LOAD EFFECT OF SINGLE-LANE TRAFFIC SIMULATIONS ON LONG-SPAN BRIDGES

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Abstract
It is well acknowledged that long-span road bridges (about 50 m long and more) are governed by congestion traffic rather than free-flow conditions. A conventional model for the design of new long-span bridges is to place over the bridge a load model representing a platoon of heavy vehicles with the gaps between them reduced to a minimum. This assumption is too conservative for existing bridges, given the large disruption costs faced by their closure for rehabilitation. In order to model the close gaps between vehicles, characteristic of congested traffic, microsimulation is needed to accurately capture drivers’ behaviour. In this work, a microsimulation model is studied and found to replicate many different known forms of congestion. As a first approach to the topic, single-lane simulations of identical vehicles have been carried out in order to obtain load effect on a sample bridge. This load effect is studied with reference to the form of traffic causing the load effect. It is found that the most extreme load effect may not be caused by purely congested traffic but also by non-stationary congested conditions.

Keywords: bridges; loading; long-span; microsimulation; traffic

1. General

It is well acknowledged that long-span road bridges (50 m long and more) are governed by congested traffic rather than free-flow conditions. In free flowing traffic, vehicles have large gaps between them, while congestion implies long queues of closely spaced vehicles. Greater load effect results, even though there is no amplification for dynamic effects (Buckland, 1981).

A conventional model for designing new bridges is to reduce the gaps between trucks to a minimum. However, this assumption is too conservative for existing bridges, given the large cost associated with disruption caused by rehabilitation works. Therefore it is imperative that as the long-span bridge stock ages, more accurate estimation methods of congested traffic are found.

As the traditional macroscopic models, which describe the flow in terms of aggregate quantities, are not able to capture this phenomenon, micro-simulation is needed to capture drivers’ behaviour in congested conditions. Further, since drivers do not usually stay between larger vehicles, cars may move out from between trucks, as traffic becomes congested. This can result in the formation of truck platoons in the slow lane (OBrien et al, 2009). Again microsimulation is the only tool than can adequately describe such movements.

In this paper, the flow of identical vehicles running on a single-lane road is studied. The different traffic states are identified and a sample load effect is calculated for each
of these traffic histories. In this way, the influence of driver behaviour on long-span load effect can be understood, before application to more complex models and traffic streams.

2. Microsimulation Model

2.1 The Intelligent Driver Model

In order to carry out the traffic microsimulation, a program called EvolveTraffic has been extensively used. EvolveTraffic implements the Intelligent Driver Model (IDM) developed by Treiber et al. (2000a, 2000b). The IDM is a car-following model, which simulates driver behaviour in time through an acceleration function which optimizes overall braking:

\begin{equation}
\begin{align*}
a(t) &= a \left[ 1 - \left( \frac{v(t)}{v_0} \right)^\delta - \left( \frac{s^*(t)}{s(t)} \right)^2 \right] \\
\end{align*}
\end{equation}

where \( a \) is the maximum acceleration; \( v_0 \) is the desired speed; \( v(t) \) the current speed; \( \delta \) the acceleration exponent; \( s(t) \) the current gap to the vehicle in front, and; \( s^*(t) \) the minimum desired gap, given by:

\begin{equation}
\begin{align*}
s^*(t) &= s_0 + s_1 \sqrt{\frac{v(t)}{v_0}} + T v(t) + \frac{v(t) \Delta v(t)}{2 \sqrt{ab}} \\
\end{align*}
\end{equation}

In which, \( s_0 \) is the minimum bumper-to-bumper distance; \( s_1 \) the ‘elastic’ jam distance; \( T \) the safe time headway; \( \Delta v(t) \) the velocity difference between the current vehicle and the vehicle in front, and; \( b \) the comfortable deceleration.

There are seven parameters in this model to capture driver behaviour. Most of these have a physical interpretation, and can be estimated through measurement and estimation. For simulation purposes, the length of the vehicle must also be known as it affects the spatial disposition of vehicles. Individual vehicles can be given their own driving parameters. However, in order to understand the fundamental behaviours, a traffic flow of identical vehicles with identical driver behaviour is considered further in this work.

2.2 Congested Traffic States

Treiber et al. (2000a, 2000b) have shown that congestion can be effectively generated by either decreasing locally the desired speed \( v_0 \) or increasing the safe headway \( T \). It has been also shown that such local parameter variations act as an equivalent on-ramp bottleneck, which instead would require an injecting flow and a lane-changing model. In this paper, inhomogeneity is generated by increasing the safe time headway \( T \) downstream, say \( T' \), which Treiber et al. (2000b) state to be more effective than decreasing \( v_0 \).

A bottleneck strength \( \delta Q \) can be defined as difference between the inflow \( Q_{in} \) and the outflow \( Q_{out} \).
\[ \delta Q(T') = Q_{in} - Q_{out}(T') \] (3)

Depending on the inflow and the bottleneck strength, the downstream traffic can take up the identifiable traffic states explained in Table 1. A combination of these congested states may also occur and these are highly dependent on the previous traffic history.

