Review Article

Smart Diagnosis and Maintenance Systems for Railway Tracks

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Abstract: In recent years, advanced technologies such as artificial intelligence (AI), the internet of things (IoT), and big data came into prominence. These technologies found an extensive area of utilization in various sectors. Railway systems as an important part of the transportation of people and goods should be improved by the integration of novel technologies. Successful detection of track faults and operating maintenance tasks accordingly are essential for the safety of railway operations. Currently, image processing and pattern recognition via machine learning applications are in common use for automated track inspections. However, it is not possible to claim that railway tracks are integrated with current technology perfectly. In this work, differences between the traditional way and the smart way of track inspection and maintenance are presented. Shortcomings of the application of advanced technologies into railway tracks are detected and required actions for further improvements are discussed. Lastly, the effects of the use of smart systems on the life cycle of the structures are evaluated.

Key words: Railway track, track inspection, track maintenance, artificial intelligence, machine learning

Demiryolu Hatlari İçin Akilli Teşhis ve Bakim Sistemleri

Özet: Son yıllarda yapay zeka (AI), nesnelerin interneti (IoT) ve büyük veri gibi ileri teknolojiler ön plana çıkmaktadır. Bu teknolojiler çeşitli sektörlerde geniş bir kullanım alanına sahiptir. İnsan ve yük taşımacılığının önemli bir parçası olan demiryolu sistemleri, bu yeni teknolojilerin entegrasyonu ile iyileştirilmelidir. Hat arızalarının başarılı bir şekilde tespiti ve bu tespitlere göre yapılan hat bakımları, demiryolu işletmesinin emniyeti için gereklidir. Şu anda, görüntü işleme ve makine öğrenimi yardımıyla örüntü tanıma uygulamaları, otomatik hat denetimleri için yaygın olarak kullanılmaktadır. Ancak demiryolu hatlarının günümüz teknolojisiyle mükemmel bir şekilde entegre olduğunu söylemek mümkün değildir. Bu çalışmada, geleneksel ve akıllı teşhis ve bakım yöntemleri arasındaki farklara yer verilmiştir. İleri teknolojilerin demiryolu hatlarına uygulanmasındaki eksiklikler tespit edilmiş ve daha iyi bir gelişim için gerekli eylemler tartışılmıştır. Son olarak, akıllı sistemlerin kullanımının, yapıların yaşam döngüsü üzerindeki etkileri değerlendirilmiştir.

Anahtar Kelimeler: Demiryolu hattı, hat denetimi, hat bakımı, yapay zeka, makine öğrenimi

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1. Introduction

The use of information, digital, and telecommunication technologies enhanced the flexibility, efficiency, and sustainability of the services for inhabitants good in smart cities (Mohanty et al, 2016). The cooperation of two closely related fields, i.e. internet of things (IoT) and big data is the key for responsive, efficient, friendly, and advanced smart cities. IoT is the inclusion of "things" to the communication by mixing physical and virtual worlds together and enabling information transfers between humans and things and/or between things themselves (Tan and Wang, 2010). "Things" are smart tools such as sensors that collect data from their environment to raise awareness about the context.

The size of the data produced by the sensors is enormous. It is discussed in terms of petabytes and continuously increasing with the installation of more data-generating tools. The type of data produced by the sensors can be unstructured, semi-structured, or structured. Collective big data contains data sets that frequently used software can not capture, organize, manage, and process the data within a tolerable elapsed time (Snijders et al, 2012). Data analytics consists of descriptive, diagnostic, predictive, and prescriptive analytics. Figure 1 shows the steps from gathering data from sources to the evaluation of them in the operations. Big data analytics can be achieved through the use of artificial intelligence (AI) techniques such as machine learning, natural language processing, data mining, etc., and thence, one can develop an understanding from the raw data. This makes system performance optimization, product improvements, and better business decisions possible.

Figure 1. *Process of data management*

Railway operations aim to achieve various goals at the same time: Providing safe, economical, fast, and comfortable transportation. New technologies allow us to not only satisfy minimum requirements but also improve track conditions further and optimize track performance. However, some concerns are raised about the implementation of advanced technologies into railways. Challenges are either railway application-specific or originated from the nature of big data use.

In this study, the degree of the integration of advanced technologies into the railway tracks is investigated. Studies of the literature about railway track applications of IoT, big data, and various artificial intelligence (AI) techniques are examined. While there are various ways of implementing discussed technologies into rail transport systems, smart monitoring and maintenance systems come to the forefront in terms of benefiting from track mechanics data to optimize performance and enhance the safety and life cycle of the track. The paper determines the shortcomings of smart track monitoring tools and provides a new direction of research for more advanced railway track monitoring. Also, it analyzes the significant effect of the proper monitoring and maintenance decisions on the sustainability of the structures.

