VISSIM Calibration for Urban Freeways

Center for Transportation Research and Education

Final Report
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16. Abstract

In urban areas, interchange spacing and the adequacy of design for weaving, merge, and diverge areas can significantly influence available capacity. Traffic microsimulation tools allow detailed analyses of these critical areas in complex locations that often yield results that differ from the generalized approach of the Highway Capacity Manual. In order to obtain valid results, various inputs should be calibrated to local conditions. This project investigated basic calibration factors for the simulation of traffic conditions within an urban freeway merge/diverge environment.

By collecting and analyzing urban freeway traffic data from multiple sources, specific Iowa-based calibration factors for use in VISSIM were developed. In particular, a repeatable methodology for collecting standstill distance and headway/time gap data on urban freeways was applied to locations throughout the state of Iowa. This collection process relies on the manual processing of video for standstill distances and individual vehicle data from radar detectors to measure the headways/time gaps. By comparing the data collected from different locations, it was found that standstill distances vary by location and lead-follow vehicle types. Headways and time gaps were found to be consistent within the same driver population and across different driver populations when the conditions were similar. Both standstill distance and headway/time gap were found to follow fairly dispersed and skewed distributions. Therefore, it is recommended that microsimulation models be modified to include the option for standstill distance and headway/time gap to follow distributions as well as be set separately for different vehicle classes.

In addition, for the driving behavior parameters that cannot be easily collected, a sensitivity analysis was conducted to examine the impact of these parameters on the capacity of the facility. The sensitivity analysis results can be used as a reference to manually adjust parameters to match the simulation results to the observed traffic conditions. A well-calibrated microsimulation model can enable a higher level of fidelity in modeling traffic behavior and serve to improve decision making in balancing need with investment.

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EXECUTIVE SUMMARY

Providing adequate roadway capacity, particularly in high-volume conditions, is an essential component of mobility, safety, and the stewardship of public funds for transportation. In urban areas, interchange spacing and the adequacy of design for weaving, merge, and diverge areas can significantly influence available capacity. Traffic microsimulation tools allow detailed analyses of these critical areas in complex locations. In order to obtain valid results, various inputs should be calibrated to local conditions. This project investigated basic calibration factors for the simulation of traffic conditions within an urban freeway merge/diverge environment.

By collecting and analyzing urban freeway traffic data from multiple sources, specific Iowa-based calibration factors for use in VISSIM were developed. In particular, a repeatable methodology for collecting standstill distance and headway/time gap data on urban freeways was applied to locations throughout the state of Iowa. This collection process relies on the manual processing of video for standstill distances and individual vehicle data from radar detectors to measure the headways/time gaps. By comparing the data collected from different locations, it was found that standstill distances vary by location and lead-follow vehicle types. Headways and time gaps were found to be consistent within the same driver population and across different driver populations when the conditions were similar. Both standstill distance and headway/time gap were found to follow fairly dispersed and skewed distributions. Therefore, it is recommended that microsimulation models be modified to include the option for standstill distance and headway/time gap to follow distributions as well as be set separately for different vehicle classes.

In addition, for the driving behavior parameters that cannot be easily collected, a sensitivity analysis was conducted to examine the impact of these parameters on the capacity of the facility. The sensitivity analysis results can be used as a reference to manually adjust parameters to match the simulation results to the observed traffic conditions. This sensitivity analysis showed that the headway and look back distance in VISSIM are the most impactful parameters on the capacity of the weaving section analyzed. A well-calibrated microsimulation model can enable a higher level of fidelity in modeling traffic behavior and serve to improve decision making in balancing need with investment.

INTRODUCTION

Providing adequate roadway capacity, particularly in high-volume conditions, is an essential component of mobility, safety, and the stewardship of public funds for transportation. For example, building excess pavement commits funds that may be better utilized at other locations, and, in contrast, inadequate capacity results in poor operational performance and the need for additional projects, often in a piecemeal, more costly fashion. In urban areas, interchange spacing and the adequacy of design for weaving, merge, and diverge areas can significantly influence available capacity. Traffic microsimulation tools allow detailed analyses of these critical areas in complex locations that often yield results that differ from the generalized approach of the *Highway Capacity Manual (HCM) 2010* (TRB 2010). In particular, the Office of Design of the Iowa Department of Transportation (DOT) is utilizing the microsimulation tool called VISSIM. In order to obtain valid results, various inputs should be calibrated to local conditions, such as fleet mix and driving behavior model parameters.

The objective of this research project was to obtain basic calibration factors for the simulation of traffic conditions within an urban freeway merge/diverge environment. By collecting and analyzing urban freeway traffic data from multiple sources, specific Iowa-based calibration factors for use in VISSIM were developed. These factors can enable a higher level of fidelity in modeling traffic behavior and serve to improve decision making in balancing need with investment.

LITERATURE REVIEW

With the growing popularity of microsimulation models in transportation fields, there has also been an increase in research efforts in calibrating these models. In this section, the body of literature pertaining to microsimulation calibration is reviewed. Additionally, two of the most important parameters in microsimulation are the average distance left between stopped vehicles (standstill distance) and the average preferred time between a leading and following vehicle (headway/time gap). Thus, literature related to the collection and analysis of standstill distance and headway data is also reviewed.

Microsimulation Calibration

There are two predominant methods of calibrating microsimulation models. Both methods involve selecting one or more measures of effectiveness that guide the ways data are collected from the existing traffic conditions. These data serve as the baseline to which the modeler attempts to match microsimulation results. Matching the measures of effectiveness is achieved through adjustments to the model parameters, and this is where the two main calibration methods differ. In the first method, the parameters are adjusted manually in a trial and error process, while in the second method the parameters are changed automatically through the use of metaheuristic algorithms. In both methods, once calibrated, the model is applied to a new time period and compared to the existing traffic during that time to assess the model's predictive abilities, which is referred to as validation.

Calibration Procedure

Two studies that were among the first to propose a methodology for calibrating microsimulation models were published in 2003. A study titled *Practical Procedure for Calibration Microscopic Traffic Simulation Models* (Hourdakis et al. 2003) proposed a general methodology with three calibration stages, with the final stage being optional. The first stage is volume-based calibration, the second stage is speed-based calibration, and the final (optional) stage is objective-based, in which the model can be fine-tuned to project-specific objectives. The methodology was applied to a case study in Minnesota. It was found to be quite effective in improving the model's performance with respect to the actual traffic patterns (Hourdakis et al. 2003). A similar study by Park and Schneeberger (2003) laid out a step-by-step calibration procedure. It involved determining the measures of effectiveness to be used, collecting the data, identifying the calibration parameters, implementing an experimental design (to reduce the number of parameter combinations), running the simulation multiple times for each parameter set, developing a function relating the measures of effectiveness to parameters, determining parameter sets, evaluating the parameter sets, and validating the model with new data. The authors also implemented this methodology with a case study and noted the benefits of calibrated results compared to uncalibrated results (Park and Schneeberger 2003). While these two methodologies may look different on the surface, they are actually structured quite similarly in essence: they match measures of effectiveness in the simulation results to the data in the field by altering simulation parameters.

In 2004, the Federal Highway Administration (FHWA) released the *Traffic Analysis Toolbox Volume III: Guidelines for Applying Traffic Microsimulation Modeling Software*, which covered all aspects of microsimulation modelling and included a chapter on calibration (Dowling et al. 2004). The calibration procedure to a large extent mirrors that of the two studies mentioned above. There are some differences in the methods; for example, rather than calibrating based on demand as in Hourdakis et al. (2003), the authors recommended calibrating based on capacity. However, the main structures of these methods were the same: alter the simulation parameters to match simulation results in the different measures of effectiveness to the observed traffic data. The authors also provide different calibration target values for a variety of measures of effectiveness. The Oregon Department of Transportation later created its *Protocol for VISSIM Simulation*, which applied the FHWA's guidance to specific modeling software and further refined the calibration process (Oregon DOT 2011).

Manual Calibration

While manual calibration is not usually the recommended procedure due to the vast number of combinations of parameters in microsimulation software, there are some advantages to this method, and it is still frequently used, particularly in private consulting. A few of its advantages are that it is low on computational demand, relatively simple to implement, and compatible with qualitative measures of effectiveness such as bottleneck length, time, and location and general driver behavior because of the analyst's ability to view the model animation and compare it with his or her experience. The main disadvantage is that the solution will likely be less optimal than one solved by an automated process.

One study that used manual calibration was *Congested Freeway Microsimulation Model Using VISSIM* (Gomes et al. 2004). In this study, the authors modeled a 15 mile stretch of I-210 West in Pasadena, California, which is a congested and complex segment. There were high-occupancy vehicle (HOV) lanes, metered on-ramps, and three interacting bottlenecks. Due to the unique situation, the authors did not use typical measures of effectiveness such as volume, travel time, or delay. Instead, they attempted to match qualitative aspects of the freeway including the location of bottlenecks, start and end times of queues, and length of queues. Manual calibration was used in large part due to a lack of computing power (Gomes et al. 2004). Additionally, this study took place in 2004, early in the body of literature examined in this study, when automated methods may not have been as well developed or well researched.

Automated Calibration

While some research studies use manual calibration for their microsimulation models, the vast majority use some form of automated calibration. This is likely because the automated process can reach a near-optimal solution. It has also become more and more feasible for researchers to use computationally intensive automated methods as computing power has increased.

One study that used the automated approach was *Microsimulation Calibration Using Speed-Flow Relationships* by Menneni et al. (2008). In this study, the authors selected five VISSIM driver behavior parameters to use for the calibration and ran an evolutionary algorithm to select the optimized parameter set. The evolutionary algorithm starts with several initial parameter sets, selects the ones that perform the best, combines them, and repeats until it converges. The objective function that determined which parameter sets performed the best was based on pattern recognition of speed-flow graphs.

Another study that used an automated method of adjusting parameters is *Methodology for the Calibration of VISSIM in Mixed Traffic* (Manjunatha et al. 2013). Though it focuses on signalized intersections, the study calibrated driver behavior parameters in VISSIM, which are used for freeway sections as well. The authors calibrated all nine main driver behavior parameters using a method similar to the evolutionary algorithm in the study by Menneni et al. (2008). The measure of effectiveness used to evaluate the parameter sets in this case was delay.

Though the vast majority of research in microsimulation calibration selects a few parameters to adjust for the calibration, one recent study adjusted all the parameters of a microsimulation model at once. In *Calibration of Micro-simulation Traffic-Flow Models Considering All Parameters Simultaneously*, Paz et al. (2014) used a simultaneous perturbation stochastic approximation algorithm to calibrate all the parameters in CORSIM at the same time based on several measures of effectiveness.

Rahman et al. (2014) delved deeper into calibration, looking specifically at calibrating the car following models themselves in *A Parameter Estimation and Calibration Method for Car-Following Models*. The authors used a large number of vehicle trajectories to improve the accuracy of car following models by making them more closely replicate driver behavior.

Aghabayk Eagely et al. (2013) calibrated VISSIM considering the heterogeneity in traffic flow, based on a particle swarm optimization (PSO) approach. This study used travel time and headway as the measurements and considered four different sets of vehicle following for this purpose (car follows car, car follows truck, truck follows car, truck follows truck). Vehicle combination type was determined at each time step based on the class of the vehicle and its lead. Depending on combination type, the specific threshold applied to the vehicle and the position of the vehicle was calculated and updated for each upcoming time step until the end of the simulation time. The results showed the significance of considering vehicle composition in microsimulation.

One main issue in calibration of the microsimulation models is the considerable amount of time required for running the simulations and evaluating the results. Menneni et al. (2008), for instance, developed a small-scale test network for producing the number of data points required for the calibration and reduced the simulation time. Aghabayk Eagely et al. (2013) improved the calibration process by integrating multithreading techniques and an evolutionary algorithm. The time required for the calibration process decreased 25 fold after implementing the methodology.

Clearly, there is a common thread in calibrating microscopic simulations: adjust simulation parameters until the simulation results match the data collected on the real roadway as closely as possible. This works well for sites that are calibrated, but it may not translate well to other projects, study sites, or potentially even future traffic patterns at the same site if major characteristics of it change. This incongruity is possible because, as numerous studies have pointed out, there are multiple sets of parameters that may provide similar results with respect to the measures of effectiveness. Because these parameter sets are not based on the actual behavior of the drivers (that is, the parameters were adjusted essentially at random), it is possible that a selected parameter set would not produce similarly accurate results when applied to other sites. This study attempts to take a different approach by collecting data on two of the most important parameters themselves, with the hope that such data could be used as the basis for a more stable and transferable parameter set.

Sensitivity Analysis

Lownes and Machemehl (2006a) presented a sensitivity analysis of the capacity output in VISSIM under different driver behavior parameters. Those parameters were the 10 default parameters included in the Wiedemann (1999) car following model, plus the look-back distance associated with VISSIM connectors. All the parameters except one were held constant during each sensitivity analysis, and the combination of calibrated parameter values was considered as the best set of parameters. For calibration purposes, the study followed FHWA guidelines. Lownes and Machemehl (2006b) conducted another sensitivity analysis for paired parameters in VISSIM. While all the other parameters were kept constant, a combination of two parameters was changed to determine the impact on capacity. The set of paired parameters was selected only if the relationship between them was logically acceptable. Hence, the combinations of CC0 and CC8, CC1 and CC4/CC5, CC2 and CC4/CC5, and CC7 and CC2, CC7 and CC4/CC5, and CC7 and CC8 were examined. (The definition of each driving behavior parameter is provided in Chapter 6 of this report.) The results were consistent with the authors' previous work and indicate that capacity is strongly dependent on CC1 and CC0. In addition, the impact of CC8 and CC4/CC5 on capacity is dependent on the value of CC0 and CC1.

Tian et al. (2002) measured the difference between the capacity and delay results in VISSIM, CORSIM, and SimTraffic at intersections. This study showed that the highest variation occurs when demand reaches capacity.

Habtemichael and Picado-Santos (2012), by conducting a set of sensitivity analyses, showed that most driving behavior parameters have a significant impact on the safety and operation of the simulated traffic.

Table 1 summarizes some of the measures of effectiveness (MOE) sensitivity analyses of microsimulators.

Table 1. Measures of effectiveness related to sensitivity analysis

Authors	MOE for sensitivity analysis	Statistical test
Lownes and Machemehl (2006a) (Single parameter evaluation)	Capacity	t-test
Lownes and Machemehl (2006b) (Multi parameter evaluation)	Capacity	Anova
Bloomberg and Dale (2000)	Delay at intersections, average travel time	Paired t-test
Habtemichael and Santos (2012)	Vehicle conflict i.e. rear-end lane changing (associated with SSAM software) sensitivity analysis for crashes(lane changing) and also driver behaviors	t-test
Tian et al. (2002)	Delay and capacity (obtained from green to cycle length and saturation flow rate)	Regression

Importance of Standstill Distance and Headway

The capacity and queuing behavior of freeway sections are significantly influenced by the standstill distance and headway distribution of the population traversing the section. Because these parameters control the amount of roadway space available in a given lane, they have a substantial impact on the facility's operations. This is true both in reality and in microsimulation models. This section examines literature validating the importance of standstill distance and headway parameters in microsimulation, as well as past data collection efforts.

Standstill distance and headway are important both in theory and in practice when it comes to microsimulation models. The standstill distance controls the maximum density (jam density) of vehicles on a roadway section, because if all the vehicles are at their standstill distance, they will be as close together as possible. Likewise, headway controls the capacity of the section. Once all vehicles are following at their headway, then any additional density will cause vehicles to begin braking and thus cause congestion. In fact, headway is the inverse of traffic flow, so if the average headway is known, the flow rate can be found, and vice versa. Time gap is closely related to headway, except it is defined as the time that elapses between the back bumper of the leading vehicle to the front bumper of the following vehicle, whereas headway is front bumper to front bumper. A number of studies have investigated the importance of standstill distance and headway/time gap to road operations. In addition to their theoretical importance, the importance of these parameters is further demonstrated in practice because most calibration studies include them in their parameter selection, and sensitivity analyses show them to have large impacts on microsimulation results.

Many textbooks and classic research studies have established that vehicle spacing is the inverse of density, and time headway is the inverse of volume (Elefteriadou 2014). This means that the smallest vehicle spacing will lead to the largest jam density, and the smallest headway will lead to the largest capacity of the facility. While standstill distance is not the exact same thing as spacing (because standstill distance ignores vehicle length), it is closely related to spacing and can be used to approximate the jam density of a facility. Likewise, the average headway value can be used to approximate the facility's capacity. Jam density and capacity are two of the most important macroscopic characteristics of a roadway from a traffic operations perspective, so clearly their corresponding microscopic characteristics also have a significant impact on the facility's operations (Elefteriadou 2014).

In discussing the difference between macrosimulation software and microsimulation software, the *HCM 2010* uses the fact that headway and flow are inverses of each other to help compare HCM results to microsimulation results:

> Microscopic simulation tools […] do not have an explicit capacity input. Most microscopic tools provide an input that affects the minimum separation for the generation of vehicles into the system. Therefore, specifying a value of 1.5 s for this input will result in a maximum vehicle entry rate of 2400 (3600/1.5) vehicles per hour per lane (veh/hr/ln).

This reaffirms the theoretical importance of the following headway value and directly establishes the relationship between the selected headway value and its impact on the maximum capacity in microsimulation.

One recent study (Wu and Liu 2013) investigated how the uncertainty of time gap selection affects traffic flow and the fundamental diagram, which displays macroscopic operation characteristics (speed, flow, and density). While this study focused on an arterial with signalized intersections, some of the same concepts apply to the urban freeways discussed in this research. The authors focused on congested flow conditions and found that drivers typically do not display as much variation in their time gap selection at constant speeds as they do when they are accelerating or decelerating. They also found that the variation in time gaps contributes to the scatter of the fundamental diagram and that when traffic is accelerating or decelerating the shape of the diagram changes (Wu and Liu 2013).

In addition to the numerous studies pointing out the theoretical importance of standstill distance and headway to traffic behavior on uninterrupted flow facilities, the majority of microsimulation calibration efforts include these two parameters if they choose to calibrate a subset of all the changeable parameters. Sensitivity analyses have also shown these two variables to be among those having the largest effect on a number of measures of effectiveness in microsimulation models.

In a case study using the microsimulation software VISSIM included with Parker and Schneeberger's (2003) proposed calibration methodology, standstill distance and headway were two of six parameters the authors chose to calibrate (Park and Schneeberger 2003). While they do not explain their rationale behind the selection of calibration parameters, it stands to reason that they selected those parameters that would have the largest impact on the model in their experience, and, according to the company that makes VISSIM, PTV Group, the headway parameter has the largest impact on capacity (PTV Group 2011). In 2004, in the FHWA's *Traffic Analysis Toolbox Volume III: Guidelines for Applying Traffic Microsimulation Modeling Software*, four examples of capacity-related parameters for freeways included "mean following headway" and "minimum separation under stop-and-go conditions" (Dowling et al. 2004). The FHWA also released guidelines for one specific microsimulation program, CORSIM, in which two car following parameters and a factor for the minimum distance between vehicles were included in the "candidate list of key parameters for calibrating freeway capacity," which comprised four parameters total (Holm et al. 2007).

In yet another microsimulation calibration project, standstill distance and headway were two of three VISSIM driver behavior parameters that were adjusted to calibrate a 15 mile long complex stretch of highway in California (Gomes et al. 2004). The fact that the authors were able to successfully calibrate such a large model with so few driver behavior parameters illustrates the important role standstill distance and headway play. Another study in California, which calibrated the model using speed flow charts as measures of effectiveness, included the headway parameter among the five they calibrated, but not the standstill distance (Mennini 2008).

Some studies have undertaken the task of conducting sensitivity analyses on the various microsimulation programs, and the results tend to agree with those found in the case studies that standstill distance and headway are two of the most important parameters for capacity, particularly headway. One study in India found that standstill distance and headway were among five VISSIM parameters that had a significant effect on capacity (Manjunatha et al. 2013). A different sensitivity analysis only indicated headway as one of three VISSIM parameters with the greatest influence capacity (Woody 2006). A third study found that both standstill distance and headway could have a statistically significant impact on capacity when they are far enough away from their calibrated values (Lowens and Machemehl 2006a). Despite the clear importance of standstill distance and headway for microsimulation models, and despite the obvious differences in behavior between cars and trucks, some models do not include an option for different preferred standstill distances and headways for different vehicle classes (PTV Group 2011).

Standstill Distance Collection

Aside from the studies on calibrating microsimulation software, there have been a number of studies investigating the distributions of following and free headways. However, there have not been nearly as many attempts to collect data on standstill distances, particularly on freeways, and observe their distribution. As with any driver behavior parameter, not every driver will behave the same; some will be more conservative, while others aggressive, etc. This variance is often not accounted for in microsimulation models, despite the abundance of research that indicates that standstill distance and headway are not constant parameters.

There have not been many efforts to collect standstill distances at all, let alone on freeways. Most of the efforts have been focused on signalized intersections where standstill distances are important for queue lengths and much easier to collect. Because traffic on each approach is guaranteed to stop every time there is a red light, one can simply create a scale on the pavement or next to the traffic that can be used to estimate the distances between vehicles.

One such study focused on calibrating a variety of VISSIM parameters to local conditions in Delaware (Delaware Valley Regional Planning Commission 2013). This was one of the only studies found that focused on calibrating microsimulation software by collecting data on the parameters themselves. Standstill distance was one of the parameters calibrated for urban and suburban settings at signalized intersections. The authors collected the data by marking 5 foot increments on the approach of a number of different intersections and approximated standstill distance to the nearest foot. They compared urban and suburban settings and compared through/right-turn lanes to left-turn lanes. The average standstill distance they found was about 9 feet, with little variation across the different conditions. This value is greater than the default VISSIM parameter. They also noted a wide variation in the measurements even within the same queue (even after they excluded "drivers who were not paying attention or left an unreasonable large gap"). Finally, they found the standstill distances when a truck was involved to be "comparable" to those of car-car pairs (Delaware Valley Regional Planning Commission 2013).

Another study collected data on the spacing of queued vehicles at a traffic signal and compared these values to the default values in the microsimulation software CORSIM and to commonly used assumptions for queue length calculations used in roadway and signal design (Long 2002). In this report, the author lamented a lack of recent data on the spacing of vehicles queued at signals. The author collected data from four locations in Florida and two locations in Chicago, Illinois, that spanned many different traffic conditions and driver populations. The author found an average spacing of 12 feet with no significant differences between sites, which is significantly higher than the CORSIM default and commonly assumed values in roadway and signal design. The distribution of spacing was not directly discussed (Long 2002).

One study, interestingly found in a physics journal, measured the standstill distances of vehicles at a traffic signal in Prague. The distances between vehicles were measured with laser technology. The study focused on modeling the distribution of the standstill distances as well as the inter-vehicle distances once the light turned green. It was found that the stopped traffic and its progression through the signal acted as a "thermodynamical [sic] gas of dimensionless particles exposed to a thermal bath" (Krbálek 2008).

While a few studies have investigated standstill distances at signalized intersections (e.g. Delaware Valley Regional Planning Commission 2013), these are quite scarce, and no studies were found that did the same for a freeway. It would not make sense to extrapolate the data from signalized intersections to freeways, because the two facilities require entirely different driving behaviors. At most signalized intersections, the lane changing immediately upstream from the signal is minimal, while it is present on freeways. Another difference is that at signalized intersections there is defined period in which all vehicles at a signal must stop and then a period when all vehicles can go, whereas in stop-and-go conditions on a freeway one lane may advance slowly while another is stopped or vehicles ahead may stop or go without warning. These differences in conditions make a separate study specifically on freeway standstill distances necessary.

Highway Capacity

The capacity of a freeway is a very important parameter that is applied in planning, design, and the evaluation of operations. From a transportation perspective, the capacity of a freeway is an essential description of the limit of the vehicle carrying ability of a roadway. In the past decades, several models have been developed to estimate capacity. Headway models, such as Branston's (1976) generalized queueing model and Buckley's (1968) semi-Poisson model, are used frequently. However, several studies have pointed out that headway models substantially overestimate observed road capacity (Hoogendoorn and Botma 1996, Botma et al. 1980). Consequently, headway models may not be the best way to derive a reliable capacity value. Moreover, the fundamental diagram method, which is based on the existence of a relationship between traffic volume, speed, and density, is a classic capacity estimation method (May 1990). However, this method needs sufficient data to be collected over a broad range of intensities to produce reliable results. Another method is to estimate capacity based solely on observed traffic volume. This method can use one of two extreme value approaches based on either observed or expected extremes (Minderhoud et al. 1997). As one of the extreme value approaches, the selected maxima method is used to estimate the freeway capacity of simulation outputs. Moreover, Skabardonis and Christofa (2011) indicated that the *HCM 2010* method provided reliable estimates for balanced major weaving sections. Consequently, the method proposed in the *HCM 2010* is used in this study to estimate the freeway capacity.

Summary

This section reviewed the research literature related to microsimulation calibration and the distribution of standstill distances and headway values. Studies related to calibration procedures were reviewed to provide a background on the current practices and illustrate the importance of standstill distance and headway for these models. Further support for the importance of these parameters was presented through calibration case studies that had selected standstill distance and headway to be among their calibration parameters, as well as several sensitivity analyses that tended to show that standstill distance and headway have significant impacts on calibration, particularly when calibrating by capacity. Finally, studies that collected data on and investigated the shapes of the distributions of standstill distances and headways were reviewed.

Overall, there is clearly a common thread in the approaches to calibrating microscopic simulations: adjust the simulation parameters until the simulation results match the data collected on the real roadway. This method works and has been shown to be effective many times over, but its results may not translate well to other projects, study sites, or potentially, if major changes occur, even the projection of future traffic patterns on the same roadway, because the parameter values are not selected with a physical basis. This study attempts to take a different approach by collecting data on two of the most important parameters themselves in the hope that such data or the data collection process could be used to streamline the calibration process by acting as a solid starting point with a basis in empirical data that would require only relatively small tweaks.

Additionally, it was discovered that efforts to collect standstill distances have been scarce and have focused solely on signalized intersections; it is believed that the present study is the first to collect standstill distances in a freeway setting. Also, despite obviously different driving behaviors between car and trucks, some simulation programs do not provide the option for different vehicle classes to have different standstill distance or time headway preferences. One of the goals of this study is to demonstrate that one or both of the parameters studied is consistent across different driver populations in the same region, which would be a useful stepping stone for future simulation calibration efforts.

DATA COLLECTION

This research required the collection and analysis of timestamped individual vehicle data. By using such data, it is possible to measure the headways and time gaps of individual vehicles and observe their distributions. Additionally, this research required the collection of data pertaining to the distance between stopped vehicles, which was not found by the literature review to have been collected in any past freeway studies. This section will detail the methodology for the data collection process.

Data Collection Methods

There were two main data collection efforts in this research. The first data collection effort was collecting individual headway/time gap data. In order to collect individual headway data, a number of options were investigated, including manual collection, loop detectors, laser-based collection, video/image processing, and radar-based collection. These options were evaluated with a number of goals in mind for the data collection, including the desire to have timestamped individual vehicle data, especially speed, vehicle class, and lane assignments. Manual collection was deemed too resource intensive, loop detectors could not be moved to different locations, and no laser-based or video processing options were found to meet the goals of the data collection as well as the selected option. In the end, it was determined that Wavetronix's SmartSensor HD side-fired radar detectors best accomplished all of these goals.

The second major data collection effort for this research was acquiring standstill distances on freeways. The literature review revealed no studies that directly collected standstill distance data on freeways. One challenge related to collecting these data on urban freeways is the lack of reoccurring stop-and-go traffic, particularly in Iowa. Unlike urban freeways in some other cities, there are no known locations where stop-and-go traffic can be observed on a regular basis. If such conditions were present, a scale could be set up next to the road at these locations, and the traffic could be recorded with video and processed relatively easily. This has been the strategy used by past studies at signalized intersections. Additionally, the methodology developed for this research proved to be fairly time consuming and required special access to the Iowa DOT's network of cameras and dynamic message signs (DMS). It involved using a program to view dynamic message signs' message histories, downloading recorded video from Iowa DOT cameras, and manually measuring the distance between stopped vehicles using Photoshop CC 2014. Without such access to the Iowa DOT network, collecting standstill distances using this process would have been impossible.

Traffic Volume Data

In order to collect aggregated traffic volumes, the existing Iowa DOT Wavetronix sensors were accessed through an online data portal called TransSuite, which is maintained by TransCore, LP. The data could be aggregated at different levels: 20 seconds; 5, 15, 30, and 60 minutes; and 24 hours. The aggregated data obtained from TransSuite included volume, average speed, and average occupancy, by lane. The volume could be broken down by vehicle class as well.

Additionally, an estimate of the data quality was provided separately for the volumes, speeds, and occupancies in the form of a percentage.

