MODELING OF TRAFFIC LOADS FOR BRIDGE SPANS FROM 200 TO 600 METERS

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ABSTRACT
Traffic load models available in building codes are most often developed for short or medium span bridges, but most unfavorable traffic situations for long span bridges are very different from the ones considered in them. For this reason funds may be used irrationally, if inappropriate traffic load models are used for long span bridge design.
Weigh – in – Motion (WIM) data from WIM station installed on 72. kilometer of highway A1, have been used in these thesis. First data cleaning was performed, then data were split into two lanes.
Long span bridge loads were calculated by using information about vehicles found in traffic flow from the cleaned WIM data. Load calculations were done for 200, 300, 400, 500 and 600 meter long spans, traffic flow was simulated using seven different traffic scenarios, out of which first six simulates traffic with varying percentage of trucks, the seventh scenario simulates traffic flow consisting entirely out of cars.
For each lane, span, traffic scenario combination Gumbel's distributions were fitted to the highest 30% of the calculated loads, by using maximum likelihood estimate for left truncated data; loads were extrapolated to the probability of exceedance of 10% in hundred years period.
Results show that Eurocode 1 part 2 load model 1 loads are too conservative for use in long span bridge design even when very unlikely scenario of only trucks in the leftmost lane is considered.

Keywords: Bridge load, WIM, Weigh-In-Motion, Load modeling, Long span brides

INTRODUCTION

Since short and medium span bridges are by far the largest percent of all bridges, transport load models given in building standards and regulations are usually meant for traffic load modeling on those kind of bridges. But the governing traffic situation isn't the same on those bridges as on long span bridges. Since accurate modeling of loads expected in the work life of a construction is an important condition for successful design, then it is necessary to develop traffic load models just for long span bridges.
Too high of a probability of exceedance of the traffic loads in bridges work life can lead to the collapse of the structure, on the other hand loads must not be too conservative, as that can make the construction of the bridge unnecessarily expensive.
Traffic scenarios, each with different amount of truck traffic were designed using data from WIM systems installed on highways A1 and A3. Authors calculated uniformly distributed loads for bridge spans from 200 to 600 meters based on developed traffic scenarios.
Using maximum likelihood method for left truncated data Gumbel's distributions were fitted to highest 30% of loads for each lane, span and traffic scenario combination. The results were compared to Eurocode 1 load model 1 (LM1).
Although high speed WIM systems are the most popular tools for gathering traffic data, they're not without their flaws. To gather accurate data, devices must be regularly calibrated and even then WIM data should be cleaned of unreasonable values. Data cleaning when vehicles are grouped by their number of axles is described in (Getachew 2003). WIM data filtering without designing filters for each class is described in (Sivakumar and Sheikh Ibrakhim 2007) and (Enright and OBrien 2011) and (Paeglitis and Paeglitis 2014) the same filters are set for all vehicles, but it has to be noted that WIM data without any trucks are used in these three studies.
Effects of truck permitting policy on US bridges are studied (OBrien, Enright and Leahy 2013). Five different filters to distinguish and filter out permit vehicles are proposed.
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 WIM data and data simulated with Monte-Carlo method in queues, splitting queue in spans of chosen length and dividing the total weight of vehicles in one segment by the length of it. Another approach is described in (Lutomirska 2009) and (Nowak, Lutomirska and Sheikh Ibrahim 2010). Loads are calculated with a similar approach to the one described before, except the vehicles in queue are put on a "span" when load are calculated the first vehicle is removed and the next one in queue is added.
Influence lines for different elements from two existing bridges in Korea together with 4 artificially

made traffic scenarios are used to calculate loads in (Hwang, Lee and Kim 2012). Different traffic simulations are used in (Chen and Wu 2011), (Hayrapetova, O.Connor and OBrien 2012) and (Enright, Carey and Caprani 2013) to calculate traffic loads for long span bridges. In all of them traffic data is simulated from real WIM data and loads are calculated in each time step.

Traffic measurements are usually done for much shorter period than bridge design life, but it is necessary to predict the maximum loads that bridge will have to carry during its life, therefore probability distribution are fitted to calculated loads and they are extrapolated to chosen probabilities of exceedance.

