Long-Run Traffic Simulations for Multi-Lane Road Bridges

Róisín Donnelly¹, Lorcan Connolly¹, Ilaria Bernardini¹
¹Roughan & O’Donovan Innovative Solutions, Arena House, Arena Road, Sandyford, Dublin 18, Ireland
email: roisin.donnelly@rod.ie, lorcan.connolly@rod.ie, ilaria.bernardini@rod.ie

ABSTRACT: This paper describes the methodologies undertaken in the simulation of long-run traffic load models for two multi-lane road bridges in the Netherlands. These were developed for use in predictive models for limit state failure at either the Ultimate Limit State (ULS) or the Fatigue Limit State (FLS). In both cases, WIM data from alternative sites were obtained and adapted within the simulation to represent the traffic at the bridge location. Vehicles from the source WIM data were classified based on axle configuration, and statistical distributions were fitted for the Gross Vehicle Weight (GVW), axle weights, and spacings for each classification. Vehicles could thus be sampled from these distributions to form a simulated “train” of vehicles. Distributions were also fitted to the inter-vehicle gaps for same-lane and adjacent-lane vehicles. These distributions allowed for vehicle spacings and overtaking scenarios to be sampled and applied to the load model. Overtaking scenarios were sampled using a Monte Carlo simulation approach. Additionally, annual traffic growth was considered by altering the number of sampled vehicles and by adjusting the sampled weight distribution. It was found that the required simulation approach varied for each of these bridges. The methodology is a function of the limit state being assessed, the shape of the influence lines, and the nature of the WIM data used. Additionally, it was found that for a single year of data the results obtained using either simulated data or statistical extrapolation were comparable. However, given the ability of long-run simulations to account for traffic growth and to generate new loading events in multi-lane scenarios, this was considered to be a more representative solution.

KEY WORDS: Long-Run Simulations; Weigh-in-Motion; Bridge Assessment; Multi-Lane Road Bridges; Monte Carlo Simulation.

1 INTRODUCTION

The maintenance and repair of ageing bridges is a significant concern for road infrastructure managers. This issue is amplified by the increasing weights and frequency of travel of freight vehicles over time. In order to assess the true risk of damage for road bridges, it is essential to have accurate representations of the bridge loading. When available, site-specific Weigh-in-Motion (WIM) data has been shown to be effective in creating representative load models for structural assessments. However, for cases where this data is not available or where future damage must be predicted, it is necessary to simulate the required data using statistical techniques.

The purpose of this study was to develop a multi-lane Monte Carlo long-run simulation technique which can be used to evaluate the impact of future traffic growth on bridges. Previous studies have been presented that have used the Monte Carlo (MC) approach to simulate traffic loading [1-4]. In each of these cases a period of traffic was generated and the characteristic load effects were then extrapolated over longer periods using extreme value statistical techniques. However, this technique fails to consider load evolution and does not allow for inspection of the characteristic loading events. In the case where extrapolation is applied directly to WIM data [5], this also fails to consider new traffic meeting events that were not measured during the WIM period. An alternative approach is long-run MC simulation, where a simulated “train” of vehicles is generated spanning a time period of many years based on distribution fits to vehicle and traffic parameters. The characteristic load effects on a bridge may then be obtained directly as a result of the generated load model. An example of this may be seen in [6], where load models over a period in excess of 1000 years were simulated. This study aims to progress this approach through the consideration of changes in traffic volumes and weights over time. In addition, this study extends to the simulation of single-direction traffic with the consideration of weight correlation in overtaking events. This study also looks at the application of the MC approach to the Fatigue Limit State (FLS) as well as the Ultimate Limit State (ULS). FLS assessment using Extreme Value extrapolation to determine maxima from a small set of simulated data was addressed in [1]. This will be progressed in herein to perform a full FLS assessment using an MC approach.

