



## COMPARISON OF CONSTANT-SPAN AND INFLUENCE LINE METHODS FOR LONG-SPAN BRIDGE LOAD CALCULATIONS

Ainars Paeglitis<sup>1</sup>✉, Andris Freimanis<sup>2</sup>

*Institute of Transport Infrastructure Engineering, Riga Technical University,  
Kipsalas str. 6, LV-1048 Riga, Latvia*

*E-mails: <sup>1</sup>ainars.paeglitis@rtu.lv; <sup>2</sup>andris.freimanis\_1@edu.rtu.lv*

**Abstract.** Traffic load models available in building standards are most often developed for short or medium span bridges, however, it is necessary to develop traffic load models just for long span bridges, because the most unfavourable traffic situations are different. Weigh-in-Motion system data from highway A1 and A3 were used in this study. Measurement errors from data were cleaned using two groups of filters. The first group was based on vehicle validity codes recorded by both systems, if any circumstances might have influenced the measurements, the second group cleaned data using general filters for all vehicles and specific filters for trucks and cars. Additionally, vehicles were adjusted for influence of temperature. Data cleaning increased the average gross vehicle, so it could be considered as a conservative choice. Six traffic scenarios, each with different percentage of cars in the traffic, were made to assess the difference in loads from different traffic compositions. Traffic loads for long-span bridges were calculated using two approaches: the first assuming constant span length, the second, using influence lines from a bridge currently in design stage. Gumbel distribution were fitted to the calculate loads and they were extrapolated to probability of exceedance of 5% in 50 year period. Results show that influence line approach yield larger loads than those from constant-span. Both approaches result in loads larger than ones in *Eurocode 1* Load Model 1, however, increase might have been caused by an increase in vehicle weight.

**Keywords:** bridge, data cleaning, loads, load modelling, long-span bridges, Weigh-In-Motion (WIM).

### 1. Introduction

Short and medium span bridges make up by far the largest part of all bridges. Therefore, transport load models, given in building standards, usually model traffic loading on them. As accurate modelling of loads expected in the work life of a structure is an important condition for successful design, it is necessary to develop traffic load models just for long-span bridges.

Traffic data from Weigh-in-Motion (WIM) systems are usually used to calculate bridge loading, but the weather, sensor deterioration, and ambient temperature will influence measurements. Therefore, erroneous data have to be deleted before calculations. Getachew (2003) used cleaning based on axle count. However, they may exclude accurately measured vehicles as vehicles with the same axle count might not have the same properties e.g. car axle loads are much lower than those of two axle trucks used the same filters for all vehicles (OBrien *et al.* 2010; Paeglitis, Paeglitis 2014; Sivakumar *et al.* 2007). However, they may exclude accurately measured vehicles, as vehicles with the same axle count might not have the same properties. Car axle loads are much lower than those of

two axle trucks used with the same filters for all vehicles (OBrien *et al.* 2010; Paeglitis, Paeglitis 2014; Sivakumar, Sheikh Ibrakhim 2007). This approach could only be used if it is reasonable to exclude cars from data, for any suitable lower truck axle load or gross vehicle weight (GVW) limit will, surely, exclude all cars. Filters just for permit vehicles and cleaning based on three-step procedure, where truck weight changes are monitored, were proposed by OBrien *et al.* (2013) and Mai *et al.* (2013) respectively. Both methods require large data samples. Because the first uses accurate filters obtained by analysing significant amount of vehicles to exclude only permit-vehicles, not simply overloaded trucks. The second method compares each month to the same month from previous years, so it requires several years of data. Authors adopt similar approach using general filters for all vehicles and specific ones just for trucks and cars separately.

Live load models for long-span bridges have been interest of a couple of authors over the years. Getachew (2003) calculates loads by forming vehicles in queues, splitting queues in fixed length parts and dividing the total weight of vehicles in a part by the length of it. This

method is wasteful as each vehicle is considered only once. Approach by Lutomirska (2009) and Nowak *et al.* (2010) forms similar queues and calculates loads in similar manner, except the length of the following vehicles that is added to the first length of vehicle till total is longer than chosen span length. Then, the GVW sum of those vehicles is divided by their total length. First, vehicle is removed, another one added and calculation is repeated until the end of the queue. Total length, however, can significantly exceed chosen span length if added vehicles are longer than those removed are. Leading to increased loads, since total GVW is greater but span-length remains the same. Vehicle queues were formed from four artificially made traffic scenarios by Hwang *et al.* (2012). They calculated loads in similar fashion only span lengths were chosen from two long-span-bridge influence line lengths. Previously described, approaches assume that each contribution of vehicle to the bridge load is the same and do not consider the impact of the position on the span. Different traffic simulations were used by Chen and Wu (2011), Hayrapetova *et al.* (2012), and Enright *et al.* (2013) and loads in each simulation step were calculated directly from influence lines. These simulations require complex software that may not be available to efficiently simulate long periods.

The aim of this study is to compare constant-span-length and influence line approaches for long-span bridge load calculation. Assess variability in calculated loads and compare them to Load model 1 (LM1) in *Eurocode 1: Actions on Structures – Part 2: Traffic Loads on Bridges*.

