University of Rhode Island

DigitalCommons@URI

2008

Development of a Multiple Truck Presence Model

Cornelius Albrecht
University of Rhode Island

DEVELOPMENT OF A MULTIPLE TRUCK PRESENCE MODEL

BY

CORNELIUS ALBRECHT

A MASTER THESIS SUBMITTED IN PARTIAL FULFILLMENT OF THE

REQUIREMENTS FOR THE DEGREE OF

MASTER OF SCIENCE

IN

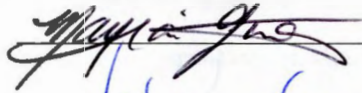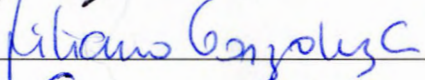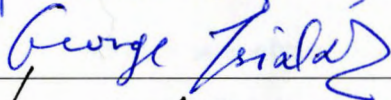CIVIL AND ENVIRONMENTAL ENGINEERING
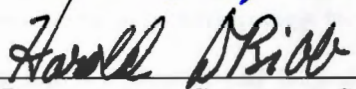
UNIVERSITY OF RHODE ISLAND

2008

MASTER OF SCIENCE THESIS

OF

CORNELIUS ALBRECHT

APPROVED:

Thesis Committee:

Major Professor

DEAN OF THE GRADUATE SCHOOL

UNIVERSITY OF RHODE ISLAND
2008

Abstract

In bridge design and evaluation, the characteristics of truck traffic is particularly important. Truck weights and axle configurations are directly used in calculations of maximum load effects including positive bending moments and shear forces in simply-supported bridges as well as negative bending moments of continuous spans. The loading event that is likely to govern a bridge design is the simultaneous occurrence of two or more heavily loaded trucks—called Multiple Presence. Consequently, the statistics of different loading patterns as well as the weight correlation among coincident trucks are equally important to live load analysis. However, studies of Multiple Presence events are either convolution models or models based on visual observation of the traffic, but very little research has been undertaken to analyze Weigh-in-Motion data.

In this study, Weigh-in-Motion data collected on highways is analyzed in order to determine the occurrence of Multiple Presence events incorporating two trucks and their weight correlation. Based on the analysis, a prediction model is developed to estimate the frequency of the Multiple Presence events using known site parameters. Also, probabilities for full weight correlations are found for the Multiple Presence loading cases. A special remark is given to the influence of the Gap distances between the trucks involved into a Multiple Presence event. It is found that the Gaps do not have a threshold distance for the influence of the lighter truck that could be utilized to reduce the Multiple Presence occurrence probabilities.

Acknowledgements

Firstly, I want to thank my major professor, *Dr. Mayrai Gindy*. She supported me with patience, encouragement and—most of all—deep knowledge of structural engineering and statistics.

Also, I want to thank the other members of my committee, *Dr. Liliana Gonzalez* and *Dr. George Tsiatas*.

Many thanks to my "editor", *Wendy Costa*, who spent so much of her precious time to assist me in phrasing and language issues.

Furthermore, I want to mention the International Engineering Program (IEP) of the University of Rhode Island and the Technische Universität Braunschweig. In this context, I explicitly want to thank *Dr. Manfred Krafczyk* of TU Braunschweig for allowing the scholarship from the Deutsche Akademische Austauschdienst (DAAD).

Finally, I want to thank my parents, my brother and all of my friends for their loving support and encouragement.

Thank You!

Contents

List of Tables

List of Figures

Abbreviations

AASHTO	American Association of State Highway & Transportation Officials
ADT	Average Daily Traffic
ADTT	Average Daily Truck Traffic
AXS	Axle Spacing
AXW	Axle Weight
CAL TRANS	California Department of Transportation
CDF	Cumulative Distribution Function
CI	Confidence Interval
DAF	Dynamic Amplification Factor
ECDF	Empirical Cumulative Distribution Function
EVD	Extreme Value Distribution
FHWA	Federal Highway Administration
FL	Following Loading Event
GEV	Generalized Extreme Value
GVW	Gross Vehicle Weight
LRFD	Load and Resistance Factor Design
Mom	Bending Moment
MP	Multiple Presence
NJ DOT	New Jersey Department of Transportation
NMom	Negative Bending Moment
SD	Side-by-Side Loading Event
SG	Staggered Loading Event
Shr	Shear Force
SN	Single Truck Loading Event
SSE	Sum of Squares Error
WIM	Weigh-in-Motion

Chapter 1

Introduction

In bridge design and evaluation, the characteristics of truck traffic is particularly important. Truck weights and axle configurations are directly used in calculations of maximum load effects including positive bending moments and shear forces in simply-supported bridges as well as negative bending moments of continuous spans. For bridge design, these effects are determined based on short-duration truck traffic datasets that are forecast to the 75-year economic design service life.

The loading event that is likely to govern a bridge design, however, is the simultaneous occurrence of two or more heavily loaded trucks—called *Multiple Truck Presence* (MP). Consequently, the statistics of different loading patterns as well as the correlation among coincident trucks are equally important to live load analysis.

Other studies of MP events have been based on either simulation of traffic or limited visual observations, but very little research has been undertaken to analyze Weigh-in-Motion data.

Weigh-in-Motion data is traffic data which is recorded by sensors that are directly installed on the roadway. The data is collected when the vehicles pass the devices without

requiring them to stop. The collected data contains various information about the vehicles and data is widely available.

The aim of the this study is to analyze Weigh-in-Motion data collected on highways to determine the occurrence of *Multiple Presence* events and their weight correlation. Based on the analysis, a prediction model will be developed to estimate the frequency of the *Multiple Presence* events using known site parameters.

1.1 Methodology

In the whole area of Civil Engineering and many other areas of expertise, models are based on probability methods with a certain level of conservativeness. Both sides, the Load side and the Resistance side of a model follow certain statistical distributions. The means of those distributions are mostly far apart, but the upper tail of the Load and the lower tail of the Resistance might overlap for extreme cases, as graphically shown in Figure 1.1 for normally distributed variables. In such an unusual case the Load is greater than the Resistance and that would inevitably lead into system failure.

For the resistance side, extensive material tests have been performed and the results are implicated into the building codes. For any material the given values in the codes are, in fact, a certain quantile that provides a balanced proportion between sufficient safety and economical factors.

For the load side, the accurate determination is far more complex. The variance of the loads is likely to be very large and cannot be found by simple tests. Current bridge load models are based on a range of assumptions that can be considered overly conservative.
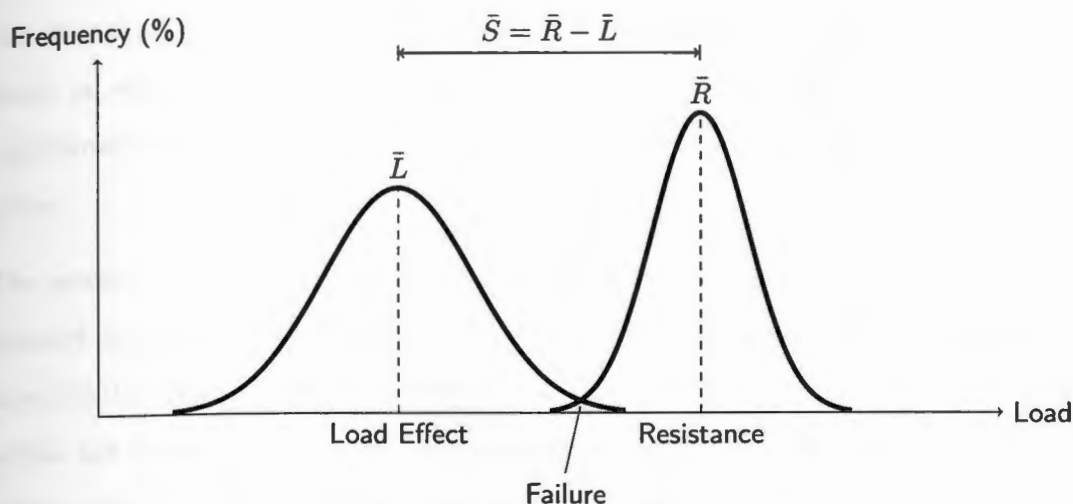
Figure 1.1: System Safety Modeling with Normally Distributed Variables

Nowak (Nowak and Hong, 1991, i.a.), for example, bases all his Multiple Presence Occurrence Probabilities and Full Weight Correlation Probabilities on assumptions after analyzing 10,000 heavy trucks from an Ontario Truck Survey (Agarwal and Wolkowicz, 1976).

The main objective of this study is to identify the probability of occurrence for Multiple Presence events on highway bridges and further the probability of trucks being fully correlated in weight, as this combination—Multiple Presence with fully correlated trucks—is most likely to induce the largest bridge responses.

This work is divided into two main parts. The first part is of rather theoretical nature, as an introduction is given of the statistical methods, that have been used in the literature and throughout the development of the model. Also, an extensive literature review is done on the various existing life load models for highway bridges. This review introduces the different approaches to determine the controlling load and reveals that many models

use Multiple Presence probabilities and weight correlation probabilities that are either based on simulation, engineering assumptions or visual evaluation of recorded traffic. Additionally, an introduction to Weigh-in-Motion (WIM) systems and data collection is given.

The second part deals with the analysis of Weigh-in-Motion data. This data contains detailed information about the vehicles that pass over the sensors, including a very accurate time-stamp and weight information. First, the data needs to be filtered as only trucks are relevant for inducing maximal bridge responses. Also, many errors in the entries have to be removed before analysis is performed.

In a next step, the weight distribution of the NJ database is evaluated and an algorithm is implemented to determine/simulate the occurrence probabilities of Multiple Presence events for several span lengths from the filtered WIM data using the timestamp of the trucks. Based on the outcomes, a prediction model for Multiple Presence occurrence probabilities is developed by utilizing the various site parameters available from the WIM data using regression analysis methods.

A special remark is given to the influence of the gap lengths for maximum bridge responses. Gap lengths denote the distance from the rear bumper of the first truck to the front bumper of a following truck.

Analysis is performed to identify the probabilities of a full weight correlation between the two trucks involved in a Multiple Presence event, as an event with two fully correlated trucks is likely to represent the most significant loading case.

The model is discussed in the conclusions, and recommendations for further studies are made. Appendix A gives an example of the practical application of the model developed for a usual 100ft highway bridge.

Chapter 2

Statistical Methods

The various live-load models that will be presented in Chapter 3 are all more or less based on statistical methods, and in order to analyze the Weigh-in-Motion data, many statistical methods have to be utilized.

This Chapter describes some of the statistical methods, that have been used in the literature and that have been applied to the data. The general procedure for regression analysis is explained including the description of variable types and generalization for more complex models. It is also explained how the parameters can be tested for significance and how the whole model is validated. A special remark is given to the Coefficient of Determination as an indicator for the model accuracy.

Furthermore, it is described how to use the models found for actual prediction and how to detect lacks of fit using Residual Analysis. The last part deals with methods of how to carry out actual regression analysis and parameter testing describing the two main methods that have been utilized in this thesis.

2.1 General Linear Regression Models

The idea of regression analysis is basically testing whether one variable is dependent on or can be expressed by using other variables. Hence, the variable that is to be predicted is called *dependent* or *response* variable, whereas the other variables are called *independent* or *predictor* variables.

Expressing the above in terms of a formula, we get

$$y = E(y) + \epsilon \tag{2.1}$$

where y is the dependent variable, $E(y)$ is the deterministic component of the model and ϵ stands for a random error that expresses random unexplained phenomena. It is assumed that the random error is normally distributed and independent for every observation. The deterministic component of the model is—for linear regression—the sum of the independent variables multiplied by a coefficient β_i.

Expressed in a mathematical formula, we get

$$y = \underbrace{\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k}_{\text{Deterministic Component}} + \underbrace{\epsilon}_{\text{Random Error}} \tag{2.2}$$

where β_0 denotes the y-intercept, when the function is plotted. For a First-Order (Straight-Line) Model, the coefficients have a geometrical meaning which is shown in Figure 2.1.
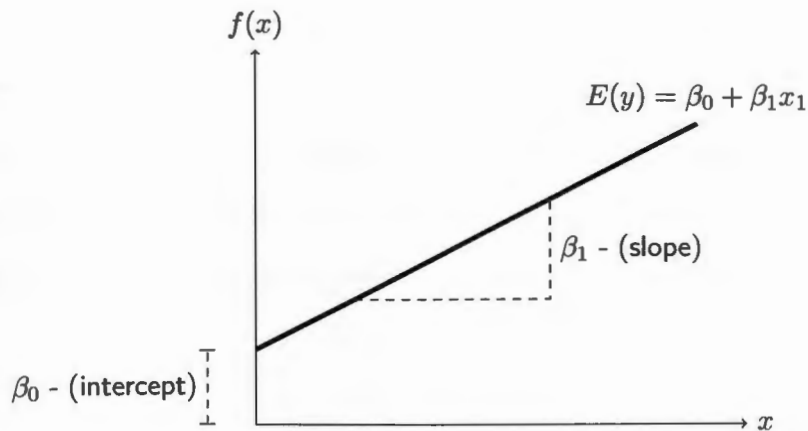
Figure 2.1: First-Order Model

In order to find the best solution for the deterministic portion, we want to minimize the error component to get the most accurate fit, so we basically want to find

$$\hat{y} = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \ldots + \hat{\beta}_k x_k \tag{2.3}$$

where the hat denotes, that the value is an estimation. For any given datapoint i, we can now calculate the difference between the prediction and the actual value. This value is called the *residual* of the ith given point:

$$(y_i - \hat{y}_i) = \left[y_i - (\hat{\beta}_0 + \hat{\beta}_1 x_1 + \ldots + \hat{\beta}_k x_k) \right] \tag{2.4}$$

The *sum of squares* of all the residuals can then be expressed

$$SSE = \sum_{i=1}^{n} \left[y_i - (\hat{\beta}_0 + \hat{\beta}_1 x_1 + \ldots + \hat{\beta}_k x_k) \right]^2 \tag{2.5}$$

and has to be minimized for the best fit. Hence, the method is called the *Method of Least Squares*.

To solve the problem, $(k + 1)$ equations[1] have to be solved, which is very complex. Therefore, regression analysis is often carried out using a computer. To numerically solve the equation, matrix algebra is applied, using the following matrices:

$$
\mathbf{Y} = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} \qquad
\mathbf{X} = \begin{bmatrix} 1 & x_{11} & x_{21} & \cdots & x_{k1} \\ 1 & x_{12} & x_{22} & \cdots & x_{k2} \\ \vdots & \vdots & \vdots & & \vdots \\ 1 & x_{1n} & x_{2n} & \cdots & x_{kn} \end{bmatrix} \qquad
\hat{\beta} = \begin{bmatrix} \hat{\beta}_0 \\ \hat{\beta}_1 \\ \vdots \\ \hat{\beta}_k \end{bmatrix}
$$

$\mathbf{Y}$ is the matrix of all the given data points we want to fit the regression model for, $\mathbf{X}$ gives the matrix of the independent variables. The 1s in the first column denote a variable x_0, which represents a variable for the β_0-coefficient (intercept).

Using the matrices, the equation for the least squares reads

$$
(\mathbf{X^T X})\hat{\beta} = \mathbf{X^T Y} \tag{2.6}
$$

where the transpose of the matrix $\mathbf{X}$ is denoted $\mathbf{X^T}$. Solving for $\hat{\beta}$ using the matrix algebra, we can calculate the estimated coefficients $\hat{\beta}_i$:

$$
\hat{\beta} = (\mathbf{X^T X})^{-1}\mathbf{X^T Y} \tag{2.7}
$$

---

[1]That is k independent variables and β_0.

To determine the Sum of Squares Error and the variance of the random error of the sample data, following equations can be used:

$$SSE = \mathbf{Y^T Y} - \hat{\beta}^\mathbf{T} \mathbf{X^T Y} \tag{2.8}$$

$$s^2 = \frac{SSE}{n - \text{Number of } \beta \text{ parameters in the model}} \tag{2.9}$$

2.1.1 Independent Variables

Independent variables for regression models can basically be divided into two categories, depending on the information they provide.

Quantitative Variables are variables that describe a numerical value, i.e. Truck Volume, Weight or other countable parameters or properties.

Qualitative Variables are variables that express a property that is not countable. These variables mainly have different *levels*, with no values in between. Some examples are Gender (male, female), Area Type, Road Type etc.

For numerical purposes, qualitative variables with two levels are recommended to be encoded as follows (for example Area Type):

$$x_i = \begin{cases} 1 & \text{if Urban Area} \\ 0 & \text{if } not \text{ Urban Area (Rural Area)} \end{cases} \tag{2.10}$$

The simple reason for this is, that only one β-coefficient has to be calculated for the variable. Using different encoding is possible but would lead to two coefficients – one for each level. If one level is set to zero, the coefficient for this level can be omitted. For

10

more than two levels, an incremental encoding is recommended, with one coefficient for every level.

2.2 Model Quality and Parameter Testing

After the general methodology of regression analysis has been shown in the previous sections, we now want to determine whether our solutions are accurate and how to test for the significance of single parameters as well as for the whole model.

2.2.1 Coefficient of Correlation

The term *correlation* expresses whether one variable is related or even linearly associated with another. The degree of of relation or association can be determined by calculating the *Coefficient of Correlation* which is often denoted r and is calculated

$$r = \frac{SS_{xy}}{\sqrt{SS_{xx}SS_{yy}}} \tag{2.11}$$

where $SS_{xx} = \sum (x_i - \bar{x})^2$, $SS_{yy} = \sum (y_i - \bar{y})^2$ and $SS_{xy} = \sum (x_i - \bar{x})(y_i - \bar{y})$.

The value of r always ranges from -1 to 1, independent of the units of the variables. Values close to -1 or 1 denote a very strong linear relationship between the two variables, as all data points fall on the least square line. Values around 0 imply very little to no relation. Negative values of the Coefficient of Correlation express a decreasing value of x with an increasing value of y. In the literature, this is often referred to as Negative Correlation. The Coefficient of Correlation can only be utilized for *linear* relationships between *two*

variables. For more complex regression models or multiple variables, the Coefficient of Determination (Section 2.2.2) is used instead.

2.2.2 Coefficient of Determination

To determine the overall accuracy of a regression model, the *(multiple) coefficient of determination*, R^2, gives a measure of the fit. Assuming that the parameters x_i are not significant for the prediction of y, a good prediction for y would be just the mean $\overline{y}$. Hence, the sum of squares of the deviations (SS_{yy}) for every y_i would be almost equal to the sum of squares error (SSE) (see Section 2.1).

$$SS_{yy} = \sum(y_i - \bar{y})^2 \qquad SSE = \sum(y_i - \hat{y}_i)^2 \qquad (2.12)$$

The multiple coefficient of determination is then defined

$$R^2 = 1 - \frac{SSE}{SS_{yy}} \quad \text{for} \quad 0 \leq R^2 \leq 1 \qquad (2.13)$$

The R^2 values expresses the accuracy of fit, whereas 1 denotes a perfect[2] fit and 0 implies a total lack of any fit. For simple linear regression models with only two variables, the Coefficient of Determination is equal to the square of the Coefficient of Correlation (Section 2.2.1) $R^2 = r^2$.

The disadvantage of this coefficient is that the data has to have significantly more data points than parameters, otherwise the R^2-values is forced to 1 (perfect fit), only if the number of data points equals the number of parameters.

---

[2]That would imply, that the regression line found would pass through every data point.

For this reason, another measure for the accuracy of fit of a regression model is introduced, which is based on the R^2 value: the adjusted R_a^2-value, which is defined

$$R_a^2 = 1 - \frac{n-1}{n-(k+1)}(1-R^2) \tag{2.14}$$

where n denotes the number of data points and k the number of parameters used in the model. It should be noted that, because of the first term, the R_a^2-value can not be forced to a perfect fit, as it is penalized by the number of variables that are used in the model. Therefore, it provides a better measure, especially for smaller datasets.

2.2.3 Parameter Test (t-Test)

To test if a parameter has a significant contribution on the regression model, a so called t-Test is utilized. With this test it is possible to test for the significance of the parameters.

To set up the test, it is hypothesized that a parameter x_i has no contribution of any significance to the regression model.

Therefore, the *Null Hypothesis*

$$H_0: \qquad \beta_i = 0 \qquad \text{(No significance of the parameter)}$$

is tested against the *Alternative Hypothesis*

$$H_a: \qquad \beta_i \neq 0 \qquad \text{(Significant influence on the model)}$$

by calculating the t-value for the parameter and testing it against a a confidence interval of the t-Distribution.

The t-value for the parameter can be calculated using the matrices introduced in Section 2.1, as information regarding the standard errors can be obtained from $\mathbf{G} = (\mathbf{X}^T\mathbf{X})^{-1}$.

Denoting the matrix values of $\mathbf{G}$ as a_{ij}, the standard errors of the β-coefficients calculate to $s_{\hat{\beta}_i} = s\sqrt{a_{ij}}$.

The t-value of the parameter can then be obtained calculating

$$t = \frac{\hat{\beta}_i}{s_{\hat{\beta}_i}} \tag{2.15}$$

So, if $|t| > t_\alpha$, the Null Hypothesis (not significant) has to be rejected and the parameter is assumed significant to the degree of the confidence level.
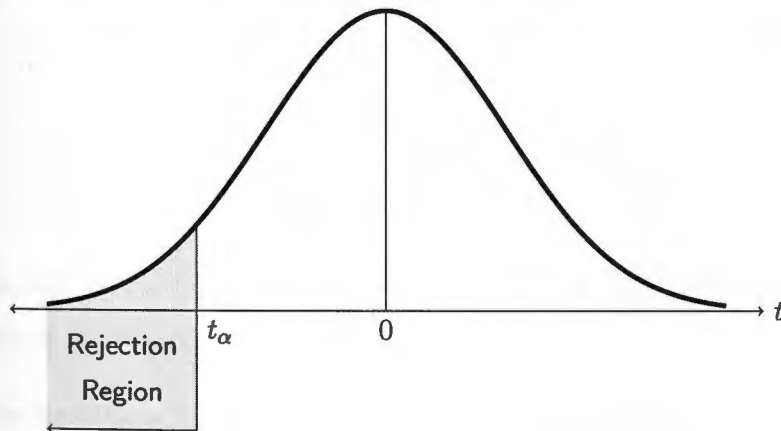
Figure 2.2: One-tailed Rejection Region for H_0

2.2.4 Analysis of Variance (F-Test)

To test for the general acceptance of a model, one could assume that carrying out t-test for each parameters might be sufficient. Even if all parameters do not contribute to the model, one might still reject the Null Hypothesis ($\beta_i = 0$) incorrectly for a parameter. To avoid this phenomenon, a global test is found for the whole model, called the F-test.

The Null Hypothesis

$$H_0 : \qquad \beta_1 = \beta_2 = \ldots = \beta_k = 0$$

is tested against the Alternative Hypothesis

$$H_a : \qquad \textit{At least one} \text{ of the } \beta_i \text{ is unequal to zero}$$

with the F-value which is calculated using

$$
\begin{aligned}
F &= \frac{\text{Mean Square for model}}{\text{Mean Square for error}} \\
&= \frac{SS(\text{Model})/k}{SSE/[n-(k+1)]} \\
&= \frac{R^2/k}{(1-R^2)/[n-(k+1)]}
\end{aligned}
$$

(2.16)

(2.17)

and tested against an F_α-value with $\nu_1 = k$ and $\nu_2 = n - (k+1)$ degrees of freedom that is obtained from the F-table or from statistical software.

If $F > F_\alpha$, the Null Hypothesis is rejected. This means that *at least one* of the parameters accounts for the model, making it legitimate. It should be noted that this outcome does not prove that the model is of any good accuracy—but only that it explains a significant

correlation. The parameters can be tested for in detail with the t-test according to Section 2.2.3.
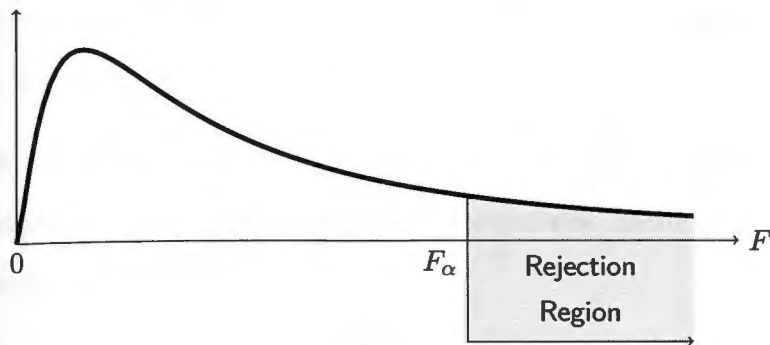
Figure 2.3: Rejection Region for the F-test

2.3 Prediction using Regression Models

When having found an appropriate (legitimate) and sufficient regression model for the data, we might want to use the model to estimate or predict dependent variables we only have the independent variables for. Generally, we have two different kinds of predictions we want to make:

Estimating the Mean means that we want to predict the *Mean* $(E(y))$ within a certain confidence level. For example, if we want to predict the occurrence of a Multiple Truck Presence (MP) event and we have a model that uses the Average Daily Truck Traffic (ADTT) as independent variable, we want to estimate the average number of occurrences of MP events for a certain volume with a specified confidence level. This would be used when we want to predict the mean MP occurrence frequencies for *multiple* bridges that have the same parameters.

Estimating a particular value means, that we want to predict the occurrences of MP events only for *one particular* bridge (that we want to estimate the loads for) within a confidence interval. It is obvious that for this prediction the confidence interval will be wider than for the mean.

