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Enriched Sensor Data for Enhanced Bridge Weigh-in-Motion (eBWIM) Applications

Final Report

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Bridge weigh-in-motion (BWIM) systems, which measure bridge deformation under live loading to estimate weights of passing vehicles, have been in development since Moses first introduced the concept in 1979. Despite advances made since its introduction, important limitations for BWIM systems still exist. A feasibility study was performed to determine if some of the limitations—including poor accuracy with multiple vehicle passage, either in tandem or side-by-side; and inability to accurately capture the passage of a vehicle moving at variable speeds—could be overcome by enriching the dataset available to the BWIM system. Non-contact measurements collected in real time on the topside of the bridge can enrich the dataset, and by taking advantage of these measurements a more accurate and effective enriched bridge weigh-in-motion (eBWIM) system can be developed. Several sensing technologies were reviewed including fiber Bragg gratings, MEMS accelerometers, microwave radar sensors, magnetic sensors, active infrared detectors, and video image vehicle detection systems. Preliminary results indicated that there was no clear candidate for a fully mature sensing system that would satisfy all the criteria in this study. However, microwave radar sensors have a reasonably low cost, are the least intrusive, and perform better in all weather conditions compared to the other sensors. A testbed using radar sensors is proposed to investigate the accuracy of the eBWIM system. If the desired accuracy of the eBWIM system can be achieved, its implementations should prove to be invaluable for enforcing bridge weight limits, studying truck traffic patterns, and managing bridge inventories.

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ENRICHED SENSOR DATA FOR ENHANCED BRIDGE WEIGH-IN-MOTION (EBWIM) APPLICATIONS

FINAL REPORT

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EXECUTIVE SUMMARY

Bridge weigh-in-motion (BWIM) systems, which measure bridge deformation under live loading to estimate weights of passing vehicles, have been in development since Moses first introduced the concept in 1979. The system includes a sensing component to measure strain and a computational component that filters out bridge dynamic response. The BWIM concept uses the entire bridge as a weight transducer and is inherently advantageous because of its non-destructive implementation if contact devices are not used on the bridge topside. The BWIM system can: 1) be used to track vehicle loads to enforce bridge limits for overweight vehicles, 2) assist in the determination of bridge capacity for permit loading; 3) enhance the knowledge of truck movement for better scheduling of bridge monitoring and replacement; and 4) provide information for the formulation of traffic spectra. Yet, despite all of the advances made since its introduction, there are some important limitations for BWIM systems. Systems that rely solely on strain measurements: 1) exhibit poor accuracy with multiple vehicle passage, either in tandem or side-by-side; 2) cannot accurately capture the passage of a vehicle moving at variable speeds; 3) are incapable of isolating bridge dynamic response, due to bridge vibration from the static response due to vehicle weight; and 4) exhibit decreasing effectiveness with increasing bridge span length. Additionally, BWIM systems that include axle detectors require lane closures and traffic disruptions to install the axle detectors and suffer from limited detector durability in areas of heavy traffic.

A feasibility study sponsored by the Center for Transportation Studies is performed to see if some of the above limitations can be overcome by enriching the dataset available to the BWIM system. Non-contact measurements collected in real time on the topside of the bridge can enrich the dataset, and by taking advantage of these measurements, a more accurate and effective enriched bridge weigh-in-motion (eBWIM) system can be developed. Several sensing technologies are reviewed including: fiber Bragg gratings, vision-based methods using roadside cameras, micro-electromechanical system (MEMS) accelerometers, microwave radar sensors, magnetic sensors, active infrared detectors, and video image vehicle detection systems. A matrix of twelve criteria for evaluating sensor systems is formulated and used to compare the potential of the sensing technologies considered in the study. Preliminary results indicate that there is no clear candidate for a fully mature sensing system that would satisfy all the criteria in this study. However, microwave radar sensors have a reasonably low cost, are the least intrusive, and perform better in all weather conditions compared to other sensors. A testbed using radar sensors is proposed to investigate the accuracy of the proposed eBWIM system. If the lower-than-desired accuracy of microwave radar sensors is overcome, BWIM implementations using this sensor system should prove to be invaluable for enforcing bridge weight limits, studying truck traffic patterns, and managing bridge inventories.

CHAPTER 1: INTRODUCTION

1.1 BACKGROUND

A bridge weigh-in-motion (BWIM) system measures the deformation of a bridge under live loading to estimate the characteristics of passing traffic loads. In the 1970s, Moses (1979) first introduced the concept of BWIM. The system consists of mainly two elements: one to measure strain and the other to detect axles on the bridge (see Figure 1.1). Moses' original method uses a weight prediction algorithm that filters out the dynamic component of bridge response and computes equivalent static axle weights by implementing least-square error minimization. The Moses algorithm assumes that the change in strain caused by a load is proportional to the bending moment caused by the load. An existing bridge is instrumented with a series of strain sensors installed on the bridge soffit. The system uses the entire bridge as a weighing device and analysis of the bridge provides the gross weight of the vehicle passing over the bridge. Axle detectors, such as tape switches or pneumatic tubes were generally used for identification of vehicle speed and axle spacing. Installation of these axle detectors requires lane closure or traffic disruption. Moreover, the durability of the detectors is also compromised in the areas of heavy traffic. Since the initial and revolutionary concept was proposed, the technology for BWIM has evolved beyond the use of pneumatic tubes and tape switches to exclusive reliance on the use of the measured bridge response to traffic loading for sensing the passage of vehicles, as well as their weight.

1.2 BWIM ADVANTAGES AND LIMITATIONS

There are several advantages to using a BWIM system: 1) it can track vehicle loads which can be used to enforce bridge limits for overweight vehicles; 2) it facilitates the load rating of older bridges and provides better estimation of bridge capacity for permit loading; 3) it enhances the knowledge of truck movement in a region and thus enables better scheduling of bridge monitoring and replacement; and 4) it provides information that can be used for the formation of traffic spectra (Snyder, Likins & Moses, 1982). Despite all the advances made in the years since its introduction, there are a few limitations for the BWIM systems that have prevented them from being used more broadly. Because of these limitations, many state departments of transportation (DOTs) have refrained from using them. For example, in the US, there is only one commercial BWIM system in use, in the state of Alabama.

Limitations for conventional BWIM systems that rely solely on strain measurements are: 1) poor accuracy with multiple vehicle passage on a bridge, either in tandem or side-by-side (O'Brien, Rowley, Gonzalez, & Green, 2009) ; 2) inability to accurately capture the variable speeds of the vehicles as they cross the bridge (Rowley, O'Brien, Gonzalez, & Znidaric, 2009); 3) lack of capability of BWIM data processing methods to currently isolate bridge dynamic response, due to bridge vibration from the static response due to vehicle weight and thus resulting in poor accuracy (O'Brien, Dempsey, Znidaric, & Baumgartner, 1999 as cited in O'Brien et al., 2009) ; and 4) decreasing BWIM effectiveness with increasing bridge span length (Helmi, Bakht, & Mufti, 2014 as cited in Lydon, Taylor, Robinson, Mufti, & O'Brien, 2015). The last two limitations are being investigated using schemes that incorporate a) bridge dynamic response (O'Brien et al., 2009; Rowley et al., 2009; Zhao, Uddin & O'Brien, 2012) and b) more accurate techniques for processing the data (Chatterjee, 2006 as cited in Lydon et al., 2015; Helmi et al., 2014 as cited in Lydon et al., 2015; Zhao et al., 2012). However, little headway has been made in addressing the first two limitations. Additionally, the limitations for BWIM systems that include axle detectors were mentioned previously: 1) lane closures and traffic disruptions are required to install the axle detectors; and 2) the detectors may have limited durability in areas of heavy traffic.

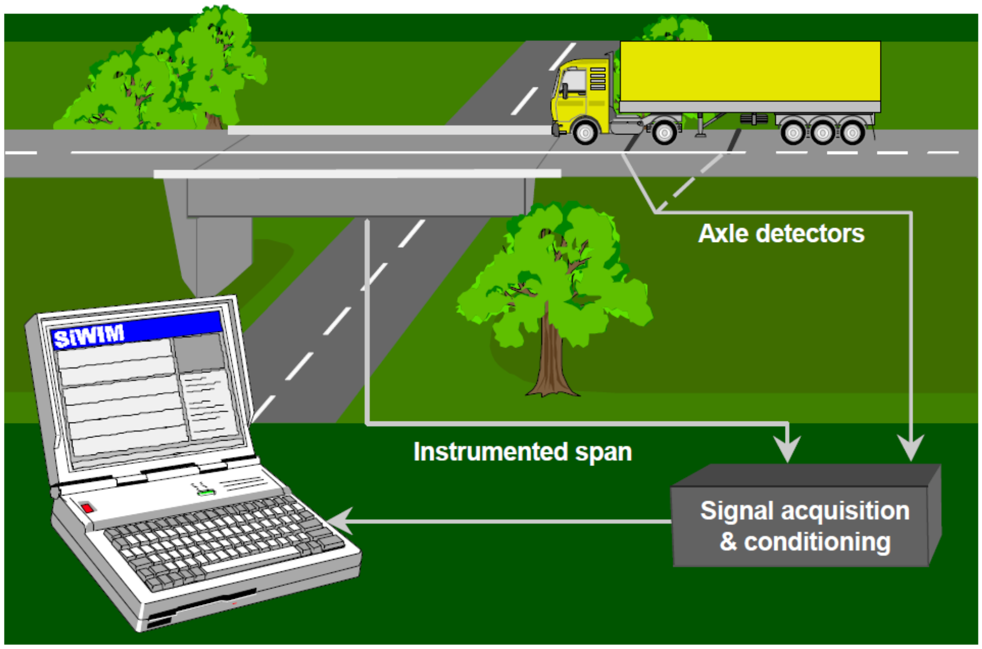

Figure 1.1: Typical BWIM system
(Source: O'Brien, Znidaric, Baumgartner, Gonzalez, & McNulty, 2001)

1.3 TRAFFIC SENSOR TECHNOLOGIES

According to the Traffic Handbook (2006), "A traffic sensor is a device that indicates the presence or passage of vehicles and provides data or information that supports traffic management applications such as signal control, freeway mainline and ramp control, incident detection, and gathering of vehicle volume and classification data to meet state and federal reporting requirements" (Klein, Mills, & Gibson, 2006). There are various sensors available that are either in use or can be used for obtaining traffic data. These sensors differ in working principle and in how they retrieve traffic information on vehicle locations, vehicle dimensions, number of axles, number of vehicles, instantaneous vehicle speed, and so on. Generally, the sensors can be classified into two broad categories based on their intrusive nature: intrusive (also known as in-roadway sensors) and non-intrusive (also known as over-roadway sensors). Inductive loops, tape switches, and magnetometers are intrusive and their installations require pavement cuts or borings. They are placed either underneath a paved roadway or bridge structure or mounted on the road surface. The commercially available, popular, and non-intrusive sensing technologies include: microwave radar sensors; active infrared (laser radar) sensors; passive infrared sensors; ultrasonic sensors; passive acoustic sensors; and video image processors, which are mounted either adjacent to the roadway or on the mast arms over the roadway. The intrusive sensing technologies include: Inductive loop and magnetic sensors. Although the inductive-loop detector is the most widely used sensor in modern traffic control systems today, because of problems with installation and maintenance of intrusive detection systems, non-intrusive detection systems are becoming more prominent.

