Development of a Scalable Digital Twin for Tram and Light-Rail Infrastructure based on Open Data for Early Prediction of Rail and Track Defects

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Abstract

Due to an increasing passenger demand in rail-based transportation and a desire for sustainable mobility, rail infrastructure is nowadays confronted with increased loads requiring timely and efficient maintenance regimes (Holzfeind et al., 2025). To improve maintenance scheduling and give rail infrastructure operators better insights into the state of their networks, a comprehensive digital twin based on open data has been developed. The digital twin allows to connect sensor data from vehicles to railway assets and enables the development of custom algorithms for condition-based maintenance of railway tracks. For practical tests and validation of the digital twin, smartphones were placed in various trams and light-rail vehicles in the city of Frankfurt (Main) to record vibration and geolocation data over a period of more than a year. The results demonstrate that infrastructure quality changes can be automatically detected and monitored through the developed digital twin framework using a low-cost measurement set-up. Hereby, new capabilities for proactive maintenance scheduling and resource allocation emerge, and infrastructure operators can prioritize interventions effectively and ensure safe and comfortable railway operations.

1. Introduction

As part of worldwide efforts to make transport more sustainable, railway systems are currently being expanded and, in some cases, newly developed from the ground up. In addition, efforts are undertaken to increase existing track capacity by deploying technologies like Automatic Train Operation (ATO). The ascent in railway transportation, however, also increases infrastructure wear and hence demand for maintenance. Since typically 30 percent of railway operating cost is connected to rail infrastructure (Steer Davies Gleave, 2015), effective maintenance regimes are necessary to keep operating costs at a minimum and to stay competitive to other modes of transportation. One promising approach to increasing the efficiency of infrastructure inspection and maintenance is transitioning from corrective or preventive maintenance to predictive and condition-based maintenance (CBM) to achieve a cost optimum (Figure 1). Conducting preventive maintenance operations too early results in higher life-cycle infrastructure costs, whereas corrective maintenance results in high cost due to required emergency measures (Holzfeind et al., 2016). Early detection of defects enables infrastructure operators to schedule maintenance more effectively, as it provides additional time for planning, staff allocation, and the procurement of external services and equipment.

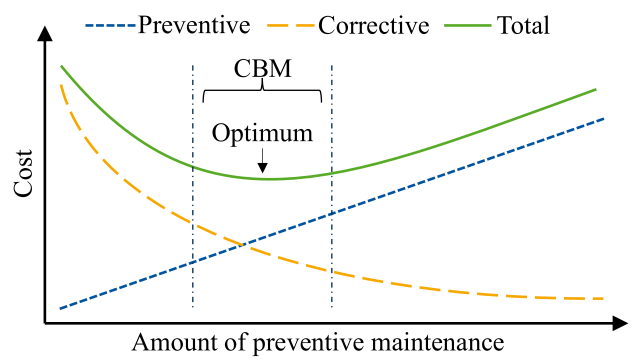

Figure 1. Cost of preventive and predictive maintenance.

To enable the shift to CBM and be able to predict the evolution of track and rail defects, continuous automated data collection and processing is indispensable. In railways, sensors can be placed either alongside the infrastructure (e.g., on bridges, switches or in depots) or on the vehicles themselves. Together they enable comprehensive monitoring possibilities (Frenz, 2020). A rather recent strategy is to install necessary sensors not on dedicated track recording vehicles (TRV), but on regular passenger trains that can gather data daily during normal operation and integrate the results into track maintenance decision-making (Yan et al., 2025). Due to the comparatively short total track length of urban transit systems, owning TRVs is often not economically viable for many operators in that area. As a result, track inspections are frequently outsourced to external companies. A common alternative involves the use of hand-pushed measurement trolleys, which are relatively inexpensive but can only be operated at walking speed. Existing monitoring solutions also often lack direct integration with Geographic Information Systems (GIS) or the ability to link analysis results to specific infrastructure assets. Instead, outcomes are frequently visualized as simple map overlays, which makes it more difficult for the infrastructure manager to draw the right conclusions. This limitation is partly due to the inconsistent use of standardized railway geodata formats across operators, or a lack of digitized infrastructure data, which necessitates custom development efforts for individual operators. To address this challenge and support a scalable solution, this study investigates the feasibility of utilizing OpenStreetMap (OSM) as the primary source of geospatial data, accessible via an Application Programming Interface (API). OSM already contains a lot of crowdsourced rail-related data such as routes and the locations of switches, level crossings, stations, and similar assets, although data accuracy varies regionally.

The rest of the paper is structured as follows: Section 2 provides a more detailed description of the defects to be monitored and explains how smartphones can be leveraged for data acquisition and analysis. Section 3 then describes the architecture of the digital twin and how the sensor data is mapped to it. Section 4 presents results obtained through digital twin–based data processing. Section 5 discusses the integration of the digital twin into the maintenance processes of a railway infrastructure operator. Finally, Section 6 summarizes the main findings and contributions of the work.

