Highway Traffic Monitoring using Bridge Weigh-in-Motion

Marcel Nowak [1] ✉, *Oliver Fischer* [1]
✉ e-mail: marcel.nowak@tum.de
[1] Technical University of Munich, TUM School of Engineering and Design, Chair of Concrete and Masonry Structures, Munich, Germany
DOI: https://doi.org/10.14459/icbdb24.39

Abstract Bridge Weigh-in-Motion (BWIM), as a method of indirect load monitoring, attempts to describe the load process of the traffic crossing a bridge by solving an inverse problem. The basic principle is to infer the causative action from traffic-induced measurement signals of the structural response (usually from strain gauges) with the help of reference data from defined proof loadings, often by solving an optimization problem. Within the scope of a research project in cooperation with *Die Autobahn GmbH des Bundes (branch Southern Bavaria)*, BWIM is applied to a bridge structure on Federal Highway A92. As a result, an extensive and detailed traffic record is obtained, covering a measurement period of about one year. Within this context, the contribution presents basic ideas on the conceptual design of the monitoring campaign, concepts and strategies for data analysis in the scope of BWIM application, the BWIM algorithm itself, and some results and essential findings.

1 Introduction

For the assessment of existing bridge structures on federal highways in Germany, traffic load models are employed that were developed based on extreme traffic data [1]. A realistic consideration of local traffic characteristics for specific bridge structures employing object-specific load models shows, in many cases, an additional potential for the reduction of the load level and, thus, also for the reduction of the calculative deficits in the bridge assessment while maintaining the required safety level [2]. A reliable, robust, and comprehensive data basis for all relevant traffic and vehicle parameters is essential for modeling local traffic characteristics. However, reliable measurement data are often unavailable for dominant parameters such as vehicle weight, vehicle headway, or congested traffic. Missing parameter information has to be replaced by corresponding assumptions, often based on measurements at other locations of the road network or from literature, usually leading to additional inaccuracies in the traffic load modeling.

Within this context, in 2019 and 2020, a long-term monitoring campaign over one year on a selected bridge structure on Federal Highway A92 was carried out to create a comprehensive data basis for all parameters relevant to traffic load modeling [3]. Under the condition of highest possible efficiency with minimum disturbance potential (installation and operation of the measurement technology should not require any intervention in the running traffic), a monitoring concept was developed, guaranteeing a complete and robust acquisition of the desired measurement variables. The core component of this monitoring concept is structural monitoring on the bridge with an application of bridge weigh-in-motion (BWIM). Based on different data analysis strategies, an automated algorithm is developed, allowing for data from multiple sensors to be evaluated towards relevant parameters from vehicles of the passing road traffic.

2 Monitoring Concept

2.1 Bridge Structure 29/1 on Federal Highway A92

To implement the monitoring campaign, bridge structure 29/1 (here: northern superstructure for the direction of travel to Munich) was selected, located northeast of Munich between the exits of Freising-Ost and Erding on Federal Highway A92. The bridge crosses a receiving ditch in five spans with nearly uniform widths of about . The bridge consists of two identical superstructures, each supporting the roadway for one driving direction with a standard configuration of two lanes plus emergency lane. The cross-section of each superstructure consists of five precast prestressed concrete t-beam girders with a height of 69 cm, with an additional cast-in-place concrete slab with a thickness of 23 cm on top. The precast beams rest on elastomeric bearings, each over a single span with no rigid connection from one span to the next. Only the cast-in-place concrete slab on top is continuous across all five spans. This design reduces the stiffness of the superstructure at the piers so that each span behaves approximately like an independent single-span system. The total width of a superstructure is 15.35 m, and the width of the roadway is 12.0 m (**Figure 1**).

Federal Highway A92 is a secondary route in the German highway network with moderate traffic volumes. Throughout 2019, construction work was carried out to rehabilitate the roadway in the section of the highway where bridge structure 29/1 is located, resulting in a variation of the traffic lane configuration on the bridge. In addition to the standard configuration with unidirectional traffic with two lanes plus emergency lane per superstructure (LC_{stan}), modified configurations with two lanes of unidirectional traffic with reduced lane width per superstructure ($LC_{mod,uni2}$) and four lanes of bidirectional traffic on a single superstructure with closure of the second superstructure ($LC_{mod,bi4}$) occurred during construction works.

