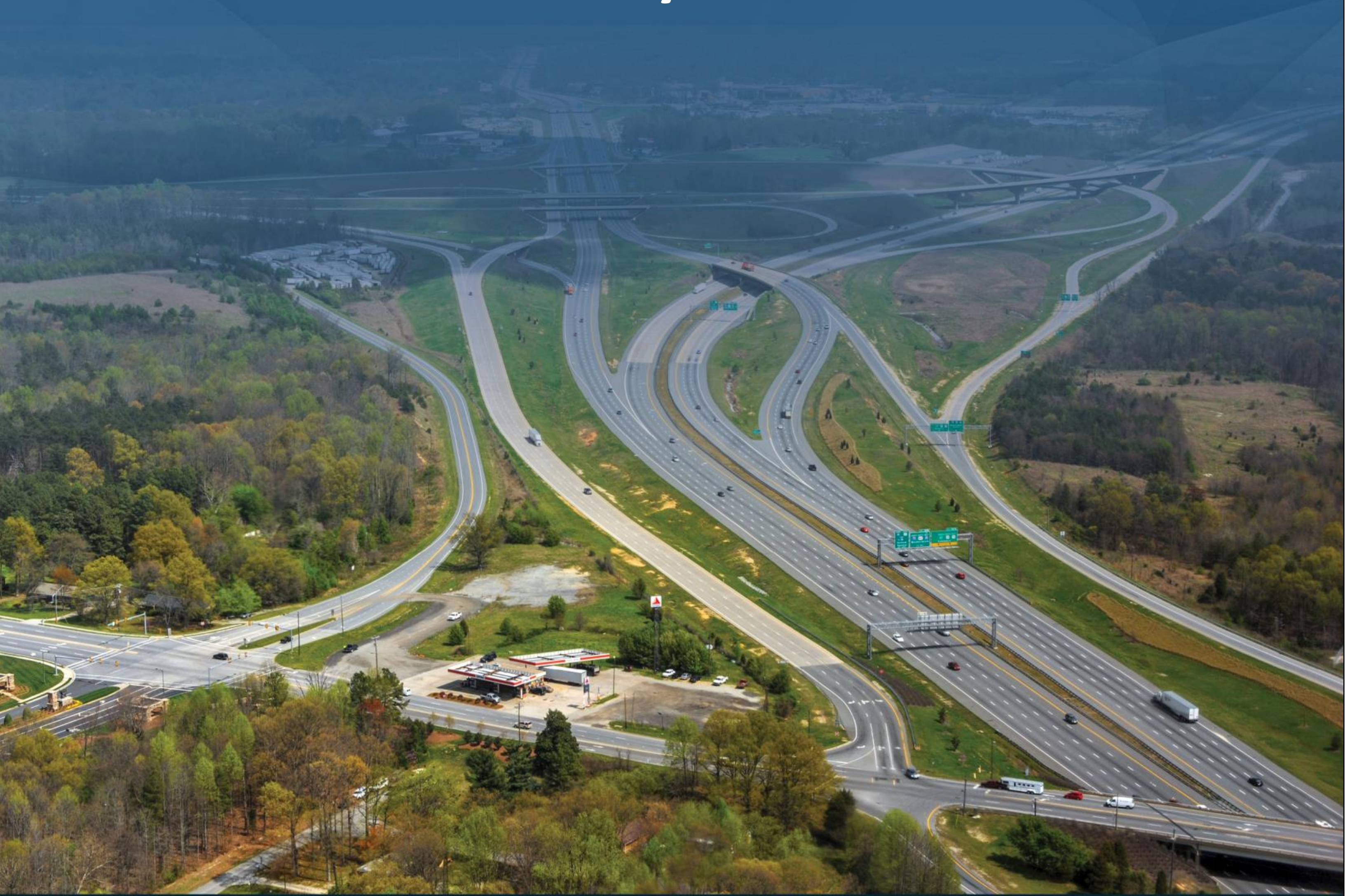
Developing Vehicle Weight Monitoring Program Design Guidelines Based on Advanced Data Analytics



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December 2023

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RESEARCH & DEVELOPMENT

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Developing Vehicle Weight Monitoring Program Design Guidelines Based on Advanced Data Analytics

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16. Abstract

As part of traffic monitoring programs, state transportation departments are required to provide information about the status of their transportation infrastructure based on traffic data collected through sensors. The Traffic Monitoring Guide (FHWA, 2016) and the American Association of State Highway and Transportation Officials (AASHTO, 2009) provide general guidance about how to collect traffic volumes, vehicle classification information, and weight data. Weigh-In-Motion (WIM) systems are the technology most used to collect the datasets used in assessing the impact of vehicles on the infrastructure; increasing the safety of the systems; and assessing road damage and facility lifetimes. The goal of this research has been to help NCDOT identify and adopt a new system for monitoring freight activity, especially truck weight distributions on the highways across the state. To that end, we have documented the current and future perceived use of WIM data by different stakeholders in the agency, elsewhere in the state, in the country more generally, and for technology providers. We have explored ways in which the state's freight truck traffic monitoring system can be used as a decision support tool for pavement design, bridge design, asset management, load rating, commercial vehicle weight enforcement support, and freight planning and logistics. The results will help NCDOT maximize the benefits of their new WIM program, offsetting the investment required. Findings include identification of the spectrum of vehicle weight data needs within the agency, an inventory of the statistics needed by stakeholders, and identification of the standards required to generate them reliably. We anticipate that these findings will be used by multiple divisions within NCDOT. They will use our findings to motivate sustainable support for a WIM program that informs decision-making among departments, including Pavement and Bridge Engineering, Freight and Logistics, Interagency Coordination, Transportation Planning, Planning and Programming, Strategic Initiatives & Program Support, Highway Operations, and Multi-Modal Transportation.

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EXECUTIVE SUMMARY

As part of traffic monitoring programs, state transportation departments are required to provide information about the status of their transportation infrastructure based on traffic data collected through sensors. NCDOT (the North Carolina Department of Transportation) is required to report annually to the FHWA data the condition of the highway network. To protect against accelerated deterioration, it needs to monitor the volumes and weights of vehicles on the interstate highway network. Implementation of a WIM system would provide the accurate data needed for reporting and overweight vehicle enforcement. This project sought to identify how states nationwide are using WIM systems to assess the quality of their roadways and the effects of use, especially by trucks.

The Traffic Monitoring Guide (FHWA, 2022) and the Mechanistic-Empirical Pavement Design Guide: A Manual of Practice (AASHTO, 2021) provide general guidance about how to collect traffic volumes, vehicle classification information, and weight data. Weigh-In-Motion (WIM) systems are the technology most used to collect the datasets used in assessing the impact of vehicles on the infrastructure; increasing the safety of the systems; and assessing road damage and facility lifetimes. This research has aimed to help NCDOT identify and adopt a new system for monitoring freight activity, especially truck weight distributions on the highways across the state. We have documented the current use of WIMs by states nationwide, as well as plans for the future, plus, within North Carolina, the perceived value that WIM data would provide.

We have explored ways in which a re-instituted weigh-in-motion (WIM) system could become a sustainable, integral part of the decision support system used for pavement design, bridge design, asset management, load rating, commercial vehicle weight enforcement support, and freight planning and logistics. We show how NCDOT can maximize the benefits of the new WIM program to offset the investment required to generate reliable traffic load data. Our research findings include an identification of the spectrum of vehicle weight data needs within the agency, an inventory of the statistics needed by stakeholders, and identification of the standards required to generate them reliably. We anticipate that the Traffic Survey Group will use our findings to seek funding for rejuvenated WIM activity. We anticipate that the beneficiaries will include Pavement and Bridge Engineering, Freight and Logistics, Interagency Coordination, Transportation Planning, Planning and Programming, Strategic Initiatives & Program Support, Highway Operations, and Multi-Modal Transportation.

1. INTRODUCTION

WIM systems provide important traffic data including traffic volume counts, growth rate, vehicle classification, vehicle speed, gross vehicle weight, individual axle loads, number of axles and axle spacing, truck percentage, monthly adjustment factor, and hourly distribution factor. These traffic parameters are used for pavement design and management, highway performance monitoring system, traffic planning, bridge design, maintenance, truck overloading and pavement damage assessment, overweight quantification, speed quantification, vehicle class distribution characterization, freight planning and logistics purposes. The requirements of the Fixing America's Surface Transportation (FAST) Act increased the need for reliable, effective, and accurate freight monitoring programs that can generate data for broad range of stakeholders.

For enforcement of weight standards, states have typically relied on static weigh stations. These installations require trucks to exit the highway to a staffed facility, where each truck must stop on a set of fixed scales for weighing. This method decreases truck travel time reliability, and the time required creates a queue when the station is operating, allowing trucks to bypass and avoid detection.

Weigh-in-motion (WIM) systems can augment these activities by improving the effectiveness of enforcement programs and the long-term costs of pavement maintenance and management. Static weigh stations cannot monitor 100% of freight movement, since they have limited operating hours, and the time required to capture static weight means long queues allow trucks to avoid the station even when it is staffed. Having a pre-screening WIM system can allow underweight vehicles to bypass the station, while overweight vehicle enforcement can improve. Since states that have higher numbers of WIM stations should have better enforcement, the reduction of overweight vehicles should correspond to better roadways as measured by the International Roughness Index (IRI). By comparing WIM and IRI data from fifteen states over a period of three years, we predict that states with more WIM stations will have better road conditions.