For the prediction model introduced in Section 5.4, the latter case will be used, as the model targets to evaluate site-specific MP occurrences. Both prediction cases are graphically shown in Figure 2.4.
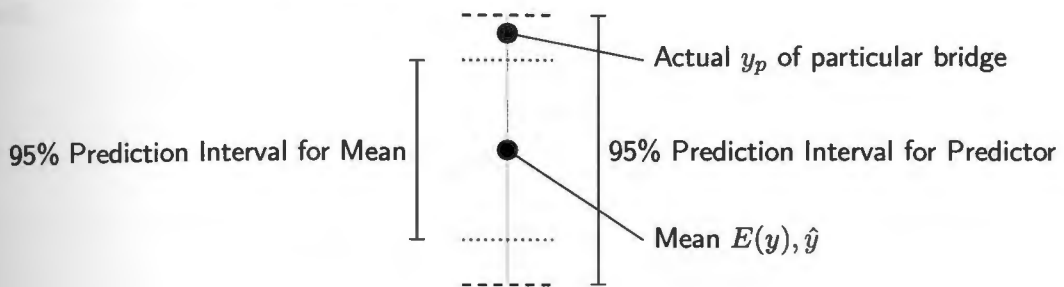
Figure 2.4: Mean and Prediction Intervals

For both kinds of estimation, we can find the prediction mean $E(y)$ and the prediction value $\hat{y}$, by utilizing our least squares model. Both of the points will be on the regression line, hence we can use the values for which we want to predict for $x_i = x_{p_i}$ in the formula of the regression model:

$$E(y) = \hat{y} = \hat{\beta}_0 + \hat{\beta}_1 x_{p_1} + \ldots + \hat{\beta}_k x_{p_{k_i}} \tag{2.18}$$

For the confidence interval, we need the standard deviation of both values. As it is nearly impossible to find the actual standard deviation, we assume, that $\sigma = s$ (see Section 2.1) is sufficient.

Using the matrix notation introduced in Section 2.1 ,the $(1 - \alpha)$ prediction interval for the mean $E(y)$ is

$$\hat{y} \pm t_{\alpha/2}\sqrt{s^2\mathbf{a}^\mathbf{T}(\mathbf{X}^\mathbf{T}\mathbf{X})^{-1}\mathbf{a}} \tag{2.19}$$

and for a particular value $\hat{y}$

$$\hat{y} \pm t_{\alpha/2}\sqrt{s^2[1 + \mathbf{a}^\mathbf{T}(\mathbf{X}^\mathbf{T}\mathbf{X})^{-1}\mathbf{a}]} \tag{2.20}$$

with

$$\mathbf{a} = \begin{bmatrix} 1 \\ x_1 \\ x_2 \\ \vdots \\ x_k \end{bmatrix}$$

It should be noted that a prediction that is outside the range of the regression model is dangerous, as the outcomes might be erroneous and do not represent the actual data. For example, a term x^2 might give an accurate curvature for the range of the data. However—for a greater range, this term represents a parabola as shown in Figure 2.5.

2.4 Multiple Regression Methods

2.4.1 Stepwise Regression

To find an appropriate model for the regression analysis, the t-Test (see Section 2.2.3) is applied to each of the parameters to test for a significant association. When performing the t-Tests, a structured process is recommended.
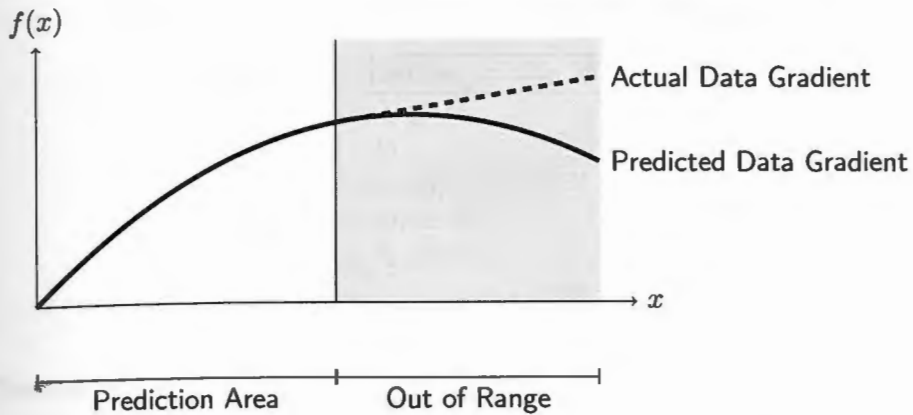
Figure 2.5: Limited Accuracy of Predictions outside the range

One approach for a structured process is a *stepwise regression*, where multiple regression models are calculated with one parameter added each run. After each run, all the parameters are checked for significance utilizing the t-Test. Non-significant[3] parameters are removed from the model. In a next step, a further parameter is added and the model is re-run and the parameters are checked for significance again.

A good method of visualizing the steps is a table, that contains the parameters with which the models have been run and the coefficient of determination (R^2-value, see Section 2.2.2) or other quality measures to track the convergence of the the accuracy of fit. An exemplary table is shown in Table 2.1.

Additional to the table, convergence plots can be provided, plotting the measure of fit (R^2) or the mean square of the errors (MSE) against the iterations.

---

[3]"Non-significant" in this context means, that the parameter is not significant to a certain level of significance that we chose prior to the calculations. This level might be 90%, 95% etc.

Table 2.1: Exemplary Table for Stepwise Regression

Iteration	Variables in the Model	R^2
1	x_1	.15
2	x_1, x_2	.24
3	x_1, x_2, x_3	.32
4	x_1, x_2, x_3, x_4	.32
5	x_1, x_2, x_3, x_5	.47
6	$\dots$	

2.4.2 Nested Models

When a good model with significant parameters is found, the question might arise whether *second-order* interaction terms play an important part in a regression model. These additional terms might, for example, describe a certain curvature in the data and might be an exponent $(\beta_j x_i^n)$, a root $(\beta_j x_i^{\frac{1}{n}})$ or the logarithm $(\beta_j \log_n x_i)$ of the data.

Their significance can be tested for with the t-Test, but that would only be appropriate for the various parameters, but not for the whole model (see Section 2.2.4) – hence, the F-Test is utilized.

The model with added terms is called the *complete* or *full* model, whereas the model without the terms is call the *reduced* or *nested* model, as it is nested within the complete model. Hypothesizing that the complete model does not have a better or more accurate fit than the nested model, the Null Hypothesis

$$H_0: \qquad \beta_{g+1} = \beta_{g+2} = \cdots = \beta_k = 0 \qquad \text{(No contribution of added terms)}$$

is tested against the Alternative Hypothesis, that the complete model provides better accuracy

$$H_0: \quad \textit{At least} \text{ one of the added terms has significant impact.}$$

The F-value is calculated

$$
\begin{aligned}
F \;&=\; \frac{(SSE_R - SSE_C)/\text{Number of added } \beta\text{'s}}{MSE_C} \\
&=\; \frac{(SSE_R - SSE_C)/(k - g)}{SSE_C/[n - (k + 1)]}
\end{aligned}
\tag{2.21}
$$

where SSE_R is the sum of squares error of the reduced and SSE_C is the sum of squares error of the complete model and MSE_C is the mean squares error of the complete model. $(k-g)$ denotes the number of added β in the complete model, $(k+1)$ is the total number of β's in the complete model and n denotes the total sample size.

The F-value calculated is tested against an F_α-value, which is retrieved from the F-table or software with $\nu_1 = k - g$ degrees of freedom for the numerator and $\nu_2 = n - (k + 1)$ degrees of freedom for the denominator.

This F_α-value represents the significance level that we want to test for. If $F > F_\alpha$, the Null Hypothesis is rejected and at least one of the added parameters in the full model has significant impact and therefore makes the model valid.

Chapter 3

Review of the Literature

As bridges are costly structures with high maintenance costs, but also high significance for public life, designers try to optimize bridges in terms of *cost-effectiveness* and *safety*. For that reason, the assumptions of the live load are crucial to be most accurate, but still provide a high level of safety. The problem about bridge loading is that *precise traffic modeling* is a very complex task. The significant increase of traffic during the last decades and changes in the traffic pattern and composition make this task even more difficult.

Hence, a lot of research has been done on the determination of bridge loading. Nevertheless, studies only dilatory deal with the most relevant loading case explicitly, the *Multiple Truck Presence* (MP).

Multiple Presence means the simultaneous presence of more than one truck on a bridge at the same time. For single lane bridges, the only MP loading case occurs, when one truck is followed by one or more other trucks with a gap distance smaller than the span length—so that all the trucks participate in the induction of structural response. For more than one lane, additional loading cases exist for multiple trucks being in adjacent lanes. One of the most influential loading cases is the Side-by-Side event, where two

trucks are located next to each other on a bridge. If the trucks are no exactly next to each other, the trucks can be considered Staggered (Gindy and Nassif, 2007). Figure 3.1 gives an overview over MP events with two trucks.
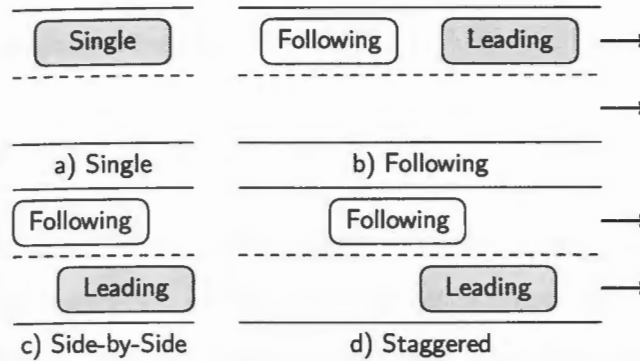
Figure 3.1: Possible Loading Patterns involving two trucks (symetrical loading patterns are also possible), a) Single, b) Following, c) Side-by-Side, d) Staggered. Adapted from Gindy and Nassif (2007)

To determine the Maximum Load, it is essential to look at the traffic that passes over a bridge. In general, the modeling of Traffic Flow can be divided into three main categories

- Traffic Flow Simulation (i.a. Monte Carlo Simulation)

- Traffic Flow based on a measured dataset

- Traffic Flow represented by statistical methods (Convolution Models)

This Chapter presents an overview of various existing Live-Load Models that consider Multiple Presence either explicitly or implicitly.

Another crucial point is the extrapolation of the maximum response per unit time analyzed to the life-span maximum response of the bridge. Several different methods will be introduced as they are an essential part of the models.

3.1 Multiple Presence Live-Load Models

3.1.1 Ghosn and Moses

In their study (Ghosn and Moses, 1986), a load model for short to medium span bridges is proposed. For this purpose, a convolution model is found that randomly generates traffic data based on traffic data sets to predict the number of loading cases utilizing a truck slot model. Each lane of a short to medium span bridge is separated into two 38ft slots, where a truck can be placed and a gap of 30ft which is observed to be the minimum gap between the trucks (Moses and Garson, 1973).

A loading event occurs, when at least one of the four slots is occupied by a truck. The different slot loading patterns are shown in Figure 3.2. Utilizing data from Ohio (O DOT) from the studies from Moses and Ghosn in 1983 and 1985, a headway model was found, based on the findings shown in Figure 3.3. The probabilities whether or not a MP event occurs are determined from the headway model. The Figure (3.3) shows a histogram of the gap times between the trucks for each loading case.

The trucks participating in a loading event are also based on probability methods concerning the gross vehicle weight, assuming that 20% of all trucks are single unit trucks and 80% are semi trailer trucks. With this assumptions, the probability of maximum loading events and the correlated maximum moments (due to superposition of the influence lines for every truck) per day can be determined for average truck volume of 2000

Lane symmetric placement is also considered
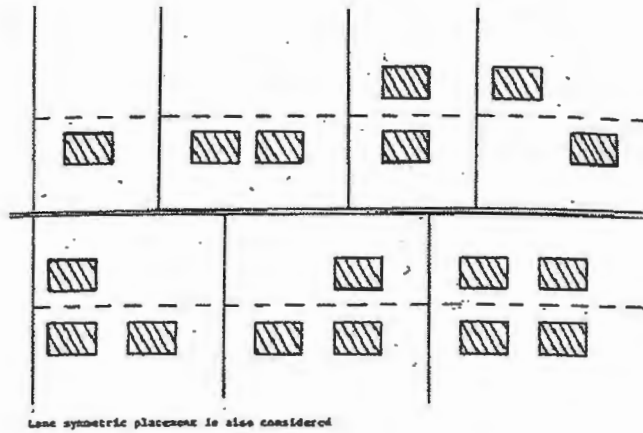
Figure 3.2: Possible Slot Loading Patterns (after Ghosn and Moses, 1986). Loading patterns which are symmetrical according to the lane are also possible.
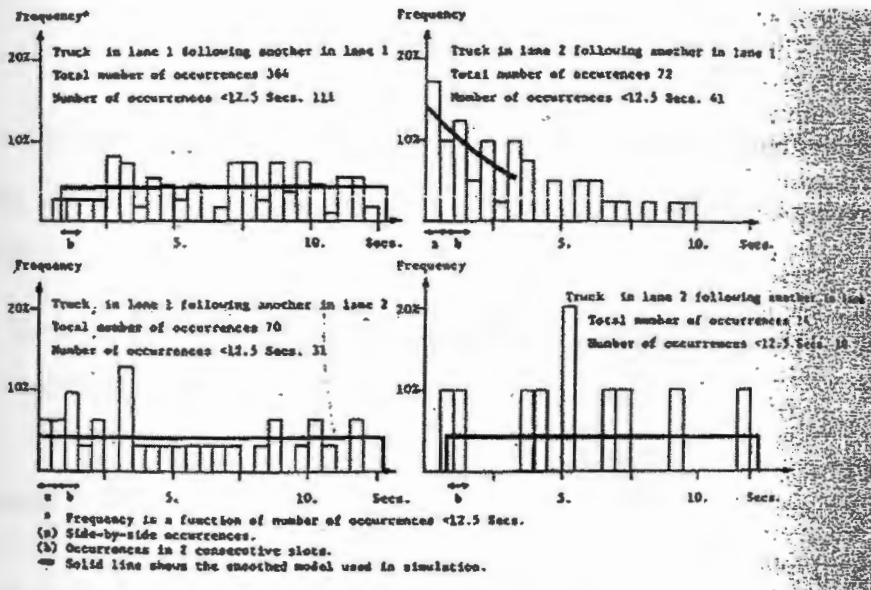
Figure 3.3: Headway Distributions for the MP events (after Ghosn and Moses, 1986)

25

trucks per day (Moses and Ghosn, 1983). For higher volumes, the model is extrapolated. For low volume sites, the number of maximum loading events reduces.

With an average of 2000 trucks per day, the maximum loading case for the life-span (in this case 50 years) of the bridge can be found by extrapolating the number of loading events to approximately $N = 35 \times 10^6$. Applying this value to the distribution of the maximum loading moment, they get

$$G_{max}(50 \text{years}) = [F_x(x)]^N \tag{3.1}$$

where $F_x(x)$ denotes the cumulative distribution function for one event. With the assumptions and the preliminary work described above, a formula is developed to calculate the median value of the maximum bending moment in 50 years. The formula reads

$$M_{median} = amW^*H \tag{3.2}$$

where H is the variable of interest for MP events. It is a random variable that describes overloading and incorporates MP loading of vehicles. H depends on truck volume and span length.

Based on these results, Ghosn and Moses develop a method to adjust the AASHTO Bridge Design Code with new safety factors and design loads.

3.1.2 Nowak

A statistical method for the assumption of Bridge Live-Load was developed by Andrzej S. Nowak, who widely published on the topic of load modeling. Many publications by

For multiple presence loading, Nowak and Hong consider Following and Side-by-Side multiple truck occurrences. For both cases, assumptions (based on observations) of the frequency of occurrence and the weight correlation are made for the trucks involved. It is stated that every 10th truck is followed by another truck with a headway distance of 50ft or less. These trucks are uncorrelated with regard to weight and are assumed to be the 7.5 year maximum truck and an average truck. Every 50th truck is involved in a following event and partially correlated to the other, where one is the maximum 1.5 year truck and the other on the maximum daily truck. Every 100th truck is followed by another one with a full wight correlation, where both are the maximum nine-month trucks. Table 3.1 gives a brief summary of the MP occurrence frequencies used by Nowak.

Plotting the normalized moment against the span for a single truck and the correlation assumptions made for 15ft and 30ft headway distance, it is found that for shorter spans to about 120ft, a single truck triggers the largest reaction of the bridge, whereas – depending on the headway – for longer spans, two fully correlated trucks controlled (Nowak and Hong, 1991), as shown in Figure 3.5.

For Side-by-Side occurrences of trucks, two trucks travel in adjacent lanes with a reduced weight compared to one single truck. From observations it is concluded, that every 50th to 100th truck is involved in a Side-by-Side event (Nowak and Hong, 1991). Is is also noted that every 50th truck has no correlation (with regard to weight) to the truck in the adjacent lane, therefore one truck is assumed to have the maximum 1.5-year lane load and the other one the average load. Every 250th truck is partially correlated and the weights used for calculation are the maximum three month and the maximum daily truck. A full correlation occurs every 500th truck and the utilized truck weights are the
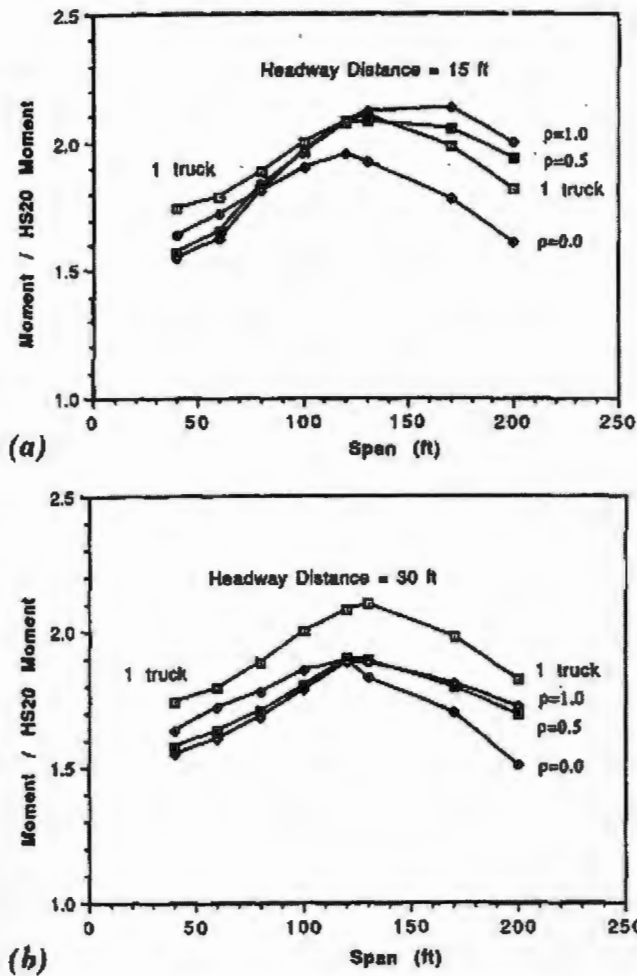
Figure 3.5: Normalized Moments vs. Span Lengths for various degrees of correlation (after Nowak and Hong, 1991)

1.5-month maxima for both trucks. An overview over the MP frequencies and full weight correlation probabilities can be found in Table 3.1.

Table 3.1: MP and Weight Correlation Probabilities after Nowak

	MP Freq.	Weight Corr.	Total
Following	10%	10%	1%
Side-by-Side	1–2%	20%	0.2–0.4%

Calculating the corresponding moments for the load pattern, it is found out that the loading case of two fully correlated trucks controls. Nowak and Hong state that the maximal 1.5-month truck used for a fully correlated Side-by-Side occurrence induces a moment of about 85% compared to the maximal 75-year truck, which is used for the Single Truck load modeling.

3.1.3 Moses

In the NHCRP Report 454 (Moses, 2001), Moses reviews the Live-Load Model developed by Nowak in a former NHCRP Report (Nowak, 1999) and calibrates the live load factors for Highway Bridges based on the truck database by Nowak (Section 3.1.2). Also a model for the occurrence of Side-by-Side Multiple Truck Presence is developed.

First, Moses introduces the proposed 3S2-design truck (AASHTO, 1994) and compares it to the Ontario Truck Database (Agarwal and Wolkowicz, 1976), that Nowak utilized for his work (Section 3.1.2). Even though the truck data is not fully normally distributed and the trucks are not 3S2 vehicles, these assumptions can be made and Moses calculates the AASHTO 3S2 design truck weights for multiple span lengths and find a good fit with the average weight $\overline{W} = 68$ kips and a standard deviation of $\sigma_W = 18$ kips, which is

quite similar to Nowak's outcomes using the HS20 design truck times the average moment response.

For Multiple Truck Presence events, namely the Side-by-side events, he recapitulates the assumptions as introduced in Nowak and Hong (1991) (see Section 3.1.2), stating that no references were given in the paper, no studies have been made on truck weight correlation and that the Ontario data represents a very high average daily truck traffic (ADTT), that makes Multiple Presence events more likely.

Despite these objections, he incorporates the assumptions and finds the governing loading case to be Side-by-Side event with two fully correlated trucks. After Nowak and Hong (1991), every 15th truck is involved in a Side-by-Side events and every 30th Side-by-Side events incorporates two fully correlated truck, implying the probability of $P = 1/450$. Hence, the maximum weight in this case is represented by the weight of the maximum 2-month weight for both trucks.

The number of MP events can be calculated

$$N_{MP} = (ADDT/5) \times 365\text{days} \times \text{years} \times P_{s/s} \tag{3.3}$$

where $ADDT/5$ represents the upper 20% of the trucks and $P_{s/s}$ the probability of MP events (1/15 after Nowak and Hong (1991)). The variate t of the probability $(1/N_{MP})$ is found to be 4.09 in a normal distribution.

With those values, the maximum weight for a 75-year Side-by-Side event for a 3S2 truck is calculated

$$\overline{W}_{T_{max}} = \overline{W}_T + t \times \sigma_{W_T} = 260\text{kips} \tag{3.4}$$

This is in a reasonable range, as the total load after Nowak (Nowak, 1999) is 286 kips. Compared the AASHTO Bridge Design (AASHTO, 1998) – where no reduction factor is applied for multiple presence loading – the total load is 384 kips.

As stated above, Nowak's assumption for the frequency of multiple truck presence events are based on engineering assumptions. Stating that every 15th heavy truck (upper 20% of truck population) is involved in a Side-by-Side event would imply, that every third truck of the whole population is involved. This seems by far too high, as Moses (Moses and Ghosn, 1983) finds that only 1% to 2% of the trucks occur at the same time. For this reason, he introduces a simple occurrence model which is dependent on the average daily truck traffic (ADTT). This model omits factors like traffic speed, road grade, platooning etc., but gives a numerical approach of calculating the number of multiple occurrences.

Assuming that trucks can move freely in the right two lanes of the traffic stream, that the average speed is 60 mph and that the length of an average truck is 60ft, the average spacing is

$$\text{Avg. Spacing (ft)} = 88\text{ft/sec} \times 108,000/\text{ADTT} \tag{3.5}$$

and the average number of slots between two trucks is

$$\text{Number of Slots} = [88\text{ft/sec} \times 108,000/\text{ADTT}]/60\text{ft} = 158,500/\text{ADTT} \tag{3.6}$$

A further assumption is made, implying that for every truck in the right lane, 0.25 trucks use the passing lane. Incorporating all the above mentioned assumptions, the probability of Side-by-Side events can be calculated as

$$P_{s/s} = \frac{0.25 \times \text{ADTT}}{158,400} = 1.578 \times 10^{-6} \times \text{ADTT} \tag{3.7}$$

32

Table 3.2 shows the probabilities for Side-by-Side events for various ADTT-values. These values are very low compared to the 0.33 assumed by Nowak (Nowak and Hong, 1991). Moses states that platooning of truck (average 5 trucks per platoon) could increase the values by a factor of five. Moses conservatively proposes the probabilities as shown in the third column of Table 3.2. It should be noticed that by doing so, he basically adapts the values from Nowak (Section 3.1.2)

Table 3.2: $P_{s/s}$-values for various ADTTs

ADTT	Equation 3.7	Proposed
20000	0.0316	N/A
5000	0.008	0.33
2500	0.004	N/A
1000	0.0016	0.01
100	0.0001578	0.001

3.1.4 Crespo-Minguillón and Casas

Crespo-Minguillón and Cases present a model which is completely based on a simulation method of traffic they developed (Crespo-Minguillon and Casas, 1997). Their work can be subdivided into the actual simulation of the traffic and the extrapolation of the extreme values to determine the maximum bridge responses.

The authors give an overview over the current traffic simulation methods and generally classify into three categories:

- Theoretical Models

- Simulation of static traffic (mostly based on observed data)

- Simulation of real traffic flow,

where the latter are assumed to be the most complete models—even though many models are not general models but are developed for a certain purpose such as the prediction of maximum load effects or the dynamic analysis of bridge structures.

The authors develop a simulation model of real traffic which is suitable for a broad variety of applications, which is globally valid and adaptable to site-specific circumstances, but simple enough not to over-capacitate modern computers. For that purpose, they find the correlations for the most important parameters, like vehicles in one lane, vehicles' type, etc. For the site-specific adaption, the average daily traffic (ADT) and the percentage of trucks are utilized, as they can be easily found in WIM datasets. As the overlapping of vehicles in a model is a commonly known source of error in traffic simulation, the algorithm developed avoids those situations. The authors summarize all the requirements stated above into two basic tasks:

- Estimation of the load effects due to real traffic simulation and

- Extrapolation of the maximum values found per reference time unit (one week) to the life-span of the structure (100 years).