## 2. WIM data cleaning

### 2.1. WIM system and raw data

Data were obtained from two WIM systems in Latvia. The first one was installed on highway A1, the second one was on highway A3. Both used piezoelectric sensors installed in the surface of pavement to measure parameters such as axle loads, axle spacing, vehicle lengths, ambient temperatures etc. Additionally, systems automatically sorted vehicles in one of 22 classes. Time stamps were available with a precision of 0.01s. A1 data were from period between 14<sup>th</sup> July 2013 and 15<sup>th</sup> January 2014, A3 was between 5<sup>th</sup> September 2013 and 15<sup>th</sup> January 2014. Measurements contained 2'127'403 and 542'941 respectively. Some of the data were erroneous; therefore, authors applied various filters described in the next chapters.

### 2.2. Data cleaning based on validity codes

WIM systems checked each vehicle's measurements for any circumstances that might have influenced them. Upon detecting such circumstances, system recorded one or more out of 18 validity codes.

Four codes (Sensor Error, Loop Failure, Sensor Failure, Sensor Count Miss Match) indicated an error in sensor. Vehicles with first three codes had unreasonable weights and/or lengths e.g. axle spacing of 29 cm or 49 kg axle weight, so they were deleted. Not all vehicles with the fourth code – Sensor Count Miss Match – had unreasonable properties. They were not touched in this step, but left

for other filters. This has a potential of introducing some bias in the data. Filtering all vehicles with axle loads or gross weight under some limit was not an option, because limit that is too low would leave erroneous trucks in data, but limit set too high would delete cars, that were needed for further calculations. Deleting data based on validity codes is a middle ground approach. Since it selects vehicles only if WIM system reported an error. A better approach would probably be to develop cleaning rules for each separate class or to rehabilitate/substitute data, but development of such method is out of scope of this article.

Temperature Error was given for some vehicles with unreasonable temperatures, but not all. Since unreasonable temperatures were examined at a later stage of data cleaning, vehicles containing this message were kept.

Two different validity codes were given depending on vehicle's position in lane. The first one (Reverse Direction) if it was driving in the wrong direction, the second one (Straddling) if it was changing lanes. Lane was changed for vehicles with the first code. The second code indicated that only wheels on one side were weighted, so straddling vehicles were deleted.

Codes – GapLessThan2s, GapLessThan5m – showed vehicles that drove unusually close to each other. This indicates that a single vehicle might have been incorrectly split in two by the WIM system or that drivers were reckless. Since not all the vehicles with these codes might not have been erroneous, they were left for other filters.

Vehicles with speed related codes (Speeding Site, Accelerating, Braking) were left in the data. While accelerating and braking can change the impact coefficient, thus changing the load on the sensor, WIM system were supposed to take in account the dynamic component of axle loads. Thus, changes due to accelerating and braking should be negligible and vehicles with these codes were not deleted. Speeding itself does not influence traffic loads, however, abnormally high speeds for heavy trucks can indicate an error in measurements. Since cars can easily achieve higher speeds than trucks, this code was not used for cleaning but a filter for truck speed was used.

Is Draw Bar Trailer and Unclassified Vehicle were two codes used to identify specific vehicles. Authors have no information regarding why there is a specific validity code for drawbar trailers, so they were left in the data. Unclassified Vehicle codes were used for very heavy vehicles that did not fit inside weight limits for any existing vehicle class and for all trucks with seven or more axles. Seven+ axle vehicles usually are permit-vehicles that are carrying oversized or overloaded cargo with an escort. They are not a part of everyday traffic as it is possible to close the bridge or provide gaps between them and the regular traffic, thus controlling maximum traffic load on a span. Because of extra control bridge, design standards commonly exclude permit vehicles from general-purpose load models and consider them separately. Authors considered every seven+ axle vehicle a permit-vehicle and deleted them; however, vehicles with less than seven axles were kept as they might have been simply overloaded trucks.

WIM systems gave four codes – Axle Weight Class Violation, Axle Weight Lane Violation, Gross Weight Class Violation, and Gross Weight Lane Violation – to vehicles breaching their class weight limits. As overloaded trucks are found in regular traffic these vehicles were left in the data.

### 2.3. Adjustment for influence of temperature

Both WIM systems recorded pavement temperature when a vehicle passed over sensors. Temperatures from

