a spatial window of 100 m for the computation of the diagnostic indicators. This outcome complies with the remarkably high R^2 parameter characterizing the linear regression model of Figure 6. In this context, it is worth mentioning that the reference standard EN 13848-5 [27] relies on a longer spatial window of 200 m for assessing track quality through the standard deviation. In light of the accuracy of the geo-localization algorithm (which allows to associate the diagnostic indicators to the corresponding milestone position with a residual error in the order of 10 m [24]) and the satisfactory results in terms of railway line geometry estimation reached along a shorter window of 100 m, the results are expected to be at least as accurate as the one previously shown in case a longer spatial window of 200 m would be considered.

3.2 Estimation of track longitudinal level peak value through the RMS of bogie vertical acceleration

The analysis proposed in Section 3.1 can provide useful information in terms of track monitoring, but a further step towards condition-based maintenance needs to address the maximum value of track longitudinal level, instead of its RMS. In accordance with the reference standard EN 13848-5 [27], infrastructure managers currently consider, indeed, the peak value of the longitudinal level to determine predefined thresholds for the assessment of track quality. As soon as the monitored parameter exceeds one threshold level, maintenance operation can be triggered.

In order to comply with the current maintenance strategy, this section is focused on the correlation between the RMS of bogie vertical acceleration, already considered in the previous section, and the maximum value of the longitudinal level of both left and right rails detected in the considered spatial window (named MAX in the following). Even if the track recording vehicle measures separately the geometry of left and right rails, the choice of selecting the maximum value among both rails is done considering that maintenance operation carried out at a specified mileage position involves track quality renewal on both rails. It should be noted that if the window length is sufficiently small, the corresponding RMS and the maximum longitudinal level are strictly related. Thus, a high degree of correlation is expected also between the RMS of bogie vertical acceleration and the maximum value of the longitudinal level, even if lower than that obtained when considering RMS against RMS. In the following, two different spatial windows are examined to compute the RMS and MAX indexes. The former, shown in Section 3.2.1, relies on 100 m spatial windows; Section 3.2.2 instead investigates the effect of windows size reduction, moving to a 25 m window, corresponding to the maximum wavelength in D1 range.

3.2.1 Linear regression model along a spatial window of 100 m

Figure 9 reports the results of the new linear regression model derived through the same methodology proposed in Section 2, but this time relating the RMS of bogie vertical acceleration and the maximum longitudinal level. The resulting RMS and MAX indexes correspond to spatial windows of 100 m.

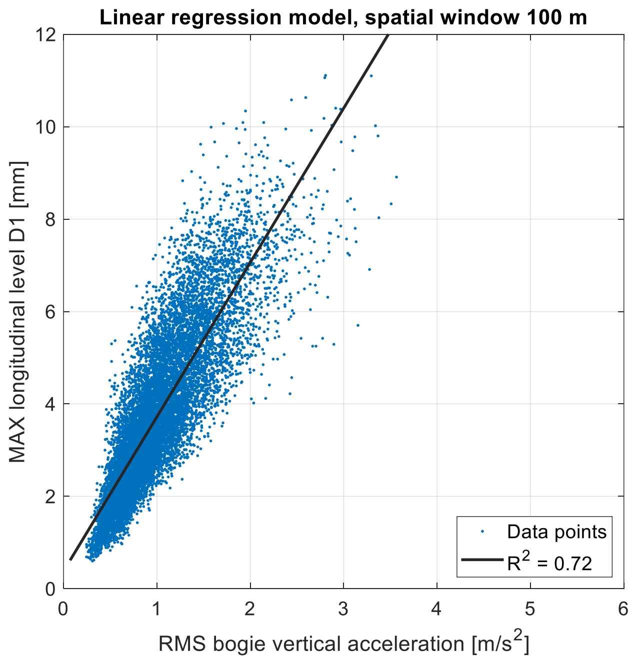


Figure 9. Linear regression model for railway line geometry estimation: maximum peak value of longitudinal level on left and right rails (MAX) as a function of the RMS of bogie vertical acceleration. D1 range, 0-40 Hz, data belonging to the training phase (March 2018 – August 2019) gathered at 300 km/h. Analysis over a 100 m window.

