UPDATING AND ENHANCING THE NORTH CAROLINA DEPARTMENT OF TRANSPORTATION'S BRIDGE MANAGEMENT SYSTEM USER COSTS

by

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ABSTRACT

JOSHUA DANIEL RAMSEY. Updating and enhancing the North Carolina Department of Transportation's Bridge Management System user costs. (Under the direction of DR. TARA CAVALLINE)

A Bridge Management System (BMS) can be used for both storage of data and to provide decision making tools for maintenance, repair, and rehabilitation (MR&R) needs and cost forecasting. The North Carolina Department of Transportation's (NCDOT) BMS currently includes bridge deterioration rates, agency costs, MR&R costs, and user costs to assist with prediction and prioritization of future needs. User costs are costs burdened by the public when a bridge is unusable by some portion of vehicles or is associated with bridge-related accidents. Key inputs required to compute user costs in NCDOT's BMS include average daily traffic, detour length, percentage of vehicles detoured due to either weight or height, vehicle operating cost associated with detour, number of bridge-related accidents, frequency of bridge-related accident severities, and the costs of accidents. To provide accurate user costs for forecasting, these BMS inputs need to be regularly updated or enhanced as better methodologies for obtaining these inputs becomes available. In this work, updates and enhancements to NCDOT's BMS user cost inputs and determination methodologies were identified, and new inputs were determined. An analysis of recent bridge-related accidents in North Carolina was performed to identify bridge characteristics most associated with bridge-related accidents and to produce an equation that predicts the number of bridge-related accidents for subsets of bridges based on data currently available in the BMS. A sensitivity analysis on user costs was also performed, indicating that user costs for NCDOT's bridges are largely driven by costs due to bridge-related accidents.

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CHAPTER 1: INTRODUCTION

A well-designed and consistently updated Bridge Management System (BMS) has been shown to provide valuable information to assist state and federal agencies in decisions regarding maintenance, repair, and rehabilitation (MR&R) or replacement of bridges. Currently the Federal Highway Administration (FHWA) requires all bridges nationwide to be inspected every two years, with updated information recorded annually within the National Bridge Inventory (NBI). The FHWA requires 116 items to be inspected, characterized, or recorded for each bridge. Additionally, each state agency typically collects and records additional data, including inspection data for the specific bridge elements, as warranted by conditions, preferences, and management practices specific to that state. This data is used in many BMS systems because it contains information pertaining to structural and functional deficiencies and functional characteristics such as detour lengths, narrow bridge deck width, load posting, and vertical clearance (Sinha et al. 2009). These input data help the BMS system compute user costs for each bridge based on its deficiencies and functional data. User costs assist an agency in forecasting the amount of money individuals and companies are expected to lose or spend due to these structural and functional deficiencies. With this cost considered, a state can better allocate how funds should be spent based on current needs, as well as forecasted future costs, to optimize the scheduling of MR&R or replacement of bridges.

The North Carolina Department of Transportation (NCDOT) initially utilized a BMS program that was developed in the late 1980's by North Carolina State University (NCSU) (Chen and Johnston 1987). Updates to this program, including user costs, were performed periodically by NCSU (Abed-Al-Rahim and Johnston 1991, Duncan and Johnston 2002, Johnston 2010). Since that time, the BMS software utilized by NCDOT has changed to a program developed by a private firm, AgileAssets Inc. It is reported that the algorithms and methodology utilized by the AgileAssets Inc. software is based largely on the work done by NCSU. The method currently utilized to compute bridge user costs has reportedly been changed only minimally from the original methodology developed by NCSU. Updates to specific inputs, including vehicle operating cost, accident costs, and Average Daily Traffic (ADT) growth rates have been performed periodically (using the original methodology), but not yearly. This reduces the fidelity of the user costs predicted by the BMS. In coordination with AgileAssets Inc., NCDOT has enhanced its BMS during the past 10 years and is preparing to move to element-level inspections as part of the FHWA mandate. With over 30 years of bridge condition data now available, as well as new data on MR&R costs and timing, improved methodologies to predict user costs should be investigated and evaluated for implementation in the BMS.

Level of service deficiencies that influence user costs are typically associated with bridge load capacity restrictions, low vertical clearances, poor roadway alignment, and narrow bridge deck widths (Son and Sinha 1997). To compute the costs associated with bridge load capacity and low vertical clearance, vehicle operating cost must be considered. This vehicle operating cost is used when determining the cost per mile of a vehicle class when it has to detour a bridge. Although many agencies have based their cost inputs and models on the work of NCSU (Son and Sinha 1997, Thompson et al. 1999), most have recently incorporated modified or enhanced methods of determining user costs into their BMS. Much of the data supporting vehicle operating costs in NCDOT's BMS is currently outdated. For example, tables developed by Chen and Johnston (1987) nearly 30 years ago are currently used to predict the proportion of each type of vehicle traveling on each type of bridge, as well as to predict the proportion of vehicles detoured due to weight.

Most data supporting the BMS cost features cannot feasibly be collected annually (Duncan and Johnston 2002). Forecasting algorithms utilized by the BMS's optimization scenarios are dependent on growth factors and inflation rates for factors including both cost and traffic. Therefore, it is critical that these BMS input values are accurate. Additionally, it is possible that the inflation indices previously utilized to update costs may be outdated.

Additionally, updated, locally calibrated data is available to support the existing methods of computing user costs. Possible vehicle operating cost enhancements to NCDOT's BMS may include those associated with vehicle classifications, vehicle distributions on roadways, new data associated with percent of vehicles detoured due to bridge postings, and others.

New truck information, including trucking traffic forecasting models developed for NCDOT as part of recent research (Stone et al. 2006) could be utilized in the BMS to better predict the user costs with truck traffic. It has been shown that truck traffic is most affected by costs due to loss of time in detour traveled (Johnston et al. 1994). Data utilized in the BMS on truck geometries and percentages at certain heights was obtained in the 1950's (Kent and Stevens 1963), data on the percentages of heavy trucks from 1980's (FHWA

1985). This key input data for the BMS should be updated so that the user costs associated with detours due to height, as well as detours due to bridge posting, are accurate.

Other costs used to predict user costs are accident costs. Accident costs can be incurred due to bridges with low vertical clearances, narrow bridge deck widths, poor alignment, and bridge length (Johnston et al. 1994). Research has been performed to determine an average number of injuries per accident type on bridges (Abed-Al-Rahim and Johnston 1991). Accident types are classified in order of decreasing severity as K (fatality), severity A, severity B, severity C, and property damage only (PDO). These values can be multiplied by an amount computed using the "Willingness-to-Pay" approach developed by the National Safety Council (NSC) to determine the average cost per bridge related accident. This approach to computing accident costs needs to be revisited and revised to reflect current day costs.

New data that would provide updated North Carolina accident rates and severities has recently been released, and the NCDOT BMS should be updated to include this data in the computation of accident costs. An outside consultant has also recently provided a report outlining accident costs based on North Carolina data. This data could also be included in the computation of accident costs in the NCDOT BMS, improving the fidelity of the user costs function of the software.

Statistics from the National Highway Traffic Safety Administration indicate that since 2005, highway fatalities have declined (NCHRP 2015). However, the reasons for the decrease in fatalities and serious injuries on highways are not completely understood, and are the subject of an ongoing study by the National Highway Cooperative Research Program (NCHRP 17-67). A revisit of a bridge-related accident study by Abed-Al-Rahim and Johnston (1991), using recent accident data and current bridge characteristics, would provide insight into bridge features linked to higher accident rates and findings could be incorporated into design of bridges statewide.

User costs to help determine which bridges are vital to the public, affecting a portion of the public sector that can no longer use a bridge due to it deficiencies or pose a high accident risk. They are often significant in magnitude and can be up to five times the cost of direct agency costs (Thompson et al. 1999). A sensitivity analysis to determine which cost inputs have the greatest effect on user costs could be utilized by the NCDOT to better understand the results of BMS optimization scenarios. This sensitivity analysis, performed using updated inputs and inflation/growth indices, will provide NCDOT more confidence in selection of bridges for maintenance, repair, and rehabilitation.

1.1 Anticipated Contribution of Research Effort

Research questions addressed as part of this work include the following:

- Is the current method of computing user costs in NCDOT's BMS valid?
- Are there improved ways to compute user costs using more current data or more appropriate methodologies?
- What can we learn from user costs that can be utilized in design, maintenance, repair, and rehabilitation decisions to improve North Carolina's bridges?
- If changes are made to the user cost inputs and methodologies to obtain these inputs, what are the effects on predicted user costs for a subset of bridges?

As part of this research, the four questions listed above were addressed. It was determined some of the current methods utilized in the NCDOT BMS for computing user costs could be enhanced, and more recent, locally calibrated data is available to support forecasting of user costs with much more fidelity. An analysis of bridge-related accidents provided insight into the bridge characteristics most associated with accidents. This information can be used to assist NCDOT in decisions regarding design, maintenance, repair, and rehabilitation needs, potentially reducing the number of bridge-related accidents and reduce the associated user costs. The findings of a sensitivity analysis of user costs will help NCDOT understand the effects of recommended changes on predicted user costs, and provide insight into the relative sensitivity of user costs to accident costs and operator costs.

1.2 Organization of the Thesis

This thesis is comprised of six chapters. Chapter 1 provides an overview of the purpose and use of user cost models in BMS, with an emphasis on the history of NCDOT's BMS user costs. Chapter 2 is a literature review that provides a more in-depth background of user cost models and associated inputs, as used in NCDOT's BMS as well as BMS used by other state highway agencies. Chapter 3 describes the research efforts utilized to update methodologies to obtain user cost inputs, as well as provides updated input tables that are suggested for use in NCDOT'S BMS. Chapter 4 provides a revisit to a study performed by NCSU approximately 25 years ago, in which bridge characteristics associated with North Carolina's bridge-related accidents were identified (Abed-Al-Rahim and Johnston 1993). The results of a similar analysis of recent bridge-related accidents (presented in Chapter 4) provide insight into changes in bridges characteristics associated with bridge-related accidents, as well as an updated equation that can be used to predict the number of annual accidents on a bridge or a subset of bridges. Once all user cost inputs and methodologies were updated and enhanced, a sensitivity analysis was performed (outlined in Chapter 5) to determine whether user costs are more sensitive to accident costs or vehicle operating costs. Chapter 6 provides the conclusions and recommendations of this work. Appendix A includes information to support the bridge-related accident analysis. Appendix B includes information supporting the sensitivity analysis.

CHAPTER 2: LITERATURE REVIEW

BMS are a vital tool for many state and federal transportation agencies. With increased agency and user costs and a growing (yet also rapidly deteriorating) infrastructure in the United States, there is a need to both protect the public's safety and to determine and implement best practices for MR&R or replacement of bridges. Currently the FHWA requires all bridges to be inspected biennially; these inspections include the collection of data on 116 different parameters such as location, bridge age, and material components among other information. Inspection data provide rating information that assists in determining the structural condition and functional condition of a bridge. This inspection data is recorded in the National Bridge Inventory (NBI) database.

Though the FHWA only requires 116 components be inspected, characterized or recorded biennially, most state agencies have data on additional inspection items and parameters they record that relate to the climate or geography of their respective state, or are other items of interest to the agency. The NCDOT records data on a total of 300 components, including geographic information, roadway type, bridge structural details, and a number of other parameters. Collection of this data can be used to develop and support a BMS. A BMS can be used to predict user costs associated with structural and functional deficiencies (Son and Sinha 1997).

2.1 Bridge Management Systems

The NBIS was developed in 1971 (NBIS 2012), and most states now have over 30 years of data collected to support decisions regarding MR&R and replacement of bridges. Many state and federal agencies have been using information collected for the NBI to support development of a BMS. North Carolina was one of the first states to develop a BMS (Chen and Johnston 1987). Since then, many other states have developed a BMS, along with the federal government. Over 40 states are currently using the AASHTOWare Pontis BMS system (Markow and Hayman 2009).

Although some states utilize their BMS strictly to store data (Markow and Hayman 2009), a well-developed BMS system will collect, process, and update data, predict deterioration, and identify and predict costs to the transportation agency and bridge users (Sinha et al. 2009). This helps allow the state agency to determine how best to allocate funding. The data supporting a BMS system is typically based upon the NBI data and state inspection data, and then enhanced with other stored inventory, which can range from accident costs to truck traffic percentages (Sobanjo and Thompson 2001). Engineering and economic models in the BMS utilize this database to predict the deterioration rates of bridges and associated costs (Sobanjo and Thompson 2001). These models are then used to predict the required MR&R or replacement of bridges, accounting for both the deterioration of bridge elements as well as the effects of inadequate level of services for users (Chen and Johnston 1987). Inadequate levels of services for users are the result of bridges being either structurally deficient or functionally obsolete.

Once a bridge is considered either structurally deficient or functionally obsolete, a cost is burdened by the public (or a portion of the public) who can no longer use the bridge because of its deficiencies. Deficiencies can be due to load postings, inadequate deck width, poor alignment, and limited vertical clearance (Chen and Johnston 1987). A load posting is given to bridges and culverts to restrict the weights of vehicles that can pass (Hearn 2014). It is implemented when the maximum legal weight of a vehicle is deemed unsafe for the structure. A BMS system should be able to predict when a bridge is nearing a load deficiency by analyzing the data input from previous inspections (Abed-Al-Rahim and Johnston 1991).

Currently most of America's transportation infrastructure is aging, while traffic volume is steadily increasing (Mach and Hartman 2008). Due to this fact, a BMS system must not only be able to utilize deterioration models to forecast bridge conditions, but perform analyses to identify how these deficiencies affect the users of the bridge. All federal and state agencies have limited funding for transportation needs and many states rely on their BMS system to determine the bridge projects that are most vital to obtain maximum levels of service to the public (Rens et al. 1999). This being noted, user costs help determine the bridge projects that provide the greatest benefit to the public. These user costs are often significant in magnitude and will affect a portion of the public sector that can no longer use a bridge due to its deficiencies, and pose a high accident risk. Thompson et al. (1999) note that these user costs can be up to five times the direct agency costs.

2.2 User Costs in Bridge Management Systems

A bridge with either a structural or functional deficiency will incur a user cost (Chen and Johnston 1987). Such costs are due to load postings, limited vertical clearances, and deck widths that result in vehicles having to detour (Son and Sinha 1997). Additional user costs are incurred due to accidents resulting from the bridge deck width, approach configuration, traffic speed, or other factors. Currently, NCDOT calculates user costs by considering narrow deck widths, low vertical clearances, poor alignment, bridge length, and reduced load capacity. This methodology was developed by Chen and Johnston (1987), and is reportedly largely applied in the BMS software utilized by the NCDOT today. The method used to determine user costs for the NCDOT BMS, as developed by Chen and Johnston (1987), is shown in Equation 2.1.

$$AURC(t) = 365\ ADT(t)\ [C_{WDA}U_{AC}+C_{ALA}U_{AC}+C_{CLA}U_{AC}+C_{CLD}U_{DC}DL+C_{LCD}(t)U_{DL}DL]$$

Equation 2.1: NCDOT BMS user costs

Where: $AURC(t)$ = annual user cost of the bridge at year t, \$/year

$ADT(t)$ = average daily traffic using the bridge at year t

C_{WDA} = coefficient for proportion of vehicles incurring accidents due to width deficiency

C_{ALA} = coefficient for proportion of vehicles incurring accidents due to poor alignment

C_{CLA} = coefficient for proportion of vehicles incurring accidents due to vertical clearance deficiency

C_{CLD} = coefficient for proportion of vehicles detoured due to a vertical clearance deficiency

$C_{LCD}(t)$ = coefficient for proportion of vehicles detoured due to a load capacity deficiency at year t

U_{AC} = unit cost of vehicle accidents on bridges, \$/accident

U_{DC} = unit cost for average vehicle detours due to vertical clearance deficiency, \$/mile

U_{DL} = unit cost for average vehicle detours due to load capacity deficiency, \$/mile

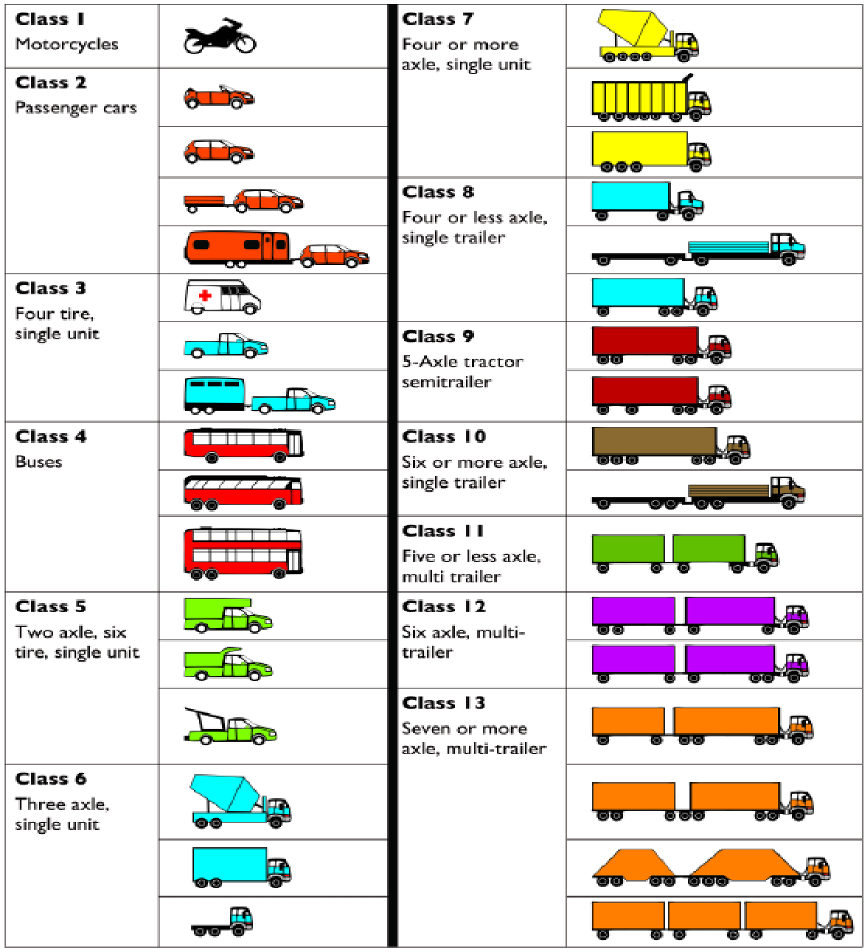
DL = detour length, miles

As can be seen in Equation 2.1, in the NCDOT BMS, user costs are incurred by vehicles that are required to detour around a bridge due to load postings or low vertical clearance, as well as due to accidents related to narrow deck widths and poor alignments.

The detour costs for both vertical clearance and load capacity are determined using vehicle operating costs, percent of vehicles detoured, and detour length. In computing the cost of accidents related to poor alignment, the alignment appraisal is based on agency-collected data or data from other sources (Chen and Johnston 1987). The width deficiency is based on the difference between the existing deck width and bridge clear deck width goals, as established by Johnston and Zia (1984).

Many agencies currently utilize the AASHTOWare Pontis BMS developed by the American Association of State Highway and Transportation Officials (AASHTO). In the development of AASHTOWare Pontis, cost considerations were largely based on the cost methodologies developed for the NCDOT BMS (Thompson et al. 1999), described previously. In recent years, other agencies have modified or enhanced the source data or methodologies utilized in the NCDOT BMS in order to support computation of user costs in their BMS. For example, in a research project to support the Indiana Bridge Management System (IBMS), which has a cost analysis component largely based on the work of Chen and Johnston (1987), Son and Sinha (1997) explored the incorporation of the effect of poor deck surface conditions to user costs. These poor deck conditions were found to cause vehicles to reduce speed on bridges adding to the travel time, which increases user costs (Son and Sinha 1997).

As shown in Equation 2.1, a key factor in determining the appropriate user costs is an accurate prediction of the volume of traffic on the bridge. This traffic information is known is Average Daily Traffic (ADT). ADT considers the traffic resulting from 13 different vehicle classifications, as denoted by the FHWA (2013), shown in Figure 2.1.



Source: Federal Highway Administration.

Figure 2.1: FHWA vehicle classification

Accurate ADT data is vital when calculating the user costs for a bridge, because a bridge with a higher volume of traffic will have an increased user cost associated with it if deficiencies are present in that bridge. Higher ADT volumes are typically seen on major roadway systems like interstates and federal and state highways. Although all 13 vehicle classifications are typically affected by user costs, passenger vehicles are not affected nearly as much as vehicles in heavier weight classes (Chen and Johnston 1987). This will be discussed in more depth in subsequent sections on vehicle operating costs and accident costs.

2.3 Average Daily Traffic Growth

ADT is the total traffic volume a roadway experiences over the course of an average day. This value is utilized in the NCDOT BMS in the computation of user costs. A bridge's ADT includes both single-unit (SU) and multi-unit (MU) vehicles as well as all other vehicle classifications. The portion of the ADT that can be attributed to trucks is known as the Average Daily Truck Traffic (ADTT). Since load posting related detours typically affect tall and heavy weight vehicles such as trucks, the ADTT (or some portion of the ADTT) is the likely set of vehicles that may incur a detour (other types of detours, like construction, would affect everyone). In contrast, user costs attributable to accidents can be incurred by all types of vehicles. Currently, the NCDOT BMS does not utilize ADTT data inputs.

ADT growth rates are used to predict the ADT of a bridge at a future date. Projected ADT is used by a BMS when estimating user costs in future years. Chen and Johnston (1987) used ADT values provided by NCDOT to develop ADT growth rates for roadways of different types. The source of the data that Chen and Johnston (1987) used to predict the original ADT growth rates used in the NCDOT BMS was automatic traffic recording (ATR) data from 1974 to 1984. At the time of development of these ADT growth rates, data was available from a total of 59 ATR stations that were placed at roadways of different classifications (Chen and Johnston 1987). Using this data, ADT growth rates were computed for the four road types in each of the state's counties. At the time of Chen and Johnston's original work, only seven of the 59 ATR stations were situated on interstates. Additionally, insufficient data was available to support development of specific ADT growth rates by county or division. Therefore, interstate ADT growth rates were considered equal for the state (Chen and Johnston 1987). The arterial ADT growth rates were assumed to be the same for all counties in a division (for each of the 14 divisions in the state). Since no ATR stations were located on local routes, the population growth rate of the county was used to determine the ADT growth rate. For collector roads, the ADT growth rate were assumed to be the average of the local and arterial growth rates for each county.

The ADT growth rates for the NCDOT BMS were later updated by Duncan and Johnston (2002) using the Bridge Management Inventory File (BMIF). The BMIF provided ADT data for all bridges from 1991 to 2000. This more robust dataset allowed Duncan and Johnston (2002) to compute an ADT growth rate (for each of the four roadway classifications) for each county. Duncan and Johnston (2002) noted that if values did not exist for a particular roadway in a county, the state average was utilized as the assumed value. Values determined by Duncan and Johnston (2002) were then reviewed by NCDOT's Traffic Forecast Unit (TFU), where personnel adjusted some values based on experience. A snapshot of the breakdown of ADT growth rates for a portion of North Carolina counties is shown in Table 2.1 (Duncan and Johnston 2002).

Table 2.1: A portion of the ADT growth rate table used in NCDOT BMS (Duncan and Johnston 2002)

```
*************************************************************
TABLE 1  GEOGRAPHIC AREA (1=COASTAL, 2=PIEDIMONT, 3=MOUNTAIN)
*************************************************************
TABLE 2  YEARLY ADT GROWTH RATES FOR BRIDGES OF VARIOUS
         FUNCTIONAL CLASSIFICATIONS (%).
*************************************************************
CO # COUNTY NAME AREA LOCAL   COLLECTOR  ARTERIAL INTERSTATE
---- ----------- ---- -----   ---------  -------- ----------
 00  ALAMANCE      2   3.82      3.50       3.50      6.81
 01  ALEXANDER     3   4.57      4.28       2.86      5.38
 02  ALLEGHANY     3   2.75      3.99       2.75      5.38
 03  ANSON         2   2.67      2.86       2.98      5.38
 04  ASHE          3   2.50      3.61       2.97      5.38
 05  AVERY         3   3.42      3.52       3.50      5.38
 06  BEAUFORT      1   2.50      2.55       2.93      5.38
 07  BERTIE        1   3.45      3.28       0.48      5.38
 08  BLADEN        1   4.93      2.50       3.00      5.38
 09  BRUNSWICK     1   5.96      4.56       3.50      5.38
 10  BUNCOMBE      3   2.50      2.55       3.50      5.47
 11  BURKE         3   2.72      3.37       3.01      5.19
```

2.4 Detour Resulting from Bridge Capacity and Vertical Clearance Limits

User costs due to detours are incurred when vehicles desiring to travel over a bridge are required to detour around the bridge due to the bridge being posted at a reduced load capacity or when vehicles that desire to travel either on or under a bridge must detour due to lack of vertical clearance either on or under a bridge. User costs associated with detours are computed by multiplying the detour length by the unit cost for vehicle detours and the coefficient of the proportion of vehicles that must detour. The NBI coding guide defines the detour length as the total additional length of travel a vehicle must go in order to remain on course (FHWA 1995). Detour length is a required component of the NBIS, and is therefore easily incorporated into most BMS. It has been noted though that the actual detour length may be longer than that posted in the NBI since posting signs are located at the bridge and not where the detour runoff is actually located (Chen and Johnston 1987).

A load posting results in the restriction of certain vehicles from using a bridge when a vehicles' weights exceeds the safe capacity of a bridge (Hearn 2014). These restrictions typically occur in older bridges that have experienced section loss or material degradation (Chen and Johnston 1987). Environmental effects, such as climate and geography, are some of the main causes of section loss and material degradation (Chen and Johnston 1987). Bridges that do not receive regular maintenance will have a higher likelihood of deteriorating quickly (Sobanjo and Thompson 2013).

A bridge can have either one or two load postings, the first being for SU vehicles and the second being for tractor-trailer semi-trailer (TTST) vehicles. As discussed previously, SU and TTST trucks comprise a segment of the ADT known as Average Daily Truck Traffic (ADTT). These load postings will cause a portion of vehicles to have to detour around any bridge where their weight is in excess of the load posting (Chen and Johnston 1987). This creates an increase in travel time as well as an incurred vehicle operating cost for all vehicles having to detour.

When determining the vehicle operating costs in a BMS, it is essential to accurately estimate the proportion of vehicles that would be required to detour due to bridge capacity (Johnston et al. 1994). In the NCDOT BMS, this proportion of legal weight vehicles required to detour due to bridge capacity is assumed to be dependent upon the type of roadway system upon which the bridge is located (Chen and Johnston 1987), as seen in Table 2.2. This percentage does not consider vehicle classifications one through three, since their weight, which is considered three tons or less, is the minimum weight a bridge must hold in order to be operational (Chen and Johnston 1987).

In the NCDOT BMS, the percentage of trucks detoured (in decimal form) is multiplied by proportion of the total traffic (ADT) that is trucks. To facilitate this, Chen and Johnston (1987) utilized data provided by the Planning and Research Branch of NCDOT to develop a table that provides a percentages of total traffic that are cars and light trucks, SV Duals or TTST. Data utilized to compute these percentages included traffic data from portable counting stations at selected locations on primary highways with known functional classifications (Chen and Johnston 1987). The Planning and Research Branch also provided data for secondary roadways where ADT was measured on bridges evaluated for replacement. Chen and Johnston (1987) compiled this information, seen in Table 2.3, which was then used in conjunction with data on truck weight distributions to produce the total percent of vehicles detoured due to bridge capacity (Table 2.2). As noted in Equation 2.1, this portion of vehicles detoured due to load is time dependent for each structure, since deterioration of bridges over time reduces the load capacity (Chen and Johnston 1987). To predict and account for reduction in load capacity, Chen and Johnston (1987) performed regression analysis using time dependent substructure and superstructure condition ratings as well as the ratio of the design load at the current state to the design load at construction time (time zero) using historical data on bridges. Chen and Johnston (1987) note that the results of the regression analysis showed poor correlation, and thus engineering judgment was used along with the regression results to produce Table 2.4. The deterioration rates in this table allow for BMS to predict deterioration in bridge load capacity and, consequently the impact on user costs associated with detour due to load posting.

Table 2.2: Percent detoured due to load posting (Chen and Johnston 1987)

Bridge Posting (tons)	Interstate		Princ. Art.		Minor Art.		Major Coll.		Minor Coll.		Local	
	SV	TT ST	SV	TT ST	SV	TT ST	SV	TT ST	SV	TT ST	SV	TT ST
3	4.40	12.50	6.00	6.60	4.60	3.30	2.60	1.10	2.60	0.80	2.40	0.60
4	3.87	12.45	5.21	6.57	4.11	3.29	2.32	1.09	2.32	0.80	2.14	0.60
5	3.35	12.40	4.41	6.54	3.61	3.28	2.04	1.09	2.04	0.79	1.88	0.60
6	2.82	12.36	3.62	6.50	3.12	3.26	1.76	1.08	1.76	0.79	1.63	0.59
7	2.30	12.31	2.82	6.47	2.62	3.25	1.48	1.08	1.48	0.78	1.37	0.59
8	1.77	12.26	2.03	6.44	2.13	3.24	1.20	1.07	1.20	0.78	1.11	0.59
9	1.52	12.24	1.70	6.33	1.78	3.19	1.00	1.05	1.00	0.77	0.92	0.58
10	1.26	12.02	1.36	6.23	1.43	3.14	0.80	1.04	0.80	0.76	0.74	0.57
11	1.10	11.65	1.22	5.97	1.28	3.01	0.72	0.99	0.72	0.73	0.67	0.54
12	0.95	11.28	1.08	5.70	1.13	2.87	0.64	0.95	0.64	0.69	0.59	0.52
13	0.82	10.74	0.97	5.39	1.02	2.71	0.57	0.90	0.57	0.66	0.53	0.49
14	0.71	10.04	0.90	5.02	0.94	2.53	0.53	0.84	0.53	0.61	0.49	0.46
15	0.60	9.34	0.82	4.66	0.86	2.35	0.48	0.78	0.48	0.57	0.45	0.42
16	0.51	8.89	0.76	4.41	0.79	2.22	0.45	0.73	0.45	0.54	0.41	0.40
17	0.42	8.35	0.69	4.16	0.73	2.09	0.41	0.69	0.41	0.51	0.38	0.38
18	0.35	8.04	0.63	3.95	0.66	1.99	0.37	0.66	0.37	0.48	0.34	0.36
19	0.30	7.71	0.58	3.78	0.60	1.90	0.34	0.63	0.34	0.46	0.31	0.34
20	0.24	7.37	0.52	3.61	0.55	1.82	0.31	0.60	0.31	0.44	0.28	0.33
21	0.21	7.06	0.44	3.50	0.47	1.76	0.26	0.58	0.26	0.43	0.24	0.32
22	0.18	6.75	0.37	3.39	0.39	1.71	0.22	0.56	0.22	0.41	0.20	0.31
23	0.16	6.46	0.30	3.28	0.32	1.65	0.18	0.55	0.18	0.40	0.17	0.30
24	0.15	6.17	0.25	3.17	0.26	1.60	0.15	0.53	0.15	0.39	0.14	0.29
25	0.13	5.89	0.20	3.06	0.21	1.54	0.12	0.51	0.12	0.37	0.11	0.28
26	0.11	5.61	0.16	2.96	0.17	1.49	0.10	0.49	0.10	0.36	0.09	0.27
27	0.09	5.32	0.13	2.86	0.13	1.44	0.08	0.48	0.08	0.35	0.07	0.26
28	0.08	5.01	0.10	2.75	0.10	1.39	0.06	0.46	0.06	0.33	0.05	0.25
29	0.07	4.68	0.07	2.64	0.08	1.33	0.04	0.44	0.04	0.32	0.04	0.24
30	0.06	4.35	0.05	2.52	0.05	1.27	0.03	0.42	0.03	0.31	0.03	0.23
31	0.05	3.95	0.03	2.38	0.04	1.20	0.02	0.40	0.02	0.29	0.02	0.22
32	0.04	3.56	0.02	2.25	0.02	1.13	0.01	0.37	0.01	0.27	0.01	0.20
33	0.04	3.11	0.01	2.09	0.01	1.05	0.00	0.35	0.00	0.25	0.00	0.19
33.6	0.00	2.81	0.00	1.98	0.00	1.00	0.00	0.33	0.00	0.24	0.00	0.18
34		2.60		1.91		0.96		0.29		0.23		0.16
36		1.74		1.56		0.78		0.24		0.19		0.14
36.6		0.00		0.00		0.00		0.00		0.00		0.00

Table 2.3: Vehicle proportions on functional classifications (Chen and Johnston 1987)

Functional Classification	Proportion of Total Vehicles (%)		
	Cars & Light Trucks	SV Duals	TTST
Interstate	83.1	4.4	12.5
Principal Arterial	87.3	6.0	6.6
Minor Arterial	92.1	4.6	3.3
Major Collector	96.3	2.6	1.1
Minor Collector	96.5	2.6	0.8
Local	97.0	2.4	0.6

Table 2.4: Estimated bridge load capacity deterioration rates (Chen and Johnston 1987)

Lower Rating of Superstructure and Substructure	Deterioration Rate (Tons/Year)		
	Timber	Concrete	Steel
6 - 9	0.00	0.00	0.00
5	0.30	0.20	0.20
4	0.60	0.30	0.30
3 or less	1.00	0.50	0.50

One factor affecting detour costs that can be difficult to determine and incorporate into a BMS is an accurate prediction of the number of (or the percentage of) vehicles with weight over the legal weight limits (Dey et al. 2014). Currently, the FHWA has a mandated maximum allowable gross weight of 80,000 pounds for vehicles, while also allowing the purchase of special permits for vehicles over this weight limit on certain roads.