2.2 Structural Monitoring

For the structural monitoring, 29 strain gauges and two temperature sensors are installed on the bottom side of the northern superstructure, which carries traffic in the driving direction of Munich. They are installed by bonding to the concrete surface, which is prepared at the sensor points by

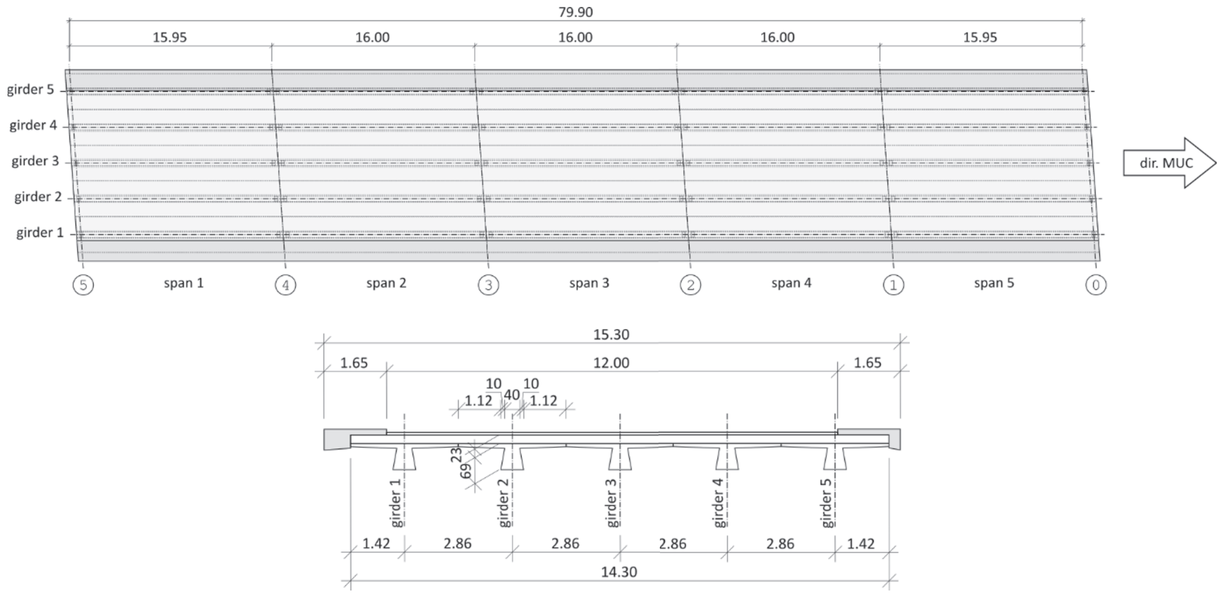

Figure 1: Top view (top) and section (bottom) of bridge structure 29/1.

grinding. The majority of the strain gauges are installed in span 4 (**Figure 2**). The measuring points in the remaining fields and the temperature sensors are only used for control and comparison purposes (not relevant to the scope of this paper). For the measurement, the sampling frequency of 400 Hz is chosen sufficiently high to ensure an accurate resolution of signal components due to the transient load from vehicle crossings, including relevant dynamic effects. The sensor layout designed for an application of BWIM mainly consists of two components [4]:

- sensors for global structural response (global sensors 4-1 to 4-5, glob) on the bottom side of the webs of the t-beam girders in the center of the span, with governing loading by the

- sensors for the local structural response (local sensors 4-11 to 4-18, loc1 and 4-21 to 4-28, loc2) on the underside of the flanges of the t-beam girders approximately at quarter span (arranged in pairs in the same transverse position with a longitudinal spacing of 2.4 m), with governing loading by the weight of individual vehicle axles

For calibration of the measuring systems and derivation of reference influence lines for the individual sensors, proof load tests are carried out, in which vehicles with known dimensions and weights (mobile crane with four axles and 48 t total weight and truck loading crane with four axles and 32 t total weight) cross the northern superstructure of bridge structure 29/1, covering the possible transverse positions of all lanes for the three traffic lane configurations LC_{stan}, $LC_{mod,uni2}$ and $LC_{mod,bi4}$.

