

Generation of a statistical Traffic Load Collective based on measured axle loads of trucks by an instrumented Swivel Joist-Expansion Joint

M.Eng. Johannes Köppl*

M.Sc. Christian Merkl **

Univ. Prof. Dr.-Ing. Ingbert Mangerig ***

* University of German Armed Forces Munich, Germany, Institute of Structural Engineering,
johannes.koepl@unibw.de

** University of German Armed Forces Munich, Germany, Institute of Structural Engineering,
christian.merkl@unibw.de

*** Professor for Steel Construction, University of German Armed Forces Munich, Germany,
ingbert.mangerig@unibw.de

Abstract:

The transport of goods especially in the Federal Republic of Germany is mainly conducted through heavy goods vehicle traffic. Therefore, the determination of the actually transported loads is important for the design of road bridges and their expansion joints. To achieve this goal, different Weigh-In-Motion-Systems (WIM) have been developed and successfully established to quantify the total loading of individual motor truck. Instrumenting a swivel joist-expansion joint presents a further development of these WIM-Systems to also detect the dynamical axle loads of each crossing truck during day-to-day traffic flow. This paper describes the instrumentation setup of the expansion joint and the analysis of the resulting measurement signals to identify each axle's load and to estimate its associated velocity. Furthermore, it depicts how the identified axles are assigned to the design trucks specified within the Eurocode 1991-2. From the amount of the thereby collected day-by-day data on axles and trucks statistical evaluation is applied to generate characteristic dynamic load diagrams per truck and consequentially a statistical Traffic Load Collective.

Keywords: Weigh-In-Motion-System, Joist-expansion joint, Traffic flow statistics, Traffic load collective

1 Introduction

Road traffic represents the main form of transportation of cargo in Germany. This is monitored by the Federal Ministry of traffic and digital infrastructure and has been recently updated via a press release [1] stating that 3593.3 tons of the totally 4563.9 tons of transported goods in Germany were carried on the road. Subsequently the use of heavy goods vehicle traffic strains the essential bridge infrastructure of German highways. This has been led to a change of the admissible traffic load considered during the initial bridge design phase, and thus it affects the intended service life of bridges [2]. Additional to this problem, there is a discussion to allow a new truck combination to carry more than 40 tons, specifically up to 60 tons, to reduce the traffic volume []. Again this represents a further increase in traffic load. These displayed challenges for existing bridges require a constant survey of the actual traffic loads to perform exact recalculations. A better knowledge concerning the real loads is necessary to maintain a sustainable highway bridge infrastructure.

Due to this reasons, Weigh-In-Motion-Systems (WIM) have been developed by various international projects, i.e. [3-5]. WIM is a system aimed at the detection of the true weights of vehicles. There are different kinds of WIM-Systems based on piezoelectric force sensors which are mainly deployed rectangular to the road lines. Alternatively to the piezoelectric ones, weighing plates exist which detect strains that are caused by bending moments. This is based on the working principle of strain gauges. Not all of those systems have the capability to quantify individual axles as well as the total vehicle loads. For more detailed explanations about the currently established WIM-Systems please refer to [3-5]. Due to the random nature of traffic, the registration of traffic data, such as traffic volume, traffic composition, vehicle velocity and especially the vehicle weight is only productive observing actual day-to-day traffic is observed.

Recently, a new WIM-System has been developed by [6], which focuses on the possibility to measure dynamic axle loads by installing an expansion joint also into a WIM-System. This new system has the benefit that every vehicle has to cross the expansion joint and that, due to its very suitable size, the measuring of any vehicle's individual axles with high accuracy is possible. This advantage results from the construction, being neither too long, so that two axles might excite it simultaneously, nor too short, so that parts of the wheel are not completely on the expansion joint. For the basics of traffic load measurement at expansion joints considering road unevenness induced wheel force fluctuations, reference is made to the work of *Friedl* [6].

2 Description of the functionality of a swivel joist-expansion joint

Resulting from temperature effects, bridges vary their length which has to be compensated for by expansion joints. Those expansion joints are therefore installed transverse to the bridge's longitudinal direction at the beginning and at the end of the bridge to enable the vehicles' transition to the bridge abutments. In the specific case of an integral bridge structure those expansion joints would not be needed.

The preassigned expansion joint's gap width depends on the relative displacement between the bridge and its abutment. In general, longer bridges require also larger width of the gap. The specific joist expansion joint considered within this paper represents an enhancement of the regular expansion joints to reduce the fatigue load.

In typical constructions of swivel joist-expansion joint the lamellas are transversally installed to the lanes. These lamellas are a kind of I-sections which are positioned in a previously determined interspace due to reasons of driving comfort, acoustic emissions, and safety regulations. The head of these I-sections is built in a special geometric form to hold a waterproof sealing profile in between the I-sections. Those lamellas are supported via a slide bearing by swivelling cross bars which are arranged obliquely to each other. This oblique arrangement of the joists is the typical characteristic of swivel joist-expansion joints. So, the lamellas with regard to the cross bars and cross bars themselves with regard to the structure's edges, are both bedded on an elastic slide bearing. A potential take-off of these components from the bedding is prevented by a pre-stressed elastomer spring.

The cross bars acting as traverses to all lamellas convey the vertical loading resulting from the vehicle crossing into a sliding bearing positioned within the (yellow) joist box which is encased in concrete in both, the bridge and its abutment. Those sliding bearings act as supports for the entire expansion joint.

