Track Quality Index Prediction Method: Systematic Literature Review

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ABSTRACT

Maintenance of railway infrastructure plays a vital and crucial role in ensuring safety and comfort during travel. The quality of railway track is determined by the Track Quality Index (TQI) which serves as the primary indicator in assessing the geometric condition of railways and forms the basis for railway infrastructure maintenance planning. This study uses the Systematic Literature Review *(SLR)* method to comprehensively review and analyze the development of TQI prediction methods. Through a systematic literature selection process from the Google Scholar, Scopus, MDPI and Indonesian national journals databases covering the period of 2010–2025, six studies relevant to this topic were identified. The six studies encompass statistical approaches**,** machine learning**,** and Bayesian Network for predicting the TQI values. The analysis result indicated that linear and stepwise regression methods serve as initial approach in TQI modeling, but exhibit limitations in capturing nonlinear relationships between geometric parameters. Further advancements have been achieved through machine learning such as Principal Component Analysis (PCA) and Tree-Augmented Naive Bayes (TAN-BN) which have improved prediction accuracy using railway big data. Recent global trends demonstrate a shift toward Bayesian-based probabilistic models to address uncertainty and enhance reliability in track condition assessment. A major limitation of previous studies is the lack of integration of spatial and temporal data in prediction models. Future research should focus on integration of Bayesian models with deep learning for real-time TQI prediction based on the Internet of Things (IoT).

Keywords: Track Quality Index, Bayesian Network, Machine Learning, Track Geometry, Prediction.

INTRODUCTION

In the railway transportation system, track quality is a crucial factor that influences operational safety, passenger comfort, energy efficiency, and the service life of railway infrastructure. One of the most widely used parameters for evaluating the geometric condition of railway track is Track Quality Index (TQI), a numerical indicator that quantifies the degree of deviation of the track geometry from the ideal condition. TQI is calculated based on geometric parameters such as alignment (horizontal deviation), longitudinal level (vertical deviation), gauge (rail spacing), and *Cant* (track superelevation) [1]. As traffic volume and travel frequency increase, the TQI value trends to decrease, serving as main indicator for determining maintenance priorities and infrastructure improvement policies.

In Indonesia, the TQI has been adopted as the official standard in the track condition assessment as stipulated in [2], which emphasizes the importance of periodic monitoring of geometric as part of both preventive and corrective maintenance strategies. To obtain the Track Quality Index (TQI), the geometry of railway tracks is measured and periodically updated using a track recording car that is integrated with visual inspection data [3]. However, the availability of TQI data remains limited due to the small number of track recording vehicles in operation, such as the EM120 and HKPW U-76501, which can only cover a small portion of the national railway network within a single inspection cycle [4]. This situation creates an urgent need for the development of a TQI prediction model capable of estimating track quality in segments that have not been directly measured.

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Various studies have been conducted to predict TQI values using a range of approaches, from classical statistical methods such as linear regression, to artificial intelligence-based models, including machine learning and Bayesian networks. These methods aim to understand the relationship between the geometric parameters, traffic load, environmental conditions, and structural factors and their influence on TQI variation over time.

Building upon this background, this present aims to evaluate various approaches to TQI prediction from both global and national perspective, as well as to identify direction for further development. It is expected to provide a comprehensive overview of methodological trends, highlight the strengths and limitations of each approach, and outline potential research directions for developing a more accurate, adaptive, and sustainable TQI prediction model for future railway systems.

RESEARCH METHODS

This study applies the Systematic Literature Review (SLR) method to search for, identify, evaluate, and synthesize relevant research findings [5]. According to [6] the Systematic Literature Review **(SLR)** approach is a systematic and transparent method for collecting and presenting evidence relevant to a specific research topic, through a structured process of gathering, evaluating, and synthesizing research findings.

The SLR procedure in this study refers to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020**)** guidelines with consist of three main stages, namely:

1. Identification – searching for relevant articles using various scientific databases.
2. Screening – filtering articles based on title, abstract, and content suitability according to inclusion and exclusion criteria.
3. Synthesis – thematically and methodologically analyzing the selected articles to develop a map of research progress and draw conclusions.

The literature search process was conducted using a combination of academic software and international databases, namely:

1. Publish or Perish (POP) to retrieve an evaluate relevant articles base on citation counts and keyword.
2. Google Scholar, Scopus, Science Direct (Elsevier), SpringerLink, and other international journal database for accesing global publications.
3. Sinta Ristekbrin Portal for Indonesian national journal publications.