In (Getachew 2003) bimodal normal and lognormal distribution were used for load description. Normal distributions were used for tail fitting in both (Lutomirska 2009) and (Nowak, Lutomirska and Sheikh Ibrahim 2010). Proposes the use of semi parametric approach to distribution fitting (OBrien, Enright and Getachew 2010). This approach is compared to parametric and non-parametric method for simulating gross vehicle weight (GVW) described by Gumbel's distribution with normal parent distribution. Moving average is used in (Žnidarič, et al. 2012) to smooth out histograms of bending moments and shear forces in bridge structure caused by traffic.

WIM DATA CLEANING

WIM system and raw data

Traffic weight data used in this study were collected from two WIM systems installed on highway A1 and A3 in Latvia where truck traffic is one of the highest in country. Vehicles were measured with piezo-electric sensors installed in the surface of the pavement.

Data from 14.07.2014. till 15.01.2014. were available from highway A1 and from 05.09.2013. till 15.01.2014. from highway A3 WIM data contained 2 127 403 vehicles from A1 and 542 941 from A3. WIM systems automatically distributed each vehicle in one of 27 vehicle classes.

It was noticed that not all data are reasonable, Python programming language's scripts were used to apply various filters.

Filtering based on error messages

Both WIM systems included error messages in the data about conditions that might have influenced measurements, there were 18 different error messages in total.

There were 4 messages that indicated an error in sensor, upon checking vehicles containing them, it was obvious that values are not reasonable. All vehicles containing these messages were deleted.

"Temperature Error" were 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 error messages were given depending on vehicles position in lane, first one if the vehicle was driving in the wrong direction and second one if it was driving in the middle of the road. Vehicles containing any of these two messages were deleted as the first message meant that vehicles can't be used to form queues for load calculations and the second that only one wheel of each axle was weighed.

Vehicles that had any of the rest 11 messages were kept in data as it was assumed that these errors won't influence calculations.

Adjustment for influence of temperature

In the whole period of measurements temperatures ranging from -32768°C to +85°C were recorded on highway A1. 93.02% of all vehicles were recorded with temperatures from -26°C to +42°C. Temperatures within this interval were considered to be reasonable for weather in Latvia. All vehicles from 14.07.2014. till 15.01.2014. were recorded with temperature of -32768°C. No connection between vehicle characteristic values or the time of day and measured unreasonable temperatures were found. It is authors' opinion that these temperatures were caused by some measuring device's malfunction. All the vehicles with unreasonable temperatures were deleted, a total of 148 370 or 6.98%.

WIM system on highway A3 had registered temperatures from -32768°C to +74°C. Only 10 vehicles were registered with temperatures outside the interval from -15°C to +35°C, which would be normal temperature range for Latvia's weather. All 10 vehicles were deleted.

WIM systems are installed in the pavement of the road and their measurements depend on the ambient temperature, since thermal expansion coefficient of asphalt concrete and the materials that WIM systems are made of are different the results are influenced by changes in temperature, other authors' research (Gajda, et al. 2013) suggest that inaccuracies in gross vehicle weight measurements can reach up to 40% from true weight of the vehicle.

Data were adjusted by changes in weight of class 55 vehicles (two axle tractors + 3 axle semi-trailers) depending on the ambient temperature. Class 55 vehicles with GVW between 50% and 95% percentiles were selected, it was assumed that this interval describes vehicles with cargo. All selected vehicles were ordered in chronological order and divided in 3 hour intervals, then mean GVW in each interval were calculated. Adjustment coefficients were calculated by dividing the mean GVW of the whole, selected vehicle population with each interval's mean GVW. Calculated adjustment coefficients for each 3 hour interval were then plotted against interval's mean temperature and 3rd degree curve were fitted to the coefficients by using least squares. Temperatures with less than 10 calculated adjustment coefficients were omitted from fitting as they were considered unreliable. Calculated adjustment coefficients and fitted function is shown in Figure1 for A1 data and in Figure 2 for A3 data.

GVW and each axle load of every vehicle were then multiplied by coefficient obtained from the fitted function. Class 55, 52 (2 axle tractor + 2 axle semi-trailer) and 41 (2 axle rigid truck + 1 or 2 axle trailer) were chosen to assess the impact of the adjustment, as those were the largest truck classes. Mean GVWs in different months before adjustment for A1 data are shown in Figure 3, after adjustment – in Figure 4, for A3 data in Figure5 and Figure6 respectively.

