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Article

Multimodal Data Analysis for Railway Switch Monitoring: Point Machine Motor Currents, Track Geometry, and Maintenance Records

Susanne Reetz [1,*], Thorsten Neumann [2], Jörn Groos [1], Douwe Buursma [3] and Wessel Roodenburg [4]

1 Institute of Transportation Systems, German Aerospace Center e.V. (DLR), 38108 Braunschweig, Germany
2 Institute of Transportation Systems, German Aerospace Center e.V. (DLR), 12489 Berlin, Germany
3 Strukton Systems, 7556 PE Hengelo, The Netherlands
4 Strukton Rail, 3542 DA Utrecht, The Netherlands
* Correspondence: susanne.reetz@dlr.de

Abstract

Condition monitoring is an important tool in the maintenance of railway infrastructure, and data-driven approaches are gaining in popularity. Switches are complex systems that include both complex track superstructure—which is by design subject to increased dynamic load compared to open track—and point machines that must operate in concert to achieve optimal performance. Existing condition monitoring methods are often limited to a specific type of measurement data to monitor one of these subsystems of a switch and only certain faults. Research and industry are now moving toward integrating all available information into a single, unified system, enabling a clearer understanding of the interactions between subsystems, more efficient maintenance, and better fault root cause diagnosis. This paper investigates the relationships between motor current curves of electric point machines, track geometry data collected by measurement trains, and maintenance logs for 58 switches in the Netherlands over almost 3.5 years. The aim is to provide a foundation for the design of such holistic monitoring systems as well to derive insights and requirements for future data gathering. The analysis reveals that maintenance actions are the dominant factor influencing the measurement data. Major track geometric modifications appear to act as persistent boundary conditions for point machine operation. Given that switches require more frequent maintenance than open track and point machines exhibit dynamic behavior, continuous track geometry monitoring during operation is essential for accurate data analysis and maintenance assessment.

Keywords: railway switch; point machine; track geometry; maintenance; condition monitoring; prognostics and health management

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1. Introduction

As railway networks deal with rising traffic density and aging assets, shifting from reactive to predictive maintenance through condition monitoring has become a strategic necessity. Monitoring infrastructure in real time enables operators to minimize unplanned downtime and optimize resource allocation. This is particularly vital for switches, which integrate complex track superstructure with electrical point machines, as these components are subject to high stress and prone to failures that cause significant operational disruptions.

1.1. State of the Art

1.1.1. Point Machines

Condition monitoring of point machines is usually carried out by measuring one or multiple variables—such as motor current, motor power, force, or vibration—during switch movement. The review [1] provides a comprehensive introduction and overview of fault detection and diagnosis methods for railway point machines up to 2019. The authors distinguish between model-based and data-driven approaches, noting that the latter are far more common. Among sensor choices, measuring motor current is by far the most popular. This view is reinforced in [2], which presents an updated review of data-driven approaches up to 2023, with a particular focus on machine learning. The authors state that the central challenge in condition monitoring of point machines is managing limited labeled data alongside abundant unlabeled data across diverse and complex operational scenarios, while building a system that is trustworthy, robust, and highly generalizable and transferable. Additional challenges, such as differences between individual point machines and changing environmental conditions, also need to be addressed.

Most existing approaches function on a per-sample basis, meaning that anomaly detection, diagnosis, and predictions are performed for each individual switch movement. Typically, the outcomes are not accumulated or analyzed over time yet. For instance, refs. [3–5] all utilize motor current curves to first perform fault detection and then diagnosis for a limited amount of fault types. In [6], this approach is augmented with the addition of the control current, to improve diagnostic accuracy. None of these approaches control for environmental factors or discuss the robustness across point machines. The authors in [7] introduce an anomaly detection approach that accounts for temperature effects using a simple normalization technique. The models are trained separately for each point machine and direction and evaluated per motor current curve, using a healthy training dataset. The dependency of the used features on humidity and precipitation data from local weather stations is explored, finding no correlation. The integration of this methodology into an operational pipeline is described in [8]. In [9] a supervised method for predicting the remaining useful life of point machines is presented. The dataset contains motor power curves, temperature and humidity measurements, and switch fault reports, the latter serving as labels. Their sensor system normalizes the collected features by the individual behavior of the point machine at installation. The authors of [10] use a digital twin to generate a balanced and labeled training dataset to test various supervised learning approaches. The models are applied on a high-performance switch system, whose behavior is supposed to be independent of the weather conditions.

The authors in [11] develop an unsupervised health indicator based on motor current curves that quantifies additional mechanical resistance in the switch throw and is comparable across point machines and operating temperatures. The model training and prediction is fully transparent and the results interpretable. The health indicator is aggregated over 28 days to produce a ranking of the point machines that is used to inform the scheduling of maintenance. Further, the results reveal short-, mid- and long-term behaviors in the measurement data, emphasizing the need for condition monitoring beyond per-sample approaches.

1.1.2. Track Superstructure

An important measure of track superstructure condition is the quality of the track geometry, which is assessed using variables such as track gauge, longitudinal level, cross-level, alignment and twist. For the EU, the norm [12] specifies how these variables are measured, evaluated, and maintained on the network level. Here, track geometry is measured continuously along the track by dedicated track measurement trains, onboard condition monitoring systems on regular trains, or portable hand-held measurement tools. Each variable is evaluated along track segments of fixed length and its standard deviation, the track quality indicator, is calculated. Limits for different actions are defined.

In [13], data analytics for the condition monitoring of railway track geometry are reviewed. The factors affecting track quality—and thus track geometry—include track design (including ballastless versus ballasted track, components, and subgrade), track loading by trains (the main cause of degradation), environmental factors (extreme temperatures, water, and weather events), and maintenance operations (such as tamping, grinding, and rail renewal). The applications presented include the reconstruction of track geometry from sensor data, the evaluation of maintenance actions by assessing track geometry in the short and long term, and the use of track geometry for degradation and fault prediction. These approaches are classified as statistical, machine learning, big data, or others. More recently, the authors in [14] provide an overview on prediction methods for railway track geometry degradation. Traditional methods include empirical, mechanical, statistical and probabilistic models, while newer methods are based on machine learning. Approaches are categorized by their application focus, namely segment track quality index forecasting, point-wise track geometry prediction, and detection of exceedance of thresholds or isolated defects. Segment-based indicators are unsuitable to monitor on local assets like switches and crossings because the considered track segments are too long and the local geometry too complex. Instead, a custom analysis of the point-wise track geometry and monitoring of events is recommended in [15], with a focus on the longitudinal level.

Dedicated measurement trains are costly, disrupt regular traffic, and provide only intermittent data on track health. Mounting condition monitoring systems on in-service trains overcomes these drawbacks by delivering frequent measurements during normal operation, often using lower-cost sensors. This research area already includes commercially deployed systems and approaches. The authors of [16] present a comprehensive introduction and literature review of train-borne condition monitoring for railway track superstructure. The main challenges include harsh environmental conditions, cost constraints, imbalanced datasets with few fault instances, precise geo-localization of measurement data, and the development of robust algorithms. Most prevalent are inertial measurement systems, consisting of accelerometers and gyroscopes mounted on the axle-box, bogie, or car body. These sensors have excellent dynamic features, withstand harsh conditions and are comparatively inexpensive. Algorithmic approaches are either model-based or data-driven, with data-driven methods gaining increasing popularity. Some alternatives are cameras and other optical systems, which often are more vulnerable to challenging environmental conditions but are recently gaining popularity, especially in combination with deep learning approaches. This assessment is confirmed in [17], which provides an updated review of approaches for track geometry quality monitoring using onboard inertial sensors systems.

Beyond open track, such systems could also be used to assess track health in switches and crossings. In [18], the crossing of switches is detected using vertical displacements derived from axle-box acceleration measurements. These switch patterns are clustered by driving direction and track in [19], where an approach for condition monitoring applications is proposed.

Track-side systems placed at critical infrastructure points, such as switches and crossings, offer an alternative to train-borne condition monitoring. These systems typically utilize vehicle–track interaction to derive track health status. For instance, the authors in [20] employed acceleration, displacement, and wheel sensors to monitor substructure and ballast condition via changes in estimated natural frequencies over time. Trains are grouped by type for separate analysis, and the results suggest that higher train speeds of 150–160 km/h are necessary for sufficient track excitation. Further sensitivity analysis in [21] suggests a sensing range of 10–15 m for ballast quality monitoring, implying that three to four sensors could cover a standard 45–60 m switch.

Signal processing methods tailored to track-side acceleration measurements in switches, specifically regarding temporal and frequency characteristics and their integration into displacements, are presented in [22]. This was extended in [23] through a model-based approach, incorporating scanned crossing rail geometries and sleeper accelerations to develop a qualitative crossing condition indicator. Further, a robust frequency-domain displacement reconstruction method and an algorithm for train type and speed identification were introduced in [24]. The presented condition monitoring framework is completely automatized from the dataset of measured accelerations to the final post-processed long-term results.

