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A BIG DATA METHODOLOGY FOR TAMPING DECISIONS USING SENSORS FROM SKY, RAILWAY TRACK AND SUBSTRUCTURE

By Karim El Laham

Karim is a fresh EngD graduate from the TU Delft where he conducted his MSc studies in structural engineering. Karim's interests lie in railway degradation mechanisms and finding ways to quantify that using data, as well as anything to do with AI and big data. Karim currently works at Fugro as a railway specialist trying to combine different datasets that are available within the company and externally to create a unified data model that can help with track maintenance assessment and planning.

This project was conducted in collaboration with Fugro as part of my EngD (engineering doctorate) study within TU Delft.

INTRODUCTION

The railway industry can strongly contribute to the Paris Agreement goals as the railway is, by design, one of the greenest transportation modes that can transport a massive amount of passengers and freight between the major cities in Europe. However, railway infrastructure degrades over time due to usage and exogenous factors (such as climate) and requires replacing components whose production and installation generate greenhouse gas emissions. Further, the increased demand, more intensive use of the infrastructure, and higher axle loads come together with exacerbated degradation mechanisms that bring extra pressure to the current frequency of maintenance operations. Thus, optimal maintenance interventions are required not only to cope with the always-increasing user expectations regarding the quality and reliability of the service, but also to address higher sustainability standards. Now more than ever, creating a prescriptive maintenance framework that fully utilises state-of-the-art sensing technologies, the latest developments in data analytics, and the most updated knowledge on railway engineering becomes essential. Otherwise, the most likely scenario for a very densely used network such as the Dutch railway is a drastic increase in reactive maintenance, with more components to be replaced on short notice, higher unavailability periods, higher CO2 footprint, and more delays, which will severely affect the trust of users in the service, affecting the economy and society as a whole.

PROBLEM STATEMENT

The manner in which most maintenance activities are being conducted in the railway industry is reactive (Kienzler, Lotz, & Stern, 2020), in the sense that corrective actions are taken when a malfunction occurs. A relevant example of reactive maintenance is the tamping of the ballast bed when geometric track deviations are observed. Tamping, however, does not always address the underlying cause of geometric track deviations, and track deviations will emerge sooner or later. As such, an expensive and vicious cycle of reactive tamping is induced while the underlying cause is not addressed.

Railway track condition is related to track geometric irregularities. Such irregularities are the cause of many different factors. However, according to research by Abadi et al., 2016 and Ionescu, D., 2004, about 40% of the operating budget on track maintenance is related to ballasted track maintenance and renewal. The high ballast maintenance costs arise not only due to frequent reactive corrective tamping with the average tamping cycle of about 40–70 million gross tonnes (Mt or MGT) (Abadi et al., 2016), but also because tamping can damage the track ballast and thus reduce its overall lifecycle (Audley & Andrews, 2013).

Geometric irregularities are depicted by the dataset called relative track geometry (RTG). Relative track geometry refers to the spatial position occupied by each rail on a track centreline relative to the straight undeformed rail representing the baseline. Usually, the centreline is depicted by points spaced by 25cm according to EU standards and by 20 cm according to UK standards (Khajehei, Ahmadi, et al., 2021). The railway track is depicted according to five different relative track geometry parameters: longitudinal level, alignment, cant (cross-level), gauge, and twist (Liao et al., 2022; Khajehei, Ahmadi et al., 2021; H Wang et al., 2019) as shown in **Figure 1**.

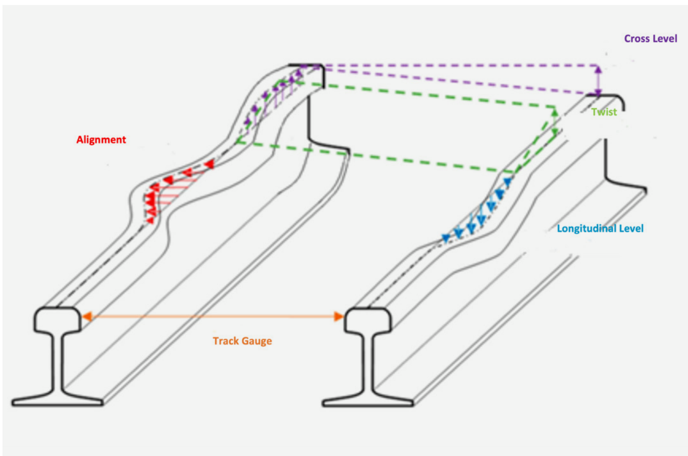

Figure 1: Representation of all relative track geometry parameters, modified from Liao et al. (2022)

According to the literature, longitudinal level and alignment were found to be the primary factors influencing planned and unplanned maintenance activities (Andrade & Teixeira, 2014; Soleimanmeigouni et al., 2020). In fact, European norms have set thresholds upon said datasets. Tamping is the remediation technique for the alignment of the track, which will affect cant, track gauge, twist, longitudinal level and alignment. This means that to decide upon tamping decisions, these datasets are used. However, the data that will be used in this project is limited to longitudinal level and alignment, because if these two defect components present problems, then the others such as cant, track gauge and twist will present problems too.

Longitudinal level and alignment are split into two wavelength domains in the processing phase using a filtering method called the Butterworth filter method. This should comply with the rules of annex C of EN-13848-1 (CEN, 2011), which gives bounds for the transfer function that should be used. The domains are called:

- D1: 3 m < λ ≤ 25 m
- D2: 25 m < λ ≤ 70 m

Longitudinal level data portrays the vertical forces that are on the wheel rail interface. Alignment highlights lateral deviations from that baseline, which are recorded as the alignment relative track geometry (CEN, 2011).