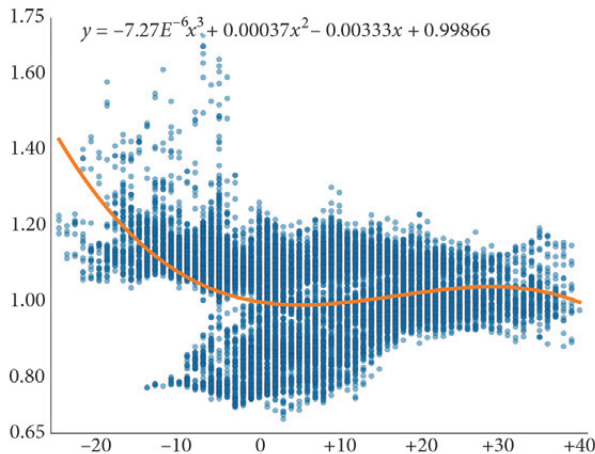


Fig. 1. Adjustment coefficients and describing function for A1 data

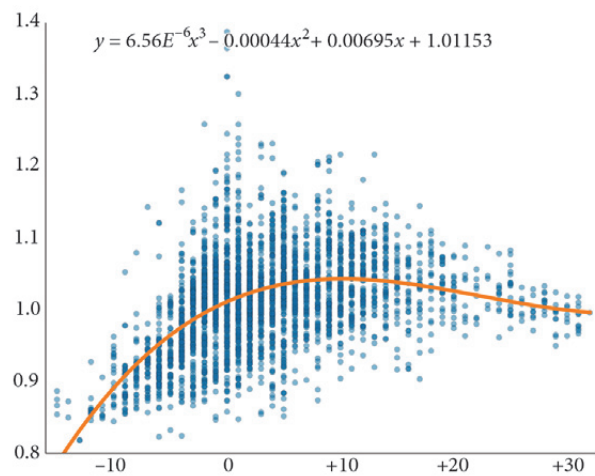


Fig. 2. Adjustment coefficients and describing function for A3 data

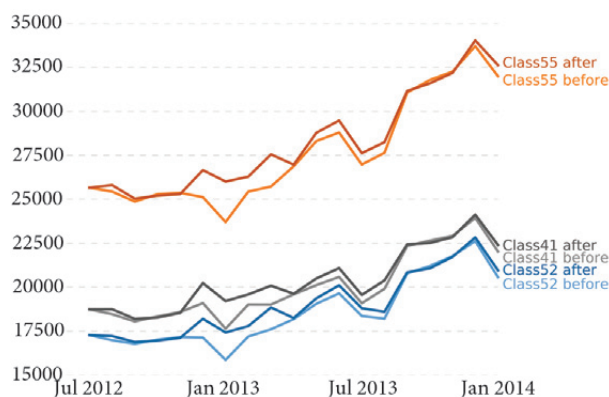


Fig. 3. Mean GVW in kg of Class 55, 52 and 41 vehicles before and after adjusting for temperatures influence – A1 data

-32 768 °C to +85 °C were recorded on highway A1. 93.02% of all vehicles were recorded with temperatures in interval from -26 °C to +42 °C, which were considered reasonable for local weather. All vehicles from 14<sup>th</sup> July 2012 until 8<sup>th</sup> August 2012 12:00 were recorded with temperature of -32 768 °C, which is the lowest possible value for 16bit signed integer. Authors assumed that this value was given because thermometer was malfunctioning or not installed yet, however, were not able to confirm this. Temperatures of +73 °C, +84 °C and +85 °C each had a single vehicle and were all assumed to be errors in measurements. 99.99% of all vehicles on A3 had an ambient temperature between -15 °C to +35 °C, four vehicles had -32 768 °C and additional four +74 °C. Most likely, these eight temperatures are measurement errors.

Measurements are influenced by changes in ambient temperature, because of the difference between asphalt concrete's and sensor's thermal expansion coefficient. Gajda *et al.* (2013) suggest that inaccuracies in GVW measurements can reach up to 40% of the true weight of the vehicle.

Approach used here is based on an assumption that average weight of a loaded Class 55 truck (two axle tractor + three axle semi-trailer) at every temperature should be equal to the average weight of all loaded Class 55 trucks and any differences are caused by changes in ambient temperature. Class 55 was chosen, as it is the most common of all truck classes. Vehicles with GVW between 50% and 95% percentiles were thought to describe loaded but not overloaded trucks. Authors' considered deleting vehicles with unreasonable temperatures, however, decided against it because a malfunction in thermometer does not mean that the rest of sensors were not working properly. It does, however, mean that adjustment coefficients cannot be calculated for them, so these vehicles were omitted for coefficient calculations and adjustment, but kept for load calculations.

All selected vehicles were ordered in chronological order and divided in 3-hour intervals. Then mean GVW and mean temperature (rounded to the nearest integer) in each interval was calculated. Adjustment coefficients were calculated by dividing mean GVW of all loaded Class 55 trucks with each interval's mean GVW. Calculated coefficients were plotted against interval's temperature and 3<sup>rd</sup> degree polynomial was fitted to the coefficients by minimizing squared error, they are shown in Fig. 1 for A1 data and in Fig. 2 for A3 data. GVW and axle loads of every vehicle were then multiplied by coefficient obtained from the fitted polynomial.

Three largest truck classes (based on number of vehicles in them) – Class 55 (two axle tractor + three axle semi-trailer), Class 52 (two axle tractor + two axle semi-trailer), and Class 41 (two axle rigid truck + one or two axle trailer) – were chosen to assess the impact of the adjustment. Mean GVWs in different months before and after adjustment from A1 are shown in Fig. 3, from A3 – in Fig. 4. The assumption was that average weight of a loaded Class 55 truck at every temperature should be equal to the average weight of all loaded Class 55 trucks and any differences are caused by changes in ambient temperature, so truck GVW should be closer to the mean value after the adjustment.



To determine whether the adjustment had worked authors calculated coefficient of variation (COV) of mean GVW for three above-mentioned truck classes before and after the adjustment. COVs are presented in Tables 1–2. Adjustment lowered coefficients in A1 data, but increased them in 2 out of 3 cases in A3 data. Limited number of data points could cause this. As A1 data are much larger and this method reduced GVW variability in them, it was decided to use it. However, further research that is out of the scope of this paper is needed to assess the usefulness of such adjustment.