Due to the complexity of the track superstructure of switches, faults in one component can propagate through the system and cause further damage to other components. The authors in [25] propose a comprehensive system model framework that enables a prediction of accumulated track damage in railway switches. At the outset of a switch's service life, the running surface of the rails in critical areas (such as the switch and crossing panels) undergoes significant plastic deformation. This deformation increases dynamic impact forces from passing vehicles. Consequently, vertical track settlement occurs, especially pronounced in the crossing area. The introduction of track settlement leads to self-reinforcing behavior within the system. The proposed framework can predict accumulated track damage by accounting for the coupling between different damage modes. It provides a robust tool for understanding and managing fault propagation in terms of track damage in railway switches.

1.1.3. Holistic Approaches

In this study, holistic railway switch condition monitoring denotes approaches that consider the interaction between the principal subsystems—track and point machine. A standard term for this concept has not yet been established in the literature. Other descriptors include whole-system or integrated monitoring. Apart from the concept itself, publications on the topic are scarce. For instance, ref. [2] notes that track geometry and train-induced loads in the switch-panel area can impact point machines, but no detailed investigations of this interaction have been reported.

In [26], a manually designed Bayesian network diagnostic model for railway point machines is presented that is based on expert knowledge, FMECA, exemplary measurement data and fault reports. Human-interpretable features of the motor current curve and other information sources are used to provide a fuzzy multi-label classification of the root cause of point machine faults as decision support for maintenance engineers. Due to the lack of a comprehensive labeled dataset, the model is designed and calibrated manually, and its outputs are interpreted qualitatively. The causal relationships between different sources of information require further investigation based on experimental or field data.

The authors of [27] discuss how a combined research dataset—comprising a train-borne measurement platform and a track-side sensor system—would stimulate new research and development, and foster innovative solutions such as modern AI-based data fusion techniques and physical or hybrid modeling approaches, across several use cases in railway infrastructure maintenance.

The importance of a holistic approach to railway switch monitoring has also been highlighted recently in invited conference talks by industrial contributors [28,29]. Commercial monitoring systems are increasingly offering a wide range of sensors for both point machine and track health in switches. The diversity of data sources and the complexity of switches result in sparse datasets, making pure machine learning approaches insufficient for predictive maintenance at present. The full potential of such datasets has yet to be uncovered or realized. In general, greater data availability does not automatically yield better insights, as the added complexity introduces new challenges [30].

Regarding sensor and IT systems, in [31], it is stated that at the time of the study railway condition monitoring is generally performed by different heterogeneous vertical systems that work in isolation, with limited cooperation, and lack the integration essential for global asset management. The study analyzes the architecture of future IoT-based railway systems to improve their reliability and security. Two different solutions for handling network and sensor failures are proposed, and their effectiveness in enhancing the overall reliability is demonstrated on the example of switch heaters.

1.2. Challenges and Contributions

Data from various sensors and their combination are the foundation for a holistic monitoring of complex railway assets such as switches. From a theoretical point of view and based on expert knowledge, interactions and dependencies are expected where parts of the infrastructure directly and physically interact with each other. But these are often still monitored and maintained separately in practice. Ballast condition and general track geometry, for instance, usually lack an integration with the health monitoring of the point machines and their mechanical elements in context of maintenance and fault diagnostics. This gap also exists in research, as to the knowledge of the authors, no analyses have specifically examined interactions between such data streams and no condition monitoring approaches have been implemented yet that explicitly model and exploit these relationships using large real-life measurement datasets.

This paper approaches the condition monitoring of railway switches from a holistic point of view. Specifically, the interactions and dependencies between track geometry, point machine health and maintenance actions are explored in a joint data analysis, using field measurements from the Dutch railway network. The aim is to provide a foundation for the design of holistic monitoring systems as well to derive insights and requirements for future data gathering.

The remainder of this paper is structured as follows. Section 2 describes and analyses each data type by itself, followed by a joint analysis and discussion in Section 3. Section 4 ends the paper with a conclusion and outlook on future work.

2. Materials and Methods

The dataset in this study consists of measurement data from 58 single switches with electro-mechanical point machines located in the Netherlands, from the beginning of January 2023 to the middle of May 2026. For each switch, the dataset contains the motor current of the point machine and the temperature recorded for every switch movement, track geometry measurements taken by measurement trains a few times per year, and records of maintenance actions performed. Each of these data types is presented and analyzed separately in the following subsections.

2.1. Point Machine Motor Current Curves

The motor current curves of the point machines, all type NSE2 [32], during switch movements are measured at their respective relay houses, using the POSS system by Strukton [33]. Temperature, which is known to influence this type of data (see [11]), is measured as the ambient air temperature outside the relay house.

In a healthy state, the motor current curve of an NSE2 point machine does not increase after the inrush peak and remains at roughly the same level or shows a slight decline in the current until the switch movement is complete and the current drops to zero. Additional mechanical resistance in the switch movement causes the motor current to locally increase; see Figure 1. For the purpose of this study, the motor current curves are pre-processed, features are extracted and a health indicator is derived, according to the methodology presented in [11]:

- (Ambient air) temperature.
- Features:
  - Area under the curve in Ampere-seconds;
  - Length of curve in seconds;
  - Inrush peak value in Ampere;
  - Maximum hump prominence in Ampere;
  - Absolute hump area in Ampere-seconds;
  - Relative hump area in percent.
- Health indicator in $[0, 1]$, based on relative hump area.

The health indicator is comparable across temperatures and point machines, and is most frequently used in the remainder of the study. Nevertheless, the other features together with temperature are useful additions to track the behavior of individual point machines over time.

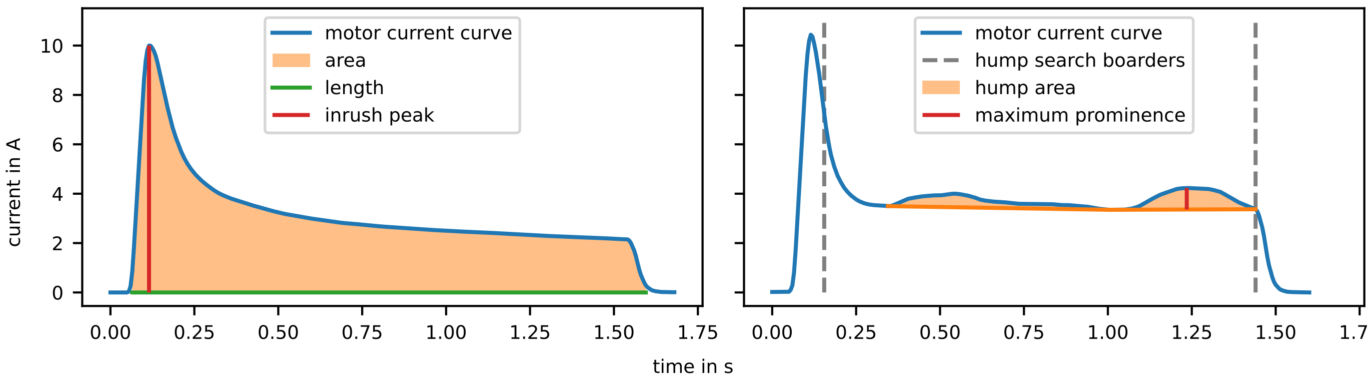

Figure 1. (**Left**): Scale features for an exemplary healthy motor current curve. (**Right**): Detection of locally increased current ("humps") due to additional mechanical resistance during the switch movement and associated shape features for an exemplary faulty motor current curves.

For each switch and direction, this results in a multidimensional time series. As most switches are moved at least several times a day, both gradual changes over time and sudden change points can be observed in the time series. The change points are manually labeled according to the following guidelines:

- Timestamp: Start time of the first switch movement that shows the new characteristic behavior after the change.
- Type:
  - Shape: Changes in mean or variance in hump-related features or health indicator not caused by temperature in either or both switch directions; simultaneous changes in other features permitted.
  - Scale: Changes in mean or variance in area, length or inrush peak value not caused by temperature in either or both switch directions; no change in hump-related features or health indicator.

Thus, shape change points annotate sudden changes in the additional mechanical resistance during the switch movement, which often does also change the area and length of the current curve. The scale change points on the other hand denote changes that only affect the dimensions of the current curve, while the characteristics of the additional mechanical resistance remains roughly the same. In the entire dataset, 96 shape and 72 scale change points were identified. Figure 2 illustrates an example of consecutive scale change points that influence the area and inrush peak. Shape change points are further classified as severe and persistent, severe and non-persistent, or non-severe. Figure 3 shows some examples of these classifications. Assigning these additional detailed labels accurately during manual labeling is challenging and somewhat subjective, yet they remain valuable for the in-depth analysis performed later in this study.