The longer wavelength domain D2, of 25m to 75m is related to the frequency domain of 0.52 Hz to 1.56 Hz using a train velocity of 140km/h. This also fits into the sensitive comfort domain, and can be used for track quality evaluations, however mostly for comfort purposes. While the D1 domain also belongs to the resonance frequency range of the sprung masses and the semi-sprung masses: a frequency range of 1.56 Hz to 12.96 Hz using train speed of 140km/h. This domain gives insight on the general track condition such as ballast and sleeper alignment problems.

STATE OF THE ART

Some work has been done to incorporate data from InSAR (Interferometric synthetic aperture radar) into railway monitoring applications (Chang et al., 2017; Hu et al., 2019). Also, much work has been done using track-based datasets from railhead laser sensors (Khajehei, Ahmadi et al., 2021; H Wang et al., 2019) to detect early warnings of rail failures. In addition to those initiatives, much research has been conducted using sensors that depict the substructure of the railway track (Burrow et al., 2007). Each of these sensors and applications show one side of the entire track's story. The combination of all sky-based, track-based and substructure-based data can depict the entire story behind the behaviour of the railway track and potentially assist in the understanding of interrelations between assets and the underlying failure mechanisms, as well as assessing the condition of assets.

From the track, relative track geometry and construction characteristics are used.

From the substructure, the subsoil map of the Netherlands is used.

From the sky, InSAR data is used to characterize settlements on the railway track.

Instead of using relative track geometry data to decide on tamping maintenance, this project combined data from sky, railway track substructure and big data methodologies to enhance tamping maintenance decisions.

The key contributions are:

1. Smart Sectioning. Such a sectioning uses different datasets to create sections of different lengths, each containing its particular homogeneous behaviour. This is a way of data segmentation for railways. This dynamic method of sectioning has been done before by Jovanović et al., 2015, yet with different rules and incorporations than Smart Sectioning.
2. Using InSAR data with RTG data and a subsoil map based on cone penetration tests is a way to circumvent looking at RTG data 1-dimensionally to make reactive tamping decisions, and understand more about what is happening behind said data. This data incorporation can help understand when tamping needs to happen and when it is not the best solution. Combining loaded and unloaded datasets from RTG data can also complete the picture by creating a notion of stiffness that is missing within the above-mentioned datasets.
3. Using an interactive geospatial dashboarding visualization is a way to help visualize trends that cannot be seen otherwise.

Within this paper, a dive into each of the above elements will be made.

Smart Sectioning: a Twist on Dynamic Sectioning

RTG data is sampled for every 20cm/25cm. It thus can become difficult to process and filter through the data due to the huge amount of it that describes thousands of kilometres of track. To do so, literature and norms have shown that a fixed-length segmentation is the most common way to process the data. What this means is that sections of the same amount of data points are put together and processed with either standard deviation for a general track quality understanding or maxima for an isolated defect analysis (Liu et al., 2017; Offenbacher et al., 2020; Sadeghi, 2009). The data is broken down into 200m/100m/50m sections in a fixed manner according to standards (EN13848-6 Annex C). Sections are formed to smoothen data and to reduce the need to watch individual data points over time. This method is called "fixed" sectioning. The problem with such a sectioning is that by creating sections in a fixed manner, some parameters regarding the track could be overlooked. For instance, a section could be created in the middle of a switch or a bridge, making the data smoothening counterproductive from an understanding of the data perspective as the data would portray two different degradation behaviours shown as one **(See Figure 2)**.

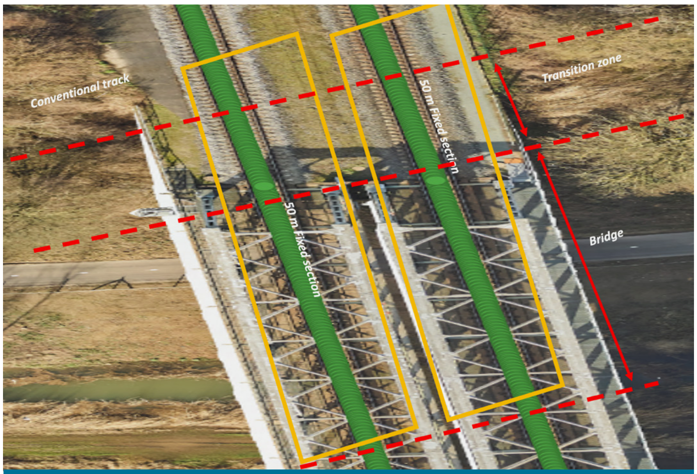

Figure 2: Fixed Sectioning highlighted in orange. The randomness of the fixed sectioning can lead to having a section with a conventional track, transition zone and bridge all in one section

The first step of this project is to use the track-based data such as construction characteristics and locations of different important track elements to break down the track into sections with a unique behaviour.

However, as mentioned above, this idea of dynamic sectioning had been introduced before and utilized in rail asset management software using the ideas of Jovanović et al., 2015. The difference in this dynamic sectioning lies in three different elements:

