Deliverable D 3.2
Section-specific fatigue load models: method and application

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Report contributors		
Name	Beneficiary Short Name	Details of contribution
Andrej Anžlin	ZAG	Main document structure and contents
Doron Hekič	ZAG	B-WIM data
Jan Kalin	ZAG	B-WIM data
Maja Kreslin	ZAG	B-WIM data
Marian Ralbovsky	AIT	Concept Wayside monitoring data Traffic management data Traffic of the past

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1. Executive Summary

Fatigue consumption of structural components is given by train load histories and structural response. In this document the work of Task 3.2 is presented and a concept for estimation of load histories is proposed. The assessment of real axle loads of trains is presented, with the aim of determination of structural components fatigue consumption. Available traffic management data, wayside monitoring data and bridge-weigh-in-motion (B-WIM) data are utilized to estimate load histories. In this way the more accurate estimation of the remaining fatigue lifetime of bridges can be performed. With such estimation of load histories, a full-probabilistic fatigue evaluation can be utilized, updating existing deterministic methods in structural codes like the Eurocode EN 1991-2.

The concept for the assessment of the current rail traffic is presented in Chapter 5. It is based on six different levels of data knowledge the first being the most simple and the sixth being the most comprehensive or sophisticated level of detail where dynamic axle forces of trains are known.

The wayside monitoring was performed on Austrian railways, just few meters before the steel railway bridge, where bridge weigh-in-motion measurements were performed. The results of the field tests and comprehensive analysis are presented in the chapters 5.2 and 5.3 respectively. Better results were obtained by considering the 2-parameter soil model for the wayside monitoring data, whereas temperature and speed compensation of B-WIM data had to be considered in order to improve the accuracy of the train weighting.

Approaches for estimating the current rail traffic when knowledge level is low are presented in Chapter 5.4. Just before the Conclusions (Chapter 6) an approach for assessing the rail traffic in the past is presented.

2. Abbreviations and acronyms

Abbreviation / Acronyms	Description
WIM	weigh-in-motion
B-WIM	bridge-weigh-in-motion
GVW	Gross vehicle weights

3. Background

The present document Deliverable 3.2 "Section-specific fatigue load models: method and application" is the first and only report from Task 3.2 Load histories and first out of four reports, which will be produced within the Work Package 3 Fatigue Consumption Assessment. It will contribute as the input data for the Work Package 2 Information modelling where an integrated platform for information modelling will be developed. This document will be further complemented in Task 3.4 with more considerations about uncertainties. The topic of bridge response to traffic loads is dealt with in Task 3.3 and is not part of this document.

4. Objective/Aim

This document has been prepared as a report with description of method for updating Eurocode fatigue load models using traffic management data, wayside train monitoring data and Bridge-Weigh-In-Motion data.

5. Assessment of actual axle load histories

Fatigue consumption of structural components is given by train load histories, structural response and fatigue-resistance of structural steel. This deliverable is concerned with the topic of train load histories. Main goal of this work was to propose methods of estimating real axle load histories. To this end, available traffic management data, wayside monitoring data and bridge weigh-in-motion (B-WIM) data should be utilized. The resulting estimate of load histories will help to produce approximate estimates of remaining fatigue lifetime of bridges, thus providing a basis for long-term planning of retrofitting measures.

The load histories calculated using the proposed methods are not intended for re-assessment of existing bridges using the deterministic approach. Thus, they are qualitatively different from fatigue load-models defined in structural codes like the Eurocode EN 1991-2. This work aims rather to produce a probabilistic description of load histories, which can be best utilized in a full-probabilistic fatigue evaluation. The uncertainties of load histories will be addressed in more detail in Task 3.4. If the definition of probabilistic load histories incl. uncertainties succeeds, it could be also used to derive a load history definition for the deterministic assessment.

The outcome will be a method that can be used on any rail section to obtain realistic, section- specific load models, by adapting fatigue load-models of Eurocode EN 1991-2 to section-specific data. Key feature of the method will be that use of any data is optional, not mandatory. Availability of different data sources will improve accuracy of assessment, while their absence will not prohibit it.

5.1. Concept

The ideal case of load history information would consist of a complete recorded data set of train axles that passed over the bridge since the time of its construction. The information that would be expected in such data would be the load of each axle and the distance between consecutive axles. In practice, this data does not exist or is not complete. Therefore, methods are required that would provide an estimate of axle load history from incomplete data.

The available information on actual axle loads varies considerably between different countries, routes and time periods. For the purposes of this investigation, we have defined 6 levels of knowledge about present axle loads. *Present* axle loads represent the *current* rail traffic, which is usually limited by a time period of 1 year (for example the past year).

Table 1. Defined knowledge levels of current rail traffic

Knowledge level	*Description*	*Available data*
1	Network aggregates	Amount of transported goods + amount of transported passengers, or gross weight of trains. (aggregated over whole country network)
2	Section aggregates	Amount of transported goods + amount of transported passengers, or gross weight of trains. (aggregated on defined track section)
3	Basic train data	Section aggregates Number of trains Commercial type of each train
4	Detailed train data	Section aggregates Number of trains Sequence of wagons (for each train) Wagon types and their data sheets
5	Static axle loads	Measured axle loads Measured / identified axle distances
6	Dynamic axle forces	Static axle loads Dynamic wheel forces

The knowledge level 5 is produced by a wayside-monitoring system or a bridge-weigh-in-motion system, both of which are able to identify the load of train axles and axle distances. More advanced processing methods of wayside-monitoring data try to estimate also the dynamic axle forces (knowledge level 6), which may be expressed in form of narrowband or third-band force spectra.

Detailed train data (knowledge level 4) includes beside number of trains also information on wagon sequences for each train. The wagon description should be sufficiently accurate to determine axle numbers, axle spacings, tare weight and maximum load of each wagon within reasonable accuracy bounds. Information on wagon types (classification type & type number) would provide detailed data of this type, provided that wagon data sheets are available. Actual loading of wagons is unknown.

Basic train data (knowledge level 3) consist of the knowledge of number of passed trains for each commercial train type (freight / passenger / high-speed passenger), additionally to the section-aggregated volumes. The number of wagons per train and wagon types are unknown.

Section-aggregated volumes (knowledge level 2) provide total amount of transported goods (net tons) and number of transported passengers within a period of 1 year for the track section under consideration. Alternatively, the aggregated gross weight of trains can be provided.

Network-aggregated volumes (knowledge level 1) provide similar information but aggregated from the whole country-wide rail network.

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To assess the fatigue damage accumulation using actual load histories, knowledge level 5 is needed as input to the algorithm.
Obviously, a transformation of data from higher to lower knowledge levels would not pose an obstacle and would be tackled using appropriate data reduction methods. However, if the available data has knowledge level < 5, it needs to be transformed from lower to higher knowledge level(s), i.e. a form of "data extension" must be carried out. In this process, certain assumptions have to be adopted and a reduced degree of accuracy has to be accepted as result.

The desired description of present train traffic is defined by:

- Clusters of trains + number of trains per year in each cluster
- Properties of all train-clusters defined by probabilistic distributions of axle loads and axle distances

The form of this traffic description is schematically shown in Table 2 and Figure 1 and is comparable to fatigue train types defined in EN 1991-2 Annex D3.

Table 2. Example of the definition of train properties

Train cluster	*Trains per year*	*Axle loads*	*Axle distances*
1	1500	$F_{tc1} = \{\mathcal{N}(\mu_{f1}, \sigma_{f1}), \mathcal{N}(\mu_{f2}, \sigma_{f2}), \dots\}$	$D_{tc1} = \{\mathcal{N}(\mu_{d1}, \sigma_{d1}), \mathcal{N}(\mu_{d2}, \sigma_{d2}), \dots\}$
2	850	$F_{tc2} = \{\mathcal{N}(\mu_{f25}, \sigma_{f25}), \mathcal{N}(\mu_{f26}, \sigma_{f26}), \dots\}$	$D_{tc2} = \{\mathcal{N}(\mu_{d25}, \sigma_{d25}), \mathcal{N}(\mu_{d26}, \sigma_{d26}), \dots\}$
⋮	⋮	⋮	⋮

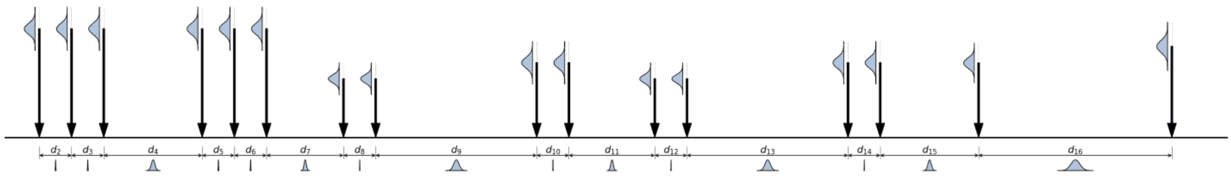


Figure 1: Example of a scheme of probabilistic properties of a train cluster.

In following chapters, different types of available traffic data are addressed, and ways of their usage in deriving a traffic description are proposed.

5.2. Wayside monitoring data

Wayside monitoring systems are able to provide data on measured axle loads and axle distances. Thus, the measurement results contain sufficient information for description of fatigue loads of present traffic (knowledge level 5).
Wayside monitoring systems exist already as commercially available products on the market. The two main measurement principles used in these products are:

- Rail strain measurement
- Load-cells under the rail

Systems based on rail strain measurements feature several strain gauges that are placed on both rails. The load transmitted from train wheels to the track causes rail deformation and strain in rails. Load-identification algorithms reconstruct from the measured rail strains the axle loads that caused the strains. Traditionally, foil-type strain sensors are glued to the rail, which requires some installation time. Recently, strain sensors were developed that are clamped on the rail bottom, which shortens the installation duration. The strain sensors typically use either the measurement principle of electrical resistance or that of optical fibres.
Lagnebäck [1] mentions a monitoring system of Damill AG, consisting of 16 strain gauges, which identifies not only vertical wheel loads but also lateral forces acting on the rail.
The Phoenix monitoring system of VoestAlpine uses optical strain sensors that are clamped on bottom of the rail. The stated accuracy [2] of identified vehicle weight is ±3%.
Another solution that uses clamped sensors on bottom of the rail was developed by TrackIQ. The wheel condition monitor with Weigh-In-Motion capability [3] states an accuracy of ±3% for measured vehicle weight.
The HBM company developed the Argos wayside train monitoring system in three variations [4]. The systems with clamped sensors state an accuracy of ±3 to 5% for the vehicle weight and ±3% for the train weight. The system with glued sensors states an accuracy of ±1.5% for the vehicle weight at train speed below 100 km/h, and ±1% for the train weight at same speeds. The accuracy is stated to drop to ±2% at train speeds between 100 and 200 km/h.

Systems based on load-cells use several load cells placed between the rails and the sleeper. The load cell is typically shaped as a short cylinder and uses the measurement principle of piezo-crystals, which produce electrical charge if a mechanical force is applied. Measured amplitude of the electrical charge allows to determine the magnitude of force acting on the load cell.
The system of Schenk Process, called "Multirail Wheelscan" states a measurement accuracy of ±2% at train speed of 60 km/h [5]. Its primary field of application is detection of wagon overloads, as well as detection of wheel damages identified from dynamic load peaks.

5.2.1. Example of rail strain measurement

Within the Assets4Rail-project, a bridge measurement was carried out in Austria in June 2019, where the mechanical response of a steel truss bridge to overpassing trains was measured. Besides the B-WIM system (chapter 5.3) and other sensors on the bridge, rail strains were measured using glued foil-type strain gauges. Since a commercial wayside monitoring system was not available to the team for the performed measurement, the data acquired from the rail strain sensors was used instead.
The strain gauges used in this application were uniaxial gauges with a measurement length of 3 mm. The strain gauges were glued on top of the rail flange, near the rail web. In longitudinal direction, the gauges were positioned in the middle between sleepers. Figure 2 shows an installed strain gauge before its covering with protective layer.

Figure 2: Foil-type strain gauge glued at top of the rail flange between sleepers (left), and a detail (right).

In total, 6 strain gauges were glued to the rails. Four of them were positioned in one track cross-section, two of them at each rail with one at each side of the rail flange (sensors R1, R4, R5, R6 in Figure 3). The remaining 2 strain gauges were shifted in longitudinal direction in relation to the first gauge (sensors R2, R3).