1.1.Background

In 1956, President Dwight D. Eisenhower signed the Federal-Aid Highway Act, which created the federal Interstate Highway System (IHS). The act supplied federal funds to state governments that helped in the construction of a system of interconnected highways, leading to high-speed vehicle traffic along well-maintained and nationally standardized roadways. To protect their investment, the federal government regulated the size and weight of vehicles that were permitted on the highway system (Hazlett, 2020). Overall enforcement of the weight standards falls on the individual states, who are responsible for accurately measuring vehicle weights and collecting permit fees and fines for overweight vehicles.

At the time of the WIM survey conducted by NCHRP in 2019 (NAS, 2019), 43 states were collecting WIM data; two had never done so; and 5 – including North Carolina – had closed their WIM programs. In NCDOT's case, there had been 45 WIM stations, one of the more developed weight monitoring programs in the nation. However, despite the federal traffic reporting requirements, the program ended due to funding problems, high maintenance costs and limited usage. Now, as part of developing a new truck weight monitoring program, NCDOT wants to see if the WIM program should be reinstated, It wants to know how WIM data could be used in the decision-making process within the agency and by the stakeholders in the transportation industry.

In this research effort, we have explored potential use of a renewed WIM program as a decision support tool for NCDOT; not just a data source for federal reporting requirements. Anticipated uses include pavement design, bridge design, asset management, load rating, commercial vehicle weight enforcement support, and freight planning and logistics. The project has sought ways for NCDOT to maximize the benefits of the new WIM program to offset the investment required to generate reliable traffic load data. By exploring the available and emerging technologies required to collect that data, we have provided design and implementation guidelines for a monitoring program and data use for:

- pavement design
- pavement management
- bridge load ratings
- bridge management
- weight enforcement support

- freight planning and logistics
- policymaking
- alternative fuels for long-haul freight transport
- transformation to smart and automated systems.

1.2.Research Need Definition

For the past five years, the NCDOT has not collected or used WIM data in spite of expectations from FHWA to do so. See the Long-Term Pavement Performance (LTPP) guide (FHWA, 2005), the USDOT Traffic Monitoring Guide (TMG) (USDOT, 2001), and AASHTO Pavement Design Guide (AASHTO, 2021). The requirements for freight monitoring imposed by the FAST Act made it important for all state DOTs to investigate ways to develop a comprehensive and cost-effective freight monitoring program that would generate timely and reliable statistics to address the needs of all stakeholders using WIM data.

From 1997 to 2014, the NCDOT Traffic Survey Group collected WIM data to support a nationwide long-term pavement performance (LTPP) monitoring program. Twenty-four (24) bi-directional LTPP monitoring stations were installed. Pavement design, bridge management, and enforcement made use of the data. However, because of sampling issues and the varying data standards of the secondary users, this program had limited value. So, the program was discontinued.

NCDOT is now considering the reinstatement of a WIM system. Before doing so, however, it wants to acquire clear information about:

- the usage area and weight data requirements of internal and external stakeholders
- data needs of the future stakeholders such as electrified road network operators, autonomous systems, etc.
- data standards that enable data reuse and interoperability across sectors
- data collection, data governance, and quality control policies
- available technologies and required investment to collect, store, process, analyze, and disseminate data
- potential integrations to broaden the use and the value of the data (e.g., WIM data combined with trip and commodity data)
- strategic approaches to design a new vehicle weight monitoring system that excels in usability, functionality, reliability, and stability.

The stakeholders that are expected to have an interest in WIM data include, but are not limited to, the following:

In-Agency Stakeholders	Out-of-Agency Stakeholders
• Construction Division	• FHWA
• Maintenance Division	• Road transport operators
• Transportation Planning Division	• Road traffic managers
• Planning and Programming Division	• Toll operators
• Traffic Survey Group	• Rail and water transport operators
• Strategic Initiatives & Program Support	• Consultants
• Highway Operations	• ICT and Technology companies
• Multi-Modal Transportation	• U.S. Military
• Freight and Logistics Director	• NC National Guard
• Interagency Director	• EPA
• Ports and terminals	• Vehicle manufacturers
• Airports	• Transportation equipment suppliers
• Multimodal facilities	• MPOs or COGs
• Pavement designers	• Counties, Cities and municipalities
• Freight planning group	• Fleet operators, drivers
• Asset management group	• Logistics service providers
• Bridge designers	• Industrial sites, hubs and cross-docking stations
• Center of Excellence	• Charging stations, fleet parking and truck stops
• R&D	• National, regional and local governments and the private sector.

1.3.State of the Art, in Research and Practice

Multiple units within NCDOT, the MPOs/RPOs statewide, and local government agencies are responsible for planning and maintaining roadways. Critical to this process is a clear understanding of the loading of the roadway which can vary greatly for nearby or similar facilities due to truck routes and the movement of goods in the state. An enhanced vehicle weight monitoring program would enable these agencies to make better, more data-informed decisions about how to accommodate and facilitate freight flows.

Hence, this project sought to:

- Inventory stakeholders' requirements for a weight monitoring program;
- Collect and analyze survey data from various WIM stakeholders;
- Perform a literature review and analysis of technologies and best practices in WIM;
- Create recommendations and guidance for the design of a reinstated WIM program; and
- Conceptualize a system design.

Our objective was to create guidance would be used by multiple divisions and groups within NCDOT. We anticipate that the immediate users of the recommendations and guidance will be the Traffic Survey Group. Other interested divisions are anticipated to be Pavements and Bridges, Freight and Logistics, Interagency Coordination, Transportation Planning, Planning and Programming, Strategic Initiatives & Program Support, Highway Operations, and Multi-Modal Transportation.

Our findings should enable NCDOT to maximize the benefits of the new WIM program to offset the investment required to generate reliable traffic load data. The use of the recommended guidelines in developing a strategic approach to vehicle weight monitoring will result in streamlined data flow and reports suited to all processes that require weight monitoring information. The ultimate impact is having increased operational efficiency, savings in both time and money, and flexibility to adopt periodical changes in vehicle weight laws. As a decision-making tool, the proposed continuous weight monitoring system design will provide real-time statistics for improved material structure, pavement, and performance.

Our understanding of stakeholders' requirements for a weight monitoring program and providing guidance for the selection of the most appropriate technologies will provide significant benefits compared to the total cost of the project. Project assesses the potential benefits of the project by identifying different impacts of the project compared to a well-defined baseline alternative. Then, potential benefits will be compared to the costs to justify the project outcomes against no-outcomes, which is no guidance on the design of a weight monitoring program.

1.4. Purpose and Scope

The goal of this research has been to perform an assessment of new and advanced technologies that could be used to monitor truck flows within the state. As was true with the previous WIM-based monitoring system, of principal interest is the distribution of truck weights and vehicle configurations, differentiated among highway facility types and regions. A re-initiation of the previous WIM stations is one option, but there are several others that have recently become available. Among these are truck-based monitoring apps (e.g., https://drivewyze.com/), video-based vehicle monitoring technologies, license plate readers, Bluetooth sensors, and tire pressure device monitoring systems. Undoubtedly, there are others. Each of these has been explored and characterized, and most options have been studied in detail so that the benefits, costs, and operational practicality are understood. Of paramount importance has been the ability of each option to meet the needs of the most interested stakeholders.

These objectives have been achieved by:

1. Doing a survey to understand the current and potential future use of truck data by all stakeholders
2. Reviewing the current state-of-the-art methodologies used for vehicle weight monitoring
3. Assessing the required data standards and policies; reporting gaps
4. Identifying ways to enhance the alignment between existing infrastructure, new data requirements, available and emerging technologies, and business requirements.
5. Developing alternative technology adoption strategies that would meet the needs of all interested stakeholders.
6. Providing a conceptual system design to store, manage and truck data; suggest integrations with the traffic and highway patrol data.
7. Conducting a cost-benefit analysis for each alternative.

Since monthly truck flow data collected from a single monitoring station can be upwards of 300 MB, several years of data from monitoring stations statewide would yield a Big Data management and analysis challenge. In light of this, we have recommended a vehicle weight monitoring system that uses Artificial Intelligence and Computer Vision (CV) algorithms to analyze WIM data. This includes features like:

(1) automatically analyze the data to discover differences in traffic groups or loading patterns, and to estimate the spectrum of full axle load data under different conditions
(2) extract usable information from the raw data for all users by developing and implementing advanced algorithms for analysis and data cleansing
(3) develop functionality that meets the needs of the stakeholders
(4) develop interfaces that can be used by participating states to access data in customized formats
(5) prepare training materials and deliver training for personnel from participating states; and
(6) provide technical support to participating states.

1.5. Research Approach

The research team followed the following methodology:

- *systematic review and meta-analysis* of the literature on weight monitoring technologies, implementations, best practices, data needs, costs, and benefits
- *semi-structured interviews* and meetings with selected stakeholders
- *survey* of stakeholders
- *review of emerging technologies*
- *recommendations for a weight-monitoring system with cost-benefit analysis* and implementation plan

To achieve the stated project objectives, The FSU / NCSU project team collaborated on executing the following project tasks:

Task 1: Project Initiation/Kick-Off Meeting: The research team met with the Steering and Implementation Committee (StIC) to discuss the overall research plan and solicit topics to highlight during the literature review. The team reviewed the initial list of stakeholders to be included in the study.

Task 2: Literature and Best Practices Review: The research team reviewed the state of the practice in vehicle weight monitoring programs around the world. The comprehensive review included both academic journal and industry reports. The review results were documented and periodically shared with the StIC. The findings of the literature review helped the research team in survey design and preparing survey questions.

Task 3: Stakeholder Interviews and On-Line Survey: The research team identified more than thousand stakeholders in four different groups. With close collaborations with the StIC, the research team designed multiple online surveys (using Qualtrics) to gain a sense of the extent and ways in which enhanced truck weight data might be used elsewhere within the department and state agencies.