Low vertical clearance on or under a bridge will also cause a portion of traffic passing on or under a bridge to detour due to the height restriction. The NCDOT BMS system predicts a portion of vehicles that will detour due to excessive height. Johnston et al. (1994) notes that only a small portion of bridges have vertical clearance shorter than average truck heights, so relatively few vehicles will be required to detour due to vertical clearance. Chen and Johnston (1987) assumed that the distribution of trucks is well distributed, and data from a report by Kent and Stevens (1963) was used to predict the percentage of trailer heights over the standard height (13.5 feet). Using this data and Table 2.3, Chen and Johnston (1987) produced an additional table used in the NCDOT BMS that estimates the percentage of vehicles that must detour due to height restrictions (Table 2.5). It is of note that the Kent and Stevens (1963) report used to determine the percentage of vehicles of each height is entitled “Dimensions and Weights of Highway Trailer

Combinations and Trucks – 1959," indicating that this data may not accurately reflect the current geometric characteristics of North Carolina truck traffic.

Table 2.5: Percent detoured due to vertical clearance (Chen and Johnston 1987)

Vertical Clearance (feet)	Interstate		Princ. Art.		Minor Art.		Major Coll.		Minor Coll.		Local	
	SV	TT ST	SV	TT ST	SV	TT ST	SV	TT ST	SV	TT ST	SV	TT ST
8.0	4.40	12.50	6.00	6.60	4.60	3.30	2.60	1.10	2.60	0.80	2.40	0.60
8.5	4.00	12.50	5.45	6.60	4.18	3.30	2.36	1.10	2.36	0.80	2.18	0.60
9.0	3.60	12.50	4.91	6.60	3.76	3.30	2.13	1.10	2.13	0.80	1.96	0.60
9.5	3.20	12.50	4.36	6.60	3.35	3.30	1.89	1.10	1.89	0.80	1.75	0.60
10.0	2.80	12.50	3.82	6.60	2.93	3.30	1.66	1.10	1.66	0.80	1.53	0.60
10.5	2.40	10.72	3.27	5.66	2.51	2.83	1.42	0.94	1.42	0.69	1.31	0.51
11.0	2.00	8.94	2.73	4.72	2.09	2.36	1.18	0.79	1.18	0.57	1.09	0.43
11.5	1.60	7.17	2.18	3.78	1.67	1.89	0.95	0.63	0.95	0.46	0.87	0.34
12.0	1.20	5.39	1.64	2.85	1.26	1.42	0.71	0.47	0.71	0.34	0.66	0.26
12.5	0.80	3.61	1.09	1.91	0.84	0.95	0.47	0.32	0.47	0.23	0.44	0.17
13.0	0.40	1.83	0.55	0.97	0.42	0.48	0.24	0.16	0.24	0.12	0.22	0.09
13.5	0.00	0.06	0.00	0.03	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00
14.0	0.00	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
14.5	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Other agencies have slightly different methods of approaching the computation of user costs due to detours. For example, the Indiana Department of Transportation's (IDOT) BMS (IBMS) computes detour due to excessive weight using a methodology similar to the NCDOT BMS, yet has a different approach for determining the portion that must detour. For the IBMS, Son and Sinha (1997) developed a system of three categories to determine the percent of vehicles that must detour due to weight. The first category includes vehicle classes in which the minimum weight of the vehicle class is greater than the load posting. In this category, all vehicles must detour, as reflected in Equation 2.2.

$$\text{If } PL < W_{MIN}(j)$$

$$N_L(j) = PADT(j) \times ADT$$

Equation 2.2: All vehicle classes detour

The second category includes vehicle classes in which the maximum weight of a vehicle class is less than the load posting, which results in no vehicles in the category having to detour (Equation 2.3).

$$\text{If } PL > W_{MAX}(j)$$

$$N_L(j) = 0$$

Equation 2.3: No vehicle classes detour

The third category is utilized for load postings that are between the minimum and maximum weights associated with a vehicle class, thereby causing only a portion of the vehicle class to detour (Equation 2.4).

$$N_L(j) = \frac{(W_{MAX}\ (j) - PL)}{(W_{MAX}\ (j) - W_{MIN}\ (j)} \times PADT(j) \times ADT$$

Equation 2.4: A portion of vehicle classes detour

Where: $W_{MAX}(j)$ = maximum weight of vehicle type j, tons
$W_{MIN}(j)$ = minimum weight of vehicle type j, tons
PADT(j) = proportion of ADT of vehicle type j
PL = posted load limit or load capacity, tons
J = vehicle type

Once the percent detour ($N_L(j)$) is found, the equation used to produce the user costs is the same as the one used by the NCDOT BMS (Equation 2.1). However, the IBMS groups vehicles into four different classifications for vehicle operating cost. In these four groups, a maximum and minimum weight is predicted for each group and these weights are then used in the equation to estimate how many vehicles must detour (Son and Sinha 1997).

2.4.1 Vehicle Operating Costs

When a vehicle must detour due to either weight or height restrictions, an added expense is incurred by the operator or owner of the vehicle. This expense can be a result of fuel consumption, oil consumption, tire wear, maintenance and repair, and vehicle depreciation (Zaniewski et al. 1982). In the NCDOT BMS, vehicle operating cost is calculated utilizing vehicle characteristics and the operator's wage rates for said vehicle, using a methodology developed by Duncan and Johnston (2002). In their initial work, Chen and Johnston (1987) computed the vehicle operating costs for vehicles of minimum weight (three tons) and vehicles of maximum legal gross weight (40 tons). For the NCDOT BMS, the vehicle operator cost for vehicles between these two weights is linearly interpolated (Chen and Johnston 1987).

To estimate the operator costs for vehicles weighing three tons or less, Duncan and Johnston (2002) first assumed the cost would be equal for all vehicles weighing three tons and less. They also assumed that the vehicle operating cost would be the sum of vehicle cost and operator cost. The vehicle cost is taken as the standard mileage rate for all business mileages, which is published by the Internal Revenue Service (IRS) and routinely updated to reflect changes in the fuel cost of fuel. The estimate for operator cost utilizes the North Carolina state government vehicle operator I minimum wage rate as a basis. This minimum salary rate per year is divided by the product of the assumed 1,920 hours worked by a person in a year and a travel speed of 40 miles per hour (Duncan and Johnston 2002), to obtain the operator cost per mile of detour. The operator cost and vehicle cost are then added to predict the vehicle operating cost of a three ton vehicle (U_{D3}), which is used in Equation 2.5.

To predict operating cost for vehicles at the maximum legal weight, Duncan and Johnston (2002) used data from the North American Industry Classification System (NAICS) 484, this information is published in the U.S. Census Bureau. NAICS 484 provides data on a variety of aspects (including costs and mileage) of overland transportation of cargo by means of tractor trailers. This report provides information on the estimated motor carrier revenue yearly in North American (U.S./Canada/Mexico), as well as the estimated miles driven per motor carrier. To calculate the vehicle operating cost, the total annual revenue is divided by the total annual number of miles driven obtain the vehicle operating cost as a cost per mile of vehicles weighing 40 tons (U_{DNP}) used in Equation 2.5.

For vehicles weighing between three tons and 40 tons, the NCDOT BMS assumes a linear relationship between the vehicle weight and vehicle operating costs (Chen and Johnston 1987). Equation 2.5 presents the linear relationship between vehicle weight and estimated vehicle operating cost at the weight (Chen and Johnston 1987). When a bridge has a load posting, vehicles at and above the posted weight must detour, so an average vehicle operating cost (U_{DL}) is determined for all weight classes having to detour. Chen and Johnston (1987) proposed using the average of the vehicle operating cost at the weight for the load posting (U_{DV}) and the vehicle operating cost at the maximum legal weight limit (U_{DNP}), to calculate U_{DL}, used in Equation 2.1.

$$U_{DV} = U_{D3} + \frac{(U_{DNP} - U_{D3})}{(NP - 3)} \times (W_V - 3)$$

Equation 2.5: Vehicle operating cost at said weight

Where: U_{DV} = operating cost for vehicle V
U_{D3} = operating cost for vehicle weighing 3 tons or less
U_{DNP} = operating cost for vehicle weighing the maximum legal load
NP = maximum legal load (non-posted capacity of bridge)
W_V = weight of vehicle V

It is noted that in NCDOT's BMS the operating cost for vehicles less than three tons is assumed to be the operating cost of a three ton vehicle. Also, vehicles weighing more than the maximum legal load (40 tons) are assumed to have an operating cost equal to the operating cost of the maximum legal weight vehicle.

Other state agencies have different means of deriving this vehicle operating cost for their BMS. In 1982, the FHWA sponsored research in which 11 different vehicle classifications were analyzed to determine the overall unit operator cost for five different components (fuel consumption, oil consumption, tire wear, maintenance and repair, and vehicle depreciation) (Zaniewski et al. 1982). The vehicles were tested on 51 different geometric test sections as well as at differing speeds to ensure accurate results (Zaniewski et al. 1982). The findings of this study have been incorporated into the IBMS by Son and Sinha (1997), after grouping the 11 different vehicle classes into a subset of four: passenger car, single unit truck, bus, and tractor trailer.

2.5 Accident Costs

Johnston (2010) states that bridge related accidents are a small portion of total accidents, but the severity of these bridge related accidents are higher than other non-bridge related accidents. This is also emphasized by Sobanjo and Thompson (2013) who stated that vehicle crashes on bridges as well as on bridge elements are more likely to be deadly than other vehicle accidents. Abed-Al-Rahim and Johnston (1991) reported studies finding that the severity of bridge related accidents can be two to 50 times more severe than non-bridge related accidents. One factor that can result in increased accident rates are narrow deck width bridges that reduce lane width (Wang 2010). Chen and Johnston (1987) report that other factors that increase the likelihood of accidents include low vertical clearance and poor deck alignment.

Accident costs can be calculated by grouping them as accidents that solely result in property damage, accidents that are injury producing, and accidents resulting in one or more fatalities (Wang 2010). NCDOT classifies accident types within their BMS in this manner (Abed-Al-Rahim and Johnston 1991). In the NCDOT BMS, a scaled system of A through C is used to determine the severity of the injury with A being the most severe and C being the least severe. Two additional components on the extremes of the scale are fatal, denoted K, for accidents resulting in loss of life, and property damage, denoted PDO, for accidents not inducing injuries.

Two approaches have been considered in determining accident costs on bridges within the NCDOT BMS (Chen and Johnston 1987): the Willingness-to-Pay approach and the Human Capital Approach. Both approaches consider direct and indirect costs involved with bridge related accidents. Direct cost for both are considered to be accident cost, emergency service cost, medical treatment expenses, and legal and court fees as stated by the National Safety Council (NSC). The indirect costs, which can be more difficult to determine (Chen and Johnston 1987), consider compensation for pain and suffering and the costs of goods and services an individual will not be able to produce as a result of the accident. The Willingness-to-Pay approach also considers an indirect cost known as value of life, which looks at possible long and short term losses in quality of life due to the accident. Both approaches provide a dollar value for each severity type (K-A-B-C-PDO). In updating the NCDOT BMS accident costs, Duncan and Johnston (2002) also considered a third approach known as the comprehensive cost method that looks at 11 different components consisting of both direct and indirect costs, similarly to the Willingness-to-Pay approach.

Costs per accident values calculated by the Human Capital Approach are published by the FHWA every few years. Since this data does not include a cost parameter for value of life, the total cost of the five different accident types is less than the Willingness-to-Pay approach (Duncan and Johnston 2002). Costs per accident values calculated by the Willingness-to-Pay approach are published by the NSC. Since data is provided more frequently and includes value of life, Duncan and Johnston (2002) recommended that the Willingness-to-Pay approach be used to predict accident costs in the NCDOT BMS.

To compute accident costs in a BMS, a means of predicting the average number of accidents occurring on a bridge is required. For NCDOT's BMS, a prediction methodology was developed by Abed-Al-Rahim and Johnston (1991). In this methodology, data compiled by NCDOT was utilized to determine the percentage of vehicle accidents occurring on bridges. At the time of this work, North Carolina required that all vehicular accident reports be stored for seven years. These accident reports provided data on whether the accident occurred on the bridge or under the bridge, or on a bridge element. It also provided information on the severity of accident. Using this data, Abed-Al-Rahim and Johnston (1991) were able to produce an estimate of the average percentage and the number of accidents of each severity type (K-A-B-C-PDO) occurring on North Carolina bridges. These values are then multiplied by the costs per accident value for the corresponding severity type from the Willingness-to-Pay approach to produce the accident costs associated with bridges. Costs associated with each of the five severity types are then summed to produce an overall average cost per accident on a bridge.

To compute accident costs in NCDOT's BMS, the accident cost value is multiplied by a coefficient expressing the expected rate of accidents occurring on a bridge. This coefficient is determined for individual bridges by an equation using bridge characteristics as inputs associated with the likelihood of future contributions to an accident. Chen and Johnston (1987) developed the equation used to determine the coefficient by conducting a literature review that showed bridge accident trends typically occur due to clear deck width and approach roadway alignment (Hilton 1973). According to prior work, alignment contributed to bridge accidents at a rate of at most half of the rate attributed to clear deck width (Ivey et al. 1979). Using that understanding Chen and Johnston (1987) developed Equation 2.6 to predict the coefficient of accidents as a function clear deck width and approach roadway alignment.

$$C_{WDA} + C_{ALA} = (6.28\times10^{7.5}CDW^{-6.5}[1+0.5(9-ALI)/7])\times10^{-6}$$

Equation 2.6: Accident rate of bridge in accidents per million vehicles

Where: $C_{WDA} + C_{ALA}$ = coefficient for proportion of vehicles incurring accidents due to width deficiency and poor alignment
CDW = clear deck width
ALI = alignment appraisal rating (scale of 1 to 9)

Later research by Abed-Al-Rahim and Johnston (1991) attempted to linked bridge accidents to features of the corresponding bridge to determine what bridge characteristics cause accidents. However, they note that there was no way to merge the two files directly since bridges were not identified on a common bases within the accident reports and the North Carolina Bridge Inventory (NCBI) file. So in order to match accidents to the bridge where the accident occurs, Abed-Al-Rahim and Johnston (1991) had to manually match accidents to bridges using information from the accident data records on county number, milepoint, route type, route number, reference road, direction toward road, distance from reference point, and direction from reference road. Due to this large undertaking, only five counties were selected for accident and bridge matching: Guilford, Harnett, Halifax, Iredell, and Wake county; these counties were picked as an overall representation of the state with high and low population density (Abed-Al-Rahim and Johnston 1991).

Abed-Al-Rahim and Johnston (1991) looked at accidents from 1983 through 1989. The records available totaled 2,895 accidents for the five counties, of which they were able to match 2,104 accidents to bridges with confidence. Once all the bridges with reported accidents were matched, Abed-Al-Rahim and Johnston (1991) used Statistical Analysis Software (SAS) to develop a prediction model for bridge related accidents based on the bridges' characteristics. A stepwise selection procedure was used first to explore the characteristics that have the most significant effect on accident rates (Abed-Al-Rahim and Johnston 1991). This procedure identified bridge clear deck width, approach roadway width, ADT, alignment appraisal rating, bridge length, and functional classification the most significant explanatory factors. These factors were then grouped into a number of different groupings and subgroupings and tested to determine their significance, through which ADT, bridge length, and the difference between clear deck width for an acceptable level of service and actual clear deck width were found to be the most significant. Using this information, the resulting Equation 2.7 was formed and recommended for use in the NCDOT BMS. Abed-Al-Rahim and Johnston (1991) note the strength of the regression was low with an R^2 value of 0.33, but justified the use of the model on the basis that the estimated number of accidents per year was close to actual accidents per year.

$$NOACC = 0.783(ADT^{0.073})(LENGTH^{0.033})(WDIFACC + 1)^{0.05} - 1.33$$

Equation 2.7: Number of accidents per year

Where: NOACC = number of accidents per year
ADT = average daily traffic
Length = bridge length, feet
WDIFACC = width difference between the goal clear deck width acceptable level of service and the actual clear deck width, but not less than zero, feet

Equation 2.7 includes a factor of 1.33 subtracted from the accident prediction equation, and is shown as published in Abed-Al-Rahim and Johnston (1991) and Abed-Al-Rahim and Johnston (1993). However, as described in these same publications, the 1.33 factor serves as an adjustment factor (denoted in both publications as AF) to account for the proportion of accidents that could not be manually matched to a specific bridge in their effort (Abed-Al-Rahim and Johnston 1991, 1993). Therefore, it is assumed that the subtraction sign is printed in error, and the adjustment factor for unmatchable accidents AF (in this case, equal to 1.33) should be multiplied by the remainder of the equation to predict the yearly accidents.

In BMS used by other state agencies, accident costs are computed or considered in a manner that differs from that utilized by NCDOT's BMS. The Florida Department of

Transportation (FDOT) sponsored research on the effect of the number of lanes on a bridge, ADT, and bridge length on accident rates (Wang 2010). Using these parameters and Florida bridge accident data, models were produced to predict accident rates based on number of lanes, ADT, and length. The three types of regression techniques used were linear regression models, Poisson regression models, and negative binomial regression models. The research concluded that negative binomial regression produced the best prediction of accidents rates due to these bridge characteristics (Wang 2010).

Other BMS systems, such as that used in Indiana (IBMS), do not account for bridge related accident costs in their user costs (Sinha et al. 2009). These accident costs are not considered in the IBMS total user costs since traffic safety is considered in their project selection module. Therefore, Sinha et al. (2009) believe that considering accident costs separately in the BMS would essentially incorporate these costs into the project planning and prioritization analysis twice.

2.6 Research Needs

A review of literature has indicated that the majority of current BMS have a history traceable to NCDOT's BMS. Researchers (Chen and Johnston 1987, Abed-Al-Rahim and Johnston 1991, Johnston et. al. 1994, Duncan and Johnston 2002, Johnston 2010) have periodically updated NCDOT's BMS, including an update as recently as 2010. However, data tables used to compute user costs in NCDOT's BMS need to be updated to improve the fidelity of user costs predictions. In some cases, new data is available to enhance the existing methodology used to compute detour and accident costs. Since these methods were first developed, NCDOT has made a number of advances in the collection and characterization of traffic data and accident data. Additionally, research by other agencies has yielded new approaches to computing user costs. Some of these approaches, as well as other approaches yet to be identified, could be used in conjunction with updated and enhanced data to improve the cost predictions of the NCDOT BMS.

Computation of all user costs in the NCDOT BMS are dependent on an accurate forecast of traffic. ADT growth rates are currently grouped by county and into the four main roadway classifications. Methods to identify ADT growth rates currently utilized in the NCDOT BMS, as described previously, are heavily reliant on date collected in the 1990's data, as well as expert opinion. However, ADT for each bridge is reported biennially to the NBI (FHWA 2012). Therefore, it is possible that the ADT for each bridge could be used to predict its own future ADT growth rate to be utilized in forecasting of more accurate user costs. Techniques developed by previous research projects (Stone et al. 2006 and Stone et al. 2011) could be used to identify methodologies to compute improved ADT growth rate estimates. Alternatively, bridges could be grouped by some reasonable set of rationale, and the grouped ADT growth rates could also be computed.

Due to both higher operating costs and higher probability of a detour due to a bridge posting, heavier weight vehicles will have a greater impact on user costs than lighter weight vehicles (Johnston et. al. 1994). North Carolina has experienced a significant increase in truck traffic over recent years (Stone et. al. 2006). However, the NCDOT BMS currently uses data from the 1980's to predict the portion of SU and TTST that must detour as well the percent ADTT associated with different roadway classifications. Therefore, there is a need to identify a better procedure to more accurately predict the number of vehicles (particularly in heavier weight classes) affected by functional deficiencies on North Carolina bridges.

Additionally, NCDOT has recently sponsored research that has resulted in the development of new truck traffic forecasting tools. A report published for the NCDOT titled "North Carolina Forecasts for Truck Traffic" (2006-28) explores the rapid increase in truck traffic in North Carolina (Stone et al. 2006). The findings of this research project, as well as those of another NCDOT research project (2008-11), could be utilized to better incorporate truck traffic estimates into the prediction of user costs in the BMS. As part of NCDOT research project 2008-11, Stone et al. (2011) combined vehicle classes four through seven as SU vehicles and vehicle classes eight through 13 as MU. Through this research, data collected on various roadways was used to predict the SU and MU portion of volume on different road classifications, thus providing an ADTT. This information could possibly be utilized to provide a more accurate set of ADTT estimates for the BMS, thereby improving user costs predictions.

Another research need lies in the estimating percentage of vehicles required to detour due to vertical clearance, which is currently based on pre-1960 data on trucks (Kent and Stevens 1963). It is very likely that the height distribution of today's truck traffic is different than that of pre-1960 traffic. Consequently, there is a need to utilize data that characterizes current-day truck heights to update the percentage of vehicles required to detour due to vertical clearance to improve user costs estimates based on this statistic. Likewise, there is also a need to update the percentages of vehicles of each weight that must detour due to bridge postings. NCDOT has sponsored research projects focused on developing improved truck forecast models by utilizing Weigh-in-Motion (WIM) stations and the NCDOT's Traffic Forecasting Unit (TFU) (Stone et al. 2009). Other reports on WIM data also exist (Ramachandran 2009). These models (or predictions obtained from these models), or recent WIM data, could be used to provide better input data regarding the percentage of vehicles in each weight class that travel different types of roadways, therefore improving the user costs predicted by the BMS.

Vehicles within a single vehicle class can have a range of weights. Since detours based on bridge postings depend on vehicle weight (not necessarily vehicle class), a means of better incorporating vehicle weight into computation of the percent of vehicles detoured would improve the fidelity of cost predictions. This would alleviate inaccuracies in cost computation that occur when an entire class of vehicles is assumed to detour when in reality only a portion of that class of vehicles would actually be required to detour as a result of the load posting.

Vehicle operating costs predictions are also important when calculating user cost due to detour or low vertical clearance. The NCDOT BMS currently computes vehicle operating cost for two vehicle weights (three ton and 40 ton), with linear interpolation of the vehicle operating cost for all vehicles between these two weights. It is possible that this relationship is not linear and an effort to develop a more accurate relationship between vehicle weight and operating cost is needed. After base values for three ton (and lighter) vehicles and maximum legal weight vehicles are updated to present time, additional published information could be utilized to determine the operating costs of vehicles of intermediate weights. This would allow for more accurate forecasting of the operating costs of vehicles with weights between three tons and 40 tons.

Vehicle operating costs for maximum weight vehicles currently depend on travel miles and revenue for motor carriers on a North American basis. Specific data for North Carolina motor carriers could be utilized to compute a more accurate vehicle operating cost for these heavier-weight vehicles. Since user costs for detours are highly dependent on the vehicle operator costs for these heavier vehicles, use of North Carolina data would improve the quality of these cost predictions.

Travel time costs due to detour are not currently included in the NCDOT BMS user costs. Travel time cost can include cost to a business for a paid employee or an unpaid consumer's personal time spent traveling (Wang 2010). The possibility of including travel time costs in NCDOT's BMS should be considered. The methodology utilized in the IBMS could provide a starting point for incorporating this consideration into the NCDOT BMS. The IBMS uses an approach developed by Son and Sinha (1997), shown below in Equation 2.8. In this equation, it is assumed that unit travel time costs are broken into four different categories that encompass the 13 vehicle classifications. Unit travel time cost for use in this equation were derived by the Texas Transportation Institute (TTI). The average speeds used for calculation are based on an estimation that is dependent upon the roadway classification.

$$TTC_L = \sum U_{TTCL}(J) \times \frac{DL}{SP(j)} \times N_L(j)$$

Equation 2.8: IBMS travel time cost

Where: $U_{TTCL}(j)$ = unit travel time cost for each vehicle of type j, \$/hour
$SP(j)$ = average speed of vehicle type j on detour, miles/hour
TTC_L = daily travel-time cost due to load capacity, \$/day
DL = detour length
$N_L(j)$ = number of type j vehicles to detour because of load capacity, per day

The AASHTOWare Pontis BMS software also accounts for travel time costs when predicting overall user cost. In order to assist FDOT enhance their BMS user costs, Thompson (et al. 1999) investigated the travel time costs utilized by the IBMS as well as another approach known as the Highway Economic Requirements Systems (HERS) approach. As outlined above, the IBMS travel time costs for the four different vehicle groups were derived by a study from the Texas Transportation Institute (TTI). The HERS travel time costs are based on values for labor wages, fringe benefits, and spoilage cost. Thompson et al. (1999) recommended the HERS approach for incorporation of travel time costs into BMS. The appropriateness of the HERS approach for the NCDOT's BMS could be investigated as a means for introducing travel time costs.

Supporting data for the computation of accident costs in the NCDOT BMS should also be updated. Using the existing methodology developed by Abed-Al-Rahim and Johnston (1991), costs per average accident across the range of severity categories could be updated to current values. Additionally, other approaches for determining accident costs should be investigated. Currently, the approach used in the NCDOT BMS uses the NSC Willingness-to-Pay values. Since the NSC Willingness-to-Pay values are not published annually, the Consumer Price Index (CPI) is used to project updated cost values to current values. The Traffic Safety Division of NCDOT publishes reports annually with Willingness-to-Pay costs per accident based solely on North Carolina data. Use of these accident costs for accidents solely in North Carolina would be an enhancement to the NCDOT BMS.

Additionally, the coefficients used for the average number of accidents per severity type occurring on bridges were determined from data collected in the 1980's. There is a need to update these inputs using more up-to-date, local statistics on accident rates. Information available from the Traffic Safety Division of NCDOT could be utilized to determine improved estimates to characterizing the number of accidents per severity type.

Overall, improvements to the NCDOT BMS could be made to facilitate project decisions on a network-level. Currently, the NCDOT Pavement Management System (PMS) uses four roadway classifications: Interstate, US, NC, and SR. In contrast, the NCDOT utilizes eleven functional classifications to describe roadways served by the bridge system. These functional classifications are shown in Table 2.6. Developing and implementing a field in the NCDOT BMS that allows for the BMS functional classification to be mapped to a corresponding PMS roadway classification would allow for more synergistic use of the BMS and PMS to support network-level project cost predictions and optimization.

Table 2.6: BMS functional classifications, codes, and descriptions

BMS Functional Classification	Code	Description
Interstate	01	Principal Arterial – Interstate (Rural)
	11	Principal Arterial – Interstate (Urban)
Arterial	02	Principal Arterial – Other
	06	Minor Arterial
	12	Principal Arterial – Other Freeways or Expressways
	14	Other Principal Arterial
	16	Minor Arterial
Collector	07	Major Collector
	08	Minor Collector
	17	Collector
Local	09	Local (Rural)
	19	Local (Urban)

CHAPTER 3: GENERAL IMPROVEMENTS TO BMS INPUTS

To update and enhance the user costs computed in NCDOT's BMS, several main focus areas of general improvements were made as part of this work. These improvements include updates of the ADT growth rates, updates to user cost prediction models for detours resulting from bridge capacity and vertical clearance limits, and accident cost input values. Specifically, the improvements to user cost inputs for detours resulting from bridge capacity and vertical clearance limits include updates to vehicle operating costs, updates to the estimated percentages of vehicles in each classification, and updates to the expected vehicle weight distributions on certain types of roadways. Updated truck geometry data was also analyzed in order to more accurately predict the percentage of trucks detoured due to excessive height in the BMS.

To accomplish these improvements, data from NCDOT and from other sources were examined and utilized. Much of this data was available from several divisions of NCDOT including Traffic Engineering, Division of Motor Vehicles (DMV), and the Traffic Survey group. In order to update ADT growth rate inputs, historical values of ADT associated with each North Carolina bridge were utilized, which are available in the BMS and the NBI. Other data that was reviewed and utilized to update the BMS was the weight of SU and TTST vehicles. Information on accidents, including frequency, severity, and location (whether on a bridge or not) was obtained from NCDOT's Traffic Engineering Division and utilized to update prediction model inputs for accident frequencies and severity. Costs associated with vehicle accidents of the different classification of severity were also obtained from NCDOT's Traffic Engineering Division, reviewed, and utilized to refine cost estimates in the user cost models. Updated costs were also determined for vehicle operating cost associated with the minimum and maximum weight limits of vehicles. A methodology for identifying the vehicle operating cost of a mid-range vehicle (vehicles approximately between the size of a passenger vehicle and maximum allowable highway load) was also developed. For cost values that could not be obtained in current (2014) cost figures, the Consumer Price Index (CPI) was to adjust the most recent cost to 2014 adjusted cost.

3.1 Average Daily Traffic Growth

As part of the bridge inspection and NBI reporting programs, NCDOT biennially updates the ADT estimate for each bridge. The BMS program therefore stores historical and current information on the ADT for each bridge. The expected ADT growth rate is an input in the BMS program that is used to predict the future ADT for user costs estimates and in optimization scenarios. Biennially updated ADT values were used to update the ADT growth rates for the four different roadway types (Interstate, Arterial, Collector, and Local). To update the average ADT inputs for each roadway type in every county, historical ADT values from the BMS were utilized. It should be noted, however, that some bridges did not have ADT values recorded in the BMS for all years. Therefore, it was decided that, for this analysis, only bridges with a minimum of ten years of data would be used. Additionally, only bridges that had an ADT value recorded for 2010 or more recent would be utilized.

Due to the large volume of data (most bridges have nearly 30 years of ADT estimates), a macro was generated in Excel to the parse the ADT data and compute an ADT growth rate for each bridge. Using the LOGEST function in Excel, the ADT for each bridge was plotted against time and an exponential curve was fit to the data. Based on the exponential best fit curve, the average growth rate for each bridge was identified. This value was converted to a percentage by subtracting one from the value and then putting the value in percentage form. This percent growth rate was then compiled with other bridges in the same counties after grouping the bridges based on one of the four types of roadways mentioned above. For each group over each county, a histogram was produced so that the distribution of the growth rates could be evaluated and a representative value for the group identified statistically. Examples of these histograms are provided in Figures 3.1 through 3.4. Some of these distributions could be visually classified as normally distributed (Figure 3.4), while others could not (Figures 3.1-3.3).