Note that there were some issues with the aggregated data from TransSuite. Not all of the sensors on the network have the information necessary for the calibration process described in this report. In particular, the data were not always provided by lane, and the vehicle classifications were not always available. It is unclear why some data were missing. The sensors themselves collect the data for each individual vehicle, and then the data are aggregated by the system. If a sensor is encountered that does not have the vehicle classifications, nearby detectors may be used to obtain the fleet composition for the calibration.

Individual Vehicle Data

Several different data collection methods were explored with respect to collecting headway data. The criteria used to evaluate the usefulness of each of the methods investigated were as follows: (1) the ability to collect individual vehicle data; (2) the inclusion of lane, class, time of arrival, and speed in the data; (3) the accessibility and cost of the data or equipment; and (4) the reliability of the method. The types of data collection evaluated were manual collection, existing freeway loop detectors, laser-based detection, video processing, and radar-based detection.

The manual collection option was deemed to be too resource intensive because several other less resource intensive options were available. The loop detectors provided the necessary data, but they were sparsely located and it was not possible to easily set up at locations where data collection would be desired. No laser-based detector options were found to meet the data requirements, so the majority of the investigative effort went into comparing the video and radar-based methods. With the video-based products, it was often difficult to determine the level of detail that was actually provided, even after inquiring with the company directly. One benefit of the video-based method is that the video can also be used to validate the data by manually counting it for a short period and comparing the count with the automated results; a video-based product is thus an all-in-one product. With the radar-based methods, there were fewer options compared; however, information about the data they provide was more readily accessible, and the products were determined to provide the individual vehicle data necessary. Additionally, a major benefit of Wavetronix radar detectors in particular was that the Iowa DOT has been installing Wavetronix radar detectors throughout its urban areas, particularly on freeways. This allowed for the possibility of connecting to the Iowa DOT's existing sensors for additional accessibility and data.

After examining all of the options, it was determined that the Wavetronix SmartSensor HD detector was the best option. According to the Wavetronix website, "each individual vehicle is detected and its speed, duration, length and lane assignment is precisely measured" (Wavetronix 2006). Wavetronix's accuracy has also been tested by a number of studies, which Wavetronix references on its website to show its product's reliability. In general, these studies showed around a 1 to 3 percent average error in volumes and about a 1 to 5 mph error in speeds (Wavetronix 2006). Figure 1 shows an image of a SmartSensor HD.

wavetronix.com

Figure 1. Wavetronix SmartSensor HD

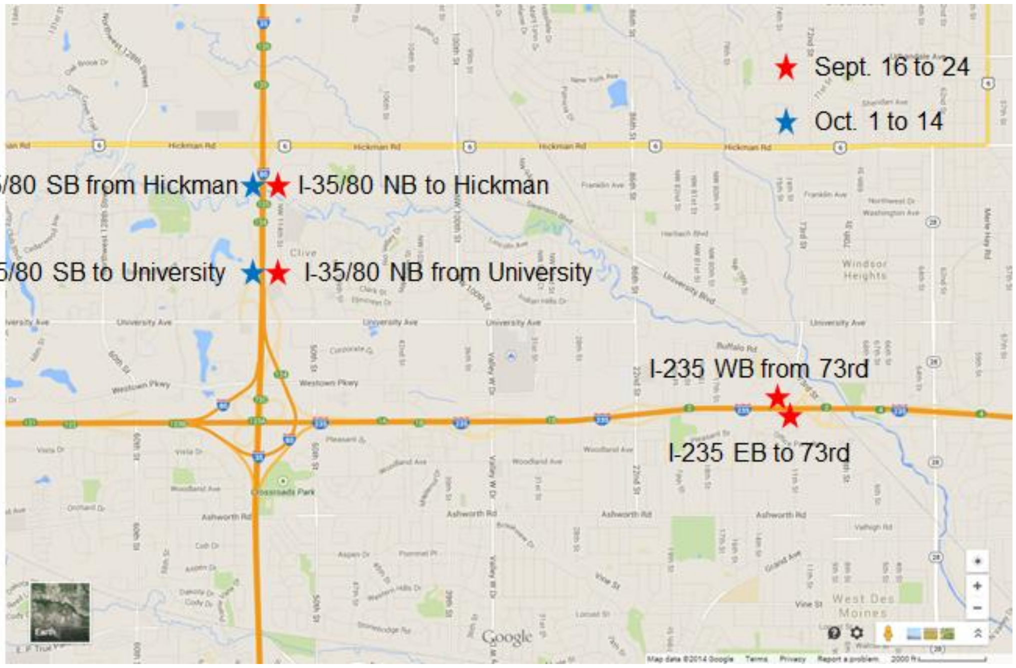
Temporary Sensor

After selecting the device for collecting headway data, it was necessary to select locations from which to collect data. Because the purpose of the research is to compare parameters for different freeway scenarios and driver populations, it was important to collect data from different urban centers in Iowa, as well as rural locations when possible. Three urban areas in Iowa were selected: Des Moines, Council Bluffs, and the Quad Cities (Davenport and Bettendorf in Iowa and Rock Island, Moline, and East Moline in Illinois). Additionally, one rural location a few miles outside of the Quad Cites was selected. While it would have been preferable to have more sites to compare, challenges with the data collection and time constraints prevented this.

In Des Moines, the Iowa DOT had not yet granted permission to use its already installed Wavetronix detectors, so a setup was created that could be installed on road signs temporarily to collect data for a few weeks at a time. This setup consisted of a metal pole on which the Wavetronix detector, a camera, and a solar panel were mounted. The solar panel charged batteries that were then used to power the camera and Wavetronix detector. Additionally, the Wavetronix detector was connected to the camera system, because the camera could be accessed through a cellular network. This also allowed for a live connection to the Wavetronix detector, which, in turn, allowed the data to be recorded. An example of this setup is provided in Figure 2.

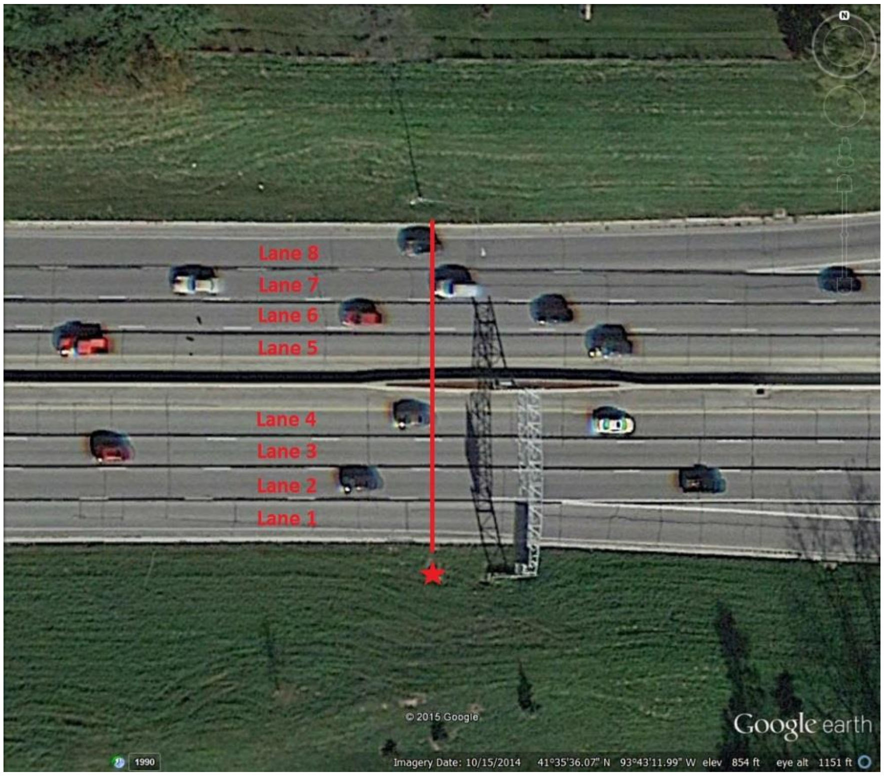
Figure 2. Example of Wavetronix detector and camera setup

This setup was installed at six locations in the Des Moines area over two separate periods. The first data collection period was from September 16 to 24, 2014, and the second period was from October 1 to 14, 2014. During the first data collection period, the temporary sensors were set up on I-235 just west of 73rd Street, directly across the Interstate from one another. Each direction of traffic has three lanes of through traffic and one auxiliary lane for exit/entrance ramps. Though Wavetronix claims that its SmartSensors have the capability of observing up to 22 lanes, in order to test the accuracy of the sensors for the farther lanes, data from two sensors collecting the same data from opposite sides of the freeway from each other were compared. The other two locations during the first collection period were northbound on I-35/80 between an entrance ramp (from University Avenue) and an exit ramp (to Hickman Road). During the second data collection period, the two locations were on southbound I-35/80 in the same section of the roadway between Hickman Road and University Avenue. These locations are shown in Figure 3. The detector locations are shown in aerial images in Figure 4 through Figure 9, which also portray the lane configurations.



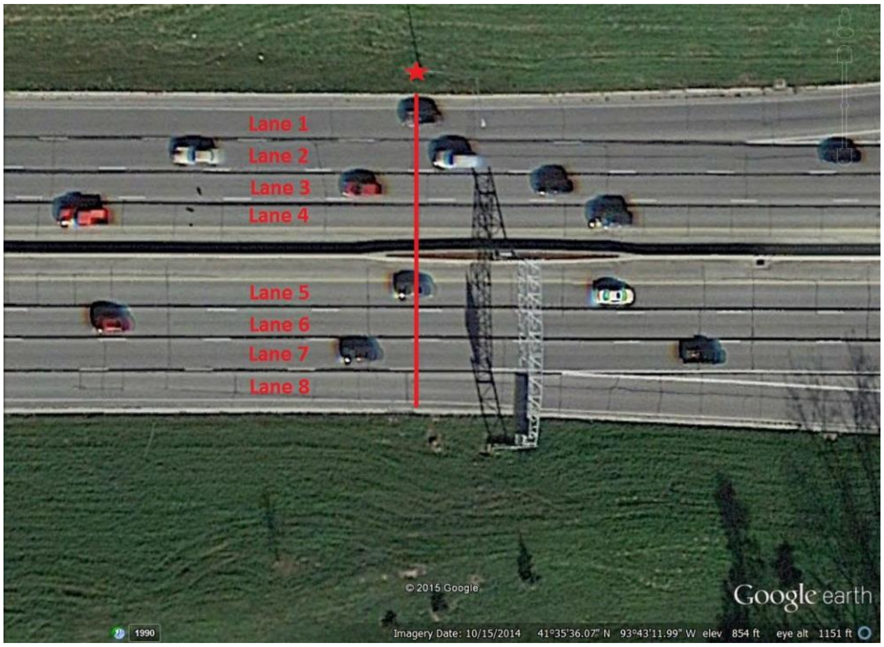
Map data ©2014 Google

Figure 3. Des Moines data collection locations



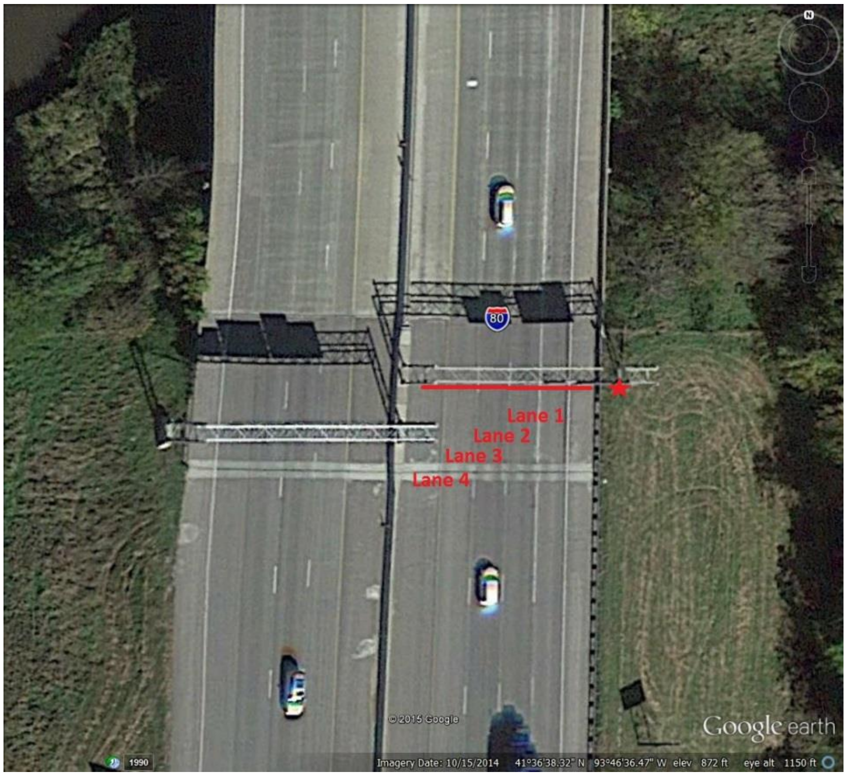
©2015 Google

Figure 4. Wavetronix setup south of I-235 at 73rd St. (Lane 1 is a weaving lane)



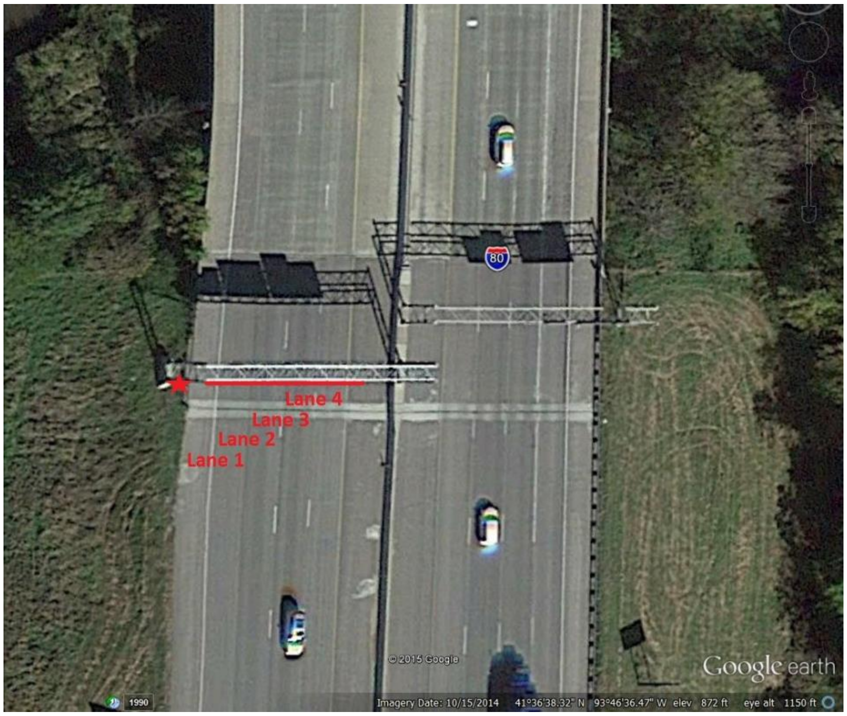
©2015 Google

Figure 5. Wavetronix setup north of I-235 at 73rd St. (Lane 1 is a weaving lane)



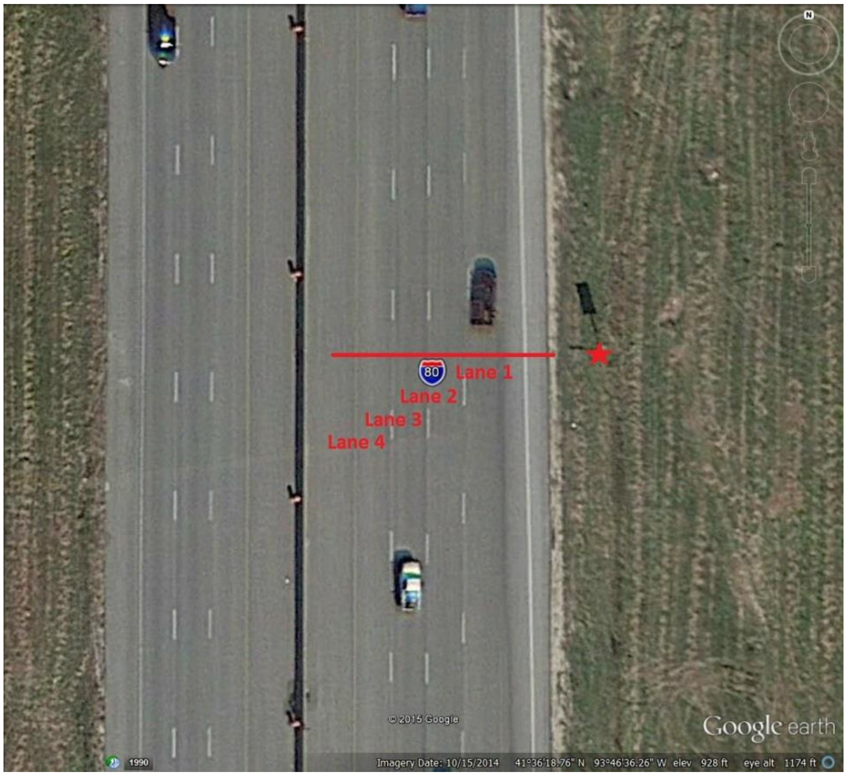
©2015 Google

Figure 6. Wavetronix setup at I-80/35 NB at Hickman Rd. (Lane 1 is an exit lane)



©2015 Google

Figure 7. Wavetronix setup at I-80/35 SB at Hickman Rd. (Lane 1 is a weaving lane)



©2015 Google

Figure 8. Wavetronix setup at I-80/35 NB at University Ave. (Lane 1 is a merging lane)

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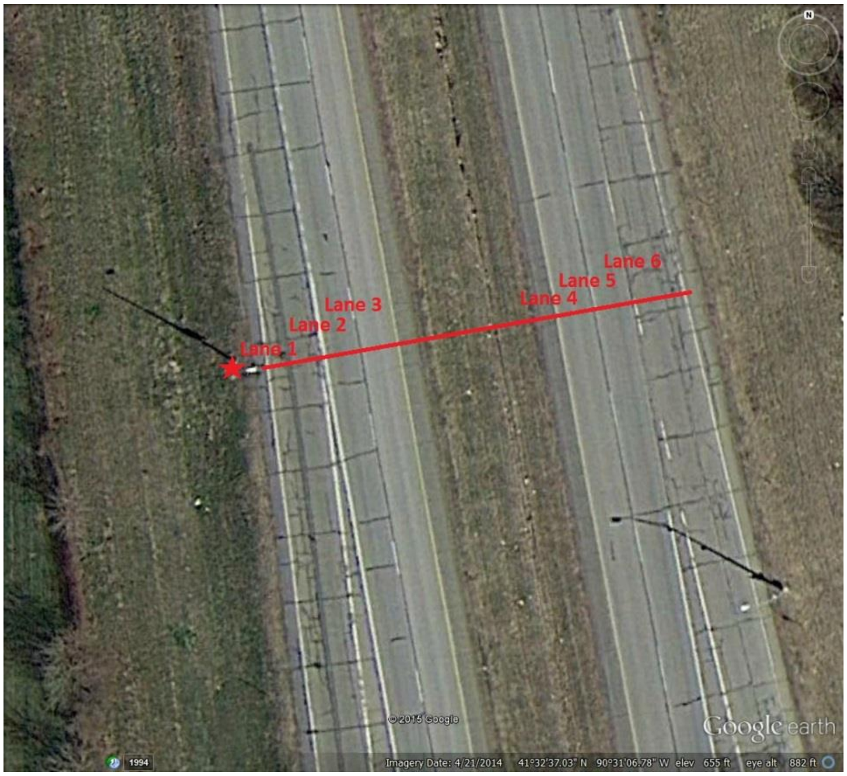
Figure 9. Wavetronix setup at I-80/35 SB at University Ave. (Lane 1 is a weaving lane)

In the communication process with TransCore, LP, it was discovered that none of the sensors in the Quad Cities were compatible with the chosen method of connecting to them. Because of this, the same temporary setup used in Des Moines was used at two urban locations in the Quad Cities and one rural location just outside of the Quad Cities. The urban locations were in the same section of I-74, with one just south of Spruce Hills Drive and the other just north of Middle Road. It should be mentioned that there was a major construction project on the I-74 bridge over the Mississippi River (south of these locations), which may have affected drivers' behavior on that freeway, particularly in the southbound direction. Despite the construction, those sites were selected because I-74 is the only urban freeway in the Quad Cities that has heavy enough traffic to see a significant amount of car following. The rural location was on I-80 a few miles west of the Quad Cities. Figure 10 shows all three locations, and Figure 11 and Figure 12 show aerial images of the two urban locations.

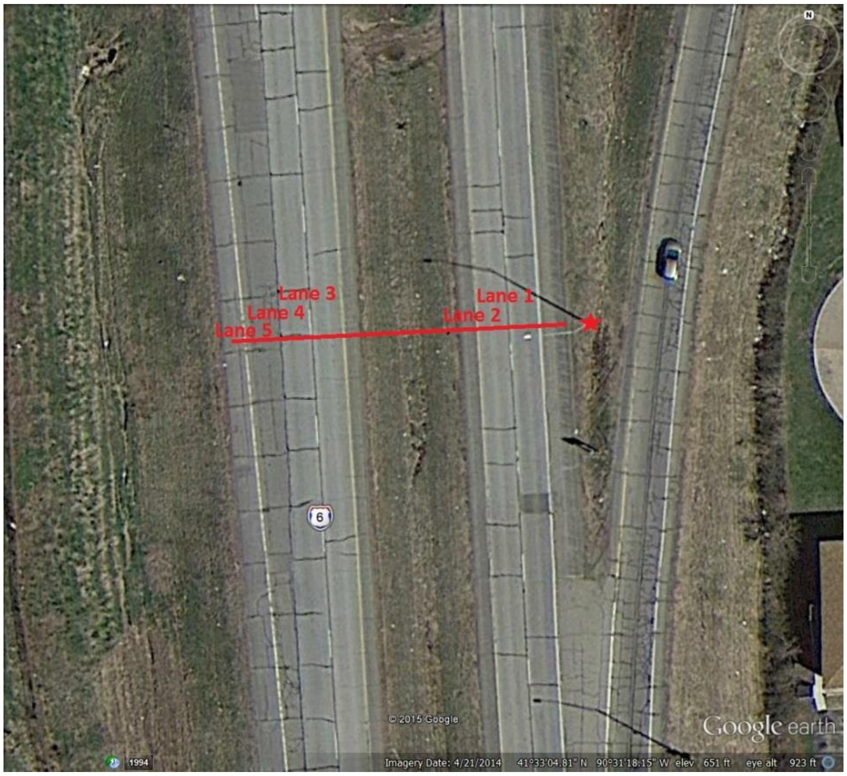
Map data ©2015 Google

Figure 10. Quad Cities detector locations



©2015 Google

Figure 11. Wavetronix setup at I-74 at Middle Rd. (Lane 1 is an exit, Lane 6 is an entrance)



©2015 Google

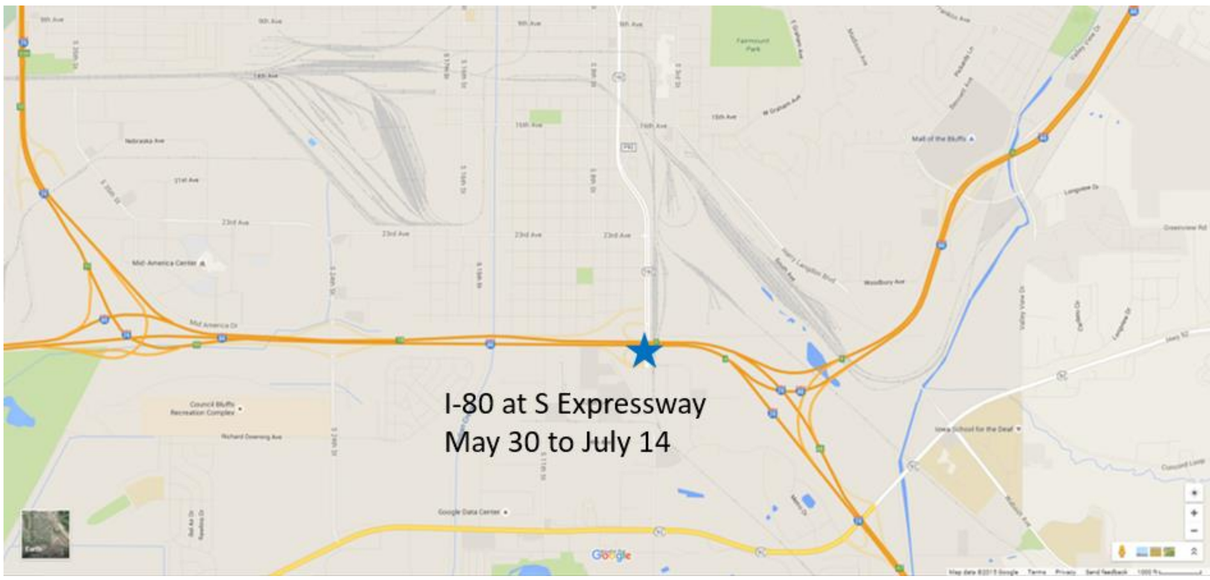
Figure 12. Wavetronix setup at I-74 at Spruce Hills Dr. (Lane 5 is an entrance)

All sensors were collecting data off and on from July 17 to 31, 2015. The periods when the temporary setups were not collecting data were all due to communication errors or depleted batteries.

Click301

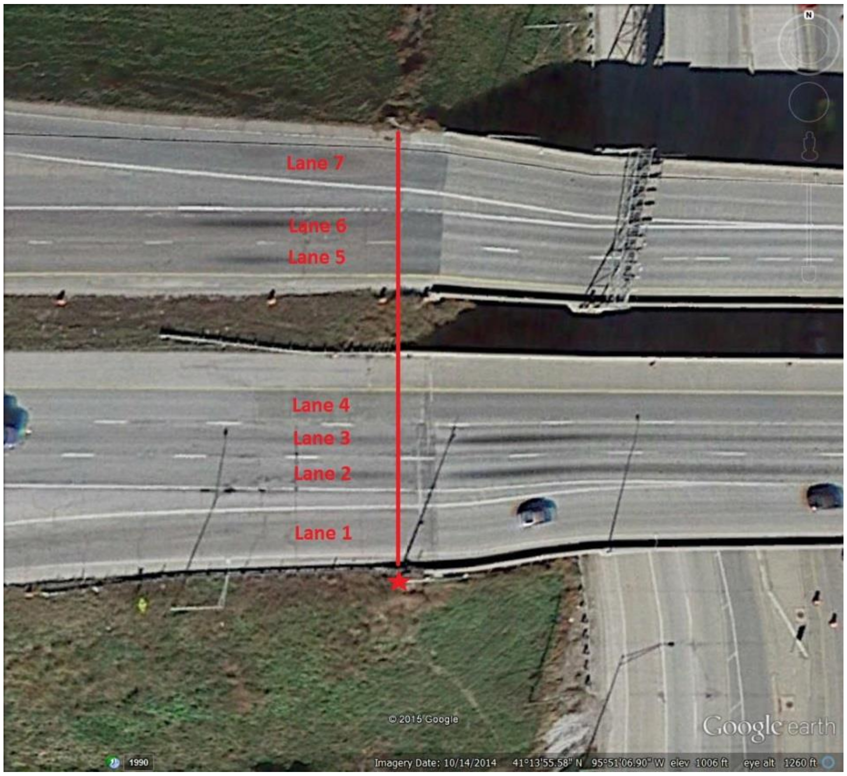
Because the data from the Des Moines locations were collected toward the end of the typical data collection season for Iowa, the rest of the data collection would have to wait for the summer of 2015. By that time, the Iowa DOT had granted permission to use its permanent sensors to obtain individual vehicle data, so at first that was the plan for the rest of the data collection. The permanent sensors were already accessible through an online data portal. However, this portal only provided aggregated data in a minimum increment of 20 seconds. The process of using the online data portal involved installing a small device made by Wavetronix called a Click301 in a cabinet where a Wavetronix detector was already installed. The Click301 receives power from the cabinet, connects to the existing Wavetronix setup, and connects to the Iowa DOT network. This setup does not interfere with the Iowa DOT's data collection; it simply creates a copy of the stream of data. The Click301 does not record the data automatically, however. It has a unique IP address that allows it to be accessed remotely. Once the connection was established, the data recording was started manually, and if the connection was lost the recording was restarted manually. The data were stored in comma separated value (CSV) files on the local computer used to access the Click301.

However, there were a number of issues with using the Iowa DOT permanent sensors. The main issue was that most of the Wavetronix sensors were not compatible with this method of connecting to them. Additionally, the company that manages the sensors for the Iowa DOT, TransCore, did not maintain an up-to-date accounting of the sensors that would be compatible. Therefore, an inquiry had to be placed with TransCore about each individual sensor and its potential connectivity, and a response had to be awaited. Each inquiry about a group of sensors, took at least a week, and after several rounds of communication only one sensor that would work could be located: a sensor on I-80 just east of the South Expressway entrance and exit ramps (see Figure 13 for the location and Figure 14 for the aerial image).