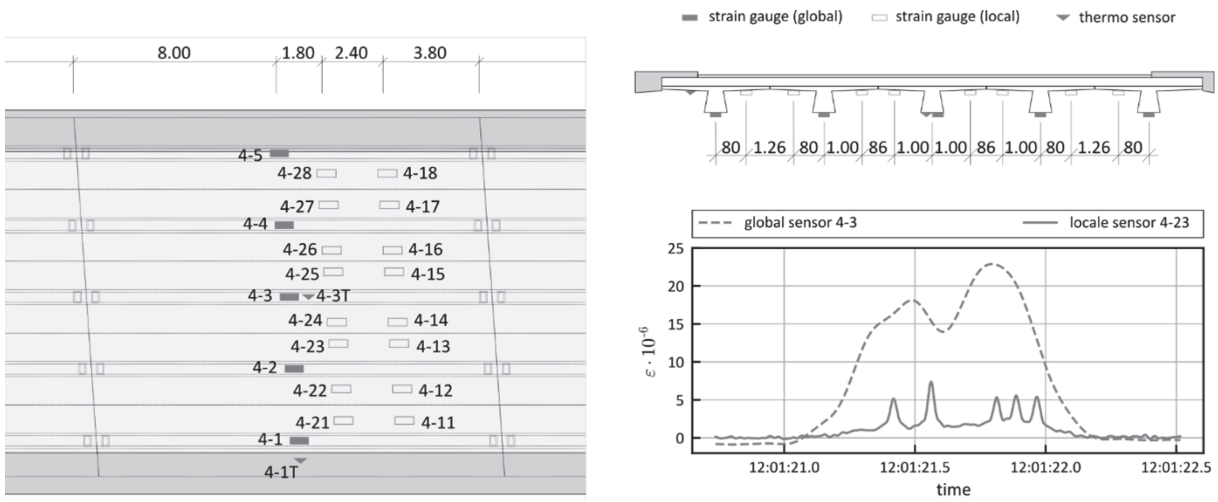

Figure 2: Scheme of sensor layout in top view (left) and cross section (right, top) of span 4, sample signal of vehicle crossing for global and local sensor (right, bottom).

3 Data Analysis Concepts

3.1 Signal Processing

The raw signal of strain sensors is composed of different parts, mainly differing in their rate of change:

- load effects due to temperature and other non-permanent constraining loads (low rate of change, usually several minutes or longer)
- road traffic (static) load effects (medium rate of change, for structure and sensor locations in this work up to a few seconds)
- dynamic effects due to excitation by passing vehicles and interaction with structure (high rate of change, fractions of second)
- measurement noise (wide range of rates of change, possibly over entire frequency spectrum)

Signal processing is necessary to extract the relevant parts of the raw signal resulting from road traffic, i.e., passing vehicles' (static) load. For this purpose, the procedure from [5] is adopted within the scope of this work, performing signal decomposition exploiting the different rates of change of the single signal components. For this purpose, mean filtering (excluding parts of the signal with a low rate of change) and low pass frequency filtering (excluding dynamic effects and most parts of measurement noise) are applied.

Mean filtering is done based on block-wise determined and linearly interpolated mean values. The choice of block size constitutes a compromise between sufficiently detailed representation of the signal parts with a low rate of change and robustness against the influence of the signal part due to traffic loading on the resulting block mean values. For low pass frequency filtering, a Butterworth filter of eleventh order is applied. The cutoff frequency f_{cutoff} is chosen based on the natural frequencies of the monitored structure. As the focus is on analyzing the load effects resulting from the static load of passing vehicles, the value should be sufficiently low to exclude all significant parts of the signal due to dynamic effects. However, it is also essential to choose the value for f_{cutoff} not too low to avoid significant alteration of relevant parts of the signal. Depending on the velocity of a passing vehicle, the signal part due to its static load results in low-frequency contents of the signal that could be affected by the low pass filter [6].

3.2 Bridge Loading Event

The measurement signals of the bridge monitoring are recorded continuously in time. For subsequent investigations, only the signal components resulting from traffic load impact on the bridge are relevant (Section 3.1). In the ideal case, the time-continuous signal component only shows non-zero values when BLEs occur, i.e. when individual vehicles or groups of vehicles pass over the bridge. In reality, however, the processed signals still contain some noise components, usually of the order of magnitude of the signal amplitudes due to lighter vehicles (e.g., passenger cars, delivery vans). Following the original definition from [7] – a BLE as continuous presence of at least one truck on the structure – BLEs can be identified based on the traffic signal from the (global) sensors, as continuous signal sections with values above a sufficiently large non-zero threshold (i.e., vehicle or group of vehicles must be sufficiently heavy to cause a significant signal amplitude). Depending on the transverse position of the vehicle crossing the bridge (e.g., slow or fast lane), the measured values for the individual global sensors vary in size during the crossing. Accordingly, the limits of the BLE are defined as the envelope of the limits from the detection of the individual sensors. This results in the greatest possible length for the BLE and ensures that no relevant signal parts are neglected.