#### 2.4. Other filters used

WIM systems sometimes failed to record an error or merged several vehicles together. To scrub data sets from such entries 3 groups of filters for different vehicle properties were used. General filters were used to remove vehicles with unreasonable properties e.g. wheelbase longer than length, and apply filters that can be used for all vehicle classes. Car filters and truck filters targeted only car or truck classes, because axle weight limits for cars and trucks have to be different. Vehicle length was limited to 23.75 m that is 18.75 m as legal limit and additional 5 m for inaccuracies in measurements; this filter was included as WIM systems could incorrectly merge two vehicles. Any vehicle with more than seven axles (all had Unclassified Vehicle validity code) were assumed to be a permit vehicle and deleted. Motorcycles (Class 0 vehicles) were deleted; since they are lightweight, this is considered a conservative choice. Lowest limit for car axles was set at 500 kg; authors concede that there could be lighter cars on highways. This choice was considered to be conservative and the difference in weight could be considered negligible. Minimum GVW for trucks was set at the legal limit – 3.5 t. Other filters were based on (Sivakumar *et al.* 2011).

General filters used (exclude if):

Class 0 (motorcycles);

- vehicle longer than 23.75 m;
- more than seven axles;
- wheelbase longer than length;
- any axle spacing less than 1 m;
- first axle spacing less than 1.5 m.

Car filters used (exclude if):

- any axle weight less than 500 kg.

Truck filters used (exclude if):

- any axle weight higher than 32 t;
- steer axle weight higher than 12 t;
- steer axle weight less than 2.5 t;
- any axle weight less than 1 t;

- GVW less than 3.5 t;
- speed higher than 160 km/h.

#### 2.5. Data after filtering

Two cleaning steps were performed – deletion based on validity codes and deletion based on filters for specific parameters. In addition, GVWs and axle loads were adjusted for influence of temperature. Out of 2'670'343 vehicles in raw data, 2'328'622 or 87% remained after cleaning. Table 3 shows minimum, average and maximum GVW of Class 55, 52 and 41 vehicles. It can be seen that data cleaning has had conservative influence – minimum and average GVW has increased for all three-vehicle classes on both highways.

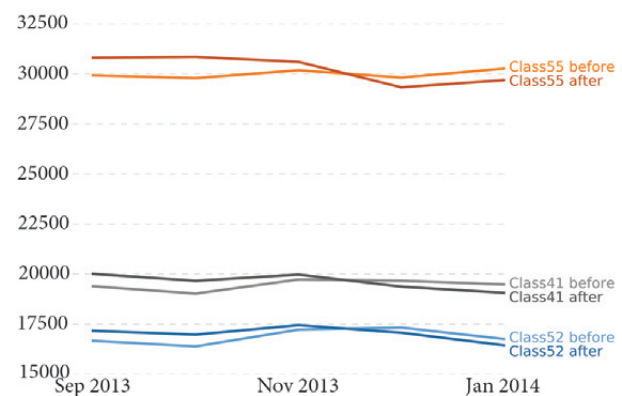


Fig. 4. Mean GVW in kg of Class 55, 52 and 41 vehicles before and after adjusting for temperatures influence – A3 data

Table 1. Coefficient of variation of mean GVW before and after the adjustment – A1 data

Vehicle class	COV of mean GVW	
	Before adjustment	After adjustment
55	0.110	0.100
52	0.105	0.095
41	0.093	0.086

Table 2. Coefficient of variation of mean GVW before and after the adjustment – A3 data

Vehicle class	COW of mean GVW	
	Before adjustment	After adjustment
55	0.007	0.023
52	0.023	0.022
41	0.014	0.021

Table 3. Minimum, average and maximum GVW for Class 55, 52, 41 vehicles before and after data cleaning

Vehicle class	A1						A3					
	55		52		41		55		52		41	
	Before	After	Before	After	Before	After	Before	After	Before	After	Before	After
Min	737	7463	410	6539	302	5171	1264	7839	613	7234	246	8348
Avg	27 506	28 215	18 523	19 190	19 663	20 992	29 812	30 367	16 767	17 410	19 365	19 984
Max	81 420	80 879	64 529	62 042	72 984	58 694	68 663	69 568	53 373	55 118	62 870	56 537

Cleaning decreased maximum GVW for A1 data, and Class 41 from A3, however, average GVW for these classes increased, so it can be assumed that impact of cleaning was conservative as average value is much more robust.

### 3. Load calculations

#### 3.1. Traffic scenarios

On highways with multiple lanes in a single direction, rightmost lane would have higher percentage of trucks than the rest, as cars would bypass slower trucks. In addition, the worst case scenario would occur if there are only trucks in the rightmost lane. Data available does not represent multiple lane traffic as they were from highways with a single lane in each direction. This is commonly solved by simulating new data or calculating loads for rightmost lane and using lane coefficients. In this study, we adopt the second approach, because software for traffic simulations was unavailable and lane with only trucks would serve as the most conservative case.

Six different traffic scenarios were made. Worst case – 100% of vehicles in the lane are trucks – and 5 others with cars added as 10%, 20%, 30%, 40% and 50% of total traffic. Scenarios hereafter will be denoted by percentage of cars in each – 0%, 10%, 20%, 30%, 40%, and 50%. Calculation of useable lane coefficients are out of the scope of this article, but 10%–50% scenarios are calculated to compare how loads would be reduced by different amount of cars in traffic.

