VALIDATION OF SCENARIO MODELLING FOR BRIDGE LOADING

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Abstract. Accurate estimates of characteristic bridge load effects are required for efficient design and assessment of bridges, and long-run traffic simulations are an effective method for estimating the effects. For multi-lane same-direction traffic, truck weights and locations on the bridge are correlated and this affects the calculated load effects. Scenario Modelling is a recently developed method, which uses weigh-in-motion data to simulate multi-lane same-direction traffic while maintaining location and weight correlations. It has been unclear however, whether the method may produce unrealistic driver behaviour when extrapolating beyond the weigh-in-motion measuring period. As weigh-in-motion databases with more than about a year of data are not available, a microsimulation traffic model, which can simulate driver behaviour, is used here to assess the accuracy of extrapolating traffic effects using Scenario Modelling. The microsimulation is used to generate an extended reference dataset against which the results of Scenario Modelling are compared. It is found that the characteristic load effects obtained using Scenario Modelling compare well with the reference dataset. As a result, for the first time researchers and practitioners can model two-lane same-direction traffic loading on bridges while being confident that the approach is generating accurate estimates of characteristic load effects as well as effectively reproducing the complex traffic correlations involved.

Keywords: bridges, highway, loads, scenario modelling, traffic, trucks.

1. Introduction

Efficient safety assessment of bridges requires accurate estimates of characteristic maximum traffic load effects. Simplified load models, where characteristic loading is represented by an idealised pattern of load, are used to calculate load effects for bridge design in particular (Miao, Chan 2002). Weigh-in-motion (WIM) systems, which measure axle weights and spacings as trucks pass at normal highway speeds, provide raw data that can be used for more accurate load modelling. Characteristic bridge load effects can be estimated from WIM data in different ways. Statistical extrapolation of the load effects generated by the WIM data is a popular method in the literature (Caprani, OBrien 2010; Nowak, Szerszen 1998). A disadvantage of this method is that it may be overlooking certain multiple-truck loading events that are not captured in the WIM measuring period. To address this, Monte Carlo simulation methods can be used (Enright, OBrien 2013). 'Long-run' simulations can generate hundreds or even thousands of years of traffic at a site. Over this simulated

period, critical combinations of trucks, which may not have been measured, will be generated and assessed.

A Monte Carlo simulation of single-lane traffic can easily be extended to two-lane bidirectional traffic where each lane is considered independent of the other (Dissanayake, Karunananda 2008). Many highway bridges however carry multi-lane same-direction traffic. This situation is more complex, with dependence between lanes producing correlations of truck location such as when one truck is overtaking another. There can also be correlations of truck weights such as when trucks from the same organisation travel together. These correlations are significant when calculating characteristic load effects on short to medium span bridges where free-flow traffic conditions govern (OBrien, Enright 2011). Same-direction traffic can be modelled as an equilibrium renewal stochastic process (Croce, Salvatore 2001), but this does not address the issue of correlation.

Calibration studies for bridge design of load models also fail to offer a satisfactory solution to the two-lane same-direction problem. The US *AASHTO LRFD Bridge*

Design Specifications were calibrated using assumptions for the frequency of side-by-side truck occurrences and the weights of the trucks involved (Nowak 1999). For this, assumptions on weight correlation were entirely based on judgement, as almost no data was available (Kulicki *et al.* 2007). The calibration of Load Model 1 in *EN 1991-1-2:2002 Eurocode 1: Actions on Structures – Part 2: Traffic Loads on Bridges* used short traffic samples (3–14 days) from a number of sites and extrapolated using Rice's Formula (O'Connor *et al.* 2001). However, as previously mentioned, only truck meeting events observed in the short measuring periods are considered in extrapolations such as this. The approach does not utilise the benefits of more recently developed long run simulations, which can simulate millions of different loading events on the bridge and generate many types of meeting events, which did not occur during the measuring period.

OBrien, Enright (2011) propose a method for modelling multi-lane same-direction traffic and show that the significant weight and gap correlations identified in extensive WIM data are modelled correctly. The method works by dividing the WIM record for the site into 'scenarios', each containing between 5 and 8 slow-lane trucks, together with any adjacent trucks in the fast lane. To simulate traffic at the site, scenarios are repeatedly selected at random from the WIM data. For each scenario, the truck weights and inter-truck gaps are varied using Kernel Density estimators. With this smoothed bootstrap method (De Angelis, Young 1992) each parameter of the selected scenario is slightly perturbed to create a new scenario with similar properties to the original, while maintaining gap and weight correlations. The bandwidth used in Kernel Density Estimation controls the amount of variation, which is applied to the original scenario. The bandwidth selection used by OBrien, Enright (2011) is acknowledged to be somewhat arbitrary and it is not clear if unrealistic driver behaviour is being created. For example, a situation may be created where a slow-lane truck is put in a position behind another truck where it should have moved to the fast lane to overtake it, or a fast lane truck is moved to a position where it should have returned to the slow lane. The accuracy of Scenario Modelling for estimating extreme loading has also not been quantified, as estimates of long term loading cannot be verified with short-term WIM records.