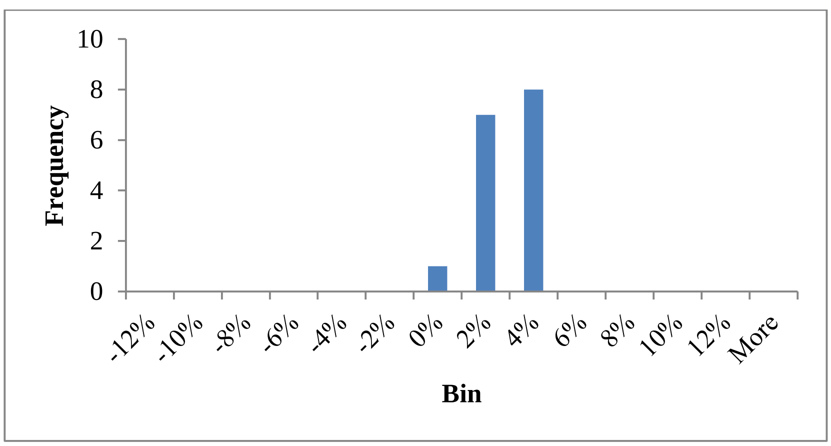


Figure 3.1: Anson County arterial histogram of ADT growth rates

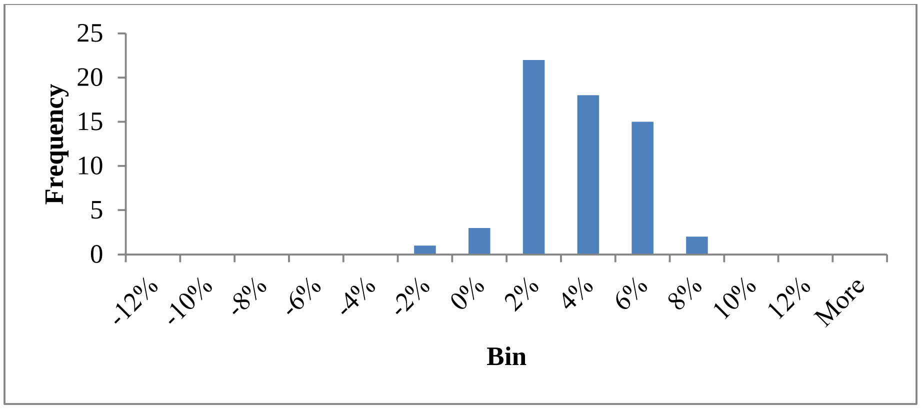


Figure 3.2: Forsyth County collector histogram of ADT growth rates

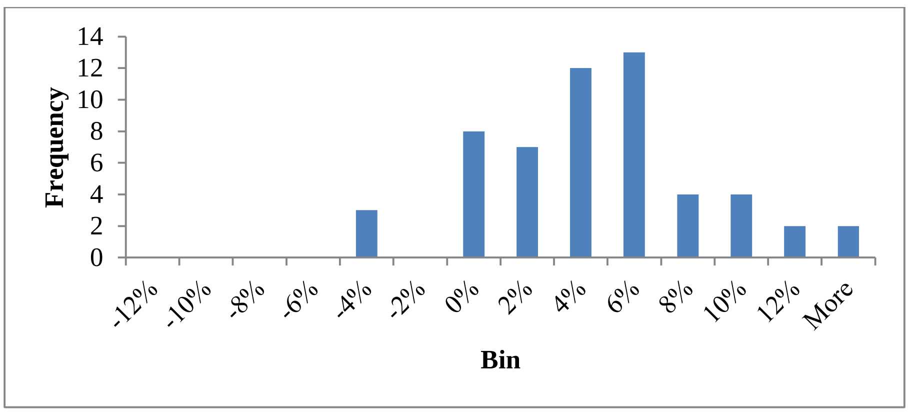


Figure 3.3: Gaston County local histogram of ADT growth rates

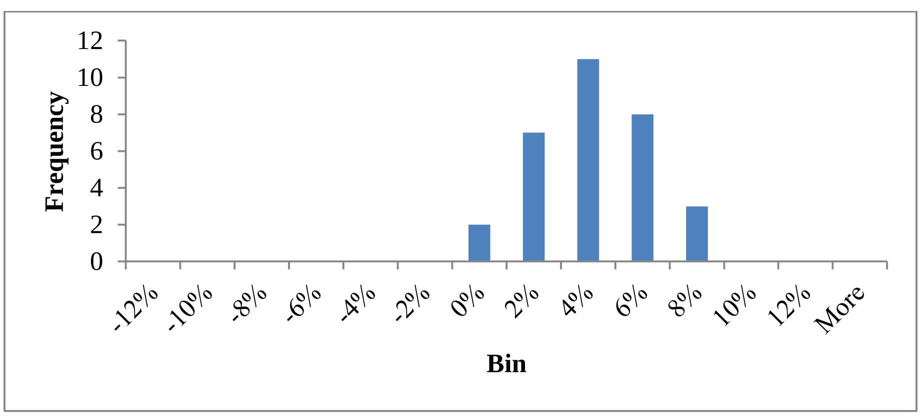


Figure 3.4: Orange County collector histogram of ADT growth rates

Table 3.1 provides the number of ADT growth rates used in each roadway grouping by county as well as the distribution type (color coded) where green indicates the data was considered to be well distributed (N>15), yellow indicates the data was considered to be not well distributed (N>15), orange indicates the data was considered to be well distrusted (N<15), red indicates the data was considered to be not well distributed (N<15), and gray indicates that no data was available. Due to a number of roadways exhibiting non-normally distributed data, it is recommended that the median, rather than mean, values be used by NCDOT as the ADT growth rate estimate to be used in the BMS. These values developed from the analysis of the current BMS database are presented in Table 3.2. Since some counties do not have Interstate or Arterial routes, the statewide average for each respectively is suggested for use in the BMS as a place holder. In the event that these routes are constructed in the future, new ADT growth rates could be developed in a manner similar to the method outlined above as data becomes available.

Table 3.1: Number of ADT growth rate values used and distribution type

County No.	County Name	Local	Collector	Arterial	Interstate
00	Alamance	68	58	19	3
01	Alexander	47	16	5	
02	Alleghany	77	4	2	
03	Anson	86	32	16	
04	Ashe	187	24	4	
05	Avery	74	8	3	
06	Beaufort	63	42	15	
07	Bertie	28	16	26	
08	Bladen	35	35	14	
09	Brunswick	40	35	28	
10	Buncombe	265	72	56	86
11	Burke	85	60	30	14
12	Cabarrus	65	43	41	8
13	Caldwell	110	20	18	
14	Camden	7	7	4	
15	Carteret	12	28	10	
16	Caswell	46	13	5	
17	Catawba	67	35	45	10
18	Chatham	70	40	33	
19	Cherokee	83	38	25	
20	Chowan	12	8	12	
21	Clay	34	17	2	
22	Cleveland	127	45	33	2
23	Columbus	75	58	33	
24	Craven	36	33	33	
25	Cumberland	57	28	72	15
26	Currituck	7	3	7	
27	Dare	8	5	11	
28	Davidson	85	51	69	21
29	Davie	29	14	8	8
30	Duplin	67	57	11	10
31	Durham	49	24	89	34
32	Edgecombe	40	47	33	
33	Forsyth	116	61	83	25
34	Franklin	38	31	8	
35	Gaston	55	36	75	5
36	Gates	12	7	5	
37	Graham	69	15	1	
38	Granville	52	33	3	7
39	Greene	24	12	5	
40	Guilford	167	69	126	37
41	Halifax	65	26	13	8
42	Harnett	38	27	10	2
43	Haywood	187	48	35	21
44	Henderson	149	33	42	10
45	Hertford	20	10	7	
46	Hoke	17	11	3	
47	Hyde	16	22	11	
48	Iredell	136	51	11	54
49	Jackson	163	27	28	

Table 3.1: Number of ADT growth rate values used and distribution type (continued)

50	Johnston	92	61	32	32
51	Jones	26	13	1	
52	Lee	19	13	17	
53	Lenoir	31	24	25	
54	Lincoln	65	22	25	
55	Macon	150	35	16	
56	Madison	140	66	8	4
57	Martin	44	12	26	
58	McDowell	102	48	8	22
59	Mecklenburg	106	28	137	103
60	Mitchell	95	21	1	
61	Montgomery	77	13	3	10
62	Moore	74	22	25	
63	Nash	67	73	62	12
64	New Hanover	9	5	22	8
65	Northampton	29	20	7	2
66	Onslow	21	30	22	
67	Orange	59	31	20	21
68	Pamlico	15	23		
69	Pasquotank	14	7	10	
70	Pender	40	28		2
71	Perquimans	17	10	4	
72	Person	39	15	6	
73	Pitt	69	45	33	
74	Polk	85	19	12	7
75	Randolph	136	61	37	13
76	Richmond	56	20	30	
77	Robeson	85	84	30	14
78	Rockingham	86	62	32	
79	Rowan	97	38	22	8
80	Rutherford	209	29	34	
81	Sampson	80	53	25	
82	Scotland	14	23	38	
83	Stanly	59	29	13	
84	Stokes	56	21	4	
85	Surry	130	41	30	29
86	Swain	75	6	16	
87	Transylvania	98	32	11	
88	Tyrrell	14	3	2	
89	Union	109	66	16	
90	Vance	18	22	13	6
91	Wake	168	55	109	54
92	Warren	52	11		2
93	Washington	9	13	1	
94	Watauga	133	12	6	
95	Wayne	42	31	37	
96	Wilkes	235	31	8	
97	Wilson	51	35	22	8
98	Yadkin	82	18	12	6
99	Yancey	130	24	4	

Table 3.2: ADT growth rates

County No.	County Name	Local	Collector	Arterial	Interstate
00	Alamance	2.55%	3.23%	2.30%	6.36%
01	Alexander	2.74%	2.98%	2.27%	3.64%
02	Alleghany	1.79%	2.35%	2.21%	3.64%
03	Anson	1.81%	2.33%	2.00%	3.64%
04	Ashe	1.69%	2.30%	3.82%	3.64%
05	Avery	2.92%	3.79%	1.05%	3.64%
06	Beaufort	2.31%	1.49%	2.45%	3.64%
07	Bertie	2.57%	2.85%	1.71%	3.64%
08	Bladen	2.95%	3.13%	1.43%	3.64%
09	Brunswick	5.26%	3.41%	2.85%	3.64%
10	Buncombe	3.20%	3.92%	3.46%	3.65%
11	Burke	2.60%	4.04%	2.48%	3.64%
12	Cabarrus	4.15%	5.07%	2.96%	4.42%
13	Caldwell	2.44%	2.11%	2.13%	3.64%
14	Camden	1.00%	3.31%	2.22%	3.64%
15	Carteret	0.61%	2.41%	1.74%	3.64%
16	Caswell	1.92%	2.39%	2.91%	3.64%
17	Catawba	3.79%	3.61%	3.38%	3.62%
18	Chatham	2.54%	3.03%	3.06%	3.64%
19	Cherokee	3.29%	2.97%	0.89%	3.64%
20	Chowan	1.57%	1.13%	1.46%	3.64%
21	Clay	3.15%	3.40%	4.21%	3.64%
22	Cleveland	2.63%	2.74%	2.38%	2.26%
23	Columbus	2.12%	2.56%	2.75%	3.64%
24	Craven	2.56%	2.94%	1.74%	3.64%
25	Cumberland	2.46%	2.57%	3.28%	2.34%
26	Currituck	2.67%	2.68%	3.59%	3.64%
27	Dare	6.34%	2.18%	2.28%	3.64%
28	Davidson	2.23%	2.87%	1.61%	2.43%
29	Davie	2.61%	2.88%	2.81%	3.42%
30	Duplin	2.63%	2.59%	0.34%	1.83%
31	Durham	3.08%	4.40%	2.84%	5.56%
32	Edgecombe	1.72%	0.79%	2.38%	3.64%
33	Forsyth	1.87%	2.39%	1.83%	4.52%
34	Franklin	3.55%	3.31%	2.38%	3.64%
35	Gaston	3.83%	3.43%	2.02%	6.60%
36	Gates	0.95%	2.68%	2.33%	3.64%
37	Graham	3.01%	3.68%	2.40%	3.64%
38	Granville	3.29%	4.05%	4.36%	2.96%
39	Greene	2.76%	2.37%	2.91%	3.64%
40	Guilford	2.57%	3.02%	2.31%	3.15%
41	Halifax	1.85%	0.96%	1.17%	2.96%
42	Harnett	3.89%	3.79%	1.92%	2.89%
43	Haywood	3.50%	2.33%	2.76%	2.76%
44	Henderson	4.28%	3.87%	1.67%	3.31%
45	Hertford	1.44%	2.79%	2.25%	3.64%
46	Hoke	2.48%	4.11%	2.90%	3.64%
47	Hyde	1.34%	4.21%	0.18%	3.64%
48	Iredell	3.24%	3.70%	3.58%	3.37%
49	Jackson	2.54%	4.20%	3.42%	3.64%

Table 3.2: ADT growth rates (continued)

50	Johnston	2.78%	3.90%	1.60%	4.46%
51	Jones	2.31%	2.08%	2.07%	3.64%
52	Lee	3.28%	3.22%	3.86%	3.64%
53	Lenoir	1.90%	1.66%	1.51%	3.64%
54	Lincoln	3.36%	3.26%	2.03%	3.64%
55	Macon	2.67%	4.40%	6.07%	3.64%
56	Madison	2.85%	2.95%	4.55%	3.26%
57	Martin	1.75%	2.90%	1.51%	3.64%
58	McDowell	2.33%	1.76%	4.31%	3.28%
59	Mecklenburg	1.49%	4.49%	2.75%	4.87%
60	Mitchell	2.36%	2.12%	2.63%	3.64%
61	Montgomery	1.70%	3.22%	3.39%	4.36%
62	Moore	3.06%	4.37%	2.68%	3.64%
63	Nash	2.70%	3.15%	2.57%	2.96%
64	New Hanover	3.12%	3.66%	2.64%	3.79%
65	Northampton	0.89%	2.02%	0.47%	2.69%
66	Onslow	3.61%	2.74%	1.92%	3.64%
67	Orange	3.82%	3.67%	2.12%	2.57%
68	Pamlico	1.77%	3.17%	2.40%	3.64%
69	Pasquotank	2.81%	2.44%	1.35%	3.64%
70	Pender	2.61%	3.75%	2.40%	4.63%
71	Perquimans	2.14%	1.61%	2.16%	3.64%
72	Person	3.16%	2.90%	2.77%	3.64%
73	Pitt	1.78%	3.09%	2.77%	3.64%
74	Polk	3.07%	2.15%	4.64%	2.71%
75	Randolph	3.20%	2.45%	2.84%	4.01%
76	Richmond	1.70%	1.92%	2.95%	3.64%
77	Robeson	2.74%	3.22%	2.56%	2.26%
78	Rockingham	2.40%	1.75%	0.77%	3.64%
79	Rowan	3.24%	2.98%	2.06%	4.20%
80	Rutherford	2.49%	2.00%	2.55%	3.64%
81	Sampson	2.89%	2.77%	2.27%	3.64%
82	Scotland	2.36%	2.58%	1.93%	3.64%
83	Stanly	2.05%	2.57%	2.19%	3.64%
84	Stokes	3.23%	2.30%	3.03%	3.64%
85	Surry	3.05%	2.78%	2.61%	3.81%
86	Swain	2.20%	4.43%	3.37%	3.64%
87	Transylvania	3.74%	2.63%	2.45%	3.64%
88	Tyrrell	0.38%	1.10%	2.92%	3.64%
89	Union	3.86%	4.90%	2.84%	3.64%
90	Vance	2.27%	3.28%	1.18%	4.60%
91	Wake	4.11%	4.79%	2.59%	5.84%
92	Warren	2.54%	2.56%	2.40%	2.83%
93	Washington	1.73%	1.54%	0.33%	3.64%
94	Watauga	2.85%	4.97%	2.63%	3.64%
95	Wayne	1.57%	2.98%	0.90%	3.64%
96	Wilkes	2.57%	2.06%	2.06%	3.64%
97	Wilson	1.74%	2.19%	0.27%	2.93%
98	Yadkin	3.13%	3.23%	2.66%	3.39%
99	Yancey	2.86%	2.38%	3.63%	3.64%

Table 3.3 provides a look at how the ADT growth rate values have changed from the study conducted by Duncan and Johnston (2002) and the work done as part of this research. To help illustrate the difference between the 2002 ADT growth rates and the current growth rates, the difference has been color coded on the table, where: yellow is a difference of plus or minus 1 percent, orange is minus 1 percent to minus 2 percent, red is minus 2 percent and less, green is plus 1 percent to plus 2 percent, and blue is plus 3 percent and greater. Additionally, Figures 3.5 through 3.8 were prepared using the same color coding key for each of the four roadway types on the counties. These figures provide a useful illustration of the areas of North Carolina experiencing higher growth rates, and could be utilized by NCDOT in a number of forecasting applications. For counties not having an Interstate, a gray color was used in Figure 3.8, since only a placeholder value is suggested for the NCDOT BMS input in Table 3.2.

Table 3.3: Change in ADT growth rates

		Local			Collector			Arterial			Interstate		
County No.	County Name	2001 (%)	2014 (%)	Diff. (%)	2001 (%)	2014 (%)	Diff. (%)	2001 (%)	2014 (%)	Diff. (%)	2001 (%)	2014 (%)	Diff. (%)
00	Alamance	3.82	2.55	-1.27	3.50	3.23	-0.27	3.50	2.30	-1.20	6.81	6.36	-0.45
01	Alexander	4.57	2.74	-1.83	4.28	2.98	-1.30	2.86	2.27	-0.59	5.38	3.64	-1.74
02	Alleghany	2.75	1.79	-0.96	3.99	2.35	-1.64	2.75	2.21	-0.54	5.38	3.64	-1.74
03	Anson	2.67	1.81	-0.86	2.86	2.33	-0.53	2.98	2.00	-0.98	5.38	3.64	-1.74
04	Ashe	2.50	1.69	-0.81	3.61	2.30	-1.31	2.97	3.82	0.85	5.38	3.64	-1.74
05	Avery	3.42	2.92	-0.50	3.52	3.79	0.27	3.50	1.05	-2.45	5.38	3.64	-1.74
06	Beaufort	2.50	2.31	-0.19	2.55	1.49	-1.06	2.93	2.45	-0.48	5.38	3.64	-1.74
07	Bertie	3.45	2.57	-0.88	3.28	2.85	-0.43	0.48	1.71	1.23	5.38	3.64	-1.74
08	Bladen	4.93	2.95	-1.98	2.50	3.13	0.63	3.00	1.43	-1.57	5.38	3.64	-1.74
09	Brunswick	5.96	5.26	-0.70	4.56	3.41	-1.15	3.50	2.85	-0.65	5.38	3.64	-1.74
10	Buncombe	2.50	3.20	0.70	2.55	3.92	1.37	3.50	3.46	-0.04	5.47	3.65	-1.82
11	Burke	2.72	2.60	-0.12	3.37	4.04	0.67	3.01	2.48	-0.53	5.19	3.64	-1.55
12	Cabarrus	3.61	4.15	0.54	3.50	5.07	1.57	2.86	2.96	0.10	7.75	4.42	-3.33
13	Caldwell	2.50	2.44	-0.06	2.50	2.11	-0.39	3.92	2.13	-1.79	5.38	3.64	-1.74
14	Camden	4.43	1.00	-3.43	3.47	3.31	-0.16	3.16	2.22	-0.94	5.38	3.64	-1.74
15	Carteret	3.50	0.61	-2.89	2.59	2.41	-0.18	3.25	1.74	-1.51	5.38	3.64	-1.74
16	Caswell	1.44	1.92	0.48	3.92	2.39	-1.53	4.24	2.91	-1.33	5.38	3.64	-1.74
17	Catawba	3.42	3.79	0.37	2.93	3.61	0.68	2.84	3.38	0.54	5.00	3.62	-1.38
18	Chatham	4.21	2.54	-1.67	3.49	3.03	-0.46	2.58	3.06	0.48	5.38	3.64	-1.74
19	Cherokee	4.28	3.29	-0.99	2.87	2.97	0.10	2.25	0.89	-1.36	5.38	3.64	-1.74
20	Chowan	2.50	1.57	-0.93	2.50	1.13	-1.37	2.60	1.46	-1.14	5.38	3.64	-1.74
21	Clay	2.40	3.15	0.75	2.47	3.40	0.93	3.50	4.21	0.71	5.38	3.64	-1.74
22	Cleveland	2.59	2.63	0.04	3.15	2.74	-0.41	2.79	2.38	-0.41	2.96	2.26	-0.70
23	Columbus	2.50	2.12	-0.38	3.87	2.56	-1.31	2.32	2.75	0.43	5.38	3.64	-1.74
24	Craven	2.41	2.56	0.15	2.22	2.94	0.72	2.50	1.74	-0.76	5.38	3.64	-1.74
25	Cumberland	2.50	2.46	-0.04	2.50	2.57	0.07	3.50	3.28	-0.22	5.00	2.34	-2.66
26	Currituck	2.50	2.67	0.17	2.5%	2.6%	0.18	3.15	3.59	0.44	5.38	3.64	-1.74
27	Dare	3.50	6.34	2.84	3.50	2.18	-1.32	4.00	2.28	-1.72	5.38	3.64	-1.74
28	Davidson	2.45	2.23	-0.22	2.99	2.87	-0.12	3.50	1.61	-1.89	5.84	2.43	-3.41
29	Davie	3.37	2.61	-0.76	3.25	2.88	-0.37	3.50	2.81	-0.69	4.50	3.42	-1.08
30	Duplin	2.55	2.63	0.08	2.55	2.59	0.04	3.50	0.34	-3.16	4.50	1.83	-2.67
31	Durham	3.39	3.08	-0.31	3.25	4.40	1.15	3.50	2.84	-0.66	5.00	5.56	0.56
32	Edgecombe	2.50	1.72	-0.78	2.50	0.79	-1.71	3.50	2.38	-1.12	5.38	3.64	-1.74
33	Forsyth	2.50	1.87	-0.63	2.55	2.39	-0.16	3.50	1.83	-1.67	3.60	4.52	0.92
34	Franklin	3.43	3.55	0.12	2.82	3.31	0.49	3.50	2.38	-1.12	5.38	3.64	-1.74
35	Gaston	2.50	3.83	1.33	2.50	3.43	0.93	3.50	2.02	-1.48	5.07	6.60	1.53
36	Gates	2.50	0.95	-1.55	2.69	2.68	-0.01	3.55	2.33	-1.22	5.38	3.64	-1.74
37	Graham	2.50	3.01	0.51	2.50	3.68	1.18	3.02	2.40	-0.62	5.38	3.64	-1.74
38	Granville	3.00	3.29	0.29	3.45	4.05	0.60	3.75	4.36	0.61	5.00	2.96	-2.04
39	Greene	2.50	2.76	0.26	3.50	2.37	-1.13	3.50	2.91	-0.59	5.38	3.64	-1.74
40	Guilford	2.50	2.57	0.07	3.55	3.02	-0.53	3.50	2.31	-1.19	5.00	3.15	-1.85
41	Halifax	3.50	1.85	-1.65	3.00	0.96	-2.04	3.50	1.17	-2.33	4.04	2.96	-1.08
42	Harnett	2.50	3.89	1.39	3.50	3.79	0.29	3.00	1.92	-1.08	5.03	2.89	-2.14
43	Haywood	4.63	3.50	-1.13	3.00	2.33	-0.67	3.61	2.76	-0.85	5.62	2.76	-2.86
44	Henderson	3.20	4.28	1.08	3.11	3.87	0.76	4.01	1.67	-2.34	5.01	3.31	-1.70
45	Hertford	2.50	1.44	-1.06	3.38	2.79	-0.59	3.75	2.25	-1.50	5.38	3.64	-1.74
46	Hoke	3.52	2.48	-1.04	2.50	4.11	1.61	3.50	2.90	-0.60	5.38	3.64	-1.74
47	Hyde	2.47	1.34	-1.13	2.50	4.21	1.71	3.50	0.18	-3.32	5.38	3.64	-1.74
48	Iredell	3.67	3.24	-0.43	3.50	3.70	0.20	3.33	3.58	0.25	4.50	3.37	-1.13
49	Jackson	2.81	2.54	-0.27	3.00	4.20	1.20	3.50	3.42	-0.08	5.38	3.64	-1.74
50	Johnston	6.68	2.78	-3.90	3.21	3.90	0.69	3.50	1.60	-1.90	4.24	4.46	0.22

Table 3.3: Change in ADT growth rates (continued)

51	Jones	2.50	2.31	-0.19	2.50	2.08	-0.42	3.00	2.07	-0.93	5.38	3.64	-1.74
52	Lee	2.50	3.28	0.78	3.50	3.22	-0.28	3.50	3.86	0.36	5.38	3.64	-1.74
53	Lenoir	3.06	1.90	-1.16	3.38	1.66	-1.72	4.11	1.51	-2.60	5.38	3.64	-1.74
54	Lincoln	2.60	3.36	0.76	3.34	3.26	-0.08	3.50	2.03	-1.47	5.38	3.64	-1.74
55	McDowell	2.54	2.33	-0.21	2.54	1.76	-0.78	3.00	4.31	1.31	5.17	3.28	-1.89
56	Macon	2.58	2.67	0.09	3.00	4.40	1.40	3.00	6.07	3.07	5.38	3.64	-1.74
57	Madison	2.50	2.85	0.35	3.20	2.95	-0.25	2.59	4.55	1.96	5.38	3.26	-2.12
58	Martin	2.50	1.75	-0.75	3.50	2.90	-0.60	3.55	1.51	-2.04	5.38	3.64	-1.74
59	Mecklenburg	2.67	1.49	-1.18	4.74	4.49	-0.25	2.90	2.75	-0.15	4.93	4.87	-0.06
60	Mitchell	1.05	2.36	1.31	1.18	2.12	0.94	2.97	2.63	-0.34	5.38	3.64	-1.74
61	Montgomery	2.02	1.70	-0.32	3.77	3.22	-0.55	5.84	3.39	-2.45	6.25	4.36	-1.89
62	Moore	5.01	3.06	-1.95	4.78	4.37	-0.41	3.43	2.68	-0.75	5.38	3.64	-1.74
63	Nash	3.00	2.70	-0.30	3.00	3.15	0.15	3.09	2.57	-0.52	4.50	2.96	-1.54
64	New Hanover	4.84	3.12	-1.72	3.06	3.66	0.60	3.50	2.64	-0.86	6.50	3.79	-2.71
65	Northampton	2.17	0.89	-1.28	2.05	2.02	-0.03	3.50	0.47	-3.03	5.25	2.69	-2.56
66	Onslow	3.06	3.61	0.55	3.25	2.74	-0.51	3.50	1.92	-1.58	5.38	3.64	-1.74
67	Orange	2.42	3.82	1.40	3.20	3.67	0.47	3.50	2.12	-1.38	4.56	2.57	-1.99
68	Pamlico	3.50	1.77	-1.73	4.16	3.17	-0.99	3.50	2.40	-1.10	5.38	3.64	-1.74
69	Pasquotank	2.50	2.81	0.31	2.50	2.44	-0.06	4.93	1.35	-3.58	5.38	3.64	-1.74
70	Pender	3.00	2.61	-0.39	3.50	3.75	0.25	3.50	2.40	-1.10	6.50	4.63	-1.87
71	Perquimans	2.50	2.14	-0.36	2.50	1.61	-0.89	3.50	2.16	-1.34	5.38	3.64	-1.74
72	Person	2.50	3.16	0.66	2.75	2.90	0.15	3.50	2.77	-0.73	5.38	3.64	-1.74
73	Pitt	2.55	1.78	-0.77	2.55	3.09	0.54	3.04	2.77	-0.27	5.38	3.64	-1.74
74	Polk	2.50	3.07	0.57	3.28	2.15	-1.13	3.50	4.64	1.14	4.42	2.71	-1.71
75	Randolph	3.50	3.20	-0.30	2.71	2.45	-0.26	3.67	2.84	-0.83	5.47	4.01	-1.46
76	Richmond	2.63	1.70	-0.93	3.20	1.92	-1.28	3.50	2.95	-0.55	6.25	3.64	-2.61
77	Robeson	3.06	2.74	-0.32	3.08	3.22	0.14	3.49	2.56	-0.93	4.50	2.26	-2.24
78	Rockingham	3.88	2.40	-1.48	2.85	1.75	-1.10	3.20	0.77	-2.43	6.25	3.64	-2.61
79	Rowan	3.00	3.24	0.24	3.50	2.98	-0.52	4.63	2.06	-2.57	6.91	4.20	-2.71
80	Rutherford	4.09	2.49	-1.60	3.25	2.00	-1.25	3.50	2.55	-0.95	5.38	3.64	-1.74
81	Sampson	2.50	2.89	0.39	2.50	2.77	0.27	3.50	2.27	-1.23	6.25	3.64	-2.61
82	Scotland	2.50	2.36	-0.14	3.50	2.58	-0.92	3.50	1.93	-1.57	5.38	3.64	-1.74
83	Stanly	2.50	2.05	-0.45	3.64	2.57	-1.07	3.08	2.19	-0.89	5.38	3.64	-1.74
84	Stokes	2.50	3.23	0.73	3.55	2.30	-1.25	3.55	3.03	-0.52	5.38	3.64	-1.74
85	Surry	2.60	3.05	0.45	2.60	2.78	0.18	3.50	2.61	-0.89	6.25	3.81	-2.44
86	Swain	2.50	2.20	-0.30	3.50	4.43	0.93	3.55	3.37	-0.18	5.38	3.64	-1.74
87	Transylvania	2.50	3.74	1.24	2.50	2.63	0.13	3.50	2.45	-1.05	5.38	3.64	-1.74
88	Tyrrell	0.84	0.38	-0.46	2.50	1.10	-1.40	2.50	2.92	0.42	5.38	3.64	-1.74
89	Union	3.00	3.86	0.86	3.00	4.90	1.90	3.50	2.84	-0.66	5.38	3.64	-1.74
90	Vance	3.25	2.27	-0.98	3.25	3.28	0.03	3.50	1.18	-2.32	5.82	4.60	-1.22
91	Wake	3.00	4.11	1.11	5.00	4.79	-0.21	4.00	2.59	-1.41	6.50	5.84	-0.66
92	Warren	2.50	2.54	0.04	3.15	2.56	-0.59	3.50	2.40	-1.10	7.51	2.83	-4.68
93	Washington	2.50	1.73	-0.77	2.50	1.54	-0.96	3.00	0.33	-2.67	5.38	3.64	-1.74
94	Watauga	2.50	2.85	0.35	3.00	4.97	1.97	3.50	2.63	-0.87	5.38	3.64	-1.74
95	Wayne	2.82	1.57	-1.25	3.00	2.98	-0.02	3.50	0.90	-2.60	5.38	3.64	-1.74
96	Wilkes	2.50	2.57	0.07	3.20	2.06	-1.14	3.50	2.06	-1.44	5.38	3.64	-1.74
97	Wilson	3.39	1.74	-1.65	2.81	2.19	-0.62	2.92	0.27	-2.65	4.50	2.93	-1.57
98	Yadkin	2.50	3.13	0.63	3.25	3.23	-0.02	3.50	2.66	-0.84	6.25	3.39	-2.86
99	Yancey	2.50	2.86	0.36	2.65	2.38	-0.27	4.35	3.63	-0.72	5.38	3.64	-1.74