Task 4: Analysis of Stakeholder Interviews and Survey Results: The survey data was analyzed and presented to the StIC multiple times, with a critical analysis of the findings. The research team organized stakeholders into a “tier” system of WIM data users where some stakeholders may find the new data products to be helpful but not necessary for operations while others may have a great need to incorporate vehicle weight data into critical programs. The findings of the survey helped inform the research team of the scope of data collection and product needs.

Task 5: Analysis of Program Needs: The summarized findings of the survey will be reviewed with the StIC to identify the priority needs that the monitoring program must address. This analysis will collect the scoping considerations needed for the system design process. The team anticipates that by prioritizing individual needs, a final system design can be considered, which may include features that are beneficial to all users while remaining cost-efficient.

Task 6: Technology Evaluation: The research team will identify the multiple technologies available for vehicle weight monitoring and document their capabilities. The team will also collect information on the equipment cost, installation costs, and maintenance needs. Finally, the team will document the potential data products supported by each of the technologies. The findings of the technology evaluation will be incorporated into the cost estimation in Task 7.

Task 7: Develop Recommendations for System Design

a) Program design – specify options for technologies, standards, and relative size
b) Product inventory – specify the data products the program design supports
c) Costs – identify the general startup and recurring costs
d) Benefits – characterize the direct and indirect benefits of a strategic approach to weight monitoring
e) Funding sources – identify sources of funding based on processes supported
f) Sourcing options – identify agency and out-sourced resources
g) Implementation plan – specify the sequence of actions necessary to implement effectively
h) Emerging technologies – identify new technologies and services that may be impactful to the program expected to be available in the near term

Task 8: Final Report and Program Guidance: The research team documented the findings of the research tasks in quarterly reports, and this final report includes the overall program guidance to inform NCDOT decision-makers in the next steps for potential implementation of the monitoring program.

Task 9: Project Management: The principal investigator organized and delivered quarterly progress reports to the NCDOT Research Unit. The research team held periodic meetings to ensure task progress and to receive timely feedback from the StIC throughout the project.

1.6. Organization of the Report

This report is organized as follows. The report begins with an introduction that provides background information on the need for weight monitoring platform, defines the research need, and describes the purpose and scope of the report. It then presents a literature review that summarizes the key findings of the existing research on weight monitoring systems (WMP) and WIM technology. Next, the report analyzes the stakeholders' requirements based on survey results. The survey analysis is used to develop a set of recommendations and guidance on the design of a comprehensive weight-monitoring platform. The report concludes with a recommended system design for a WMP that incorporates emerging WIM technology. The system design is based on the recommendations and guidance developed in the previous section. It includes a discussion of the system architecture, key components, and data flows. Overall, this report provides a valuable resource for transportation agencies and other stakeholders who are considering implementing a weight monitoring platform. It provides a comprehensive overview of the key issues and considerations, as well as a conceptual system design that can be used as a starting point for developing a specific WMP.

2. LITERATURE REVIEW

In this section, we present the scope and the results of our literature review. Please note that numerous research studies exist that focus on weight monitoring with various WIM technologies. Most of the literature centers around the use of WIM in pavement design, bridge design, asset management and load rating. As WIM technology and ICT systems have advanced, WIM applications have extended to commercial vehicle weight enforcement, and freight planning and logistics (NAS, 2020).

2.1. Overall Scope of the Literature Review

The literature review covers a wide range of topics related to weigh-in-motion (WIM) systems, including data analysis, new technologies, industry reports, technology reviews, integration with imaging, accuracy, and reliability, bridge WIM (BWIM), efficiency and impact, direct enforcement, piezoelectric sensors, calibration, and portable WIM systems.

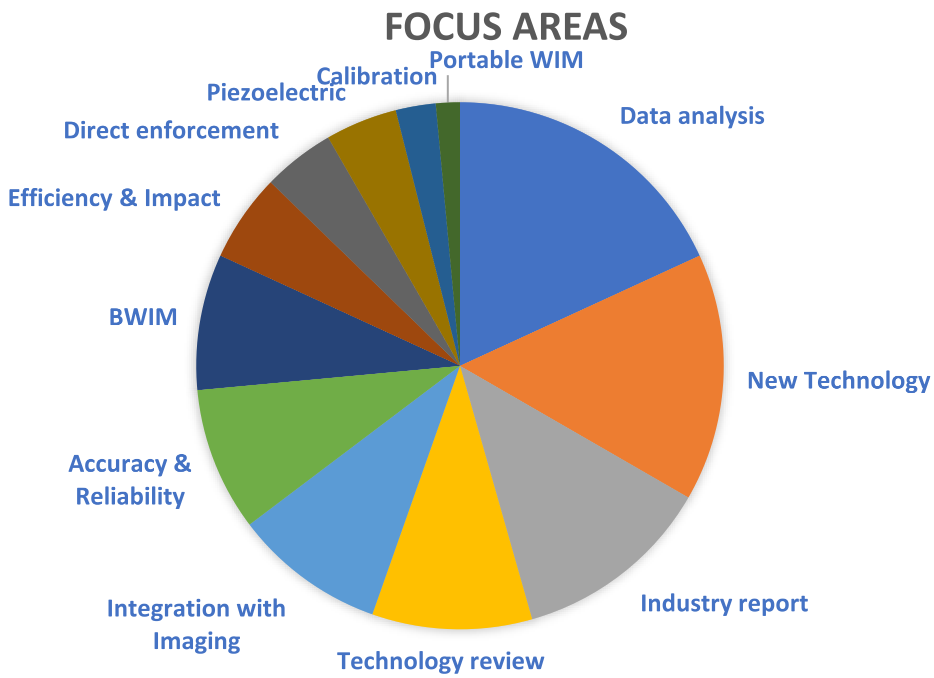


Figure 1 Distribution of publications by focus areas

Focus area of the articles	Count of Publications
Data analysis	37
New Technology	31
Industry Report	25
Technology Review	20
Integration with Imaging	19
Accuracy & Reliability	18
BWIM	17
Efficiency & Impact	11
Direct enforcement	9
Piezoelectric	9
Calibration	5
Portable WIM	3
Grand Total	**204**

2.2.Key Findings

Our key findings from the literature review are as follows:

- *Data analysis*: Most publications in this area focused on developing and evaluating new data analysis methods for WIM systems. This is an important area of research, as it is essential to be able to extract accurate and reliable data from WIM systems in order to use it effectively.
- *New technology*: There is a growing interest in developing new WIM technologies, such as those that use video or radar to weigh vehicles. These technologies have the potential to improve the accuracy and efficiency of WIM systems.
- *Industry reports*: Industry reports provide valuable insights into the current state of the WIM market and the challenges that need to be addressed.

- *Technology reviews*: Technology reviews provide a comprehensive overview of the latest WIM technologies and their applications.
- *Integration with imaging*: There is a growing trend towards integrating WIM systems with imaging systems. This allows for the collection of additional data about vehicles, such as their license plate numbers and vehicle types.
- *Accuracy and reliability*: Accuracy and reliability are essential for WIM systems to be effective. The literature review includes a number of studies that have evaluated the accuracy and reliability of different WIM systems.
- *BWIM*: Bridge-WIM systems are becoming increasingly popular, as they can be used to weigh vehicles without disrupting traffic flow. The literature review includes a number of studies that have evaluated the performance of BWIM systems.
- *Efficiency and impact*: The literature review includes a number of studies that have evaluated the efficiency and impact of WIM systems. These studies have found that WIM systems can be effective in reducing overweight vehicles on the road and improving road safety.
- *Direct enforcement*: Direct enforcement is a new trend in WIM technology. Direct enforcement systems use WIM data to automatically issue tickets to overweight vehicles. The literature review includes a number of studies that have evaluated the effectiveness of direct enforcement systems.
- *Piezoelectric*: Piezoelectric sensors are the most common type of sensor used in WIM systems. The literature review includes a number of studies that have evaluated the performance of piezoelectric sensors in WIM systems.
- *Calibration*: Calibration is essential for WIM systems to be accurate. The literature review includes a number of studies that have evaluated different calibration methods for WIM systems.
- *Portable WIM*s: Portable WIM systems are becoming increasingly popular, as they can be used to collect WIM data at any location. The literature review includes a number of studies that have evaluated the performance of portable WIM systems.

2.3. Literature Map

Literature maps, as with the one shown in Figure 2, indicate connections that exist between authors and their published manuscripts. The nodes are the authors and the edges are connections between their publications. The size of a node indicates the number of citations, and the thickness of an edge represents the number of co-authored manuscripts. This map shows that some authors contribute more to the WIM topic than do others. The map also shows that there are different clusters of authors more closely connected to each other than they are to authors in other clusters. This helps us identify influential authors, research communities, and potential collaborators. It can also be used to track research development in a particular field over time.