The effect of considering the maximum value of the longitudinal level rather than the RMS of its mean value is firstly discussed by comparing the linear model of Figure 9 to the one of Figure 6, representing the RMS of mean longitudinal level as a function of the same RMS of bogie acceleration. In Figure 9 a higher data dispersion around the regression line can be identified, and a lower degree of correlation between the two parameters, with the R^2 value decreasing from 0.93 (Figure 6) to 0.72 (Figure 9). This outcome suggests that in general, when inferring the MAX of the longitudinal level based on bogie vertical acceleration, a lower degree of accuracy can be achieved in the geometry prediction, compared to the case in which the RMS of mean longitudinal level is estimated. Data dispersion around the best-fitting line suggests that the exploitation of the regression line to predict track geometry might lead to either over or underestimation of track geometry, to be managed in order to avoid unneeded maintenance operation (i.e. false positives) or false negatives.

The reason for the decrease of correlation can be explained by considering the nature of the track defects and the intrinsic characteristics of the RMS and MAX indexes: the typical wavelength of a defect in the longitudinal level for the considered high-speed line has been identified in the range 9-12 m (see Section 2, Figure 2). However, different defect typologies can be found in different portions of a railway line, being either series of adjacent defects (i.e. distributed defect, see Figure 2a) or isolated defects (see Figure 2b). For a given MAX value detected in a 100 m window, different RMS of mean longitudinal level and of bogie vertical acceleration are expected to be found for either distributed or isolated defects. Higher RMS values are obtained in the first case, lower in the latter. Thus, the correlation between bogie vertical acceleration and MAX longitudinal level is reduced.

Figure 10 shows the results obtained by applying a 100 m spatial window on the very same portion of line already analysed in Figure 8, to estimate this time the MAX longitudinal level based on bogie acceleration RMS. The considered defect is a distributed one.

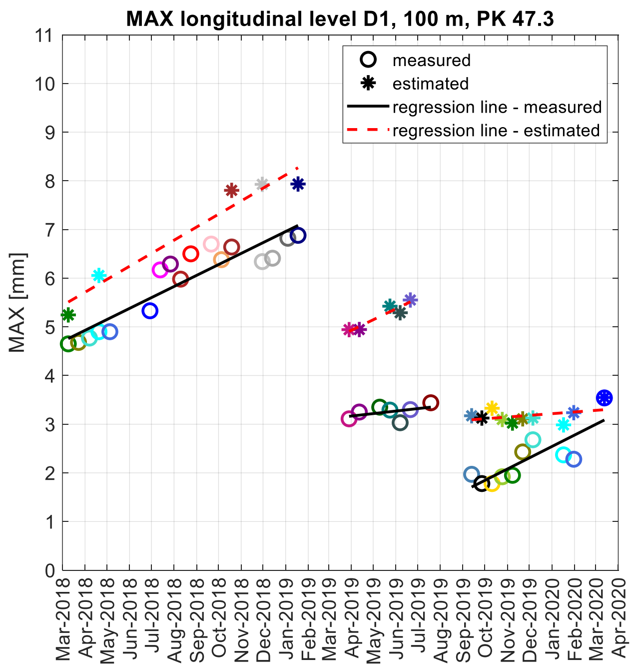


Figure 10. Results of the linear regression model relating RMS of bogie vertical acceleration to MAX of longitudinal level D1, spatial window 100 m, distributed defect. Comparison of time trends measured by the diagnostic train and estimated by means of the proposed linear regression model.

The direct measures of the MAX of longitudinal track geometry carried out by the dedicated recording vehicle are reported with circle markers, whereas the values predicted by exploiting the linear regression model of Figure 9 are reported with circle markers. An overestimation of the geometry index is observed, ranging from 1 up to 2 mm, depending on the monitoring period, on account of the distributed nature of the defect.