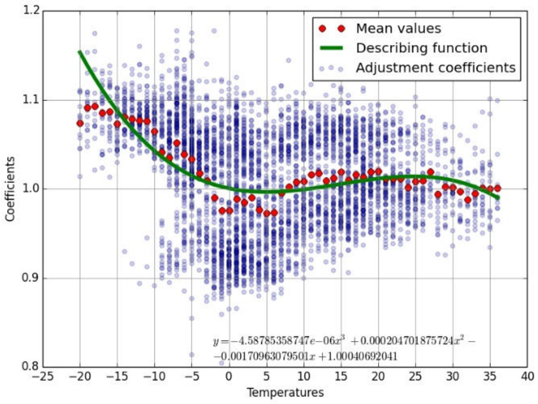

Figure 1. Adjustment coefficients and describing function for A1 data.

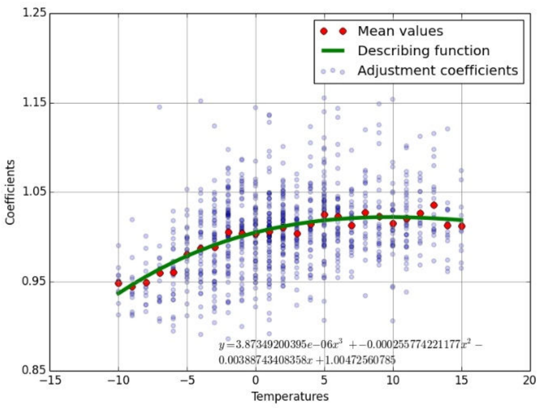

Figure 2. Adjustment coefficients and describing function for A3 data.

Figure 3, and Figure 4 shows that there is a large jump in a GVWs from A1 data at the end of measurement period even after adjustment. Since there has been no increase in legally allowed maximum GVWs, it is assumed that the increase was caused by the lack of calibration of WIM system. Fluctuations in GVWs of ±10% from the mean value were considered as reasonable. Data with mean values outside these bounds were deleted and calculations and adjustment were performed again with methods described above. Calculated coefficients and fitted function is shown in Figure 7.

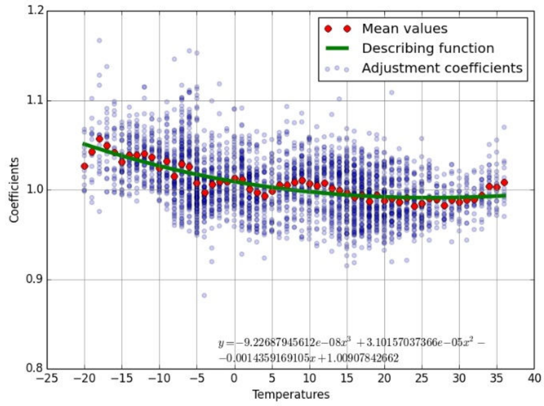

Figure 7. Adjustment coefficients and describing function. A1 data.

Table 1.

Mean GWVs' coefficients of variation before and after adjustment. A1 data.

Vehicle class	Coefficients of variation	
	Before	After
55	0.057	0.048
52	0.059	0.051
41	0.047	0.042

Table 2.

Mean GWVs' coefficients of variation before and after adjustment. A3 data.

Vehicle class	Coefficients of variation	
	Before	After
55	0.008	0.013
52	0.023	0.018
41	0.015	0.013

Figure 8 shows mean GVWs in first 13 months before adjustment, Figure 9 – after adjustment. Coefficients of variation for mean GVWs are shown in Table 1 for A1 data and in Table 2 for A3 data. It can be seen that they are lower after adjustment for influence of temperature, except for class 55 data.

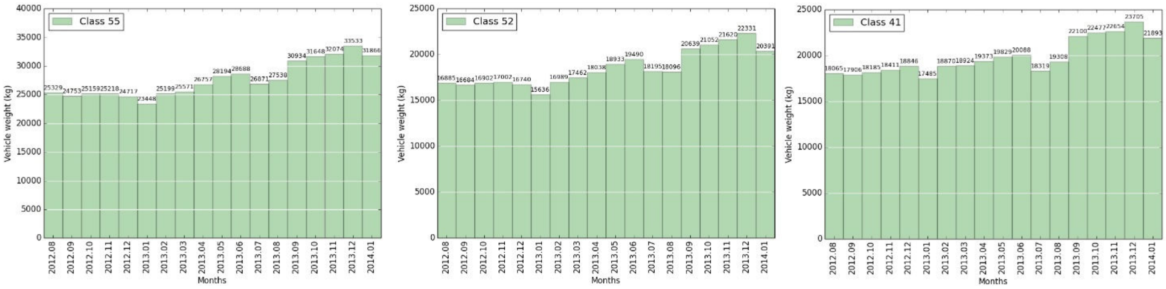

Figure 3. Mean GVWs of class 55, 52 and 41 vehicles from A1 data before adjusting for temperature.