2. Traditional way of track maintanence

Safety is the essential and serious theme of railway transportation. Railway tracks must be designed to meet safety criteria as well as maintaining acceptable track conditions, however, geometry and structural defects may occur under the repeated wheel loads over their service lives. Detection and adjustment of railway defects via a regular maintenance plan is crucial for the safety and also economical benefits of the railway track. In the United States only, rail defect-related accidents caused a $108.7 million loss, constituting %34.8 of the total train accidents in 2009 (Peng, 2011). In the Netherlands, it is estimated that railway track maintenance constitutes half of the maintenance budget each year (Zoeteman et al, 2014). Therefore, a maintenance plan is necessary for enterprises to accurately predict the changes in track conditions so that they may guarantee the economical advantage of the track.

Track quality conditions can be simply measured by the track quality index (TQI). Equation 1 presents the formulation of a basic linear model for TQI prediction proposed by Shangai Railway Bureau, Weichang Xu. represents initial TQI, K represents the deterioration rate, and T is the total accumulated weight. This model can simply predict the short-term changes in TQI, however, relatively larger deviations occur in the long-term because track degradation is not only based on the total weight but also geographical location, temperature, precipitation, measurement errors, and so on (Song et al, 2014) Besides, one must know the probable rate of track deterioration to use the given formula. However, the literature review of Melo et al. (2020) reveals that currently there is no track deterioration method available to analyze the condition of the track (Andre et al, 2020) Their extensive survey detected more than 100 studies related to track deterioration but most of the methods can not be used when several track deteriorations occur.

$$TQI = TQI_0 + K * T \quad (1)$$

Currently, special track inspection curs run 2-4 times a year to gather data from the track. Repairment decisions are made by comparing track obtained irregularity data with the limits specified in the regulations such as EN 13848-5 which specifies track gauge and longitudinal level values for various train speeds (EN 13848-5:2008+A1:2010). For instance, if the mean to the peak value of the level difference in the track data is 7-12 mm for the wavelength of 20 m and train speed of 200 km/h, it is the alert limit that requires the track geometry condition to be analyzed and considered in the regularly planned maintenance operations. Likewise, 9-14 mm is the intervention limit that requires corrective maintenance, and 20 mm is the immediate action limit that requires taking immediate actions against the risk of derailment. AREMA guides the railway experts through comparison of the strip chart output of Track Geometry Measuring Vehicle (TGMV) with predetermined thresholds set by railway administrators to evaluate the condition of the track (AREMA, 2016). Interestingly, threshold criteria for maintenance decisions have not changed in about 50 years (Yokoyama, 2015).

DEFECT NAME	FROM POST/FEET	TO POST/FEET	LENGHT(FEET)	MAXIMUM VALUE	THRESHOLD	SPEED	TRACK TYPE
L PROFILE	47 + 678	47 + 685	7	3/4	5/8	60	T
R PROFILE	47 + 678	47 + 685	7	3/4	5/8	60	T

Table 1. *An example of strip chart produced by TGMV (AREMA, 2015)*

Constantly evolving data-driven methods, on the other hand, may help to achieve smart management decisions. Big data in railway track maintenance is the vast amount of train and test data gathered from the track and used for the track condition evaluation. This can also help to perceive the equipment condition rapidly, tracing all historical data and obtaining a specific historical condition of the equipment. Data-driven track diagnosis can be achieved by implementing machine learning (ML) algorithms. In the next chapter, the foundation of the AI-based evaluation: ML will be overviewed. In the following chapter, shortcomings of the smart diagnosis and maintenance systems in the railway tracks will be discussed. Lastly, the effects of smart maintenance on the sustainability of railway tracks will be examined by analyzing their life cycle costs.

3. Overview of machine learning

Machine learning is a trending branch of AI, that builds a mathematical model based on the collected data to make predictions and decisions without being programmed. In this chapter, data types, ML learning methods, algorithms, and data analysis methods will be introduced briefly.

ML applications consist of three types of data: train, test, and validation data. ML algorithms use trained data to create a mathematical model. The ultimate goal is the training the model with the train data to produce the results that give the correct answers to questions as much as possible. Most of the collected data is used as train data (%60-90). After, the created model is tested with the test data. The results of the trained data are removed and the machine is allowed to make predictions. Estimates and actual outputs of the data are compared. Test data determines the accuracy of the predictions and measures the performance of the algorithms. With the validation data, the trained model is tried to be improved. For this, the most optimum coefficients are found by trying hyperparameter tuning applications. In a dataset with very large data, 15-20% of the data is used for validation, since train or test data can not be used for this development.

There are two learning methods that ML applications use for training. In supervised learning, inputs and outputs are known in the dataset, so that the model can be trained by building relationships between input and outputs of the data. Supervised learning can be used for railway management. The numbers and condition of the line, the effect of the traffic level that may occur in certain hours and days on the arrival time of the train from one place to another can be measured on the basis of time. By correlating all (input) variables with the travel time parameter (as output), a model can be created to make predictions about the travel time of a train. A few of the most frequently used supervised learning algorithms can be listed as follows:

• *Decision Trees:* It is used to divide a data set into smaller sets according to certain rules. However, overfitting can be problematic in the decision tree.