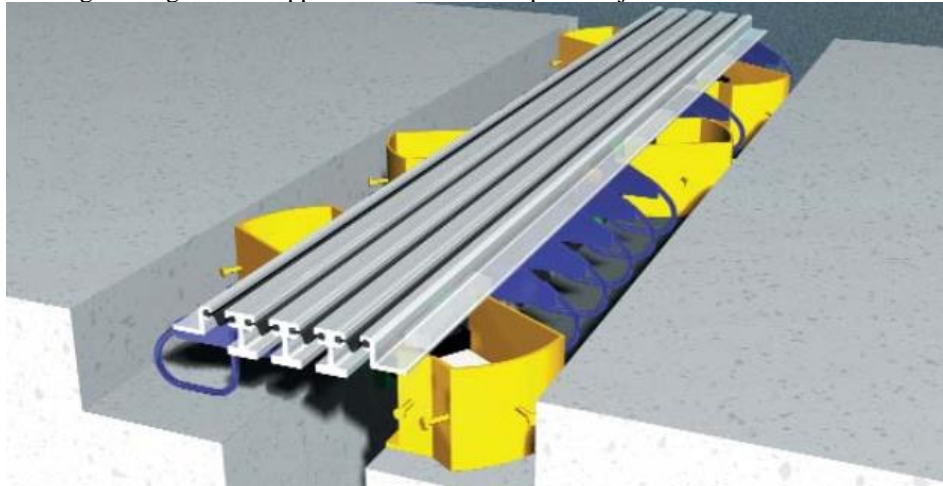


Figure 1: Swivel Joist-Expansion Joint [7]

3 Measurement Instrumentation of the Swivel Joist-Expansion Joint

For the specific expansion joint under consideration, two CFW-force sensors have been installed underneath the previously explained supporting sliding bearings in the joist boxes. Those linear force sensors measure the vertical load of the crossing traffic based on the piezo electrically action principle. In total, twelve of those force-measuring-rings have been installed per traffic lane. To avoid interactions between the two traffic lanes of the bridge, each one is constructed with its own expansion joint.

The principle of the piezo electrically force sensors is based on varying electric capacities of individual charge carriers. This change resulting from the variations of the intervals between the charge carriers is registered as measurement signal. With the help of a charge amplifier, the registered signals are being transferred into a simple voltage signal. The calibration of the force sensors was carried out through two point-calibration at the sensor's electrical sphere of action ($\pm 10V$) to achieve linear proportionality between voltage and force. Hence, $\pm 10 V$ represented $\pm 75kN$. Caused by the electrical setup, a certain numerical drift could not be completely avoided during the measurement intervals which were therefore set to ten minutes each. Due to this principle of operation, the sensor sensitivity is independent of the range of the maximum force to be measured by the sensor. Thus, the Sensitivity η of these sensors is the proportion between measurable voltage difference ΔU and the according force difference ΔF .

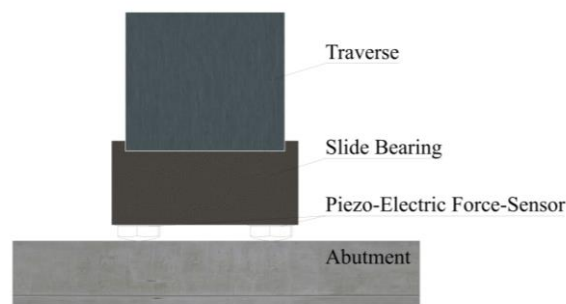


Figure 2: principal cut through the modified sliding bearing with the installed force-measuring rings

Additionally, a displacement sensor was also installed to measure the actual distance of the gap width between the expansion joint's supports on the bridge side and on the abutment side, because of its influence on the following analysis.

4 Signal Analysis and Identification of Axles and Trucks

The initial raw data is being stored on site in two formats: the original catman and, additionally, in a bin-file. A single raw data file ranges over a time period of exactly ten minutes. The reason for this is due to reducing the initial data to a manageable size which is caused by a sampling frequency of 2500 Hz. As an initial step of the evaluation procedure, all the force sensor signals per traffic lane must be summed up. The result of this is exemplarily display in the following figure 3.

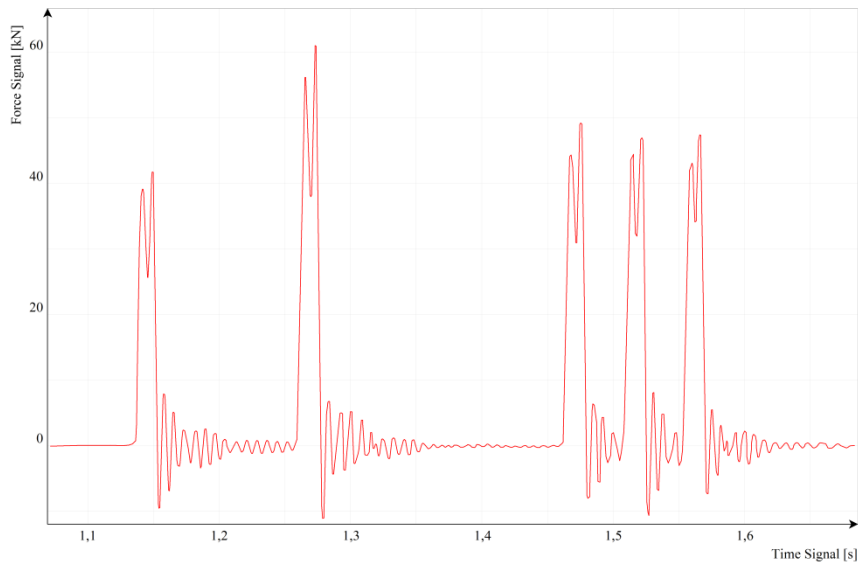


Figure 3: Summated force signal of a five-axle truck (ten-wheeler)

The Figure 3 displays the summation of all twelve force sensor signals for the time of a single five-axle-truck crossing. For truck crossings with a velocity greater than thirty kilometres per hour the axle amplitudes can be seen with clearly visible two, three or more peaks visible in the previous picture. Those peaks will later be detected as individual maxima. This effect can be explained via the following points:

- The crossing of an axis or the resulting force curve is comparable to the line of influence of a single-span beam. This can be traced back to the rolling over process of the axle, as the force sensors on the edge beams experience the maximum load on the axle with a time delay, like the load under a travelling force on a single-span beam.
- An additional influence results from the non-equivalent distribution of the load on all force sensors of the individual elastomer bearings, which leads to a certain torsional effect.
- Finally, the hardly determinable dynamic behaviour of the truck itself emphasizes these small sharp peaks through rolling and pitching movements.