2. RAIL AND TRACK DEFECTS

In railway operation different defects on the rail and track occur. This section focuses on defects that are relevant in the scope of track monitoring only.

Track geometry defects (or track irregularities) describe the deviations of a track in space compared to the intended design. The four major track geometry defects are shown in Figure 2 which include the longitudinal height error, cant error, alignment error and gauge error. The track geometry defects shown are of a wavelength in the meter-range and result from damage to the underlying ballast. Main influence factors in the formation of track geometry defects are the number of vehicles, vehicle type, vehicle speed and vehicle load (per axle) as well as the type and quality of the superstructure. In curves the main influence factor is the track geometry (e.g. curve radius) and not the dynamic vehicle-track interaction. (Holzfeind et al., 2025)

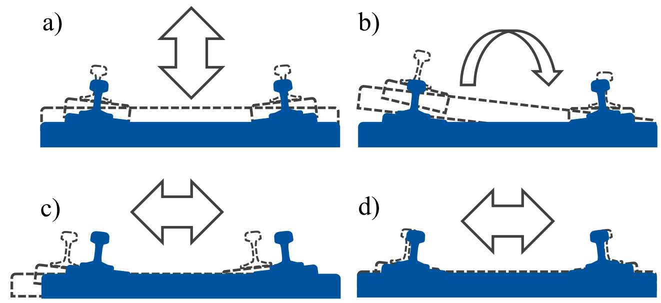

Figure 2. Track geometry defects, a) Longitudinal height error; b) Cant error; c) Alignment error; d) Gauge error

Rail defects describe defects directly related to the rail body. For example, corrugations (Figure 3) and damage to the inner rail flange, which is especially prevalent in curves. Corrugations are identifiable by short, centimeter-range wavelength deformations at the top of the rail. These deformations are often caused by acceleration and deceleration of vehicles around stations or in curves. The resulting vibrations cause noise pollution and higher stress to rail and track.

Wear on the inner flange of the outer rail of the curve is caused by the wheel flange coming into contact with the outer rail, causing wear. This phenomenon is particularly evident in tram and light-rail networks, where the curve radius is much smaller than on mainline railway, constraining proper track guidance. (Rail defects, 2002)

Figure 3. Rail corrugation (Rail defects, 2002).

All described errors lead to ride comfort issues and depending on the severity of the error can pose a threat to safe railway operation. Therefore, regular inspection of the infrastructure is needed.

2.1. Track Monitoring using Low-Cost Devices

In recent years, low-cost measurement devices equipped with MEMS (micro-electromechanical systems)-based sensors have been becoming of increasing interest for monitoring solutions in railways (Paixão et al., 2019; Tsunashima et al., 2023). Smartphones are easily accessible, portable and don't need integration into the vehicles operating system or an alteration of any mechanical component of the vehicle. Therefore, no regulatory implications emerge and the barrier to use smartphones in existing trains is low. Further advantage is the inbuilt internet connection which allows for automatic data transfers into a cloud environment. Disadvantages include sensor accuracy, limited sampling frequency, and possible inconsistencies in the placement of the device (Leibner et al., 2022).

To enhance the significance of smartphone-based measurements, continuous monitoring of the track conditions is important. This enables multiple measurements to be compared and reduces the need for each measurement to be precise at every point. Furthermore, trend analysis of the recorded data is possible because the time between measurements decreases compared to traditional measurements. Frequent data recording allows for error prediction, enabling smartphones to support the transition to condition-based maintenance. Figure 4 shows the development of track geometry errors over distance and time qualitatively. The upper graph shows this development in general whereas the lower graph shows the development in condition-based maintenance, with measurement events and maintenance actions after the error exceeds a defined threshold.

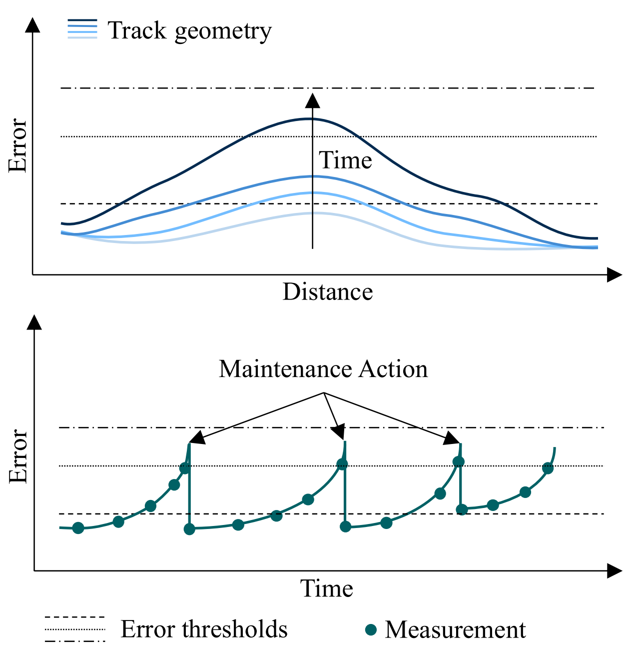

Figure 4. Error development in condition-based maintenance.