Regardless of the degree of accuracy, the analysis confirms that acceleration measurements can be considered to predict the evolution of a geometric defect with time. Even though the degradation trend is in some cases slightly over/underestimated, as visible by comparing the slopes of the solid and dashed regression lines in Figure 10, the progressive increase of the level of track geometry is correctly caught. Moreover, the effectiveness of both maintenance operations (carried out in January and September 2019) is correctly identified, the reduction of MAX index measured by the dedicated track recording vehicle in correspondence of the first maintenance intervention being very close to the reduction detected by the estimated index (i.e. 4 mm, from 7 mm to 3 mm, against 3 mm, from 8 mm to 5 mm). Similar conclusions can be drawn also when considering the second maintenance intervention carried out in September 2019.

Figure 11 reports an exemplary result of an isolated defect type. As in the previous Figure 10, direct measures are reported with circle markers, the predicted values with star markers.

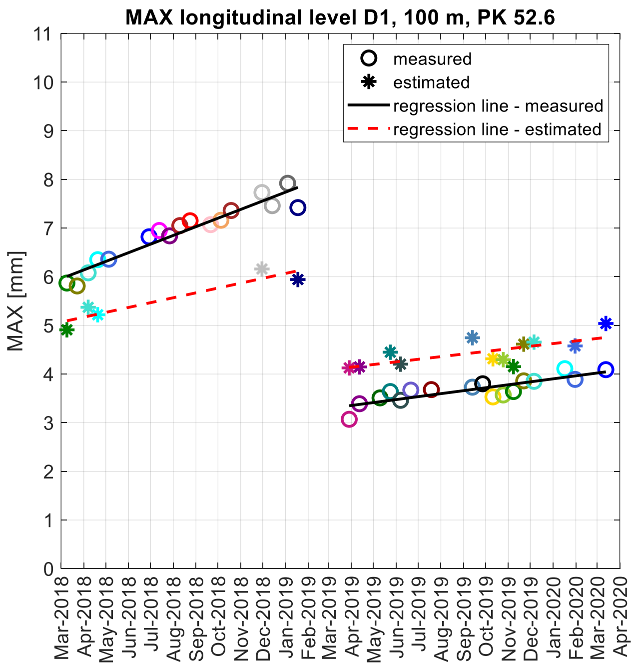


Figure 11. Results of the linear regression model relating RMS of bogie vertical acceleration to MAX of longitudinal level D1, spatial window 100 m, isolated defect. Comparison of time trends measured by the diagnostic train and estimated by means of the proposed linear regression model.

In this second case, considering the data before January 2019, the adoption of the regression model of Figure 9 leads to an underestimation of the maximum (MAX) of track longitudinal level, in accordance with the isolated nature of the defect. On the other hand, after the maintenance intervention the track longitudinal level appears overestimated. This is a consequence of the defect nature becoming closer to a distributed one.

Compared to the previous Figure 10, the absolute values of the estimated index MAX are closer to the measured data, with a maximum discrepancy of 1.5 mm. Also in this case the slopes of the best fitting lines of the measured and estimated parameters (i.e. solid and dashed lines respectively) show a good agreement. In order to assess the quality and accuracy of the prediction, it is worth mentioning that the reference standard EN 13848-4 [28] requires a measuring uncertainty of 1 mm for the track recording vehicle, so that an accuracy of estimation below 1 mm would be considered excellent for the considered application.

The presented results confirm the possibility to monitor the peak value of the track longitudinal level through the RMS of the bogie vertical acceleration, exemplifying how the prediction of track conditions shows the same degree of accuracy considering the different nature of the defects.

Provided that the actual degradation rate can be correctly identified by the estimated data, the adoption of data-fusion techniques, integrating the daily available estimated data with the periodical direct measurement achieved by track recording vehicles, would allow to compensate periodically the absolute error between measured and estimated data, and to exploit the estimated evolution rate trends to conduct predictive maintenance relying on acceleration measurements.

In order to take advantage of a more direct correspondence between the considered MAX of longitudinal level and the RMS of bogie acceleration, the effect of reducing the window width to 25 m is investigated as a further step of the work.