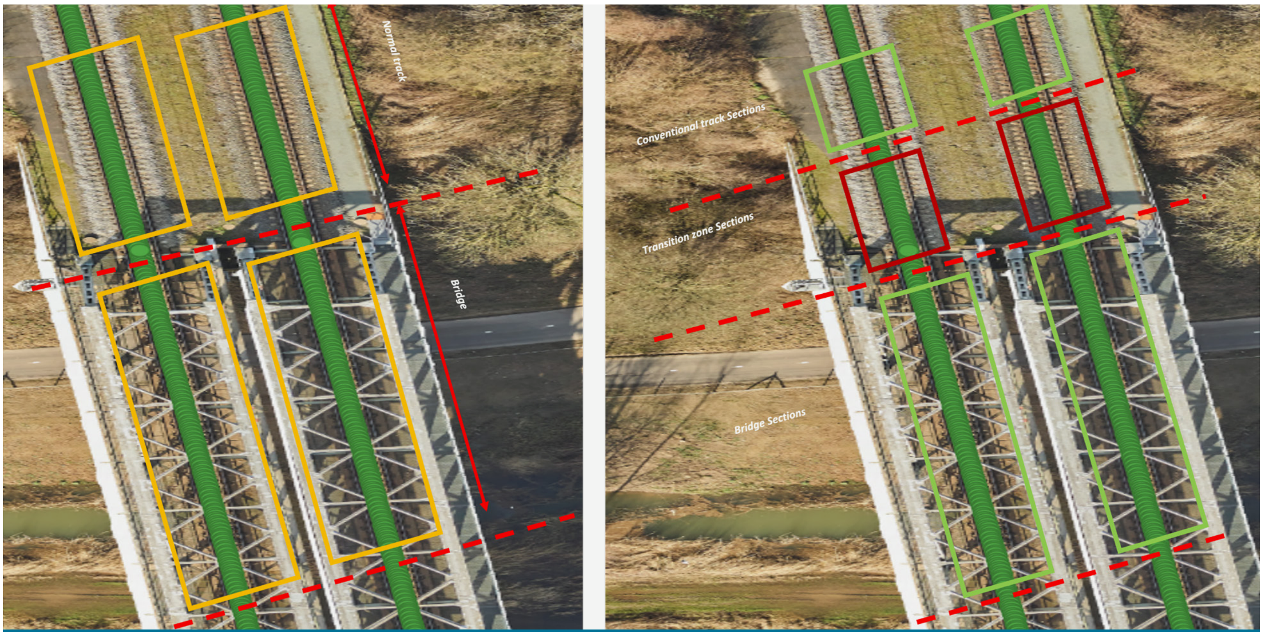

Figure 3: Comparison between literature's Dynamic Sectioning (left) and Smart Sectioning (right)

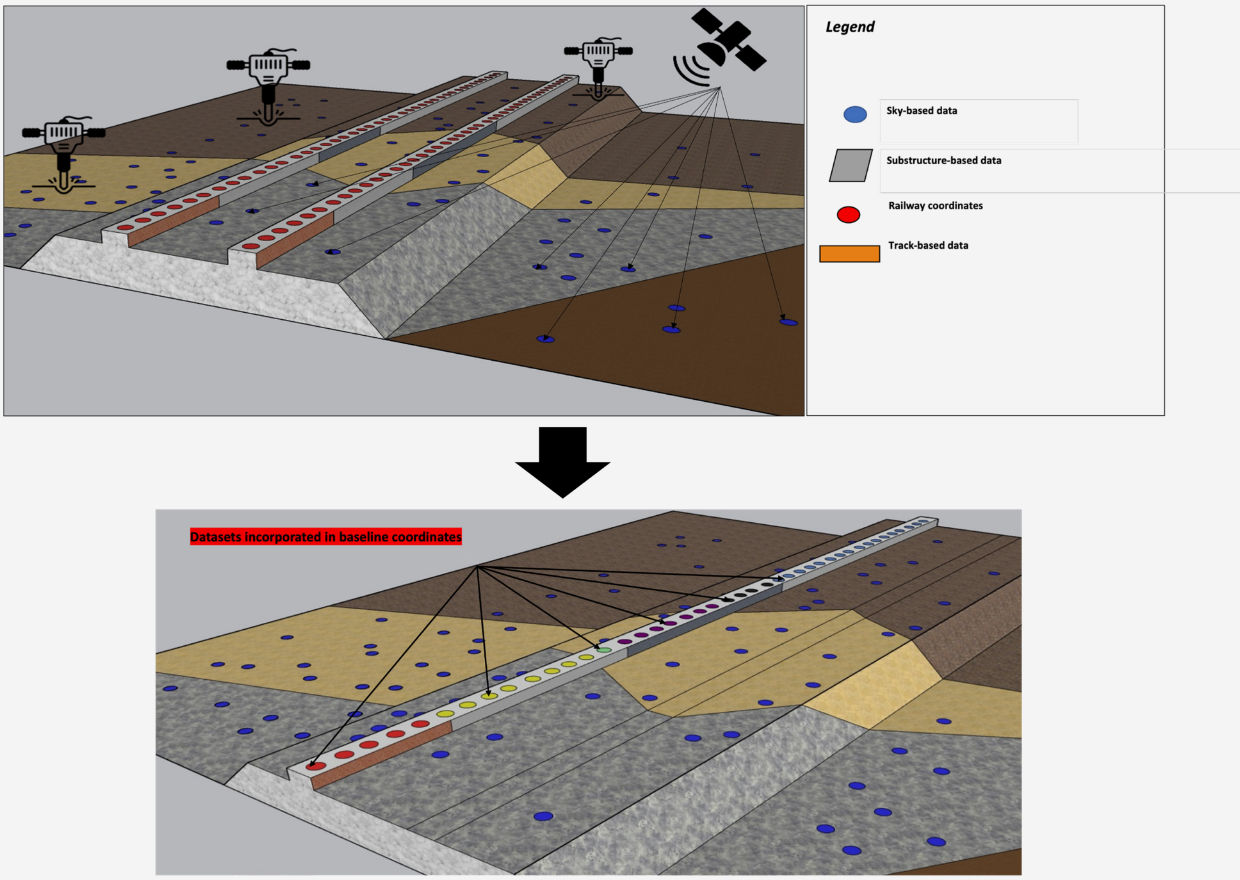

Figure 4: The effect of smart sectioning. The top figure shows the different datasets all included in the same map. The lower image represents Smart Sectioning that took those datasets into consideration to break down the track into different assets according to the contextual information

1- The creation of transition zones. According to Coelho (2013), transition zones and switches need 4–8 times as much maintenance as a typical plain track. Previous practice considers specific elements that will define the start and the end of a section/segment. In comparison, dynamic sectioning goes beyond that and breaks down tracks before/after special structures (bridges/culverts/level crossings tunnels, switches, and crossings etc…) and labels them as transition zones **(Figure 3)**. This is because for a limited length, which is a function of train speed, these transition zones exhibit higher settlements than other areas.