The initial search yielded 335 articles related to TQI topics and track quality prediction methods. After screening base on the inclusion and exclusion criteria, six journal articles were selected for in-depth analysis, as they met all methodological and substantive requirements.

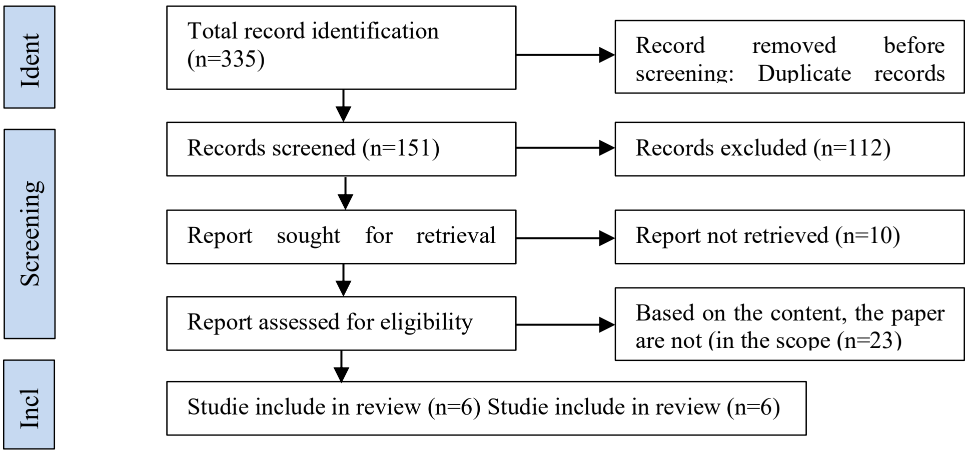

Figure 1. PRISMA Diagram

The PRISMA diagram in the figure illustrates the stages of literature selection in the *Systematic Literature Review* (SLR) process.

1. Identification Stage
   This is the initial stage of the literature search, conducted based on predefined criteria. At this stage, 335 articles were identified as the initial search results.
2. Screening Stage
   In this stage, articles were filtered according to specific inclusion and exclusion criteria. The screening process was carried out using the Rayyan platform resulting in 39 articles that met the selection criteria.
3. Eligibility
   This stage involves a more detailed evaluation of the screened articles to ensure their relevance and methodological suitability, yielding 23 eligible articles.
4. Inclusion (Included)
   The final stage of the literature selection process involved a critical analysis of the eligible studies. After passing all stage, six articles were included for in depth analysis.

RESULTS AND DISCUSSION

The discussion in this study is structured around the main findings, which consist of six reviewed studies related to the development of TQI prediction methods.

Summary of Key Findings

1. Deterministic Regression-Based Approach

Regression-based studies such as [4] and [7], employ multiple linear regression as the primary method for predicting TQI based on traffic parameters and track geometry. The resulting models are capable of explaining more than 90% of the variation in TQI values, with traffic frequency and load identified as the dominant factors influencing track quality degradation. These studies indicate that the relationship between operational intensity and TQI values is linearly positive, meaning that an increase in traffic frequency and load corresponds directly to a decrease in track quality.

Although this regression model is simple and practical for routine applications, its main limitation lies in its deterministic nature, which fails to account for field uncertainties such as dynamic deformation due to temperature changes and the cumulative effects of repetitive loading. Consequently, when applied to tracks with diverse physical and operational characteristics such as those found in Indonesia and other tropical countries its prediction accuracy tends to decrease.

2. Multistage Models and Degradation Cycle Analysis

Research conducted by [8] Introducing a Multistage Linear Prediction Model (MLPM) to describe the degradation pattern of TQI, which is not constant over time. By dividing the degradation curve into several stages namely, the initial stage is stable (initial stage), rapid decline levels (deterioration stage), and critical stage (failure stage) This model successfully represents the life cycle of the railway tracks more realistically.

The results indicate that the MLPM model can reduce prediction errors by up to 25% compared to the single linear model**.** Moreover, it demonstrates higher accuracy in identifying the critical point for maintenance intervention. These findings suggest an early transition from static prediction models to dynamic models that consider time as a significant variable in rail quality degradation analysis.