The case studies presented in this paper both concern multi-lane road bridges with steel orthotropic decks. Both bridges are located in the same region in The Netherlands and are regularly exposed to high volumes of freight traffic. The purpose of performing an analysis on each of these bridges was to investigate the robustness of the long-run simulation methodology and to compare the approach required to carry out each individual assessment. The determination of the safety of these particular bridges was not within the scope of this exercise. Details of the case study bridges may be found in the following sections.

1.1 Case Study 1: 6-lane Steel Arch Bridge

The bridge analysed in the first case study consists of two identical adjacent tied-arch structures, each with a span of 300m. Each of these bridges carries six lanes of road traffic
travelling in the same direction. Two of these six lanes do not carry Heavy Goods Vehicle (HGV) traffic. This study was carried out on a single span only. This newer part of the bridge was constructed in 1990 and consists of a steel deck plate supported by longitudinal box girders and I-section cross-girders. The deck is stiffened longitudinally with trough stiffeners. The longitudinal girders are supported by prestressed cables, connected to the arch structure.

The Case Study 1 bridge is a long-span road bridge, and hence is likely to be more sensitive to the effects of traffic growth. Thus, the aim of this study was to determine the likelihood of bridge failure at ULS with consideration of the frequency, loading and patterns of predicted future traffic.

1.2 Case Study 2: 4-lane Bascule Bridge

The second Case Study concerns a 4-span bascule bridge with a steel orthotropic deck that was constructed in 1972. The fixed spans of the bridge are 56m, 95m and 41m from the south end to the north end of the bridge. The bascule section is located between the 95m and 41m spans. The road bridge in question carries a total of four traffic lanes, two for each direction of travel. The bridge superstructure consists of a steel deck plate supported by 2 no. longitudinal girders spaced 13.95m apart, with cantilevering sections outside these girders. Steel T-section cross-girders are located at approximately 4.5m centres over the length of the bridge. The deck plate is stiffened longitudinally by trough stiffeners.

The bridge in question undergoes frequent inspections to identify and monitor damage locations throughout the structure. The inspection reports produced for the bridge have identified fatigue cracking as the key structural issue faced by the bridge. Hence for this case study, the long-run traffic load model was created for the purpose of determining the reliability of the structure at the FLS. This required the development of a model that represents all traffic that has crossed the bridge from its opening until the present day. Additionally, future traffic loading was simulated so that future fatigue damage may be predicted.

2 Case Study 1: 6-lane Steel Arch Bridge

2.1 FE Model

For the purpose of this case study, a global FE model of the Case Study 1 (CS1) bridge was built in Midas Civil software. In this model, all bridge members were modelled as linear-elastic beam elements, with the deck plate modelled as plate elements. The deck plate was assigned a fine mesh and had shared nodes with the I-section cross-girders such that the composite action of the members could be accounted for.

A deterministic assessment of the bridge, detailed in [7], ascertained that the critical elements in the bridge at ULS were in the longitudinal girders and the arch section. Deterministically, it was found that both elements failed in yielding. Thus, the stress influence lines at the critical point in each member were extracted from the FE model. These may be seen in Figure 2.1 and Figure 2.2 below for the longitudinal girder and the arch section, respectively.

![Figure 2.1 Stress influence line for the critical longitudinal girder for loading in each lane of the Case Study 1 bridge](image1)

![Figure 2.2 Stress influence line for the critical arch section for loading in each lane of the Case Study 1 bridge](image2)

2.2 WIM Data

No WIM data is available for the CS1 bridge, and it is unlikely to be installed in the future. For the purpose of demonstrating the methodology, however, WIM data recorded in Ireland over a period of one year was used. The available data was recorded for a four-lane motorway and any erroneous data was cleaned using the method outlined in [8]. All permit trucks within the data were removed as the passage of permit trucks over the bridge should form part of an alternative modelling exercise. In addition, all trucks with 7 axles or more were removed due to their low frequency within the data.

The vehicle positions could be obtained from the WIM data based on the time stamps, lengths and speed of travel for each vehicle. These positions are plotted in Figure 2.3 for each of the traffic lanes. Discrepancies in the termination point for each lane are apparent in this figure due to the varying relative speed between vehicles. Thus, in order to perform this analysis, this data was converted to the time domain (see Figure 2.4). The influence lines were also converted to the time domain with a 0.1s increment.