Map data ©2015 Google

Figure 13. Council Bluffs detector location



©2015 Google

Figure 14. Wavetronix setup at I-80 at S. Expressway (Lane 1 is an entrance, Lane 7 is an exit)

Once access to that sensor was gained, it recorded data off and on from May 30 to July 14, 2015. Interruptions to the recording were due to communication failures and malfunctions in the Wavetronix detector itself.

Video

Unfortunately, the process for collecting standstill distance measurements was not nearly as automated as that for collecting the headway data. There was some discussion of trying to find video processing software that could automate some of the measuring process or of crowd sourcing some of the steps of the process. However, ultimately, it was decided that those processes were either not feasible or the return would not be worth the time and resource investment. An undergraduate student at Iowa State University, Mary Warhank, was hired to do the majority of the video collection and measuring once the process was established.

The first step in the process was to identify locations where stop-and-go traffic would be likely to have occurred. In order to do this, a report was created using TransSuite TIS software, which listed every message posted on any DMS in Iowa during the time period specified at the creation of the report. Then, the message of any sign whose message was changed by an event manager was examined. The locations of signs that displayed messages indicating an accident, slow traffic, roadwork, or anything else that may cause congestion were recorded for later use. Almost all of these DMSs are located in urban areas, so, unfortunately, this process made it extremely difficult to collect standstill distances for rural locations. However, the fact that standstill distances were directly collected was a contribution to this research area.

The next step was to use the Iowa DOT network video recorder (NVR) software to access recorded video from Iowa DOT cameras to visually review each of the potential stop-and-go incidents. If the incident in question did cause stop-and-go traffic, video from the time at which traffic was affected was downloaded. After all the relevant videos for that report were downloaded, each video was watched, and each time there were stopped vehicles in the frame a screenshot was taken and the vehicles that were moving were marked (so the moving vehicles would not be measured by mistake).

Finally, the vanishing point filter option in Photoshop CC 2014 was used to find the actual bumper-to-bumper standstill distance measurements. The vanishing point filter allows the user to create a flat plane on which measurements are to be made. If there is an object or a mark of known length in the established plane, that reference point can be used to create a baseline measurement that Photoshop uses to measure anything else in that plane. In the case of this research, the painted lane lines were used as the baseline measurement. The standard for painted lane lines on freeways is that they be 10 feet in length, and they are painted using an automated system. Google Earth was used to measure these lines and confirm that they meet the 10 foot standard. An example of one fully processed image is shown in Figure 15.

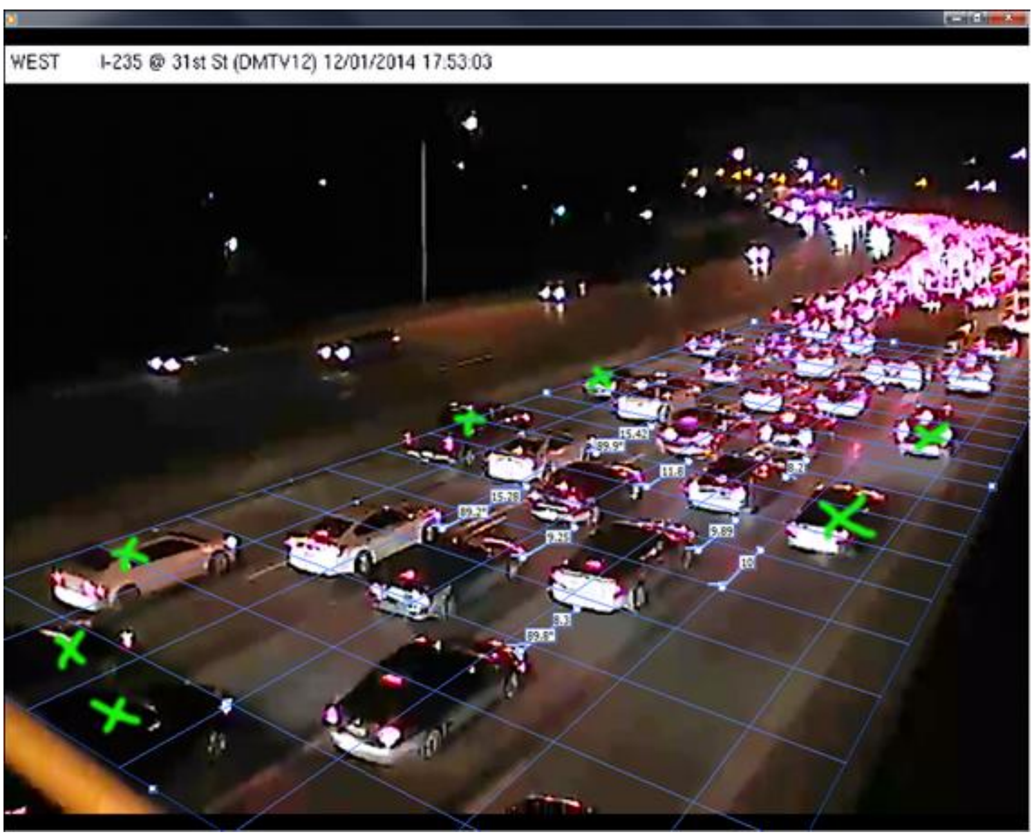


Figure 15. Example of an image processed for standstill distance measurements

In addition to the standstill distance measurement, the following combination for each pair was also recorded. The conditions surrounding the incident were also noted.

Data Validation

Once the data were collected, their accuracy was evaluated. The accuracy of the standstill distances was validated by confirming lane line lengths with Google Earth and testing the accuracy of the Photoshop measuring tool. The headway data were validated through conducting a 30 minute manual count at each of the detector locations and comparing this count to what the temporary Wavetronix detector counted as well as what the closest Iowa DOT–owned sensor counted (the research team had access to aggregated counts but not individual vehicle data for all Iowa DOT sensors). In addition to the aggregated counts, relative vehicle class frequency and lane detection frequency were also compared. Finally, one 10 minute peak count was conducted during which the vehicle arrivals were recorded so headways could be calculated directly, and the average of those manually counted headways was compared to the average of the Wavetronix headways.

Wavetronix SmartSensor HD Accuracy

Before the Wavetronix SmartSensor HD was selected, its accuracy was researched. There were a number of studies on the accuracy of Wavetronix's SmartSensor HD that had been completed. The SRF Consulting Group tested the accuracy of the detector's volume measurement in Minnesota as part of an on-ramp queue length measurement system and found the volume error was within 3 percent of the manual counts (MnDOT 2009). In South Korea, the accuracy of the Wavetronix detector was tested during different times of the day, and the study found a 95 percent volume accuracy and a 98 percent speed accuracy at all times (South Korea ITS Performance Test Institute 2008). In a study conducted at University of Maryland, a volume error of -3.6 to 2.7 percent, an average speed error of -1 to -2 mph, and an average absolute speed error of 2 to 5 mph were found (University of Maryland 2008). In a study conducted by Florida State University in association with the Florida DOT, 1 to 1.5 percent errors in daily volume and 2 to 9 percent (1 to 4 mph) errors in daily average speed were found (Moses, 2008). In Denmark, the speed measurements were tested, and 1 to 5 percent average speed errors were observed (Hansen and Henneberg 2008). Finally, the speed measurements were compared to those of a highly calibrated piezo sensor system in West Virginia, and it was found that 92 percent of speed observations fell within 5 mph of the true speed, and that number increased to 98 percent when a 2 mph bias was removed (Wavetronix 2006). These past studies established that the Wavetronix detector should be accurate, but it was still important for the present research to validate each detector in case there was an error in setting up the system.

For each detector from which data was recorded, whether it was a temporary setup or a connection to an existing Iowa DOT sensor, a 30 minute period of peak traffic was manually counted from video data. In the manual counting process, the lane, vehicle type, and the minute during which the vehicle arrived were recorded for each vehicle in a Microsoft Excel spreadsheet. This allowed for a comparison of the total counts, the minute-by-minute counts, the lane assignments, and the vehicle length measurement (vehicle class assignments).

The validation for the locations in Des Moines is summarized in Table 2 and Table 3.

Table 2. Des Moines Wavetronix detector accuracy summary (first collection period)

		Locations				
		I-235 EB (73rd)	**I-235 WB (73rd)**	**I-80/35 NB (Hickman)**	**I-80/35 NB (Hickman)**	**I-80/35 NB (University)**
	Time Observed	9/19/14 7:15-7:45	9/19/14 17:00-17:30	9/18/14 17:00-17:30	9/18/14 12:00-12:30	9/17/14 17:00-17:30
Error (in %)	**Count**	-50.71	-54.26	2.99	1.06	9.12
	Lane 1 %	-0.41	1.85	-0.23	-0.2	-0.68
	Lane 2 %	0.6	-0.35	0.04	0.33	-1.62
	Lane 3 %	-0.5	-0.44	-0.09	-0.44	-1.97
	Lane 4 %	0.3	-1.06	0.29	0.31	4.27
	Car %	0.7	9.4	1.9	3.3	1.72
	Truck %	-0.4	-9.2	-1.6	-3.2	1.72

Table 3. Des Moines Wavetronix detector accuracy summary (second collection period)

		Locations	
		I-80/35 SB (Hickman)	**I-80/35 SB (University)**
	Time Observed	10/8/14 17:00-17:30	10/6/14 17:00-17:30
Error (in %)	**Count**	1.01	7.27
	Lane 1 %	1.86	-1.59
	Lane 2 %	-3.1	-0.01
	Lane 3 %	1.05	-1.42
	Lane 4 %	0.18	3.02
	Car %	1	-0.42
	Truck %	-0.6	0.42

Overall, the total Wavetronix detector counts were within 1 to 9 percent of the manual video counts, with the exception of the detectors on I-235, which counted half as much traffic as was actually present. These differences could have been due to an issue with how the detectors were set up at those locations; whatever the cause, the I-235 locations were excluded from the analysis. The lane assignments and vehicle class assignments were also generally within 1 to 4 percent of reality, and often less than 1 percent off. Where temporary setups were used, nearby Iowa DOT sensors were also used to further validate the temporary setup counts. Examples of visual comparisons including all three data sources are shown in Figure 16 through Figure 18.

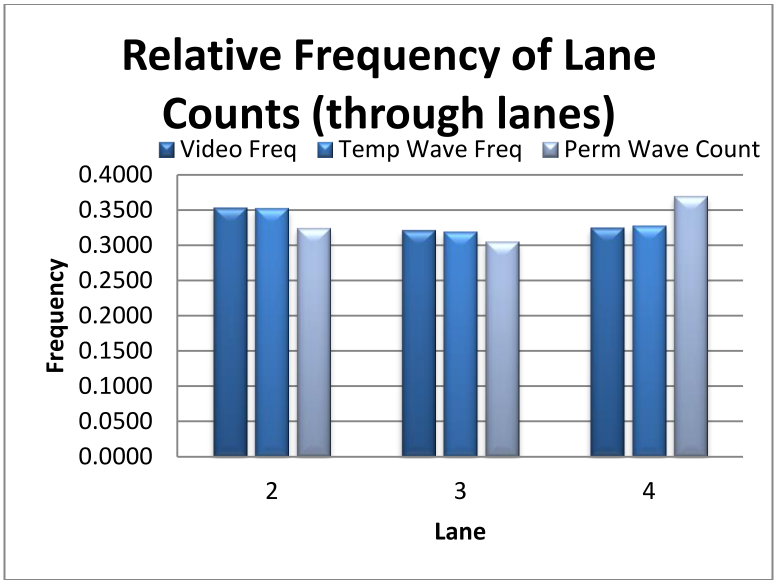


Figure 16. Example of visual comparison of lane proportions (NB I-35/80 at Hickman, September 18, 5:00 to 5:30 p.m.)

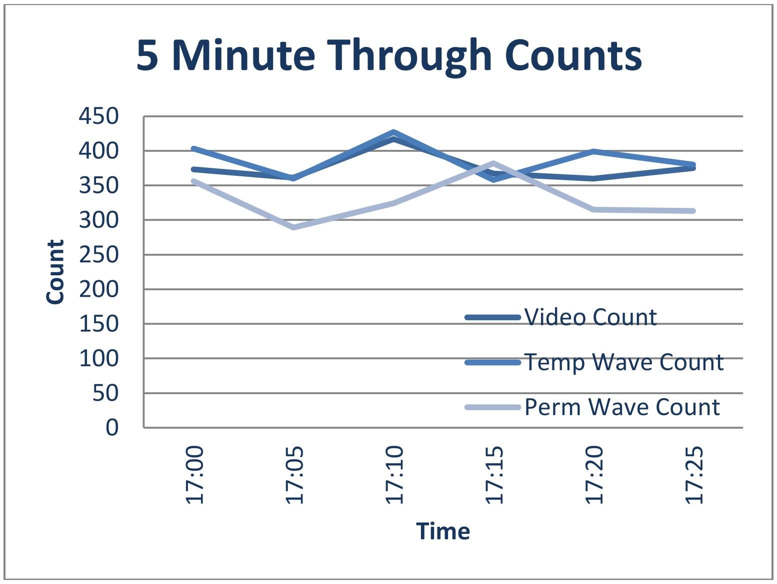


Figure 17. Example of visual comparison of five-minute counts (NB I-35/80 at Hickman, September 18, 5:00 to 5:30 p.m.)

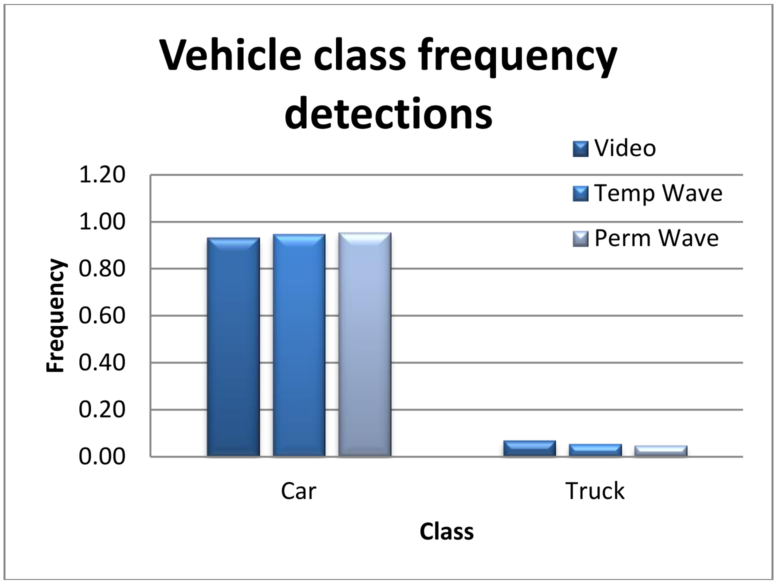


Figure 18. Example of visual comparison of lane proportions (NB I-35/80 at Hickman, September 18, 5:00 to 5:30 p.m.)

Through counts were used when comparing the temporary setups to the Iowa DOT Wavetronix detectors, because the data obtained from the Iowa DOT detectors were only recorded for the through lanes.

In addition to the 30 minute aggregate comparison, one 10 minute count was conducted at the I-80/35 northbound location at Hickman Road, during which the vehicle arrival time was recorded in addition to the vehicle's lane and class. These individual vehicle arrival times were used to calculate individual headway and were compared with the individual vehicle headways of the Wavetronix detector. The average of the headways from the video was 2.7 seconds, and the average of the headways from the Wavetronix detectors was 2.73 seconds. A histogram of both the video's and the Wavetronix detector's individual headways is shown in Figure 19.

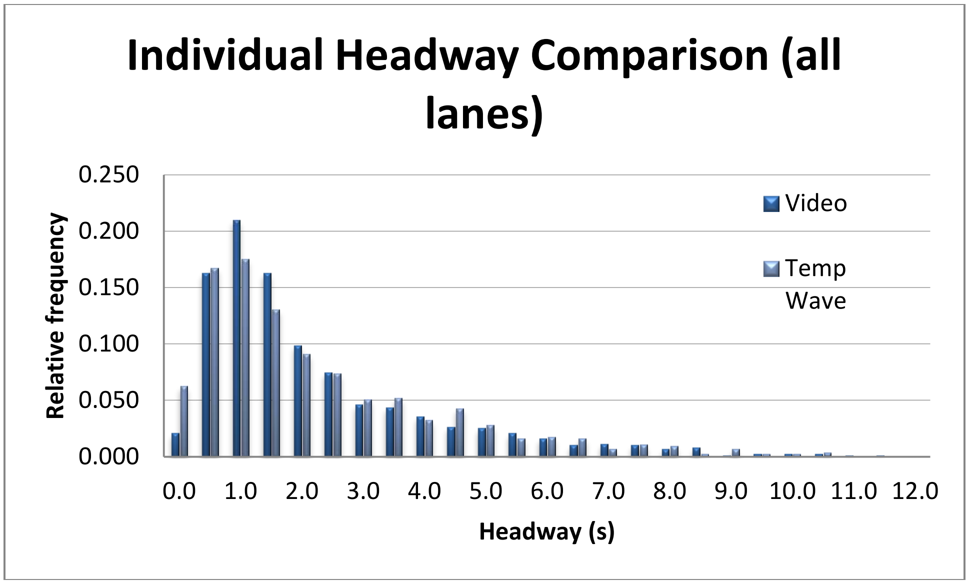


Figure 19. Histogram comparing individual vehicle headways from manual count and Wavetronix detectors

The three temporary Wavetronix setups in the Quad Cities were not functioning for a large portion of their time in the field. In particular, the device at Spruce Hills Drive was only functioning for about seven hours on one day. However, the accuracy of all three detectors was validated using the same process as that used in Des Moines. In general, all detectors were fairly accurate. The Wavetronix detector counts were all lower than the video counts: the rural I-80 location by 0.62 percent, the I-74 location at Middle Road by 2.44 percent, and the I-74 location at Spruce Hill Drive by 3.58 percent. The relative lane percentages were all off by less than 1.5 percent. The car and truck percentages were off by 1 to 3 percent. These results are summarized in Table 4 through Table 6.

Table 4. I-74 at Spruce Hills Drive Wavetronix detector accuracy

		I-74 Spruce Hills
	Time Observed	7/29/2015 9:00 to 9:30
Error (in %)	**Count**	-3.58
	Lane 1 %	0.42
	Lane 2 %	0.41
	Lane 3 %	0.1
	Lane 4 and 5 %	-0.93
	Car %	2.13
	Truck %	-2.13

Table 5. I-74 at Middle Road Wavetronix detector accuracy

		I-74 Middle Road
	Time Observed	7/23/15 17:00 to 17:30
Error (in %)	**Count**	-2.44
	Lane 1 %	-0.14
	Lane 2 %	0.45
	Lane 3 %	0.04
	Lane 4 %	0.05
	Lane 5 %	-0.76
	Lane 6 %	0.35
	Car %	1.25
	Truck %	-1.25

Table 6. Rural I-80 west of Quad Cities Wavetronix detector accuracy

		I-80 West of Quad Cities
	Time Observed	7/23/15 17:00 to 17:30
Error (in %)	**Count**	-0.62
	Lane 1 %	0.24
	Lane 2 %	1.37
	Lane 3 %	-1.13
	Lane 4 %	-0.48
	Car %	-3.21
	Truck %	3.21

In Council Bluffs, access to recording the individual vehicle data at one Iowa DOT–owned Wavetronix detector was obtained, so the data used for the analysis were only compared to those obtained from the manual count from the video (i.e., not to data from an additional separate Wavetronix detector as well). Additionally, the video corresponding to the times the individual vehicle data were being recorded was mistakenly not downloaded. Therefore, the video was downloaded later and compared to the 20 seconds of aggregated data obtained from the online data portal. Unfortunately, for some reason the vehicle class counts were not recorded in the aggregated data, so these data could not be compared. However, experience with the other detectors indicated that the class percentages are close, even if the counts are off, so it was assumed that the class percentages were reliable as well.

For the overall count, the detector counted 6 percent more vehicles than the video. The detector also appeared to be more accurate for the near lanes (eastbound) than the far lanes, with errors of

0.5 percent in the eastbound on-ramp and 5 percent in the eastbound through lanes compared to 1 percent in the westbound exit ramp and 7 percent in the westbound trough lanes. These results are summarized in Table 7. Council Bluffs Wavetronix detector accuracy summary.

Table 7. Council Bluffs Wavetronix detector accuracy summary

		I-80 S. Expressway
	Time Observed	8/24/15 17:00 to 17:30
Error (in %)	**Count**	6.03
	EB On Ramp %	-0.55
	EB Through %	-5.21
	WB Through %	7.10
	WB Exit Ramp %	-1.34

Standstill Distance Measurement Error

Because the standstill distances were measured after the fact, it was not possible to directly validate the accuracy of the standstill distances by comparing the distances measured in Photoshop to the actual distances. However, the accuracy of the key assumption (the length of the lane line) and the accuracy of Photoshop's measuring capabilities were evaluated. The lengths of a number of lane lines in the areas of the stop-and-go traffic incidents were measured in Google Earth. All of the lane lines were within 0.9 feet of 10 feet, more than 93 percent of lines were within 0.6 feet, and the average error was 0.29 feet. There was also no observed trend of one city having longer or shorter lane lines than other cities. This supports the assumption that the lane lines measured 10 feet. In order to evaluate the accuracy of the Photoshop measurements, photos of a grid with known dimensions were taken from different angles and measured using the same method described in the methodology chapter above. The average of the absolute relative error of these measurements was 1.2 percent. Additionally, the primary source of error appeared to be in determining the exact end points to be measured, which is limited by the image quality rather than the software. An example of one of these test images is shown in Figure 20.

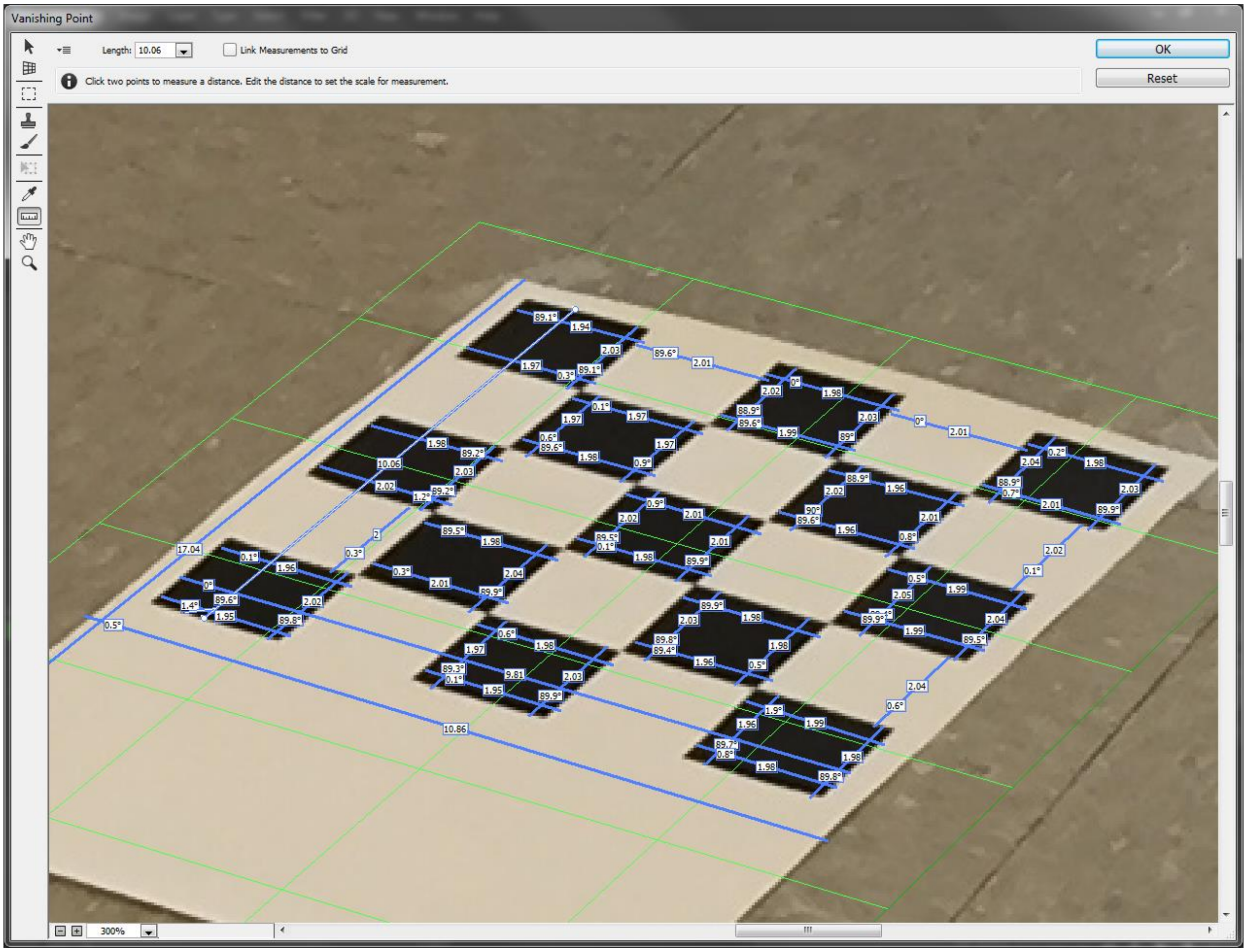


Figure 20. Example of Photoshop accuracy test image using 2 in. x 2 in. squares in a grid pattern

To evaluate the human error, two researchers, one graduate and one undergraduate, processed the same video and found an average standstill distance approximately 0.5 feet off from each other. The remainder of the videos were all processed by the undergraduate student, so any potential bias should not have affected the comparisons within this dataset. With an accurate base measurement assumption and an accurate measuring method, the accuracy of the measurements overall can be reasonably be assumed.

DATA ANALYSIS

Vehicle Fleet Composition

While the Wavetronix detector assigns each vehicle to one of seven vehicle classes based on its length, this research was focused only on comparing passenger cars with trucks. It was therefore necessary to define a threshold length to distinguish between cars and trucks. With any chosen length, there is always some overlap in the types of vehicles and the capabilities included in each group. In particular, small trucks can sometimes behave as cars and other times as larger trucks. So, with that in mind, 35 feet was the length cutoff selected because the Iowa DOT uses four classes for its permanent sensors (0–10 feet, 10–19 feet, 19–35 feet, and 35–256 feet). Additionally, the distribution of vehicle lengths was observed through histograms. These revealed two distinct peaks, one for cars (which small trucks spill into) and a much smaller one for large trucks (see an example in Figure 21).

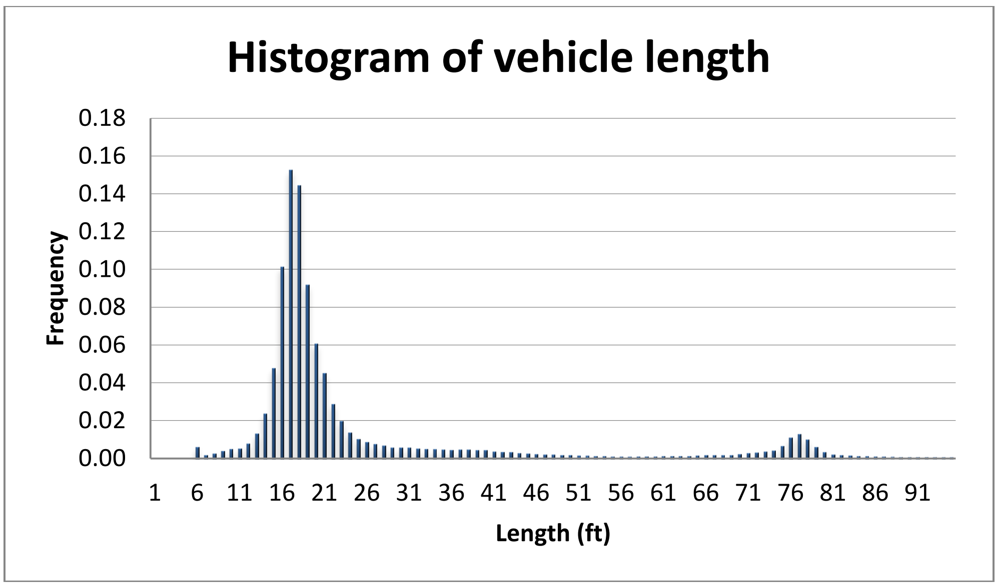


Figure 21. Example of a histogram of vehicle length (taken from I-80/35 NB at Hickman)

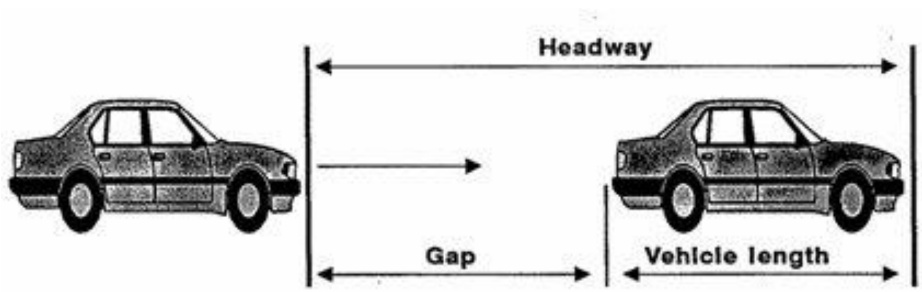
By observing the distribution, it was clear that 19 feet should not be selected as the cutoff, because this would have split the cars into separate groups. The 35 foot mark also appeared to divide the long tail of the cars group (which represents small trucks) in half, which would cause the small trucks to be split fairly evenly between the car and truck groups.

