Microsimulation Modelling of Congested Traffic on Long Span Bridges

By

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Declaration

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Abstract

This thesis contributes to the development of traffic microsimulation for long span bridges. Microsimulation is used to model measured traffic flow conditions taking into account the effects of vehicle interactions and driver behaviour. Current bridge design loading models in design codes are far too conservative. This is not an issue in most new builds, as an increase in the strength of the bridge is not too expensive. However in the area of existing bridges that are presumed to require repair or replacement, great cost savings can be made by proving that an existing bridge is safe for the load carried during its lifetime. Traffic microsimulation allows greater volumes of traffic data to be generated that would otherwise be very costly and time consuming to accumulate. Therefore more traffic can be analysed using traffic microsimulation, resulting in a more accurate assessment of the ultimate traffic loading on long span bridges.

The maximum load on long span bridges occurs due to congested traffic. This thesis assists in the further development of accurate and efficient modelling of congested traffic. *Evolvetraffic* is a traffic microsimulation model for bridge loading and uses the IDM car following model and the MOBIL lane changing model to simulate real traffic flow. Between the IDM and MOBIL, there are 10 parameters that can be altered by the user to describe different driver characteristics. This thesis carries out a sensitivity analysis on these parameters and discovers which parameters have the most effect on the lifetime load of long span bridges. By neglecting parameters which have no effect on congested traffic loading, the process of simulating congested traffic can be made simpler with less variables and therefore more user friendly.

Acknowledgements

I would like to thank Prof. Eugene O’ Brien for his guidance throughout this work and also to Dr. Colin Caprani whose support and help when approached was always forthcoming and greatly appreciated.

To Jessica, my beautiful girlfriend, thanks for waiting until I got this thesis finished before bringing our baby boy into this world. I know we had a few close calls with both due in the same week, but we got there in the end.

To Shane and Aoife, thanks for your combined expertise with Excel. Your advice saved me more than a few hours’ worth of compiling results.

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1 Introduction

Highway bridge load models in bridge design codes are generally quite conservative. Whilst this is not a problem for most newly constructed bridges, the codes are particularly conservative for the renovation of existing bridges. The cost of repairing existing bridges to the existing conservative loading codes is considerable and is an area where large savings can be made. This has given rise to the increase in the development of accurate assessments of the actual loads that a bridge may be subject to.

Traffic microsimulation can be used be estimate rare extreme loading events that may result from the traffic at a measured site in the bridge lifetime. This thesis aims to assist in the advancement of such microsimulation techniques by conducting a sensitivity analysis on *EvolveTraffic,* a traffic microsimulation model for bridge loading. This study is particularly interested in congested traffic on long span bridges. By varying each individual IDM parameter while keeping every other variable at a constant level and simulating the traffic travelling across a 100m long simply supported bridge, the change in the moments in the bridge due to each parameter can be calculated. The significance of each parameter with respect to the moment in the bridge can then be determined. This will allow greater knowledge of which parameters benefit traffic microsimulation and which are not required.

2 Literature Review

2.1 Introduction

This chapter introduces the relevant information related to the microsimulation of congested traffic on long span bridges. Section 2.2 briefly introduces to concept of Weigh-In-Motion (WIM) and its advantages. Section 2.3 reviews the simulation of traffic. It lists the three main types of traffic models for bridge load effect and discusses in more detail the simulation of real traffic flow and outlines the various modelling methods previously developed.

2.2 Weigh-In-Motion

In order to define realistic traffic load models and to make realistic predictions for future flow effects, high quality information concerning the traffic flow on a bridge is required. The most appropriate method for long-span bridges is the application of Weigh-in-Motion (WIM) technology, *Hayrapetova, 2007*. Weigh-in-motion technology, *Moses, 1979,* paved the way for the use of precise measured traffic streams for the modelling of bridge loading. Prior to this, bridge load modelling involved sampling the traffic population through the use of static weigh stations as shown by *Agarwal and Wolkowicz, 1976*, or simply estimating the properties of traffic. These static weigh stations however, are known to give biased results as the drivers of overweight trucks often become aware of the weigh stations and avoid them, *Caprani, 2005*. The advantage of WIM is the ability to obtain more reliable modelling of the truck weight distribution as there is no pre-selection of vehicles and therefore, statistical bias of data is greatly reduced. *Hayrapetova, 2007,* states that this is crucial for the development of equivalent uniformly distributed load for individual lanes on long span bridges. *Caprani, 2005*, states that WIM technology has given unbiased statistics of traffic characteristics and therefore allowed for more accurate traffic models to be used for bridge load modelling.

2.3 Simulation of Traffic Loading

Crespo-Minguillón and Casas, 1997 and *O'Connor, 2001* note that there are 3 main types of traffic models for bridge load effect. These are Theoretical statistical models, Static Traffic Configurations and Simulation of real traffic flow and are described in further detail below.

2.3.1 Theoretical statistical models

Caprani, 2005 states that stochastic process theory and distributions representing traffic characteristics are used in statistical convolution to determine the distribution of traffic loads that result. *O'Connor et al, 2002; Fu and Hag-Elsafi, 1995; Ghosn and Moses, 1985; Ditlevsen, 1994;* and *Ditlevsen and Madsen, 1994* are examples. Theoretical statistical models are not of relevance to this particular study and therefore are not researched further.

2.3.2 Static Traffic Configurations

This model uses measured (or estimated) traffic data which is obtained from static weight stations and is used to calculate the resulting load effects on a bridge. *Caprani, 2005,* has noted that variation in the traffic stream is not allowed; therefore the quantity of traffic used is of major importance. This represents a significant drawback to this approach. Static traffic configurations are not relevant to this study and therefore are not considered further.

2.3.3 Simulation of real traffic flow

This model is of significant interest to this work and involves using measured traffic data from WIM technology as the basis for statistical distribution of traffic characteristics. Monte–Carlo simulation is used to generate artificial, yet representative traffic which is then used to calculate load effects on bridges. This model allows for unobserved traffic to be modelled accurately so as it represents measured traffic, therefore allowing greater volumes of traffic loading to be simulated. *O'Connor, 2001, Nowak, 1993 and Crespo-Minguillón and Casas, 1997,* identifies problems with the load effects that result when this process is not undertaken.

It is this simulation of real traffic flow that is of particular importance to this study. By basing traffic models, defined by statistical distributions for each of the traffic characteristics, on a set of measured traffic, the traffic model can be claimed to represent real traffic, *Caprani, 2005.* There are a number of different real traffic load models that have been developed previously and they are outlined below.

2.3.3.1 Bailey, 1996

Bailey, 1996, developed a detailed statistical traffic load model for medium to long length bridges and allows for different types of traffic flow. Bailey's model is based on WIM data taken from various sites across Switzerland. The traffic is made up of 14 different types of vehicle which make up 99% of all Swiss truck traffic. The frequency of each vehicle type is observed and used in the simulations. Bailey considers axle groups as having a single weight, and assumes that the weight is evenly distributed between closely spaced axles. A generalized bi-modal beta distribution is used to fit the observed axle group weights, as shown below in Figure 2-1. Correlation of this weight with the GVW is allowed for, through generation of the other axle weights based on the axle group weight. The geometries of the vehicles are modelled by a beta distribution for each of the axle spacings and overhangs of each type of truck.

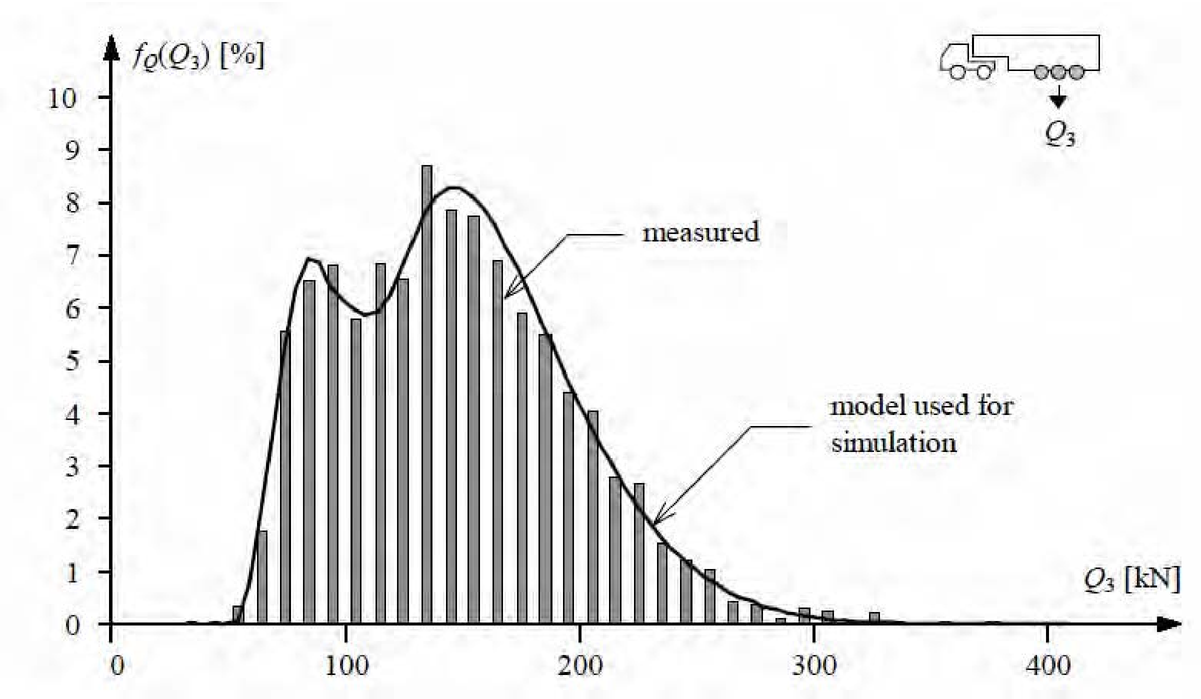


Figure 2-1: Axle-group weight distribution, *Bailey, 1996*

2.3.3.2 Crespo-Minguillón and Casas, 1997

Crespo-Minguillón and Casas' generation of traffic and their modelling of each of the traffic characteristics, are outlined in the sequence below:

- The annual mean daily flow is selected for the site under analysis.
- Calibration curves for the traffic flow during the day of the week and the hourly variation are then used as shown in Figure 2-2.
- A binomial decision making process is then used to determine whether the traffic state will be jammed or free-flowing, the parameters of this process are not given

by the authors, yet they are stated to be dependent on the hour. Therefore the increased probability of traffic jams occurring during rush hour is taken into account.

- Given the state of the traffic and its flow, the traffic density can then be determined from measured flow-density curves shown in Figure 2-3.

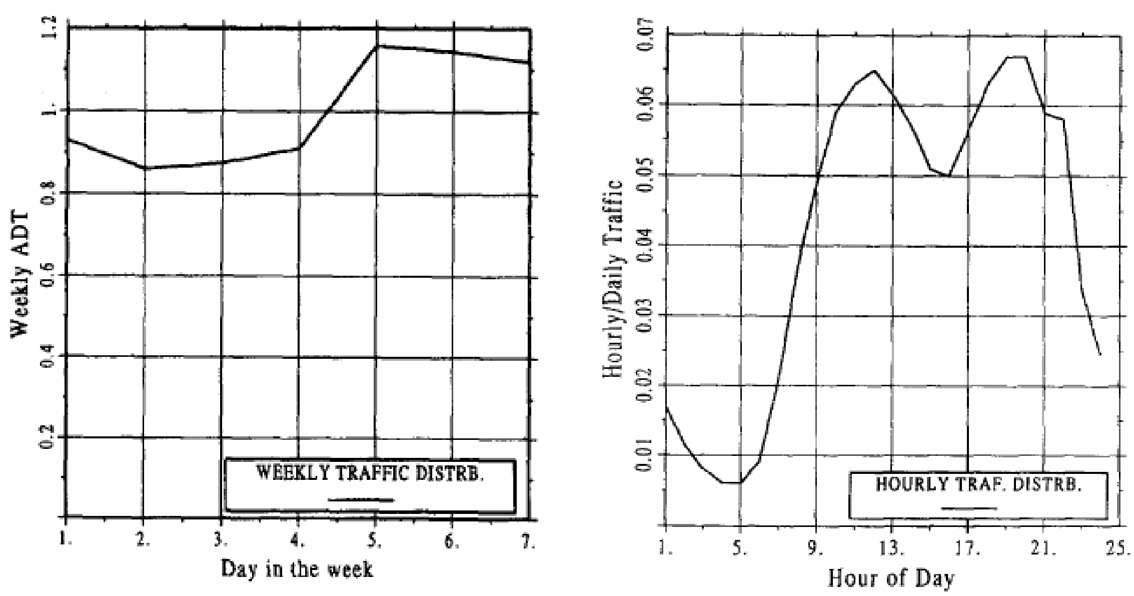


Figure 2-2: Calibration curves for traffic flow, Crespo-Minguillón and Casas, 1997

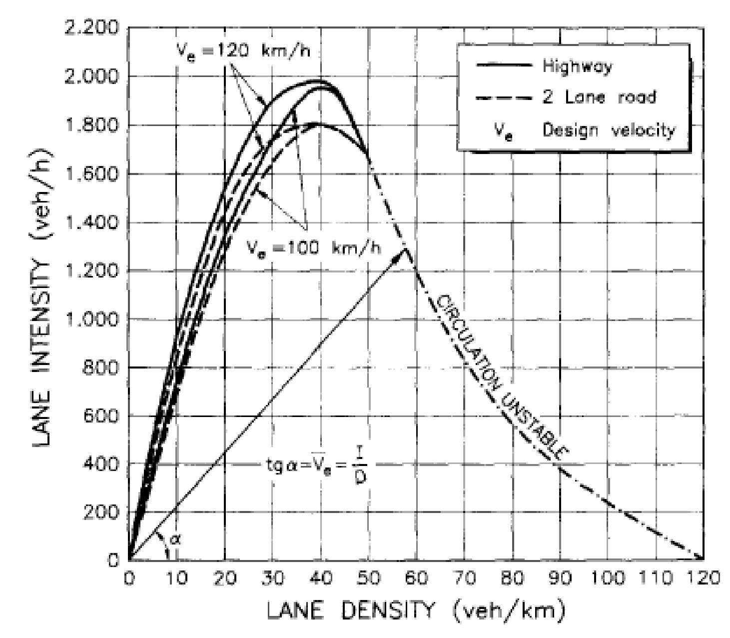


Figure 2-3: Flow-Density curves for traffic condition, ***Crespo-Minguillón and Casas, 1997***

- The traffic compositions are taken from measured WIM data at the site. The vehicle type, for the next vehicle arriving on the bridge, is calculated using a Markov-chain method, with transition matrices based on those of the measured WIM data.
- The velocities are then allocated to each vehicle based on a normalised velocity function which can then be related to the flow-density graph for the current flow condition.
- Headway is assigned using the normalised headway model. Different such models are specified for different forms of driver behaviour, vehicle weights and lanes.
- Weights and geometries are then allocated to each vehicle. Axle weights and Gross Vehicle Weight (GVW) are allocated based on measured correlations as shown in Table 1, between GVW and axle weights. Geometries are based on measured correlation coefficients for axle spacings. The GVW and axle weight distributions are defined numerically from measured cumulative distribution functions derived from the histograms of Figure 2-4. In running this model across a bridge, the authors allow for interaction between the vehicles; i.e. overtaking events and changes in speed are modelled.

Correlation matrix of weights for vehicles type 8. W_i = axle weight i; W_G = gross weight

	W_1	W_2	W_3	W_G
W_1	1.00	0.40	−0.74	−0.04
W_2	0.40	1.00	−0.89	0.11
W_3	−0.74	−0.89	1.00	−0.02
W_G	−0.04	0.11	−0.02	1.00

Table 1: Correlation values between axle weights and GVW, *Crespo-Minguillón and Casas, 1997*

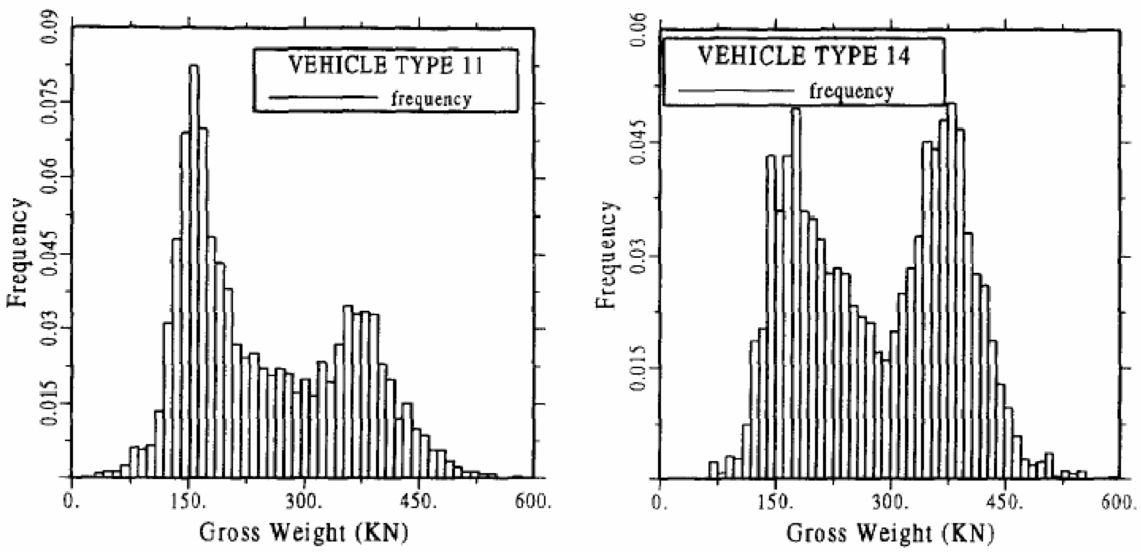


Figure 2-4: GVW histograms for 2 vehicle types, *Crespo-Minguillón and Casas, 1997*

2.3.3.3 Grave, 2001

Grave, 2001, also develops a comprehensive traffic load model for use on short to medium length bridges. Most of the traffic characteristics have been modelled statistically by Grave. Only traffic composition percentages and flow rates are deterministic. The headway model used by Grave is the same as that of *Crespo-Minguillón and Casas, 1997.* The number of vehicle types is more limited than that of the other studies mentioned. Grave points out that the added complexity is not required for the WIM data under study.

2.3.3.4 Treiber, Hennecke, Helbing, 2000

The Intelligent-Driver Model (IDM) was developed by *Treiber, Hennecke, Helbing, 2000*, to simulate the longitudinal dynamics, i.e. accelerations and braking decelerations of the drivers. Treiber explains that the IDM is a "car-following model". That is, the traffic state at a given time is characterised by the positions, velocities and the lane index of all vehicles. The decision of any driver to accelerate or to brake depends only on his own velocity and on the vehicle immediately in front of him, while lane changing decisions depend on all the surrounding vehicles.

The IDM has seven intuitive parameters:

- Desired velocity on a free road (v_0)
- Desired safe time headway when following other vehicles *(T)*
- Maximum acceleration *(a)*
- Comfortable braking deceleration *(b)*
- Minimum bumper to bumper distance to the vehicle in front when stopped *(s_0)*
- Elastic jam distance to the vehicle in front *(s_1)*
- Acceleration exponent *(δ_a)*

According to *Treiber*, *Hennecke, Helbing, 2000*, the applied IDM belongs to the class of deterministic follow-the-leader models like the optimal-velocity model of *Bando et al, 1995,* but it has the following advantages:

- It behaves as if accident-free because of the dependence on the relative velocity,
- All model parameters have a reasonable interpretation, are known to be relevant, are empirically measurable, and have the expected order of magnitude.
- The fundamental diagram and the stability properties of the model can be easily (and separately) calibrated to empirical data,
- It allows for a fast numerical simulation, and
- An equivalent macroscopic version of the model is known, which is not the case for most other microscopic traffic models.

2.3.3.5 Kesting, Treiber, Helbing, 2007

Kesting, Treiber, Helbing, 2007, developed a general model minimizing overall braking induced by lane change (MOBIL), to derive lane-changing rules for discretionary and mandatory lane changes for a wide class of car-following models. Both the utility of a given lane and the risk associated with lane changes are determined in terms of longitudinal accelerations calculated with microscopic traffic models, i.e. the IDM in this work. This determination allows for the formulation of compact and general safety and incentive criteria for both symmetric and asymmetric passing rules. Although the safety criterion prevents critical lane changes and collisions, the incentive criterion takes into account the advantages and disadvantages of other driver associated with a lane change via the "politeness factor *(P)*". The politeness factor allows for the variation of the motivation for lane changing from purely egoistic to more co-operative or polite driving behaviour. This means that lane changes that obstruct other drivers can be prevented and also that an aggressive driver can induce a lane change in order to no longer be obstructed.