![Figure 2.3 Vehicle position in units of distance for each lane from the WIM data](image3)
Vehicle Simulation

In order to simulate new vehicles in the load model that would be representative of the vehicles from the WIM data, it was necessary to define the number and type of truck classes to be included. As Irish WIM database was used in this study, the truck classes considered were as defined in [9]. A total of 10 vehicle classes were considered, which represented 99% of the vehicles in the WIM data. Although additional classes of vehicles existed in the data, the number of occurrences of these was too low to fit an accurate statistical model.

Vehicle simulation was performed by fitting statistical distributions to vehicle parameters such as axle spacings, vehicle speed, GVW and axle weight distribution for each class and then randomly sampling from these distributions. Axle spacings, speed, and axle weight distributions were fitted using empirical distributions. For GVW, previous work in [10] suggested fitting the tail of a normal distribution to the tail of the data to ensure that heavy loading events are accurately modelled. The approach taken in this study, however, involves fitting a multimodal distribution to the GVW for each vehicle class. This allows for accurate modelling and consideration of all GVWs in the data, including the heavy vehicles at the tail of the distribution. Figure 2.5 shows an example of a multimodal normal distribution fit to measured GVW data for a single vehicle class.

2.4  Gap Simulation and Overtaking Events

The influence lines shown previously in Figure 2.1 and Figure 2.2 show that the global distribution of load over the bridge has a significant impact on the critical elements to be assessed. Therefore, the gaps between vehicles in the same lane (inter-vehicle gaps) and the gaps between vehicles in adjacent lanes (inter-lane gaps) must be modelled to be representative of real truck meeting events.

One of the limitations of using statistical extrapolation methods is that the resulting model may only include inter-vehicle or inter-lane combinations that occurred during the collection period of the source WIM data. The approach taken in this case study addresses this by fitting empirical distributions to the inter-vehicle gaps from which simulated spacing may be sampled. Therefore, the time gaps between vehicles are representative of the types of spacing seen in the source data without being restricted to only include the exact time gaps recorded. In this particular data set, it was found that inter-vehicle gaps varied significantly for different hours of the day, thus an individual empirical distribution was fitted for each hour.

The location of the peak in the influence lines for each lane shown in Figure 2.1 indicates that events where multiple vehicles are adjacent to each other at a point in time (i.e. overtaking events) will be the most critical in the assessment of this element. Using statistical extrapolation for load modelling only allows for overtaking events as recorded in the WIM data to be included. To address this issue, inter-lane gaps during overtaking events were randomly sampled from representative statistical distributions. Previous work in [11] highlighted the importance of considering the weight correlation between vehicles during an overtaking event. An investigation into the relationship between vehicle GVW in the slow and fast lanes during an overtaking event was carried out using this WIM data and returned similar results. Figure 2.6 shows the significant peak in the GVW of fast-lane trucks when they are within 2s of a slow lane truck.

Figure 2.5 GGV data and fitted multimodal normal distribution for a single vehicle class

Figure 2.6 Inter-lane GVW correlation between slow lane vehicles (upper line) and fast lane vehicles (lower line) from the WIM data
This correlation was accounted for in this study by fitting a multi-dimensional normal distribution to the inter-lane gap data and the corresponding GVW in each lane. Thus, when sampling inter-lane gaps from this distribution, the correlated weights are assigned to certain vehicles in the fast lane that are part of overtaking events. In addition, the new GVWs are only assigned to truck classes where they do not severely impact the GVW CDF of the simulated data.

2.5 Dynamic Amplification

For this case study, the Dynamic Amplification Factor (DAF) was not applied directly to the simulated trucks within the load model. Instead, a stress-varying DAF model was developed that considers the fact that higher stresses tend to have lower associated dynamics [12]. This model consisted of a 2-dimensional probability distribution that was fitted to the dynamic increment (ε) and associated stress (σ) for each of the structural elements analysed. Dynamic increments were then randomly sampled from these distributions for each calculated stress value and applied directly to these stresses. More detail on this approach may be found in [7].