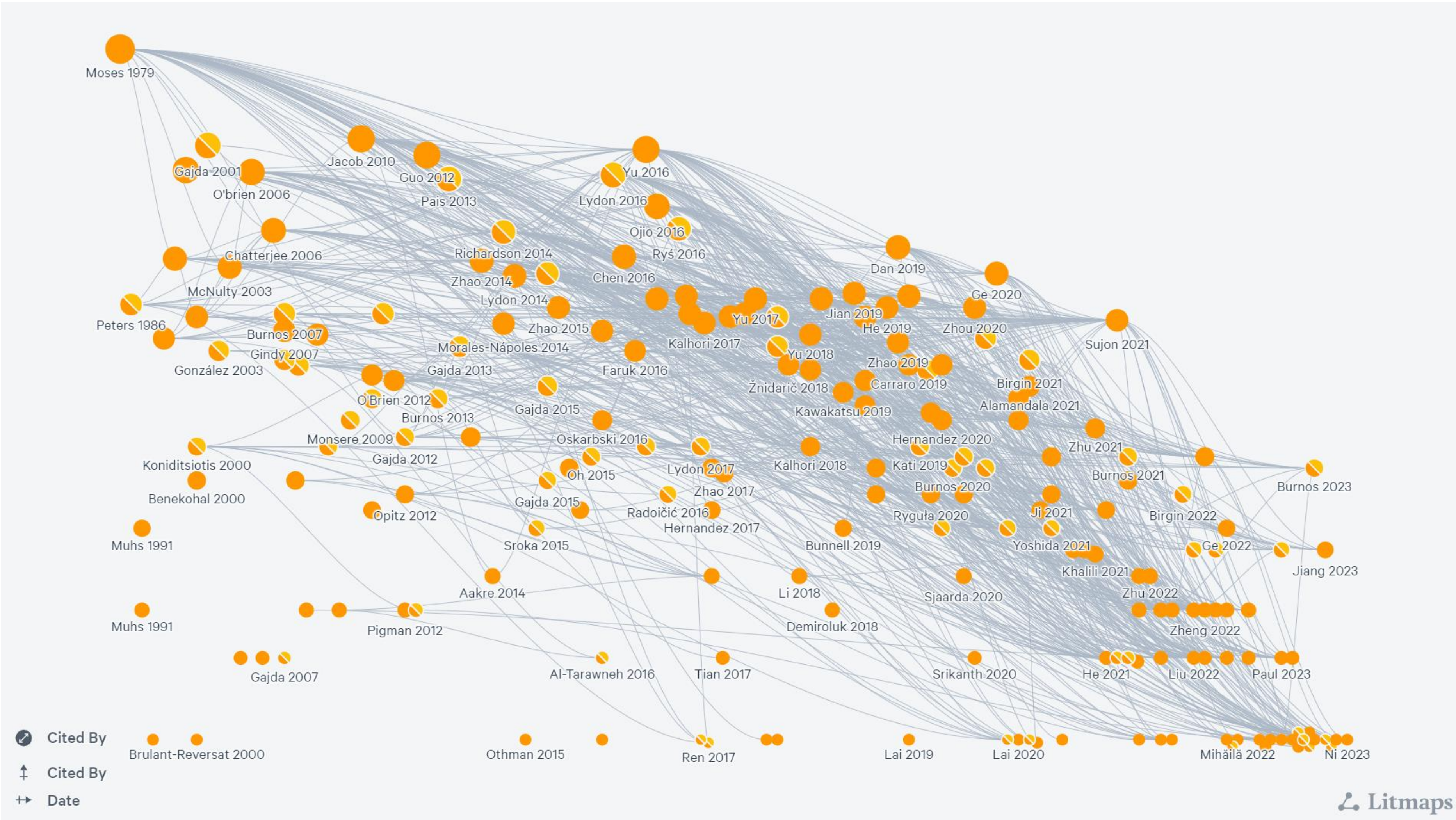


Figure 2 The map of published manuscripts on WIM Systems. [1]

[1] An interactive version of the map is available here: https://app.litmaps.co/shared/074a8eb1-ac9e-490f-b48b-e13e5c62c997

Figure 3 shows the number of publications on WIM systems by year. The number of publications has been increasing, with a particularly significant increase in recent years.

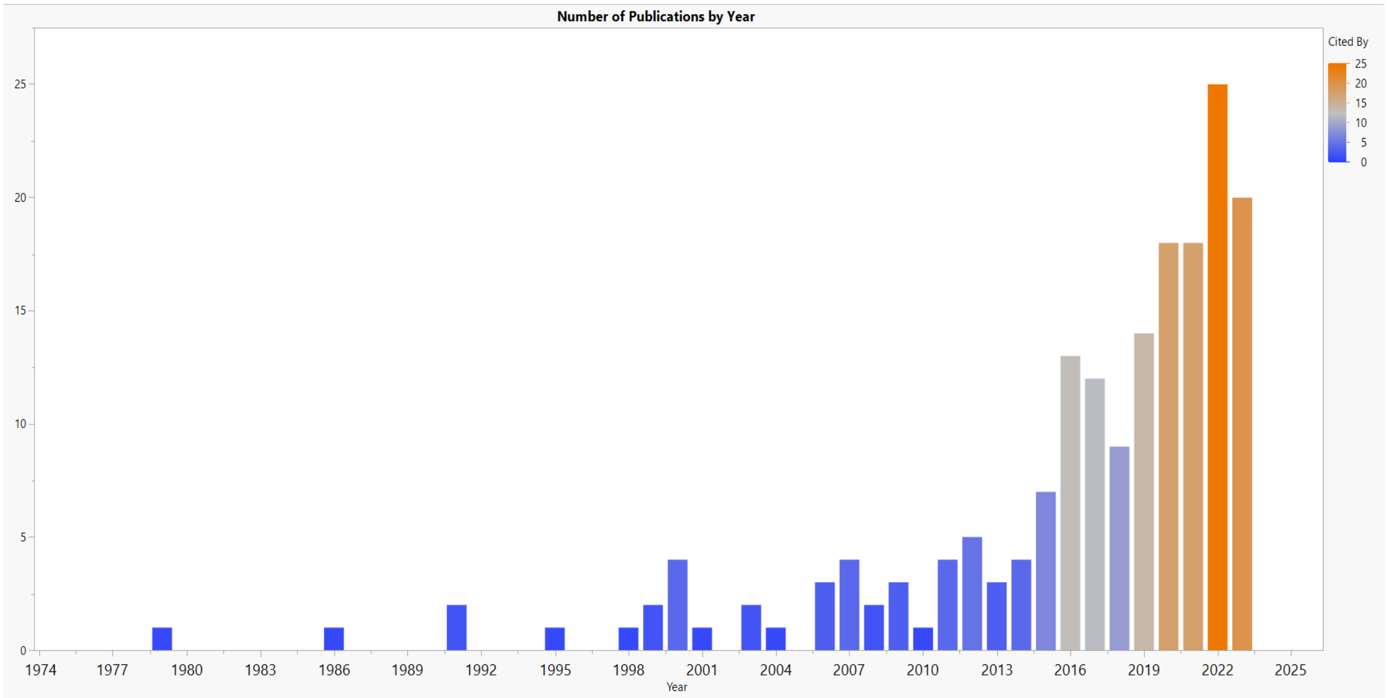


Figure 3 Number of Journal Articles by Year

There are a three main reasons for this increase in publications:

- **Growing awareness of the benefits of WIM systems**: WIM systems can be used to improve road safety, reduce road damage, and enforce weight restrictions. As more and more people become aware of these benefits, there is a growing demand for WIM systems. This is leading to more research and development in the field, which is resulting in more publications.
- **Technological advancements:** WIM technology has advanced significantly in recent years. New WIM technologies are more accurate, reliable, and affordable than older technologies. This is making WIM systems more attractive to users, which is further driving demand for WIM systems and research.
- **Expanding applications of WIM systems:** WIM systems are now being used in a wider range of applications than ever before. For example, WIM systems are now being used to monitor traffic flow, collect data on vehicle weights, and enforce weight restrictions on bridges. This expansion of applications is also contributing to the increase in publications on WIM systems.

Overall, the increase is a positive development. It shows a growing interest in WIM systems and that the technology is advancing rapidly. This should lead to even more benefits from WIM systems in the future.

Table 1 shows a list of the top twenty journals that have published weigh-in-motion (WIM) papers. The most common journals are Sensors, Italian National Conference on Sensors, and Measurement. These journals are all focused on sensors and measurement technologies, which are essential for WIM systems. Other common journals include Electronics, Engineering Structures, and IEEE International Instrumentation and Measurement Technology Conference Proceedings. These journals are focused on electronics, engineering, and instrumentation, which are also important for WIM systems. The table also shows that WIM papers have been published in a variety of other journals, including:

- Journals focused on transportation engineering, such as Transportation Research Record and Journal of Intelligent Transportation Systems.
- Journals focused on civil engineering, such as Engineering Structures and Journal of Bridge Engineering.
- Journals focused on materials science and engineering, such as IOP Conference Series: Materials Science and Engineering.
- Journals focused on electrical engineering, such as IEEE Sensors Journal and Electronics.

Table 1 Top 20 journals publishing WIM relevant articles

Journal Published	**N**
Sensors	13
Measurement	5
Electronics	3
Engineering Structures	3
IEEE International Instrumentation and Measurement Technology Conference Proceedings	3
IEEE Sensors Journal	3
International Journal of Heavy Vehicle Systems	3
IOP Conference Series: Materials Science and Engineering	3
Journal of Bridge Engineering	3
Journal of Civil Structural Health Monitoring	3
Metrology and Measurement Systems	3
Structural Control and Health Monitoring	3
Applied Sciences	2
Journal of Testing and Evaluation	2
Remote. Sens.	2
Smart Structures and Materials	2
Structure and Infrastructure Engineering	2
Transportation Research Procedia	2

The diversity of journals shows that WIM systems are a topic of interest to researchers from a variety of different fields. It also suggests that WIM systems have a wide range of potential applications. Our findings shows that WIM systems are a well-established and active research area. There is a large body of published research on WIM systems, and this research is being published in a variety of different journals. This suggests that WIM systems have a bright future and that they will continue to play an important role in transportation engineering.