3. Dimensional Analysis and Machine Learning (PCA) Integration

In large scale data processing, the study conducted by [9] represents an important step through the implementation of Principal Component Analysis (PCA). This method effectively reduces the complexity of extensive rail geometry datasets into three principal components, which together explain more than 85% of the variation in the original data.

By applying PCA, it becomes easier to efficiently identify track degradation patterns and to construct a more representative composite index, compared to conventional TQI calculations that rely on a

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single dimension. These findings demonstrate that dimensionality reduction using PCA can enhance the predictive capability of TQI models without compromising accuracy, while simultaneously addressing the problem of multicollinearity among geometric parameters.

4. Strengthening Statistical Models through the Stepwise Method

The study conducted by [10] Introducing the stepwise regression as an enhancement of the traditional linear model. By gradually selecting independent variables based on their statistical significance, the study succeeded in simplifying the model without sacrificing accuracy, achieving a determination coefficient value of R^2 = 0,997. These findings indicate that not all geometric parameters significantly influence the TQI only Height, Lift, and Twist contribute predominantly to variations in the index.

The stepwise approach also highlights the importance of multicollinearity, an aspect that has often been overlooked in previous studies. Overall, the results confirm that TQI prediction can be optimized through statistical filtering of input variables, resulting in a more stable and efficient model for periodic monitoring systems.

5. Bayesian Network-Based Probabilistic Approach

The probabilistic method primarily aims to estimate unknown variables and make predictions. This approach provides a descriptive framework that transforms machine learning into a computation of the probability distributions of input and output variables [11]. A study conducted by [12] demonstrated a methodological shift in prediction techniques through the application of Bayesian Networks and intelligent stochastic models. The researchers developed a Bayesian Intelligent Index capable of accounting for measurement uncertainty and the interrelationships among track geometry parameters. The Bayesian method is recognized for its ability to predict the probability of an event based on prior occurrences [13]. Through the Bayesian updating process, the model can adaptively update the predicted TQI values as new data become available.

Meanwhile, [14] further developed this approach by proposing a Tree-Augmented Naïve Bayes (TAN-BN) model applied within a Track Grid Health Index (TGHI) system based on Big Data. The TAN-BN model successfully improved the accuracy of track condition evaluation by 15-20% compared to traditional deterministic methods, while also enabling spatial analysis at a 200-meter grid level. These two studies highlight the advantages of Bayesian models in addressing data uncertainty and irregularity, as well as their ability to integrate spatial, temporal, and stochastic factors within a unified inferential framework.

6. Machine Learning - Based Multinomial Regression

The study conducted by [15] represents the most advanced stage in the development of TQI prediction models in Indonesia. Using a Machine Learning - Based Multinomial Regression approach, the research analyzed more than 233,000 data points from the railway network on the island of Java. The model was designed to classify TQI into four categories based on geometric parameters such as superelevation, leveling, alignment, and gauge. The results showed an accuracy rate exceeding 90%, making it the most reliable model in the national context. Furthermore, the study found that the physical location of the track including curves, bridges, and crossings has a direct influence on the probability of degradation. Therefore, the integration between structural and geometric factors is essential in developing an effective predictive maintenance system.

General Synthesis of Findings

When synthesized as a whole, the study shows a systematic pattern of methodological development:

- Stage 1 (Empirical – Linear Regression): Focused on deterministic relationships between parameters, achieving high accuracy results but low sensitivity to environmental variability.
- Stage 2 (Advanced Statistics – Stepwise & Multistage): Improved model performance through variable selection and temporal segmentation, resulting in enhanced model stability.
- Stage 3 (Machine Learning – PCA & Multinomial Regression): Integrated big data learning and dimensionality reduction, leading to greater efficiency and predictive accuracy.

- Level 4 (Probabilistic – Bayesian Network & TAN-BN): Combined stochastic inference and intelligent learning capable of accounting for uncertainty

Thus, this methodological evolution illustrates a paradigm shift from deterministic models toward intelligent and adaptive models. Scientifically, Bayesian-based models have proven superior in dealing with the systemic uncertainty, which is a fundamental characteristic of the railway environment. Practically, machine learning models such as multinomial regression and PCA demonstrate strong potential for integration into big databased maintenance management systems in Indonesia.