In previous works the general capabilities of smartphone sensors for measuring infrastructure defects, specifically longitudinal height errors, were shown (Leibner et al., 2023). The presented approach was also adopted for this study. For monitoring track and rail defects using smartphones, acceleration and Global Navigation Satellite System (GNSS) sensors are utilized. The sampling frequency of the vibration data recording is set to 100 Hz. GNSS data is recorded with approximately 1 Hz and then resampled to 100 Hz to achieve a single tabular measurement structure. The GNSS localization enables the mapping of recorded acceleration data to specific locations. To achieve an estimate of the longitudinal track error ($\widehat{LL}(s)$) the bandpass filtered vertical acceleration ($z''_{vb,bp(s)}$) is integrated twice over path (s) and divided by the square of the vehicle speed (v), giving an approximation of the vehicle vertical movement which closely correlates to the vertical track irregularity (Equation 1).

$$\widehat{LL}(s) = \iint \frac{z''_{vb,bp(s)}}{v^2} ds.$$

Equation 1. Estimation of longitudinal track error. (Leibner et al., 2023)

Comparing single measurements of smartphones placed in the driver's compartment of a light-rail vehicle show a good agreement between the estimated height error and the measurement from a track geometry recording trolley (Figure 5).

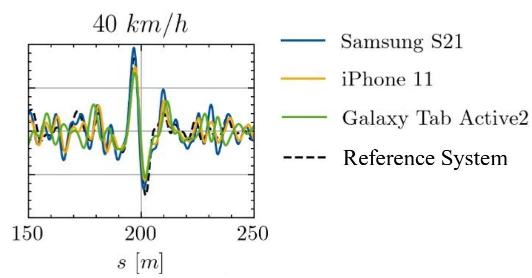

Figure 5. Longitudinal height errors measured by smartphones and conventional measurement system (Leibner et al., 2023).

Leibner et al. state, that smartphone measurements showed good repeatability with absolute deviations in measured longitudinal height errors of 0.5 mm, based on tests according to DIN EN 13848-2. Further tests in passenger service yielded favorable results, with only 5% of the compared measurement points deviating by more than 2-3 mm. (Leibner et al., 2023)

As the smartphones are placed in the driver's compartment the resulting accelerations are influenced by the first and second stage suspension of the vehicle whereas special measurement equipment is not influenced by any suspension. This mostly explains the difference in the measurement results. This effect is more dominant for mainline vehicles, but less distinctive for the case of tram and light-rail vehicles, which commonly have rather stiff suspension systems, which do not distort the track irregularity excitation too much.

Other measurement systems, such as commercial on-board measurements systems (OBM) or special track recording vehicles (TRV) were not further investigated due to their different application scopes. OBMs are not common in older, operating tram and light-rail vehicles. Tram and light-rail network operators utilize dedicated TRVs, but only every few years, so they don't enable condition-based monitoring but conduct precise track measurements instead.

To be able to store and analyze all collected data a digital twin platform was developed which will be explained in the following section.

3. DIGITAL TWIN

A digital twin is a second entity that describes the current and future behavior of a physical system. Therefore, data is transferred from the physical system to the digital twin, and vice versa (Grieves & Vickers, 2017).

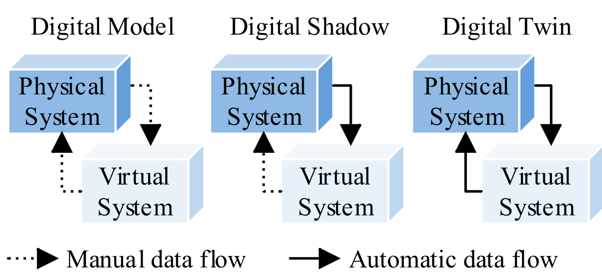

Figure 6. Digital Model, Shadow and Twin.

Depending on their state of data flow or the complexity of behavior modelling, there are several definitions for digital twins, such as digital model or digital shadow (Figure 6) (Kritzinger et al., 2018). In this paper, the term "digital twin" is employed for the purpose of simplicity.

3.1. Digital Twin Architecture

The developed digital twin consists of different software layers and interfaces with data sources as shown in Figure 7. Measurement data, consisting of GNSS, acceleration and timestamps, is recorded using a dedicated smartphone app, which uploads data to a cloud database automatically at the end of the recording process. Data handling checks for new measurements daily and starts data processing on new datasets. Datasets are checked for completeness, filtered and matched to the associated track segments as described in detail in Section 3.2. Data checks include verifying that the smartphone was placed correctly, the measurement was sufficiently long, and that all necessary data was uploaded.