The MOBIL model has 3 intuitive parameters:

- Lane change politeness factor *(P)*
- Outside lane bias factor (δ_{bias})
- Lane change threshold (δ_{thr})

The MOBIL model allows lane changes to take place, if

a) The potential new target lane is more attractive, i.e., the *"incentive criterion"* is satisfied, and
b) The change can be performed safely, i.e., the *"safety criterion"* is satisfied.

In the MOBIL model, both criteria are based on the accelerations on the old lane and on the prospective new lane, as calculated with the IDM.

2.3.3.6 Caprani et al, 2008

Caprani et al, 2008 developed *EvolveTraffic,* a traffic micosimulation model for bridge loading using *Treiber et al's* IDM and MOBIL models. Caprani expands the capabilities of the IDM and MOBIL models by allowing the use of probabilistic IDM parameters as opposed to deterministic IDM parameters as used in all of Treiber's work to date. This enables each vehicle within each vehicle class to have slightly different IDM parameters distributed according to 7 different distributions. The supported distributions, with parameters and some comments are listed below:

- **Exponential:** Location and Scale parameters – may be useful for some parameters such as Safe Time Headway. Not suitable for most parameters, for example, Desired Velocity *(v_0)*.
- **Log-Normal:** Location and Scale parameters – used in this work.
- **Gamma:** Location and Scale parameters.

- **Gumbel:** Location and Scale parameters.
- **Poisson:** Location and Scale parameters – provides a continuous approximation to the discrete distribution only valid when the location parameter is greater than 10.
- **GEV:** Location, Scale and Shape parameters – although strictly an extreme value distribution, its flexibility (due to its 3 parameters) allows many phenomena to be modelled accurately.
- **Normal:** Location and Scale – the standard Gaussian distribution of parameters mean and standard deviation.
- **Constant:** Location – this is the deterministic option as no random numbers are generated and the parameter takes the value Location for all vehicles in the class – used in this work.

The IDM and MOBIL models are used for the microsimulation of traffic in this research through the use of *EvolveTraffic*, a traffic micro simulation model for bridge loading, developed by *Caprani et al, at University College Dublin in collaboration with Laboratoire Central des Ponts et Chausées, France, 2008*.

3 Fundamental Theories

3.1 Characteristic value and Extrapolation

The characteristic value is the value of a random variable that is expected to be exceeded once in a given return period. For bridge design, it is usual to design the bridge for a return period of 1,000 years. The probability of exceeding a value (u) is given below in Equation 3-1, where (X) is a random variable and ($F_X()$) is the distribution function.

$$P[X > u] = 1 - F_X(u)$$

Equation 3-1: Probability of exceeding (*u*)

For a given return period (R), consider (n) repetitions of the sampling period (T_X), from which (X) was determined, such that:

$$n = \frac{R}{T_X}$$

Equation 3-2: Repetitions of the sampling period

The probability of the characteristic value (u) being exceeded in (n) repetitions is therefore given as:

$$P[X > u \text{ in } n \text{ repetitions}] = n(1 - F_X(u))$$

Equation 3-3: Probability of exceeding (*u*) in (*n*) repetitions

By definition of a characteristic value, the value is expected to occur at least once in (n) repetitions; therefore the probability must be equal to unity and Equation 3-3 goes to Equation 3-4.

$$1 = n(1 - F_X(u))$$

$$F_X(u) = 1 - \frac{1}{n}$$

Equation 3-4

The characteristic value may then be calculated as shown below in Equation 3-5.

$$u = F_X^{-1}\left(1 - \frac{1}{n}\right)$$

Equation 3-5: Characteristic value

For this type of work, it is common to have 50 working weeks in the year with 5 working days per week. The distribution obtained from the simulations in this work is the maximum per day. This totals 250 days in a year and 250,000 days in 1000 years, therefore:

$$n_{1000} = 250{,}000$$

Equation 3-6: Return period

$$u_{1000} = F_X^{-1}\left(1 - \frac{1}{250{,}000}\right) = F_X^{-1}(0.999996)$$

Equation 3-7: Characteristic value

This characteristic value will correspond with a standard extremal variant derived from the Gumbel distribution as shown below in Equation 3-8.

$$G_I^{-1} = \ \ln(\ \ln(0.999996)$$

$$G_I^{-1} = 12.429$$

Equation 3-8: Characteristic value for Gumbel distribution

A sample extrapolation method on Gumbel probability scale is shown below in Figure 3-1.

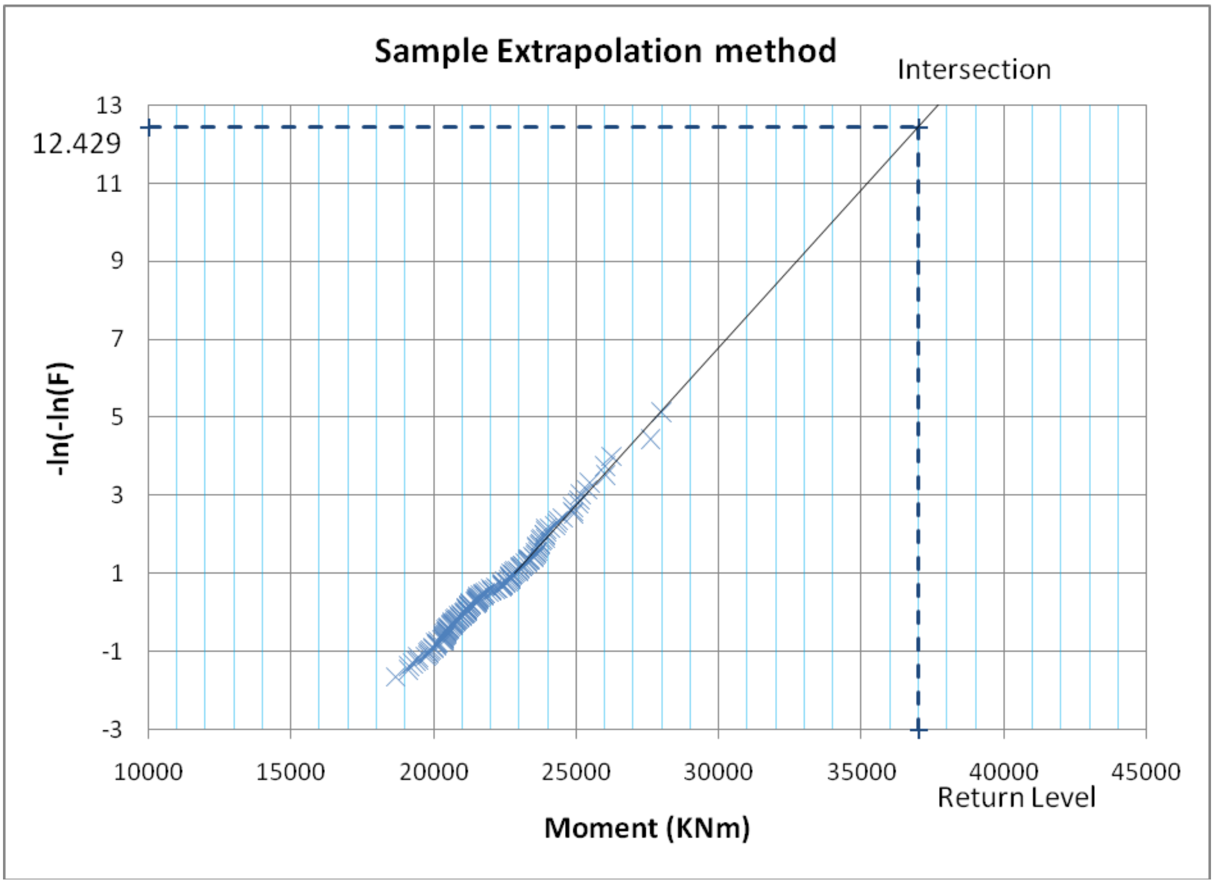


Figure 3-1: Sample Extrapolation method

4 Independent Driver Model

4.1 EvolveTraffic

EvolveTraffic is a traffic microsimulation model for bridge loading and was developed by *Caprani et. al. at the School of Architecture, Landscape and Civil Engineering, University College Dublin, Ireland in liaison with Laboratoire Central des Ponts et Chausées, France, 2008. EvolveTraffic* is the traffic microsimulation model used in this work.

EvolveTraffic simulates traffic behaviour for the purpose of analysing Highway Bridge loading. Vehicles are read into the program and are simulated driving along a length of road that can have speed limited features and gradient features. The vehicles interact with each other and can perform lane changes. When the vehicles pass the output detector, they are written to the output traffic file. The output traffic file contains the same vehicles as the input traffic file but in a different configuration. The configuration of the output file depends on the road and traffic features that the user has specified. It is this configuration of the output traffic file that is of interest to us as it allows us to obtain traffic data without physically measuring real traffic, which is both expensive and time consuming. *EvolveTraffic* considers 5 classes of vehicle:

Class 0 – Cars: any vehicle under 3.5 tonnes

Class 1 – Small trucks: any vehicle with less than 4 axles and greater than 3.5 tonnes

Class 2 – Large trucks: any vehicle that is not a car, small truck, crane or low-loader

Class 3 – Cranes: any vehicle that is not a car and has a maximum axle spacing of 4.5m and average axle spacing less than 2.5m

Class 4 – Low- Loaders: any vehicle that is not a car and has a maximum axle spacing not less than 7.5m

The longitudinal model used in *EvolveTraffic* is the Intelligent Driver model (IDM) developed by *Treiber et al, 2000*. The Lane Change model MOBIL (*Minimise Overall Braking decelerations Induced by Lane changes*), developed by *Kesting, Treiber, Helbing, 2007*, controls the lane changes for the car following model, i.e., the IDM. For each particular class of vehicle, there are 10 parameters to be set for the IDM and MOBIL models.

EvolveTraffic allows vehicles within each class to have varying parameters, i.e. *EvolveTraffic* allows probabilistic IDM parameters.

4.2 Intelligent driver Model (IDM)

The Intelligent Driver Model (IDM), developed by *Treiber, Hennecke, Helbing, 2000*, is a car following model, i.e., the traffic state at any given time is characterised by the positions, velocities and lane position of all the vehicles. The decision of any driver to accelerate or decelerate depends not only on his or her velocity but on the velocity of the vehicle directly in front. However the decision of any driver to change lane depends on all the neighbouring vehicles.

The IDM has seven intuitive parameters:

- Desired velocity on a free road (v_0)
- Desired safe time headway when following other vehicles *(T)*
- Maximum acceleration *(a)*
- Comfortable braking deceleration *(b)*
- Minimum bumper to bumper distance to the vehicle in front when stopped *(s_0)*
- Elastic jam distance to the vehicle in front *(s_1)*
- Acceleration exponent *(δ_a)*

The acceleration ($\frac{dv}{dt}$) of any given driver at any given time depends on his/her own maximum acceleration *(a)*, actual velocity (v_α), desired velocity (v_0), the distance (s_α) to the vehicle directly in front and on the velocity difference or approach rate (Δv) to the vehicle in front as shown in Equation 4-1.

$$\frac{dv}{dt} = a^{(\alpha)}\left[1 - \left(\frac{v_\alpha}{v_0^{(\alpha)}}\right)^{\delta_a} - \left(\frac{s^*(v_\alpha, \Delta v_\alpha)}{s_\alpha}\right)^2\right]$$

Equation 4-1: Acceleration of driver at any given time

Where:

$a^{(\alpha)}$ = maximum acceleration

v_0 = desired velocity

δ_a = acceleration exponent

(s_α) = distance to vehicle directly in front

$s^*(v_\alpha, \Delta v_\alpha)$ = desired gap

The desired distance to the vehicle directly in front ($s^*(v_\alpha, \Delta v_\alpha)$) is given below in Equation 4-2.

$$s^*(v_\alpha, \Delta v_\alpha) = \left[s_0^{(\alpha)} + s_1^{(\alpha)} \sqrt{\frac{v_\alpha}{v_0^{(\alpha)}}} + T^{(\alpha)} v + \frac{v_\alpha \Delta v_\alpha}{2\sqrt{a^{(\alpha)} b^{(\alpha)}}} \right]$$

Equation 4-2: Desired distance to vehicle directly in front

Where:

$s^*(v_\alpha, \Delta v_\alpha)$ = desired gap

$s_0^{(\alpha)}$ = minimum distance between congested vehicles

$s_1^{(\alpha)}$ = elastic distance between congested vehicles

v_α = actual velocity

$v_0^{(\alpha)}$ = desired velocity

$T^{(\alpha)}$ = safe time headway

Δv_α = velocity difference between own vehicle *(α)* and vehicle immediately in front

$a^{(\alpha)}$ = maximum acceleration

$b^{(\alpha)}$ = comfortable deceleration

4.3 MOBIL model

The Lane Change model MOBIL (Minimise Overall Braking decelerations Induced by Lane changes) developed by *Kesting, Treiber, Helbing, 2007,* controls the lane changes for the car following model, i.e., the IDM. Both the utility of a given lane and the risk associated with lane changes are determined in terms of longitudinal accelerations calculated with the IDM. This determination allows for the formulation of compact and general safety and incentive criteria for both symmetric and asymmetric passing rules. Although the safety criterion prevents critical lane changes and collisions, the incentive criterion takes into account the advantages and disadvantages of other drivers associated with a lane change via the politeness factor *(P)*. The politeness factor allows for the variation of the motivation for lane changing from purely egoistic to more co-operative or polite driving behaviour. This means that lane changes that obstruct other drivers can be prevented and also that an aggressive driver can induce a lane change in order to no longer be obstructed.

The MOBIL model has three intuitive parameters:

- Lane change politeness factor *(P)*
- Outside lane bias factor (δ_{bias})
- Lane change threshold (δ_{thr})

The MOBIL model allows lane changes to take place, if

c) The potential new target lane is more attractive, i.e., the *"incentive criterion"* is satisfied, and
d) The change can be performed safely, i.e., the *"safety criterion"* is satisfied.

In the MOBIL model, both criteria are based on the accelerations on the old lane and on the prospective new lane, as calculated with the IDM.

4.3.1 The safety criterion

The safety criterion is satisfied, if the IDM braking deceleration *(acc')* imposed on the back vehicle (*B'')* of the target lane after a possible change does not exceed a certain limit (b_{safe}), this means, the safety criterion as shown below in Equation 4-3 is satisfied.

$$acc'(B') > -bsafe$$

Equation 4-3: The Safety Criterion

Where:

B' = the back vehicle on the target lane
acc' = the acceleration after the possible lane change
b_{safe} = limited value for brake deceleration

4.3.2 The incentive criterion

For the incentive criterion, the drivers own advantage on the target lane, measured by the increased acceleration or reduced braking deceleration, is weighted against the disadvantage imposed to other drivers, measured by the decrease acceleration or increased braking deceleration for these drivers. Since drivers tend to be selfish, the disadvantage imposed on other drivers is weighted with a Politeness factor *(P)* whose values are typically less than 1, resulting in the following *incentive criterion*. An outside lane bias factor (δ_{bias}) is introduced for European traffic which has asymmetric passing rules, and is included in the equation. The right lane is taken as the default lane and the left lane is the passing lane, i.e., a "keep right" directive is implemented by the outside lane bias factor (δ_{bias}). The *incentive criterion* for lane changes from "right to left" is given in Equation 4-4 below.

$$acc'(M') - acc(M) + P[acc'(B') - acc(B')] > \delta thr + \delta bias$$

Equation 4-4: Incentive Criterion - Right to Left

The *incentive criterion* for lane changes from "left to right" is given in Equation 4-5 below.

$$acc'(M') - acc(M) + P[acc'(B) - acc(B)] > \delta thr - \delta bias$$

Equation 4-5: Incentive Criterion – Left to Right

Where:

acc = the actual IDM acceleration

acc' = the acceleration after the possible lane change

M = "Me" i.e., the driver changing lane, before the possible lane change

M' = "Me" after the possible lane change

B = the back or following vehicle on the old lane

B' = the back or following vehicle on the target lane

δ_{thr} = Lane change threshold

δ_{bias} = Outside lane bias

The first part of the equation *[acc' (M") - acc (M)]* relates to the drivers own advantage as a result of the possible lane change. The second part of the equation *[acc' (B') - acc (B')]* or *[acc' (B) - acc (B)]*, is the disadvantage to the vehicle following directly behind as a result of the possible lane change. The disadvantage to the following vehicles is then multiplied by the Politeness factor *(P)*. The politeness factor *(P)* determines to which degree these vehicles affect the lane changing decision and allows lane changes to take place in congested traffic. Instead of simply modelling purely selfish behaviour, the MOBIL parameter *(P)* can be changed so as to model driver behaviour ranging from very courteous behaviour (P=1) to malicious behaviour (P<0). When P = 0-0.5, realistic driver behaviour is modelled, i.e., the advantages of other drivers have a lower priority than that of the drivers own, but they are not neglected. When P=0, purely selfish behaviour is modelled but the safety criterion is still satisfied. When P<0, malicious behaviour is modelled. The safety criterion is still satisfied but malicious drivers thwart and cause disadvantage to others, even at the cost of their own advantage. The right hand side of the equation consists of the Lane Change Threshold (δ_{thr}) and the Outside Lane Bias factor (δ_{bias}). It can be clearly seen from the "left to right" *incentive criterion* equation that even though (δ_{bias}) is small, it must be greater than (δ_{thr}); otherwise the Lane Changing Threshold would prevent changes to the right-hand lane even on an empty road. The Lane Changing Threshold is included in order to stop lane changes that are only marginally more advantageous than not changing lane. This prevents lots of pointless lane hopping. It should also be noted that the Lane Change Threshold *(δ_{thr})* and the Outside Lane Bias factor *(δ_{bias})* influences the lane changing behaviour globally whereas the Politeness factor *(P)* affects the lane changing behaviour depending on the disadvantage of the involved vehicles.

5 Data Acquisition and Processing

5.1 Input Traffic

The input traffic is generated using *GenerateTraffic,* a program created by *Caprani, 2005*. *GenerateTraffic* uses Monte-Carlo simulation to generate a traffic file whose statistical distributions are the same as the input distributions. *GenerateTraffic* allows the user to generate synthetic traffic using measured traffic data from various sites across Europe. The user can choose the number of days of traffic required, the number of lanes and directions of traffic required, the percentage of cars in the traffic, which site traffic flow data to be used and which site traffic weight data to be used. The traffic flow data and weight data can also be selected separately from different sites in order to obtain different traffic configurations.

For this work, I required a large flow of heavy traffic. I used the traffic flow data coupled with the traffic weight data from the Auxerre WIM site in France as analysed by *Grave, 2001*, in order to represent real measured traffic. After some trial runs with different amounts of days of traffic, I chose to generate 28 days of traffic using *GenerateTraffic* as on average it took 45 minutes to analyse in *EvolveTraffic* on my laptop. For this work, I was looking for the daily maximum moment in the bridge and therefore needed the daily

TFGin.txt - Notepad

File Edit Format View Help

```
//
// START OF TRAFFIC FLOW GENERATOR INPUT
//
// Name of output file
85cars_20day.txt
// Distance for which overlaps are prevented (m):
300
// No. of days of traffic required:
20
// Site flow data to be used:
2
// Site weight data to be used:
2
// Vehicle buffer size
10000
// No lanes in direction 1
1
// No lanes in direction 2
0
// Nominal congested spacing, front to back (m):
5
// Congested speed (km/h):
10
// Congested gaps coefficient of variation:
0.05
// Headway model to be used:
// (0 - Auxerre NHM, 5 - Congestion (w/ or w/out cars), 6 - free-flow, cars included)
5
// Proportion of cars (less than 1.0) - only used if Headway Model is 5 or 6
0.85
// END OF TRAFFIC FLOW GENERATOR INPUT
```

Ln 1, Col 1

maximum amount of traffic, i.e. rush hour traffic. I assumed 4 hours of rush hour traffic in a day, 2 hours in the morning and 2 hours in the evening. This meant that for every 24 hours of traffic simulated, I simulated 6 days worth of rush hour traffic. In total, this amounted to 168 days of rush hour traffic for each Traffic Input file. The Traffic Input file has the same format as the Traffic Output file as shown in Figure 5-4 below. 168 days of traffic proved to be good mix between computation time and quantity of results. *Hayrapetova, 2007*, from her study of the Moerdijk link on the A16 highway in the Netherlands, stated that the average percentage of HGVs was 12.1% and peaked at 13.4% during rush hour times. I decided upon a 15% HGV content which is equal to 85% car content in order to model a high percentage of heavy goods vehicles (HGVs) in realistic rush hour traffic. I opted for a single direction input traffic file to save on unnecessary computation time and decided on a single lane configuration so that all the vehicles would be positioned in the outside lane at the start of the simulation process and that any lane changes would occur during simulation. The *GenerateTraffic* input file that was used for the synthetic traffic generation is shown below in Figure 5-1.