3.3 Reference Influence Line

Reference influence lines (RILs) describe the structural response at a specific location in the structure as a result of a single vehicle axle with unit weight crossing the bridge structure – as a section of the influence surface of the bridge superstructure for a given transverse position, corresponding to the center of the traffic lane in which the vehicle axle is traveling. The RILs are determined based on the measured signals from defined proof load tests by solving an optimization problem. Based on the known vehicle parameters (velocity, axle spacings, axle weights), the measured signal of a proof load test is approximated by a superposition of multiple RILs corresponding to the number of axles of the proof load vehicle. The RIL is described by a section-wise defined linear function whose values at predefined supporting points represent the optimization variables. The optimum for the RIL is obtained by the method of least-squares between measured signal and approximating RIL superposition (**Figure 3**).

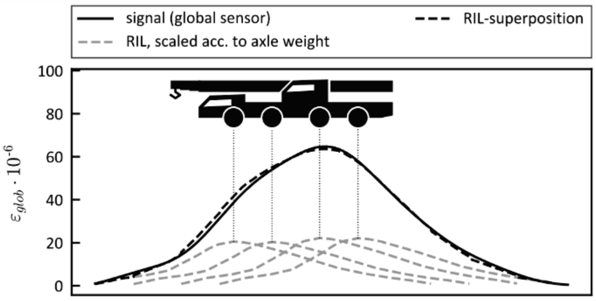

Figure 3: Scheme of RIL optimization (left) and exemplary RIL for global sensor (right).

3.4 Transverse Distribution Factor for Global Response

The transverse position of the load impact on the bridge roadway is of interest for various aspects within the scope of BWIM. The processed traffic signal describes the structural response due to the traffic flow over the bridge at selected measurement points. These strain time histories do not contain any specific information about the causal load impact (including its transverse position). However, it is possible to conclude the transverse position by fusing data from several (global) sensors. For this purpose, the transverse distribution factor (TDF) is introduced [8], which describes the relative proportion of the structural response at sensors at a defined reference time t_{ref} for a representative set of n selected sensors (TDF sensors) at the same longitudinal but different transverse positions:

$$f_{TDF,t_{ref}|s} = \frac{\varepsilon_s(t = t_{ref})}{\Sigma_{j=1}^{n} \varepsilon_j(t = t_{ref})} \tag{1}$$

This concept is based on the assumption of linear-elastic structural behavior under usual traffic loading. In this case, the transverse distribution of the structural response depends only on the transverse position of the passing vehicles and not on their total weight[9]. The reference time t_{ref} for evaluating the TDF can be defined differently depending on the application. For the application in the context BWIM, the time is chosen at which a certain axis a_{xi} of a passing vehicle is located at a reference point x_{ref} on the structure (e.g., mid-span):

$$t_{ref} = t_{\varepsilon_{ax_i}, x_{ref}} \tag{2}$$

For subsequent investigations, sensors 4-2 and 4-4 are specified as TDF sensors.

4 Application of Bridge Weigh-in-Motion

4.1 BWIM Algorithm

BWIM is one of the methods of indirect impact monitoring, which describe the load process of the traffic passing over a bridge by solving an inverse problem. The basic principle is to infer the causative action from traffic-induced measurement signals of the structural response with the help of findings from defined proof load tests [10]. The following explains in detail the BWIM algorithm developed for application on bridge structure 29/1 on Federal Highway A92 [3].