The way the previous practice would handle a section with a special structure is to take the bridge as one section on its own and break down before and after according to contextual information **(Figure 3)**. This would lead to capturing two different behaviours instead of three, with the interface between the special structure and the conventional track not taken into consideration on its own. Although, transition zones require 4-8 more maintenance than a regular free track (as mentioned before), and that is what smart sectioning captures.

2- Prior practice does not label each section and has a different end goal. It breaks down the different sections also to capture the different behaviour and change of data with respect to time. However, it does not have an end goal to try to understand using the labels of each section, what is happening on each track and to identify root causes of degradation. In this twist on dynamic sectioning, on the other hand, the tracks are labelled and enriched with more information over time, and thus could correlate to any KPI, for example, monthly degradation (mm/year). The ultimate end goal is having this interlinked system of data that would allow for predictive modelling and data visualization **(see Figure 10)**. This would later help to look at a track with specific labels and information to understand, for instance, why it degrades faster than other tracks **(See Figure 5 and Figure 6)**. Prior practice uses dynamic sectioning to create a forecasting model for track degradation and also help with maintenance advice. Similar yet different ends and methodologies.

3- An important aspect of smart sectioning is what happens after sectioning, and that is the big data fusion where each created section is enriched with extra datasets such as how many small wavelength irregularities are in each section (welds, joints etc....), and data from other sources such as satellite InSAR data.

It has to be noted that the nomenclature of smart sectioning refers to the automatedness of the sectioning and the taking into consideration of influence lengths of transition zones and contextual information. It does not intend to discriminate against any sectioning.

Moving back to the elements that defined smart sectioning, some research also points towards the fact that most tracks on soft subsoils require double the maintenance of tracks that are on stiff subsoils (López-Pita et al., 2008; Zhai et al., 2004). Other research points towards the effect of curvature on the railway track. Finally, sleeper type, ballast type and thickness, and rail type have also been shown to affect the way the railway track force translates from the wheel-rail interface all the way to the substructure.

This is why it is not optimal to section a transition zone with different parts of the track, seeing as the transition zone has to be studied on its own. The same holds for sections with soft subsoils. That is why this project capitalizes on Smart Sectioning, a state-of-the-art innovation on dynamic sectioning that considers all the above spatial elements to break down the track into different assets instead of doing it in a 'blind' fixed manner.

This step **(Figure 4)** is characterized by an uploading of the different datasets within a spatial database using the same CRS (coordinate reference system). It is important to create a data model thinking of the endpoint. The starting point is railway coordinates as points **(Figure 4)** and the endpoint is railway sections as line elements. Smart Sectioning gives the points a label depending on certain data parameters based on their availability and their effect on track alignment degradation.

The parameters used to break down the track into different assets is listed below:

- Local Maximum Velocity allowed on the Track,
- Subsoil Type from the Dutch subsoil map,
- Ballast Type,
- Rail Type,
- Sleeper Type,
- Special Structures (1-2s of local velocity),
- Switches and Crossings,
- Rail dampers,
- Expansion joints,
- Maximum section length of 200m.

After this step, sections containing different contextual information are treated differently, as different assets. Each section is unique in its expected behaviour and thus in its RTG data and the change of its RTG data with respect to time. Moreover, each section is now labelled with the information that was used to section it. This will help to understand the change of data with respect to time.

FIXED SECTIONING VS DYNAMIC SECTIONING FROM THE DATA PERSPECTIVE

The first strategy for sectioning is the current fixed sectioning method. With this method, one cannot understand why the data is as it is **(Figure 5)**.

Figure 5: Two railway tracks in the Netherlands (one being Southward and the other being Northward) are sectioned according to standards. For each of the generated sections (200m and a remainder section) we have plotted the peak value of vertical deformation (height) with respect to time. We can see trends and evolutions but no real understanding of why the bottom right track is behaving the worst compared to the others. We can track that within the bottom right section of 200m maintenance has occurred in 2015 and 2020