Figure 5-1: *GenerateTraffic* input file

5.2 Road Configuration

For this work I required the traffic to become congested. Therefore I decided on a road configuration that consists of a 3000m long, 2 lane, single direction road with a 10km/hr speed limit section between 2000m and 3000m. Two lanes were chosen to allow lane changes to take place. The road is in one direction to minimise unnecessary computation. The distance of 2000m before the speed limit section was chosen in order to allow the traffic to interact with each other and to allow lane changes to take place as the traffic approached the speed limit section. 10km/hr is the lowest speed limit that *EvolveTraffic* allows and was chosen to force the traffic to become congested. The Output detector is at 2200m along with the Flow-Density detector and Headway detector as shown in Figure 5-2. The Lane Change detector writes the number of lane changes per 60 second time step per 200m intervals to the lane change output files.

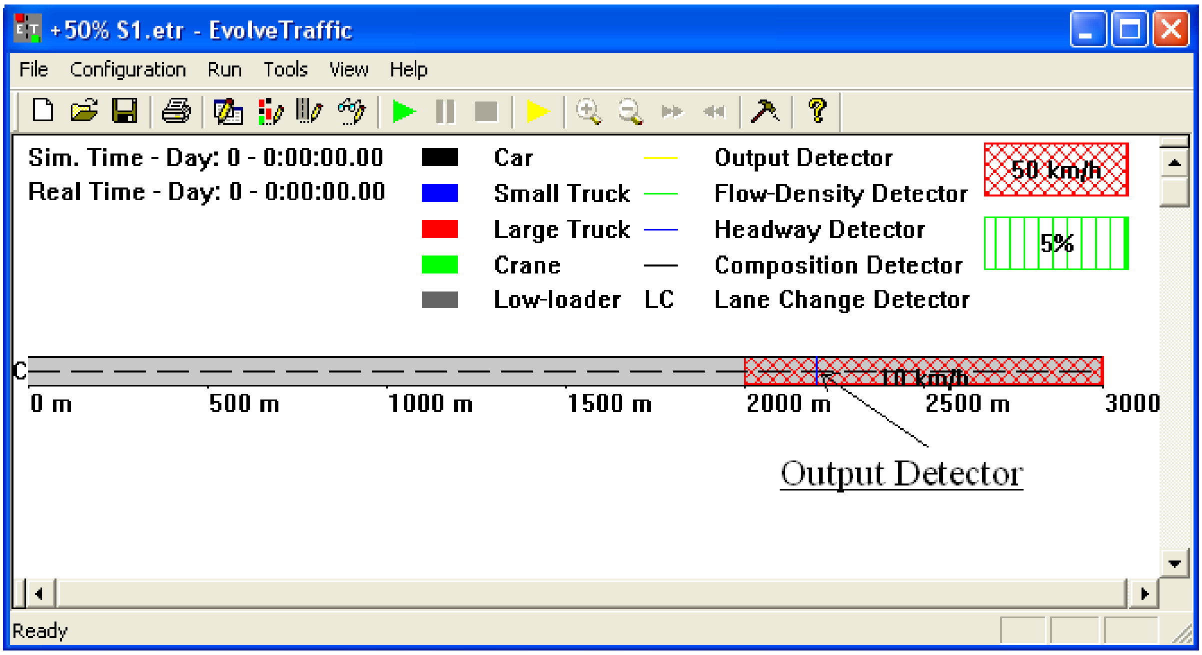


Figure 5-2: *EvolveTraffic* road configuration

Each vehicle is read from the generated traffic input file and enters the road at 0m. The vehicles then proceed along the road, interacting with the neighbouring vehicles and the road features until it reaches the end of the length of road. When each vehicle reaches the Output Detector, it is written to the traffic output file along with the time of arrival at the Output Detector.

As the traffic approaches the speed limit section, the vehicles decelerate down from their old desired velocity to their new desired velocity which is dictated by the speed limit of 10km/hr. Subsequent vehicles decelerate and bunch up behind the lead vehicle by reducing the distance between vehicles because of the lower speed limit as shown in Figure 5-3.

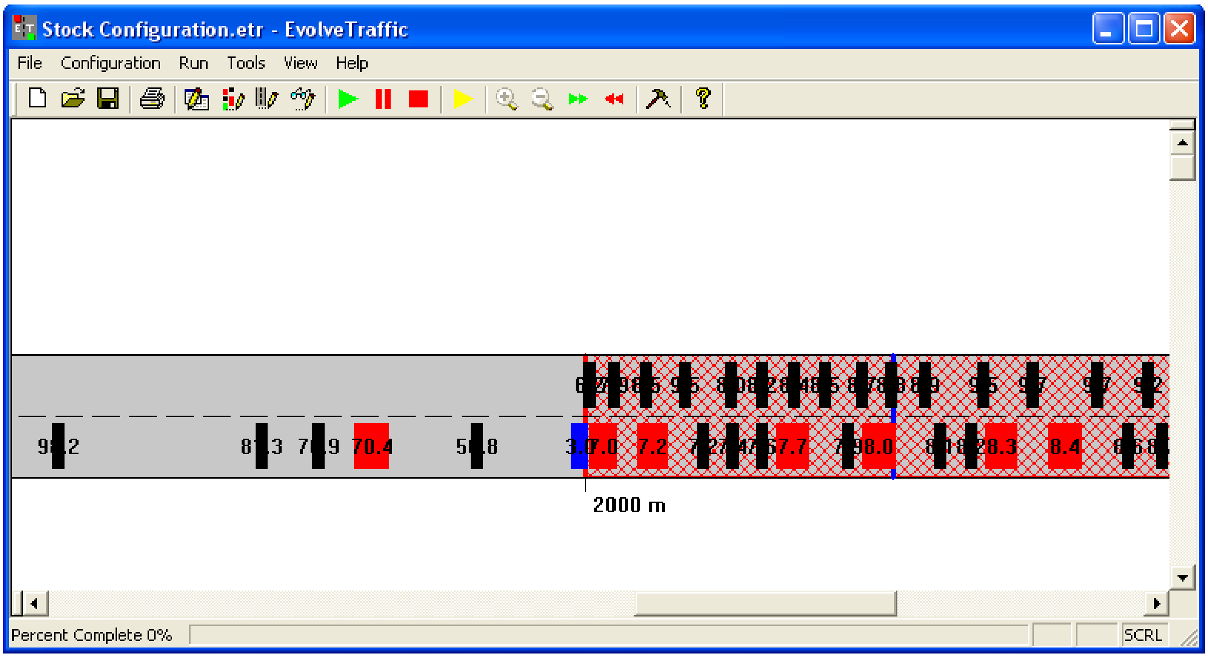
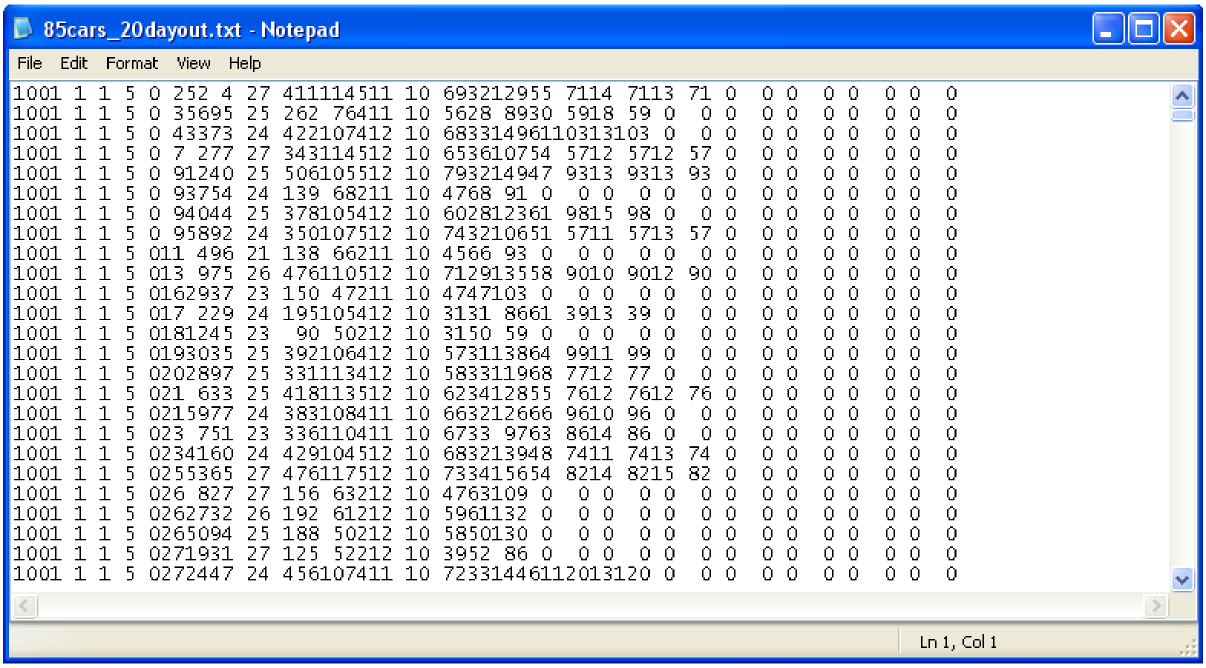


Figure 5-3: Traffic entering speed limit section in *EvolveTraffic*

5.3 *EvolveTraffic* Output

EvolveTraffic writes the traffic to the Traffic Output file when the traffic reaches to Output Detector. This Traffic Output File contains the same vehicle data eg. weight, length, number of axles, axle weights etc., as the Traffic Input file but in a different configuration due to the microsimulation of the traffic along the length of road. The Traffic Output file does not include cars so as to minimise file size and further unnecessary analysis. Because the cars are not heavy enough to significantly affect the load on the bridge, they are excluded in the analysis of the bridge bending moment. Cars are still a very important aspect of traffic microsimulation. Even though they do not contribute significantly to the overall load on the bridge directly, they do act as spacers between HGVs which has a huge effect on the maximum load on the bridge. Therefore cars must be included in traffic microsimulation to determine the distance between HGVs. A typical Traffic Output File is shown below in Figure 5-4.



85cars_20dayout.txt - Notepad

File Edit Format View Help

```
1001 1 1 5 0 252 4 27 411114511 10 693212955 7114 7113 71 0  0 0  0 0  0 0  0
1001 1 1 5 0 35695 25 262 76411 10 5628 8930 5918 59 0  0 0  0 0  0 0  0 0  0
1001 1 1 5 0 43373 24 422107412 10 68331496110313103 0  0 0  0 0  0 0  0 0  0
1001 1 1 5 0 7 277 27 343114512 10 653610754 5712 5712 57 0  0 0  0 0  0 0  0
1001 1 1 5 0 91240 25 506105512 10 793214947 9313 9313 93 0  0 0  0 0  0 0  0
1001 1 1 5 0 93754 24 139 68211 10 4768 91 0  0 0  0 0  0 0  0 0  0 0  0 0  0
1001 1 1 5 0 94044 25 378105412 10 602812361 9815 98 0  0 0  0 0  0 0  0 0  0
1001 1 1 5 0 95892 24 350107512 10 743210651 5711 5713 57 0  0 0  0 0  0 0  0
1001 1 1 5 011 496 21 138 66211 10 4566 93 0  0 0  0 0  0 0  0 0  0 0  0 0  0
1001 1 1 5 013 975 26 476110512 10 712913558 9010 9012 90 0  0 0  0 0  0 0  0
1001 1 1 5 0162937 23 150 47211 10 4747103 0  0 0  0 0  0 0  0 0  0 0  0 0  0
1001 1 1 5 017 229 24 195105412 10 3131 8661 3913 39 0  0 0  0 0  0 0  0 0  0
1001 1 1 5 0181245 23  90 50212 10 3150 59 0  0 0  0 0  0 0  0 0  0 0  0 0  0
1001 1 1 5 0193035 25 392106412 10 573113864 9911 99 0  0 0  0 0  0 0  0 0  0
1001 1 1 5 0202897 25 331113412 10 583311968 7712 77 0  0 0  0 0  0 0  0 0  0
1001 1 1 5 021 633 25 418113512 10 623412855 7612 7612 76 0  0 0  0 0  0 0  0
1001 1 1 5 0215977 24 383108411 10 663212666 9610 96 0  0 0  0 0  0 0  0 0  0
1001 1 1 5 023 751 23 336110411 10 6733 9763 8614 86 0  0 0  0 0  0 0  0 0  0
1001 1 1 5 0234160 24 429104512 10 683213948 7411 7413 74 0  0 0  0 0  0 0  0
1001 1 1 5 0255365 27 476117512 10 733415654 8214 8215 82 0  0 0  0 0  0 0  0
1001 1 1 5 026 827 27 156 63212 10 4763109 0  0 0  0 0  0 0  0 0  0 0  0 0  0
1001 1 1 5 0262732 26 192 61212 10 5961132 0  0 0  0 0  0 0  0 0  0 0  0 0  0
1001 1 1 5 0265094 25 188 50212 10 5850130 0  0 0  0 0  0 0  0 0  0 0  0 0  0
1001 1 1 5 0271931 27 125 52212 10 3952 86 0  0 0  0 0  0 0  0 0  0 0  0 0  0
1001 1 1 5 0272447 24 456107411 10 72331446112013120 0  0 0  0 0  0 0  0 0  0
```

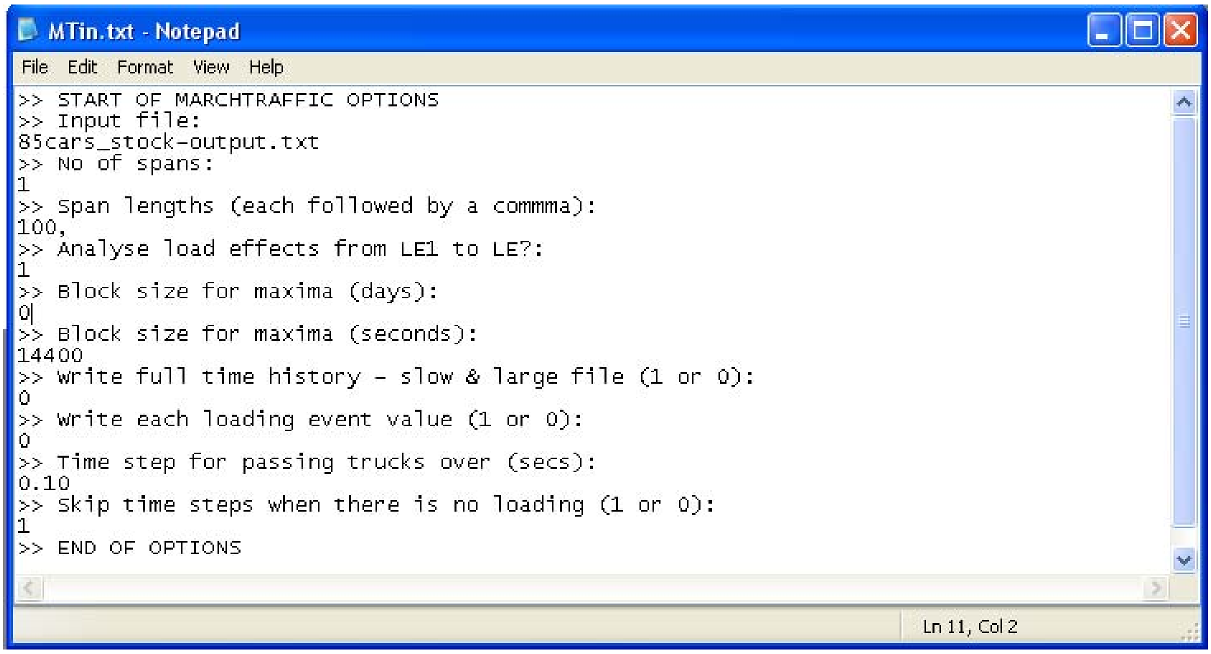
Ln 1, Col 1

Figure 5-4: Typical Traffic Output File

5.4 Bridge bending moment analysis

For this work I am analysing the sensitivity of the IDM parameters on congested traffic on long span bridges. *Caprani, 2005,* has previously examining the effect of micro simulation of traffic on short to medium span bridges, i.e. 20m to 50m. For long span bridges the governing loadcase is congested traffic, i.e. the greatest static load on the bridge. I decided to use a 100m single span, simply supported, 2 lane, single direction bridge for this work. The maximum moment is calculated at mid-span with a lane factor of 1, i.e. the two lanes load the bridge equally. The Traffic Output file is analysed using a program developed by *Caprani, 2005*, called *MarchTraffic.* The influence line for a single span bridge is Load Effect 1 in *MarchTraffic.* This helped simplify the analysis of the results.

MarchTraffic simulates the effect of the traffic file crossing the bridge and produces, for each effect, a block maxima value. To save on unnecessary processing time, only Significant Crossing Events (SCEs) are processed. These are defined as any Multiple Truck Presence Event (MTPE) or the occurrence of any truck with Gross Vehicle Weight (GVW) of over 40 tonnes. When a SCE is found, the trucks involved are passed to an algorithm that uses the required influence line to calculate the induced load effect. The trucks are passed across the bridge in 0.02 second steps (less than 0.05m for a speed of 8km/hr as used in this work). The load effect is calculated at each step and the maximum value of each load effect is kept for further analysis along with the time it occurs at and the position of the front axle of the first truck on the bridge. A typical *MarchTraffic* input file is shown below in Figure 5-5.


MTin.txt - Notepad

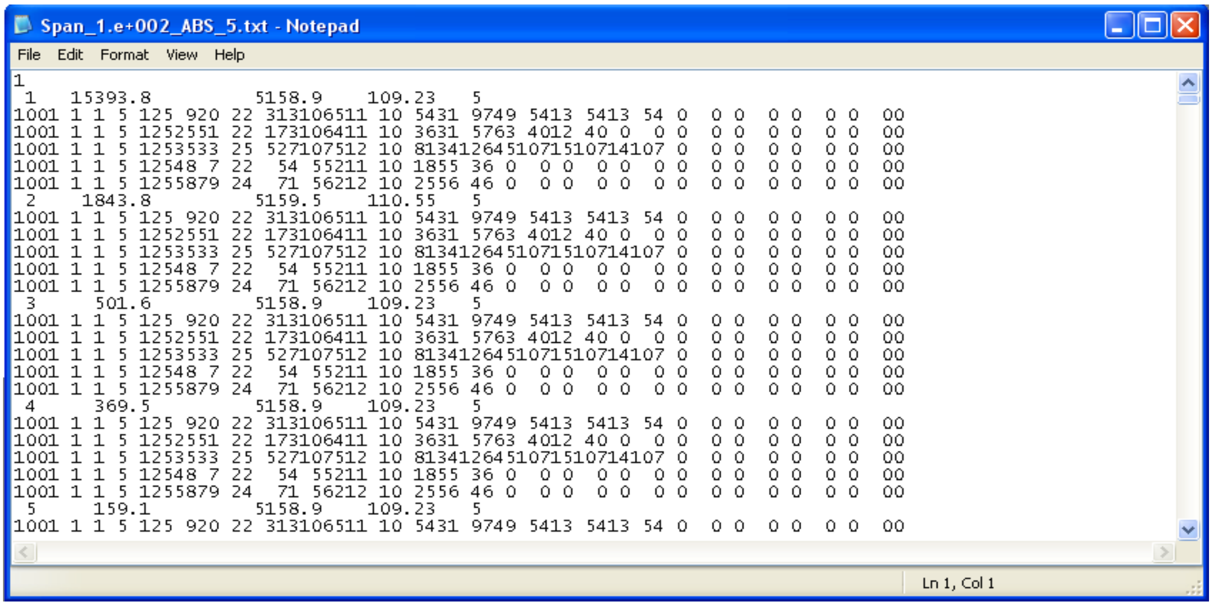
File Edit Format View Help

```
>> START OF MARCHTRAFFIC OPTIONS
>> Input file:
85cars_stock-output.txt
>> No of spans:
1
>> Span lengths (each followed by a commma):
100,
>> Analyse load effects from LE1 to LE?:
1
>> Block size for maxima (days):
0
>> Block size for maxima (seconds):
14400
>> Write full time history - slow & large file (1 or 0):
0
>> Write each loading event value (1 or 0):
0
>> Time step for passing trucks over (secs):
0.10
>> Skip time steps when there is no loading (1 or 0):
1
>> END OF OPTIONS
```

Ln 11, Col 2

Figure 5-5: Typical *MarchTraffic* input file

A typical *MarchTraffic* output file for a 5 truck event is shown below in Figure 5-6. Line 2 of the *MarchTraffic* output file below is the load effect information line. The format is Load Effect ID, Value, Time, Distance, Number of Trucks. Lines 3-7 contain the full truck information from the Traffic Output file for all the trucks involved in the event.