The basis for the application of the BWIM algorithm is the sequence of BLEs obtained by evaluating the measured data of the structural monitoring, as well as the RIL determined based on the signals of the proof load test. If a single vehicle axle passes the bridge structure in one of the traffic lanes, this usually leads to a distinctive peak in the signals of at least one of the local sensor pairs of this lane. The time interval of this peak between the two signals of the sensor pair depends on the spacing of the sensors of a pair (fixed value 2.4 m by the installation of the sensors, see Section 2.2) and the velocity of the passing vehicle axle (variable per vehicle crossing). Accordingly, the crossing of a vehicle leads to a peak sequence at both sensors, whose time intervals between the sensors are (approximately) equal. By identifying such decisive peak sequences in the signals of the local sensor pairs, individual vehicles are detected within the BLE. The number of peaks within a sequence corresponds to the number of axles of the vehicle. The velocity can be determined from the time intervals of the peak sequence between the sensors of a pair and their spacing. Finally, with the help of the now-known velocity and the time intervals of successive peaks of a sequence on the signal of the same sensor, the axle spacings can be inferred (see **Figure 4**). The local sensor pairs are assigned to the possible transverse positions for each traffic lane configuration, allowing a conclusion for the transverse position of the identified vehicles. Several vehicles driving behind each other within a BLE lead to a merged peak sequence within the same lane. A division into peak subsequences for the individual vehicles' differentiation occurs by identifying sufficiently strongly deviating velocities (and thus deviating temporal distances between the sensors) or by sufficiently large axle spacings. At the end of the vehicle detection, a plausibility check is performed concerning the "meaningfulness" of the axle patterns and their possible overlapping in the case of multiple vehicles within a lane. In addition, vehicles that have been incorrectly identified but are not present (dummy vehicles) are removed. An unclear transverse position during the vehicle crossing (e.g., during overtaking, peak sequence of a vehicle occurring in signals of two adjacent lanes), as well as noise and interference effects during the measurement (random peak sequence in the measurement signals), are possible causes for dummy vehicles. The identification of dummy vehicles is based on the TDF of the vehicle axles. For this purpose, a valid TDF value range is defined in advance for each traffic lane.

The parameters determined for the detected vehicles based on the local sensors form the basis for determining the axle weights. For this purpose, an optimization problem is defined whose optimization variables are the individual axle weights. The objective function corresponds to the sum of squared errors between the decisive global measurement signal due to the crossing of the (unknown) vehicle and the approximation by scaling and superposition of RIL of the global sensor according to the previously determined axle layout and the velocity (see **Figure 4**). The optimum for the axle weights is determined by minimizing the objective function.

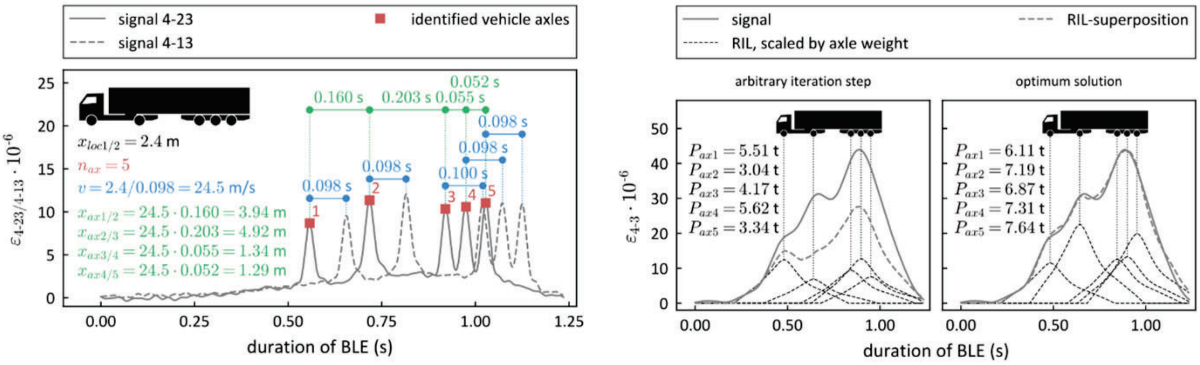

Figure 4: Vehicle parameter determination based on local sensor signals (left) and optimization of axle weights based on global sensor signal (right).

4.2 Exemplary Bridge Loading Events

In the course of the monitoring campaign at bridge structure 29/1, nearly 7,700 h of measurement signals were analyzed, and more than 675,000 truck vehicles were detected and their parameters determined. **Figure 5** shows selected evaluation examples of the BWIM algorithm.