For infrastructure data a combined approach of OpenStreetMap and operator specific data is used. Tram and light-rail networks used in this study, such as the network in Frankfurt (Main), Germany, are mapped to a high level of detail, including railway assets, such as switches, crossings, signals, and stops. In addition, operator specific data is mapped on the OSM data. This includes information on track sections and their identification and information on switches and crossings. Discrete point data, such as switches and crossings are mapped per route utilizing PostGIS closest point function. Track sections are matched per route as well, further work to improve accuracy by adapting the matching algorithm described in Section 3.2 is currently performed. Operator specific information enhances the quality of OSM data and ensures that employees of the operator can subsequently identify infrastructure elements in the notation they are accustomed to. At the same time the data of OSM ensures that the system is also usable for smaller operators that don't have digital information about their infrastructure.

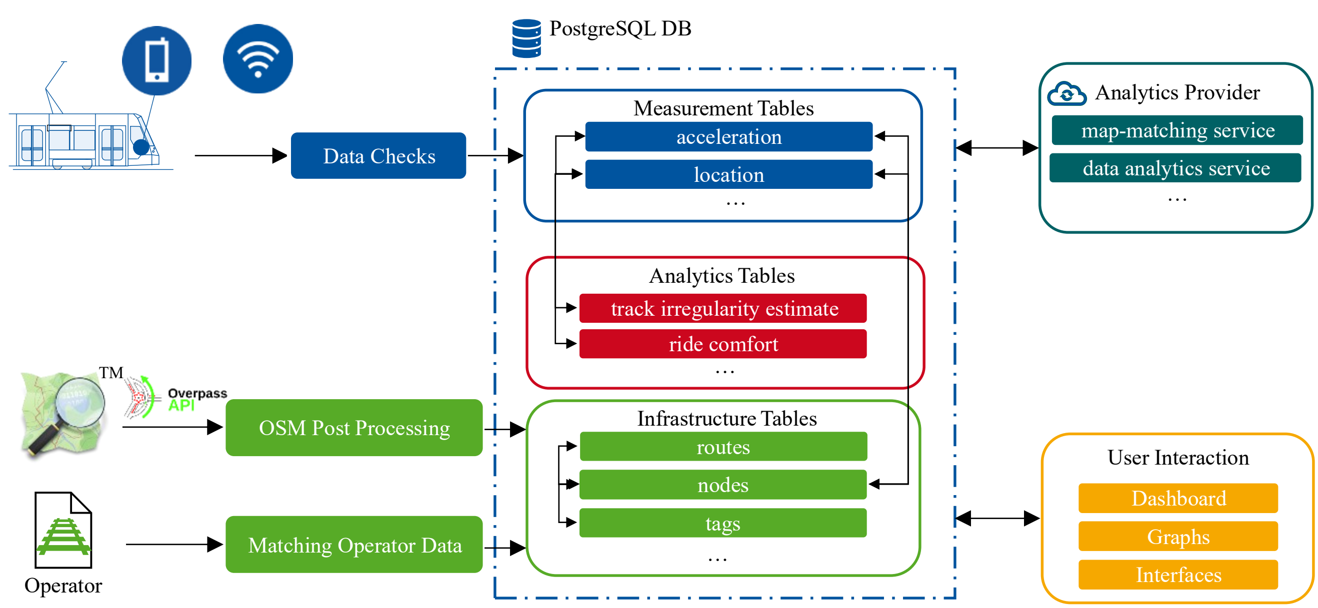

Figure 7. Digital Twin Architecture.

The user interaction layer completes the architecture of the digital twin. Currently under development is a web-dashboard with detailed views of track sections and analysis of measurements, as well as an overview with performance indicators for user interaction. The dashboard will serve as a central hub to the operator to identify hotspots in the network, on certain lines or line sections. Further details on the integration in the operator's processes are described in section 5.

OSM is using a system of geographical points (nodes), combined into linear elements (ways). Multiple ways are combined to describe a track or railway line (relation) (N.N., 2025). Metadata, e.g. line names, are saved as key-value pairs. The OSM data structure is modified and simplified for the digital twin, utilizing only nodes and relations with the corresponding metadata. All data is stored in a PostgreSQL database with the PostGIS extension enabled. Infrastructure data is therefore saved as spatial data in the form of points and lines that resemble the nodes and relations of OSM, respectively. OSM data is downloaded into the digital twin's database via the Overpass API considering geographical boundaries for an operator's local area. Since mapping measurement data requires a high density of geographical points to accurately represent data, points between the infrequent distanced OSM nodes are interpolated at approximately every meter to achieve a balance between data accuracy and data volume. All metadata from OSM is saved, though currently, primarily information about switches, crossings and stops is used. The diverse meta information mapped in OSM may be utilized further in the future.