The model developed for the simulation of traffic accounts the mean daily traffic flow (ADT) and calibrates it for daily and furthermore for hourly variation. For the now hourly traffic, a binomial decision is made whether the highway is congested or not. This decision is influenced by the previous (weekday and hour) and the intensity of traffic for each is derived from theoretical density curves. Further the types of vehicles are chosen randomly by a Markov-chain process which is merely influenced by the site parameter given (percentage of trucks, determined from WIM data). For the last step, headways, velocities, geometries and weights are assigned. Additionally the authors implemented

an algorithm that allows overtaking and passing of vehicles, making the model even more realistic.

3.1.5 Caprani, O'Brien and McLachlan

Caprani, O'Brien and McLachlan (Caprani et al., 2007) develop a statistical method to calculate accurate load extrapolations and to determine governing loading cases.

Evaluating the conventional method of linearly extrapolating the cumulative distribution functions (CDF) of all bridge responses (as, for example, utilized by Nowak and Hong (1991)), the authors identify that the assumption of independent and identically distributed (iid) loading events is violated, as, for example, loading events with multiple trucks (Multiple Presence events) are more complex than loading events with only one truck. The MP events incorporate distributions for the number of trucks, the geometric properties and the location of the trucks on the bridge. Therefore, the conventional methods might be inaccurate for extreme value extrapolations.

Conventionally (as also described in Ghosn and Moses (1986)), the bridge span is partioned into j slots on the bridge, with a maximum number of trucks n_t. The probability of load event i being the maximum loading event for a time period, $\hat{S}$ is less than some value s. For n_d loading events per day, the probability equates to

$$P\left[\hat{S} \leq s\right] = \left(\sum_{j=1}^{n_t} F_j(s) f_j\right)^{n_d} \tag{3.8}$$

where $F_j(s)$ denotes the cumulative distribution function of s and f_j is the probability of occurrence for event involving j trucks. Even though the number of loading events per day varies, the utilization of the average gives a sufficient accuracy.

Applying their method for the evaluation of WIM data, they find that MP events involving 4 trucks are not governing for maxima of shorter periods of time, but become more significant over the period of time, as shown in Figure 3.6—this is a very important finding that should be considered in the future calibration of Bridge Design Codes.
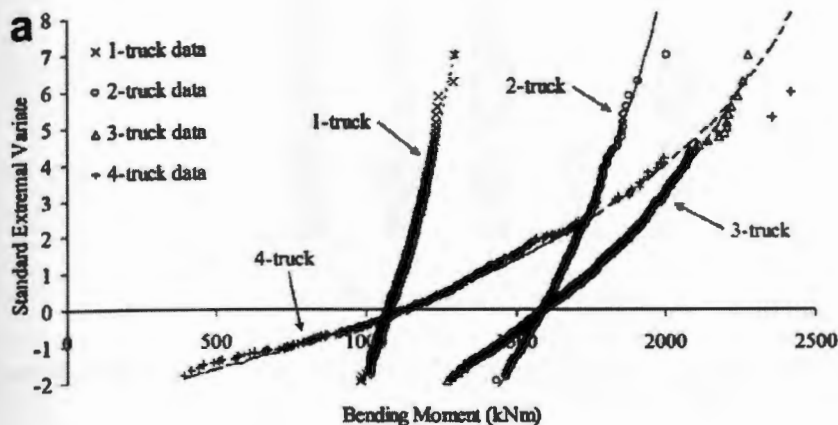
Figure 3.6: Daily Maxima by Event Type (after Caprani et al., 2007)

3.1.6 Guzda, Bhattacharya and Mertz

Guzda, Bhattacharya and Mertz (Guzda et al., 2007) propose a model to estimate the live load of bridges by visually counting trucks and estimating Multiple Presence occurrences. Their study is based on a total of 2.5 hours of videotaped traffic on a highway near a bridge in Delaware. All gap distances are not exactly measured but estimated during the analysis of the videotapes. This might be source of inaccuracies.

Stating that MP events with gap (rear bumper to front bumper) distances of more than two truck lengths do not have an impact on the maximum load, they found that 6.4% of

the counted trucks are involved in a following event. Figure 3.7 shows the gap distances of the Following events from their study.
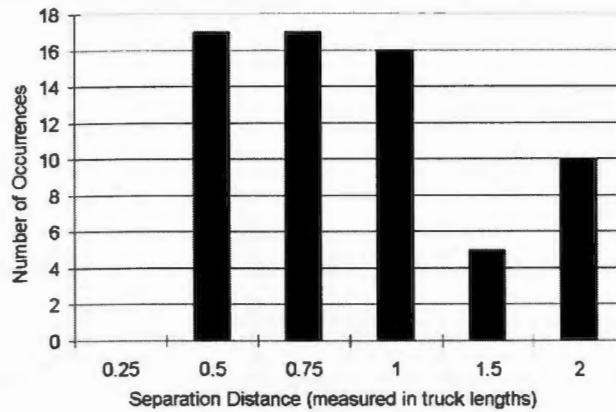
Figure 3.7: Gap Distances for Following events (after Guzda et al., 2007)

Defining Side-by-Side as two trucks in adjacent lanes with a headway (front bumper to front bumper) separation of maximal two truck length, it was found that 7.6% of all trucks were involved in a Side-by-Side event. For smaller headways they found the Side-by-Side events to involve 6.0% of all trucks when the maximum headway was 1.5 truck lengths and 4.4% with a headway of one truck length, respectively. All the MP occurrence probabilities are summarized in Table 3.3.

Table 3.3: MP Occurrence Probabilities after Guzda et al. (2007)

	Headway		
	$\leq$ 2.0 Trucks	$\leq$ 1.5 Trucks	$\leq$ 1.0 Trucks
Following	6.4%	N/A	N/A
Side-by-Side	7.6%	6.0%	4%

For a validation, their model is benchmarked against a simple Poisson based headway model. This model is a Poisson Pulse Model that generates truck traffic in each lane

based on a Poisson Distribution with a constant rate λ_i and a random magnitude X_i. Even though it is stated that this Poisson model might not be accurate on multi-lane highway traffic, they find their outcomes to be in the same range as the analytical solution.

3.1.7 Gindy and Nassif

In their paper, Gindy and Nassif (Gindy and Nassif, 2007) develop a method to determine Multiple Truck Presence statistics from Weigh-in-Motion data. Their database contains of 48 directional WIM sites, geographically dispersed all over New Jersey. This is a previous version of the database used in this study and described in greater detail in Section 4.3. The average daily truck traffic (ADTT) is derived from the WIM data and the sites are categorized into Light (ADTT<1,000 truck per day), Average (1,000< ADDT<2,500) and Heavy (ADTT>2,500).

For the multiple truck presence, Gindy and Nassif consider the four most common loading cases for bridges: Single, Following, Side-by-Side and Staggered shown in Figure 3.8 and also address, that parameters like truck volume, span length, area- and road type etc. have influence on the occurrence of multiple truck presence events. From their data analysis, a mean weight $W_\mu = 45$ kips and a 95th percentile weight $W_{95} = 79$ kips are determined, which is about the same range as other studies (i.e. Nowak and Hong, 1991; Moses, 2001).

To determine the probability for the Multiple Presence events, the truck traffic is simulated for multiple span lengths of 20-200ft by using the timestamp, the length and the lane of travel of each truck. The timestamp is accurate to 1/100th of second for each
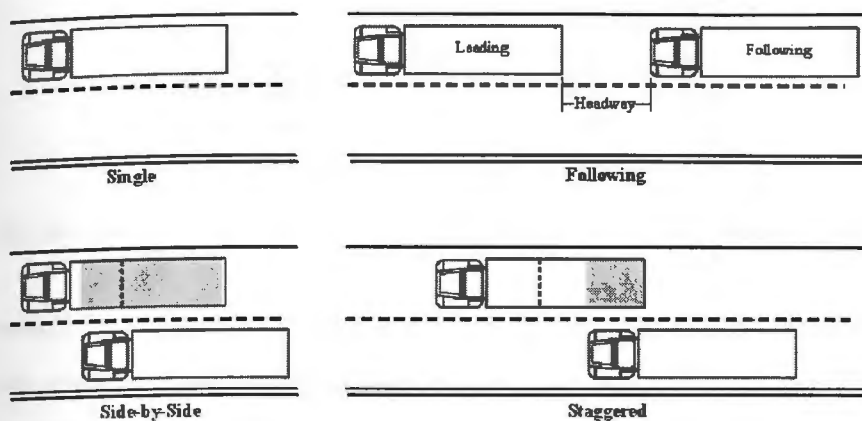
Figure 3.8: MP Loading Cases (after Gindy and Nassif, 2007)

truck and therefore provides a high accuracy for the determination of entrance and exit times when simulating the traffic over a bridge. This accuracy is about 11.4 in for a truck with a speed of 65 mph. Rounded to the next full second, the accuracy would decrease to 95ft at the same speed and would not be suitable for the analysis.

Events with more than two simultaneous trucks on the bridge are discarded as they are not part of the study. Figure 3.9 exemplary shows in influence of the Volume (ADTT) for a 120ft span. For higher volumes the probability of single trucks on the bridge decreases and consequently the probability of a Multiple Truck Presence increases at different slopes per loading case. Similar analysis is done to determine the influence of some of the parameters (in particular: area and road type and span length) stated above. It was found that the major parameters for the occurrence of MP events are the truck volume (ADTT) and the span-length, while area and road type only had a slight effect. The results of the MP analysis are summarized in Table 3.4.

	Truck Volume		
	Light	Average	Heavy
Following	3%	6%	8%
Staggered	2%	4%	6%
Side-by-Side	1%	1%	1%

Table 3.4: MP Occurrence Probabilties after Gindy and Nassif (2007)

For the weight correlation between two trucks involved in a Multiple Presence loading case, it was found out that average volume sites have a higher tendency of scattering than sites with lower or higher volumes.

3.2 Summary and Discussion

Many different methods have been introduced which present effective ways of calculating bridge live-loads. The methods represent a good cross-section of the different types of models available. All of the methods explicitly or implicitly show that the multiple presence of two or more trucks will trigger the maximum structural responses of bridges.

Even though a variety of different models exist, many of them incorporate assumptions, which have not been validated but considered to represent the reality with a good accuracy. Nowak, for example, makes assumptions about the percentage of Multiple Presence events. He also assumes weight correlations between those trucks based on "Engineering Judgement". Moses identifies those assumptions as too conservative and introduces a simple model for the determination of multiple truck presence (MP) events—by applying similar assumptions (e.g. Number of Trucks traveling in the passing lane). When proposing MP occurrence probabilities for sites with a higher ADTT, he conservatively adapts Nowak's assumptions.
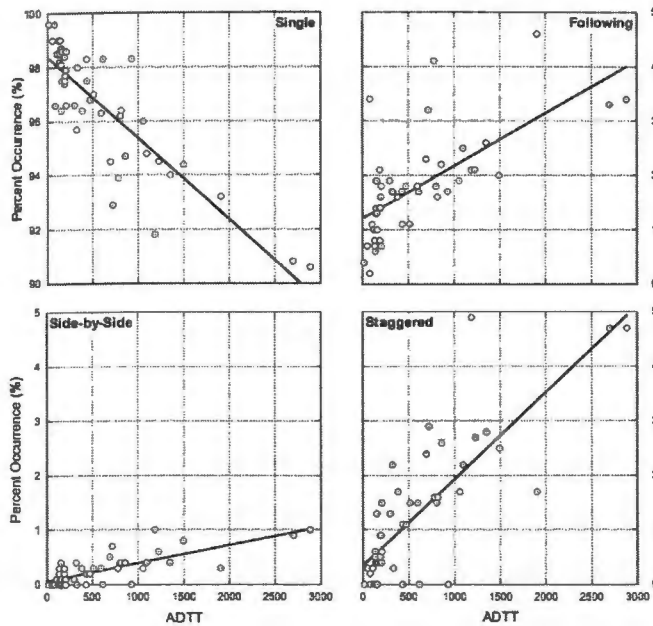
Figure 3.9: The Probability of Occurrence plotted against the Truck Volume for a 120ft Span (after Gindy and Nassif, 2007)

Methods which simulate the traffic or the truck traffic respectively, are mostly based on Monte Carlo Simulations. The parameters simulated are fitted distributions of measured or observed data. In many cases, WIM data is utilized for that purpose. The model have the advantage that they accurately reflect the traffic and therefore can be used not only for the load estimation but also, for example, for the design of signals or other traffic-related issues. Simulation models show increased accuracy for higher complexities. In that context, Crespo-Minguillón and Casas present a very complex method, that considers many parameters like e.g. daily and hourly traffic or congestion and free-flow cases when simulating traffic flow.

A big disadvantage of this is, that due to the need for high complexity for accurate results, the simulation requires many parameters which are not necessarily available. Also,

simulation algorithms generate a very high processing load even on high-end computers, so that large-scale simulations can take weeks or longer and therefore can become costly. MP events are implicitly accounted for when the bridge responses are simulated.

Hence, an approach to directly determine the probabilities of MP events, without the inaccuracy of major assumptions, that bypasses the utilization of complex traffic flow modeling would provide a fast, accurate and cost-efficient way of predicting site-specific expected live-loads.

Guzda, Bhattacharya and Mertz present a method that is based on visual counting of MP events from a videotape of a traffic camera. This method is limited to only 2.5 hours of traffic in one site, as the data analysis is very complex task with many possible sources of errors and additionally extremely time-consuming. Utilizing this method for longer periods of time and/or multiple sites is not practicable.

The study of Gindy and Nassif also targets at the determination of MP probabilities. In their study, the time-stamp of WIM datasets is used to identify MP events. This method proves to be effective for larger amounts of data from multiple sites and over longer periods of time. Their methods and algorithms will be utilized for the analysis of WIM data further in this study.

All of the above studies that identify MP occurrence probabilities deliver results in the range of around 8–10% for Following events and around 1–4% for the Side-by-Side events (compare Tables 3.1, 3.2, 3.3 and 3.4), depending on the exact definition of the various MP loading cases and the underlying data.

42

Chapter 4

Weigh-in-Motion Systems

To develop a Multiple Truck Presence Model, *Weigh-in-Motion* (WIM) data is used to assess the traffic volume and the associated trucks weights. WIM data is widely available nearly throughout all U.S. states and has been collected for more than two decades.

The main advantage of WIM systems for our purpose is, that they provide *unbiased* truck data. Heavy vehicles often avoided or bypassed the traditional weigh stations located at the highways. However, the WIM sensors are often times not even recognized by the drivers. Another advantage accompanying this is that the trucks do not have to stop, as the data is collected while the vehicles are in motion. This is beneficial as the *processing rate increases* (a sensor measures within a fraction of a second, while the clearance at weigh stations is a matter of minutes) and the vehicles can *avoid unnecessary stops*. WIM stations also require *less personnel* and therefore have *lower maintenance costs* than traditional weighing stations.

A slight disadvantage of WIM stations is, that they are less accurate than the traditional scales. After initial calibration, the wheel load is accurate to about ±1%, according to the National Bureau of Standards (ASTM, 2002). During the lifecycle of a system the

inaccuracy will increase to about ±2%, before maintainance and re-calibration is required (McCall and Vodrazka, 1997; ASTM, 2002).

Another disadvantage is the reduced information that is collected at the WIM stations. Information about engine (fuel) type, year and model of the vehicle or origin and destination are not available. As this information is neither required nor relevant for this study, they can be neglected.

The following Sections describe the various WIM systems that are most commonly used and the site parameters necessary for installation. Also, an introduction to the WIM database will be given that has been used for this study.

4.1 WIM Sensors

Even though many different methods of measuring traffic flow and hence various types of sensors exist, the most commonly utilized sensors throughout the U.S. are

- Piezoelectric sensors
- Bending Plate sensors and
- Load Cell sensors.

The American Society for Testing and Materials (ASTM) classifies WIM systems into four different categories from I to IV according to speed range, accuracy and capability of the whole system (ASTM, 2002). A photo of the three types of WIM sensors is shown in Figure 4.1.
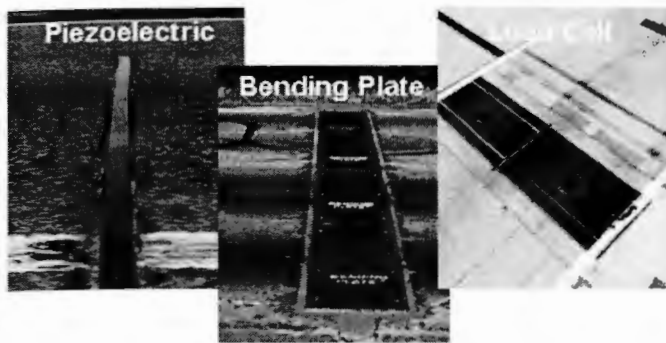
Figure 4.1: The different types of WIM sensors

4.1.1 Bending Plate sensors

Bending Plate sensors are scale systems that consist of a metal plate with strain sensors applied underneath. When vehicles run over those sensors, the deflection is measured and the dynamic load is calculated from the deflection. The actual static load is then calculated using calibration data, speed and other parameters.

The usual setup of WIM stations with Bending Plate sensors consists of at least one scale and two inductive loops. Normally, one scale is placed into each wheelpath of a lane and two inductive loops are used. The upstream inductive loop detects approaching vehicles, while the downstream loop is used for speed measuring. Some stations have an optional sensor for the axle spacing. A sample setup is shown in Figure 4.2.

4.1.2 Piezoelectric sensors

Piezoelectric sensors detect the vehicle loads by a change in voltage that is induced when the sensor is pressurized by the wheels. From the change in voltage the dynamic and static loads can be calculated using the calibration and speed data.
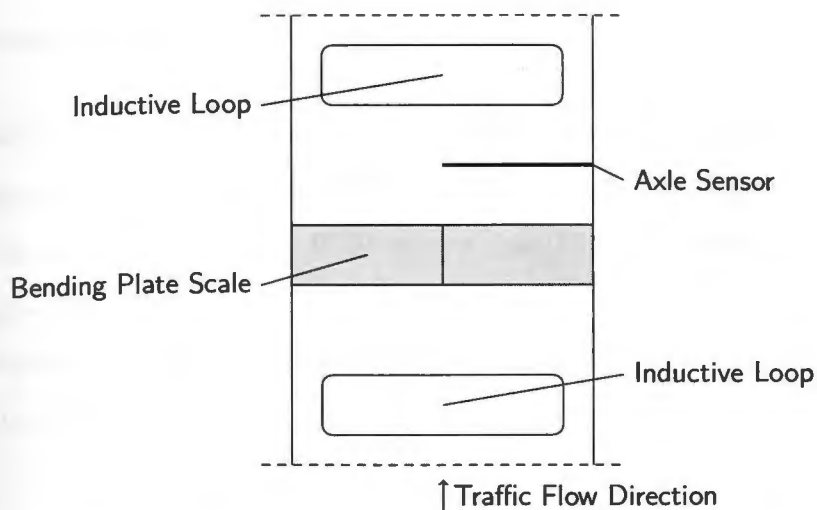
Figure 4.2: Schematic sample setup of a Bending Plate WIM station, adapted from McCall and Vodrazka (1997)

A typical WIM station setup normally includes one or two Piezoelectric sensors for the loads as well as one or two inductive loops for system initialization and speed detection.

4.1.3 Load Cell sensors

A single Load Cell sensor normally contains two scales next to each other, measuring axle weights simultaneously by summing up the values of the two scales. A normal system setup consists of a Load Cell sensor, an off-scale sensor to determine whether vehicles do not pass the Load Cell correctly and at least one inductive loop for speed measurement. A normal layout mostly also has an axle sensor and two inductive loops for the same reasons stated in Section 4.1.1.

4.1.4 Site Specifications

When a particular location of interest is determined for setting up a WIM station, some site specifications are required for adequate and precise measurements. These specifications vary according to the WIM system type (I-IV) and include geometrical as well as geographical parameters. The most important parameters are listed below and the actual values for the types can be found in the *Standard Specification for Highway Weigh-in-Motion (WIM) Systems with User Requirements and Test Methods* (ASTM, 2002).

- Horizontal Curvature

- Roadway Grade

- Cross Slope

- Lane Width and Marking

- Pavement Design

For a WIM station setup, it should also be considered that power and communication lines are needed as well as an adequate drainage. It should be noted that it is preferable to setup a WIM station in a spot where the traffic is uniform. That means, that slow traffic (congestion) and multiple lane changes (in areas near exits) is to be minimized for most accurate measurements.

4.2 Data Collected by WIM systems

After a WIM station is installed and calibrated, various traffic data can be collected. In this section, only the parameters relevant for this study is presented. Generally the information gained can be partitioned into two main components:

Site Information is data that is not gained from the sensors. This data describes the WIM station and the site specifications. This information includes

- Location of the WIM station,

- Area type (Rural or Urban Area),

- Roadway type (Major or Minor Road),

- Local Speed Limits,

- Number of Lanes and

- FHWA (Federal Highway Administration) Functional Class.

When developing a traffic prediction model, these factors may have a significant impact on a model found.

Vehicle Information is data, that is collected by the sensors. The following list is an excerpt of the most relevant data that is collected by the sensors

- Timestamp (with an accuracy to 1/100th of a second),

- Speed,

- Travel Lane,

- Vehicle Class,

- Vehicle Length,

- Gross Vehicle Weight (GVW) and

- Axle Data (Number of Axles, Axle Loads, Axle Spacing).

The data collected by the sensors is mostly logged into a continuous binary file. The data can be downloaded from the stations using a data modem and then be converted to a ASCII-standard comma separated file.

4.3 WIM Database

The Multiple Presence prediction model introduced in Section 5.4 is based on WIM data provided by the New Jersey Department of Transportation (NJDOT). The data was collected from 1993 to 2003 from 55 WIM stations geographically dispersed over the state as shown in Figure 4.3.

For this analysis, only two consecutive months of truck data were utilized, as the processing of the data is very time-consuming. Hence, seasonal trends are not eliminated from the data. The database for the two months includes a total of about 1.4 million trucks and includes WIM stations with a broad variety of parameters as shown in Table 4.1 and is therefore a good basis for the development of a prediction model. Some sites are at the same geographical location but are separated into directional sites. This was done to be able to identify directional trends in the weight distributions.

Table 4.1: Overview of the NJ Database

No. of Lanes	Area Type	Major Roadway Site Volume [†]			Minor Roadway		
		Low	Avg.	High	Low	Avg.	High
2	Rural	8	4	-	12	-	-
	Urban	12	7	2	2	1	-
3	Rural	-	1	1	-	-	-
	Urban	-	1	-	-	-	-
	Unknown	-	1	2	-	-	-
4	Rural	-	-	-	-	-	-
	Urban	-	-	1	-	-	-

[†] Low Volume: <1000, Avg. Volume: >1000 and <3000, High Volume: >3000

4.4 Data Filtering

The logging systems collect data of all the vehicles that pass the sensors without in-depth consistency checks. Even though the systems work with a high accuracy, some of the collected data is subjected to errors due to (for example) a sudden change of speed while passing the sensors, a change of lanes within the measuring section or slow traffic due a congested road.

Furthermore, for this study, only truck data was analyzed so that a set of filters had to be applied to the raw data, as described below.

Error Code = 0 The WIM systems are capable of diagnosing the sensors. If an error occurs, an error code is written into the collected dataset. An error code 0 means that no errors occurred.

Speed <10 mph For very slow traffic, the WIM sensors tend to be inaccurate, so very slow traffic is filtered out.

Figure 4.3: WIM Stations in New Jersey (after Gindy and Nassif, 2007)

Speed >120 mph It is very unlikely for a truck to travel faster than 120 miles per hour and so it is assumed that this data is subjected to errors.

Class >13 Class 13 is the highest class of the FHWA classification system. So if a truck is classified higher than Class 13 it is likely to be an exceptional heavy vehicle that needs a special permit and is not relevant for common traffic or the dataset is subjected to errors.

GVW <15 kips If the Gross Vehicle Weight (GVW) is smaller than 15 kips the vehicle should not be considered a truck but a heavy panel truck and is not relevant for this study.

AXW <2 kips If the weight of one axle (AXW) is less than 2 kips, the vehicle can be considered a car or a panel truck and again is not relevant.

AXW >70 kips An axle weight of more than 70 kips is most likely an exceptional heavy vehicle with a special permit or the dataset is subjected to an error.

Sum of AXS >LE If the sum of all axle inter-spaces (AXS) is greater than the total length of the vehicle (LE), the dataset is considered erroneous.

The filtered data was then separated by direction as the original data was recorded in one file with a parameter for the direction. This filtering is interesting as directional differences in the traffic pattern occur (i.e. commuter traffic etc.).

4.4.1 Filter Results

Applying the filters to the raw WIM data from the NJ DOT, around 75% of all datasets were filtered out meeting one of the criteria stated above. About three percent of the data was filtered out because of errors detected by the WIM-system and an error-flag set to other than zero. The speed filters and the vehicle filter only filtered out a marginal share of far less than one percent each. Around 55% of all the WIM data was filtered out by the Gross Vehicle Weight (GVW) filter. This is due to light truck traffic that is usually lighter than 15 kips. For the axle-weight filters, less than one percent of the data was filtered out. With the filter of the axle-weight being higher than 70 kips, no entries were detected.