1.4 TRAFFIC SENSOR ADVANTAGES AND LIMITATIONS

Traffic sensors have been in use since the 1920s in the US. Since then, traffic sensors have proven to be a highly effective and instrumental tool in fields like traffic signal control, traffic planning and design, and pavement and bridge design. There are numerous advantages to using a traffic sensor; however, the advantages and the ability of the sensors relevant to the present paper are: identification and classification of vehicles, and computation of instantaneous speed. Moreover, the sensors can be simultaneously used for obtaining data for other purposes like traffic count, incident detection, thus sharing and reducing the cost of the systems as compared to using them solely for classification and speed computation.

The traffic sensors' limitations apposite to the current study, i.e., ability to detect and identify vehicle type and speed are: 1) placement and orientation; 2) poor inclement weather performance (performance varies based on different sensing technology); 3) high cost (initial and life-cycle cost) of sensors; and 4) poor performance in different lighting condition (poor performance due to shadow effect). Regarding the first item, the mounting location should provide an unobstructed view of vehicles for optimum performance. Some structures (e.g. bridges) might have limitations concerning mounting location (side-fire and overhead) and mounting height. The intrusive sensors might not be approved by some bridge owners because of issues with their intrusive nature. The mentioned limitations can prohibit their use for the present study purpose. Thus, the sensor type, mounting height and location, vehicle mix, road configuration, performance accuracy in inclement weather and lighting condition, and cost are needed to be evaluated to choose a sensor for the intended eBWIM application.

1.5 MARRIAGE OF BWIM AND TRAFFIC SENSOR—THE PROMISE OF DATA ENRICHMENT

The greatest opportunity for BWIM systems to overcome some of the limitations outlined in section 1.2, especially issues of multiple vehicle passage and variable vehicle speed, is predicated on enriching the dataset available to the BWIM system. It is likely that little useful new information can be gained from further enhancements in the analysis of bridge strains measured underneath the bridge. However, measurements collected in real time on the topside of the bridge can enrich the BWIM dataset by providing useful new information, including vehicle location, vehicle dimension, number of axles, number of vehicles, and instantaneous vehicle speed. The topside measurements could be in the form of processed video images or data collected using any of the currently available traffic sensors such as inductive loop detectors, magnetic sensors, microwave radar sensors, infrared sensors, and laser sensors. Of these, however, processed video images are of special interest because of their ubiquitous nature in modern roadways.

A BWIM system can currently provide reliable gross vehicle weight (GVW) of the vehicle on the bridge using data from appropriate strain sensor(s) installed under the bridge soffit processed using an appropriate algorithm, but the accuracy of the contemporary BWIM to determine the number of axles and individual axle weight is low. This effect worsens when there is more than one vehicle present on the bridge either in tandem or side-by-side. Using traffic sensors to compute the size of vehicle (or number of axles) and identify all of the different kinds (size) of vehicles present on the bridge can mitigate the limitation of a BWIM system in determining accurate individual axle weight. Traffic sensors can provide very accurate instant speed of the vehicles, which will assist in improving the performance of the conventional BWIM system. The proposed idea of combining the data from the conventional BWIM and the traffic sensor is named the enhanced bridge weigh-in-motion (eBWIM). Refer to Figure 1.2 for the components of the eBWIM system.

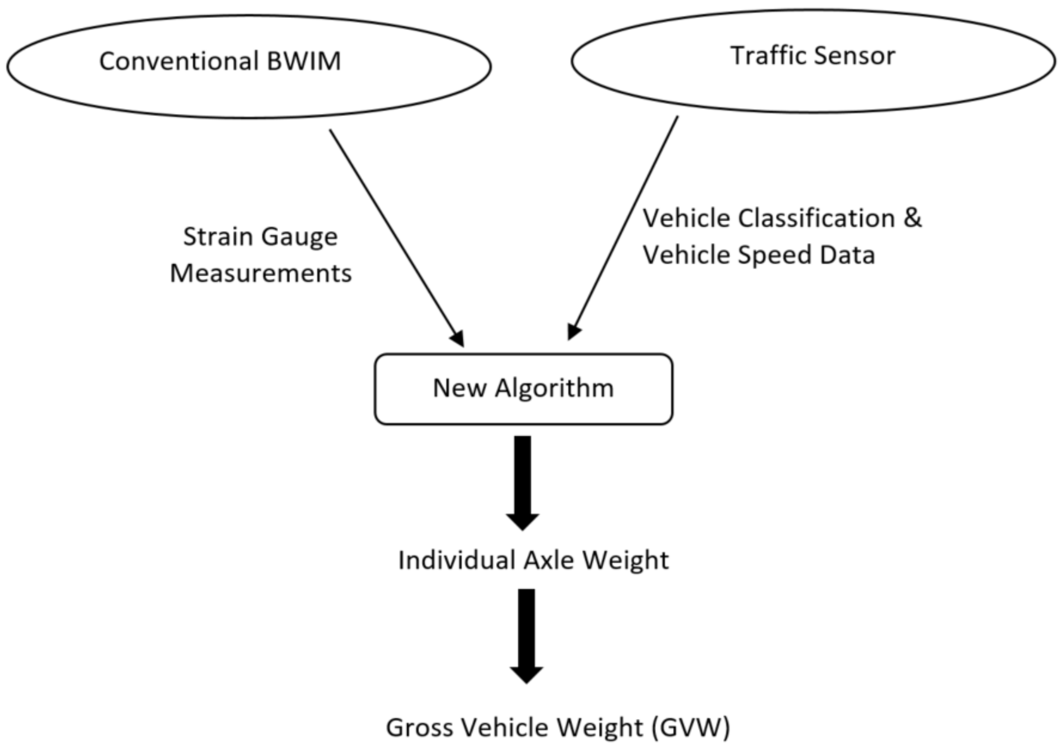

Figure 1.2: eBWIM system components chart diagram

eBWIM may remedy some of the traffic sensor limitations. For example, some traffic sensors have poor performance in inclement weather like heavy rain or snowfall. During such weather conditions, the traffic sensors are likely to miss vehicle presence on the bridge. The strain sensor of the BWIM system, which is unlikely to be affected by inclement weather, will be able to identify the presence of vehicles, and this information can be used to check the performance of the traffic sensor. Therefore, BWIM certainly can verify any instance when the traffic sensor misses the vehicle presence and when the data from the traffic sensor cannot be trusted.

CHAPTER 2: OBJECTIVES

In this project, a feasibility study is performed to see if the limitations outlined above, particularly the 'multiple vehicle passage' and the 'variable vehicle speed' issues could be overcome by enriching the dataset available to modern BWIM systems. The present study reviews the literature on the performance of BWIM systems and the literature on vehicle classification performance of traffic sensors to see if the vehicle identification relevant measurements from traffic sensors can enable the development of a more accurate and effective bridge weigh-in-motion system called enriched bridge weigh-in-motion (eBWIM) system.

In Chapters 3 and 4, a review of some of the improvements in the BWIM algorithm and the BWIM sensing technologies that have been proposed and tested in the years ensuing Moses' first introduction of the BWIM concept are presented. A review of various traffic sensors capable of vehicle identification is presented in Chapter 5. Chapter 6 gives an overview of the characteristics of traffic sensors. Based on the information presented in Chapter 5, a qualitative assessment of traffic sensors is presented in Chapter 7. Chapter 8 briefly discusses the need for new algorithms for eBWIM, and a description of a proposed testbed plan is presented in Chapter 9. Finally, Chapter 10 concludes the report.

CHAPTER 3: IMPROVEMENTS IN THE ALGORITHM

The Moses algorithm is designed to work when there is only one truck on the bridge at any point in time. The BWIM system using the Moses algorithm generally tends to be more accurate in estimating gross vehicle weights than individual axle weights (O'Brien et al., 2009). This happens because it is difficult to distinguish the contribution of each axle from a long continuous strain record owing to the whole truck weight (O'Brien et al., 2009). The final system of equations, obtained from the Moses algorithm, used to compute axle weight becomes ill-conditioned resulting in poor axle weight estimation (O'Brien et al., 2009). Also, bridge and vehicle dynamics is the main source of error for Moses' algorithm (O'Brien, Dempsey, Znidaric, & Baumgartner, 1999 as cited in O'Brien et al., 2009). Extensive research has been carried out to improve the original Moses algorithm in terms of vehicle weight estimation accuracy and to overcome the unsuitability in a multiple-vehicle presence situation. Some of the improvements in Moses' original algorithm proposed and tested in recent years, their performance and their application limitations are discussed below.

In 2009, Moving Force Identification (MFI) theory was used to dynamically model the bridge and Tikhonov regularization combined with the L-curve for the selection of the optimal regularization parameter was applied to reduce the error and calculate the static axle weights from the strain measurements (O'Brien et al., 2009; Rowley et al., 2009). The authors observed that MFI has helped reduce errors by allowing for the dynamic vibration associated with BWIM, and Tikhonov regularization was proven to be valuable in axle detection. During field trials, it was found that this method, when applied to filter the results from a BWIM acquisition system, could significantly increase the accuracy of identified axle weight, but the convergence of regularized solution becomes slower with more noticeable vehicle dynamics (Rowley et al., 2009). Although MFI methods have the potential to be very accurate, this method requires expensive computation as compared to static BWIM algorithms, and it requires a detailed finite element (FE) model of the bridge. Besides, most of the current MFI theories are based on simple bridge models (Yu, Cai, & Deng, 2016). Due to these drawbacks, MFI is not implemented in modern commercial BWIM (Yu et al., 2016).

Another technique, Wavelet Theory, has been used in conjunction with the outcomes of strain sensors installed on the underside of a bridge to improve axle detection (Chatterjee, 2006 as cited in Lydon et al., 2015). The strain results generated from an in-service bridge in Slovenia were put through a series of wavelet approaches. Each approach scaled the results differently and determined different peaks. The reverse biorthogonal wavelet gave distinct peaks representing axles. Typically, the wavelet theory is accurate in axle detection and spacing but produces magnified errors if an error exists in the original data (Chatterjee, 2006 as cited in Lydon et al., 2015).

In 2012, a method of strain signal filtering was investigated by Zhao et al. to improve the accuracy in Gross Vehicle Weight (GVW) and axle detection. In this method, a commercial BWIM system (SiWIM®) was used to measure the strain response, an FE model was used to predict the response, and a filter was applied to remove some of the dynamic effects. These effects include moment variation due to vibration of the structure, stiffness of the bridge, boundary conditions, and time delay from wheel load to the sensor location. The filtered data represent true static response which can be used in the calculation of GVW axle detection with higher accuracy. This filtered algorithm improved prediction in both single-axle weights and GVW. When tested, on data from SiWIM® deployed on a three-span bridge (42 feet span length) in Alabama, the error obtained was less than 5% and 1% for single axle and GVW respectively (Zhao et al., 2012). However, the efficiency of this method for a number of bridge spans other than three, and span lengths other than 42 feet is unknown.