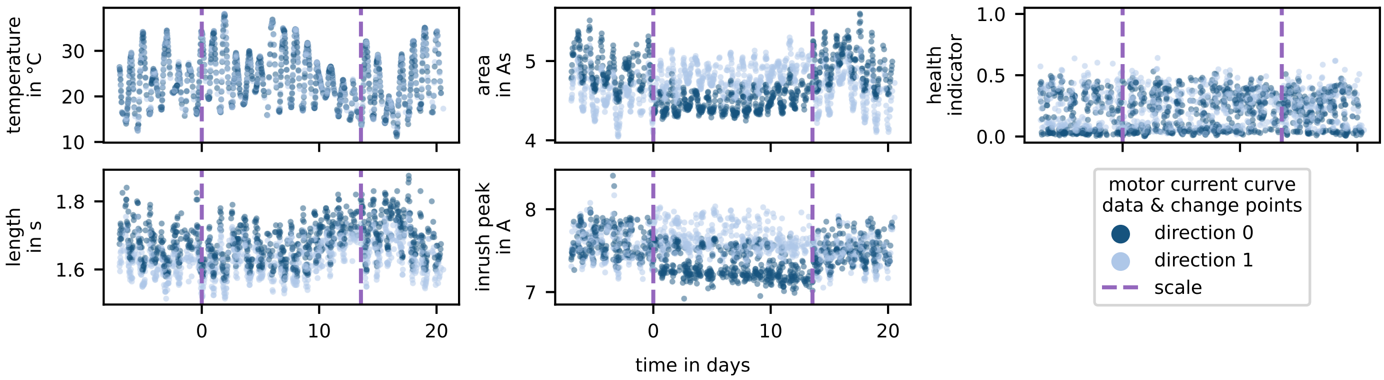

Figure 2. Example of two consecutive motor current curve scale change points in a switch that affect the area and inrush peak.

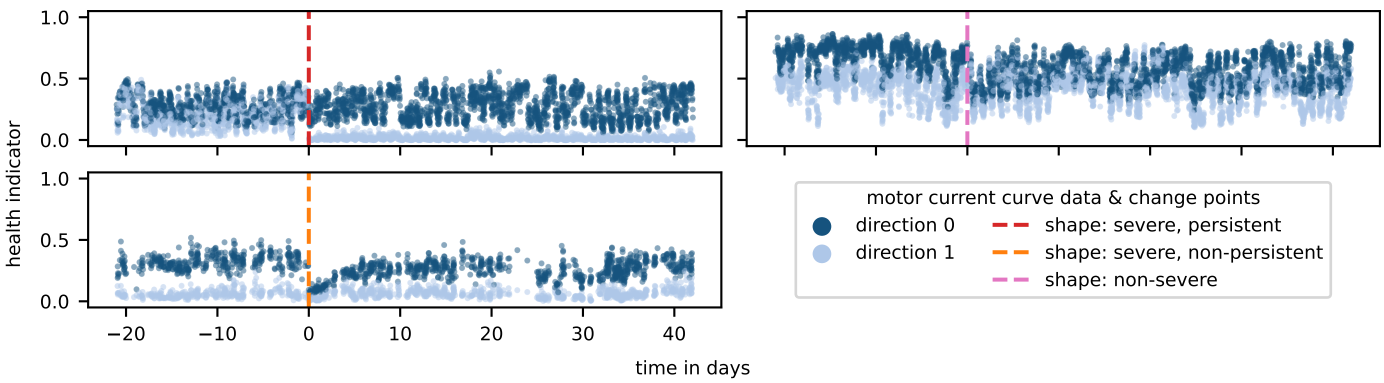

Figure 3. Examples of motor current curve shape change points at different switches.

2.2. Track Geometry

The track geometry at the switches is measured by the measurement trains SIM and UFM120 [34], in compliance with EN-13848 [12]. This study is focused on switches, particularly the area of the movable switch blades, a track section of comparatively short length. Thus, the following short-range variables are selected:

- Alignment for wavelength D1, i.e., 3-25 m, in the middle of the track;
- Gauge, expressed as deviation from standard gauge of 1435 mm;
- Longitudinal level for wavelength D1, i.e., 3-25 m, in the middle of the track;
- Cant;
- Twist over 3 m;
- Twist over 12 m.

In this dataset, the designed cant is zero and the ideal twist is zero in all switches. Not all variables are available for all measurements. The data is geo-referenced and aligned over the switch panel, as shown in Figure 4. Measurements are typically available one to three times a year for each measurement vehicle, for one or both tracks of a switch. While UFM and SIM do measure the same variables, a direct comparison of the measurements is not advisable, due to different measurement characteristics. Thus, the data is only merged at a later state after processing; see below.

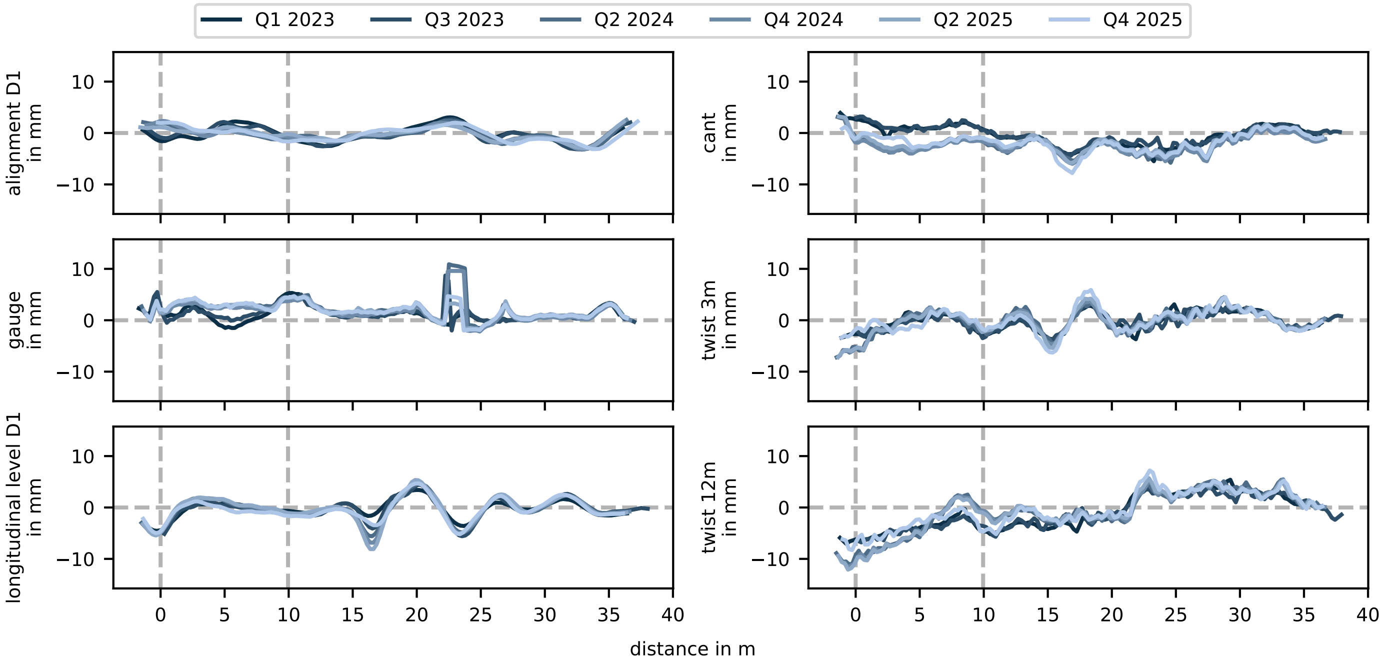

Figure 4. Track geometry measurements by UFM for the straight track of an exemplary switch. The vertical dashed lines mark the region of the switch blades, with the point of the switch blades on the left and the transition to the closure rails on the right.

For this study, the track geometry in the region of the switch blades, marked by the two vertical gray dashed lines in Figure 4, is of interest. For switch tracks with multiple measurements by the same vehicle per year, the following behavior is often observed. The geometry in the switch blade region is mostly stable over time, with little to no changes between consecutive measurements, but for rare instances of significant changes between two consecutive measurements that are visible in multiple, but not necessarily all variables, as shown in Figure 4. Clearly visible gradually developing changes, as in the longitudinal level D1 in Figure 4 around a distance of 17 m, are not prevalent in the switch blade region in this dataset. Unfortunately, for most of the switch tracks in the dataset, the time frequency of measurements is too low to make such detailed observations. Therefore, a clear differentiation between gradual changes and sudden change region is not possible. On another note, the gauge does have a higher variation in the switch blade region than in the rest of the switch. Both alignment D1 and longitudinal level D1 refer to wavelengths of 3 m to 25 m and are smoother than the other variables, such that the differentiation between natural variation and small changes is less distinct than in gauge, cant, twist 3 m and twist 12 m.