3.2.2 Linear regression model along a spatial window of 25 m

The beneficial effects of window shrinkage are expected to be related to the capability to better focus on the specific defect inside the window, even if, in the case of distributed defects, bogie accelerations would still be dependent on track defectiveness preceding the considered defect.

Figure 12 reports the linear model relating the geometry MAX value to the bogie vertical acceleration RMS obtained by adopting a 25 m window length.

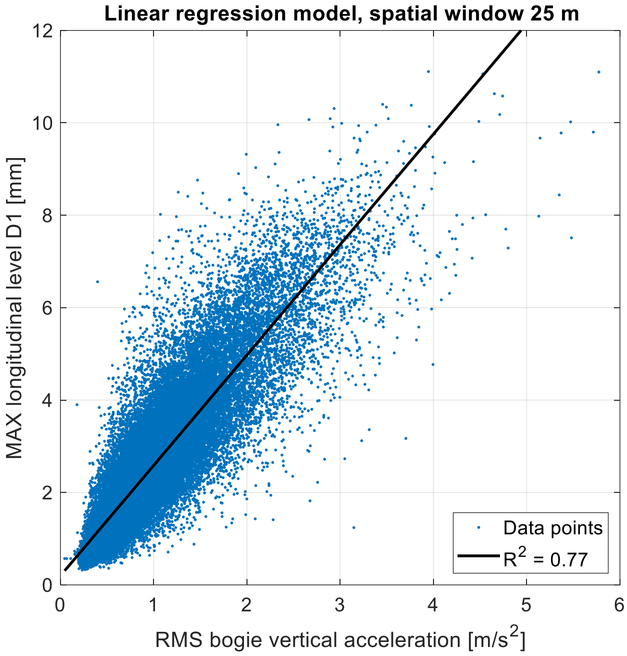


Figure 12. Linear regression model for railway line geometry estimation: maximum peak value of longitudinal level on left and right rails (MAX) as a function of the RMS of bogie vertical acceleration. D1 range, 0-40 Hz, data belonging to the training phase (March 2018 – August 2019) gathered at 300 km/h. Analysis over a 25 m window.

Even though a higher dispersion of data around the linear regression is observed, an increase of the degree of correlation (from 0.72 up to 0.77) is reached when reducing the window size from 100 m (Figure 9) to 25 m (Figure 12), confirming a closer relation between the MAX value and the considered acceleration RMS. The same defects of Figure 10 and Figure 11 are then re-analysed, by using the shorter window of 25 m, so as to evidence the effect of window length reduction.

Figure 13 reports the results achieved for the distributed defect previously considered in Figure 10.

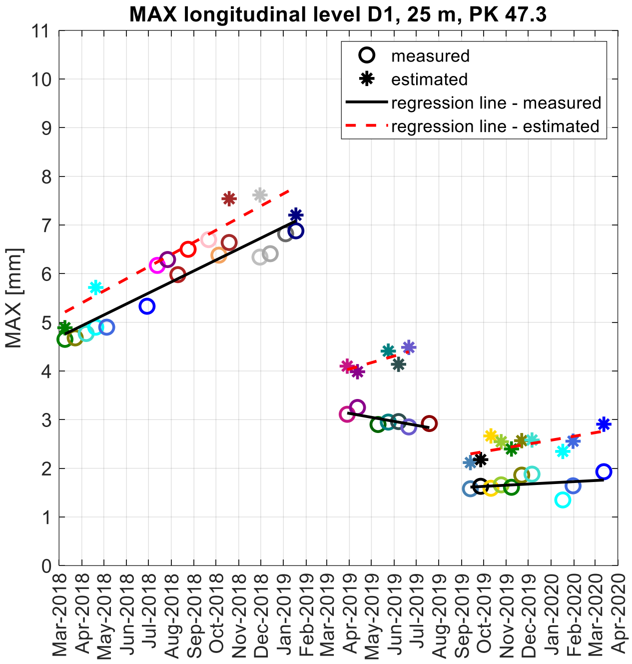


Figure 13. Results of the linear regression model relating RMS of bogie vertical acceleration to MAX of longitudinal level D1, spatial window 25 m, distributed defect. Comparison of time trends measured by the diagnostic train and estimated by means of the proposed linear regression model.