Comparative Methods Analysis

The comparative analysis of the reviewed literature indicates that research on the *Track Quality Index (TQI),* both globally a nationally, has undergone a paradigmatic transformation from deterministic mathematical models to more complex probabilistic and machine learning models that are adaptive to the dynamic condition of railway tracks. This shift is driven by the increasing demand for predictive systems that are not only accurate but also capable of handling the inherent uncertainty in track geometry measurement data, while remaining compatible with data-driven predictive maintenance systems. The comparison of various TQI prediction methods in the literature is summarized in Table 1.

Table 1 Comparison of Prediction Methods

Yes	Method	Excess	Limitations
1	Return Line	Simple, easy to interpret	Unable to handle nonlinearity
2	Stepwise	Identify significant variables	Vulnerable to multicollinearity
3	PCA	Efficient for big data processing	Loss of physical interpretability
4	Multinomial Regression	Suitable for TQI classification	Depends on data distribution
5	Bayesian Network	Dealing with uncertainty, adaptive	High complexity in training
6	TAN-BN	Probabilistic and structural combinations	Need big data and parameter validation

Global Trends and Relevance for Indonesia

Global research trends indicate that studies on the Track Quality Index (TQI) are now converging toward three main directions:

1. The integration of probabilistic and machine learning, where the Bayesian Network serve as the backbone for adaptive inference.
2. Utilization of railway big data, enabling the training of predictive models with millions of track geometry measurement points.
3. Spatial-temporal contextualization, involving the integration of spatial information (grid segmentation) and temporal dimensions (deterioration curves) to generate dynamic predictive maps.

Indonesia is currently at the third stage employing machine learning regression for track condition classification, as developed by [15]. However, there is significant potential to integrate Bayesian Network and Internet of Things (IoT) approaches, particularly for establishing a national predictive track maintenance system capable of real-time updates based on field sensor data.

Research Gaps

The synthesis of the reviewed literature indicates that, although research on the Track Quality Index (TQI) has advanced significantly over the past two decades, several conceptual, methodological, and practical gaps remain. These limitations hinder the optimal implementation of predictive models in real-world railway maintenance. The gaps primarily arise from constraints in data availability,

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probabilistic modeling, spatial-temporal integration, and adaptation to geotechnical and tropical climatic contexts such as those found in Indonesia.

1. Limitations on Spatial and Temporal Representations

Most of the reviewed models, such as linear regression [4] dan stepwise regression [10], do not account for the temporal and spatial dynamics of TQI variation. These models typically assume static relationships between geometric variables and track conditions, whereas track degradation is inherently evolutionary and spatial being influenced by positional variations, topography, traffic loads, and drainage conditions. The Multistage Linear Prediction model [8] introduces a temporal dimension; however, it still fails to capture spatial interdependencies between track segments. Consequently, the predictive accuracy of such models remains limited to short-term intervals and cannot support long-term maintenance planning.

2. Lack of Integration of Environmental and Structural Factors

Conventional TQI models primarily focus on track geometry parameters such as alignment, levelling, gauge, and cant without incorporating environmental factors like soil moisture, subgrade stability, rainfall intensity, or thermal variations, which are particularly significant in tropical regions. Study [16] highlights the importance of including both superstructure and substructure characteristics in predictive modeling. However, most existing research (especially in Indonesia) has yet to integrate these environmental parameters. As a result, the models tend to be less representative of real field conditions, particularly in areas with complex geotechnical characteristics such as mountainous or coastal railway segments.

3. Limited adoption of Probabilistic Approach in the National Context,

Although probabilistic approaches such as Bayesian Intelligent Index [12] and TAN-BN [14] have proven effective at the global level, the application of Bayesian-based models in Indonesia remains very limited. Domestic studies, such as [4] and [15] continue to rely primarily on deterministic regression or machine learning models. The absence of stochastic Bayesian models results in point estimate predictions without reliability assessment or error probability estimation. In railway maintenance, such uncertainty quantification is crucial for decision-making and prioritization of track interventions under resource constraints.

4. There is no integration of Bayesian–machine learning hybrid models yet

Until 2025, no studies have been found that integrate the strengths of Bayesian Networks and deep learning algorithms for TQI prediction, particularly within the Southeast Asian context. Most research adopts only one approach either probabilistic models without adaptive learning (pure Bayesian) or machine learning models without stochastic inference (pure ML). However, the global research trend is moving toward (Hybrid Bayesian - Deep Learning) models, which have begun to be implemented in the railway sectors of Japan and Europe for real-time infrastructure degradation detection. This gap presents a significant opportunity for developing intelligent TQI prediction systems in Indonesia that can learn from new data while accounting for uncertainty probabilistically.