**Table 1 – Traffic States Definitions**

<table>
<thead>
<tr>
<th>Acronym</th>
<th>Explanation of traffic state</th>
</tr>
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<tbody>
<tr>
<td>FT</td>
<td>Free traffic</td>
</tr>
<tr>
<td>MLC</td>
<td>Moving localized cluster, which moves upstream</td>
</tr>
<tr>
<td>PLC</td>
<td>Pinned localized cluster, which remains near the inhomogeneity</td>
</tr>
<tr>
<td>TSG</td>
<td>Stop and go waves</td>
</tr>
<tr>
<td>OCT</td>
<td>Oscillatory congested traffic</td>
</tr>
<tr>
<td>HCT</td>
<td>Homogeneous congested traffic</td>
</tr>
</tbody>
</table>

It is also possible to output the usual macroscopic quantities of interest, such as flow and density. In fact, *EvolveTraffic* counts the number of vehicles passing over specified virtual detectors, that is it returns the flow \( Q \), and outputs the speed as well. The traffic density is found using the space mean speed, for \( n \) vehicles, defined as:

\[ \bar{v} = \frac{n}{\sum_{i=1}^{n} 1 / v_i} \] (4)

Through the fundamental relation of traffic, the density, \( \rho \), is thus found as:

\[ \rho = \frac{Q}{\bar{v}} \] (5)

Phase diagrams are very informative for investigating the different forms of congestion that can occur, as they show the spatio-temporal variation of density along the roadway.

**2.3 Model and Simulation Parameters**

For this study, the vehicle stream is taken as being homogenous (i.e. all cars). Each vehicle is given the same set of driver behaviour parameters, shown in Table 2. These parameters are based on those used by Treiber et al. (2000b) and are found to give good match to real traffic.

A single-lane 5000 m long road is used in this work. The safe time headway is \( T \) from 0 to 2700 m (see Table 2), then increases gradually to 3300 m until it reaches the value \( T' \). We examine a range of values of \( T' \).
Table 2 - Model parameters of the IDM model

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Desired velocity, $v_0$</td>
<td>120 km/h</td>
</tr>
<tr>
<td>Safe time headway, $T$</td>
<td>1.6 s</td>
</tr>
<tr>
<td>Maximum acceleration, $a$</td>
<td>0.73 m/s$^2$</td>
</tr>
<tr>
<td>Comfortable deceleration, $b$</td>
<td>1.67 m/s$^2$</td>
</tr>
<tr>
<td>Acceleration exponent, $\delta$</td>
<td>4</td>
</tr>
<tr>
<td>Minimum jam distance, $s_0$</td>
<td>3 m</td>
</tr>
<tr>
<td>Elastic jam distance, $s_1$</td>
<td>0 m</td>
</tr>
<tr>
<td>Vehicle length, $l$</td>
<td>4 m</td>
</tr>
</tbody>
</table>

Eight different values of $T'$ (1.9, 2.05, 2.2, 2.5, 2.8, 3.4, 4.0 and 4.6 s) and two inflows $Q_{in}$ (1580 and 1200 veh/h) are considered for the simulations, each of which is 30 minutes long. All the vehicles have an initial velocity of 30 km/h.

Nine output detectors are set at 500 m intervals from 1000 m. However, after the inhomogeneity gradient finishes at 3300 m, the traffic is uncongested. Therefore the results of the detectors from 1000 to 3000 m are most relevant. Figure 1 gives an illustration of typical stop-go waves in congested traffic.

![Figure 1 – Typical traffic behaviour: the black lines are vehicles (not to scale).](image)

3. Traffic Behaviour

3.1 Bottleneck Strength and Safe Time Headway

For the values of $T'$ considered, the bottleneck strengths (found from Equation (3)) are plotted in Figure 2. As can be seen, in the main, three different kinds of congestion have been found: stop-and-go waves (TSG), oscillating congested traffic (OCT) and a complex state with stationary congested traffic near the inhomogeneity, and oscillatory congestion further upstream (HCT/OCT). Such a state has been found in Treiber et al. (2000b) as well.

It is worth noting that the flow does not break down until the safe time headway is increased to 2.05 s ($Q_{in} = 1580$ veh/h) and 2.8 s ($Q_{in} = 1200$ veh/h). Below these threshold values, the change in $T$ only has the only effect of reducing the flow. As may be expected, the 1200 veh/h curve lies beneath the 1580 veh/h, since a significant increase in the safe time headway is needed to generate congestion for lower flows.
Figure 2 – Variation of bottleneck strength with safe time headway (for the explanation of the abbreviations see Table 1).

3.2 Identifying Traffic Phases

The traffic phase diagram is extremely useful for diagnosing traffic states. Figure 3 shows four phase diagrams corresponding to those obtained for \( Q_{in} \) of 1580 veh/h and \( T' \) of 1.9 s (FT), 2.2 s (TSG), 2.8 s (OCT), and 4.6 s (HCT/OCT). In these diagrams, the flat areas correspond to free traffic since the density is the same.