• *Random Forest:* In these algorithms, multiple decision trees are created. Then, it is tried to find the right way.

• *Logistic Regression:* It is a regression where there are two possibilities. For instance, True or False; 0 or 1.

• *Neural Nets:* There are algorithms that use large amounts of training data to identify correlations between many variables to learn how to manipulate future *data*.

The second type of learning is unsupervised learning in which there are only inputs and no outputs. In this type of learning, the relationship between inputs is determined. After, data samples can be categorized based on the similarities of their input data. For instance, collected data from railway tracks can be evaluated and clustered according to their importance (predictive maintenance). Some of the unsupervised learning algorithms are as follows:

• *K-means:* It is an algorithm to classify data in a data set into k different predetermined sets.

• *DBScan:* It is an algorithm used to distinguish between high-density clusters and low-density clusters.

• *Expectation Maximization:* It is an algorithm used to perform the highest probability estimation with unobservable variables.

Since ML applications are built on sample data, it is necessary to collect big amounts of data and prepare them for the training. The quality of the data determines the quality of the model. This is where data analysis comes into prominence. Data analysis consists of 5 main steps. These steps can be listed as follows:

1. Defining the question: Firstly, it is necessary to determine the problem encountered so that a hypothesis can be created by asking the right questions.

2. Collecting the data: There are various types of data such as numerical data, images, audio, and questionnaires. Seize and quality of the data determines the quality of the solution. Thus, data must be collected using various techniques and different datasets can be merged if required.

3. Processing the data: Collected data do not make sense at first. These raw data need to be made suitable for analysis. This can be achieved by data cleaning and data manipulation. Data manipulation is the whole process of making the data suitable for use without destroying its content. It has 4 main steps:

a. Data Cleaning: There may be inaccuracies and/or inconsistencies in the data collected. This inconsistent data is removed in this process. Various deletion techniques can be applied when there are missing values in the data. If a list contains one or more missing values, listwise deletion is applied by removing all data for that list. Usually, this is a disadvantage. It is possible to produce biased parameters and estimates. Column deletion is the process of deleting a feature in the data. It is not generally preferred, but if the number of missing data in the same variable is more than 2/3, this variable can be removed from the dataset. In pairwise deletion, the needed variables are selected and the missing data are deleted and analyzed.

b. Data Integration: Gathering data from different sources is called data integration. Some data may have been entered several times during this integration. Data with the same inputs and outputs must be entered as single data. Missing values can be also imputed instead of being deleted. It can be filled with the value above or below the field in which the missing data is located in the column. Another favorable way to the imputation of the missing data is to use the means, median, and mode of the variable. By using the mode, the missing data can be filled with the value according to the highest frequency. Also, linear regression can be used. Missing data can be estimated by defining the column containing the missing values as the dependent variable and the other columns as the independent variable. The disadvantage is that it will be filled according to other variables, so there may be overfitting in the dataset. Lastly, imputation with categorical data can be applied. Then, missing data can be labeled and prepared for analysis.

c. Data Transformation: The collected data may not be in the desired format. This step is applied to convert these undesired formats to the format of the target format.

d. Data Reduction: Data reduction is the process of reducing the required storage capacity. This increases storage efficiency and lowers storage costs. It is the reduction of dimensions.

4. Analyzing the Data: Once the collected data is processed properly, it is ready for analysis. There are 4 types of data analysis:

a. Descriptive Analysis: It examines the data and determines what happened. It is the step before proceeding with detailed examinations.

b. Diagnostic Analysis: It focuses on understanding why an event occurred.

c. Predictive Analysis: It is an analysis method that enables the prediction new results based on past data.

d. Prescriptive Analysis: It is a type of analysis that plays a role in determining the actions to be taken for the future.

4. Smart track diagnosis & maintenance

Smart track diagnoses and maintenance systems are achieved through the integration of advanced technologies into railway tracks such application of IoT for data collection and using ML algorithms for data analytics. Railway track monitoring systems can be both track-side or on-board systems. Track-side monitoring is achieved by the mounted sensors around the track to detect the wheel profile irregularity, dynamic impact forces, and evaluate bogie performance. However, this method allows monitoring at only selected positions. On-board monitoring systems, on the other hand, mostly focus on the real-time detection of rail defects. Sensors carried on the vehicles gather information about the response of the vehicle to track excitation and component faults such as acceleration, rotation rate, displacement, noise, and temperature (Chunsheng et al, 2017). They typically include accelerometers, gyros, noise detectors, and GPS.