On open track, geometry is often assessed by calculating track quality indicators for segments of fixed length, for example standard deviation of the longitudinal level over 200 m. Using this approach for each variable in the switch blade region is too rough a feature to accurately model the behavior described above. Instead, the normalized area between curves (NABC) of a variable is obtained by dividing the area between two consecutive measurements in the switch blade region by the length of that region. For any two successive measurements taken by the same vehicle, the NABC of each variable quantifies changes in track geometry. NABC is robust to small shifts in distance synchronization between measurements and does capture changes in wave form as well as mean. Thus, NABC accurately track changes between consecutive measurements of the same vehicle. The NABC values of SIM and UFM are combined together for the remainder of this study.

In addition to the continuous NABC values that quantify changes in track geometry between two consecutive measurements of the same vehicle, a manual labeling into three classes—definitive changes, uncertain changes, no changes—is also performed. In Figure 4, the twist over 3 m remains the same between consecutive measurements, except for the change between the third and fourth measurement and between the fifth and sixth measurement. These changes still have a low NABC value, but it is significant when the consistency of the other measurements is considered. Manual labeling can capture such subtle changes qualitatively. However, when only two or three measurements are available, manual labeling can be more subjective, while using the NABC values directly yields a quantitative and more objective metric. Replacing manual labeling with an algorithmic approach—such as time-contiguous clustering of measurements using the NABC values—is only feasible when measurement frequency and the total number of measurements are high enough that each resulting cluster contains multiple samples.

2.3. Maintenance Data

The information on maintenance comprises all actions performed on the switches. Instead of using the various categories and descriptions, for this study the actions are labeled by experienced maintenance operators by their potential effect on the measurement data:

- Action can affect motor current curves (“can affect mcc”);
- Action can affect track geometry at the switch blade region (“can affect geometry”).

Each maintenance action is associated with a single timestamp, regardless of the duration of the work performed. If a team performs various actions within one visit to a switch, several entries into the maintenance logs can be made. The logs are manually entered by the maintenance teams directly in the field or after a shift, which naturally introduces inaccuracies in the documentation. While these inaccuracies are expected and acceptable in terms of the maintenance process documentation, they are relevant to the in-depth correlation analyses presented in this study. Further, the action categorization is designed for work orders and documentation from a maintenance point of view, and not tailored to data analysis. The interpretation of the categorization in terms of their potential effect on the measurement data performed for this study is thus limited in its specificity.

Maintenance actions that can affect both types of measurement data make up 39% of the entries, while 53% of the actions should not have any effect on either measurement data type, for example, inspections. Only 6% of the actions can only affect the motor current curves and 2% can only affect the track geometry at the switch blade. This can partially be explained by the limited specificity of the categorization system. Conversely, there are many, often complex, maintenance actions that in fact should affect both the switch movement—reflected in the point machine motor current curves—and track geometry at the switch blade area. For example, replacing a switch blade can change the track geometry and always requires an adjustment of the point machine.

3. Results and Discussion

3.1. Statistics on Motor Current Curves Versus Maintenance

To explore the relations between the motor current curve data and logged maintenance events, the latter are compared to the labeled change points and the health indicator.

Figure 5 displays the distribution of maintenance actions and motor current curve change points across the switches. In general, there are far fewer change points than there are maintenance actions that could affect the motor current curves. Scale change points are unevenly distributed: most switches have none, while a few have many. Shape change points are more evenly spread across the switches.

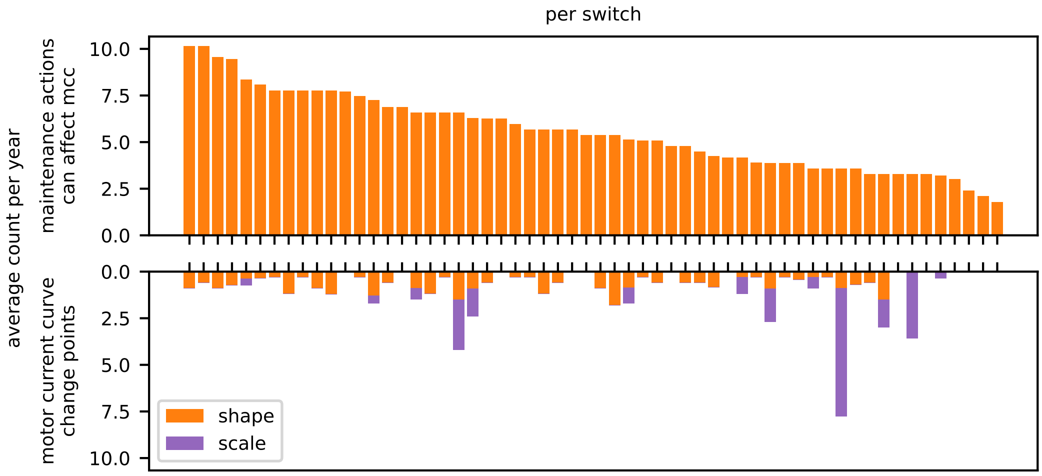

Figure 5. Average number of maintenance actions and motor current curve change points per year, per switch.

Any comparison between motor current curve change points and maintenance actions must include a tolerance to account for timestamp inaccuracies. Manual data entry by field teams can reduce the accuracy of maintenance action timestamps, and the manual labeling of change points can be subjective about the exact sample at which the change occurs. Moreover, the duration of maintenance actions can range from a few minutes to work that extends over multiple days. Based on practical experience and sensitivity analysis, for each change point, all maintenance actions occurring within the window from three days before to seven days after the change point are considered related. Because several actions can be performed on a switch during a single maintenance shift, actions whose timestamps differ by less than 24 h are regarded as simultaneous.

Figure 6 shows the statistical effect of maintenance actions on motor current curve data in proximity of a given change point, grouped by change point type. As a baseline reference, the same statistic is calculated for random timestamps instead of change points. The probability of a maintenance action that can affect motor current curves within proximity of a randomly selected point in time is 10%. For shape change points, this number increases to 76%. In more detail, severe—persistent or non-persistent—shape change points correlate to 82% and 89% with maintenance actions that that can affect motor current curves, while non-severe shape change points only do so by 58%. Due to the low number of samples and the subjectivity of the severity labeling, these numbers are of limited accuracy. In contrast, scale change points correlate with maintenance actions that can affect motor current curves by only 15%.

Vice versa, in Figure 7, for a group of simultaneous occurring maintenance actions that can affect the motor current curves, there is a 12% chance of a shape change point in proximity. At random control timestamps, this probability is 2%. For groups of maintenance actions that can affect the motor current curves, the probability of a scale change point in proximity is 1%, which is the same as for random control timestamps.

The same pattern can be seen in the change in the health indicator before and after groups of maintenance actions (Figure 8) and change points (Figure 9). Groups of maintenance actions that can affect motor current curve data more frequently lead to an improvement of the health indicator than groups of maintenance actions that should have no effect on the motor current curve data or random control timestamps, although the effect is very slight. When shape change points are present, the health indicator usually shows a significant improvement compared to random control timestamps. Note that change points are labeled per switch for both directions, even if the sudden changes occur only in one direction; this may explain the worsening of the health indicator for a few shape change point samples.

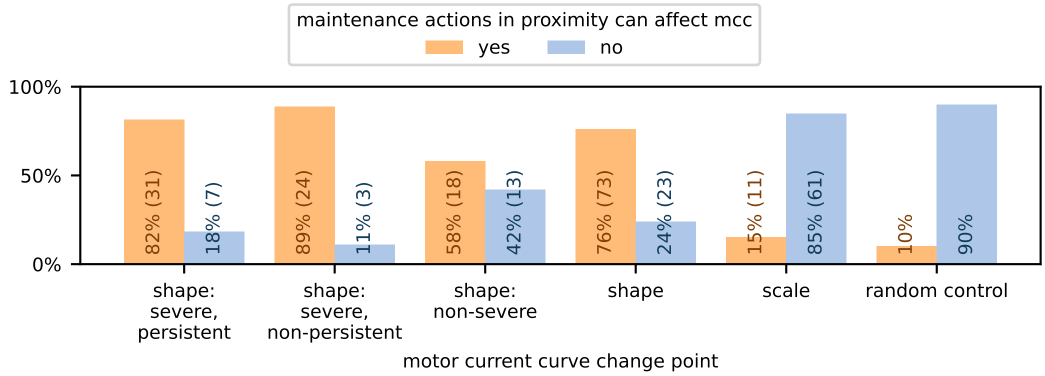

Figure 6. Distribution of the aggregated effect of maintenance actions on motor current curves, given a motor current curve change point.