In a case study by Helmi et al. in 2014, three analytical improvements to estimate GVW were tested on a seven-span slab and girder bridge in Canada (as cited in Lydon et al., 2015). The first method, the Asymmetric Coefficient Method, assumes that the total load of a truck is uniformly spread over a fraction of the bridge span, and it uses the asymmetric shape of the bending moment diagram to calculate the gross vehicle weight. The test concluded that the results were inconsistent and the deviation from the measured GVW was quite large (as cited in Lydon et al., 2015). The second method, the Two-Station Method, also assumes that the truck load is uniformly distributed, and it calculates the GVW from the girder responses at two instrumented longitudinal locations, the locations being approximately near the first quarter span and the second third span. This method provided good results only when the length of the truck was less than half the length of the bridge (as cited in Lydon et al., 2015). In the last method, the Beta Method developed by Ojio & Yamada (2002), the influence area ($\boldsymbol{A_c}$) of a truck of known gross vehicle weight ($\boldsymbol{GVW_c}$) was used to find out the influence area ($\boldsymbol{A}$) of the trucks passing the bridge and the unknown gross vehicle weight ($\boldsymbol{GVW}$) was calculated using equation 3.1. The speed of the vehicle was calculated from the peak strains at different longitudinal locations on the bridge, and a direct velocity was calculated from the distance between two locations and the time interval between the corresponding peaks, which enhanced the accuracy of GVW estimation. The Beta Method has the potential to estimate GVW with the error below 5%, provided the vehicle speeds are obtained accurately (as cited in Lydon et al., 2015).

$$\boldsymbol{GVW = \frac{A}{A_c} \times GVW_c} \qquad (3.1)$$

Another method, the Strip Method, was proposed by Znidaric et al. (2012) to overcome the multiple-presence problem (as cited in Lydon et al., 2015). This method uses groups (strips) of sensors placed under each lane, and the sensors used for calculation are selected considering the transverse position of the vehicles rather than using all sensors for every calculation. It was determined to be more effective than using all the sensors (as cited in Lydon et al., 2015). In this method, when a vehicle passed over a lane, the group of sensors under the lane showed higher response than the other sensors which contributed stronger signal-to-noise ratios. When tested on bridges in Slovenia and Brazil, the results showed significant enhancement in accuracy. The error in GVW obtained was as low as 2% (as cited in Lydon et al., 2015).

While the improvements in the algorithm that have been reviewed above have improved some of the known limitations of BWIM systems, these algorithm-assisted BWIM systems are mainly either insufficiently robust to handle all the situations that are likely to be encountered in highway bridges where vehicle weights are needed, or have high computation and calibration demand which severely restricts their use. More importantly, these systems are unable to detect the number of axles, axle weights and vehicle speeds accurately and perform poorly in multiple vehicle passage in a bridge, either in tandem or side-by-side. Since the above-mentioned methods use information from under the bridge that is obtained from the sensors installed under the bridge deck, the improved algorithm application is likely to be confined to cases where the strain gauges can accurately capture the number of axles, detect the presence of multiple vehicles and speed of vehicles. However, strain gauges are incapable of doing so in some cases. The most widely used BWIM system developed by Cestel Corporation, SiWIM®, uses an adapted Moses algorithm for weight computation. The accuracy of SiWIM® is enough for preselection of potentially overloaded vehicles (Cestel Corporation, n.d.), but not sufficient for law enforcement.

CHAPTER 4: IMPROVEMENTS IN THE SENSING TECHNOLOGIES

In general, a BWIM system consists of strain measurement sensors, axle detection sensors, data acquisition systems and a computer (Figure 1.1). One category of the sensor is the weighing sensor, and another category is the axle-detecting sensor. Advances have been made in the selection of the type of strain gauges used as well as replacing the conventional BWIM sensors, either the strain measurement sensors or the axle detection sensors, or both, with new sensing technologies like Free-of-Axle Detector (FAD) sensors, accelerometers and videos. These improvements were investigated with an intention to improve the accuracy of BWIM systems or to provide an alternative to sensing technologies used in modern BWIM systems. Some of the improvements evaluated in recent years, their performance and their limitations are discussed next.

Strain responses are used in modern commercial BWIM systems, and hence the selection of an appropriate type of sensor for strain measurement becomes crucial to ensure the accuracy of the measurement and reliable operation of the system (Yu et al., 2016). One of the most common strain measurement systems relies on the use of electrical resistance strain (ERS) gauges. ERS gauges consist of a metallic foil in a grid pattern adhered to a substrate. The electrical resistance of the foil grid varies in proportion to the applied strain, and the recorded changes in electrical resistance is used for strain estimation. A recent review of a system using ERS gauges suggested that the accuracy was not sufficient for enforcement of overloaded vehicles (Richardson, Jones, Brown, O'Brien, & Hajializadeh, 2014 as cited in Lydon et al., 2015), and this system requires wiring effort and power consumption which can limit its use in rural sites (Lydon et al., 2015).

A more accurate, high-speed, small, lightweight, and electrically passive sensing system using optical sensors such as fiber Bragg gratings (FBGs) are considered more suitable for modern BWIM application (Lydon et al., 2015). Some of the major advantages of FBG sensors compared to the conventional ERS gauges are: 1) FBG sensors exhibit less noise because these sensors are immune to electromagnetic interference; 2) FBG sensors are suitable for long-term measurements because of their superior durability; and 3) FBG sensors are small and can be multiplexed for easy installation of multiple sensors on large structures (Yu et al., 2016). Queens University Belfast (QUB), University College Dublin and the University of Alabama, Birmingham combinedly developed a BWIM system using FBG sensors (Lydon et al., 2015). For a small sample, the fiber optic system was observed to provide much more accurate results as compared to systems with conventional ERS gauges, but further work is needed to confirm the success of the system (Lydon et al., 2015). Nonetheless, the FBG system is considered to have superior accuracy than ERS gauges and has been recommended for BWIM applications.

Axle-detecting sensors are used to identify the presence of vehicles from which the speed and axle spacing of the vehicle on the bridge can be computed. Axle detection is an inseparable part of the BWIM system since the identified vehicle speed and axle spacing of the vehicle directly affect the result of axle weight calculation (Yu et al., 2016). The traditional axle-detecting sensors include tape switches and pneumatic tubes. Since such intrusive axle detection system installed on the road surface can disturb traffic flow, and the systems can be easily damaged or destroyed by heavy traffic, 'nothing-on-road' (NOR) BWIM systems were developed and implemented. NOR systems are the systems that have no sensor deployed on the road or the bridge surface so that it is invisible to the drivers. Instead, sensors under the bridge are used for axle detection.

In 2001, the traditional instrumentation for axle detection was replaced by a free-of-axle-detector (FAD) system, an application of Nothing-On-Road (NOR) BWIM, was developed by which the velocity, the number of axles and axle spacing were determined from the strain gauges underneath the bridge (O'Brien et al., 2001). In other words, additional strain gauges under the bridge were used to identify the velocity, number of axles and their spacing. New algorithms were developed to calculate axle and gross vehicle weights using data from the sensors installed under the bridge (O'Brien et al., 2001). Generally, two FAD sensors are installed at different longitudinal locations on each lane, and they record a sharp peak upon passage of a vehicle. Although the FAD algorithm solves the durability problem of the traditional axle detectors, it requires additional sensors only for axle detection purpose. Also, the FAD algorithm is suitable for bridges with: 1) a short span, or a relatively long span but with transverse supports which would divide the bridge into short sub-spans; 2) a thin superstructure; and 3) a smooth road surface and approach span (O'Brien et al., 2001). However, the FAD system has been in continuously improvement, and its implementation has widened to different types of bridges (O'Brien, Znidaric, & Ojio, 2008). FAD data acquisition is the most common type of BWIM in used in Europe, SiWIM® (O'Brien et al., 2008).

In 2012, O'Brien, Hajializadeh, Uddin, Robinson, & Opitz proposed a novel axle detection system using shear strain sensors based on the assumption that each axle passage induces a sudden change in the shear strain, but further work is needed to assess the feasibility of this method (as cited in Yu et al., 2016).

BWIM systems in which sensing technologies other than strain gauges are used for strain measurement and axle detection have also been investigated during the recent years. A couple of such BWIM systems reviewed in the present study have been presented below.

Ojio, Carey, O'Brien, Doherty, & Taylor (2016) investigated a BWIM system using vision-based methods that rely on cameras and image processing algorithms. The vision-method is also referred as contactless bridge weigh in motion (cBWIM). In total, it uses two cameras that are time-synchronized. The first camera measures sub-millimeter deflections of the underside of the bridge and is positioned in the underpass of the bridge. A telescope is attached to the camera to detect the deflection of the bridge. A second camera set up on the bridge surface monitors the passing traffic and is used to determine the axle spacing. A motion tracking software package (PV-Studio 2D, in this case) was used to capture the deflection of the target point, which was a sensor bolt in the mid-span of girder, and the axle spacing distances were calculated from the number of frames between the axles passing a notional vertical line in the video images frames of vehicle traversing the bridge. The accuracy of GVW measurement by this system was found relatively low. Moreover, some environmental conditions, such as when the camera is affected by wind-induced vibration or ground vibration and when it is too dark to capture images, makes the determination of deflection with a camera difficult (Lee & Shinozuka, 2006; Yoneyama & Ueda, 2012 as cited in Sekiya, Kubota, & Miki, 2017).

Sekiya, Konishi, Kinomoto, & Miki (2016) proposed a portable BWIM - pBWIM system for GVW estimation and vehicle axle detection that consist of only accelerometers (as cited in Sekiya et al., 2017). The acceleration recorded by the accelerometer was integrated twice to determine the displacement of a bridge. However, determination of displacement from acceleration is difficult as the accuracy of the integrated displacement data is lost because of the measurement errors like sensor self-noise and errors resulting from the limitations of analog-to-digital conversion (Gindy, Vaccaro, Nassif, & Velde, 2008; Park, Sim, & Jung, 2014 as cited in Sekiya et al., 2017). Moreover, the initial velocity and displacement, bridge conditions that are essential for the double integration, were unknown because of the continuous vibration of the bridge caused by moving traffic. To overcome the difficulty caused by sensor self-noise, Sekiya, Kimura, & Miki (2015) divided the bridge displacements into two components, a component attributable to vehicle weight and another attributable to free vibration ignoring the vehicle-bridge dynamic interaction (as cited in Sekiya et al., 2017). The accuracy of the pBWIM was verified by only one vehicle of known axle weight (as cited in Sekiya et al., 2017). It is crucial to verify the accuracy for vehicles of different shapes and weight. Also, the number of accelerometers was high (8 accelerometers for vehicle axle detection and 3 for estimating displacements) (as cited in Sekiya et al., 2017). Construction of such a system is time consuming.