2.6 Traffic Growth

It is estimated that European road freight transport could grow by as much as 1.8% annually until 2030 [13]. This will result in an increase in both the weight and the frequency of passage of freight trucks. There is also an expectation that allowable GVW limits may be raised by NRAs in coming years. For the purpose of this study, it is conservatively assumed that there will be an annual weight increase of freight vehicles of 1%, and an increase in frequency of freight trucks of 1% per annum. These increases were considered both as individual scenarios (i.e. either 1% weight increase or 1% frequency increase per annum) and as a combined scenario (i.e. both parameters increase by 1% per annum simultaneously).

The long-run simulation methodology developed in this study is well suited to consideration of traffic growth. GVW increases are accounted for by increasing the mean value of the multimodal GVW distribution by 1% for each year of simulation. This approach works under the assumption that the weights of empty or lightly loaded vehicles are not affected by the weight increase and that the standard deviation of the distribution remains constant.

The increase in frequency of freight trucks was carried out by reducing the vehicle gap data by 1% with each year of simulation. This ensures that the CDF of the inter-vehicle spacings is modified such that more vehicles may be included in a given time frame.

3 CASE STUDY 2: 4-LANE BASCULE BRIDGE

3.1 FE Model

The most recent inspection report of the Case Study 2 (CS2) bridge superstructure identified the location of the most critical fatigue crack at the northmost support of the 41m span. There is a discontinuity in the deck at this location between the 41m span and the back leaf of the bascule span, meaning that for the purposes of this assessment the span of interest may be considered as an independent structure. Initially, a global model of the bridge was created in Midas Civil software using beam elements for the girders and plate elements for the deck plate. The geometry of this model was based on construction stage drawings of the bridge. The stress influence lines extracted from the model indicated that any loading placed more than 11.8m from the support location had negligible effect on the critical crack, thus it was concluded that only an 11.8m length of bridge was required in a local bridge model.

In order to reduce the computational intensiveness of the local model, a multi-scale approach was taken. In this approach, all structural elements were built using plate elements and a fine mesh across the whole width of the deck up to a 2.25m longitudinal distance from the critical crack location. The remainder of the bridge deck was modelled with a coarse mesh, using beam elements for all girders and stiffeners and plate elements for the deck plate.

The axial stress influence lines at the critical crack location were extracted from the FE model for each traffic lane and may be seen in Figure 3.1 below. Note that lanes 1-2 and lanes 3-4 each contain same-direction traffic.

![Figure 3.1 Influence lines for axial stress at the critical crack location for all lanes of the Case Study 2 bridge](image-url)

3.2 WIM Data

As for the previous case study, no WIM data was available at the bridge location. However, traffic count data was available for the bridge in the year 2018. This data consisted of the average daily vehicles that passed over the bridge in a given direction. These vehicles were classed into 3 categories based on the front-to-rear axle length. These classes are summarised in Table 3.1.

<table>
<thead>
<tr>
<th>Class</th>
<th>$L_{axle}$</th>
<th>Examples</th>
</tr>
</thead>
<tbody>
<tr>
<td>L1</td>
<td>$&lt; 3.7m$</td>
<td>cars, light vans</td>
</tr>
<tr>
<td>L2</td>
<td>$3.7m – 7.0m$</td>
<td>small trucks, buses</td>
</tr>
<tr>
<td>L3</td>
<td>$&gt; 7.0m$</td>
<td>larger trucks, 3+ axles</td>
</tr>
</tbody>
</table>

As no axle weights or spacings were measured at the site, it was necessary to utilise WIM data from alternative locations. The available WIM data was measured at two sites in the vicinity of the bridge location and consisted of approximately 4 months of data, collected between November 2018 and March 2019.