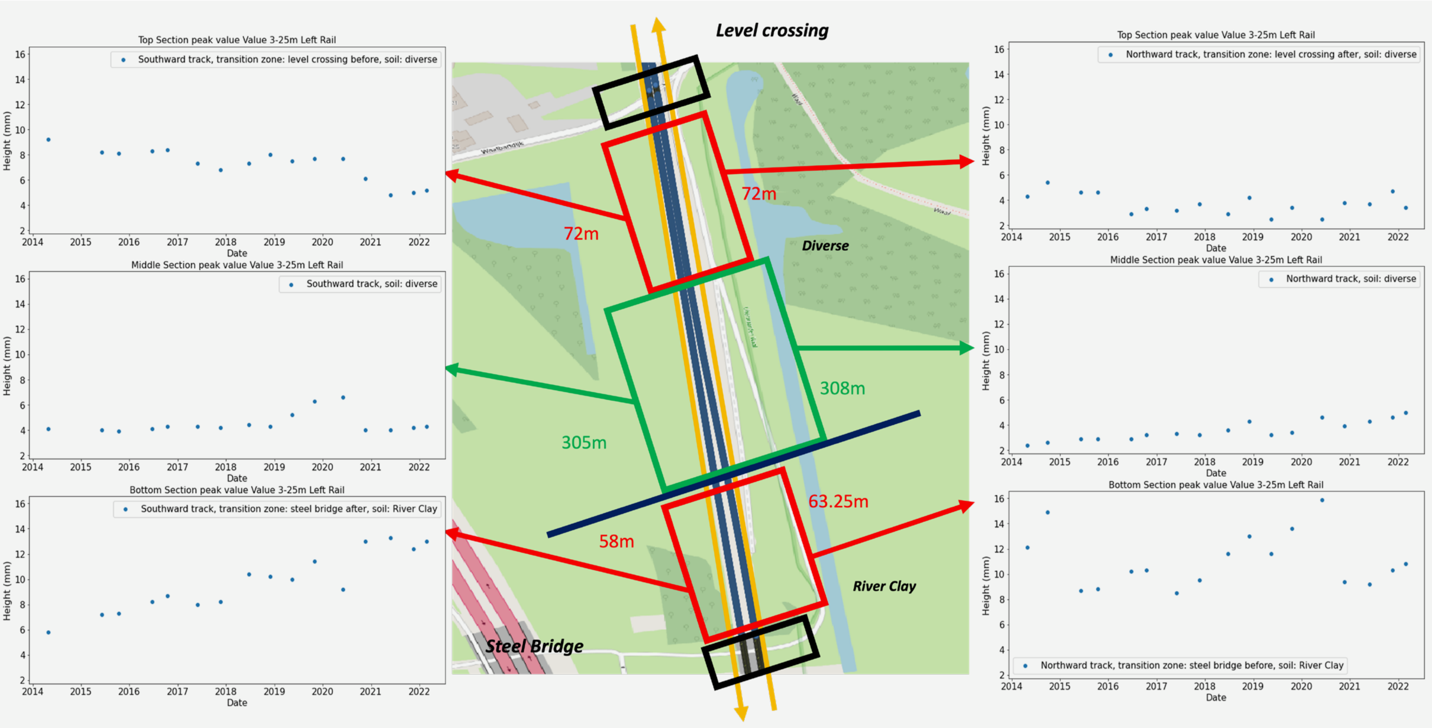

Figure 6: Smart Sectioning

The second sectioning strategy is smart sectioning **(Figure 6)**. The local velocity values used here were 130km/h for both track centrelines.

Comparing the data segmentation methods from fixed sectioning with the data segmentation used in smart sectioning, the peak values of smart sectioning are the highest in the bottom right section of 200m. Why that is, is not known by only looking at the available data **(Figure 5)**.

However, with smart sectioning **(Figure 6)**, it becomes known that the bottom right section is behaving the way it is behaving due to its underlying subsoil and that it is in a transition zone. Furthermore, in literature, the direction of the train in a transition zone has been proven to be quite deciding in terms of degradation. Also, it is now known that the maintenance works must be focused on the bottom right section, in a span of 63.25m and not 200m.

BIG DATA FUSION: POST-SMART SECTIONING

After having created sections that all contain a unique behaviour using contextual/spatial data, the next step is to enrich these sections with the following datasets:

- Tonnages with respect to time
- Loaded/Unloaded differences
- RTG data
- InSAR data for settlements
- Speed of vertical degradation.

The graphic that describes this step is shown in **Figure 7**.

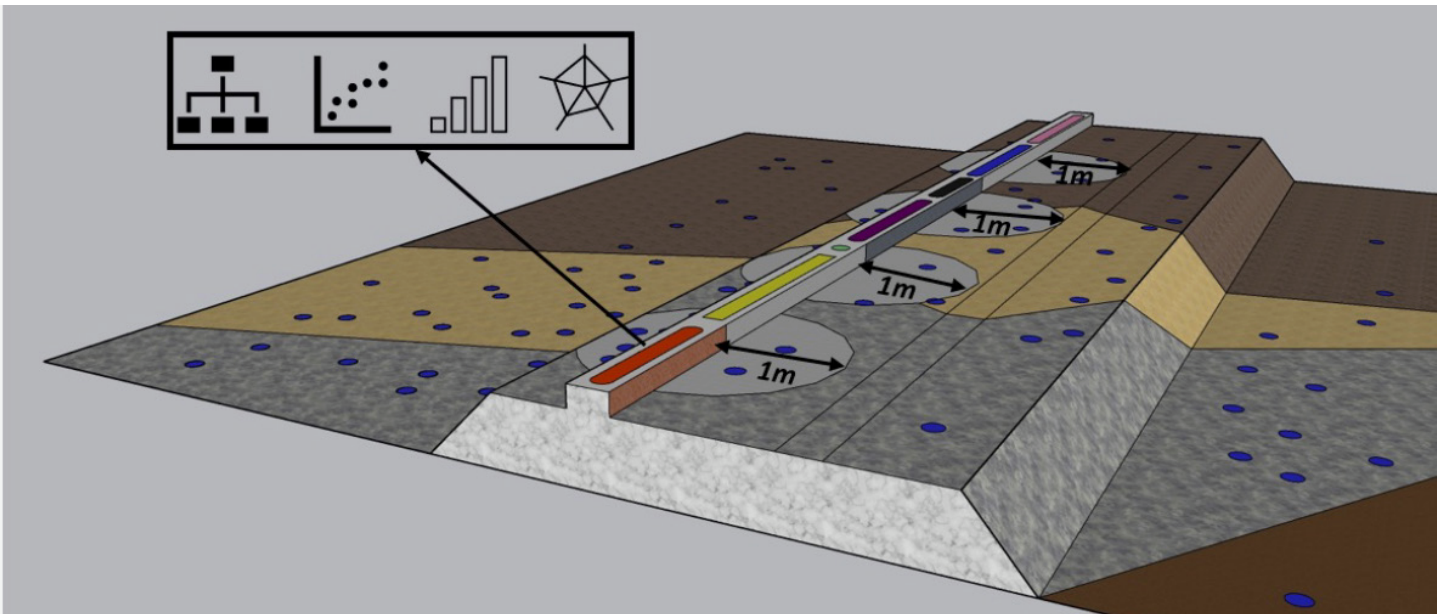

Figure 7: Graphic describing big data fusion. The different sections are portrayed as line elements with different colours. Each section will be enriched with temporal-based datasets using spatial aggregations or just linking with the segment name, depending on the data type to be added.