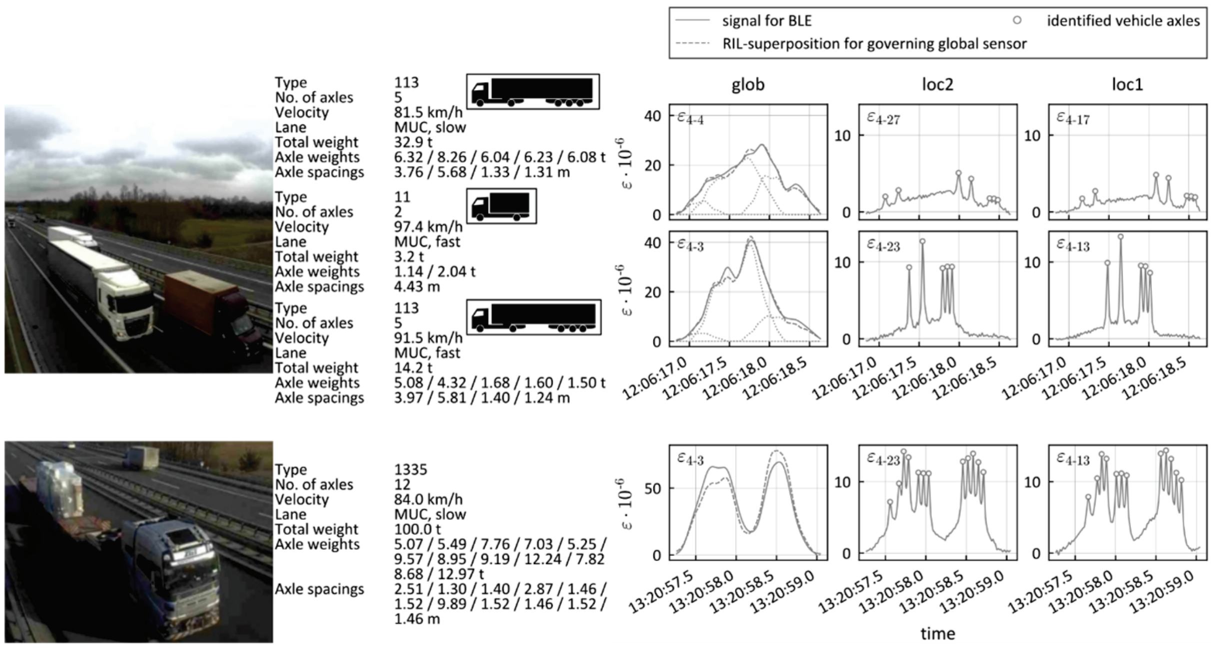

Figure 5: Exemplary BWIM results for overtaking with three trucks (top) and crossing of a single permit truck (bottom), with display of signals from governing global and local sensors.

4.3 Performance and Limitations

Based on internal quality controls [3], the BWIM algorithm performs very well in terms of vehicle detection and lane assignment. Axle detection shows a slightly weaker – but still satisfying – performance. In general, it can be observed that the performance for modified lane configurations –

compared to the standard case – slightly decreases. Further analyses of the BWIM evaluations show a dependence of the quality of results on the complexity of the BLE (single crossing vs. simultaneous crossing of several vehicles). However, the influence is only marginal as long as the corresponding BLE occur in regular free-flowing traffic with sufficiently large velocities. Traffic situations with very low or not constant velocity during the crossing (congested traffic with “stop-and-go”) or even stationary vehicles on the bridge structure (traffic jam) cause much more significant problems for the BWIM algorithm. One of the essential prerequisites and assumptions for the BWIM algorithm – a constant crossing velocity for each vehicle – is no longer fulfilled. A correct detection and parameter determination for vehicles with the BWIM algorithm is not possible in such situations. However, regarding the total duration of the monitoring, such events occur only very rarely.

5 Evaluation of Relevant Traffic Parameters

5.1 Vehicle Weights

The total vehicle weight is modeled as a multi-modal normal distribution, which is represented by the model parameters mean value, standard deviation and modal contribution. For this purpose, different variants with up to three modes are evaluated for each vehicle type and the best model approximation is adopted. Figure 6 shows the model approximation to the BWIM data for selected vehicle types as well as the model used in [1] for the traffic simulation based on measurement data from Federal Highway A61 (“extreme traffic”). In some cases, significant differences can be observed between the two models.