Figure 3(a) shows free-traffic, with a slight density increase after the inhomogeneity due to the flow slowing-down; in Figure 3(b) it is easy to identify two stop-and-go waves. Figure 3(c) shows a typical oscillating traffic with a rough surface, while
Figure 3(d) shows a smooth-edged wall near the inhomogeneity (HCT), in front of the oscillating surface (OCT). These are similar to those of Treiber et al. (2000a, 2000b).

4. Load Effects due to Single Lane Traffic

4.1 Comparison of Approaches

There are two approaches to calculating load effects: time-based - a traffic ‘image’ is taken at the same location during the simulation; or space-based - a traffic image is taken on a stretch of road every time interval.

In the latter case, the spatial distribution of the vehicles can be directly output. Thus it is simple to calculate the load effects on a bridge. However, changes in gaps due to differing vehicle velocities cannot be taken into account, and this may affect the resulting load effect. On the other hand, the time-based image represents the actual EvolveTraffic virtual detectors’ measurements, and can also uses data collected from typical real traffic measurements. However, this has the disadvantage that vehicle gaps must be monitored. In fact, for longer spans, if vehicles keep their own velocity, it is very likely that physically-impossible overlapping will occur in non-stationary conditions. Therefore, it is preferable to set a constant velocity, thus effectively ‘freezing’ the time headways, effecting a space-based solution. However, this ‘homogenous’ velocity is not straightforward to set. For instance, a sensible option would be to choose an average speed. In this case, this method provides reliable results when the actual velocity is close to the average one, but in non-stationary conditions, where there can be a wide range of velocities, two cases are likely to occur:

- the actual velocity is lower than the average (for instance, during a stop-and-go event): then the space headways will be overestimated and the load effects underestimated. In this case, as we are interested in congestion conditions, important pieces of information may be missed;
- the actual velocity is higher than the average (for instance, during free-flowing traffic): then the space headways will be underestimated and the load effects overestimated, which may be even higher than the ones during congestions.

4.2 Present Approach

Load effects are calculated on a sample bridge with 100 m span. The bridge is taken to be simply-supported and the overall bending moment at mid-span is calculated through the influence line theory. Each vehicle is represented as a single concentrated load of 2 t (19.6 kN).

The time-based approach is used, but the authors propose to find a spatial vehicle distribution by multiplying the time headways between the current vehicle and the front one by the current vehicle's own speed, thus effectively "freezing" the space headways. There is still some degree of approximation, as one vehicle may change its speed crossing the bridge, but the approximation of the constant speed is dropped and therefore the program can beneficially adapt to the different kinds of traffic.

As a result of this approach, for each vehicle passing over the 2000 and 2500 m detectors, we find the space headways between the current vehicle and as many following vehicles as occur on the bridge.

Moreover, rather than passing the whole traffic data across the bridge, the current leading vehicle is positioned over the last bearing. This assumption significantly
reduces the amount of data, but is non-conservative in free-traffic, as it strongly depends on the free-flowing space headway. However, as the number of vehicles on the bridge increases, this difference becomes smaller and smaller, providing reliable results for congested traffic.

Figure 4 summarises the different time-based approaches discussed above. A traffic sample with slightly oscillatory congestion has been analysed. It can be seen that the moments calculated with the proposed approach are similar to those calculated by setting a constant velocity equal to the average of the traffic. Also shown are the moments calculated with variable velocity which, as can be seen, leads to higher bending moments for the reasons described earlier.

![Figure 4](image)

**Figure 4** – Comparison of methods of calculation of load effect.

5. Results and Conclusions

Figure 5 shows the bending moments obtained for $Q_{in} = 1580$ veh/h at the 2500 m detector for the most congested situations ($T' = 3.4, 4.0, 4.6$ s). Figure 6 shows how the maximum moment is related to the safe time headway and the bottleneck strength. It can be noted that the OCT state for $Q_{in} = 1200$ veh/h and $T' = 2.8$ s does not affect the traffic at the detector 2000 m, providing a free-flow traffic moment load effect. Also, the homogeneous congestion conditions in the HCT/OCT states do not reach the 2000 m detector, although give almost the same moment values in both conditions.

It can be also seen that for high safe time headways the result tends to reach approximately the same bending moment of approximately 2550 kNm, regardless of the inflow and the corresponding bottleneck strength.

On conclusion, this research provides a valuable basis for further extension to multi-lane traffic micro-simulations. The method is also applicable to real traffic data (vehicle composition and distribution) to obtain load effects.
Figure 5 – Mid-span bending moment for $Q_m = 1580$ veh/h at the 2500 m detector.

Figure 6 – Variation of maximum moment with: (a) bottleneck strength, and; (b) safe time headway. In (a) only changes in the type of congestion are marked.

References