This approach presents challenges in the form of data inconsistencies between OSM and operator data. OSM data may have metadata mapping inconsistencies where certain elements, such as crossings or switches, are not mapped or are defined with different meta-information as expected. For instance, a switch and a pedestrian crossing that are mapped by the same node in OSM may only have the pedestrian crossing mapped as metadata. Therefore, further data processing is needed. In our case an algorithm to find missing crossings and switches in OSM data was implemented.

Measurement data recorded via a smartphone app is sent to the cloud platform and integrated into the database daily. Currently only acceleration and GNSS data is processed but the digital twin's architecture and database structure allow the implementation of different data types such as images or videos. Incoming data is matched by geolocation as described in the following section.

3.2. Map Matching

To connect the recorded sensor data with the operator's railway assets, the integration of a map-matching algorithm into the digital twin architecture is necessary. The algorithm connects the recorded GNSS locations to the meter spaced nodes in the database. Existing algorithms often rely on Hidden Markov Models (HMMs) (Paul Newson & John Krumm, 2009), which come with high computational costs. Since smartphones are deployed in regular in-service trams and light-rail vehicles, the vehicles operate exclusively on predefined and known routes. Consequently, it is not necessary to employ an algorithm capable of mapping recorded GNSS coordinates to arbitrary paths through the entire rail network. Instead, the task reduces to identifying the most likely route from a finite set of known trajectories. Once the correct route is determined, the GNSS coordinates can be matched to the closest corresponding nodes along that path. The downside of this approach is, however, that railway depot tracks and other track sections not part of a tram or light-rail line are not being considered. Typically, these tracks however only make up a very small portion of the entire network. Pseudocode for the developed map matching algorithm is listed in Algorithm 1.

Algorithm 1. Pseudo code for the simplified map matching algorithm.

```
kd_tree_osm ← KDTree(x_osm, y_osm) # OSM node coordinates projected to x/y [m]
(x_sm, y_sm) ← utm_proj(sm_lon, sm_lat) # Smartphone coords projected to x/y [m]

sm_start ← (x_sm[0], y_sm[0])
sm_end   ← (x_sm[-1], y_sm[-1])
# Vector pointing from start to end of measurement
sm_vec ← (sm_lon[-1] - sm_lon[0], sm_lat[-1] - sm_lat[0])

(dd, ii) ← kd_tree_osm.query((x_sm, y_sm), k=1, distance_upper_bound=10)
unique_indices ← unique(ii)
candidate_relations ← [osm_nodes[i].relations for i in unique_indices]
most_common_relations ← most_common(3) over all items in candidate_relations

for relation in most_common_relations:
    r_nodes ← relation.nodes
    (r_x, r_y) ← utm_proj(r_nodes.lon, r_nodes.lat)
    kd_tree_rel ← KDTree(r_x, r_y)

    (d1, i1) ← kd_tree_rel.query(sm_start)
    (d2, i2) ← kd_tree_rel.query(sm_end)

    rel_start ← r_nodes[min(i1, i2)] (as longitude, latitude)
    rel_end   ← r_nodes[max(i1, i2)] (as longitude, latitude)
    # Vector pointing from start to end of relation
    rel_vec ← rel_end - rel_start
    if dot_product(sm_vec, rel_vec) > 0:
        break # Vectors pointing in the same direction
else:
    continue
# Final mapping of Smartphone to location to closest nodes
(dd, ii) ← kd_tree_rel.query((x_sm, y_sm), k=1, distance_upper_bound=15)
```

First, potential OSM relation candidates are identified by querying a k-dimensional tree (k-d tree) constructed from all OSM nodes, projected into a meter-based coordinate system (e.g. Gauss-Krueger). This tree is queried using the smartphone-recorded locations. K-d-trees were selected due to their significantly lower computational complexity compared to pairwise nearest-neighbor searches. A maximum distance threshold of 10 meters is applied to ensure that only