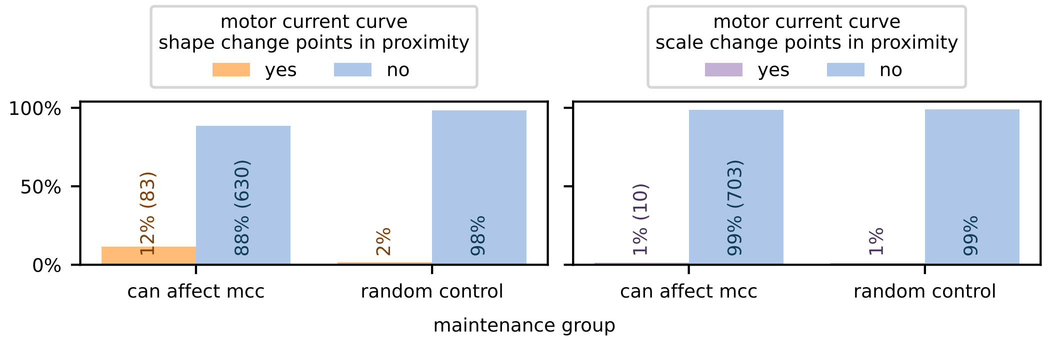

Figure 7. Probability of a motor current curve change point, given a group of simultaneously occurring maintenance actions.

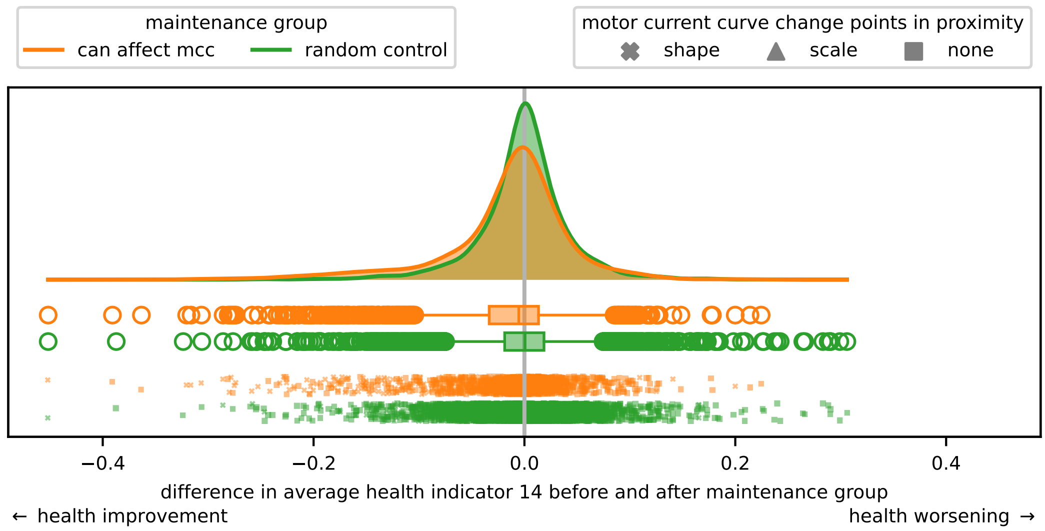

Figure 8. Raincloud plot of the statistical impact of grouped maintenance actions on the health indicator for point machines.

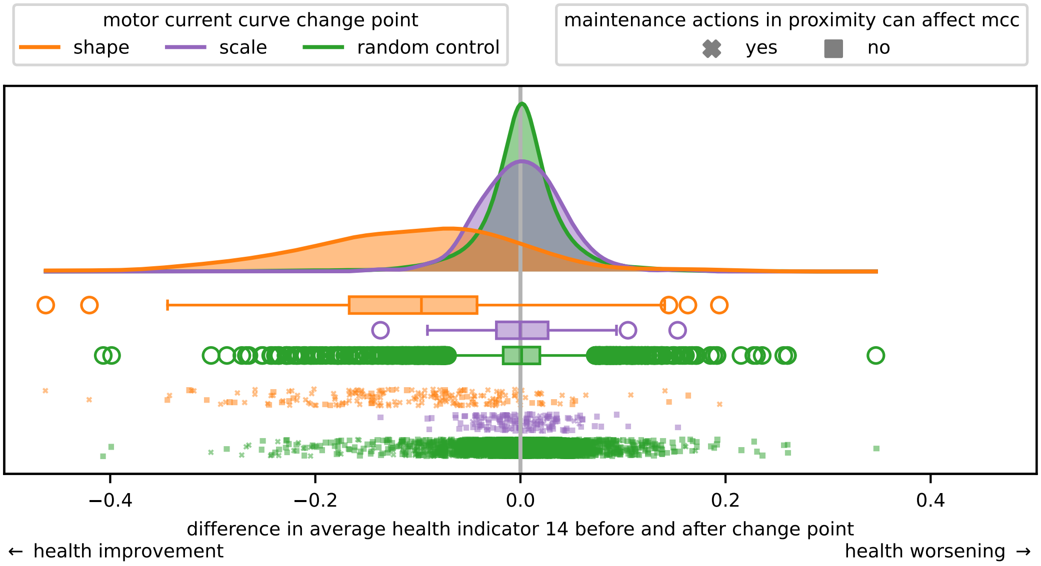

Figure 9. Raincloud plot of the statistical impact of change points on the health indicator for point machines.

The results indicate that sudden changes in the shape of motor current curves are mainly caused by maintenance actions that alter the mechanical resistance during switch movements, especially when the changes are significant. Shape change points that show a significant improvement in the health indicator but have no correlated maintenance actions could be partially explained by missing maintenance logs or imprecise timestamps. Aside from maintenance, non-severe shape change points may have causes outside of maintenance or may arise from errors in the manual labeling process.

Statistically, scale change points only have a slightly higher correlation with maintenance actions than randomly chosen reference time points. Thus, most of them are likely caused by other influencing factors that are not controlled for in this study. For example, changes in the no-load supply voltage available to the point machines can affect the length, as well as possibly the height and inrush peak of the current curves; see [35]. In their dataset of almost six months of motor current and voltage data of six point machines in a small yard, the no-load voltage jumps between several levels. Overlapping switch movements of multiple point machines connected to the same power supply change the operational voltage. Additionally, changes in the data collection chain can impact the scale of the measurement data. This interpretation would also serve to explain the more uneven distribution of scale change points across the switches in comparison to both shape change points and maintenance actions. The maintenance actions that are causally related to scale change points are likely to target the electrical systems in general or influencing the sensor system, thereby explaining the impact on the scale of the motor current curve without altering their shape. Changes in the mechanical point-machine movement are unlikely to be a root cause, because such changes would not affect the motor current curves uniformly, and the concurrent back-and-forth shifts shown in Figure 2, which are common for scale change points in this dataset, are implausible for a mechanical origin. To definitively determine the root cause(s) of scale change points, no-load and operational voltage should be measured consistently across multiple switches that exhibit scale change points. In addition, the sensor systems can be inspected manually for faults and their readings verified, since inaccuracies here are particularly difficult to detect.

The available maintenance labels and their timestamps lack sufficient precision to determine the expected impact on motor current curve data or the location of change points. Given a more precise labeling of maintenance actions that indicates whether an action should improve the mechanical resistance in the switch movement with exact timestamps, the health indicator could be used as a measure to quantify the effect of maintenance actions. This is not feasible yet; however, the existing labeling already reduces the number of the maintenance actions to be considered for comparison with motor current curve data to 45% of all maintenance actions.

3.2. Statistics on Track Geometry Versus Maintenance and Motor Current Curves

Due to the intermittent nature of track geometry measurements, a change in geometry between two consecutive measurements obtained by the same vehicle is compared to all events (i.e., current curve change points and maintenance actions that can affect track geometry) occurring between the two measurement dates. Figure 10 show the amount of events that on average occur between such measurements. There are typically multiple maintenance actions happening, that potentially have an impact on track geometry, between two consecutive measurements of the same vehicle. In the case of motor current curve change points, the dynamic nature of the motor current curve data, as shown in Figures 2 and 3, has to be considered as well. This reveals why a direct comparison between absolute values of motor current curve health indicator on the day of a track geometry measurement and the measured track health (e.g., quantified calculated according to EN-13848 [12]) is not a feasible approach. Instead, the following analysis focuses on the comparison of the changes in track geometry with aggregated events between measurements.