Throughout the whole monitoring period, an improvement of the prediction of the longitudinal level is registered, the estimated values being closer to the corresponding measurements, especially in the first monitoring period, and the maximum gap between the measured and estimated MAX being now 1.5 mm (Figure 13) instead of 2.5 mm (Figure 10). In the second period between January and September 2019, the MAX values directly measured by the track recording vehicle (circle markers) suggest no relevant evolution with time, with variation included in the measure uncertainty of 1 mm, whereas the MAX values estimated based on acceleration RMS (star markers) highlight a small increase of the index. It must be noted, however, that in this period the absolute level of the MAX value is low (around 3 mm), and therefore a higher relative error can be admitted. Finally, considering the third monitoring period, similar results and comments can be made regarding the accordance between the measured and predicted values. In general, the analysis of several occurrence of defects allowed to infer that when adopting a 25 m window for the analysis, the increase of the acceleration RMS is more strictly related to the defect growth rate, giving better results in terms of prediction of trend evolution.

The adoption of a short 25 m window is finally tested in correspondence of isolated defects. Figure 14a shows the results corresponding to the isolated defect previously analysed with a 100 m window in Figure 11, to allow a direct comparison. Figure 14b reports another example, selected out of several cases investigated for its peculiar variation of the degradation rate: a bilinear evolution trend is registered, with faster degradation rate during the initial phase of index evolution, and a significant reduction of the growth rate when the MAX index approached the value of 6 mm, without any maintenance intervention having taken place. The variations in the deterioration rate can be associated with different phases in ballast degradation [20][29]. In fact, after a major renewal work or tamping operation a fast and significant deterioration caused by the initial settlements of the track is observed. The duration of this first phase is highly unpredictable and differs considerably from one track section to another. A second phase follows, where progressive ballast particle rearrangement and breakdown, which is caused by the fracture and abrasive wear of each stone composing the ballast, determine a reduced deterioration rate.

