Review Article

Institution of MECHANICAL ENGINEERS

Journal of RAIL AND RAPID TRANSIT

Modeling of track geometry degradation and decisions on safety and maintenance: A literature review and possible future research directions

Proc IMechE Part F:
J Rail and Rapid Transit
2018, Vol. 232(5) 1385–1397

DOI: 10.1177/0954409717721870
journals.sagepub.com/home/pif
SAGE

Christian Higgins[1] and Xiang Liu[2]

Abstract

In a railroad track, the inherent and small geometrical deviations in the position of rails from their ideal design states constitute imperfections that can have a significant impact on the safety and the rate of degradation of the rail system. These deviations are measured by various technologies and further assessed using various algorithms and statistical techniques to quantify the condition of the system. This paper reviews the existing research regarding the collection of track geometry data, analysis of degradation, and the associated safety and maintenance decisions. The knowledge gaps in the existing literature are identified and possible future research directions are suggested. The review can be used as a reference by practitioners and researchers to determine optimal practices for assuring the safety of tracks.

Keywords

Track geometry, data collection, degradation modeling, safety, maintenance

Date received: 21 September 2016; accepted: 24 June 2017

Introduction

Railroad track geometry, the three-dimensional layout and positioning of the track components, is an important indicator of safety of tracks. Geometric deviations, characterized by displacements in the range of millimeters, can significantly decrease the safety and reliability of the infrastructure. In 2015, the failure of track geometry was the second leading cause of derailments on freight railroads in the United States (broken rails being the first).[1] Additionally, with track-related costs accounting for well over half of maintenance budgets,[2] infrastructure managers need to understand how tracks function and degrade.

Because degradation can occur across multiple components, there is a need to understand how the different track components, including ballast and crossties, interact with one another. The main track geometry defects (Table 1) include alignment, profile, gauge, cant, and twist. Some of these parameters are visualized in Figure 1.[3–5]

This review aims to build upon relevant reviews by Liden,[6] Soleimanemgoui and Ahmadi[7] and Weston et al.[8] Devoted to the planning of rail maintenance, Liden's review includes some works that address the maintenance of track geometry, but does not address data collection or modeling. Soleimanemgoui and Ahmadi devote their review to track geometry but only focus on degradation prediction models and not on maintenance planning or data collection. Weston et al. specifically review in-service vehicle track geometry condition monitoring systems at varying phases of implementation and development. This review attempts to consider all elements of track geometry and the application of risk management, including data collection technologies, modeling, maintenance planning and safety decisions.

Collection of track geometry data

Some technologies and measurement equipment used to collect track geometry data are introduced in this section. This section also introduces the advantages and potential issues associated with these technologies. Additionally, a comprehensive review of data

[1]The Center for Advanced Infrastructure and Transportation (CAIT), the State University of New Jersey, Rutgers, NJ, USA
[2]Department of Civil and Environmental Engineering, the State University of New Jersey, Rutgers, NJ, USA

Corresponding author:
Xiang Liu, Department of Civil and Environmental Engineering, the State University of New Jersey, Rutgers, NJ, USA.
Email: xiang.liu@rutgers.edu

Table 1. Selected types of defects in track geometry.

Defect type	Description
Alignment/profile	The horizontal/vertical deviation
Gauge defect	Change of distance between the inner sides of the two load-bearing rails
Crosslevel defect	The extra difference in elevation between the top surface of the two rails, compared to the designed value
Twist defect	The extra difference between two cross-level measurements a certain distance apart, compared to the designed value

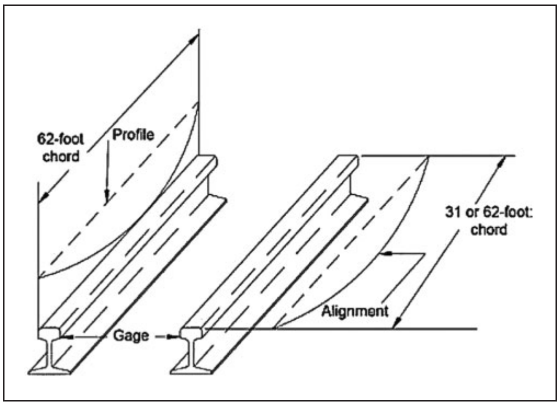

Figure 1. Schematic of Track Geometry and Type of Defects.[5]

collection technologies of in-service vehicles from around the world is the subject of Weston et al.[8]

In the United States, Carr et al.[9] and Stuart et al.[10] described the general technology, data collection methodology, efficiency and calibration of the Autonomous Track Geometry Measurement Systems (ATGMS) technology (Figure 2).

Spearheaded by the US Federal Railroad Administration (FRA), the track geometry data collection module can be equipped to revenue-service passenger trains containing available head-end power supply (HEP). Sadaat et al.[11] utilized a similar approach, while additionally providing an update on efforts to equip ATGMS with energy-harvesting technology to enable data collection on freight trains where HEP is unavailable. Preliminary analysis reveals that solar power harvesting is highly feasible in such scenarios.

The FRA also funded the development of the Gauge Restraint Measurement System (GRMS) vehicle, which is used to collect gauge measurement data (Figure 3). An automated prototype of this vehicle and its corresponding data output were introduced by Alfelor et al.[12] with updates on test runs provided by Choros et al.[13] and Martin et al.[14] Since then, limited updates on the research and development project have been provided. These systems as described in literature[8–14] are actively utilized to evaluate track conditions in the United States, but not nearly as prevalent in safety and maintenance planning and decision making.

Andani et al.[15] discussed the application of light detection and ranging (LIDAR) technology in the collection of horizontal alignment data. Based on bandwidth dissimilarities generated from two light beams reflecting off opposite rail gauges, changes in track geometry can be visualized. These devices can also be used to accurately collect geometry data over long segments of track and during inclement weather. Scott et al.[16] described the use of an unattended track geometry measurement system (UTGMS), currently implemented on revenue passenger rail service in the United Kingdom. Also in the United Kingdom, McAnaw[17] described an acceleration measurement system utilized to measure and monitor track geometry. It utilizes automated video inspection and track condition-monitoring software to collect cant and twist data. The system is currently utilized in the London underground rapid transit system.