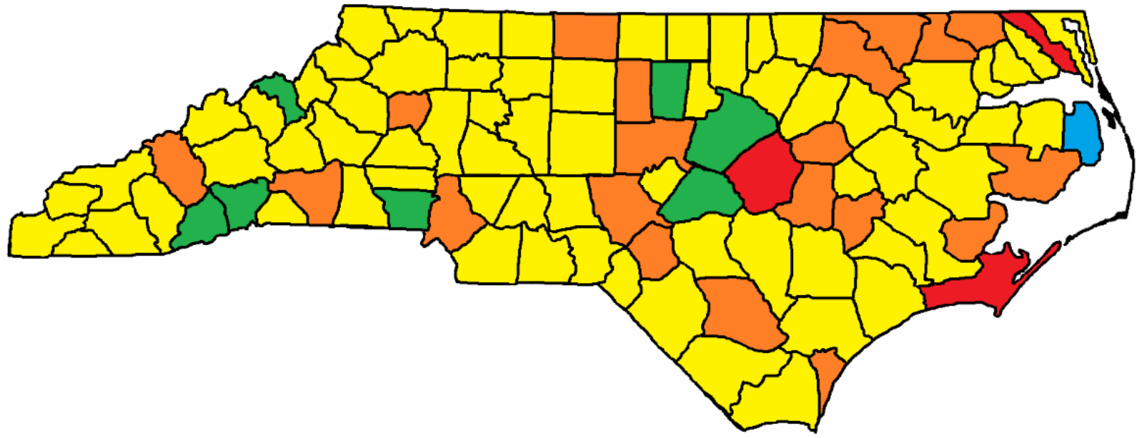


Figure 3.5: Change in ADT growth rates for Local Routes

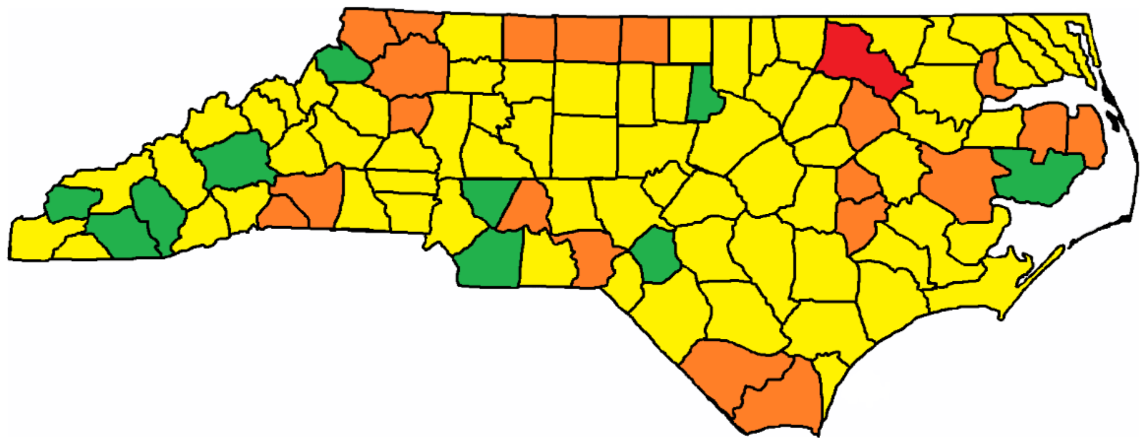


Figure 3.6: Change in ADT growth rates for Collector Routes

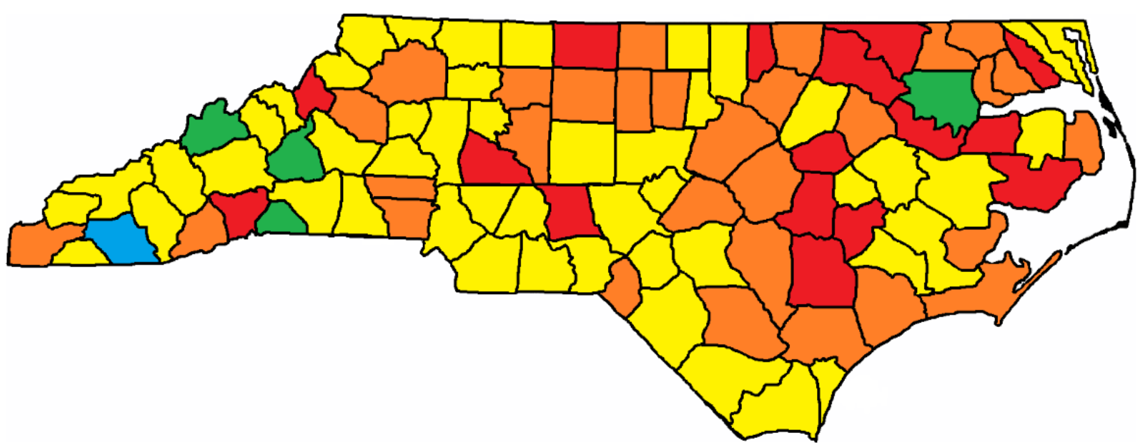


Figure 3.7: Change in ADT growth rates for Arterial Routes

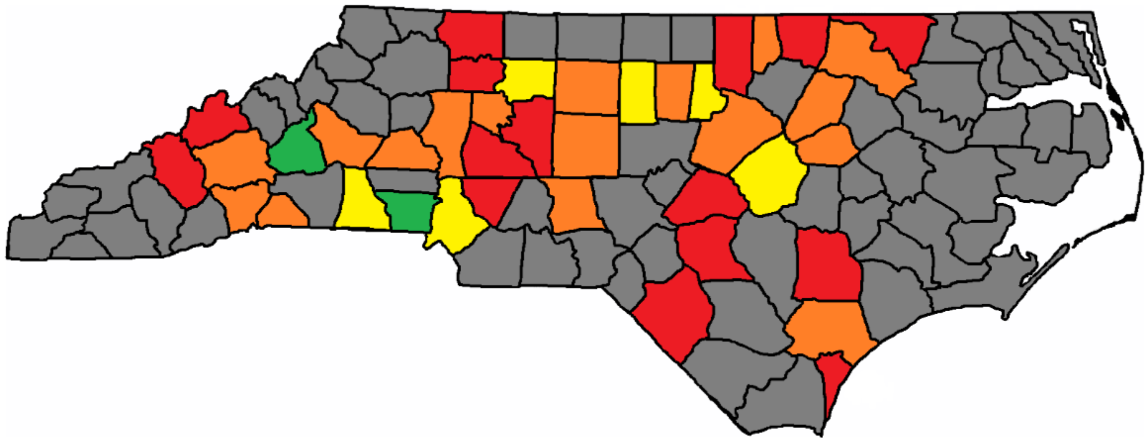


Figure 3.8: Change in ADT growth rates for Interstate Routes

3.2 Detour Resulting from Bridge Capacity and Vertical Clearance Limits

To compute user costs associated with detours, it is necessary for the BMS to accurately predict the number of vehicles that are too heavy or oversized to traverse each individual bridge. This is accomplished in the software by multiplying the overall ADT by a percentage (in decimal form) of each type of vehicle class (SU and TTST) restricted from traveling over the bridge due to load posting or vertical clearance. To update the percentages of vehicles that will have to detour due to bridge posting or low vertical clearance, data collected from North Carolina WIM stations was utilized in addition to data from a research study in Florida (Sobanjo and Thompson 2004). The WIM data was used to compute percentages of vehicles in each classification and distributions of vehicle weight for each vehicle class, while the Florida study provided data on vertical clearance distributions for modern trucks (Sobanjo and Thompson 2004). The vehicle classes were grouped into two different categories, SU or TTST. The capacity and vertical clearance distributions for each category can then be calculated by the percentage it accounts for on any particular roadway. This can be used to generate an updated table showing the percentage that will have to detour based on different bridge postings or vertical limits, ultimately improving the accuracy of user costs computed by the NCDOT's BMS. These percentages are then multiplied by an associated vehicle operating cost per mile, supplied from state and government sources, which is used to determine an overall detour cost.

3.2.1 Vehicle Operating Costs

Currently, vehicle operating costs used in the NCDOT BMS are based on values computed for two vehicles: a passenger car (3-tons) and a vehicle at maximum allowable load (40-tons). Vehicle operating cost for the minimum and maximum vehicle weights were updated using current locally calibrated data. Additionally, an effort was made to obtain an intermediate value for vehicle operating costs, with the intent of identifying whether the currently utilized linear relationship between user vehicle operating cost and vehicle weight was applicable.

To obtain user costs at the 3-ton weight limit (the minimum used in the BMS), the North Carolina State government employee wage rate for a Vehicle Operator I was obtained from the North Carolina Office of State Human Resources ($23,975). This employee wage rate is noted as a Grade 53 (OSHR 2014). This value was then be divided by the product of the estimated number of hours worked in a year (1920 hrs) and an assumed average speed (40 mph). Lastly, the value was added to the Internal Revenue Service (IRS) standard mileage rate for business use ($0.56), which is published yearly (IRS 2014), resulting in a vehicle operating cost for a 3-ton vehicle of:

$$[\$23{,}975 / (1920\text{hrs} \times 40\text{mph})] + \$0.56 = \$0.87 \text{ per mile}$$

To determine user costs at the 40-ton weight limit (maximum in the BMS), information published by the U.S. Census Bureau was utilized. This organization publishes a report called the Service Annual Survey which uses the North American Industry Classification System (NAICS) to sort data. This report contains a section on transportation of cargo using tractor-trailers. In this section of the report, a table is provided that contains a value for the estimated motor carrier revenue ($183,496 million) and another table that provides the estimated total distance traveled for a one year period (76,740 million miles) (U.S. Census Bureau 2012). The revenue was divided by the distance traveled to produce a vehicle operating cost for the maximum legal weight vehicles. For any values not current, the appropriate CPI (2015) was used to adjust to current costs as follows for the vehicle operating cost at 40 tons:

($183,496 / 76,740miles) = $2.39 per mile (year 2012)
CPI inflation: year 2014 / year 2012 = 2.20/2.03 = 1.069
$2.39 per mile × 1.069 = $2.59 per mile

As mentioned earlier, a study was conducted to determine vehicle operating costs for vehicles with an operating rate between the minimum (3-ton) and maximum (40-ton) values. This method developed in this study used the U.S. Army Corps of Engineers' (USACE) Construction Equipment Ownership and Operating Expense Schedule report for Region III, which includes North Carolina. This report is published annually and includes operating costs for a wide variety of different machines and equipment in units of dollars per hour. After reviewing this report, a 3-axle dump truck was chosen as an intermediate point for computation of a vehicle operating cost. The USACE lists its average operating costs for the vehicle at $60.87 per hour (USACE 2014). This value was divided by the assumed average speed (40 mph), resulting in an operating cost of $1.52 per mile for the vehicle.

To determine the operator costs, the method used for the minimum value (3-ton vehicle) was utilized, though this time the wage rate was for a Vehicle Operator III, since driving a larger vehicle such as a dump truck is a skilled operation since is requires a special driver license. The North Carolina Office of State Human Resources lists this wage rate at $26,159 (OSHR 2014). This rate was divided by the product of the estimated number of hours worked in a year (1920 hrs) and assumed average speed (40 mph), which results in an operating cost of $0.34 per mile. The two values were added together to produce a vehicle operating costs of $1.86 per mile. North Carolina law governs the maximum weight permitted for a vehicle and its load by the number of axles the vehicle has and by the distance between the axles. A 3 axle dump truck has an average spacing of 22 feet from the two furthest axles, allowing for a gross vehicle weight of 26.25 tons. Values for the vehicle operating costs at the three weights are presented in Table 3.4. This table also shows the increase in cost over time.

Table 3.4: Vehicle operating costs for minimum and maximum weights over time

Vehicle Operating Costs at each individual weight (U_{DV}) ($ per mile)			
	Year		
Weight	2002	2010	2014
3 tons	0.60	0.81	0.87
26.25 tons	N/A	N/A	1.86
40 tons	1.95	2.39	2.59

To determine the costs at intermediate weights, the three costs (from year 2014) were plotted against their respective weights, this was done once for weights between 3 ton and 26 ton, and then for weights between 27 ton and 40 ton, providing linearly functions for both segments. A best fit line can be used to provide intermediate values for the vehicle operating costs of vehicles with other operating weights. The equation for the best fit line shown in Equation 3.1 can be used to compute the vehicle operating costs, U_{DV}, between the weights of 3 and 26 tons, while the best fit line shown in Equation 3.2 can be used to compute the vehicle operating costs, U_{DV}, for vehicles weighing between 27 and 40 tons.

$$U_{DV} = 0.0426 \times (W) + 0.7423$$

Equation 3.1: Vehicle operating cost at weight X (between 3 and 26 tons)

$$U_{DV} = 0.0531 \times (W) + 0.4664$$

Equation 3.2: Vehicle operating cost at weight X (between 27 and 40 tons)

Where: U_{DV} = Vehicle operating costs at weight X ($/mile)
W = Weight (tons)

In order to determine the average operating costs for all vehicles that would have to detour around a bridge posted at a specific weight, U_{DL}, the vehicle operating cost associated with vehicles with weights equal to the posted weight is added to the maximum allowable weight, and then divided by two, providing the U_{DL} used in Equation 2.1. Figure 3.9 provides a comparison of the average operating cost (U_{DL}) estimated for vehicles between 3 and 40 tons using the traditional method with two point linear interpolation and using the newly proposed method of adding a third intermediate point.

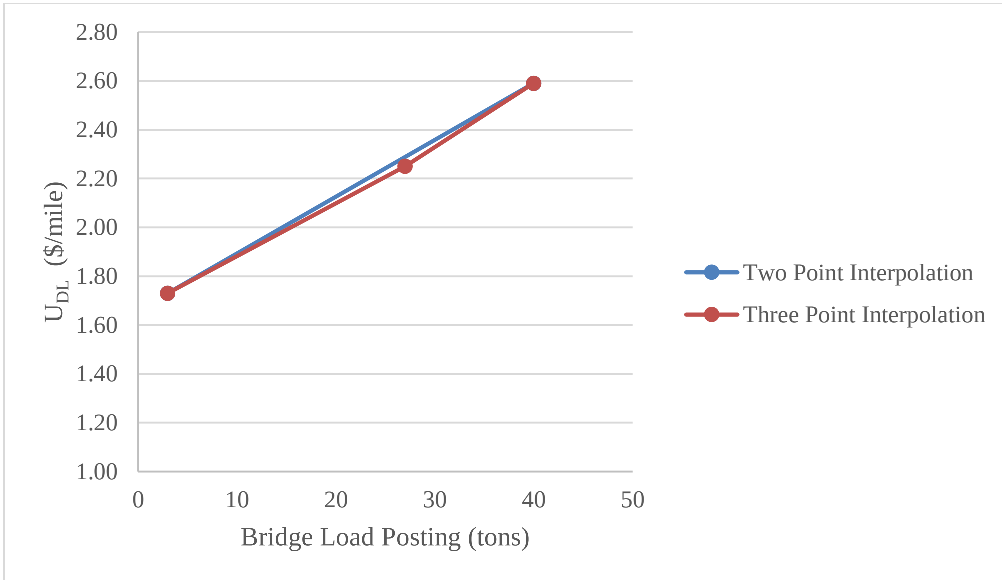


Figure 3.9: Average vehicle operating cost for detoured vehicles

It can be seen in Figure 3.9 that the two approaches provide similar vehicle operating costs throughout. Given the similarity between the two approaches, it seems the two point linear interpolation method currently used in NCDOT's BMS is acceptable, and a modification to this approach is not suggested at this time.

3.2.2 Vehicle Distribution

In order to determine the percentage of vehicles that will be required to detour due to load postings or vertical clearance, an input table listing the percentages of different types of vehicles (SU and TTST) operating on different roadway types is needed. As outlined in Chapter 2, the FHWA currently classifies vehicles into 13 different classes. To estimate the percentile of different vehicle classes operating on different routes, data collected from North Carolina Weigh-in-Motion (WIM) stations on four different roadway types (Interstate, US, NC, and SR) was obtained. This data was compiled and provided by NCDOT's Traffic Survey Group (Traffic Statistics Section) from data obtained at a number of Weigh-in-Motion (WIM) stations. WIM stations count the different vehicle types passing over a sensor installed along a roadway.

During discussions with Traffic Survey Group personnel, it was determined that WIM data could be provided on the four different roadway types. Due to roadway accidents and aging of the WIM systems, most of the North Carolina WIM stations are currently not in operation. To provide most current data, Traffic Survey Group personnel selected eight different WIM stations from the stations with operational data available within the range of 2007 to 2014. WIM stations at two locations for each roadway type were selected to provide a representative data set to estimate North Carolina vehicle classification percentages on the different roadways. Maps of the locations of the eight stations, provided by NCDOT, are shown in Figures 3.10 through 3.17.

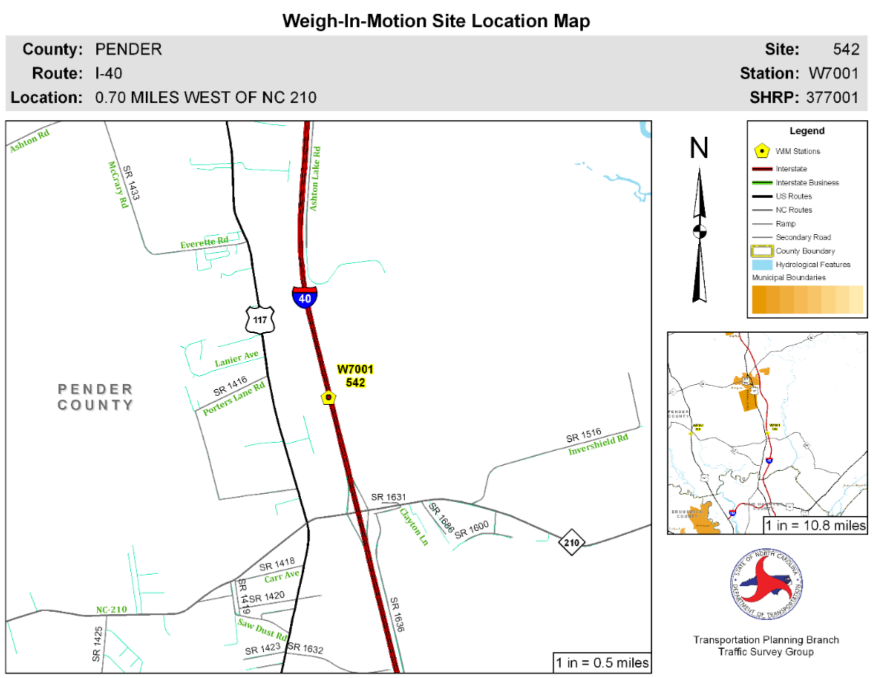


Figure 3.10: Interstate site 542 (Source: NCDOT)

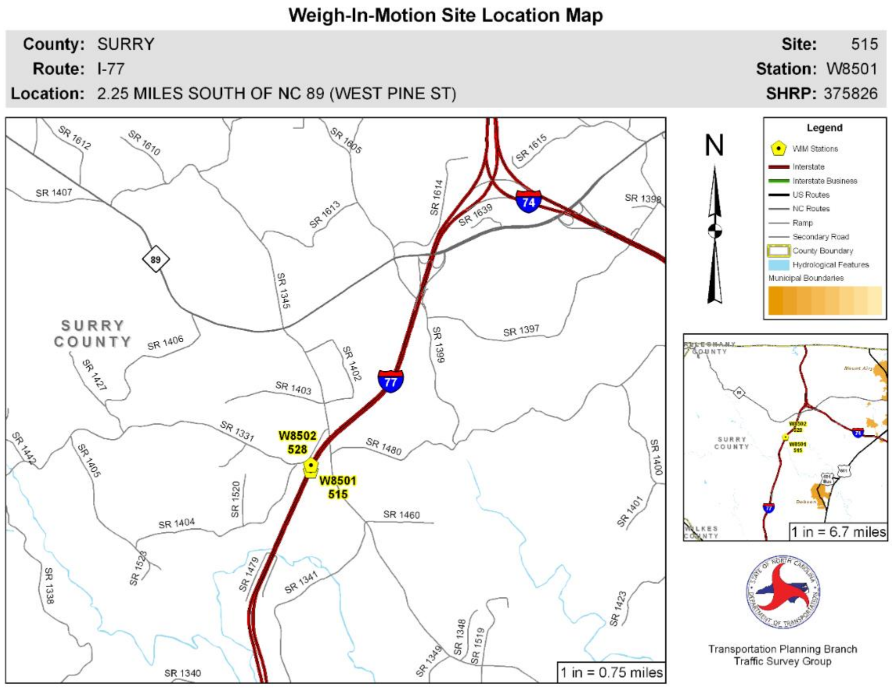


Figure 3.11: Interstate site 515 (Source: NCDOT)

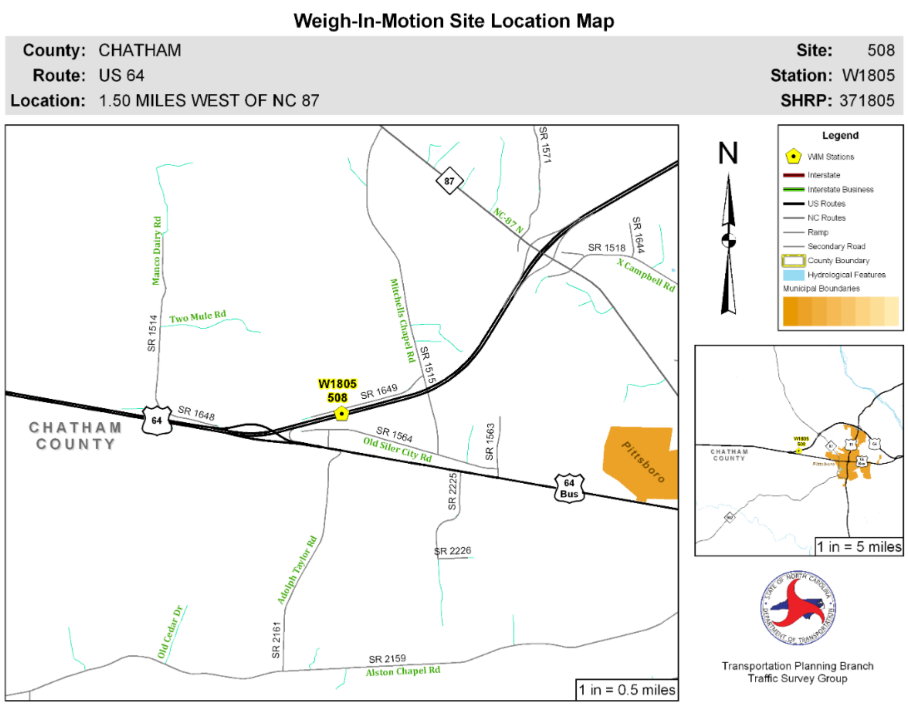


Figure 3.12: US site 508 (Source: NCDOT)

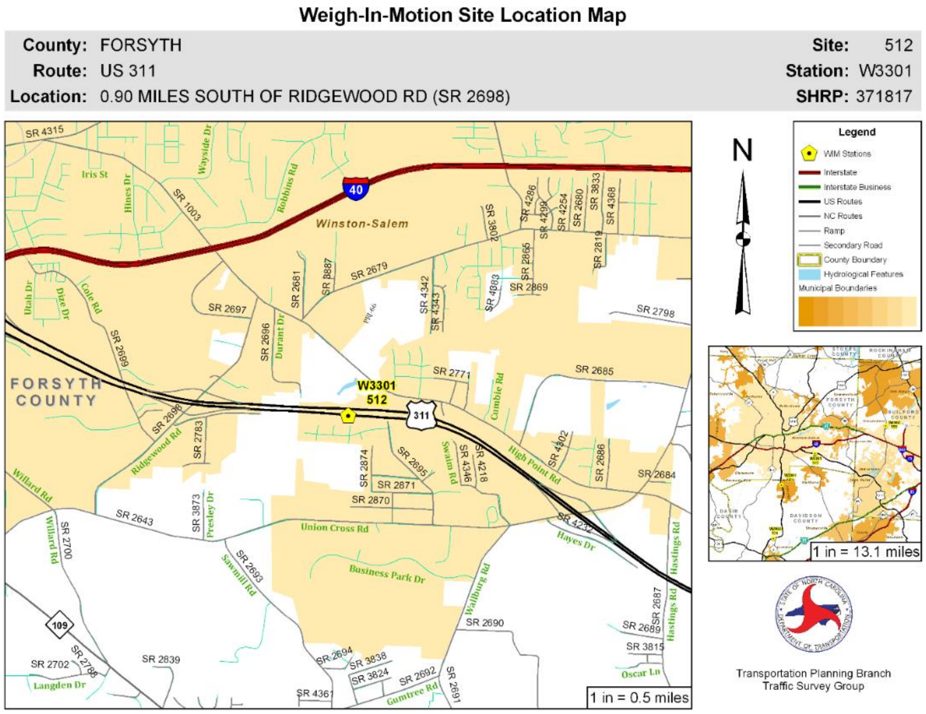


Figure 3.13: US site 512 (Source: NCDOT)

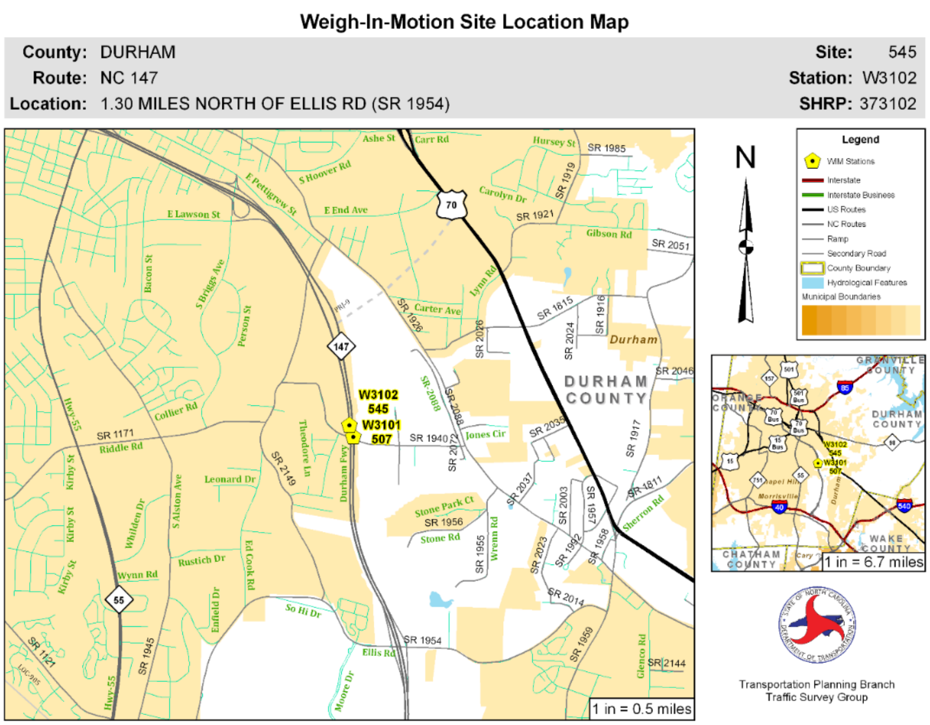


Figure 3.14: NC site 545 (Source: NCDOT)

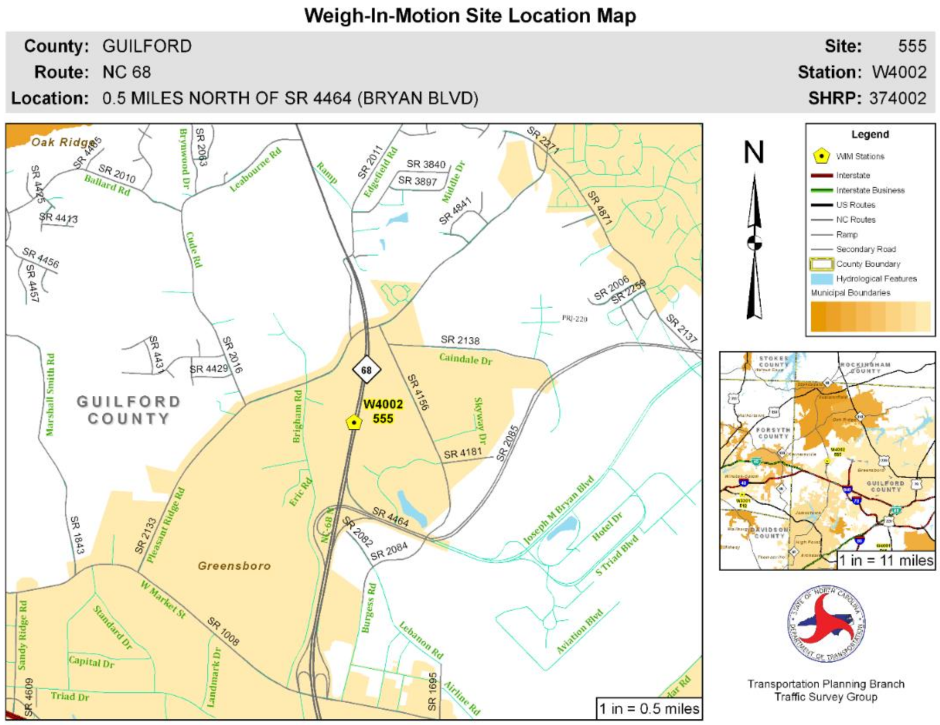


Figure 3.15: NC site 555 (Source: NCDOT)

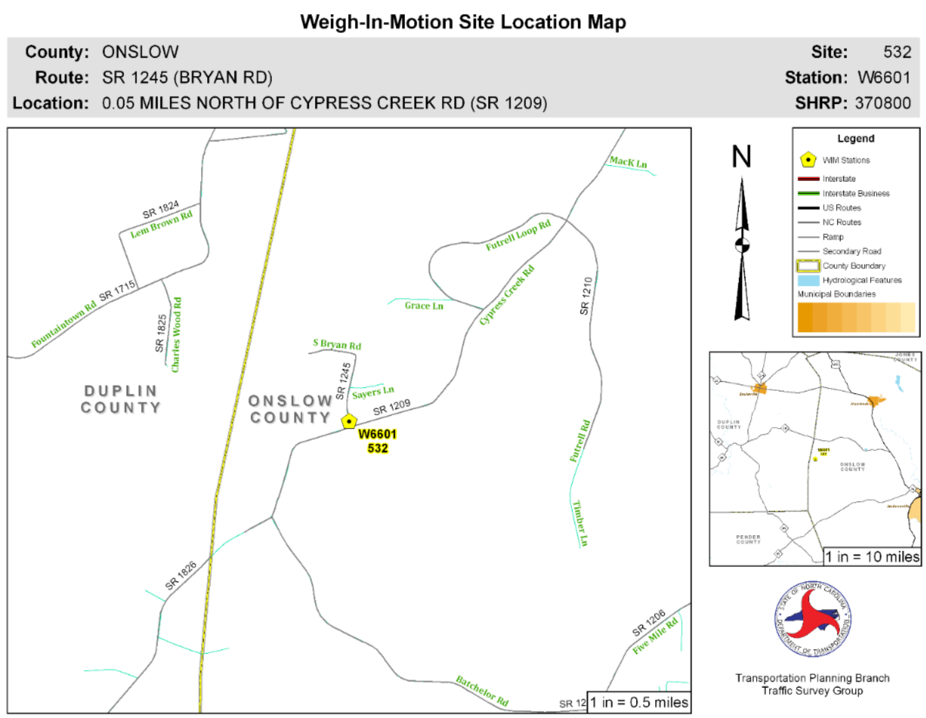


Figure 3.16: SR site 532 (Source: NCDOT)

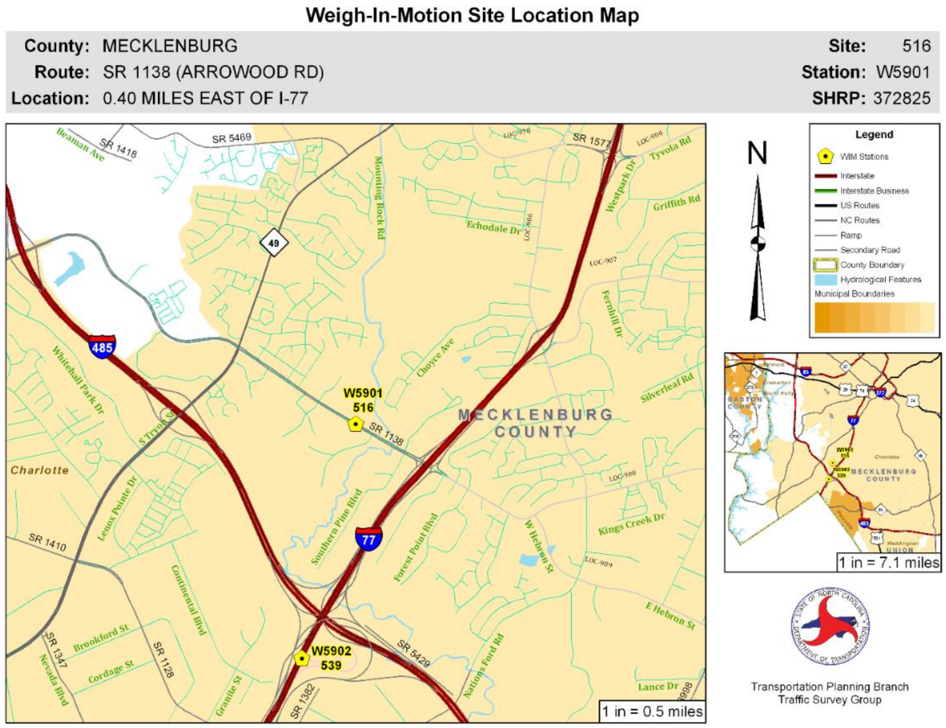


Figure 3.17: SR site 516 (Source: NCDOT)

One year of continuous data from each site was provided by NCDOT for analysis. Since NCDOT's Traffic Survey Group also utilizes the vehicle classification counts for other purposes, the data had already been cleansed of anomalies and adjusted using correction factors typically utilized by NCDOT's Traffic Statistics Section. Data was provided in an Excel spreadsheet and listed the recorded counts for vehicles within each of the 13 vehicle classes. From the spreadsheets provided, vehicle classes were grouped into three categories: cars (classes 1-3), SU (classes 4-7), and TTST (classes 8-13). These three categories were subsequently used to determine overall percentage of occurrence of each type of vehicle group on each specific roadway. After analyzing individual roadways the vehicle distribution percentages obtained from the two WIMs on similar roadway types were averaged together. The averaged results for each roadway type are presented in Table

3.5. These percentages can be used in the NCDOT BMS to update the input tables for vehicles required to detour due to either load postings or vertical clearance, as they provide more current estimates of vehicle distribution. The roadway grouping shown in Table 3.5 differs from the roadway grouping currently used for vehicles detoured due to weight or height. However, it is suggested that the grouping shown in Table 3.5 be used since it is consistent with the roadway grouping used in NCDOT's PMS. This would allow NCDOT to eventually move to corridor-level analysis (consideration of both roads and bridge together) to assist in condition forecasting and project selection.