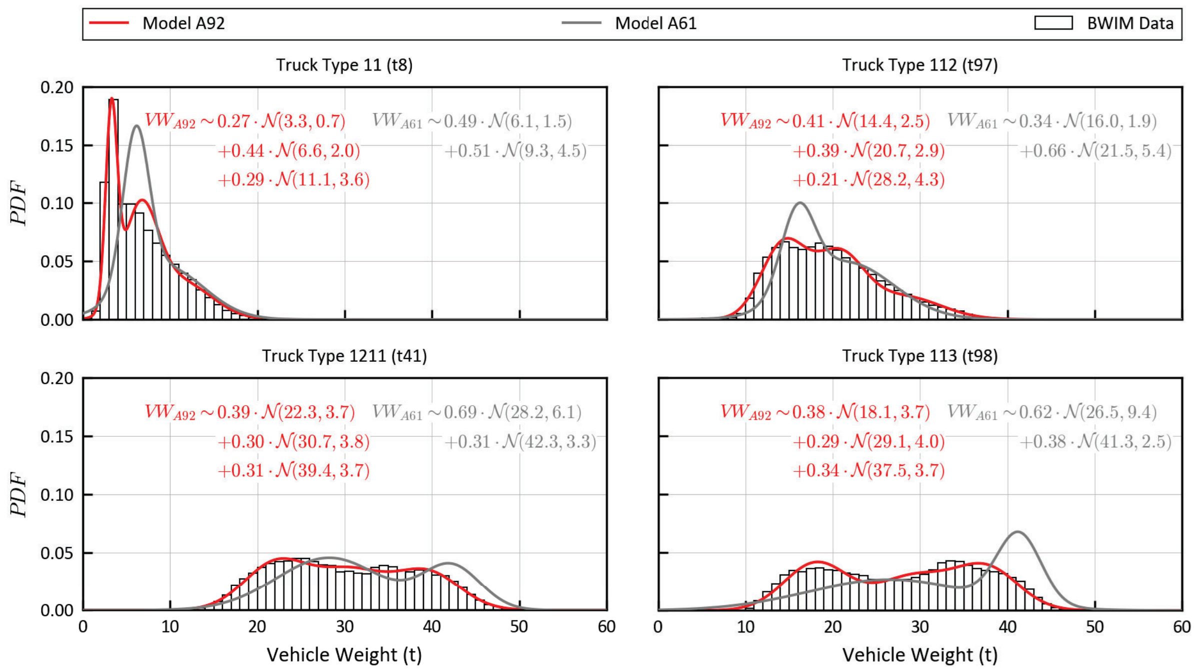

Figure 6: Model approximation (probability density function) to BWIM data for total vehicle weight (VW) of different vehicle types, and comparison to model for A61 data (with respective multi-modal normal distribution function).

5.2 Inter-Vehicle Gaps

For modeling inter-vehicle gaps in free-flowing traffic, a simplified model with lognormal distribution depending on the truck traffic flow rate is adopted (as in [11]). The expected value of the lognormal distribution is calculated based on the truck traffic flow rate, an average vehicle length (based on traffic composition and axle spacing) and an average vehicle speed. The coefficient of variation is derived from a traffic flow–dependent trend model. This model is obtained by analyzing the BWIM data. The data of all complete working days are divided into individual blocks of six hours each (for comparison purposes analogous to [11]; other time blocks can also be selected). The truck traffic flow is determined for each block (and each individual lane) and a lognormal distribution with a corresponding coefficient of variation is approximated to the empirical distribution of vehicle distances. The vehicle distances are calculated from the net time gap between the last axle of the preceding vehicle and the first axle of the following vehicle as well as the mean value of the driving speeds of both vehicles. The model for the coefficient of variation as a function of the traffic flow is determined by approximating a power law (with pre-factor a and power factor b) to the resulting data set of coefficients of variation for all 6-hour blocks. **Figure 7** shows the model approximation to the evaluations of the BWIM data set, as well as the model used in [11] based on measurement data from Federal Highway A61. A clear deviation between the two models can be observed. For higher traffic flow rates, the difference between the two models is only slight, but increases with decreasing flow rates. One possible reason for this could be the difference in traffic volumes and flow rates for the two different traffic data sets. For the A92 traffic, data points for the truck traffic flow rate per 6-hour block are below 1,500 vehicles. For the A61 traffic, data points are between 1,000 and up to 3,500 vehicles (see [11]) and are therefore not representative of lower flow rates.

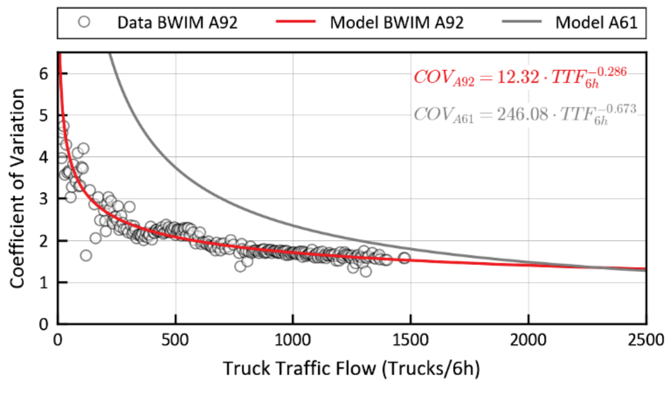

Figure 7: Model for the coefficient of variation of lognormal distribution for inter-vehicle gaps in free-flowing traffic, as a function of truck traffic flow per 6 h (TTF_{6h}).