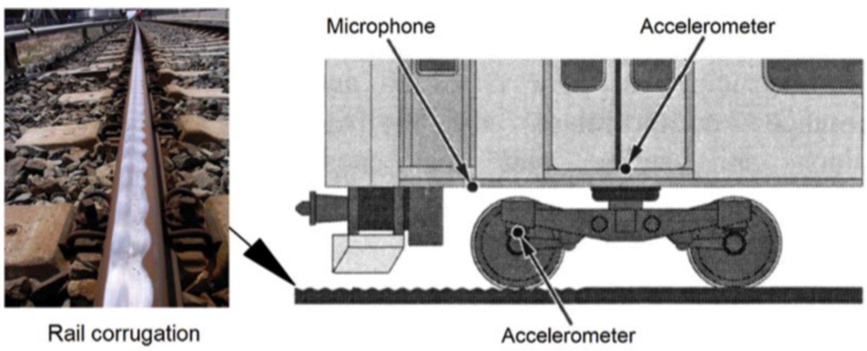

Figure 2. *An example of an on-board rail corrugation detection system (Hayashi et al, 2006)*

There are various non-destructive methods to be used for rail defect inspection such as ultrasonic devices, high-resolution video cameras, 3D-laser cameras, and eddy current inspection.

Results of the survey conducted by Nakhaee reveal that the most popular data source for ML applications is video cameras (Nakhaee et al, 2019). Video cameras located on the measurement trains capture high-resolution images from the track from different angles. The collected data can be separated to train and test data. A model can be trained via ML algorithms and tested afterward. Such being the case, anomalies in the rail track can be detected via the created ML model.

The Research and Development Center of JR East Group has presented the “Smart Maintenance Initiative” which is defined as “21st-century innovation in the maintenance of railway equipment” (Yokoyama, 2015). This initiative has 4 fundamental components: 1) Achieving condition-based maintenance (CBM), 2) Introduction of asset management, 3) Maintenance work support by AI and 4) Integrated database. CBM means transformation from the traditional philosophy of maintenance, e.g. time-based maintenance to performance-based planning. With more data, it is possible to perceive the trend of the deterioration better and predict the future irregularity, thus, make better decisions for maintenance by finding optimal repairment time. CBM allows daily and dynamic basis inspection so that more data can be gathered. Figure 4 presents the difference between time-based management (TBM) and CBM.

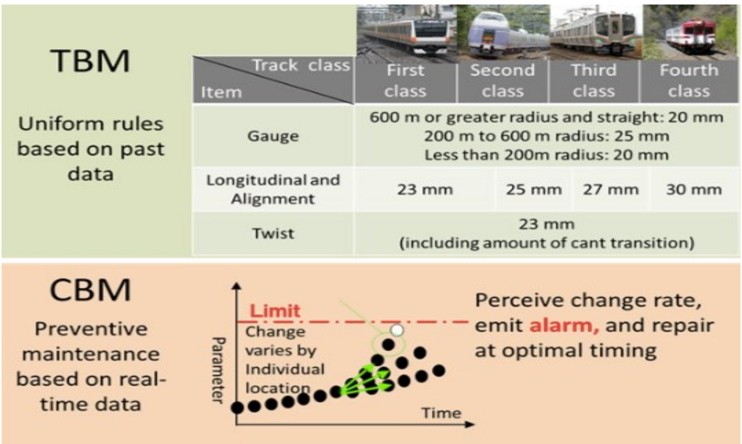

Figure 3. *Comparison of traditional TBM and innovative CBM (Yokoyama, 2015)*

Asset management aims to make optimal maintenance plans for the lifespan of the track. Work support by AI aims to organize an environment where humans and AI work collaboratively. The process begins with the presentation of gathered data by data scientists and then continues with the interpretation of the results by both experts of the field and AI algorithms. Therefore, storage of the data, integration of databases, and hiring skilled data scientists come into prominence as well as improving the existing AI algorithms. Smart, more frequent, and proper detection of faults increases the sustainability of the structure by contributing to the extension of its life cycle. Thus, smart diagnosis and maintenance systems for the railway tracks suit the goal of developing smart and sustainable cities of the future. However, the literature review of the existing smart railway track applications showed some challenges to overcome for full integration of the discussed technologies and thus, to provide better performance. In the below chapter, the most mentioned problems of the literature are listed and explained.

5. Shortcomings of the integration

The cause of a system failure or an accident is now currently identified by experts in the field. Since experts are expected to have the background knowledge and sufficient experience, it is their job to find the causes and offer solutions. However, there may be a knowledge gap in a specific area, or the company may have relatively inexperienced engineers, and making a proper decision may not be possible. Maintenance engineers may take advantage of AI algorithms since they have the potential to solve complex problems and they constantly advance like an engineer who gains experience over time. Machine learning, text mining, and natural language processing can be used to develop AI experts. However, human language is a still complex issue for computers and NLP techniques must be developed further especially in common sense-based reasoning, conversation support, and context awareness areas (Kugurakova et al, 2015; Balci, 2019).

The use of IoT produces a large volume of data that must be stored, managed, and operated. These stages require effort and also storage of the data can be sometimes problematic. Thus, companies must invest in data centers, hire skilled data scientists and personnel should work collaboratively to get the most out of the data. For example, video cameras collect approximately 10 terabytes of image data in the Dutch railway system each year (Jamshidi et al, 2017). Another challenge is the quality of the data; images may not be clear, resulting in inaccurate training of the model. The existence of oil and dust residuals can affect the performance of ML-based training negatively (Santur et al, 2016).