The consistency check for the truck lengths filtered out about 15% of the data. For many trucks, the overall length was not equal to the sum of the axle spacings. This might be due to a change in speed while passing the measuring section or to lane changes, where the trucks did not pass the sensors properly. The remaining about 25% of the data can be considered clean truck data, that will be used for further analysis. Table 4.2 summarizes the filter results of the New Jersey data.

Table 4.2: Results of the Data Filtering

Filter	% Filtered
Err $\neq 0$	3.0883%
Speed <10 mph	0.0202%
Speed >120 mph	0.0006%
Class >13	0.0325%
GVW <15 kips	55.8205%
AXW <2 kips	0.3408%
AXW >70 kips	0.0000%
AXS <3 ft	0.5973%
AXS1 <5 ft	0.0241%
$\sum$AXS >LE	15.3588%
Total	**75.2831%**

4.5 Weight Distribution of the NJ data

The weight distribution of truck traffic is important for estimating the weight correlation among multiple trucks. A first visual impression of the weight distribution is given in Figure 4.4. The data of the gross vehicle weight was partitioned into 100 intervals. The relative frequency denotes the number of occurrences divided by the total number.

Even though, the weight data of trucks is not normally distributed, many models fit the weight data to a normal distribution with the parameters μ (mean) and σ (standard
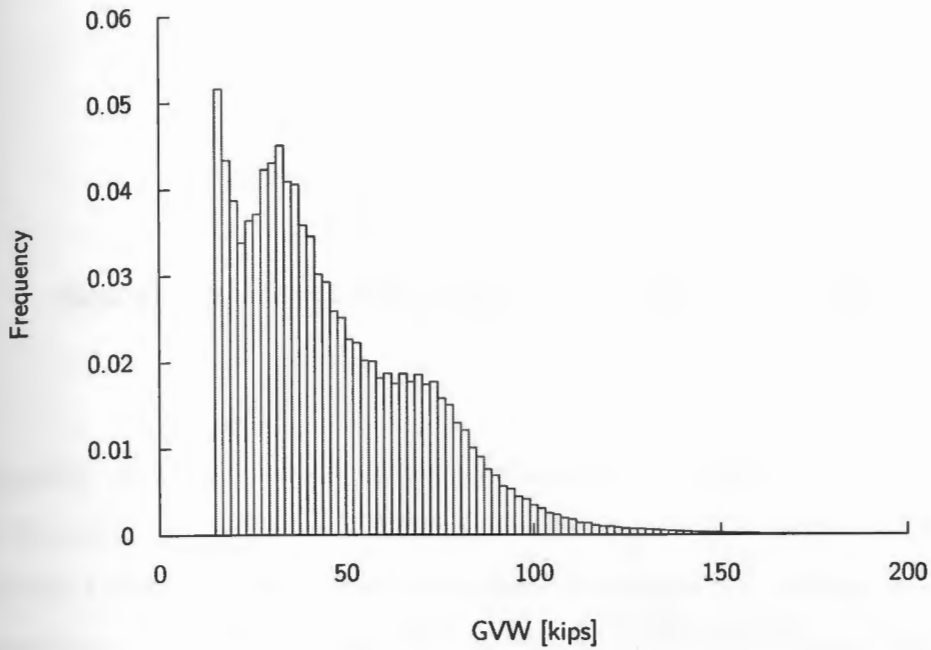
Figure 4.4: Histogram of the NJ GVW data

deviation) for further analysis. When fitting the normal distribution to the NJ data, the mean is found to be $\mu = 46.4$ kips and the standard deviation is $\sigma = 24.5$ kips.

Chapter 5

Multiple Presence Determination and Model Development

As discussed in the previous Chapters, a determination of loading cases that involve more than one truck (MP) from WIM data provides an accurate base for further loading evaluation. To determine the different loading patterns for short to medium span bridges, the *timestamps of the trucks are utilized to check whether other trucks are in the vicinity*, as described in Gindy and Nassif (2007). The information of the *travel lane is also considered to identify the MP event type.*

This Chapter defines various loading patterns and describes an algorithm to determine those events from the New Jersey WIM data. The outcomes are presented and discussed. This analysis considers MP events with only two trucks, as this is the most likely to be the governing loading case for short to medium span bridges (40–200ft).

5.1 Multiple Presence Loading Cases

To identify loading patterns involving multiple trucks, these loading patterns have to be clearly defined. In this study, the detection of five basic loading patterns is implemented. These are namely

Single Truck: A Single Truck event occurs, when only one truck at a time passes the bridge. No trucks in the vicinity are close enough to be on the bridge at the same time.

Following: Two trucks pass the bridge at the same time. Both of the trucks travel in the same lane with a Gap[1] distance, which is less than the bridge span.

Side-by-Side: In a Side-by-Side event, two trucks pass the bridge at the same time but travel in different lanes with an overlap of at least half of the body length of the leading truck. These events are most likely to generate the maximum expected bridge responses.

Staggered: A Staggered event is basically the same as the Side-by-Side event with the exception that the overlap is less than half of the body length of the leading truck.

Other: Events that involve at least three or even more trucks are not considered in this study. For further studies these events are nevertheless detected and classified as "Other".

An overview of all the loading cases considered can be found in Figure 5.1.

5.2 Multiple Presence Detection Algorithm

With the loading cases clearly defined in Section 5.1, the algorithm from Gindy and Nassif (2007) was adapted to determine the Multiple Presence events from the various information of the WIM data (see Section 4.2). For this purpose, the timestamp was

---

[1] *Gap* denotes the distance from the rear bumper of the first truck to the front bumper of the following truck. *Headway* is the distance from the front bumper of the leading truck to the front bumper of the following truck.
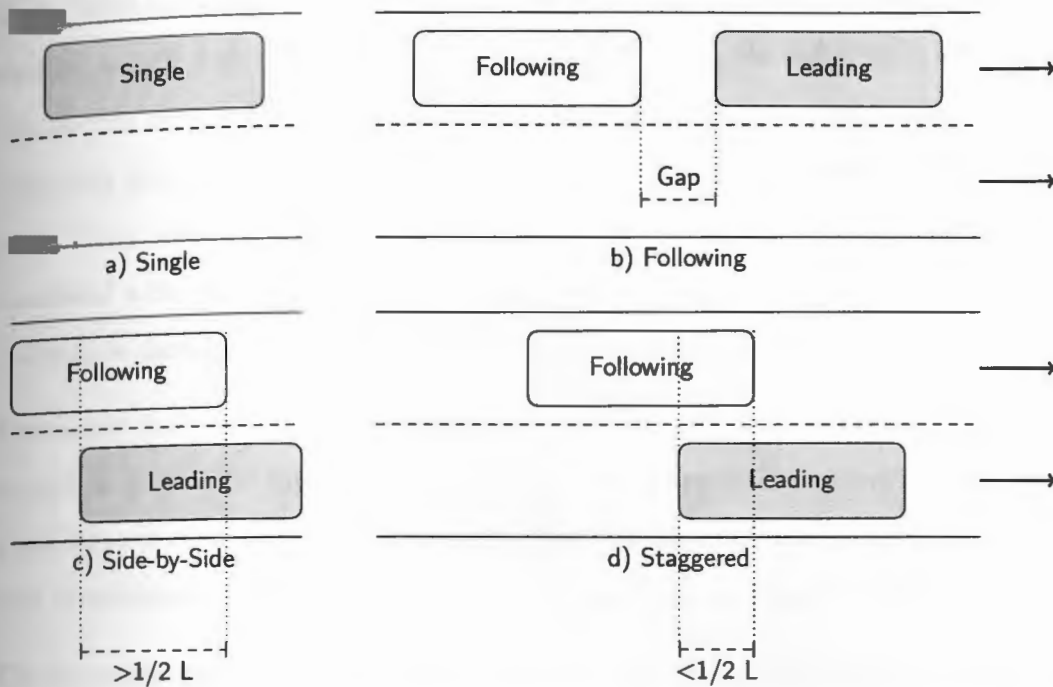
Figure 5.1: Definition of the Loading Patterns (symetrical loading patterns are also possible and considered in the study), a) Single, b) Following, c) Side-by-Side, d) Staggered. Adapted from Gindy and Nassif (2007).

utilized. The timestamp can be used to calculate the entrance and exit times for a simulated bridge as accurate as 11.4 in for a speed of 65 mph when it is exact to 1/100th of a second. A timestamp only being precise to the full second would produce an error of more than 90ft, which exceeds the smallest chosen span length by a factor of more than two.

Assuming that the trucks maintain constant speed and stay in the travel lane in which they entered the bridge, the entrance and exit times of each truck can be calculated for various simulated span lengths. If one truck is still on the simulated bridge while another truck enters, a MP event is detected.

As the WIM data also contain information about the lane of travel, it can be determined whether an MP event is a Following event (trucks are in the same lane) or if it is a Side-by-Side or Staggered event. The latter two cases are detected by calculating and comparing the overlap distance between the two trucks to the length of the leading truck. If the overlap is greater than or equal to half the truck length, the loading case is considered a Side-by-Side event. For a gap distance smaller than half the truck length, the event is considered a Staggered event (cp. Section 5.1).

Trucks that have been involved in one MP event are discarded by the algorithm and can not be involved in further MP events to avoid a numerical exaggeration. MP events where three or more trucks were detected to be on the simulated bridge at the same time were considered as "Other". These other events were not analyzed in this study.

The algorithm was run for every truck and every WIM location in the database with span lengths from 40ft to 200ft with steps of 20ft, so that sufficient data is available for every location and for multiple span lengths. Figure 5.2 shows a flowchart of the algorithm implemented.

5.3 Results of the Analysis

The algorithm was run with all datasets available from the NJDOT and therefore a representative number of Multiple Presence events was detected. As some parameters of the WIM station were known—namely the average daily truck traffic (ADTT), the number of lanes, the area in which the WIM station is located (rural or urban) and the importance of the road type (major or minor highway)—the next step was to identify their association with the occurrence of Multiple Truck presence events. As the outcomes
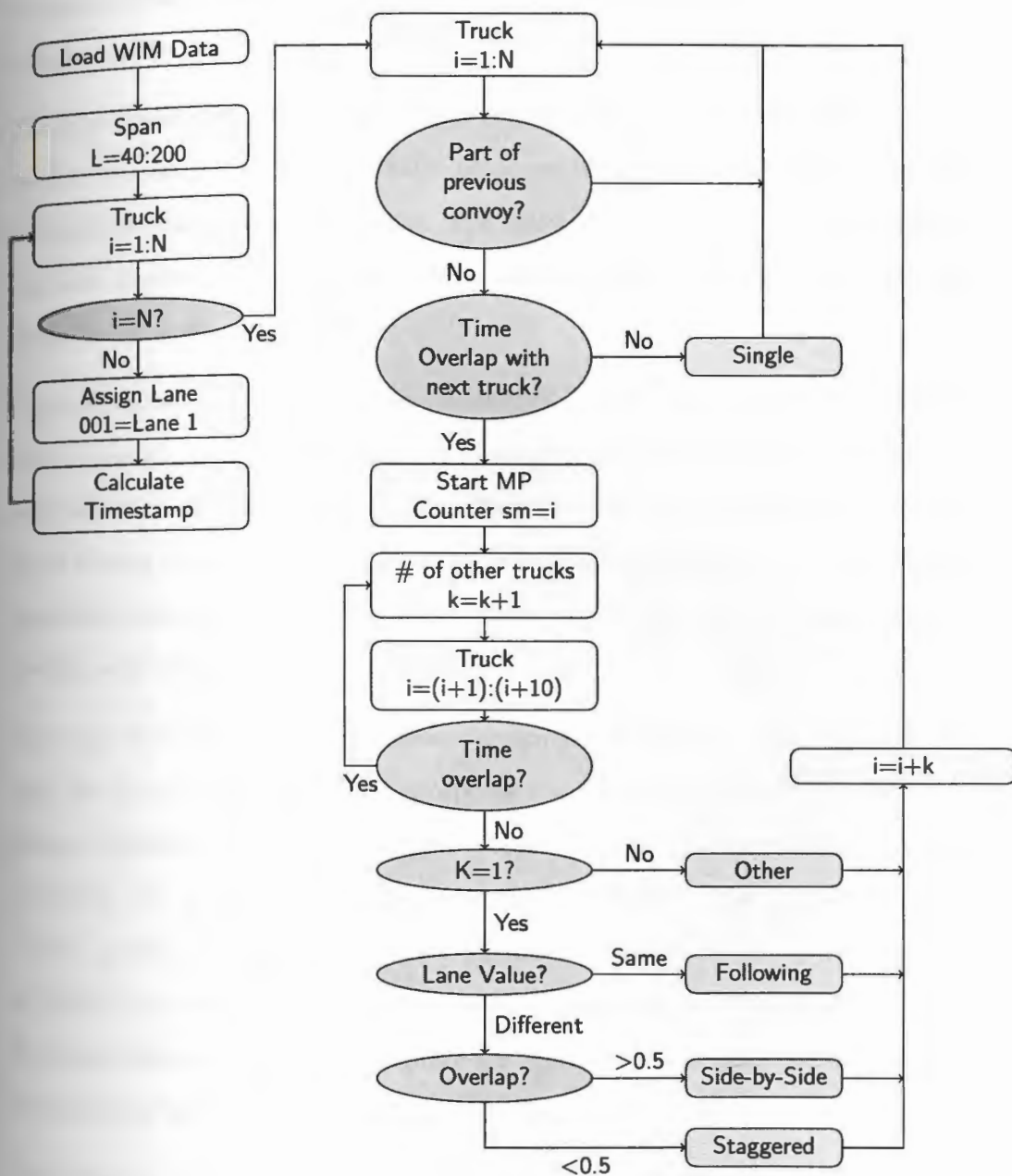
Figure 5.2: Flowchart of the MP Detection Algorithm

are quite similar for all span lengths, a 120ft span was chosen for the visualization of the influence of the parameters.

The most obvious parameter is the truck volume that passes a bridge. As shown in Figure 5.3, the occurrence of Single trucks decreases with increasing truck volume, whereas the Multiple Presence events increase. This is logical as the space on a highway is limited and with increasing truck volume, trucks are likely to be closer together and the Gap distances decrease, respectively.

Figure 5.4 shows the results of the analysis split by area type, namely urban (circles) or rural (squares). Lines showing the trend using simple linear regression (see Section 2.1) were added to visualize similarities or differences between the parameters. Except for the Following events, the trendlines seem to have the same parameters and therefore no significant influence of the area type is evident. A detailed analysis is done in the Model Development (Section 5.4).

The same was done for the importance parameter (major or minor highway). In this case, the trends vary significantly except for the Staggered events. This denotes a significant influence of the highway type. Again, a more detailed analysis is performed in Section 5.4. It should be also noticed, that for higher truck volumes of more than ~1,700, no data is available for minor highways. This is obvious as the classification of highway importance highly depends on the traffic volume. Therefore, the trend line for minor highway may not be accurate for volumes greater than ~1,700, as regression extrapolation by be erroneous (see Section 2.3).

The influence of the span length is shown in Figure 5.6. For Single events the rate of occurrence decreases with longer spans, as expected, because the longer the span, the

more probable is the occurrence of two or more trucks, as the trucks remain on the bridge for longer time when assuming constant speed. For the Following and Side-by-Side events, an increase of the MP probability is detected for longer spans for the same reason. Noticeable is the slight decrease of the occurrence probabilities for longer spans for Side-by-Side events. This phenomenon is due to the fact that for longer spans, the arrangement of the trucks on the bridge is more variable than for shorter spans. Hence, the probability of overlapping by more than half the truck length becomes less likely, and more complex loading patterns occur as the span lengths increase.

Even though the number of lanes is another parameter that has to be considered in the development of a prediction model, *no other study* was found where analysis of Multiple Presence events was performed for more than two lanes (cp. Chapter 3). As only one site in the database had four lanes and six sites had three lanes, a graphical trend is not noticeable, as seen in Figure 5.7. Nevertheless, the number of lanes will be included and tested for significance in Section 5.4.

The algorithm introduced by Gindy and Nassif (2007) (Section 3.1.7), which utilizes the time-stamps to identify MP events was implemented and the New Jersey WIM database was evaluated for Multiple Truck Presence events. The results show that the probability of Multiple Presence events is far below the assumptions made be Nowak and Hong (1991) (Section 3.1.2) and vary according to the loading cases defined in Section 5.1.

The Side-by-Side event, which is commonly referred to as the governing loading event, is least probable according to the outcomes. This is due to the definition that the overlap of the two trucks in adjacent lanes has to be more than half of the truck length of the leading truck to be considered as Side-by-Side. The probabilities found maximize at around two percent. These values are also less than the values observed by Guzda et al.

(2007) (Section 3.1.6). In the latter case, this might be due to the different definition of Side-by-Side events in their study (Headway distance of maximal two truck lengths). Tables 5.1, 5.2 and 5.3 give an overview over the average MP occurrence probabilities found for each MP loading case for multiple spans and multiple ADTT ranges[2].

Also, some parameters and their influence were identified. As expected, truck volume, the highway importance and the span-length seem to have the most influences. The location of the WIM site seems less important.

---

[2]Truck Volume Ranges are Light (ADTT<1000), Average (1000<ADTT<3000) and High (ADTT>3000)

Table 5.1: Average Following MP Probabilities for three representative spans

Span	Following		
	Light	Average	High
40	0.09%	0.16%	0.40%
120	1.64%	2.79%	4.69%
200	3.66%	5.90%	9.24%

Table 5.2: Average Side-by-Side MP Probabilities for three representative spans

Span	Side-by-Side		
	Light	Average	High
40	0.20%	0.63%	1.39%
120	0.20%	0.59%	1.20%
200	0.18%	0.54%	0.99%