As the bridge span increases congested traffic instead of free-flowing becomes the most unfavourable (Getachew 2003; Hwang *et al.* 2012; Lutomirska 2009; Nowak *et al.* 2010; Sedlacek *et al.* 2008). Authors were not able to obtain measured data about inter-vehicle distances in case of traffic jam. Therefore, it was decided to use a constant distance between two vehicle wheelbases. Other authors have used different values: Hwang *et al.* (2012) assumed 4.5 m distance between last axle of the leading vehicle and first axle of the following, Lutomirska (2009) used 7.62 m (25 ft) spacing between two vehicle wheelbases and Getachew (2003) used 2 m gap between two vehicles. For this study, it was assumed a constant distance of 5 m between leading last axle of a vehicle and first of following.

WIM data contains four different lanes, two from each highway. Authors considered them as separate samples, so load calculations and extrapolation was done for each separately. In original data, these lanes were denoted as Lane1 and Lane2 for each highway. To avoid confusion, A1 Lane1 will be referred to as Lane A, A1 Lane2 – Lane B, A3 Lane1 – Lane C and A3 Lane2 – Lane D.

A queue of vehicles, with a set distance between them, was formed for each day. Method used to include cars in traffic assigned a random number to each car and deleted those below threshold, which was based on the percentage of cars in a considered scenario. It introduced some randomness in calculations as car might break up a group of trucks. However, trucks were not deleted, only spread further apart and span lengths are large enough to still have a single group of trucks on them. In addition, queues were pushed over span and loads were calculated for each step, so all the vehicles in a single group were on a span in at least one of the steps. This should have only minor impact on calculated loads. Randomness in car deletion might change calculated loads as heavier cars might be deleted and lighter kept, however, car gross weight is much lower than that of the trucks thus effect on loads should be negligible.

#### 3.2. Calculation of uniformly distributed loads

Traffic loads for long-span bridges were calculated using two approaches. The first was similar to the one used by Lutomirska (2009) and was done for span lengths of 200 m to 600 m. Gross weight and wheelbase (with 5 m distance between two wheelbases) of following vehicles in a queue was added to the first till the sum of wheelbases (total length) was longer than the span length. Total gross weight was then divided by total length resulting in the first uniformly distributed load (UDL). First vehicle's gross weight and wheelbase was then subtracted from totals and total length was again checked against the span length. If it was shorter, then next vehicle in queue was added, if it was longer then next UDL was calculated. Calculations were done until the end of a queue and repeated for each day.

The second approach used influence lines for a cable-stayed bridge currently in a preliminary design stage near Jēkabpils, Latvia, showed in Fig. 5. Authors selected

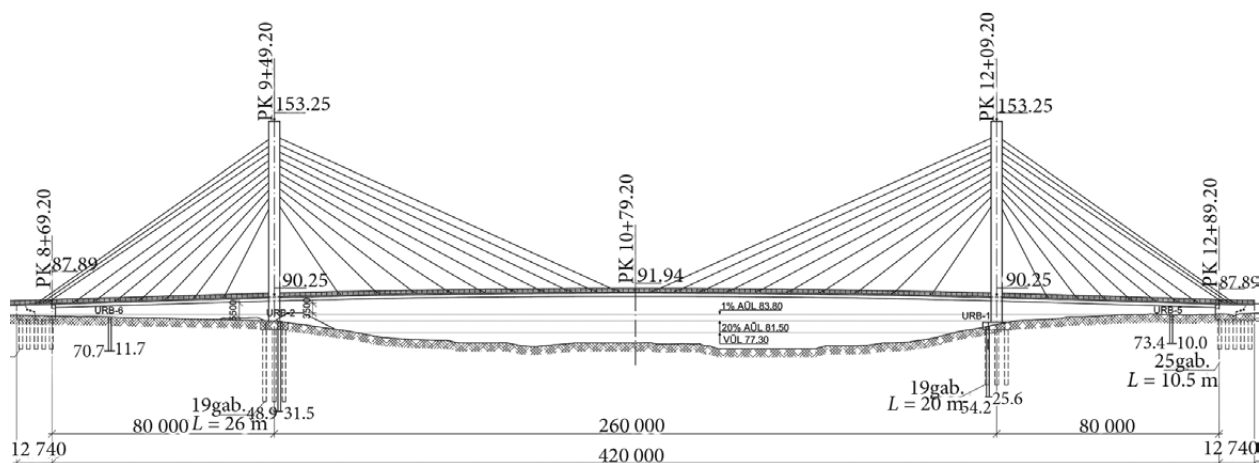


Fig. 5. Draft of a cable-stayed bridge near Jēkabpils, Latvia

and drew influence lines for nine cross-sections, shown in Fig. 6. The same queues were then formed and pushed over each influence line with a 5 m step. At each step, each axle load on span was multiplied by ordinate from influence line at axle's position. Then positive and negative values were summed separately, positive sum was divided by positive area of the influence line and vice versa. Largest one was chosen as equivalent uniformly distributed load.