As a general rule, large datasets can provide better results for ML training. Large datasets are generally created by combining multiple datasets. Thus, publicly available and labeled datasets can enhance the performance of railway tracks ML applications. However, very small numbers of datasets that include rail track data are publicly available, since companies and government bodies prefer to keep data for themselves. Sharing datasets publicly or supporting ML researches in universities will allow the contribution of academics and independent researchers to the field. Labeled data is another issue since captured data through inspection are mostly not labeled. There are some studies where researchers labeled the data manually (Raghih et al, 2016; Jamshidi et al, 2018). However, for more efficient use of ML-based applications, auto-labeling systems must be developed.

Attoh-Okine (2014) determined 5 main challenges for big data use in railway engineering (Attoh-Okine, 2014): Heterogeneity, inconsistency, and incompleteness, merging data, timelines, and privacy and data ownership. Firstly; rail defect, track geometry, and tonnage data are not homogeneous. Secondly, data collection tools do not always provide certain, complete, and accurate data. Missing values reduce the success of the models. Merging data is another challenge because healthy big data analytics not only requires large datasets but also the merging of different databases. However, in railway applications, it may not be always possible. For instance, if one has ballast condition data and also track geometry or operational data, he or she can not take advantage of these two datasets, since they do not offer standardized values. Another challenge is that efficient and effective implementation of timely maintenance sets a time limit for real-time data analytics. Finally, any electronic information such as electronic ticket info brings privacy worries.

6. Effects of smart ınspection systems on the sustainability of the structures

Big data gathered by the smart sensors contributes not only to the environmental development process of the smart and sustainable transport systems but also to understanding, evaluation, and planning of them. There are already IoT integrated big data applications and smart-sustainable initiatives in some of the ecologically and technologically advanced cities (Al Nuaimi et al., 2015; Bibri and Krogstie, 2016, 2017a, 2017b, 2017c; Tokody et al., 2015). In below, some of the studies which attempt to make railway tracks smarter are shown, and later, some of the studies that show the effect of the digital transformation on sustainability are cited.

Jo et al. (2018) suggest that IoT is a fundamental enabler of the CBM in order to make the maintenance period more efficient. Even though IoT may be costly, railway maintenance can be a great business model for the implementation of IoT. However, various communication schemes and circuit design schemes must be adopted to achieve low power consumption and higher reliability (Baker et al., 2015; Kelly et al., 2013; Martinez et al., 2015; Baker et al., 2013; Kuila and Jana, 2013). Continuously advancing technology of the smart sensors has given rise to miniaturized devices with new signal processing methods, higher performance, and higher speed electronic circuits (Bibri, 2015). Castillo-Mingorance et al.'s (2020) study shows that advanced but simple sensors are able to measure diverse parameters such as deformations, vibrations, track oscillations, and dynamic impact forces. Fiber optic sensors are among the most versatile sensors, however, they have a higher cost compared to alternatives. Edwards et al. (2021) offered a concept design to improve safety and respond to maintenance-related concerns of the track infrastructure by monitoring and estimating track health. IoT is a suitable technology for the sustainability development of railways since remote monitoring will result in faster troubleshooting and issues identification.

Johansson and Reim (2019) conducted 26 35-to-80 min interviews with a digital railway maintenance development company and the traffic agency in order to find out the outcomes of the transition to eMaintenance. It has found that implementation of eMaintenance leads to advanced information on condition, enhanced capacity, more efficient maintenance, optimized costs, and also increased sustainability. Kaewunruen and Lian (2019) developed a 6D BIM of railway turnout system which is a big data-sharing platform to provide logic, efficiency, sustainability, and enhanced collaboration for the planning work schedules. It is shown that BIM or digital twin can help visualization and prioritization of the maintenance options and estimation of the associated costs. Wyman (2014) states that companies whose top priority is sustainability will gain massive advantage against their competitors.

This paper concerns the disadvantages of traditional systems compared to smart systems, shortcomings of the integration of advanced technologies into the railway tracks, and also achieving sustainability and gaining long-term benefits by using smart systems. The first two are discussed above. The last one will be the issue of this chapter. Usually, the long-term effects of a structure are evaluated by its life cycle. The life cycle is the examination of the entire process from the raw material state of a product to its production, use, maintenance, and recycling or removal from production. The life cycle cost (LCC) concept, throughout the life cycle of a system or product; is defined as the sum of the costs incurred for the development, production, operation, and removal of the system from the inventory (ORR, 2017).

In the railway, which is built with the aim of long-term use with high construction costs, the maintenance periods that will occur during use are very important for the life of the railway line. This has created the life cycle concept in terms of enabling us to make the system work with a maximum performance by establishing the life cycle of all products in our system, from the smallest part to the largest part, and maintaining and changing them at the right times.