Headway and Time Gap

Procedure

The analysis of the headway data was initially conducted using Microsoft Excel, then streamlined using Microsoft Access and R. It was discovered that working with individual vehicle data in Excel is unwieldy or even impossible due to the size of the dataset (hundreds of thousands of rows or more). Therefore, instead of using Excel, the raw data were imported into Microsoft Access so that each detector was in a table of its own. Then, using the built-in Windows program “Data Sources (ODBC),” a database was created using the Access file with all the detector data in it. Finally, the “RODBC” package in R was used to establish a connection to the ODBC database and import data from each detector into R. By doing this, the headway analysis was sped up considerably and was much more reproducible. This is because R is a statistical programming language, so the code can be written for one detector and tweaked slightly for other detectors.

The headway analysis itself consisted in part of calculating the headway and time gap for each vehicle pair, defining cars versus trucks, defining a maximum headway threshold for car following, filtering the data to congested conditions and following vehicles only, fitting statistical distributions to the data, finding summary statistics for the headway for each following combination for each site, and comparing all the results. It should be noted that headway and time gap are two different variables. Headway is the time between successive vehicles measured from the same point on each vehicle (the front bumper in the case of the Wavetronix data). Time gap is the time from the back bumper of the leading vehicle to the front bumper of the following vehicle, as shown in Figure 22. Thus, a car can be following another car with the same headway as a car following a truck, but due to the length of the truck, the car following the truck will have the shorter time gap.



FHWA Office of Operations. 2013. *Traffic Control Systems Handbook: Chapter 3. Control Concepts - Urban and Suburban Streets*. ops.fhwa.dot.gov/publications/fhwahop06006/chapter_3p1.htm

Figure 22. Difference between headway and time gap

In the raw individual vehicle data from Wavetronix, each vehicle was represented by a row in a CSV file. Each vehicle is assigned a lane, length (in feet), speed (in mph), vehicle class, range (distance from detector in feet), and time of detection. An example of this data is shown in Figure 23.

2	LANE	LENGTH	(MPH)	CLASS	RANGE	YYYY-MM-DD HH:MM:SS.sss
3	LANE_01	19	71.7	2	32	9/16/2014 18:49:10.41
4	LANE_03	55	68.4	4	56	9/16/2014 18:49:11.10

Figure 23. Sample Wavetronix data

One important note about the raw data is that not all vehicles are assigned a speed by the detector due to an internal quality control mechanism. Because the speed of the leading vehicle is required to calculate the time gap, only vehicle pairs in which the leading vehicle had an assigned speed were used in the analysis. The analysis of these data was broken up into four main parts: headway and time gap calculation, vehicle class threshold determination, vehicle following determination/filtering, and headway and time gap distribution analysis. The overall process from data collection to analysis is shown in the flowchart in Figure 24.

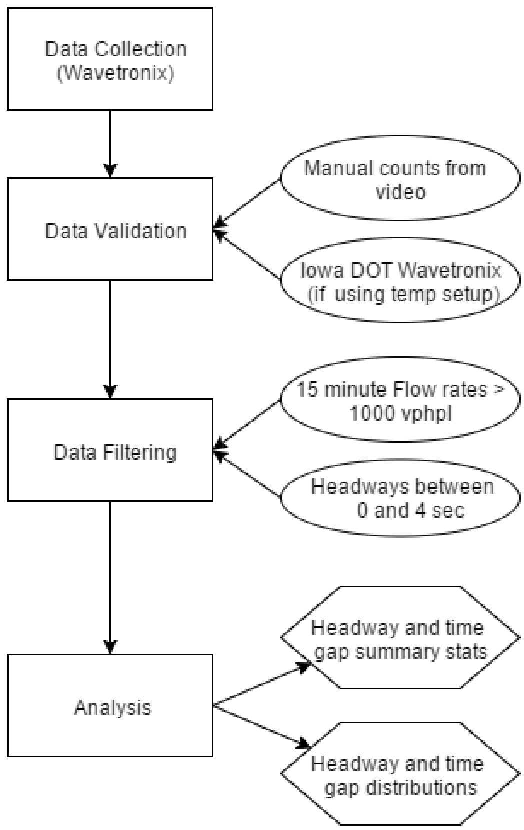


Figure 24. Flowchart for headway analysis

Headway and Time Gap Calculation

To calculate the headway for each vehicle, the differences between successive vehicle arrival times in the same lanes were found. Once the data were imported into an Access database and that database was accessed through R, it became much faster to isolate the lanes and calculate the headways. Isolating lanes can be accomplished many ways in R, but this research used the filter() function in the “dplyr” package to assign each lane’s data to a separate object in R. Then, a “for” loop was used to calculate the headway, where the headway of the *i*-th vehicle was determined by subtracting the (*i*-1)-th time of arrival from the *i*-th arrival.

$$Headway_{ij} = t_{ij} - t_{(i-1)j} \quad \textbf{(1)}$$

Where:

$Headway_{ij}$ = the headway of the ith vehicle in the jth lane (in seconds)
t_{ij} = time of arrival of the ith vehicle in the jth lane
$t_{(i-1)j}$ = time of arrival of the (i-1)th vehicle in the jth lane

It should be noted that the time of arrival variable is stored as the number of days from the start of the year 1900, so January 1, 1900 is stored simply as "1" and times are stored as decimals because they are fractions of days. So, to get the headway value in seconds, the difference is multiplied by 86400 (the number of seconds in a day).

Because the headways are measured from the front bumper of the leader to the front bumper of the follower, and the time gap is measured from the back bumper of the leader to the front bumper of the follower, the only difference between headway and time gap is that the time gap is shorter by the length of time it takes for the leading vehicle to clear the detector. That time can be calculated simply by dividing the length (in feet) of the leading vehicle by its speed (in feet per second). Then, the time gap of the following vehicle is its headway minus the time for the leading vehicle to clear the detector.

$$TimeGap_{ij} = Headway_{ij} - \frac{Length_{(i-1)j}}{Speed_{(i-1)j}} \quad \textbf{(2)}$$

Where:

$TimeGap_{ij}$ = the time gap of the ith vehicle in the jth lane (in seconds)
$Length_{(i-1)j}$ = the length of the (i-1)th vehicle in the jth lane (in feet)
$Speed_{(i-1)j}$ = the speed of the (i-1)th vehicle in the jth lane (in feet per second)

It is important to remember that because the time gap calculation introduces two more measurements than the headway calculation, there is a reduced level of confidence in each individual time gap measurement. However, as long the measurements are not biased in one direction or the other from the true measurement and there is a sufficiently large sample size, the sample average time gap should be close to the actual average gap time. Again, because all the vehicles did not have assigned speeds, only pairs where the leading vehicle had a speed could be used to calculate time gaps.

Vehicle Following Threshold and Filtering

Another step in the analysis was determining the maximum headway at which the second vehicle could still be considered following the first vehicle. There have been a few efforts to establish this threshold in past studies, but these studies were mostly focused on rural two-lane roads. For example, the *HCM 2010* sets the threshold for rural two-lane roads to 3 seconds, but it does not offer any explanation for how this value was determined (TRB 2010). However, a study from Sweden outlined a process for determining which vehicles can be considered "free" by finding the correlation between leading and following vehicle speeds at different headway values (Vogel 2002). This methodology was applied with the opposite mentality in mind: which vehicles can be considered following? Thus, for the data from each of the detectors, the headways were rounded to the nearest second, and the Pearson correlation coefficient was calculated between the leading vehicle's speed and the following vehicle's speed (as long as both vehicles were assigned speeds) for each group of rounded headway data, and the results were plotted.

$$r_{xy} = \frac{\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i-\bar{x})^2 \sum_{i=1}^{n}(y_i-\bar{y})^2}} \tag{3}$$

Where:

r_{xy} = Pearson correlation coefficient
xi = the ith value of variable x
yi = the ith value of variable y
$\bar{x}$ = the mean value of variable x
$\bar{y}$ = the mean value of variable y
n = number of observations

An example of this for the detector on I-80 at South Expressway in Council Bluffs is shown in Figure 25.

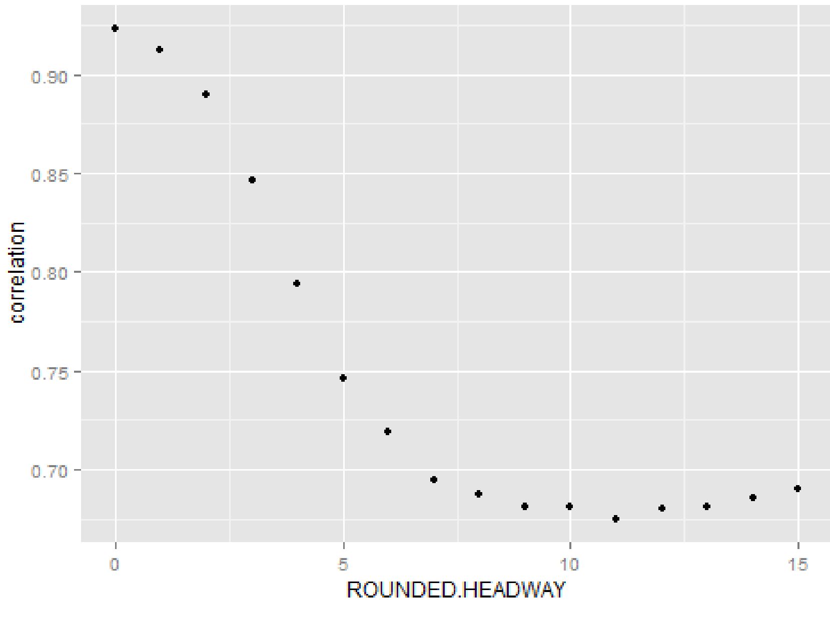


Figure 25. Correlation of leading and following vehicle speeds versus headway (from I-80 at S. Expressway)

It can be seen from the graph that leading and following vehicle speeds are highly correlated at small values of headway, and that as the headway increases, the correlation decreases. This makes sense intuitively, but the advantage of this method is that it is possible to quantify how much of an influence the leading vehicle has at each headway value. The correlation drops from a peak of approximately 0.95 at a rounded headway of 0 seconds (i.e., headways of 0 to 0.5 seconds) to a baseline of approximately 0.65 to 0.7. It can also be seen in Figure 25 that the point of inflection of the graph (where it switches from concave down to concave up) is at a headway of approximately 4 seconds. This can be interpreted as the point where the influence of the lead vehicle begins to dissipate and the vehicles are more likely to select their own speeds. The correlation at 4 seconds is about 0.8, which is still quite high. Similar trends were observed for most of the other detectors. From Vogel's (2002) perspective (where truly free vehicles are always observed), the speed correlation levels off at around 6 or 7 seconds, which is what that study found as well. However, the focus of the present research is following vehicles, so the 4 second threshold was selected.

The selection of this 4 second value is strengthened by Wasielewski's (1979) similar finding that the following vehicle distribution ranges from 0 to 4 seconds (Wasielewksi 1979). In that study, the author measured 42,000 headways in one lane of an urban freeway over a variety of flow ranges. The study established that free flowing headways are exponentially distributed. The author thus looked for the smallest headway such that if an exponential distribution were fitted to the values higher than this headway, there would be no significant deviation from the exponential distribution above that headway, and there would be significant deviation within 0.5 seconds less than that headway. The results would indicate that traffic above this value is in free flow, while traffic below this value has enough car following to create a statistically significant difference from the free flow distribution.

In addition to filtering out headways larger than the 4 second cutoff, the individual vehicle data were also filtered to when the roadway was not in free flow. The purpose of this filtering was to limit the scope of the analysis to situations in which low headways are more likely representative of actual car following situations. If traffic on the road is minimal, then some low headway values are possibly the result of a following vehicle approaching a slower leading vehicle in the same lane and then passing the slower vehicle. This headway value would not necessarily be representative of the headway the driver may select in a following situation. The *HCM 2010* suggests 1,000 passenger cars per hour per lane (pc/hr/ln) as the maximum value for which an uninterrupted flow facility can be said to be operating in free flow (TRB 2010).

Fifteen-minute flow rates were therefore calculated for each direction of travel using only the through lanes, giving an average flow rate in veh/hr/ln for each direction. Vehicles that arrived during a 15 minute period of less than 1,000 veh/hr/ln were excluded from the analysis. The flow rates were not converted to pc/hr/ln partly for simplicity and partly because 1,000 veh/hr/ln equates to more than 1,000 pc/hr/ln due to the presence of trucks, which slightly increases the level of congestion at the threshold flow rate (which is the point of eliminating free flow periods). The average headway was also observed to level out starting at 1,000 veh/hr/ln and higher traffic volumes. While a higher flow threshold would be beneficial for analysis, the traffic volumes throughout Iowa are not typically high enough that there would be enough data to analyze, particularly in the Quad Cities.

Additionally, in the filtering process, entrance and exit ramp lanes were excluded due to the different behavior of drivers in comparison with drivers in through traffic. Finally, consideration was given to including a filter for a speed difference of less than a certain threshold, extending the idea that following vehicles have similar speeds to the leading vehicles. However, the speed error of the Wavetronix detector would not make such a filter meaningful.

Headway and Time Gap Results

Introduction to Headway and Time Gap Results

Due to the data validation process as well as the filtering process, the data from several detectors were excluded from the analysis. Regarding data validation, both Wavetronix detectors placed on I-235 in Des Moines counted around half as many vehicles as were counted manually, so the data obtained from these detectors were not used. Additionally, it was determined that in order to filter the data to mostly following vehicles, only through lane headways of four seconds or less and headways observed during a period of time when the 15 minute through vehicle flow rate exceeded 1,000 veh/hr/ln would be used. This filtering completely eliminated the detector on I-74 at the Spruce Hills Drive exit in the Quad Cities because it was not operating for long and the flow rate never exceeded 1,000 veh/hr/ln. Limited high-traffic intervals also significantly reduced the sample size of the other two locations in the Quad Cities area (I-74 at the Middle Road exit and the rural location on I-80 west of the Quad Cities). Finally, for consistency's sake, the same data set was used for analyzing the headways and time gaps for each detector; this required that both the leading and following vehicle had a speed measured by the detector. For most detectors, at least 60 to 70 percent of vehicles had speeds, but the detector on I-80/35 southbound at the Hickman Road entrance only had speeds for 17 percent of vehicles (and only 2 percent of through vehicles). The percentages of vehicles with speeds and the detectors that were excluded are summarized in Table 8.

Table 8. Summary of detectors used in the analysis

Detector	City	% vehicles with speed	Data used in analysis?	Reason for Exclusion
I-80 S Expressway	Council Bluffs	81.7	Yes	N/A
I-80/35 SB @ Hickman	Des Moines	16.9	No	% vehicles with speed (sample size)
I-80/35 SB @ University	Des Moines	89.5	Yes	N/A
I-80/35 NB @ Hickman	Des Moines	73.2	Yes	N/A
I-80/35 NB @ University	Des Moines	95.8	Yes	N/A
I-235 EB @ 73rd	Des Moines	N/A	No	Validation counts
I-235 WB @ 73rd	Des Moines	N/A	No	Validation counts
I-74 @ Middle Road	Quad Cities	81.0	Yes	N/A
I-74 @ Spruce Hills	Quad Cities	90.4	No	No flow rates > 1,000 veh/hr/ln
I-80 West of Quad Cities	Quad Cities	62.8	Yes	N/A

While it would have been ideal to have multiple detectors in each city to check for consistent headway values within the same driving population, the locations in Des Moines and the two directions in Council Bluffs were used to check this assumption before comparing the different cities.

Additionally, lower flow rate data excluded from the actual calculation of the summary statistics for headways and time gaps were still used to compare how average headways varied as the flow rate changed for the different detectors, as outlined in the methodology chapter above. This comparison showed that the average headways and time gaps measured by different detectors in different parts of the state were consistently similar for similar flow rates. Figure 26 and Figure 27 show this consistency: there is not one detector or one city for which flow rate was consistently higher or lower than that of any other (other than the rural location, which was expected to be different), and all were tightly grouped for almost all flow rates.

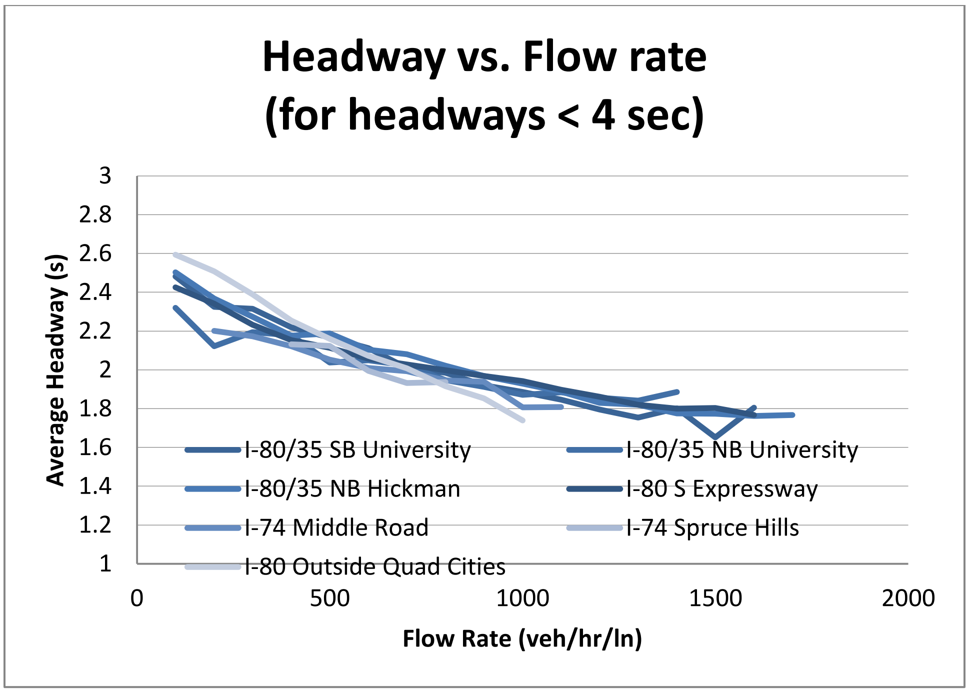


Figure 26. Average headway versus flow rates for headways less than 4 seconds

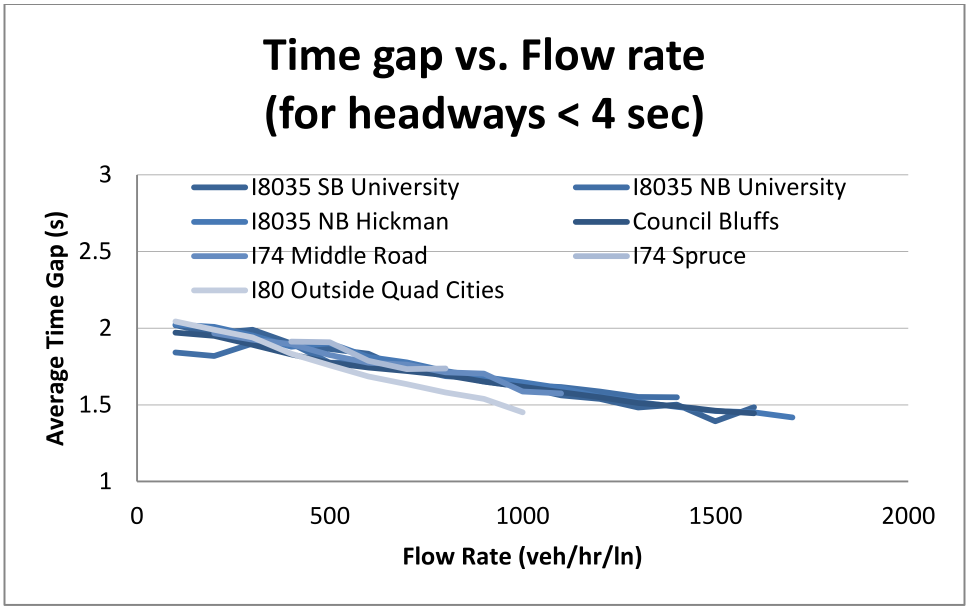


Figure 27. Average time gap versus flow rates for headways less than 4 seconds

These figures also demonstrate that headway (and, to a lesser extent, time gap) starts to level off at flow rates greater than 1,000 veh/hr/ln. This leveling off is even more pronounced at higher flow rates (approximately 1,300 veh/hr/ln), but this higher threshold would exclude even more sites and data, so 1,000 veh/hr/ln was used as the threshold for “congested” traffic. Similar graphs were produced for each vehicle pair type (e.g., car-truck), and the graphs show similar trends, but the graphs were shifted up or down based on the vehicle pair type.

Des Moines Headway/Time Gap Results

Three detectors from Des Moines produced data that could be used to analyze headways and time gaps: I-80/35 southbound at the University Avenue exit, I-80/35 northbound at the University Avenue entrance, and I-80/35 northbound at the Hickman Road exit (see Figure 3). These locations experienced the same driver population (mostly commuters to and from the center of Des Moines). Though the roadway segments were similar geometrically (all had three through lanes and one weaving/merge lane), the detector locations were different: two were located at exit ramps and one was at an entrance ramp. Additionally, in the southbound direction there was a weaving lane, whereas in the northbound direction the University Avenue entrance merged into four lanes and the fourth lane became an exit-only lane for the Hickman Road exit.

The means, medians, and standard deviations for each pair type for each detector in Des Moines are reported in Table 9 through Table 11.

Table 9. Headway and time gap summary statistics for I-80/35 SB at University

Pair Type (Lead-Follow)	Count	No. of Congested Intervals	Mean Headway (s)	Median Headway (s)	Std. Dev. Headway (s)	Mean Time Gap (s)	Median Time Gap (s)	Std. Dev. Time Gap (s)
CC	23472	47	1.72	1.58	0.92	1.51	1.31	0.92
CT	2832	47	2.30	2.14	0.85	2.09	1.95	0.85
TC	3278	47	1.82	1.73	0.88	1.09	0.88	0.88
TT	636	47	2.36	2.18	0.84	1.59	1.50	0.85

Table 10. Headway and time gap summary statistics for I-80/35 NB at University

Pair Type (Lead-Follow)	Count	No. of Congested Intervals	Mean Headway (s)	Median Headway (s)	Std. Dev. Headway (s)	Mean Time Gap (s)	Median Time Gap (s)	Std. Dev. Time Gap (s)
CC	13069	26	1.79	1.74	0.94	1.58	1.48	0.94
CT	1678	26	2.34	2.18	0.87	2.13	1.97	0.87
TC	1920	26	1.86	1.78	0.89	1.12	0.91	0.88
TT	383	26	2.25	2.05	0.85	1.49	1.33	0.85

Table 11. Headway and time gap summary statistics for I-80/35 NB at Hickman

Pair Type (Lead-Follow)	Count	No. of Congested Intervals	Mean Headway (s)	Median Headway (s)	Std. Dev. Headway (s)	Mean Time Gap (s)	Median Time Gap (s)	Std. Dev. Time Gap (s)
CC	46886	123	1.75	1.67	0.92	1.53	1.43	0.92
CT	6797	123	2.24	2.08	0.91	2.02	1.87	0.91
TC	8814	123	1.85	1.77	0.88	1.16	0.99	0.89
TT	1951	123	2.25	2.09	0.87	1.52	1.40	0.87

When comparing the means, t-tests were not used because the large sample sizes led to a situation where differences in headways that are within the error of the detector were rejected by the t-test as being significantly different. For example, the mean difference of headways from car following car (CC) between I-80/35 southbound at University Avenue (in Table 9) and I-80/35 northbound at University Avenue (in Table 11) is only 3 hundredths of a second, but the sample size leads the t-test to conclude that they are different, with a p-value of 2.586×10^{-5}. This is not always the case; because observations involving trucks are less frequent, this phenomena of "false rejections" is less common outside the CC observations. For the sake of consistency, however, all comparisons were made assuming that a practical difference of headway or time gap is one tenth (0.1) of a second. The selection of the 0.1 second value was based on the measurement error of the Wavetronix detector. While it was not possible to validate the accuracy of the time stamp for individual vehicles, the average of individual headways was found to differ by 0.03 seconds from a manual measurement for a 10 minute peak period at the I-80/35 northbound location at Hickman Road. Because this was a relatively short period, the true error of the detector could be higher or lower than this; to be conservative, this error was assumed to be 0.05 seconds. Therefore, if two detectors were off by that error in opposite directions, that would lead to a difference of 0.1 without there being a true difference in means.

For the mean headway, only 2 comparisons out of the 12 possible were outside 0.1 seconds: the average for truck following truck (TT) for I-80/35 southbound at University Avenue was 2.36 seconds, while the average for each of the other two sites was 2.25 seconds, a difference of 0.11 seconds, which was just outside the established threshold. For the median headway, 2 out of the 12 comparisons were outside 0.1 seconds: differences of 0.16 seconds for CC and 0.13 seconds for TT between I-80/35 southbound at University Avenue and I-80/35 northbound at University Avenue. The mean time gaps were even more consistent, with only one comparison outside the range: a difference of 0.11 seconds for car following truck (CT) between I-80/35 northbound at University Avenue and I-80/35 northbound at Hickman Road. The median time gaps were the worst, with 4 out of the 12 comparisons outside of 0.1 seconds: 0.17 seconds for CC and TT between I-80/35 southbound at University Avenue and I-80/35 northbound at University Avenue and 0.12 seconds for CC and 0.11 seconds for truck following car (TC) between I-80/35 southbound at University Avenue and I-80/35 northbound at Hickman Road.

In all, 9 out of 48 comparisons fell outside 0.1 seconds of each other, and most of those were not far out of that range, which is summarized in Table 12.

Table 12. Number of differences greater than 0.1 between summary statistics for Des Moines sites

	Number of differences greater than 0.1 sec (of 3 possible)			
Pair Type (Lead-Follow)	**Mean Headway**	**Median Headway**	**Mean Time Gap**	**Median Time Gap**
CC	0	1	0	2
CT	0	0	1	0
TC	0	0	0	1
TT	2	1	0	1

The maximum difference between any two values was only 0.17 seconds. The closeness of these summary statistics indicates that there are not practical differences in headway and time gap values at these sites with the same driver populations. This means that the preferred headway and time gap should be fairly consistent throughout Des Moines, unless there are significantly different roadway geometries or other factors. The summary statistics of the three Des Moines locations combined are presented in Table 13.

Table 13. Summary statistics for headway and time gap data for Des Moines overall

Pair Type (Lead-Follow)	Count	No. of Congested Intervals	Mean Headway (s)	Median Headway (s)	Std. Dev. Headway (s)	Mean Time Gap (s)	Median Time Gap (s)	Std. Dev. Time Gap (s)
CC	83427	170	1.74	1.66	0.92	1.53	1.42	0.92
CT	11307	170	2.27	2.10	0.89	2.05	1.91	0.89
TC	14012	170	1.85	1.77	0.88	1.14	0.95	0.88
TT	2970	170	2.27	2.11	0.86	1.53	1.40	0.87

Council Bluffs Headway and Time Gap Results

I-80 at the South Expressway entrance in Council Bluffs was the one location where an existing Iowa DOT–owned sensor was used to collect the data. This allowed for the collection period to last much longer than it did for the other sites and allowed for an even larger sample size. The detector was recording data off and on for six weeks and detected over 2.5 million vehicles in total. It recorded data for both the eastbound and westbound directions. The eastbound direction has three through lanes and one auxiliary entrance ramp lane. The westbound direction has two through lanes and an exit ramp. Having the data for both directions allowed for the opportunity to support the finding in Des Moines that the observed headway and time gap values do not vary within the same driver population despite differences in geometry. The summary statistics for the eastbound and westbound directions are reported in Table 14 and Table 15, respectively.