Table 5.3: Average Staggered MP Probabilities for three representative spans

Span	Staggered		
	Light	Average	High
40	0.45%	1.42%	3.53%
120	0.92%	2.80%	7.05%
200	1.22%	3.72%	9.08%
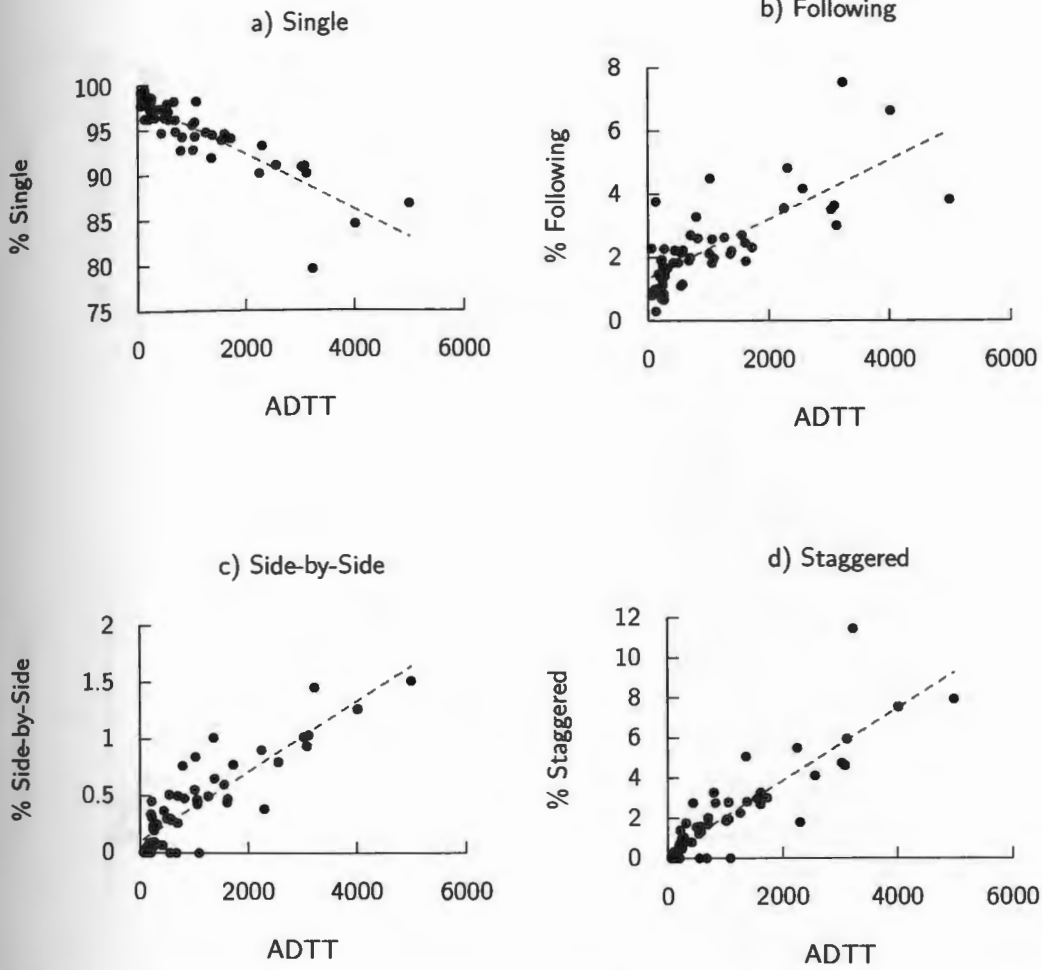
Figure 5.3: Variation of the Multiple Presence occurrences vs. Truck Volume (ADTT) for a 120ft-span for a) Single Trucks, b) Following, c) Side-by-Side and d) Staggered. The dashed line represents the trend.
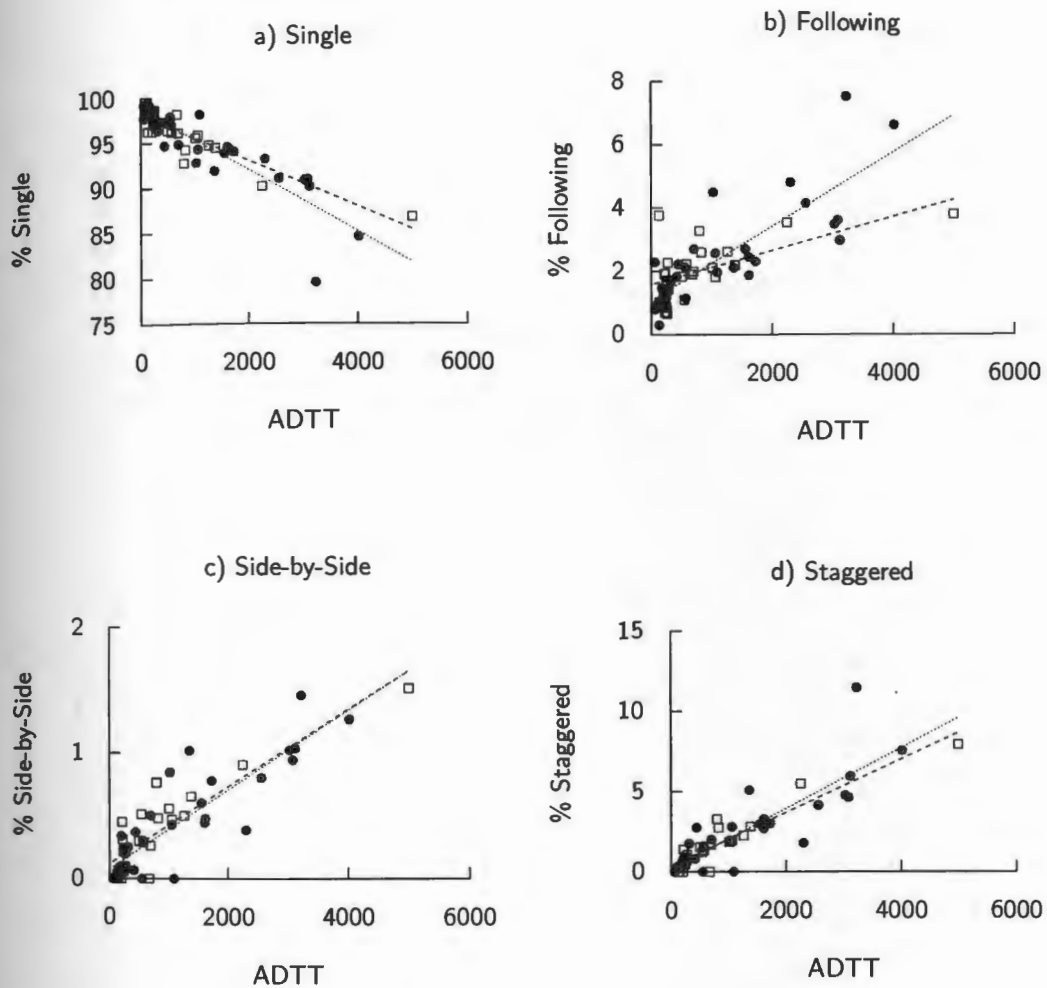
Figure 5.4: Variation of the MP occurrence rate in Rural and Urban Areas vs. ADTT for a 120ft-span for a) Single Trucks, b) Following, c) Side-by-Side and d) Staggered. The circles denote Urban Sites and the squares denote Rural Sites. The lines represent the trend of each area type.
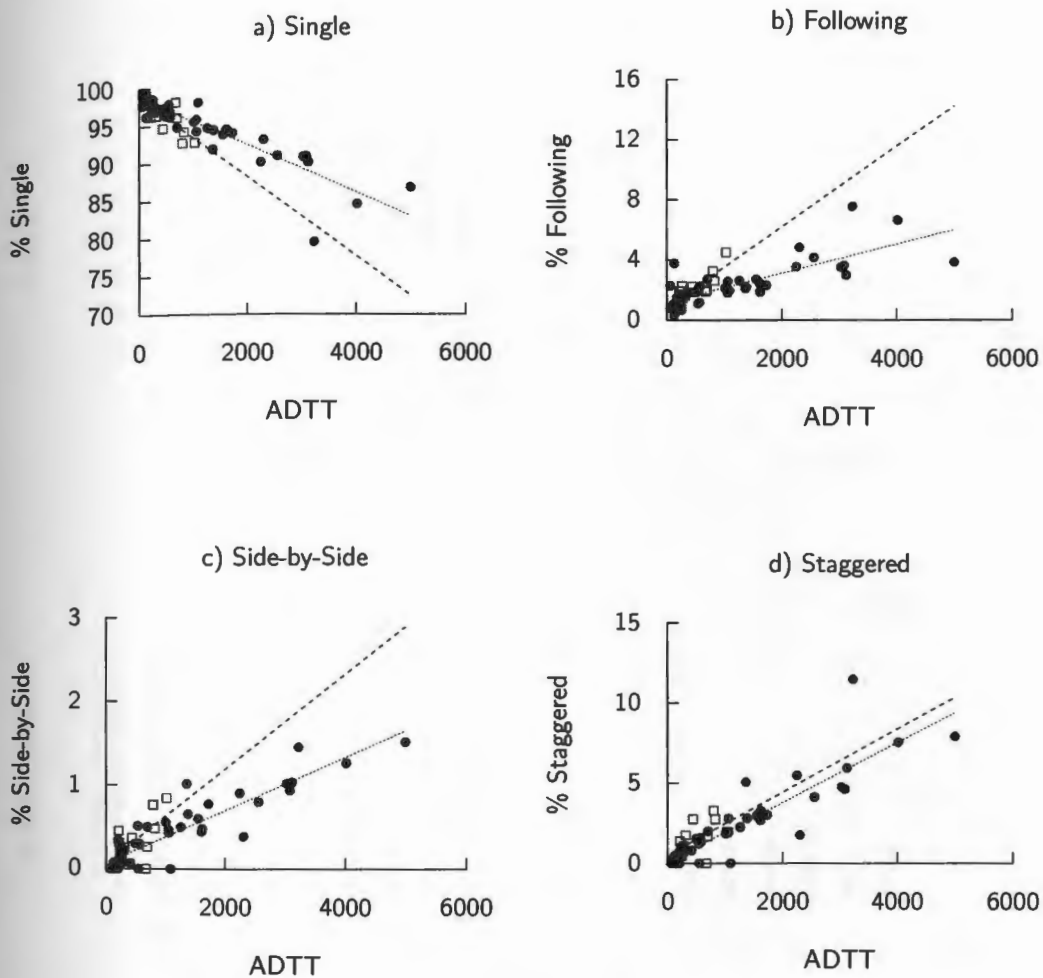
Figure 5.5: Variation of the MP occurrence rate for Major and Minor Roadways vs. ADTT for a 120ft-span for a) Single Trucks, b) Following, c) Side-by-Side and d) Staggered. The circles denote Major Roadways and the squares denote Minor Roadways. The lines represent the trend of each importance.
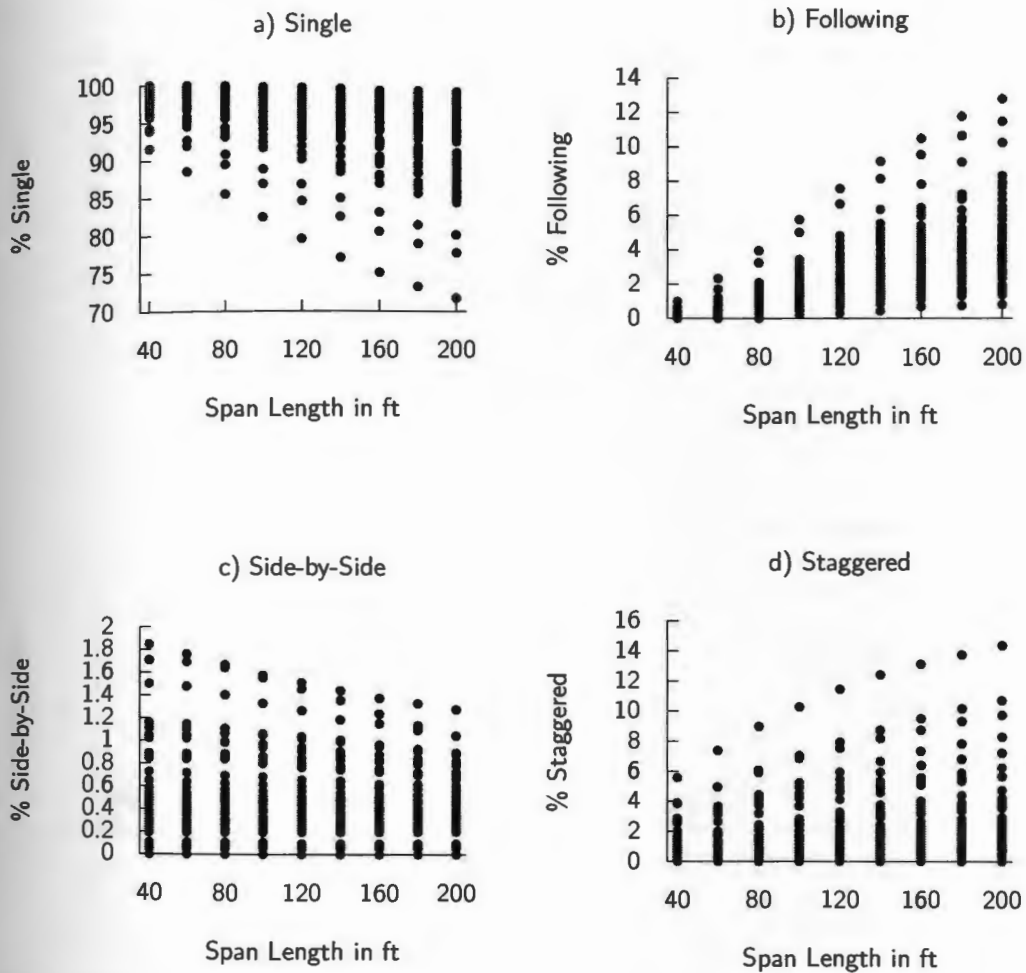
Figure 5.6: Variation of the MP occurrence rate for various Span Lengths for a) Single Trucks, b) Following, c) Side-by-Side and d) Staggered.
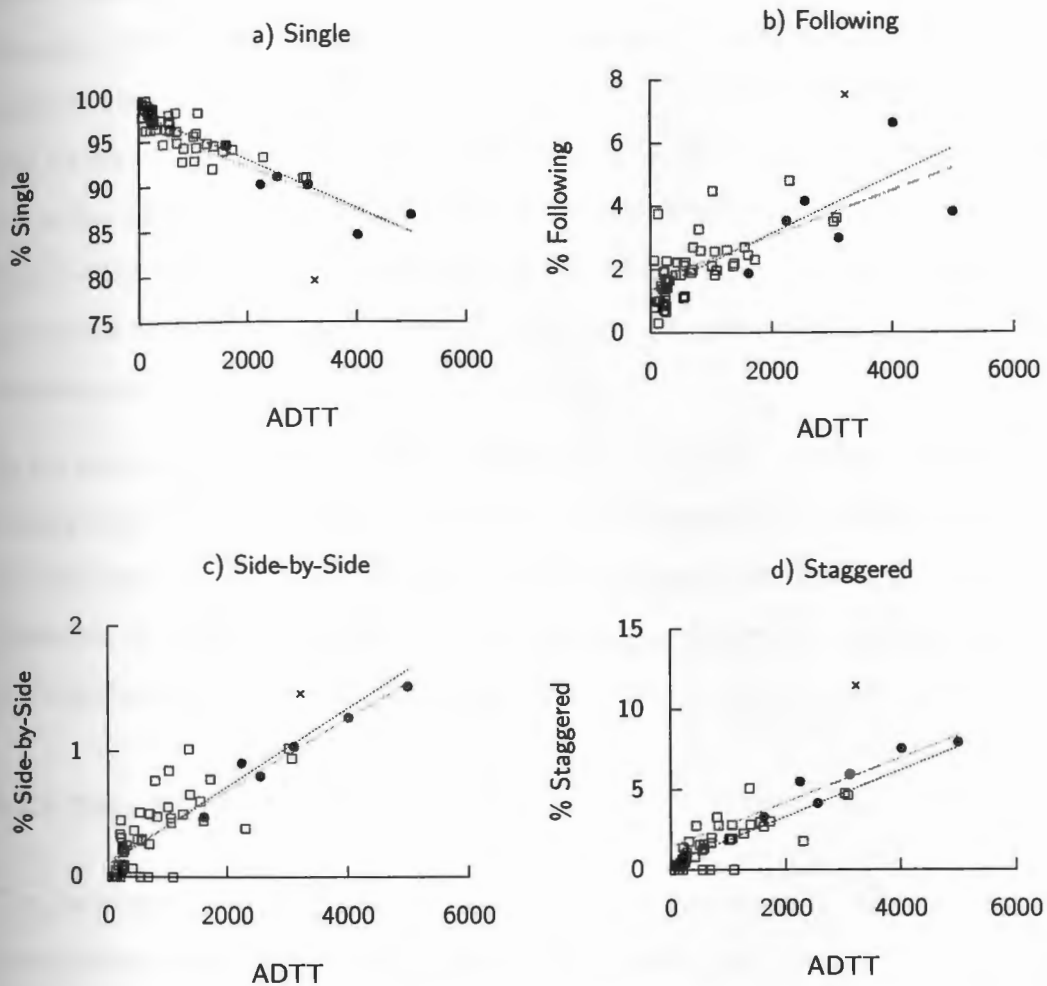
Figure 5.7: Variation of the MP occurrence rate for number of lanes vs. ADTT for a 120ft-span for a) Single Trucks, b) Following, c) Side-by-Side and d) Staggered. The squares denote sites with two lanes, the dots denote three lanes and the cross is the site with four lanes. A trendline for four lanes was not drawn for obvious reasons.

5.4 Development of a Prediction Model

When assessing the load for a bridge, the occurrence probabilities of Multiple Truck Presence events have *significant impact on the maximum expected loading cases*. The parameters like Span length, Area- and Roadtype or Number of Lanes as discussed in Section 5.3 are known to the designer. An accurate truck volume (ADTT) can be estimated via in-situ traffic counts or from WIM stations from the vicinity of the bridge. Weight Distributions can either be obtained from the literature or—even more accurately—determined from WIM data. The latter gives more accurate results for the site-specific requirements.

In the previous Section 5.3, the probability of occurrence for Multiple Truck Presence loading cases was derived from WIM data. The underlying WIM database from the NJDOT has a great variety of sites, each with different parameters (see Section 4.3). Therefore, this WIM data will be used to develop a *site-specific* prediction model for Multiple Presence events based on regression methods in the following Sections.

5.4.1 Data Encoding

The parameters used in the regression models are described above. For better clarity, these parameters are abbreviated in the following Sections as shown in Table 5.4.

Span-length, truck volume and number of lanes are quantitative parameters, while Area- and Roadtype are qualitative parameters and hence have to be encoded into levels (appropriately 0 or 1) for numerical analysis for the reasons stated in Section 2.1.1.

Table 5.4: Abbreviated Parameters

Abbr.	Parameter
S	Span-length
V	Volume (ADTT)
L	Number of Lanes
A	Area-Type (Rural, Urban)
R	Road-Type (Major, Minor)

Therefore, the encoding was chosen as follows for Areatype

$$A = \begin{cases} 0 & \text{if Urban} \\ 1 & \text{if not Urban } (= \text{if Rural}) \end{cases} \qquad (5.1)$$

and for Roadtype

$$R = \begin{cases} 0 & \text{if Major} \\ 1 & \text{if not Major } (= \text{if Minor}) \end{cases} \qquad (5.2)$$

5.4.2 Simple Linear Regression

To develop an appropriate prediction model for each of the three loading cases, regression analysis is utilized. To check for the significance of each parameter, the stepwise regression methods are used as described in Section 2.4.1. After each step, a t-test (Section 2.2.3) is performed to test for the significance of the parameter added. The Null hypothesis, that the β_i of the added parameter is equal to zero is tested against the alternative hypothesis $\beta_i \neq 0$. The percent values for "Significance" given in Tables 5.5, 5.6 and 5.7 denote the probability that rejecting the Null Hypothesis was right, according to the t-test.

The significance threshold for added parameters is set to 95%, meaning that all added parameters with a probability of the right decision to reject H_0 of less than 95% will be declared as "not significant" and omitted in the next step. This threshold value is commonly used and provides a sufficient level of accuracy.

After a model has been found, the overall model is assessed with an F-test (see Section 2.2.4) and the model quality is identified using the adjusted R_a^2-value (see Section 2.2.2). A residual analysis reveals unequal variances and hence the need for a stabilizing transformation.

Following

The first stepwise regression was performed for the Following events, as shown in Table 5.5. In the first step, the Span length is significant within a level of more than 99%. Hence, this parameter is also included in the next step. In step four, the added parameter Areatype failed to reach the predefined 95% significance and is considered insignificant. This means that the contribution of this variable is negligible for the model accuracy. Therefore it is omitted for further steps.

Table 5.5: Stepwise Regression for Following

Iter.	Model	$1 - \mathbf{Pr}(> |t|)$	$\mathbf{R_a^2}$
1	$y = \beta_0 + \beta_1 S$	>99%	0.5231
2	$y = \beta_0 + \beta_1 S + \beta_2 V$	>99%	0.7262
3	$y = \beta_0 + \beta_1 S + \beta_2 V + \beta_3 L$	>99%	0.732
4	$y = \beta_0 + \beta_1 S + \beta_2 V + \beta_3 L + \beta_4 A$	not significant	0.7315
5	$y = \beta_0 + \beta_1 S + \beta_2 V + \beta_3 L + \beta_5 R$	>99%	0.7406

Figure 5.8 shows the convergence of the adjusted R_a^2-value and the Sum of Square Error for the Following events. It is evident that the most significant increase in the model

accuracy is gained by adding the parameter Traffic Volume parameter to the model. This confirms the assumption from the graphical evaluation in Section 5.3.
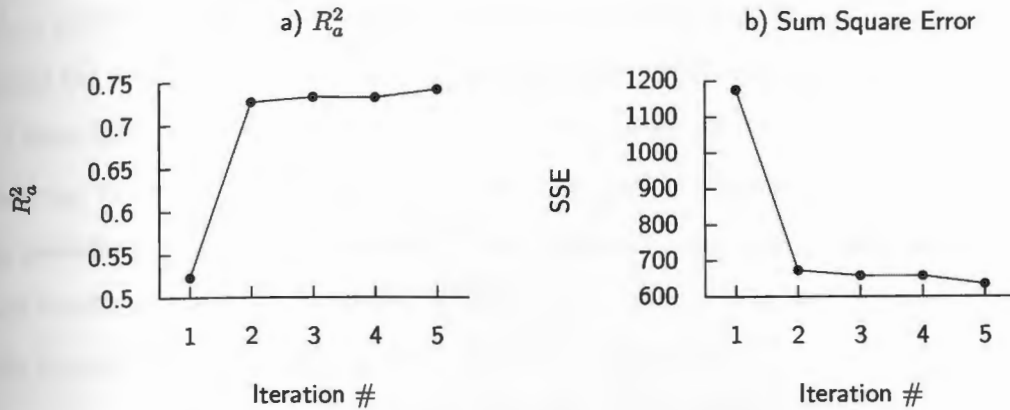
Figure 5.8: Convergence Plots of a) R_a^2 and b) Mean Square Error for Following events

To validate the overall model legitimation, an F-Test was performed. The Null Hypothesis that *all* $\beta_i = 0$ is tested against the Alternative Hypothesis, that *at least one* $\beta_i \neq 0$. The F-value of the model found in interation 5 equates to 353.6 which is much higher than the value found from the F-Distribution, which is 2.39. Therefore the Null Hypothesis is rejected and the overall model validity is confirmed. Replacing the β_is with the values from the regression model (rounded to three decimal places), the equation becomes

$$y_{Follow} = -3.702 + 0.031S + 0.001V + 0.616L + 0.505R \qquad (5.3)$$

with a residual standard error of 1.139 and returns percentage values for the Following occurrence probabilities.
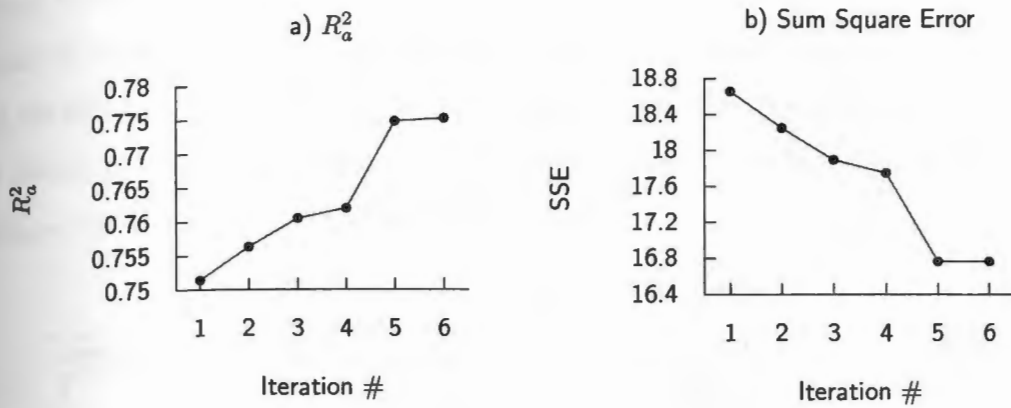
Figure 5.9: Convergence Plots of a) R_a^2 and b) Mean Square Error for Side-by-Side events

The legitimation of the model found in iteration 6 is confirmed by the calculated F-value from the model being much higher than the value from the F-distribution, namely $426.9 \gg 2.39$.

Replacing the β_is with the values found from the regression model (iteration 6), the complete model reads

$$y_{Side} = -0.0570 + -0.0006V + 0.0003S + 0.0931L + 0.1132R \tag{5.4}$$

The coefficients are rounded to four decimal places and the equation returns the percentage of trucks involved in a Side-by-Side event with a residual standard error of 0.185.

Staggered

Also, for the Staggered event, a linear regression model was found by adding variables step by step as shown in Table 5.7. This analysis shows, that for this loading case the

Truck Volume is the most important predictor again. The influence of the Span Length tends to be slightly smaller than for the Following case but considerably higher than for the Side-by-Side events. This behavior was expected after the discussions above and in Section 5.3. Again, the Areatype does not have a great contribution to the overall accuracy of the model and therefore can be omitted.

Table 5.7: Stepwise Regression for Staggered

Iteration	Model	$1 - \Pr(> |t|)$	R_a^2
1	$y = \beta_0 + \beta_1 S$	99%	0.05439
2	$y = \beta_0 + \beta_1 S + \beta_2 V$	>99%	0.7337
3	$y = \beta_0 + \beta_1 S + \beta_2 V + \beta_3 L$	>99%	0.8014
4	$y = \beta_0 + \beta_1 S + \beta_2 V + \beta_3 L + \beta_4 A$	not significant	0.801
5	$y = \beta_0 + \beta_1 S + \beta_2 V + \beta_3 L + \beta_5 R$	>99%	0.8082

The convergence plots in Figure 5.10 are a good indicator for the importance of the Volume as a model parameter. For this loading case it can also be seen, that the Number of Lanes have a greater contribution compared to the other loading cases. However, this influence can be questioned as only one site with four lanes and ten sites with three lanes exist in the database, while all other sites have two lanes.

Validating the model found in iteration 5, significant evidence is found that at least one of the β_i-coefficients is unequal to zero, as the computed F-value of 521.5 exceeds the value from the F-distribution (2.39) by far. The model equation after substituting the β_is with the values found (rounded to four decimal places) from the model becomes

$$y_{Stag} = -5.1787 + 0.0107S + 0.0013V + 2.0935L + 0.4661R \tag{5.5}$$

with a residual standard error of 1.016 and returns the percentage of trucks involved in a Staggered event.
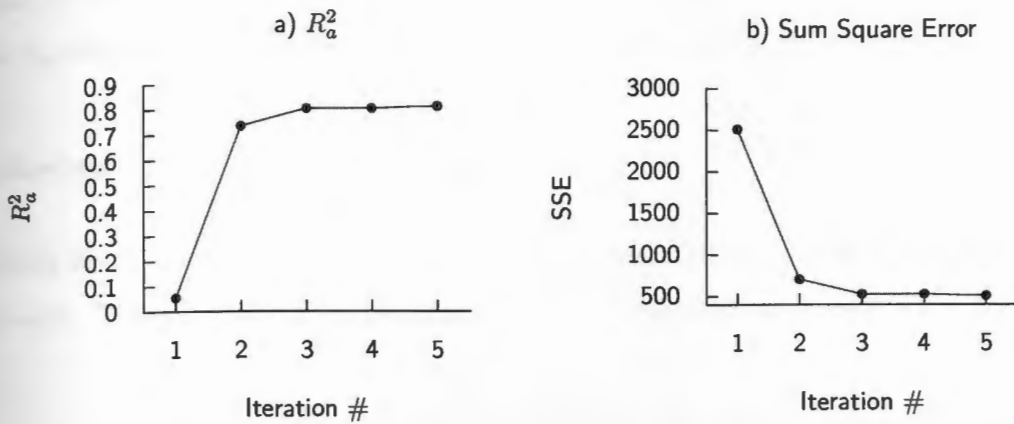
Figure 5.10: Convergence Plots of a) R_a^2 and b) Mean Square Error for Staggered events

5.4.3 Regression with Logarithmic Terms

The occurrence probabilities of Multiple Presence events are not assumed to increase linearly over increasing Traffic Volume or Span Length, but are expected to converge against a maximum value. Hence, additional Logarithmic terms for these parameters were introduced into the regression model. The logarithmic terms are based on the natural logarithm based on e. The terms are added to the best model found in Section 5.4.2 and tested for legitimation using the F-Test introduced in Section 2.2.4 with the methods for the nested models, introduced in Section 2.4.2.

In the latter test, the Null-Hypothesis, that the added logarithmic terms do not contribute to the model accuracy, is expressed by assuming that the β_i-coefficients for the added logarithmic terms are zero. This hypothesis is then tested against the Alternative Hypothesis, that at least one of the added logarithmic terms is legitimate and contributes to the model. That means, in mathematical terms that at least one β_i-coefficient is un-

equal to zero. The hypotheses are tested by comparing the calculated F-Values against the F_α-values from the F-Distribution with a significance level of $\alpha = 0.05$.

Following

Adding logarithmic terms to the Following event data shows a slight increase in the R_a^2-value. The equation for the regression model for the Following events becomes

$$y^* = \beta_0 + \beta_1 S + \beta_2 \log(S) + \beta_3 V + \beta_4 \log(V) + \beta_5 L + \beta_6 R \tag{5.6}$$

The R_a^2-value increases from 0.8331 found in the linear model to 0.8493 when the logarithmic terms are used. The Null Hypothesis is rejected, as the found F-value of 27.3 is much greater than the $\alpha = 0.05$ significance level of the F-Distribution, which is 3.0. This means that at least one of the two added logarithmic terms contributes to the accuracy of the model.

Side-by-Side

For the Side-by-Side events the same analysis is performed, adding logarithmic terms for span-length and volume. Again, a slight increase in the model accuracy is found, as the R_a^2-value increases from 0.7752 to 0.7907 when the logarithmic terms are added. Performing the hypothesis testing, that the reduced model has the same accuracy as the complete model leads to a calulated F-value of 19.13 which is by far larger than the $\alpha = 0.05$ significance level of the F-Distribution, which is 3.0. Therefore, the Null-

Hypothesis is rejected and at least one of the two added logarithmic terms has significant contribution to the model.

Staggered

Also for the Staggered loading case, logarithmic terms were added and the overall model accuracy increased slightly from a R_a^2-value of 0.8082 from the linear model to a R_a^2-value of 0.8171 when adding logarithmic terms. The hypothesis testing is again performed on the Staggered data and the calculated F-value from the model was found to be 12.8. This is again greater than the $\alpha = 0.05$ significance level from the F-Distribution, which is 3.0. Again, the Null Hypothesis is rejected in support of the Alternative Hypothesis that at least one of the added logarithmic terms has a β_i-coefficient unequal to zero.

5.4.4 Residual Analysis

One of the major assumptions of the validity for regression models is the so-called homoscedasticity of the residuals. Homoscedasticity implies that the residuals ϵ all have the same variance σ^2. Unequal residual variances are called heteroscedastic.