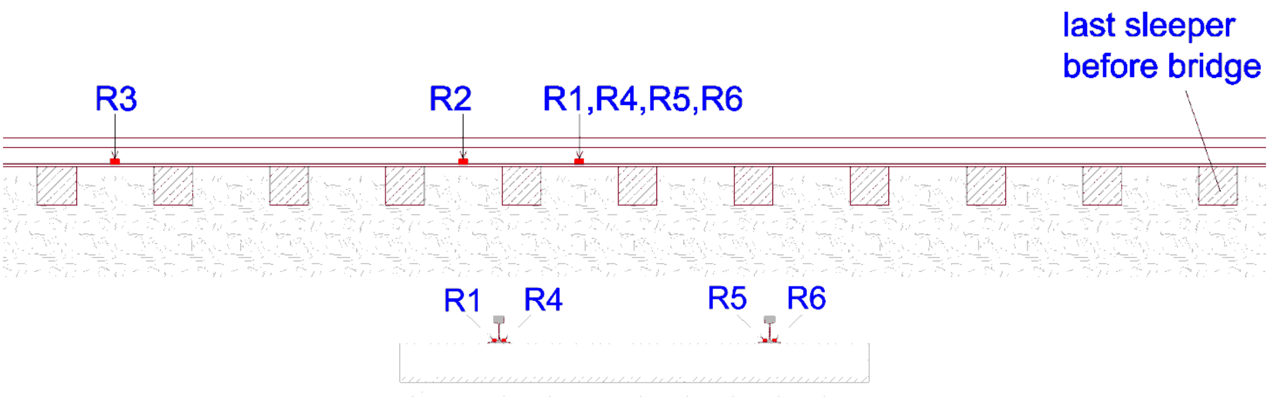


Figure 3: Position of installed strain gauges R1-R6 in longitudinal direction (top) and in transverse direction (bottom).

The measured strains (Figure 4) allow identification of the axles, axle distances and train speeds. Further, amplitude of the strain peaks is related to wheel loads, and therefore enables their identification.
The acquired measurements contain recorded rail strains during 103 passages of the same train, in both travel directions.

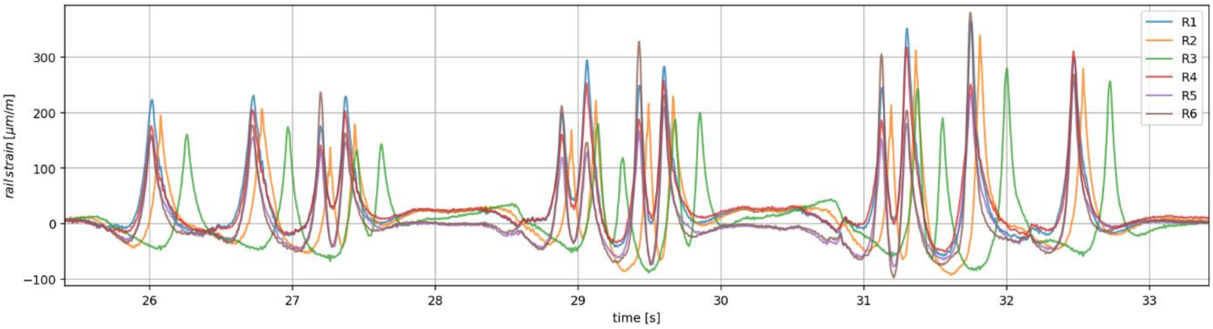


Figure 4: Measured rail strains during one train passage.

For the purposes of this work, a rudimentary algorithm of wheel load identification was implemented. The wheel load identification is handled here as an optimization problem, where the theoretical rail response is compared to the measured rail response. The wheel loads are adjusted in such way that the difference between model and measurement is minimized.
To perform wheel load identification in this way, mechanical track parameters must be first determined. The track is assumed to behave as a continuously supported Euler-Bernoulli beam. This type of track model was chosen primarily due to its simplicity and ease of application, since a simple analytical solution for such model exists. Although a more accurate model where the rail is supported by discrete sleepers could be formulated and solved using a set of linear equations, the simpler model used here is deemed adequate for the intended purpose. The continuous support is modelled as a two-parameter foundation, so called Pasternak foundation. The governing equation of this system [6] is Equation 1. In this simplified analysis, dynamic effects were neglected and rail response to a static wheel load F_w was considered. The governing equation is then simplified to Equation 2, where x is distance from the wheel, w is vertical rail displacement, EI is the rail bending stiffness and k_1, k_2 are track parameters. The track parameter k_1 is related to vertical stiffness of the track foundation, while k_2 is related to its shear stiffness. Solution of this problem is easily obtained; analytical solutions for rail deflection, bending moment and shear force are listed for example in [7].

$$EI\frac{\partial^4 w}{\partial x^4} + \rho\frac{\partial^2 w}{\partial t^2} + c\frac{\partial w}{\partial t} - k_2\frac{\partial^2 w}{\partial x^2} + k_1 w = F(x,t) \qquad \text{Equation 1}$$

$$EI\frac{\partial^4 w}{\partial x^4} - k_2\frac{\partial^2 w}{\partial x^2} + k_1 w = F_w \qquad \text{Equation 2}$$

To identify the track parameters, the measured rail response caused by one approaching wheel was used. This response was acquired from a train passage with a larger first axle distance (7.5 m in this case), where it can be assumed that only the first axle determines

the rail response at sensor locations at least up to the point where the first axle reaches the sensor location. The rail strain signal caused by the approaching first wheel was used in an optimization routine, which sought the best solution of k_1, k_2 to minimize differences between theoretical and measured responses.
Comparison of theoretical and measured responses with optimized track parameters is shown in Figure 5. On the left, a one-parameter soil model was used ($k_2 = 0$), which is equal to the Winkler soil model. On the right, results for the Pasternak foundation are shown.

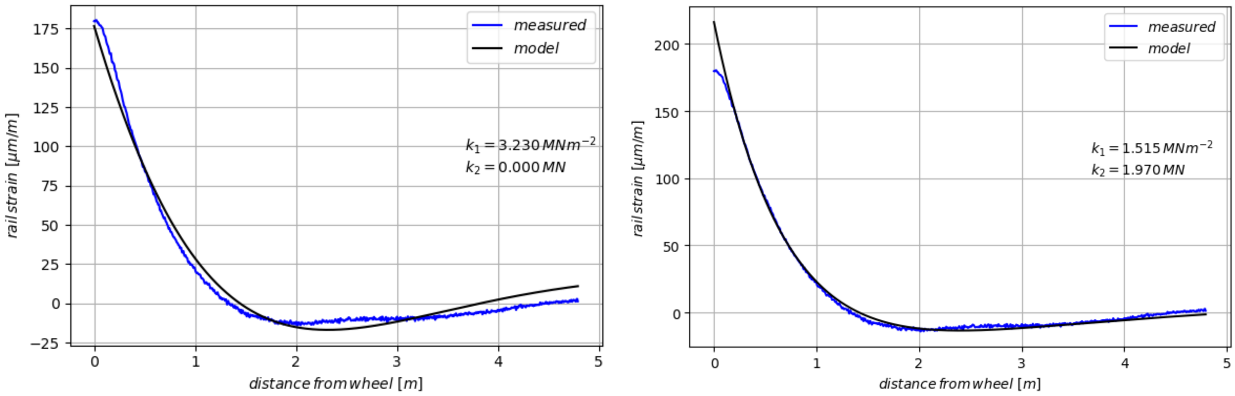


Figure 5: Comparison of measured rail strain and rail strain according to analytical model. Shown results are after optimization of track parameters of 1-parameter model (left) and 2-parameter model (right).

From this comparison it is obvious that the 2-parameter model (Pasternak) represents the actual behaviour more accurately than the 1-parameter (Winkler) soil model. In here, the rail response at close wheel-sensor distances (in this case $x < 18\, cm$) was discarded, since the beam theory of the analytical model is not applicable there, and the continuous support of the rail-beam lacks accuracy at the small scale between two sleepers. Therefore, differences between model and measurement at close wheel-sensor distances are normal and expected.

Once the track parameters k_1, k_2 were known, the algorithm for wheel force identification optimized the wheel forces using rail strains at each train passage. Since the train was the same for all passages, the variation of results represents variation due to the wheel force identification method. A scheme of identified axle distances, force amplitudes and their uncertainties is shown in Figure 6.

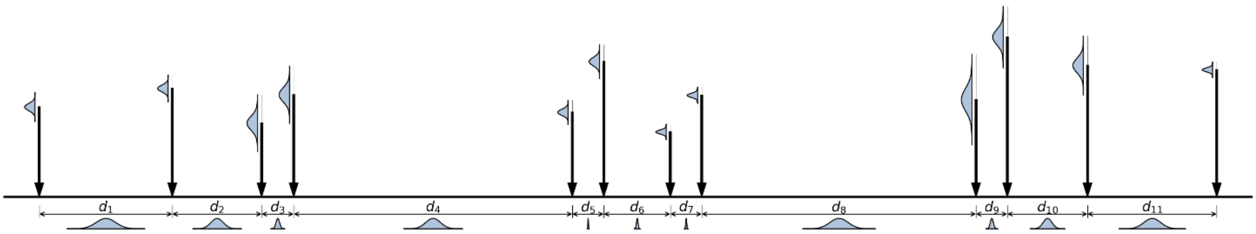


Figure 6: Scheme of identified axle forces, axle distances, and their uncertainties.

The scattering of identified axle forces was different at each axle. Detailed look on the comparison between measured strains and theoretical model showed that the model does not match the measurements well at axles that show large scatter of values. Figure 7 shows such comparison for different axles: the diagram on the left shows a good match, while the middle diagram contains signals with significant deviations. This might be caused by influences that were not accounted for in our simplified approach, for example the dynamic effects. In Figure 7 right it is obvious that the measured strain peak is not symmetrical but skewed. Such behaviour cannot be reproduced using the quasi-static approach that was implemented here.

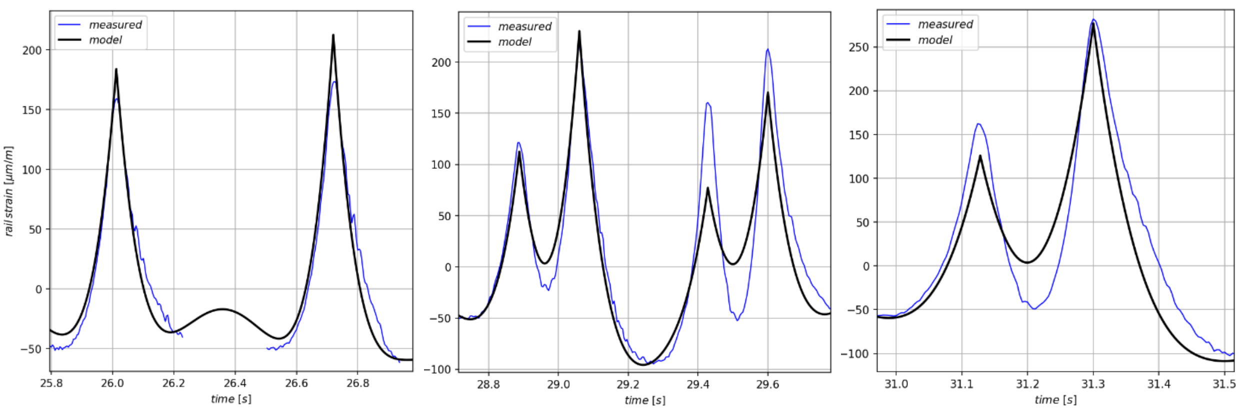


Figure 7: Comparison of measured rail strain and rail strain synthesized using identified wheel forces. Shown a two-axle wagon (left), group of 4 axles (middle) and a group of 2 axles (right).

The example shown above demonstrated the basic principle of a strain-based wayside-monitoring system, which has shown a limited accuracy. For actual application, it is recommended to use a commercial B-WIM or wayside-monitoring system. Available commercial wayside monitoring systems are expected to use more sophisticated methods and achieve better results. The above-mentioned commercial systems state accuracies between ±1.5% and ±5% for the vehicle weight, depending on the chosen system and the train speed.

This project has received funding from the Shift2Rail Joint Undertaking under the European Union's Horizon 2020 research and innovation programme under grant agreement no. 826250 Assets4Rail).

5.2.2. Extraction of wagon properties

To construct the probabilistic traffic description in the format described in chapter 5.1, it is necessary to process the wayside monitoring data. The procedure proposed here consists of following steps:

- Group axles in each train passage to individual wagons
- Group similar wagons of the whole data record to form wagon-clusters
- Evaluate statistical properties of each wagon cluster

The grouping of axles to individual wagons requires an algorithm that can distinguish which of the individual axle distances separate different wagons (Figure 8). This may not be straightforward if the train contains many different wagon types, which can be the case for some freight trains.

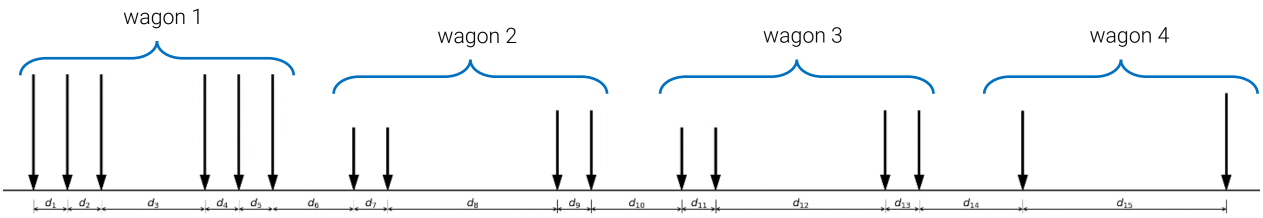


Figure 8: Grouping of axles to individual wagons.