Table 14. Summary statistics for headway and time gap data for I-80 at S. Expressway EB

Pair Type (Lead-Follow)	Count	No. of Congested Intervals	Mean Headway (s)	Median Headway (s)	Std. Dev. Headway (s)	Mean Time Gap (s)	Median Time Gap (s)	Std. Dev. Time Gap (s)
CC	11315	32	1.82	1.75	0.91	1.63	1.55	0.91
CT	1095	32	2.52	2.60	0.83	2.33	2.40	0.83
TC	1655	32	1.90	1.80	0.86	1.11	0.93	0.85
TT	243	32	2.45	2.33	0.82	1.61	1.54	0.79

Table 15. Summary statistics for headway and time gap data for I-80 at S. Expressway WB

Pair Type (Lead-Follow)	Count	No. of Congested Intervals	Mean Headway (s)	Median Headway (s)	Std. Dev. Headway (s)	Mean Time Gap (s)	Median Time Gap (s)	Std. Dev. Time Gap (s)
CC	294480	1206	1.76	1.68	0.91	1.54	1.45	0.91
CT	40439	1206	2.38	2.22	0.86	2.17	2.02	0.86
TC	59207	1206	1.89	1.80	0.86	1.13	0.97	0.86
TT	14205	1189	2.44	2.24	0.80	1.63	1.51	0.82

It is important to note that there were only 32 intervals when the 15 minute flow rate exceeded 1,000 veh/hr/ln for the eastbound direction compared to about 1,200 intervals for the westbound direction. This is mainly due to the fact that there are three through lanes eastbound and two through lanes westbound.

Despite this difference in traffic operation and sample size, the summary statistics are quite similar between the two directions. The differences in measurements were less than 0.1 seconds for the mean and median headway and time gap values for CC, TC, and TT. For CT, the mean headway was off by 0.14, the median headway was off by 0.38, the mean time gap was off by 0.16, and the median time gap was off by 0.38. It is interesting that the means are not much different than the 0.1 second threshold while the medians are both off by 0.38 seconds (lower for the westbound traffic). Overall, it appears that there is enough evidence to support the finding in Des Moines that headway and time gap values do not vary much when considering the same driver population faced with different geometries. This is especially true if the focus is narrowed to only mean values, because the median values have been shown to be more volatile when comparing sites.

The combined data for I-80 at South Expressway is presented in Table 16.

Table 16. Summary statistics for headway and time gap data for I-80 at S. Expressway overall

Pair Type (Lead-Follow)	Count	No. of Congested Intervals	Mean Headway (s)	Median Headway (s)	Std. Dev. Headway (s)	Mean Time Gap (s)	Median Time Gap (s)	Std. Dev. Time Gap (s)
CC	305795	1208	1.76	1.68	0.91	1.55	1.45	0.91
CT	41534	1208	2.39	2.22	0.86	2.18	2.02	0.86
TC	60862	1208	1.89	1.80	0.86	1.13	0.97	0.86
TT	14448	1194	2.44	2.24	0.80	1.63	1.51	0.82

Because the westbound traffic had so many more observations meeting the filtering criteria, the overall statistics are essentially the same as the westbound statistics. These values are similar to the values found in Des Moines, though a few measurement differences were outside of 0.1 seconds. For CT, the mean headway difference was 0.12 seconds, the median headway difference was 0.12 seconds, the mean time gap difference was 0.13 seconds, and the median time gap difference was 0.11 seconds. For TT, the mean headway difference was 0.17 seconds, the median headway difference was 0.13 seconds, and the median time gap difference was 0.11 seconds. While it seems like a lot of measurements are off, they are not substantially more than the threshold for the most part, and the biggest difference is still only 0.17 seconds.

Quad Cities Headway and Time Gap Results

In the Quad Cities, two temporary Wavetronix detectors were set up on an urban freeway (I-74 at Middle Road and I-74 at Spruce Hills Drive), and one temporary Wavetronix detector was set up on a rural freeway (I-80 west of the Quad Cities). All detectors recorded traffic flowing in both directions on and off for about two weeks. The I-74 Spruce Hills Drive location only functioned for about 8 hours and did not experience any 15 minute flow rates greater than 1,000 vehicles per hour. The I-74 Middle Road location only observed one 15 minute flow rate greater than 1,000 vehicles per hour in the southbound direction, compared to 16 intervals northbound. Due to these data collection limitations, the consistency found within driver populations in Des Moines and Council Bluffs could not be confirmed with data in the Quad Cities. The consistency was therefore assumed to hold true, and the data collected from the I-74 Middle Road location were deemed representative of the Quad Cities. Geometrically, the I-74 Middle Road location had two through lanes in both directions and an entrance ramp (northbound) and exit ramp (southbound) that did not have auxiliary lanes associated with them.

The summary statistics for the detector at I-74 at Middle Road are presented in Table 17.

Table 17. Summary statistics for headway and time gap data for I-74 at Middle Road

Pair Type (Lead-Follow)	Count	No. of Congested Intervals	Mean Headway (s)	Median Headway (s)	Std. Dev. Headway (s)	Mean Time Gap (s)	Median Time Gap (s)	Std. Dev. Time Gap (s)
CC	4508	16	1.79	1.72	0.92	1.58	1.50	0.92
CT	87	16	2.36	2.16	0.88	2.14	1.96	0.88
TC	143	16	1.93	1.84	0.87	1.32	1.14	0.89
TT	10	5	2.26	2.24	0.49	1.70	1.75	0.40

It should be noted that only 10 instances of TT pairs meeting the filtering criteria were observed by this detector, which is not a large enough sample size to judge its similarity to the other locations. However, it is still included in the table for the sake of consistency and completeness. The numbers of CT and TC pairs observed were also fairly low but were still substantial enough to get an idea of the true measurements. In order to be 95% confident that the true mean is within $\pm$0.2 seconds of the estimated mean, at least 78 observations are necessary, according to the sample size formula based on the normal distribution and using a standard deviation of 0.9, which was observed at this site and others.

$$n = \left(\frac{Z_{\frac{\alpha}{2}} * \sigma}{E}\right)^2 \quad \textbf{(4)}$$

Where:

n = number of observations needed
$Z_{\frac{\alpha}{2}}$ = the critical z-score for a significance level of $\frac{\alpha}{2}$
σ = sample standard deviation
E = acceptable error

While the headway and time gap distributions were not normal (they were somewhat skewed), this equation gives a low-end approximation. Though it would have been helpful to have more confidence in a narrower margin (such as the 0.1 second threshold), these observations provided a decent estimate of the mean. Despite this small sample size, there were still only a few measurements outside of the 0.1 second threshold. For the TC pairs, between the I-74 Middle Road detector and Council Bluffs detector the mean time gap difference was 0.19 seconds, and the median time gap difference was 0.17 seconds. Between the I-74 Middle Road detector and the Des Moines detectors, the mean time gap difference was 0.18 seconds, and the median time gap difference was 0.19 seconds. All of these differences were from the measurements at the I-74 Middle Road location and were consistently higher than at the other two locations.

This consistent difference in time gaps but not headways could be due to various reasons. First, it could just be a result of the small sample size. However, none of the other measurements differed much from the other two locations, and they were consistently off by about the same amount, so this does not appear to be the most likely explanation. The most likely explanation is that there is a higher percentage of small trucks on I-74 compared to the locations in Des Moines and Council Bluffs. Cars may interact with these smaller trucks differently than they interact with 18 wheelers. If cars do interact differently with smaller trucks and these vehicles are present in different proportions, this could affect the overall average, because both smaller and larger trucks are considered trucks by this analysis. It appears that this could be the case, as evidenced by the histograms of vehicle length, in which the Quad Cities location clearly has more small trucks than the other locations (see Figure 28).

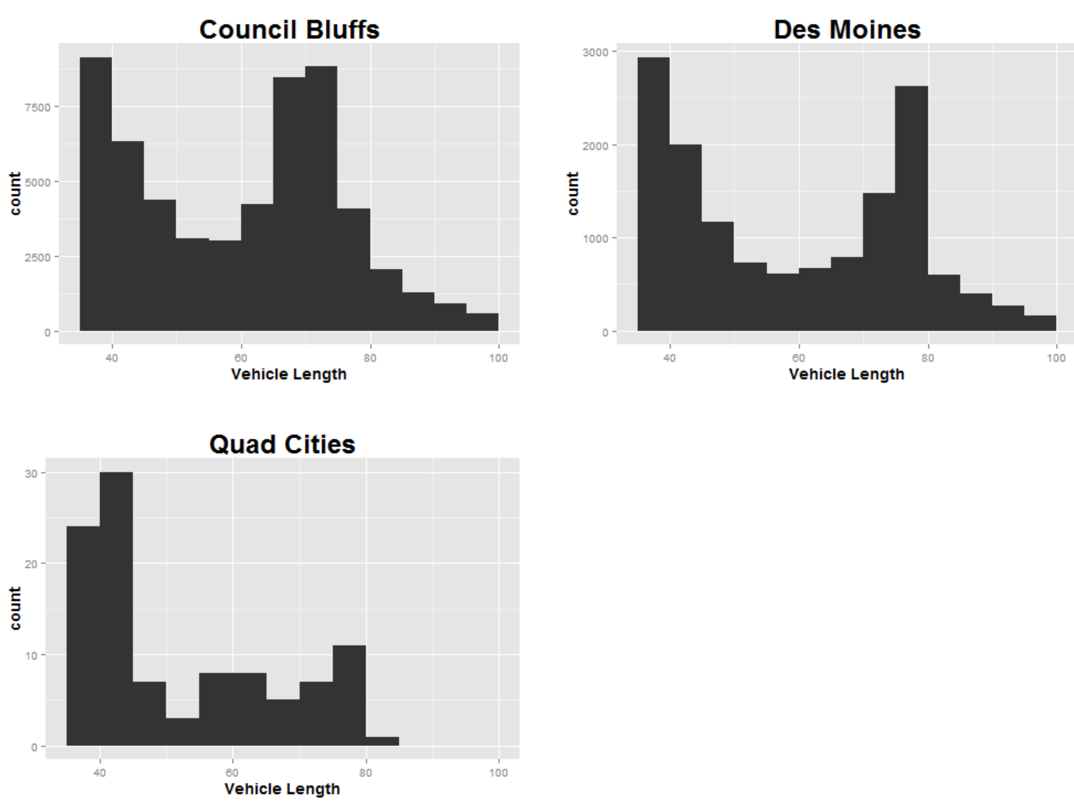


Figure 28. Truck length histograms for the three urban areas

Finally, the consistent difference in time gaps but not headways could just be an anomaly in the data collection process. Without more sites to investigate, it is not possible to make a strong assertion about the cause of this difference. Despite this difference in time gaps for TC, overall the data from the I-74 Middle Road detector in the Quad Cities matched the data from Des Moines and Council Bluffs fairly well.

Conclusion of Headway and Time Gap Results

Overall, it was observed through the data collected in three different regions of Iowa that headway and time gap measurements are largely similar within the same driver population as well as across different driver populations, provided that the environment is generally the same (urban conditions and somewhat similar geometries). These regions were compared mostly on the similarities of the mean, median, and standard deviation values, as well as on a visual examination of the distributions. The data were filtered to include only observations that occurred during intervals that exceeded a 15 minute flow rate of 1,000 veh/hr/ln and observations with headways of 4 seconds or less.

In the central portion of Iowa, data were analyzed from threes sites in close proximity with one another on I-80/35 between the University Avenue and Hickman Road interchanges. The sites had fairly similar geometries but slightly different lane configures, and it was found that they had similar measurements for headway and time gap. This finding established the consistency of measurements within the same driver population. In the western portion of Iowa, data were collected from Council Bluffs on I-80 eastbound and westbound at the interchange for South Expressway. The eastbound and westbound directions had similar headway and time gap measurements, further supporting the finding that the same driver population produces similar headways and time gaps. In the eastern portion of Iowa, data were used from one site in the Quad Cities located on I-74 at the Middle Road interchange. It was not possible to further confirm consistency within driver population in the Quad Cities, because the other detector set up nearby did not provide any data meeting the filtering criteria and the amount of data in both directions of I-74 at Middle Road was not sufficient to compare. However, the data from Des Moines, Council Bluffs, and the Quad Cities were compared, and it was found that the headways and time gaps across the different cities were similar.

Additionally, data from a rural location on I-80 west of the Quad Cities were used as a point of comparison for the three urban locations. Not as much data met the filtering criteria as at some of the other sites, but this was expected due to the site's lower flow rates. The usable data indicated a substantial difference in the rural location compared to the three urban locations. This difference can be seen visually in Figure 26 and Figure 27, which show average headway versus flow rate for each site, and it appears that the rural location follows a slightly different pattern from the others. This is particularly pronounced for the time gap data in Figure 27, where the rural location consistently shows time gaps lower than those of the urban locations.

Standstill Distance

Standstill Distance Analysis Procedure

Introduction to Standstill Distance Results

While the standstill distance data were compiled in Microsoft Excel, for reproducibility's sake the statistical software R was used for the analysis. For each stop-and-go incident, in addition to the standstill distance measurements, the conditions surrounding the incident were also recorded. These conditions included weather, presence of a curve, day or night conditions, the cause of the incident (if known), and the city in which it occurred. R was used to find sample statistics while stratifying the data in different ways. For example, the mean standstill distance was calculated for each of the incident types (accident, construction, slow traffic, stalled vehicle, and unknown). R was also used to plot the histogram of data to observe the distribution. Because it was a skewed distribution, it was transformed to make it more symmetric so t-tests could be used to compare the means of the different groups.

While the collection of the standstill distance measurements was more time consuming and tedious than that of the headway data, analyzing the data was much more straightforward. The standstill distance measurements from each stop-and-go incident were compiled into one Excel file and saved as a CSV file. As mentioned above, in addition to the distance measurement and the vehicle pair type, the location, lighting, cause of incident, presence of curve, and weather conditions were recorded (if known) for each stop-and-go incident, as shown in Figure 29.

	A	B	C	D	E	F	G	H	I	J	K
1	ID	Video	City	File	Distance	PairType	Lighting	Cause	Curve?	Weather	Notes
2	1	AMTV1 Nov 21 1030 to 1130 Distances	Ames	10 33 47	17.88	CC	Day	Accident	No	Clear	
3	2	AMTV1 Nov 21 1030 to 1130 Distances	Ames	10 33 47	8.61	CC	Day	Accident	No	Clear	
4	3	AMTV1 Nov 21 1030 to 1130 Distances	Ames	10 33 47	14.22	CC	Day	Accident	No	Clear	

Figure 29. Sample standstill distance data

Once everything was in one file, this file was imported into R using the read.csv() command. An overall histogram of the distances was created that revealed a skewed distribution and led to the exclusion of some outliers that did not fit with normal driving behavior (see Figure 30).

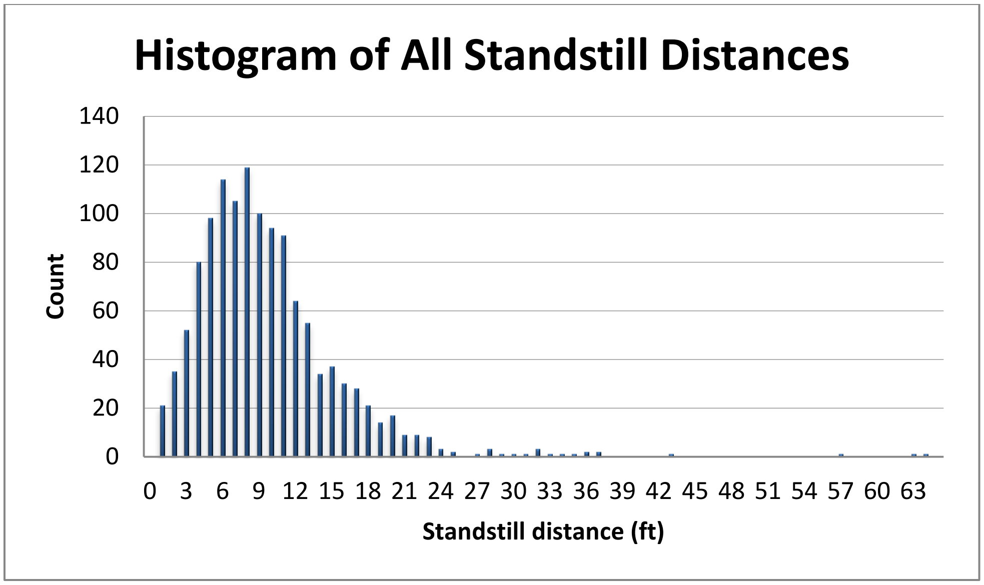


Figure 30. Histogram of unfiltered standstill distances

It is apparent from this histogram that there are some excessively long measurements. From a visual inspection of the histogram, it was determined that measurements of longer than 25 feet fell outside typical standstill distances, and such measurements were excluded. These measurements could have been a result of vehicles stopping for reasons other than stopping for the vehicle in front of them (e.g., to perform a lane change maneuver).

Then, the mean, median, and standard deviations were calculated for different stratifications of the data to compare the standstill distance measurements across different groups. To compare between groups for statistically significant differences, t-tests were used. Rather than hypothesis tests for specific significance levels, p-values were used to get a better idea of the strength of the t-tests' conclusions. Because the standstill distances were a skewed distribution, they were transformed to be more symmetric before using the t-test to compare them. The distribution was right-skewed (long tail to the larger values), and the data were transformed by taking the square root of each observation. The entire process of collecting and analyzing the standstill distances is summarizes in the flowchart in Figure 31.

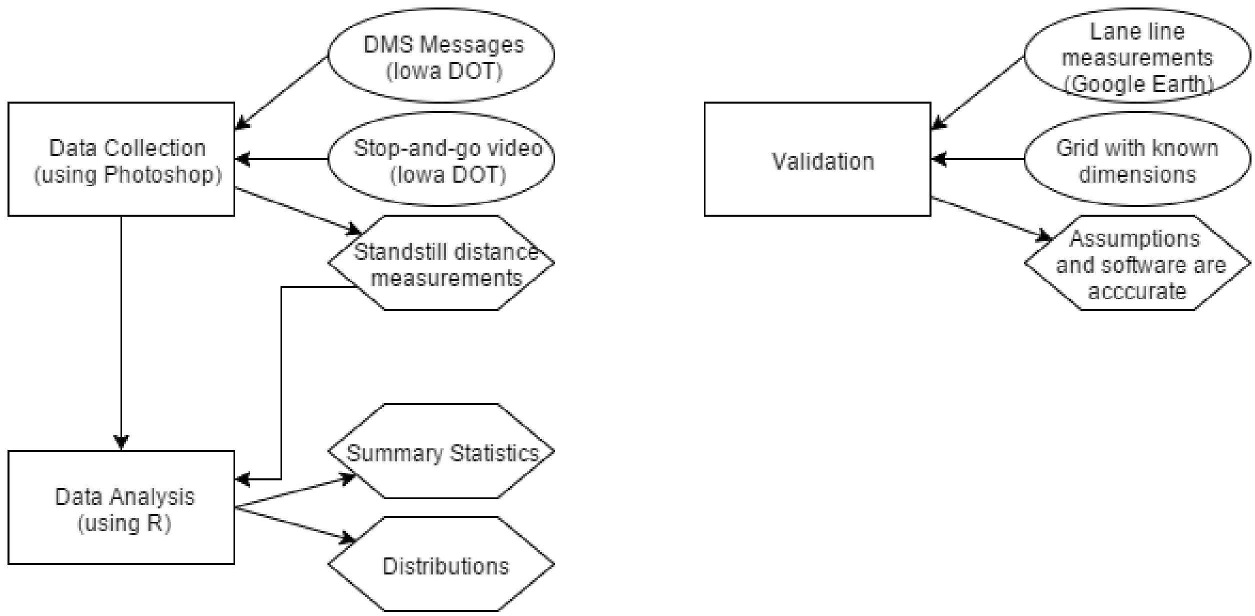


Figure 31. Flowchart for standstill distance analysis

Standstill distance measurements for urban freeways in Iowa were collected from stop-and-go traffic incidents across the state. The process involved finding potential incidents, reviewing video of them, taking screenshots when vehicles were stopped in the video, and measuring the distances between these stopped vehicles using Photoshop. For a more complete description of this process, see the data collection chapter above. This data collection process precluded data from rural locations because the required infrastructure was not installed at many locations that could be considered rural and because stop-and-go traffic was not observed at those locations where the infrastructure was present. Additionally, it was decided that measurements of greater than 25 feet would be excluded because they were deemed to be outside of normal behavior based on observations of vehicles during the data collection process as well as observations of the histogram of the measurements.

Along with the actual standstill distance measurement, the vehicle pair type (CC, CT, TC, or TT) was recorded for each observation. Additionally, a number of other attributes for each incident were recorded for each observation: the city in which the incident took place, the lighting at the time, the weather at the time, whether a curve was present, and the cause of the incident. Having this additional information allowed for the exploration of the potential influence of these data on standstill distances. This section will present the summary statistics and relevant distributions of standstill distances for the different levels of the variables recorded.

Standstill Distance by City

Due to the distribution of cameras, sensors, dynamic message signs, and traffic in the state of Iowa, the majority of stop-and-go incidents that were processed came from Des Moines. Des Moines is the largest city in the state, so it has the most traffic and the largest build out of ITS equipment, having more cameras, sensors, and dynamic message signs than any other urban area in the state, which provided many opportunities to capture stop-and-go incidents. Additionally, the traffic load in Des Moines, especially during the peak hours, is large enough that even relatively small disturbances (e.g., a stalled vehicle on the shoulder) can be enough to cause stop-and-go conditions. These factors all led to a much larger number of measurements being observed for Des Moines (a total of 693) than other cities. However, some data were collected for Ames, Cedar Rapids, Council Bluffs, Iowa City, the Quad Cities, and Sioux City. The top two cities other than Des Moines were the Quad Cities, with 277 observations, and Sioux City, with 126 observations.

The mean, median, and standard deviations for the standstill distance measurements for each city are reported in Table 18.

Table 18. Summary of standstill distance by city

City	Count	No. of Incidents	No. of Photos	Mean (ft)	Median (ft)	Std. Dev. (ft)
Ames	50	1	13	11.57	9.66	5.71
Cedar Rapids	59	3	11	11.17	10.65	5.45
Council Bluffs	22	1	10	12.33	11.05	4.16
Des Moines	693	25	153	8.59	7.95	4.37
Iowa City	11	2	3	9.69	9.98	5.11
Quad Cities	277	8	74	10.19	9.51	4.36
Sioux City	126	6	33	12.53	12.00	4.81

It is interesting that the means are generally around 10 to 12.5 feet, except for those in Des Moines and Iowa City, but Iowa City only has 11 observations. However, the data from Ames, Cedar Rapids, and Council Bluffs were also limited. Therefore, the statistical analysis focused on only the top three cities: Des Moines, the Quad Cities, and Sioux City. The histograms for these three cities are presented in Figure 32.

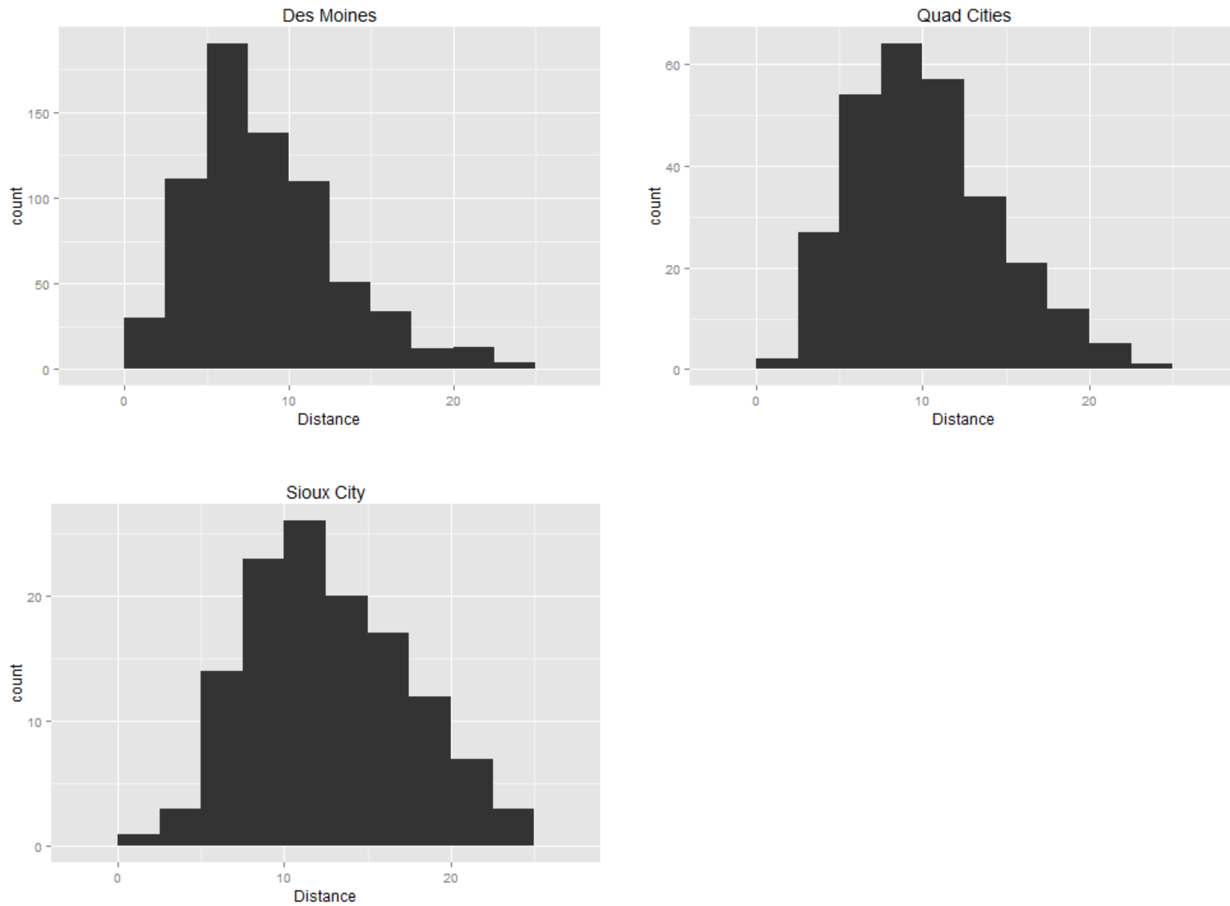


Figure 32. Standstill distance histograms by city

Because these distributions are skewed, they needed to be transformed in order to use the t-test for difference of means. By taking the square root of the distance, these distributions become more symmetric (see Figure 33), so that t-tests can be used to compare them.

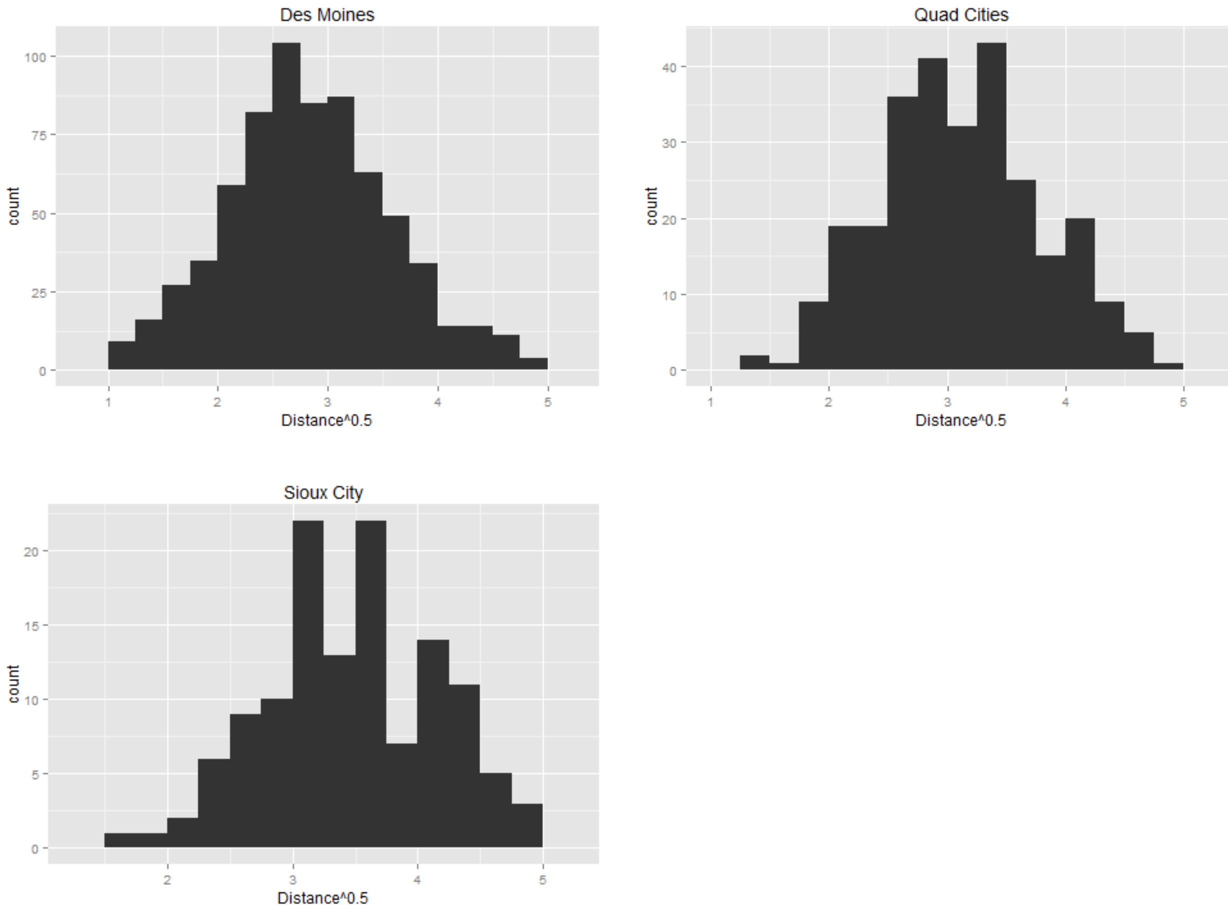


Figure 33. Square root of standstill distance histograms by city

The t-test comparisons resulted in the p-values reported in Table 19.