Tsunashima et al.[18] summarized the track condition monitoring system used on conventional and high-speed Japanese railways. The conventional system utilizes a gyroscope, spectral peak analysis and a GPS to detect and pinpoint rail defects, including vertical alignment, horizontal alignment, gauge, cant and twist defects. For high-speed rail lines, RAIDARSS-3 devices are utilized.

Farritor and Fateh[19] described the methodological framework for track geometry collection technology that can be used to measure vertical deflection. Cameras and lasers are utilized as part of this methodology to capture deflection through finite element beam analysis. This application is tested on multiple United States freight railroads. Further testing is still needed to completely validate positive results of this technology. A significant issue identified by Al-Nazer[20] is the potential for error in measuring acceleration-based wheel-to-rail interactions. This stems from the suspension systems of rail cars that affect both high and low vibration frequencies. To correct this, the authors designed a deconvolution filter that eliminates these associated amplification and attenuation effects of railcar suspension systems. Real et al.[21] proposed an inertial data collection procedure used to collect vertical alignment data on tram tracks. The procedure involves the collection of axle-box vertical accelerations from vehicle accelerometer sensors at a frequency of 100 Hz. The results of the procedure show a strong capability to capture vertical alignment data, with a total error within 0.4% and primary defects occurring at wavelengths between 30 and 50 m.

An additional problem identified in the collection of track geometry data is the milepost error, in which vehicle-derived milepost locations differ from actual

Table 2. Track geometry data collection-related literature (presented in alphabetical order).

Literature	Approach	Wavelength range	Location of research
Alfelor et al.[12]	Gauge restraint measurement system	Not specified	United States
Al-Nazer[20]	Filtering of amplification and attenuation effects from rail cars	9.45–18.9 m	United States
Andani et al.[15]	Light detection and ranging (LIDAR) technology for collection of horizontal alignment data	9.45–18.9 m	United States
Asmunsen[29]	Filtering of short wavelengths to monitor vertical alignment	0.5–3 m	Sweden, Switzerland, United Kingdom
Association of American Railroads[27]	Utilization of drones to monitor track quality	Not applicable	United States
Carr et al.[9]	Autonomous track geometry measurement system	Not applicable	United States
Choros et al.[13]	Gauge restraint measurement system	Not specified	United States
Farritor and Fateh[19]	Methodology to capture deflection of vibration through tracks	Not specified	United States
Haigermoser et al.[29]	Relationship between vehicle response and track geometry quality	3–25 m	Multiple European Countries
Lewis[28]	Track geometry data filtering process	35–70 m	United Kingdom
Li and Xu[24]	Optimization model to align correctly historical track data	Not specified	China
Luber et al.[31]	Relationship between vehicle response and track geometry quality	3–25 m	Austria
Martin et al.[14]	Gauge restraint measurement system	Not specified	United States
McAnaw[17]	Acceleration measurement system to monitor track geometry	Not specified	United Kingdom
Real et al.[21]	Tram track data collection	30–50 m	Spain
Sadaat et al.[11]	Autonomous track geometry measurement system	Not specified	United States
Scott et al.[16]	Unattended track geometry measurement system for data collection	Not specified	United Kingdom
Selig et al.[25]	Cross correlation analysis to correctly align historical track data	Not specified	United States
Sowinsky[30]	Relationship between vehicle response and track geometry quality	3–25 m	Poland
Stuart et al.[10]	Autonomous track geometry measurement system	Not specified	United States
Tsunashima et al.[18]	In-service-vehicle track geometry condition monitoring system	10 m	Japan
Xu et al.[22]	Milepost error reduction model	Not specified	China
Xu et al.[23]	Dynamic sampling position matching to correctly align historical track data	Not specified	China
Xu et al.[26]	Dynamic time warping model to correctly align historical track data	Not specified	China

locations. To reduce this error, Xu et al.[22] developed a model entitled ''Key Equipment Identification'' that can address track curvature, divergences and other irregularities using global positioning systems (GPS) and radio frequency identification (RFID). While the key equipment identification model is an effective method for error reduction in future data collection,[23] the model does not correct for data that have already been collected. In an attempt to correct for possible historical inaccuracies, Li and Xu[24] developed an optimization model to determine a constant value for milepost shifts between two inspections for a 1 km track segment. Selig et al.[25] used a cross-correlation analysis (CCA) to align two inspections, based on a specified interval. According to Xu et al.,[23] however, such models have limitations in that milepost shifts are bound to a fixed value. They also assumed that no maintenance has been conducted in between two milepost inspections. As a result, Xu et al.[23] developed a model entitled ''Dynamic Sampling Position

Matching (DSPM)" to correct for these errors, as detected by waveform discrepancies. The model is successfully tested using data from the Jinan Bureau of China Railways. Further, Xu et al.[26] developed an additional model with these capabilities using a dynamic time warping methodology.

The use of drones by the BNSF Railway of the United States, as a means of collecting and monitoring track quality was presented by the Association of American Railroads.[27] The breakthrough is part of the Federal Aviation Administration's research and development pilot 'Pathfinder Program' which was developed to explore the application of drones other. While the project is still in its early phases, the use of drones may allow for increased capabilities of track geometry collection, including in cases of inclement weather.

Figure 2. Autonomous Track Geometry Measurement System Technology (ProgressiveRailroading.com/railproducts, 2016).

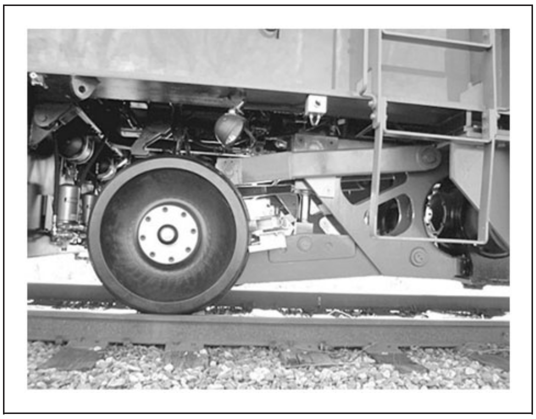

Figure 3. Gauge Restraint Measurement System (ProgressiveRailroading.com/railproducts, 2016).