The basic principles of the axle-grouping algorithm that was implemented are:

- Large axle distances are mostly (not always) located near wagon centers,
- Axle distances tend to be not-increasing from wagon-centre to wagon-borders.

The actual algorithm that was implemented contains several logic conditions supported by clustering methods, and we will omit its detailed description here. Although most wagons exhibit the feature of symmetric axle distances, it was not used in this identification algorithm due to presence of many 3-axle locomotives, for which it does not apply.

Grouping of similar wagons is the second step of the process. In here, wagons from the whole recorded traffic (for example from a period of 1 year) are grouped to clusters based on their similarity. The similarity of wagons is given particularly if wagons have same number of axles, similar axle distances and a similar mass. These three criteria form also the steps of the algorithm:

- Group wagons by number of axles
- Split each group into subgroups by similarity of their axle distances
- Splits each subgroup into further subgroups by similarity of wagon masses

Group-splitting by similarity of axle distances was done using a Density-Based Spatial Clustering algorithm (DBSCAN) [8], where the spatial coordinates X were entered according to Equation 3. In here, d_i is the distance from the i-th to the following axle, and n is the number of axles. The logarithm transforms the axle distances to logarithmic scale, which improves the distinction of shorter axle distances. X are the spatial coordinates in

$n-1$ dimensional space created from axle distances of each wagon. The algorithm groups the points in space that are close to each other, i.e. forms wagon-clusters with similar axle distances. In here, the order of axle distances is a distinguishing feature; for example 3-axle wagons with axle distances $\{d_1 = 2.3m,\ d_2 = 9m\}$ would form a separate cluster (subgroup) to wagons with axle distances $\{d_1 = 9m,\ d_2 = 2.3m\}$.

$X = \{\log d_1, \log d_2, \dots, \log d_{n-1}\}$ Equation 3

Optionally, the wagons grouped by axle distances can be further split by wagon masses. This step is meaningful for freight wagons, to distinguish between empty and full loading. In here, clustering methods can also be applied, where the wagon mass as the only parameter would enter the algorithm (wagon mass = coordinate in 1-dimensional space).

Statistical properties of wagon-clusters are then determined using simple statistical methods. Normal distributions can be used to describe the probabilistic properties. Therefore, the statistical evaluation should contain at least mean and standard deviation of each variable. Variables that describe the wagon are axle distances and axle forces.
The implemented algorithms were tested using wayside-monitoring data provided by ÖBB, which were acquired at a monitoring site in Austria. The data set comprised 5 days of traffic on 2 tracks, with a total of 25080 registered axles in 967 trains. The provided data included besides loads and axle distances also other information, but for the purposes of this analysis only axle distances and axle loads were used. Using this data, the axle-grouping algorithm and the wagon-clustering algorithm were tested. Properties of the identified wagon-clusters were then statistically evaluated.

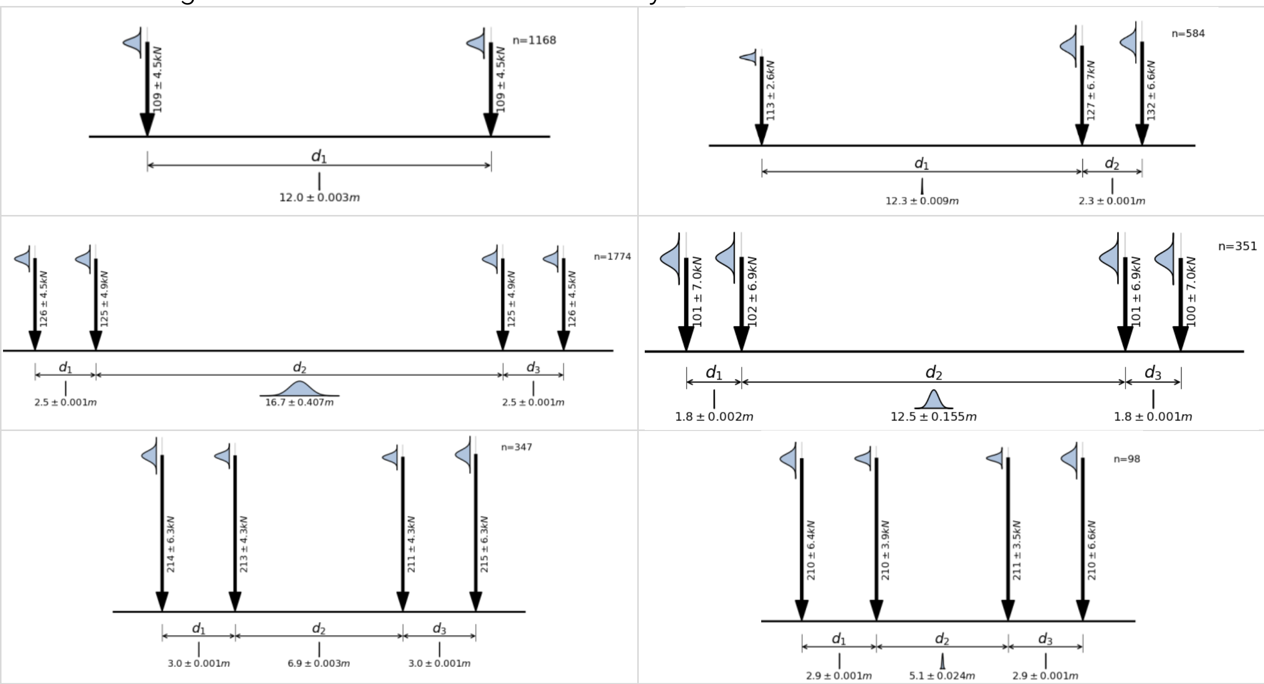


Figure 9: Properties of selected wagon-clusters, identified from wayside-monitoring data from an Austrian monitoring site.

In total, the algorithm created 28 wagon-clusters from the input data. Statistical evaluation of the properties of selected clusters is shown in Figure 9. In here, distances and axle forces are annotated using their means and standard deviations in "μ±σ" format. Number of wagons in the cluster within the available data-set is denoted in the upper-right corner as "n".

5.2.3. Train configurations

To describe the rail traffic that passes a bridge, train configurations and number of trains must be defined. From the point of view of fatigue loading, the sequence of wagons is important, especially which wagon types follow after each other, since the concentration of axle loads near wagon buffers influences the stress amplitudes in the bridge parts.
Trains are often configured in such way that wagons of the same type are joined to form a sequence. This will be considered in the model of the train traffic.
The traffic model implemented here describes a train-type in the following way:

- Train consists of wagon-sequences. A train type has fixed number of wagon sequences.
- A wagon sequence is defined as:
    - The wagon type (i.e. wagon-cluster number), which is a single number
    - Number of wagons in the sequence, defined by probabilistic integer distribution. Wagon-sequence may contain only 1 wagon, which is mostly the case for locomotives.
- Order of wagon sequences, described by the probability of occurrence of each wagon sequence at a particular position in the train configuration.

This definition was considered as a good compromise between forming too many train-types with narrow range of variation in each, and forming small number of train types with too loose definition of their properties.
Using this definition, one train type allows variation of:

- The order of wagon sequences (if probability of the occurrence of wagon-sequences at some specific position is less than 1 and more than 0),
- Number of wagons in each sequence (if its integer distribution has range between its limits larger than 1).

Using this definition, one train type does not allow variation of:

- The number of wagon sequences,
- Definition of wagon-sequences, which includes the wagon types (wagon-cluster numbers) and distributions of wagon-numbers.

The algorithm was applied on the available data of the Austrian wayside monitoring system. From the 967 train passages, 40 train-types were identified. Most frequently, the identified train types consisted of 3 and 2 wagon sequences.

5.3. B-WIM data

Bridge Weigh-In-Motion system that collects/measures the true train axle loads on roadway bridges was adapted for application on the railway bridges. Data from these case studies will be used here to demonstrate the proposed calibration of load histories for more accurate fatigue lifetime assessment.

5.3.1. Introduction to B-WIM

Bridge Weigh-in-Motion (B-WIM), first proposed by Moses in the 1970's [9], is a common technique used for road traffic load measurements. While Weigh-in-Motion (WIM) technology refers generally to the various methods of calculating axle and gross vehicle weights (GVW) of vehicles travelling at full speed, B-WIM is a method of collecting such data using measurements taken from an instrumented bridge.

Until recently the B-WIM systems have been mostly used for road bridges. However, the BridgeMon project [10] showed that the algorithms used for road bridges can be relatively easily adapted for use on railway bridges. For this purpose the structures are typically instrumented with strain measuring devices. Traditionally, strains are measured on the main longitudinal members of the bridge to provide response records of the structure under the moving vehicle load, but other locations can be used to improve the results. Measurements during the entire vehicle passage over the structure provide redundant data, which facilitates evaluation of axle loads.

The first step in the weighing procedure involves selecting and combining parts of the continuous stream of measured data into so-called events that contain signals from one or more vehicles whose influence on the bridge could possibly overlap. Axles of passing vehicles within events are then identified, their speeds calculated and the individual axles joined into vehicles.

Finally the unknown axle weights $A_i$are calculated from a set of equations $s(t_j) = \sum_{i=1}^{N} A_i I\left(v_i(t_i - t_j)\right); \quad j = 1 \dots J \geq N$, where $s(t_j)$ are the summed values from sensors, which are calculated at J different times t_j, N is the number of axles, $I(x) = I\left(v_i(t_i - t_j)\right)$ is the known influence line at location x, v_i is the axle velocity and t_i are the arrival times of individual axles. In the current commercial SiWIM® software [11], used in this project, this over-determined system of equations is solved for A_i in the least-square sense with the use of the singular value decomposition algorithm [12].

Influence lines, defined as the strain response of the bridge at the sensor location to the passage of a unit axle, are the key structural parameter that is directly related to the quality of B-WIM measurements. The first generation of B-WIM systems used theoretical influence lines, which was sufficient for calculation of relatively accurate gross weights, but it simply could not provide reliable axle loads, especially on shorter spans. Therefore,

This project has received funding from the Shift2Rail Joint Undertaking under the European Union's Horizon 2020 research and innovation programme under grant agreement no. 826250 Assets4Rail).

the latest generations of B-WIM systems always use influence lines that are directly derived from the measured data on the site [13].

5.3.2. Calibration train and sensor location selection

ÖBB provided us with a calibration train, consisting of a two-axle locomotive, two four-axle carriages (carriages A and B) and one two-axle carriage (carriage C), shown on the Figure 10.


(a)

(b)

(c)

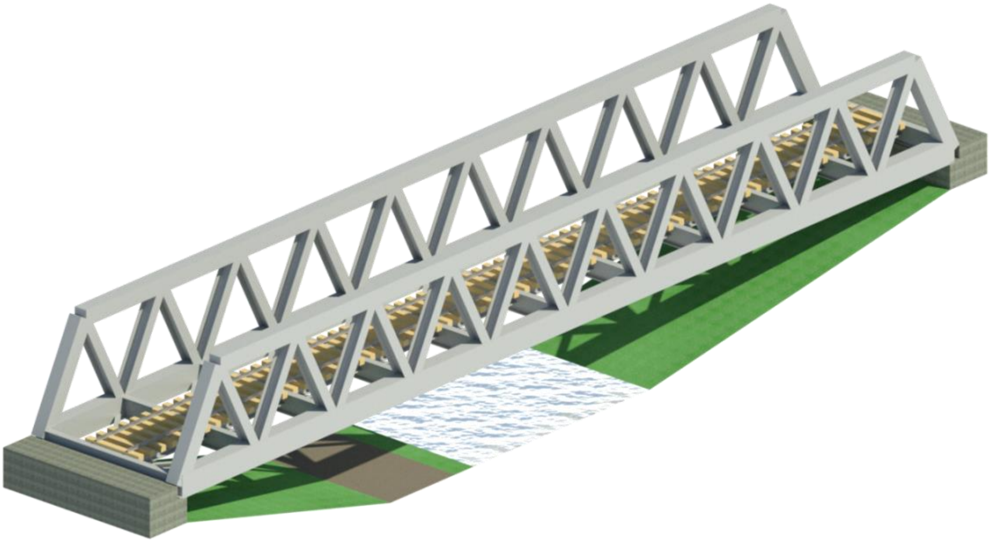
(d)

Figure 10: Calibration train: (a) calibration train, (b) carriage A, (c) carriage B, (d) carriage C

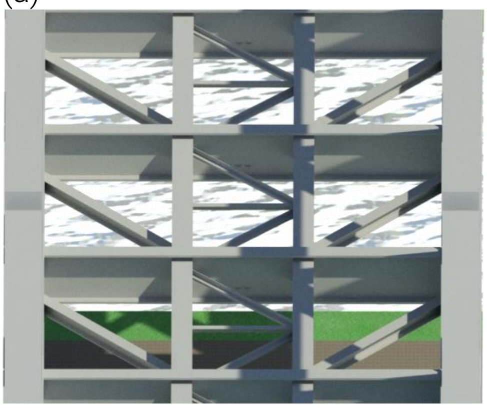
The masses of the carriages A and B were measured on 6th June 2019 at ÖBB station Wiener Neustadt and were 78.4t and 49.45t, respectively. The mass of carriage C was read from the technical documentation as 18t. The mass of the locomotive was read from a label on the side of the locomotive to be 32t plus 5t allowable load.