Table 3.5: Vehicle distribution by functional classification

	Cars	SU	TTST
Interstate	81.64%	4.13%	14.23%
US	91.77%	3.85%	4.38%
NC	93.75%	3.70%	2.54%
SR	92.04%	7.50%	0.46%

3.2.3 Vehicle Height and Weight Distributions

Like many states, North Carolina has a number of bridges with load postings. This results in a significant number of vehicles (primarily trucks) detoured at these bridges due to loads in excess of the bridge posting. As mentioned in Chapter 2, truck traffic has grown significantly over the past several decades. To improve user cost predictions in the BMS, weight distributions of different SU and TTST vehicles need to be updated as part of this work. Current North Carolina vehicle weight distribution data was also provided by the Traffic Survey Group and was used to update the weight distribution estimates. Weight data from each of the eight WIM stations described in Section 3.2.2 were provided for a one-week span. This WIM data included weights on each vehicle class of 4 through 13 separately, the WIM station is able to determine the vehicle class based on the number of axles and their spacing. Upon providing this data to UNC Charlotte, NCDOT personnel noted that this data should be considered "raw," as anomalies had not been removed, and no correction factors for the weights had been applied. To provide a basis for weight ranges of different classes, Table 3.6 was used (U.S. Department of Energy 2012). This table lists average weight ranges for commercial classes, which are grouped differently from the 13 vehicle classifications used be the FHWA, though the commercial classes are equal to the FHWA'S vehicle classes 4 through 13.

Table 3.6: Vehicle weight ranges

Gross Vehicle Weight Ratings (lbs)	Federal Highway Administration	
	Vehicle Class	GVWR Category
<6,000	Class 1: <6,000 lbs	Light Duty <10,000 lbs
10,000	Class 2: 6,001-10,000 lbs	
14,000	Class 3: 10,001-14,000 lbs	Medium Duty 10,001-26,000 lbs
16,000	Class 4: 14,001-16,000 lbs	
19,500	Class 5: 16,001-19,500 lbs	
26,000	Class 6: 19,501-26,000 lbs	
33,000	Class 7: 26,001-33,000 lbs	Heavy Duty >26,001 lbs
>33,000	Class 8: >33,001 lbs	

Using the information in Table 3.6, the vehicle classes 4 through 13 were assigned minimum and maximum weight ranges, which bounded the expected weights for each class and thereby allowed for developing a method for cleaning the data set. Table 3.7 shows the weight ranges utilized for grouping the vehicle classes, with SU classes separated in this initial step due to the wide variance in weight range of these vehicle classes.

Table 3.7: Minimum and maximum weight ranges

Vehicle Class	Minimum Weight (lbs.)	Maximum Weight (lbs.)
4 and 5	6,000	26,000
6 and 7	10,000	80,000
8 - 13	26,000	90,000

Using Excel, the WIM data obtained from each of the eight stations were filtered by weight to bound the data in records obtained within the minimum and maximum range developed for each respective class. The records for vehicles with weights within the range limits were then exported. These records were then grouped by vehicle classes 4 through 7 (SU) and vehicle classes 8 through 13 (TTST) by weight. Data from WIM stations on similar roadway types were also combined prior to statistical analysis. Table 3.8 shows the cumulative percentage of truck weights distributed amongst the different roadway types. These percentages were then multiplied by the corresponding percentage of occurrence (shown in Table 3.5) to determine the overall percent of ADT that is expected to be detoured at bridges with different load capacities across the four different roadways types. A table of the analysis as results is presented in Table 3.9. These percentages are used in Equation 2.1, in decimal form (as a coefficient) to determine the overall ADT that must detour due to load restrictions (C_{LCD}).

Table 3.8: Truck weight distribution cumulative percent

	SR		**NC**		**US**		**Interstate**	
Weight (tons)	**SU**	**TTST**	**SU**	**TTST**	**SU**	**TTST**	**SU**	**TTST**
> 3	100%	100%	100%	100%	100%	100%	100%	100%
> 4	70.78%	100%	82.93%	100%	86.87%	100%	86.36%	100%
> 5	53.74%	100%	64.09%	100%	72.34%	100%	63.39%	100%
> 6	44.05%	100%	52.31%	100%	62.82%	100%	51.07%	100%
> 7	38.03%	100%	44.08%	100%	53.28%	100%	44.12%	100%
> 8	31.37%	100%	36.88%	100%	43.59%	100%	38.17%	100%
> 9	26.28%	100%	30.34%	100%	35.15%	100%	31.98%	100%
> 10	20.80%	100%	23.99%	100%	27.59%	100%	24.73%	100%
> 11	16.20%	100%	19.48%	100%	21.62%	100%	18.10%	100%
> 12	11.66%	100%	15.75%	100%	17.19%	100%	12.29%	100%
> 13	6.81%	100%	12.62%	100%	13.45%	100%	7.67%	100%
> 14	6.39%	94.39%	10.70%	94.67%	11.36%	92.10%	6.98%	98.84%
> 15	5.75%	88.27%	8.96%	88.17%	9.80%	83.32%	6.19%	97.22%
> 16	5.21%	80.10%	7.31%	81.78%	8.28%	75.52%	5.21%	95.02%
> 17	4.69%	71.68%	6.22%	75.56%	7.29%	68.84%	4.50%	92.30%
> 18	4.15%	63.52%	5.56%	70.30%	6.22%	63.00%	3.97%	89.38%
> 19	3.78%	56.38%	4.85%	65.34%	5.14%	57.89%	3.51%	86.59%
> 20	3.33%	48.72%	4.39%	60.71%	4.47%	53.18%	3.03%	83.65%
> 21	2.82%	44.13%	3.93%	56.61%	3.73%	49.39%	2.56%	80.81%
> 22	2.51%	37.50%	3.58%	53.30%	3.20%	46.30%	2.15%	77.99%
> 23	2.36%	32.14%	3.21%	50.07%	2.72%	43.03%	1.84%	75.28%
> 24	2.09%	29.34%	2.85%	46.84%	2.29%	39.91%	1.60%	72.57%
> 25	1.82%	27.55%	2.49%	44.08%	1.87%	37.09%	1.35%	69.82%
> 26	1.57%	26.02%	2.13%	41.97%	1.37%	34.07%	1.08%	67.11%
> 27	1.36%	23.21%	1.78%	40.01%	1.12%	31.32%	0.93%	64.43%
> 28	1.09%	20.92%	1.40%	37.62%	0.89%	28.56%	0.79%	61.60%
> 29	0.97%	19.64%	1.19%	35.35%	0.67%	25.72%	0.59%	58.78%
> 30	0.79%	17.60%	0.98%	33.09%	0.51%	23.00%	0.47%	56.03%
> 31	0.65%	15.82%	0.81%	30.05%	0.39%	20.67%	0.36%	53.20%
> 32	0.42%	13.52%	0.66%	27.63%	0.28%	18.24%	0.30%	50.24%
> 33	0.30%	13.27%	0.47%	24.94%	0.23%	16.00%	0.20%	47.17%
> 34	0.27%	11.48%	0.30%	22.35%	0.20%	13.81%	0.17%	44.02%
> 35	0.15%	9.44%	0.19%	19.92%	0.12%	11.77%	0.14%	40.57%
> 36	0.15%	8.67%	0.09%	17.29%	0.07%	10.07%	0.09%	36.88%
> 37	0.09%	6.38%	0.07%	14.93%	0.05%	8.66%	0.05%	32.55%
> 38	0.03%	5.36%	0.04%	12.29%	0.02%	7.37%	0.04%	27.65%
> 39	0%	3.57%	0.01%	9.89%	0.01%	5.97%	0.02%	22.30%
> 40	0%	3.06%	0%	7.48%	0%	4.59%	0%	16.65%
> 41	0%	2.30%	0%	5.37%	0%	3.49%	0%	11.95%
> 42	0%	1.02%	0%	3.45%	0%	2.54%	0%	8.15%
> 43	0%	0.26%	0%	1.96%	0%	1.62%	0%	4.98%
> 44	0%	0%	0%	0.81%	0%	0.78%	0%	2.36%
> 45	0%	0%	0%	0%	0%	0%	0%	0%

Table 3.9: Percentage of ADT detoured by bridge load posting level

Bridge Posting (tons)	SR		NC		US		Interstate	
	SU	TTST	SU	TTST	SU	TTST	SU	TTST
3	7.50%	0.46%	3.70%	2.54%	3.85%	4.38%	4.13%	14.23%
4	5.31%	0.46%	3.07%	2.54%	3.34%	4.38%	3.56%	14.23%
5	4.03%	0.46%	2.37%	2.54%	2.79%	4.38%	2.62%	14.23%
6	3.30%	0.46%	1.94%	2.54%	2.42%	4.38%	2.11%	14.23%
7	2.85%	0.46%	1.63%	2.54%	2.05%	4.38%	1.82%	14.23%
8	2.35%	0.46%	1.37%	2.54%	1.68%	4.38%	1.58%	14.23%
9	1.97%	0.46%	1.12%	2.54%	1.35%	4.38%	1.32%	14.23%
10	1.56%	0.46%	0.89%	2.54%	1.06%	4.38%	1.02%	14.23%
11	1.21%	0.46%	0.72%	2.54%	0.83%	4.38%	0.75%	14.23%
12	0.87%	0.46%	0.58%	2.54%	0.66%	4.38%	0.51%	14.23%
13	0.51%	0.46%	0.47%	2.54%	0.52%	4.38%	0.32%	14.23%
14	0.48%	0.44%	0.40%	2.41%	0.44%	4.03%	0.29%	14.07%
15	0.43%	0.41%	0.33%	2.24%	0.38%	3.65%	0.26%	13.84%
16	0.39%	0.37%	0.27%	2.08%	0.32%	3.31%	0.22%	13.53%
17	0.35%	0.33%	0.23%	1.92%	0.28%	3.01%	0.19%	13.14%
18	0.31%	0.29%	0.21%	1.79%	0.24%	2.76%	0.16%	12.72%
19	0.28%	0.26%	0.18%	1.66%	0.20%	2.53%	0.14%	12.32%
20	0.25%	0.22%	0.16%	1.54%	0.17%	2.33%	0.13%	11.91%
21	0.21%	0.20%	0.15%	1.44%	0.14%	2.16%	0.11%	11.50%
22	0.19%	0.17%	0.13%	1.35%	0.12%	2.03%	0.09%	11.10%
23	0.18%	0.15%	0.12%	1.27%	0.10%	1.88%	0.08%	10.72%
24	0.16%	0.14%	0.11%	1.19%	0.09%	1.75%	0.07%	10.33%
25	0.14%	0.13%	0.09%	1.12%	0.07%	1.62%	0.06%	9.94%
26	0.12%	0.12%	0.08%	1.07%	0.05%	1.49%	0.04%	9.55%
27	0.10%	0.11%	0.07%	1.02%	0.04%	1.37%	0.04%	9.17%
28	0.08%	0.10%	0.05%	0.96%	0.03%	1.25%	0.03%	8.77%
29	0.07%	0.09%	0.04%	0.90%	0.03%	1.13%	0.02%	8.37%
30	0.06%	0.08%	0.04%	0.84%	0.02%	1.01%	0.02%	7.98%
31	0.05%	0.07%	0.03%	0.76%	0.02%	0.90%	0.01%	7.57%
32	0.03%	0.06%	0.02%	0.70%	0.01%	0.80%	0.01%	7.15%
33	0.02%	0.06%	0.02%	0.63%	0.01%	0.70%	0.01%	6.71%
34	0.02%	0.05%	0.01%	0.57%	0.01%	0.60%	0.01%	6.27%
35	0.01%	0.04%	0.01%	0.51%	0.00%	0.52%	0.01%	5.78%
36	0.01%	0.04%	0.00%	0.44%	0.00%	0.44%	0.00%	5.25%
37	0.01%	0.03%	0.00%	0.38%	0.00%	0.38%	0.00%	4.63%
38	0.00%	0.02%	0.00%	0.31%	0.00%	0.32%	0.00%	3.94%
39	0.00%	0.02%	0.00%	0.25%	0.00%	0.26%	0.00%	3.17%
40	0.00%	0.01%	0.00%	0.19%	0.00%	0.20%	0.00%	2.37%
41	0.00%	0.01%	0.00%	0.14%	0.00%	0.15%	0.00%	1.70%
42	0.00%	0.00%	0.00%	0.09%	0.00%	0.11%	0.00%	1.16%
43	0.00%	0.00%	0.00%	0.05%	0.00%	0.07%	0.00%	0.71%
44	0.00%	0.00%	0.00%	0.02%	0.00%	0.03%	0.00%	0.34%
45	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%

Figures 3.18 and 3.19 provide a graphical representation of the overall percentage of ADT detoured due to load posting on the four roadway classifications for SU and TTST respectively, using the updated data from Table 3.9. These plots illustrate that the majority of detours are by heavier vehicles. SU trucks must detour when the load posting is below 15 tons. It can be observed in Figure 3.18 that since SU vehicles represent a higher portion of traffic on SR Routes, user costs from SU are highest on SR Routes (when a bridge has a load posting below 15 tons). TTST traffic is most frequent on Interstates, and all TTST's must to detour if a load posting is below 13 tons. It can be observed in Figure 3.19 that user costs due to TTST are most incurred on interstates. It is noted that it would be of interest to compare the percent detoured due to load posting using the previous NCDOT BMS inputs. However, due to the change in grouping of roadways to match the NCDOT PMS roadway grouping (Section 3.2.2), it is not possible to compare these at this time.

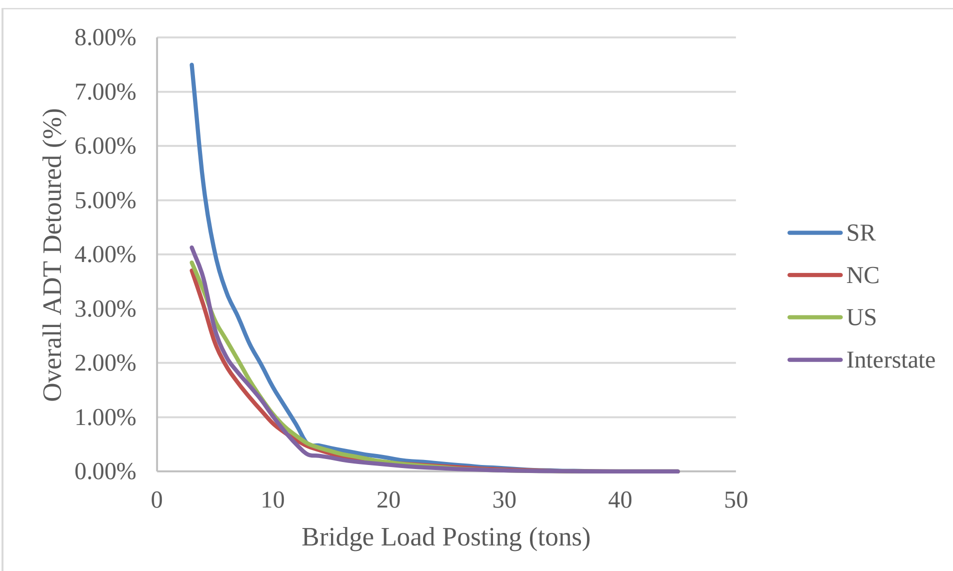


Figure 3.18: SU portion of ADT detoured due to load posting

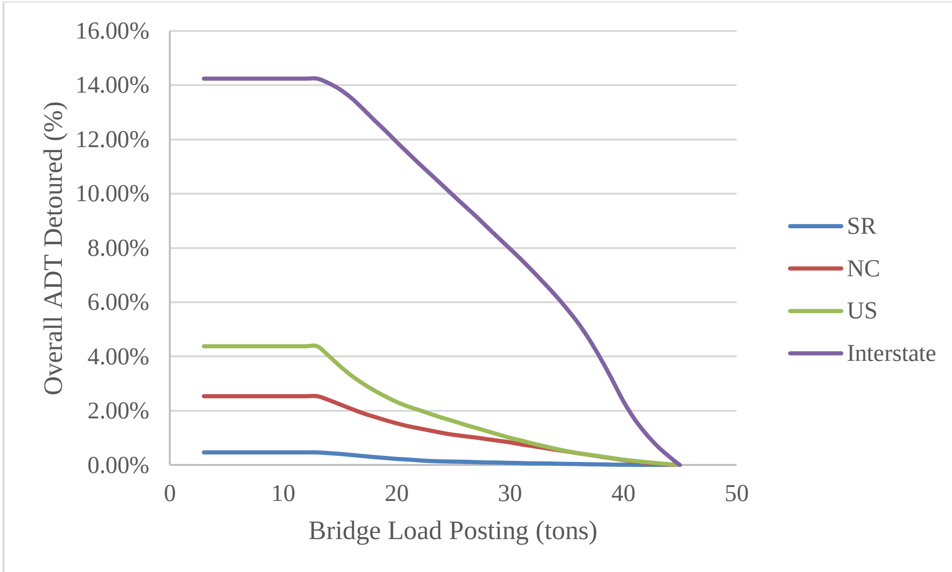


Figure 3.19: TTST portion of ADT detoured due to load posting

User costs are also incurred due to vehicles detoured due to vertical clearance. NCDOT does not currently have data to support development of a height spectrum for vehicles utilized today. Since the current input parameters in NCDOT's BMS are based on vehicle height data from the 1950's (Kent and Stevens 1963), it was important to identify more current data to support this key parameter associated with BMS user costs. A review of literature identified a report published for FDOT by Sobanjo and Thompson (2004). In this study, vehicle scanners and a laser range finder were used to sample the heights of trucks on roadways of different functional classifications in Florida. The results found using the laser range finder were calibrated based on distance from the truck to the laser, while sample hand measurements were taken to ensure scanner accuracy (Sobanjo and Thompson 2004). In total, Sobanjo and Thompson (2004) produced a dataset comprised of the height data obtained from 273,532 trucks. After binning the data into height ranges, a cumulative percent of trucks that would need to detour due to vertical clearance was computed (Table 3.10). Since the study by Sobanjo and Thompson (2004) was so extensive and heights of truck traffic in Florida could reasonably be expected to represent the distribution of truck traffic heights in North Carolina, the data obtained by Sobanjo and Thompson for FDOT was used to create an updated table for NCDOT's BMS detour to height prediction model. Although these values are not based on local measurements, they do provide data more current than that sourced from the Kent and Stevens study. It should also be noted that previous data used to develop the prediction model was not locally based and was a much smaller sample size than the one generated by this FDOT study. Additionally, the previous study had only one point of data for SU and TTST (13.6 foot height), and that "heights of duals were assumed to be well distributed between 8.0 and 13.5 feet; and between 10 and 13.5 feet for trailer combinations" (Chen and Johnston 1987). It is recommended that the results from the Sobanjo and Thompson (2004) report, shown in Table 3.10, be used to update the percentage of trucks detoured due to height in NCDOT's BMS.

Table 3.10: Sampled distribution of truck heights from Sobanjo and Thompson (2004)

Height (ft.)	Percent Detoured
< = 10	100%
10.1-11.9	93.7%
12-12.9	79.25%
13-13.9	36.2%
14-15.9	0.245%
> 16	0%

As a comparison, Figure 3.20 provides the percent of vehicles that would have to detour around a bridge due to vertical clearance using the data previously used in NCDOT's BMS (labeled "old"), and the new suggested data (labeled "new"). Note that the previous method provided data for SU and TTST, while the new approach provides data on all trucks (both SU and TTST together). These percentage of detours are a step function since both the previous and new data provide percent detoured in brackets of height ranges. Figure 3.20 illustrates that by using the previous truck height data from Kent and Stevens (1963), NCDOT BMS has been under estimating the percent of vehicles that would have to detour due to height, and therefore underestimating user costs associated with detours due to height. For design purposes, it could also be of interest to NCDOT to be aware that the findings of Sobanjo and Thompson (2004) indicate that over 99 percent of vehicles are under 14 feet in height.

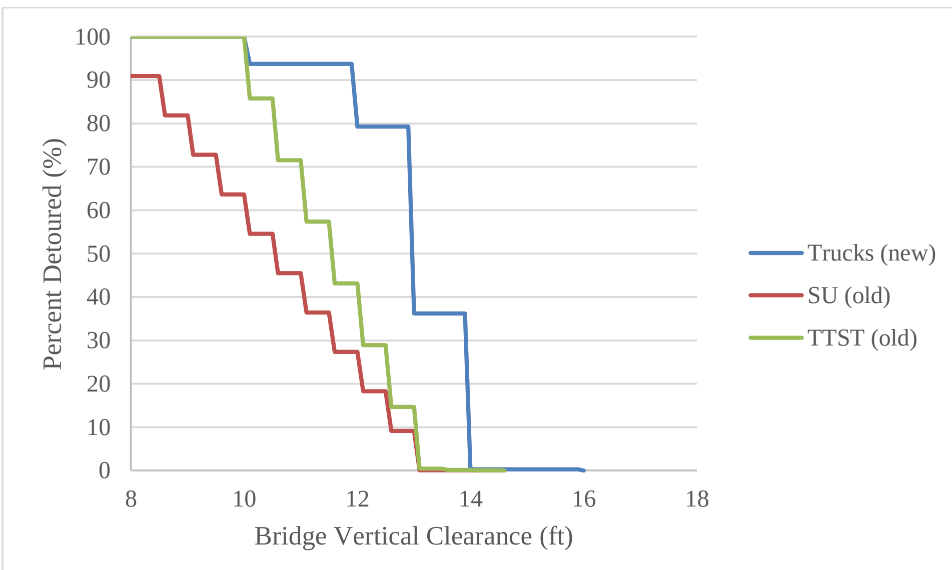


Figure 3.20: Percentage of trucks detoured due to vertical clearance

From this the percentages of trucks expected to be operating at various heights (Table 3.10) were then multiplied by their percentage of occurrence (Table 3.5), found in Section 3.2.2, to determine the total percentage of vehicles estimated to be detoured due to vertical clearances. This is updated estimate is presented in Table 3.11, these percentages are used in Equation 2.1, in decimal form (as a coefficient) to determine the overall ADT that will detour due to height (C_{CLD}).

Table 3.11: Percentage of ADT expected to be detoured by bridge vertical clearance posting level

	SR		NC		US		Interstate	
Height (ft)	SU	TTST	SU	TTST	SU	TTST	SU	TTST
< = 10	7.50%	0.46%	3.70%	2.54%	3.85%	4.38%	4.13%	14.23%
10.1-11.9	7.02%	0.43%	3.47%	2.38%	3.61%	4.10%	3.87%	13.34%
12-12.9	5.94%	0.37%	2.94%	2.01%	3.05%	3.47%	3.27%	11.28%
13-13.9	2.71%	0.17%	1.34%	0.92%	1.39%	1.58%	1.49%	5.15%
14-15.9	0.02%	0.00%	0.01%	0.01%	0.01%	0.01%	0.01%	0.03%
> 16	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%

3.3 Accident Costs by Injury Severity

Currently, user costs associated with accidents are calculated utilizing the percentage of accidents that occur on a bridge, providing an accident rate for each bridge. These accident rates are then multiplied by the corresponding accident costs predicted using the NSC methodology and occurrence of severity type as outlined in Section 2.5. Similar to some of the data contained in other input tables that currently support NCDOT's BMS, these percentages of accident severity types occurring on bridges have not been updated in the BMS since the original tables were generated by previous researchers (Abed-Al-Rahim and Johnston 1991).

The North Carolina DMV currently keeps a record of all accidents in the state for a designated period of time. NCDOT's Traffic Engineering Division provided records on all accidents (both bridge-related and non-bridge-related) in North Carolina occurring over a period of five years (1/1/2009-12/31/2013). Using these records, the accidents that occurred on a bridge, bridge approach, or on a bridge rail were extracted from the full dataset. The number of accidents of each severity was totaled for each of the five accident severity types (K-A-B-C-PDO). The percentage of each accident type observed was used to produce the expected frequency of each severity of accident occurring on a bridge in North Carolina, which is a key user cost input in the BMS. Table 3.12 shows the average number of injuries per bridge related accident, along with the values that were previously used. From Table 3.12, it is noted that the occurrence of deaths due to bridge-related accidents has been reduced by half. The occurrence of the two most severe injuries types (A and B), have also decreased significantly. The causes of these reductions in accident rates are likely complex, but research (ongoing) is being undertaken to understand the factors driving the reduction in fatal and severe injury causing accidents (NCHRP 2015). Therefore, and it is beyond the scope of this study to suggest causes for the reductions in accident occurrence. From a user cost perspective, the reduction in accident rates for the most severe types of accidents (K, A, and B) will significantly reduce the overall accident cost predicted per accident.

Table 3.12: Bridge related accidents

Avg. # of injuries per bridge related accident		
	Year	
Severity	1991	2013
K	0.02	0.01
A	0.13	0.02
B	0.20	0.13
C	0.34	0.40
PDO	N/A	N/A

3.4 Accident Costs

Once the occurrence rate of accidents for each of the different severities was calculated, a cost for each accident severity was needed to determine an overall accident cost for bridges (U_{AC}). The bridge accident costs currently utilized in the BMS are obtained from information published by the National Safety Council (NSC), as outlined in the Section 2.5. In computing accident costs in the BMS, costs per severity type are multiplied by the percent (in decimal form) of occurrence, from Table 3.12. Values can be summed to produce one total cost figure for use statewide as the cost per accident (U_{AC}) on bridges. Since these NSC costs are not always updated annually, an appropriate CPI value can be utilized to update values between periodic updates to the NSC costs, if needed.

As part of this work, a different approach to computing accident costs in the NCDOT BMS was utilized, since it was deemed more appropriate than the method developed by Duncan and Johnston (2001). Recently, NCDOT has been retaining an outside expert to produce a report on annual Standardized Crash Cost Estimates for North Carolina (2013). The locally calibrated accident cost values provided in this report, prepared by a private consultant (Dr. Ted Miller of Child's Safety Network), can be used in lieu of the accident costs obtained via the NSC methodology. For this user cost update, these locally calibrated accident costs were multiplied by the average number of injuries by severity category for North Carolina specific accidents, providing North Carolina specific values, presented in Table 3.13.

Table 3.13: Accident costs

	Currently Used Method			New Method Suggested		
Severity	Avg. # of injuries per bridge related accident	W-to-P Cost per injury, (NSC Updated with CPI)	Cost per bridge-related accident	Avg. # of injuries per bridge related accident	W-to-P Cost per injury, (NC Values)	Cost per bridge related accident
K	0.0103	$4,687,150	$48,370	0.0103	$4,287,340	$44,244
A	0.0172	$237,177	$4,069	0.0172	$216,026	$3,706
B	0.1258	$60,630	$7,630	0.1258	$55,322	$6,962
C	0.3987	$28,921	$11,531	0.3987	$26,325	$10,496
PDO	N/A	$2,582	$2,582	N/A	$5,388	$5,388
		Total (U_{AC}) =	$74,182		Total (U_{AC}) =	$70,796

Using Table 3.13, the accident costs computed using the current method can be compared to the accident costs computed using the new method suggested in this work. In the data presented for the currently utilized method, NSC cost figures from 2012 were updated using the CPI inflation rate (2015) and are multiplied by the updated frequency of severity type. Using the new method based on the North Carolina specific accident cost study and updated accident likelihoods, the cost per accident decreases by approximately 5%. This new suggested cost per accident has decreased from the value presented by Duncan and Johnston (2001) in large part due to a decrease in the likelihood of fatal (Type K) accidents and severe (Type A and Type B) accidents, where costs are greatest.

The report on Standardized Crash Cost Estimates for North Carolina, was not available at the time of previous enhancements to NCDOT's BMS, but is reportedly going to be produced annually according to NCDOT personnel. It is likely that these cost values produce more accurate user costs in NCDOT's BMS, since they are based on North Carolina data and updated annually. It is therefore suggested that these figures be utilized in conjunction with regularly updated accident rates in order to compute the accident costs used in NCDOT's BMS

To further evaluate the impact of the changes in predicted user costs associated with updated accident likelihoods and locally calibrated costs, in Table 3.14, the cost per accident (using updated NSC values multiplied by the original frequency severity values) is shown. Using this old approach, the cost per accident is double the value of the new, suggested approach, resulting in a significant overestimation of user costs for bridges with higher accident rates.