The actual analysis of the thus obtained raw data is done via the Bin-files and MATLAB at the institute of structural engineering at the University of the German Armed Forces Munich. Therefore, the relevant data channels of the structured BIN-files are extracted into the workspace. Those relevant channels are composed of the one time signal K00, twelve force signals K01-K12, and five cable pull sensors W1-W5. To achieve an entire force signal of a truck's axle crossing, all twelve force sensor signals have to be summed up. The result of this summation is depicted in figure 9 and shows a clearly identifiable ten wheeler. If this is done for a whole ten minute interval of random traffic, then a force signal similar to them shown in figure 10 can be plotted with vertical line signalling the crossing of a vehicle which might either be an automobile, a truck or the after effects of a trucks crossing.

The currently analysed data of random traffic contain as part of December 2016 671 measurement intervals (= 6710 minutes) with a total storage size of 268.5 GB. However, due to a measurement error, this certainly does not correspond to the entire month of December.

For automatically filtering the relevant characteristics of truck crossings from the huge amount of initial data, the following list of criteria were implemented and applied to identify individual axles.

To initially differentiate between measurement noise and actual signal coinciding with a vehicle's axle, a detection boundary of 2.5 kN was implemented, which you can see in figure 4. Below this threshold, the entire signal is being ignored. The selection of the specific boundary value resulted from manual evaluation of multiple measurement intervals. Yet, as soon as the force signal crosses this threshold an event is detected and the gradient based search for peak value is initialized. Then all maxima are stored until the force signal drops again under the fixed threshold value. However, only the absolute maximal value is stored as the actual peak value of the event.

As a further benefit, this boundary value avoids too many considerations of every lightweight vehicle which is initially assumed to be neglectable in comparison to the much heavier trucks.

In addition to the peak coordinates, the time and force coordinates of the initial and final crossing of the preset threshold has been saved too.

Based on the adoption of the ever applicable method 5 described in report [20], both each loading's beginning as well as its ending resulting from an axle crossing can be detected. By additionally relating the loading's duration with width of the joist joint gap, the axle velocity may be calculated via velocity equation. The accuracy of this velocity estimation can further be increased by introducing the distance measured through the cable pull sensor into the equation.

To achieve a differentiation between four-wheeled trucks and heavy personal vehicles, additional filter criteria have been introduced. At first a minimal load of 10 kN (= 1 tonne) per axle has been prescribed, because truck axles with a weight less than this are not realistic as shown by [BG]. Yet, this will not hinder the detection of personal vehicles in general. This results from the steady increase of personal vehicle's size and weight, specifically for SUVs. During further developments, also these problematic will be addressed via analysing the spatial gaps in between the detected axles.

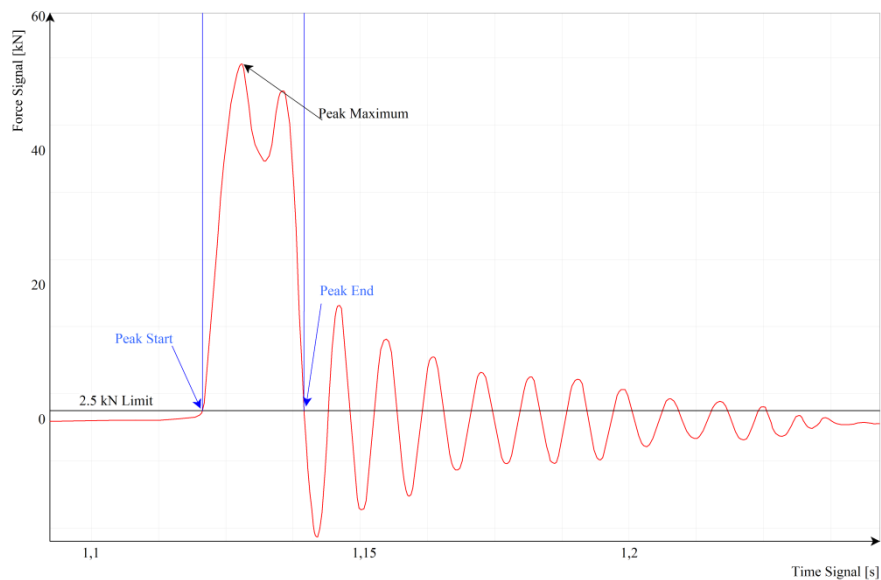


Figure 4: Pairs of values for peak characterization of an axis

The algorithm has been verified through two manual BIN-file evaluations of the ten-minute measurements. These manual evaluations and the subsequent comparisons showed that the results obtained by the algorithm matched those of the manual one within an error margin of 1-2%. In average, this corresponds to a misidentification of a single truck per ten-minute cycle.

In addition, scheduled overrun tests were carried out with different speeds and trucks whose static axle load is known. This is a first approach to assess a dynamic factor for the existing system without having to respond to the complex vehicle dynamics. The corresponding regression curve of the dynamic factor is shown in Figure 5. This factor has already been taken into account in the following evaluations.