Lewis[28] described the filtering processes necessary to represent track geometry quality, primarily applied to the wavelengths of the vertical alignment, which responds and deteriorates most to traffic loading. A filter is needed because not all vehicle-to-rail wavelengths correspond to track quality. The two main forms of wavelength measurements are chord offset and inertial systems. The vertical alignment filter applied to these measurements essentially multiplies initial unfiltered wavelength data by a trigonometric function relating total vibration frequency.

Asmunsen[29] proposed the need to filter out small wavelengths of the vertical alignment, between 0.5 and 3 m in length. Additionally, track geometry collection coaches currently utilized by infrastructure managers in Switzerland, Sweden and the United Kingdom, with capabilities to incorporate multiple wavelength measuring filter systems, are reviewed. Lastly, Sowinsky[30] explored the relationship between car-body accelerations and multiple track geometry parameters. The authors confirm that track deterioration is influenced to a certain extent by the dynamic influences of passing vehicles. Correlations between vehicle responses and track geometry quality are further studied in Luber et al.[31] and Haigermoser et al.[32] From these works, vehicle reactions are found to vary significantly, even on tracks with indistinguishable geometry quality levels.

Characterization of track geometry data

Data characterization refers to the methods used to characterize the overall track quality, given the different types of data collected. These methodologies are used to develop track quality indices (TQIs) (Table 3).

El-Sibaie and Zhang[33] develop TQIs for multiple speed-based FRA track classes in the United States. A higher FRA track class has a higher maximum allowable operating speed and correspondingly has more stringent track safety standards. The TQIs take into

Table 3. Selected track quality indices in the literature.

Literature	Approach	TQI parameters
Arasteh et al.[35]	Description of TQI utilized in Swedish railways	Vertical alignment, cant
Bai et al.[36]	Description of TQI utilized in Chinese railways	Vertical alignment, horizontal alignment, gauge, cant
El-Sibaie and Zhang[33]	Development of updated TQI for American railways	Vertical alignment, horizontal alignment, gauge, cant
Li and Xiao[37]	Development of generalized energy index for Chinese railways	Wavelengths from vehicle vibration
Sadeghi et al.[34]	Development of updated TQI for Iranian railways	Vertical alignment, gauge, cant, twist

TQI: track quality indices.

Table 4. Track geometry component degradation modeling literature.

Literature	Approach	Inputs	Track components	Location of research
Andrade and Teixeira[54]	Probabilistic modeling	Vertical alignment (3–25 m wavelength)	200-m sections of switch, stations, bridges and plain tracks	Portugal
Andrade and Teixeira[55]	Bayesian modeling	Vertical alignment (3–25 m wavelength)	200-m Track section	Portugal
Andrade and Teixeira[56]	Bayesian modeling	Vertical alignment (3–25 m wavelength)	200-m Track sections (467 km in length)	Portugal
Andrade and Teixeira[57]	Bayesian modeling	Vertical alignment (3–25 m wavelength), horizontal alignment	200-m Track sections (467 km in length)	Portugal
Audley and Andrews[50]	Probabilistic modeling	Vertical alignment (35 m wavelength)	220-m Track sections (collected from entire network)	United Kingdom
Bai et al.[39]	Markov Chain modeling	Chinese TQI: vertical alignment, horizontal alignment, gauge, cant, twist	200-m track sections	China
Chang et al.[40]	Multi-stage modeling	Chinese TQI: vertical alignment, horizontal alignment gauge, cant, twist	200-m track sections (184 km total in length)	China
Guo and Han[41]	Multi-stage linear prediction model	Vertical alignment, horizontal alignment, gauge, cant, twist	3-m track sections	China
Jia et al.[42]	Medium-term prediction model for cross-level	Vertical alignment, horizontal alignment, gauge, cant, twist	Not specified	China
Jovanovic[51]	Universal degradation model	Vertical alignment	200-m track sections	Croatia
Li et al.[48]	Artificial neural network	Vertical alignment, horizontal alignment, gauge, cant	Varying lengths of track sections (257 km total in length)	United States
Liu et al.[43]	Short range prediction model	Vertical alignment, horizontal alignment, gauge, cant, twist	24 25-m sections	China
Lyngby[49]	Multivariate analysis	Vertical alignment, horizontal alignment, cant	871 track sections of unspecified lengths	Norway
Prescott and Andrews[45]	Markov Chain modeling	Vertical alignment (35 m wavelength) horizontal alignment, gauge, cant twist	200-m track section	United Kingdom
Quiroga and Schneider[53]	Probabilistic modeling	Vertical alignment	250 km total in length	Germany
Quiroga and Schneider[60]	Exponential smoothing	Vertical alignment	1-km track section	Germany
Sadeghi and Askarinejad[46]	Relationship between track geometry and other rail defects	Vertical alignment, horizontal alignment, gauge, cant, twist	20 km of track	Iran

(continued)

Table 4. Continued

Literature	Approach	Inputs	Track components	Location of research
Sagedhi and Askarinejad[38]	Artificial neural network	Vertical alignment, horizontal alignment, gauge, twist	250 30-m sections	Iran
Vale and Ribeiro[52]	Probabilistic modeling	Vertical alignment	51.2 km total in length	Portugal
Xin et al.[59]	Grey box modeling	Vertical alignment	130 km total in length	Sweden
Xu et al.[44]	Data mining	Vertical alignment, horizontal alignment, gauge, cant, twist	Not specified	China
Zarembski and Attoh-Okine[47]	Relationship between track geometry and other rail defects	Vertical alignment, horizontal alignment, gauge, cant, twist	33,796 km of track in total	United States
Zhu et al.[58]	Gaussian random process	Vertical alignment	2 1 km track sections	China

account vertical and horizontal alignments, gauge, and cant. The TQIs are tested in their ability to characterize track geometry. For each of these identified parameters, the TQI is expressed in the form of the ratio of traced space curve length and the track segment length.[33]

Sadeghi et al.[34] propose a TQI that includes the vertical alignment, gauge, cant, and twist. The proposed methodology assigns coefficient values based on the identified parameters' contributions to track quality. As opposed to the TQIs described above for the United States, one entire quality index taking into account all identified parameters is computed in Iran. The TQI currently utilized for Swedish freight and passenger railways was described by Arasteh et al.[35] The TQI utilizes the standard deviation of the cant and vertical alignment. This TQI has been used to test the effectiveness of the Swedish Transport Administration's tamping strategy.