As no long-term WIM records for two-lane same-direction traffic are available, microsimulation is used here to generate a substitute "WIM" dataset. This extended traffic record is then used to assess the ability of Scenario Modelling to accurately model driver behaviour while performing long run traffic simulations. Microsimulation is a process whereby the behaviour of individual drivers in a traffic stream is modelled. It is used here to generate an extended record of realistic traffic to which Scenario Modelling simulations can then be compared. The objective is to see if the Kernel Density Estimation process generates scenarios that result in significantly different characteristic load effects.

Microsimulation models have been applied to highway traffic for decades, and simulate driver behaviour based on how a vehicle responds to the vehicle in front.

Many different microsimulation models exist (Brockfeld *et al.* 2004; Punzo, Simonelli 2005) and can be calibrated using different approaches (Chen *et al.* 2010; Hoogendoorn, Hoogendoorn 2010). These models are mostly used to generate patterns of congestion. Here microsimulation is used to model free flowing traffic, as simulation of truck overtaking events is required. The method works by calculating the behaviour of all vehicles on the modelled road, at successive time steps. Due to the computationally intensive nature of the microsimulation process, it is not practical to simulate traffic loading for the entire lifetime of a bridge. For the purposes of this study, 10 years of traffic is generated using microsimulation, and this is used as a reference dataset for comparison with traffic produced by Scenario Modelling. Although this period is not as long as the lifetime of the bridge, it is significantly longer than any two-lane WIM measurements, which are available. Random samples of 100 days of traffic are drawn from the 10 years of micro-simulated traffic. These samples aim to represent a typical WIM measuring period. Scenario Modelling is then performed with these samples, and a variety of load effects and bridge lengths are examined to find their 10-year return period values. These 10-year values are then compared with the corresponding values obtained from microsimulation to assess the accuracy of Scenario Modelling. WIM data from a site in Poland is used as input data for the microsimulation model. Although bridge loading codes of practice such as the *AASHTO LRFD Bridge Design Specifications* and *EN 1991-1-2:2002* treat permit trucks separately from normal truck traffic, the extrapolation to 10-year values here is based on all measured trucks, including those extremely heavy trucks which would normally be expected to have permits.

The steps used in the validation of Scenario Modelling are shown in Fig. 1. The aim is to show that Scenario Modelling can accurately estimate characteristic bridge load effects from short term WIM measurements while also reproducing the complex correlations in two-lane same-direction traffic. There is no other method in the literature, which can do this. The goal is to demonstrate the suitability of the method for the site-specific assessment of these very common bridges and also its use for generating more general load models for bridge design/assessment.

2. Scenario Modelling

In Scenario Modelling, the WIM data for a site is divided into a series of scenarios, which are then used to simulate new traffic at that site (OBrien, Enright 2011). Scenario Modelling is concerned only with the trucks in the WIM data; the cars are ignored as they are considered insignificant for short-span bridge loading. Some simple rules are used to identify scenarios for different traffic flow rates. The aim is to maximise the variability of the scenarios while preserving patterns of correlation in the measured traffic. In the simulation, randomly selected scenarios are placed in the traffic in sequence, with the last truck in one scenario being replaced by the first truck in the following
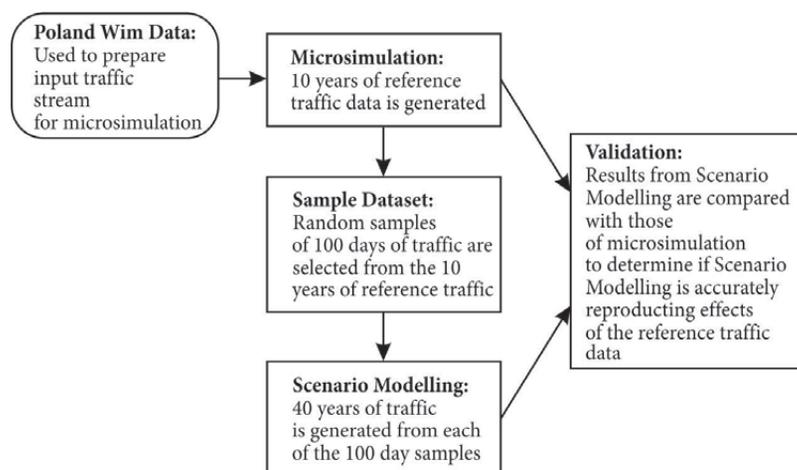
Fig. 1. Scenario Modelling validation procedure