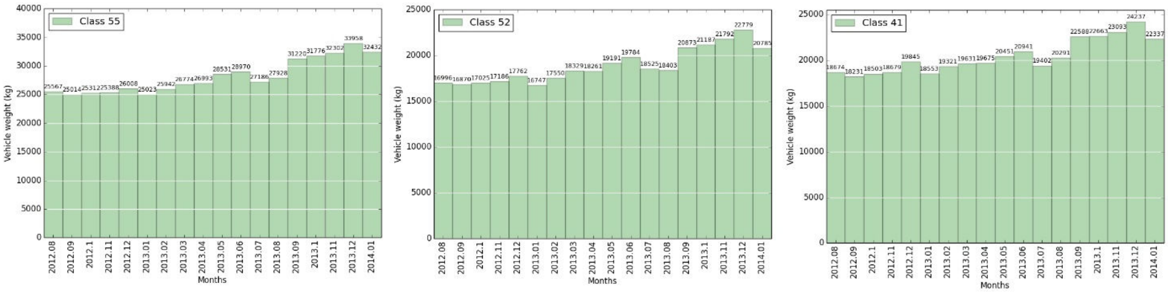

Figure. 4. Mean GVWs of class 55, 52 and 41 vehicles from A1 data after adjusting for temperature.

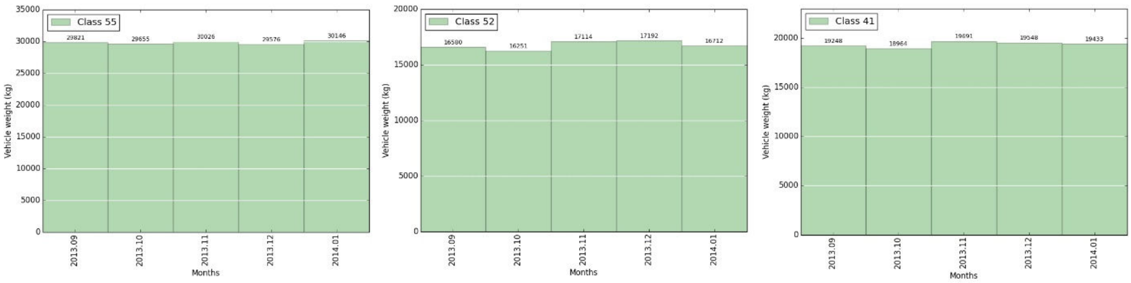

Figure 5. Mean GVWs of class 55, 52 and 41 vehicles from A3 data before adjusting for temperature.

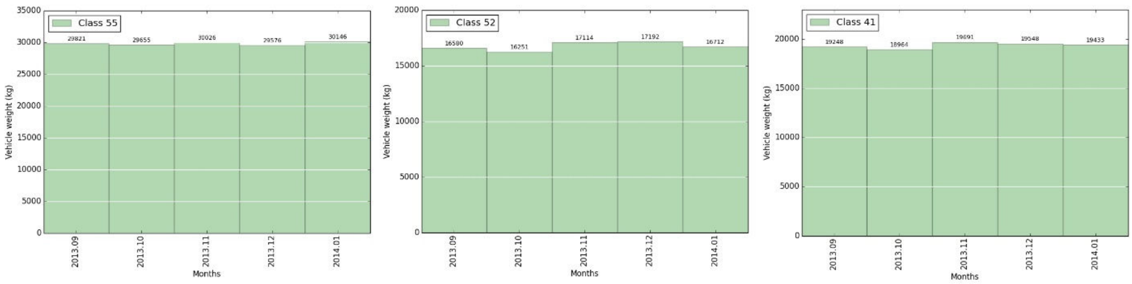

Figure 6. Mean GVWs of class 55, 52 and 41 vehicles from A3 data after adjusting for temperature.