5. Limited Availability and Quality of Measurement Data

The most critical technical limitation in the national context lies in the scarcity and inconsistency of track geometry measurement data. According to [15], only about 78.84% of railway lines in Java are currently covered by TQI data obtained from the EM120 track recording car. The dependence on a single measurement unit result in infrequent temporal data collection, leaving a large portion of tracks to be evaluated manually. This limitation constrains the implementation of big data driven prediction models and Bayesian updating, both of which require large, continuous datasets to produce reliable and robust predictive outcomes.

6. Lack of Global–National Standardization

Research in Indonesia has not fully adopted the TQI categorization system that is consistent with international standards such as EN 13848 (European Union) or AREMA (United States). Although the study by [7] made partial adaptations to national conditions, there is still no standardized mathematical formulation for calculating TQI across different track environments urban, mountainous, and coastal. This lack of standardization hinders comparative analysis between regions and limits the interoperability and scalability of predictive systems within broader railway maintenance frameworks.

Future Research Direction

To address the aforementioned research gaps, several future directions for TQI development can be proposed from conseptual, methodological, and perspectives.

1. Development of a Spatial -Temporal Bayesian Network Model

Future studies are encouraged to develop a dynamic Bayesian Network capable of incorporating both temporal and spatial dimensions. Such a model would enable continuous prediction updates based on sequential measurement data obtained from track recording cars or on-board sensors. By integrating spatial-temporal probabilistic modeling, the system could predict long term track degradation patterns and generate real time degradation risk maps. The implementation of this approach may follow the Dynamic Bayesian Network (DBN) framework, which has been applied in intelligent transportation systems in Japan and Germany.

2. Integration of Hybrid Bayesian–Deep Learning Model

Further research should focus on developing hybrid models that combine the inferential capability of Bayesian methods with the predictive power of deep learning. This approach can be implemented through the integration of Convolutional Neural Network (CNN) for spatial analysis and Bayesian inference for uncertainty quantification. Consequently, the system would not only predict TQI values but also provide confidence intervals, serving as a probabilistic basis for maintenance prioritization according to the likelihood of track deterioration.

3. Utilization of IoT and Real Time Sensing

Future TQI prediction systems should leverage Internet of Things (IoT) technology and accelerometer sensors installed on operational trains. By collecting real time data on vibration, acceleration, and track deviation, these measurements can be directly processed using Bayesian models to update track condition predictions without the need for periodic manual inspections. This approach has the potential to reduce manual measurement frequency by up to 40% and significantly enhance the efficiency of data-driven maintenance systems.

4. Standardization of Quality Classification and TQI Categories

Another research direction involves the development of an adaptive and probabilistic TQI categorization system, replacing the current deterministic classification (Categories 1–4). Through the implementation of fuzzy Bayesian classification, the system could accommodate borderline conditions between categories, allowing classification results to more accurately represent real-world track conditions.

Academic and Practical Implications

From the overall analysis of research gaps and future directions, it can be concluded that the future of TQI research is moving toward intelligent, dynamically probabilistic prediction systems that integrate Bayesian inference, deep learning, and real-time sensing technologies. From an academic perspective, this direction opens interdisciplinary research opportunities bridging civil engineering, computer science, and intelligent systems. From a practical standpoint, the implementation of such models in Indonesia will foster a transformation from reactive maintenance to predictive maintenance, resulting in a more efficient, safer, and data-driven railway infrastructure management approach.

CONCLUSION

Based on the overall comparative and synthesized analysis, it can be concluded that the methodological evolution of TQI prediction has been progressive and continuously advancing. Deterministic approaches provide a strong empirical foundation, statistical methods optimize model

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structure, machine learning techniques enhance computational capability, and Bayesian models offer the most mature probabilistic framework for addressing the inherent complexity of railway systems. Global research trends indicate a growing shift toward hybrid Bayesian–Machine learning models**,** which combine the strengths of probabilistic inference and nonlinear learning. In the future, TQI prediction systems are expected to be integrated with IoT and edge computing technologies, enabling real-time track condition prediction that enhances both the safety and operational efficiency of railway systems at national and international levels.

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