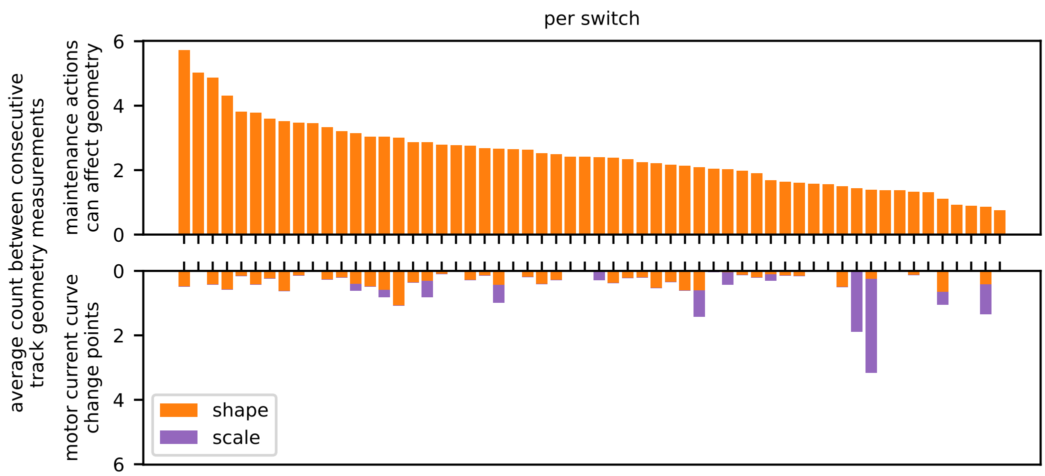

Figure 10. Average number of maintenance actions and motor current curve change points between two consecutive measurements of the same vehicle, per switch.

For the aggregation of events, only maintenance actions that can affect track geometry are considered. Following the logic of the motor current change point definition, if a shape change point exists in the time interval, the aggregated motor current change point label is shape. If only scale but no shape change points exist, the aggregated label is scale. The last option are no motor current curve change points. Figures 11 and 12 show raincloud plots of track geometry changes measured by NABC, grouped by aggregated maintenance actions and by motor current curve change points, respectively. When maintenance is performed, the NABC distributions reach higher values and shows heavier tails than in the no-maintenance case. For alignment D1 and gauge the differences are small, for longitudinal level D1, cant, and twist 3 m the differences are clearer, and for twist 12 m they are most pronounced. This trend is also visible in the box plots. For longitudinal level D1, cant, twist 3 m and twist 12 m, the maintenance case covers almost all higher NABC values, with no outliers in the no-maintenance case. The smaller number of samples in the no-maintenance group may influence this observation. The NABC distributions in the presence of motor current curve scale change points and the no-change-points case are very similar, with minor deviations that can be attributed to the lower sample sizes in the scale change point case. In contrast, the presence of shape change points produces markedly different NABC distributions that extend to higher values and have heavier tails than the no-change-point case. This effect is most pronounced for cant, twist 3 m, and twist 12 m and is more visible than the maintenance grouping. Unlike the maintenance case, the shape-change-point case does not cover all extreme NABC values.

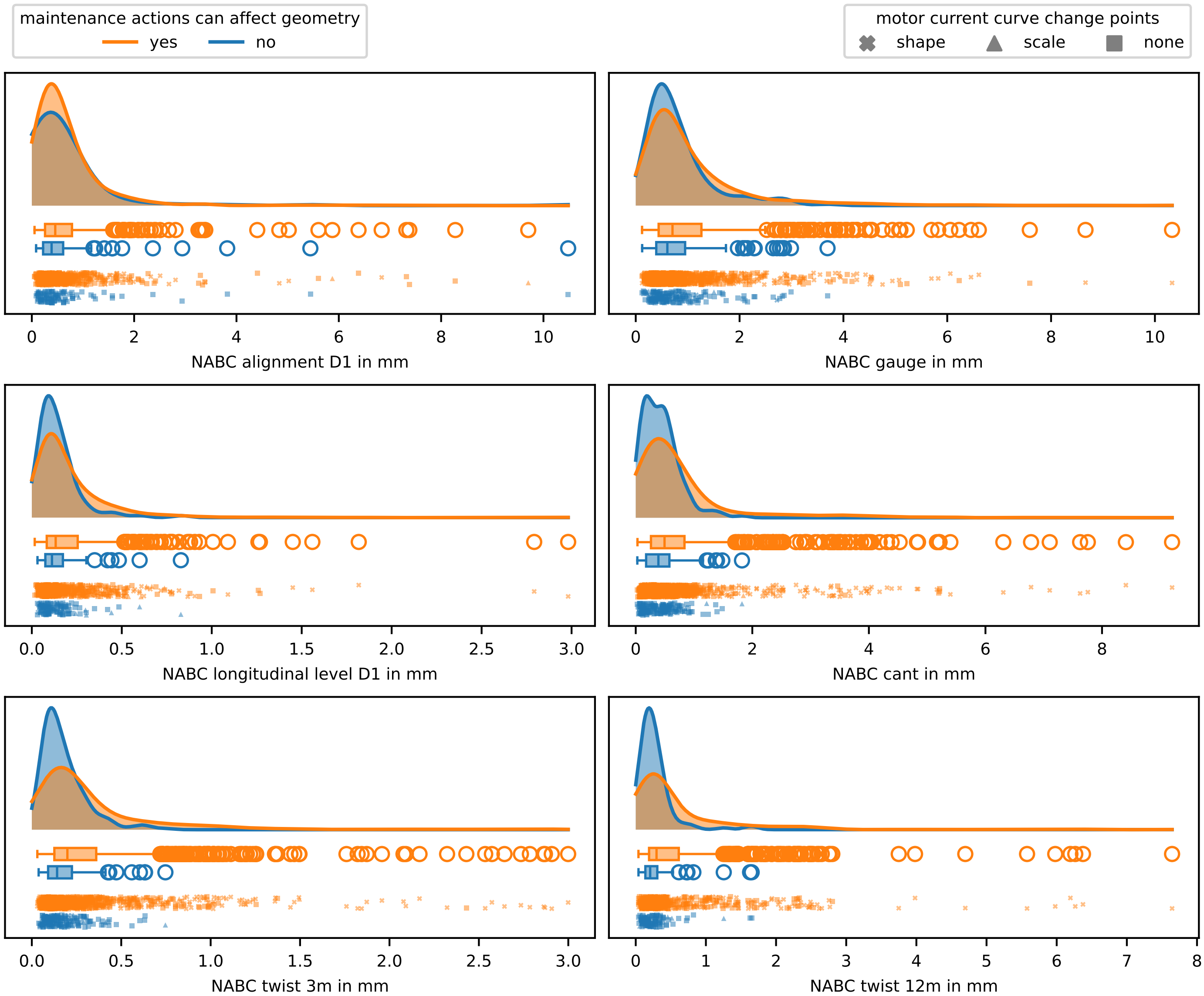

Figure 11. Raincloud plot of the statistical relation between track geometry changes and maintenance.

For easier comparison, the relations are summarized with a single correlation coefficient. Figure 13 displays the point-biserial correlation coefficient between track geometry changes, maintenance actions, and motor current curve shape change points (scale change points treated as no change points). The coefficient, ranging from -1 to 1, measures the association between a dichotomous and a continuous variable and is equivalent to Pearson's correlation coefficient for continuous data [36]. The confidence intervals quantify the reliability of an estimate; i.e., the true correlation coefficient lies within the p confidence interval with probability p, for example $p = 95\%$. Correlation between track geometry changes and motor current curve shape change points is substantially higher than that between track geometry changes and maintenance actions. With respect to maintenance, twist 3 m, twist 12 m and cant have the highest correlation, followed by longitudinal level D1, gauge, and alignment D1. However, the 95% confidence intervals for the estimation of the point-biserial correlation are rather large and have some overlap. For motor current curve shape change points, cant, twist 3 m and twist 12 m have markedly higher correlations, while longitudinal level D1 and gauge show moderate correlations, and alignment D1 shows the lowest correlation and a less significant increase compared to maintenance. This observation still holds true when the 95% confidence intervals for the estimation of the point-biserial correlation are taken into account.