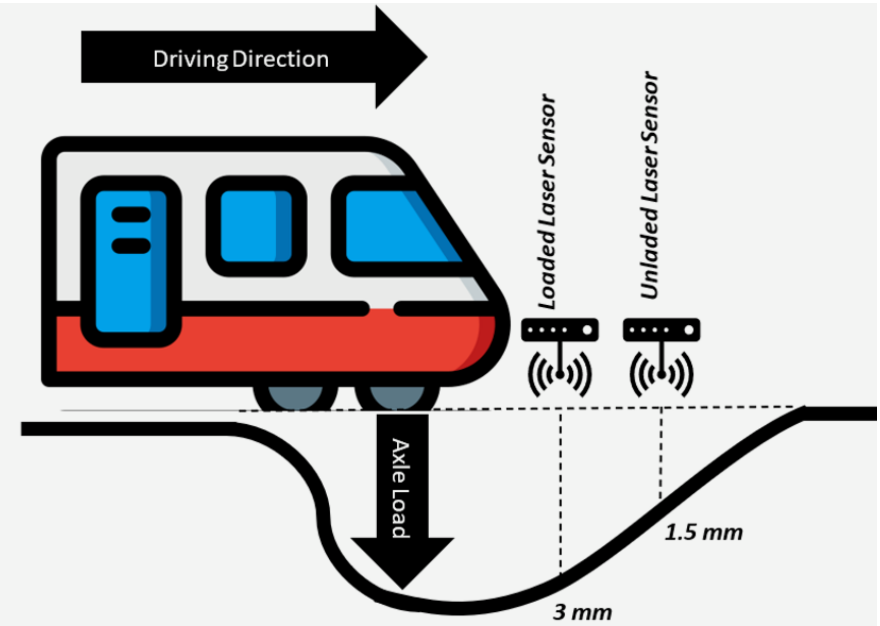

Figure 8: Relative positions of data collection points on measurement train

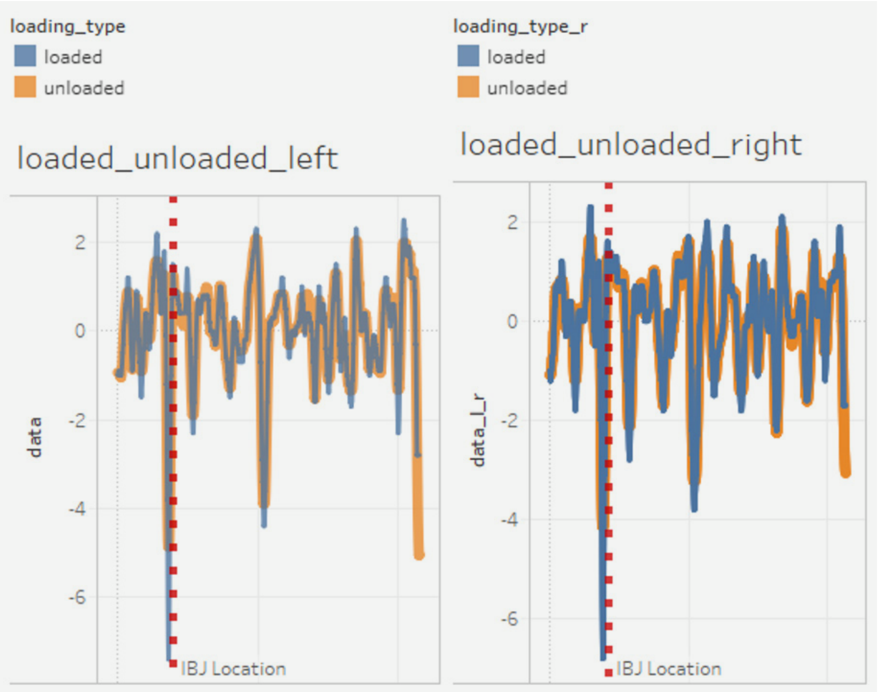

Figure 9: Loaded/Unloaded signals plotted for a section. The y-axis represents vertical deformation in mm, while the x-axis represents the position along the track.

What is important to note in this step is that the loaded/unloaded datasets are both vertical deformation RTG data that describe a specific section at a similar time. The idea behind this data is that two similar datasets are put on top of each other to infer something extra about the railway track. In short, one dataset comes from a measurement train whose laser scanner is close to the axle (1.1m), while the other dataset is in the exact same format; however, it is collected by a sensor 3.1m away from the axle. **(See Figure 8)**.

Prior to this, these two datasets were never combined to create extra knowledge. The theory became very clear once those two datasets were put on top of each other. The differences between both RTG datasets about the exact location with similar dates (max. 15 days apart) are related to areas with low local stiffness: hanging sleepers in transition zones, degraded insulated joints, rolling contact fatigue areas, etc.

This is portrayed by looking at **Figure 9**, where the data matches very well except for the insulated joint location, whose condition can now be determined to deteriorate. That is already an extra dimension of understanding that one can achieve by connecting different data sources together.

Each created section now contains its behaviour and the datasets describing it. The next step is to visualize all these elements in a dashboard.

DASHBOARD DESIGN FOR EFFECTIVE VISUALIZATION

Some elements will be reviewed to understand how to use the dashboard **(Figure 10)**. A map can be navigated to sift through the sections on the top side. Once a section is selected, the datasets update according to that section and the thresholds.

The two created KPIs: loaded/unloaded differences and TDR (track degradation rate) expressed in percentage change/month, were normalized so that the values can be compared with other sections.

The graphs relating to these KPIs show that they are in the same range by looking at the reference lines. The average value for the loaded/unloaded difference for both rails across sections is around 0.1876. If a section has an average value above that, one can start thinking about some instability/local stiffness problems and some RCF.

As for the track degradation rate, the average value across all the sections is around 2.5%/month. Each section has values above the average and some below it. What matters is the average value of these, which will describe the section. Then by comparing the average of a section for TDR with the average across all sections, one can already understand whether a section degrades quicker than average or slower than average.