Railway use is an important point in the choice of transportation investment type of many developed and developing countries due to its being safe, sustainable, environmentally friendly, and efficient. In growing and producing societies, the need for railways for the fast, safe and economical transportation of products and people day is increasing. By the end of 2025, worldwide rail freight transport is expected to increase by approximately 14.75%, with 11912 tons of freight per kilometer. Likewise, it is expected that by 2025, passenger transportation by rail worldwide will increase by 37,2% compared to 2015 (Attoh-Okine, 2014).

In addition, although railway investments have been made in many countries, it has been observed that these investments cannot meet the increasing demands. For example, despite advanced rail investments in the UK, there was an increase of approximately 4,8% in human transport between 2010-2011 and 2016-217, making the British railways the second busiest railway line in Europe (ORR, 2017). Similarly, over the same years, the number of people traveling by rail increased by 11%, although there was only a 4,8% increase in rail track length in the United States. Likewise, although the railway investments in India are only 4,5%, the number of passengers has increased by 6%. (APTA, 2017) With the increase in the number of people using the railway line, the density of the line will increase with the increase in the number of trips. With such increases, the line will deteriorate with the use of the line above its capacity and the maintenance costs of the line will increase. In order to keep the life cycle of railway lines built with high investment costs long and reliable, it is necessary to use the available resources in the best way. Especially in conventional ballasted railway lines, railway line maintenance directly affects the condition of the railway line, the possibility of accidents that may occur with the settlements or deformations, fuel rates of railway vehicles and wheel and rail maintenance costs, travel time costs, and emissions. Taking good care of the railway line affects driving safety and driving comfort. It also increases the lifetime of the line.

For these reasons, an effective asset management system that systematically takes into account all life cycle costs (WLCC) and the lifecycle benefits of the line is needed in order to get maximum efficiency from the railway line and to use the line safely (see Figure 5). This approach finds the causes of cost factors and allows the most cost-effective fixes to be found, as well as comparing alternative care options and finding where to use maintenance resources first.

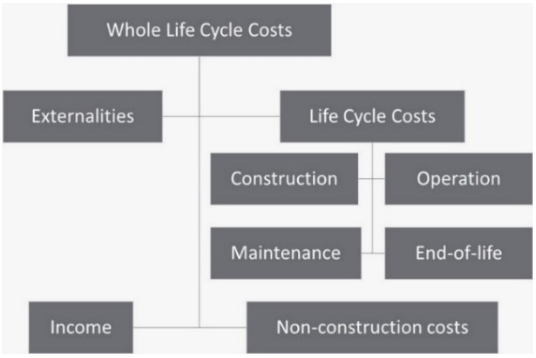

Figure 4. *All Lifecycle Costs adapted from ISO 15686-5 (2017) (Sasidharan et al, 2020)*

Maintenance periods for railway infrastructure in general use proceed according to pre-planned schedules according to time and road carrying capacity. However, with the increase in the use of railways, the railway may need maintenance and renovation works in earlier periods. However, when acting according to pre-planned maintenance times, maintenance cannot be carried out under optimum conditions. In the absence of maintenance and repair work under optimum conditions, maximum benefit cannot be obtained from the railway. This situation is gradually changed towards intelligent maintenance and maintenance at the right time.

Railway line maintenance and renewal costs include direct costs to examine the condition of the railway line, to operate it, and to renew the places deemed necessary and indirect costs that require line maintenance such as delays, accidents, and emission situations. The useful life cost is the cost of the railway system at the end of its useful life.

In Figure 5, different cost variables that may occur in the life cycle of the railway line are given as a function for the average railway line construction and expenses (Marschnig, 2016). As can be seen from the given function graph, higher construction and maintenance costs are required to build a better quality and durable railway line. On the other hand, the higher the quality of the railway line, the longer the maintenance and renewal times of the line, so the costs will decrease. The figure shows the minimum total transport cost (TCS1) the ideal average rail condition (TQS1) or the optimum maintenance conditions. Line construction cost in ideal standards has been shown at MCS1 point. In the line construction condition (TQS2) lower than the ideal line condition, maintenance costs may decrease (MCS2), but it causes an increase in the usage and operating costs of the line (UCS2). An increase in rail line operating costs is more costly than maintenance under optimum conditions (TQS1), resulting in higher transport costs. In another way, building a better quality and larger rail line than ideal conditions (TQS3) causes an increase in maintenance costs but decreases usage costs.