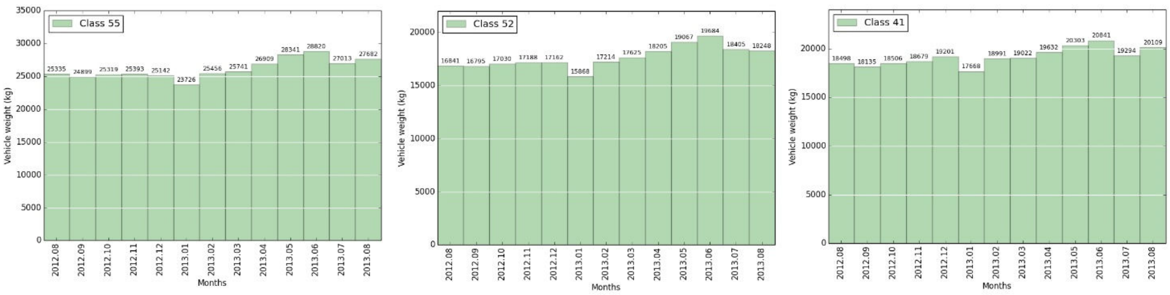

Figure 8. Mean GVWs of class 55, 52 and 41 vehicles in first 13 months before adjusting for temperature.

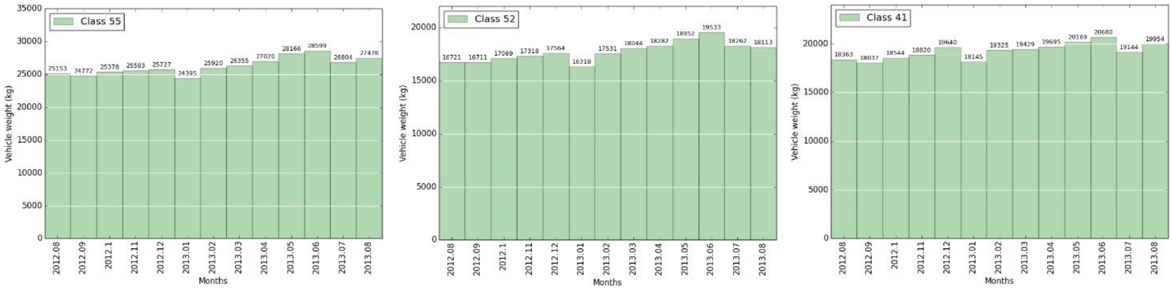

Figure 9. Mean GVWs of class 55, 52 and 41 vehicles in first 13 months after adjustment for influence of temperature.

Other filters used

In the next two filtering steps general filters for all vehicles and different filters for each class were applied.

General filters used (vehicles were excluded if):

- speed was lower than 40 km/h;
- number of axles weren't equal to number of axle loads;
- difference between length and wheelbase was negative;
- number of axle spacings is equal or greater than number of axles;
- the sum of axle spacings is greater than length of vehicle;
- any axle spacing is less than 70 cm.

Class filters were used because cars weren't excluded from data and the same filters for trucks and cars would not clean the unreasonable cars.

Motorcycles and mopeds were deleted from data. Filters for car vehicle classes were based on 5% and 95% percentiles of their lengths, GVWs and axle loads. Maximum GVW was set to 3.5 t.

For trucks (and busses) legal limits were used were applicable. 2 t was set as lowest limit for all axle loads, first axle was limited by legally allowed 10 t, the rest of the axle loads were limited by $10 \times 1.75 = 17.5$ t, to allow for overloading. Minimum GVW was set to 3.5 t.

There were filters set up to ensure that two and three axle groups are at the rear of the truck.

Permit vehicles, identified here as any vehicle with more axles than 6, were excluded from the data.

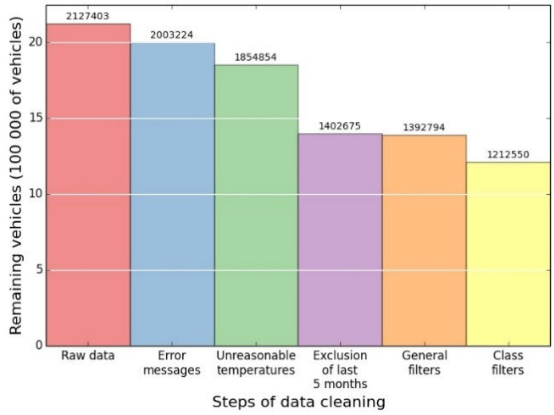

Figure 10. Amount of vehicles in A1 data after each data cleaning step.