Table 2 Authors over the last five years

First Author	**Number of Publications**
Birgin	5
Gajda	4
Burnos	4
Jian	2
Feng	2
Dontu	2
Chen	2
Kawakatsu	2
Sadeghi Kati	1

Table 2 lists the top authors who have published weigh-in-motion (WIM) papers over the last five years. Most prolific is Birgin, who has published five WIM papers in the last five years. Gajda and Burnos are close behind, with four papers each. This shows that WIM research is a vibrant and active field with a large community of researchers who are dedicated to advancing the state of the art in WIM technology.

2.4.Initial Research

The earliest investigation of WIM systems is Moses (1979). He presents the development and testing of a weigh-in-motion (WIM) system that uses instrumented bridge girders and timing information from tape switches to predict the axle and gross weight of trucks in motion. The system is based on the principle that a concentrated load moving across a bridge will induce stresses in proportion to the product of the influence value and the magnitude of the load. Moses tested the system on a three-span continuous beam-slab bridge and obtained promising results. The truck weight predictions were quite accurate, and the system was able to operate reliably in real-world conditions. Despite the initial tests' success, some challenges still need to be addressed before the system can be widely implemented. One challenge is the need for specialized equipment and expertise to install and operate the system. Another challenge is that the accuracy of the system depends on the quality of the bridge girders.

Moses suggests that these challenges can be overcome by designing self-contained, stand-alone WIM units that can be easily transported and attached to bridges. He also suggests that further research is needed to develop methods for calibrating the system on different types of bridges. Overall, this paper presents a significant contribution to the field of WIM technology. Moses has demonstrated the feasibility of using instrumented bridge girders to weigh trucks in motion. Over four decades, WIM systems revolutionized the way that truck weights are measured and enforced. In addition to the traditional applications of truck weight enforcement and pavement monitoring, the WIM system has been used for a variety of other purposes as listed by Moses (1979):

- Collecting data on truck traffic patterns and flows
- Identifying bridges that are at risk of overload
- Monitoring the condition of bridges over time
- Developing new pavement design and maintenance strategies

Since the publication of this paper, the benefits of WIM systems have become more evident. WIM systems are used to support freight planning and logistics by providing real-time information on the movement of goods through transportation networks. By automating the truck weight enforcement process, the system could help to improve safety and reduce the damage to roads and bridges caused by overloaded vehicles. The system could also help to improve the efficiency of transportation networks by providing real-time information on truck traffic patterns and flows. With further development, this system could have a significant impact on transportation safety, efficiency, and sustainability.

2.5. Sensor Technology Review

The ASTM E1318 standard for WIM systems classifies WIM systems according to the following four distinct types (Type I through Type IV), depending on the application and functional performance requirements:

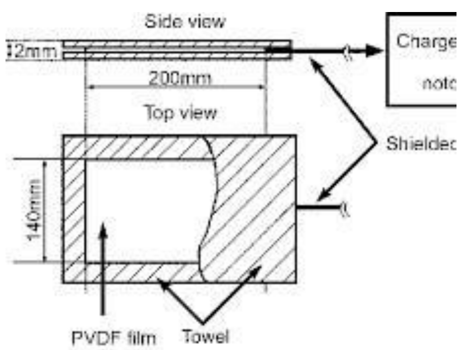
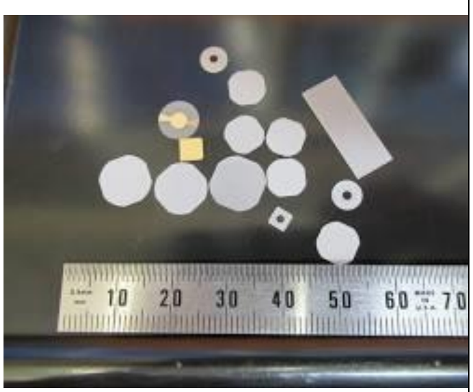
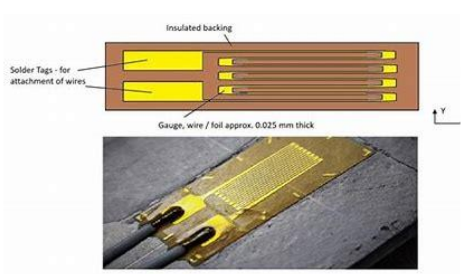
- *Type I and Type II systems*: Suitable for traffic data collection purposes, with Type I systems having slightly more stringent probability of conformance requirements. The vehicle speed range to meet functional performance requirements is 10 to 80 mi/h.
- *Type III systems*: Suitable for screening vehicles suspected of weight limit or load limit violations and have stricter functional performance requirements than Type I and Type II systems. The vehicle speed range to meet functional performance requirements is 10 to 80 mi/h.
- *Type IV systems*: Not approved for use in the United States but intended for use at weight enforcement stations. The vehicle speed range to meet functional performance requirements is 2 to 10 mi/h.

WIM technology has advanced considerably due to the advent of new sensor technology. There are three categories of WIM stations based on the speed of the vehicle: static, slow, and high-speed WIM. As the names suggest, they can measure the speed of the vehicle when they are stationary, moving slowly, or moving at their normal speed, respectively. WIM stations can also be permanent or temporary. One of the major components of the WIM system is its sensors. There are intrusive (piezoelectric sensor, bending plates, pneumatic road tube, indusctive loop) and non-intrusive devices (passive and active infrared microwave/radar, ultrasonic, magnetic, passive acoustic and image detection) used for the collection of count speed, class and WIM data (Skszek, 2001). These technologies use different types of techniques for measuring weights. Besides these types of sensors, the video camera is also used to capture important data like the class/type of the vehicle or number plate through image processing. Multiple cameras can be used to capture a moving vehicle's trajectory and location through information fusion and motion fusion

(Dan et al. 2019). Another technology uses a completely unique type of sensor compared to traditional sensors we have discussed so far. These sensors are based on micro-optical fibers. When the pressure on the fibers causes it to deform, then the loss of the light output inside the fiber optic helps us to measure the weight of the vehicle (Bin, M., &Xinguo, Z., 2010). To understand the different cost of the various WIM Technologies and sensors, we have performed some research on various WIM implementations and captured various information from the research.

Table 3 Sensor Types

Weight Sensor Type	**Image**	**Description**	**Advantages**	**Disadvantages**
Bending plate sensor		A weigh-in-motion (WIM) sensor that utilizes strain gages mounted to the underside of high-strength, rectangular steel plates called weigh pads.	Durable, accurate, and can be used in a variety of traffic conditions.	More expensive than other WIM sensor types and requires a dedicated installation.
Load cell sensor		A WIM sensor that uses load cells to measure the weight of vehicles.	Highly accurate and durable, and can be used for weighing vehicles of all sizes and types.	More expensive than other WIM sensor types and requires a reinforced concrete foundation.
Piezoelectric sensor		A WIM sensor that uses piezoelectric materials to generate a voltage in proportion to the applied force.	Relatively inexpensive and easy to install, and can be used for vehicle classification and weight measurement.	Less accurate than bending plate and load cell sensors, and not suitable for static weight measurements.

Weight Sensor Type	Image	Description	Advantages	Disadvantages
Piezo-ceramic sensor		A type of piezoelectric sensor that uses ceramic powder to generate a voltage in proportion to the applied force.	Relatively inexpensive and easy to install, and can be used for vehicle classification and weight measurement.	Less accurate than bending plate and load cell sensors, and not suitable for static weight measurements.
Piezo-polymer sensor		A type of piezoelectric sensor that uses piezoelectric polymer material to generate a voltage in proportion to the applied force.	Relatively inexpensive and easy to install, and can be used for vehicle classification.	Less accurate than bending plate and load cell sensors, and not suitable for static weight measurements.
Piezo-quartz sensor		A type of piezoelectric sensor that uses piezo-quartz material to generate a voltage in proportion to the applied force.	Highly accurate and durable, and can be used for vehicle classification and weight measurement.	More expensive than other piezoelectric sensors.
Strain gauge strip sensors (Intercomp)		Strain gauges are thin, flexible sensors embedded within the strip that measure the amount of bending or deformation caused by the weight of a vehicle passing over.	Offer a high degree of accuracy at high speeds. ±0.5% to ±1.0% of axle weight	Performance can be slightly affected by extreme temperatures, moisture, and debris on the road surface.

2.6. State of the Art and Development Trends

Weigh-in-motion (WIM) sensors allow the control of vehicle weights without disruption of traffic. WIM systems bring very important savings by traffic monitoring and by reducing the number of overloaded vehicles. This paper discusses the present status and developmental trends of high-speed weigh-in-motion (HS-WIM) technologies. Both commercial and new types of WIM sensors are presented. Strengths and weaknesses of different type of WIM sensors are discussed, as well as the economic aspects of the different technologies. Possible future developments of WIM technologies concerning the measurement performance are also described.

WIM data can also be used in estimating truck flows, locally and statewide. Stone et al. (2009) demonstrated for the first time that WIM data could be employed as inputs in developing a statewide truck flow model. It was the precursor to the current statewide freight model. Their work was based on earlier methodological work by List and Turnquist (1995), List et al. (2002) and Nozick, Turnquist and List (1996). In all these cases, observations of truck flows on network links, including data from WIM stations, were used as inputs in the flow matrix development process.

WIM data have also been used to inform pavement design and investment decisions by NCDOT. List, Stone, and Demers (2009) used WIM data to develop trip making profiles for various highway facilities statewide, especially the interstates and principle rural arterials. The strength of these estimates was predicated on the clustering analysis of Sayyady et al. (2011). The data were also used to examine placement strategies for WIM stations, as portrayed by the authors. These studies clearly show that WIM data have value for managing the integrity of the highway infrastructure, for making pavement investment and rehabilitation decisions, and for determining how to be cost-effective about determining where the best places are for having WIM stations.