Table 3.14: Accident costs (currently used severity frequency and updated costs)

Severity	Avg. # of injuries per bridge related accident	W-to-P Cost per injury, (NSC Updated with CPI)	Cost per bridge-related accident
K	0.02	$4,687,150	$ 93,743
A	0.13	$237,177	$30,883
B	0.2	$60,630	$12,126
C	0.34	$28,921	$9,833
PDO	N/A	$2,582	$2,582
		Total (U_{AC}) =	$149,166

CHAPTER 4: ANALYSIS OF BRIDGE CHARACTERISTICS ASSOCIATED WITH ACCIDENTS

4.1 Bridge Related Accident Data

The methodology currently utilized by NCDOT's BMS to predict the number of annual accidents was developed as part of research conducted to produce an earlier report for NCDOT, Research Project 1990-06 (Abed-Al-Rahim and Johnston, 1991). This methodology predicts accident costs by multiplying the number of annual accidents predicted to occur on or at each bridge by the cost per accident. The researchers utilized data from bridge-related accidents from five North Carolina counties (Halifax, Harnett, Iredell, Guilford, and Wake) over a six year period to develop an equation that could be used to predict the number of annual accidents associated with individual bridges. A bridge-related accident was defined as any accident occurring on or near a bridge, as detailed in the road feature field of the accident report. As part of this work, each accident record for accidents occurring on or at a bridge was individually matched to the bridge at which it occurred. For the research performed as part of Research Project 1990-06 (Abed-Al-Rahim and Johnston 1991), a total of 2,895 bridge-related accident records were obtained and reviewed. Of these, 2,104 accidents were matched to a specific bridge, for a total of 72.7% of the total bridge-related accidents.

Statistical analysis was performed on the characteristics of the bridges matched to the accident reports to predict the bridge characteristics or features that are most influential in affecting the rate of bridge-related accidents. To perform this analysis, Abed-al-Rahim and Johnston (1991) used statistical analysis to identify bridge characteristics that may contribute to accidents, with two objectives considered when producing an equation to estimate accident rates. The first goal was to produce a prediction equation that is useful for and capable of reliably predicting the dependent variable (accident rate), with a coefficient of multiple determination (R^2) closest to one. The second goal was to produce an equation that would be economical, meaning that is should utilize a minimum of independent variables needed to sufficiently achieve the first objective (Abed-Al-Rahim and Johnston 1991). Analysis was performed using a stepwise regression procedure to determine the bridge characteristics associated with the greatest influence on bridge-related accidents, using a significance level of 5 percent associated with the null hypothesis. The characteristics found to be significant were then fit with higher order polynomial models to determine an equation that could predict accidents on bridges (Abed-Al-Rahim and Johnston 1991). Abed-Al-Rahim and Johnston (1991) found that ADT, bridge length, and the difference in deck width between acceptable and actual level of service had the most significance. The prediction equation for bridge accident rates based on bridge characteristics that resulted from their work is shown as Equation 2.7 in Section 2.5 Accident Costs, where it is discussed in further detail.

As part of the current research, the techniques utilized by Abed-Al-Rahim and Johnston (1991) were revisited, and a similar analysis was performed to identify the characteristics and features of bridges most influential in affecting the rate of bridge-related accidents. The purpose of this work is to provide a nearly 25-year revisit of the 1991 study, which will provide useful insight into the bridge characteristics that have been most associated with bridge-related accidents currently. To perform this analysis, the previously mentioned accident reports provided by the North Carolina DMV via NCDOT's Traffic Engineering division over five years (1/1/2009-12/31/2013) were utilized. Bridge related accidents in the same five counties from the 1991 study (Halifax, Harnett, Iredell, Guilford, and Wake) were analyzed as part of this 2015 research.

A total of 2,416 bridge-related accidents occurred in the five selected counties during this five-year time frame. These accidents were denoted as either occurring on a bridge, a bridge approach (within 500 ft.), or on a bridge railing in the accident report. It should be noted that the information about each accident's location, as well as other information on the accident report, is based on a police officer's judgment and, therefore, includes some subjectivity in the data collection. Furthermore, The North Carolina DMV accident reports are not directly linked to the structure numbers assigned by the NCDOT. Therefore accidents had to be manually matched to bridges using features coded in the accident reports that indicate the "facility carried," "road measured from," and "road measured to" (a snapshot is presented in Appendix A, Table A-1). This manual matching was similarly done in the original study by Abed-Al-Rahim and Johnston (1991).

The NCDOT BMS also includes a field for the facility carried by each structure, which was used to link the accidents and bridges; Appendix A, Table A-2 provides a snapshot of this information. Other tools utilized to facilitate matching of bridges to accident reports were maps sourced from the NCDOT Geographic Information Systems (GIS) unit that depict where bridges are located on the facilities carried. For bridges not found on the NCDOT maps, Google Maps was used to determine the bridge location. However, since accidents needed to be manually matched to bridges, there were instances where some accidents could not be matched to bridges using the limited data provided in the accident reports. This obstacle was similarly recounted within the experiences of the researchers performing the original 1991 study, in which a number of accidents could also not be matched to specific bridges (Abed-Al-Rahim and Johnston 1991). The researchers indicated that likely explanations for "unmatchable" accidents could have been associated with recorded locations being incorrectly coded on accident reports, a culvert being denoted as a bridge in the accident report, or the accident occurring under the bridge instead of on the bridge or approach. As found in the 1991 study some accidents reported had actually occurred on culverts. To maintain consistency in the analysis, accidents occurring on culverts in the 2009-2013 dataset were excluded from the analysis, similar to the 1991 study. A number of reported accidents were also not successfully matched either because the accident occurred near two closely-spaced but separate bridges, or where a roadway featured separate bridges for each direction and the direction of traffic was not stated in the accident report to allow for identification of the bridge the accident occurred on. Others were simply not found because they were recorded incorrectly, or because the accident did not occur on or near a bridge and was accidently mid-coded by the responding officer.

For the current study, 1,938 of the 2,416 reported accidents, or 80.2% of the total accidents that occurred over the five year span, were successfully matched to a specific bridge. This percentage is comparable to but higher than the percentage of matches obtained in the previous study (72.7%).

4.2 Statistical Analysis of Bridge Related Accidents

After the matching procedure was completed for this research, statistical analysis was performed in a manner similar to the previous study conducted by Abed-Al-Rahim and Johnston (1991). Since some percentage of the total number of accidents reported could not be matched to a specific bridge, the number of accidents predicted by the statistical regression should be less than the reported number of accidents (since the sum of the dependent variables would be less than the reported total). To account for this difference, an adjustment factor (AF) can be produced and multiplied by the resulting equation to correct for the difference. This is consistent with the approach taken by Abed-Al-Rahim and Johnston (1991). To compute the AF for the current analysis, the number of accidents identified as occurring on a culvert (29), a closed bridge (1), private bridge (2), and railroad bridge (1) were subtracted from the total number of reported accidents (2,416). This value was then divided by the total number of accidents linked to a bridge (1,938), which produced an AF of 1.23.

Once the accident-to-bridge matches were completed manually, statistical regression of the accident data in the five counties using the bridge characteristics as independent variables was performed to identify the bridge features most influential in the rate of bridge-related accidents. In multiple linear regression modeling, independent variables (bridge characteristics) are used as the predictor of an equation, while the dependent variable (number of accidents) is the resulting prediction of those variables in the regression model. To facilitate this analysis, an Excel spreadsheet was used to organize and prepare the data. Specifically, relevant bridge characteristics were provided for each bridge and a column was created in which the number of accidents occurring on each particular bridge was recorded. Table 4.1 shows a snapshot of this bridge-accident dataset with the number of accidents associated with the total observed over the five year period. This data was then exported from Excel to Minitab to facilitate the multiple linear regression.

Table 4.1: Snapshot of number of accidents associated with bridge data

Structure No.	# of accidents	ADT	Approach Align. Appraisal	Approach Rdwy Width	Bridge Deck Width
400001	1	22000	7	40	45.333
400002	0	23000	8	68	80.70
400003	0	23000	8	52	79.50
400004	0	12750	7	38	42.80
400005	1	12750	7	38	42.8
400006	0	13000	7	38	42.80
400007	0	13000	7	38	42.80
400009	0	130	7	21	27.00
400010	0	2700	7	23	25.42
400011	1	2550	8	18	36.3
400012	2	8900	7	62	71
400013	2	11000	7	56	77
400015	4	27000	7	88	102
400016	2	1000	7	19	27.5
400017	3	17750	7	40	49.417
400018	6	17000	7	40	49.5

Prior to running the statistical analysis on the accident data, the specific bridge characteristics to be included in the analysis as potential independent variables needed to be determined. Based on a review of the literature (Chen and Johnston 1987; Abed-Al-Rahim and Johnston 1991; Wang 2010) as well as relevant items available in the NCDOT BMS, the following thirteen bridge characteristics were selected:

- ADT
- Approach Alignment Appraisal
- Approach Roadway Width
- Bridge Deck Width
- Bridge Roadway Width
- Deck Geometry Appraisal
- Structure Length
- Structure Appraisal
- Through Lanes On
- Average Index (BMS)
- Total Horizontal Clearance
- WDIFACC (width difference between goal clear deck width for acceptable level of service and actual clear deck width)
- Functional Classification (referenced as categorical data)

Functional Classification includes six categorical data listed in the NCDOT BMS Sorting Code as: Interstate, US Route, NC Route, SR Route, Municipal Road not in contact with State System road, and Municipal Road over State System. Since this is non-continuous and not linearly related data, it must be treated differently in the linear regression reference cell coding. As shown in the Minitab Figure 4.1, binary variables were given to the terms in place of these original classification data. Minitab software uses this reference cell coding to determine an independent regression coefficient depending on the bridge functional classification.

To begin the multiple linear regression analysis, a multicollinearity check was performed on all of the independent variables. Multicollinearity occurs when one or more of the independent variables are correlated to each other. Multicollinearity introduces significant inaccuracies in the final model because the model will use more than one of these variables in the prediction, but the data provided with it is no more helpful; this will also reduce the significance of other variables in the equation (Rawlings et al. 1998). To measure the severity of multicollinearity, Minitab uses a linear regression analysis to generate a variance inflation factor (VIF) for each independent variable. VIF is computed as shown in Equation 4.1, where the coefficient of determination (R^2) is determined from the regression of each independent variable on the other independent variables being tested (Rawlings et al. 1998). Variables that exhibit high correlation with other variables must be removed one at a time, and then linear regression can be rerun to generate an updated VIF for the remaining independent variables. This step is repeated until all remaining independent variables are shown to be uncorrelated. A threshold of 10 is commonly used as a maximum VIF to determine whether variables are highly correlated or not (Rawlings et al. 1998). Shown in Figures 4.1 and 4.2 is the result of removing independent variables that are highly correlated. This resulted in the removal of bridge roadway width and bridge deck width, with 11 independent variables remaining for further analysis (Figure 4.3).

$$VIF_j = \frac{1}{1 - R^2{}_j}$$

Equation 4.1: Variance inflation factor

Where: VIF_j= Variance Inflation Factor (for variable $_j$)
$R^2{}_j$= coefficient of determination (for variable $_j$)

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	0.643	0.849	0.76	0.449	
ADT	0.000080	0.000008	10.41	0.000	3.54
Approach Align. Appraisal	-0.133	0.102	-1.30	0.194	1.12
Approach Rdwy Width	0.00173	0.00854	0.20	0.840	7.63
Bridge Deck Width	0.0153	0.0195	0.78	0.434	49.23
Bridge Rway Width	-0.0938	0.0247	-3.80	0.000	65.22
Deck Geometry Appraisal	-0.1522	0.0507	-3.00	0.003	2.64
Structure Length	0.001034	0.000473	2.19	0.029	1.30
Structure Appraisal	-0.0125	0.0938	-0.13	0.894	4.24
Through Lanes On	0.306	0.155	1.98	0.048	7.39
Average Index (BMS)	-0.208	0.138	-1.51	0.132	4.10
Total Horiz. Clearance	0.0980	0.0111	8.82	0.000	8.96
Acceptable - actual deck width	0.0038	0.0200	0.19	0.850	1.29
FC					
1	1.930	0.283	6.81	0.000	1.48
10	1.870	0.329	5.69	0.000	1.58
100	1.366	0.250	5.46	0.000	3.35
1000	0.407	0.374	1.09	0.277	1.99
10000	1.861	0.617	3.02	0.003	1.19

Figure 4.1: Minitab output showing VIF prior to removal of bridge roadway width

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	0.478	0.852	0.56	0.575	
ADT	0.000073	0.000008	9.77	0.000	3.38
Approach Align. Appraisal	-0.118	0.103	-1.15	0.250	1.11
Approach Rdwy Width	-0.00501	0.00840	-0.60	0.551	7.30
Bridge Deck Width	-0.0474	0.0105	-4.50	0.000	14.14
Deck Geometry Appraisal	-0.2014	0.0493	-4.09	0.000	2.47
Structure Length	0.001244	0.000472	2.64	0.008	1.29
Structure Appraisal	0.0066	0.0941	0.07	0.944	4.23
Through Lanes On	0.248	0.155	1.60	0.109	7.32
Average Index (BMS)	-0.209	0.139	-1.50	0.133	4.10
Total Horiz. Clearance	0.0855	0.0107	8.02	0.000	8.18
Acceptable - actual deck width	0.0149	0.0198	0.75	0.453	1.26
FC					
1	1.978	0.284	6.95	0.000	1.48
10	1.885	0.330	5.71	0.000	1.58
100	1.444	0.250	5.77	0.000	3.32
1000	0.897	0.353	2.54	0.011	1.75
10000	2.286	0.609	3.75	0.000	1.15

Figure 4.2: Minitab output showing VIF prior to removal of bridge deck width

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	0.918	0.852	1.08	0.281	
ADT	0.000064	0.000007	8.82	0.000	3.13
Approach Align. Appraisal	-0.106	0.103	-1.02	0.307	1.11
Approach Rdwy Width	-0.01576	0.00810	-1.94	0.052	6.71
Deck Geometry Appraisal	-0.2533	0.0482	-5.25	0.000	2.34
Structure Length	0.001375	0.000474	2.90	0.004	1.28
Structure Appraisal	-0.0175	0.0945	-0.19	0.853	4.22
Through Lanes On	-0.016	0.144	-0.11	0.914	6.27
Average Index (BMS)	-0.207	0.140	-1.48	0.139	4.10
Total Horiz. Clearance	0.06006	0.00910	6.60	0.000	5.88
Acceptable - actual deck width	0.0150	0.0200	0.75	0.454	1.26
FC					
1	1.832	0.285	6.44	0.000	1.46
10	1.804	0.332	5.44	0.000	1.58
100	1.288	0.250	5.16	0.000	3.26
1000	0.662	0.352	1.88	0.060	1.71
10000	2.183	0.613	3.56	0.000	1.15

Figure 4.3: Minitab output showing reduced set of uncorrelated independent variables

Once all highly correlated independent variables were removed, a best subsets stepwise regression was computed in Minitab on the remaining 11 independent variables. A best subsets in Minitab provides the two best fitting regression models with X number of variables, up to the regression model containing all of the variables. These best subset results in Minitab provide different coefficient of determination values along with the Mallows C_p. The Mallows C_p is a statistic that provides an approximation of the quality fit for a particular model, penalized by the number of independent variables included in the model, (Rawlings et al. 1998) and is calculated by Equation 4.2.

$$C_p = \frac{SSE_p}{S^2} - N + 2P$$

Equation 4.2: Mallows C_p

Where: C_p= Mallows C_p Statistics
SSE_p= Error sum of squares (for P variables)
S^2= Residual mean square
N= Sample size
P= Number of variables

Use of the Mallows C_p to determine the model size balances the two previously mentioned objectives of developing an effective prediction model with minimal number of independent variables required. From the Mallows C_p equation, it is noted that the model associated with the smallest Mallows $C_{p,}$ should be used in the final regression model. The Mallows C_p should be approximately equal to (or approaching) the number of variables in the output. The results of the Minitab analysis performed on the best subsets for the 11 different independent variables are shown in Figure 4.4. The results indicate that seven variables: Average Daily Traffic, Approach Roadway Width, Deck Geometry Appraisal, Structure Length, Average Index (BMS), Total Horizontal Clearance, and Functional Classification are the most influential bridge characteristics on bridge-related accidents and should be retained in the final regression model.

Vars	R-Sq	R-Sq (adj)	R-Sq (pred)	Mallows Cp	S	D T	a l	t h	a l	t h	a l	O n	S)	c e	F C	t h
1	13.6	13.6	13.1	93.2	2.7375	X										
1	9.7	9.6	9.1	163.4	2.7996							X				
2	15.0	14.9	14.3	70.3	2.7161	X								X		
2	14.8	14.7	14.0	74.6	2.7200	X						X				
3	17.6	17.4	16.7	27.5	2.6763	X			X					X		
3	16.2	16.0	15.3	51.4	2.6981	X							X	X		
4	18.2	17.9	17.1	18.7	2.6673	X			X				X	X		
4	18.0	17.8	17.0	21.2	2.6696	X			X		X			X		
5	18.6	18.3	17.5	12.4	2.6606	X			X	X			X	X		
5	18.5	18.3	17.4	13.9	2.6620	X		X	X				X	X		
6	19.0	18.6	17.7	8.2	2.6558	X		X	X	X			X	X		
6	18.9	18.5	17.6	10.6	2.6580	X		X	X	X	X			X		
7	19.1	18.7	17.8	7.9	2.6546	X		X	X	X			X	X	X	
7	19.1	18.7	17.6	8.2	2.6549	X		X	X	X		X	X	X		
8	19.2	18.8	17.6	8.0	2.6537	X		X	X	X		X	X	X		X
8	19.2	18.8	17.7	8.1	2.6538	X		X	X	X			X	X	X	X
9	19.3	18.8	17.6	8.2	2.6530	X		X	X	X		X	X	X	X	X
9	19.2	18.7	17.7	9.8	2.6545	X		X	X	X	X		X	X	X	X
10	19.3	18.8	17.6	10.0	2.6537	X		X	X	X	X	X	X	X	X	X
10	19.3	18.8	17.4	10.2	2.6539	X	X	X	X	X		X	X	X	X	X
11	19.3	18.7	17.4	12.0	2.6547	X	X	X	X	X	X	X	X	X	X	X

Figure 4.4: Minitab output showing lowest Mallows C_p

Once the seven variables associated with the final regression model were identified, multiple linear regression analysis was performed in Minitab to generate a prediction equation for bridge-related accidents specific to individual bridges in North Carolina. Equation 4.3 shows the representative equation associated with a multiple linear regression model, where each independent variable (x_i) is multiplied by a coefficient (b_i) and then these products are summed to return a result (y) for the prediction. With Functional Classification coded as a categorical variable, the intercept value (b_0) will vary based on the bridge's Functional Classification coding. Using Minitab's multiple linear regression analysis algorithm, the seven variables produced the regression model presented in Figure 4.5.

$$y = b_0 + b_1x_1 + b_2x_2 + \cdots + b_nx_n$$

Equation 4.3: Multiple linear regression model

Where: y= dependent variable
b_0= Intercept
b_i= Coefficient assoicated with independent variable i
x_i= Independent variable i

Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	0.341	0.506	0.67	0.501	
ADT	0.000065	0.000007	9.76	0.000	2.63
Approach Rdwy Width	-0.01671	0.00666	-2.51	0.012	4.54
Deck Geometry Appraisal	-0.2603	0.0449	-5.80	0.000	2.03
Structure Length	0.001420	0.000464	3.06	0.002	1.23
Average Index (BMS)	-0.2431	0.0753	-3.23	0.001	1.19
Total Horiz. Clearance	0.05908	0.00776	7.62	0.000	4.28
FC					
1	1.823	0.281	6.49	0.000	1.42
10	1.794	0.324	5.53	0.000	1.51
100	1.279	0.230	5.57	0.000	2.76
1000	0.701	0.339	2.07	0.039	1.59
10000	2.179	0.603	3.62	0.000	1.11

Figure 4.5: Minitab output showing model for multiple linear regression

As can be seen in Figure 4.5, the constant (intercept) term has a p-value of 0.501. Therefore, the regression analysis performed again, this time constrained to eliminate the intercept. The results of the final model are presented in Figure 4.6. In Table 4.2 is a list of the coded values for Functional Classification represent in the equation.

```
      S    R-sq  R-sq(adj)  R-sq(pred)
2.60263  35.77%     35.27%      34.15%


Coefficients

Term                          Coef   SE Coef  T-Value  P-Value    VIF
ADT                       0.000066  0.000007    10.15    0.000   3.73
Approach Rdwy Width       -0.01679   0.00666    -2.52    0.012  16.31
Deck Geometry Appraisal    -0.2611    0.0449    -5.82    0.000  13.35
Structure Length          0.001434  0.000464     3.09    0.002   2.91
Average Index (BMS)        -0.2016    0.0433    -4.65    0.000  15.85
Total Horiz. Clearance     0.05936   0.00774     7.66    0.000  23.77
FC
  1                          1.879     0.268     7.01    0.000   1.43
  10                         1.849     0.313     5.90    0.000   1.52
  100                        1.356     0.199     6.80    0.000   4.75
  1000                       0.781     0.317     2.46    0.014   1.50
  10000                      2.248     0.594     3.79    0.000   1.09


Regression Equation

FC
0      C2 = 0.0 + 0.000066 ADT - 0.01679 Approach Rdwy Width - 0.2611 Deck Geometry Appraisal
            + 0.001434 Structure Length - 0.2016 Average Index (BMS)
            + 0.05936 Total Horiz. Clearance

1      C2 = 1.879 + 0.000066 ADT - 0.01679 Approach Rdwy Width
            - 0.2611 Deck Geometry Appraisal + 0.001434 Structure Length
            - 0.2016 Average Index (BMS) + 0.05936 Total Horiz. Clearance

10     C2 = 1.849 + 0.000066 ADT - 0.01679 Approach Rdwy Width
            - 0.2611 Deck Geometry Appraisal + 0.001434 Structure Length
            - 0.2016 Average Index (BMS) + 0.05936 Total Horiz. Clearance

100    C2 = 1.356 + 0.000066 ADT - 0.01679 Approach Rdwy Width
            - 0.2611 Deck Geometry Appraisal + 0.001434 Structure Length
            - 0.2016 Average Index (BMS) + 0.05936 Total Horiz. Clearance

1000   C2 = 0.781 + 0.000066 ADT - 0.01679 Approach Rdwy Width
            - 0.2611 Deck Geometry Appraisal + 0.001434 Structure Length
            - 0.2016 Average Index (BMS) + 0.05936 Total Horiz. Clearance

10000  C2 = 2.248 + 0.000066 ADT - 0.01679 Approach Rdwy Width
            - 0.2611 Deck Geometry Appraisal + 0.001434 Structure Length
            - 0.2016 Average Index (BMS) + 0.05936 Total Horiz. Clearance
```

Figure 4.6: Minitab output showing final model for multiple linear regression

Table 4.2: Functional classification code

Code	Functional Classification	Intercept Value
0	Interstate	0
1	US Route	1.879
10	NC Route	1.849
100	SR Route	1.356
1000	Municipal Road not in contact with State System road	0.781
10000	Municipal Road over State System	2.248

Once the final bridge accident prediction equation was produced in Minitab, the equation was manipulated algebraically to provide an estimate that predicts the annual number of accidents. To do this, the result of the prediction equation was divided by 5, since 5 years of accidents were used to build the equation. To account for the number of accidents that could not be matched to specific bridges, the equation was then multiplied by the AF, which was computed to be 1.23 as previously discussed. After this manipulation, the final equation that can be used to predict the annual number of bridge-related accidents is shown in Equation 4.4.

$$NOACC = ((FC+(ADT\times 0.000066)+(ARW\times -0.01679)+(DGA\times -0.2611)+$$
$$(SL\times 0.001434)+(AI\times -0.2016)+(THC\times 0.05936))/5) \times 1.23$$

Equation 4.4: Prediction equation for annual number of bridge-related accidents with AF

Where: NOACC = Number of Accidents, per year
FC = Functional Classification (values from Table 4.1)
ADT = Average Daily Traffic
ARW = Approach Roadway Width
DGA = Deck Geometry Appraisal
SL = Structure Length
AI = Average Index (BMS)
THC = Total Horizontal Clearance

To provide a cleaner equation to be used in NCDOT BMS, coefficients in Equation 4.4 (including the functional classification intercept values presented in Table 4.2) were divided by 5 and then multiplied by 1.23, giving Equation 4.5, with Table 4.3 providing the updated intercept values for the functional classifications.

$$NOACC = FC + (0.00001624\times ADT) - (0.004130\times ARW) - (0.06423\times DGA) +$$
$$(0.0003528\times SL) - (0.04959\times AI) + (0.01460\times THC)$$

Equation 4.5: Prediction equation for annual number of bridge-related accidents

Table 4.3: Functional classification code for prediction equation

Code	Functional Classification	Intercept Value
0	Interstate	0
1	US Route	0.4622
10	NC Route	0.4549
100	SR Route	0.3336
1000	Municipal Road not in contact with State System road	0.1921
10000	Municipal Road over State System	0.5530

As is current practice in the BMS user costs equation, the number of predicted accidents on any bridge cannot be less than zero. Applying this constraint in Excel, and utilizing Equation 4.5, the number of bridge-related accidents occurring on all bridges statewide was calculated. By using the prediction equation on the bridges contained in all 100 counties in North Carolina (a total of 13,928 bridges), the total predicted number of accidents per year was 3,304 accidents. Over the last 5 years, the actual annual average number of accidents was 2,985 accidents per year (obtained by dividing a total of 14,923 accidents that were reported statewide over 5 years). This demonstrates that Equation 4.4 is reasonably plausible, as it predicts the statewide number of accidents within 11 percent of the actual reported total. Utilizing this equation to predict the number of accidents occurring on the bridges in the 95 North Carolina counties not used in the regression analysis yields a prediction of 2,807 accidents annually. The actual annual average number of accidents in those 95 counties over the last 5 years was 2,502 accidents per year (obtained by subtracting 2,416 accidents from 14,923 then dividing by 5 years). This again shows that the prediction equation provides plausible results.

A key purpose of this analysis was to identify the bridge characteristics that could be most closely linked to bridge-related accidents (i.e. the characteristics showing the strongest predictive capability). When comparing the results of this analysis to those from the analysis performed by Abed-Al-Rahim and Johnston (1991), some bridge characteristics were found to be consistent amongst the models are influential factors related to accident rates. Bridge characteristics that were determined to be influential in bridge-related accidents by both Abed-Al-Rahim (1991) and in this analysis are ADT and structure length.

Ultimately, this analysis provides a very useful look at bridge-related accidents and can be used to provide insight into accident causes over the past 25 years. Based on the associated negative coefficients, it is evident that having a larger approach roadway width and increased deck geometry appraisal helps decrease the incidence of bridge-related accidents. Likewise, the model indicates that regular and preventative maintenance to maintain or improve condition ratings will reduce bridge-related accidents, since the Average Index (BMS) is developed from the average of the deck, superstructure, and substructure condition ratings.

As stated earlier, in comparing the 1991 and 2015 studies, ADT remained an influential factor. This shows the continued role of traffic on bridge-related accidents. Structure length, identified as an influential factor in the 1991 study, also remained an influential factor in the 2015 study. This demonstrates that longer bridge lengths are associated with increased incidence of bridge-related accidents. The larger the total horizontal clearance, the higher the likelihood a bridge will have an increased number of accidents. This is potentially due to bridges being wider because of number of lanes needed for traffic. Lastly, the functional classification of a bridge will affect the likelihood of having an accident. As evidenced by the intercept values, interstate bridges are associated with lower incidences of bridge-related accidents, while municipal roads over a state system, US, and NC routes (with higher intercept values) are more likely to have an accident. This information could be incorporated by NCDOT in the design of non-interstate bridges statewide, possibly reducing the possibility of bridge-related accidents.

As shown in Figure 4.6, the predictive equation developed has a poor fit, with an R^2 value of only 35.77 percent. Some reasons for the inaccuracies in the bridge-related accident prediction equation produced as part of the current work are that only recorded characteristics related to each bridge could be considered as coefficients. Accidents can be the result of numerous causes, or contributing causes, such as weather, speed, time of day, and cell phone use. It is noted that cell phone use was likely not a human factor during the original study. Obviously, these factors cannot be easily accounted for within a predictive accident forecasting tool for use within the BMS. Another factor contributing to the inaccuracy of the equation was the inability to match all of the accidents reported over the last 5 years. This was due to the fact that some accidents were coded incorrectly. As seen in the Abed-Al-Rahim and Johnston (1991) report, the previous researchers determined that roughly 3.5 percent of the accidents listed actually occurred on a culvert. A similar rate of occurrence was observed within this study, as it was determined that 29 of 2,416 accidents (or 1.2 percent) occurred on a culvert. An additional error recognized in this study but not discussed in the previous study, is the presence of accidents that occurred under a bridge instead of on it. This would be a result of incorrect coding in the responding officer's report which is used in the bridge-accident matching procedure. Based on the manual bridge-accident procedure utilized, it is estimated that 189 of the 2,416 accidents in this current study potentially occurred under a bridge.

This effort provided a useful look at bridge characteristics linked to bridge-related accidents. As discussed, the results of this analysis, including the bridge-accident prediction equation, could be influenced by a number of additional unaccounted for factors. If NCDOT finds this analysis useful, a key procedural recommendation that would result in an improvement in this analysis would be to introduce a field on the accident for the Structure ID (six-digit code). To facilitate this, a means for the responding officer to identify the Structure ID would also need to be provided. This would involve placing a marker, plaque, or other indicator of the code on and/or beneath all bridges. It is noted that many bridges in North Carolina already have a sign posted indicating the Structure ID. Implementing this change in the accident report would eliminate the time needed to manually match bridges to accident reports and would help to reduce the number of errors associated with coding in the accident reports.