scenario. This preserves the appropriate gap distributions, but care needs to be taken to avoid a very light truck replacing a heavy truck or vice versa. This is achieved when extracting scenarios from the WIM data by specifying that the first and last slow-lane truck in the scenario must have a gross vehicle weight (GVW) less than 30 tonnes. These lighter trucks are assumed not to be significant for critical bridge loading and therefore swapping one of these trucks for another will not affect the characteristic load effects obtained from simulation. Four types of scenario are extracted from the WIM data, with successive scans based on a minimum of five, six, seven and eight slow-lane trucks per scenario, together with any adjacent fast-lane trucks (Fig. 2). In each scan, if the last truck is greater than 30 t then more trucks are included until the scenario can finish on a slow-lane truck, which is less than 30 t (OBrien, Enright 2011). The different scans allow for more variation in the scenarios and capture more scenario configurations.

In the simulation, as each scenario is selected, the values of the parameters, which define it – vehicle weights and inter-truck gaps – are perturbed using Kernel Density estimators. Kernel Density Estimation is a general method for estimating the probability density function (PDF) of sample data using kernel functions. Each sample data point is replaced with a kernel function and these functions are summed to build the PDF. The kernel functions are typically unimodal, with the Normal distribution often used. In Monte Carlo simulation, the PDF of a random variable can be constructed numerically from sample data using Kernel Density Estimation, and this can be used to construct the cumulative distribution function (CDF) from which random values can be generated. A simpler alternative, which achieves the same result, is to use the smoothed bootstrap approach (De Angelis, Young 1992) where values are taken randomly from the sample data, and these values are then be perturbed by adding a random value drawn from a kernel function. This is the technique used in the Scenario Modelling approach.

For each random variable being simulated, decisions must be made on the type of kernel function to be used and, more importantly, the bandwidth of the chosen function. The bandwidth is a measure of the amount of
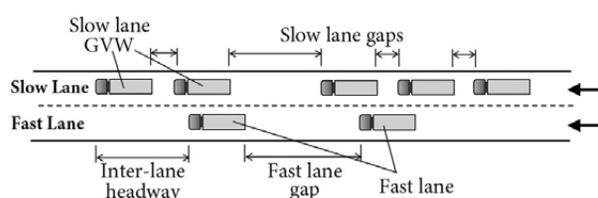
Fig. 2. Sample scenario showing the properties which are varied in Scenario Modelling (GVW = gross vehicle weight)

Table 1. Bandwidths used for kernel functions

Variable (x)	Kernel Type	Bandwidth
Slow lane GVW, t[a]	Normal	$0.08\dfrac{x^2}{\max(x)}$
Fast lane GVW, t	Normal	$0.065\dfrac{x^2}{\max(x)}$
Slow lane gap, s	Triangle	$\min(0.2x, 0.6)$
Fast lane gap, s	Triangle	$\min(0.3x, 0.6)$
Inter lane gap, s	Triangle	$\min(0.08|x|, 0.16)$
Slow lane speed, km/h	Triangle	0.6
Fast lane speed, km/h	Triangle	1.0

Note: [a] – $\max(x)$ is the maximum observed GVW in that lane for the 100 day traffic sample.

perturbation being added to the selected data value. For example, if using Normal kernel functions the bandwidth is the standard deviation of the Normal distribution used. For a triangular kernel function, the bandwidth is equal to half the length of the base. The bandwidths used here for Kernel Density Estimation are those used by OBrien, Enright (2011) and are listed in Table 1.