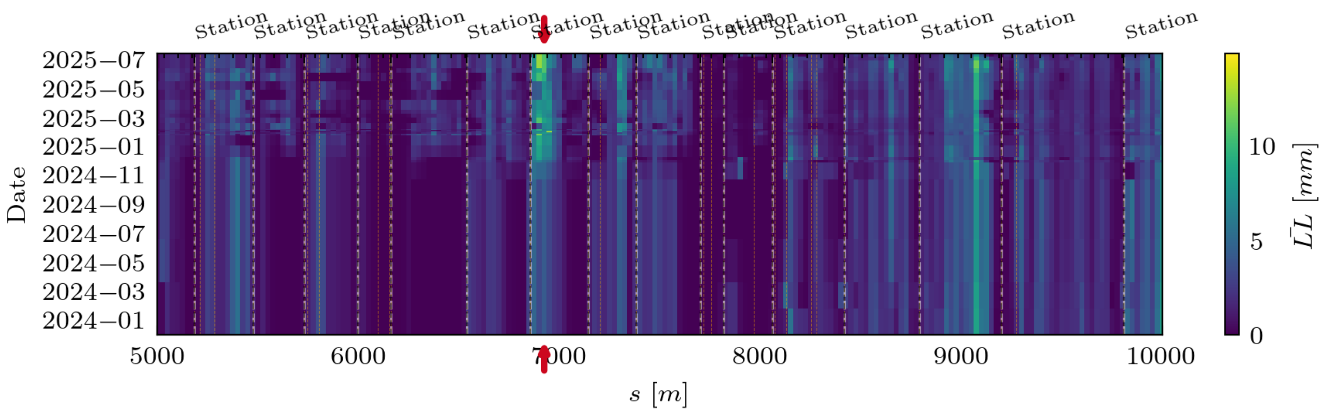

Figure 8. Development of a five-kilometer-long track section in terms of longitudinal track quality over a period of more than a year. The red arrows point to the location shown in Fig. 9.

nearby nodes are considered. Next, all OSM relations associated with the identified nodes are extracted. Among these, the three most frequently occurring relations are evaluated to determine which one aligns with the direction of travel. This step mitigates incorrect associations with rail lines traveling in the opposite direction. Directional consistency is assessed by constructing vectors from the start to the end point of both the smartphone trajectory and the relation geometry. The dot product of these vectors is used to determine alignment; a positive dot product indicates an angle less than 90°, suggesting similar directionality and a likely correct match. Once the correct relation is identified, a new *k*-d tree is built for the matched line, consisting of nodes spaced at 1-meter intervals. Each recorded location is then associated with its nearest node within a 15-meter threshold, preventing incorrect matches in cases where a vehicle deviates from its expected route. These associations are stored in the database for each recorded measurement. The algorithm has proven to be both efficient and accurate, successfully matching measurements to a corresponding line in the current dataset. However, in rare cases where two lines share most of their track but diverge only at the beginning or end, mismatches may occur. In such cases, some measurements may fall outside the specified distance threshold and thus remain unassociated. Since queries are typically made by track section rather than by line - and track sections are associated with the same nodes - this has not been considered a significant limitation. Nonetheless, some measurements are not matched possibly due to too short trip length or GNSS positions exceeding the 10-meter boundary mentioned above. Of the 1,015 trips analyzed, the algorithm successfully matched 74.6% to a tram or light-rail line, while no corresponding match could be identified for the remaining 25.4%, due to the reasons mentioned above.

4. RESULTS

As outlined in Section 2.1, smartphones show good performance in monitoring track defects in comparison to reference measurement systems. In the tests conducted for this research paper Samsung Galaxy S24 smartphone devices were placed by driving personnel in the driver's compartment at the start of their shift. The correct placement was explained in a handout, and the importance of consistent placement and orientation of the device is emphasized. The tests show good results, with 86% of 1,175 measurements been placed correctly and usable data uploaded. Correct placement and data usability are verified in the digital twin (Section 3.1).

By employing a monitoring approach based on periodic measurements at short intervals, changes in track quality can be effectively detected over time. So far, several hundred measurements using smartphones have been recorded spanning a period of at least one year on most of the lines in the city of Frankfurt. In addition, some measurements from 2023 of earlier tests were available.

Plotting the resulting data with color-coded indicators that reflect variations regarding the longitudinal track irregularity enables the visualization of temporal changes in infrastructure condition. This method provides a clear representation of how track quality evolves, supporting the identification of potential degradation or anomalies. An example of such a visualization based on smartphone measurements is shown in Figure 8. The plot shows the changes in track quality over a five-kilometer-long track section over a period of approximately one and a half years. Significant changes were observed at around 6,900 meters, where degradation was observed in the winter of 2024/2025. Figure 9 shows the evaluation over time of this location including the individual track quality estimates. Between December 2024 and February 2025, the city experienced multiple days with sub-zero temperatures. Similar to the formation of potholes, these conditions likely initiated track degradation through repeated freezing and thawing of the track bed, which was subsequently exacerbated in the following months by dynamic loads from tram traffic.

Track sections with an identified alteration in quality were visited and inspected. In contrast to the identified quality degradation shown in Figure 8 and Figure 9, peaks in track degradation at level crossings and switches were identified.

These peaks did not result from a decrease in quality, but rather from the transition from conventional rails to grooved rails embedded in concrete at level crossings. In case of switches the resulting peak is attributable to the passage of the switches crossing. With the connection between measurements and infrastructure elements, these false positive readings can be automatically identified in the future.