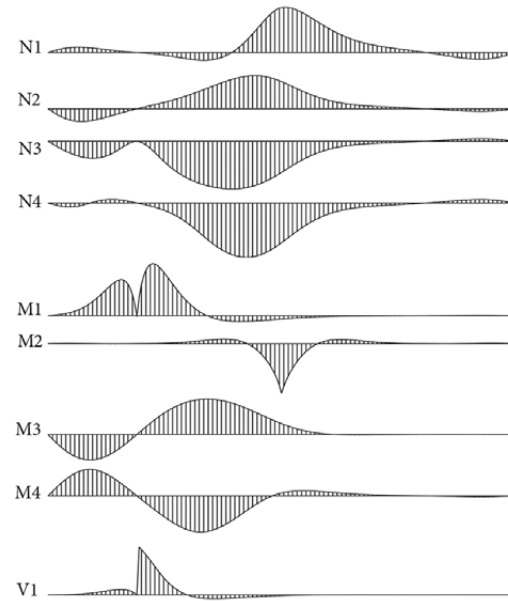
$$q_i = \max \left( \frac{\sum P \cdot y > 0}{A_{pos}}; \frac{\sum P \cdot y < 0}{A_{neg}} \right), \quad (1)$$

where  $q_i$  – calculated equivalent distributed load, kN/m;  $P$  – axle load, kN;  $y$  – ordinate from influence line;  $A$  – positive or negative area of influence line.

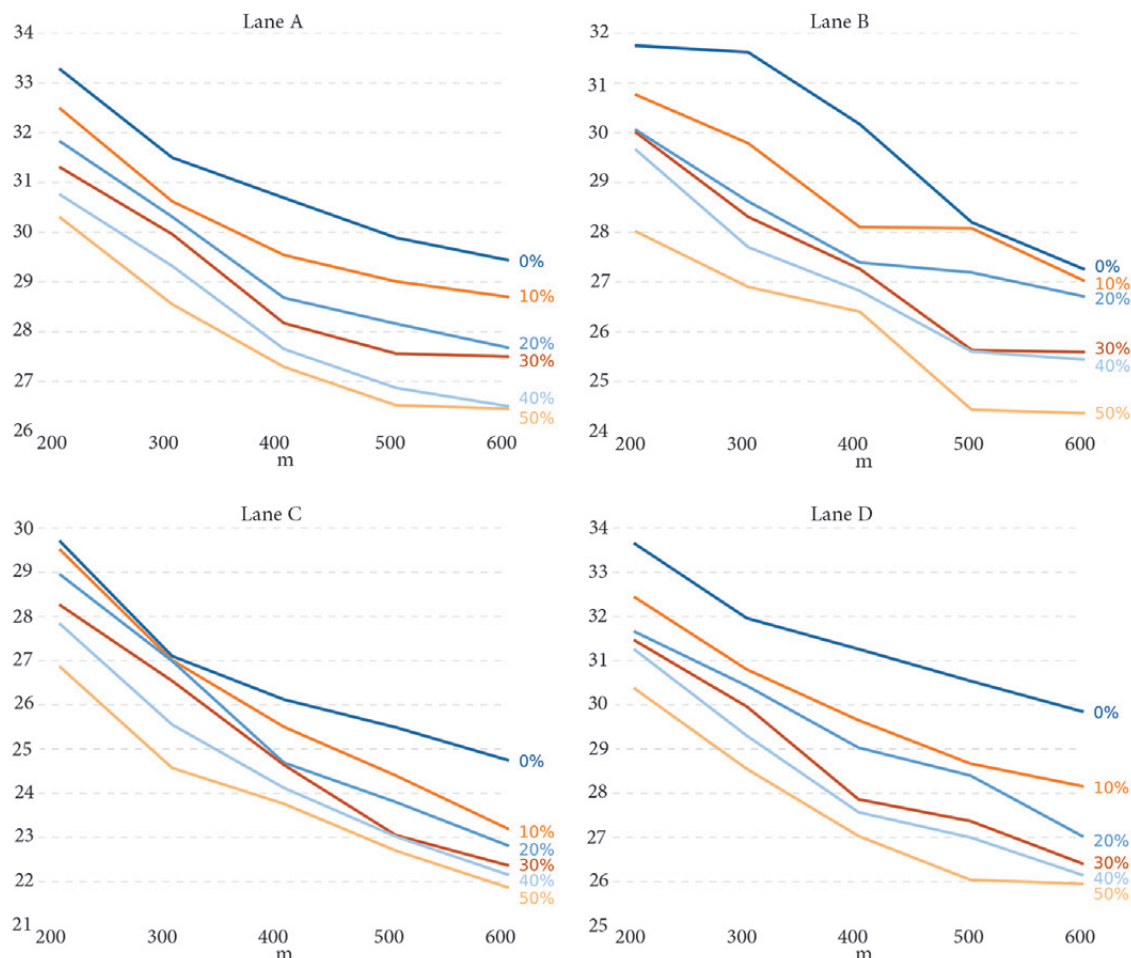
For both approaches, daily maximums were chosen and Gumbel distribution was chosen based on other authors' research (Žnidarič *et al.* 2012) and was fitted to the data using maximum likelihood estimation. Loads were then extrapolated to exceedance probability of 5% in 50 year period.