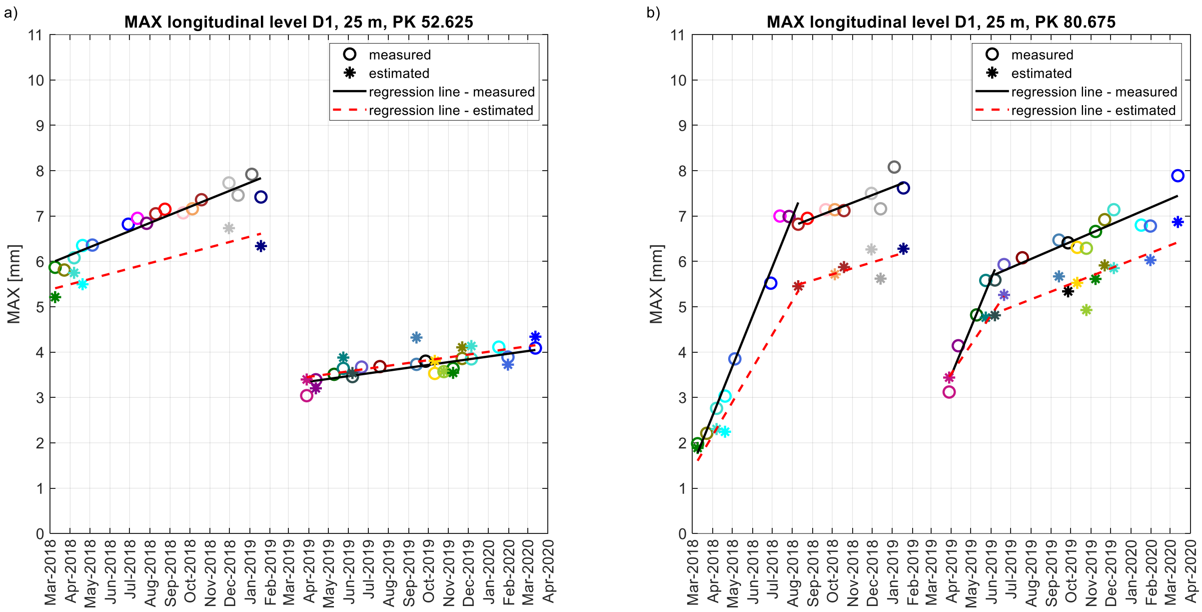


Figure 14. Results of the linear regression model relating RMS of bogie vertical acceleration to MAX of longitudinal level D1, spatial window 25 m, isolated defects. Comparison of time trends measured by the diagnostic train and estimated by means of the proposed linear regression model. a) Milestone position 52.625 km. b) Milestone position 80.675 km.

An accurate geometry estimation is achieved directly through the adoption of acceleration RMS and the regression line model of Figure 12, allowing both a correct monitoring of the evolution of track quality and a limitation of the maximum deviation.

Despite the defects considered in Figure 14a and Figure 14b present different evolution rate, both of them are properly caught by the estimated data and the deviations are kept in the order of 1.5 mm maximum. The reductions of the MAX value occurring in correspondence of maintenance interventions (January 2019 in both Figure 14a and Figure 14b) are correctly identified in terms of absolute values, as well as the changes of evolution rates occurring in August 2018 and June 2019 in the data of Figure 14b.

These outcomes confirm the 25 m spatial window to reduce the difference between the measured longitudinal defects and the estimated values. Within the entire set of analysed cases where an estimate is available, not reported here for the sake of conciseness, the maximum estimation error detected is 1.5 mm, which is fully satisfactory for the proposed application. In any case, considering the entire dataset, the improvement induced by the usage of the 25 m window can be quantified computing the standard deviation of the estimation error, which is reduced from 0.91 mm (100 m window) to 0.71 mm (25 m window).

The satisfactory accuracy of the results achieved confirms the feasibility of condition monitoring of track longitudinal level through acceleration measurements recorded daily by in-service vehicles, and consequently the possibility to enable condition-based maintenance using the proposed approach. Based on the continuous flow of indexes estimating the track longitudinal level, resulting from commercial train data and the linear regression model, significant parameters related to track geometry can be achieved and managed. As a possible result, more efficient scheduling of the track recording vehicles runs along a specific line and, eventually, of maintenance operations could also be achieved.

4 Conclusions

The paper describes a methodology, specifically designed for high-speed applications, for condition monitoring of track longitudinal level, based on the analysis of acceleration measurements taken onboard of an in-service vehicle. The exploitation of synthetic indexes like acceleration RMS of bogie vertical acceleration, in conjunction with linear regression models preliminary established, allows to predict the status of the track geometry. The aim was that of predicting the magnitude of track longitudinal level in D1 range from a simple measuring setup, compatible with the installation on a commercial fleet, that is the main advantage of the proposed solution. On the other hand, the methodology is not suitable for the reconstruction of the track geometry profile, in comparison to other approaches available in literature that rely on more complex measurement systems and data processing.

At first, inspired by the prescriptions of the reference standard [26], a linear model relating the RMS of bogie vertical acceleration to the RMS of track mean longitudinal level has been considered, on account of the overall energy content of the track defectiveness. The corresponding results obtained along a spatial window of 100 m have been presented and discussed. Acceleration measurements proved to be able to predict railway line evolution with time, which poses the basis for the development of conditioned-based maintenance strategies for railway applications.

To comply with the current standard EN 13848 [26] and the maintenance strategy of track infrastructure manager, a second analysis has been proposed. New linear models have been established between the same acceleration RMS index and the peak value of the longitudinal level. The 100 m spatial window showed a worse accuracy in the prediction of the track geometry, with an overestimation of the distributed defects and an underestimation of the isolated ones. The effect of window size reduction has been investigated, proving the 25 m window capability to reduce the estimation error of the longitudinal level. Provided that the evolution trend is well caught by the regression models, the estimation bias can be possibly compensated for by means of data fusion with direct measurements periodically recorded by a track recording vehicle.