The Scenario Modelling approach was developed to model multi-truck bridge loading events. For short-span bridges, the critical events often consist of two or more relatively common trucks on the bridge at the same time, such as that in Fig. 3a. However, not all bridge load effects are governed by events of this type. Some critical load effects are caused by extremely rare single truck loading events where the Kernel Density approach does not work as well. These are
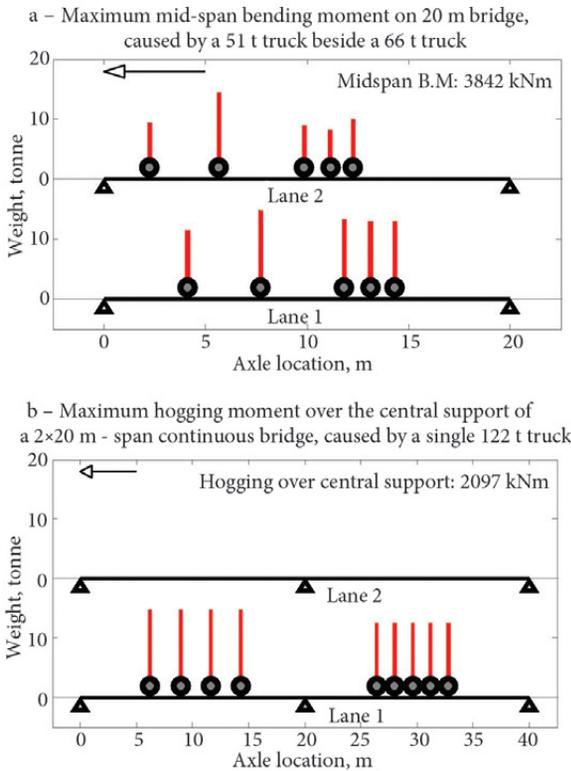
Fig. 3. Examples of the events causing maximum load effects for the 10 years of microsimulation
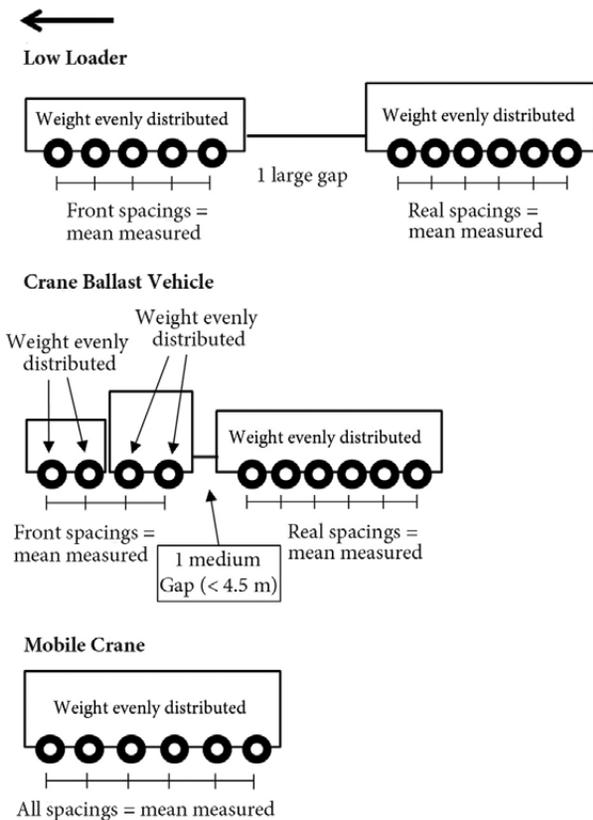
Fig. 4. Simplified vehicles used in simulation to represent the three permit truck types found in Poland WIM data (Enright *et al.* 2015)

events which are caused by low frequency extremely heavy permit trucks (Fig. 3b). Over the lifetime of a bridge, it is expected that permit trucks which are significantly heavier than those recorded in the WIM measuring period will cross the bridge. The Kernel Density approach will not generate these trucks correctly as the extrapolation of weight is restricted by the bandwidth used. To allow for these trucks in Scenario Modelling, when a scenario is selected which includes a permit truck above a certain weight, this truck is replaced with a new, randomly generated, one.

A process similar to the methodology described in (Enright *et al.* 2015) is used to generate the new very heavy permit trucks. Permit trucks are first separated into the three categories (Enright *et al.* 2015) which have been found at the Poland WIM site (Fig. 4). The tail of a bivariate Normal distribution is then fitted for each category (Enright, OBrien 2013) of truck above a certain weight threshold, as in Fig. 5. This bivariate Normal distribution, along with univariate Normal distributions fitted to the other truck characteristics shown in Fig. 4, is then used to simulate new trucks. This allows permit trucks, which are heavier and which have more axles than those in the measured scenarios, to be generated. This approach is similar to that used by OBrien, Enright (2011) and is necessary for the accurate simulation of the different categories of permit trucks, which are important for bridge loading.

3. Microsimulation

Microsimulation is used in this work to produce a stream of free-flowing traffic based on the measured WIM data. A computer program, *Simba* (*Sim*ulation for *B*ridge *As*sessment), developed by Caprani (2012) is used to perform the microsimulation. This program is based on the Intelligent Driver Model (IDM) described by Treiber and others (Treiber *et al.* 2000), and on the MOBIL lane changing model (Kesting *et al.* 2007).