Table 19. P-values for t-tests for mean standstill distance comparisons by city

	Des Moines	**Quad Cities**	**Sioux City**
Des Moines	xxx	2.22e-08***	< 2.2e-16***
Quad Cities	2.22e-08***	xxx	3.32e-06***
Sioux City	< 2.2e-16***	3.32e-06***	xxx

* for 95% confidence, ** for 99%, *** for 99.9%

A p-value of less than 0.05 means there is a statistically significant difference between the means with 95% confidence. All three t-tests were highly statistically significant, but more investigation is necessary to determine whether this difference is due to different driver populations or differences in the circumstances of the stop-and-go traffic collected in each of the cities.

If one set of conditions producing stop and go traffic is overrepresented in one city compared to the others, this can skew the results of the comparisons. For example, in Table 20, the number of incidents for each cause is reported for each city.

Table 20. Number of incidents resulting from different causes by city

		No. of Incidents for each cause type				
City	Total No. of Incidents	Accident	Construction	Slow Traffic	Stalled Traffic	Unknown
Ames	1	1	0	0	0	0
Cedar Rapids	3	3	0	0	0	0
Council Bluffs	1	1	0	0	0	0
Des Moines	25	11	0	6	1	7
Iowa City	2	1	1	0	0	0
Quad Cities	8	0	3	4	1	0
Sioux City	6	0	6	0	0	0

It should be noted that all six incidents in Sioux City were the result of construction, whereas none of the incidents in Des Moines was the result of construction. To attempt to address this, the summary statistics for each cause type within each city are reported in Table 21 and Table 23 for Des Moines and the Quad Cities, respectively. These two cities were the only ones reported because they are the only ones with two or more cause types to compare and a sufficient number of observations. The p-values for the t-test comparisons for each incident cause combination in Des Moines and the Quad Cities are given in Table 22 and Table 24, respectively.

Table 21. Summary of standstill distances for Des Moines by cause of incident

Cause	Count	No. of Incidents	No. of Photos	Mean (ft)	Median (ft)	Std. Dev. (ft)
Accident	252	11	56	8.63	8.00	4.41
Slow Traffic	162	6	37	8.12	7.66	4.28
Stalled Vehicle	32	1	12	7.72	7.31	3.29
Unknown	247	7	49	8.96	8.30	4.50

Table 22. P-values for t-tests for mean standstill distance comparisons by incident cause for Des Moines

	Accident	Slow Traffic	Stalled Vehicle	Unknown
Accident	xxx	0.238	0.285	0.377
Slow Traffic	0.238	xxx	0.754	0.0499*
Stalled Vehicle	0.285	0.754	xxx	0.120
Unknown	0.377	0.0499*	0.120	xxx

* for 95% confidence, ** for 99%, *** for 99.9%

Table 23. Summary of standstill distances for the Quad Cities by cause of incident

Cause	Count	No. of Incidents	No. of Photos	Mean (ft)	Median (ft)	Std. Dev. (ft)
Construction	104	3	19	11.50	11.45	4.43
Slow Traffic	154	4	51	9.60	8.95	4.17
Stalled Vehicle	19	1	4	7.85	7.79	3.61

Table 24. P-values for t-tests for mean standstill distance comparisons by incident cause for the Quad Cities

	Construction	Slow Traffic	Stalled Vehicle
Construction	xxx	0.000565***	0.000812***
Slow Traffic	0.000565***	xxx	0.067
Stalled Vehicle	0.000812***	0.067	xxx

* for 95% confidence, ** for 99%, *** for 99.9%

In Des Moines, the only statistically significant result is the extremely marginally significant comparison (p-value of 0.0499) between slow traffic and unknown cause, which does not have a strong interpretation. The Quad Cities data, however, show a highly significant difference between construction and slow traffic and between construction and stalled vehicle.

Standstill Distance by Vehicle Pair Type

The summary statistics for standstill distance for each vehicle pair type are presented in Table 25.

Table 25. Summary of standstill distance by vehicle pair type

Pair Type (Lead-Follow)	Count	No. of Incidents	No. of Photos	Mean (ft)	Median (ft)	Std. Dev. (ft)
CC	1140	45	287	9.41	8.80	4.54
CT	40	24	38	13.35	13.15	6.32
TC	48	26	41	12.37	11.20	5.78
TT	10	7	10	11.07	10.56	3.69

An initial look at the summary statistics seems to indicate that vehicle pairs involving a truck tend to have larger standstill distances. To evaluate this impression statistically, t-tests were used. Though the smaller datasets for CT, TC, and TT make it difficult to assess the normality of their distributions, it can be seen in the overall distribution that the data are skewed and can be made more symmetric by taking the square root of the distances. Applying this procedure to the distances by vehicle pair type and conducting t-test comparisons yields the results presented in Table 26.

Table 26. P-values for t-tests for mean standstill distance comparisons by vehicle pair type

	CC	CT	TC	TT
CC	xxx	0.000421***	0.000861***	0.118
CT	0.000421***	xxx	0.515	0.276
TC	0.000861***	0.515	xxx	0.548
TT	0.118	0.276	0.548	xxx

* for 95% confidence, ** for 99%, *** for 99.9%

The table shows that there is high confidence that CC standstill distances are significantly different than CT and TC standstill distances, but the sample size of TT pairs is too small to indicate that there is a difference between CC and TT. None of the other vehicle pair types were found to be significantly different.

These results were not likely to be overly influenced by the Des Moines data, as some of the other incident-based variables, because the data were fairly well spread out throughout the different cities, as seen in Table 27.

Table 27. Number of observations of each pair type in each city

City	No. of CC Observations	No. of CT Observations	No. of TC Observations	No. of TT Observations	Total No. of Observations
Ames	42	2	3	3	50
Cedar Rapids	43	6	8	2	59
Council Bluffs	17	2	2	1	22
Des Moines	663	13	16	1	693
Iowa City	6	1	3	1	11
Quad Cities	264	6	6	1	277
Sioux City	105	10	10	1	126

Every city contributes something to each pair type, and Des Moines contributes fairly evenly across the different pair types. About 58 percent of CC observations are from Des Moines, and about 33 percent of CT and TC observations are from Des Moines. While these numbers are somewhat unbalanced, they are much more balanced than most of the incident-based variables described subsequently.

Standstill Distance by Lighting

The summary statistics for standstill distance for each lighting condition (day or night) are shown in Table 28.

Table 28. Summary of standstill distance by lighting conditions

Lighting	Count	No. of Incidents	No. of Photos	Mean (ft)	Median (ft)	Std. Dev. (ft)
Day	1076	44	265	9.87	9.20	4.78
Night	159	1	31	8.33	7.44	4.21

While a t-test of the means shows that there is a statistically significant difference (p-value of 5.96e-05), there is not enough coverage within the data to make any conclusions with respect to the influence of lighting conditions. All of the nighttime observations occurred in Des Moines as the result of one incident. This is not acceptable for analysis.

Standstill Distance by Weather

The summary statistics for standstill distance in different weather conditions are provided in Table 29.

Table 29. Summary of standstill distance by weather conditions

Weather	Count	No. of Incidents	No. of Photos	Mean (ft)	Median (ft)	Std. Dev. (ft)
Clear/Cloudy	1202	43	287	9.70	9.02	4.75
Rainy	36	3	10	8.40	7.69	3.77

The weather conditions were observed from the video of each incident. Due to the small sample size and the lack of a theoretical basis for a difference in standstill distance between clear and cloudy conditions, the data for these conditions were combined and compared to the rainy condition data using a t-test. Again, this t-test was conducted on the square roots of the measurements. This test resulted in a p-value of 0.0884, which means that there is not a statistically significant difference with a minimum confidence level of 95%. Even if the distance had been found to be significantly significant, it would have to be taken with a grain of salt, again because of the sample size and coverage. All three incidents involving rain occurred in Des Moines.

Standstill Distance by Curve Presence

The summary statistics for standstill distance when a curve was or was not present are provided in Table 30.

Table 30. Summary of standstill distance by curve presence

Curve	Count	No. of Incidents	No. of Photos	Mean (ft)	Median (ft)	Std. Dev. (ft)
No	915	40	214	9.83	9.15	4.83
Yes	323	7	83	9.19	8.57	4.41

The presence of a curve was noted from watching the video of the incidents. A t-test comparison barely did not show a statistically significant difference at the 95% confidence level (p-value of 0.0564), and there was fairly good coverage of the data in this case, which lends support to this conclusion. The incidents for which data were recorded on a curve were found in Des Moines, Cedar Rapids, and the Quad Cities, and the causes of these incidents included an accident, slow traffic, construction, and an unknown cause.

Standstill Distance by Cause

The causes of the stop-and-go incidents were ascertained by noting the message displayed on the dynamic message board sign, which indicated the cause that led to the video being downloaded. For example, if a sign said ACCIDENT AHEAD PREPARE TO STOP, that incident was coded as being caused by an accident. There is clearly some ambiguity involved in this method, because a sign warning of slow traffic does not necessarily mean that the incident was not caused by an accident. The message could simply mean that the traffic management center was unaware of the cause or that the message was displayed automatically because the Iowa DOT detectors recorded the speed dropping below a certain threshold. Despite this ambiguity, this method was the best option because video rarely showed what caused the stop-and-go conditions directly.

The summary statistics for standstill distance for each cause are reported in Table 31.

Table 31. Summary of standstill distance by cause

Cause	Count	No. of Incidents	No. of Photos	Mean (ft)	Median (ft)	Std. Dev. (ft)
Accident	392	17	92	9.61	8.94	4.95
Construction	232	10	53	12.05	11.50	4.64
Slow Traffic	316	10	88	8.84	8.16	4.28
Stalled Vehicle	51	2	16	7.77	7.50	3.38
Unknown	247	7	49	8.96	8.30	4.50

The summary statistics indicate that incidents caused by a stalled vehicle tended to have the smallest standstill distances, and incidents caused by construction tended to have the highest. While the stalled vehicle category has the fewest observations, its two incidents are from different cities (Des Moines and the Quad Cities) and have a similar number of observations (32 in Des Moines and 19 in the Quad Cities). The means of the standstill distances are 7.72 feet for the Des Moines incident and 7.85 for the Quad Cities incident (see Table 36). When this is tested using a t-test in a similar fashion to the preceding analyses, the p-value is 0.891, indicating no statistically significant difference. This does not completely validate the result, because the sample size is small and there could be interacting factors in both the observed and unobserved information about each site leading to this result, but the consistency between the two sites lends support to the conclusion that stalled vehicle incidents tend to have lower standstill distances.

The t-test p-values for each combination of incident type are reported in Table 32.

Table 32. P-values for t-tests for mean standstill distance comparisons by the cause of the incident

	Accident	**Construction**	**Slow Traffic**	**Stalled Vehicle**	**Unknown**
Accident	xxx	3.60e-11***	0.0534	0.00465**	0.122
Construction	3.60e-11***	xxx	< 2.2e-16***	4.24e-10***	6.358e-14***
Slow Traffic	0.0534	< 2.2e-16***	xxx	0.0859	0.820
Stalled Vehicle	0.00465**	4.24e-10***	0.0859	xxx	0.0708
Unknown	0.122	6.358e-14***	0.820	0.0708	xxx

for 95% confidence, ** for 99%, *** for 99.9%

However, caution should be used when interpreting these results due to the unbalanced nature of the data. Because Des Moines yielded so many more observations than the other cities and appears to have consistently lower standstill distances than other cities, the influence on the means of other variables can be large.

In general, there was a good spread of locations for each of the incident causes. For a simple breakdown of the locations of incidents for each cause, refer to Table 20. Every cause was present in at least two cities, except for the unknown cause, which was only present in Des Moines. To further break down the data, it is possible to look at the variation between cities for each specific incident type; these results are presented in Table 33 through Table 36 (unknown cause was not included because all incidents occurred in Des Moines, so there was no variation between cities for this cause).

Table 33. Summary of standstill distances for incidents caused by accidents for each city

City	Count	No. of Incidents	No. of Photos	Mean (ft)	Median (ft)	Std. Dev. (ft)
Ames	50	1	13	11.57	9.66	5.71
Cedar Rapids	59	3	11	11.17	10.65	5.45
Council Bluffs	22	1	10	12.33	11.05	4.16
Des Moines	252	11	56	8.63	8.00	4.41
Iowa City	9	1	2	9.40	8.08	5.66

Table 34. Summary of standstill distances for incidents caused by construction for each city

City	Count	No. of Incidents	No. of Photos	Mean (ft)	Median (ft)	Std. Dev. (ft)
Iowa City	2	1	1	11.02	11.02	0.71
Quad Cities	104	3	19	11.50	11.45	4.43
Sioux City	126	6	33	12.53	12.00	4.81

Table 35. Summary of standstill distances for incidents caused by slow traffic for each city

City	Count	No. of Incidents	No. of Photos	Mean (ft)	Median (ft)	Std. Dev. (ft)
Des Moines	162	6	37	8.12	7.66	4.28
Quad Cities	154	4	51	9.60	8.95	4.17

Table 36. Summary of standstill distances for incidents caused by a stalled vehicle for each city

City	Count	No. of Incidents	No. of Photos	Mean (ft)	Median (ft)	Std. Dev. (ft)
Des Moines	32	1	12	7.72	7.31	3.29
Quad Cities	19	1	4	7.85	7.79	3.61

The most noticeable results that these tables show are that the means for Des Moines are typically lower than for other cities and that there is generally variation between cities for each cause.

Standstill Distance Results Conclusion

Overall, it appears that mean standstill distance throughout Iowa is generally between 8 and 12 feet. Due to the way the data were collected, more than half of the observations were from Des

Moines. Additionally, it appears that Des Moines had significantly lower standstill distances than the other cities. These two factors, along with some other imbalances in the data, made it difficult to assess the effects of other incident-based characteristics such as the cause of incident, the weather at the time, etc. The vehicle pair types were spread among the incidents and the locations fairly well, so the mean standstill distances could be reasonably tested for each of the vehicle pair types. It was found that the CC pair type had a significantly lower mean than the CT and TC pair types, while the data were not sufficient to reach the same conclusion for the TT pair type.

Capacity of Weaving Sections

The *HCM 2010* defines weaving as "the crossing of two or more traffic streams traveling in the same direction along a significant length of highway without the aid of a traffic control device." Thus, the weaving segments are formed when merge segments are closely followed by diverge segments. Roess and Uliero (2008) proposed a methodology, later included in the *HCM 2010*, to analyze the capacity of freeway weaving segments. The detailed computational procedure to estimate the capacity of the weaving section located on southbound I-35 between Hickman Road and University Avenue is explained below.

First, the demand volume and flow rates are converted to their ideal equivalents by using the following equation:

$$v_i = \frac{V_i}{PHF \times f_{HV} \times f_p} \tag{5}$$

Where:

v_i = flow rate *i* under ideal conditions (pc/hr)
V_i = hourly volume for flow *i* under prevailing conditions in vehicles per hour (veh/hr)
PHF = peak hour factor
f_{HV} = adjustment factor for heavy-vehicle presence
f_p = adjustment factor for driver population

The subscript for the type of flow *i* can take the following values:

FF = freeway to freeway
FR = freeway to ramp
RF = ramp to freeway
RR = ramp to ramp

Second, in studying the freeway segment, the two weaving movements are the ramp-to-freeway and freeway-to-ramp flows. The minimum rate at which weaving vehicles must change lanes to complete all weaving maneuvers successfully is calculated by the following equation:

$$LC_{min} = (LC_{RF} \times v_{RF}) + (LC_{FR} \times v_{FR}) \quad \textbf{(6)}$$

Where:

LC_{min} = minimum rate at which weaving vehicles must change lanes to complete all weaving maneuvers successfully (lc/hr)
LC_{RF} = minimum number of lane changes that must be made by one ramp-to-freeway vehicle to execute the desired maneuver successfully
LC_{FR} = minimum number of lane changes that must be made by one freeway-to-ramp vehicle to execute the desired maneuver successfully

The maximum length of a weaving segment is computed as follows:

$$L_{max} = [5728(1 + VR)^{1.6}] - [1566N_{WL}] \quad \textbf{(7)}$$

Where:

N_{WL} = number of lanes from which a weaving maneuver may be made with one or no lane changes
VR = volume ratio, v_w/v
v_w = weaving demand flow rate in the weaving segment (pc/hr), $v_w = v_{RF} + v_{FR}$
v_{Nw} = nonweaving demand flow rate in the weaving segment (pc/hr), $v_w = v_{FF} + v_{RR}$
v = total demand flow rate in the weaving segment (pc/hr), $v = v_w + v_{Nw}$

If the length of a weaving segment is less than the maximum length, the next step is executed. Otherwise, the merge and diverge junctions need to be analyzed as separate segments.

Third, the capacity of weaving segment is calculated as follows:

$$C_{IWL} = C_{IFL} - [438.2(1 + VR)^{1.6}] + [0.0765L_S] + [119.8N_{WL}] \quad \textbf{(8)}$$

Where:

C_{IWL} = capacity of the weaving segment under equivalent ideal conditions, per lane (pc/hr/ln)
C_{IFL} = capacity of a basic freeway segment with the same free flow speed as the weaving segment under equivalent ideal conditions, per lane (pc/hr/ln)
L_S = length of the weaving segment (ft)

The capacity of the weaving segment under equivalent ideal conditions is converted to capacity prevailing conditions by using the following equation:

$$C_w = C_{IWL} f_{HV} f_p \quad \textbf{(9)}$$

For the I-35 section, the adjustment factor for heavy-vehicle presence is 0.95, and the peak hour factor is 0.88. The resulting flow rates under prevailing and ideal conditions are shown in Table 37.

Table 37. Flow rates under prevailing and ideal conditions

	Flow Rate (pc/hr)	
	Prevailing Condition	**Ideal Condition**
FF	2573	3077.751
RF	1538	1839.713
FR	711	850.4785
RR	257	307.4163

Because the free flow speed of the freeway examined in this research is 65 mph, according to the *HCM 2010*, the capacity of the freeway segment under ideal conditions is 2,350 pc/hr/ln. The length of the weaving segment is 1,268 ft. The minimum number of lane changes that must be made by one ramp-to-freeway or freeway-to-ramp vehicle to execute the desired maneuver successfully is one. Additionally, the number of lanes from which a weaving maneuver may be made is two. Following the calculation procedure, the capacity of the study freeway is 1,803 pc/hr/ln.

VISSIM CALIBRATION

Simulation Model Development

Network

The weaving segment located in the southbound direction of I-80/35 between Hickman Road and University Avenue was modeled as a case study. As is common in modeling practice to achieve realistic outputs, the network model was extended to one mile north and one mile south of the study segment. The layout of the study area as it was modeled is shown in Figure 35. This location is part of the greater Des Moines metropolitan area and experiences considerable traffic congestion during peak hours due to a large amount of commuters using I-80/35 and the adjacent roads. Figure 34 plots the speeds measured by the Wavetronix detectors on different work days.

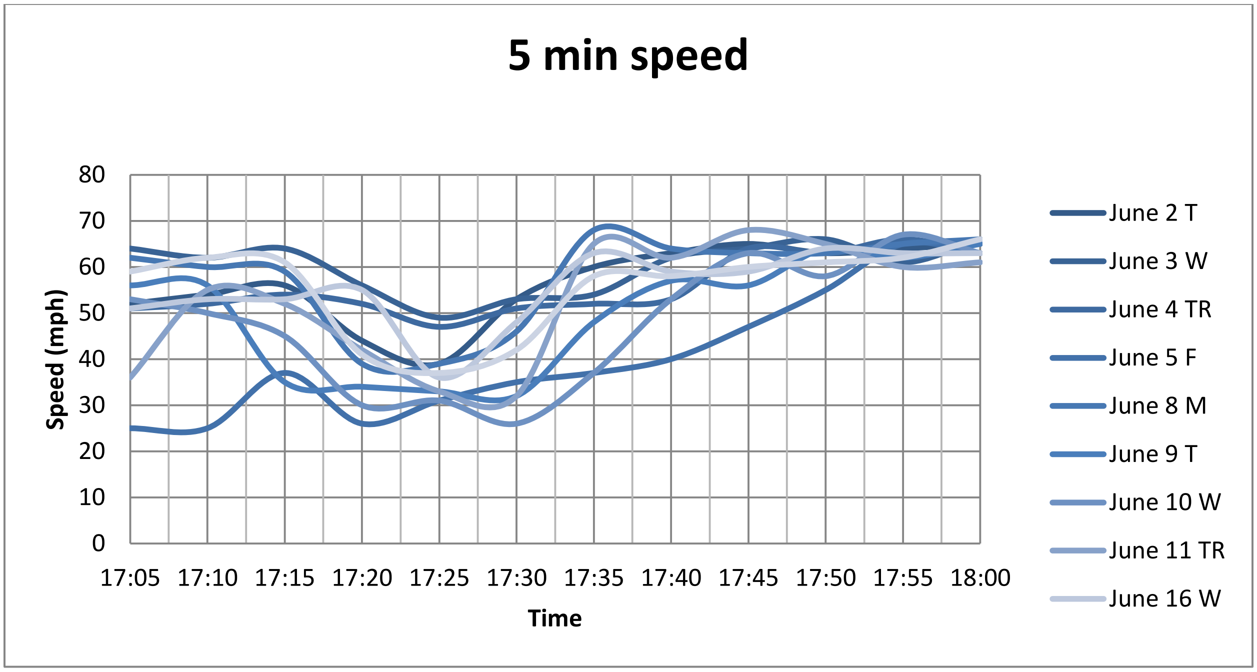


Figure 34. Average speed on weekdays

Recurrent congestion is observed between 5:15 p.m. and 5:30 p.m., when speeds drop to almost half of the speed limit. The geometric characteristics of the network, including the number of lanes, lane widths, link lengths, and levels were coded in VISSIM version 7 using the Microsoft Bing Maps live map feature. In addition, lane width and length were verified with Google Earth Pro because previous studies indicated that Google Earth positional images were accurate for assessing horizontal positions (Potere 2008).

To collect data from the simulation, four sets of detectors were coded in VISSIM, as illustrated in Figure 35.

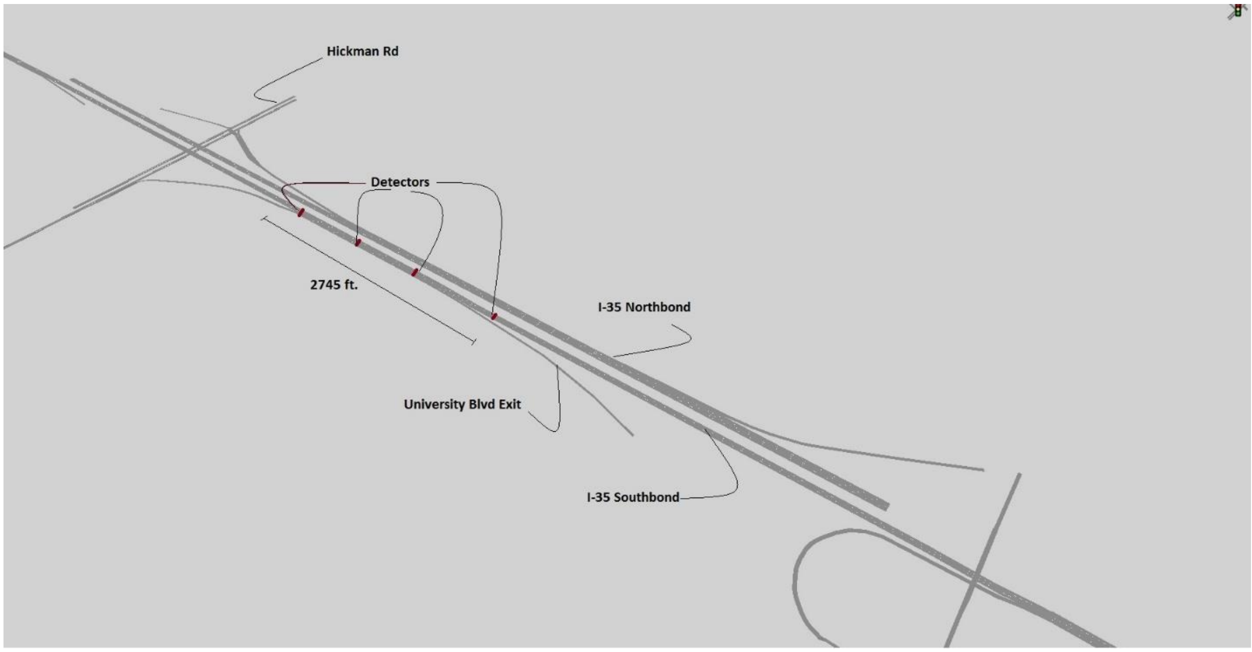


Figure 35. Case study network coded in VISSIM

One set of detectors was placed at the same location as the Iowa DOT detectors to compare the simulation results with the field observations. Three additional sets of detectors were placed throughout the study area: at the middle, at the end, and after the weaving section.

Desired Speed Distribution

The desired speed distribution was created based on the free flow speeds obtained from the Wavetronix detectors. Free flow speed data were used instead of the complete data set in order to ensure that the measured speed was a result of the driver's selection of that speed rather than a result of congested conditions. Any 15-minute flow rates less than 1,000 veh/hr/ln were considered to be in free flow. This selection corresponds to the threshold used in the *HCM 2010* of 1,000 pc/hr/ln. The cumulative speed distribution curve was plotted for the free flow time intervals because the cumulative speed distribution curve is the input used in VISSIM for desired speed. The curve in Figure 36 was manually matched in the VISSIM input. This process should be done separately wherever there is a major change in roadway geometry or speed limit.

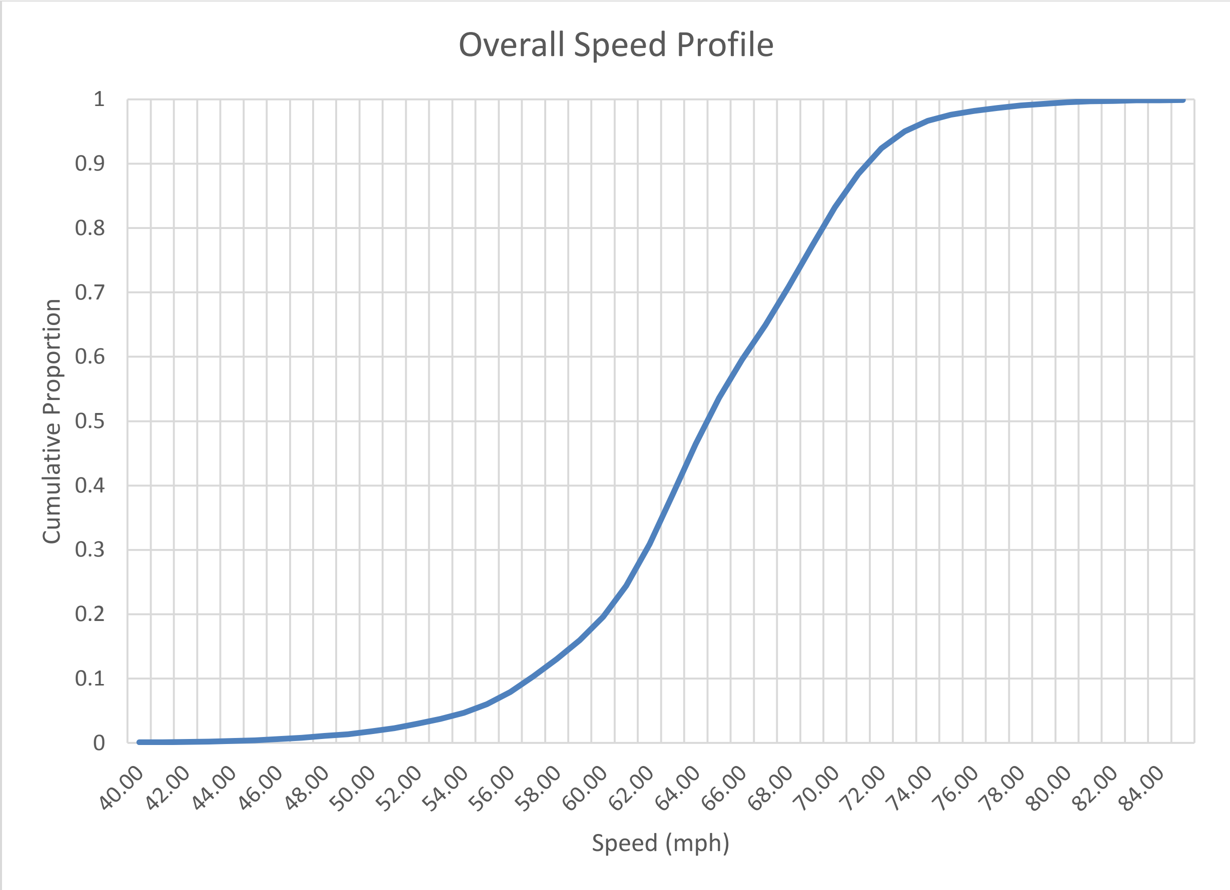


Figure 36. Cumulative distribution of free flow speed

Demand

Video of the peak hour traffic was observed to compute the relative flows of through, merging, and diverging traffic. By rotating the Iowa DOT camera at Hickman Road to face south, the weaving movements between the weaving lane and the through lanes were noted. The results show that more than 85 percent of the vehicles entering the freeway from Hickman Road merge onto the freeway, while 20 percent of the vehicles on the freeway diverge to University Avenue. The rest of the vehicles represent the through movement traffic. Figure 37 shows the percentages of traffic movements on the segment.