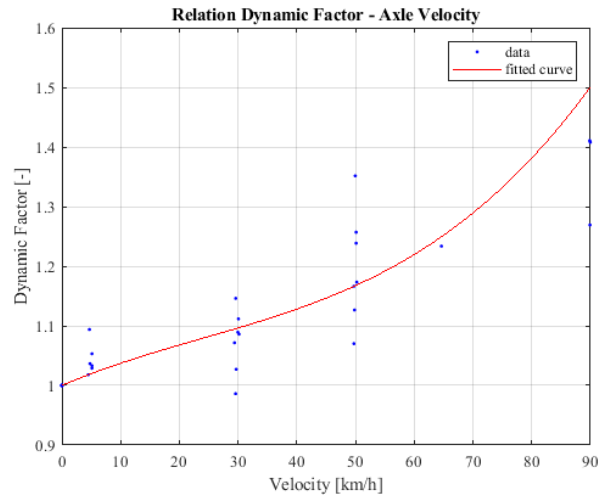


Figure 5: Relation of the Dynamic Factor to each Axle's Velocity

5 Statistical Depiction of the collected data in comparison with Eurocode 1991-2

The current evaluation contains data of nearly three months which coincides with a total of 4200 ten minutes measurements. During this complete measurement time of 42000 minutes 116356 freight vehicles were detected and assigned to the four different vehicle classes. This classification is shown within the following figure 6.

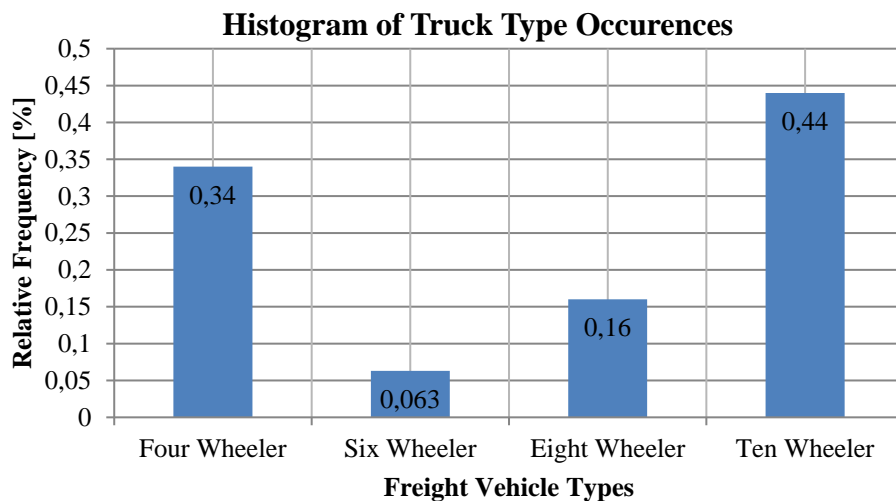


Figure 6: Frequency distribution of the respective truck types based on the evaluation

By extrapolating this data over a whole year, a total number of approx. 1.5×10^6 trucks can be expected travelling on the right-hand lane. According to DIN EN 1991-2 [11] appendix C, this corresponds to a motorway with a traffic volume containing a high amount of commercial road vehicles.

Though this apparently represents already quite valid data, specifically the identified four wheelers may still contain some heavy personal vehicles, such as SUVs, due to their axle load being similar to that of a rather unloaded truck. This problem further will be approach as part of the following studies on the algorithm.

6 Explanation of current heavy traffic modelling

In general, vehicles are characterized by their number of axles, the distances in between the axles, and each axle's loading. During previous works [15], [16] and [18] two methodologies have been developed to specify the load distributions of axles.

6.1 Description of every axle via its individual probability density function (PDF)

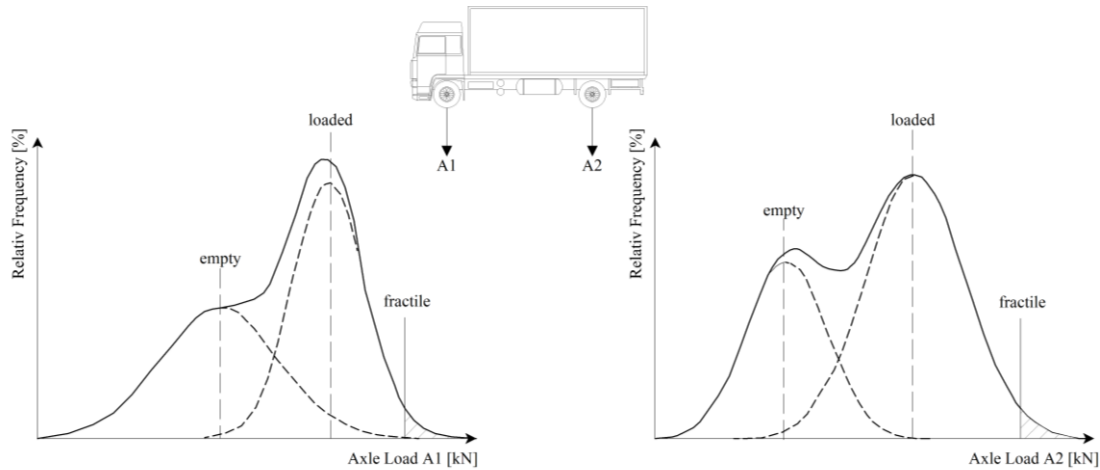


Figure 7: Literature Axle Load Modelling based on Normal Distributions

For this modelling approach, each axle of any truck type is represented by a specific PDF. E.g. for a four wheeler there exist two PDFs one for the front axle and one for the rear axle as shown in the figure 7 above. Yet, during traffic modelling this consequentially results in a lacking stochastic dependency in between a trucks axles, and may therefore generate unrealistic vehicles. A possible solution to this dilemma could be yielded by introducing the correlation between all axles of a truck [19].