As a future development, a methodology to distinguish the defect type could be implemented, so as to recognise a priori the degree of accuracy of the geometry estimates, and eventually correct them. To this aim, the distinction between isolated and distributed defect could be carried out by computing the crest factor, which is a parameter defined as the ratio of the absolute peak amplitude over the rms value of the signal, that indicates how extreme peaks are in a waveform.

The obtained regression models are characteristic of the considered train-track system. As a result, they can be successfully adopted by a fleet of commercial train of the same type. Similarly, the proposed methodology can be extended to different railway vehicles running along different lines, with different nominal characteristics, by computing new linear regression models. When fully operational, the system will constitute a useful tool to support infrastructure monitoring, providing a continuous flow of data in terms of track geometry estimation, enabling the possibility to continuously monitor the line defectiveness and to carry out preventive maintenance actions when really needed along the railway line.

Acknowledgments

This work is part of the CBM project of the Joint Research Center (JRC) for Transportation, established by Fondazione Politecnico di Milano.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

References

[1] C. P. Ward, P. F. Weston, E. J. C. Stewart, et al., Condition Monitoring Opportunities Using Vehicle-Based Sensors. Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit. 2011;225(2):202-218. doi:10.1177/09544097JRRT406.

[2] S. L. Grassie, Measurement of railhead longitudinal profiles: a comparison of different techniques. Wear. 1996, 191, 245-251.

[3] H. E. McAnaw. The system that measures the system. NDT&E, 2003, 36, 169-179.

[4] P. Ackroyd, S. Angelo, B. Nejikovsky, J. Stevens. Remote ride quality monitoring of Acela train set performance, Proceedings of the IEEE/ASME Joint Railroad Conference, (2002) pp. 171-178.

[5] E. J. OBrien, P Quirke, C Bowe, et al. Determination of railway track longitudinal profile using measured inertial response of an in-service railway vehicle. (2017) Struct Health Monit.;17:1425-1440.

[6] P. F. Weston, C. S. Ling, C. Roberts, C. J. Goodman, P. Li, R. M. Goodall, Monitoring vertical track irregularity from in-service railway vehicles. (2007). Proceedings of The Institution of Mechanical Engineers Part F-journal of Rail and Rapid Transit - PROC INST MECH ENG F-J RAIL R. 221. 75-88. 10.1243/0954409JRRT65.

[7] P. F. Weston, C. S. Ling, C. Roberts, C. J. Goodman, P. Li, R. M. Goodall, Monitoring lateral track irregularity from in-service railway vehicles. (2007). Proceedings of The Institution of Mechanical Engineers Part F-journal of Rail and Rapid Transit - PROC INST MECH ENG F-J RAIL R. 221. 89-100. 10.1243/0954409JRRT64.

[8] P. F. Weston, P. Li, C. S. Ling, C. Goodman, R. Goodall, C. Roberts, et al., Track and Vehicle Condition Monitoring during Normal Operation Using Reduced Sensor Sets. (2006) HKIE Transactions. 13. 47-53. 10.1080/1023697X.2006.10668031.

[9] S. Nicks. Condition monitoring of the train/track interface. In Proceedings of the IEEE Seminar – Condition Monitoring for Rail Transport System, London, 10 November 1998, pp. 7/1-7/6.

[10] G. Lederman, S. Chen, J. H. Garrett, et al., Track monitoring from the dynamic response of a passing train: a sparse method. Mech Syst Signal Process. 2017; 90:141-153.

[11] EN 13848-1:2019. Railway applications – Track – Track geometry quality. Part 1: Characterisation of track geometry, 2019.

[12] M. Bocciolone, A. Caprioli, A. Cigada, A. Collina, A measurement system for quick rail inspection and effective track maintenance strategy, Mech. Syst. Signal Process. 21 (3) (2007) 1242–1254.