The train was always oriented in the same direction: when passing in the south-easterly direction (which we designated as direction or lane 1), the order of passage was locomotive then carriages A through C. In lane 2 the order was reversed.

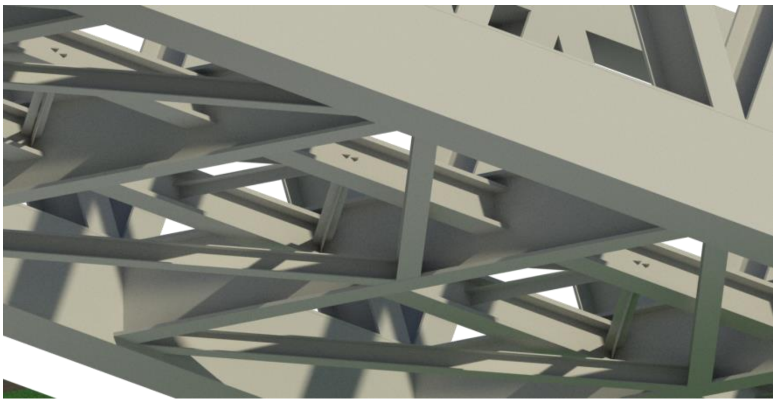
Considered bridge is a steel truss bridge, that consists of 10 sections with the length of 4.17 m, which all together bridge the span of 41.67 m as shown on Figure 11 and Figure 12. The load from slippers is transmitted directly to the secondary longitudinal HEM 340 beams, that are rigidly connected to transverse HEB 800 beams. The load from the latter is carried forward to the primary box section longitudinal beams. Lower (tension) as well as upper (compression) part of the bridge is made of steel box sections that are connected with 'I shaped' cross section diagonals inside, and with box sections diagonals on both ends.



(a)



(b)



(c)

Figure 11: Considered bridge: (a) general picture of the bridge model, (b) over the deck photo below slippers, (c) view from below

Three potential locations for strain gauges to be used for weighing were considered. Referring to the Figure 12 were:

- SG1 and SG2, located on the main longitudinal beams,

- SG3 and SG4, located on the secondary longitudinal beams, directly supporting the sleepers and
- SG5, located on the transverse beam, supporting the secondary longitudinal beams.

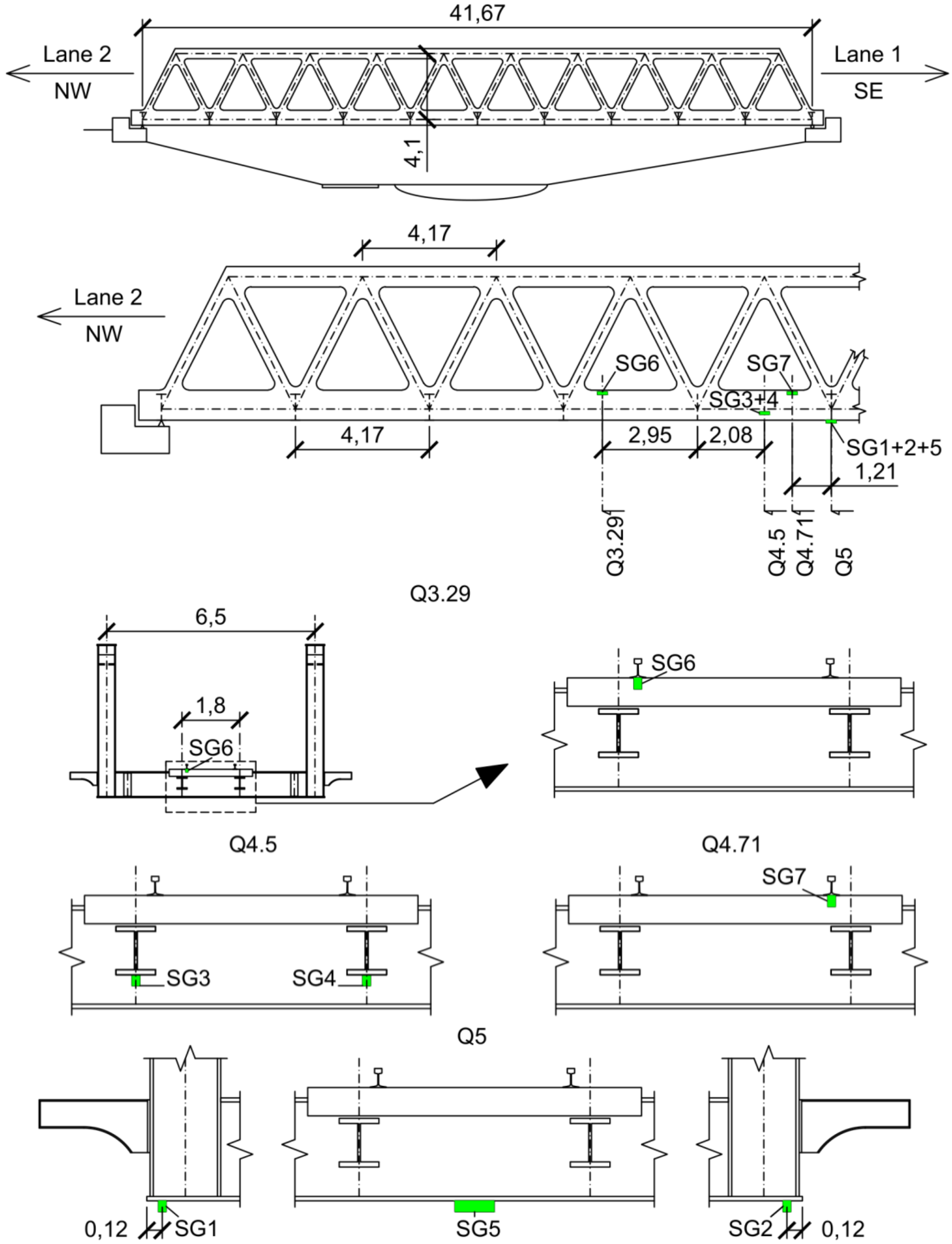


Figure 12: Potential locations for strain gauges to be used for weighing

Figure 13 shows the typical signals from these strain gauges captured during a train passage. From left to right, the signals displayed are SG1 and SG2; SG3 and SG4; SG5. The black spikes at the bottom of the graphs indicate the locations of axles. The passage was in the north-westerly direction.

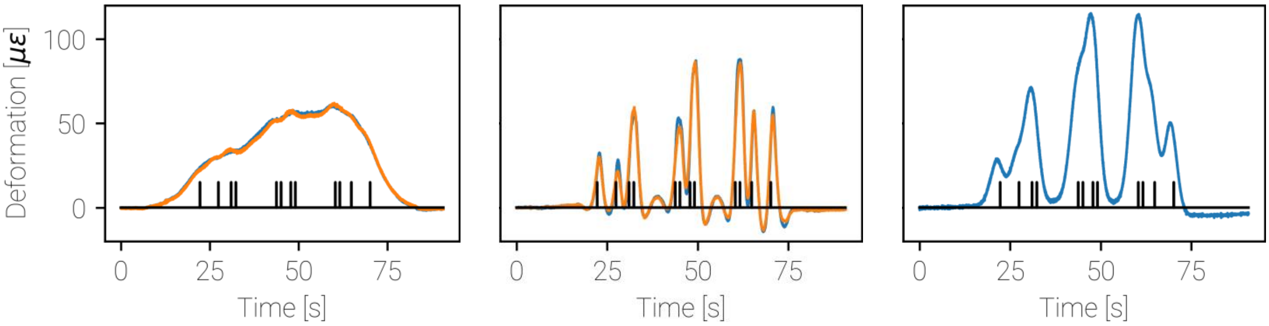
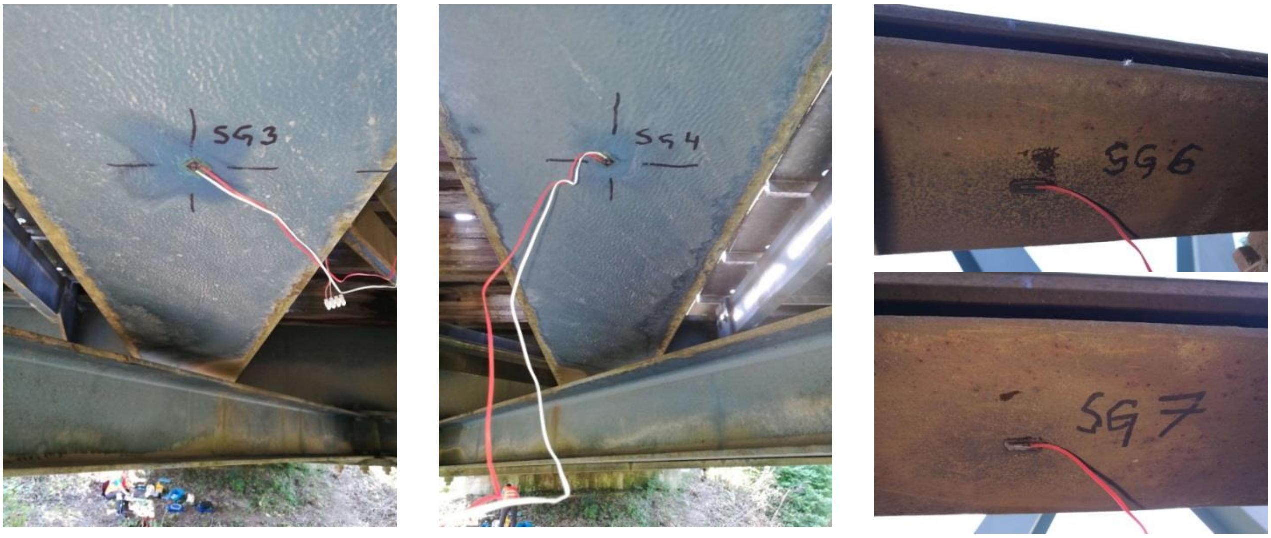


Figure 13: Signals from strain gauges

It was decided to use SG3 and SG4 for weighing, since the individual axles and bogies are clearly visible. If these were not available, SG5 could have been used, whereas using SG1 and SG2 would perhaps suffice for gross-weights, but the axle load accuracy would be quite poor.

Additionally a B-WIM system needs sensors at two different longitudinal locations to capture data needed to calculate vehicle speeds and detect axles. Two strain gauges were glued directly on bottom of one of the rails, at locations SG6 and SG7 in Figure 12. Installed strain gauge sensors SG3, SG4, SG6 and SG7 are shown on the Figure 15.



(a) (b) (c), (d)

Figure 14: Installed strain gauges: (a) SG3, (b) SG4, (c) SG6, (d) SG7

Figure 15 shows the signals SG6 and SG7 during a typical passage of the train.

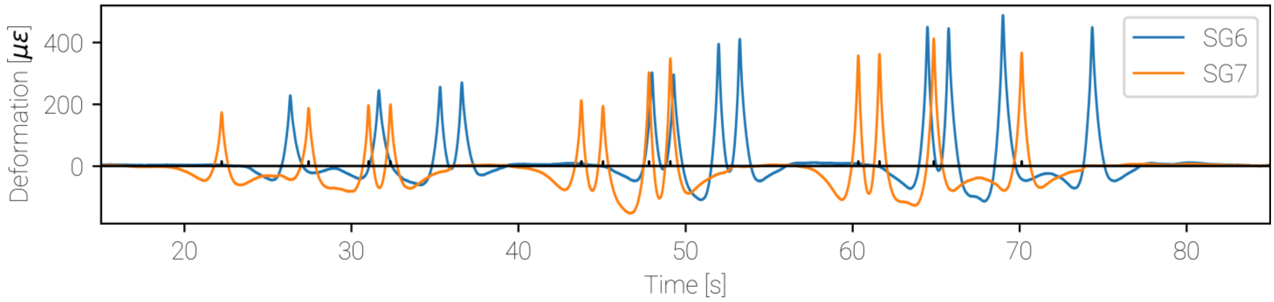


Figure 15: Speed and axle detection signals

The individual axles are clearly seen and both speed and axle detection proved to be straightforward.

5.3.3. Measurement, weighing and corrections

In total there were 113 passages recorded with the measurement system. However, due to problems with triggering software, a few of the events did not capture the complete passage of a train. When the incomplete events were eliminated, 55 runs in lane 1 and 47 runs in lane 2 remained.