6.2 Assignment of a PDF to the total truck load and distinction between axles via present coefficients

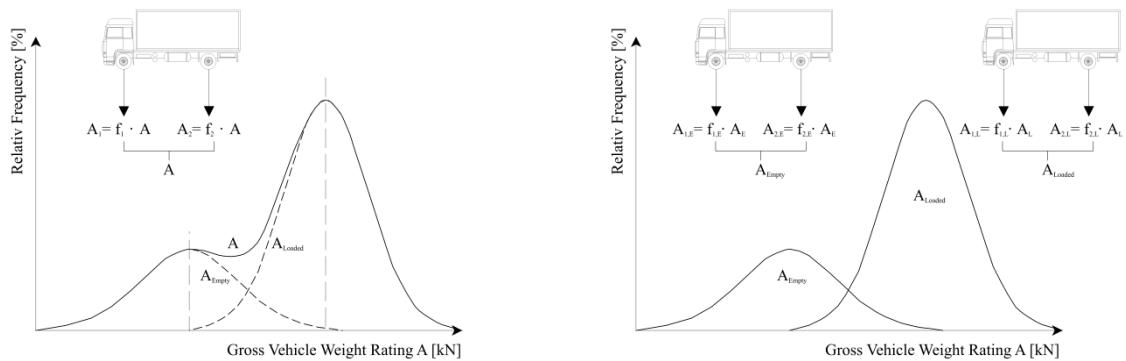


Figure 8: Literature Vehicle Modelling via bimodal, yet statistically unrelated distributions

Here, a PDF is assigned to the total truck load. So, at first a random truck load is generated and afterwards that load is allocated to the single axles via statistically predetermined factors (f_1, f_2, \dots). To further differentiation between loaded (L) and unloaded (V) vehicles, a more detailed list of factors has been developed in [15],[18] using ($f_{1V}, f_{2V}, \dots, f_{1L}, f_{2L}, \dots$), shown in figure 8 on the left. Alternatively, two PDFs could be employed to separately substitute unloaded and loaded trucks which are shown in figure 8 on the right. The latter modelling approach has been the basis for the statistical vehicle evaluations in multiple research works, such as [14], [15], [19].

6.3 Discussion of the current modelling

This certainly presents a usable way of modelling traffic, yet in the opinion of the authors and supported by the newly measured data, a more detailed and well-founded analysis seems to be possible.

Main challenges are given by the bimodal distribution functions and the reasonable distinction between loaded and unloaded vehicles. Thus, the following part of this paper focuses on the statistical distribution and correlation of the measured individual axle loads with reference to the total truck loads. Therefore, it is intended to improve the current modelling by identifying more appropriate distribution functions for all truck types, their axles as well as their statistical dependencies between one another which may be finally stated based on their correlation coefficients.

Due to new and detailed measurement results, a more in depth modelling will be described in the following.

7 Statistical Analysis of the gather data

7.1 Introduction to the proposed traffic load modelling approach

Through the obtained currently data with dynamic effects and their previously explained evaluation, the aim is to devise a reasonable probabilistic traffic load collective including a maximum of actual correlations to factually approach real traffic. The steps towards this goal are performed by the following descriptive statistical description of the data, and the subsequent Therefore, all identified trucks over the entire evaluated time period are being statistically interpreted with respect to their total loading.

7.2 Evaluation of the measured traffic data focusing on the total vehicle loads

At first, all trucks were separated into the types of trucks, and, subsequently, every truck axle was summed up to obtain each trucks total load. This load could then be used to create a histogram of the trucks` total loading for each truck type. Those are shown below via plots containing the relative frequencies of the occurrences within the subplots (1 – four wheeler, 2 – six wheeler, 3 – eight wheeler, 4 – ten wheeler) of figure 9. The expected fluctuation range of the underlying classes (bins) was calculated based on the definition of Scott [10] shown by the following equation

$$h = \frac{3,49 \cdot \sigma}{\sqrt[3]{n}} \quad (7.1)$$

with n as the number of data points, and σ representing the standard deviation. Yet, it should be noted, that this rule holds only for normally distributed data. However, this is considered to be applicable for the present work in accordance with the existing literature. A further argument to use normally distributed functions as a first step for the analysis provides the JCSS Probabilistic Model Code [11], and this modelling approach is assumed to be sufficiently accurate. To adopt the current heavy traffic modelling described within the preceding section, an empirical boundary value was selected to divide the histograms of the truck types into lightweight and heavyweight freight vehicles. As an example, the subplots of the following pictures show both histograms for unloaded and loaded trucks, in total most frequent, ten wheeler. The following figure 9 depicts the histograms of all four truck types. In each case a clear distinction between heavily loaded and rather unloaded trucks is visible.

For a four-wheeler, the majority of total vehicle weights occurs below 4 tons. The heavier four-wheelers ranging regularly up to 13 tons are distributed over a larger interval of loading. Beyond some exceptions occur. In case of six-wheelers, lighter trucks can be assumed below 5 tons. Yet, the larger number of vehicles is determined with a loading around 10 tonnes and an additional peak at about 15 tons. The appropriates display of different this can be observed for the eight-wheelers. Here, two very clear functions of shapes consistent with normal distribution functions are recognizable. The lower (unloaded) one at around 4.8 tons, and the higher (loaded) one at about 13 tons. For the ten-wheeler, the standard type with a high occurrence rate, as described in section 5, is apparently depicted by the main relative frequency maxima. The left one between 12 and 13 tonnes represents the rather unloaded trucks, and the steep right one above 24 tonnes shows the loaded freight vehicles. Over 30 tonnes, the recognized heavy-duty vehicles are assumed to be fully loaded with respect to the trucks` loading area as well as with regard to the weight of loading. Furthermore, as a result of the definitions applied within the evaluation algorithm, special-purpose vehicles have not yet been separated within all four vehicle classes.