3.1. Intelligent Driver Model

The Intelligent Driver Model (Treiber *et al.* 2000) uses a continuous function of acceleration and deceleration terms,
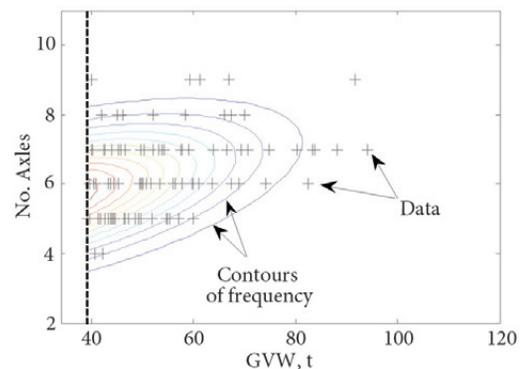
Fig. 5. The tail of a bivariate Normal distribution fitted to gross vehicle weight (GVW) and numbers of axles, for low loaders above a certain weight threshold at the Poland WIM site

which describes the longitudinal motion of each vehicle in response to its surroundings. The model is parameterized with some easily measured physical, mechanical, and driver performance parameters. In particular, the IDM is based on the idea that a driver tries to minimize braking decelerations. Eq (1) defines the acceleration a vehicle undergoes:

$$\frac{dv(t)}{dt} = \alpha\left[1 - \left(\frac{v(t)}{v_0}\right)^4 - \left(\frac{s^*(t)}{s(t)}\right)^2\right], \qquad (1)$$

where $v(t)$ – current speed, m/s; α – maximum acceleration, m/s^2; v_0 – desired speed, m/s; $s^*(t)$ – desired minimum gap, m; $s(t)$ – current gap, m.

Eq (2) gives the desired minimum gap:

$$s^*(t) = s_0 + Tv(t) + \frac{v(t)\Delta v(t)}{2\sqrt{ab}}, \qquad (2)$$

where s_0 – minimum jam distance, m; T – safe time headway, s; $\Delta v(t)$ – speed difference between current vehicle and vehicle in front, m/s; a – maximum acceleration, m/s^2; b – comfortable deceleration, m/s^2.

3.2. MOBIL Lane Changing Model

In the microsimulation, lane-changing behaviour is determined by the MOBIL model (Kesting *et al.* 2007). The model can accommodate symmetric passing – passing on either side of the vehicle ahead – but here it is used for asymmetric passing where only the fast lane is used for overtaking. For a lane change to take place, there must be an incentive for the driver to do so as well as it being safe to do so. The incentive criterion for a slow to fast lane change is given in Eq (3) and is shown in Fig. 6:

$$\tilde{a}_c - a_c > \Delta a_{th} + \Delta a_{bias} + p(a_n - \tilde{a}_n), \qquad (3)$$

where $\tilde{a}$ – acceleration after lane change, m/s; a – acceleration before lane change, m/s; Δa_{th} – acceleration threshold (prevents lane changes with marginal advantage), m/s; Δa_{bias} – bias acceleration (bias of vehicles to occupy slow lane), m/s; p – politeness factor (reflects driver consideration for other road users).

For a lane change to take place, the increase in acceleration for the current vehicle $\tilde{a}_c - a_c$ must exceed the acceleration threshold and the bias. The disadvantage to the new following vehicle $a_n - \tilde{a}_n$, weighted by the politeness factor, is also considered. A lane change for a vehicle returning to the slow lane from the fast lane is also influenced by the disadvantage it is imposing on the following vehicle in the fast lane. The incentive criterion for such a slow-to-fast lane change is:

$$\tilde{a}_c - a_c > \Delta a_{th} - \Delta a_{bias} + p\left[\left(a_n - \tilde{a}_n\right) + \left(a_0 - \tilde{a}_n\right)\right]. \quad (4)$$

The safety criterion $\tilde{a}_n \geq -b_{safe}$ is used to restrict the model from imposing an unsafe deceleration on the new following vehicle in the target lane. The maximum safe braking is given by b_{safe}.

3.3. Simulations

The microsimulation model requires an input stream of vehicles of all types, both cars and trucks. Although trucks generate the significant load effects on bridges, cars are also required to space the trucks correctly. Two-lane same-direction WIM data, including cars, recorded at a site on the A4 near Wroclaw in Poland in 2008. It is used as the input for microsimulation. Various input parameters, listed in Table 2, determine driver behaviour in the microsimulation. Some of these parameters are taken from Kesting *et al.* (2007), while others are specifically calibrated to match important characteristics of multi-truck bridge loading events as observed in the recorded traffic at the site in Poland.