6 Conclusion and Discussion

This paper presents the application of bridge weigh-in-motion (BWIM) during a long-term monitoring campaign at a selected bridge structure on Federal Highway A92 over one year to comprehensively describe local traffic characteristics. An automated algorithm is developed based on suitable strategies and concepts for collecting, processing, and evaluating all available measurement data, allowing for a comprehensive analysis of data from multiple sensors towards relevant parameters from vehicles of the passing road traffic. By an intelligent arrangement of the measurement sensors and the time-synchronous evaluation of measurement signals for local and global structural responses, some of these parameters can be determined directly from the measurement data. As a result, the number of optimization variables and, thus, the complexity of the optimization problem in the BWIM algorithm is reduced. BWIM proves to be an economical, robust, and powerful monitoring option. The data acquisition - measured by accuracy standards of common engineering practice - is highly reliable, even for a wide range of boundary conditions (different lane configurations and loading constellations), and the obtained data set covers a large part of the relevant parameter spectrum of traffic load modeling. Overall, the monitoring campaign provides a comprehensive and valuable data basis for the detailed and realistic modeling of local traffic characteristics. First data analysis results on relevant traffic parameters show some significant differences to the extreme traffic characteristics on which current code load models are based, revealing the potential of considering local traffic characteristics for object-specific traffic load models in bridge assessment. However, further investigations are required to quantify the actual benefit.

7 References

[1] Freundt, U., Böning, S.: Verkehrslastmodelle für die Nachrechnung von Straßenbrücken im Bestand. Berichte der Bundesanstalt für Straßenwesen: Brücken- und Ingenieurbau Heft B 82. Bundesanstalt für Straßenwesen, Bergisch Gladbach (2011).

[2] Nowak, M., Fischer, O.: Objektspezifische Verkehrslastansätze für Straßenbrücken. Beton- und Stahlbetonbau 112(12), 804–814 (2017).

[3] Nowak, M., Fischer, O., Tepho, T., Willberg, U.: Verkehrsmonitoring an einer Autobahnbrücke – Datenerfassung zur lokalen Verkehrscharakteristik als Grundlage für objektspezifische Verkehrslastmodelle. Beton- und Stahlbetonbau 118(9), 636–648 (2023).

[4] Lubasch, P.: Identifikation von Verkehrslasten unter Einsatz von Methoden des Soft Computing. Dissertation, Universität Duisburg-Essen, Fakultät für Ingenieurwissenschaften, Abteilung Bauwissenschaften (2009).

[5] Nowak, M., Fischer, O., Müller, A.: Realitätsnahe Verkehrslastansätze für die Nachrechnung der Gänstorbrücke über die Donau. Beton- und Stahlbetonbau 115(2), 91–105 (2019).

[6] Nowak, M., Fischer, O.: Estimation of truck weights based on strain measurements from tendons of a post-tensioned concrete bridge. In: Chen, A., Ruan, X., Frangopol, D. (eds.) Life-Cycle Civil Engineering: Innovation, Theory and Practice, 1667–1676. CRC Press, Leiden (2021).

[7] Caprani, C. C., OBrien, E. J., McLachlan, G. J.: Characteristic traffic load effects from a mixture of loading events on short to medium span bridges. Structural Safety 30(5), 394–404 (2008).

[8] Nowak, M., Fischer, O.: On the effects of modified lane configuration due to construction works on bridge loading. Acta Polytechnica CTU Proceedings 36, 149–160 (2022).

[9] Znidarič, A.: Influence of number and quality of weigh-in-motion data on evaluation of load effects on bridges. Dissertation, Univerza v Ljubljani, Fakulteta za gradbeništvo in geodezijo (2017).

[10] Moses, F.: Weigh-in-motion system using instrumented bridges. Journal of Transportation Engineering 105(3), 233–249 (1979).

[11] Freundt, U., Böning, S.: Anpassung von DIN-Fachberichten „Brücken“ an Eurocodes – Teil 1: DIN-FB 101: „Einwirkungen auf Brücken“. Berichte der Bundesanstalt für Straßenwesen: Brücken- und Ingenieurbau Heft B 77. Bundesanstalt für Straßenwesen, Bergisch Gladbach (2011).