#### 4. Results and discussion

Thirty loads were calculated for each lane using constant-span approach, shown in Fig. 7. – using influence lines, shown in Table 4. Results from both approaches are not



**Fig. 6.** Influence lines for Jėkabpils bridge: N1 – axial force in the longest cable of the central span; N2 – axial force in the longest cable of side span; N3 – axial force at the bottom of a pylon; N4 – axial force in the middle of a pylon; M1 – hogging bending moment in the deck; M2 – bending moment in the middle of the central span; M3 – bending moment at the bottom of a pylon; M4 – bending moment in the middle of a pylon; V1 – shear force in the deck next to a pylon



**Fig. 7.** Loads in kN/m calculated using the first approach

**Table 4.** Loads in kN/m calculated using influence lines

Lane	Scenario	N1	N2	N3	N4	M1	M2	M3	M4	V1
A	0%	34.85	36.68	39.68	38.20	36.76	42.57	38.13	36.67	42.95
	10%	34.66	36.47	39.10	36.61	36.50	41.57	38.65	36.38	42.17
	20%	34.26	35.98	39.08	34.99	36.36	41.53	38.48	36.34	42.10
	30%	34.04	35.80	38.62	34.80	35.86	41.44	38.09	35.84	42.08
	40%	34.03	35.50	38.52	34.26	35.84	41.34	37.59	35.58	41.71
	50%	33.93	35.23	38.06	34.09	35.23	41.32	36.86	35.20	41.54
B	0%	35.76	40.20	33.40	40.48	35.46	34.06	33.21	32.39	33.65
	10%	35.43	39.43	32.68	40.42	34.95	33.35	33.11	31.79	33.16
	20%	35.16	39.39	32.19	40.03	34.85	33.01	32.75	31.55	32.90
	30%	34.89	39.37	31.84	39.92	34.50	32.80	32.51	31.29	32.56
	40%	34.68	39.26	31.76	39.68	34.46	32.66	32.35	30.99	32.48
	50%	34.67	38.92	31.64	39.65	34.12	32.64	32.20	30.97	32.19
C	0%	33.77	34.16	34.50	39.49	33.26	36.80	32.37	36.32	40.32
	10%	33.42	33.90	34.13	39.46	32.55	36.73	31.85	36.12	40.02
	20%	32.23	33.33	33.13	39.23	32.15	36.61	31.70	35.65	39.53
	30%	31.67	33.25	32.76	38.99	31.84	36.06	30.94	35.05	39.43
	40%	31.53	32.60	32.75	38.91	31.76	35.80	30.75	35.02	39.16
	50%	31.40	32.51	32.48	38.84	31.57	35.60	29.8	34.82	39.05
D	0%	38.20	36.21	36.48	38.54	43.46	35.24	35.88	41.72	36.15
	10%	37.89	36.01	36.28	38.48	42.39	34.34	35.72	41.68	36.04
	20%	37.78	35.93	35.99	38.31	42.05	34.27	35.71	41.11	35.21
	30%	37.61	35.32	35.39	38.01	41.65	34.02	34.70	41.06	35.08
	40%	37.01	34.82	35.33	37.96	41.58	33.85	34.64	40.88	34.43
	50%	36.96	34.69	35.28	37.55	41.40	33.05	34.61	40.30	34.07

directly comparable since the length of influence lines is not the same as spans considered in the first approach.

As expected there are differences between lanes, since traffic flow differs from lane to lane even on the same highway. Relative differences between 0% and 50% scenarios are in the range of 1.6% (Lane C N4) to 10.8% (Lane A N4) for influence line loads and between 9% (Lane A 200m) to 14.9% (Lane B 300m) for constant-span approach. This shows that calculations based on influence lines produce results closer to the average value (in relative terms). Additionally influence line method is less sensitive to inclusion of cars in the traffic.

Largest difference between 0% and 50% scenario for influence line loads is 4.11 kN/m (Lane A N4) and average is 1.54 kN/m, for constant-span approach – 4.72 kN/m (Lane B 300 m) and 3.37 kN/m. In absolute values they are small (around 10%) compared to loads themselves, which shows that cars have a small impact on the bridge loading.

Loads from constant-span approach in different scenarios do not follow the same slope. This shows that the method used to include cars in traffic has broken up truck groups for some spans but not for others and introduced some randomness in calculations. All calculated loads follow the same pattern of being lower as span length and

the ratio of trucks-to-cars increases, so this method does lower the loads. Although not as well as expected.

Influence line approach used nine influence lines to calculate loads. For Lanes A and C largest loads are calculated from shear force's influence line (V1), for Lane B – from axial force's in the middle of pylon (N4), and for Lane D – from hogging moment's in the bridge deck near pylon (M1). It could be expected that influence line for a single internal force would yield the highest loads for all lanes. Since all single scenarios' loads for all influence lines were calculated, using the same queues these changes cannot be caused by randomness in order of vehicles. It is probable that the step for calculations (5 m) was too large. For further studies, smaller step should be considered.

Load model 1 in *Eurocode 1* is a general traffic load model used for bridge design in Latvia with a largest single lane load of 27 kN/m. It is noted that it can be considered conservative for bridges with spans longer than 200 m. Calculated loads, however, are larger for most spans and traffic scenarios. This could indicate that the weight of vehicles have increased since development of LM1. It is possible that data cleaning filters did not catch all of the permit vehicles, such as construction cranes and trucks carrying heavy construction equipment. As WIM systems were not equipped with cameras it



was impossible to check vehicles with weight above the legal limit and it was decided to leave them in data, as it would have a conservative influence.

## 5. Conclusions

1. Influence line loads are on average less influenced by traffic composition as shown by lower relative differences in loads between 0% and 50% traffic scenarios.

2. Cars have a small impact on the calculated bridge loads as loads themselves decreased by about 10% traffic loads while the number of cars in traffic increased by 50%.

3. Loads calculated mostly exceed those defined in Eurocode's Load Model 1; this could be due to increase in gross vehicle weight or filters for data cleaning might not have caught all of the permit-vehicles. Authors currently do not recommend adoption of these load values for use in bridge design.