As the WIM data is traffic data, it might follow a Poisson-Distribution. For the regression model above this becomes obvious if the residual variance increases for higher Volumes, as exemplary shown for the Following events in Figure 5.11 a). Hence, a heteroscedasticity is evident and the Following data follows a Poisson-Distribution. However, this phenomenon could not be observed for the Side-by-Side and Staggered loading patterns.
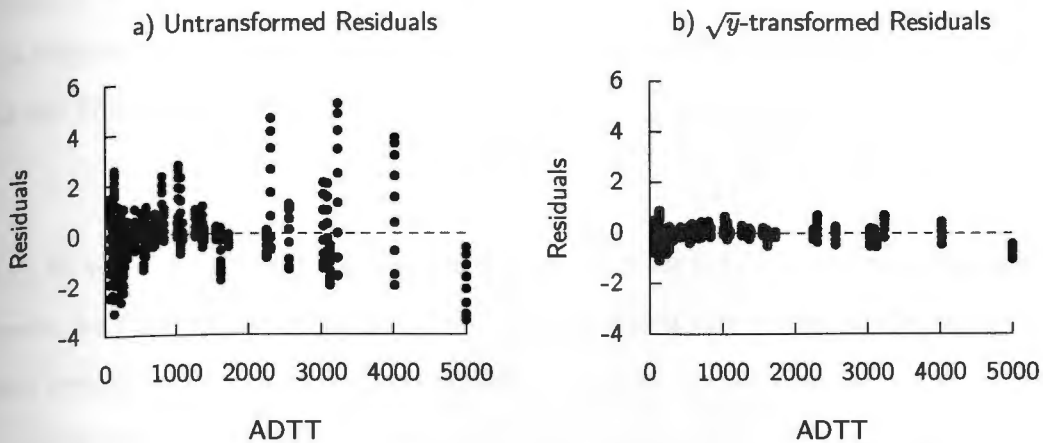
Figure 5.11: Residuals vs. ADTT for a) untransformed y and for b) $\sqrt{y}$-transformed y^* for the Following event.

To regain homoscedasticity, the dependent variable has to be transformed to stabilize the variance. A common transformation for Poisson data is a square-root transformation to achieve a approximately constant variance (Mendenhall and Sincich, 1996, p. 394). So, the transformed dependent variable becomes

$$y^* = \sqrt{y} \tag{5.7}$$

and hence the overall model becomes

$$y^* = \beta_0 + \beta_1 x_1 + \cdots + \beta_k x_k + \epsilon \tag{5.8}$$

A plot of the residuals after transformation to stabilize the variance are shown in Figure 5.11 b). The variance of the residuals for the Following event now appears constant.

Utilizing the model for prediction, the values y^* found have to be transformed back into the original units by using the reverse of the transformation, which is the square of y^* for the Poisson data, so

$$y = (y^*)^2 = \sqrt{y}^2 \tag{5.9}$$

The R_a^2-values for the best models found in the Sections 5.4.2–5.4.2 are compared to the results for the transformed data in Table 5.8. As stated above, only the Following event data seemed to profit from the transformation to stabilize the variance.

Table 5.8: R_a^2-values from untransformed y compared to y^* for transformed data

Loading Case	R_a^2 with y	R_a^2 with y^*
Following	0.7406	0.8331
Side-by-Side	0.7752	0.6111
Staggered	0.8082	0.6952

The variances of the Side-by-Side and the Staggered events seemed already constant and therefore a transformation had no reasonable advantage for the overall model accuracy— actually, a slight decrease in the model accuracy is detected when the dependent variable was transformed.

5.5 Conclusions

The regression models found for the three different Multiple Truck Presence loading cases are developed, tested for legitimacy and provide a good base for predicting the MP occurrences when certain parameters are known.

The β_i coefficients found and the known parameters can now be inserted into the equation as described in Section 2.3 to compute the occurrences of the Multiple Presence events within the intervals also described that Section.

Adding logarithmic terms to the regression models increases the accuracy of all three models slightly but about 1–2%. As a traffic model for practical application should not be overly complex, the logarithmic terms should be omitted, as the extra work to incorporate these terms is disproportionate to the gains in accuracy which are negligible.

An extrapolation for Average Daily Truck Traffic Volumes higher than 5,000 should be executed with extreme caution and skepticism with regard to the results, as this is common pitfall in regression analysis: as the underlying regression model is a linear model, the MP probabilities could rise over 100% with a certain extemely high volume that is far out of range.

A logarithmic model approaches a maximal value asymtotically, which might be below 100%—but again: as this value is far out of range of the orginal regression region, it is most likely to be erroneous.

Looking at the residuals in the regression model, values of up to ±2% occur. The regression model found will graphically result in a line which is representative for the data, with the actual datapoints scattered around that line, as it can be observed similarly in the plots in Section 5.3. Considering this effect, a rather complex equation will lead to reasonable results but is not very practical as the β_i-coefficients found have numerous decimal places.

A good approach to solve this problem is implicitly given by Moses (see Section 3.1.3 and Moses, 2001), as he categorizes the Side-by-Side event probabilities according to

ADTT intervals (cp. Table 3.2). This can be done for arbitrary intervals and levels of conservativeness with respect to the MP probabilties.

An idea of the outline of a table for Multiple Presence occurrence probabilities is shown in Table 5.9. To use the Table, the ADTT interval is chosen and gives a base probability of the loading case, as the Volume was identified to be the most important parameter. The other parameters are found on the right and give additional probabilities, which are to be added to the base probability.

No actual values are given in the table as it is just a suggestion how a table for practical engineers could be designed. For this study and the sake of consistency, the best linear models found for each loading case will be used for the further work and the applied example in Appendix A.

Table 5.9: Proposal for the Design of a MP Table for practical applications

ADTT		0–500	500–1,000	1,000–2,000	⋯
Base Probability		a%	b%	c%	⋯
No. of Lanes	1	+d%	+e%	+f%	⋯
	2	+g%	+h%	+i%	⋯
	⋯	⋯	⋯	⋯	⋯
Span Length	0–50ft	+j%	+k%	+l%	⋯
	50–100ft	⋯	⋯	⋯	⋯
	⋯	⋯	⋯	⋯	⋯
Roadtype	major	+m%	+n%	+o%	⋯
	minor	⋯	⋯	⋯	⋯
Result Interval	min	x%	⋯	⋯	⋯
	max	y%	⋯	⋯	⋯

Chapter 6

Influence of the Gap Distances

Another phenomenon that has not been subject to research in the literature reviewed is the influence of the gap or headway distances. For a Side-by-Side event, the maximum headway distance is defined to be one half of the length of the leading truck, so the influence is very obvious.

For the other types of MP events (Following and Staggered), the gap or headway distances are more variable and might play an important role for the maximum bridge response. The two trucks produce higher responses when being closer together or further apart depending on the loads of the trucks and the static system. In this Chapter, the influence of the gaps and headways for the most common static systems that are used for small to medium span highway bridges—namely a simple supported beam and a continuous beam with one support—is analyzed.

The gaps or headways are normalized to the bridge span length to identify whether a threshold gap to span exists for the MP events to become irrelevant for the maximum responses. The analysis is performed for both Moments and Shear forces, and the outcomes are discussed.

6.1 Static Systems and Influence Lines

The most common static systems for short to medium span highway bridges are either simply supported beams or continuous beams with one support at around midspan. This support is oftentimes the column between the directional lanes when one highway crosses another. These static systems are very simple to calculate and to design for. Figure 6.1 shows the two static systems as models.
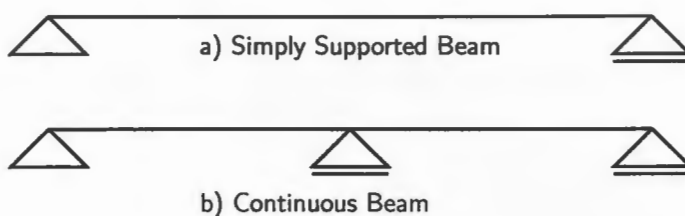
Figure 6.1: The two most common Static Systems for small to medium span Highway Bridges. a) simply supported beam, b) continuous beam with one support

The gap or headway distances are—within their definitions—variable over the span length. Therefore, the influence lines of the moments and the shear forces can be utilized for evaluation. Influence lines represent the variation of the effects or responses (deflections, moments, shear forces) at a certain point when a load is moved over the structure. Multiple loads can simply be superimposed in linear systems.

The placement of the load on the structure that induces the greatest responses can easily be determined from the influence lines. Figure 6.2 shows the influence lines of a concentrated load at midspan for a simply supported beam and a continuous beam with one support at midspan.
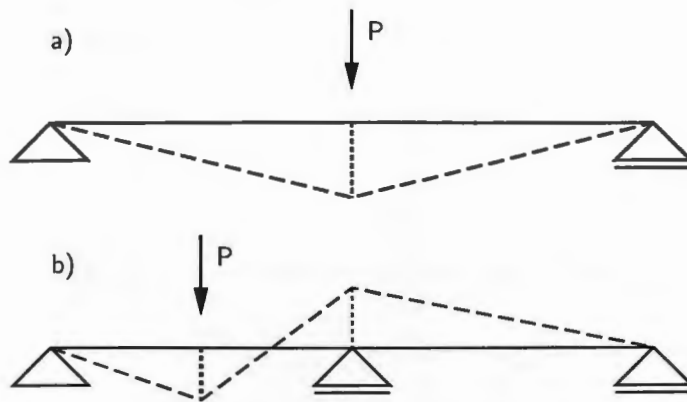
Figure 6.2: Influence Lines for the moments for a) simply supported beam and b) continuous beam with middle support

6.2 Algorithm

When a truck runs over the bridge, the resulting influence line can be superimposed with the influence line of the other truck that is involved in a Multiple Presence, as shown in Figure 6.3. To determine whether a MP event produces greater responses than one of the trucks on its own, the influence of the heavier truck is utilized and the influence of the lighter truck is added with a multiplication factor so that the total Response (R) becomes

$$R_{total} = R_{max} + a \cdot R_{min} \tag{6.1}$$

This has the advantage that it is now easy to determine the influence of the lighter truck, as it is expressed by the factor a. For a equal zero, the influence of the lighter truck is negligible and the maximum response is merely produced by the heavier truck (i.e. at

midspan for the simply supported beam). For a greater than zero, both trucks induce the greatest response together.
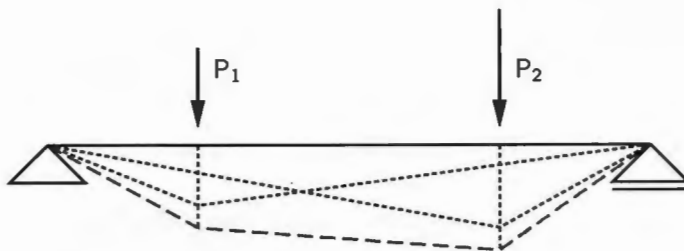
Figure 6.3: Superimposing Loads: The influence lines of each concentrated load can be added up to get the influence line of the whole system

To determine the influence of the positions on the bridge or the headway distances, respectively, the headways are normalized by division through the span length. A threshold gap or headway distance can now be found when a is plotted against the normalized span length. The point where all a-factors converge against zero is the threshold point.

The concentrated loads shown in Figure 6.2 and 6.3 were used for illustration of the theoretical background. For the algorithm, the actual truck configurations of the database were normalized to the HS20 and HL93 loads and utilized for the calculations.

6.3 Analysis and Results

6.3.1 Following

The analysis described above was executed for every Following event in the database for the maximum moment and maximum shear for a simply supported beam and for the maximum negative moment over the column for a continuous beam with one support.

Figure 6.4 shows the outcomes for the maximum moment for a simply supported bridge separated by span length for span lengths of 40ft, 80ft, 120ft and 200ft. It becomes quite obvious that the a-factor declines with greater gap over span ratio and converges to zero at 0.5 gap to span. For greater span lengths of more than 120ft, it is inevitable for small gaps (up to about 0.1 gap to span) that both trucks contribute to the maximum moments. For even greater span lengths, this value increases to about 0.2.

It should be noticed that in Figure 6.4 that only a-values are plotted that vary from zero due to clarity reasons. This represents only about 5–7% of all a-values found—93–95% of the a-values calculated are, in fact, equal to zero.

For the maximum moments of a simply supported beam this means that the threshold of the second truck being influential is when the gap is less than 0.5 of the span length of the bridge. This is comprehensible when looking at the influence lines in Figure 6.3.

For maximum shear for the simply supported beam, the threshold is voided again, as influences of the lighter truck occur for gap to span ratios longer than 0.5. This is also logical as it follows the influence line. Figure 6.5 shows a plot of a vs. gap to span for 40ft and 200ft for the shear. Again a-values equal to zero were omitted in the plot to retain clarity.

The influence of the lighter truck for maximum negative moments over a support of a continuous beam is also not limited to a certain threshold. This again is explainable with the shape of the influence line. Maximum negative moments are generated when each truck is at midspan of a field. Being closer together, the maximum moment becomes smaller. Hence, a wave-shape observed as shown in Figure 6.6 with the greatest influence of the lighter truck at around 0.5 to 0.8 gap to span.
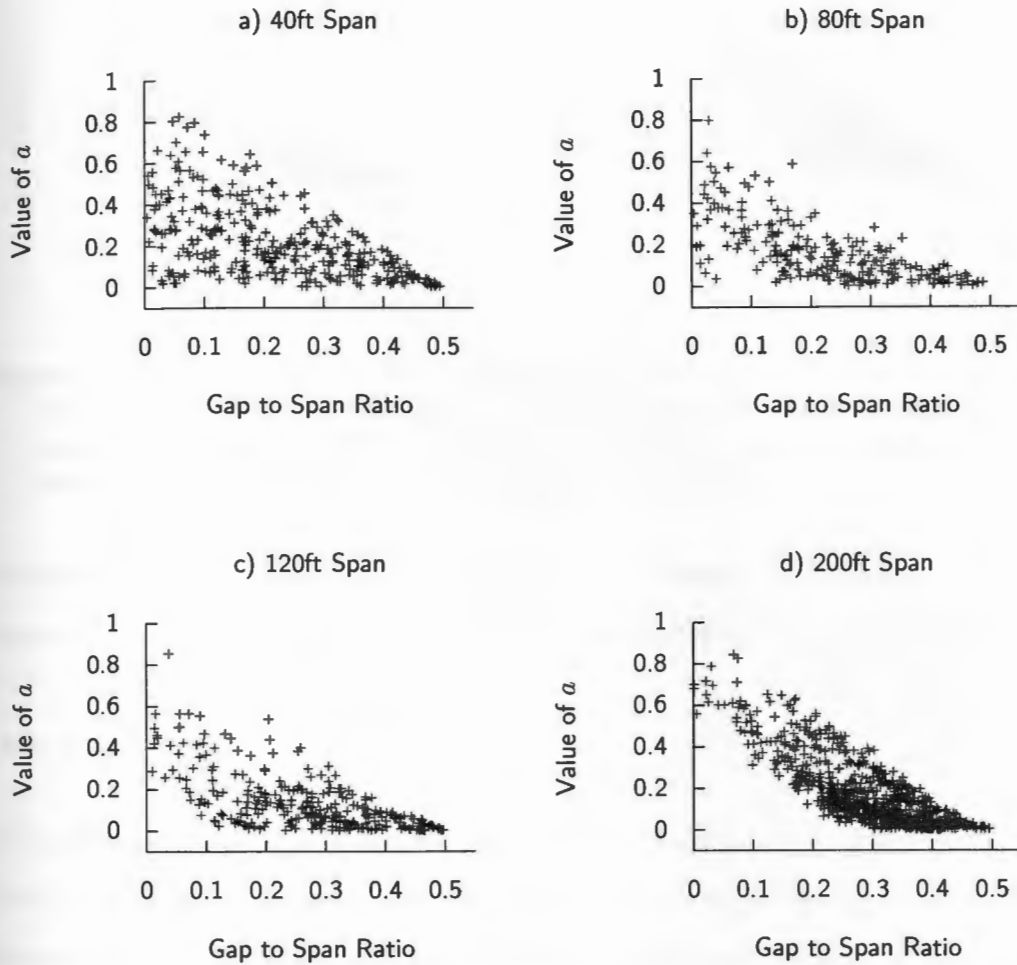
Figure 6.4: Influence factor a for various spans (a) 40ft, b) 80ft, c) 120ft and d) 200ft) for the bending moments of a simply supported beam. It should be noted that for 80ft, only every fifth, for 120ft, only every tenth point was plotted and for 200ft, only every twentieth point was plotted for clarity reasons. Values with a being zero were not plotted at all.

a) 80ft Span   b) 200ft Span
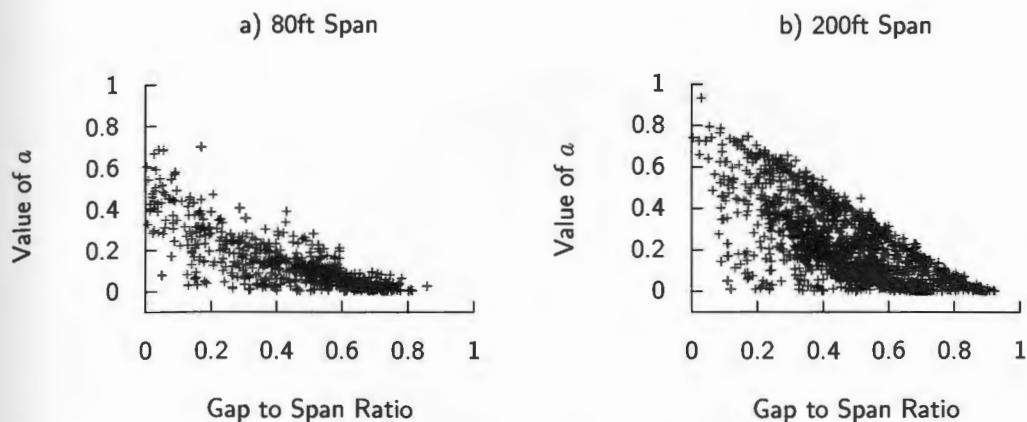
Figure 6.5: Influence factor a for various spans (a) 80ft and b) 200ft) for the shear forces of a simply supported beam. It should be noted that for 80ft, only every fifth point was plotted and for 200ft, only every twenty-fifth point was plotted for clarity reasons. Values with a being zero were not plotted at all.

It should be noted, that for this loading case, no a-values were omitted in the plot, because of being zero. Hence for this loading case, the lighter truck is *always* influential.

6.3.2 Staggered

For the Staggered events, the same analysis was performed as was used for the Following events in Section 6.3.1. The outcomes are quite similar, as the Staggered loading case induces nearly the same responses of longitudinal to a bridge. Torsional bridge or beam responses are not part of this study.

The only difference between Following and Staggered loading cases is that the trucks travel in adjacent lanes rather than in the same lane. In a Staggered event, trucks are allowed to overlap up to half of the truck length of the first truck. A greater overlap is considered a Side-by-Side event.
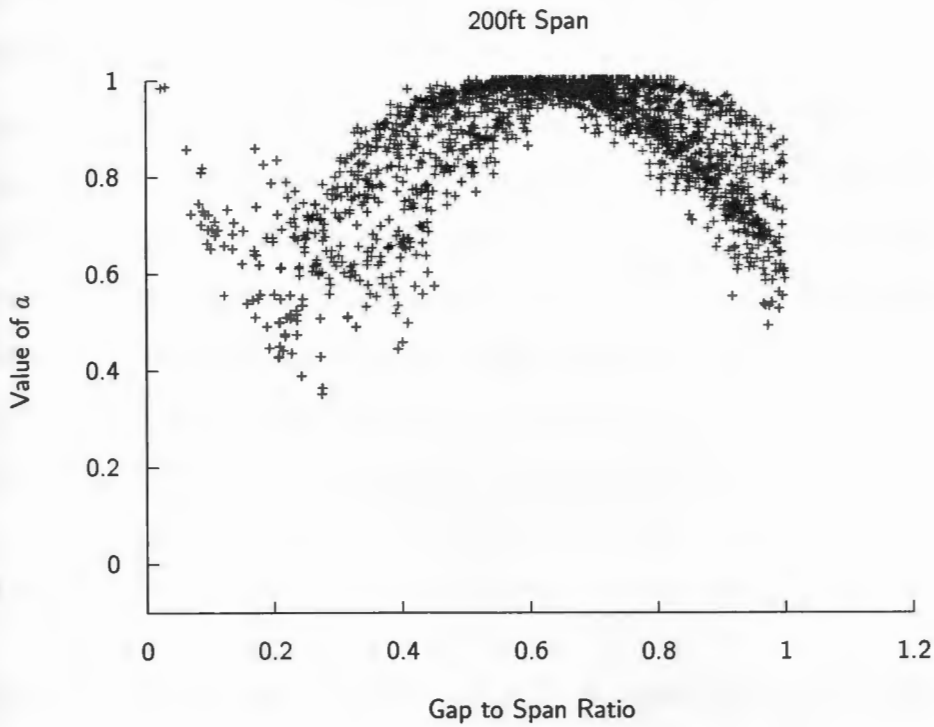
Figure 6.6: Influence factor a for 200ft for the negative moments of a continuous beam at a support. It should be noted that only every fiftieth point was plotted for clarity reasons.

Figure 6.7 shows the results of the analysis for a 200ft span for the three effects, Moment, Shear (for a simply supported beam) and Negative Moment (for a continuous beam with one support). Obviously, the results are very similar to the results found for the Following event for the reasons above. The only difference between the loading cases can be observed in a shift of the thresholds or the wave-shape, respectively, to the right. This shift can be most certainly traced back to the allowance of the overlap. For obvious reasons, Following trucks in one lane can not overlap but have a headway additionally to

the no-overlap criterion. The Staggered event can have an overlap which is per definition less than half of the length of the first truck.

A threshold found is that the smallest gap to span ratio is 0.2. Gap distances less than 0.2 gap to span can be considered as Side-by-Side events. Figure 6.7 also shows, that the influence threshold of the Moments is shifted to the right by about 0.2 gap to span compared to the Following event. The same shift occurs for the Negative Moments, as the wave-shape peaks at about 0.2 gap to span to the right. The 0.2 gap to span shift would also theoretically apply to the Shear as seen in Figure 6.7 b). As a gap to span ratio of greater than 1.0 is not possible, no actual threshold can be found.

6.4 Conclusions

The influence of the gap distance between two trucks in a Following Multiple Presence event (with two trucks) did have an influence on the maximum bridge response for the moments of a simply supported beam. A threshold could be found that denoted the maximum gap distance between two trucks to be influential. A greater distance means that the heavier truck has a greater effect on the moment response when at midspan—regardless of the other truck. For this loading case, the approach would have been very promising, as the analysis shows that for a 200ft span only around 30% of the Following loading cases have a gap distance smaller than 0.5 gap to span, while 70% of the gap distances were found to be between 0.5 and 1.0 gap to span. For smaller spans, these values obviously tend to be even less for <0.5 gap to span and larger for >0.5 gap to span, respectively.
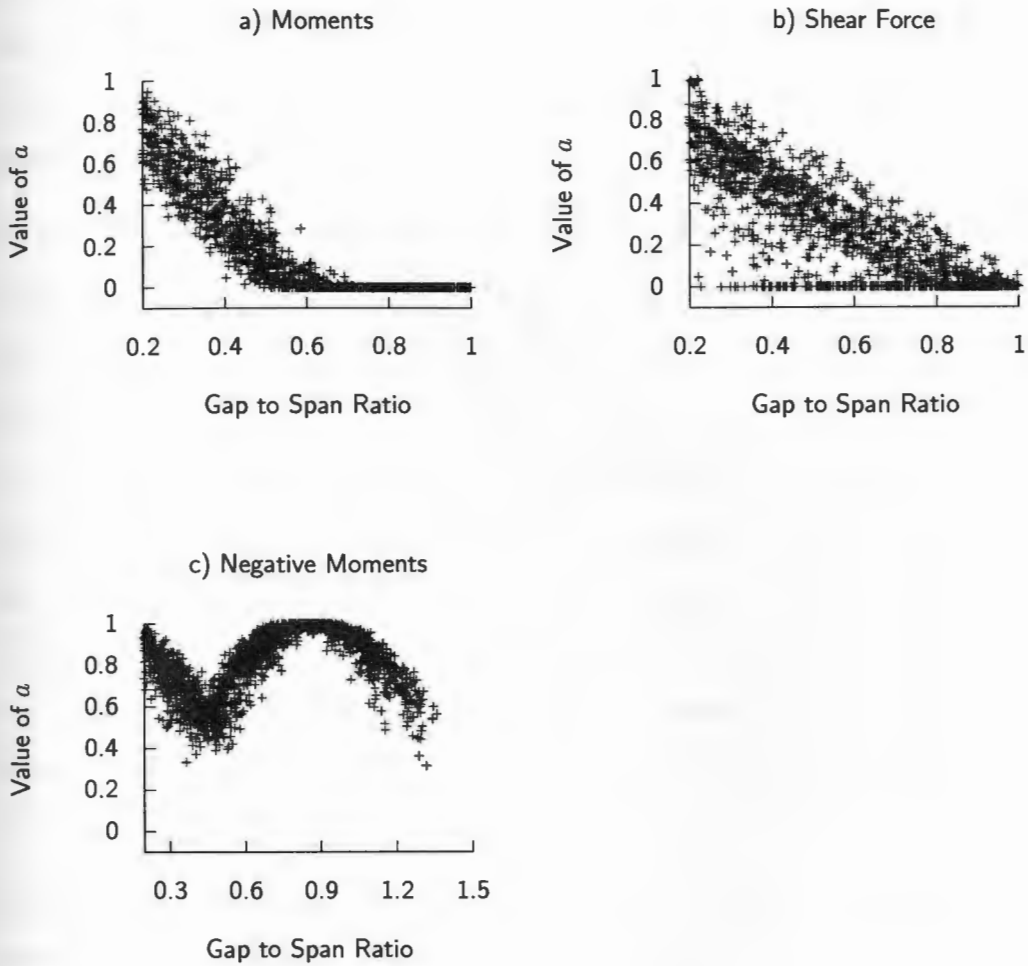
Figure 6.7: Influence factor a for a 200ft span for the Staggered event for a) Moments of a simply supported beam, b) Shear for a simply supported beam and c) Negative Moment for a continuous beam. It should be noted that only every tenth point was plotted for clarity reasons.