The desired speeds for cars and trucks are adjusted so the model produces a distribution of speeds similar to those measured. Variation in desired speed is important to facilitate overtaking, which generates side-by-side bridge loading events. A Normal distribution for speed is used as it gives a good fit to the measured data. The politeness factor, lane-changing threshold and slow lane bias are also adjusted to give the measured proportion of trucks and cars in the slow and fast lane. This adjustment is important as the number of side-by-side bridge loading events is proportional to the number of trucks in the fast lane. The number of lane changes per kilometre per hour was also checked and found to be in agreement with measured lane changing data at other sites for the same traffic flow (Sparmann 1979; Yousif, Hunt 1995). Previous work (Enright *et al.* 2012) has shown that microsimulation reproduces behaviour such as platooning of trucks which arises from the different desired speeds applicable to
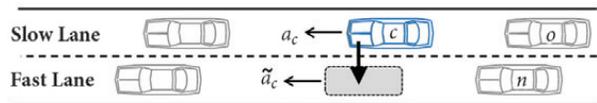
Fig. 6. Lane changing with the MOBIL model: a_c – acceleration before lane change; $\tilde{a}_c$ – acceleration after lane change; c – current vehicle being examined; o – old following vehicle; n – new following vehicle

Table 2. Microsimulation parameters

Parameter	Cars	Trucks
Kesting *et al.* (2007):		
Safe time headway, T	1.2 s	1.2 s
Maximum acceleration, a	1.5 m/s^2	1.5 m/s^2
Comfortable deceleration, b	2 m/s^2	2 m/s^2
Minimum jam distance, s_0	2 m	2 m
Maximum safe deceleration, b_{safe}	4 m/s^2	4 m/s^2
Site-specific:		
Desired speed, v_0	95.5 km/h*	88.0 km/h**
Politeness factor, p	0.1	0.5
Lane-changing threshold, Δa_{th}	0.1	0.5
Bias for the slow lane, Δa_{bias}	0.1	0.8

Note: * – Normal distribution: $\mu = 95.5$, $\sigma = 17.5$; ** – Normal distribution: $\mu = 88$, $\sigma = 14.5$.

trucks and cars. This gives correlations between gaps similar to those found in measured traffic. While no allowance is made in this work for weight-dependent variations in truck speeds, Scenario Modelling will reproduce any patterns of correlation found in the traffic generated by microsimulation.

The microsimulation is run over a 10 km road, and bridge load effects are calculated for a bridge at the end of this road. This allows the simulated traffic to reach a steady state before load effects are calculated. To ensure

Fig. 7. Comparison of the microsimulation results with one of the Scenario Modelling runs, with a histogram showing the results for all 25 Scenario Modelling runs

consistency with Scenario Modelling, the relatively small load effects produced by cars are ignored.

The WIM data used contains 84 weekdays of traffic, with 340 650 trucks and 986 087 cars. In the microsimulation of 10 years of traffic, it is necessary to allow for trucks, which are heavier and have more axles than those in the relatively short measurement period. The input stream of vehicles is generated by randomly selecting vehicles from the measured data. When a permit truck above a certain weight limit is selected it is replaced with a new, randomly generated, one. The new permit trucks are generated from the tail of a bivariate normal distribution using a methodology similar to that described in section 2.

4. Methodology and results

The accuracy of Scenario Modelling is assessed using the output from 10 years of microsimulation as the reference data. Random samples of 100 days of traffic are selected from the reference data and they are used as the input for Scenario Modelling. The load effects with a return period of 10 years are calculated from each run of Scenario Modelling, and compared with the values calculated from the microsimulation. The choice of the 10-year return period as the basis for comparison avoids the need to extrapolate beyond the 10-year microsimulation period, which would increase the uncertainty involved. In order to reduce the variability in the estimation of the 10-year return period values from Scenario Modelling, 40 years of traffic is modelled. This process is repeated with 25 random 100-day samples. A Weibull extreme value distribution is fitted to the maximum daily load effects, from both the microsimulation and Scenario Modelling, to smooth the random variation in the data. As only the trend in the tail of the data is of interest, the distribution is fitted to the top $2\sqrt{n}$ data points (Castillo 1988).