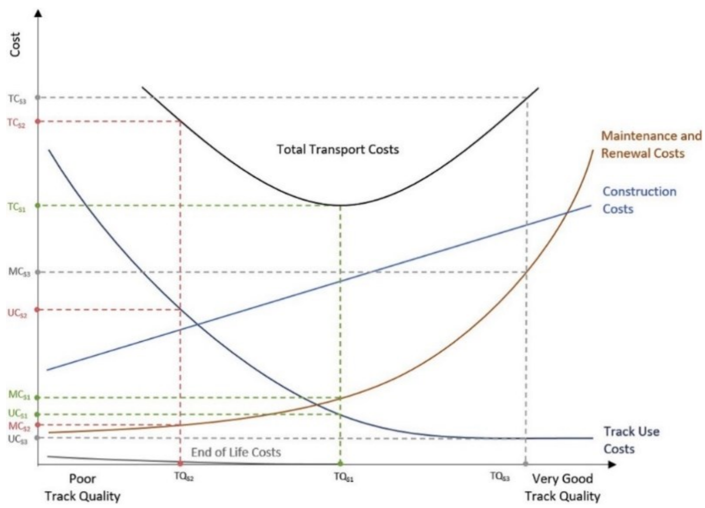

Figure 5. *Optimal railway track maintenance standard (Sasidharan et al. 2020)*

Railway maintenance of the railway line until the line construction costs and manage operating costs is also very important. Because the construction costs of railway line investments are very high, therefore, the expected service life of the railway line can be extended by managing the maintenance and operating costs under optimum conditions. As can be seen in Figure 7, the long-term effects of investments and measures made in the short term are shown.

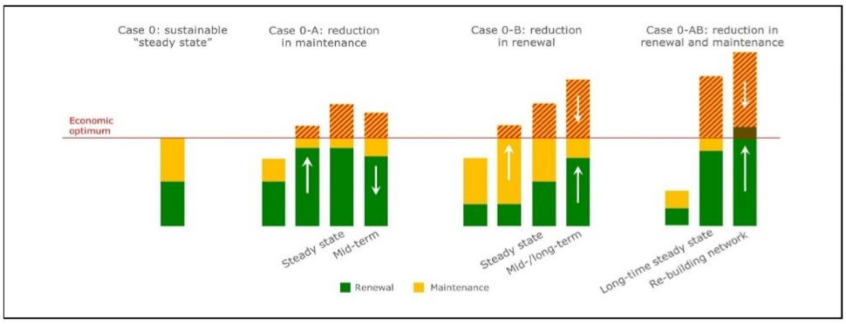

Figure 6. *Short-term savings and their long-term consequences (Veit 2007).*

The life cycle cost of the railway line can be defined as the sum of maintenance, operation and renewal, and depreciation costs. When costs are analyzed in the life cycle of railway lines, economic analyzes are calculated over annual revenues, as the depreciation value is the main factor as the useful service life of the line (Veit, 2007). As the service life of the railway line increases, the number of depreciation decreases. Maintenance and replacement costs increase over time. As a result, optimum time can be found to renew or maintain the line, so that the railway line reaches its maximum service life with minimum costs.

In order to provide maximum service life with minimum cost in the life cycle cost of the railway line, the life cycle of all kinds of parts used in line construction should be analyzed and all analyzes should be brought together and the maintenance and operation system should be planned. Otherwise, the railway line may become unusable in its maximum service life, or maintenance costs may be higher than expected.

The technical service life of the railway line can be used longer than its calculated economic life. However, maintenance costs may become higher than calculated here, so the life cycle cost of the line increases. As a result, using the line beyond its technical service life will increase the life cycle cost, thus deviating from the optimum cost.

The life cycle cost of the railway line may increase or decrease due to the reasons described, as well as the deformations that may occur in the railway line and in the infrastructure of the railway line with the increase in the usage density of the line. For this reason, the control engineers of the line have a very important task in taking sustainable measures and establishing follow-up periods.

There are three basic situations for short-term savings in asset management in the rail system. The first case is the reduction of maintenance work, the second case is the reduction of line renewal efforts, and the third is the reduction of both line maintenance and line renewal efforts.

Figure 6 defines the situation as the steady state, which shows that the line aspect and renewal costs of the railway line in the most basic case in the reference state of 0 are approximately the same for all lines and all units in the line. Looking at the 0-A situation, it is seen that short-term reductions in maintenance lead to a shortened service life of the parts of the railway line. In this way, they can be out of service before reaching their technical life. In this way, if maintenance periods are extended as not timely, parts may need to be replaced before they reach the end of their service life. This situation raises the life cycle costs to a higher level. When looking at the 0-B situation from Figure 6, the results of the savings made in the short term with regard to the renewal studies, which are more important, can be seen. If the demands for renewal in the railway line decrease, it may be that the parts on the line are subject to excessive deformation. This requires high maintenance costs to restore parts to their old quality. When we look at the 0-AB situation, it means that both maintenance and replacement costs are cut at the same time and the other two situations come together. When we consider in the long term, life cycle and life cycle costs increase at the same time with both high maintenance costs and frequent renewal. This situation can be used at times when maximum benefit is desired by deviating from optimum conditions.

To summarize the comparison of the three scenarios with state 0, it ceases to be sustainable in state 0, although both maintenance and replacement costs are important for short-term savings. This situation brings with it a great cost of change in the railway line in the long run. Particularly in the 0-B situation and in the 0-AB case, parts will require replacement with new parts in the long run due to the early reach of their useful life, and in this case, there may be shutdowns or speed restrictions for a certain period of time due to the works in the infrastructure and superstructure.