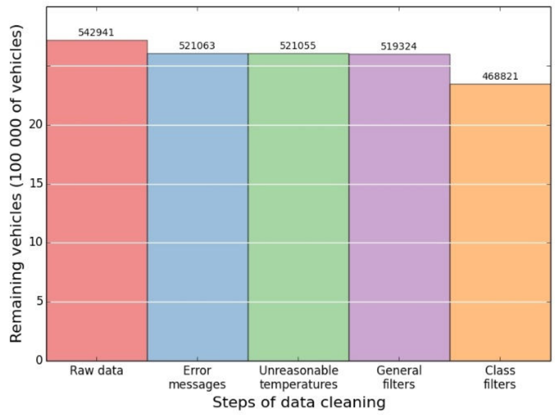

Figure 11. Amount of vehicles in A3 data after each data cleaning step.

Data after filtering

After all the cleaning steps only the data between 08.08.2012 and 31.08.2013. were retained and used for load calculations from A1 data. Raw data contained 2 127 403 vehicles out of which 1 212 550 were kept after cleaning, a total of 914853 or 43% were deleted, lions share (452 179 vehicles) after exclusion of data from 01.09.2013 till 15.01.2014. The amount of vehicles in A1 WIM data after each cleaning step is shown in Figure 10. After cleaning of A3 data 468 821 out of 542 941 vehicles in the raw data, or 86% remained. The amount of vehicles after each cleaning step is shown in Figure 11.

After cleaning the minimum GVW of vehicle increased multiple times, maximum GVW had decreased from 1.05 to 1.6 times, mean GVW had increased slightly. Since effect of a single very heavy vehicle on a bridge construction decreases with an increase in span length, it can be assumed that data cleaning had conservative impact. To show the effect of data cleaning the same three vehicle classes as before were used, maximum, minimum and mean GVWs of those classes are shown in Table 3 and Table 4 below.

Table 3.
Maximum, minimum and mean GVWs of class 55, 52, 41 vehicles from A1 data before and after cleaning.

Vehicle class	Gross vehicle weight (kg)					
	Minimum		Mean		Maximum	
	Before	After	Before	After	Before	After
55	737	11224	27506	27544	81420	59299
52	410	8975	18253	18337	64529	48223
41	302	9615	19663	20642	72984	46476

Table 4.
Maximum, minimum and mean GVWs of class 55, 52, 41 vehicles from A3 data before and after cleaning.

Vehicle class	Gross vehicle weight (kg)					
	Minimum		Mean		Maximum	
	Before	After	Before	After	Before	After
55	246	12173	19365	32904	62870	59373
52	613	9992	16767	17861	53373	43274
41	302	10212	19365	21079	62870	44207

LOAD CALCULATIONS

Traffic scenarios

Since WIM systems used in this study are installed on a 2 lane bidirectional highways, accurate data about truck distribution in lanes on highway with more than a single lane in each direction are not available. Also it cannot be said that available data represent any real traffic flow because vehicles were deleted in data cleaning. For these reasons it was decided to create 7 different traffic scenarios.
Only one lane of traffic was simulated by these scenarios. First traffic scenario simulates flow consisting only of trucks. Second to sixth scenario simulates traffic with, respectively 10%, 20%, 30%, 40% and 50% cars in the traffic flow. The seventh scenario consists only of cars.

Calculation of uniformly distributed loads

In this study uniformly distributed loads (UDL) from 7 different traffic scenarios for 200, 300, 400, 500, 600 m long bridge spans were calculated.
Traffic jam situation is the most unfavorable as the bridge span increases as shown in other authors' works (Getachew 2003), (Leonardo Da Vinci Pilot Project 2005), (Sedlacek, et al. 2008), (Lutomirska 2009), (Nowak, Lutomirska and Sheikh Ibrahim 2010) and (Hwang, Lee and Kim 2012).
Vehicles from WIM data from both highways were divided in to two lanes, hereafter referred to as Lane 1 and Lane 2. There were 388 days of data available. Data were further divided into days and each days' vehicles were formed into a queue with a constant spacing of 5 m between vehicle wheelbases.
Calculation of loads where done in similar fashion as in (Lutomirska 2009) and Python programming language scripts were used for calculations. Following parameters were assigned to each vehicle:

- vehicle weight, kN:

$$a_i$$

- required space for vehicle, m:

$$l_i = d_i + 5\ m \tag{1}$$

where d_i – wheelbase of a i –th vehicle, m; $5\ m$ – assumed distance between two vehicle wheelbases.
Then the weight and the required space of the vehicles in queue following the first one will be added to the weight and the required space of the first vehicle (summed vehicles will be considered "on span"),

$$A_i = a_i + a_{i+1} + \cdots + a_n \tag{2}$$

$$L_i = l_i + l_{i+1} + \cdots + l_n \tag{3}$$

where A_i – total weight of vehicles on span, kN; L_i – total required space by the vehicles on span, m. When L_i exceeded chosen span length B a uniformly distributed load q_i were calculated by dividing total weight of the vehicles on span A_i by total required space by the vehicles on span L_i.

$$L_i > B; \quad q_i = \frac{A_i}{L_i} \tag{4}$$

where L_i – total required space by the vehicles on span, m; B – chosen span length, m; q_i – calculated uniformly distributed load, kN/m. This process was repeated by removing the first vehicle from the span.

$$A_{i+1} = A_i - a_i \tag{5}$$

$$L_{i+1} = L_i - l_i \tag{6}$$

The required space was then once again compared to the chosen span length, if the chosen span was longer then next vehicle in queue was added and the check was performed again,

$$L_{i+1} < B; \; A_{i+1} = A_{i+1} + a_{i+1} \qquad (7)$$

$$L_{i+1} < B; \; L_{i+1} = L_{i+1} + l_{i+1} \qquad (8)$$

if the required space L_{i+1} was longer than chosen span length then the calculation was repeated

$$L_{i+1} > B; \; q_{i+1} = \frac{A_{i+1}}{L_{i+1}} \qquad (9)$$

This process was repeated till there were no more vehicles in queue. Then daily maximum UDL was chosen from days' data:

$$Q_i = \max\{q_i\,;\, q_{i+1}\,; \dots ; q_{n-1}; q_n\} \qquad (10)$$

where Q_i – daily maximum UDL.
These calculations were repeated until loads for all days were calculated. When all the daily maximum UDLs for all the spans, traffic scenarios and lanes were obtained, Gumbel's distributions were fitted to the upper 30% of the loads from each span, traffic scenario and lane combination as described in (Faber, Kohler and Sorensen 2004). Loads were then extrapolated to the probability of exceedance of 5% in 50 year period.

RESULTS

35 loads were calculated for each highway and lane combination. Loads calculated from A1 data are presented in Figure 13 and Figure 14, loads from A3 – in Figure 15 and Figure 16, also Table 5 shows all of the loads. Scenario 7 was omitted from all figures due to visibility reasons.

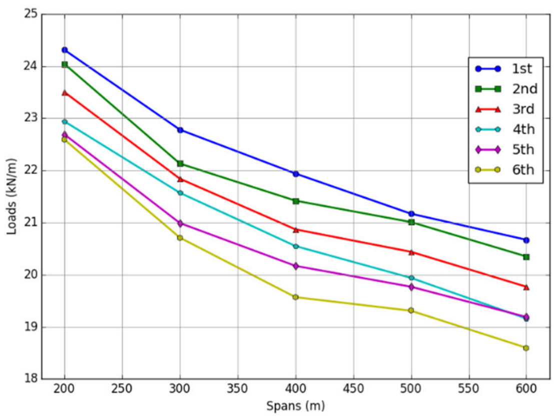

Figure 12. Calculated loads for highway's A1 Lane 1.

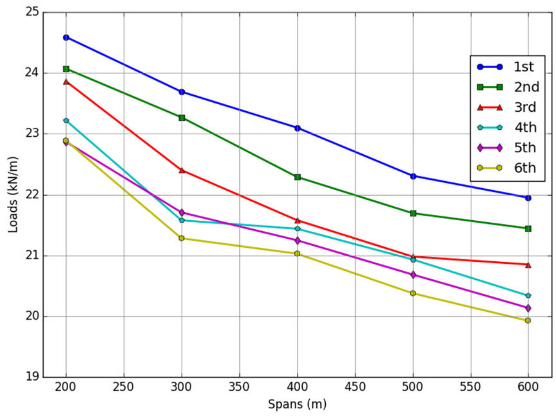

Figure 13. Calculated loads for highway's A1 Lane 2.