The load effects used are calculated using simple influence lines. The relative positions of the trucks are fixed as they are passed across the influence line. Whilst this is unrealistic, if variable truck velocities are allowed for, trucks might get too close to each other as they move across the bridge. The load effects examined are mid-span bending moment on a simply supported bridge (LE1), shear at the exit support of a simply supported bridge (LE2) and hogging moment over the central support of a two-span continuous bridge (LE3). The load effects are calculated for total bridge lengths of 20 m, 30 m, 40 m and 50 m. Lane factors (Enright, OBrien 2013) are used to account for the transverse stiffness. Maximum bridge load effects are assumed to occur under the slow lane, and the contribution of trucks in the fast lane is calculated by applying a suitable lane factor. For the purposes of this work, the bridge is assumed to have a high transverse stiffness, with both lanes contributing equally to load effects LE1 and LE3 (bending moment). For LE2 (shear), the contribution of fast-lane trucks is reduced by applying a factor of 0.45. High transverse stiffness is chosen because side-by-side loading events are more critical for this type of bridge, and it is these events that Scenario Modelling is intended to model most accurately.

Fig. 7 shows an example of results from the simulations. The 10 year return period load effects, from the
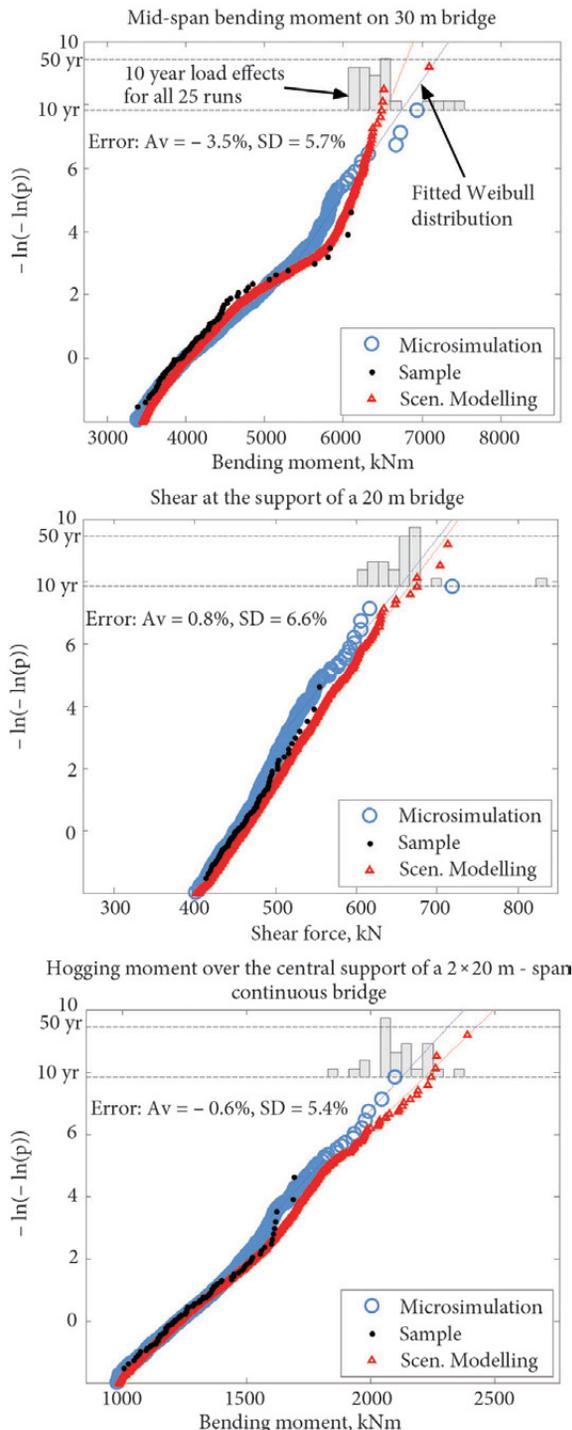
reference microsimulation data set, are compared with the 10year estimates from Scenario Modelling. Scenario Modelling is performed using 25 random 100day samples, which are drawn from the 10 years of reference data. The repeated simulations allow the distribution of the errors to be examined and these are shown in histogram form in Fig. 7.

Table 3 shows the errors relative to the microsimulation reference results, for all the load effects and spans examined. The mean and standard deviation is calculated for the errors of the 25 Scenario Modelling runs. It can be seen that, on average, mid-span bending moment is slightly underestimated for all spans whereas the error for shear and hogging moment is generally close to zero. All mean errors are within ±5% of the reference microsimulation dataset and the highest standard deviation is 6.6%.