Sekiya et al. (2017) subsequently proposed a simplified pBWIM (spBWIM) to increase the accuracy by using four test trucks and to increase the usability by reducing the number of accelerometers. spBWIM uses only one accelerometer to measure the displacement and two accelerometers in each lane for vehicle axle detection. The system uses micro-electromechanical system (MEMS) accelerometers that are inexpensive, small and consume low amounts of power (Lynch, Wang, Loh, Yi, & Yun, 2006; Pakzad & Fenves, 2009; Shinozuka, Papakonstantinou, Torbol, & Kim, 2015 as cited in Sekiya et al., 2017). The GVWs for three test trucks estimated by the spBWIM system were within ±15.3% of static truck values, and the vehicle speed and axle spacing were accurately determined for the three test trucks. The accuracies of identification of individual axle weights were poorer than those of the conventional BWIM system based on strain measurements. Also, the accuracy of the spBWIM system to determine the displacement response when multiple vehicles are present simultaneously needs to be verified before it can be used in the field.

In summary, several sensing technology improvements have been proposed and tested. While some of the proposed improvements seem to be promising, further research and testing are warranted. Some of the tested improvement techniques illustrate how some limitations of conventional BWIM system could be overcome, but their accuracy is still not enough for implementation. Specifically, these methods lack acceptable accuracy in the determination of individual axle weight, and the accuracy degrades further for a multiple vehicle presence situation. As mentioned before, the most widely used BWIM system, SiWIM® has limitations. Detection of number and category of vehicles present on the bridge can facilitate computation of individual axle weight from the strain gauge measurements, accurately. A better axle detection (number and spacing of axles) accuracy can be achieved with the data from traffic sensors. By coupling the BWIM system data and traffic sensor data, a more accurate and effective BWIM system, called eBWIM system, can be developed. Some of the traffic sensors that could be possibly used for collecting real-time traffic data for axle detection are discussed in the following chapter.

CHAPTER 5: SENSORS/TECHNOLOGIES FOR DATA ENRICHMENT

Traffic sensors can be broadly categorized as intrusive and non-intrusive sensors/detectors. Although both intrusive and non-intrusive are found in use, because of problems with installation and maintenance of intrusive detection system, non-intrusive detection systems have become more prominent. The non-intrusive systems are seen as cost-effective replacements of intrusive systems. Because of the advantages of non-intrusive sensors, they have an increasing popularity. These technologies will serve the motive of vehicle detection (vehicle speed, number of vehicles, and vehicle classification), and hence is also referred as detection system in this paper. The term ‘traffic sensors’ and ‘detection system’ are used interchangeably throughout the paper.

The commercially available popular non-intrusive sensing technologies include: microwave radar sensors; active infrared (laser radar) sensors; passive infrared sensors; ultrasonic sensors; passive acoustic sensors; and video image. Intrusive sensing technologies include: inductive loop and magnetic sensors. However, the Traffic Detector Handbook-2006 has identified three non-intrusive technologies capable of vehicle classification: microwave radar, active infrared and video image processor and one intrusive technology capable of classification: inductive loop (Klein et al., 2006). Inductive loop is not considered as an option in this study because of the necessity of boring or pavement cut for its installation which can cause degradation of bridge deck life and can cause serious traffic delay during its installation and maintenance. In 2005, Cheung et al. investigated use of magnetic detectors capable of vehicle classification. These are wireless magnetic sensor nodes (SNs) glued to the pavement and it does not require boring and causes less traffic delay. The working principle of the four traffic sensing technologies: microwave radar; active infrared; and video image processors (VIPs)/video image vehicle detection system (VIVDS); and magnetic sensors and their performance in vehicle classification or vehicle length estimation observed in the studies/field tests conducted in the recent years are discussed next. Though a good speed estimation accuracy is essential, this study is inclined to finding a traffic sensor that has acceptable classification accuracy, more importantly in a multiple vehicle presence situation. Thus, the performance of sensors in vehicle classification is considered the controlling criteria in the selection of the best candidate. Moreover, the limitations of the sensors’ classification performance in inclement conditions, if any, will represent the limitations of the sensors’ performance in speed calculation as well.

5.1 MICROWAVE RADAR SYSTEM

A microwave radar system transmits electromagnetic signals and receives echoes from the objects of interest within its volume of coverage. The echoes are processed to extract desired information like speed, length, and the number of vehicles. Companies like Electronic Integrated Systems, Inc. (EIS), Image Sensing Systems, Inc (ISS) and Wavetronix LLC are leading manufacturers of microwave radar sensors. Microwaves can diffract around corners and can detect vehicles hidden by other vehicles (Edgar, 2002). This device can be mounted either overhead (see Figure 5.1) or in a side-fire position aimed perpendicular to traffic (see Figure 5.2 and Figure 5.3). A review of orientation, performance, and limitations of microwave sensors based on recent studies reviewed are presented next.

Minnesota Guidestar Phase I researchers tested Remote Traffic Microwave Sensors (RTMS) X2 by EIS which were found easy to mount and required a moderate amount of calibration to achieve optimal performance (Kranig, Minge, & Jones, 1997 as cited in Middleton, Parker, & Longmire, 2007a). However, they noted that rainwater entering the device affected the performance of the RTMS. In another study, Texas Transportation Institute (TTI) observed it have the lowest life-cycle cost for freeway applications among those detectors included in their research (Middleton & Parker, 2002 as cited in Middleton et al., 2007a). The study also concluded that it has ease of set-up, being mounted only 17 feet above the roadway in side-fire orientation, and has a good user interface. Coifman's (2005) test on RTMS revealed poor performance due to small detection zone and occlusion (as cited in Middleton et al., 2007a). Occlusion is a phenomenon whereby a tall vehicle in a lane nearer to an overhead or side-fire detector either causes false activation of a detection zone in a lane further from the detector, or "hides" a vehicle in a lane further from the detector, causing a missed detection (Grone, 2012). Grone (2012) observed that RTMS G4 classification ability is affected by the combination of dusk lighting and rain. Based on this observation, the author hypothesized that the G4 classification accuracy was affected by heavy rain. (Grone, 2012).

Figure 5.1: Wavetronix radar sensor mounted in doppler mode

(Source: Medina, Ramezani, & Benekohal, 2013)

A research project conducted by Ohio Research Institute for Transportation and the Environment (ORITE) used two Wavetronix SmartSensor model SS105 in a custom-built trailer mounted in side-fire orientation, with each detector pointed in the same direction and operating in parallel. The researchers, Zwahlen, Russ, Oner, & Parthasarathy (2005) observed that the Wavetronix system missed some vehicles due to occlusion and sometimes registered phantom vehicles from extraneous radar echoes, e.g., from a truck in an adjacent lane (as cited in Middleton et al., 2007a). In addition, the authors concluded that the results based on vehicle length (or classification) were not as accurate and the system does not reliably estimate the number of trucks in the traffic stream. In a study conducted by Kotzenmacher, Minge & Hao (2005) for Minnesota DOT, Wavetronix SS105 and RTMS were tested and yielded about 6% and 5% error in length-based vehicle classification in freeways and urban networks, respectively (as cited in Middleton, Longmire, & Turner, 2007b). Later in 2007, Zhang, Rilett, Jones, Bhaven, & Appiah, tested the count accuracy of SmartSensor SS105, in side-fire orientation at a mounting height of 18 feet and 19 feet away from the closest lane, and concluded that rainy weather and lighting condition did not affect its performance (as cited in Middleton et al., 2007b).

Figure 5.2: Wavetronix SmartSensor HD mounted on a lighting pole

(Source: Minge, Kotzenmacher, & Peterson, 2010)

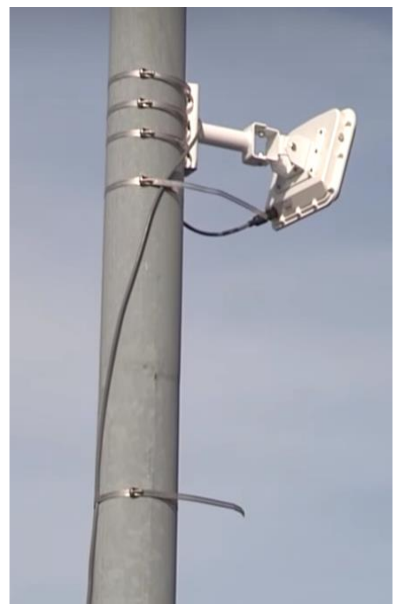

Figure 5.3: Wavetronix SmartSensor HD installed on a pole

(Source: Wavetronix LLC, n.d.)

According to the perspectives and clarifications extracted from vendor resources, Wavetronix SmartSensor HD is a frequency modulated continuous wave radar sensor, uses patented Digital Wave Radar II for the detection and measurement, and has five times the resolution of the original SmartSensor, and a detection range of 250 feet enough to detect up to 10 lanes of traffic simultaneously (see Figure 5.4) (Wavetronix LLC, n.d. as cited in Middleton et al., 2007). Also, SmartSensor HD is advertised as incredibly accurate in providing individual vehicle speeds as well as more precise vehicle classifications, and is accurate in detecting partially occluded vehicles. It is easy to install, includes a pointing assistant for precise alignment, and its patented auto-configuration is quick, simple and has been developed especially for Pocket PC®, handheld devices and laptops (Wavetronix LLC, n.d. as cited in Middleton et al., 2007a). SmartSensor HDs were used by some researchers. Their evaluation is presented below.

A limited research study at California PATH in cooperation with California DOT concluded that the classification performance of SmartSensor HD was inferior to SmartSensor SS105 in uncongested traffic (Banks, 2008 as cited in Yu, Prevedouros, & Sulijoadikusumo, 2010). A study (first phase) by Yu et al. (2010) noticed that SmartSensor HD, in side-fire orientation (30 ft. high and 20 ft. offset from the first lane), resulted in an overall error of 20 to 30% in classification, and the accuracy of classification per lane was evaluated to be sensitive to the distance between lane and location of sensor. The manufacturer's claim that HD is capable of detecting occluded vehicles was found not to hold true (Yu et al., 2010). In the second phase, in free flow traffic conditions where lane changing and stop-and-go traffic did not exist during the observation period and the sensor was calibrated and tested by technicians before deployment, the accuracy of volume count was obtained to be unacceptable (Yu, Sulijoadikusumo, & Prevedouros, 2011). The reason for unsatisfactory volume count was attributed partly to deficiencies in microwave technology by the authors (Yu et al., 2011). Overall, SmartSensor HD was observed to be indifferent to weather conditions but provided unsatisfactory classification and inconsistent vehicle count (Yu et al., 2011). Factors affecting performance of the SmartSensor HD are given in Table 5.1.

Figure 5.4: Wavetronix SmartSensor HD microwave emission in side-fire orientation

(Source: Wavetronix LLC, n.d.)