Within the Vertical and Horizontal track quality index parts, where the standard deviation of Alignment/ Longitudinal level D1 datasets was plotted, one can track the history of the railway sections in terms of track quality. Maintenance activities could also be spotted due to a sudden drop in standard deviation from one date to another.

The same could be said about the peak values of the chord value elements. It is quite easy to compare the data with the thresholds. That is a way to understand how close we are to having to maintain the section.

In terms of tonnages, they are plotted concerning time. It is quite interesting to note the drop in tonnage/train loading for the section in the example during COVID-19 times.

As for the loaded/unloaded signals, it is a nice feature to highlight the loaded signal and compare it to the unloaded counterpart. Seeing the insulated joint location is quite important because those could be a reason for high loaded/unloaded differences. One can track the health of insulated joints using this visualization.

In the case of section: 117_1834V_6.3 – Section 1 in **Figure 10**, 3mm difference between the loaded and unloaded signal at the insulated joint location can be seen. The other peaks match well in terms of amplitude, which is why the average loaded/unloaded difference is lower for that section than compared to other sections. Then, looking at the history of vertical and horizontal data, it inferred that the track is vertically okay. Horizontally, however, the track seems to be suffering (exceeded PGO contract threshold a couple of times), in the left rail more than the right rail, which could be due to a slight non-zero curvature that is within that section: 0.4 degrees.

However, the track has a switch and a crossing before it of slope 1:15. It is not on a transition zone. According to InSAR data, the settlement is of -7 mm/year compared to an average across sections of -3 mm. The subsoil up to 1.2m is indeed clayey. In terms of TDR, the section is behaving better than other sections. However, in some instances,

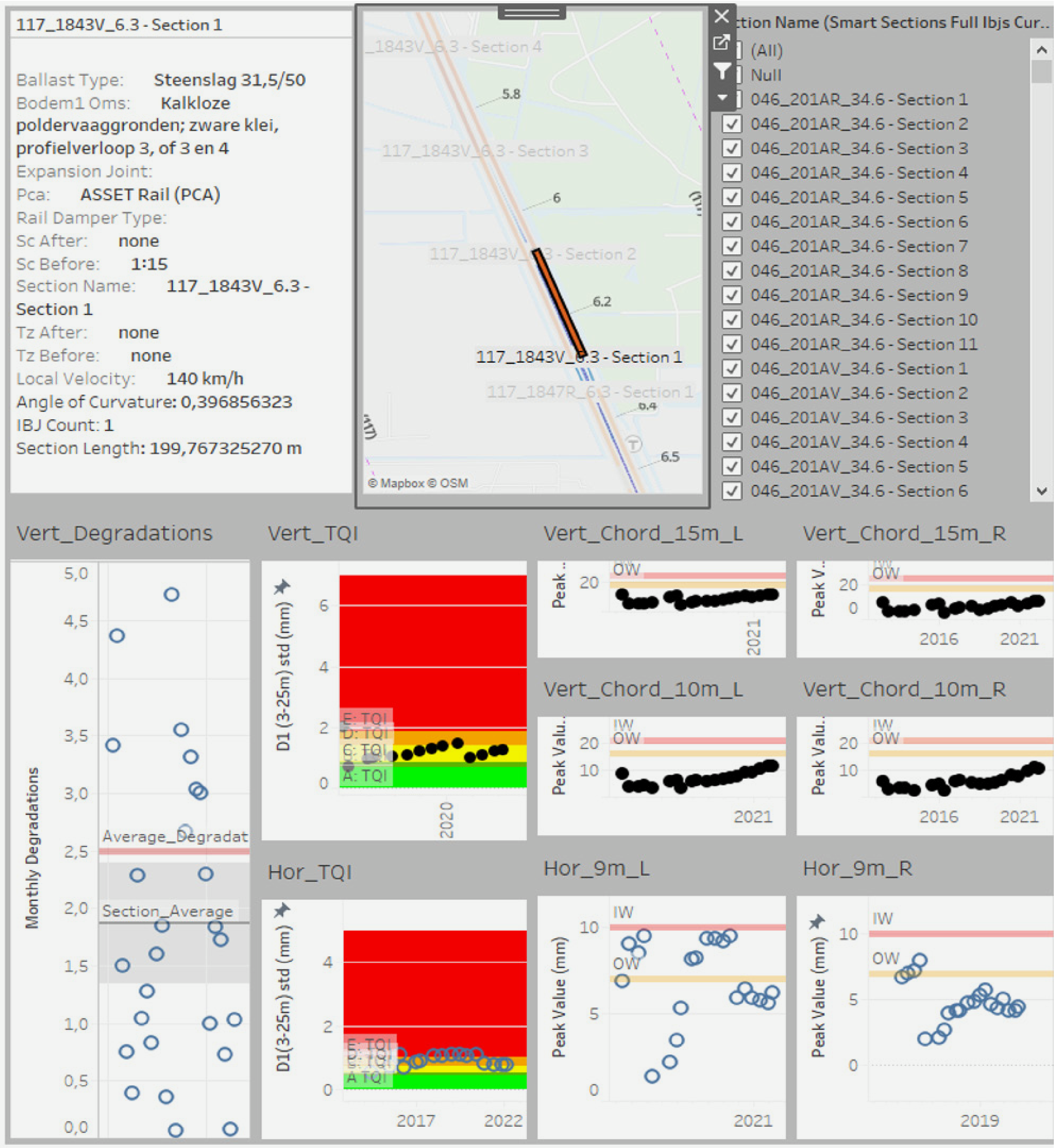

Figure 10: Geo-spatial Dashboard connecting everything together.

there have been quick degradations. These could be related to the instances/dates where the tonnage was higher than average.