Erroneous records were removed from the data using the WIM data cleaning rules identified in [8]. Additionally, any vehicles with a Gross Vehicle Weight (GVW) of less than 3.5
tonnes were removed, as these would have a negligible effect on fatigue damage for the analysed detail. As in CS1, the WIM data and influence lines were converted to the time domain in order to remove any errors due to varying relative speed between vehicles.

3.3 Vehicle Simulation

Due to the lack of WIM data available at the bridge site, representative data was required to be simulated using a combination of vehicle load data from alternative sites and traffic count data from the bridge in question. Unlike in ULS failure, where damage is assessed as the result of a single load configuration, assessment of fatigue damage is a function of cumulative stress cycles over time. Therefore, it is important to ensure that the load model used is representative of the historical and future loading of the structure.

The traffic simulation began with the classification of the vehicles in the WIM data into 17 no. typical vehicle classes, accounting for vehicles up to 6 axles. The data also contained axle weights for vehicles for 7-9 axles, however these were removed due to low frequency of occurrence. Additionally, any class of vehicle that made up less than 0.5% of the total number of vehicles for each of the 4 lanes was excluded as the amount of data for these vehicles was considered to be insufficient for sampling. Hence, a total of 13 vehicle classes were included in this simulation, which represented at least 95% of the total number of vehicles provided in the cleaned WIM data. Details of these classes may be found in [14].

The traffic count information from the bridge site was used in order to correctly proportion the WIM data to reflect the number and types of vehicles traversing the bridge. The traffic counts for L1 vehicles were disregarded as vehicles such as cars and light vans (i.e. those under 3.5 tonnes) had been removed from the WIM data. With the exclusion of L1 vehicles, the traffic counts showed that 17% of vehicles travelling northbound and 26% of vehicles travelling southbound were of the L2 category. The remainder of vehicles were in the L3 category. Given that the traffic counts were collected per direction only, with no individual counts given per lane, the proportion of vehicles in the fast and slow lanes were determined by the WIM data.

As described for CS1, traffic simulation for CS2 began by fitting a multimodal normal distribution to the GVW of the WIM vehicles for each class. Empirical distributions were then fitted to each axle spacing. Finally, empirical distributions were fitted to the weight distribution of each axle for a given vehicle class. These distributions were then used to sample a given number of vehicles based on the correct proportions of each class as defined by the WIM data and the traffic counts. Unlike in CS1, a distribution was not fitted for vehicle speed in this study. This is due to the difference in the method for gap simulation as described in the following Section 3.4.

3.4 Gap Simulation and Overtaking Events

Given the length of the influence line considered and the highly localised nature of the axial stress effects at the critical damage location, it was determined that no two vehicles in the same lane would induce significant stress load effects at this point simultaneously. Hence the inter-vehicle gap did not need to be modelled in this analysis and a constant spacing was maintained between all vehicles on a given day. This inter-vehicle gap was defined for the slow lane in seconds, based on the number of vehicles passing over the bridge per day, see Eq. 2:

\[ \text{Gap} \ [s] = \frac{86400}{n_{veh} \times T} \]  

(1)

Where 86400 is the number of seconds in a day and \( n_{veh} \) is the number of vehicles passing through that lane per day, based on traffic count data.

Fast lane vehicles were positioned within the population by randomly selecting slow lane vehicles and inserting fast-lane vehicles mid-way between the first axles of consecutive vehicles in the slow lane. An exception to this approach was in overtaking events. Given the length of the influence lines (11.8m), the bridge speed limit (80 km/h), and an approximate vehicle length of 8m, a significant overtaking event in the WIM data was defined as a time gap of 1.2s or less between the front axles of vehicles in adjacent lanes. By this definition, the number of overtaking events that occurred per day in the WIM data was extracted, and an empirical distribution was fitted to the inter-lane time gaps during these events. Slow lane vehicles were then selected at random, and the closest fast-lane vehicle was positioned relative to that vehicle based on an inter-lane gap sampled from the empirical distribution.