From the data the measured influence line (IL) was obtained. It must be noted that the calculated IL is not optimal. The B-WIM software that was used for weighing was originally intended for use on road bridges, where the number of axles on vehicles used to construct the IL is at most 5. In contrast, in this case the number of axles is 12. Additionally the IL is relatively long and as such the calculation is sensitive to noise in the signal and is intrinsically badly conditioned. When all these factors are combined it becomes impossible to obtain an optimal IL with the current software. Nevertheless, as results will show, even with the suboptimal IL, the accuracy of calculated GVWs was quite high. Additionally the problems were noted and a new algorithm is currently being developed.

Once the IL was determined, the 102 runs were processed. The calibration factor was chosen on the basis of the two four-axle carriages. Figure 16 shows the GVWs of the carriage A for runs in lane 1.

This project has received funding from the Shift2Rail Joint Undertaking under the European Union's Horizon 2020 research and innovation programme under grant agreement no. 826250 Assets4Rail).

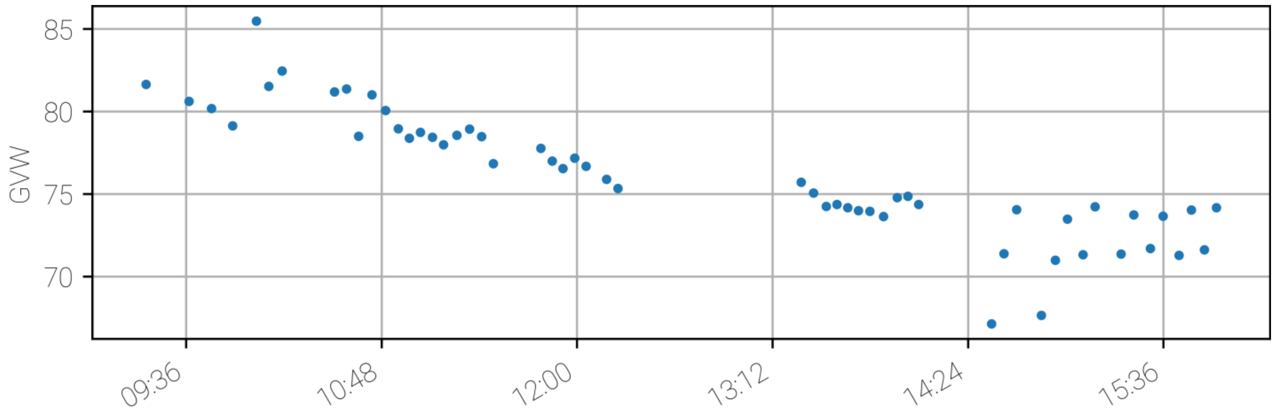


Figure 16: GVWs carriage A in lane 1

Two effects are apparent in the graph on the Figure 16. While the mean GVW is around 78t, as expected, the weights are higher in the morning and lower in the afternoon. Additionally, in the afternoon the weights seem to jump around randomly. After some consideration it became clear that the weights on this bridge depend both on speed and temperature.
The temperature of the structure in the vicinity of the SG3 and SG4 on the day of measurement varied by around 8 degrees Centigrade, from 17 degrees in the morning to 25 degrees in the afternoon. This explains the weights' decrease throughout the day.
The runs up until 14:30 were performed in batches during which the speed was constant, 5, 10, 15, 20, 30 and 40 km/h. Conversely, during the afternoon runs the speed varied from run to run. It became apparent that an increase in speed brought about an increase in weights.

In order to compensate for these two effects, we first concentrated on speed dependence. Since the temperature was more or less constant in the afternoon, a reasonable assumption is that the weights at those times depended only on speed. Figure 17 shows the dependence of GVWs for the heaviest carriage on speed, runs on lane 1 are on the left and on lane 2 on the right.

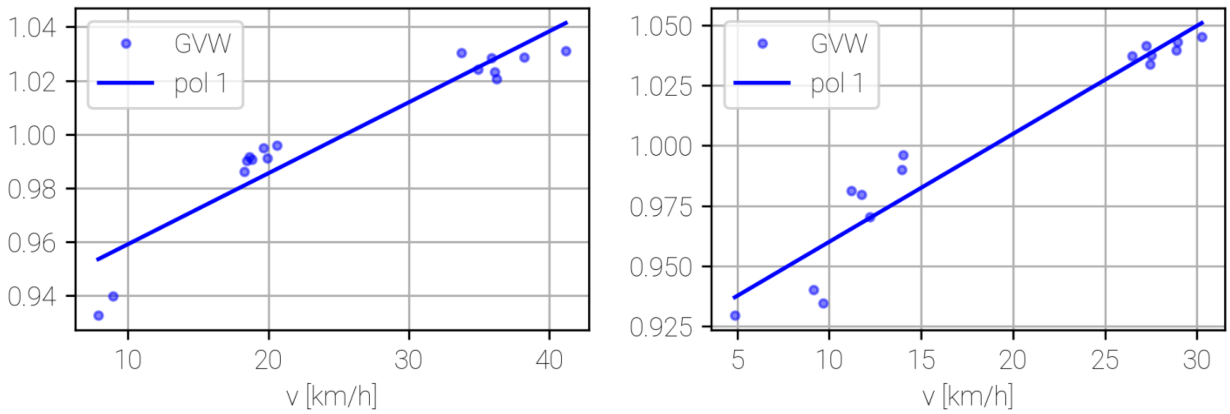


Figure 17: Speed dependence of GVWs of carriage A

Abscissas represent the GVW from a particular run relative to the mean GVW of the carriage. The fitted lines have slopes of 0.26 %/(km/h) and 0.45 %/(km/h) and R^2 values of 0.89 and 0.93 on lanes 1 and 2 respectively. Once the speed compensation function was obtained, all the runs were reweighed.

For the temperature compensation all the runs were considered. Since the B-WIM system was not configured to read temperature, the temperatures for all the optical sensors were kindly provided by AIT. The temperature chosen for the compensation was measured by sensor os11, which is the closest to the B-WIM sensors SG3 and SG4. Figure 18 shows the temperature dependency of GVWs for carriage A on lanes 1 (left) and 2 (right).

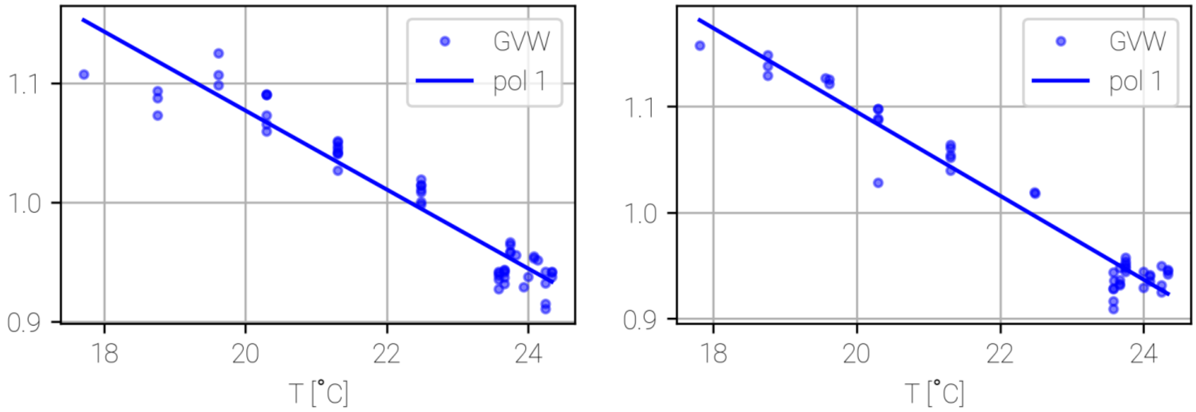


Figure 18: Temperature dependence of GVWs carriage A

In this case the slope of the fitted lines are relatively high: -3.3 %/°C and -4.0 %/°C with R^2 values of 0.92 and 0.95 on lanes 1 and 2, respectively.

5.3.4. Final results

After the temperature compensation function was obtained, all the data were finally reweighed and recalibrated. Figure 19 shows the GVWs for all vehicles and runs. The carriages are labelled A through C, the locomotive L and lanes are 1 and 2.

The mean GVWs are shown in Table 3. The columns "std" and "err (min, max)" are the standard deviation of GVWs and mean, minimum and maximum errors in respect to the static GVWs, in percent, respectively.

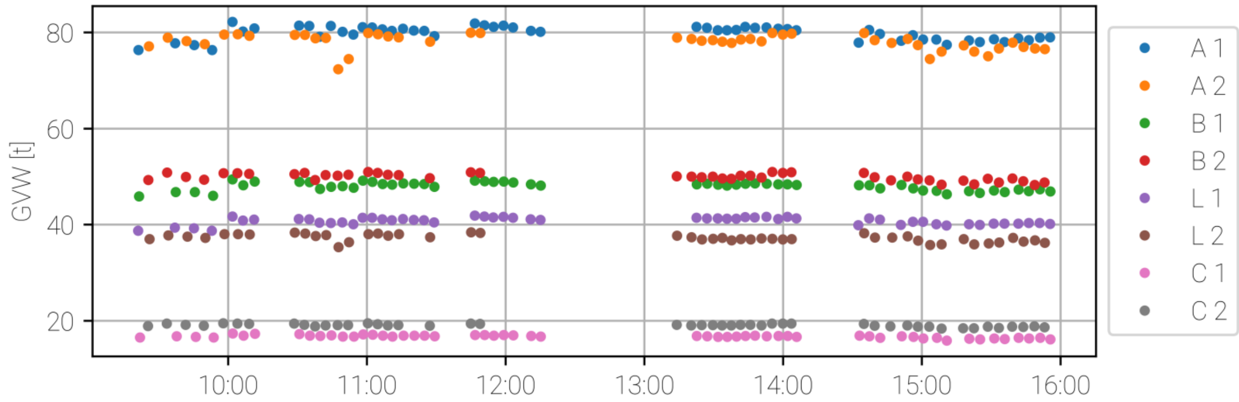


Figure 19: GVWs for all vehicles

Table 3: Weighing results

		Lane 1 B-WIM			Lane 2 B-WIM		
vehicle	GVW	GVW	std	err (min, max)	GVW	std	err (min, max)
carriage A	78.40t	79.86t	1.8%	1.9% (-2.6%, 4.8%)	78.08t	2.1%	-0.4% (-7.7%, 2.0%)
carriage B	49.45t	47.99t	1.8%	-3.0% (-7.1%, -0.1%)	49.95t	1.5%	1.0% (1.2%, 3.2%)
carriage C	18.00t	16.76t	1.8%	-6.9% (-11.6%, -3.3%)	19.07t	1.5%	5.9% (2.4%, 8.4%)
locomotive	37.00t	40.79t	1.8%	10.2% (4.7%, 13.2%)	37.23t	2.0%	0.6% (-4.5%, 3.9%)

Note that static GVWs of neither carriage C nor the locomotive have actually been measured, so the comparison for those two vehicles is less relevant. However, for carriages A and B the results are quite good.

Using COST323 specifications (COST323, 2002), the accuracy classes are A(5) for carriage A on both lanes and carriage B on lane 2 and B+(7) for carriage B on lane 1. Broadly speaking, we expect that 95% of GVWs of all weighed heavy carriages passing this bridge would fall within 5% (or 7%) of the static GVW.

5.4. Traffic management data

Although the data of axle loads measured by wayside monitoring or B-WIM provide the best input for deriving a traffic load model, they are often not available. In most European countries, weigh-in-motion systems are usually not in operation. Therefore, traffic management data can provide an estimate of actual rail traffic, with less accuracy.
In chapter 5.1, different knowledge levels about actual rail traffic were described. Traffic management data can have various knowledge levels, depending on type of information they contain, but all are lower than 5. In this chapter, types of data at various knowledge levels is presented, and a method of "data extension" to the next higher knowledge levels is proposed.

Knowledge level 4 contains detailed train description with exact train configurations including number of wagons and exact wagon types. Hence, it is assumed that number of axles and axle distances are known. Further, tare weight and maximum weight of each wagon is known. The missing information that creates the difference to knowledge level 5 is the actual loading of wagons and distribution of load between axles of a wagon. To extend this data and artificially lift the knowledge level to 5, the missing information is filled based on assumptions about the properties of the missing information.
The assumptions about loading of wagons can be extracted from published works. Available literature that shows results of measured data on axle loads or wagon utilization is relatively rare. Lin et.al. [14] presented measured axle loads (Figure 20 left) measured on a track section in Sweden, where heavy haul wagons operate. In here, axle load exceeded the target of 31 t in 0.37% cases. Steenbergen et.al. [15] presented axle loads measured in the network of Netherlands (Figure 20 right). In here, 1.1% of freight traffic axles exceeded 23 t. Clear distinction between axle load distributions of passenger and freight traffic is visible. Whereas axle loads of passenger traffic show a distribution with one broad peak, the distribution of freight traffic axle loads concentrates around 2 peaks in the extremes, which indicate empty and full wagons (light-green curve in Figure 20 right).