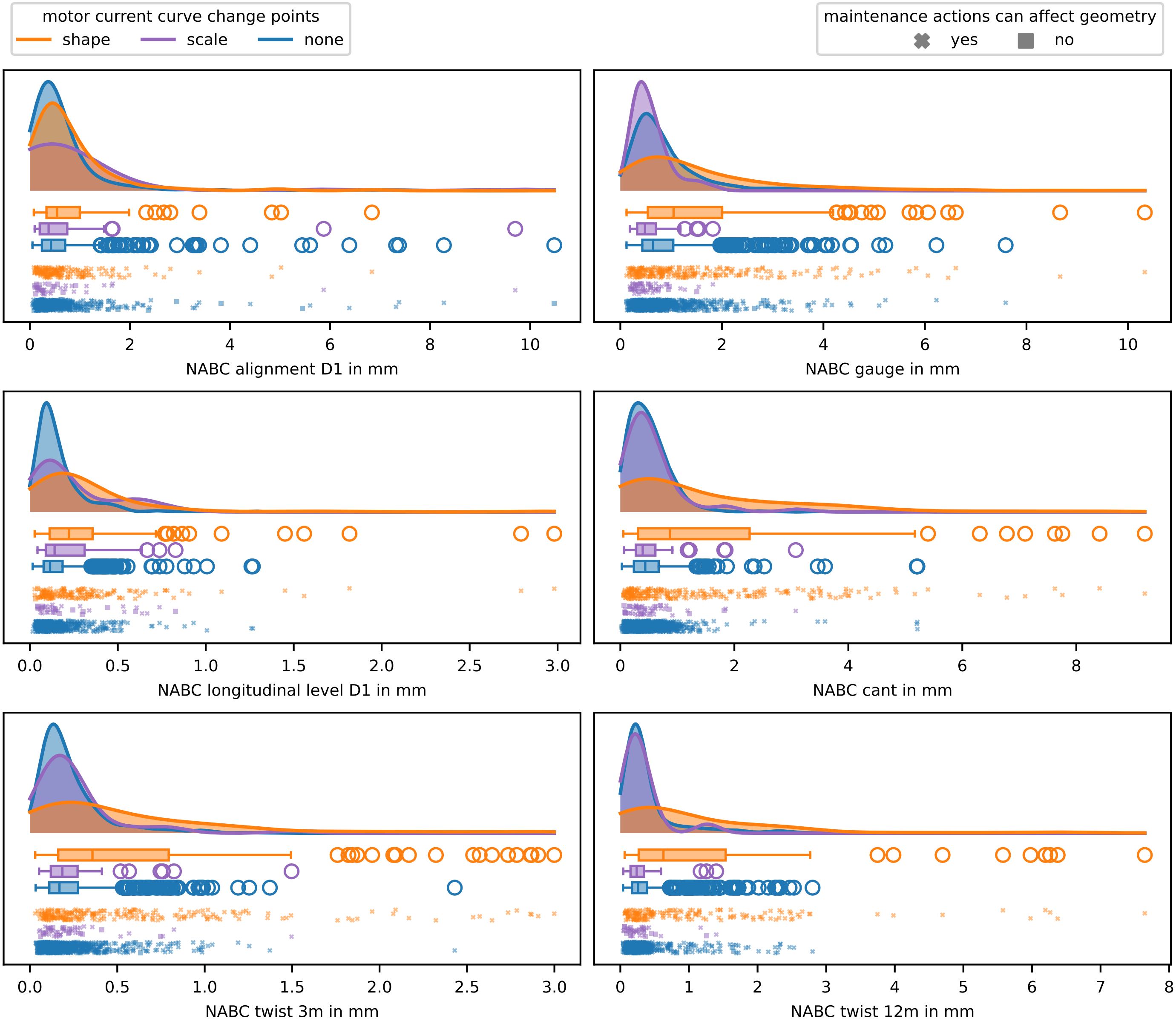

Figure 12. Raincloud plot of the statistical relation between track geometry changes and motor current curve change points.

Changes in track geometry show a low positive correlation with maintenance and a stronger correlation with motor current curve shape change points. This is particularly evident for cant and twist. Both longitudinal level D1 and alignment D1 are measured across a range of wavelengths, whereas the other variables refer to the track state at a specific reference position or between two reference positions. Local changes in the short switch blade area may be better captured by the latter than the former. Thus, it could be argued that track geometry variables describing the vertical state of the track show stronger correlations than those describing the horizontal state. As motor current curve shape change points are associated with maintenance actions that impact the mechanical resistance during the switch throw, a viable hypothesis would be that these often complex maintenance actions are also responsible for the changes in track geometry. This would mean that certain maintenance actions are a common confounder for both motor current curve data and track geometry measurements, and any shared analysis always needs to control for this factor. Further, given that especially for cant and twist maintenance covers almost all extreme changes in these variables, the first-order effects caused by maintenance actions are likely to dominate the data compared to other processes, such as degradation. There appears to be no correlation between changes in track geometry and motor current curve scale change points. This aligns with the previous interpretation that the scale change points are caused by changes in the electrical system, sensor system or maintenance that affects those, all of which are not causally related to track geometry.

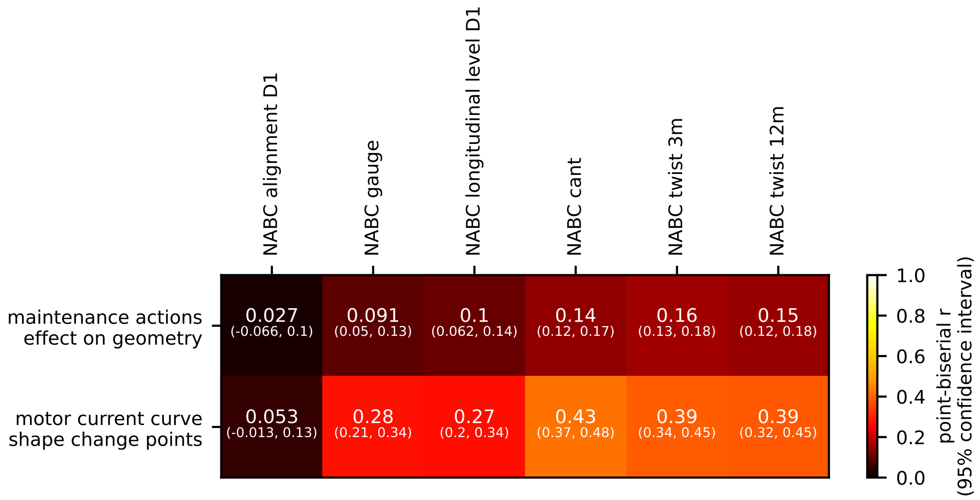

Figure 13. Correlations between track geometry changes and maintenance and motor current curve change points.

However, the very low time resolution of the track geometry measurements makes the comparison with events that happened between measurements difficult. As shown in Figure 10, typically multiple events are present. There is no way to definitively determine if a change in the track geometry is related to a specific or multiple events, if it has happened gradually over time, or if it is a combination of both. So far, causation cannot be proven, only argued.

As before, the limited specificity of maintenance labeling reduces the informational value of the data, because it is unclear which actions truly should affect the geometry. Nevertheless, this labeling allows focusing on only 41% of all maintenance actions when comparing them with track geometry.

3.3. In-Depth View on Track Geometry Versus Motor Current Curves

For a more detailed view of the relationship between track geometry changes and motor current curve shape change points, their detailed labels are used. This enables a better characterization of both, but it reduces the sample size in each category and in their combinations, so statistics should be interpreted as indications rather than precise numbers. As before, for each two consecutive track geometry measurements collected by the same vehicle, all motor current curve shape change points that occur between the two measurement dates are aggregated. The resulting aggregated label reflects the strongest change point in that interval, following the hierarchy “severe, persistent”, “severe, non-persistent”, “non-severe”, and “none”.

Figure 14 shows the composition of the aggregated change point labels, for each of the track geometry change labels. Definitive changes in track geometry correlated best with severe, persistent motor current curve shape change points. Severe, non-persistent shape change points in the motor current curves do have a lower but visible correlation, the same as for non-severe shape change points. This effect is strongest for cant and twist 3 m, followed by twist 12 m, longitudinal level D1, gauge and lastly alignment D1. A similar pattern can be observed for uncertain changes in track geometry, but to a lesser extent.