In line with all these plans, the right interventions should be made at the right times by establishing a maintenance and renewal program in order to ensure the sustainable operation of the railway line under optimum conditions. The contents of this plan should answer some questions; "When will which part of the railway line be taken into maintenance?", "What are the service lives and remaining service lives of the materials used? "and "If the railway line needs to be renewed, what are the reasons?". Since railway structures consist of multi-factor components and all components affect each other, it may not be possible to find the optimum time by combining each value. However, the best program can be created with various approaches. For these reasons, the railway line should be analyzed in detail and the areas that need maintenance or replacement should be determined first. The causes of malfunctions that may occur afterward should be determined and measures should be taken accordingly. After these evaluations, it should be decided that ongoing maintenance or renovation works are economical and sustainable. In order to use the available financial resources efficiently, additional costs that may occur in case of postponement of possible maintenance or renewal works should be calculated. If all these are done with the order and analysis shown in Figure 7, the efficient use of the budget will ensure maximum efficiency from the railway line.

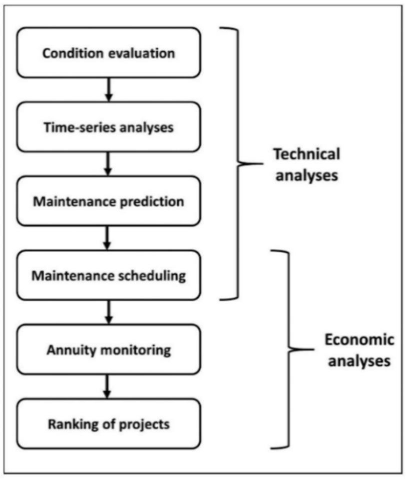

***Figure** 7 Life cycle process of assets (Neuhold et al, 2020)*

In summary, by preparing a suitable life cycle management for the railway line and applying this management at the right time and conditions, maximum benefit is achieved with optimum maintenance and renewal costs. In the part of managing the railway line throughout its life cycle, the main purpose is to perform the line renewal when necessary by keeping the quality of the line at optimum levels with effective maintenance techniques. The time of maintenance techniques and how they will be done can be determined with the help of smart systems and appropriate maintenance or replacement where necessary.

All these findings reveal the importance of smart diagnosis and maintenance methods in life cycle analysis. The first step of life cycle analysis is condition evaluation, and this step is achieved more effectively with smart systems. Because in the innovative system, more frequent data collection has been suggested, so that training can be carried out on larger data sets. By using ML techniques, predictions are made for future failure base on historical data.

Using smart methods enables us to locate the steps we take in the life cycle accurately and on time. If we do the right maintenance and repairs in the right places at the right time, we will run our system in the most optimum condition. This provides an economy throughout its life cycle and makes it more sustainable.

7.Conclusion

This paper investigated the application of smart diagnosis and maintenance systems to the railway tracks in order to increase the performance of failure prediction, establish an optimal maintenance plan, and extend the structure's service life. Comparison of the traditional way with the smart way of track maintenance highlights a significant difference between their technique for the determination of the threshold that is used as the evaluation criteria for maintenance. In traditional maintenance, the threshold is set by the standards. Maintenance decisions are made through the comparison of track geometry data collected from measurement vehicles with the threshold value. Smart maintenance systems, on the other hand, may detect the deterioration rate of the track. In addition to measurement trains, measurement systems can be implemented to various types of track and more frequent data collection can be achieved. In other words, preventive maintenance based on real-time data takes place instead of uniform rules based on past data. The size and quality of the data provide better failure prediction models for ML and a more proper maintenance plan.

A literature review of the existing smart diagnosis and maintenance applications shows that advanced technologies are not fully integrated into the railway tracks so far and there are some challenges to overcome for better performance. AI is used not only for prediction models but also for decision-making assistance. In order to develop AI experts that can interpret the situation, more improved NLP techniques must be used. The large volume of data produced by sensors requires proper storage, management, and operation which can be a challenge for the companies. Image processing can also be challenging in railway track use because of the existence of oil and dust that lower the quality of the images. Publicly available labeled datasets can increase the performance of the ML models. However, most of the rail data are not publicly available and not labeled. Therefore, sharing datasets or supporting professionals will increase the performance. Also, auto-labeling systems must be developed. Recent studies show that one of the most important drawbacks of the integration of IoT to the railway system is its high price. Inspection of railway tracks require sensors with various functionalities whose instrumentation can be costly. Thus, further research and development must be done about IoT devices to reduce the costs. Besides, technology companies must build the understanding that intelligence and sustainability of the systems are connected to each other. Therefore, sustainability must be one of the priorities of these companies to enhance the efficiency of their products.

Once these challenges are overcome, railway tracks may be an integrated part of the future's smart and sustainable cities. Railways can be evaluated as high initial cost investments but they provide long-term benefits. The use of smart systems allows engineers to create an optimum maintenance plan and the proper plan contributes to the extension of the life cycle of the track, making it not only smart but also sustainable.

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Conflict of Interest

No conflict of interest was declared by the authors.

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