In 2009, Minnesota Guidestar study returned to the testbed used in the previous phases to assess the performance of newer detectors like SmartSensor HD (Minge, Kotzenmacher & Peterson, 2010). The author identified that SmartSensor HD (mounted 28 ft. high and 30 ft. offset) has error with classifying single-unit trucks as large trucks and classifying passenger vehicles as single-unit trucks. Manual observation revealed that this error was prominent for pickups and SUVs and large vans (Minge et al., 2010). Evidence for misclassification due to multiple vehicles arriving at once was also found (Minge et al., 2010). Another source of error was when trucks were hauling trailers (Minge et al., 2010). The overall error was 3% in classification (Minge et al., 2010). The test revealed that the SS HD volume accuracy was not affected due to extreme cold, rain, snow and slightly affected by fog (error < 5%) (Minge et al., 2010). A later study by Minge & Petersen (2013) discovered that the average absolute length error of SmartSensor HD was 2.49 ft. when vehicle length from a video capture was used as the baseline length; the baseline method had an absolute error of 0.43 ft. when tested against the field data (tape measured length).

Despite the lack of a superior accuracy, microwave radar system has gained a lot of popularity in recent years because of its ease of set-up and insensitivity to inclement weather. This technology is becoming more reliable with time, and the cost is not as high when compared to Video Image Processing (VIPs) (Romero, Prabuwono & Hasniaty, 2011).

5.2 ACTIVE INFRARED DETECTORS

An active infrared sensor detects vehicle presence by throwing a laser beam towards the detection area and measuring the time required for the reflected beam to return to the receiver. The beam is interrupted by a mass, a vehicle in this case, and the return time is reduced signaling the presence of a vehicle in the detection area. Some infrared sensors can be placed at the roadside or overhead (see Figure 5.5), possibly on sign structures. A review of orientation, performance, and limitations of active infrared sensors based on studies reviewed are presented next.

In phase I of the Minnesota Guidestar project, Kranig, Minge, & Jones (1997) evaluated an active infrared device, the Schwartz Electro-Optics (SEO) Autosense I for detection of traffic on a freeway (as cited in Middleton et al., 2007a). Autosense I can obtain vehicle profile, which can be used for classification (Kranig et al., 1997 as cited in Middleton et al., 2007a). In the field test, the device was observed to suffer reduced count accuracy in heavy snowfall, heavy rainfall and freezing rain (Kranig et al., 1997 as cited in Middleton et al., 2007a). During snowfall, the undercounting was attributed to the vehicles traveling out of the detection zone and the overcounting was suspected as the result of falling snow reflecting the laser beams causing false detections (Kranig et al., as cited in Middleton et al., 2007a). In 1997, TTI tested the accuracy of SEO Autosense II to identify trucks and observed that in a sample of 160 vehicles, it only missed 3% and misclassified 7.5% vehicles (Middleton, Jasek, Charara, & Morris, 1997 as cited in Middleton et al., 2007a). Moreover, the author suspected the device to perform satisfactorily in all weather and lighting conditions, based on the characteristics of the technology rather than on specific sensor, though they did not test the sensor during inclement weather (Middleton et al., 1997 as cited in Middleton et al., 2007a). The upside identified by the authors is its easy setup and immediate data collection following installation whereas the downside is that deployment of Autosense II requires mounting the device directly over lanes, which may require a special pole and mast arm (Middleton et al., 1997 as cited in Middleton et al., 2007a). Also, the high cost of the sensor was identified as a possible constraint for some agencies (based on the detector list price that was $10,000 in 1995) (Middleton et al., 1997 as cited in Middleton et al., 2007a).

In 2009, Minnesota Guidestar researchers tested the infrared traffic logger (TIRTL) to determine the sensor's classification performance (Minge et al., 2010). See Figure 5.6 for an image of TIRTL. Two TIRTL are required, one on each side of the subject roadway. Each sensor is required to be set up and aimed towards each other. The TIRTL base can sit directly on a roadway or could be mounted on the curb. Caution should be taken with sensor height placement to avoid detecting non-axle vehicle components (Minge et al., 2010). The sensor identified axle spacings within about 2% of the actual spacing measured by the baseline (TH 52 WIM), but the classification by axle count was unsatisfactory as the sensor grouped two passenger vehicles into a 4-axle vehicle, and 3-axle vehicles were broken into smaller vehicles due to occlusion (Minge et al., 2010). The author concluded that due to the lack of a presence-sensor (sensor to detect the presence of a vehicle) to determine gaps between vehicles, closely spaced vehicles are easily grouped. Though falling rain has little or no effect on sensor performance, road spray can occlude the laser, and poor drainage, wheel path rutting, ponding or extremely heavy rain causing significant road spray can degrade sensor performance (Minge et al., 2010). Moreover, snow plowing can deposit snow on the sensors if they are located close to the roadway. This issue can be solved by placing the sensor away from the roadway, but in doing so, accumulation of snow in the path of the sensor's beam will pose a problem (Minge et al., 2010).

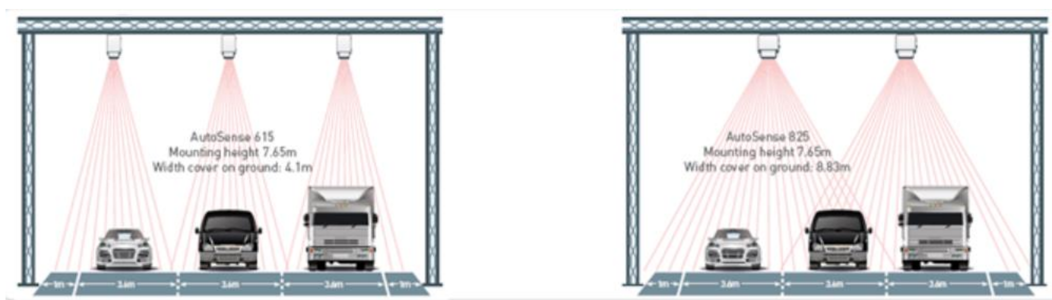

Figure 5.5: Autosense mounted in doppler mode

(Source: OSI LaserScan, n.d.)

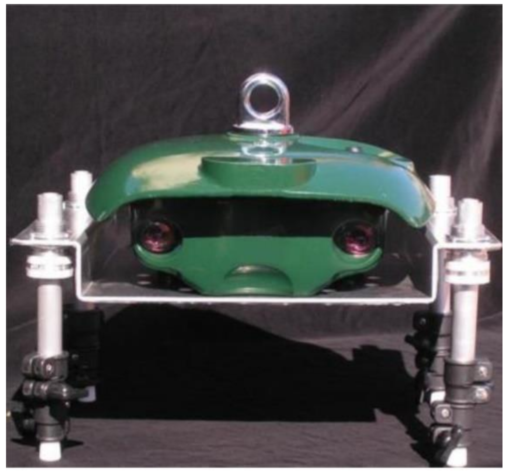

Figure 5.6: The infrared traffic logger (TIRTL)

(Source: Minge et al., 2010)

In 2011, Xu et al. (2011) evaluated TIRTL sensors. TIRTL were deployed on five test sites to evaluate the performance under high-speed highway traffic and the error noted in classification was 1 to 2 % for class 1-5 vehicles (FHWA axle-based classification scheme), and no error was seen for class 6-15 vehicles. The discrepancy was based on manual count, and the manual count was verified to be correct from the video record. FHWA Class 6 to Class 15 represented heavy or large vehicles with three of more axles. The outcome of another TIRTL tested on an urban arterial site was a considerably compromised accuracy for a pavement surface with pronounced crown or slope; the error was as large as almost 50% (Xu et al., 2011). Furthermore, based on the research carried in 2010 and 2011 combined, the researchers concluded that the proper balance and alignment of the TIRTL transmitter and receiver unit and flat surface are crucial for optimal vehicle classification, especially, for heavy vehicles with three or more axles (Xu et al., 2011). Also, the accuracy of TIRTL in vehicle classification was highly compromised due to congestion and lane change whereas moderately compromised due to rainfall (Xu et al., 2011). Table 5.1 presents the factors affecting TIRTL.

In general, disadvantages of infrared sensors include: high cost; inconsistent beam patterns caused by changes in infrared energy levels due to passing clouds, shadows, fog, and precipitation; lenses used in some devices may be sensitive to moisture, dust, or other contaminants; and the system may not be reliable under high-volume conditions (Middleton, Jasek & Parker, 1999 as cited in Middleton et al., 2007a). The disadvantage of Autosense is its deployment directly over lanes which may require a special pole or mast arm. Generally, TIRTLs are installed on the curbs, and hence its deployment on a freeway is not possible. TIRTL experience compromised accuracy due to the presence of pronounced crowns. Also, heavy rainfall causing significant road spray and snow deposit pose problems to its performance.

5.3 VIDEO IMAGE VEHICLE DETECTION SYSTEMS (VIVDS)/VIDEO IMAGE PROCESSING (VIP)

Video cameras are regularly deployed to capture traffic. The recorded video feed can be then processed through an algorithm to obtain the information of interest like vehicle speed, count, and classification. Image processing more or less follows a general algorithm in which the system takes a sequence of traffic-images obtained from a camera or a recorded video and then identifies the portions of the scene that might contain a vehicle (Mallikarjuna, Phanindra, & Rao, 2009). Once the identification is completed, the potential portions are segmented out and further analyzed to extract features that assist in the classification of the vehicles in different categories (Mallikarjuna et al., 2009). The increasing popularity and the omnipresence of cameras can be attributed to the decreasing hardware cost and rich amount of information that can be generated from the images. Some systems like Autoscope Solo can be mounted either overhead or on side of the road.

Figure 5.7: Autoscope

(Source: http://mysite.myhostcenter.com/s0096b13/Cameras_Installation.html.)

Review of the technical literature indicates that most of the VIVDS have been used/tested to obtain speed and volume data. Use of VIVDS for the classification of the traffic was not found to be common. While the systems have been used mostly for purposes other than the classification of the vehicles, some of the limitations stated in the literature may reflect the limitations of VIVDS in general.

MnDOT researchers tested four VIVDS during the Phase I of Minnesota Guidestar project (1997). Some of their findings regarding the use and performance of the system were: 1) mounting video detection devices is more complicated compared to mounting of other types of devices; 2) camera placement impacts the success and optimal performance of the device; 3) lighting variations were noted to impact the accuracy of the device; and 4) shadows from vehicles or other sources and transition between day and night also compromised the performance of the system (Kranig et al., 1997 as cited in Middleton et al., 2007a). MnDOT Phase I researchers observed Autoscope 2004 to undercount during light-changing transition periods. In another research project by TTI in 2002, the researchers tested Autoscope Solo Pro and determined that the count accuracy decreased when 5-minute interval speeds dropped below 40 mph and was worse for stop-go-condition whereas during free flow it overcounted vehicles within 10% of the baseline flow (Middleton & Parker, 2002 as cited in Middleton et al., 2007a). The observed the errors in vehicle counts after dark were up to 40% (Middleton & Parker, 2002 as cited in Middleton et al., 2007a).