[13] T. Kojima, H. Tsunashima, A. Matsumoto. Fault detection of railway track by multi-resolution analysis. Computer in Railway X. WIT Press. Pp 955-964. 2006.

[14] H. Tsunashima, Y. Naganuma, A. Matsumoto, T. Mizuma, H. Mori. Japanese railway condition monitoring of tracks using in-service vehicle. (2011). IET Conference Publications. 2011. 1-6. 10.1049/cp.2011.0587.

[15] H.Tsunashima, R. Hirose. Condition monitoring of railway track from car-body vibration using time–frequency analysis. (2020). Vehicle System Dynamics, DOI: 10.1080/00423114.2020.1850808.

[16] G. Lederman, S. Chen, J. H. Garrett, et al. Track-monitoring from the dynamic response of an operational train. Mech Syst Signal Process. 2017; 87:1-16.

[17] I. A. Iliopoulos, J. S. Sakellariou, S. D. Fassois. Track segment automated characterisation via railway-vehicle-based random vibration signals and statistical time series methods. (2021). Vehicle System Dynamics, DOI: 10.1080/00423114.2021.1948079.

[18] G. Lederman, S. Chen, J. H. Garrett, et al. A data fusion method for track monitoring from multiple in-service trains. Mech Syst Signal Process. 2017; 95:363-379.

[19] T. Karis, M. Berg, S. Stichel, M. Li, D. Thomas, B. Dirks. Correlation of track irregularities and vehicle responses based on measured data. (2018). Vehicle System Dynamics, 56:6, 967-981.

[20] J. Nielsen, E. Berggren, A. Hammar, F. Jansson, R. Bolmsvik. Degradation of railway track geometry – Correlation between track stiffness gradient and differential settlement. (2020). Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit. 234. 095440971881958. 10.1177/0954409718819581.

[21] H. Tsunashima, Y.Naganuma, T. Kobayashi. Track geometry estimation from car-body vibration. (2014). Vehicle System Dynamics. 52:sup1, 207-219, DOI: 10.1080/00423114.2014.889836.

[22] H. Tsunashima, Y. Naganuma, A. Matsumoto, T. Mizuma, H. Mori. Condition monitoring of railway track using in-service vehicle. In: Perpinya X, editor. Reliability and safety in railway. InTech; 2012.

[23] A. De Rosa, S. Alfi, S. Bruni. Estimation of lateral and cross alignment in a railway track based on vehicle dynamics measurements. (2019). Mechanical Systems and Signal Processing, Volume 116, Pages 606-623, https://doi.org/10.1016/j.ymssp.2018.06.041.

[24] M. Carnevale, I. La Paglia, P. Pennacchi. An algorithm for precise localization of measurements in rolling stock-based diagnostic systems, Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit (2020), DOI: 10.1177/0954409720965798.

[25] A. De Rosa, R Kulkarni, A Qazizadeh, M. Berg, E. Di Gialleonardo, A. Facchinetti, S. Bruni (2021). Monitoring of lateral and cross level track geometry irregularities through onboard vehicle dynamics measurements using machine learning classification algorithms. DOI:10.1177/0954409720906649. pp.107-120. In PROCEEDINGS OF THE INSTITUTION OF MECHANICAL ENGINEERS. PART F, JOURNAL OF RAIL AND RAPID TRANSIT - ISSN:0954-4097 vol. 235 (1).

[26] EN 13848-6:2014. Railway applications – Track – Track geometry quality. Part 6: Characterisation of track geometry quality, 2014.

[27] EN 13848-5:2017. Railway applications – Track – Track geometry quality. Part 5: Geometry quality levels – Plain line, switches and crossings; 2017.

[28] EN 13848-4:2011. Railway applications – Track – Track geometry quality. Part 4: Measuring systems – Manual and lightweight devices; 2011.

[29] S. Jovanovic, G. Evren, H. Guler. Modelling railway track geometry deterioration. (2011). Proceedings of the ICE - Transport. 164. 65-75. 10.1680/tran.2011.164.2.65.