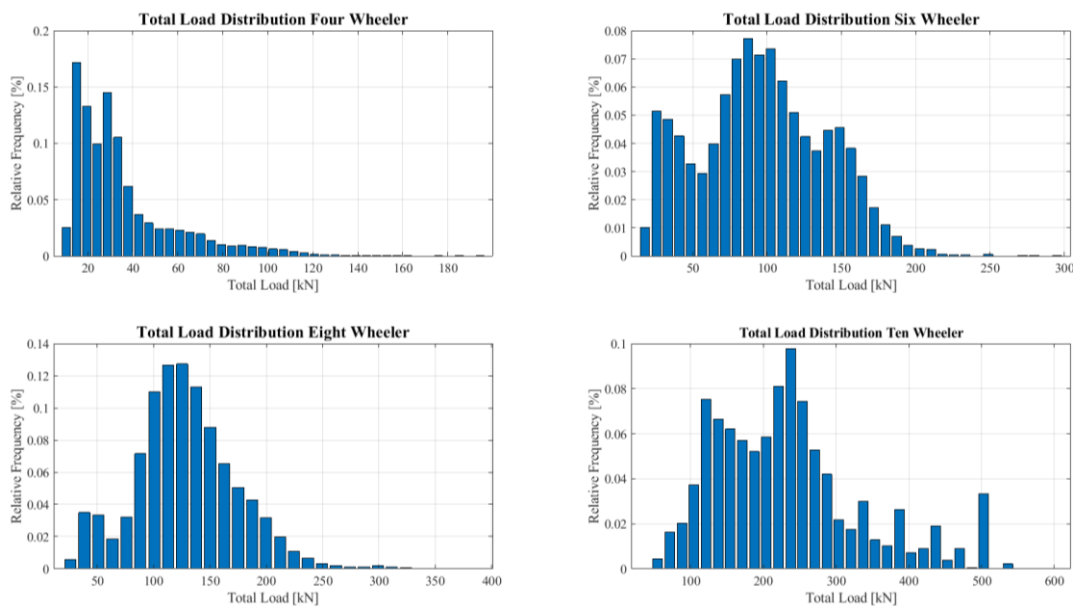
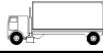


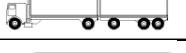



Figure 9: Histograms for the four classified freight vehicle types

The following table contains the prescribed standard mean values for the truck types tested in accordance with the Road Traffic Licensing Regulations in Germany.

Table 1: Mean values of empty and fully loaded trucks

Truck Type	Average unladen weight [kN]	Total average weight [kN]
	50	180
	80	280
	100-130	350
	100-150	450
		

7.3 Descriptive Statistical data evaluation

For the evaluation of each measured data, descriptive statistical methods have been exercised. Below, these are briefly summarized and characterized via their underlying equations:

- calculation of the sample's mean

$$\bar{x} = \frac{1}{n} \sum_{i=1}^n (x_i) \quad (7.2)$$

- determination of the sample's variance

$$s^2 = \frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})^2 \quad (7.3)$$

- and the resulting standard deviation

$$s = \sqrt{\frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})^2} \quad (7.4)$$

- computation of the sample's covariance based on a multidimensional data set (in particular, any truck's axles)

$$c_{XY} = \frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y}) \quad (7.5)$$

- computation

$$r_{XY} = \frac{c_{XY}}{s_X \cdot s_Y} \quad (7.6)$$

7.4 Characterization of Axle load correlations

The following figure displays the recognized axles' loads in form of histograms for the four wheeler. Both distributions portray a leftist asymmetric skewness which indicates that both axles' loads are significantly influenced by the vehicles empty weight. In either case, the most frequent occurrences lie within an interval ranging from 8 to 17 kN. In accordance to relevant literature [], axle loads are usually modelled via a normal distributed function. On the basis of the given distributions, a more reasonable approximation of the data may result from fitting either a skewed normal distribution function, or a lognormal distribution, or an extreme value distribution. For the subsequent initial data assessment, however, such an approximation will not yet be implemented, but rather the proceeding according to literature is adopted as sufficiently accurate.

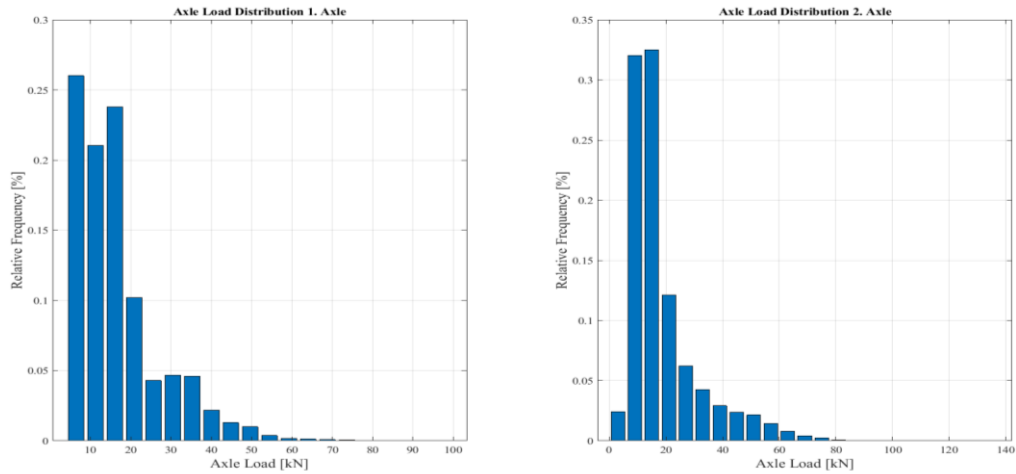


Figure 10: Histograms for the Axles of the recognized Four Wheelers

Furthermore, the correlation between the axle loads is depicted in the next figure. In its upper two subplots, the relations between the first and the second axle to the total vehicle load are displayed. Below that, the left subplot shows the relationship between the two axles themselves. And finally at the right side, all dependencies between axles and the resultant vehicle load are illustrated via a three-dimensional graph. These scatter plots visualize the interrelation among the derived data set, and can be expressed mathematically through the statistical parameters provided in section 7.3.