Bai et al.[36] described the TQI utilized in the Chinese railroad system. It includes the vertical and horizontal alignment, gauge, cant, and twist. For each of these parameters, standard deviations are computed and aggregated to develop a TQI value. Unlike Sadeghi's TQI model used in Iran, the Chinese model assigns equal value to each of the parameters. Instead of a track quality index, Li and Xiao[37] describe a generalized energy index (GEI), citing the inability of general TQIs to adequately account for the influence of different-wavelength components of track irregularity. Unlike traditional TQIs, the GEI measures the effects of varying wheel-to-rail wavelength vibrations. According to the authors, especially for higher speeds, longer vibration-based wavelengths should be accounted for.

Although only a few TQIs are introduced, differences among their formats are noticeable. For example, the TQIs described by Sowinsky[30] are solely for each individual parameter. Other TQIs, however, represent a more holistic approach to geometry evaluation, aggregating values for each track geometry parameter. Of these remaining TQIs, equal weight is assigned to each parameter in the Chinese Index. On the other hand, Sweden's TQI assigns twice as much weight to the cant error as the vertical alignment error. While a number of TQIs have been developed, only a few are publically accessible. Additionally, comparisons among the different TQIs are limited, making it difficult to evaluate effectiveness.

Analysis of track geometry component degradation

To characterize and predict degradation over time, track geometry can be classified into mechanistic and statistical forms of modeling.[38] Mechanistic models examine track degradation through the physical modeling of the track structure. Statistical forms of modeling, which have comprised much of the

Table 5. Track geometry maintenance planning and safety decisions.

Literature	Method	Inputs	Track components	Location of research
Andrade[61]	Economic life cycle cost analysis	Vertical alignment	200 m sections (100 km total in length)	Portugal
Andrade and Teixeira[65]	Biobjective maintenance optimization	Vertical alignment	Varying track sections with lengths between 2.4 and 6.8 km	Portugal
Andrade and Teixeira[66]	Maintenance planning using Bayesian modeling	Vertical alignment (3–25 m), horizontal alignment	200-m track sections (467 km in length)	Portugal
Andrade and Teixeira[67]	Maintenance planning using Bayesian modeling	Vertical alignment (3–25 m), horizontal alignment	200-m track sections (467 km in length)	Portugal
Andrade and Teixeira[68]	Unplanned maintenance planning using logistic regression modeling	Vertical alignment (3–25 m), horizontal alignment	200-m track sections (467 km in length)	Portugal
Antoni and Meier-Hirmer et al.[72]	Cost-based maintenance planning	Entire track section	Not applicable	France
Arasteh et al.[71]	Swedish tamping strategy description modeling incorporating risk factor	Vertical alignment, horizontal alignment	Not specified	Sweden
Caetano and Teixeira[62]	Economic life cycle cost analysis	Vertical alignment (3–25 m), horizontal alignment	Varying lengths of 21 track sections (336 km in length)	Portugal
Cardenas-Gallo et al.[70]	Track geometry risk management using multiple models	Entire track section	3219 km of track	United States
He et al.[69]	Track geometry risk management using multiple models	Entire track section	3219 km of track	United States
Liu and Magel[73]	Track geometry interaction map relating vertical and horizontal alignments	Vertical alignment, horizontal alignment	5 km section	Canada
Meier-Hirmer et al.[63]	Gamma distribution-based tamping optimization	Vertical alignment, horizontal alignment	Not specified	France
Vale et al.[64]	Linear programming-based tamping optimization	Vertical alignment (3–25 m)	200-m track sections (collected from three sections of 34.4 km, 51.2 km and 200 km in length)	Portugal

recent work on track geometry modeling, rely on analyzing how the various track structure components interact and mathematically relate to one another.

Statistical approach

Haigermoser et al.[29] evaluated the quality indicators of track geometry to develop TQIs, in order to determine which are most conducive to accurately describing and predicting track geometry. The research employed multiple regression applied to varying parameters (vertical and horizontal alignments, gauge, cant and twist) and filtered wavelengths across curved and straight tracks. The standard deviation of the vertical alignment with a wavelength between 3 and 25 m was found to be a good parameter to describe the influence of track geometry on vehicle behavior. However, employing some additional parameters and methods only marginally increased the overall statistical fit.

Of those surveyed works, two employed the direct use of a TQI. Bai et al.[39] employed the use of a Markov chain model that utilizes the Chinese TQI described by Bai et al.[36] In a Markov chain model, the probability of an event depends on the state attained in the previous event, making such models 'memoryless'. Additionally, Chang et al.[40] utilized a multi-stage linear model with data consisting of 200-m track sections totaling 184 km from the Beijing-Jiulong Railway Line. In China, Guo and Han[41] also used a multi-stage linear model on 3-m sections of track. For the time-period between two tamping actions, unique linear equations are derived to fit the exponential growth in degradation. Jia et al.[42] developed a gray box methodology to develop a medium–long-term prediction model of the vertical alignment. A short range prediction model was developed by Liu et al.[43] to analyze track quality up to approximately 550 days. Their results show a non-linear pattern of track surface changes and varying non-linear patterns exhibited across different track sections. A data mining methodology is proposed by Xu et al.[44] In such a methodology, based on historical track geometry data, deterioration trends can be analyzed. Developed in China, these methodologies utilize the parameters comprising Chinese TQI, but the authors do not specify whether the TQI itself is directly employed in the modeling.

The following authors also utilized all five parameters described in Table 1, although not necessarily in the form of a TQI. Prescott and Andrews[45] developed a Markov-based model. Sadeghi and Askarinejad[46] and Zarembski and Attoh-Okine[47] developed methodologies to predict track geometry conditions, based on the presence of structural track defects. Both works find varying correlations between the two deficiencies. Zarmebski and Attoh-Okine conduct correlation and probabilistic analyses on 33,796 km of track and find a greater probability of rail defects in tracks already containing a geometric defect.

Additionally, Sadeghi and Askarinejad[38] developed an artificial neural network applied to 250 30-m track sections but do not utilize the cant parameter. The neural network is applied on 500 sections of 30-m long straight and curved tracks. Li et al.[48] also utilized a neural network but do not consider twist. Lyngby et al.[49] conducted a multivariate regression considering three parameters, including vertical alignment, horizontal alignment, and cant. They determined a non-linear relationship between axle load and degradation.