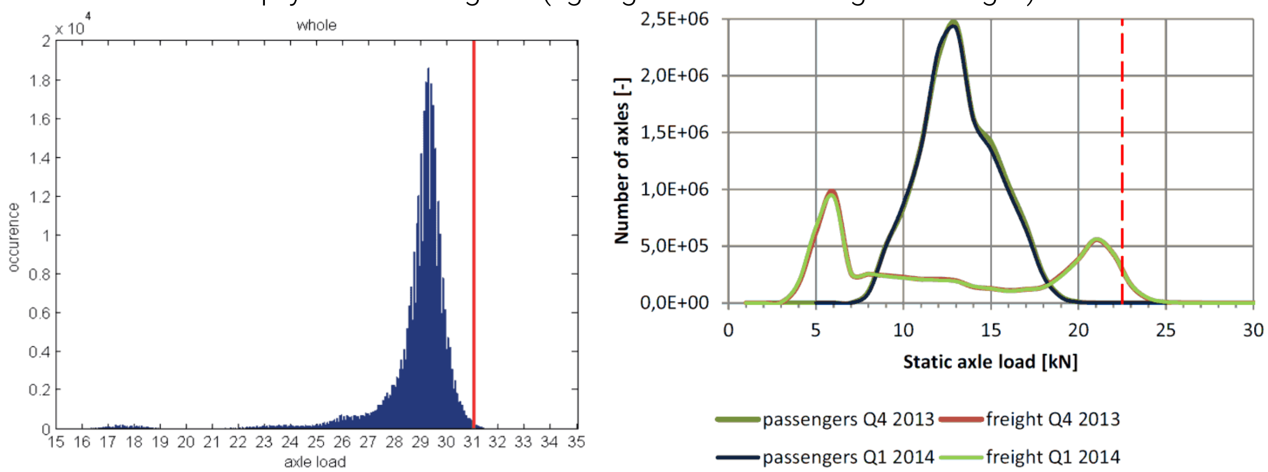


Figure 20: Occurrence of axle loads on Malmbanan line in Sweden, figure from publication of Lin et.al. [14] (left); measured axle loads in rail network of Netherlands, figure from publication of Steenbergen et.al. [15] (right).

Woodburn [16] investigated the capacity utilisation of freight trains that are incoming and outgoing from four British naval ports. The mean capacity utilization of trains was 72.2%, which varied from port to port between 54% and 80%.
The European Environment Agency published in 2010 a document [17] on load factors for freight transport, which uses data of Danmarks Statistics from 2007 [18], where utilization of available capacity in rail freight in selected European countries was presented (Figure 21). Although from this data it is hard to derive load factor distributions, it provides a hint about ratio of empty and full wagon numbers.

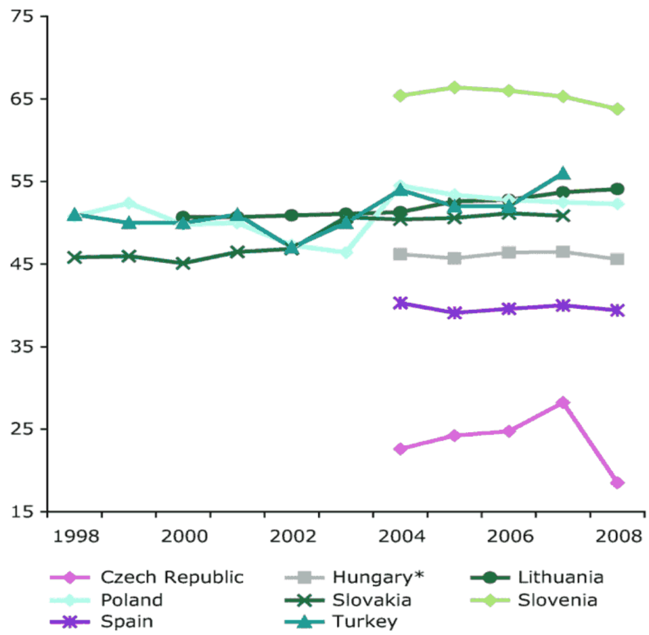


Figure 21: Utilization of available capacity [%] in rail freight in selected European countries, figure from publication of the European Environment Agency [17].

The load utilization of wagons is to a large degree specific to routes / track sections, since it depends on types of transport that operate there. Therefore, any assumptions regarding load utilization should be set in cooperation with the local railway authorities, which have information about the operating traffic.
Within this work, we propose a description of the load utilization of wagons in the following way:

- Load utilization of wagons is defined by a probabilistic distribution, separately for passenger wagons, empty freight wagons and full freight wagons.
- Load utilization is given as ratio of actual net weight to maximum net weight (as given in wagon specifications), which means that value 0 stands for empty wagon, 0.5 for half-loaded and for 1.0 fully-loaded wagon. Values larger than 1 represent an overloaded wagon.
- In the current implementation, wagon weight is assumed to be evenly distributed to all axles.

The distribution of passenger wagon load utilization (Figure 22 left) uses the beta-distribution. In the current implementation, two parameters can be adjusted to better

represent the local conditions: mode of the distribution (i.e. position of its maximum) and upper limit. The example below shows a distribution with mode=0.6 and upper limit=1.05.
The distribution of freight wagon utilization (Figure 22 right) consists of two distributions that represent empty and full wagons. Both use the gamma distribution, but with a different shape parameter. In the current implementation, three parameters can be adjusted to better represent the local conditions: ratio of number-of-empty-wagons to total-number-of-wagons, mode of the distribution for full wagons (i.e. position of its maximum) and portion of overloaded wagons. The example below shows a distribution with 50% empty wagons, mode-for-full-wagons=0.85 and 2% of overloaded wagons.

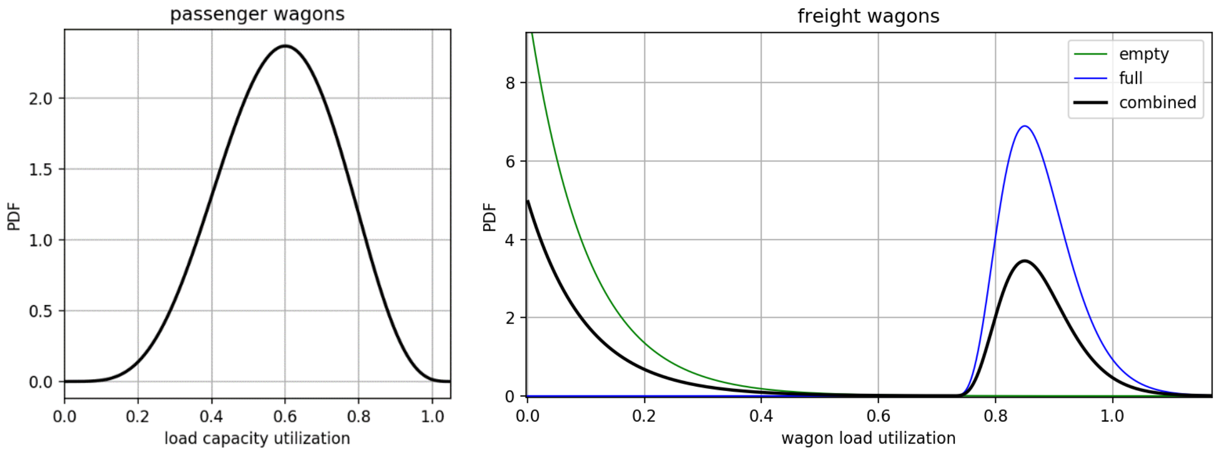


Figure 22: Initial distributions of load utilization for passenger wagons (left) and empty&full freight wagons (right).

The stated distributions are used to generate the missing information of load factors using a randomization algorithm, which enables to calculate static axle loads as the next step.

Knowledge level 3 provides information on number of passed trains for each commercial train type (freight / passenger / high-speed passenger), additionally to aggregated traffic volumes. The information is specific for the analysed route / track section. The number of wagons per train and exact wagon types are unknown.
This type of information is often available to railway operators. For example, in Italy the available information includes number of train passages of each commercial train type (weight of the train and other detailed information remains unknown). A traffic management data sample from Portugal, which was provided by the Shift2Rail-research-project "In2Track2", showed more detailed information: number of passages of each train type, locomotive type and total weight & length of each train. Aggregated values of gross weight / year and number of trains are shown in Figure 23.

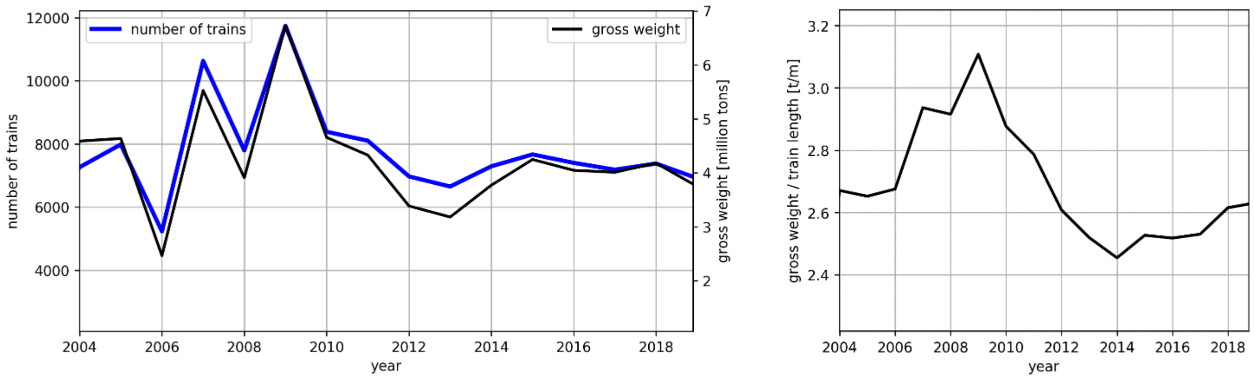


Figure 23: Aggregated traffic data, evaluated from traffic management data on a track in Portugal.

The missing information that distinguishes knowledge level 3 from knowledge level 4 is especially the number of wagons and exact wagon types. Again, to extend this data and artificially lift the knowledge level to 4, the missing information is filled based on assumptions about the properties of the missing information.
This means that assumptions about exact wagon types must be made. In here, it is sufficient to assume the wagon types on the level of information of axle distances and tare & maximum weights. More specific information is not needed. Here again, cooperation & consultation with local rail authorities is necessary to adjust the initial assumptions to the local conditions.
The procedure implemented here takes following steps:

1. Gather a database of wagon types, which represent the wagons operating on the track section,
2. Define train configurations using wagon-sequences, as well as their relative occurrence frequencies in operating traffic,
3. Artificially generate train configurations that match the definitions above.

The database of wagon types includes at least the information of axle distances, length over buffers, tare weight and maximum weight of each wagon. As of the current status, the database includes freight wagons described in a catalogue of DB Schenker [19], from which 114 wagon types were extracted and stored. The maximum weight depends on the rail line category, in which the wagon operates, and this information is also included. The database is expandable and should be complemented based on consultation with local rail authorities.
Definition of train configurations determines, which wagon sequences constitute a train. In here, randomization can be introduced, so that the train configurations are not completely fixed. In the current implementation and due to the lack of more information from rail operators, the freight wagons are randomly chosen from the present database and wagon sequences of 2 – 10 wagons are formed. The wagon sequences are stacked to form a freight train until the target train length or the target train weight is reached, depending on which of the two is known from traffic management data. If neither the train length nor its weight is known, a target train length in randomly chosen from a specified range.
Passenger trains would have a more rigid train configuration, with a fixed number of

wagons ordered in a fixed sequence.
The generation of axle sequences was tested using the available traffic management data of the track in Portugal and the currently implemented database of freight wagons. Since detailed information on the operating wagon stock was not available, the wagon types were randomly chosen from the implemented freight wagon database. Wagon load factors were assigned according to the distribution shown in Figure 22. For the year 2017, which included 7185 trains, the sum of axle sequences consisted of 109672 axles in total. Figure 24 shows relative occurrence of difference axle distances and axle loads in the whole axle sequence that was generated for the track in Portugal and the year 2017.