In Phase II (2002) MnDOT tested Traficon NV mounted directly over the lanes and observed the efficiency of the system in counting to be compromised (MnDOT & SRF, 2002 as cited in Middleton et al., 2007a). The researchers suspected snow flurries and sub-optimal calibration to be the reasons for the inaccuracy (MnDOT & SRF, 2002 as cited in Middleton et al., 2007a). In August 2006, TTI observed that Traficon classification error to be ±20%, but could be improved with calibration (Middleton et al., 2007a). In 2007, Zhang et al. observed the count accuracy of Autoscope Rack Vision by Econolite, mounted 63.1 feet above the roadway in overhead orientation, to be unaffected by rainy weather and light conditions (as cited by Middleton et al., 2007b). In a study in 2010 about the selection and test of sensors for vehicle classification, Yu et al. concluded that Autoscope, mounted at a 20 ft. offset from the nearest lane and at a height of 30 ft., provided classification (length-based, 2 to 3 classes) accuracy within 5% to 10 % during daytime at the site with light to moderate traffic volume, whereas the classification accuracy degraded to an unacceptable level during the nighttime. The authors observed Autoscope's accuracy to degrade due to the shadow of surrounding obstacles, illumination and weather condition (Yu et al., 2010).

In the follow-up study by Yu et al., (2011), they analyzed the performances of non-intrusive sensors, including Autoscope (mounted in side-fire orientation), under various traffic and environmental conditions. The seven-hour tests of volume data collection under low speed and light traffic of urban arterial site and 24-hour long tests under high speed and heavy traffic demonstrated the adverse effect of shadow and low illumination in volume and classification. For example, the error observed in the volume classification of traffic at an urban arterial site that was attributed to the shadow and low illumination was about 13% and 38%, respectively (Yu et al., 2011). Cloudless weather with strong sunshine observed to worsen the shadow effect on volume and classification (Yu et al., 2011). Moreover, the performance of the system degraded significantly during rainy periods (Yu et al., 2011). The factors affecting the performance of Autoscope is summarized in Table 5.1. Some of the effects are presented in Figure 5.8. In 2012, Grone observed that Solo Pro II was misclassifying long vehicles as short. The author also concluded night lighting conditions exacerbated the Solo Pro II's classification problem. Other than camera mounting height, these systems have some other problems like complexity of use, periodic lens cleaning, and high cost (Middleton et al., 2007b).

Figure 5.8: Glare (Left), Rain (Middle), and Combination (Right) effects of Autoscope

(Source: Yu et al., 2011)

Table 5.1: Factors affecting the performance of Autoscope, SmartSensor HD & TIRTL

Influence factors	Autoscope RackVision Terra			SmartSensor HD			TIRTL		
	Classification	Volume	Speed*	Classification	Volume	Speed**	Classification	Volume	Speed***
Illumination	●	●	◑	○	○	○	○	○	○
Shadow	●	◑	○	○	○	○	○	○	○
Rainfall	●	●	◑	○	○	○	◑	◑	◑
Congestion	●	●	●	●	●	●	●	●	◑
Lanes change	●	●	◑	●	●	◑	●	●	◑
Wind	●	◑	◑	○	○	○	○	○	○
Distance of detection area from sensor	○	○	○	●	○	○	○	○	○
Pavement with pronounced crown	○	○	○	○	○	○	●	◑	◑

Note:
● Influence factor has a large effect ---Increase in %error >10%
◑ Influence factor has some effect ---Increase in %error = 5%~10%
○ Influence factor has a small effect ---Increase in %error = 0%~5%
* Speed over 8 mph can be detected; ** Speed over 4 mph can be detected; *** Speed over 2 mph can be detected

(Source: Yu et al., 2011)

Despite the aforementioned limitations of the video image processing systems, there are records of research work that illustrate the viability of the promising nature of the video image processing system if the proposed methodology or advancement is applied. In 2009, Mallikarjuna et al. (2009) proposed an offline image processing-based system that obtains data from video film. The system classifies vehicles into four different categories, namely light motor vehicles (LMVs), heavy motor vehicle (HMVs), motorized two-wheelers (TWs), and motorized three-wheelers (autos) (Mallikarjuna et al., 2009). The system, TRaffic AnalyZer and EnumeratoR (TRAZER), can handle up to 30% occlusion and can detect and classify the vehicles even under dense traffic conditions with an average detection accuracy of 95% and an average classification accuracy of 85% (Mallikarjuna et al., 2009). In 2016, Nemade proposed a system which combines many existing methods like background subtraction, Kalman filter, 2-line algorithm, headlight detection, license plate detection algorithm. This system uses a Kalman filter to apply the 2-line algorithm and vehicle classification for the day time, whereas headlight-based detection is implied for the night time (Nemade, 2016). The license plate detection uses edge detection, Gaussian analysis, feature extraction and character recognition for the day as well as night time (Nemade, 2016). Nemade claims that the vehicle classification using the proposed system will yield an accuracy of more than 90%. However, the current video image processing systems in use perform very poorly in inclement weather and are very sensitive to light conditions.

5.4 MAGNETIC SENSORS

Magnetic sensors work under the assumption that the steel masses of the vehicles have an effect on the magnetic field of the Earth. When a vehicle passes through a detection zone, it temporarily distorts Earth's quiescent magnetic field, which can be read by passive magnetic devices like 3M's micro-loop, Safetran IVHS Sensor 232E. Magnetic sensors are of intrusive nature. The device needs to be close to the vehicles it is detecting; therefore, it is mostly installed below the pavement or bridge deck. Clearly, it is intrusive for the pavement, but can be non-intrusive for bridges if installed under the bridge deck.

In 2005, Cheung et al. investigated use of single wireless magnetic detectors which constitutes a magnetic sensor, a microprocessor, a radio and a battery encased in 5-inch diameter sensor nodes (SNs) glued to the pavement on the center of a lane. The traffic at Heart Avenue in Berkeley, California was monitored for two hours, and the accuracy of average vehicle length and speed estimates were recorded to be as high as 90%. Measurements from the magnetic sensors were used to classify the vehicles, using a simple algorithm, into six categories: passenger vehicle, SUV, van, bus, mini-truck, and truck. The detector correctly classified 24 vehicles out of a sample of 37 vehicles (63%). The classification when combined with the FHWA classification scheme resulted in 83% accuracy. The sensors had problems detecting SUVs and mini-trucks and its accuracy to detect trucks needed to be determined through further experiments. In comparison to the inductive loops, magnetic signatures provide more detail on the vehicles and hence are an improved classifier. Also, it is a safer option compared to inductive loop for bridges where saw-cuts would weaken the structure. The authors suggest that the accuracy of classification could be improved significantly by using two magnetic sensors spaced known distance apart, and they estimate a likely accuracy of 80%. However, further testing is required to confirm the performance and the limitations of magnetic sensors (Cheung et al. (2005).

5.5 CONCLUDING REMARKS ON TRAFFIC SENSORS

Based on the information presented above, it can be inferred that none of the detection sensors reviewed have acceptable accuracy and performance in vehicle classification. These systems have limitations that can impede them from reaching the full potential of data enrichment for eBWIM applications. But, almost all of the systems that were tested have newer and updated versions available now, and the vendors advertise their latest models to have overcome these limitations. Hence the deployment of newer versions could perform better and assist in realizing the potential for data enrichment in eBWIM. Additionally, until an eBWIM system is implemented and tested, the minimum accuracy requirements for traffic sensors will not be known. It is possible that traffic sensors with less than perfect or ideal accuracy can markedly improve BWIM effectiveness. Therefore, it is suggested that one of the traffic sensors mentioned above be selected for testing.

CHAPTER 6: TRAFFIC SENSOR CHARACTERISTICS FOR EVALUATION

In the view of the discussion on traffic sensor performance and limitations in Chapter 5, the characteristics that they exhibit are evaluated in this chapter. The characteristics concern sensor performance (mostly, vehicle length estimation) as well as other properties like deployment (mount and orientation) and cost (initial cost and routine maintenance cost). Overall, these characteristics affect the use and selection of the best sensor for the desired eBWIM application. In order to determine the best candidate, recognition of their inherent characteristics is needed. Once the available characteristics are recognized, they can be evaluated to assist selection of the most suitable sensor or technology for eBWIM applications. The detection systems reviewed in Chapter 5 will be evaluated relative to the following characteristics.

1. Intrusiveness
2. Mounting
3. High-speed traffic detection capability
4. Classification accuracy in optimal condition
5. Accuracy in tandem or side-by-side vehicle detection
6. Weather condition sensitivity
7. Sensitivity to lighting conditions (rain, wind, solar radiation, and snow)
8. Life cycle cost (including maintenance and repair cost)
9. Lane change detection
10. Power source

The foregoing characteristics and attributes are used for assessment of the current state of applicability for the four categories of traffic sensors outlined earlier. These attributes need to be evaluated to find if a sensor system can serve properly for vehicle detection. Once the attributes are investigated, they can be used to filter the traffic sensors possessing some or all the attributes of a detection system. To do so, the characteristics listed above can be compared against the minimum requirements for an “ideal” detection system as listed below.

1. Layout of sensor system

    a) Nothing-on-road-surface system (for least traffic disruption and lower risk to traffic personnel during installation and maintenance)

    b) Nothing close to the sides of the roadways (for runaway vehicles, debris, snow removal, etc.)

2. Intrusiveness and driver hazards

    a) Non-intrusive (for easy and economical installation and maintenance, and durability)

b) Non-dangerous to drivers (either getting hurt or distracted such as flashing lights, radiation, etc.)

3. Spatial requirement

   a) Side mount (for the minimum interference of traffic during maintenance and for the safety of workers)

   b) If overhead, they should be at least easily mountable on sign support structures, bridges, and other overhead structures

4. Effectiveness for high-speed traffic (for use in high-speed traffic conditions)

5. Accuracy requirement: accuracy of 90% or more

   a) Vehicle classification accuracy (specifically, truck classification)

   b) Accurate detection and classification of vehicles in tandem

   c) Accurate detection of side-by-side vehicles

   d)Capable of detecting lane-changing vehicles accurately

6. Insensitive to lighting conditions (for acceptable performance in any lighting condition)

7. Insensitive (or resistant) to weather (rain, wind, solar radiation, and snow) (for acceptable performance in all-weather condition)

8. Low cost (initial and maintenance costs)

9. Longevity (durability under the elements is one concern, but another is simply how long the system will last under ideal environmental conditions – how long will circuitry, sensors, and other components last before burning/wearing out) (for long-term use)

10. Power requirements – is AC needed or can they be run using batteries/solar/self-powering (by harvesting of vibration energy) (for use in rural areas)

Upon comparison of current vs. desirable attributes, it can be inferred that even though all the categories of traffic sensor possess some of the attributes of an "ideal" detector, none of them have all the attributes of an "ideal" detector. This points to the fact that the commonly used traffic sensors have some limitations. In other words, there are qualities that are lacking and hence hold an opportunity for improvement. This situation can be assessed in a couple of ways. First, with improvements of some properties, the incorporation of some traffic sensors in eBWIM applications will yield systems that are not only accurate but also economical and sustainable. To achieve that either additional effort should be made to improve the current detection system attributes or testing is done after the advanced traffic sensors are available in the market. Second, any sensor system will provide an eBWIM system information that is not currently available for BWIM, thereby offering the promise for eBWIM performance that may be superior to that of the comparable BWIM system. It will be beneficial to test one of the currently available traffic sensors, and hence, it is proposed that the available characteristics of these sensors are exploited for the use of data enrichment required for eBWIM. The available qualities of the four sensors are compared with each other in the next chapter, and the best candidate is selected.