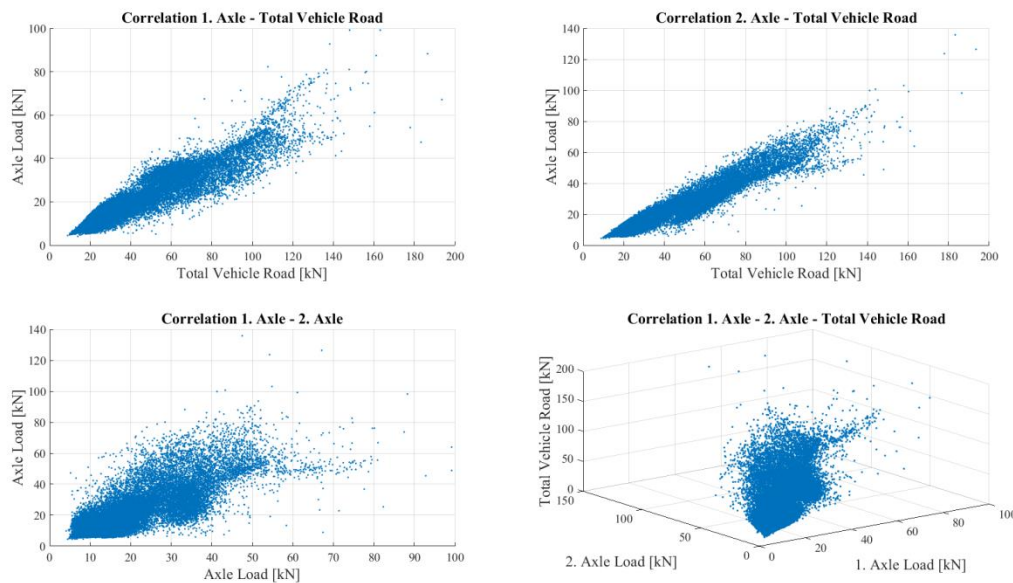


Figure 11: Graphical representation of the dependencies between the axles and to the total weight for a two-axle truck

Now, table 2 comprises the calculated attendant statistical parameters. Herein, all correlation coefficients reach values greater than 0.83, and, therefore, point towards a firm correlation among all the contemplated loads.

Table 2: Parameters of the individual distributions and the corresponding correlation coefficients

Four Wheeler				
Distribution			Correlation	
Set of Data	Mean μ [kN]	standard deviation σ [kN]	Set of Data	correlation coefficient r
Axle 1	16,63	10,54	Axle 1 - Axle 2	0,83
Axle 2	18,39	13,02	Axle 1 - TVL	0,95
Total Vehicle Load (TVL)	35,02	22,54	Axle 2 - TVL	0,97

The entire preceding evaluation process has been performed for any truck type, yet – for matters of this work's extent – the detailed procedure was only explicated for the four wheeler.

8 Proposed Modelling Approach for a consistent Traffic Load Collective

8.1 Automated Fitting of multi-dimensional Gaussian Distributions to the Correlated Data

As described within the foregoing section, all the correlated axle data of real day-by-day traffic have been obtained and have been evaluated. In addition and as described in section 7.2, an inherent difference can be seen within the histogram charts depicting the total vehicle loads. Thus, a differentiation of loaded and unloaded vehicles can be accomplished analogously to the literature sources in section 6.3 via bimodal distributions. The herein proposed expansion of this model considers the stochastic relation of the axles among themselves for both states of vehicle loading by introducing the obvious previously described correlations in between axle loads and their respective contribution to the total vehicle load.

At first, the associated stochastic correlations have to be approximated in form of multi-dimensional Gaussian distributions. This can be achieved through the predefined MATLAB function “fitgmdist” [21] based on the theoretical as described in [20]. This MATLAB function performs a multi-dimensional fitting on the n-tuple data set of each vehicle type. Through this fitting, the underlying data sets are differentiated into two Multi-Normal Gaussian Distributions. Their general probability density function is given in equation (8.1).

$$f(x) = \frac{1}{(2\pi)^{\frac{n}{2}} \sqrt{\det \Sigma_{XX}}} e^{(-\frac{1}{2}(x-M_x)^T \Sigma_{XX}^{-1} (x-M_x))} \quad (8.1)$$

Furthermore, the multi-dimensional parameters for this probability density function are represented in (8.2) by the mean vector M_X and by the covariance matrix Σ_{XX} .

$$M_X = \begin{bmatrix} \mu_1 \\ \mu_2 \\ \vdots \\ \mu_n \end{bmatrix}; \Sigma_{XX} = \begin{bmatrix} Var[X_1] & & & sym. \\ Cov[X_2, X_1] & Var[X_1] & & \\ \vdots & \vdots & \ddots & \\ Cov[X_n, X_1] & Cov[X_n, X_2] & \dots & Var[X_1] \end{bmatrix} \quad (8.2)$$