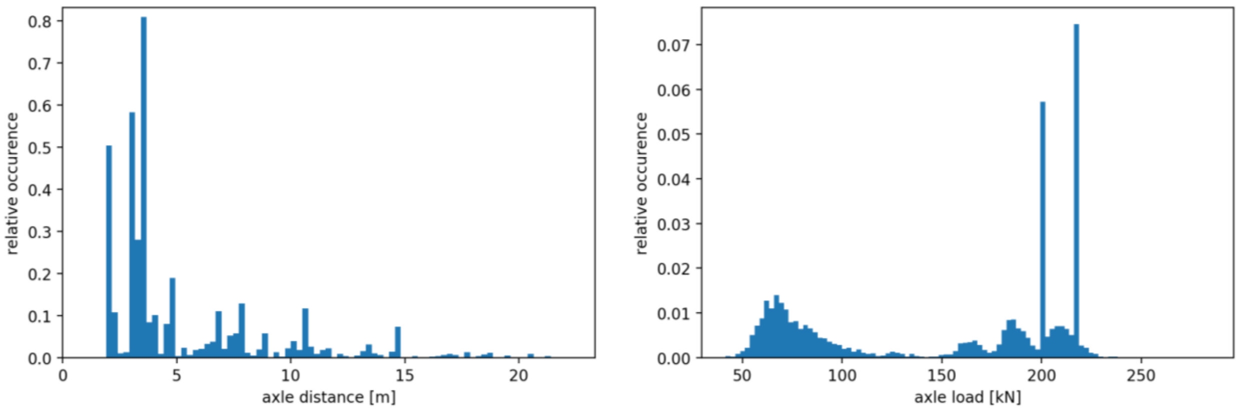


Figure 24: Histograms of axle distances (left) and axle loads (rights) evaluated from generated axle sequences for a track in Portugal, using traffic management data of year 2017.

Knowledge level 2 provides only the aggregated traffic volumes at a specific track section. The traffic volumes can be stated either in its net form (weight of transported goods, number of transported passengers), or as total gross weight of passed trains. The distinction to knowledge level 3 is that number of trains is unknown, as well as any information on individual trains (length, weight, speed).
The procedure that was followed here to artificially extend the data to higher knowledge levels, is almost the same as for knowledge level 3 described above. The trains are artificially generated using defined information about train configurations and using a wagon database. Since the number of trains is unknown, the train generation is continued until the target traffic volume is reached.

Knowledge level 1 provides only the aggregated traffic volumes from the whole network. The distinction to knowledge level 2 is that the regional distribution of country's traffic in unknown. Information on knowledge level 1 is available from different institutes that focus on country statistics (see for example Figure 25). Extension of this data to artificially lift the knowledge level would require making assumptions about regional traffic distributions of the total traffic volumes. Although rough estimates could be determined by consultation with local rail authorities, in general this step is not recommended due to the high amount of speculation that would be involved.

5.5. Traffic of the past

Previous chapters dealt with description of the present traffic. To assess the load history beginning from the bridge construction, it is necessary to estimate the traffic of the past. Rail traffic changes over time and older bridges might have been exposed to different traffic volumes decades ago. Therefore, it would be helpful to have the traffic information described above for the present traffic, in similar form for the traffic of the past. However, data availability regarding past traffic is limited. Main reasons are:

- Traffic data was not recorded in the past, or was recorded with less detail
- Data was archived as hardcopy and is difficult to retrieve
- Data was destroyed or is missing

Although some data is possibly available in archives, the extraction of relevant information from there might require significant personal resources. Therefore, an alternative approach is needed. The approach may vary depending on which data about the past is available. Following data availability scenarios are considered:

- Traffic volumes per track section are available,
- Network-aggregates of traffic volumes are available,
- Macroeconomic data are available.

Traffic volume per track section represents the most detailed information among the listed scenarios. Ideally, the gross weight of passed trains [t] would be provided, eventually also number of passed trains. This information corresponds to knowledge level 2 – 3. Modelling the traffic of the past years is then simply done in the same way as for the present traffic, only with adjusted total traffic volume to be generated.
The composition of the wagon material is assumed as equal to the present traffic, unless some information about the wagon material of the past can be retrieved. In that case, properties of the wagons in the traffic model could be adjusted for the past years, particularly for wagons with heavy axle loads.

Network-aggregates of traffic volumes provide information about total rail traffic volume in a country. Besides railway operators, this information is available at institutes that concentrate on country-statistics like Eurostat [20] (statistical office of the European Union) or the World Bank. Figure 25 shows the openly available data of the World Bank [21], which is available from the year 1996 for most European countries. The data is separated to passenger traffic, which is given in [passenger-km] (number-of-transported-passengers × transport-distance), and freight traffic, which is given in [ton-km] (weight-of-transported-goods × transport-distance). A plausibility check revealed one erroneous data entry: amount of passenger-km in Austria in the year 2016. Other than that, the volume of passenger traffic seems to have experienced only minor changes over time in most of the countries shown in Figure 25. On the other hand, temporal changes of the freight traffic volume are larger. In number of countries, the trend of total rail freight volumes is decreasing in years 1996-2018. In here, usage of known present traffic volumes for the whole past bridge life (i.e. assuming constant traffic over time) may lead to underestimation of fatigue loads.

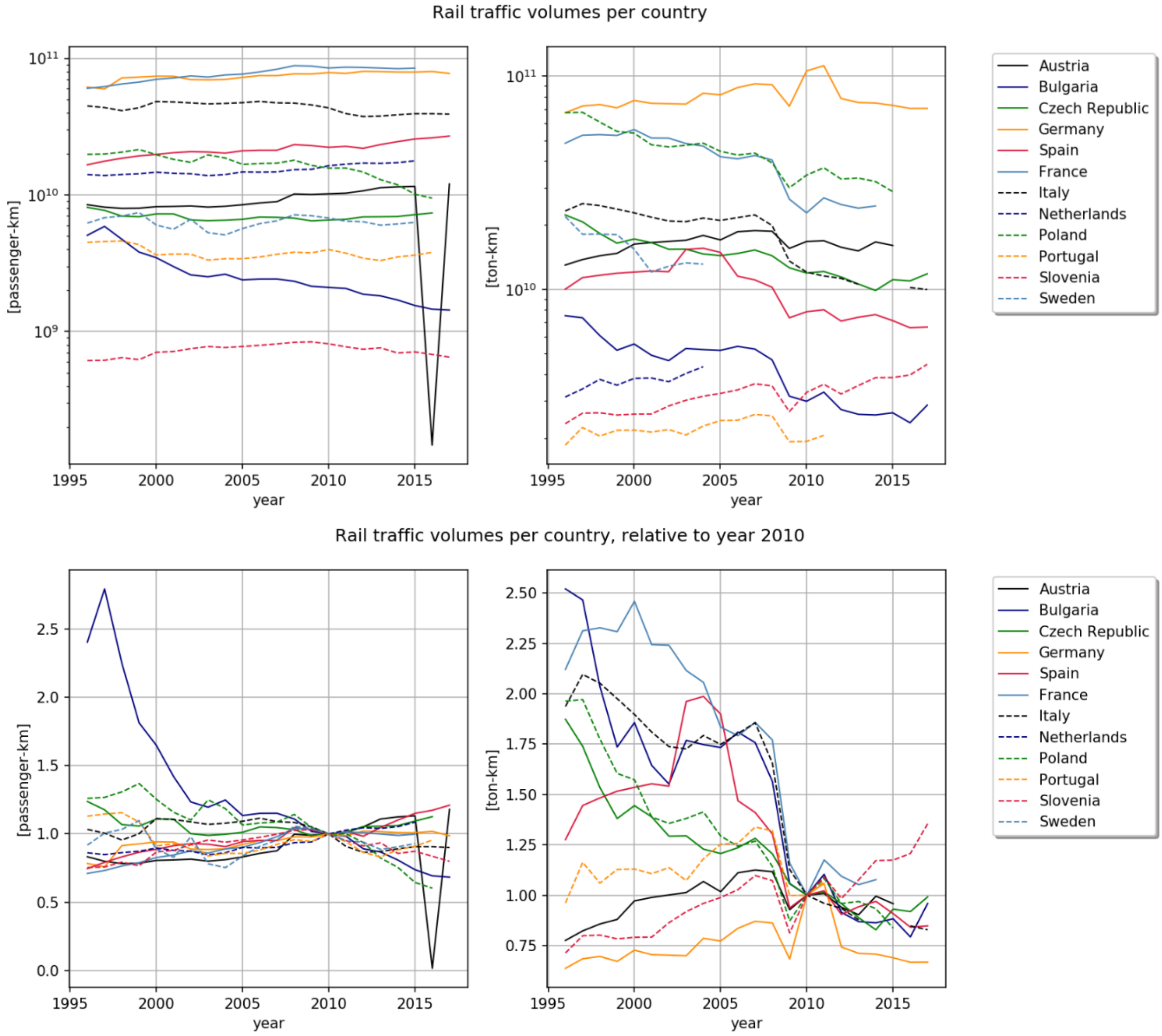


Figure 25: Rail traffic volumes of passenger traffic (left) and freight traffic (right) of selected European countries. Data is in passenger-kilometers and ton-kilometers, respectively, in absolute values (top) and as relative change to the year 2010 (bottom).

The model of present traffic can be converted to create model of past traffic using simple scaling (Equation 4) of the present total gross train weights per year ($V_{freight,present}$ for freight) with a ratio of past and present net-country-volumes ($NW_{freight}$ for freight) available from the network-aggregates.

$$V_{freight,i} = V_{freight,present} \frac{NW_{freight,i}}{NW_{freight,present}} \qquad \text{Equation 4}$$

This simple conversion implies following assumptions:

- The distribution of country's rail traffic to different track sections / routes is constant,
- Past wagon material and load-factors + passenger-occupancy is same as present.

Accuracy of the result depends on how well these assumptions correspond with reality. Distribution of overall rail traffic to different routes / sections changes depending on regional traffic demands. These may change considerably if heavy industry emerges or declines in individual regions. The simple conversion proposed above could be adjusted to accommodate information on temporal changes of regional traffic demands, if such information would be available. However, lack of such information forces the use of the assumption of constant distribution of regional traffic.
The same applies for load-factors of freight wagons and passenger-occupancy of passenger trains. Since the country-aggregates (Figure 25) are available in net volumes (weight-of-goods, number-of-passengers), constant ratio of gross (total weight of trains) and net volumes has to be assumed constant, unless more accurate information is available.

The data of network-aggregated volumes help to estimate the traffic between 1996 (for most countries) and the present. To estimate the traffic before 1996, next level of approximation must be introduced.

Macroeconomic data summarize the basic economic indicators of a country. The World Bank provides data of Gross Domestic Product, population, energy use per capita, and many other indicators. The traffic demand is given by needs of the industry and the population. Development of industry and population is reflected in macroeconomic indicators, therefore a correlation between these indicators and rail traffic is expected. However, many other factors (aside from country's macroeconomic indicators) influence also the rail traffic demand, and these are unknown. For example, a country is not a closed system and experiences some transit traffic that is mostly related to economic development of other countries. Nevertheless, the existing correlation (although not perfect) can be used to provide an estimate with some limited degree of accuracy.
The relation between macroeconomic indicators and rail traffic was already used to predict future traffic needs, as presented in research article [22]. In here, machine learning techniques were used to establish the relation between indicators and traffic volumes. Eight indicators were used: CO_2 emissions from transport, energy production, energy use, energy depletion, GDP per capita, GNI per capita, net income from abroad and road sector energy consumption.
The implementation used in this project is simpler – only two indicators were used: GDP and energy consumption. Also, a simpler analysis method was used: linear regression. Open data of macroeconomic indicators by the World Bank were used. The GDP used was in constant 2010 USD. That means, the GDP-values are corrected for currency inflation with year 2010 as reference. Further, domestic currencies are converted to USD using 2010 official exchange rates. The energy consumption is given kg-of-oil-equivalent and was calculated from the energy consumption per capita and country's population.
The macroeconomic indicators are available starting from 1960 for many European countries, for some countries later (1970 or 1980). Many countries of Eastern Europe experienced splitting and major political changes around 1990. Therefore, data of macroeconomic indicators start around 1990 for these countries.

Figure 26 shows development of macroeconomic indicators of selected European countries.