Refai et al. (2014) discusses the implementation of different types of WIM system and presents a portable WIM practice in Oklahoma, where they observe significant cost reductions compared to permanent WIM stations commonly used by the Federal Highway Administration (FHWA) and state DOTs. In a similar study conducted in Minnesota, Kwon (2012) evaluates the performance of weigh-pad-based portable WIM systems, reporting positive correlations between the portable and permanent systems in measuring the gross vehicle weight, speed, and axle specification data. More recently, Faruk et al. (2016) reported 87-90% accuracy in collecting weight data through portable WIM stations in Texas, although NCDOT has not found this to be a defensible conclusion based on its own experimentation.

2.7.Integrated Solutions

Reliable and accurate monitoring of traffic loads is of significance for the operational management and safety assessment of bridges. Traditional WIM techniques can identify moving vehicles with satisfactory accuracy and stability, whereas the cost and construction-induced issues are inevitable. Xia et al. (2019) proposed a traffic sensing methodology, combining computer vision techniques and traditional strain-based instrumentation with extra focus on complicated traffic scenarios. Rather than a single sensor, a network of strain sensors of a pre-installed bridge structural health monitoring system is used to collect redundant information and hence improve the accuracy of identification results. Field tests were performed on a concrete box-girder bridge to investigate the reliability and accuracy of the method in practice.

Dan, Ge, and Yan (2019) proposed a novel information fusion-based method for the identification of transverse and longitudinal loads on the full deck of bridges of different lengths. This method utilizes a pavement-based weigh-in-motion system (WIMs) at the bridge's entrance to obtain the weights of vehicles captured by cameras. Multiple cameras arranged along the bridge's length are used to acquire traffic flow videos, which are then processed to calculate the trajectories and locations of vehicles. The weight and location data are matched when the vehicle in the video crosses the piezoelectric sensor of the WIMs, which records the weight information at the same time. Since vehicles can be modeled as concentrated loads, the values and locations of all moving loads on the entire bridge can be identified in real-time. The reliability and accuracy of the proposed approach were verified using multi-view 3D simulation video data and field data from a ramp bridge.

Ge et al. (2022) developed a random traffic flow load (TFL) simulation that integrates machine vision and weigh-in-motion (WIM) technology for bridge design and safety assessment. This system uses a deep learning method to accurately detect vehicles and wheels in video footage and extract key parameters for TFL modeling. Based on long-term monitoring data, statistical distributions of key parameters are determined, and an intelligent TFL model is derived from the Intelligent Driver Model (IDM) to consider vehicle car-following behavior. The paper also proposes a TFL simulation method that achieves accurate TFL simulation. A cable-stayed bridge was used to validate the feasibility of the proposed method. The results showed that, compared to modeling and simulation methods that rely only on WIM systems, the proposed method reduced the measurement error of vehicle dimensions by nearly four times and achieved higher resolution in time measurement. The proposed method effectively overcomes the shortcomings of existing schemes and has good application potential in engineering.

Table 4 Sensor Types and AI Integration Capability

Sensor type	*AI Integration*	*Infrastructure*	*Quality-accuracy*	*High/low speed*
Piezoelectric sensors (ceramic, polymer and quartz)	No	Asphalt and concrete slab roads. Epoxy resin material reinforced by an aluminum support	Error: I (±7%) or 0 (±3%) GVW 95%: ±15%	High Speed
FAD sensors	No	one camera and eight sensor setups	Error: 15%	High Speed
Strain transducers and tape switches	An algorithm is presented which weighs each vehicle regardless of the presence of vehicles in other lanes.	Reusable strain transducers and tape switches are mounted on bridges to provide a continuous and complete traffic and load picture.	N/A	High Speed
Novel capacitive flexible weighing sensor constructed by rubber materials	NA	N/A	The maximal error of vehicle's gross weight is ±7.72% and average error is ±1.715%, whose accuracy surpasses error of gross weight is ±10% when confidence is 95%	Low Speed
Piezoelectric sensor with Video Cameras	Yes	N/A	N/A	High Speed
Plate & Strip Sensors	No	External structures, either a road surface or a bridge, which is the physical framework.	5% error	High Speed
Vehicle separator, weighing pad, axle identifier, induction coil sensors, video camera, and data processor.	No	WIM systems and detection technology should be installed at freeway entrances to prevent access by severely overloaded trucks.	error ≤2%.	High Speed
Graded index optical fiber	No	The weight sensor-based micro bending graded index fiber.	0.55% error	Static

Sources: Jiang, X. et al.(2009), Hitchcock, W. et al.(2011), Moses, F. (1983), Cheng, L., Zhang, H., & Li, Q. (2007), Dan, D., Ge, L., & Yan, X. (2019), Oskarbski, J., &Kaszubowski, D. (2016), Huang, H. et. al. (2019), Faruk, et. al.(2016), Ula, R. K., &Hanto, D. (2017).

2.8 Applications of Artificial Intelligence for Weigh-in-motion

An increasing global concern exists regarding overloaded vehicles causing damage to civil infrastructure. Traditional methods of vehicle weight measurement, like static weighing and pavement-based WIM, have limitations like time consumption, traffic disruptions, and high costs. Bridge WIM (B-WIM) systems, while different, still depend on extensive bridge sensor instrumentation and are costly. In contrast, Artificial Intelligence (AI) and, in particular, its sub-topic of Computer Vision (CV) offers technology at a low-cost, non-contact, and non-destructive alternative for WIM, with applications in structural health monitoring and vehicle mass estimation.

Feng et al. (2020) discuss an innovative computer vision-based, non-contact vehicle weigh-in-motion (WIM) method. This method calculates the weight of vehicles, particularly heavy trucks, by analyzing tire deformation parameters like tire-roadway contact length and tire vertical deflection. It also uses tire pressure data from on-board sensors. Experiments with concrete trucks and an SUV demonstrated the accuracy of this method, suggesting its potential as a non-contact means for weighing vehicles in motion. This proof-of-concept study aims to show the feasibility and accuracy of the computer vision-based non-contact WIM method. The document describes the methodology and presents experimental validation, highlighting the potential of this approach to revolutionize traditional static weighing and other WIM methods.

In another study, Feng et al. (2020) describe developing and testing a computer vision-based non-contact weigh-in-motion (WIM) system for heavy vehicles, addressing the need for cost-effective monitoring to prevent infrastructure damage. The system calculates the force exerted by each tire on the road by measuring tire-road contact area and pressure. It uses computer vision to (1) measure tire deformation parameters, thereby estimating the contact area, and (2) recognize sidewall markings on the tire to determine the manufacturer-recommended tire pressure. The system, comprising a camera and software, employs techniques like edge detection and optical character recognition for accuracy. Field tests with concrete trucks showed that the system's weight estimates closely matched those obtained by static weighing. This novel application of computer vision technology, which does not require sensor installation on roads or vehicles, demonstrates potential for widespread implementation due to its cost-effectiveness and non-contact nature.

Wang et al. (2023) outline a novel method combining machine vision and a BP (Back Propagation) neural network for identifying vehicle loads on orthotropic deck steel box girder bridges. The process involves two main steps:

1. *Vehicle Detection and Parameter Identification*: Initially, dynamic object detection technology is used to detect vehicles. Then, image processing technology identifies the vehicle's spatiotemporal parameters, such as transverse position, speed, number of axles, and wheelbase.
2. *Strain Response Signal Measurement and Neural Network Analysis*: The longitudinal strain response signal of the bridge's U-rib is measured. This data, combined with the spatiotemporal parameters, is used to establish a BP neural network model. This model is designed to identify the vehicle's axle load and total weight.

The effectiveness and anti-noise performance of this method were validated through a numerical simulation and an experimental test with a vehicle crossing a steel box girder bridge. The results demonstrated high accuracy and robustness against noise. The identification errors for vehicle spatiotemporal parameters were below 2.5%, the total weight error was no more than 3%, and axle load errors were within 5%. This indicates the proposed method's potential for accurate and efficient vehicle load monitoring on bridges.

Zhu et al. (2021) discuss the importance of accurately determining vehicle loads for bridge design, assessment, and maintenance, and introduces a new method for obtaining precise vehicle weight and spatiotemporal information using computer vision. The proposed method involves use of WIM Technology: While vehicle weight can be obtained using Weigh-in-Motion (WIM) technology, current methods for gathering comprehensive vehicle information have limitations in accuracy. To overcome these limitations, the paper proposes a more accurate method that uses computer vision to reconstruct a 3D bounding box of the vehicle. This involves:

- Utilizing a deep convolutional neural network (DCNN) and the "You Only Look Once" (YOLO) detector to detect vehicles and obtain a 2D bounding box.
- Establishing a relationship between the 2D and 3D bounding boxes to reconstruct a 3D model of the vehicle, providing detailed sizes and positions.
- Spatiotemporal Information Acquisition: The method includes the use of multiple object tracking (MOT) to gather spatiotemporal information about vehicle loads.
- Validation and Testing: A Bridge Vehicle Loads Identification System (BVLIS) was developed and tested on a cable-stayed bridge in operation to validate the approach. The testing confirmed that the method is accurate and reliable.