CHAPTER 5: USER COSTS SENSITIVITY ANALYSIS

5.1 Overview of User Costs Sensitivity Analysis

As outlined in previous chapters, user costs and BMS input tables were updated over the course of this research. In some cases, new methodologies to obtain these user costs were utilized and in other cases, previous methods used to obtain these input values were determined to still be the most appropriate method and only new, updated values were obtained. Equation 5.1 shows the original NCDOT BMS user costs equation based on research conducted by Chen and Johnston (1987). As a result of work performed as part of this project, it is recommended that the user costs equation be modified to Equation 5.2 to predict user costs for bridges in the NCDOT BMS.

$$AURC(t) = 365ADT(t)\,[\overbrace{C_{WDA}}^{\text{Accident cost due to width}}U_{AC}+\overbrace{C_{ALA}}^{\text{Accident cost due to alignment}}U_{AC}+\overbrace{C_{CLA}}^{\text{Accident cost due to under vertical clearance}}U_{AC}+\overbrace{C_{CLD}}^{\text{VOC due to vertical clearance}}U_{DC}DL+\overbrace{C_{LCD}(t)}^{\text{VOC due to load capacity}}U_{DL}DL]$$

Equation 5.1: NCDOT BMS user cost equation (Chen and Johnston 1987)

Where: $AURC(t)$ = annual user cost of the bridge at year t, $/year

$ADT(t)$ = average daily traffic using the bridge at year t

C_{WDA} = coefficient for proportion of vehicles incurring accidents due to width deficiency

C_{ALA} = coefficient for proportion of vehicles incurring accidents due to poor alignment

C_{CLA} = coefficient for proportion of vehicles incurring accidents due to vertical clearance deficiency

C_{CLD} = coefficient for proportion of vehicles detoured due to a vertical clearance deficiency

$C_{LCD}(t)$ = coefficient for proportion of vehicles detoured due to a load capacity deficiency at year t
U_{AC} = unit cost of vehicle accidents on bridges, \$/accident
U_{DC} = unit cost for average vehicle detours due to vertical clearance deficiency, \$/mile
U_{DL} = unit cost for average vehicle detours due to load capacity deficiency, \$/mile
DL = detour length, miles

$$AURC(t)=365ADT(t)[\overbrace{C_{LCD(SU)}(t)U_{DL}DL}^{\boxed{\text{VOC due to load capacity for SU}}}+\overbrace{C_{LCD(TTST)}(t)U_{DL}DL}^{\boxed{\text{VOC due to load capacity for TTST}}}+\overbrace{C_{CLD}(t)U_{DC}DL}^{\boxed{\text{VOC due to vertical clearance}}}] + \overbrace{NOACC(t)U_{AC}}^{\boxed{\text{Annual total accident cost}}}$$

Equation 5.2: Updated user costs equation

Where: AURC = annual user cost of the bridge at year t, \$/year
ADT = average daily traffic using the bridge at year t
U_{AC} = unit cost of vehicle accidents on bridges, \$/accident
DL = detour length, miles
U_{DC} = unit cost for average vehicle detours due to vertical clearance deficiency, \$/mile
U_{DL} = unit cost for average vehicle detours due to load capacity deficiency, \$/mile
C_{LCD} = coefficient for proportion of vehicles detoured due to a load capacity deficiency at year t
C_{CLD} = coefficient for proportion of vehicles detoured due to a vertical clearance deficiency
NOACC = number of annual accidents per year at year t

As reflected in the difference between Equation 5.1 and 5.2, changes to the user costs equation are recommended based on the results of this work. An extensive analysis of recent bridge-related accidents resulted in the development of an updated bridge-related accident prediction model. As part of this work, the characteristics most significantly correlated to bridge-related accidents were identified and are included in Equation 4.4, which is in turn utilized in Equation 5.2. It is noted that the accident cost is also no longer multiplied by the ADT and 365 days, since NOACC, predicted by Equation 4.4, directly estimates the annual number of bridge-related accidents. To assist the reader, Equation 4.4 is again presented below.

$$NOACC = FC + (0.00001624 \times ADT) - (0.004130 \times ARW) - (0.06423 \times DGA) + (0.0003528 \times SL) - (0.04959 \times AI) + (0.01460 \times THC)$$

Equation 4.5: Prediction equation for annual number of bridge-related accidents

Where: NOACC = Number of Accidents, per year
FC = Functional Classification
ADT = Average Daily Traffic
ARW = Approach Roadway Width
DGA = Deck Geometry Appraisal
SL = Structure Length
AI = Average Index (BMS)
THC = Total Horizontal Clearance

Accident costs due to the vertical clearance under a bridge are not specifically included in Equation 5.2, as data currently included in the BMS does not support this calculation. However, accidents occurring as a result of vertical clearance issues are considered as part of the accident prediction equation (Equation 4.4), since this model was developed with actual bridge-related accident data that includes accidents due to vertical clearance issues. Also included in Equation 5.2 are the vehicle operating costs separated into two separate components (for SU and for TTST). This is now possible because the current BMS provides load postings for both SU and TTST. Since these load postings can be different for SU and TTST, treating the user costs of these types of vehicles separately (as shown in Equation 5.2) should result in more accurate prediction of user costs.

Changes to these user cost input values will result to changes in the user costs predicted by the NCDOT BMS. When forecasting an outcome in the future, such as bridge user costs, inputs will not always remain constant, due to economic and inflation rate uncertainties. In order to analyze the impact of the model inputs on the calculated user costs, a sensitivity analysis was performed on the updated equation. Sensitivity analysis is used to analyze an equation to determine which inputs (when varied) have the greatest effect on the outcome of an equation. In this case, the sensitivity analysis was performed to determine the cost inputs (user costs due to accidents or user costs due to vehicle operating costs) that have the greatest impact on the resulting user costs for a given set of parameters.

Identifying the key factors influencing user costs will assist in MR&R, preventative maintenance, and replacement decisions. Results of this sensitivity analysis can also assist NCDOT in identifying future design requirements that could provide improved long-term user costs, as well provide a prioritized listing of key input values that should be updated regularly (or more frequently) to more accurately predict bridge user costs. Ultimately, factors deemed most influential in user costs estimation could also provide data to support design and MR&R decisions that could reduce accident occurrences on bridges.

The sensitivity analysis for the NCDOT BMS user costs was performed using an add-on program within Excel, called @RISK, developed by Palisade Corporation. In order to perform the sensitivity analysis, a representative subset of bridges was selected. To provide continuity with prior work developing and enhancing the NCDOT's BMS, a method similar to the one developed by Abed-Al-Rahim and Johnston (1991) was utilized. This approach should facilitate some comparison between the analyses of the most significant inputs driving user costs approximately 25 years ago and today. It is noted, however, that the sensitivity analysis performed by Abed-Al-Rahim and Johnston (1991) additionally studied the effects of input variability on costs other than user costs, including agency costs such as maintenance costs, rehabilitation costs, and replacement costs. A sensitivity analysis to this extent was beyond the scope of the current research.

In the sensitivity analysis performed for this work, as well as for the 1991 study, four counties were selected for testing: Guilford, Halifax, Harnett, and Haywood. A total of 969 bridges are included in these four counties, which represents roughly 7 percent of the 13,928 bridges statewide. Consistent with the method and constraints utilized by Abed-Al-Rahim and Johnston (1991), a 20-year horizon was used for the sensitivity analysis with a 6 percent rate of return and net present value (NPV) utilized as the evaluation method. @RISK uses a Monte Carlo simulation to perform a user-specified number of independent analyses for the sensitivity analysis. For this work, based on the input distributions assigned to the accident and VOC costs uncertainties, 1,000 analyses were utilized in the @RISK Monte Carlo simulation, with the output of each analysis being the user costs in NPV terms.

5.2 Time Dependent Variables Utilized in the Sensitivity Analysis

Six items associated with the user costs equation will vary with time. In order to accurately predict the user costs over the 20 year horizon, the change in the variables listed below were estimated:

- Accident cost
- Vehicle operating cost (VOC)
- ADT
- Deck geometry appraisal
- Average index (BMS)
- Bridge capacity

Accident and VOC Cost

Since changes in economic behavior and inflation largely drive cost, accident costs and vehicle operating costs (VOC) were identified as the two variables to be evaluated in the sensitivity analysis. Similar to the sensitivity analysis performed by Abed-Al-Rahim and Johnson (1991), the sensitivity of the user costs was evaluated using the variance of the user cost increase predicted over a 20 year timeframe.

ADT

ADT is used in nearly all aspects of the user costs equation, so predicting future ADT values was very important to this process. As discussed in Section 3.1, ADT growth rates for each county were computed for four different roadway types. These growth rate percentages were used to predict the future ADT of the bridges and a snapshot is provided in Appendix B, Table B-1.

Deck Geometry Appraisal

Deck geometry appraisal is listed as Federal Item 68 in the FHWA Recording and Coding Guide (FHWA 1995). The FHWA Recording and Coding Guide provides two comparative methods by which to appraise a bridge deck geometry (vertical clearance or number of lanes). This method consists of identifying the appropriate deck geometry appraisal rating from three different tables in which a bridge is rated, with the lowest appraisal rating from the table used for the condition rating assignment. In one method, a bridge is given a deck geometry appraisal rating based on its vertical clearance and functional classification, therefore it is assumed that this rating will remain constant for the bridge's service life. The other method to determine a bridge's appraisal rating is based on the total number of lanes. A bridge with three or more lanes is assigned a deck geometry appraisal rating based on its number of lanes and roadway width. If a deck geometry appraisal rating is assigned in this manner it is also assumed to remain constant for the bridge's service life, unless major reconstruction occurs. Bridges with two lanes and two-way traffic are differentiated by their ADT and assigned a lower deck geometry appraisal rating with increasing ADT. Using Table 5.1 provided by the FHWA (1995) for Federal Item 68, bridges analyzed in this study that fit the two-lane, two-way traffic classification were assigned future appraisals based on the their future ADT (discussed above) and their bridge roadway width. A snapshot of these bridges is provided in Appendix B, Table B-2.

Table 5.1: Snapshot of Deck Geometry Appraisal Tables (FHWA 1995)

	TABLE 2A						TABLE 2B	
Deck Geometry Rating Code	Bridge Roadway Width 2 Lanes; 2 Way Traffic						Bridge Roadway Width 1 Lane; 2-Way Traffic	
	ADT (Both Directions)						ADT (Both Directions)	
	0-100	101-400	401-1000	1001-2000	2001-5000	>5000	0-100	>100
9	>9.8	>11.0	>12.2	>13.4	>13.4	>13.4	-	-
8	9.8	11.0	12.2	13.4	13.4	13.4	<4.9	-
7	8.5	9.8	11.0	12.2	13.4	13.4	4.6	-
6	7.3	8.5	9.1	10.4	12.2	13.4	4.3	-
5	6.1	7.3	7.9	8.5	10.4	11.6	4.0	-
4	5.5	6.1	6.7	7.3	8.5	9.8 (8.5)*	3.7	-
3	4.9	5.5	6.1	6.7	7.9	9.1 (7.9)*	3.4	<4.9
2	Any width less than required for a rating code of 3 and structure is open.							
0	Bridge Closed							

Average Index (BMS)

Average Index (BMS) is calculated as the average of the deck, superstructure, and substructure condition ratings for a particular bridge. As part of ongoing work being completed for updating the BMS, a new set of deterministic models were developed using the Duncan and Johnston (2001) methodology to determine the deterioration rates of these condition ratings (Goyal, 2015). Table 5.2 provides a sample table (for timber decks) that illustrates the typical number of years that a timber deck condition remains at each condition rating prior to changing to the next lower rating. These tables provide the years in each condition rating for timber, steel, concrete, and prestressed concrete deck bridges based on different ADT bins. Tables for deck, substructure, and superstructure condition deterioration rates, illustrating the typical number of years the each component can be expected to remain at each condition rating, are provided in Appendix B, Table B-3 through B-12. The bins were then averaged for each condition rating associated with the deck, substructure, and superstructure over each material type. This average was used to provide a slope, which serves in this analysis to compute the expected change in each condition rating over time. Using these material-specific deterministic models to predict how long each part of the bridge structure (deck, superstructure, and substructure) can be expected to remain at each condition rating, a predicted condition rating for deck, superstructure, and substructure of each bridge was computed for the 20-year timeframe of the sensitivity analysis. Snapshots of this work are provided in Appendix B, Tables B-13 through B-15. The Average Index (BMS) was additionally computed at each year for each structure. A snapshot of this calculation is provided in Table 5.3. It is noted that the lowest rating that a bridge component could be assigned at any point in the 20-year timeframe was a condition rating of 3.

Table 5.2: Deterministic timber deck condition ratings (Goyal 2015)

Timber Deck (Years in Rating)						
	Rating 9	Rating 8	Rating 7	Rating 6	Rating 5	Rating 4
Timber 0-200	2.9361	8.4615	7.3584	6.9167	4.9352	4.302
Timber 200-800	3.0151	8.3017	7.9498	6.8142	4.8426	4.4534
Timber 800-2000	3.0517	7.4764	7.8105	6.8052	4.5854	4.203
Timber 2000-4000	2.6429	7.3468	7.8414	6.217	4.9135	3.959
Timber >4000	3.1667	8.9063	6.7352	5.2826	5.5646	5.1196
Timber Average	2.9625	8.09854	7.53906	6.40714	4.96826	4.4074
Slope	0.33755	0.123479	0.13264	0.156076	0.20128	0.22689

Table 5.3: Snapshot of typical Excel spreadsheet showing prediction of average index (BMS) deterioration

	Averge Index (BMS)										
Structure No.	year 0	year 1	year 2	year 3	year 4	year 5	year 6	year 7	year 8	year 9	year 10
400001	5.67	5.67	5.33	5.33	5	5	4.67	4.67	4.33	4	4
400002	6.33	5.67	5.33	5.33	5.33	5.33	5.33	5	5	4.33	4.33
400003	5	4.67	4.67	4.33	4.33	4.33	3.67	3.67	3.67	3.67	3.67
400004	6.33	5.67	5.33	5.33	5.33	5.33	5.33	5.33	5	5	4.33
400005	6.33	5.67	5.33	5.33	5.33	5.33	5.33	5.33	5	5	4.33
400006	6.33	5.67	5.33	5.33	5.33	5.33	5.33	5.33	5	5	4.33
400007	6.33	5.67	5.33	5.33	5.33	5.33	5.33	5.33	5	5	4.33
400009	6.67	6.33	6.33	5.67	5.33	5.33	5.33	5.33	5.33	5	5
400010	5	4.33	4.33	4.33	4	3.33	3.33	3.33	3.33	3.33	3.33
400011	7	6.67	6.67	6.67	6.33	6	6	6	6	6	5.67
400012	4	3.67	3.67	3	3	3	3	3	3	3	3
400013	5	5	4.67	4.67	4	4	4	3.67	3.67	3.33	3.33
400015	5.67	5.33	5.33	5	4.67	4.67	4.67	4.67	4.33	4.33	3.67
400016	5.67	5.33	5.33	5	5	4.33	4.33	4.33	4.33	4.33	4.33
400017	5	5	5	4.67	4.33	4	4	3.67	3.67	3.33	3.33
400018	5	5	5	4.67	4.33	4	4	3.67	3.67	3.33	3.33
400019	7	6.33	6.33	6.33	6	6	6	6	5.67	5.67	5.67
400020	7	7	7	7	6.67	6	6	6	6	6	6
400021	7	6.67	6.67	6.67	6.67	6.67	6	6	6	6	5.67
400022	5.67	5	5	5	5	4.67	4.33	4.33	4	4	4
400023	7	6.67	6.67	6.67	6.67	6.33	6	6	5.67	5.67	5.67
400024	7	7	7	7	6.33	6	6	6	6	6	6
400025	5.33	5.33	5.33	5	4.67	4.67	4.33	4.33	4	4	4
400027	5.67	5	4.67	4.67	4.67	4.33	4.33	4.33	4.33	4	3.67
400028	5	5	5	5	4	4	4	4	4	4	4
400030	5	4.33	4.33	4.33	4	4	3.33	3.33	3.33	3.33	3.33
400031	6.33	6.33	6.33	6.33	6	5.67	5.33	5.33	5.33	5	5
400032	5.67	5	4.67	4.67	4.67	4.67	4.33	3.67	3.67	3.67	3.67

Bridge Capacity

The estimated future bridge capacity reduction is currently predicted based on the substructure condition rating, as outlined by Johnston et al. (1994). This is explained in Section 2.4. Based on the substructure material type and condition rating at each year (as determined as part of this project and presented by Goyal 2015), the capacity of the bridge will either remain constant or will be reduced. As part of work performed by others involved in this research project, an updated table that provides the predicted reduction in capacity of a bridge based on its substructure condition rating was developed and is presented in Table 5.4 (Goyal 2015).

Table 5.4: Predicted load capacity deterioration rates (Goyal 2015)

Load Capacity Deterioration Rates (tons/year)				
Substructure Condition Rating	Bridge Main Structural Material			
	Timber	Concrete	Steel	Prestressed
5-9	0	0	0	0
4	0	0.22	0.06	0.84
3	0.57	1.67	0.61	1.61

As can be seen in Table 5.5, a snapshot of the TTST capacity for each bridge was predicted for the 20-year horizon. A snapshot of calculations for load capacity deterioration rates for SU is provided in Appendix B, Table B-16. Both SU and TTST loads were constrained so that they would not go below 3 tons, which is the minimum load a bridge must hold to remain open to traffic.

Table 5.5: Snapshot of TTST load capacity deterioration prediction

	TTST Load Capacity Deterioration										
Structure No.	year 0	year 1	year 2	year 3	year 4	year 5	year 6	year 7	year 8	year 9	year 10
400001	99	99	99	99	99	99	99	99	99	98	97
400002	99	99	99	99	99	99	99	99	99	99	99
400003	99	99	99	99	99	99	99	99	99	99	99
400004	99	99	99	99	99	99	99	99	99	99	99
400005	99	99	99	99	99	99	99	99	99	99	99
400006	99	99	99	99	99	99	99	99	99	99	99
400007	99	99	99	99	99	99	99	99	99	99	99
400009	99	99	99	99	99	99	99	99	99	99	99
400010	99	99	98	97	96	96	94	92	91	89	88
400011	99	99	99	99	99	99	99	99	99	99	99
400012	99	99	99	99	98	97	96	95	95	94	93
400013	99	99	99	99	99	99	99	99	99	99	98
400015	99	99	99	99	99	99	99	99	99	99	99
400016	99	99	99	99	99	99	99	99	99	99	99
400017	99	99	99	99	99	98	97	96	96	95	93
400018	99	99	99	99	99	98	97	96	96	95	93
400019	99	99	99	99	99	99	99	99	99	99	99
400020	99	99	99	99	99	99	99	99	99	99	99
400021	99	99	99	99	99	99	99	99	99	99	99
400022	99	99	99	99	99	99	99	98	97	96	95
400023	99	99	99	99	99	99	99	99	99	99	99
400024	99	99	99	99	99	99	99	99	99	99	99
400025	99	99	99	99	99	98	97	96	95	95	94
400027	99	99	99	99	99	99	99	99	99	99	99
400028	99	99	99	99	99	99	99	98	98	98	98
400030	19	19	19	19	19	19	19	18	17	16	15
400031	99	99	99	99	99	98	97	96	96	95	93
400032	99	99	99	99	99	99	99	98	97	96	95

Inflation Rate

A base inflation rate was required for prediction in @RISK as the base percentage of increase in accident and VOC costs at each year. Using CPI (2015), a median inflation rate of 2.50 percent was calculated from the annual indexes of years 1999 through 2014. Each inflation rate is assigned a distribution and parameter type in @RISK with which it will vary in the analysis, based on the inflation rate being the mean value of increase. A normal distribution was assigned to the inflation rate along with a standard deviation of 1.04 percent, which was calculated using the CPI (2015) annual indexes of year 1999 through 2014.

5.3 Sensitivity to Accident and Vehicle Operating Costs

The result of the @RISK Monte Carlo simulation used to perform the sensitivity analysis is a series of predicted NPV user costs for bridges in Guilford, Halifax, Harnett, and Haywood over the 20 year horizon with the uncertainties due to accident and VOC costs. The @RISK output for the range of predicted NPV is shown in Figure 5.1 as a probability density histogram prepared from the 1,000 analyses performed on the user costs equation in @RISK (Palisades 2015). From Figure 5.1, it can be noted that the uncertainty in change of both the accident and vehicle operating costs will have a large effect on the resulting predicted NPV user costs. This is depicted in the x-axis where the predicted NPV user costs range from 645 million dollars to 967 million dollars. In Figure 5.1, values on the y-axis indicate the probability density of the histogram, where the area of each bar is the proportion of samples within it, the y-axis is scaled so that the total area of the histogram bars is 1 (Palisade 2015). It is noted that the standard deviation is over 47 million dollars.

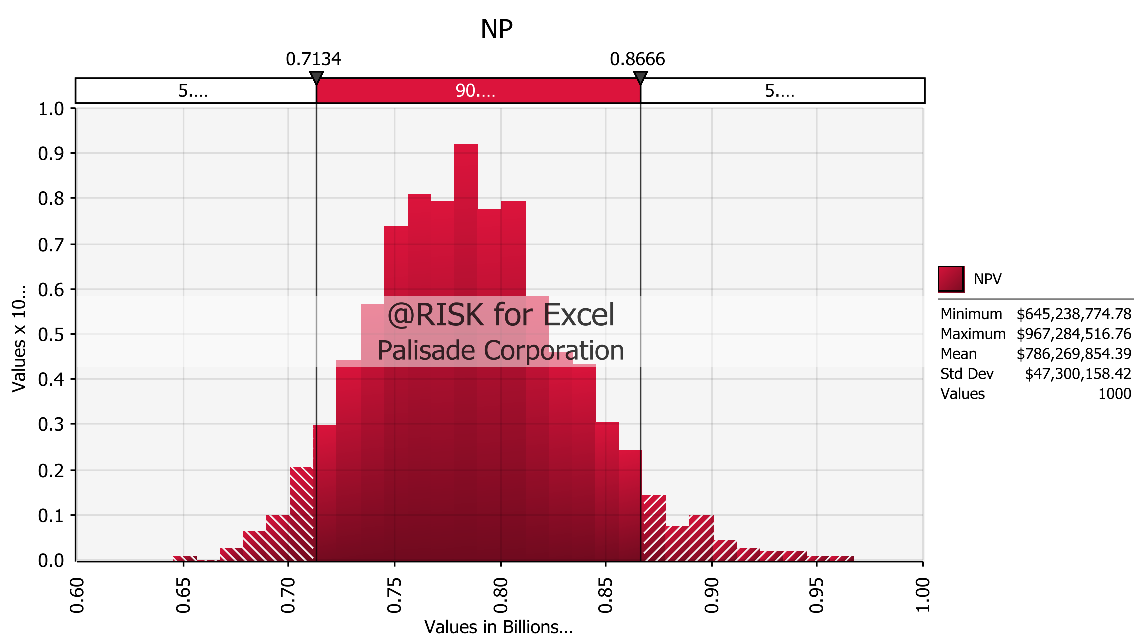


Figure 5.1: @RISK output showing user NPV costs, 20-year horizon for bridges in (Guilford, Halifax, Harnett, and Haywood)

Table 5.6 provides an in-depth look at the increase in predicted NPV user costs increase at each percentile, due to the range of accident and vehicle operating costs used in the analysis. Based on the 20-year sensitivity analysis performed using the parameters discussed above, it can be observed that the median NPV user cost predicted for bridges in the selected four counties is just over 786 million dollars.

Table 5.6: @RISK output showing summary statistics for sensitivity analysis of NPV user costs for bridges in (Guilford, Halifax, Harnett, and Haywood), over 20-year horizon

Summary Statistics for NPV			
Statistics		**Percentile**	
Minimum	$ 645,238,774.78	**5%**	$ 713,419,833.49
Maximum	$ 967,284,516.76	**10%**	$ 727,916,723.29
Mean	$ 786,269,854.39	**15%**	$ 737,465,819.82
Std Dev	$ 47,300,158.42	**20%**	$ 746,972,525.60
Variance	2.2373E+15	**25%**	$ 752,804,979.27
Skewness	0.353863083	**30%**	$ 759,122,160.22
Kurtosis	3.2223143	**35%**	$ 766,013,018.03
Median	$ 783,022,696.32	**40%**	$ 771,513,065.41
Mode	$ 765,691,814.78	**45%**	$ 778,461,340.41
Left X	$ 713,419,833.49	**50%**	$ 783,022,696.32
Left P	5%	**55%**	$ 789,447,058.36
Right X	$ 866,625,226.62	**60%**	$ 795,669,919.78
Right P	95%	**65%**	$ 801,597,208.62
Diff X	$ 153,205,393.13	**70%**	$ 808,511,342.41
Diff P	90%	**75%**	$ 816,244,890.40
#Errors	0	**80%**	$ 824,573,385.39
Filter Min	Off	**85%**	$ 834,907,274.40
Filter Max	Off	**90%**	$ 847,213,270.63
#Filtered	0	**95%**	$ 866,625,226.62

To illustrate how user costs are affected by each variable (the sensitivity to each variable), @RISK computes how each uncertain variable affects the predicted NPV user costs. The @RISK output is formatted to show the variance in costs from the lowest (bottom of the chart) to the highest (top of the chart). The results of the sensitivity analysis of the user costs based on accident costs and vehicle operating costs (VOC), compared separately, is shown in Figure 5.2. The results indicate that accident costs have a much larger effect on the resulting predicted NPV user costs than the VOC. For clarity the range of computed values (corresponding to the bars in Figure 5.2) are provided in Table 5.7.

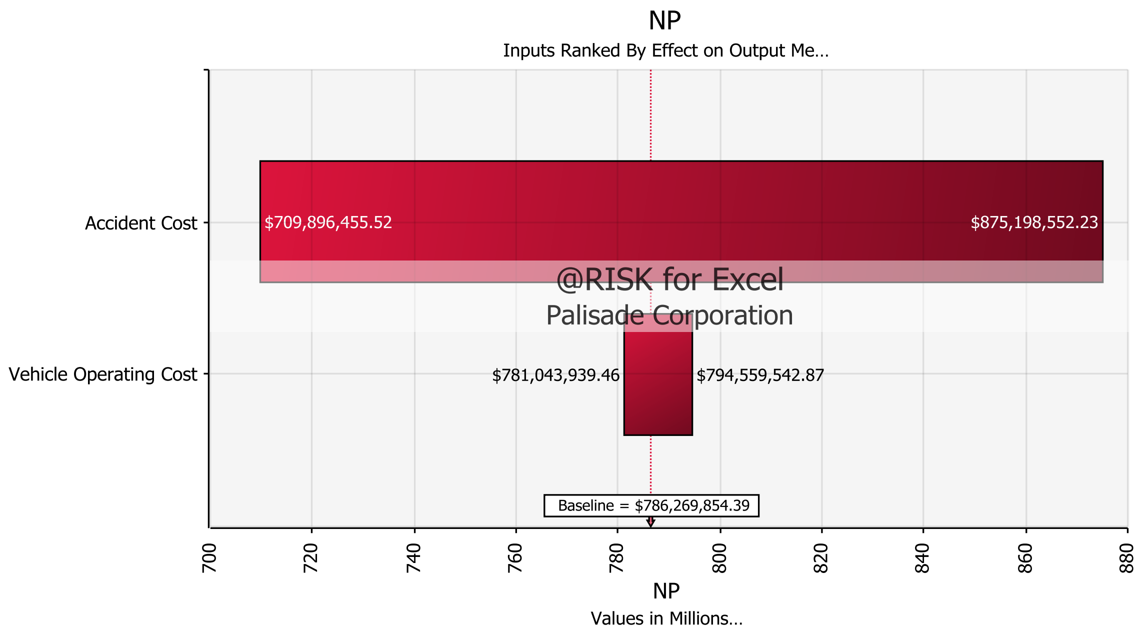


Figure 5.2: @RISK output showing sensitivity analysis

Table 5.7: @RISK output showing NPV output change

Change in Output Statistic for NPV			
Rank	**Name**	**Lower**	**Upper**
1	Accident Cost	$ 709,896,455.52	$ 875,198,552.23
2	Vehicle Operating Cost	$ 781,043,939.46	$ 794,559,542.87

Ultimately, the results of this sensitivity analysis should allow NCDOT to identify ways to reduce user costs. Since user costs are most sensitive to accidents, and because the cost associated with an accident is something that NCDOT cannot directly control, it is apparent that reducing accidents themselves is the key to reducing future user costs for the state's bridges. As presented in Chapter 4, bridge characteristics most associated with recent bridge-related accidents were identified as part of this work. Possible methods for reducing accidents on both existing bridges and design of new bridges were discussed in Section 4.2. To conclude, this sensitivity analysis reinforces that an increased focus on addressing factors that most greatly influence bridge-related accidents will greatly reduce user costs, as well as improve the safety North Carolina's traveling public in the future.

CHAPTER 6: CONCLUSIONS

6.1 Conclusions

The purpose of this study was to update and enhance inputs and methodologies utilized to compute user costs in NCDOT's BMS. As part of this work a number of input tables and methodologies for computing costs, were updated, including:

- ADT growth rate
- Vehicle operating cost
- Vehicle distribution
- Vehicle weight distribution
- Vehicle height distribution
- Accident injury severity
- Accident cost
- Predicted number of annual accidents

It is recommended that the updated and enhanced input tables and methodologies presented be considered for implementation into NCDOT's BMS.

Additionally, an analysis of bridge-related accidents was performed, resulting in the identification of seven bridge characteristics that are most associated with bridge-related accidents. These seven characteristics are:

- Average Daily Traffic
- Approach Roadway Width
- Deck Geometry Appraisal
- Structure Length
- Average Index (BMS)
- Total Horizontal Clearance
- Functional Classification

The findings of this analysis resulted in the generation of an equation that can be used to compute the predicted number of bridge-related accidents per year for a specific set of bridge characteristics (Equation 4.4).

$$NOACC = FC + (0.00001624 \times ADT) - (0.004130 \times ARW) - (0.06423 \times DGA) + (0.0003528 \times SL) - (0.04959 \times AI) + (0.01460 \times THC)$$

Equation 4.5: Prediction equation for annual number of bridge-related accidents

Where: NOACC = Number of Accidents, per year
FC = Functional Classification (values from Table 4.1)
ADT = Average Daily Traffic
ARW = Approach Roadway Width
DGA = Deck Geometry Appraisal
SL = Structure Length
AI = Average Index (BMS)
THC = Total Horizontal Clearance

Consolidating this work resulted in the generation of a new equation suggested for estimating the annual user costs for NCDOT's BMS, Equation 5.2.

$$AURC(t)=365ADT(t)[C_{LCD(SU)}(t)U_{DL}DL+C_{LCD(TTST)}(t)U_{DL}DL+C_{CLD}(t)U_{DC}DL]+NOACC(t)U_{AC}$$

Equation 5.2: Updated user costs equation

Where: AURC=annual user costs per bridge (at year t)
ADT= average daily traffic (at year t)
U_{AC}= cost per accident
DL= detour length
U_{DC}= cost per mile of vehicles detoured due to vertical clearance
U_{DL}= cost per mile of vehicles detoured due to load
C_{LCD}= coefficient of vehicles detoured due to load (at year t)
C_{CLD}= coefficient of vehicles detoured due to vertical clearance
NOACC= number of annual accidents per year (at year t)

The bridge-related accident analysis provides a useful look-back on bridge related accidents, providing insight into changes in causes and severities over the past 25 years.

The total number of bridge related accidents occurring per year in these five counties has remained constant, even with an increase in population (and subsequently higher ADT), which is promising. Based on the analysis results, increased ADT and increased structure length continue to be associated with an increased number of bridge related accidents. It is evident that having a larger approach roadway width and increased deck geometry appraisal help decrease the incidence of bridge-related accidents. Regular and preventative maintenance to maintain or improve condition ratings will reduce bridge-related accidents, since the Average Index (BMS) was found to be influential. The larger the total horizontal clearance, the higher the likelihood a bridge will have an increased number of accidents. As evidenced by the equation's intercept values, interstate bridges are associated with lower incidences of bridge-related accidents, while municipal roads over a state system, US, and NC routes (with higher intercept values) are more likely to have an accident.

The results of a sensitivity analysis on user costs indicated that NCDOT's BMS user costs are most sensitive to accident costs. Since the cost associated with each accident is something that NCDOT cannot directly control, it is apparent that reducing the number of accident occurrences is the key way to reduce future user costs for the state's bridges.

6.2 Recommendations for Future Work

Future work identified as part of this study includes further study of accident causes and identifying design or operational tactics that could reduce the occurrence of bridge-related accidents. Continued preventative maintenance to existing bridges has been shown to reduce user costs. Recommended future work could include a study of past maintenance, repair, and rehabilitation work and its effect on Average Index (BMS), and subsequently accident rates. The costs of more severe injuries and fatalities are significantly higher than those of less severe and property-damage-only accidents. Study of the bridge-related characteristics associated with fatal and very severe accidents could be useful.

Forecasting using user costs will help NCDOT optimize MR&R strategies, as well as assist with design decisions recommended future work also includes an implementation plan for use of these new user costs inputs as updated methodologies develop as part of this work.