Span_1.e+002_ABS_5.txt - Notepad

File Edit Format View Help

```
1
 1    15393.8           5158.9     109.23    5
1001 1 1 5 125 920 22 313106511 10 5431 9749 5413 5413 54 0   0 0   0 0   0 0   00
1001 1 1 5 1252551 22 173106411 10 3631 5763 4012 40 0   0 0   0 0   0 0   0 0   00
1001 1 1 5 1253533 25 527107512 10 81341264510715107141O7 0   0 0   0 0   0 0   00
1001 1 1 5 12548 7 22   54 55211 10 1855 36 0   0 0   0 0   0 0   0 0   0 0   00
1001 1 1 5 1255879 24   71 56212 10 2556 46 0   0 0   0 0   0 0   0 0   0 0   00
 2     1843.8           5159.5     110.55    5
1001 1 1 5 125 920 22 313106511 10 5431 9749 5413 5413 54 0   0 0   0 0   0 0   00
1001 1 1 5 1252551 22 173106411 10 3631 5763 4012 40 0   0 0   0 0   0 0   0 0   00
1001 1 1 5 1253533 25 527107512 10 81341264510715107141O7 0   0 0   0 0   0 0   00
1001 1 1 5 12548 7 22   54 55211 10 1855 36 0   0 0   0 0   0 0   0 0   0 0   00
1001 1 1 5 1255879 24   71 56212 10 2556 46 0   0 0   0 0   0 0   0 0   0 0   00
 3      501.6           5158.9     109.23    5
1001 1 1 5 125 920 22 313106511 10 5431 9749 5413 5413 54 0   0 0   0 0   0 0   00
1001 1 1 5 1252551 22 173106411 10 3631 5763 4012 40 0   0 0   0 0   0 0   0 0   00
1001 1 1 5 1253533 25 527107512 10 81341264510715107141O7 0   0 0   0 0   0 0   00
1001 1 1 5 12548 7 22   54 55211 10 1855 36 0   0 0   0 0   0 0   0 0   0 0   00
1001 1 1 5 1255879 24   71 56212 10 2556 46 0   0 0   0 0   0 0   0 0   0 0   00
 4      369.5           5158.9     109.23    5
1001 1 1 5 125 920 22 313106511 10 5431 9749 5413 5413 54 0   0 0   0 0   0 0   00
1001 1 1 5 1252551 22 173106411 10 3631 5763 4012 40 0   0 0   0 0   0 0   0 0   00
1001 1 1 5 1253533 25 527107512 10 81341264510715107141O7 0   0 0   0 0   0 0   00
1001 1 1 5 12548 7 22   54 55211 10 1855 36 0   0 0   0 0   0 0   0 0   0 0   00
1001 1 1 5 1255879 24   71 56212 10 2556 46 0   0 0   0 0   0 0   0 0   0 0   00
 5      159.1           5158.9     109.23    5
1001 1 1 5 125 920 22 313106511 10 5431 9749 5413 5413 54 0   0 0   0 0   0 0   00
```

Ln 1, Col 1

Figure 5-6: Typical *MarchTraffic* output file for a 5 truck event

5.5 Processing of Results

I have compiled nearly 100GB of results from nearly 300 hours of traffic microsimulation during this work so finding an efficient way to process these results was crucial. The output files from *MarchTraffic* and *EvolveTraffic* are in *.txt* and *.csv* format, both of which are easily transferable into Microsoft Excel, which I used throughout this work. I developed Excel spreadsheets to sort and compile the relevant data from the output files but even still, the analysis of results proved to be a very tedious process.

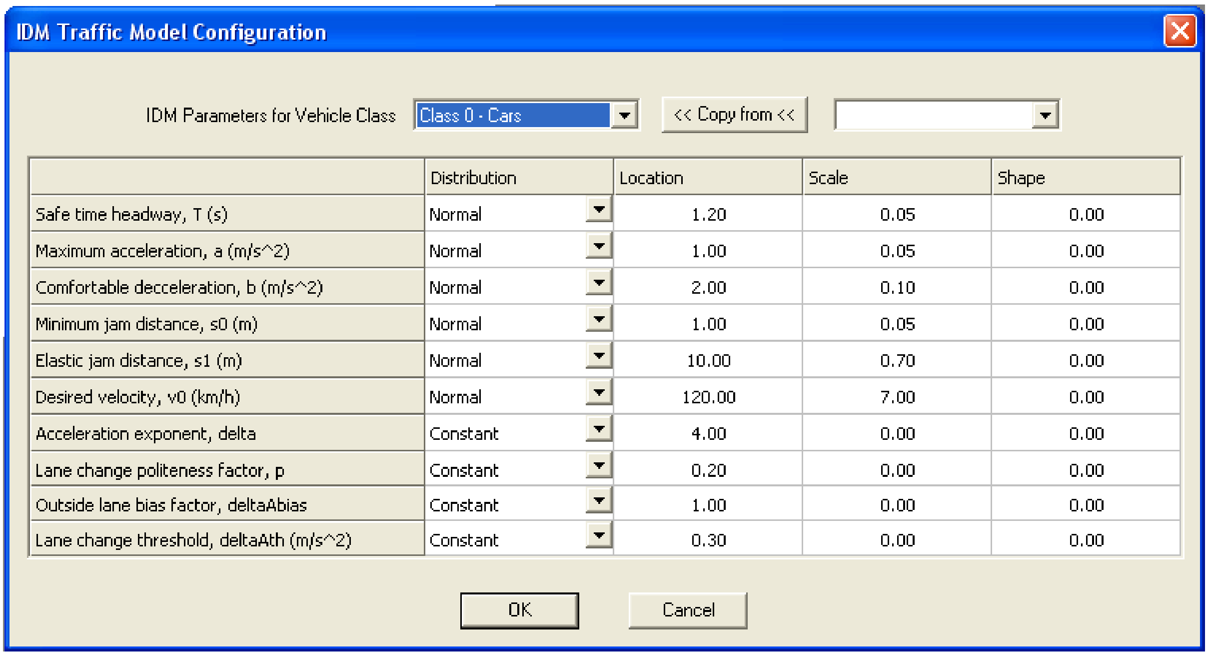
6 Analysis of Results

6.1 Layout of analysis

Firstly I ran the traffic Input file with a base set of Independent Driver Model (IDM) parameters to get a base result for the characteristic moment for a 1000 year return period for the bridge. Because *EvolveTraffic* allows probabilistic IDM parameters i.e. each parameter can be distributed according to a number of different distributions, running the exact same settings twice will result in slightly different results. *EvolveTraffic* also allows for the IDM parameters to be set constant across each vehicle class. In an attempt to combat this, I repeated the base simulation 10 times and averaged the results to give a better estimate of the characteristic moment value.

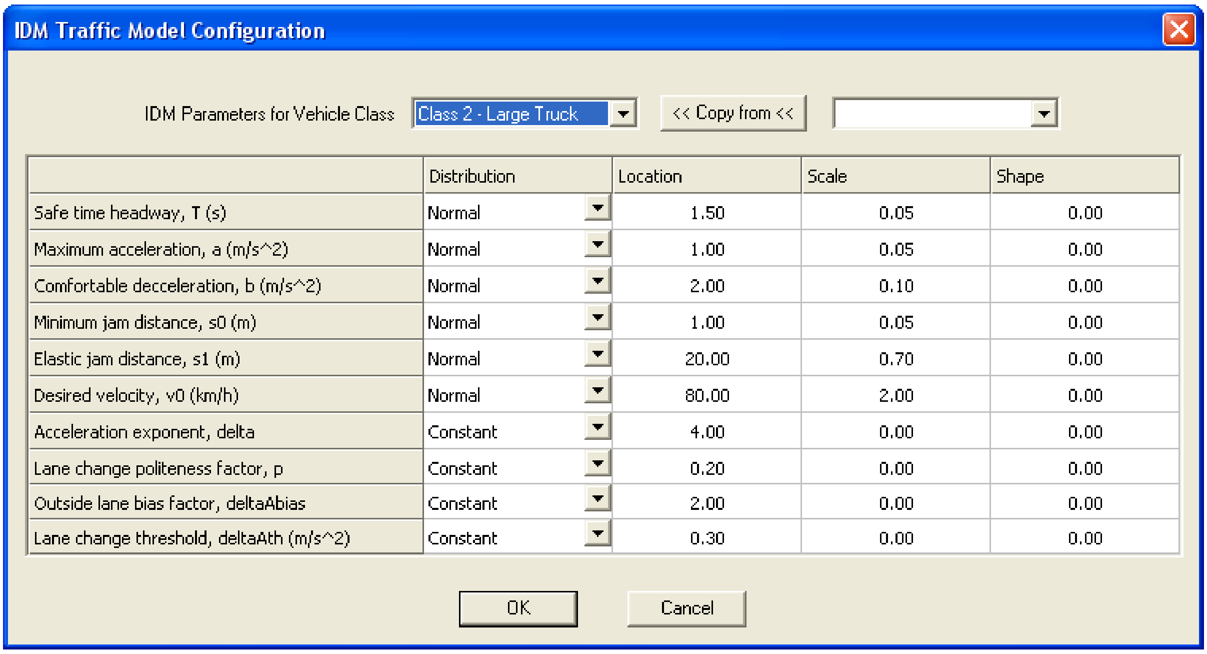
6.2 Base IDM parameter values

In order to be able to conduct a sensitivity analysis on the IDM parameters, I first needed to have a base from which I could compare future results. Each of the 5 vehicle classes can have different IDM parameter values. In order to simplify matters, I set Cars and Small Trucks to have the same parameter values and Large Trucks, Cranes and Low-loaders to all have the same parameter values. The parameters *T, a, b, s0, s1 and v0* are distributed across a normal distribution, while the parameters δ_a, P, δ_{bias} and δ_{thr} are set constant across each vehicle class. The Location value is the mean and the Scale value is the standard deviation. The base values for Cars and Small Trucks are shown in Figure 6-1, while the base values for Large Trucks, Cranes and Low-Loaders are shown in Figure 6-2.



	Distribution	Location	Scale	Shape
Safe time headway, T (s)	Normal	1.20	0.05	0.00
Maximum acceleration, a (m/s^2)	Normal	1.00	0.05	0.00
Comfortable decceleration, b (m/s^2)	Normal	2.00	0.10	0.00
Minimum jam distance, s0 (m)	Normal	1.00	0.05	0.00
Elastic jam distance, s1 (m)	Normal	10.00	0.70	0.00
Desired velocity, v0 (km/h)	Normal	120.00	7.00	0.00
Acceleration exponent, delta	Constant	4.00	0.00	0.00
Lane change politeness factor, p	Constant	0.20	0.00	0.00
Outside lane bias factor, deltaAbias	Constant	1.00	0.00	0.00
Lane change threshold, deltaAth (m/s^2)	Constant	0.30	0.00	0.00

Figure 6-1: Base IDM parameter values for Cars



	Distribution	Location	Scale	Shape
Safe time headway, T (s)	Normal	1.50	0.05	0.00
Maximum acceleration, a (m/s^2)	Normal	1.00	0.05	0.00
Comfortable decceleration, b (m/s^2)	Normal	2.00	0.10	0.00
Minimum jam distance, s0 (m)	Normal	1.00	0.05	0.00
Elastic jam distance, s1 (m)	Normal	20.00	0.70	0.00
Desired velocity, v0 (km/h)	Normal	80.00	2.00	0.00
Acceleration exponent, delta	Constant	4.00	0.00	0.00
Lane change politeness factor, p	Constant	0.20	0.00	0.00
Outside lane bias factor, deltaAbias	Constant	2.00	0.00	0.00
Lane change threshold, deltaAth (m/s^2)	Constant	0.30	0.00	0.00

Figure 6-2: Base IDM parameter values for Large Trucks

6.3 Max Moment per Day

After running the base model 10 times I compiled the results in Microsoft Excel and plotted the relevant graphs. A portion of the Max Moment per Day (MMPD) graph is shown below in Figure 6-3. It can be clearly seen in Figure 6-3 that the probabilistic nature of the traffic simulation in *EvolveTraffic* and the fluctuation in the normally distributed parameters can lead to quite different max moment per day values for the same time period in each simulation, up to 17% in some cases.

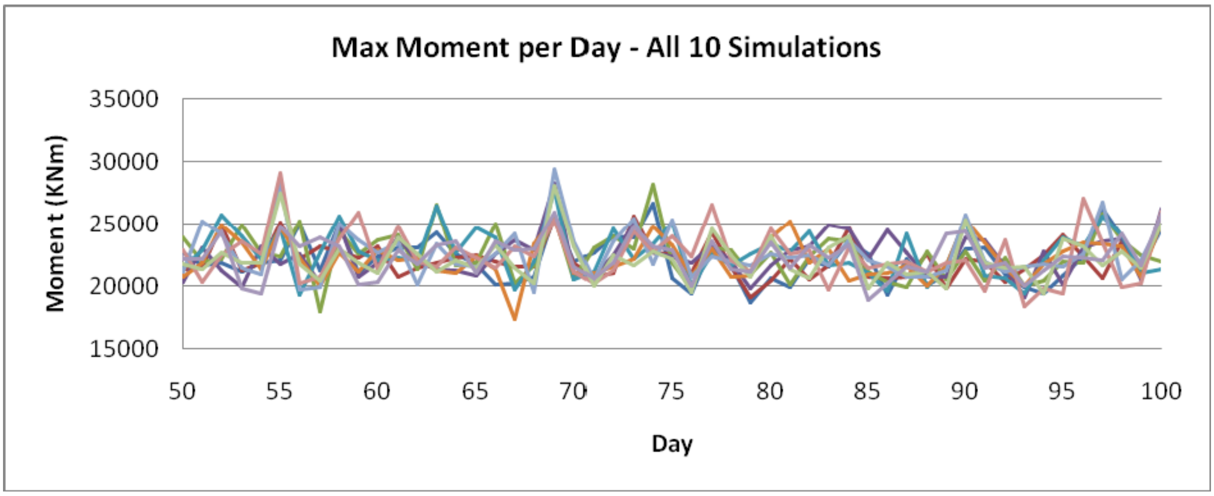


Figure 6-3: Max Moment per Day Graph for all 10 Simulations of Normal Distribution Base Model

The Average MMPD graph is plotted below in Figure 6-4. This shows that the average max moment per day fluctuates between 20000KNm and 25000KNm with the highest peaks reaching up to 27000KNm.

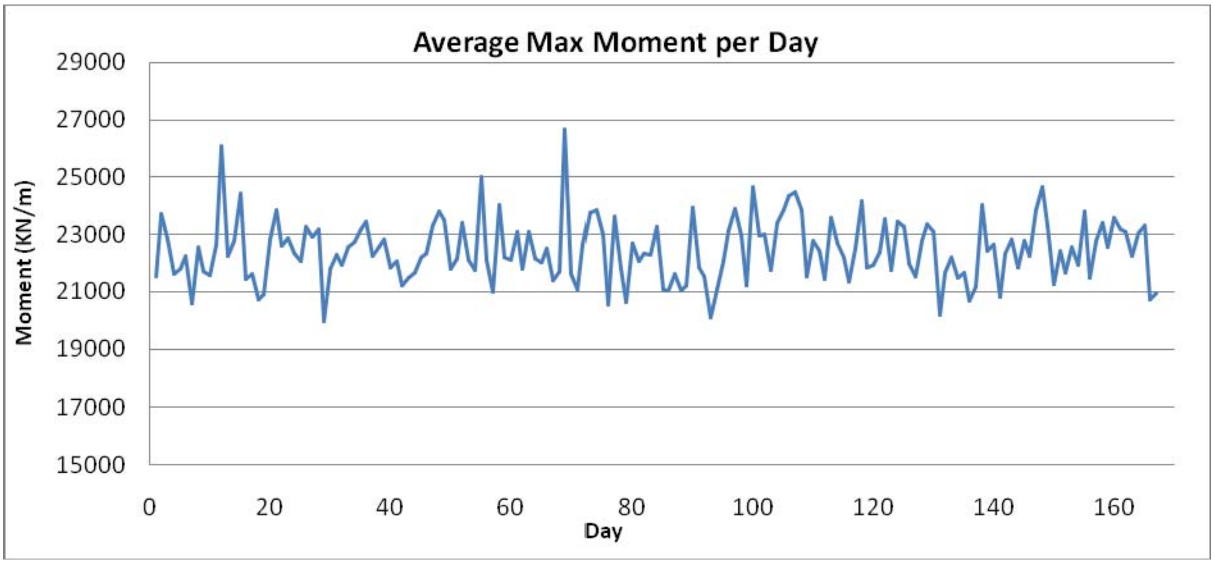


Figure 6-4: Average Max Moment per Day of Normal Distribution Base Model

Due to the high degree of variance of the MMPD values between each simulation, I decided to simulate the Base Model with all the IDM parameters set constant across each vehicle class to see what difference, if any, the fluctuations of the IDM parameters due to the normal distribution makes to the MMPD values. I found that, when the IDM parameters are set to constant values across each vehicle class, there is no change in the MMPD graph for each subsequent simulation. This means that the variance in the MMPD values in Figure 6-3 are caused by the distribution of the IDM values across a normal distribution. The MMPD of the Base Model with constant IDM parameter values versus the average MMPD with IDM values distributed across a normal distribution are shown below in Figure 6-5. The blue line is from the constant IDM values model and the red line is from the normally distributed IDM values model.

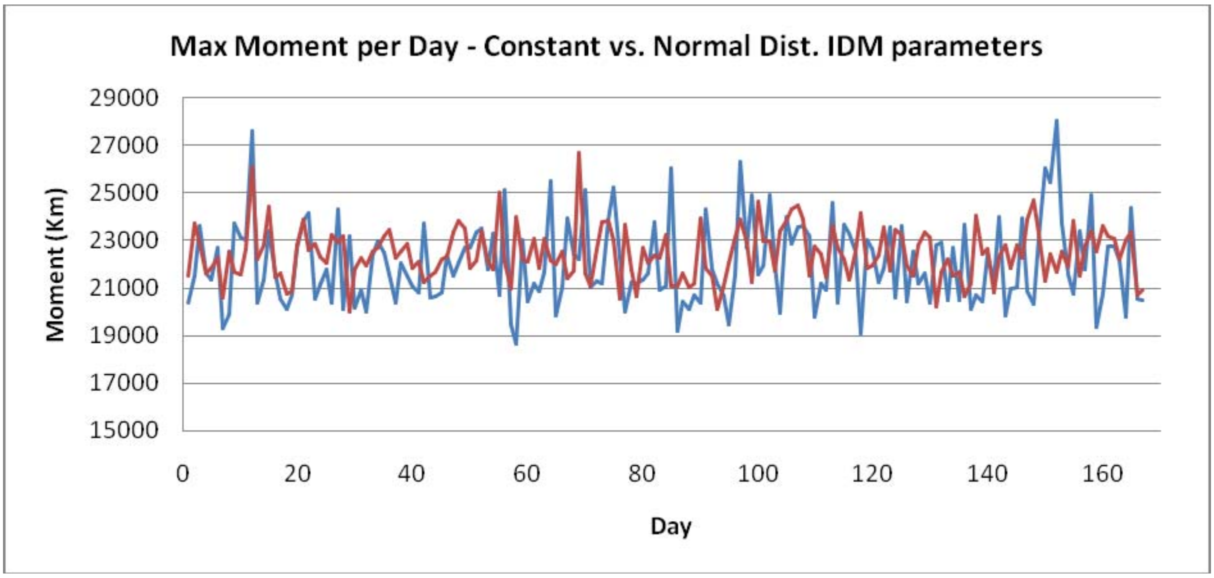


Figure 6-5: Max Moment per Day – Constant vs. Normal Distribution IDM parameters

The maximum moment of all 10 normal distribution simulations of the base model is 30251KNm from a 5-truck load event. 6-truck and 7-truck load events did occur but did not govern due to lesser amount taking place compared to 5-truck events. 22% of the total load events were 5-truck load events, 3% were 6-truck load events and 0.2% were 7-truck load events. The truck configuration of the max moment load event on the bridge is shown below in Figure 6-6. The trucks are shown in blue. The bridge is 100m long and is shown in grey. The weights of the trucks are labelled on the trucks and are given in tonnes (t) eg. 53.4t and the distances are given in metres.