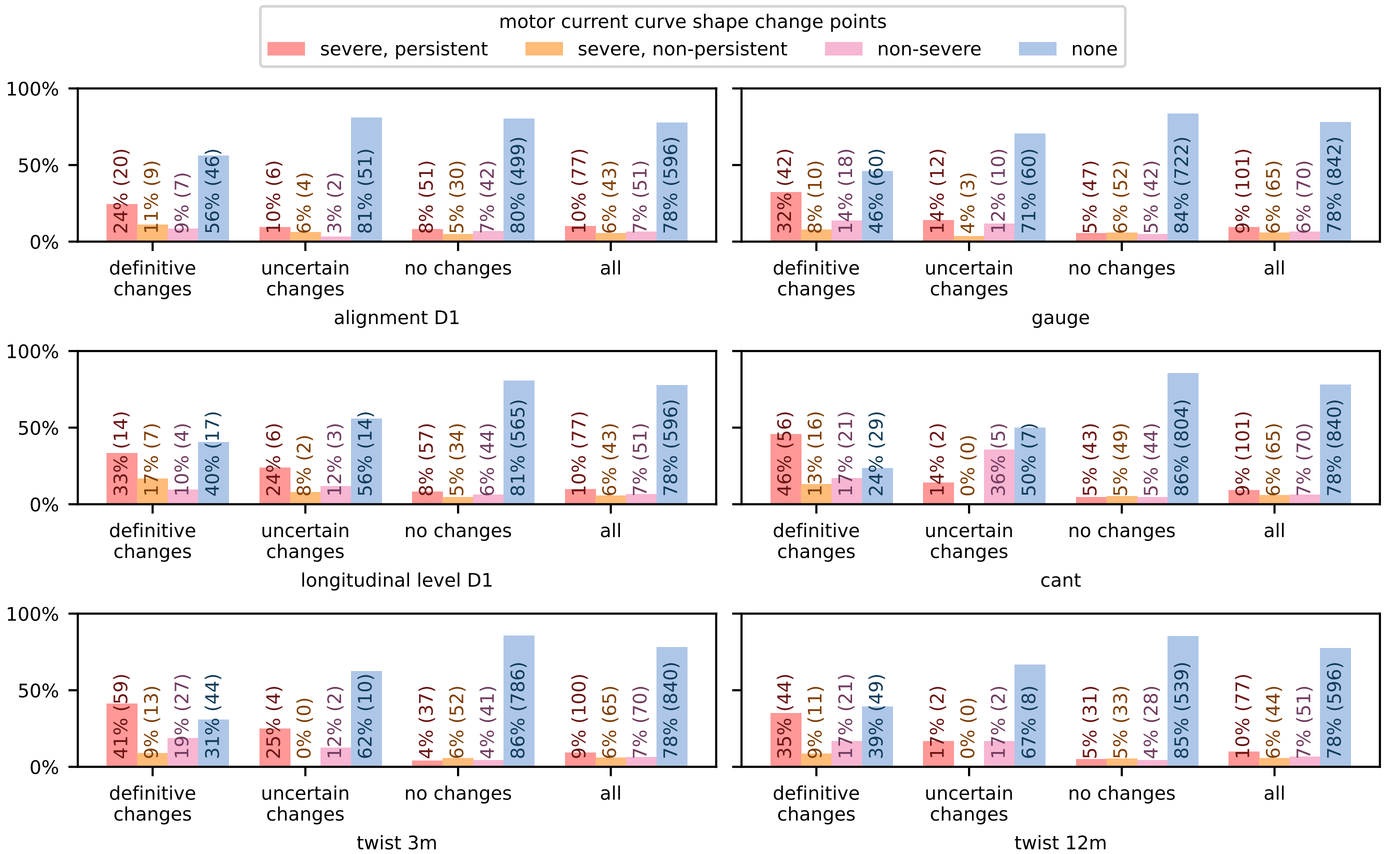

Figure 14. Relation between track geometry changes and motor current curve shape change points.

The shape of motor current curves, which quantifies additional mechanical resistance during switch movement, can show a very dynamic behavior, with severe persistent, severe non-persistent and non-severe shape change points. Track geometry measurements appear to be more stable over time, with few but persistent changes, although this cannot be said for certain due to the low frequency of measurements. Severe persistent shape change points in the motor current curves align with persistent changes in track geometry and are likely caused by complex maintenance actions that affect both at the same time. Other severe, non-persistent change points in point machine data align with maintenance but not with persistent track geometry changes, which may be due to smaller, less significant maintenance actions. It is uncertain whether similar non-persistent or non-severe changes in track geometry occur but cannot be ruled out, due to the limited number of measurements. The data suggests that for the mechanical resistance in the switch movements of point machines, significant persistent changes in track geometry—in particular in cant and twist—caused by maintenance have to be treated as a persistent change of the framework conditions under which the point machine operates and is maintained. To assess the success of maintenance actions, which includes both immediate improvement of the measurement data and the persistence of the improvements, simultaneously occurring changes in track geometry have to be taken into account.

Increasing the frequency of track geometry measurements by measurement trains, for example, every one to three months, and extending the timeframe would help to better understand these processes, but still holds limited explanatory power. A precise comparison with the dynamic behavior of the point machines and event type data, which includes maintenance actions, requires daily data instead. Due to cost and operational constraints, such datasets can only be obtained by implementing condition monitoring approaches that generate continuous data during normal operations. Examples include sensor systems on in-service trains [19] and permanently installed track-side sensor systems in switches [20,24]. Due to their complexity and increased dynamic impact on track superstructure, switches are subject to maintenance actions much more frequently than open track. This heavily impacts the development of track geometry over time, such that switches need to be monitored much more closely than open track to fully understand their behavior.

4. Conclusions and Outlook

4.1. Conclusions

First-order effects of maintenance dominate the measurement data in this study.

Change points in the scale of point machine motor current curves are likely connected to changes in the electrical system, sensor system or (partially) maintenance actions that affects these. Change points in the shape of motor current curves, which characterizes the additional mechanical resistance during the switch throw, are almost always correlated with maintenance actions, especially if they are severe. However, not all maintenance actions that could possibly affect the motor current curves are related to change points in the data, as the labeling is not specific enough.

The relationship to track geometry is explored by comparing maintenance actions and motor current curve change points with the changes in track geometry recorded between intermittent measurements. Changes in track geometry, especially cant and twist, have a low correlation with maintenance and a higher correlation with motor current curve shape change points. Maintenance covers most quantitative higher changes in track geometry, but again the labeling is not specific enough to rule out actions with no effect on the data. Severe persistent motor current curve shape change points are most strongly correlated with definitive changes in track geometry, implying these are caused by complex maintenance actions that affect both, while non-persistent or non-severe shape points are likely caused by maintenance that is limited to the point machine. This implies that for the mechanical resistance in the switch movements of point machines, significant persistent changes in track geometry—in particular in cant and twist—caused by maintenance have to be treated as a persistent change of the framework conditions under which the point machine operates and is maintained. To assess the success of maintenance actions, which includes both immediate improvement of the measurement data and the persistence of the improvements, simultaneously occurring changes in track geometry have to be taken into account. Switches undergo maintenance more frequently than open track and therefore require closer monitoring.

4.2. Outlook

While the obtained results provide important new and relevant insights into the holistic relationship between point machine, track geometry and maintenance, several aspects of this analysis require further research and improvements to the underlying datasets.

Labeling of maintenance actions specifically tailored for use with measurement data is needed, as well as precise documentation of the start and end times of these actions. A common practice is to record maintenance activities using both standardized categorical labels and free-text comments, with the former being more amenable to automated analysis. The categorization schema should be both suitable for the documentation of actions from the perspective of a worker and have a clear link to the expected effect on measurement data. For point machines, for example, actions that impact the electrical circuit of the motor, the control and the mechanics of the switch movement are recommended to be distinguished. In addition, the categorization should capture the impact of each action on track geometry and indicate which panel of the switch is affected. Modern tools that improve the convenience and speed of documentation in the field are essential, as well as dedicated training of the workers. The results of this study demonstrate that any analysis or condition monitoring application that relies on long-term measurement data from switches must explicitly account for maintenance activities. Moreover, if the expected outcomes of a maintenance action are known, the corresponding data can be used to evaluate the success of that intervention.

Increasing the frequency of track geometry measurements via measurement trains to a monthly schedule and extending the duration of the study or increasing the number of switches would address challenges such as low sample sizes in detailed analyses. However, these improvements would not remove the fundamental limitation of intermittent measurements, when comparing these with maintenance actions or the more dynamic point machine data. Instead, daily condition monitoring data on the health state of the switch track superstructure, collected during normal operations, is required. Possible approaches are onboard sensor systems mounted to in-service trains and track-side sensor systems that capture the vehicle–track interaction of train passages over the switch. Track-side systems based on acceleration sensors, such as [20,24], are most suitable for monitoring track health at specific points of interest, such as the transition area between switch blades and stock rails. With multiple track-side sensors in a network, entire switches could be covered as well. For onboard system, multi-sensor approaches that include at least axle-box accelerations, inertial measurement units and GNSS are recommended. Research on onboard condition monitoring approaches with in-service trains for open track is already well advanced, while adaptions specifically tailored to switches, such as in [19], remain rare. The data would allow for a precise comparison with the dynamic point machine behavior and events such as maintenance actions. Among the considered track geometry variables, cant and twist appear to be most relevant so far. However, other aspects of track health, such as the gap between switch blades and the stock rail, may also be relevant and should be explored in the future.

Another approach would be to adopt a life-cycle view that compares maintenance, measured point machine health, measured track geometry and potential influencing factors over the entire lifetime of switches. In [37], such an analysis was performed for the track superstructure of switches, but point machines were excluded due to data accessibility. This would enable the derivation of the statistical interaction between point machine and track health regarding the technical lifetime of various components. It is reasonable to assume that fault propagation in switches is not contained within subsystems but can spread across the entire system. A better understanding of these relations could enable the overall optimization of maintenance strategies. Since such datasets are difficult to obtain, an alternative could be to combine detailed physical models—so called digital twins—that simulate point machine (for example [38,39]) and track behavior (see [40]) into a comprehensive model of the entire switch, to simulate behavior over long time frames, with or without maintenance interventions.

The present dataset contains 58 single switches equipped with NSE2 point machines in the Netherlands, with data recorded over 3.5 years. While the results may be directly transferable to other models of the same point machine series—namely the models NSE4 and NSE-S, which are also prevalent in the Netherlands—different track layouts and other point machine types should be investigated as well. Both measurement data analysis and life-cycle analysis on datasets that combine various switch layouts or point machine types must account for these differences, adding another layer of complexity.

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