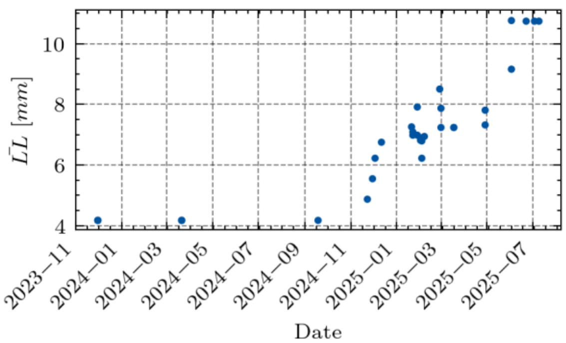

Figure 9. Change in infrastructure quality over time at $s = 6{,}900\ m$.

5. Process Integration

For many operators, current maintenance operations are conducted via yearly manual visual inspection of the tracks. A foot patrol walks through the entire network to assess and document issues. In parallel, switches are inspected in detail. More expensive measurement equipment, such as TRVs, is only used every five years, which corresponds to mandatory inspections by German law (BOStrab, 1987). Maintenance task planning is based on the documented issues.

The digital twin aims to integrate into the interface between the visual inspection and task planning stages (Figure 10). With the possibility to continuously monitor track conditions, defects are identified by the digital twin's algorithms and task planning can then be executed based on the information from the digital twin. Therefore, visual inspections by walking the entire network aren't necessary anymore; however, some detected issues may require further examination.

This offers the opportunity for more current and frequent information on track conditions and better allocation of resources. At the same time, with changing working environments, workplaces like the visual inspection team lack attractivity and operators face issues with finding qualified employees. A digital twin with onboard measuring devices such as smartphones integrates condition-based monitoring and its advantages into the processes of tram and light-rail operators. Therefore, limited staff can be allocated more efficiently and due to enabling better resource planning operational disruptions can be minimized.

Full commercial implementation with the goal of replacing current measurement systems, such as measurement trolleys, requires approval of authorities and proof of equivalent safety to reference systems in use. Without approval of authorities the digital twin presented in this paper provides advantages in staff allocation and better planning of measurement equipment deployment in detected hot spots.

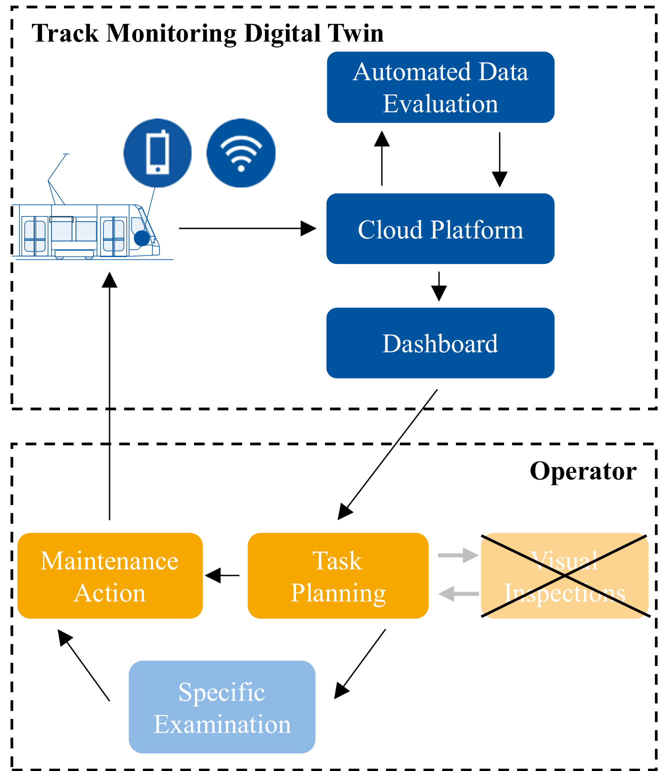

Figure 10. Integration into the maintenance process.

6. Conclusion

This research paper focused on a digital twin for tram and light-rail networks enabling condition-based monitoring of the network's infrastructure. The approach of using smartphones in combination with a cloud-based, open-data digital twin can enable time-dependent condition-based infrastructure monitoring. Data mapping to discrete infrastructure elements, in particular, has the potential to identify track and rail defects specific to local areas. Challenges with data inconsistencies between different GIS data sources were resolved and a custom map matching algorithm to map measurement data to single geographical points was highlighted.

This approach enables continuous observation and comparison of the development of infrastructure conditions over time. Integrating the proposed approach into current maintenance processes would allow operators to utilize advantages of condition-based maintenance such as improved staff and resource planning. However, further research on identifying more defects is advised.

Further research will be conducted into using smartphone cameras for detecting rail defects such as corrugations or worn rail flanges in combination with the acceleration data.

Local tests with operators using different camera placements, angles, shutter speeds, and lighting conditions need to be caried out. In addition, the digital twin must be expanded to handle image data, and new algorithms utilizing current object-detection capabilities. Camera data also offers the possibility of detecting other objects within the clearance zone of the vehicle. Intruding vegetation, potholes or unexpected events such as flooded tracks are suitable candidates for detection which influence daily operation of tram and light-rail networks.