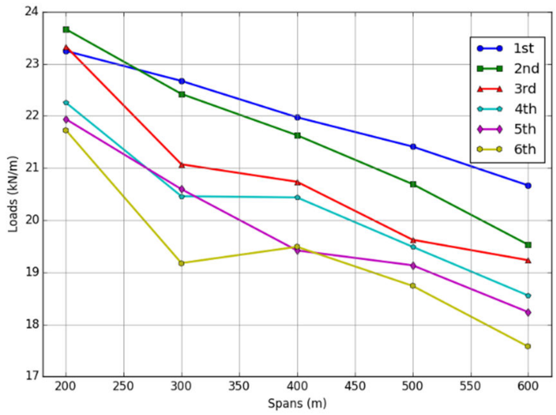

Figure 14. Calculated loads for highway's A3 Lane 1.

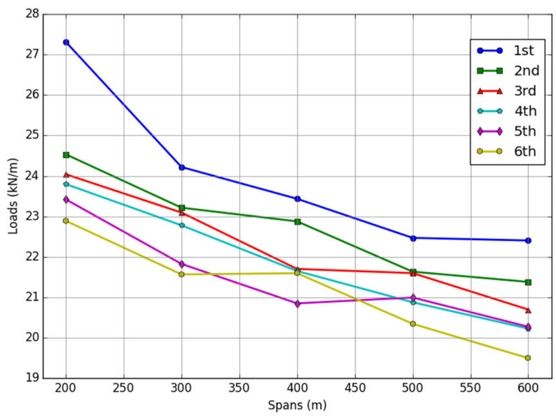

Figure 15. Calculated loads for highway's A3 Lane 2.

CONCLUSIONS

In this study comprehensive WIM data cleaning was performed based on four different types of filters. Then cleaned data were used to calculate uniformly distributed loads for 200, 300, 400, 500, 600 meters long bridges spans were calculated.

Load values decrease with an increase in bridge span and a decrease in amount of trucks in traffic flow, although there are some exceptions. They could have arisen because cars that were included in the traffic flow was selected randomly but chronological order was preserved, it is therefore possible that cars have been included in the middle of a long truck platoon, that has been preserved in other scenarios.

If compared to UDL of the most loaded lane in LM1. even the loads calculated from first traffic scenario where traffic flow consists of only trucks in traffic flow are lower than 27 kN/m, the only exception here is A3 Lane1 200 meter span, but that has been addressed in conclusion 2. But it has to be noted that calculated loads have not been increased to provide room for future increase in truck weights. If load calculated from 7th traffic scenario that simulates traffic flow with only cars in it is compared to the load model's 1 remaining lane loads (7.5 kN/m), it can be seen that calculated load is much lower than the ones currently used, however it would be unreasonable to assume that there would be a lane without any trucks.

These calculated loads still must be compared to loads calculated from specific bridge's influence lines as currently they are only for a case when maximum stresses are achieved with whole deck.

Acknowledgments

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Table 5.

Loads calculated, in kN/m

Span length	Traffic scenario							Highway and lane
	1	2	3	4	5	6	7	
200 m	24.31	24.04	23.50	22.94	22.69	22.59	3.22	A1 lane 1
300 m	22.78	22.13	21.84	21.57	20.99	20.71	3.15	
400 m	21.94	21.42	20.87	20.55	20.17	19.57	3.12	
500 m	21.17	21.01	20.44	19.94	19.77	19.31	3.10	
600 m	20.67	20.35	19.77	19.16	19.19	18.60	3.08	
200 m	24.59	24.07	23.86	23.22	22.87	22.89	3.17	A1 lane 2
300 m	23.69	23.27	22.40	21.58	21.71	21.28	3.06	
400 m	23.10	22.29	21.58	21.44	21.25	21.03	3.04	
500 m	22.31	21.70	20.98	20.94	20.69	20.38	3.00	
600 m	21.95	21.45	20.85	20.34	20.14	19.93	2.97	
200 m	23.25	23.67	23.34	22.26	21.94	21.73	3.01	A3 lane 1
300 m	22.67	22.42	21.07	20.46	20.6	19.18	2.99	
400 m	21.98	21.63	20.74	20.44	19.42	19.49	2.93	
500 m	21.41	20.69	19.63	19.49	19.14	18.74	2.9	
600 m	20.67	19.53	19.23	18.56	18.24	17.58	2.88	
200 m	23.25	23.67	23.34	22.26	21.94	21.73	3.01	A3 lane 2
300 m	22.67	22.42	21.07	20.46	20.6	19.18	2.99	
400 m	21.98	21.63	20.74	20.44	19.42	19.49	2.93	
500 m	21.41	20.69	19.63	19.49	19.14	18.74	2.9	
600 m	20.67	19.53	19.23	18.56	18.24	17.58	2.88	

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