CHAPTER 7: QUALITATIVE ASSESSMENT OF TRAFFIC SENSORS

In Chapter 6, it was observed that none of the four traffic sensors: microwave radar; active infrared; and video image processors (VIPs)/video image vehicle detection system (VIVDS); and magnetic sensors have all the desirable attributes of an "ideal" detection system. Despite, it was concluded that any sensor system would provide eBWIM performance superior to that of the comparable BWIM system and hence it was suggested that a traffic sensor should be used for data enrichment.

The four categories of traffic sensors are observed to vary in nature, functioning, and performance. A summary of these attributes (nature, functioning, and performance) of the sensors is presented in this chapter in a tabular format for side-by-side comparison. The comparison will assist the selection of the best candidate among them. Table 8.1 compares microwave radar, active infrared sensor, VIVDS, and magnetic sensors qualitatively based on the level of disruption caused to the traffic during installation and maintenance, mounting orientation, insensitivity to inclement weather and lighting condition, accuracy in vehicle classification and cost of the sensor system (including sensor unit and processor).

A qualitative rating scale is used here to express the general degree performance of the various characteristics. The ratings used are: very low, low, moderate, high, and very high. It is essential to note that the scale used here is relative, and it does not represent the actual value. For example, microwave radar has an accuracy rating of "high", but it does not depict that microwave radar has adequate accuracy. In other words, it signifies that it has higher accuracy compared to other sensors like VIP and magnetic sensors, but it is not necessarily adequate. Usually, an accuracy of 90% or more is preferred for a sensor system to be adequately accurate.

Also, attention should be paid to the fact that the evaluation of the distrubane or interference posed by a sensor is based on the placement of the sensors. For instance, microwave radar is usually placed at some distance from the end of the lane hence provide less disruption to the traffic during installation and maintenance. Therefore, its disturbance rating is "very low". On the other hand, infrared sensors are either placed directly above the lane or very close to the end of the lane at a very small height from the road surface and possess higher disruption (compared to the radar sensor) to the traffic during installation and maintenance. Hence, it is rated a disruption value of "low". Magnetic sensors are rated to have a disruption value of "very high" because they are placed on the road surface and provide the highest disruption to the traffic compared to other sensors.

The cost presented in the table does not strictly apply to the system's initial cost or its life cycle cost. It gives a tentative idea of the general initial costs of the various sensor systems with some consideration to maintenancs cost.

Table 7.1 is based on information obtained from a limited number of sources, and hence the analysis results should not be generalized.

The sensors are listed in the table in order of decreasing preference, with the microwave radar having the best ratings of any sensor in all categories. Microwave radar still could benefit from improved accuracy (to very high), but it is possible that the current accuracy could markedly improve BWIM effectiveness. The active infrared sensor is presently considered to be too expensive for practical application, and it does not perform as well as desired in inclement weather. Although unlike other sensors, TIRTL detects the number of axles in a vehicle, but it is not selected as the best candidate because of its very high cost, relatively high disruption level and moderate insensitivity to inclement weather. Also, TIRTL has relatively more issues in heavy snowfall compared to other sensors (details in section 5.4 for) which make it less suitable for state with heavy snowfall like Minnesota. The VIP/VIVDS and magnetic sensors are not as accurate as the other sensors. In summary, the microwave radar sensor is proposed as the best candidate currently for use in eBWIM applications.

Table 7.1: Qualitative assessment of traffic sensors

Detection System	Disruption	Mount		Insensitivity to		Accuracy	Cost**
		Orientation	Ease	Lighting	Inclement weather		
Microwave radar	Very Low	Both	High	Very High	Very High	High	Low
Active Infrared Sensor	Low*[a]	Doppler*[b]	Moderate*[c]	Very High	Moderate	High*[d]	High*[d]
VIP/VIVDS	Very Low	Both	High	Low	Low	Moderate	Low
Magnetic Sensors	High	On surface	Very low*[e]	Very High	High	Low	Low

*a High for TIRTL

*b Both sides of the roadway for TIRTL

*c Low for TIRTL

*d very high for TIRTL

*e because of intrusive nature

Both means side orientation and overhead (Doppler)

** Doppler orientation cost higher than side-fire orientation

CHAPTER 8: A NEED FOR NEW ALGORITHMS

The most widely used BWIM systems uses two groups of strain sensors. One group of strain sensors are used for bridge deflection due to passing vehicle load measurements whereas the other group of sensors are used for the detection of number of axle and axle spacing. However, the axle detection system of contemporary BWIM systems lack adequate accuracy. To improve the axle detection accuracy and improve the accuracy of the BWIM systems, the current study proposes to use traffic sensors to determine number of axles, spacing of axles, and speed of vehicle. Traffic sensors can provide very accurate instant speed of the vehicles, which will assist in improving the performance of the conventional BWIM system. Also, in the multiple vehicle presence situation, accurate determination of the number of vehicles, the number of axles in the vehicle and their spacing and the vehicle speed data should prove to be beneficial in improving the accuracy of vehicle weight estimation.

The traffic sensors selected, microwave radar, can be used in two possible ways. One, replacing the axle detection system in the current BWIM system with the traffic sensor. Second, the data from the traffic sensor can be combined with the data from the axle detection system currently in use in the BWIM system. The viability of second method would require a detailed knowledge of and integration with the functioning of current axle detection systems. Given the additional effort that would likely be required for the second method, the first one is considered to more viable in the short term.

For the development of an eBWIM system, the vehicle classification data obtained from the microwave radar would require processing to yield the number of axles and their spacing in the vehicles identified. An algorithm would be required to fulfill this purpose. Next, the data obtained from the conventional BWIM system and the data obtained from traffic sensor (vehicle speed, number of axles, and axle spacing) need to be coupled in order to estimate the individual axle weight and gross vehicle weight with higher accuracy compared to modern BWIM. The coupling of the BWIM system data and radar data can be achieved using an additional algorithm, which requires formulation, implementation and verification. One possibility for such an algorithm is as follows: the conventional BWIM algorithm is modified such that it takes the processed radar data to obtain the speed and axle information, in addition to the processed BWIM system data, and combines the two types of data in a procedure to compute vehicle weight. The other possibility is the creation of an entirely new algorithm that has both the kinds of unprocessed data as input. This algorithm would reside in a separate “control” processor that receives information from both the traffic-sensing system and the conventional BWIM system to compute the vehicle weight. The viability of such an algorithm seems achievable in today’s advanced computing world. At this instance, the design of the new algorithm seems entirely feasible, and this task is proposed for future work.

This report proposes the use of SiWIM® as the BWIM system in the development, implementation and testing of eBWIM. SiWIM® uses an adapted Moses algorithm for weight computation. The SiWIM® adapted algorithm might have to be modified to improve its inherent inefficiencies, if any present. Identification of any such inefficiencies requires testing the SiWIM® which is proposed as a future task.

CHAPTER 9: PROPOSED TESTBED PLAN

A testbed will be required to execute the eBWIM concept for the purpose of exploratory research, concept validation, algorithm development and system calibration. The preferred case would be to find a bridge that is already instrumented with the appropriate type of strain measuring equipment with which to provide the strain measurements required in a BWIM system. This would prove most economical and less labor-intensive. A bridge instrumented with strain gauges capable of capturing the dynamic behavior of the structure would suffice provided its accuracy is acceptable, and durability is not an issue. The best available strain gauges for the present study would be fiber Bragg Grating (FBG) optical sensors because of the advantages mentioned in Chapter 4. However, electrical resistance strain gauges that are properly protected would serve the goal effectively.

The Structures Group in the Department of Civil, Environmental, and Geo- Engineering (CEGE) has instrument several Minnesota bridges in the process of carrying out various research or monitoring tasks for the Minnesota Department of Transportation (MnDOT). The instrumentation dates for these bridges are one decade old or more. These bridges could be considered as possible candidates for the eBWIM testbed. However, a bridge suitable for an eBWIM testbed requires a dynamic system (strain gauges capable of recording dynamic measurements like electrical strain gauges) be installed under the deck. Some of the instrumented bridges in Minnesota that were investigated previously are mentioned next.

The I-35 St. Anthony Falls Bridge has an ERS array, but these are not installed under the bridge deck (French, Shield, Stolarski, Hedegaard, & Jilk, 2012). Hence this bridge cannot be used. The new Wakota Bridge was instrumented in 2013 for a thermal monitoring program (Scheevel, Morris, & Schultz, 2013). The sensors used in this bridge are vibrating wire gauges which are incapable of recording dynamic behavior. The Cedar Avenue Bridge in Burnsville, Minnesota has acoustic sensors (Schultz et al., 2014), but data from these acoustic sensors cannot be used for BWIM systems. Either the sensors deployed are not a dynamic system, or the sensors were installed in locations that are not suited for BWIM applications. In any case, the currently available bridges in Minnesota that have been instrumented by the CEGE Structures Group are not applicable for an eBWIM testbed.

Apart from the type of strain gauge, other factors have to be considered in order to select an optimal testbed. The shorter the span length of the bridge and the fewer the number of lanes, the more controlled the environment will be for early testing of the eBWIM concept. Once the concept of eBWIM is validated through field testing, next the eBWIM could be tested for longer span length bridges and higher numbers of lanes to evaluate the full range of its performance. The selected bridge should be in a route where heavily loaded traffic is present in order to test eBWIM's accuracy for heavy vehicles. However, the traffic loading should be well quantified (number of vehicles per day, size and weight of vehicles approximate vehicle speed) in order to verify the performance of the eBWIM system. Also, a bridge that has room for installation of a side pole or a mast pole for mounting of the traffic sensor (microwave radar sensor in this case) is necessary. A bridge that already has either a side lamp pole, for the side-fire mount, or a sign mast pole, for doppler mount would be preferable. The present study suggests the use of microwave radar sensors. Since radar sensors work effectively in the side-fire mount, a side lamp pole is preferred. In summary, a bridge having a smaller number of lanes, short span length, a side lamp pole or room for installing a side pole, and which will pose minimum amount of interference to traffic during installation of the eBWIM system is recommended.