In the context of light-rail networks, often characterized by a greater proportion of tunnels, the development of effective methods for tunnel localization is currently underway. This challenge arises due to limited availability of GNSS signals in tunnels which hinders precise localization with the current approach.

Additionally, user interaction and information displayed concerning operator specific data must be further investigated in direct contact with operators. Research areas include ease of use, integration into an operator's existing software infrastructure and training requirements needed. Furthermore, the quantification of financial advantages in the utilization of the proposed approach in comparison to existing maintenance processes constitutes a consequential step in the direction of product development.

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REFERENCES

Frenz, W. (Ed.). (2020). *Handbuch Industrie 4.0: Recht, Technik, Gesellschaft*. Springer. https://ebookcentral.proquest.com/lib/kxp/detail.action?docID=6144690

Grieves, M., & Vickers, J. (2017). Digital Twin: Mitigating Unpredictable, Undesirable Emergent Behavior in Complex Systems. In F.-J. Kahlen, S. Flumerfelt, & A. Alves (Eds.), *Transdisciplinary Perspectives on Complex Systems: New Findings and Approaches* (pp. 85–113). Springer International Publishing. https://doi.org/10.1007/978-3-319-38756-7_4

Holzfeind, J., Liu, J., & Pospischil, F. (Eds.). (2025). *Handbuch Eisenbahninfrastruktur*. Springer. https://doi.org/10.1007/978-3-662-68960-8

Holzfeind, J., Wilczek, K., & Nerlich, I. (2016). swissTAMP -big data in proactive track asset management. *European Railway Review*, *22*(6). https://www.researchgate.net/publication/333224284_swissTAMP_-big_data_in_proactive_track_asset_management_TRACK_ASSET_MANAGEMENT_European_Railway_Review

Kritzinger, W., Karner, M., Traar, G., Henjes, J., & Sihn, W. (2018). Digital Twin in manufacturing: A categorical literature review and classification. *IFAC-PapersOnLine*, *51*(11), 1016–1022. https://doi.org/10.1016/j.ifacol.2018.08.474

Leibner, P., Stübinger, L., Hempel, T., Wolf, L., & Schindler, C. (2023). *Optimierung der Instandhaltung von Straßenbahngleisen durch eine intelligente Überwachung mittels Smartphone-Sensorik*. IRSA, Aachen.

Leibner, P., Von Stillfried, A., & Schindler, C. (2022). *Potential of estimating track irregularities from in-service vehicles using smartphones*. 1–5. https://doi.org/10.4203/ccc.1.10.21

N.N. (2025). Elements. In *OpenStreetMap Wiki*. https://wiki.openstreetmap.org/wiki/Elements

Paixão, A., Fortunato, E., & Calçada, R. (2019). Smartphone's Sensing Capabilities for On-Board Railway Track Monitoring: Structural Performance and Geometrical Degradation Assessment. *Advances in Civil Engineering*, 1–13. https://doi.org/10.1155/2019/1729153

Paul Newson, & John Krumm. (2009). Hidden Markov Map Matching Through Noise and Sparseness. *17th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems (ACM SIGSPATIAL GIS 2009), November 4-6, Seattle, WA*, 336–343.

Rail defects (UIC report No. 712E). (2002). UIC.

Steer Davies Gleave. (2015). *Study on the Cost and Contribution of the Rail Sector*. European Commission Directorate General for Mobility and Transport.

Tsunashima, H., Honda, R., & Matsumoto, A. (2023). Track Condition Monitoring Based on In-Service Train Vibration Data Using Smartphones. In *New Research on Railway Engineering and Transportation [Working Title]*. IntechOpen. https://doi.org/10.5772/intechopen.111703

Verordnung über den Bau und Betrieb der Straßenbahnen (1987).

Yan, T.-H., Hoelzl, C., Corman, F., Dertimanis, V., & Chatzi, E. (2025). Integration of on-board monitoring data into infrastructure management for effective decision-making in railway maintenance. *Railway Engineering Science*, *33*(2), 151–168. https://doi.org/10.1007/s40534-024-00369-x

BIOGRAPHIES

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Raphael Pfaff studied Mechatronics, Mathematics and Control Engineering in Bochum, Hagen and Coventry. After graduating with a master's degree in control engineering, he in system engineering and management roles with Siemens and Faiveley Transport while pursuing his PhD studies in part-time. In 2014 he followed the call for a professorship in rail vehicle engineering to FH Aachen University of Applied Sciences. Since February 2025 he holds the chair of rail vehicles at RWTH Aachen University. His research interest lies mainly in digitalisation of rail vehicle technologies and processes, particularly modelling and simulation, prognostics and health management as well as the development of self-driving capabilities in the shunting space.