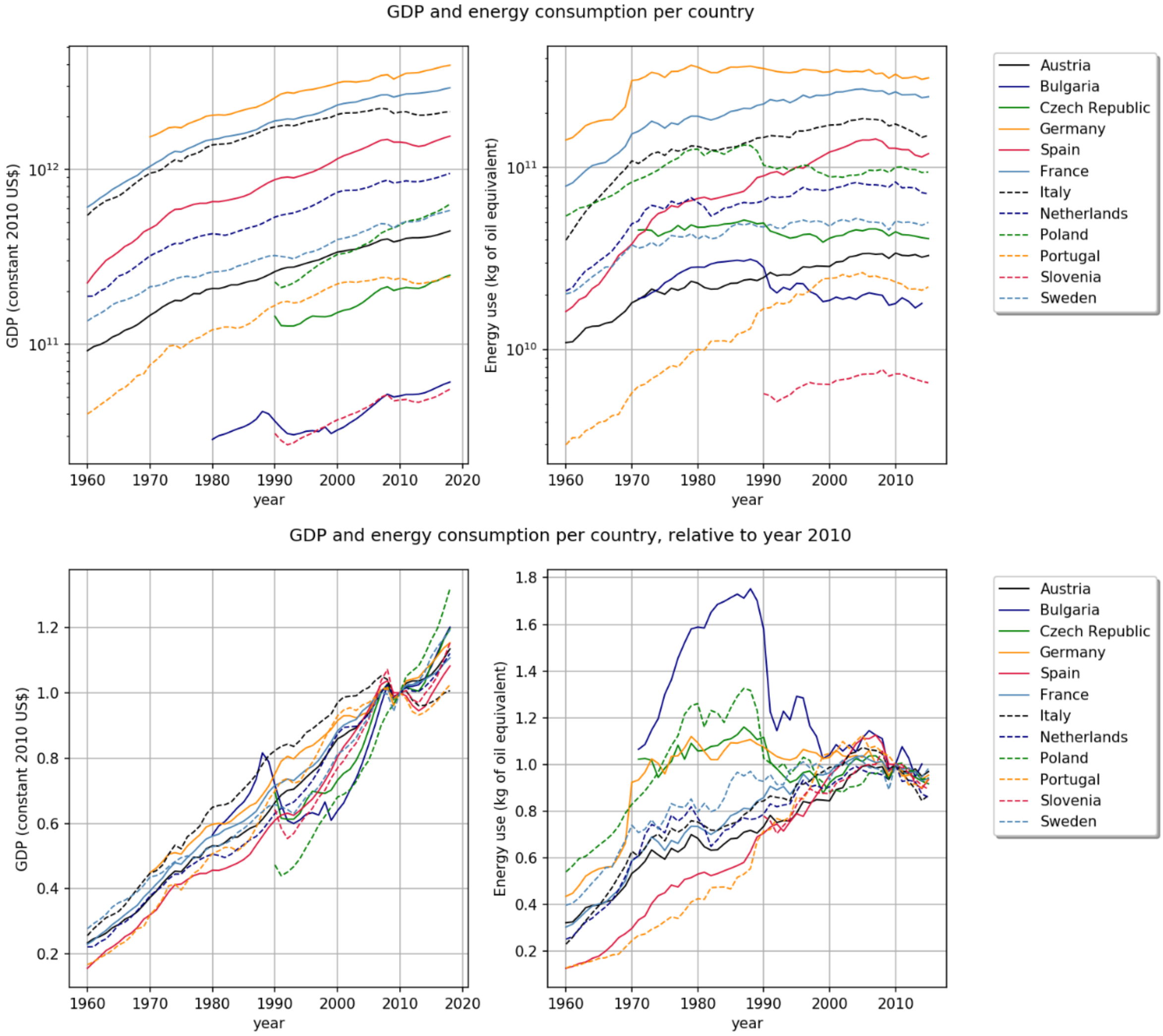


Figure 26: GDP (left) and energy use (right) of selected European countries. Data is in in absolute values (top) and as relative change to the year 2010 (bottom).

The overlap of country's traffic volume data and macroeconomic-indicator data enables to establish a relation between the two. This relation is established using linear regression, applied separately on data of each country. This relation is then used to calculate an estimate of traffic volume for past years, before traffic volume data was available. Figure 27 and Figure 28 show the traffic volumes predicted from macroeconomic indicators, compared to actual traffic volumes, for the countries of Spain and Portugal.

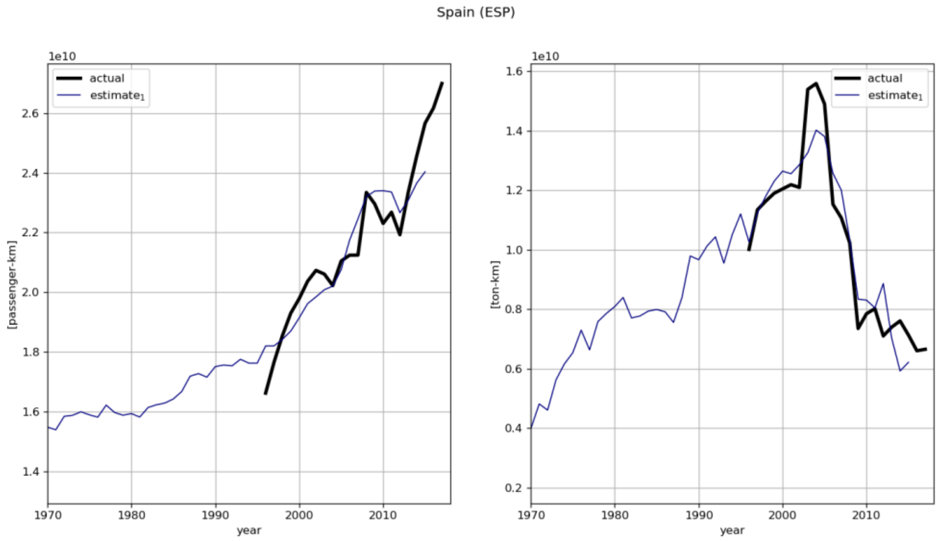


Figure 27: Net traffic volumes of passenger (left) and freight (right) traffic, as estimated from macroeconomic indicators (thin blue line), compared to actual volumes (thick black line). Country: Spain.

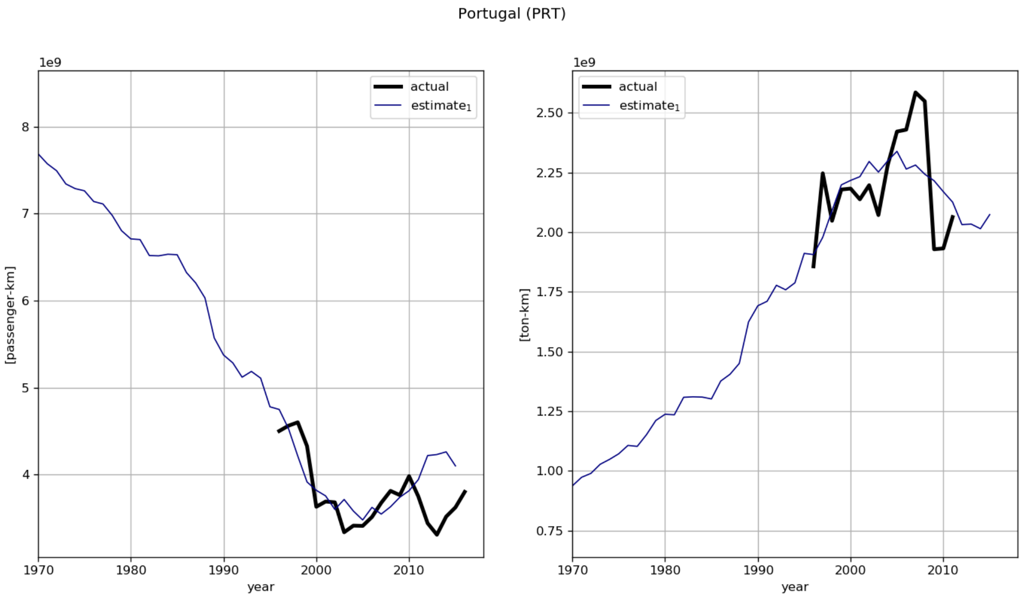


Figure 28: Net traffic volumes of passenger (left) and freight (right) traffic, as estimated from macroeconomic indicators (thin blue line), compared to actual volumes (thick black line). Country: Portugal.

However, the accuracy of these estimates is difficult to assess. Therefore, it is recommended that railway operators check plausibility of such estimates before its use. For example, Italy experienced between 1996 and 2018 increase of GDP and energy use, while the freight traffic shows a decreasing trend in this period. Therefore, the linear regression established a negative correlation between macroeconomic data and freight traffic. This resulted in high volumes of freight traffic predicted for the years before 1984 (Figure 29 right). Similar situation applies to passenger traffic volumes in Portugal (Figure 28 left).

Typically, a positive correlation between macroeconomic indicators and traffic volumes would be expected. In case of negative correlation, a plausibility check is essential.

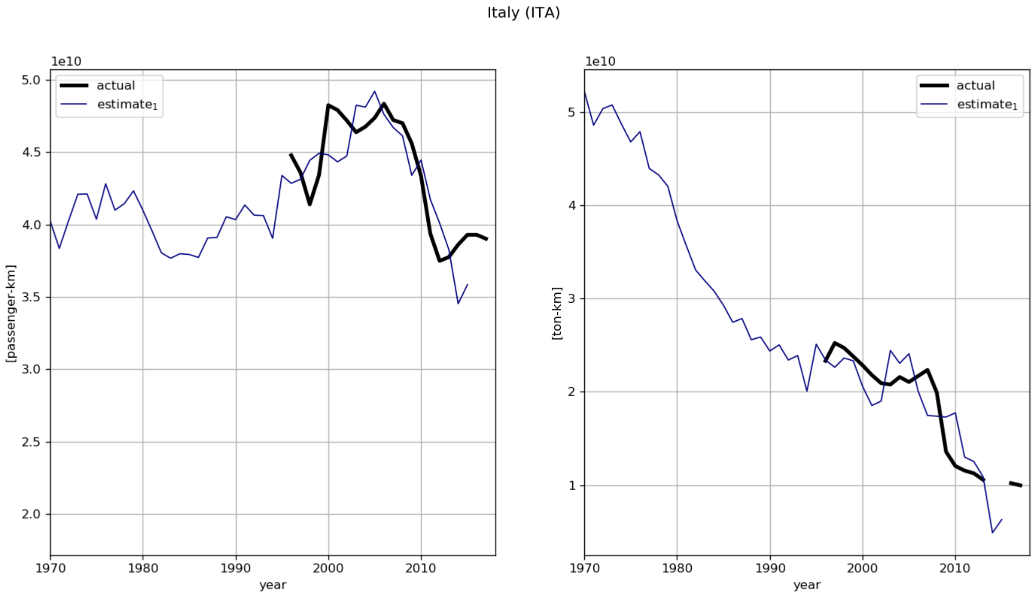


Figure 29: Net traffic volumes of passenger (left) and freight (right) traffic, as estimated from macroeconomic indicators (thin blue line), compared to actual volumes (thick black line). Country: Italy.

Since the age of rail infrastructure can reach farther to the past than the available data on macroeconomic indicators, it is necessary to make additional assumption for the period where macroeconomic data is missing. Here again, if reliable traffic data such as traffic records or actual train schedules are available, they should be used to derive traffic volume estimates. However, in most cases such data is not expected to exist. In here, an extrapolation into the past using constant traffic volumes would usually provide a conservative estimate.

The approach presented here is meant to provide an estimate of past traffic volumes. Its accuracy might be limited. If the retrieval of actual traffic data of the past is feasible, it should be preferred to these estimates.

6. Conclusions

A concept for creating a model of traffic loading with respect to knowledge levels of rail traffic was presented. Goal of this model is to provide a realistic estimate (without safety factors) of traffic loads for a specific track section, from the point-of-view of bridge fatigue. Procedures for deriving the traffic load model from data sources with various detail-of-information were proposed. The proposed procedures are intended for machine-based calculations; they generate axle-sequences that simulate whole year of traffic.

Creation of traffic load models from traffic management data is less accurate, since here assumptions must be made, which fill the missing information. The assumptions are related to wagon loading factors, exact wagon types and number of wagons per train. In here, close cooperation with rail operators is needed, so that the assumptions do not deviate from the reality too much. Uncertainties of axle-sequences generated from traffic management data were not evaluated at this point, since comparison of generated and actual axle-sequences would require additional input data. Future uncertainty evaluation would possibly allow to determine safety factors using specific quantile-values.

Most accurate traffic models can be derived from wayside-monitoring or B-WIM data, since these measurement systems provide actual axle loads and axle distances. The former and latter are processed by wagon-identification and train-identification algorithms, which group similar wagons and trains, and construct probabilistic descriptions of their properties.

Using comprehensive instrumentation of the railway bridge in Austria the B-WIM measurements were performed. The results are very promising in spite of the current software's slight inadequacy to construct an optimal influence line. The results of weighing of the calibration train proved to be quite accurate – mostly in the highest class according to the COST323 specifications. The speed dependence of the weights was expected, based on the less than optimal influence line. The temperature dependence proved to be relatively high, but within the values that we've already seen on other structures. We can thus say that the B-WIM is applicable to railway bridges as a method of measuring load histories

The use of network-aggregated traffic volumes to generate model of present traffic on specific track sections is not recommended, since it would require assumptions about regional traffic distribution, which are difficult to make without further information.

To estimate the traffic of the past, retrieval of actual traffic occurrences on specific track sections from archived records presents a reliable, but very time-consuming method, given that archived records are not available in a format that allows machine-processing. Therefore, scaling of model for present traffic to past traffic volumes was proposed here. The scaling method uses the relative change of network-aggregated traffic volumes of the past in relation to the present. The data for the past is either directly available from

country's statistics (data start usually from 1996), or it can be estimated from country's macroeconomic indicators (data start from 1960-1990, depending on country). However, the estimates derived from macroeconomic indicators require plausibility check and are generally less reliable.
Similarly as in case of the past data, macroeconomic indicators can be used to estimate future traffic volumes, if a prognosis of the development of macroeconomic indicators exists.

7. References

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8. Appendices