Table 4 shows the types of event that cause the greatest effects for all the bridge lengths and load effects examined. The governing events for mid-span bending (LE1) consist of multiple trucks, mostly two standard trucks side-by-side. On the other hand, the critical events for shear (LE2) are mainly single-truck events consisting of one extremely heavy truck alone on the bridge. The main reason for this is the relatively low contribution from fast-lane trucks for this load effect, and the importance of groups of closely-spaced axles adjacent to the bridge support. The important events for hogging (LE3) are multi-truck events but single-truck events also feature. The majority of multi-truck events in Table 4 consist of two trucks side-by-side on the bridge, but, for the 40 m and 50 m spans, some events are found that involve more than two trucks, at least partly on the bridge, simultaneously.

The extremely heavy trucks that tend to govern for shear are generated from both microsimulation and Scenario Modelling by the bivariate Normal distribution described earlier, and therefore close agreement can be expected between the two approaches. The multi-truck events that govern for mid-span bending and support hogging moments (LE1 & LE3) consist of two, or sometimes more, relatively common trucks on the bridge at the same time. In these multi-truck events the Kernel Density estimators, which vary the weight and relative positions of the trucks in the scenarios, are important. The Kernel Density approach in Scenario Modelling underestimates the required values for LE1 by an average of 3.3%, with the error reducing as span increases, and slightly overestimates for LE3.

6. Conclusion

1. The accuracy of Scenario Modelling for performing two-lane same-direction traffic simulations for bridge loading purposes is assessed. As extended weigh-in-motion records for two-lane same-direction traffic are not available, Microsimulation is used to create a reference dataset of traffic, which is used to assess the accuracy of Scenario Modelling. Microsimulation is used as it can model realistic driver behaviour in such traffic, including truck-overtaking manoeuvres, which are important for loading on two-lane same-direction bridges. The overall driver behaviour of the reference dataset is not representative of traffic at any particular site, but the important truck overtaking events are calibrated against measured weigh-in-motion data from a site in Poland.

2. The results of this study show that, when modelling 10 years of traffic from a 100-day sample, Scenario Modelling does not distort driver behaviour in any way that would significantly change the estimates of 10-year load effects.

3. Mean errors are examined for a variety of 10-year load effects, and all are within ±5% of the reference value,

Table 3. Errors for all load effects examined in 25 Scenario Modelling runs (LE1 = mid-span bending, LE2 = shear, LE3 = hogging moment over central support)

	LE1		LE2		LE3	
	Mean	SD	Mean	SD	Mean	SD
20 m	–4.6	5.2	0.8	6.6	3.6	5.3
30 m	–3.5	5.7	–0.6	6.2	0.6	5.1
40 m	–2.8	5.6	–1.1	6.1	–0.6	5.4
50 m	–2.2	5.4	–1.2	6.1	0.6	4.2
Mean	–3.3	5.5	–0.5	6.2	1.0	5.0

Table 4. Event types for the 20 greatest load effects for the reference microsimulation and Scenario Modelling traffic, for all bridge lengths and load effect types (LE1 = mid-span bending, LE2 = shear, LE3 = hogging moment over central support)

Bridge length, m	Simulation	LE1		LE2		LE3	
		No. Single Truck Events	No. Multi-Truck Events	No. Single Truck Events	No. Multi-Truck Events	No. Single Truck Events	No. Multi-Truck Events
20	Reference	0	20	15	5	2	18
	Scen. Mod.	0	20	20	0	3	17
30	Reference	0	20	16	4	5	15
	Scen. Mod.	0	20	19	1	5	15
40	Reference	2	18	18	2	8	12
	Scen. Mod.	0	20	20	0	4	16
50	Reference	2	18	18	2	6	14
	Scen. Mod.	0	20	16	5	4	16

with a maximum standard deviation of 6.6%. With any simulation, some random variation in results is inevitable, and the differences between the results from microsimulation and from Scenario Modelling are considered to be acceptably low.

4. It is also found that Scenario Modelling works well for both multi-truck loading events, for which it was originally developed, and for single-truck events. This is significant because the relative importance of different event types for different load effects can be expected to vary from site to site, and the model must work well for all event types.

5. The results indicate that Scenario Modelling, which has previously been shown to be capable of modelling the important correlations of inter-truck weights and gaps, can also accurately extrapolate to characteristic load effects. As is shown in the literature review, there is no other approach for modelling two-lane same-direction traffic loading on bridges, which can do this. Therefore, the Scenario Modelling approach has significant potential to be used to obtain accurate estimates of characteristic load effects for the assessment of existing bridges or for the development of load models for bridge design.

Acknowledgements

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