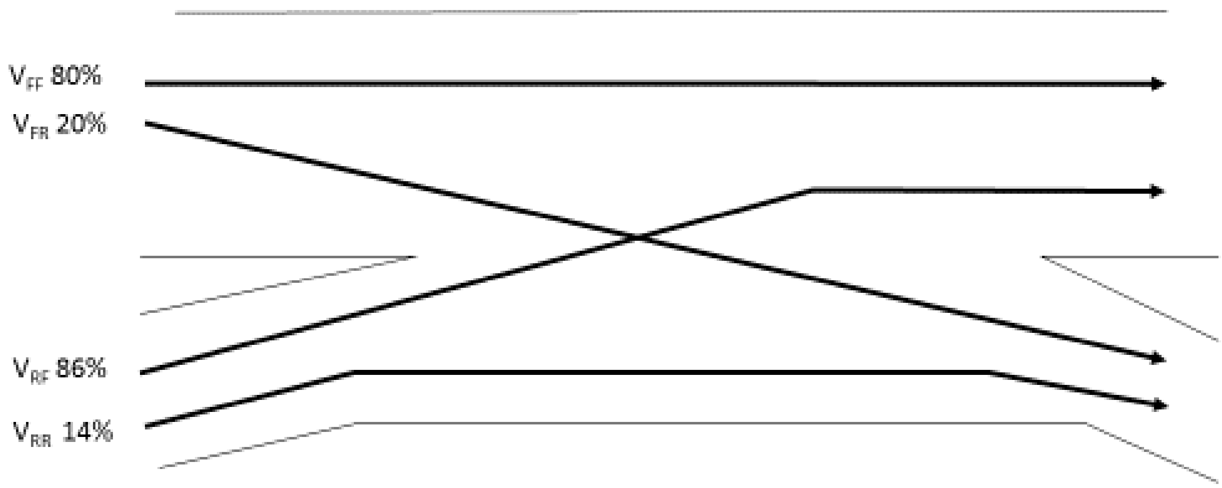


Figure 37. Traffic movements in the case study

A similar procedure was used for calculating vehicle composition. Vehicles were divided into passenger cars and heavy vehicles (trucks and buses). The results show that trucks and buses account for 10 percent of the total traffic on the freeway section during the peak hour. Figure 38 and Figure 39 show screenshots from the cameras used to determine the vehicle composition and the weaving percentages, respectively.

Figure 38. Screenshot of video monitoring for vehicle count and vehicle composition

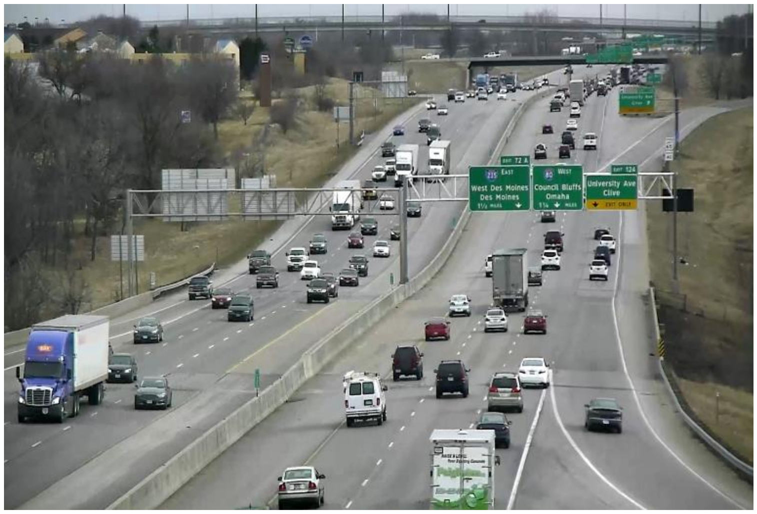


Figure 39. Screenshot of video monitoring for weaving percentage

Simulation Results with Default Parameters

The warm-up period for the network was set to twice as long as the free flow travel time. Ten replication runs were simulated for each scenario using random seeds from 55 to 100 with a five-unit increment. The average of these replications was used to compare the simulation results to the observed data. The driver behavior parameters were kept at the VISSIM default values. Figure 40 and Figure 41 compare the speed and flow density plots between the field observations and simulation outputs. The plots show that the VISSIM default parameters do not lead to an accurate simulation.

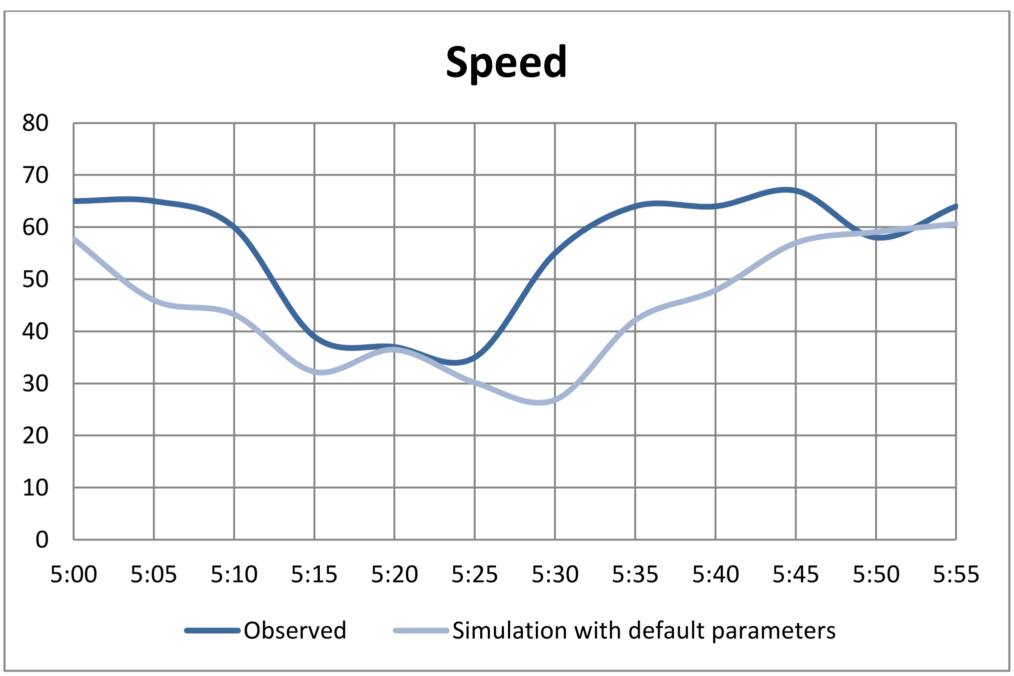


Figure 40. Speed comparison between simulator outputs and field data

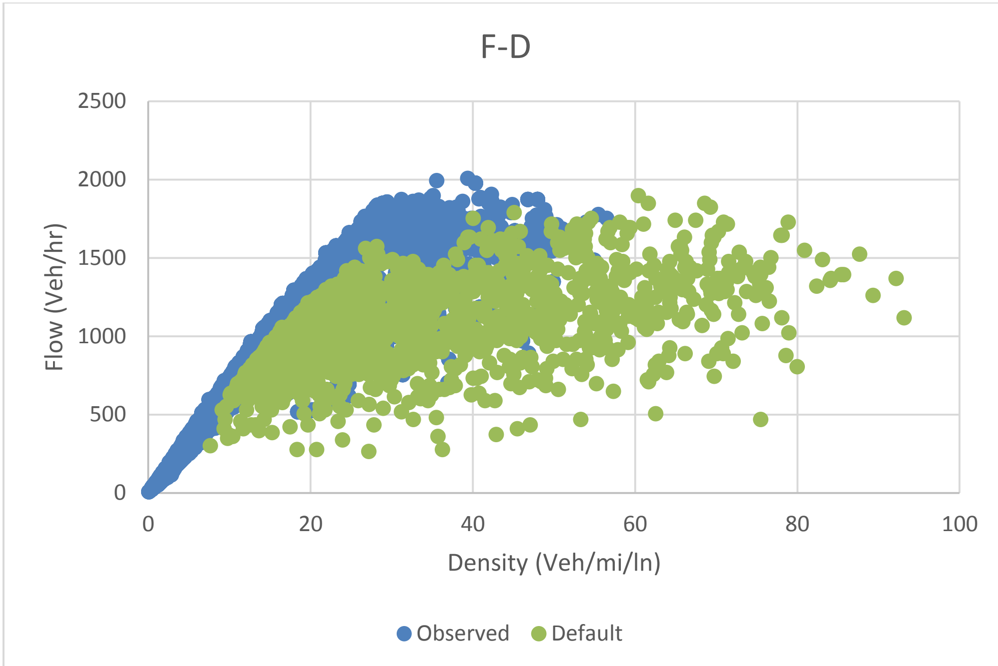


Figure 41. Flow density comparison

By observing the animated simulation in VISSIM, it was found that drivers' lane changing behavior was unrealistic. For instance, some simulated drivers tended to change lanes from the innermost lane to exit the freeway at the last minute, which caused traffic to stop in order to accommodate such maneuvers. As a result, VISSIM simulated heavier congestion than that seen in the field observations. To resolve this issue, the lane change distance on connectors was adjusted manually in the subsequent analysis.

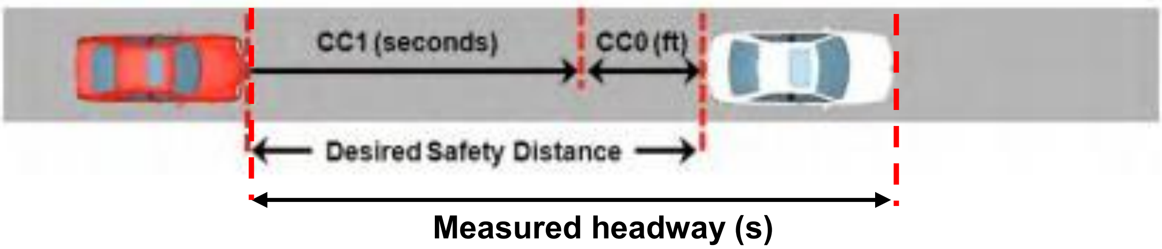
Sensitivity Analysis

Eleven driving behavior parameters were investigated in this report. The first 10 were the parameters in the Wiedemann (1999) model for urban (motorized) segments in VISSIM. The last parameter was the lane change distance on the connectors, which was shown to have a significant impact on the weaving segment. Each of the eleven parameters was evaluated at four values: low, medium, default, and high. The range of each parameter was obtained from a study by Lownes and Machemehl (2006a). The capacity of each stage was calculated and a t-test assuming unequal variances at a 95% confidence level was conducted to infer whether there is a significant difference between the mean capacities of the two groups.

VISSIM Driver Behavior Parameters

VISSIM uses a psycho-physical car following model based on Wiedemann (1999). According to the VISSIM manual (PTV Group 2011), the model parameters are defined as follows:

- CC0 (Standstill Distance) is the average desired standstill distance between two consecutive vehicles.
- CC1 (Headway) is the distance in seconds that a driver tends to keep at certain speeds. VISSIM's CC1 differs from the traditional definition of headway. The traditional headway definition (used throughout this report) is the time elapsing between the same points, usually the front bumper, on two consecutive vehicles passing a spot on a roadway. CC1 does not include the vehicle length and does not include the CC0 parameter (standstill distance). This is illustrated in Figure 42.



Adapted from Wu/Wikibooks contributors 2015

Figure 42. Difference between CC1 and headway

- CC2 (Following Variation) restricts the difference in distance between two vehicles. That is, for example, if this value is set to five, this value is added to the safety distance.
- CC3 (Threshold for Entering "Following") controls the deceleration procedure.
- CC4/CC5 (Negative/Positive Following Threshold) defines negative/positive speed differences during the following process.
- CC6 (Speed dependency of oscillation) is the effect of distance on speed oscillation during following.
- CC7 (Oscillation Acceleration) is the oscillation during acceleration.
- CC8 (Standstill Acceleration) is the desired acceleration after standstill.
- CC9 (Acceleration with 50 mph) is the desired acceleration at 50 miles per hour.
- Look-back distance is defined as the distance upstream of a ramp or section of roadway requiring some degree of maneuvering for which drivers begin to position themselves before the maneuver (Lownes and Machemehl 2006a).

Capacity Estimation

Capacity represents the maximum sustainable hourly flow rate at which vehicles can reasonably be expected to traverse a point or a uniform section of a lane or roadway during a given time period under prevailing roadway, environmental, traffic, and control conditions (TRB 2010). As mentioned in the literature review, several models have been developed to estimate the capacity. The models are classified into the following categories: headway models, fundamental diagram methods, and the extreme value approach.

The headway models, such as Branston's (1976) generalized queueing model and Buckley's (1968) semi-Poisson model, are used frequently. The headway models assume that driver-vehicle elements in any traffic stream can be categorized into constrained drivers (followers) and free drivers (leaders). For constrained drivers, the tracking headway distribution at the road capacity level is expected to be the same as that in any stable traffic stream. Therefore, the reciprocal of the mean time headway of constrained vehicles is an estimator of the capacity at a cross section of the road. However, several studies have pointed out that the headway models substantially overestimate observed road capacity (Hoogendoorn and Botma 1996, Botma et al. 1980).

Another method, known as the fundamental diagram method, which is based on the existence of a relationship between traffic volume, speed, and density, is a classic capacity estimation method (May 1990). This method does not require data downstream of a bottleneck. However, the results of the method depend heavily on the type of curve chosen for analysis. Furthermore, it is necessary to collect sufficient data over a broad range of flow rates to allow for reliable curve fitting.

Another widely utilized category of capacity estimation methods is the extreme value approach. One of the most widely used of these methods is the selected maxima method. The selected maxima method assumes that the road capacity is equal to the selected traffic flow maxima observed during the total observation period. After evaluating different alternatives, the selected maxima method was used to estimate the freeway capacity in the subsequent analysis. In particular, the maximum five-minute flow rate is used as the proxy of the road capacity.

Sensitivity Analysis Results

Using the default driving parameters, the simulated capacity was 1,896 veh/hr/ln. To examine the impact of different driving behavior parameters on the capacity of the weaving section, a set of sensitivity analyses were conducted based on the procedure recommended by Lownes and Machemehl (2006a). For each scenario, all 10 parameters except one were kept as the default values, and 10 simulations were run to determine capacity.

Table 38 shows the results of the one-sided two-sample t-tests assuming unequal variances to infer whether there is a significant difference (at the 95% confidence level) between the mean capacity of the tested scenario and the base scenario (with default parameters).

Table 38. Sensitivity analysis of driving behavior parameters

Parameter	Level	Value	Obtained capacity (veh/hr/ln)	t-statistic	df	Critical t-value	Significantly different from default parameter?
CC0	LOW	2.0	1824	0.6681	17	1.736907	N
CC0	DEF	4.9	1896				
CC0	MED	5	1812	1.33145	16	1.745884	N
CC0	HIGH	10	1872	0.0431	18	1.734064	N
CC1	LOW	0.5	2064	-3.00382	14	1.761310	Y
CC1	DEF	0.9	1896				
CC1	MED	1.0	1836	1.2186	18	1.734064	N
CC1	High	1.5	1836	3.02552	15	1.753050	Y
CC2	Low	5	1980	0.01541	10	1.812461	N
CC2	Med	10	1908	0.29677	17	1.739607	N
CC2	DEF	13.12	1896				
CC2	High	20	1872	1.435278	17	1.734064	N
CC3	Low	-4	1908	1.26046	16	1.745884	N
CC3	DEF	-8	1896				
CC3	Med	-10	1872	0.93863	18	1.734064	N
CC3	High	-15	1860	0.76028	16	1.745884	N
CC4	Low	0.1	1920	-0.72567	15		
CC4	DEF	0.35	1896				
CC4	MED	0.5	1884	-0.60123	18	1.734064	N
CC4	High	1.0	1884	-0.60123	18	1.734064	N
CC6	Low	2.0	1932	-0.21557	17	1.739607	N
CC6	Med	8.0	1884	-0.20767	18	1.734064	N
CC6	DEF	11.44	1896				
CC6	High	20.0	1836	0.4309	18	1.734064	N
CC7	LOW	0.5	1848	0.88736	18	1.734064	N
CC7	DEF	0.82	1896				
CC7	MED	1.0	1932	-0.94174	16	1.745884	N
CC7	High	1.5	1956	0.72242	16	1.745884	N
CC8	LOW	6.4	1848	0.50629	18	1.734064	N
CC8	MED	8.0	1956	-0.1272	15	1.753050	N
CC8	High	10.0	1848	1.10158	17	1.739607	N
CC8	DEF	11.48	1896				
CC9	LOW	2.10	1968	0.07814	18	1.734064	N
CC9	MED	4.5	1812	1.71305	16	1.745884	N
CC9	DEF	4.92	1896				
CC9	High	7.50	1932	0.3622	18	1.734064	N
Look-back	Low	300	1992	-0.035	10	1.815461	N
Look-back	Def	656.2	1896				
Look-back	High	1000	1752	4.22687	18	1.734064	Y

Headway (CC1) is the most significant parameter among the 10 in the Wiedemann 99 car following model. As expected, increasing and decreasing the value of the headway results in decreasing and increasing the capacity, respectively. Note that according to the Oregon DOT VISSIM calibration guideline the value for CC1 in weaving segments should not be less than 0.9 seconds (Oregon DOT 2011). Changing the values of CC3 through CC9 does not affect the capacity significantly. This result is consistent with the Oregon DOT guideline, which suggests keeping these values as defaults.

As shown in Figure 43 through Figure 51, changing all driver behavior parameters except for the headway does not have a significant effect on the dispersion of the data.

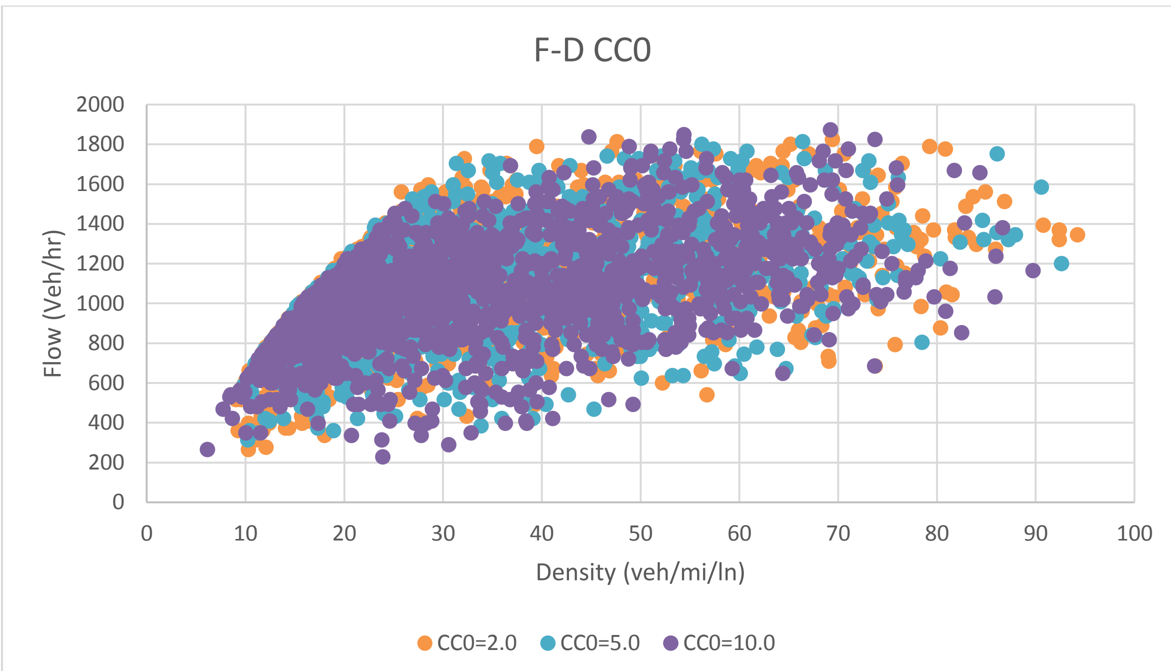


Figure 43. Flow density plot by varying standstill distance

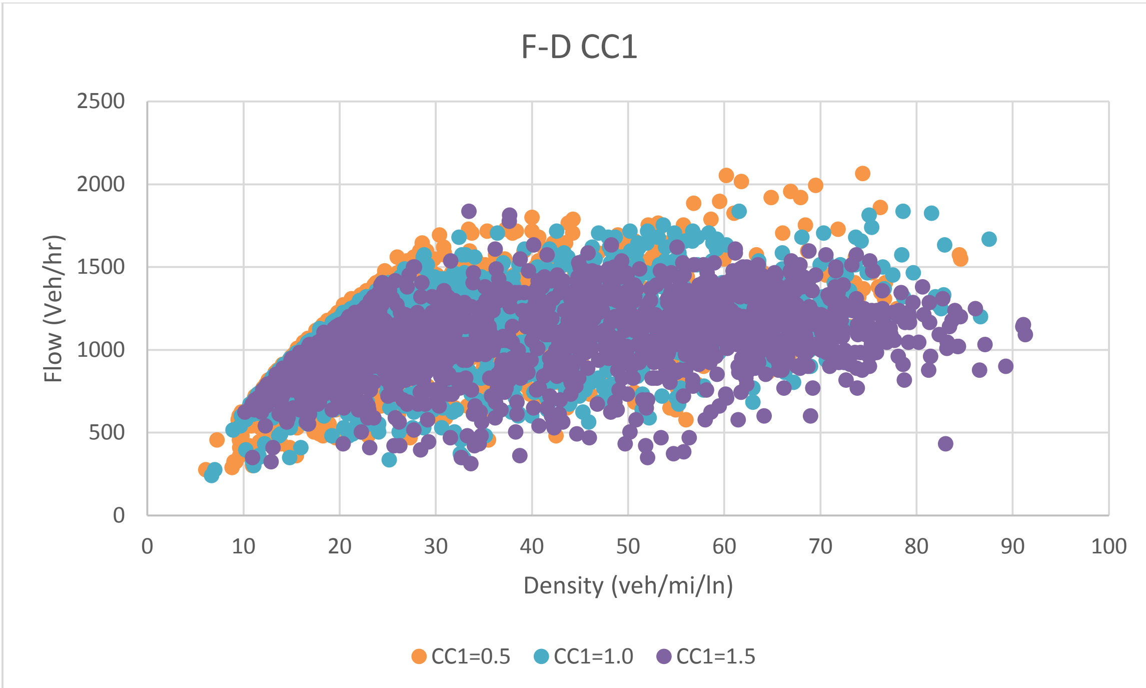


Figure 44. Flow density plot by varying headway

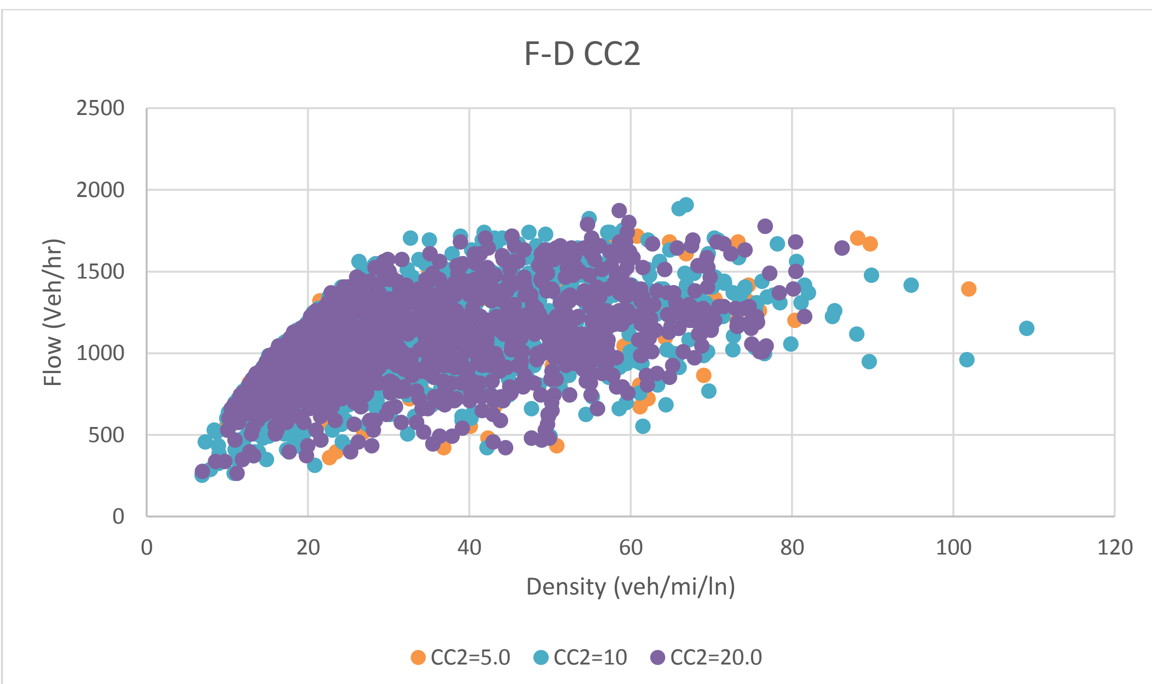


Figure 45. Flow density plot by varying following variation

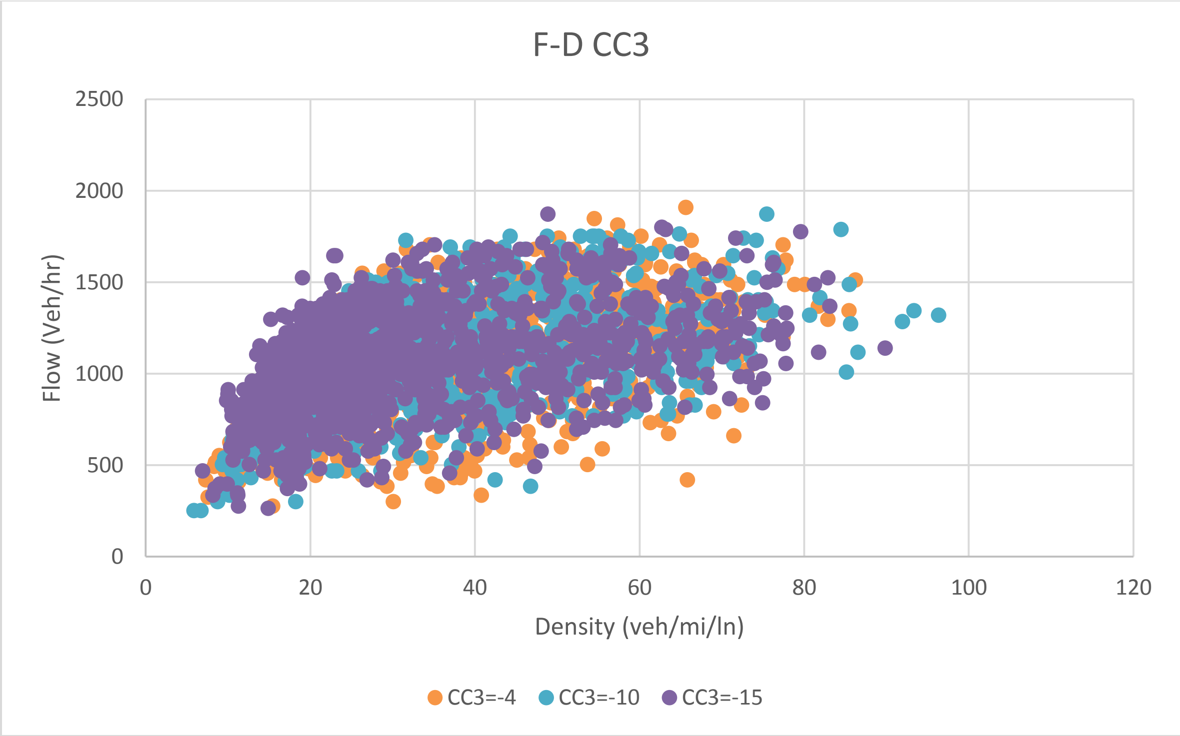


Figure 46. Flow density plot by varying threshold for entering "following"