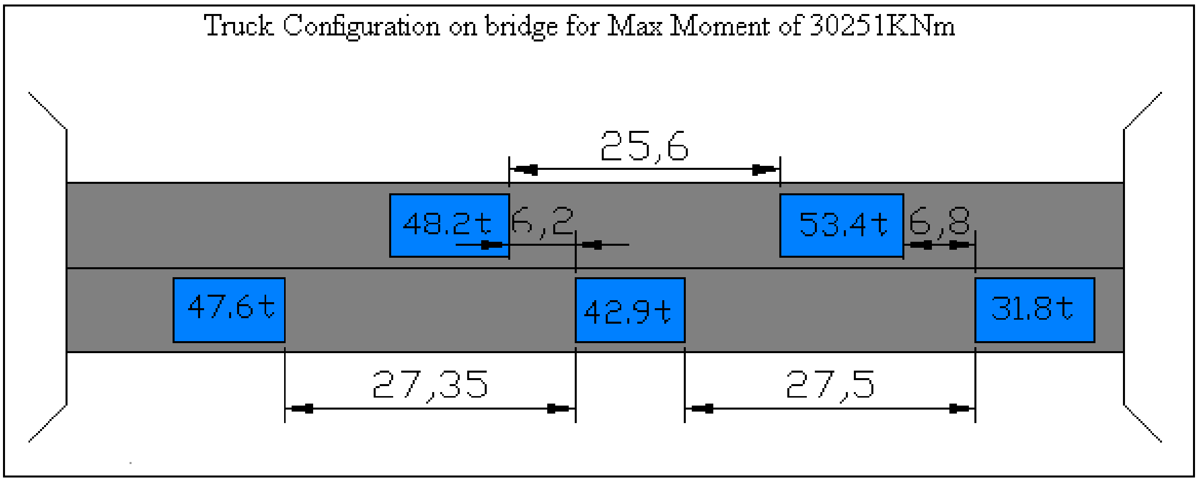


Figure 6-6: Truck Configuration on bridge for Base Model Max Moment of 30251KNm

As can be seen above in Figure 6-6, the average headway distance is 27m. The trucks are travelling at a speed of 2.2m/s, this relates to a headway time of 12 seconds which is greatly removed from the Safe Time Headway (*T*) of 1.5 seconds set for the simulation. This is due to the equation for the desired distance to the vehicle directly in front ($s^*(v_\alpha, \Delta v_\alpha)$) as shown below in Equation 4-2. The headway distance of 27m between vehicles is due to the large value of 20m for the elastic distance between congested vehicles (s_1) with respect to the minimum distance between congested vehicles (s_0), (1-3m), and the safe time headway (*T*), (1-2secs). In Equation 4-2 below, it can be seen that (s_1) outweighs (s_0) and (*T*) considerably.

$$s^*(v_\alpha, \Delta v_\alpha) = \left[s_0^{(\alpha)} + s_1^{(\alpha)} \sqrt{\frac{v_\alpha}{v_0^{(\alpha)}}} + T^\alpha v + \frac{v_\alpha \Delta v_\alpha}{2\sqrt{a^{(\alpha)} b^{(\alpha)}}} \right]$$

Equation 4-2: Desired distance to vehicle directly in front

6.4 Extrapolation

In order to find the characteristic moment value for the Base Model, I plotted the standard extremal variate of the Gumbel distribution versus the maximum moment per day. I fitted a trendline to the top 30% of the data and extrapolated up to the return period value of 12.429 to find the characteristic max moment value.

Firstly I plotted the 10 simulations with normally distributed IDM parameters and noticed the variability between each plot. This can clearly be seen in Figure 6-7 below. In order to compare this variation of the characteristic value with future parameter changes, I calculated the standard deviation of the 10 characteristic values and plotted + and - 1 standard deviation on Figure 6-7.

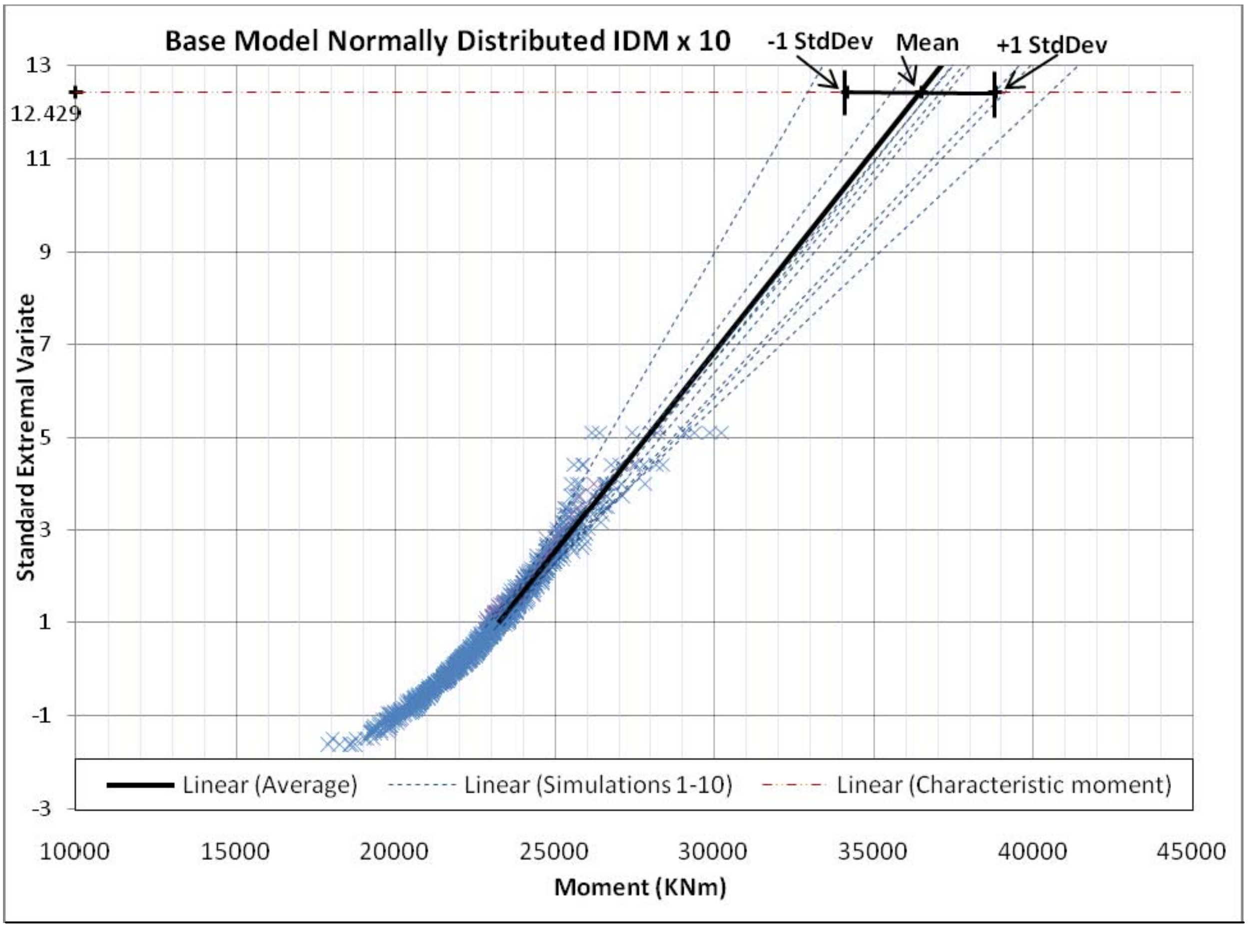


Figure 6-7: Base Model Normally Distributed IDM values x10

Seen as I am only using the top 30% of the data, which represents only 50 data points, to extrapolate to find the characteristic value, I choose to simulate 1680 days of data and plot it versus the average of the 168 days of data plotted above in Figure 6-7. The top 30% of the 1680 days data contains 500 data points, therefore will provide a relatively more accurate extrapolation. As can be seen in Figure 6-8, the 168 day average and the 1680 extrapolations are remarkably similar. The characteristic value of the 1680 day simulation is within 0.5% of the characteristic value of the average for the 168 simulation. Also plotted on Figure 6-8 is the 168 simulation with constant IDM parameters. The constant IDM characteristic value is within 1.6% of the characteristic value of the average for the 168 simulation. Therefore the average extrapolation of the 10 normally distributed simulations is an accurate approximation of the characteristic moment on the bridge for the base IDM parameters.

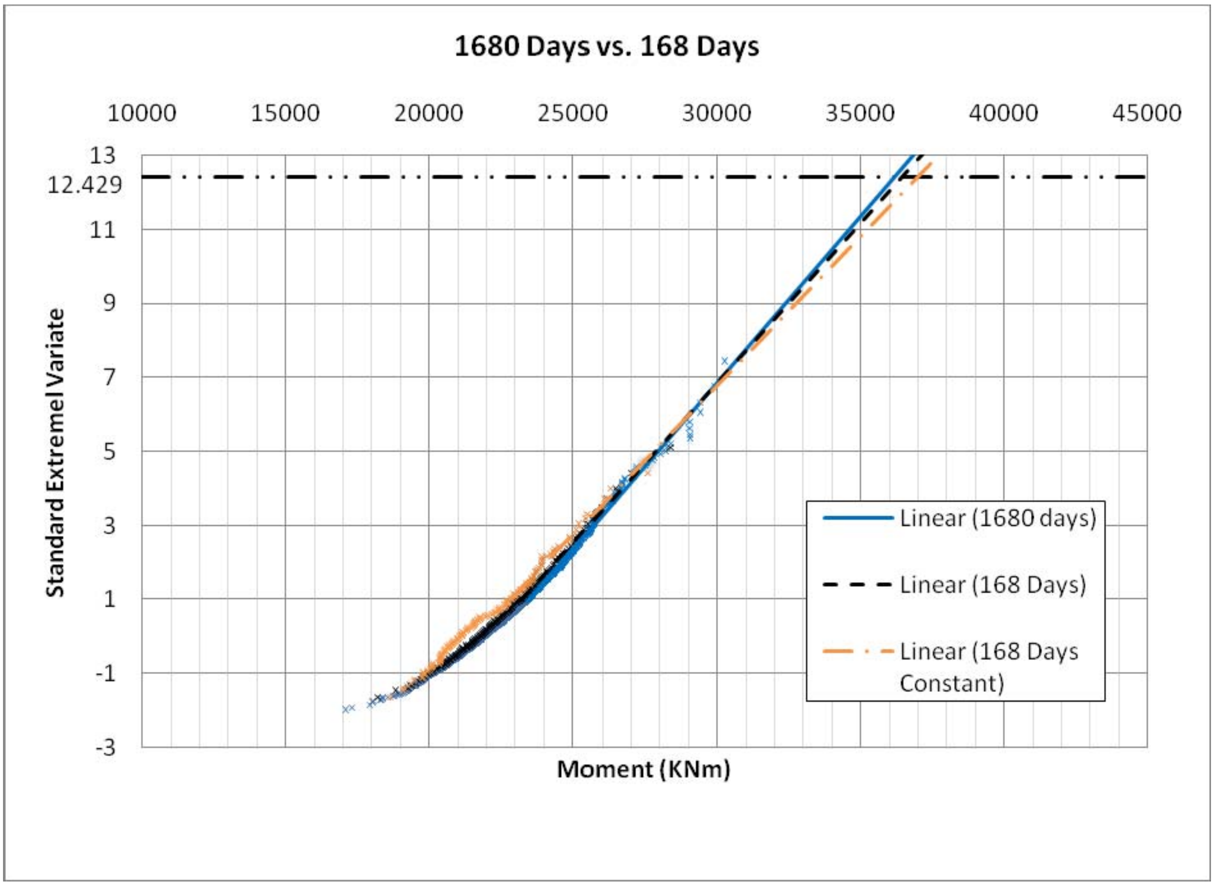


Figure 6-8: Base Model Extrapolation 1680 Days vs. 168 Days

6.5 Lane Changes and Density

The greatest amounts of lane changes takes place as the vehicles enter the speed limit section. The simulations with normally distributed IDM parameters have an average lane change rate (LC) of 2823 LC/hr/km while the simulation with constant IDM parameters has a LC rate of 3037 LC/hr/km. The normally distributed IDM simulation has an average density of 80.20 veh/km while the constant IDM simulation has a density of 76.32 veh/km.

6.6 Number of Trucks in Load Events

As discussed above in Section 6.3, the maximum moment on the bridge was caused by a 5-Truck load event even though 6-Truck and 7-Truck load events occurred. Figure 6-9 below, shows each load event type plotted with respect to the standard extremal variate of the Gumbel distribution for 840 Days of normally distributed simulated traffic. It can be seen from Figure 6-9, that 1 Truck, 2 Truck, 3 Truck and 4 truck load events have a steep slope indicating that they will converge at a maximum moment much sooner than 5 Truck and 6

Truck load events. 1 Truck, 2 Truck, 3 Truck and 4 truck load events have the most data points, 20% of the total load events each. The 5 Truck load events have nearly as much with 18%. The 6 Truck load events have much less data points, only 2% of the total load events and this is why a 6 Truck load event does not govern. Only 1 7 Truck load event was recorded which incidentally has the smallest magnitude of moment recorded. 6 Truck and 7 Truck load events do have the potential to govern but a much greater amount of data must be simulated.

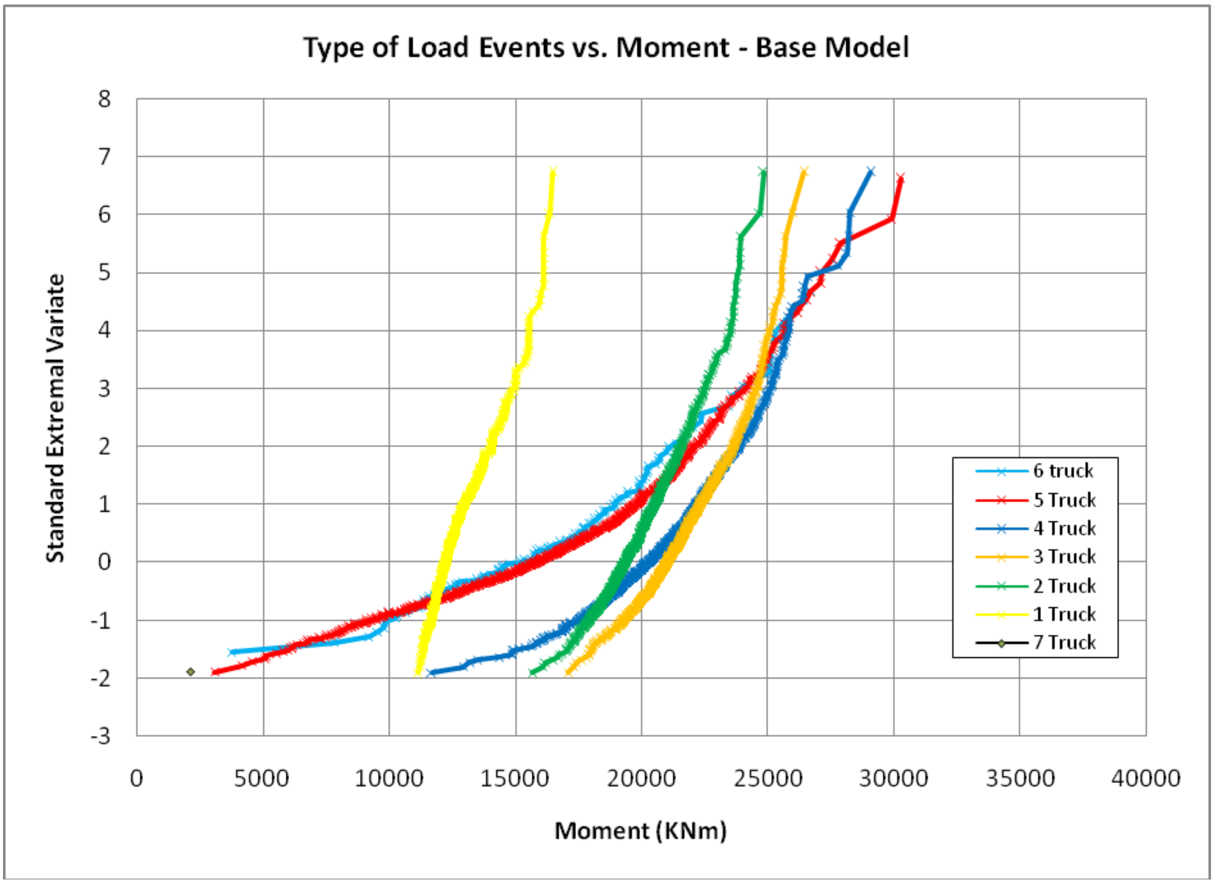


Figure 6-9: Type of Multiple Truck Load Events vs. Moment

6.7 Free Flow Model

In order to have a base to compare the congested traffic results to, I simulated the traffic input file in free flow without the 10km/hr speed limit section and calculated the maximum moments per day in the bridge, as shown below in Figure 6-10. It can be clearly seen that the moment is much less than that of congested traffic in Figure 6-4. The maximum moment per day varies from 12000KNm to 17000KNm for free flow traffic and from 20000KNm to 27000KNm for congested traffic.

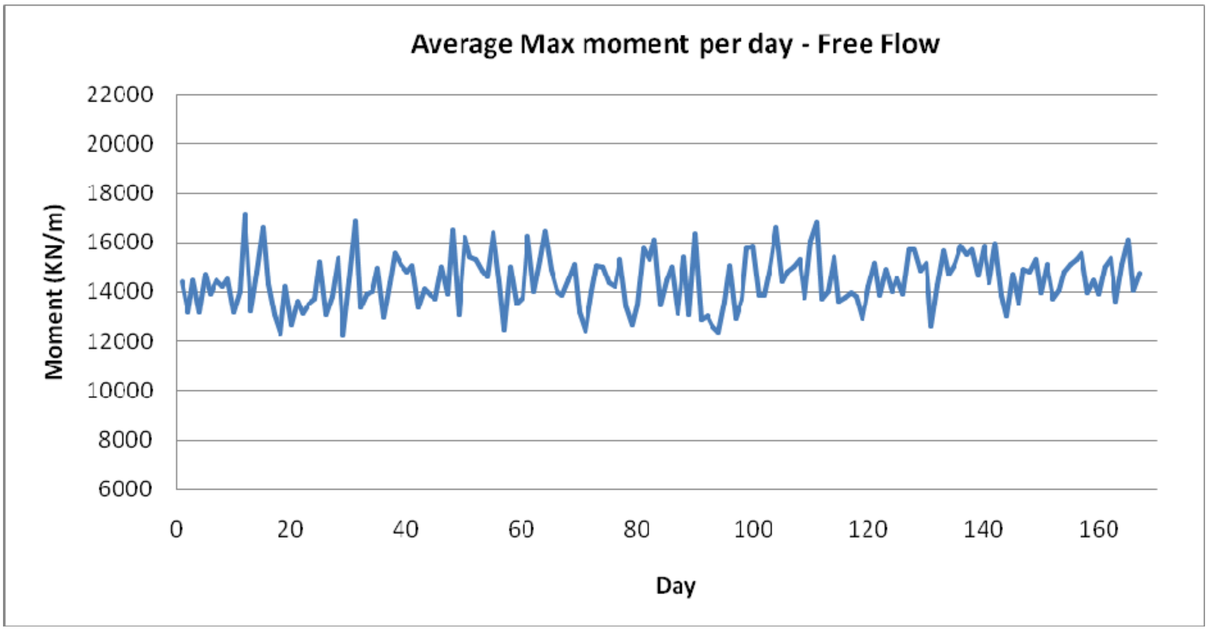


Figure 6-10: Average Max Moment per Day of Normal Distribution Free Flow Model

The maximum moment on the bridge was caused by a 2-Truck event. Figure 6-11 below, shows each load event type plotted with respect to the standard extremal variate of the Gumbel distribution for 1680 Days of normally distributed simulated free flow traffic. A 4 truck load event did not occur. It can clearly be seen that 1-Truck and 2-Truck load events have a steep slope as in Figure 6-9, and will converge to a maximum moment quickly. This indicates that the characteristic load will converge quickly. From Figure 6-9, it can be seen that 2 Truck and 3 truck load events will converge below 30000KNm.