The approach in this paper can be used to obtain detailed vehicle information and provide load boundary conditions for finite element modeling of bridges. Zhou et al. (2020) propose a new, low-cost, non-contact vehicle identification method for assessing vehicle loads on bridges, addressing the limitations of the costly bridge weigh-in-motion (BWIM) system. The key points of this method are:

- *Machine Vision and Deep Learning*: The method uses machine vision technology and deep learning algorithms to distinguish a vehicle and its load.
- *Vehicle Information Gathering*: Vehicle data (type, weight, position, motion trajectory, etc.) is obtained from roadside monitoring surveillance cameras.
- *Statistical Analysis*: Axle-weight distribution intervals for nine classified vehicle types are derived from statistical data of 8,402 delivery vehicles, establishing a relationship between vehicle types and their corresponding weight information.
- *Deep Convolutional Neural Network (DCNN) Training*: A dataset containing 8,624 vehicle images was used to train the DCNN. Nine rough-grained vehicle classifications were included to enhance the network's generalizability. Optimization analysis improved the accuracy of vehicle type identification.
- *Faster Region-Based Convolutional Neural Network (Faster R-CNN)*: This network effectively detects vehicle positions and utilizes a pre-trained DCNN with 98.17% accuracy in vehicle type classification as a co-shared network layer for increased computational efficiency.
- *Real-Time Tracking and GUI Integration*: The Faster R-CNN, combined with a Kalman filter, allows real-time tracking of moving vehicles through monitoring videos. A graphical user interface (GUI) is incorporated into the video camera for automatic identification.
- *Post-Processing and Field Testing*: A post-processing module based on this method was established, and a field test was conducted to validate the system's reliability.

The paper presents a novel approach for accurately identifying and tracking vehicle loads on bridges using advanced machine vision and deep learning techniques, offering a cost-effective alternative to traditional BWIM systems. Ge et al. (2020) focuses on improving traffic load monitoring (TLM) technology for bridge health monitoring and safety early warning. The key aspects of the paper are:

- Combining WIMs with Machine Vision: The study integrates weigh-in-motion systems (WIMs) with machine vision to develop a comprehensive TLM technology for monitoring the entire bridge deck.
- Challenges with Existing TLM Methods: Current TLM methods struggle to simultaneously achieve real-time processing, high accuracy, and robustness to changing lighting conditions.
- Improved Full-Bridge TLM Method: The paper proposes an enhanced TLM method using the YOLO-v3 convolutional neural network. The method focuses on:
    - Training a dual-target detection model to identify entire vehicle profiles and their tails, marking them with compact rectangular boxes.
    - Developing an optical geometry model based on the corner points of these boxes to measure vehicle dimensions and correct vehicle centroids for more accurate location estimation.
- Real-Time Accurate Traffic Load Distribution Identification: By synchronizing the timing of cameras and WIMs, each load measured is matched with the corresponding vehicle “pixel cluster” detected in video footage. This allows for the accurate, real-time identification of traffic load distribution across the bridge deck.
- Field Test Verification: The method was tested on a ramp bridge and demonstrated improved accuracy in vehicle location identification, better adaptability to lighting changes, and faster calculation speed.

- Suitability for Field Monitoring: The proposed method successfully meets the requirements for field monitoring of traffic load distribution, proving significant for bridge health monitoring and safety early warning systems.

The paper presents an innovative approach to traffic load monitoring on bridges, enhancing accuracy, real-time processing, and lighting condition adaptability, which are crucial for effective bridge health monitoring and safety. Dan et al. (2019) address the challenge of accurately identifying both transverse and longitudinal moving loads on the entire deck of bridges, which is crucial for effective bridge health monitoring. The key points of the proposed method are:

- *Information-Fusion-Based Method*: The paper introduces a method that combines different data sources for load identification on bridges of various lengths.
- *Use of Pavement-Based WIMs*: Weigh-in-motion systems (WIMs) installed at the bridge's entrance capture the weight of vehicles. This data is one part of the information-fusion approach.
- *Video Analysis with Multiple Cameras*: Multiple cameras along the bridge capture videos of traffic flow. These videos are used to calculate each vehicle's trajectory and location.
- *Data Matching and Load Identification*: The weight data from the WIMs and the location data from the videos are matched in real-time when a vehicle crosses the WIMs' piezoelectric sensor. This synchronization allows for the identification of both the values and locations of all moving loads across the entire bridge deck.
- *Real-Time Processing and Concentrated Loads*: The system processes the data in real-time and treats vehicles as equivalent to concentrated loads, enhancing the accuracy of load distribution analysis.
- *Verification and Accuracy*: The reliability and accuracy of this method were verified using multi-view 3D simulation video data and field data from a ramp bridge.

This research paper presents a novel approach for the simultaneous identification of transverse and longitudinal loads on the full deck of bridges. By integrating pavement-based WIMs and video analysis, the method achieves real-time, accurate monitoring of moving loads, contributing significantly to the field of bridge health monitoring.

Kong et al. (2022) outline a study on a new non-contact method for identifying vehicle weight, addressing the issue of vehicle overloading, which damages roads and bridges and can lead to traffic accidents. The key elements of their method are:

- *Problem of Vehicle Overloading*: Overloaded vehicles are a common problem, causing significant damage to transportation infrastructure and increasing the risk of accidents.
- *Limitations of Current Weighing Methods*: Traditional vehicle weighing methods like static weighing, pavement weigh-in-motion (PWIM), and bridge weigh-in-motion (BWIM) are contact technologies. They have drawbacks such as complex installation, poor durability, short service life, and high maintenance costs.
- *Proposed Non-Contact Method*: The study proposes a non-contact vehicle weight identification method that does not require sensors or scales on or under roads and bridges.
- *Tire-Road Contact Model and Computer Vision*: The method is based on the Hertz contact theory, deriving a tire-road contact model that relates tire vertical force to tire deformation. Computer vision techniques, including image segmentation and character recognition, are used to identify tire deformation and inflation pressure.
- *Application of the Theoretical Model*: These measurements are combined with the theoretical model to determine the tire's vertical force and, consequently, the vehicle's weight.
- *Field Testing and Results*: The method was tested in the field on passenger cars and trucks. The results show that it outperforms existing methods in the literature, demonstrating high accuracy and robust performance under various conditions, including different inflation pressures, vehicle weights, motion states, and tire types.

The study introduces a novel, non-contact method for vehicle weight identification using a combination of a theoretical tire-road contact model and advanced computer vision techniques, showing promise for improved management of vehicle overloading and aiding in transportation infrastructure design and maintenance. A more recent study by Zhang et al. (2023) proposes a computer vision (CV)-based method for vehicle weight measurement, and the factors affecting its accuracy are analyzed by the researchers. The key aspects of this method and study are:

- *CV-Based Weight Measurement Process*: The method involves capturing tire images, processing them to extract tire edges, calculating vertical tire deformations, determining actual tire pressures, and using a tire mechanics model to calculate the weight of each tire and the gross vehicle weight.
- *Analysis of Factors Affecting Accuracy*: Parametric studies were conducted to understand how various factors impact measurement accuracy. These factors include the distance between the camera and the tire, camera parameters, illumination, background contrast, and vehicle speed.
- *Results of the Study*: The study found that high accuracy in weight measurement is achievable under optimal conditions. These include a short distance between the camera and the tire, suitable camera settings, normal illumination levels, a distinct contrast between tires and their background, and low vehicle speeds.
- *Comparative Accuracy and Application*: In practical applications, the identification error of the gross vehicle weight is within 15% at a 95% confidence interval. This level of accuracy is comparable to that of traditional weigh-in-motion systems.

The study presents a promising non-contact method for vehicle weight measurement using computer vision. It demonstrates that while several factors can influence the accuracy of this method, under optimal conditions, it can achieve accuracy comparable to traditional systems, offering a potential alternative for traffic data collection and infrastructure safety assessment.

The swift and precise determination of vehicle weight is crucial for managing and controlling vehicle overload, as well as for assessing road and bridge usage. The Bridge Weigh-in-Motion (BWIM) technique, when integrated with camera systems, has become increasingly popular in traffic load monitoring. BWIM is utilized for acquiring vehicle load data, while cameras are employed to ascertain the temporal and spatial distribution of vehicle loads on bridges. In recent years, various scholars have also incorporated computer vision (CV) techniques in the identification of vehicle weight parameters.

The summary of non-contact Bridge Weigh-in-Motion (BWIM) methods and their applications is as follows:

- *Non-Contact BWIM Methods*: This method measures vehicle weights using bridges without the need for installing sensors on the bridge. It offers the advantages of easy installation without traffic disruption, no road damage, and allows for real-time, fast weighing.
- *Computer Vision (CV)-Based BWIM Methods*: Ojio et al. proposed a CV-based non-contact BWIM method using two cameras, one for measuring sub-millimeter bridge deflections and the other for monitoring traffic and determining axle spacing. Ding et al. developed a system for vehicle load and load centroid measurement based on CV and the vehicle's vertical displacement. The vehicle load is determined using parameters resolved from the vertical distance recognized by a side camera. Chen et al. presented a method for identifying the temporal and spatial distribution of vehicle loads on long-span bridges, using BWIM for weight information and CV techniques for tracking vehicle loads. The effectiveness and accuracy of these methods were verified by field tests.
- *Additional Research and Methods*: Micu et al. used adaptive thresholding and morphological reconstruction methods to extract vehicle length from traffic videos, correlating it with weight measured by the BWIM system. Zhou et al. categorized a vehicle database into nine types of axle weight distribution intervals, establishing a link between vehicle types and weight. They used a deep convolutional neural network (DCNN) for accurate vehicle type identification and corresponding weight determination. Dan et al. proposed an information fusion-based method for load identification on bridges of varying lengths, using pavement-based WIMs at bridge entrances to measure vehicle weight and multiple cameras along the bridge to calculate vehicle trajectory and location.