This apparent advantage is voided again, when looking at the shear forces of the following events for a simply supported span bridge. Here, the influence of the second (lighter) truck is evident up to a threshold at about 0.9 gap to span. Analysis shows that for a 200ft span, around 90% of the gap distances are smaller than 0.9 gap to span, so that one can say that the threshold found is of rather theoretical nature and should not be included into a life-load model.

For the continuous beam with one middle-support, no threshold value can be found, as the lighter truck always contributes to the the maximum bridge moment responses. The wave-shape of the plot in Figure 6.6 is obviously connected to the influence line in Figure 6.2.

As the Staggered events are very similar to the Following event when looking at the longitudinal load effects, the outcomes resemble the results of the Following events analysis. A slight difference is found in the threshold and the wave-form of the Negative Moments, respectively. The thresholds or peaks seem to be offset by about 0.2 gap to span compared to the Following events. This can be most certainly explained with the different definitions of the loading cases, as the Staggered event allows overlapping of the trucks, while the Following event does not for obvious reasons.

Recapitulatory, the analysis of the influence of the gap distances educed that the probabilities of Multiple Presence Occurrences can not be narrowed down, as no threshold gap distance between the trucks exists that is applicable for all load effects (namely Moments and Shear). Even though many Multiple Presence events occur, where the heavier truck at the most adverse position on the bridge induces greater structural responses than two trucks with a certain gap distance, no distinctive threshold gap distance for all load effects can be determined.

For further analysis in this study, the full probabilities for MP occurrences will be used. The theoretical threshold for simply supported beams at about 0.9 gap to span is omitted on the conservative side.

Chapter 7

Weight Correlation

As stated in Section 3.2, not only the probability of occurrence of Multiple Truck Presence events are critical, but also the weight correlation between the two trucks involved, for determination of the maximum lifetime response. Nowak (Section 3.1.2 and Nowak and Hong (1991); Nowak (1993)) uses correlations that are assumed from the biased Ontario truck data (Agarwal and Wolkowicz, 1976) and therefore appear to be very conservative, as remarked by Moses (Section 3.1.3 and Moses (2001). Other models, based on simulation, treat the MP events entirely through the structural responses, without correlating the truck weights.

For models that explicitly incorporate the Multiple Presence occurrence probabilities, the correlation between the truck weight is a crucial factor for precise maximum load prediction. Therefore, the weight correlation between the two trucks involved is determined throughout this Chapter. To determine whether the weight correlations depend on the event type, the analysis is performed separately for each of the three event types with the two truck weights involved into the MP event.

7.1 Methodology

To find the correlation between the truck weights, a rather simple algorithm is utilized. The loads (GVW) of the two trucks involved in the MP event will be divided to find a ratio between the truck weights. For a full correlation between the truck weights, this ratio will be exactly one.

Testing for the ratio to be exactly one would omit correlated weights that vary only marginally from the ratio to be exactly one, and the result will not reflect the real situation. Therefore, a threshold interval around one was implemented to also consider insignificant differences.

An orientation for the threshold was given by the values that were found by Nowak (Section 3.1.2 and Nowak and Hong (1991)). After a few tests, the most reasonable threshold was found to be around one percent difference. These values provide results that are in the same range as those found by Nowak. Weight differences from up to 0.5 kips for 50 kips trucks seems acceptable, as a like event will definitely induce a great structural response, even though the weights are not fully correlated by theoretical means.

To determine the percentage of fully correlated trucks, the weights of each loading case were divided and the ratio was checked against the interval. If the ratio is within the interval, a counter for fully correlated events is increased. After all occurrences of the particular MP event were checked, the ratio between the fully correlated events and the total number of events is calculated.

7.2 Results

Analysis of correlation was performed for all MP events in the database separated by the loading cases. To determine whether the span length also has an influence on the weight correlation, the analysis was run again for two representative span lengths for each MP loading case.

For the Following MP event, the percentage of fully correlated trucks according to the definition above was found to be 2.4955%, which is about a quarter of the findings of Nowak, who found that every tenth truck in a Following event is fully correlated. The difference might occur because the Following event, according to Nowak, is defined by a maximum gap distance of 50ft (see Section 3.1.2), while in this study the maximum gap distance for a Following event is the bridge span (see Section 5.1). Trucks of equal weight might not be able to pass each other and remain behind each other in close distance. This might explain why Nowak found the correlation to be as high as 10%. It should also be noted that Nowak only examined the upper heavy 20% of the truck population and based his assumptions on this data and visual observation. Figure 7.1 shows a plot of the gross vehicle weight (GVW) of the first truck against the GVW of the second truck for the Follwoing events on a 200ft span.

In this analysis, the correlation is found to be vice versa: for smaller spans, the correlation was found to be less than for longer spans. A 60ft span showed a full weight correlation in 2.04% of the cases, while a 200ft span showed to have 2.537% of full weight correlation.

For the Side-by-Side events, a full weight correlation was found to occur in 1.58% of the Side-by-Side loading cases. This is about in the same range as in Nowak's work, who finds a full correlation in 3–5% of the Side-by-Side cases. The difference again might be
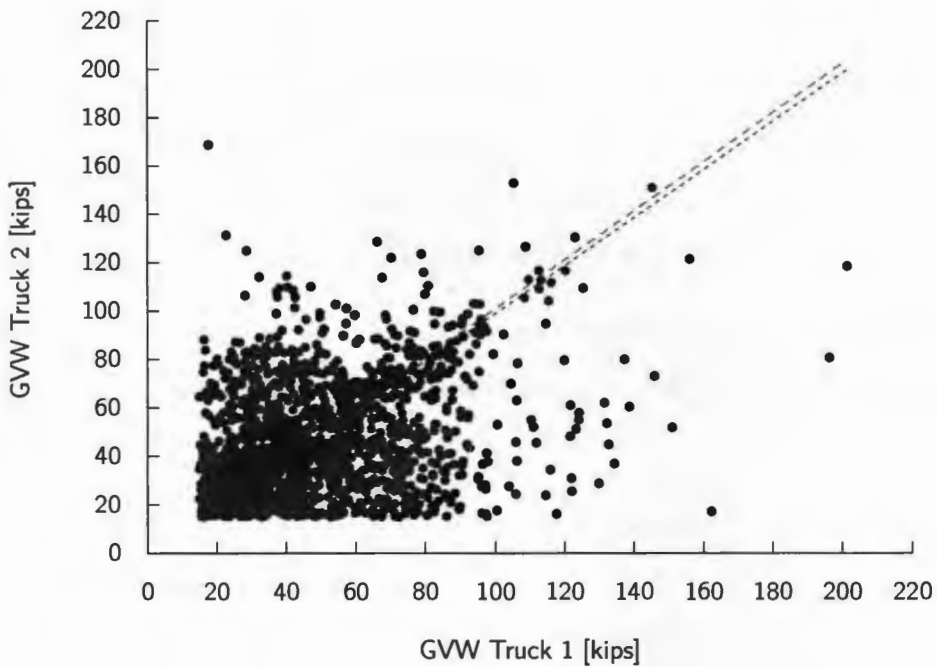
Figure 7.1: Scatterplot of the GVW of the first truck against the GVW of the second truck for the Following events on a 200ft span. For clarity reasons, only every fiftieth data point is plotted. The lines denote the interval that was defined to represent a full correlation. Points within the envelope are considered fully correlated in weight.

explicable with different definitions of a Side-by-Side event and the use of biased data of heavy trucks in Nowak's work. Again, the correlation seems to increase marginally for longer spans, as the full correlation for a 60ft span occurs in 1.57% of all events and in 1.6% of all the events for a 200ft span.

The Staggered event shows a full weight correlation in 1.3829% of all Staggered loading cases. This could be explained, as in a Staggered event, the truck in the left lane is likely to be in the process of passing the assumed heavier truck in the right lane. As the process of passing tends to happen faster when the passing truck is lighter, the chance of being detected as Staggered event is more likely than to be detected as Side-by-Side event. Therefore, a full correlation in weight might be less likely.

The difference in weight correlation only varies marginally with the span length. For a 60ft span, a full correlation probability was found to be 1.37% and for a 200ft span, this probability increased slightly to 1.40%.

All the probabilities for a full weight correlation for the two trucks involved for each loading event are given in Table 7.1.

Table 7.1: Probabilities of a Full Weight Correlation

	60ft	200ft	total	Nowak
Following	2.0392%	2.5369%	2.4955%	10%
Side-by-Side	1.5706%	1.6004%	1.5825%	3–5%
Staggered	1.3707%	1.3998%	1.3829%	N/A

Chapter 8

Conclusions and Recommendations

An extensive review of the literature revealed that basically three different approaches of live-load modeling for bridges exist, namely methods based on statistical methods (also referred to as "Convolution Models"), models based on simulation (i.a. Monte Carlo simulations) and methods that are based on sets of actual traffic data. The first two modeling methods normally involve deep knowledge of the statistical backgrounds (i.a. Moses and Ghosn, Section 3.1.1) or require a decent amount of numerical complexity (i.a. Crespo-Minguillón and Casas, Section 3.1.4) to be applied for practical use. Methods based on traffic datasets (i.a. Nowak, Section 3.1.2) are found to be comparably easy to apply, but incorporate a lot of assumptions concerning the occurrence probabilities and the probabilities of a total weight correlation between the trucks involved in a Multiple Presence event. Other studies (i.a. Guzda et al., Section 3.1.6) develop methods to determine those probabilities from visual evaluation of videos of recorded traffic—which proves to be very time-consuming. Gindy and Nassif (Section 3.1.7) develop a method to determine the Multiple Presence probabilities from WIM data, which is widely available throughout the U.S.

Based on the findings of the latter study, a database was set up for New Jersey WIM data. As only truck data is relevant for maximum live loads, the data was filtered to dispose of car data and faulty entries. The weight distribution was determined, and an algorithm based on the findings of Gindy and Nassif was implemented to detect the probabilities of Multiple Presence events in the NJ data. Based on the outcomes, a regression model was developed to estimate the MP occurrence probabilities based known parameters, such as traffic volume (ADTT), span length, number of lanes, area and road type (Section 5.4). Also, the probabilities of full weight correlation between the two trucks involved in a MP event were identified and found to vary slightly among the MP event types (Chapter 7).

A closer look was taken at the gap distances between the two trucks in a MP event to determine whether a certain gap to span ratio denotes a threshold where the heavier truck induces a greater response on its own than when considered in an MP event. This is done by comparison of the maximum values derived from influence lines of the MP events with both trucks and the heavier truck by itself. The outcomes showed the threshold for the moments of a simply supported beam to be at a gap to span ratio of 0.5. The advantage of the the eventually lesser probability of "true" Following events is voided when looking at the shear forces for the same static system. For continuous beams with one support, no threshold could be detected. However, it was identified, that for this static system, the lighter truck is always influential. Similar results were found for the Staggered loading case (Chapter 6).

The overall findings in this study proved that the assumptions made by Nowak (Section 3.1.2) are overly conservative. The MP probabilities as well as the probabilities of full weight correlations were widely overestimated on the conservative side. Compared

to the outcomes of the simple model developed by Moses (Section 3.1.3) for Side-by-Side events, the resulting MP probabilities found in this study are in about the same range but even tend to be slightly less. Compared to the findings of Guzda et al. (Section 3.1.6) the MP probabilities for Side-by-Side events found in this study are again in the same range but slightly less. This slight variation may be due to the different definitions of a Side-by-Side event.

Based on the findings in this study, a live load model was developed that only requires a few parameters to accurately predict the MP occurrence probabilities and full weight correlation probabilities. The regression model found can be replaced with a table for practical application, as proposed in Table 5.9. The probabilities of full weight correlation could be tabulated in a similar way for easy application.

The two components—MP and full weight correlation probabilities—are a crucial base to evaluate site-specific bridge loading and are of major importance for the accuracy of the overall results. Figure 8.2 gives an overview over the work flow for the evaluation of MP bridge loading. The components of this study are highlighted.

For further research, it is recommended to evaluate the loading cases that have been refered to as "Other" in the detection algorithm. These are loading cases with three or more trucks involved. Even though these loading cases are likely to have a small probability of occurrence, they might become relevant as maximum live-load for the life span of the bridge as identified by Caprani et al. (Section 3.1.5).

For the analysis, two consecutive months of data from New Jersey were used, so seasonal and regional trends are not eliminated from the data. To validate the results found, other WIM data can be used to check for those trends.

As for the regression analysis, a closer look is to be taken whether the linear regression models can be replaced with Logistic Regression methods. Logistic Regression is a special model that is used to estimate or predict the probability of occurrence of an event by fitting data to a logistic curve. A logistic curve or function is a sigmoid curve. That means, an S-curve is modeled with some set of P. It equates

$$P(t) = \frac{1}{1 + e^{-t}} \tag{8.1}$$

First, the growth is exponential and than slows down and stops at maturity as shown in Figure 8.1.
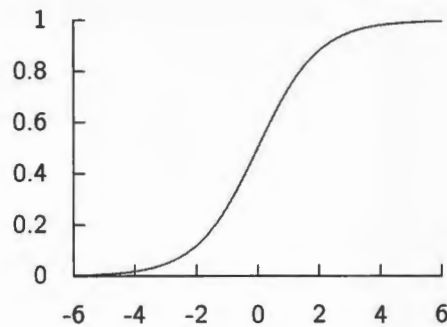
Figure 8.1: The logistic curve

These methods are extensively used in medical and social sciences to predict probabilities of events and therefore seem suitable for the estimation of MP occurrence probabilities. The most apparent advantage of this method is that the probability values cannot exceed a 100% or become less than 0% due to appropriate transformation of the dependent variable $P(Y_i = 1)$.
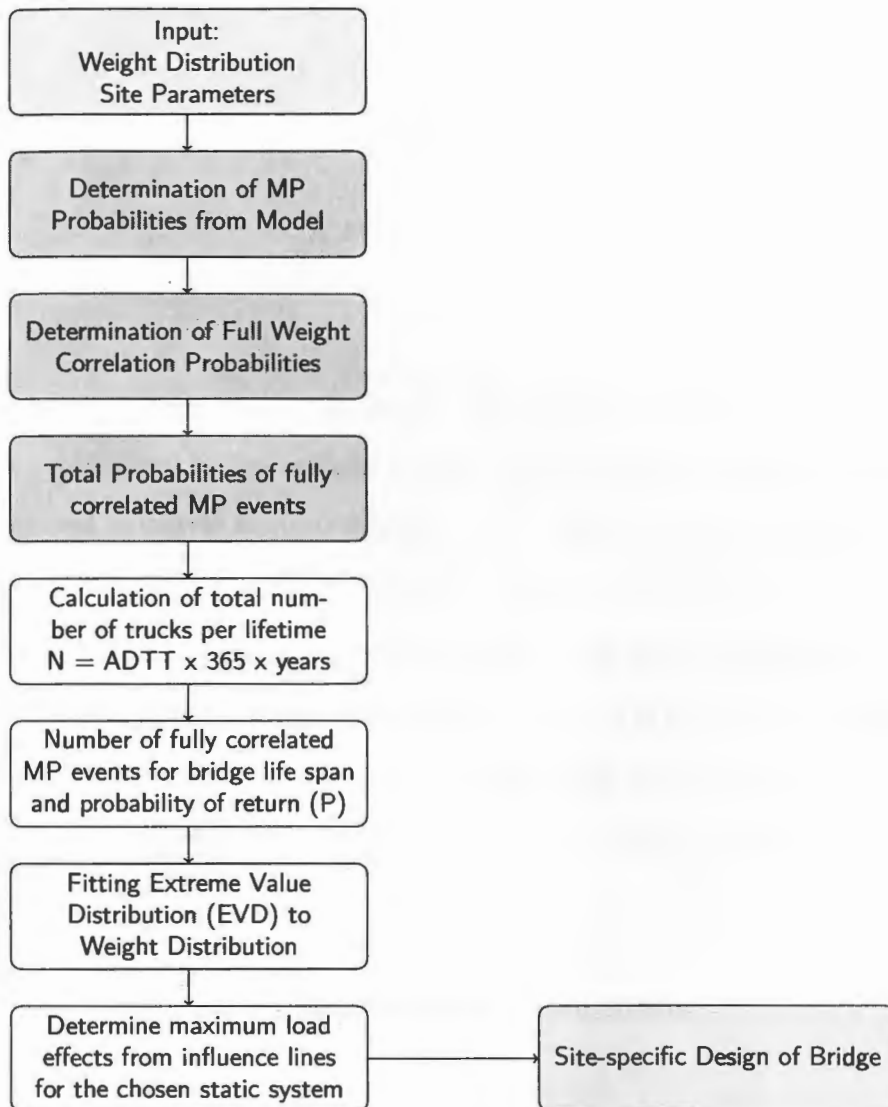
Figure 8.2: Flowchart of a site-specific bridge load evaluation. This study covers the first three steps highlighted. The accuracy of these steps is one of the most crucial parts for an accurate bridge live-load evaluation.

Appendix A

A Practical Example

In this Chapter, the outcomes of this study will be applied to evaluate the total probabilities for an exemplary bridge to show a practical application of the work. This example is not supposed to deliver accurate design values but is to exemplary show how the work from the previous Chapters can be applied to a practical problem.

In this example, a bridge is assumed that has that same weight distribution as the New Jersey data. The Average Daily Truck Volume (ADTT) is assumed to be 4,000 trucks per day. The highway is a major route, and the bridge is located in a rural area and has two lanes in each direction. The span length of the simply supported bridge will be 100ft.

A.1 Determination of Multiple Presence Probabilities

In a first step, the regression model found in Section 5.4 is utilized to determine the probability of the Multiple Presence events. With the parameters from above inserted in the Regression Model, following MP probabilities are found and shown in Table A.1.

Table A.1: Used Probabilities for the MP events

	Exact	Assumed
Following	3.330746%	3.5%
Side-by-Side	1.265878%	1.4%
Staggered	5.13763%	5.3%
Single Trucks	90.2657%	89.8%

A.2 Determination of the Probability of Full Weight Correlation

After Nowak (see Section 3.1.2) and Moses (see Section 3.1.3), the loading cases with the largest bridge responses are those which incorporate two trucks that are fully correlated in weight. Therefore, the probability of full weight correlations was subject to evaluation in Chapter 7. The probabilities for full weight correlation for the three MP loading cases are determined from Table 7.1 in Section 7.2. To be slightly conservative—and thus on the safer side—the probabilities are assumed as shown in Table A.2.

Table A.2: Used Probabilities of a Full Weight Correlation

	Table 7.1	Assumed
Following	2.4955%	3%
Side-by-Side	1.5825%	2%
Staggered	1.3829%	1.75%

These assumptions are not supposed to be a recommendation for general use, but are merely used for this example to retain clarity throughout this example.

A.3 Total Probabilities

The found probabilities from the last two Sections are now simply multiplied to determine the total probabilities of the Multiple Presence events with two fully correlated trucks. Table A.3 shows the results of this simple step.

Table A.3: Total Probabilities of the MP events incorporating two fully correlated trucks

	% Occ.	% Corr.	% Total Prob.
Following	3.5%	3%	0.1050%
Side-by-Side	1.4%	2%	0.0280%
Staggered	5.3%	1.75%	0.0927%

The total probabilities found denote the probability of a truck being involved in one of the three MP events and being fully correlated in weight to the second truck involved in the MP event. With these total probabilities, the number of MP events with two fully correlated trucks can be determined by multiplication with the total number of trucks expected for the lifetime of the bridge. With an Extreme Value Distribution fitted to the ECDF of the weight distribution, the GVW for the maximal trucks involved in such a MP event can be determined and the bridge can be designed according to the findings. The extrapolation of the inverse ECDF of truck weight distributions and/or fitting of extreme value distributions to weight distributions is a wide field of research in bride design and covered by many of the literature introduced on Chapter 3.

Appendix B

Source Code Listings

The following Source Code Listings are written in Matlab (v7.0.1.24704 (R14) Service Pack 1) and are designed for WIM files that have been converted to ASCII and are filtered, or the output-files of the Multiple Presence Detection Algorithm, respectively.

B.1 Multiple Presence Detection Algorithm

```
1   % computeMP.m
2   %
3   % ─────────────────────────────────────────────────────────────────
4   % This program classify loading events as Single, Follow, Side-by-Side, Staggered or Multiple
        (3 or more trucks)
5   % for IRD-format WIM data for different span lengths.  The program:
6   %        (1) Ignores the last truck in each day (because the TimeStamp resets each day)
7   %        (2) Counts the truck that enters second and leaves first ONCE (as part of the multiple
        occurrence)
8   %        (3) Ignores Following trucks with a Headway <= 0 (~ first truck changed lanes after
        entering allowing second truck to enter same lane before full length of Truck 1 passed)
9   %        (4) Accepts only DIRECTIONAL WIM data
10  %        (5) Considers up to 6 lanes in each direction
11  %
12  %
13  % Input    = Directional IRD-format WIM Data (i.e. WIMD1-050801TR.116)
14  % Output   = MP Statistics:  Number of loading events (STATE...) and Percent of loading events
        (STATP...)
15  %
16  % Function programs used are:
17  %    (1)  Timestamp
18  %    (2)  FastTruck
19  %    (3)  LaneValue
20  %    (4)  Refine_Side
21  %    (5)  Refine_Stag
22  % ─────────────────────────────────────────────────────────────────
23  %clear;
24  %clc;
25  %set(0, 'DefaultAxesFontSize', 12);
26
27  function computeMP(filename)
28
29
30  % Load ASCII file
```

```matlab
wim=dlmread(filename);
N=size(wim,1);
yr=wim(:,1);
mo=wim(:,2);
dy=wim(:,3);
hr=wim(:,4);
mn=wim(:,5);
sec=wim(:,6);
hsec=wim(:,7);
err=wim(:,8);
rcd=wim(:,9);
ln=wim(:,10);
sp=wim(:,11);
cl=wim(:,12);
le=wim(:,13);
gvw=wim(:,14);
esal=wim(:,15);
axw1=wim(:,16);  axw2=wim(:,18);  axw3=wim(:,20);  axw4=wim(:,22);  axw5=wim(:,24);  axw6=
    wim(:,26);  axw7=wim(:,28);  axw8=wim(:,30);  axw9=wim(:,32);  axw10=wim(:,34);
    axw11=wim(:,36);   axw12=wim(:,38);   axw13=wim(:,40);   axw14=wim(:,42);
axs1=wim(:,17);  axs2=wim(:,19);  axs3=wim(:,21);  axs4=wim(:,23);  axs5=wim(:,25);  axs6=
    wim(:,27);  axs7=wim(:,29);  axs8=wim(:,31);  axs9=wim(:,33);  axs10=wim(:,35);
    axs11=wim(:,37);   axs12=wim(:,39);   axs13=wim(:,41);

% For each span length:
for LL=2:2:20 % LL=2:2:20

    % Zero out variables
    clear L TStamp Tin Tout omit LN
    clear d dum1 dum2 Headway
    clear Single Follow Side Stag Multiple multiple Total;

    MPS=[];      MPF=[];      MPSD=[];      MPSG=[];      MPM=[];

    L=LL*10; % Span length (ft)

    % Calculate Timestamp
    TStamp  =Timestamp(wim,L);
    Tin     =TStamp(:,1);
    Tout    =TStamp(:,2);

    % Identify trucks that enter second and leave first
    omit    =FastTruck(wim,Tout);

    % Assign Lane Value
    LN      =LaneValue(wim);

    % Start Multiple Presence Statistics
    i=0; % Truck number counter  = 0
    is=1; % Single event counter  = 1
    ifo=1; % Follow event counter  = 1
    isd=1; % Side event counter     = 1
    isg=1; % Staggered event counter = 1
    im=1; % Multiple event counter= 1
    mpe=1; % Loading event counter = 1

    d=LN(1); % Dummy/lane counter for multiple presence
    sm=0; % Truck number for the start of multiple presence = 0
    k=0; % Number of other trucks part of multiple presence = 0

    MP=0; % MP = Total lane value for each multiple event
    jj=1; % jj = counter for the omit vector
    Tend=[]; % Tend = Truck numbers in a loading event

    for I=1:N-1; % FOR LOOP #1 | Loops through all trucks
        i=i+1; % Truck number i

        if i==N; % Checks if last truck in the file
            break % Yes = breaks out of FOR LOOP #1
        end % No  = goes on...

        if i==omit(jj,1); % Checks if truck is part of vector omit
            if jj==size(omit,1); % Yes = skip truck and go to next one (Continue FOR
                LOOP #1)
                jj=jj; % No  = goes on...
```