In Europe, many authors only consider the vertical alignment parameter, based on the standard deviation of the 3- to 25-m wavelength. A probabilistic analysis of tamping operations was provided by Audley and Andrews.[50] Tamping processes improve track quality in the short-term, but also affect degradation rates. In their analysis, they fit nine probability distributions to model degradation on 220-m segments of British passenger rail track. Jovanovic[51] introduced a universal deterioration model and also emphasized the need for more inspection and tamping data. Vale and Ribeiro[52] used a probabilistic stochastic approach. They tested 52 probabilistic distributions on three speed intervals. Quiroga and Schneider[53] also used a probabilistic approach by conducting a Monte Carlo Simulation to assess the impacts of tamping on track quality. The same approach was used by Andrade and Teixeira[54] in which statistical correlation analyses are performed for switch, station, bridge, and plain types of high-speed passenger rail track in Portugal. Bayesian theory is the focus of additional efforts by Andrade and Teixeira.[55,56]

Two works analyzed the applicability of the horizontal alignment parameter. Andrade and Teixeira[57] conducted separate Bayesian analyses for the vertical and horizontal parameters. They found the horizontal alignment to be a worse indicator of track quality. Zhu et al.[58] modeled both parameters using a Gaussian random process but do not compare their abilities to characterize track quality.

Lastly, model comparisons were conducted by Xin et al.[59] and Quiroga and Schneider.[60] Xin et al. compared gray box models to linear and exponential regression models. The gray box models were found to have higher accuracy and more stable results. Quiroga and Schneider compared double exponential smoothing, generic polynomial, autoregressive and hybrid forms of gray box models. The hybrid model was found to have the best fit of track geometry over time and across an increased number of tamps.

Maintenance planning and safety decisions

The methodologies used to predict the quality and degradation of track geometry are most valuable in their application to risk management and maintenance planning. Liu et al.[43] indicate that more maintenance is required to consistently maintain tracks at excellent rather than satisfactory or acceptable quality levels. In practice, however, given the limited resources across generally large rail networks, the effort for track inspection and maintenance is finite and constrained by various factors. Applied to track geometry, maintenance planning is conducted through inspections of the parameters defects as described in Table 1. Identified track segments are either refurbished, primarily by means of ballast tamping, or replaced. Ballast tamping, the packing together of track ballast, is explained in further detail in Audley and Andrews.[50]

A literature review devoted to track maintenance is provided by Liden.[6] Liden's review, introducing certain track geometry maintenance models, also includes maintenance-based work related to crew scheduling, resource scheduling, and broken rail prevention.

General maintenance planning models

The literature revealed multiple methods of optimized maintenance planning. Those methods include in life-cycle cost and time-based maintenance plans, as well as those models which seek to minimize unplanned maintenance needs and delays.

Andrade[61] used LCC to support rail and ballast maintenance and renewal decisions based on accumulated tonnage. The results of the analysis show that as accumulated tonnage increases, LCC is further influenced by unavailability costs. These are defined as the costs associated with the infrastructure being taken out of service. This approach was also considered by Caetano and Teixeira[62] who proposed an optimization for scheduling and integrating maintenance actions based on ballast, rail, and sleeper component degradation.

The following works developed time-based maintenance plans. Mercier et al.[63] used a Gamma process considering both the vertical and horizontal alignments. The results of the analysis showed that taking into account multiple parameters produces more frequent but accurate maintenance needs. Vale et al.[64] developed a linear programming model to optimize tamping operations over a finite time horizon.

The following models aimed to minimize unplanned maintenance needs and delays. Andrade and Teixeira[65] developed a biobjective non-linear integer programming model that minimizes maintenance costs while also minimizing the delays caused by maintenance. Andrade and Teixeira[66] utilized the Hierarchical Bayesian model set forth in Andrade and Teixeira[67] to expand the biobjective model to include unplanned delay and maintenance costs. Further, Andrade and Teixeira[68] conducted a logistic regression to model the probability that unplanned maintenance needs will arise. They considered all five parameters, including the presence of bridges or switches in track sections.

Safety and risk-based decision making

Assurance of railway safety should form the basis behind railway infrastructure planning decisions. Even so, only a few maintenance-based works directly incorporated safety and risk analysis in varying formats. He et al.[69] and Cardenas-Gallo et al.[70] approached maintenance planning by proposing a model that optimizes track rectification issues based on yellow or red tag defect classifications. Red-tagged defects must be rectified or remediated immediately, while yellow-tagged defects can be fixed more leniently, based on location and severity. Three models are proposed in literature,[69] including a logarithmic deterioration prediction model, Cox partial-likelihood model predicting derailment risks from red-tagged defects and lastly a mixed-integer maintenance optimization model. The latter was designed to rectify red-tag defects by certain due dates and repair yellow-tagged defects in efficient clusters before they deteriorate into red-tagged defects. Arasteh et al.[71] described the Swedish Transport Authority's tamping strategy. In addition to unavailability costs, the model takes into account collision risk. However, the model did not provide details on the quantification of risk or the effects of speed reductions and also assumes constant rates of track geometry degradation.

An additional framework that incorporates risk analysis is provided by Antoni and Meier-Hirmer.[72] The proposed model is broad and not specific to track geometry and instead is meant for application to various sectors of railway infrastructure planning, including signaling equipment and overhead line maintenance. In this case, risk is considered as a single variable representing the probability of observing an instant failure of the infrastructure given a certain time period.

Lastly, Liu and Magel[73] proposed the concept of a track geometry interaction map (TGIM) that analyzes the contours associated with vehicle responses from track deviations. This concept was proposed as a new parameter that relates the 62-foot longitudinal and horizontal chord alignment errors to vehicle responses. Based on test results on a 5-km segment of Class 4 freight track in the United States, the authors find that use of the TGIM parameter can reduce operation risk in areas with high interaction zones.

Research gaps and potential future directions

These gaps are explained by means of data collection, data to information and lastly, information to decision, the operations of the infrastructure manager.