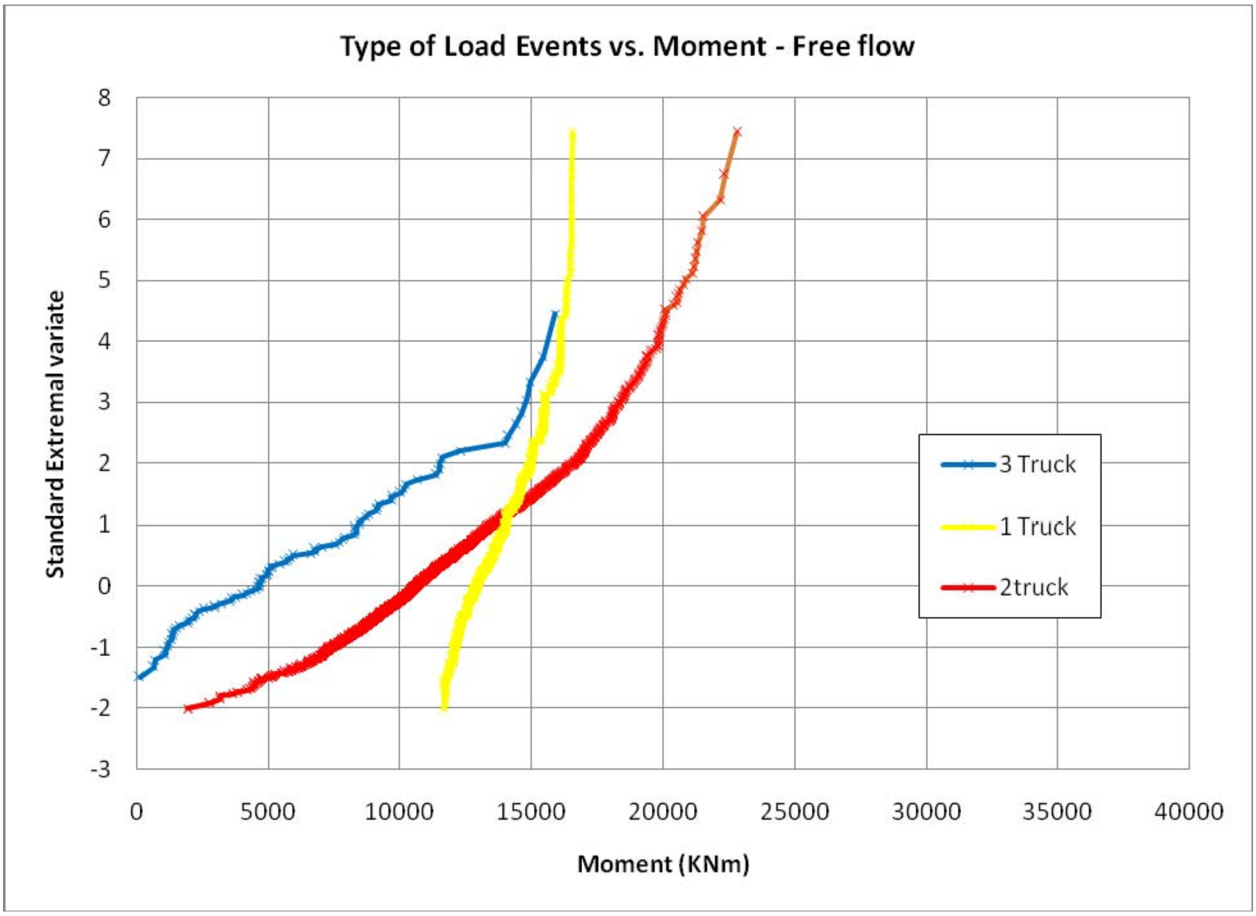


Figure 6-11: Type of Multiple Truck Load Events vs. Moment for Free Flow

Figure 6-12 below show the data points for the 1680 max moment per day free flow simulation. It can be seen that when the data is extrapolated with a linear trendline for the top 30% of the data, the characteristic value of 33500KNm is quite large and the extrapolation does not seem to match the trend in the data. I then extrapolated the top 5% of the data, which matches to final trend of the data. The characteristic value of 27500KNm is more like what is expected for a maximum of a 3 Truck load event. This is 25% less than the average characteristic value in Figure 6-7 of the Base Model for congested traffic.

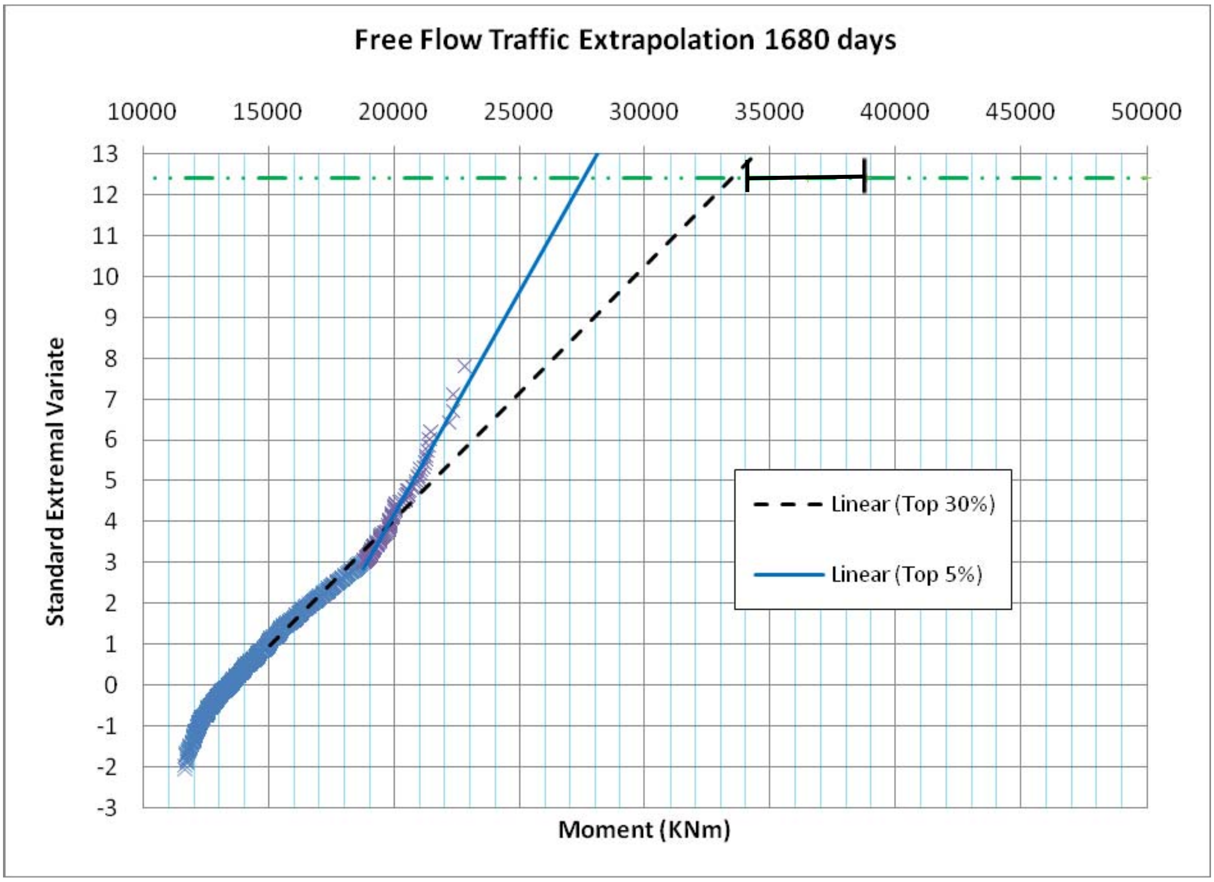


Figure 6-12: Free Flow Extrapolation 1680 days

7 Sensitivity Analysis

7.1 Parameters and layout

There are 10 IDM parameters that can be altered to change the configuration of the traffic. This work focuses on 6 parameters, $S_{1,}$ T, δ_{bias}, P, S_1 and δ_{thr}, because of their relevance to lane changing and to headway distances. The aim of this work is to find out which parameters make the most difference to the max moment on the bridge and why. Each parameter is changed by -50%, -25%, +25% and +50%, while leaving all other parameters at the base model values.

7.2 S_1 – Elastic jam distance

S_1 is the elastic jam distance, and affects the desired distance between vehicles ($s^*(v_\alpha, \Delta v_\alpha)$) as seen in Equation 4-2.

$$s^*(v_\alpha, \Delta v_\alpha) = \left[s_0^{(\alpha)} + s_1^{(\alpha)} \sqrt{\frac{v_\alpha}{v_0^{(\alpha)}}} + T^{(n)} v + \frac{v_\alpha \Delta v_\alpha}{2\sqrt{a^{(\alpha)} b^{(\alpha)}}} \right]$$

Equation 4-2: Desired distance to vehicle directly in front

I changed the S_1 factor by -50%, -25%, +25% and +50%, ran each simulation 5 times and plotted the average data on the standard extremal variate graph for the Gumbel distribution. I then extrapolated the top 30% of each data set as discussed in Chapter 6 and plotted them below in Figure 7-1. It is quite evident from Figure 7-1 that a decrease in S_1 results in an increase in the characteristic moment on the bridge. Likewise when S_1 is increased, the characteristic moment decreases. Also included in Figure 7-1 is an error bar showing + and – 1 standard deviation of the Base Model as discussed in Chapter 6. This shows the magnitude of the change in the characteristic moment due to S_1 compared to the Base Model.

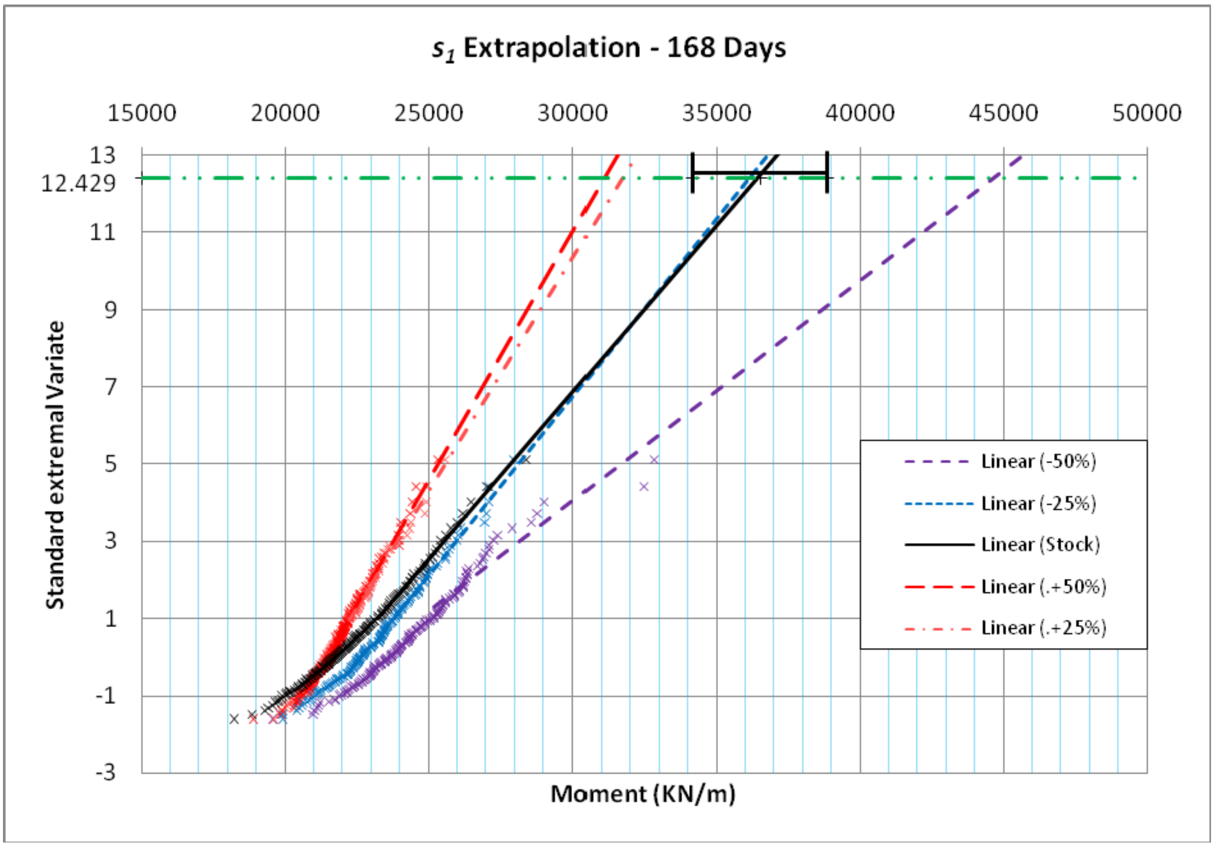


Figure 7-1: s_1 Extrapolation of 168 day normally distributed IDM

However, it is noted that a decrease in S_1 by 25% has no effect on the characteristic moment and an increase of 25% has a large effect on the characteristic moment. This implies that they extrapolation is not very accurate and requires more data points. In order to get a more accurate extrapolation, I decided to simulate the change in S_1 with 168 days of constant IDM parameters and also with 840 days of normally distributed IDM parameters in a similar manner to the Base Model in chapter 6. The resultant graphs are plotted in Figure 7-2 and Figure 7-3 respectively.

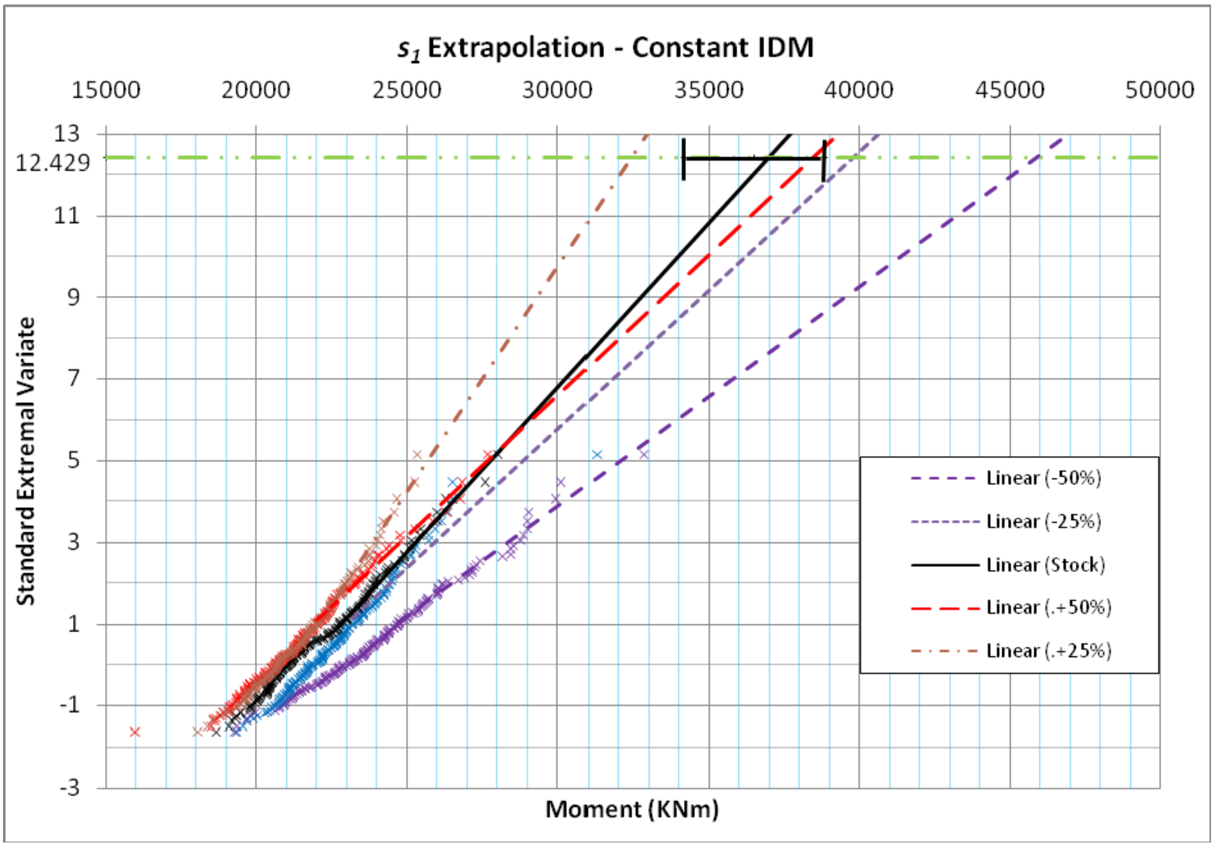


Figure 7-2: s_1 Extrapolation of 168 day constant IDM

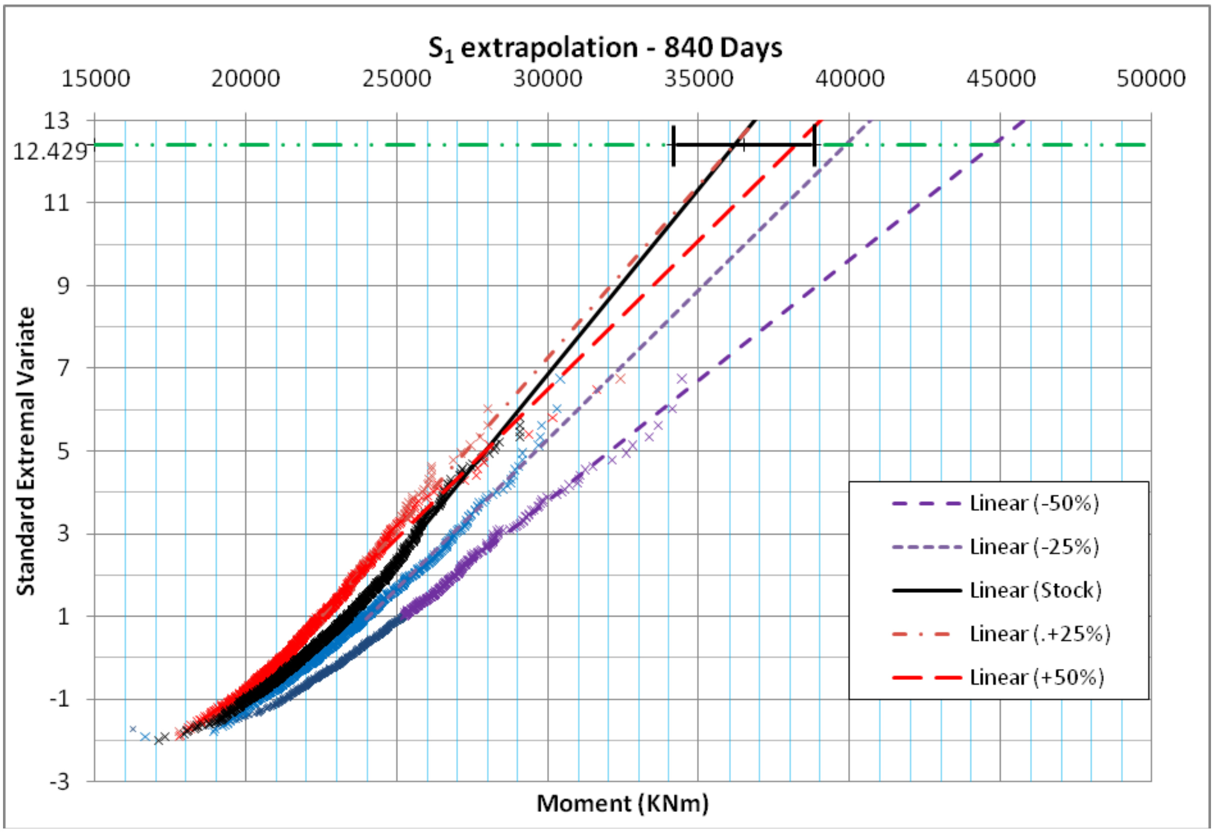


Figure 7-3: s_1 Extrapolation of 840 day normally distributed IDM

Figure 7-2 and Figure 7-3 are very similar except for +25% S_1. In Figure 7-2, the +25% S_1 characteristic value is 32500KNm which is similar to that of Figure 7-1 but quite different to the characteristic value of the 840 day simulation in Figure 7-3 of 36400KNm. Due to the much higher number of data points in Figure 7-3, 840 vs. 168, Figure 7-3 is presumed to have a better extrapolation of the characteristic value. The characteristic values of both +50% S_1 and +25% S_1 are within 1 standard deviation of the characteristic value of the normally distributed Base Model.

7.2.1 -50% S_1

A decrease of 50% in S_1 from 20m to 10m has caused the characteristic moment to change from 36400KNm to 44700KNm, which is an increase of 23%. This is the most significant increase out of all the parameters. However, the percentage increase in the characteristic moment is only half that of the decrease in S_1. As shown in Figure 7-6, the LC rate increases by 5% from 2823 LC/hr/km to 2966 LC/hr/km while the density decreases from 80.20 veh/km to 77.73 veh/km. This decrease in density is only 2.47 veh/km or 3% of the base level, which equates to 0.247 veh/100m and therefore negligible to the load affect on the bridge.

The maximum moment from the -50% S_1 normally distributed IDM parameters simulations is 34478KNm and is a 5-truck load event. As with in the base model, 6-truck and 7-truck load events did occur but did not govern. A note of interest from Figure 7-4 is that the same 5 trucks make up the maximum moment for the Base Model in Figure 6-6, but are in a different configuration and most importantly, the headway distances in lane 1 are smaller due to S_1 being decreased from 20m to 10m. The reduction in the headway distance is the reason why the moment has increased. The dimensions of the headway distances given in Figure 7-4 are in metres.