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APPENDIX A: BRIDGE-RELATED ACCIDENTS

Table A-1: Snapshot of accident report location summary (Source: NCDOT)

CRASHID	CNTY_NBR	ON_RD	DSTNC	DRCTN	FRM_RD	TWRD_RD	MLPST_RD	MLPST	ACDNT_DT_TM
102483531	40	I 40	1	N	I 85	I 85BUS	I 40	22.849	2-Jan-09
102483567	40	US 29	0.019	S	NC 150	SR 4771	US 29	29.578	2-Jan-09
102483971	40	US 220	0.1	S	SR 2104	SR 2313	US 220	28.819	2-Jan-09
102484225	40	I 85BUS	0.42	N	I 85	*MILE 121	I 85BUS	999.999	3-Jan-09
102486906	40	I 85BUS	1	N	SR 1129	HOLDEN	I 85BUS	11.425	3-Jan-09
102505459	40	SR 3056	0.2	NW	SR 3232	SR 3143	SR 3056	3.82	2-Jan-09
102506038	40	SR 3411	0.3	E	SR 3621	SR 3412	SR 3411	0.3	28-Jan-09
102507237	40	I 85BUS	0		I 85	I 73	I 85BUS	999.999	31-Jan-09
102513181	40	US 29	0		NC 150	SR 2510	US 29	29.597	7-Feb-09
102526222	40	JOSEPH BRYAN	1	W	FLEMING	INMAN	SR 2085	3.205	6-Jan-09
102526231	40	CONE	0	NE	US 29	US 29	CONE	0	6-Jan-09
102526244	40	WENDOVER	0.019	W	I 40	STANLY	SR 1541	1.569	6-Jan-09
102526966	40	I 40BUS	0	E	I 840	GUILFORD COLLEGE	I 40BUS	999.999	3-Jan-09
102526981	40	FREEMAN MILL	0		SPRING GARDEN	LEE	FREEMAN MILL	3.884	2-Jan-09
102527279	40	I 840	0	W	I 85	MT HOPE CH	I 840	999.999	2-Jan-09
102530146	40	WENDOVER	0	E	I 40	BIG TREE	SR 1541	1.55	14-Jan-09
102530995	40	SR 2022	0.2	N	SR 2096	SR 2028	SR 2022	1.884	28-Feb-09
102531836	40	SUMMIT	0		SUNRISE VALLEY	*LCL PHLLIPS AVE	SR 2526	9.496	7-Jan-09
102532788	40	MCCONNELL	0	E	US 29	US 29	MCCONNELL	10.922	20-Jan-09
102534844	40	SR 1546	0.4	N	SR 1546	SR 4178	SR 1546	999.999	12-Feb-09

Table A-2: Snapshot of BMS structure location

Structure No.	Facility Carried	Location
400001	SR2254 WBL	0.1 MI. N. JCT. SR1598
400002	S.ELM-EUGENE ST.	1.1 MI.N.JCT.VANDALIA RD.
400003	S.ELM-EUGENE STREE	0.15 MI.S.JCT.I40
400004	I73, US220 NBL	1.4 MI. S. JCT. SR1104
400005	I73, US220 SBL	1.4 MI. S. JCT. SR1104
400006	I73, US220 NBL	1.3 MI. N. JCT. NC62
400007	I73, US220 SBL	1.3 MI. N. JCT. NC62
400009	SR3392	0.5 MI. S. JCT. SR3393
400010	SR3394	0.45 MI. N. JCT. SR3397
400011	SR3394	0.4 MI. S. JCT. US421
400012	SR1970	0.4 MI. N. JCT. US311
400013	SR1278	0.1 MI. N. JCT. SR1970
400015	US220	0.6 MI. N. JCT. SR1118
400016	SR3411	2.45 MI. E. JCT. NC22
400017	US70 EBL	0.9 MI. S. JCT. US29A
400018	US70 WBL	0.9 MI. S. JCT. US29A
400019	SR1993	0.2 MI. S. JCT. SR1970
400020	SR4121	0.8 MI. N. JCT.SR1332

APPENDIX B: SENSITIVITY ANALYSIS

Table B-1: Snapshot of ADT growth rate forecast

Structure No.	ADT Growth Rate	ADT year 0	ADT year 1	ADT year 2	ADT year 3	ADT year 4	ADT year 5	ADT year 6	ADT year 7	ADT year 8	ADT year 9	ADT year 10
400001	2.31%	22000	22508	23028	23560	24104	24661	25231	25814	26410	27020	27644
400002	2.57%	25000	25643	26302	26977	27671	28382	29111	29859	30627	31414	32221
400003	2.57%	25000	25643	26302	26977	27671	28382	29111	29859	30627	31414	32221
400004	3.15%	13500	13925	14364	14816	15283	15764	16261	16773	17302	17847	18409
400005	3.15%	13500	13925	14364	14816	15283	15764	16261	16773	17302	17847	18409
400006	3.15%	14000	14441	14896	15365	15849	16348	16863	17395	17942	18508	19091
400007	3.15%	14000	14441	14896	15365	15849	16348	16863	17395	17942	18508	19091
400009	2.57%	130	133	137	140	144	148	151	155	159	163	168
400010	3.02%	2700	2782	2866	2952	3041	3133	3228	3325	3426	3529	3636
400011	3.02%	2550	2627	2706	2788	2872	2959	3048	3140	3235	3333	3434
400012	2.31%	9200	9413	9630	9852	10080	10313	10551	10795	11044	11299	11560
400013	2.31%	10000	10231	10467	10709	10957	11210	11469	11733	12005	12282	12566
400015	2.31%	27000	27624	28262	28915	29583	30266	30965	31680	32412	33161	33927
400016	2.57%	1000	1026	1052	1079	1107	1135	1164	1194	1225	1257	1289
400017	2.31%	17750	18160	18580	19009	19448	19897	20357	20827	21308	21800	22304
400018	2.31%	17000	17393	17794	18206	18626	19056	19497	19947	20408	20879	21361
400019	2.31%	16000	16370	16748	17135	17530	17935	18350	18774	19207	19651	20105
400020	2.31%	12500	12789	13084	13386	13696	14012	14336	14667	15006	15352	15707
400021	2.57%	20000	20514	21041	21582	22137	22706	23289	23888	24502	25131	25777
400022	2.31%	19000	19439	19888	20347	20817	21298	21790	22294	22809	23335	23875
400023	2.57%	530	544	558	572	587	602	617	633	649	666	683
400024	3.02%	5400	5563	5731	5904	6082	6266	6455	6650	6851	7058	7271
400025	2.57%	1200	1231	1262	1295	1328	1362	1397	1433	1470	1508	1547
400027	2.57%	1300	1333	1368	1403	1439	1476	1514	1553	1593	1634	1676
400028	2.31%	40000	40924	41869	42837	43826	44838	45874	46934	48018	49127	50262
400030	3.02%	2200	2266	2335	2405	2478	2553	2630	2709	2791	2876	2962
400031	2.31%	1100	1125	1151	1178	1205	1233	1262	1291	1320	1351	1382
400032	2.57%	90	92	95	97	100	102	105	107	110	113	116
400033	2.57%	320	328	337	345	354	363	373	382	392	402	412

Table B-2: Snapshot of deck geometry appraisal forecast

Structure No.	Deck Geometry Appraisal 0	year 1	year 2	year 3	year 4	year 5	year 6	year 7	year 8	year 9	year 10
400001	4	4	4	4	4	4	4	4	4	4	4
400002	5	5	5	5	5	5	5	5	5	5	5
400003	9	9	9	9	9	9	9	9	9	9	9
400004	6	6	6	6	6	6	6	6	6	6	6
400005	6	6	6	6	6	6	6	6	6	6	6
400006	6	6	6	6	6	6	6	6	6	6	6
400007	6	6	6	6	6	6	6	6	6	6	6
400009	5	5	5	5	5	5	5	5	5	5	5
400010	2	2	2	2	2	2	2	2	2	2	2
400011	4	4	4	4	4	4	4	4	4	4	4
400012	6	6	6	6	6	6	6	6	6	6	6
400013	9	9	9	9	9	9	9	9	9	9	9
400015	9	9	9	9	9	9	9	9	9	9	9
400016	4	4	4	4	4	4	4	4	4	4	4
400017	2	2	2	2	2	2	2	2	2	2	2
400018	2	2	2	2	2	2	2	2	2	2	2
400019	2	2	2	2	2	2	2	2	2	2	2
400020	9	9	9	9	9	9	9	9	9	9	9
400021	7	7	7	7	7	7	7	7	7	7	7
400022	2	2	2	2	2	2	2	2	2	2	2
400023	6	6	6	6	6	6	6	6	6	6	6
400024	4	4	4	4	4	4	4	4	4	4	4
400025	4	4	4	4	4	4	4	4	4	4	4
400027	5	5	5	5	5	5	5	5	5	5	5
400028	5	5	5	5	5	5	5	5	5	5	5
400030	2	2	2	2	2	2	2	2	2	2	2
400031	5	5	5	5	5	5	5	5	5	5	5
400032	4	4	4	4	4	3	3	3	3	3	3
400033	6	6	6	6	6	6	6	6	6	6	6

Table B-3: Deterministic concrete deck condition ratings (Goyal 2015)

Concrete Deck (Years in Rating)						
	Rating 9	Rating 8	Rating 7	Rating 6	Rating 5	Rating 4
Concrete 0-200	3.7451	9.5058	7.9186	9.5769	6.6521	8.5954
Concrete 200-800	3.7467	9.4109	8.3469	10.8644	7.3464	7.7575
Concrete 800-2000	3.8162	8.7405	8.4399	11.0959	7.3481	8.0029
Concrete 2000-4000	3.1431	8.1471	8.5608	10.7817	7.6112	6.8569
Concrete >4000	3.725	6.7675	7.9295	10.4082	6.6865	8.11
Concrete Average	3.63522	8.51436	8.23914	10.54542	7.12886	7.86454
Slope	0.27509	0.117449	0.12137	0.094828	0.14027	0.12715

Table B-4: Deterministic steel deck condition ratings (Goyal 2015)

Steel Deck (Years in Rating)						
	Rating 9	Rating 8	Rating 7	Rating 6	Rating 5	Rating 4
Steel 0-200	4.7125	13.9435	8.0621	8.0815	3.5468	5.8889
Steel 200-800	3.4	12.8483	7.9489	8.0594	4.02	3.5222
Steel 800-2000	4.4167	12.0412	7.6999	7.9808	4.9801	4.5533
Steel 2000-4000	3.5347	11.5146	6.8626	8.1006	5.0948	4.3061
Steel >4000	2.9	6.8583	6.7492	8.4368	7.0507	4.2552
Steel Average	3.79278	11.44118	7.46454	8.13182	4.93848	4.50514
Slope	0.26366	0.087404	0.13397	0.122974	0.20249	0.22197

Table B-5: Deterministic timber substructure condition ratings (Goyal 2015)

Timber Substructure (Years in Rating)						
	Rating 9	Rating 8	Rating 7	Rating 6	Rating 5	Rating 4
Timber Coastal	3.5714	3.7829	4.8219	7.1158	7.55	5.1827
Timber Piedmont	3.8571	3.716	4.7011	7.2793	7.1357	5.4644
Timber Mountain	2.4828	4.5874	6.996	9.3507	5.1218	3.6215
Timber Average	3.3038	4.02877	5.50633	7.91527	6.6025	4.7562
Slope	0.3027	0.24821	0.18161	0.12634	0.15146	0.2103

Table B-6: Deterministic concrete substructure condition ratings (Goyal 2015)

Concrete Substructure (Years in Rating)						
	Rating 9	Rating 8	Rating 7	Rating 6	Rating 5	Rating 4
Concrete Coastal	7.6667	6.3412	7.5895	11.1303	7.2854	8.5743
Concrete Piedmont	4.25	5.3788	8.8016	11.1221	7.9547	8.82
Concrete Mountain	5.3	6.2894	11.8728	11.3939	6.0848	5.1627
Concrete Average	5.7389	6.00313	9.4213	11.2154	7.1083	7.519
Slope	0.1742	0.16658	0.10614	0.08916	0.14068	0.133

Table B-7: Deterministic steel substructure condition ratings (Goyal 2015)

Steel Substructure (Years in Rating)						
	Rating 9	Rating 8	Rating 7	Rating 6	Rating 5	Rating 4
Steel Coastal	3.3794	7.0468	6.6435	8.7156	7.1533	5.9018
Steel Piedmont	4.3031	8.6568	7.6843	8.8638	6.6995	5.9895
Steel Mountain	3.6946	8.1939	9.1922	9.7371	5.2814	4.2883
Steel Average	3.7924	7.96583	7.84	9.1055	6.37807	5.3932
Slope	0.2637	0.12554	0.12755	0.10982	0.15679	0.1854

Table B-8: Deterministic prestressed substructure condition ratings (Goyal 2015)

Prestressed Substructure (Years in Rating)						
	Rating 9	Rating 8	Rating 7	Rating 6	Rating 5	Rating 4
Prestressed Coastal	3.6537	7.4576	5.5805	8.5565	6.1615	5.815
Prestressed Piedmont	4.1304	9.0317	6.205	9.6623	5.6743	4.903
Prestressed Mountain	3.621	9.9501	7.434	9.6117	5.0374	3.8633
Prestressed Average	3.8017	8.81313	6.4065	9.27683	5.6244	4.8604
Slope	0.263	0.11347	0.15609	0.1078	0.1778	0.2057

Table B-9: Deterministic timber superstructure condition ratings (Goyal 2015)

Timber Superstructure (Years in Rating)						
	Rating 9	Rating 8	Rating 7	Rating 6	Rating 5	Rating 4
Timber State System 1, Mulit-Beam	3	5.2143	6.3492	8.3945	8.3754	3.6382
Timber State System 2, Multi-Beam	2.8718	7.3554	7.5268	7.9011	6.0105	4.1333
Timber Average	2.9359	6.28485	6.938	8.1478	7.19295	3.88575
Slope	0.34061	0.15911	0.14413	0.12273	0.13903	0.25735

Table B-10: Deterministic concrete superstructure condition ratings (Goyal 2015)

Concrete Superstructure (Years in Rating)						
	Rating 9	Rating 8	Rating 7	Rating 6	Rating 5	Rating 4
Concrete State System 1, Slab	2	6.3377	9.0555	11.9508	6.5447	6.7905
Concrete State System 2, Slab	4.2	7.6139	9.7329	11.0284	7.2725	9.7722
Concrete State System 1, Tee-Beam	n/a	6.3637	9.8673	11.6001	7.0814	7.7721
Concrete State System 2, Tee-Beam	2	6.9713	11.4245	11.6894	7.3262	9.8259
Concrete Average	2.73333	6.82165	10.0201	11.5672	7.0562	8.54018
Slope	0.36585	0.14659	0.0998	0.08645	0.14172	0.11709

Table B-11: Deterministic steel superstructure condition ratings (Goyal 2015)

Steel Superstructure (Years in Rating)						
	Rating 9	Rating 8	Rating 7	Rating 6	Rating 5	Rating 4
Steel State System 1, Multi-Beam	4.4206	11.4589	7.4071	7.8273	5.0145	5.2466
Steel State System 2, Multi-Beam	3.2702	10.0682	10.3105	7.97	4.4272	4.2707
Steel State System 2, Truss	5.2083	5.6058	6.668	7.3878	6.5156	5.9543
Steel State System 1, Floor-Beam	n/a	6.1688	6.4777	6.6292	6.5335	4.767
Steel State System 2, Floor-Beam	3.1429	6.9651	7.6751	6.7853	4.8972	4.4541
Steel Average	4.0105	8.05336	7.70768	7.31992	5.4776	4.93854
Slope	0.24935	0.12417	0.12974	0.13661	0.18256	0.20249

Table B-12: Deterministic prestressed superstructure condition ratings (Goyal 2015)

Prestressed Superstructure (Years in Rating)						
	Rating 9	Rating 8	Rating 7	Rating 6	Rating 5	Rating 4
Prestressed State System 1, Multi-Beam	4.582	10.888	5.5108	7.8039	4.3542	5.0316
Prestressed State System 2, Multi-Beam	4.2044	13.3114	5.3833	5.7458	2.5653	3.5833
Prestressed State System 1, Slab	3.8018	9.218	5.9944	9.049	3.232	5.875
Prestressed State System 2, Slab	3.8508	9.8914	6.2964	7.998	2.886	3.5833
Prestressed State System 2, Tee-Beam	2.6481	8.8033	9.5877	9.0104	5.6423	5.4577
Prestressed Average	3.81742	10.4224	6.55452	7.92142	3.73596	4.70618
Slope	0.26196	0.09595	0.15257	0.12624	0.26767	0.21249

Table B-13: Snapshot of spreadsheet showing prediction of deck deterioration

Structure No.	Deck Structure Type	Deck Condition	year 1	year 2	year 3	year 4	year 5	year 6	year 7	year 8	year 9	year 10
400001	1	7.69	7.571528109	7.45016	7.32878	7.20741	7.08604	6.96467	6.86984	6.77501	6.68018	6.58536
400002	1	6.11	6.012272103	5.91744	5.77717	5.63689	5.49662	5.35634	5.21607	5.07579	4.93552	4.80837
400003	1	4.35	4.225246982	4.09809	3.97094	3.84379	3.71663	3.58948	3.46233	3.33518	3.20802	3.08087
400004	1	5.01	4.869725117	4.74257	4.61542	4.48827	4.36111	4.23396	4.10681	3.97965	3.8525	3.72535
400005	1	5.01	4.869725117	4.74257	4.61542	4.48827	4.36111	4.23396	4.10681	3.97965	3.8525	3.72535
400006	1	5.01	4.869725117	4.74257	4.61542	4.48827	4.36111	4.23396	4.10681	3.97965	3.8525	3.72535
400007	1	5.01	4.869725117	4.74257	4.61542	4.48827	4.36111	4.23396	4.10681	3.97965	3.8525	3.72535
400009	2	7.31	7.189428109	7.06806	6.94668	6.85186	6.75703	6.6622	6.56737	6.47254	6.37772	6.28289
400010	1	5.49	5.345225117	5.20495	5.06468	4.9244	4.79725	4.67009	4.54294	4.41579	4.28864	4.16148
400011	1	7.45	7.332528109	7.21116	7.08978	6.96841	6.87358	6.77876	6.68393	6.5891	6.49427	6.39945
400012	1	4.01	3.882846982	3.75569	3.62854	3.50139	3.37423	3.24708	3.11993	2.99278	3	3
400013	1	5.49	5.347925117	5.20765	5.06738	4.9271	4.79995	4.67279	4.54564	4.41849	4.29134	4.16418
400015	1	5.01	4.869725117	4.74257	4.61542	4.48827	4.36111	4.23396	4.10681	3.97965	3.8525	3.72535
400016	2	5.62	5.482025117	5.34175	5.20148	5.0612	4.92093	4.79377	4.66662	4.53947	4.41231	4.28516
400017	1	5.63	5.490425117	5.35015	5.20988	5.0696	4.92933	4.80217	4.67502	4.54787	4.42071	4.29356
400018	2	5.69	5.549325117	5.40905	5.26878	5.1285	4.98823	4.86107	4.73392	4.60677	4.47961	4.35246
400019	2	7.01	6.888628109	6.7938	6.69897	6.60414	6.50932	6.41449	6.31966	6.22483	6.13	6.03518
400020	1	7.60	7.482028109	7.36066	7.23928	7.11791	6.99654	6.90171	6.80688	6.71206	6.61723	6.5224
400021	1	7.68	7.557328109	7.43596	7.31458	7.19321	7.07184	6.95047	6.85564	6.76081	6.66598	6.57116
400022	1	5.63	5.488625117	5.34835	5.20808	5.0678	4.92753	4.80037	4.67322	4.54607	4.41891	4.29176
400023	2	7.65	7.531328109	7.40996	7.28858	7.16721	7.04584	6.92447	6.82964	6.73481	6.63998	6.54516
400024	1	7.57	7.443828109	7.32246	7.20108	7.07971	6.95834	6.86351	6.76868	6.67386	6.57903	6.4842
400025	6	7.71	7.571733272	7.43777	7.3038	7.16983	7.03587	6.9019	6.77893	6.65595	6.53298	6.41
400027	1	5.27	5.124925117	4.98465	4.8575	4.73034	4.60319	4.47604	4.34889	4.22173	4.09458	3.96743
400028	1	5.56	5.417825117	5.27755	5.13728	4.997	4.86985	4.74269	4.61554	4.48839	4.36124	4.23408
400030	1	5.49	5.350325117	5.21005	5.06978	4.9295	4.80235	4.67519	4.54804	4.42089	4.29374	4.16658
400031	1	7.68	7.559628109	7.43826	7.31688	7.19551	7.07414	6.95277	6.85794	6.76311	6.66828	6.57346
400032	8	7.01	6.877357469	6.72128	6.56521	6.40913	6.25305	6.09698	5.9409	5.73962	5.53835	5.33707
400033	2	7.58	7.461428109	7.34006	7.21868	7.09731	6.97594	6.88111	6.78628	6.69146	6.59663	6.5018

Table B-14: Snapshot of spreadsheet showing prediction of substructure deterioration

Structure No.	Structure Type Main	Substructure Condition	year 1	year 2	year 3	year 4	year 5	year 6	year 7	year 8	year 9	year 10
400001	302	5.2612	5.1044	4.9476	4.7622	4.5768	4.3914	4.2060	4.0205	3.8351	3.6497	3.4643
400002	302	6.0304	5.9206	5.7638	5.6070	5.4502	5.2934	5.1366	4.9799	4.7944	4.6090	4.4236
400003	302	6.5709	6.4611	6.3513	6.2414	6.1316	6.0218	5.9120	5.7552	5.5984	5.4416	5.2848
400004	302	7.01	6.8824	6.7726	6.6628	6.5530	6.4432	6.3333	6.2235	6.1137	6.0039	5.8940
400005	302	7.01	6.8824	6.7726	6.6628	6.5530	6.4432	6.3333	6.2235	6.1137	6.0039	5.8940
400006	302	7.01	6.8824	6.7726	6.6628	6.5530	6.4432	6.3333	6.2235	6.1137	6.0039	5.8940
400007	302	7.01	6.8824	6.7726	6.6628	6.5530	6.4432	6.3333	6.2235	6.1137	6.0039	5.8940
400009	501	7.3957	7.2396	7.0835	6.9274	6.8196	6.7118	6.6040	6.4962	6.3884	6.2807	6.1729
400010	522	5	4.7943	4.5885	4.3828	4.1770	3.9713	3.7655	3.5598	3.3541	3.1483	2.9426
400011	302	7	6.8902	6.7804	6.6705	6.5607	6.4509	6.3411	6.2312	6.1214	6.0116	5.9018
400012	402	4.4586	4.2732	4.0878	3.9023	3.7169	3.5315	3.3461	3.1607	2.9753	3.0000	3.0000
400013	402	5.4709	5.3141	5.1573	5.0005	4.8438	4.6583	4.4729	4.2875	4.1021	3.9167	3.7312
400015	402	5.6235	5.4667	5.3099	5.1531	4.9964	4.8109	4.6255	4.4401	4.2547	4.0693	3.8838
400016	501	7.3957	7.2396	7.0835	6.9274	6.8196	6.7118	6.6040	6.4962	6.3884	6.2807	6.1729
400017	502	5.6183	5.4405	5.2627	5.0849	4.9071	4.7014	4.4956	4.2899	4.0841	3.8784	3.6727
400018	502	5.5527	5.3749	5.1971	5.0193	4.8415	4.6358	4.4300	4.2243	4.0185	3.8128	3.6071
400019	501	7.5714	7.4153	7.2592	7.1031	6.9470	6.8392	6.7314	6.6236	6.5159	6.4081	6.3003
400020	602	7.6034	7.4473	7.2912	7.1351	6.9790	6.8712	6.7634	6.6556	6.5479	6.4401	6.3323
400021	302	7	6.8902	6.7804	6.6705	6.5607	6.4509	6.3411	6.2312	6.1214	6.0116	5.9018
400022	302	5.01	4.8532	4.6678	4.4824	4.2970	4.1115	3.9261	3.7407	3.5553	3.3699	3.1844
400023	501	7.6431	7.4870	7.3309	7.1748	7.0187	6.8626	6.7548	6.6471	6.5393	6.4315	6.3237
400024	602	7.5652	7.4091	7.2530	7.0969	6.9408	6.8330	6.7252	6.6174	6.5097	6.4019	6.2941
400025	302	4.6017	4.4163	4.2309	4.0454	3.8600	3.6746	3.4892	3.3038	3.1184	2.9329	3.0000
400027	522	7.01	6.8539	6.7461	6.6383	6.5305	6.4227	6.3149	6.2071	6.0993	5.9915	5.8137
400028	104	5.5432	5.4025	5.2618	5.1212	4.9805	4.8475	4.7145	4.5815	4.4485	4.3155	4.1825
400030	302	5	4.8146	4.6292	4.4437	4.2583	4.0729	3.8875	3.7021	3.5167	3.3312	3.1458
400031	502	5.6117	5.4339	5.2561	5.0783	4.9005	4.6948	4.4890	4.2833	4.0775	3.8718	3.6661
400032	302	5	4.8146	4.6292	4.4437	4.2583	4.0729	3.8875	3.7021	3.5167	3.3312	3.1458
400033	501	7.5637	7.4076	7.2515	7.0954	6.9393	6.8315	6.7237	6.6159	6.5082	6.4004	6.2926

Table B-15: Snapshot of spreadsheet showing prediction of superstructure deterioration

Structure No.	SuperStructure Type - Material (det)	Superstructure Condition	year 1	year 2	year 3	year 4	year 5	year 6	year 7	year 8	year 9	year 10
400001	3 - Steel	5.6760	5.4934	5.3109	5.1283	4.9458	4.7433	4.5408	4.3383	4.1358	3.9333	3.7308
400002	3 - Steel	7.0952	6.9655	6.8288	6.6922	6.5556	6.4190	6.2824	6.1458	6.0092	5.8726	5.6900
400003	3 - Steel	5.0100	4.8274	4.6249	4.4225	4.2200	4.0175	3.8150	3.6125	3.4100	3.2075	3.0050
400004	3 - Steel	7.2491	7.1194	6.9896	6.8530	6.7164	6.5798	6.4432	6.3066	6.1699	6.0333	5.8967
400005	3 - Steel	7.2491	7.1194	6.9896	6.8530	6.7164	6.5798	6.4432	6.3066	6.1699	6.0333	5.8967
400006	3 - Steel	7.2491	7.1194	6.9896	6.8530	6.7164	6.5798	6.4432	6.3066	6.1699	6.0333	5.8967
400007	3 - Steel	7.2491	7.1194	6.9896	6.8530	6.7164	6.5798	6.4432	6.3066	6.1699	6.0333	5.8967
400009	5 - Prestressed Concrete	6.0000	5.7323	5.4647	5.1970	4.9293	4.7168	4.5044	4.2919	4.0794	3.8669	3.6544
400010	5 - Prestressed Concrete	5.0000	4.7875	4.5750	4.3625	4.1501	3.9376	3.7251	3.5126	3.3001	3.0876	2.8751
400011	3 - Steel	7.5336	7.4039	7.2741	7.1444	7.0146	6.8849	6.7483	6.6117	6.4751	6.3384	6.2018
400012	4 - Steel Continuous	4.4586	4.2561	4.0536	3.8511	3.6486	3.4462	3.2437	3.0412	2.8387	3.0000	3.0000
400013	4 - Steel Continuous	5.2899	5.1073	4.9248	4.7223	4.5198	4.3173	4.1148	3.9123	3.7098	3.5074	3.3049
400015	4 - Steel Continuous	7.3325	7.2028	7.0730	6.9433	6.8067	6.6701	6.5334	6.3968	6.2602	6.1236	5.9870
400016	5 - Prestressed Concrete	5.0000	4.7875	4.5750	4.3625	4.1501	3.9376	3.7251	3.5126	3.3001	3.0876	2.8751
400017	5 - Prestressed Concrete	5.5588	5.2911	5.0235	4.7558	4.5433	4.3308	4.1183	3.9058	3.6934	3.4809	3.2684
400018	5 - Prestressed Concrete	5.6295	5.3618	5.0942	4.8265	4.6140	4.4015	4.1890	3.9765	3.7641	3.5516	3.3391
400019	5 - Prestressed Concrete	7.0000	6.8738	6.7475	6.6213	6.4950	6.3688	6.2426	6.1163	5.9901	5.7224	5.4547
400020	6 - Prestressed Concrete Continuous	7.6240	7.4714	7.3189	7.1663	7.0137	6.8612	6.7349	6.6087	6.4824	6.3562	6.2300
400021	3 - Steel	7.6499	7.5202	7.3904	7.2607	7.1309	7.0012	6.8715	6.7348	6.5982	6.4616	6.3250
400022	3 - Steel	7.0100	6.8803	6.7436	6.6070	6.4704	6.3338	6.1972	6.0606	5.9240	5.7414	5.5588
400023	5 - Prestressed Concrete	7.0000	6.8738	6.7475	6.6213	6.4950	6.3688	6.2426	6.1163	5.9901	5.7224	5.4547
400024	6 - Prestressed Concrete Continuous	7.5260	7.3734	7.2209	7.0683	6.9157	6.7895	6.6633	6.5370	6.4108	6.2845	6.1583
400025	3 - Steel	5.5205	5.3379	5.1554	4.9728	4.7703	4.5678	4.3653	4.1629	3.9604	3.7579	3.5554
400027	5 - Prestressed Concrete	5.0000	4.7875	4.5750	4.3625	4.1501	3.9376	3.7251	3.5126	3.3001	3.0876	2.8751
400028	1 - Concrete	5.5188	5.3771	5.2354	5.0936	4.9519	4.8348	4.7177	4.6006	4.4835	4.3665	4.2494
400030	3 - Steel	5.0100	4.8274	4.6249	4.4225	4.2200	4.0175	3.8150	3.6125	3.4100	3.2075	3.0050
400031	5 - Prestressed Concrete	7.6974	7.5448	7.3923	7.2397	7.0871	6.9346	6.8083	6.6821	6.5558	6.4296	6.3034
400032	3 - Steel	5.2988	5.1162	4.9337	4.7312	4.5287	4.3262	4.1237	3.9212	3.7187	3.5163	3.3138
400033	5 - Prestressed Concrete	7.0000	6.8738	6.7475	6.6213	6.4950	6.3688	6.2426	6.1163	5.9901	5.7224	5.4547

Table B-16: Snapshot of SU load capacity deterioration prediction

	SU Load Capacity Deterioration										
Structure No.	year 0	year 1	year 2	year 3	year 4	year 5	year 6	year 7	year 8	year 9	year 10
400001	99	99	99	99	99	99	99	99	99	98	97
400002	99	99	99	99	99	99	99	99	99	99	99
400003	99	99	99	99	99	99	99	99	99	99	99
400004	99	99	99	99	99	99	99	99	99	99	99
400005	99	99	99	99	99	99	99	99	99	99	99
400006	99	99	99	99	99	99	99	99	99	99	99
400007	99	99	99	99	99	99	99	99	99	99	99
400009	99	99	99	99	99	99	99	99	99	99	99
400010	41	41	40	39	38	38	36	34	33	31	30
400011	99	99	99	99	99	99	99	99	99	99	99
400012	99	99	99	99	98	97	96	95	95	94	93
400013	99	99	99	99	99	99	99	99	99	99	98
400015	99	99	99	99	99	99	99	99	99	99	99
400016	99	99	99	99	99	99	99	99	99	99	99
400017	99	99	99	99	99	98	97	96	96	95	93
400018	99	99	99	99	99	98	97	96	96	95	93
400019	99	99	99	99	99	99	99	99	99	99	99
400020	99	99	99	99	99	99	99	99	99	99	99
400021	99	99	99	99	99	99	99	99	99	99	99
400022	99	99	99	99	99	99	99	98	97	96	95
400023	99	99	99	99	99	99	99	99	99	99	99
400024	99	99	99	99	99	99	99	99	99	99	99
400025	40	40	40	40	40	39	38	37	36	36	35
400027	99	99	99	99	99	99	99	99	99	99	99
400028	99	99	99	99	99	99	99	98	98	98	98
400030	15	15	15	15	15	15	15	14	13	12	11
400031	99	99	99	99	99	98	97	96	96	95	93
400032	99	99	99	99	99	99	99	98	97	96	95