Additionally, it is recommended that the renowned and worldwide trusted BWIM system, SiWIM®, manufactured by Cestel Corporation be deployed. Using SiWIM® as the BWIM system will furnish trustworthy data. Also, the third generation SiWIM® modular system introduced in the year 2008 allows for easy implementation of external programs to test new and modified algorithms (O'Brien et al., 2008). This property will be instrumental for the eBWIM since a new algorithm will be required. Furthermore, Cestel Corporation claims that radar technology can be implemented with SiWIM®. Moreover, SiWIM® has an effective non-intrusive axle detecting system -- FAD algorithm. The number of axles, and axle spacings generated by FAD can be compared with the data obtained from the traffic sensor and the data from the traffic sensor will assist in detecting the number of axles and axle spacing with higher accuracy. Microwave radar sensors manufactured by Wavetronix LLC are recommended for use since this sensor has been found to be used the most by researchers and bridge agencies, and thus it has been characterized in greater depth than other microwave sensors. Location and orientation of SiWIM® sensors and microwave radar should be selected according to manufacturer's recommendation and in consideration of the characteristics of the selected bridge.

Since there do not appear to be Minnesota bridges that are appropriately instrumented for the proposed eBWIM testbed plan, another bridge must be identified. Also, instrumenting a previously uninstrumented bridge will allow the use of a commercial BWIM system, which is expected to perform better than a generic array of strain gauges. An attractive option is to consider one of the bridges in the University of Minnesota Transitway.

The University of Minnesota owns several bridges along the University of Minnesota Transitway, and it is recommended that one of the bridges be instrumented. Because the bridges are owned by the University of Minnesota, the process for obtaining permission to instrument them is expected to be more expedient, even though permission from and coordination with other agencies and organizations may be required. The vehicles carried by these bridges, especially the large vehicles, i.e., University of Minnesota shuttle buses (Campus Connector), are known entities. Information on the number of axles, axle spacing and weight of the vehicle, and travel schedule can be easily obtained. The weight of the buses during peak hour can be estimated with little effort. This will provide a well-controlled environment for the experiment. Also, knowledge of peak hours will assist in instrumentation and maintenance schedule. The proximity of the site from the CEGE Department is another benefit. Site visits during the instrumentation phase and maintenance afterward will be convenient. In such bridge instrumentation scenarios, several trips may be required, and the proximity of the site to the University of Minnesota will provide a huge relief on travel time and cost.

There are three possible candidate bridges along the University of Minnesota Transitway. All of them have two lanes of opposing traffic. The bridges are referred as 'first', 'second' and 'third' bridges for identification purposes, and the terms do not signify a ranking. The first bridge along the Transitway is adjacent to the Fairview System Credentialing Office and Koch Logistics (see Figure 9.1 for an aerial view). This bridge lies over railway tracks. Thus, instrumenting this bridge may pose difficult scheduling to avoid conflicts with railway traffic and will require permission from the concerned authority. Additionally, a side post has to be installed on the bridge for mounting the radar sensor (refer to Figure 9.2).

The second bridge along the Transitway spans over Raymond Avenue in St. Paul (see Figure 9.3 for an aerial view). Instrumenting this bridge will intervene with the traffic on Raymond Avenue (refer to Figure 9.4). Also, a side post will have to be installed for radar sensor mounting.

The third bridge along University Transitway is near a St. Paul Fire Department Station and a St. Paul Public School property (see Figure 9.5 for location's aerial view). This location facilitates the installation of strain gauges under the span because it is above the parking lot in front of St. Paul Public Schools property (see Figure 9.6 and Figure 9.7). Doing so will avoid interference with the rail traffic present on the other end of the bridge. Also, the bridge has lamp-posts installed on it (see Figure 9.7) that could be used to mount the radar sensors.

Since the first two bridges could potentially interfere with the traffic during the instrumentation and maintenance phase and a new side pole would have to be installed to mount the radar sensor, and whereas the third bridge would pose no interference with the traffic and has side lamp posts that could be easily used for radar mounting, the first two bridges are considered less ideal compared to the third one. Hence, the third bridge is considered the most appropriate candidate bridge and is recommended for instrumentation.

Figure 9.1: Aerial view showing the first candidate bridge and its vicinity
(Source: Google Maps)

Figure 9.2: Elevation of the first candidate bridge
(Source: Google Maps)

Figure 9.3: Aerial view showing the second candidate bridge and its vicinity
(Source: Google Maps)

Figure 9.4: Elevation of the second candidate bridge
(Source: Google Maps)

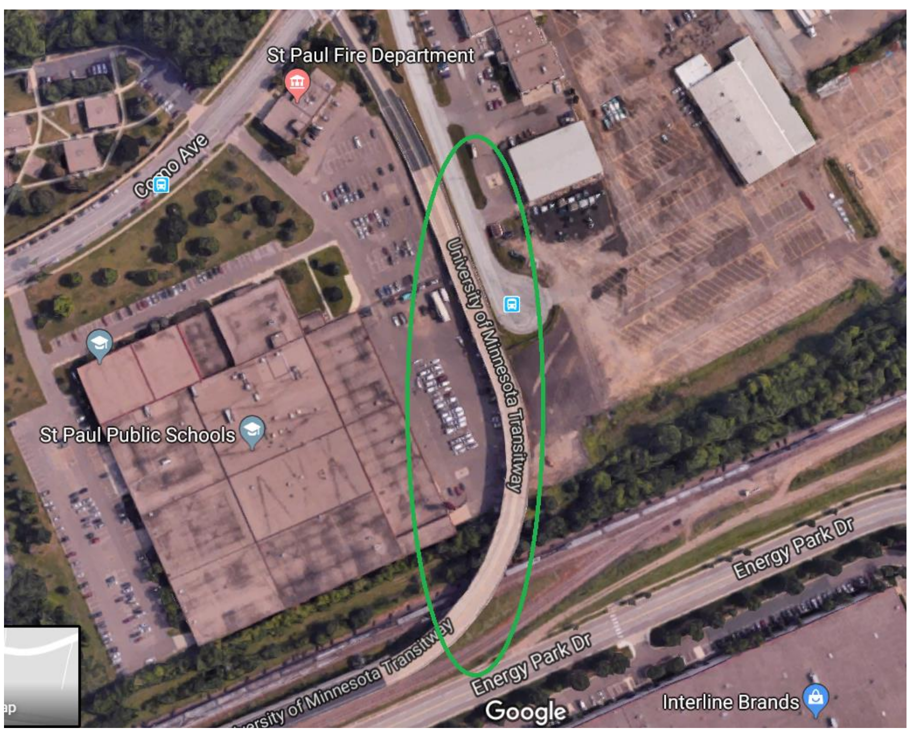

Figure 9.5: Aerial view showing the third candidate bridge and its vicinity
(Source: Google Maps)

Figure 9.6: Elevation of the third candidate bridge
(Source: Google Maps)

Figure 9.7: Elevation showing the suitable location for strain gauge and radar sensor installation
(Source: Google Maps)

CHAPTER 10: CONCLUSIONS

BWIM systems have undergone many improvements from the time it was first invented by Moses. Researchers have suggested advancements in the original Moses algorithm as well as the sensing technologies, both strain sensing and axle detection technology. These advancements when executed properly can overcome some of the limitations of the original BWIM system. However, due to reasons like inadequate accuracy, high computational demand, or necessity of further research, most of these advancements have not been applied to commercial BWIM systems. The technology associated with the FAD algorithm is the only advancement that has been found to have been incorporated in a commercial BWIM, SiWIM®. Also, SiWIM® uses an adapted Moses algorithm for weight computation. The accuracy of SiWIM® is enough for preselection of potentially overloaded vehicles (Cestel Corporation, n.d.), but not sufficient for law enforcement. This paper proposes to use SiWIM® data coupled with data from traffic sensors to improve the accuracy of SiWIM® in estimating individual axle weight and gross vehicle weight.

In Chapter 5, four different categories of traffic sensors were reviewed to study their performance and select the best traffic sensor. Based on what other researchers or organization have observed during their field deployment and testing of different categories of the traffic sensors used, the following conclusions can be made.

1. The traffic sensors reviewed in the present paper have limitations. The limitations can be attributed to factors like occlusion, inclement weather, poor lighting, and cost.
2. Although processed video images are special because of their ubiquitous nature in modern roadways, the performance of video image processors is highly affected by lighting and weather conditions.
3. Systems like microwave radar and active infrared perform satisfactorily in inclement weather, but the accuracy is not adequate, i.e., less than 90%.
4. Among all, the best accuracy (greater than 90%) was shown by an active infrared sensor TIRTL, but this sensor requires deployment near to the road surface on either side, and it is an expensive sensor compared to other sensors. Snow and poor drainage pose problems to this sensor as well. Also, pronounced roadway crowns pose a problem to the sensor's functioning.

Preliminary results indicate that there is no clear candidate for a fully mature sensing system that would satisfy all the criteria in this study. However, microwave radar sensors have a reasonably low cost, are the least intrusive, and perform better in all weather conditions compared to other sensors. Thus, radar sensors with their current characteristics can be investigated to see if they can enhance the accuracy of the existing BWIM system. Additionally, until an eBWIM system is implemented and tested, the minimum accuracy requirements for traffic sensors will not be known. Also, if the lower-than-desired accuracy of microwave radar sensors is improved, BWIM implementations using this sensor system should prove to be invaluable for enforcing bridge weight limits, studying truck traffic patterns, and managing bridge inventories.

For the development of an eBWIM system, an algorithm would be required to be developed to obtain the vehicle classification data from the microwave radar measurements. Next, coupling of the data obtained from the conventional BWIM system and the data obtained from the traffic sensor (vehicle speed, number of axles, and axle spacing) demands the development of one more algorithm. The two possibilities of development of such an algorithm are suggested in Chapter 8. Hence, a testbed project would require a significant computational component. Development of the algorithms are recommended as a future task.

A testbed is required to execute the eBWIM concept for the purpose of exploratory research, concept validation, algorithm development and system calibration. Preference was given to find a bridge that is already instrumented with the appropriate type of strain measuring equipment, but some reviewed bridges instrumented by the CEGE Department of the University of Minnesota for the Minnesota Department of Transportation were found to be inadequate for BWIM applications. Thus, a bridge owned by the University of Minnesota along the Transitway is recommended to be instrumented and used as a testbed for eBWIM research. Out of the three bridges along the Transitway reviewed in Chapter 9, the bridge near the St. Paul Fire Department and St. Paul Public School property (see Figure 9.5 for location's aerial view) is recommended to be instrumented. This bridge has advantages over other bridges along the Transitway because there is no traffic under the bridge and the bridge has lamp posts for radar sensor mounting.

In summary, data enrichment of the existing BWIM system using microwave radar sensor seems to hold the potential to enhance the accuracy of the existing BWIM system. The coupling of strain gauge measurement data from the BWIM system and microwave radar data will require development of algorithms. The authors recommend deployment of SiWIM® and the Wavetronix microwave radar sensor on a bridge along the University of Minnesota Transitway for exploratory research, concept validation, algorithm development, and system calibration.

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