Data collection and assembling

The following research gaps and possible directions for future research were revealed with regard to data collection and assembling ('Collection of track geometry data' section):

- There is limited insight on the collection of track geometry data of small wavelengths, below 3 m, which may still affect track quality. Further development of full-spectra track geometry filtering systems with capabilities for equipment to revenue trains is needed.
- A limited number of works related to data collection specified the necessary wavelength filtering and processing information captured with each technology.
- There is a lack of statistical analyses comparing track quality when considering comprehensive geometry wavelength spectra ranging from 0 to 100 m, as opposed to narrow band spectra of under 35 m.
- Little research has examined the implementation of more than one car per train in order to conduct reliability analyses of available technologies.
- The statistical correlations between track geometry quality and vehicle dynamics are still challenging, given varying relationships even on areas of identical track quality.
- Little research exists examining the economic feasibility of comparing single-parameter data collection to multi-parameter data collection.

Data to information

Data to information research gaps are those related track geometry characterization and track geometry degradation modeling. The research gaps are as follows:

- Some TQIs assign equal or less weight to the vertical alignment than other geometry parameters even though the vertical alignment is generally accepted as the strongest single indicator of geometric quality.
- Some component degradation models utilized small track sections for case studies and did not specify wavelength intervals for geometric data. As a result, these models may be of limited practicality to infrastructure managers.
- Although the literature shows strong capabilities in data collection on a large scale, these capabilities and large-scale data sets do not yet appear to be reflected in modeling efforts.
- While all applicable works incorporated the vertical alignment, there is limited insight on how incorporating additional parameters improves modeling results.
- Only two works[56,57] provided comparisons of multiple mathematical approaches to statistical modeling utilizing the same track data.
- Existing research does not focus on modeling of tram and light-rail passenger railroad tracks. Light-rail track geometry standards are covered in literature,[74–76] but are not modeled.
- Information to decision
- Lastly, information to decision research gaps are those related to maintenance planning and safety decisions/risk management ('Maintenance planning and safety decisions' section):
- Even though track degradation modeling is done based on standards set forth by railroad administrations and companies, limited research has focused on the effects of surpassing these standards. Risk analysis should be applied to determine how railroad safety, particularly derailment probabilities, are affected when these standards are surpassed. Given the increasing maintenance needs and limited maintenance budgets, this topic will require significant attention.
- Existing research does not advise infrastructure managers on how to quantify the safety risk of track geometry. Of the additional works that address risk management, primary for maintenance planning-purposes, risk is considered to be a predetermined variable as part of a larger economic optimization model.
- Additional research is needed to better quantify uncertainty costs due to unavailable infrastructure, which may comprise significant portions of total costs.
- Existing research does not compare the effects of optimizing different objectives, aiming to maximize costs, delays or safety risk on network safety and overall costs to the infrastructure manager.

Conclusion

Track geometry plays a critical role in railroad track functionality and provides a basis for safety decisions and planning. The prior literature has focused on track geometry data collection, characterization, modeling, as well as safety and economic decision making. Further research is needed in the following directions. First, future effort can explore the use of advanced inspection technologies, individually or in combination, to provide an accurate and timely monitoring of track geometry data. Second, there is a research need to calibrate and compare alternative statistical modeling techniques to understand their respective advantages and limitations in terms of fitting empirical data. Third, future research can be developed to better relate track geometry data to vehicle dynamics and various types of track defects, and incorporate engineering risk analysis into safety decisions.

Acknowledgements

The authors thank the anonymous reviewers for their insightful comments that have substantially improved the quality of the original manuscript. However, any remaining errors are our own.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: The first author was partially funded by a USDOT Eisenhower Transportation Fellowship (DTFH6416G00079) and the second author was partially funded by the Federal Railroad Administration of USDOT (DTFR5317C0004), at the time of writing this paper.

References

1. Liu X, Saat R and Barkan C. Analysis of causes of major train derailment and their effect on accident rates. *J Transp Res Board* 2012; 2289: 154–163.
2. Lopez-Pita A, Teixeira P, Casas C, et al. Maintenance Costs of high-speed lines in Europe: state of the art. *J Transp Res Board* 2009; 2043: 13–19.
3. Berawi A, Raimundo D, Calcada R, et al. Evaluating Track geometrical quality through different methodologies. *Int J Technol* 2010; 1: 38–47.
4. Australian Rail Track Corporation LTD. Track geometry section 5, https://extranet.artc.com.au/docs/eng/track-civil/procedures/track-geo/ETF-05-01.pdf (2015, accessed 20 April 2016).
5. He Q, Li H, Bhattacharjya D, et al. Track geometry defect rectification based on track deterioration modelling and derailment risk assessment. *J Oper Res Soc* 2014; 101: 1–13.
6. Liden T. Survey of railway maintenance activities from a planning perspective and literature review concerning the use of mathematical algorithms for solving such planning and scheduling problems, www.diva-portal.org/smash/get/diva2:754942/FULLTEXT01.pdf (2014, accessed 7 July 2017).
7. Soleimanmeigouni I and Ahmadi A. A survey on track geometry degradation modeling. In: U Kumar, A Ahmadi, AK Verma and P Varde (eds) *Current trends in reliability, availability, maintainability and safety*. 1st ed. Cham, Switzerland: Springer, 2016, pp.3–12.
8. Weston P, Roberts C, Yeo G, et al. Perspectives on railway track geometry condition monitoring from in-service railway vehicles. *Veh Syst Dyn* 2015; 53: 1063–1091.
9. Carr G, Tajaddini A and Nejikovsky B. Autonomous Track inspection systems – today and tomorrow. In: *AREMA 2009 annual conference*, Chicago, Illinois, 20–23 September 2009, www.arema.org/files/library/2009_Conference_Proceedings/Autonomous_Track_Inspection_Systems-Today_and_Tomorrow.pdf (accessed 1 July 2017).
10. Stuart C, Carr G and Sherrock E. Development of autonomous track geometry measurement systems for overall track assessment. In: *AREMA 2011 annual conference*, Minneapolis, Minnesota, 18–21 September 2011, www.arema.org/files/library/2011_Conference_Proceedings/Development-Autonomous_Track_Geometry_Measurement_Systems-Overall_Track_Assessment.pdf (accessed 1 July 2017).
11. Sadaat S, Stuart C, Carr G, et al. Development and use of FRA autonomous track geometry measurement system technology. In: *AREMA 2014 annual conference*, Chicago, Illinois, 28–1 October 2014.
12. Alfelor R, Carr G and Fateh M. Track degradation assessment using gage restraint measurements. *J Transp Res Board* 2001; 1742: 68–77.
13. Choros J, Sussman T, Mahmood F, et al. Gage restraint measurement system comparison tests: railbound and hi-rail vehicles. Report for the United States federal railroad administration. Report no. DOT-VNTSC-FRA-03-11, December 2003.
14. Martin G, Bloom J and Lee S. The deployable gage restraint measurement system – description and operational performance. In: *AREMA 2006 annual conference*, Louisville, Kentucky, 17–20 September 2006.
15. Andani M, Ahmadian M, Munoz J, et al. On the application of LIDAR sensors for track geometry monitoring. In: *2015 joint rail conference*, San Jose, California, 23–26 March 2015.
16. Scott G, Chillingworth E and Dick M. Development of an unattended track geometry measurement system. In: *2010 joint rail conference*, Urbana, Illinois, 27–29 April 2010.
17. McAnaw H. The system that measures the system. *NDT & E Int* 2003; 36: 169–179.
18. Tsunashima H, Naganuma Y and Kobayashi T. Track geometry estimation from car-body acceleration. In: *5th IET railway condition monitoring and non-destructive testing (RCM 2011)*, Derby, United Kingdom, 29–30 November 2011.
19. Farritor S and Fateh M. Measurement of vertical track modulus from a moving rail car. report for the united states federal railroad administration, http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.516.5019&rep=rep1&type=pdf (2013, accessed 7 July 2017).
20. Al-Nazer L. Track profile approximation using Railcar body acceleration data. Federal Railroad Administration, https://trid.trb.org/view.aspx?id=1341313 (2014, accessed 7 July 2017).
21. Real J, Montalban L, Real T, et al. Development of a system to obtain vertical track geometry measuring axle-box accelerations from inservice trains. *J Vibroeng* 2012; 14: 813–826.
22. Xu P, Sun Q, Liu R, et al. Key equipment identification model for correcting milepost errors of track geometry data from track inspection. *Transp Res Board Part C: Emerg Technol* 2013; 25: 85–103.
23. Xu P, Sun Q, Liu R, et al. Optimizing the alignment of inspection data from track geometry cars. *Computer-Aided Civ Infrastruct Eng* 2014; 30: 19–35.
24. Li H and Xu Y. A method to correct the mileage error in railway track geometry data and its usage. *Traffic Transp Stud* 2010; 2010: 1130–1135.
25. Selig E, Cardillo G, Stephens E, et al. Analyzing and forecasting railway data using linear data analysis. *WIT Trans Built Environ* 2008; 103: 25–34.
26. Xu P, Liu R, Sun Q, et al. Dynamic-time-warping-based measurement data alignment model for