3.5 Dynamic Amplification

Due to the inherent complexity of the analysis of bridge stresses for FLS, the approach taken in CS1 for consideration of dynamic amplification could not be applied in this study. Instead, the DAF was calculated using the method recommended in [15] for each vehicle. The DAF value was applied directly to all axle loads for a single vehicle.

3.6 Traffic Growth

As mentioned in previous sections, it was important for the analysis of fatigue damage to ensure that the frequency of vehicle passage was representative of historical and future traffic counts. Historical traffic count data for the bridge in question from its day of opening was obtained from the relevant infrastructure managers. Future traffic growth was predicted using detailed network models and considering four traffic growth scenarios. Details of these may be found in [7].

Traffic growth was modelled by changing the number of vehicles to be sampled for each year. As the inter-vehicle gaps are directly dependent on the number of vehicles passing over the bridge per day, this meant that these gaps were automatically modified when the traffic count was altered.

4 COMPARISON TO STATISTICAL EXTRAPOLATION

The long-run simulation methodology outlined in this paper was designed to be a more robust alternative to the use of statistical extrapolation methods for determining characteristic loading and carrying out probabilistic assessment. In order to verify this method with respect to statistical extrapolation, the stress results obtained using the long-run model developed for the longitudinal girder in CS1 were compared to the results found using statistical extrapolation of the WIM data using Extreme Value Theory.

This process began by simulating 100 years of traffic as “trains” of trucks. These “trains” were then run over the influence lines for stress at the longitudinal girder. From this,
100 maximum yearly stresses were calculated. The CDF of these simulated maximum stresses are shown in Figure 4.1. These are compared to a fit obtained from maximum daily stress values from the WIM data using statistical extrapolation.

It can clearly be seen from the above Figure 4.1, that the fits to the simulated data (purple) and extrapolated data (green) are very similar. This indicates that for one year of data, both methods yield similar results. However, it should be noted that the 100-year stress value from the extrapolation of maximum daily stress is 69MPa, while the maximum stress value obtained using simulation is 76MPa, an increase of over 10%. This illustrates the impetus for these simulations, as potentially more accurate loading events that may be critical for assessment may be identified.

5 CONCLUSIONS

The objective of this paper was to present and compare the methodologies adopted in the development of long-run traffic simulations for the assessment of two road bridges with orthotropic steel decks.

It was found that the required approach varied for each of the studies as a result of data availability, the shape of the influence lines, and the limit state being assessed. Therefore, it can be concluded that this methodology must be adapted on a case-by-case basis, and that it is flexible enough to accommodate this.

In both cases, WIM data from the exact bridge site was not available and data from alternative sites was used. However in CS2, traffic count data was available and hence the WIM data had to be manipulated to reflect the accurate traffic counts.

In CS1, the influence lines for the critical elements indicated that they were sensitive to load application over the full length of the bridge. As a result, the simulation of inter-lane and inter-vehicle gaps were of significance in this study. Conversely, the influence lines in CS2 showed highly local effects, meaning that detailed gap simulation was not required.

The methodology developed demonstrates a significant progression beyond the current state of the art. The use of a Monte Carlo approach which can be applied to multi-lane, multi-directional traffic allows the calculation of past and future load effects, considering increases / decreases in traffic volume over time. The approach considers the correlation in overtaking events and allows calculation of the complete fatigue loading history of a structure. Crucially, future traffic growth can be quantified from the perspective of characteristic loading events and calculation of potential fatigue damage.

Finally, a verification of the long-run simulation methodology was carried out with respect to statistical extrapolation, a more common approach to load modelling. This comparison of results for one of the critical elements in the CS1 bridge showed that the two methods return similar results. However, it is important to consider the added flexibility in the proposed simulation approach, where parameters such as traffic growth, potential increases in weight limits of freight vehicles, and new truck meeting events may be accounted for. Thus, the methodology presented herein may be considered to be more representative of actual loading.

ACKNOWLEDGMENTS

This project has received funding from the European Union’s Horizon 2020 Research and Innovation Programme under Grant Agreement Number 723254.

REFERENCES