4. Method used to include cars in traffic lowers the loads as expected, but it also introduces some randomness. It might have broken up truck groups for some spans but not for others. Calculations should be repeated with simulated data that would allow avoid such situation.

## Acknowledgments

The authors would like to thank Aleš Žnidarič from ZAG (Slovenian National Building and Civil Engineering Institute) for sharing WIM data temperature adjustment method, Latvian Road Administration for providing WIM data, and Verners Straupe from AS Ceļu Projekts for help with Jēkabpils bridge influence lines. The research leading to these results has received the funding from Latvia State Research Programme under grant agreement "Innovative materials and smart technologies for environmental safety, IMATEH".

## References

- Chen, S. R.; Wu, J. 2011. Modeling Stochastic Live Load for Long-Span Bridge Based on Microscopic Traffic, *Computers and Structures* 89(9–10): 813–824.  
<http://dx.doi.org/10.1016/j.compstruc.2010.12.017>
- Enright, B.; Carey, C.; Caprani, C. 2013. Microsimulation Evaluation of Eurocode Load Model for American Long-Span Bridges, *Journal of Bridge Engineering* 18: 1252–1260.  
[http://dx.doi.org/10.1061/\(ASCE\)BE.1943-5592.0000546](http://dx.doi.org/10.1061/(ASCE)BE.1943-5592.0000546)
- Gajda, J.; Sroka, R.; Zeglen, T.; Burnos, P. 2013. The Influence of Temperature on Errors of Wim Systems Employing Piezo-electric Sensors, *Metrology and Measurement Systems* 20(2): 171–182. <http://dx.doi.org/10.2478/mms-2013-0015>
- Getachew, A. 2003. *Traffic Load Effects on Bridges. Statistical Analysis of Collected and Monte Carlo Simulated Vehicle Data*: PhD thesis. Stockholm: Royal Institute of Technology. 50–55.
- Available from Internet: <http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.13.5299&rep=rep1&type=pdf>
- Hayrapetova, A. A.; O'Connor, A. J.; O'Brien, E. J. 2012. *Traffic Load Models for Long Span Bridges*. Stresa, Lake Maggiore; Italy, Taylor & Francis, 2589–2596.
- Hwang, E. S.; Lee, K. T.; Kim, D. Y. 2012. *Modelling of Truck Traffic for Long Span Bridges*. Stresa, Lake Maggiore; Italy, Taylor & Francis Group, 1100–1107.
- Lutomirska, M. 2009. *Live Load Models for Long Span Bridges*: PhD Thesis. Lincoln, University of Nebraska, 61–67. Available from Internet: <http://digitalcommons.unl.edu/cgi/viewcontent.cgi?article=1000&context=civilengdiss>
- Mai, D.; Turochy, R. E.; Timm, D. H. 2013. Quality Control of Weigh-in-Motion Data Incorporating Threshold Values and Rational Procedures, *Transportation Research Part C* 36: 116–124. <http://dx.doi.org/10.1016/j.trc.2013.08.012>
- Nowak, A. S.; Lutomirska, M.; Sheikh Ibrahim, F. I. 2010. The Development of Live Load for Long Span Bridges, *Bridge Structures* 6(1–2): 73–79.
- O'Brien, E.; Enright, B.; Getachew, A. 2010. Importance of the Tail in Truck Weight Modeling for Bridge Assessment, *Journal of Bridge Engineering* 15(2): 210–213.  
[http://dx.doi.org/10.1061/\(ASCE\)BE.1943-5592.0000043](http://dx.doi.org/10.1061/(ASCE)BE.1943-5592.0000043)
- O'Brien, E. J.; Enright, B.; Leahy, C. 2013. *The Effect of Truck Permitting Policy on US Bridge Loading*. New York, NY; United States, Taylor & Francis, 3761–3766.
- Paeglitis, A.; Paeglitis, A. 2014. Traffic Load Models for Latvian Road Bridges with Span Length up to 30 m, *The Baltic Journal of Road and Bridge Engineering* 9(2): 139–145.  
<http://dx.doi.org/10.3846/bjrbe.2014.18>
- Sedlacek, G.; Merzenich, G.; Paschen, M.; Bruls, A.; Sanpaulesi, L.; Croce, P.; Calgaro, J. A.; Pratt, M.; Jacob, M. Leendertz, v. de Boer; Vrouwenfelder, A.; Hanswille, G. 2008. *Background Document to EN 1991 – Part 2 – Traffic Loads for Bridges – and Consequences for the Design*. JRC European Commission. 109 p.
- Sivakumar, B.; Ghosn, M.; Moses, F. 2011. *Protocols for Collecting and Using Traffic Data in Bridge Design*. National Cooperative Highway Research Program (NCHRP) Report 683, Washington, D. C.: Lichtenstein Consulting Engineers, Inc.
- Sivakumar, B.; Sheikh Ibrahim, F. I. 2007. Enhancement of Bridge Live Loads Using Weigh-in-Motion Data, *Bridge Structures* 3(3–4): 193–204.  
<http://dx.doi.org/10.1080/15732480701515386>
- Žnidarič, A.; Kreslin, M.; Lavrič, I.; Kalin, J. 2012. *Modeling Traffic Loads on Bridges, a Simplified Approach Using Bridge-WIM Measurements*. Dallas: John Wiley & Sons: 418–428.

Received 16 June 2014; accepted 1 February 2016