condition-based railroad track maintenance. *IEEE Trans Intell Transp Syst* 2015; 16: 799–812.
27. Association of American Railroads. Safety and innovation state of the industry report, www.aar.org/report/Documents/AAR%20State%20of%20the%20Industry%202016%20Full%20Report.pdf (accessed 7 July 2017).
28. Lewis R. Track geometry recording and usage: notes for a lecture to Network Rail. Raymond Lewis C Eng F.I.E.T. Technical Consultant Derby 2011, www.infrastructuremonitoring.co.uk/wp-content/uploads/2011/10/Track-Recording-And-Usage.pdf (accessed 7 July 2017).
29. Asmunsen B. Overview of methods for measurement of track irregularities important for ground-borne vibration. *RIVAS – Railway Induced Vibration Abatement Solutions Collaborative Project* 2013, www.rivas-project.eu/fileadmin/documents/RIVAS_CHALMERS_WP2_D2_5_FINAL.pdf (accessed 7 July 2017).
30. Sowinsky B. Interrelation between wavelengths of track geometry irregularities and rail vehicle dynamic properties. *Arch Transp* 2013; 25–26: 97–108.
31. Luber B, Haigermoser A and Grabner G. Track geometry evaluation method based on vehicle response prediction. *Veh Syst Dyn* 2010; 48: 157–173.
32. Haigermoser A, Eickhoff B, Thomas D, et al. Describing and assessing track geometry quality. *Veh Syst Dyn* 2014; 52: 189–206.
33. El-Sibaie M and Zhang Y. Objective track quality indices. *J Transp Res Board* 2004; 1863: 81–87.
34. Sadeghi J, Fathali M and Boloukian N. Development of a new track geometry assessment technique incorporating rail cant factor. *Proc IMechE, Part F: J Rail and Rapid Transit* 2008; 223: 255–263.
35. Arasteh I, Larsson-Krilik P, Nissen A, et al. Cost-effective track geometry maintenance limits. *Proc IMechE, Part F: J Rail and Rapid Transit* 2014; 230: 611–622.
36. Bai L, Liu R, Sun Q, et al. Classification-learning-based framework for predicting railway track irregularities. *Proc IMechE, Part F: J Rail and Rapid Transit* 2014; 230: 598–620.
37. Li H and Xiao T. Improved generalized energy index method for comprehensive evaluation and prediction of track irregularity. *J Stat Comput Simul* 2013; 84: 1213–1231.
38. Sadeghi J and Askarinejad H. Application of neural networks in evaluation of railway track quality condition. *J Mech Sci Technol* 2012; 26: 113–122.
39. Bai L, Liu R, Sun Q, et al. Markov-based model for the prediction of railway track irregularities. *Proc IMechE, Part F: J Rail and Rapid Transit* 2013; 229: 150–159.
40. Chang H, Liu R and Li Q. A multi-stage linear prediction model for the irregularity of the longitudinal level over unit railway section. *Trans Built Environ J* 2010; 114: 641–650.
41. Guo R and Han B. Multi-stage linear prediction model for railway track irregularity. *J Appl Mech Mater* 2013; 361: 1811–1816.
42. Jia C, Xu W, Futian W, et al. Track irregularity time series analysis and trend forecasting. *Discrete Dyn Nat Soc J* 2012; 2012: 1–15.
43. Liu R, Xu P and Wang F. Research on a short-range prediction model for track irregularity over small track lengths. *J Transp Eng* 2010; 136: 1085–1091.
44. Xu P, Liu R, Wang G, et al. Railroad track deterioration characteristics based track measurement data mining. *Math Probl Eng J* 2013; 2013: 1–7. doi: 10.1155/2013/970573.
45. Prescott D and Andrews J. Modelling maintenance in railway infrastructure management. In: *Reliability and Maintainability Symposium (RAMS), 2013 proceedings – annual*, Orlando, Florida, 28–31 January 2013.
46. Sadeghi J and Askarinejad H. An investigation into the effects of track structural conditions on railway track geometry deviations. *Proc IMechE, Part F: J Rail and Rapid Transit* 2009; 223: 415–425.
47. Zarembski A and Attoh-Okine N. Using big data techniques to determine the relationship between rail defects and track geometry defects. In: *Track maintenance planning in the era of big data,* Newark, Delaware, 9 December 2014.
48. Li D, Meddah A, Hass K, et al. Relating track geometry to vehicle performance using neural network approach. *Proc IMechE, Part F: J Rail and Rapid Transit* 2006; 220: 273–281.
49. Lyngby N. Railway track degradation: shape and influencing factors. *Int J Performability Eng* 2009; 5: 177–186.
50. Audley M and Andrews J. The effects of tamping on railway track geometry degradation. *Proc IMechE, Part F: J Rail and Rapid Transit* 2012; 227: 376–391.
51. Jovanovic S. Railway track quality assessment and related decision making. In: *IEEE international conference on systems, man and cybernetics*, The Hague, Netherlands, 10–13 October 2004.
52. Vale C and Ribeiro I. Railway condition-based model with stochastic deterioration. *J Civil Eng Manage* 2013; 20: 686–692.
53. Quiroga L and Schneider E. Monte Carlo simulation of railway track geometry deterioration and restoration. *J Risk Reliab* 2011; 226: 274–282.
54. Andrade A and Teixeira P. Uncertainty in rail-track geometry degradation: Lisbon-Oporto line case study. *J Transp Eng* 2011; 137: 193–200.
55. Andrade A and Teixeira P. A Bayesian model to assess rail track geometry degradation throughout its life-cycle. *Res Transp Econ J* 2012; 36: 1–8.
56. Andrade A and Teixeira P. Hierarchical Bayesian modelling of rail track geometry degradation. *Proc IMechE, Part F: J Rail and Rapid Transit* 2013; 227: 364–375.
57. Andrade A and Teixeira P. Statistical modelling of railway track geometry degradation using hierarchical Bayesian models. *Reliab Eng Syst Saf J* 2015; 142: 169–183.
58. Zhu M, Cheng X, Miao L, et al. Advanced stochastic modeling of railway track irregularities. *Adv Mech Eng J* 2013; 2013: 1–7.
59. Xin T, Famurewa S, Gao L, et al. Grey-system-theory-based model for the prediction of track geometry quality. *Proc IMechE, Part F: J Rail and Rapid Transit* 2015; 230: 1735–1744.
60. Quiroga L and Schneider E. Modelling of high speed rail geometry aging as a discrete-continuous process. In: *Stochastic modeling techniques and data analysis international conference*, Chania, Crete, Greece, 8–11 June 2010.
61. Andrade A. Renewal decisions from a life-cycle cost (LCC) perspective in railway infrastructure: an