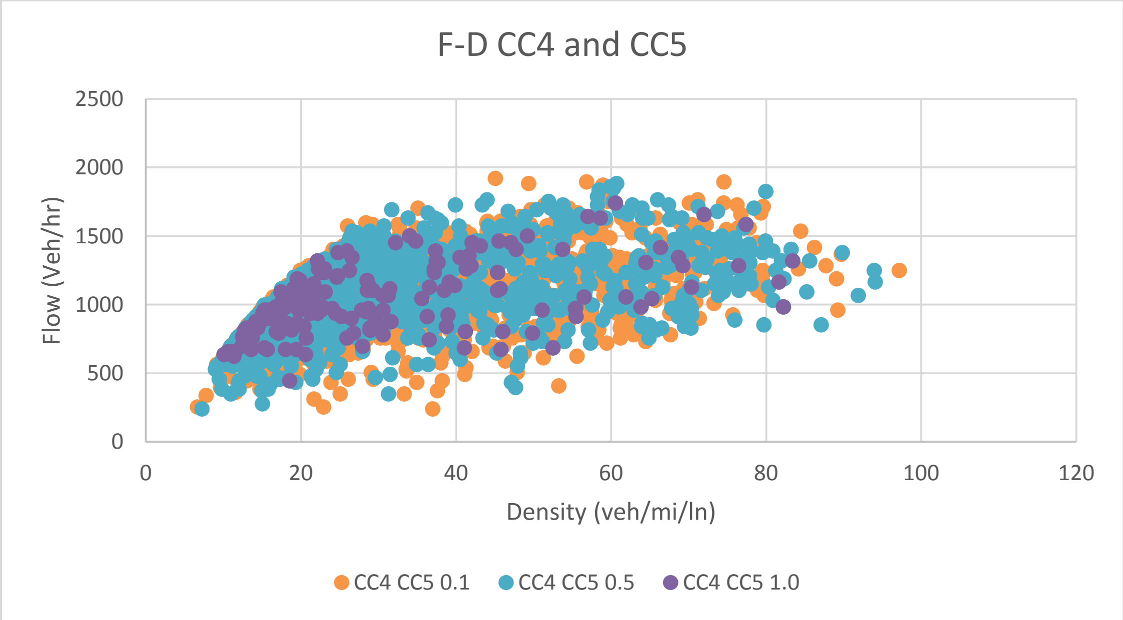


Figure 47. Flow density plot by varying following thresholds

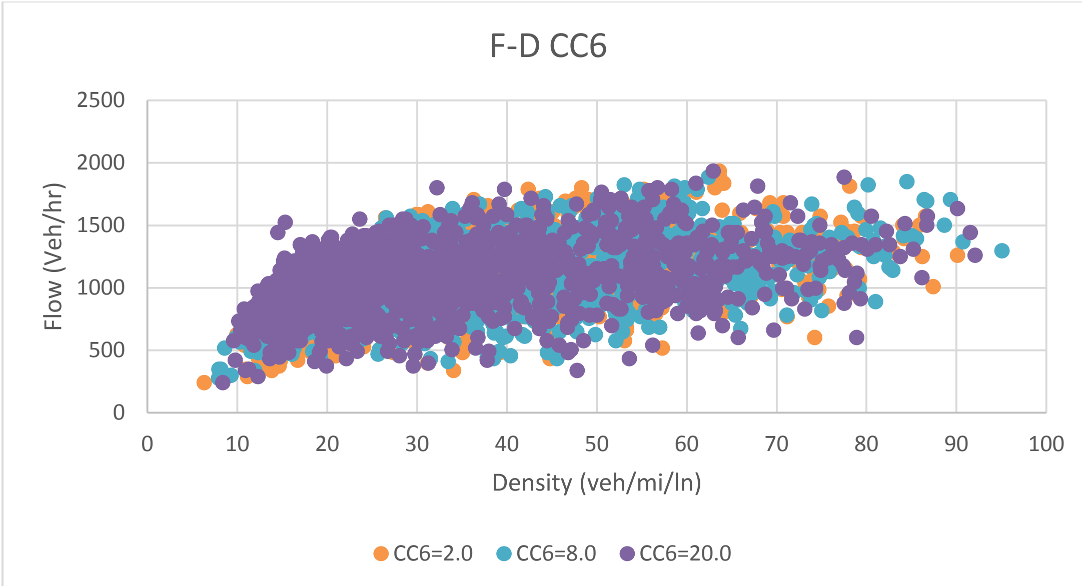


Figure 48. Flow density plot by varying speed dependency oscillation

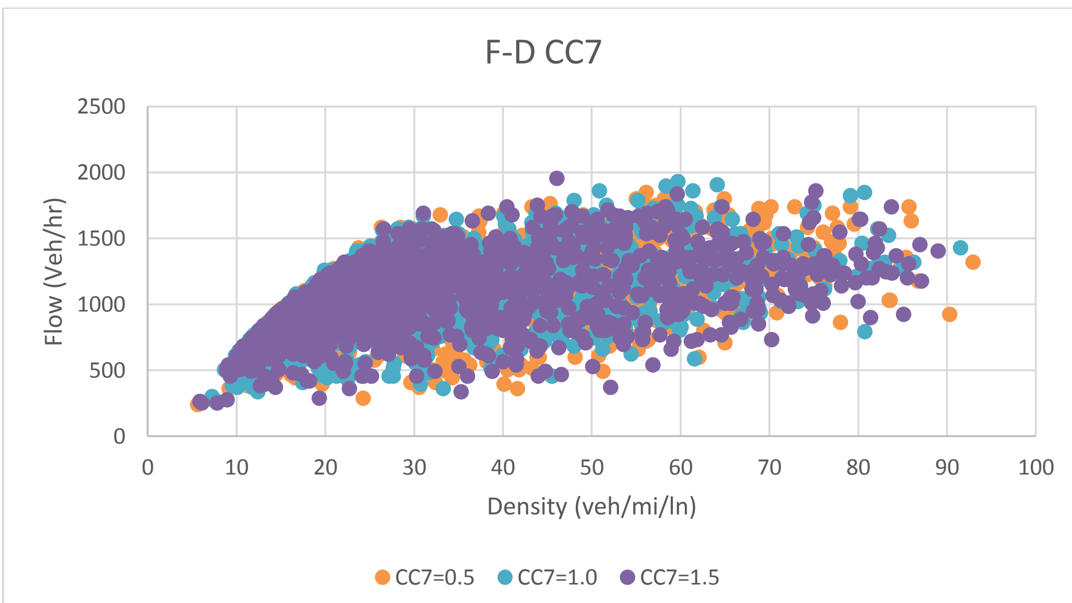


Figure 49. Flow density plot by varying oscillation acceleration

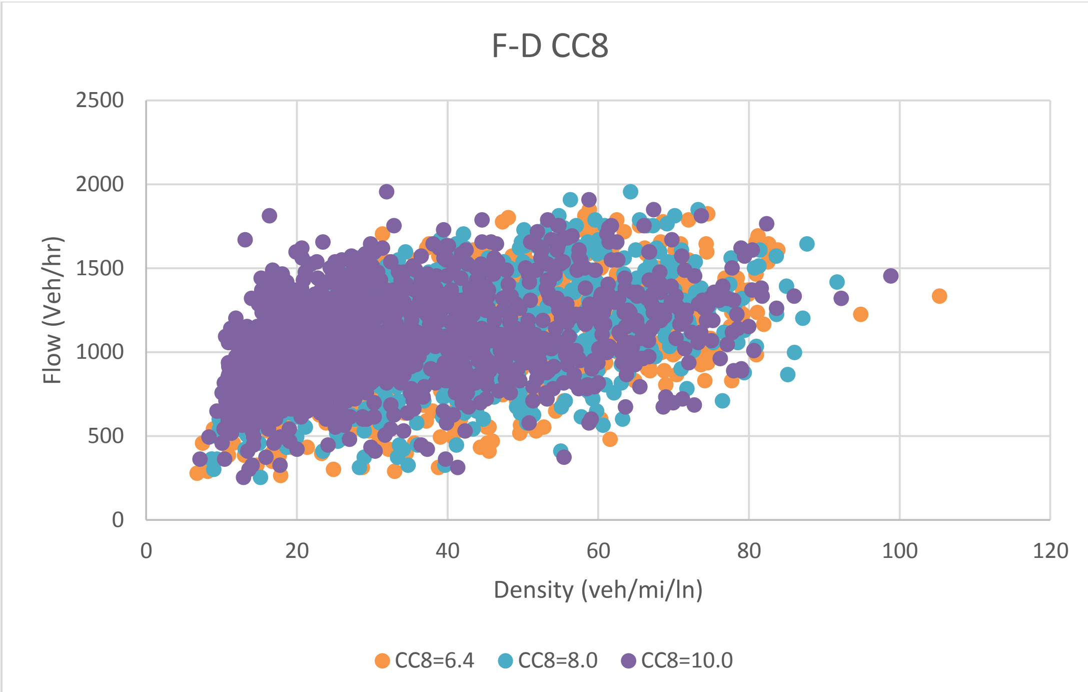


Figure 50. Flow density plot by varying standstill acceleration

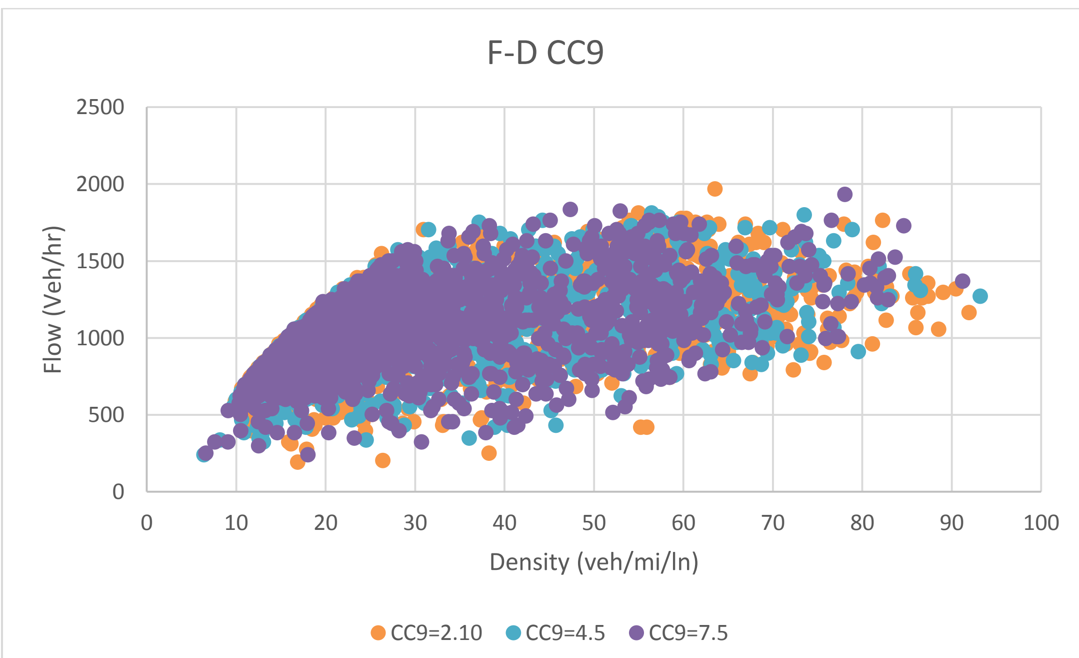


Figure 51. Flow density plot by varying acceleration with 50 mph

Calibration

The measured standstill distances (CC0) rangeed from approximately 8 to 12 feet throughout the state. For the purposes of calibration, a CC0 of 10 feet was selected. The measured time gaps range from 1.54 to 1.58 seconds, which were converted to CC1 values that ranged from 1.43 to 1.47 seconds. This conversion was accomplished by subtracting an assumed CC0 of 10 feet divided by an average speed of 60 mph. The middle value of 1.45 seconds was selected for the purposes of calibration. In addition, the lane change distance was set to 1,000 feet based on a trial and error approach. CC2 was calibrated to 20.31 based on FHWA Traffic Analysis Toolbox calibration recommendations. All other parameters were kept as defaults. A VISSIM simulation using these calibrated parameters resulted in a capacity of 1,801 veh/hr/ln. Figure 52 through Figure 54 show the speed, cumulative vehicle count, and flow density plot comparisons between the observed data, calibrated simulation data, and default simulation data.

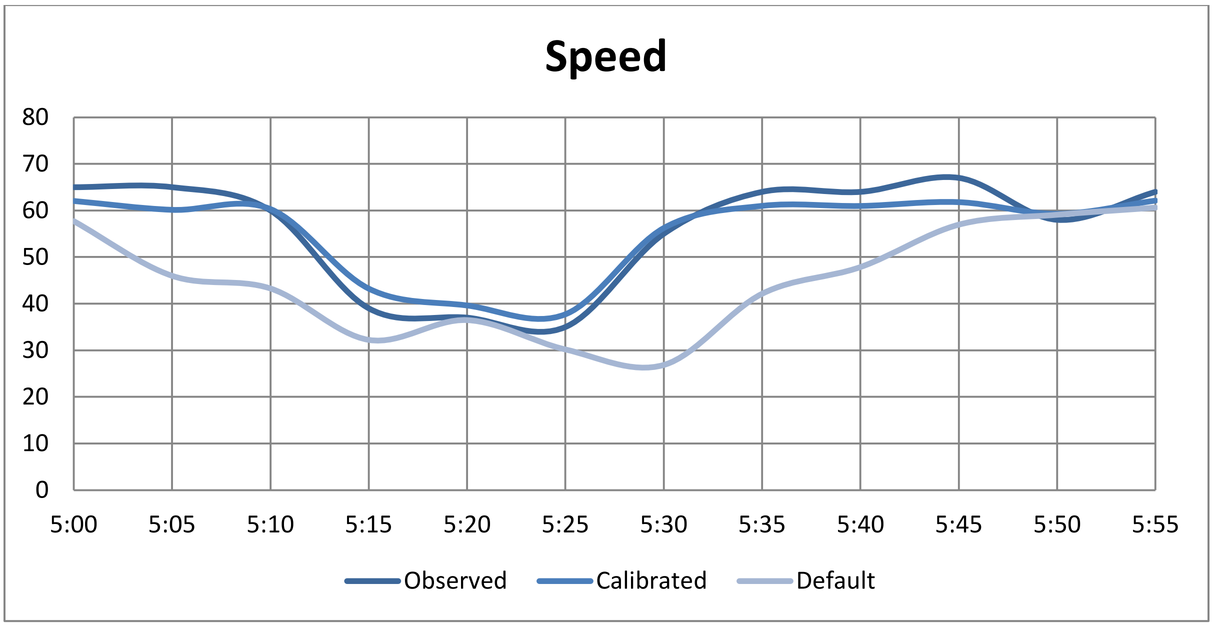


Figure 52. Speed comparison between the observed data, calibrated simulation data, and default simulation data

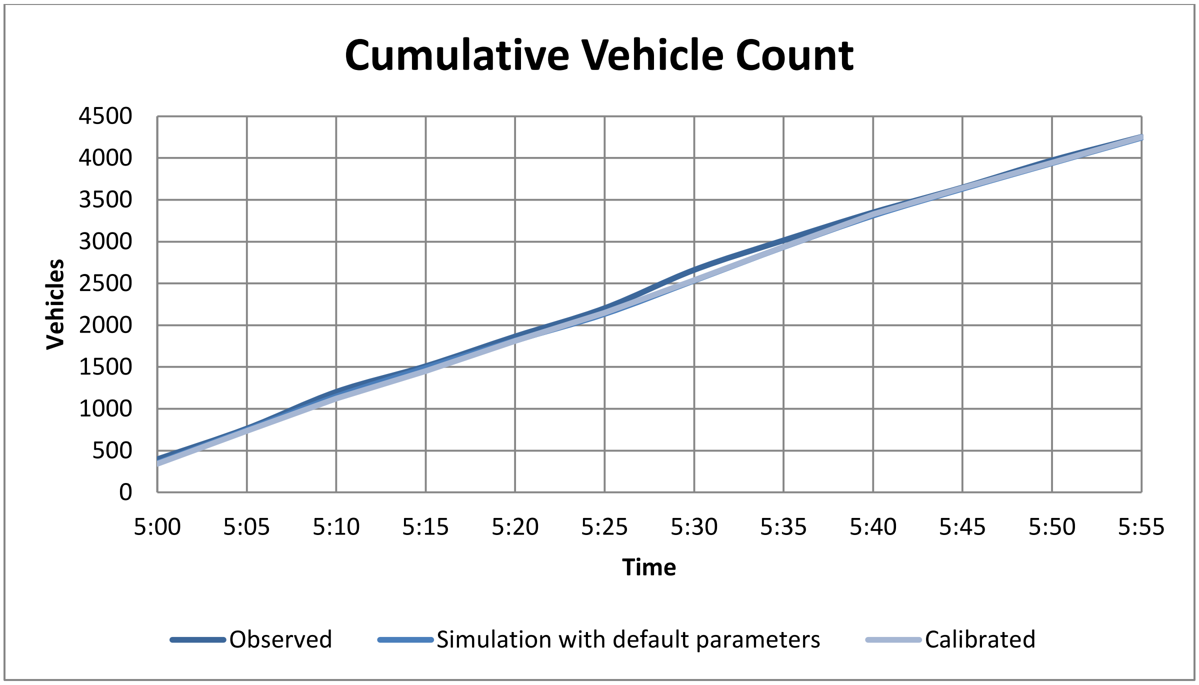


Figure 53. Cumulative vehicle count comparison between the observed data, calibrated simulation data, and default simulation data

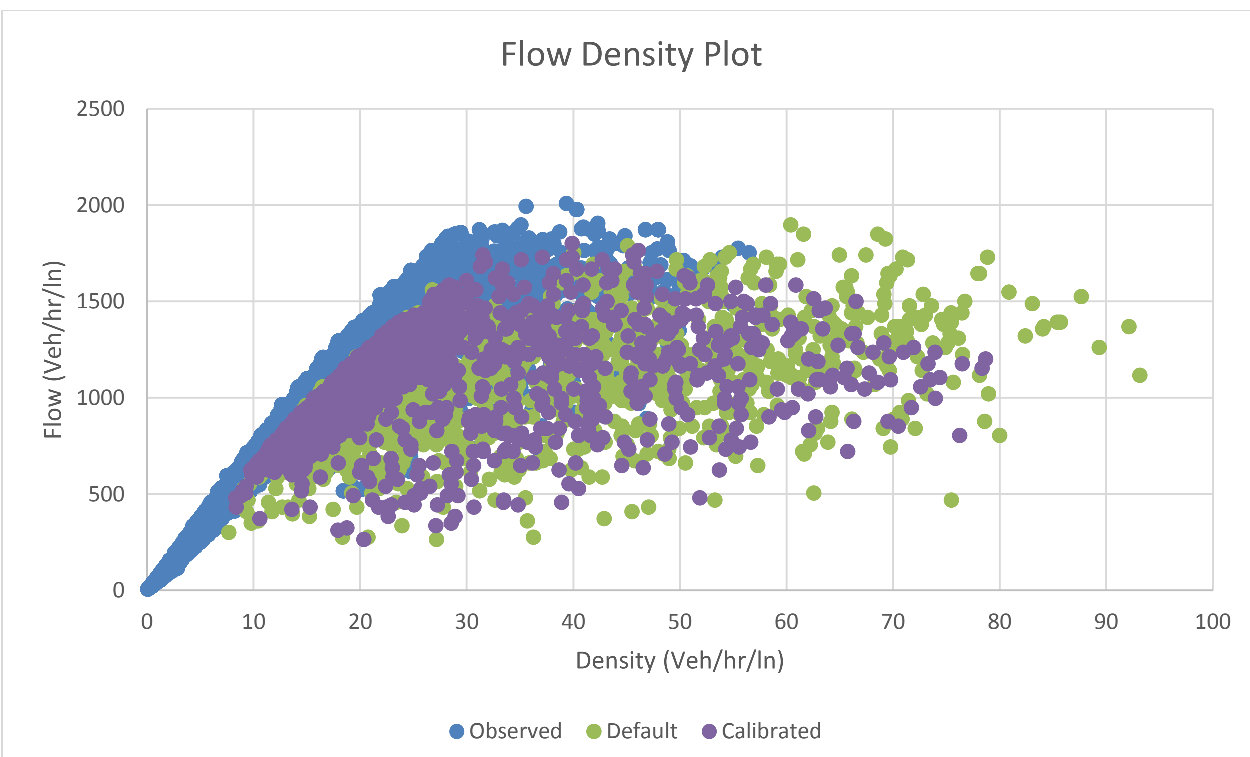


Figure 54. Flow density plot comparison between the observed data, calibrated simulation data, and default simulation data

One reliable measure to compare simulation inputs and outputs is the GEH formula (Oregon DOT 2011). The GEH formula is used to evaluate how closely volume input and output are matched.

$$GEH = \sqrt{\frac{2(m-c)^2}{m+c}} \quad \textbf{(10)}$$

Where:

m = output traffic volume from the simulation model (vph)
c = input traffic volume (vph)

For the simulation results with calibrated parameters, GEH is calculated as 3.841, which is in the acceptable range (see Table 39).

Table 39. GEH interpretation guide

GEH < 5.0	Acceptable fit
5.0 <= GEH <= 10.0	Caution: possible model error or bad data
GEH>10.0	Unacceptable

Source: Oregon DOT 2011

CONCLUSIONS

This project investigated basic calibration factors for the simulation of traffic conditions within an urban freeway merge/diverge environment. By collecting and analyzing urban freeway traffic data from multiple sources, specific Iowa-based calibration factors for use in VISSIM were provided. Because standstill distance and headway (or time gap) are two of the most important parameters for microsimulation calibration, a repeatable methodology for collecting data on these two parameters was presented. This collection process relies on manual processing of video to obtain standstill distances and individual vehicle data from radar detectors to obtain the headways/time gaps.

These data were then validated and analyzed using Microsoft Excel and the statistical software R. Standstill distance analysis consisted of a comparison of group means for different variables using t-tests and examining the distribution of the data. The headway/time gap analysis consisted of a filtering process to limit the data to mostly following vehicles, comparisons of summary statistics of those data sets within the same city and across different cities, and the fitting of statistical distributions to the data. The standstill distance was found to vary from city to city and between CC and CT, TC, and TT. Headways and time gaps tended to be consistent for the same vehicle pair types for the same driver population and for different driver populations. These findings have significant implications for future microsimulation models. They demonstrate the need to allow standstill distances and headways/time gaps to be treated as distributions. Additionally, headways/time gaps should be set separately for different vehicle classes.

A weaving section on southbound I-35 between Hickman Road and University Avenue was chosen for modeling and calibration purposes. A set of sensitivity analyses was performed for the 10 Wiedemann (1999) car following model parameters and look-back distance to determine the impact of driving behavior on the capacity of the simulation. The results showed that the headway and look-back distance variations are more sensitive to changes than other parameters. A set of new parameters based on calibration findings were then input into the model. Comparing the results of speed, vehicle count, and flow density plots between the observed data, simulation data with default parameters, and simulation data with calibrated parameters showed that the model needed to be calibrated to replicate real-world operations.

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APPENDIX A. IMPLEMENTATION PLAN FOR DATA COLLECTION AND VISSIM CALIBRATION

1. Data Collection

1.1. Aggregated Vehicle Data

Data to be collected:

- Peak hour vehicle volumes (shorter aggregation intervals preferred)
- Heavy vehicle percentage
- Average speeds (shorter aggregation intervals preferred)

Methods of data collection:

- Iowa DOT Wavetronix radar detector data accessed through TranSuite data portal
- Automatic traffic recorders (loop detectors) collected by the Office of Systems Planning

1.2. Individual Vehicle Data

Data to be collected:

- Vehicle arrival time
- Vehicle lane assignments
- Vehicle speeds
- Vehicle lengths
- Headways (calculated using the following equation)

$$Headway\_ij = t\_ij - t\_(i-1)j$$

Where:

$Headway_{ij}$ = the headway of the i^{th} vehicle in the j^{th} lane (in seconds)
t_{ij} = time of arrival of the i^{th} vehicle in the j^{th} lane
$t_{(i-1)j}$ = time of arrival of the $(i-1)^{th}$ vehicle in the j^{th} lane

- Time gaps (calculated using the following equation):

$$TimeGap_{ij} = Headway_{ij} - \frac{Length_{(i-1)j}}{Speed_{(i-1)j}}$$

Where:

TimeGap$_{ij}$ = the time gap of the ith vehicle in the jth lane (in seconds)
Length$_{(i-1)j}$ = the length of the (i-1)th vehicle in the jth lane (in feet)
Speed$_{(i-1)j}$ = the speed of the (i-1)th vehicle in the jth lane (in feet per second)

Methods of data collection:

- Iowa DOT Wavetronix radar detectors accessed using a Click301 device
- Set up a mobile/temporary Wavetronix radar detector at the desired location

2. VISSIM Parameter Calibration

2.1. CC0 (Standstill Distance)

Option 1: Collect location-specific data:

- Collect videos of stop-and-go traffic in the area
- Use Photoshop's "vanishing point filter" to measure the distance between stopped vehicles
- Collect at least 100 observations from at least 3 separate incidents if possible
- Use the average of the observations, excluding outliers due to drivers not paying attention, waiting to change lanes, etc.

Option 2: Select the mean standstill distance for the city closest to the city of the simulation location from the table below.

City	Count	No. of Incidents	No. of Photos	Mean (ft)	Median (ft)	Std. Dev. (ft)
Des Moines	693	25	153	***8.59***	7.95	4.37
Quad Cities	277	8	74	***10.19***	9.51	4.36
Sioux City	126	6	33	***12.53***	12.00	4.81

2.2. CC1 (Preferred Headway)

Option 1: Collect individual vehicle data

- Filter the data to vehicles that arrived during a 15 minute flow rate of greater than 1000 veh/hr with a headway of 4 seconds or less
- Calculate the CC1 parameter of each vehicle using the following equation:

$$CC1_i = TimeGap_i - \frac{CC0}{Speed_i}$$

Where:

$CC1_i$= VISSIM CC1 parameter (headway) of vehicle i, in seconds
$TimeGap_i$ = the time gap of vehicle i, in seconds
$CC0$ = VISSIM CC0 parameter (standstill distance), in feet
$Speed_i$ = the speed of vehicle i, in feet per second

- Calculate the mean of CC1 values of all the filtered vehicles and use it as the input for the CC1 parameter.

Option 2: Use aggregated vehicle data

- Calculate $CC1$ based on the fleet mix and the average speed using the following equation (only applicable to urban freeways):

$$CC1 = (P_C \times P_C)1.55 + (P_C \times P_T)2.15 + (P_C \times P_T)1.15 + (P_T \times P_T)1.60 - \frac{CC0}{Speed_{avg}}$$

Where:

P_C = the proportion of cars in the traffic stream
P_T = the proportion of trucks in the traffic stream

2.3. Desired Speed Distribution

Collect aggregated flow rate and speed data. Select free flow speeds when the 15-minute flow rate is less than 1,000 veh/hr/ln. Plot the cumulative speed distribution curve, which is the input used in VISSIM for desired speed.

2.4. CC2 (Following Variation) and Look-Back Distance

Manually adjust *CC2* and *look-back distance* to match the simulated and observed flow, speed, and density.

It is recommended to keep *CC3-CC9* as defaults.

2.5. Calculate GEH

After running the simulation using the calibrated parameters, calculate the GEH statistics using the following formula:

$$GEH = \sqrt{\frac{2(m-c)^2}{m+c}}$$

Where:

m = output traffic volume from the simulation model (vph)
c = input traffic volume (vph)

Determine if an acceptable fit is achieved by referencing to the following table, which provides the GEH interpretation guide (Oregon DOT 2011).

GEH < 5.0	Acceptable fit
5.0 <= GEH <= 10.0	Caution: possible model error or bad data
GEH > 10.0	Unacceptable

Source: Oregon DOT 2011