8.2 Stochastic Characterisation of the obtained Modelling for single freight vehicles

From the resulting computational distribution objects in MATLAB, those characterising parameters for Multi-Normal Distributions can be directly obtained, and they provided within the following equations (8.3)-(8.10) for all freight vehicle types (with M_4 representing the four-wheeler, and so forth).

$$M_{4 \text{ empty}} = \begin{bmatrix} 11,83 \\ 12,48 \end{bmatrix}; \Sigma_{XX} = \begin{bmatrix} 19,74 & 15,50 \\ 15,50 & 21,91 \end{bmatrix} \quad (8.3)$$

$$M_{4 \text{ loaded}} = \begin{bmatrix} 28,69 \\ 33,19 \end{bmatrix}; \Sigma_{XX} = \begin{bmatrix} 136,80 & 110,42 \\ 110,42 & 233,56 \end{bmatrix} \quad (8.4)$$

$$M_{6 \text{ empty}} = \begin{bmatrix} 22,00 \\ 19,83 \\ 17,48 \end{bmatrix}; \Sigma_{XX} = \begin{bmatrix} 142,65 & 89,18 & 50,45 \\ 89,18 & 82,27 & 38,60 \\ 50,45 & 38,60 & 48,26 \end{bmatrix} \quad (8.5)$$

$$M_{6 \text{ loaded}} = \begin{bmatrix} 38,74 \\ 45,42 \\ 38,82 \end{bmatrix}; \Sigma_{XX} = \begin{bmatrix} 140,77 & 72,83 & 79,25 \\ 72,83 & 202,27 & 77,48 \\ 79,25 & 77,48 & 240,21 \end{bmatrix} \quad (8.6)$$

$$M_{8 \text{ empty}} = \begin{bmatrix} 37,77 \\ 40,26 \\ 26,60 \\ 28,67 \end{bmatrix}; \Sigma_{XX} = \begin{bmatrix} 17,07 & 34,50 & 16,59 & 17,50 \\ 34,50 & 201,52 & 81,42 & 85,28 \\ 16,59 & 81,42 & 87,70 & 89,60 \\ 17,50 & 85,28 & 89,60 & 99,30 \end{bmatrix} \quad (8.7)$$

$$M_{8 \text{ loaded}} = \begin{bmatrix} 29,52 \\ 36,25 \\ 26,61 \\ 29,36 \end{bmatrix}; \Sigma_{XX} = \begin{bmatrix} 215,41 & 206,67 & 157,32 & 155,06 \\ 206,67 & 395,81 & 191,90 & 189,83 \\ 157,32 & 191,90 & 261,88 & 214,10 \\ 155,06 & 189,83 & 214,10 & 318,30 \end{bmatrix} \quad (8.8)$$

$$M_{10 \text{ empty}} = \begin{bmatrix} 39,09 \\ 48,11 \\ 35,07 \\ 36,02 \\ 36,92 \end{bmatrix}; \Sigma_{XX} = \begin{bmatrix} 77,14 & 97,77 & 64,96 & 66,41 & 67,40 \\ 97,77 & 290,35 & 132,04 & 137,78 & 144,23 \\ 64,96 & 132,04 & 151,67 & 148,20 & 151,82 \\ 66,41 & 137,78 & 148,20 & 157,19 & 159,10 \\ 67,40 & 144,23 & 151,82 & 159,10 & 168,10 \end{bmatrix} \quad (8.9)$$

$$M_{10 \text{ loaded}} = \begin{bmatrix} 55,58 \\ 55,10 \\ 55,47 \\ 55,49 \\ 55,45 \end{bmatrix}; \Sigma_{XX} = \begin{bmatrix} 878,14 & 600,06 & 509,36 & 455,90 & 428,15 \\ 600,06 & 858,07 & 608,63 & 516,80 & 459,15 \\ 509,36 & 608,63 & 906,05 & 607,10 & 513,71 \\ 455,90 & 516,80 & 607,10 & 915,67 & 626,95 \\ 428,15 & 459,15 & 513,71 & 626,95 & 926,04 \end{bmatrix} \quad (8.10)$$

Based on these quantitative parameters any vehicle type can be modelled in accordance with the observed day-by-day traffic.

8.3 Stochastic Characterisation of the obtained Modelling for an entire Traffic Load Collective

To complete the required modelling parameters, also the component proportions between empty and loaded commercial vehicles are needed to achieve a reasonable Monte Carlo simulation of a traffic load collective for the specific case without violating the probability's finite measure. These component proportions for investigated truck types can also be directly taken from the generated MATLAB "gmdistribution" objects, and they are provided in table 3.

Table 3: Component Proportions to differentiate between loaded and rather unloaded trucks

Component Proportion		
Set of Data	empty	loaded
Four Wheeler	0.2850	0.7150
Six Wheeler	0.5894	0.4106
Eight Wheeler	0.4176	0.5824
Ten Wheeler	0.4537	0.5463

9 Discussion and Outlook

The increasing traffic volume in the Federal Republic of Germany and its bridges requires a regular adjustment of the traffic loads through measures described above. Based on the now applied stochastic descriptions of the measurement data, approximations of the currently normally distributed functions are still necessary for this.

It should also be noted that, despite the dynamic factor introduced, which was determined by the calibration runs described, these are dynamic loads. In a next step, this factor has to be developed with the help of a measuring vehicle under laboratory conditions, without taking into account the complex dynamic vehicle behaviour, as already explained in the literature [6]. Furthermore, after the described stochastic additions with the data obtained, the crossings of trucks over the expansion joint will be simulated using the finite element method for a better understanding the dynamic behaviour of the joint and to prevent its fatigue.

10 References

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