integrative approach using separate LCC models for rail and ballast components. Report, Instituto Superior Tecnico, Universidade Tecnica de Lisboa, Portugal, 2008. Retrieved from www.researchgate.net/publication/242112040_Renewal_decisions_from_a_Life-cycle_Cost_LCC_Perspective_in_Railway_Infrastructure_An_integrative_approach_using_separate_LCC_models_for_rail_and_ballast_components (accessed 1 July 2017).

62. Caetano L and Teixeira P. Optimization model to schedule track renewal operations: a life-cycle cost approach. *Struct Infrastruct Eng* 2015; 11: 1524–1536.
63. Mercier S, Meier-Hirmer C and Roussignol M. Bivariate Gamma wear processes for track geometry modelling, with application to intervention scheduling. Struct Infrastruct Eng *J* 2011; 8: 357–366.
64. Vale C, Ribeiro I and Calcada R. Integer programming to optimize tamping in railway tracks as preventative maintenance. *J Transp Eng* 2012; 138: 123–131.
65. Andrade A and Teixeira P. Biobjective optimization model for maintenance renewal decisions related to rail track geometry. *J Transp Res Board* 2011; 226: 163–170.
66. Andrade A and Teixeira P. Hierarchical Bayesian modelling of rail track geometry degradation. *Proc IMechE, Part F: J Rail and Rapid Transit* 2013; 227: 364–375.
67. Andrade A and Teixeira P. Unplanned-maintenance needs related to rail track geometry. *Proc Instit Civil Eng* 2013; 167: 400–410.
68. Andrade A and Teixeira P. Optimal maintenance and renewal strategy due to rail track geometry. In: *13th World conference on transport research*, Rio de Janeiro, Brazil, 14–18 July 2013.
69. He Q, Li H, Bhattacharjya D, et al. Track geometry defect rectification based on track deterioration modelling and derailment risk assessment. *J Oper Res Soc* 2014; 101: 1–13.
70. Cardenas-Gallo I, Sarmiento C, Morales G, et al. An ensemble classifier to predict track geometry degradation. *Reliab Eng Syst Saf* 2017; 161: 53–60.
71. Arasteh I, Juntti U, Nissen A, et al. Evaluation of track geometry maintenance (Tamping) in Swedish heavy haul railroad – a case study. *Proc IMechE, Part F: J Rail and Rapid Transit* 2014; 228: 496–503.
72. Antoni M and Meier-Hirmer C. Economic correlation between maintenance and regeneration – optimization of maintenance strategies for tracks, signaling equipment and overhead line components. In: *18th Euro Working Group on Transportation, EWGT*, Delft, The Netherlands, 14–16 July 2015.
73. Liu Y and Magel E. Performance-based track geometry and the track geometry interaction map. *Proc IMechE, Part F: J Rail and Rapid Transit* 2009; 223: 111–119.
74. Ahac M and Lakusic S. Tram track maintenance-planning by gauge degradation modelling. *Transp J* 2015; 30: 430–436.
75. Madejski J. Light rail, tram track and turnout geometry measurement and diagnostic tools. *WIT Trans Built Environ* 2005; 77: 185–195.
76. Novales M, Orro A and Bugarin M. Track geometry for light rail systems. *Proc IMechE, Part F: J Transp Res Board* 2146: 18–25.