This already shows the extra understanding of the track that one can have thanks to the big data methodology employed by this project. Moreover, thanks to the data visualization made possible by the dashboard, the health of insulated joints can also be evaluated, something that could not be done previously. The visualization made possible by the dashboard also has the power to highlight elements that would not be possible to infer without visualization, such as the dip of tonnage during COVID-19 times or maintenance occurrences that can be seen due to drops in standard deviation values.

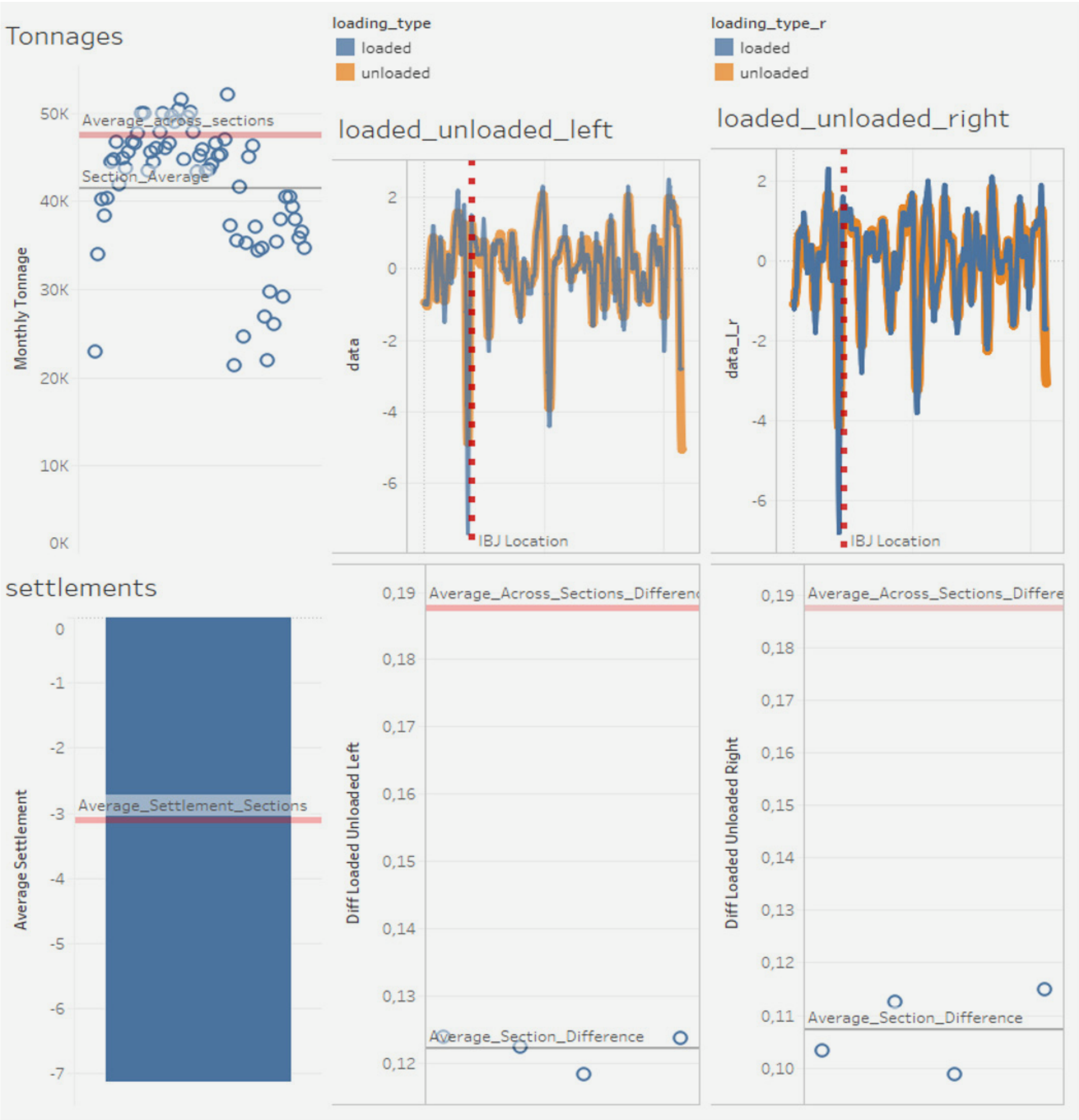

Figure 10: Geo-spatial Dashboard connecting everything together.

CONCLUSIONS

This project aims to capitalize on datasets obtained by sensors from the sky, onboard trains, and substructures to obtain extra insights into the health condition of the railway track. This project will use sensing technologies that are not yet in the standards, such as RILA (unloaded train-borne system) and satellite measurements. While the general principles of the sensing technologies are known, their synergies, complementarities, impact on the maintenance decision of tamping, and the possible paths for their implementation in practice have not been addressed before, to the best of our knowledge. By using analytics techniques from the field of big data and railway engineering know-how on the physical process, the final goal of this project is to lead to better tamping maintenance decisions.

This project addressed this problem by fusing different datasets, using the ideas of dynamic sectioning, aligning loaded and unloaded measurement signals, and designing a dashboard.

Dynamic sectioning uses contextual information to break down the track into different behaving assets according to the railway engineering knowledge based on sky, track, and substructure datasets. It allows for the creation of a system of data that all relates to the railway track. This can unlock machine learning usages as well as predictive capabilities. Loaded and unloaded relative track geometry is used to infer track instability, a form of local stiffness, and understanding their complementarities allows for the integrated use of less frequent measurements (track geometry) and measurements that can be obtained daily with passenger trains in operation (RILA). The dashboard has shown its efficacy in showing trends and behaviours that were not extracted in the past by the maintenance contractor, such as insulated joint condition behaviour in the loaded/unloaded signal spectrum.

Finally, although current practices around maintenance/tamping are within standards and widely accepted, they are not the most efficient way to do it. Trying to understand the full picture behind RTG data on which tamping decisions are made can benefit the environment and the railway track itself and reduce maintenance costs.

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