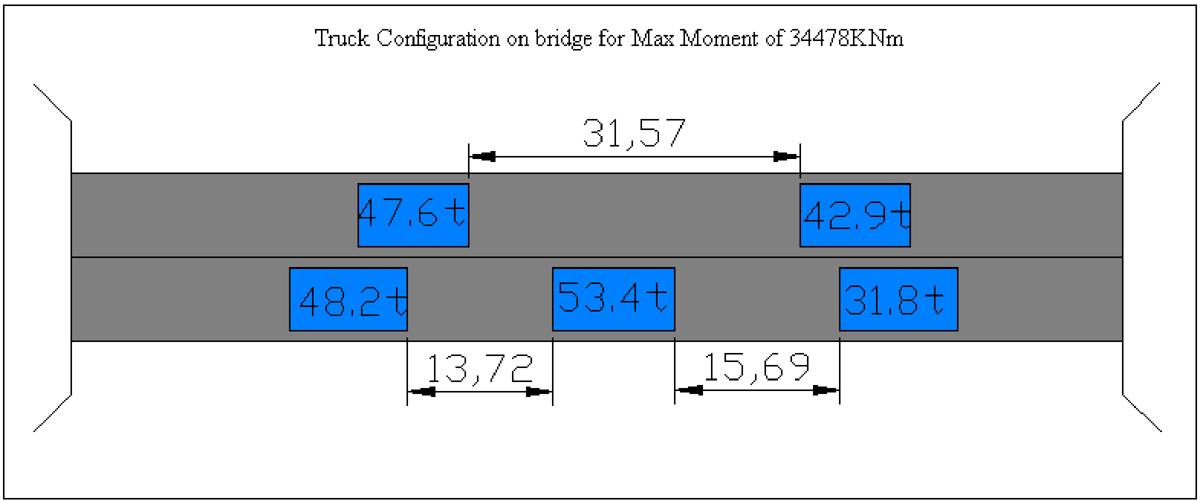


Figure 7-4: 5-Truck load event Configuration for Max Moment for -50% S_I of 34478KNm

As discussed above, the maximum load event is a 5 Truck event as shown in Figure 7-4. Figure 7-5 below, shows each load event type plotted with respect to the standard extremal variate of the Gumbel distribution for 840 Days of normally distributed simulated traffic. It can be seen from Figure 7-5, that 1 Truck, 2 Truck, 3 Truck and 4 truck load events have a steeper slope than that of 5 Truck and 6 Truck load events, indicating that they will converge at a maximum moment much sooner than 5 Truck and 6 Truck load events. 1 Truck, 2 Truck, 3 Truck and 4 truck load events have the most data points, 19% of the total load events each. The 5 Truck load events have nearly as much with 18%. The 6 Truck load events have much less data points, 5.5% and the 7 truck load events have only 0.5% of the total load events. It is because of these small percentages that a 6 Truck load event or a 7 truck load event does not govern. Only 1 8 Truck load event was recorded. 6 Truck, 7 Truck and 8 Truck load events do have the potential to govern but a much greater amount of data must be simulated in order for heavy 6 Truck, 7 Truck and 8 Truck load events to occur.

By comparing Figure 6-9, the type of load events vs. moment for the Base Model, against Figure 7-5, it can be seen that the 1 Truck and 2 Truck lines are nearly the exact same, while the 3 Truck, 4 Truck, 5 Truck and 6 Truck slopes slacken out more on Figure 7-5, which leads to greater moment. This makes sense as the decreased headway distance between vehicles makes little or no difference to 1 Truck or 2 Truck load events but does affect 3 Truck, 4 Truck, 5 Truck and 6 Truck load events by allowing the vehicles to drive closer together which means more vehicles on the bridge, therefore greater bending moment on the bridge.

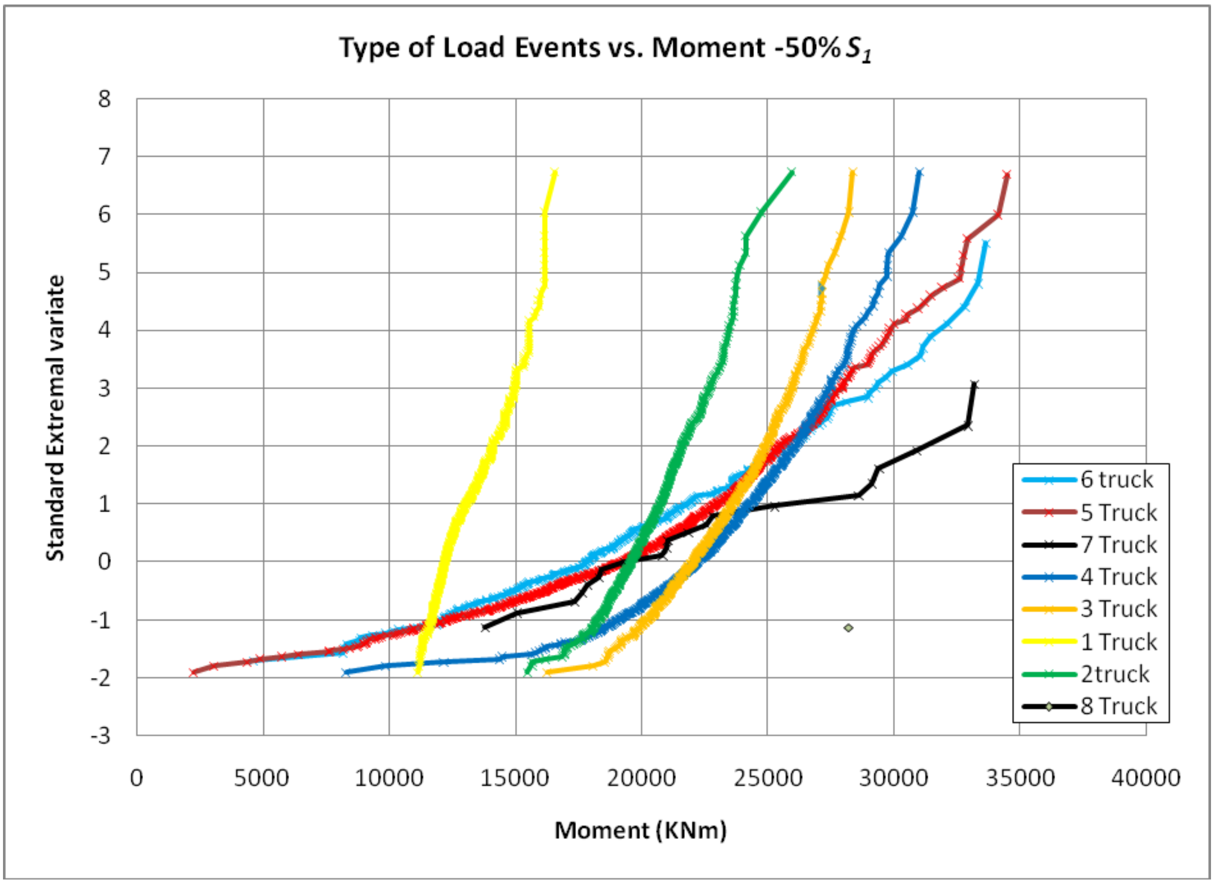


Figure 7-5: Type of Multiple Truck load Event vs. Moment -50% S_I

7.2.2 Lane Change ratio and Density

As S_I is increased, the density of vehicles (veh/km) increases and the lane change ratio (lane changes/hr/km) decreases, as shown in Figure 7-6. The density increases from 77.7 veh/km for -50% S_I to 88 veh/km for +50% S_I. This is an increase of 10.3 veh/km or 13%, which is the greatest change in the density of all the parameters tested. The lane change rate decreases from 2966 LC/hr/km for -50% S_I to 2515 LC/hr/km for +50% S_I. This is a decrease of 451 LC/hr/km or 15% which is also the greatest change in the lane change rate of all the parameters analysed. These changes in the lane change rate of +15% and in the density of -13% are quite small in comparison to the fact that S_I is changed across a 100% range. It is strange that an increase in the lane change rate corresponds with a decrease in the density. However this is consistent across all of the parameters analysed.

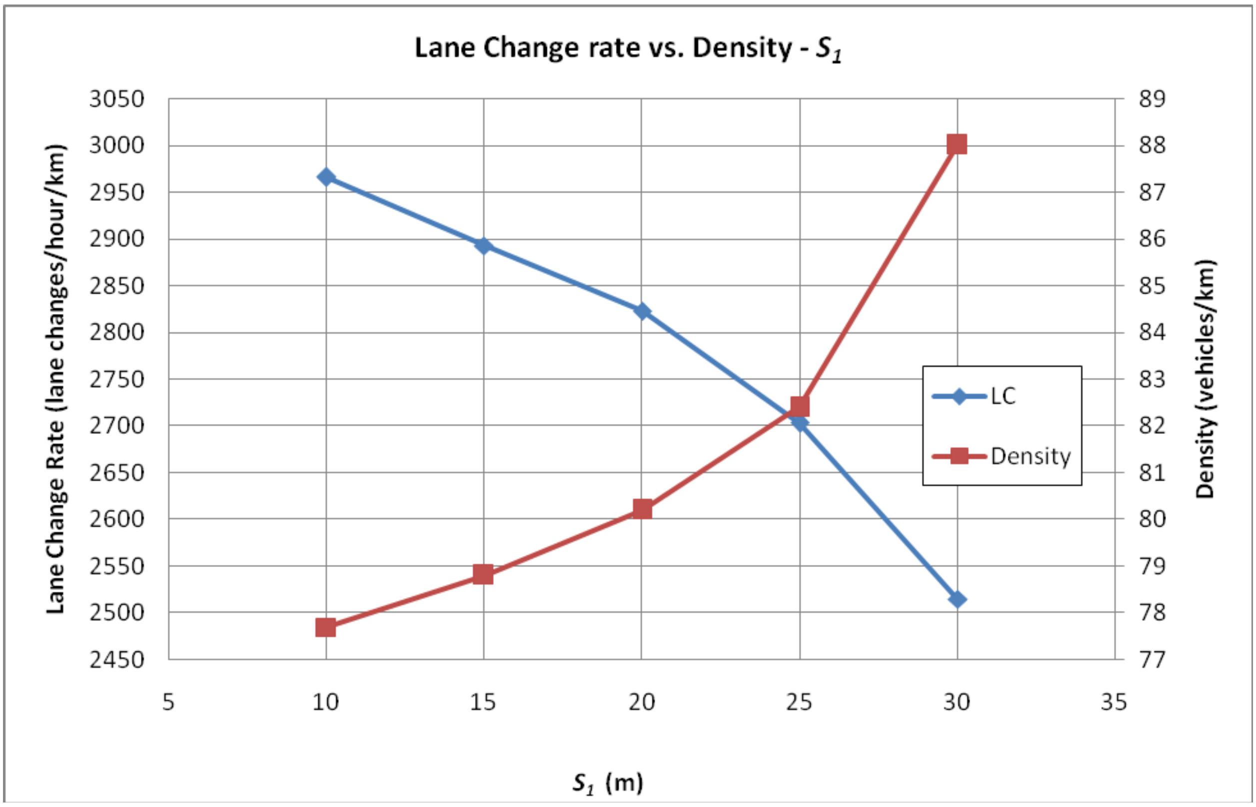


Figure 7-6: Lane Change rate vs. Density for changes to S_1

7.3 Desired Headway Time (T), Outside Lane Bias (δ_{bias}) and Politeness factor (P)

The same procedures and analysis techniques are used for the following parameters as have been used for S_1. In an effort to reduce the length of this dissertation, the results of the following parameters are summarised and presented below.

T is the Desired Headway Time between vehicles and effects the desired headway distance ($s^*(v_\alpha, \Delta v_\alpha)$) in Equation 4-2 below. T is multiplied by the current velocity (v) of the vehicle. It is clear to see that at low velocities, the effect T has on the desired headway distance is reduced. It is for this reason that s_1 has a bigger effect on the desired headway distance in congested traffic than T.

$$s^*(v_\alpha, \Delta v_\alpha) = \left[s_0^{(\alpha)} + s_1^{(\alpha)} \sqrt{\frac{v_\alpha}{v_0^{(\alpha)}}} + T^* v + \frac{v_\alpha \Delta v_\alpha}{2\sqrt{a^{(\alpha)} b^{(\alpha)}}} \right]$$

Equation 4-2: Desired distance to vehicle directly in front

δ_{bias} is the Outside Lane Bias factor and is used in the '*incentive criterion'* for lane changes. δ_{bias} is added to the Lane Change Threshold (δ_{thr}) if a vehicle is changing from the outside lane to the inside lane, and is subtracted from the Lane Change Threshold (δ_{thr}) if the vehicle is changing from the inside lane to the outside lane. This is shown below in Equation 4-4 and Equation 4-5.

$$acc'(M') - acc(M) + P\,[acc'(B') - acc(B')] > \delta thr + \delta bias$$

Equation 7-1: Incentive Criterion - Right to Left

$$acc'(M') - acc(M) + P\,[acc'(B) - acc(B)] > \delta thr - \delta bias$$

Equation 7-2: Incentive Criterion – Left to Right

P is the Politeness factor and is also used in the '*incentive criterion'* for lane changes and is shown above in Equation 4-4 and Equation 4-5. P is multiplied to the disadvantage of the vehicles directly behind the vehicle considering changing lane. This weights the disadvantage to others with respect to the vehicles own advantage.

7.3.1 Desired Headway Time (T)

T behaves as would be expected. As T is increased, the moment in the bridge decreases. Likewise, as T is decreased, the moment in the bridge increases. When T is changed by +50%, the characteristic moment reduces by 3.6%. When T is changed by -50%, the characteristic moment increases by 7.2%. This equates to an overall change in the characteristic moment of 10.8% for a 100% change in T. Also the greatest change in the characteristic moment is just outside 1 standard deviation of the Base Model characteristic value as show below in Figure 7-7.

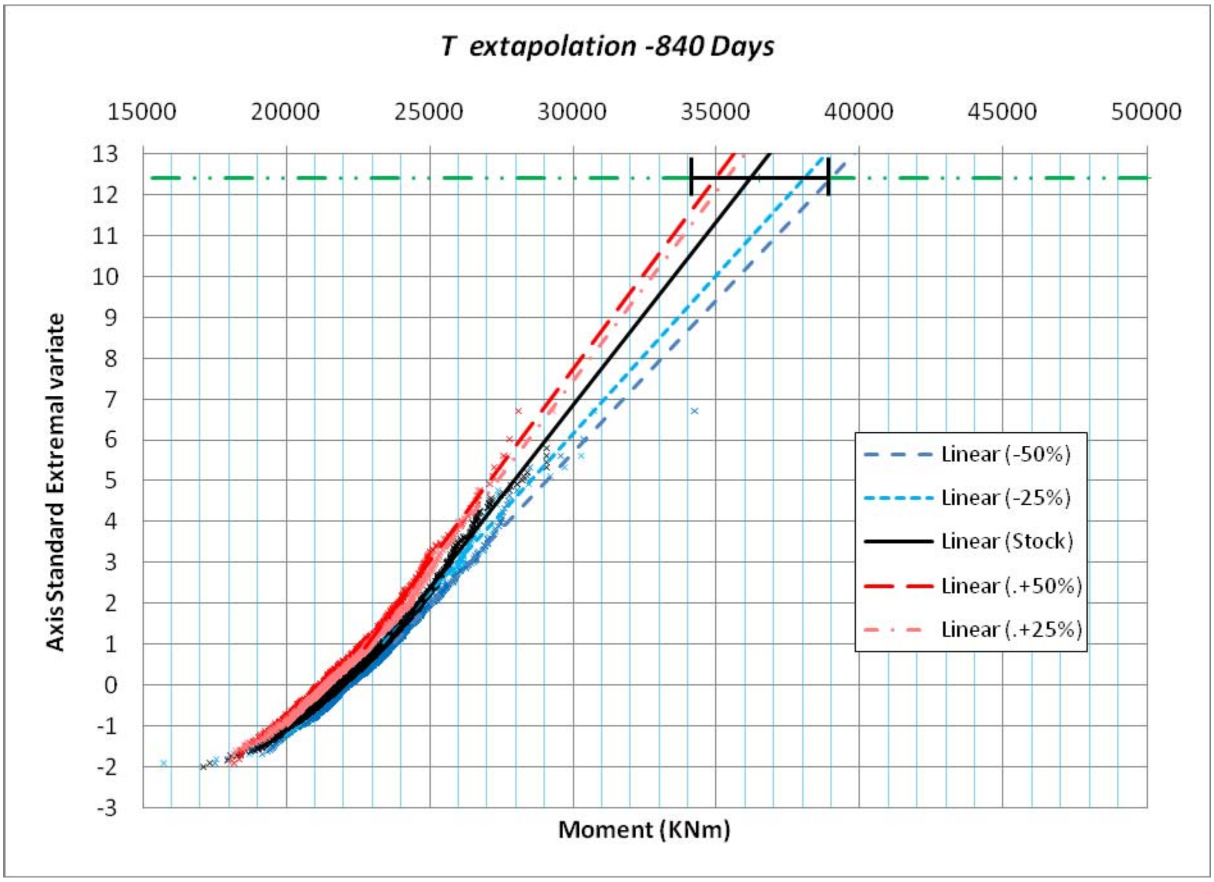


Figure 7-7: ***T*** **Extrapolation of 840 Day normally distributed IDM**

The lane change rate for *T* decreases by 7.4% from 2900 LC/hr/km to 2685 LC/hr/km between -50% *T* and +50% *T*. The density increases by 0.5% from 76.6 veh/km to 81 veh/km between -50% *T* and +50% *T*. This change in density relates to 0.04 veh/100m and therefore has no effect on the load on the bridge.

It can be seen clearly that changing *T* does affect the characteristic moment on the bridge but a change of -50% needs to be made to *T* to change the characteristic moment by +7.2%. The change in the characteristic moment due to -50%*T*, +7.2%, is just outside 1 standard deviation of the variability of the IDM parameters being distributed across a normal distribution, +6.4%. Therefore a change in *T* affects the characteristic moment only slightly more than the distribution of the IDM parameters across a normal distribution does. It can also be noted that unlike in Figure 7-3 for S_1, all the data points are quite near each other in Figure 7-7, which adds strength to the argument that *T* does not affect the characteristic moment significantly when traffic is congested.

7.3.2 Outside Lane Bias (δ_{bias})

Figure 7-8 below shows the extrapolation of δ_{bias} as it is increased and decreased by 25% and 50%. When δ_{bias} is changed by -25%, the characteristic moment decreases by 3.6%. When *δbias* is changed by +50%, the characteristic value increases by 5.2%. This is a total change of 8.8% across a 100% change in δ_{bias} and as before with *T,* is within 1 standard deviation of the Base Model Characteristic value. Changes of -25% *δbias* and +50% δ_{bias} do not change the characteristic moment. It can also be seen in Figure 7-8 that all the data points are quite near each other like in Figure 7-7 for *T*. This indicates that like *T*, δ_{bias} only has a small effect on the characteristic moment for congested traffic. A decrease in the lane change rate of only 0.5% and an increase in the density of only 0.35% across a 100% change in δ_{bias} strengthens the above statement.

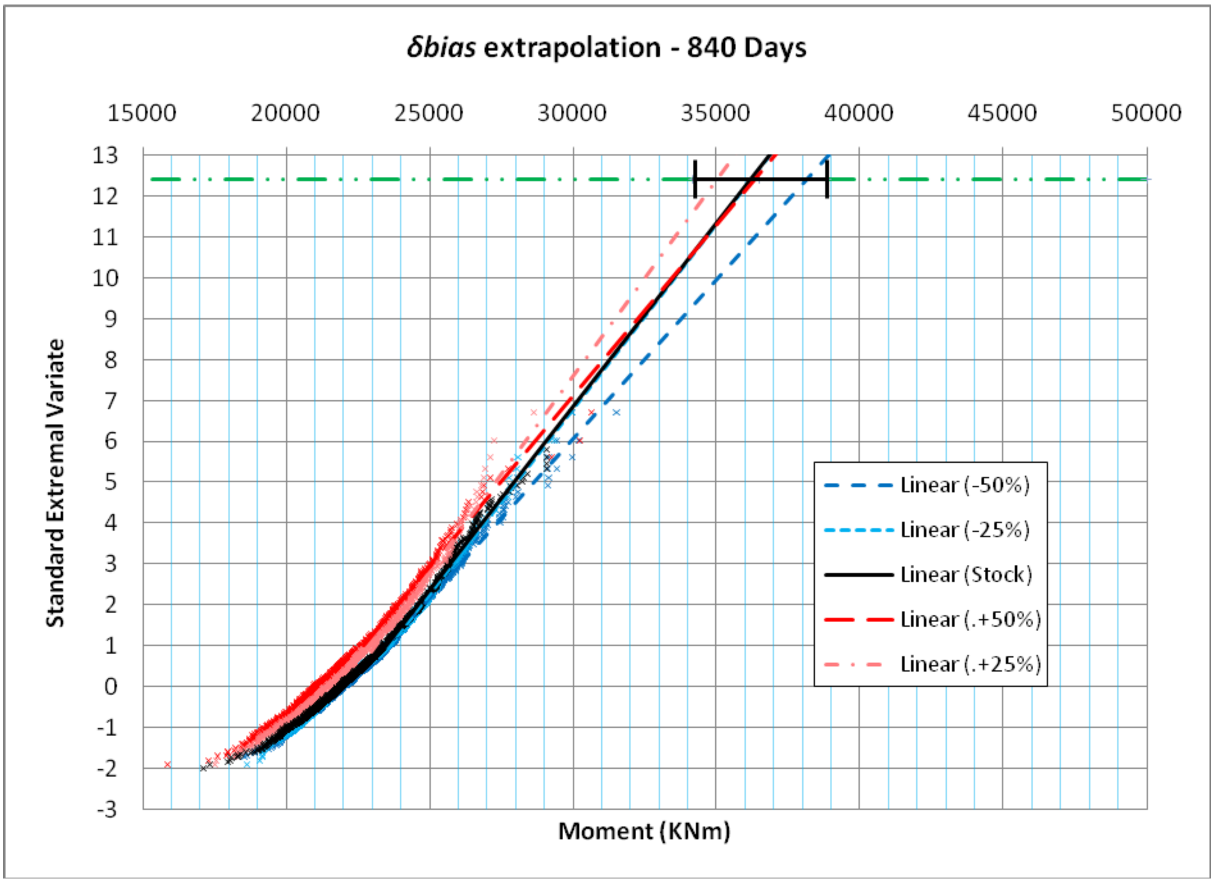


Figure 7-8: δ_{bias} Extrapolation of 840 Day normally distributed IDM

7.3.3 Politeness factor (P)

Like T and δ_{bias} previously, changing P does affect the characteristic moment but not in a linear manner. The minimum characteristic value, 5.2% less than the base value, is when P is increased by 50%. The maximum characteristic value, 3.8% greater than the base value occurs when P is increased by 25%. This implies that increasing P, i.e. increasing the politeness of the drivers, can affect the moment on the bridge in either a negative or a positive manner.