110

```
102         d=LN(i+1);
103             continue
104     else
105         jj=jj+1;
106         d=LN(i+1);
107             continue
108     end
109 end
110
111 if dy(i+1)==dy(i); % Checks if trucks occur on the same day
112 % No  = skip truck and go to next one (Continue FOR LOOP #1)
113     if Tin(i+1)<Tout(i); % Yes = Checks if trucks overlap in time
114 % No  =  goes on to 'Begin Single'
115         sm=i; % Yes = starts the multiple presence counters
116         k=k+1;
117         d=d+LN(i+1);
118
119         for id=1:10; % FOR LOOP #2 | For the next 10 trucks
120             for j=0:k; % FOR LOOP #3 | For all the trucks that are part of
                    multiple presence
121                 if dy(i+k+1)==dy(sm+j); % Checks if day overlaps
122                 % No  = go to End of FOR LOOP #3 (go to Point 1)
123                     if Tin(i+k+1)<Tout(sm+j); % Yes = Checks if time overlaps
124                     % No  = goes on to Follow/Side or Multiple
125                         if j==k; % Yes = Check if this is the last truck to be
                                checked
126                             break % Yes = go to End of FOR LOOP #3 (go to Point
                                1)
127                         else % No  = check with the next truck (Continue FOR
                                LOOP #3)
128                             continue
129                         end
130
131                     else
132
133                         MP(mpe)=d;
134                         mpe=mpe+1;
135
136                         if k==1; % =============== Follow/Side ===============
137
138                             dum2=0;
139                             for a=0:k; % FOR LOOP #4 | For all trucks that are
                                    part of this multiple presence
140                                 dum1=find((i+a)==Tend); % Check if they are all
                                        part of the previous multiple presence
                                        occurrence
141                                 if dum1>0
142                                     dum2=dum2+1;
143                                 end
144                             end
145                             dum2;
146                             if dum2<(k+1) % No  = New vector for truck numbers
                                    that are part of multiple occurrence ...
                                    classify
147                                 Tend=[i:i+k]; % Yes = go to End of FOR LOOP #3
                                        (go to Point 1)
148                             else
149                                 break
150                             end
151
152                             if (MP(mpe-1)==2)|(MP(mpe-1)==20)|(MP(mpe-1)==200)
                                    |(MP(mpe-1)==2000)|(MP(mpe-1)==20000)|(MP(mpe
                                    -1)==200000)      % Follow
153                                 Headway=(Tin(i+1)-Tin(i))*(sp(i,1)*5280/3600)-
                                        le(i,1);
154                                 if Headway > 0
155                                     MPF(ifo,:)=[wim(i,:) wim(i+1,:) Headway];
156                                     Headway=0;
157                                     ifo=ifo+1;
158                                 end
159                             else
160                                 % It's either a Side or Staggered
161                                 Gap     =(Tin(i+1)-Tin(i))*(sp(i,1)*5280/3600)
                                        % Distance of the gap between the two
                                        trucks (ft)
```

111

```matlab
162                                     Overlap =le(i,1)-Gap % Overlap between the two
                                            trucks (ft)
163
164                                     if Overlap>=0.5*le(i,1);
165                                         isd=isd+1; % Side-by-Side
166                                         MPSD(isd,:)=[wim(i,:) wim(i+1,:) Gap];
167                                     else;
168                                         isg=isg+1;
169                                         MPSG(isg,:)=[wim(i,:) wim(i+1,:) Gap];
170                                     end;
171                                 end
172
173                             else
174                                 % =========== Multiple ===========
175                                 dum2=0;
176                                 for a=0:k; % FOR LOOP #5 | For all trucks that are
                                        part of this multiple presence
177                                     dum1=find((i+a)==Tend); % Check if they are all
                                            part of the previous multiple presence
                                            occurrence
178                                     if dum1>0
179                                         dum2=dum2+1;
180                                     end
181                                 end
182
183                                 dum2;
184                                 if dum2<(k+1) % No = New vector for truck numbers
                                        that are part of multiple occurrence ...
                                        classify
185                                     Tend=[i:i+k]; % Yes = go to End of FOR LOOP #3
                                            (go to Point 1)
186                                 else
187                                     break
188                                 end
189
190                                 for imm=0:k;
191                                     MPM(im+imm,:)=wim(i+imm,:);
192                                 end
193                                 im=im+k+1;
194
195                             end
196
197                             break % Break out of FOR LOOP #3 (go to Point 1)
198                         end
199                     else
200                         break % Break out of FOR LOOP #3 (go to Point 1)
201                     end
202                 end % End of FOR LOOP #3
203
204                 % POINT 1
205                 if j==k % If 'next' truck checked out with all trucks that are part
                        of the multiple occurrence
206                     d=d+LN(i+k+1); % it becomes a part of that multiple and check
                            the next truck (Continue FOR LOOP #2)
207                     k=k+1;
208                     continue
209                 else
210                     d=LN(i+1); % Otherwise, throw back to the main loop (break out
                            of FOR LOOP #2; go to Point 2)
211                     k=0;
212                     sm=0;
213                     break
214                 end
215             end % End of FOR LOOP #2
216
217             % POINT 2
218         else
219             % ============ SINGLE ============
220             dum2=0;
221             for a=0:k; % FOR LOOP #6 | For all trucks that are part of this
                    multiple presence
222                 dum1=find((i+a)==Tend); % Check if they are all part of the
                        previous multiple presence occurrence
223                 if dum1>0
224                     dum2=dum2+1;
225                 end
```

112

```
226              end
227
228              dum2;
229              if dum2<(k+1) % No = New vector for truck numbers that are part of
                     multiple occurrence ... classify
230                  Tend=[i:i+k]; % Yes = go to next truck (Continue FOR LOOP #1)
231              else
232                  d=LN(i+1);
233                  continue
234              end
235
236              MP(mpe)=d;
237              mpe=mpe+1;
238              d=LN(i+1);
239              MPS(is,:)=wim(i,:);
240              is=is+1;
241
242          end
243      else
244          continue % Continue FOR LOOP #1 (next truck)
245      end
246  end
247
248              % Refine SideStag Matrix: SIDE is when two trucks overlap by more than
                     1/2 the body length of the first truck otherwise STAG
249  %MPSD=Refine_Side(MPSS);
250  %MPSG=Refine_Stag(MPSS);
251
252  % Calculate MP Stats
253  Single  =size(MPS,1);              % Number of Single events
254  Follow  =size(MPF,1);              % Number of Follow events
255  Side    =size(MPSD,1);             % Number of Side events
256  Stag    =size(MPSG,1);             % Number of Stag events
257  Multiple=size(MPM,1);              % Number of TRUCKS that take part in a
         multiple loading of 3 trucks or more
258
259  if Single==0;    MPS=[0];    end;
260  if Follow==0;    MPF=[0];    end;
261  if Side==0;      MPSD=[0];   end;
262  if Stag==0;      MPSG=[0];   end;
263  if Multiple==0;  MPM=[0];    end;
264
265  multiple           =fix(Multiple/3);                    % approximate number of
         loading events for Multiple event assuming 3 trucks per event
266  Total              =Single+Follow+Side+Stag+multiple;   % total number of
         loading events
267  x=LL/2;
268  StatEvents(x,:)    =[Single Follow Side Stag multiple];
269  StatPercent(x,:)   =[(Single/Total)*100 (Follow/Total)*100 (Side/Total)*100 (Stag/
         Total)*100 (multiple/Total)*100];
270
271  MPresence(1,x)={MPS};
272  MPresence(2,x)={MPF};
273  MPresence(3,x)={MPSD};
274  MPresence(4,x)={MPSG};
275  MPresence(5,x)={MPM};
276
277  % Save MP files for each span length
278  if L==20;
279      datei = sprintf('MPS020-SN-%s', filename)
280      save (datei,'MPS','-ascii')
281
282      datei = sprintf('MPS020-FL-%s', filename)
283      save (datei,'MPF','-ascii')
284
285      datei = sprintf('MPS020-SD-%s', filename)
286      save (datei,'MPSD','-ascii')
287
288      datei = sprintf('MPS020-SG-%s', filename)
289      save (datei,'MPSG','-ascii')
290
291      datei = sprintf('MPS020-MT-%s', filename)
292      save (datei,'MPM','-ascii')
293  end;
294
295  if L==40;
```

```
296      datei = sprintf('MPS040-SN-%s', filename)
297      save (datei,'MPS','-ascii')
298
299      datei = sprintf('MPS040-FL-%s', filename)
300      save (datei,'MPF','-ascii')
301
302      datei = sprintf('MPS040-SD-%s', filename)
303      save (datei,'MPSD','-ascii')
304
305      datei = sprintf('MPS040-SG-%s', filename)
306      save (datei,'MPSG','-ascii')
307
308      datei = sprintf('MPS040-MT-%s', filename)
309      save (datei,'MPM','-ascii')
310
311   end;
312
313   if L==60;
314      datei = sprintf('MPS060-SN-%s', filename)
315      save (datei,'MPS','-ascii')
316
317      datei = sprintf('MPS060-FL-%s', filename)
318      save (datei,'MPF','-ascii')
319
320      datei = sprintf('MPS060-SD-%s', filename)
321      save (datei,'MPSD','-ascii')
322
323      datei = sprintf('MPS060-SG-%s', filename)
324      save (datei,'MPSG','-ascii')
325
326      datei = sprintf('MPS060-MT-%s', filename)
327      save (datei,'MPM','-ascii')
328
329   end;
330
331   if L==80;
332      datei = sprintf('MPS080-SN-%s', filename)
333      save (datei,'MPS','-ascii')
334
335      datei = sprintf('MPS080-FL-%s', filename)
336      save (datei,'MPF','-ascii')
337
338      datei = sprintf('MPS080-SD-%s', filename)
339      save (datei,'MPSD','-ascii')
340
341      datei = sprintf('MPS080-SG-%s', filename)
342      save (datei,'MPSG','-ascii')
343
344      datei = sprintf('MPS080-MT-%s', filename)
345      save (datei,'MPM','-ascii')
346
347   end;
348
349   if L==100;
350      datei = sprintf('MPS0100-SN-%s', filename)
351      save (datei,'MPS','-ascii')
352
353      datei = sprintf('MPS0100-FL-%s', filename)
354      save (datei,'MPF','-ascii')
355
356      datei = sprintf('MPS0100-SD-%s', filename)
357      save (datei,'MPSD','-ascii')
358
359      datei = sprintf('MPS0100-SG-%s', filename)
360      save (datei,'MPSG','-ascii')
361
362      datei = sprintf('MPS0100-MT-%s', filename)
363      save (datei,'MPM','-ascii')
364
365   end;
366
367   if L==120;
368      datei = sprintf('MPS0120-SN-%s', filename)
369      save (datei,'MPS','-ascii')
370
371      datei = sprintf('MPS0120-FL-%s', filename)
```

```
372        save (datei , 'MPF', '−ascii ')
373
374        datei = sprintf('MPS0120−SD−%s', filename)
375        save (datei , 'MPSD', '−ascii ')
376
377        datei = sprintf('MPS0120−SG−%s', filename)
378        save (datei , 'MPSG', '−ascii ')
379
380        datei = sprintf('MPS0120−MT−%s', filename)
381        save (datei , 'MPM', '−ascii ')
382
383    end ;
384
385    if L==140;
386        datei = sprintf('MPS0140−SN−%s', filename)
387        save (datei , 'MPS', '−ascii ')
388
389        datei = sprintf('MPS0140−FL−%s', filename)
390        save (datei , 'MPF', '−ascii ')
391
392        datei = sprintf('MPS0140−SD−%s', filename)
393        save (datei , 'MPSD', '−ascii ')
394
395        datei = sprintf('MPS0140−SG−%s', filename)
396        save (datei , 'MPSG', '−ascii ')
397
398        datei = sprintf('MPS0140−MT−%s', filename)
399        save (datei , 'MPM', '−ascii ')
400
401    end ;
402
403    if L==160;
404        datei = sprintf('MPS0160−SN−%s', filename)
405        save (datei , 'MPS', '−ascii ')
406
407        datei = sprintf('MPS0160−FL−%s', filename)
408        save (datei , 'MPF', '−ascii ')
409
410        datei = sprintf('MPS0160−SD−%s', filename)
411        save (datei , 'MPSD', '−ascii ')
412
413        datei = sprintf('MPS0160−SG−%s', filename)
414        save (datei , 'MPSG', '−ascii ')
415
416        datei = sprintf('MPS0160−MT−%s', filename)
417        save (datei , 'MPM', '−ascii ')
418
419    end ;
420
421    if L==180;
422        datei = sprintf('MPS0180−SN−%s', filename)
423        save (datei , 'MPS', '−ascii ')
424
425        datei = sprintf('MPS0180−FL−%s', filename)
426        save (datei , 'MPF', '−ascii ')
427
428        datei = sprintf('MPS0180−SD−%s', filename)
429        save (datei , 'MPSD', '−ascii ')
430
431        datei = sprintf('MPS0180−SG−%s', filename)
432        save (datei , 'MPSG', '−ascii ')
433
434        datei = sprintf('MPS0180−MT−%s', filename)
435        save (datei , 'MPM', '−ascii ')
436
437    end ;
438
439    if L==200;
440        datei = sprintf('MPS0200−SN−%s', filename)
441        save (datei , 'MPS', '−ascii ')
442
443        datei = sprintf('MPS0200−FL−%s', filename)
444        save (datei , 'MPF', '−ascii ')
445
446        datei = sprintf('MPS0200−SD−%s', filename)
447        save (datei , 'MPSD', '−ascii ')
```

```
448
449                         datei = sprintf('MPS0200-SG-%s', filename)
450                         save (datei,'MPSG','-ascii')
451
452                         datei = sprintf('MPS0200-MT-%s', filename)
453                         save (datei,'MPM','-ascii')
454
455                 end;
456
457             end;
458
459             % Save MP Statistics Files
460             datei = sprintf('MPEvent-%s', filename)
461             save(datei, 'StatEvents','-ascii')
462
463             datei = sprintf('MPPerct-%s', filename)
464             save(datei, 'StatPercent','-ascii')
```

B.2 Full Correlation Detection

```
1    %    Weight Correlation
2    %    correlation.m
3    %
4    %    This program analyses the correlation between truck weights for the MP
5    %    Outputs. Range is variable but preset to +- 1%
6    %
7    %    Cornelius Albrecht @ June 2008
8
9    % Clear
10   clear
11   clc
12   % Input
13   %L = 120
14   input = dir('*200-FL-*')
15
16   % Read Files and Extract GVWs
17   GVW1=0;
18   GVW2=0;
19   for i=1:size(input)
20       wim=dlmread(input(i).name);
21       N=size(wim,1);
22
23       % Check if empty file
24       if (N > 1)
25           if GVW1 == 0
26               GVW1 = wim(:,14);
27           else
28               GVW1 = [GVW1; wim(:,14)];
29           end
30
31           if GVW2 == 0
32               GVW2 = wim(:,56);
33           else
34               GVW2 = [GVW2; wim(:,56)];
35           end
36       end
37   end
38
39   % Count for Correlation
40   % Counter set to 0
41   in=0;
42   out=0;
43
44
45   % Difference to check for correlation
46   diff = GVW1 ./ GVW2;
47
48   % Check for Correlation
49   for i=1:size(diff)
50       % Full Correlation
```

116

```
51      if ( diff ( i ) <=1.01 && diff ( i ) >=0.99)
52          in = in +1;
53      else
54      % No correlation
55          out = out +1;
56      end
57  end
58
59  % Determine Percentage
60  all = in + out;
61  % Print In/All Ratio
62  (in/all)*100
```

B.3 Gap Influences

```
1   % Analysis of Following loading events
2
3   % Import filenames for span length. EDIT HERE
4   L = 160
5   input = dir ('*160*')
6
7
8   % Convert filenames to characters
9   %NF=size(filenames,1)
10
11  for i =1:size (input)
12      %file=char(filenames(f,1))
13      wim=dlmread(input(i).name);
14      N=size(wim,1);
15
16      % Check if empty file
17      if N == 1
18          Output{i ,1}=[0];
19          continue
20      end
21
22          % Parameter definition
23          YR   =[wim(:,1)  wim(:,43)];
24          MO   =[wim(:,2)  wim(:,44)];
25          DY   =[wim(:,3)  wim(:,45)];
26          HR   =[wim(:,4)  wim(:,46)];
27          MN   =[wim(:,5)  wim(:,47)];
28          SEC  =[wim(:,6)  wim(:,48)];
29          HSEC=[wim(:,7)  wim(:,49)];
30          ERR  =[wim(:,8)  wim(:,50)];
31          RCD  =[wim(:,9)  wim(:,51)];
32          LN   =[wim(:,10)  wim(:,52)];
33          SP   =[wim(:,11)  wim(:,53)];
34          CL   =[wim(:,12)  wim(:,54)];
35          LE   =[wim(:,13)  wim(:,55)];
36          GVW  =[wim(:,14)  wim(:,56)];
37          ESAL=[wim(:,15)  wim(:,57)];
38
39          Head    =wim(:,85);
40          MomHS20 =[wim(:,86:88)];
41          MomHL93 =[wim(:,89:91)];
42          ShrHS20 =[wim(:,92:94)];
43          ShrHL93 =[wim(:,95:97)];
44          NMomHL93=[wim(:,98:100)];
45
46      % Following = Max(Truck) + A*Min(Truck)
47      HeadR=Head/L;
48      MaxTruck=max(MomHS20(:,1),MomHS20(:,2));
49      MinTruck=min(MomHS20(:,1),MomHS20(:,2));
50      A=(MomHS20(:,3)-MaxTruck)./MinTruck;
51
52      % Percentage Split of Headway Ratio @ 0.50
53      BinHeadR=[0:0.5:1]';
54      Count   =histc(HeadR,BinHeadR);
55      Close   =Count(1,1)/N;
```

```matlab
56          Apart    =Count(2,1)/N;
57
58      % Output
59      OutHead{i,1}=[Head HeadR A];
60      OutPerc{i,1}=[Close Apart];
61
62      % Clear out variables
63      clear file wim
64      clear YR MO DY HR MN SEC HSEC ERR RCD LN SP CL LE GVW ESAL
65      clear Head MomHS20 MomHL93 ShrHS20 ShrHL93 NMomHL93
66      clear HeadR MaxTruck MinTruck A
67      clear BinHeadR Count Close Apart
68  end
69
70  % *************************************************************
71  % **            Histogram by Distance
72  % *************************************************************
73
74      % Combine OutHead files
75      OUTHead=vertcat(OutHead{:,:});
76
77      % Combine OutPerc files
78          for f=1:size(input)
79              Flag=isempty(OutPerc{f,1});
80              if Flag==1
81                  OutPerc{f,:}=[0  0];
82              end
83          end
84          OUTPerc=vertcat(OutPerc{:,:});
85
86      % Save files
87      percname = sprintf('PERC_FO-Inf-S%d', L)
88      headname = sprintf('HEAD_FO-Inf-S%d', L)
89      dlmwrite(percname , OUTPerc)
90      dlmwrite(headname, OUTHead)
91
92      clc;
```

Bibliography

This Bibliography includes *all* references that have been used for preparation of this Master Thesis and also includes references that have not explicitly been cited in the text. The following list is sorted in alphabetical order of the surnames of the authors/names of institutions and does not represent the order of citation.

Weigh-in-Motion of Road Vehicles for Europe (WAVE) - A Data Quality Assurance System for the European WIM-Database, 2000a.

Weigh-in-Motion of Road Vehicles for Europe (WAVE) - Calibration of WIM Systems, 2000b.

AASHTO. Bridge design standard specifications. Technical report, AASHTO, Washington D.C., 1989.

AASHTO. Aashto lrfd bridge design specifications. Technical report, AASHTO, Washington, D.C., 1994.

AASHTO. Lrfd bridge design specifications. Technical report, AASHTO, Washington D.C., 1998.

A.C. Agarwal and M. Wolkowicz. Interim report on ontario commercial vehicle survey. Technical report, Research and Development Branch, Ontario Ministry of Transporation and Communication, Downsview Ontario, 1976.

ASTM. E1318-02 standard specification for highway weigh-in-motion (wim) systems with user requirements and test methods. Technical report, 2002.

S. Bailey and R. Bez. A parametric study of traffic load effects in medium span bridges, 1994. URL `citeseer.ist.psu.edu/bailey94parametric.html`.

S. Bailey and R. Bez. Site specific traffic load models for bridge evaluation, 1995. URL `citeseer.ist.psu.edu/bailey95site.html`.

Battelle. Traffic data quality management. Technical report, U.S. Department of Transportation, 2004.

Colin C. Caprani. *Probabilistic Analysis of Highway Bridge Traffic Loading.* PhD thesis, National University of Ireland, 2005.

Colin C. Caprani, Eugene J. OBrien, and Geoff J. McLachlan. Characteristic traffic load effects from a mixture of loading events on short to medium span bridges. *Structural Safety*, 11.006:1–11, 2007.

E. Castillo. *Extreme Value Theory in Engineering.* Academic Press, London, 1991.

Anil K. Chopra. *Dynamics of Structures (3rd Edition).* Prentice Hall, 2006.

Cesar Crespo-Minguillon and Juan R. Casas. A comprehensive traffic load model for bridge safety checking. *Structural Safety*, 19(4):339–359, 1997.

Dr. Nathan Gartner, Dr. Carroll J. Messer, and Dr. Ajay K. Rathi. Revised monograph on traffic flow theory. Online. URL http://www.tfhrc.gov/its/tft/tft.htm.

Michael Ghosn and Fred Moses. Reliability calibration of bridge design code. *Journal of Structural Engineering*, 112:745–763, 1986.

Mayrai Gindy and Hani H. Nassif. Multiple presence statistics for bridge live-load based on weigh-in-motion data. *Transporation Research Board*, 2028:125–135, 2007. Published 02/2008.

E.J. Gumbel. *Statistics of Extremes*. Columbia University Press, New York, 1958.

Mark Guzda, Baidurya Bhattacharya, and Dennis R. Mertz. Probabilistic characterization of live load using visual counts and in-service strain monitoring. *Journal of Bridge Engineering*, 12:130–134, 2007.

Mark Hallenbeck. Ltpp: Traffic data collection equipment calibration. Technical report, Long Term Pavement Performance Program, 1998.

C. Han, W. Boyd, and M. Marti. Quality control of weigh-in-motion-systems. *Transporation Research Record*, 1501:72–79, 1995.

R.J. Heywood and A.S. Nowak. Bridge live load models. In *International Conference on Structural Safety and Reliability, San Francisco*, pages 2147–2154, 1989.

Abryan J. Katz and Hesham A. Rakha. Final report of its center project: Weigh-in-motion evaluation. Technical report, Virginia Tech Transportation Institute, 2002.

A. May. *Traffic Flow Fundamentals*. Prentice Hall, 1990.

Bill McCall and Walter C. Vodrazka. States successful practices weigh-in-motion handbook. Technical report, U.S. Department of Transportation, Federal Highway Administration, 1997.

William Mendenhall and Terry Sincich. *A second course in Statistics: Regression Analysis*. Prentice Hall, 1996.

F. Moses and R. C. Garson. Probability theory of highway bridge fatigue stresses. Technical report, Ohio Department of Transportation, 1973.

F. Moses and M. Ghosn. Instrumentation for weighing trucks-in-motion for highway bridge loads. Technical report, FHWA/OH-81/008, 1983.

F. Moses and M. Ghosn. A comprehensive study of bridge loads and reliability, final report to odot. Technical report, Case Western Reservce University, Cleveland, OH, 1985.

Fred Moses. Calibration of load factors for lrfr bridge evaluation. Technical report, NCHRP Rep. No. 454, National Academy Press, Washington, 2001.

Charles R. Nelson. *Applied Time Series Forecasting*. Holden-Day, 1973.

Andrew Nichols and Darcy Bullock. Quality control procedures for weigh-in-motion data. Technical report, School of Civil Engineering Purdue University, 2004.

Andrew P. Nichols and Darcy M. Bullock. Automatic speed calibration methodology for traffic monitoring sites. *Journal of Transportation Engineering*, 132:30–39, 2006.

Andrezj S. Nowak and Young-Kyun Hong. Bridge live-load models. *Journal of Structural Engineering*, 117:2757–2767, 1991.

A.S. Nowak. Live load model for highway bridges. *Structural Safety*, 13:36–49, 1993.

A.S. Nowak. Load model for bridge design code. *Canadian Journal of Civil Engineering*, 21:36–49, 1994.

A.S. Nowak. Calibration of lrfd bridge design code. Technical report, NCHRP Report 368, Transportation Research Board, National Research Council, Washington, D.C., 1999.

A. O'Connor and E.M. Eichinger. Site-specific traffic load modelling for bridge assessment. *Bridge Engineering 160*, BE4:185–194, 2007.

New York State Department of Transportation. Traffic data report for new york state. Technical report, New York State Department of Transportation, 2004.

US Department of Transportation. Traffic monitoring guide. Technical report, US Department of Transportation, 2001.

W. C. Ottl and A. T. Papagiannakisl. Weigh-in-motion data quality assurance based on 3-s2 steering axle load. *Transporation Research Board*, 1356:12–18, 1996.

Robert S. Pindyck and Daniel L. Rubinfeld. *Econometric Models & Economic Forecasts*. McGraw-Hill, 1991.

R. Snyder, G. Likins, and F. Moses. Loading spectra expe- rienced by bridges in the united states. Technical report, Federal Highway Administration, FHWA/RD-85/012, Washington, D.C., 1985.

X. Zhi, A. Shalaby, D. Middleton, and A. Clayton. Evaluation of weigh-in-motion-systems. *Canadian Journal of Civil Engineering*, 26:655–666, 1999.

Unit Conversion

To convert from empirical	to SI	multiply by
Length		
inch (in.)	meter (m)	0.0254
foot (ft)	meter (m)	0.3048
yard (yd)	meter (m)	0.9144
Force		
kip	newton (N)	4448.0
pound (lb)	newton (N)	4.448
Stress		
pounds/square inch (psi)	kilopascal (kPA)	6.895
Mass (Weight per Length)		
pound/linear foot (klf)	newton/meter (N/m)	14.593
Bending Moment or Torque		
inch-pound (in.-lb)	newton-meter (Nm)	0.1130
foot-pound (ft-lb)	newton-meter (Nm)	1.356

"Statistical thinking will one day be as necessary for efficient citizenship as the ability to read or write."
—H.G. Wells