When P is changed from -50% to +50% of the base value, the lane change rate decreases from 2840 LC/hr/km to 2788 LC/hr/km. That is a decrease of only 2%. As the drivers become more polite, less lane changes take place but only marginally less. This is interesting, because like δ_{bias}, P is related to lane changes but has barely any effect on the lane change rate in congested traffic, much like $\delta bias$.

The density changes from 80.3 veh/km to 80.17 veh/km when P is changed from -50% to +50% of the base value. This is a decrease of 0.2% which is negligible. P shares other similarities with T and δ_{bias} as can be seen below in Figure 7-9. Firstly all the data points are very close together for all the increments of P and secondly the maximum and minimum characteristic values are within 1 standard deviation of the characteristic value from the Base Model. P does have an effect on the characteristic moment of the bridge but it is only a small effect and is within a standard deviation of the base value, therefore it has no more effect on the characteristic moment than the distribution of the parameters across a normal distribution does.

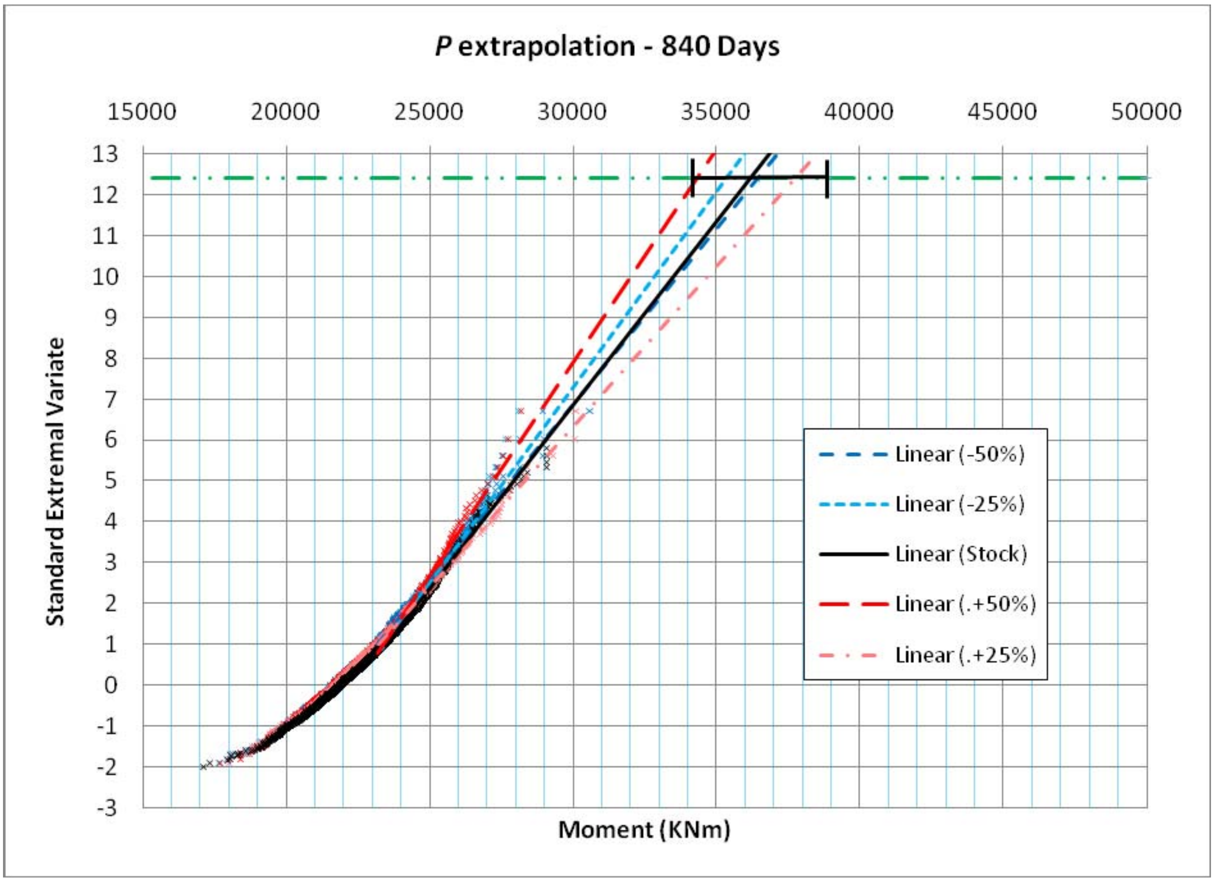


Figure 7-9: ***P*** **Extrapolation of 840 Day normally distributed IDM**

7.4 Minimum Jam Distance (S_0)

S_0 affects the desired headway distance between vehicles ($s^*(v_\alpha, \Delta v_\alpha)$) as shown in Equation 4-2.

$$s^*(v_\alpha, \Delta v_\alpha) = \left[s_0^{(\alpha)} + s_1^{(\alpha)} \sqrt{\frac{v_\alpha}{v_0^{(\alpha)}}} + T^{(\alpha)} v + \frac{v_\alpha \Delta v_\alpha}{2\sqrt{a^{(\alpha)} b^{(\alpha)}}} \right]$$

Equation 4-2: Desired distance to vehicle directly in front

Because S_0 is small (1m) compared to S_1 (20m) and *T(v)* (1.5*8), it has very little effect on the desired distance between vehicles and therefore the maximum moment on the bridge. The change in the lane change rate between -50% S_0 and +50% S_0 is -1%. The density is changed by +0.3% for the same increments. Both the change in the lane change rate and the change in density are negligible. When S_0 is changed by -50%, the characteristic moment changes by

+3%. The maximum negative change to the characteristic value, -0.8%, is caused by changed S_0 by +25%. This is a total of 3.8% of a change in the characteristic moment while S_0 is varied by 100%. As the minimum jam distance is decreased, the characteristic moment increases and as the minimum jam distance increases, the characteristic moment decreases. This makes sense but the magnitude by which a change in S_0 effects the characteristic moment is quite small. Once again, as with *T*, *δbias* and *P,* the maximum changes to the characteristic moment due to changes in S_0, are within 1 standard deviation of the Base Model characteristic moment and all the data points are very close to each other. Therefore S_0 does not significantly effect the characteristic moment on the bridge for congested traffic.

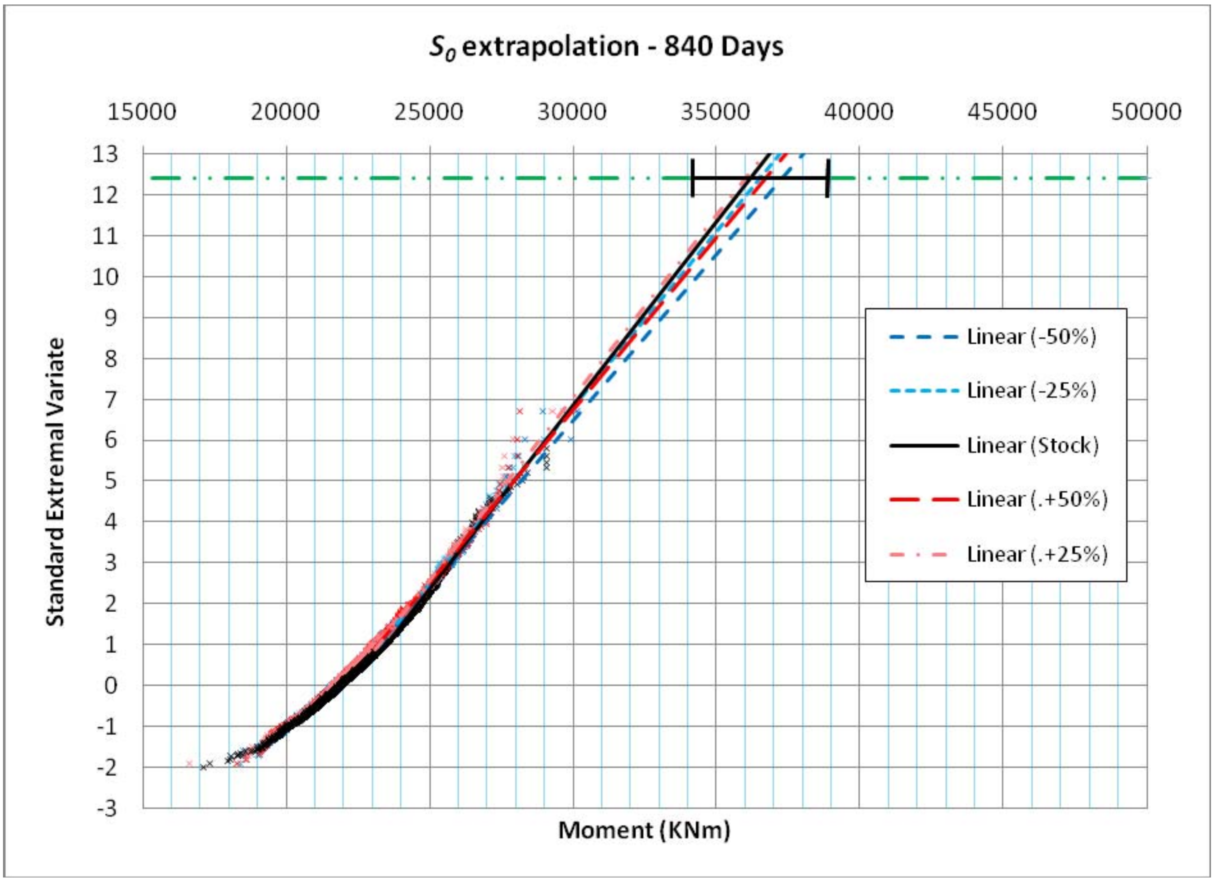


Figure 7-10: S_0 Extrapolation of 840 Day normally distributed IDM

7.5 Lane Change Threshold (δ_{thr})

δ_{thr} is a factor in the '*Incentive Criterion'* for lane changes and is included in the equation to prevent lane changes taking place that are only of marginal advantage to the driver i.e. lane hopping. The '*Incentive Criterion'* is shown below in Equation 4-4 and Equation 4-5.

$$acc'(M') - acc(M) + P\,[acc'(B') - acc(B')] > \delta thr + \delta bias$$

Equation 7-3: Incentive Criterion - Right to Left

$$acc'(M') - acc(M) + P\,[acc'(B) - acc(B)] > \delta thr - \delta bias$$

Equation 7-4: Incentive Criterion – Left to Right

As can be seen in Figure 7-11, when δ_{thr} is increased by 50%, the characteristic moment changes by +3.6% and when δ_{thr} is decreased by 50%, the characteristic moment decreases by 2.2%. This equates to a total change of 5.8% when δ_{thr} is varied by 100%. Like the previous parameters, the maximum changes to the characteristic moment are within 1 standard deviation of the characteristic moment from the Base Model and all the data points are very close to each other. There is no change in the lane change rate or in the density when δ_{thr} is varied. This is significant as δ_{thr} is included to stop lane hopping. From this it can be said that δ_{thr} has little or no effect on the maximum moment on the bridge for congested traffic.

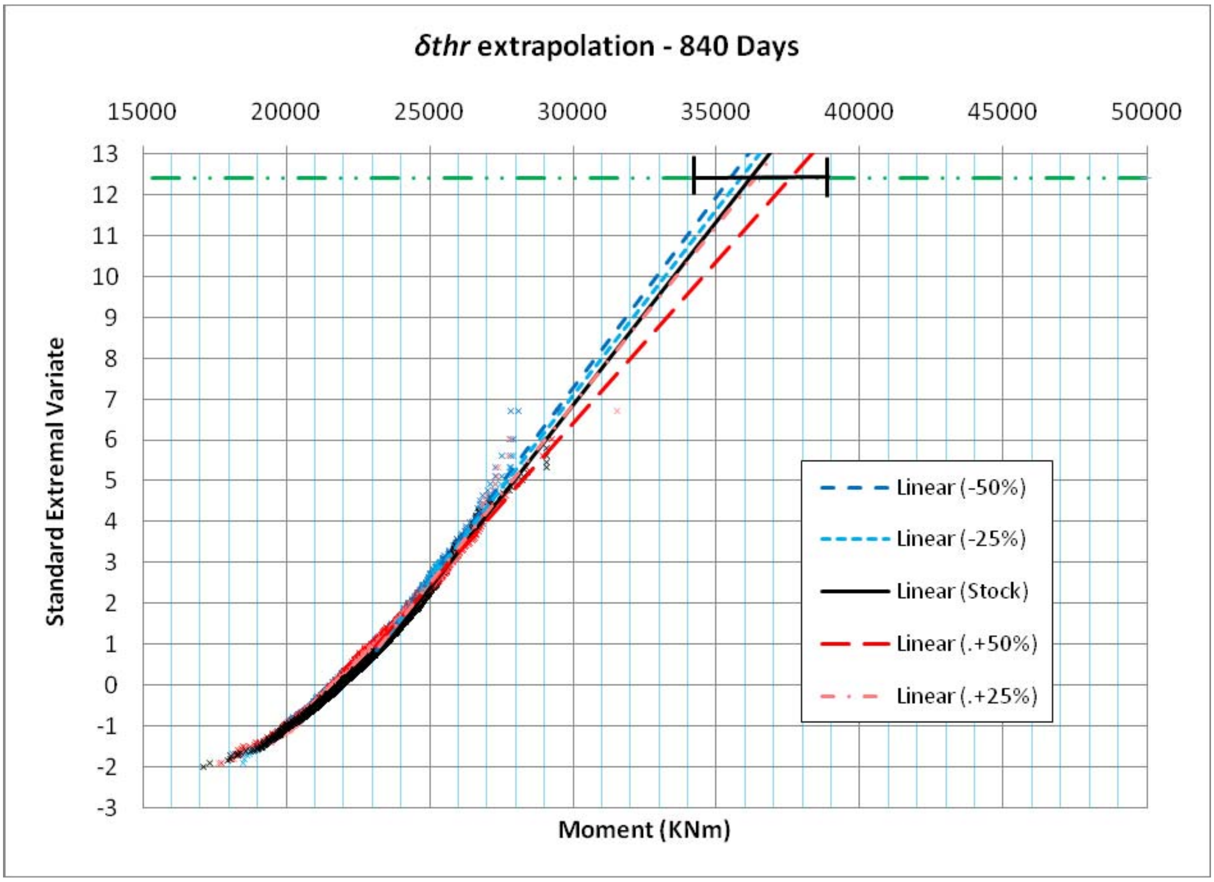


Figure 7-11: δ_{thr} Extrapolation of 840 Day normally distributed IDM

8 Conclusions

8.1 Sensitivity Analysis

A sensitivity analysis was carried out on a 2 lane, 100m long, simply supported bridge. 6 IDM and MOBIL parameters were analysed for increases and decreases of 25% and 50%. A Base Model was set and analysed using both constant parameters and normally distributed parameters. It was found that the normally distributed parameters caused each of the 10 base simulations to yield slightly different characteristic values, even though the parameters were set at the same value for all 10. This variation in the characteristic values proved to be significant, with a minimum variation from the mean of -9.3% and a maximum variation from the mean of +11.2%. This resulted in a standard deviation of + or - 6.4% of the mean which is greater than the variations in the characteristic values due to the variations of the parameters δ_{bias}, P, S_0 and δ_{thr} by + and – 25% and 50%.

The amount of days of data used versus the accuracy of the extrapolation to the 1000 year return period was briefly studied. It was found that more data means more accuracy in predicting a characteristic value. The extrapolations for 168 day simulations were far less organised than the extrapolations for 1680 day simulations.

It was shown that T, δ_{bias} and P, do affect the characteristic value when changed but the percentage at which they affect the characteristic value compared to the percentage that they are changed is quite small. For instance, a decrease of -50% in T, results in an increase in the characteristic moment of +7.2%. This is only 14.4% of the change in T and only +0.8% more than +1 standard deviation of the Base Model. The characteristic value due to -50% T is the only characteristic value from all the variations of T, δ_{bias} and P that is greater than 1 standard deviation of the Base Model. It was also noted that P and δ_{bias} have a negligible effect on the lane change rate in congested traffic. This is significant as both P and δ_{bias} are included in the *'incentive criterion'* to increase or decrease lane changes. A decrease of -50% in T, changes the lane change rate by only 3% which is also negligible compared to the decrease in T.

The parameters S_0 and δ_{thr} are shown to effect the characteristic moment on the bridge less than T, δ_{bias} and P. This is interesting as S_0 is the minimum jam distance in congested traffic. It was shown that because the traffic analysed was travelling at a speed of 2m/s and not at a stop, S_0 has a negligible effect on the moment on the bridge. Changing δ_{thr} by + and - 50%

has no effect on either the lane change rate or density. This is a significant discovery because δ_{thr} is included in the *'incentive criterion'* to decrease random lane changes. The effect S_0 has on the lane change rate and density is also negligible.

The Elastic Jam Distance (S_1) was found to have the most significant effect on the characteristic moment on the bridge in congested traffic. A change of -50% in S_1, results in a change in the characteristic moment of +23%, far greater than 1 standard deviation of the characteristic value from the Base Model. A change of -25% in S_1 also resulted in an increase, +9.9%, in the characteristic moment, beyond the range of 1 standard deviation of the Base Model. Increasing S_1 did not effect the characteristic moment beyond 1 standard deviation of the Base Model. It should be noted that this work did not carry out a study to see how realistic an S_1 value of 10m or 30m is compared with measured traffic. This work concentrated on changing each parameter by the same percentage in order to be able to compare results.

From this work it is apparent that the variability of the parameters across the normal distribution has more effect on the characteristic value than most of the parameters.

- S_1 has a greatest effect on the characteristic moment on the bridge for congested traffic but even still must be changed by a large percentage in order to induce a significant change in the characteristic moment.

- T has a small effect on the characteristic moment on the bridge for congested traffic but it is negligible.

- δ_{bias} and P have a small effect on the characteristic moment on the bridge for congested traffic but it is less than 1 standard deviation of the base model. This effect on the characteristic moment is negligible and therefore δ_{bias} and P could be neglected.

- S_0 and δ_{thr} have barely any effect on the characteristic moment on the bridge for congested traffic and so can be neglected.

Considering that long span bridges are designed for the worse load that may occur in its lifetime, it is reasonable to neglect the parameters that do not affect the characteristic moment significantly. These parameters seek to model traffic as realistically as possible but in doing so add unnecessary complexity and variability to the process of traffic microsimulation loading for long span bridges. By excluding the parameters that do not contribute to the characteristic moment, traffic micosimulation for long span bridges can be made simpler and more user friendly.

8.2 Further Research

Throughout this work various opportunities for further research have presented themselves and have remained unexplored. These are outlined below.

The traffic analysed in this study was congested traffic at a speed of 2m/s but did not come to a halt and induce the '*accordion effect'* at any stage during the simulations. An interesting research opportunity would be to double to flow of traffic to induce such effects and also to run the traffic in free flow to see if the results from this study were consistent across different traffic flows.

To fully realise what effect δ_{bias}, P, S_0 and δ_{thr} have on the characteristic moment on a long span bridge, it would be of interest to exclude them from the traffic microsimulation model and simulate the traffic as in this work to see what effect, if any this has on the characteristic moment of the bridge.

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