Various scholarly efforts to identify vehicle weight parameters by focusing on vehicle tires, using computer vision (CV) techniques and theoretical models were reviewed. The key points include:

- *CV-Based Vehicle WIM Method*: CV-based vehicle weigh-in-motion (WIM) method calculates the tire-roadway contact force as the product of contact pressure and area. The contact area is estimated by measuring tire deformation parameters like tire-roadway contact length and tire vertical deflection using CV techniques, while tire pressure data is obtained from onboard sensors.
- *Enhancement with Edge Detection and OCR Technology*: Feng et al. also applied edge detection and optical character recognition (OCR) to identify marking texts on tire sidewalls. This allowed them to find the manufacturer-recommended tire inflation pressure and obtain information like the tire brand, model, and size.

- *Non-Contact Vehicle Weight Identification Method*: A new non-contact method for vehicle weight identification is based on a tire-road contact model and CV techniques. The theoretical tire-road contact model they used was based on an improved Hertz contact theory.
- *Identification of Tire Deformation and Inflation Pressure*: CV techniques, such as image segmentation and character recognition, were used for identifying tire deformation and inflation pressure.
- *Field Experiments and Verification*: Kong et al.(2022) analyzed the tire-road contact mechanism and conducted numerical analyses to develop tire contact force equations. The methodology for identifying the tire-road contact force by combining these equations and CV techniques was verified with field experiments on passenger cars and trucks, showing good agreement with measured results.

Compared to traditional methods, the developed method based on tire mechanics and CV offers high accuracy and efficiency, easy operation, low cost, and does not require the placement of sensors, providing a new approach to vehicle weighing. In summary, these studies demonstrate significant advancements in vehicle weight identification using CV techniques, focusing on tire mechanics and the tire-road contact model, offering a more accurate, efficient, and cost-effective alternative to traditional methods. These studies demonstrate various advancements in non-contact BWIM and CV techniques for accurate and efficient vehicle weight measurement and load identification on bridges.

2.9. Safety and Enforcement Review

The use of weigh-in-motion sensors is now being expanded for enforcement purposes to provide virtual weigh stations for screening vehicles in traffic streams for overweight violations. Nichols & Bullock (2004) found that static weigh stations in Indiana were effective for identifying safety violations, but ineffective for identifying overweight vehicles. It was also determined that the alternative approach to identifying overweight vehicles using virtual weigh stations requires a high level of WIM data accuracy and reliability that can only be attained with a rigorous quality control program.

Overloaded trucks pose serious threats to road transport operations with increased risks for road users, deterioration of road safety, and severe impact on the durability of infrastructure. An overloaded vehicle is more likely to be involved in an accident and have more severe consequences than a legally loaded vehicle. Overloading also means violation of the taxation rules, such as vehicle registration fees, axle taxes, and toll infrastructure fees. It is, therefore, necessary to enforce vehicle weight and dimension regulations to minimize the number of overloaded and oversized vehicles. For protecting infrastructure and improving road safety approaches, WIM system implementation has been proven to be a trending approach worldwide.

Rising truck traffic volumes are increasing the strain on roads and transportation infrastructure. Highway owners and operators must prioritize sustainable management of road use and respond by taking action to prevent road damage and ensure safety. WIM systems collect critical information from vehicles traveling at widely varying speeds. Using accurate measurement data, stakeholders can monitor traffic in real-time and collect vehicle data (such as a number of axles, weight per axle, or axle distance). The WIM system for weight-based tolling helps to generate additional revenue for road construction and ensures that road usage fees are fair. Aided by these accurate and reliable systems, road owners and operators can sanction weight limit violations immediately. WIM systems use can use integrated cameras to identify vehicles directly, so tolls can be levied automatically without hindering traffic flow.

The development of advanced vehicle monitoring systems—either on-board or on the road—as part of intelligent transport systems, offers important potential and alternative solutions to traditional roadside enforcement by compliance officers. Traditionally, static weighing was the only method approved by the legal metrology up until the mid-1990s. Weighbridges, along with wheel and axle scales, are used to measure gross vehicle weight and wheel or axle load. Static weighing suffers from some limitations: it requires staff and time to perform static weighing. Staff is needed to select and intercept vehicles in the traffic flow, to perform the weighing operation on the static control area, and to fine the violators and apply other penalties as needed.

Low Speed WIMs are the most accurate technology. They use wheel or axle scales, mainly equipped with load cells, installed in concrete or strong asphalt platforms of at least 30 to 40 meters in length. The software of the data acquisition and processing system is designed to analyze the signal of the loadcells, considering the speed, and to accurately calculate the wheel or axle loads. Such systems are installed either outside the traffic lanes, on weighing areas, or in toll gates or any other controlled area. The operating speed is generally in the range of 5 to 15 km/h and accuracy is 3 to 5 % (Jacob, B., 2010)

Considering the 600,000+ bridges and 4+ million miles of roadways across the entire nation, preventing overloading from overweight trucks, i.e. effective automated enforcement becomes the most critical implementation of an advanced WIM system. Burnos et al. (2021) introduces WIM systems for direct enforcement (e-WIM) and presents practical aspects related to the identification of factors disturbing measurement in WIM systems as well as methods of controlling, improving and stabilizing the accuracy of weighing results.

Overweight trucks cause significant damage to roads and bridges, which can lead to shorter lifespans, increased maintenance costs, and safety hazards. The cost of repairing and replacing damaged infrastructure is often borne by taxpayers. However, in some jurisdictions, transportation agencies issue permits to overweight trucks in exchange for a fee. The goal of these permit fees is to offset the cost of the damage caused by these vehicles. A recent study by Nassif et al. (2023) found that New Jersey's current permit fee schedule for overweight trucks is able to recoup the cost of the damage caused by these vehicles. However, this is not the case in all states. According to the study, New Jersey ranks fourth highest among all states in terms of permit fees for overweight trucks. The study also found that the infrastructure damage cost for bridges and pavement were about 37% and 63% of the total damage cost due to the overweight permit trucks, respectively. The total damage attributed to bridge structures was $1.7 million per year, while the damage cost to pavement was $2.9 million per year.

The findings of this and similar studies suggest that other states should consider updating their permit fee schedules to reflect the true cost of the damage caused by overweight trucks. This would help to ensure that taxpayers are not subsidizing the use of overweight vehicles, and that transportation agencies have the resources they need to maintain and improve their infrastructure. In addition to updating permit fee schedules, states could also consider other measures to reduce the damage caused by overweight trucks, such as:

- Increasing enforcement of weight limits
- Investing in new technologies to weigh trucks in real time
- Developing alternative routes for overweight vehicles
- Promoting the use of lighter-weight materials in truck construction

By taking these steps, states can help to protect their infrastructure and improve safety for all road users. The following recommendations are made to transportation agencies and other stakeholders:

- Transportation agencies should review their current permit fee schedules for overweight trucks to ensure that they are adequate to offset the cost of the damage caused by these vehicles.
- Transportation agencies should invest in new technologies to weigh trucks in real time. This would help to identify and apprehend overweight vehicles before they can cause damage to infrastructure.
- Transportation agencies should develop alternative routes for overweight vehicles. This would help to reduce the wear and tear on heavily trafficked roads and bridges.
- Transportation agencies should promote the use of lighter-weight materials in truck construction. This would help to reduce the damage caused by overweight vehicles.

These recommendations are intended to help transportation agencies protect their infrastructure and improve safety for all road users.

2.10. Data Quality and Accuracy

Several studies in the literature discuss the quality of weigh-in-motion (WIM) data for a variety of transportation applications, including pavement design, weight enforcement, and freight planning in different states. Several factors and conditions affect the WIM system accuracy. The potential site-related factors include road geometry, pavement stiffness, pavement surface distresses, road roughness, and climate. The WIM calibration and equipment-related factors may include sensor type and array, calibration speed and speed points, and sensors' age. The WIM data for Long-Term Pavement Performance (LTPP) research-quality sites were considered by Haider et al., (2020) to estimate benchmark accuracies for different sensors and evaluate the effects of different factors on WIM measurement errors. These are the 35 sites with WIM calibration data that meet the ASTM E1318-09 error tolerances for Type I WIM systems and are consistently calibrated using the LTPP protocol with a complete set of supporting data about WIM site performance and WIM site conditions. The data for the LTPP research-quality sites showed that for the sensor arrays utilized, the best achievable total errors based on GVW are +- 5% for load cell (LC),+- 9% for bending plate (BP), and +-9.8% for the quartz piezo (QP) sensors. These accuracy levels for different sensor types provide highway agencies with benchmark values demonstrating the practically achievable accuracy of WIM measurements after calibration for different WIM sensor types. Based on available data, WIM sensor accuracy can be significantly affected by climate, especially for QP and polymer piezo sensors. Also, the longitudinal roadway slope at a WIM site, sensor array, and speed points may significantly affect the WIM system accuracy.

For North Carolina, Ramachandran (2009) describes a quality control procedure for WIM data that identifies incomplete datasets, out-of-range values, and other potential problems. He reports that the NCDOT WIM data is reliable, with only 0.97% and 6.42% anomalies for vehicle class and weight, respectively. The authors analyze truck traffic profiles in NC urban and rural roads. He finds that the class 5 and 9 gross vehicle weight (GVW) plots for all categories of WIM stations show expected trends. This information can be used by highway planners and pavement designers to quickly determine typical truck traffic profiles in the various NC regions and to gain insight into NC truck transportation flows.

In a follow-up study, Ramachandran et al. (2011) compared the WIM quality control methods used by the North Carolina State University (NCSU)/NCDOT and the University of Arkansas (UARK). He finds that the UARK Pavement Designer software has better mapping functions and supports data analysis and design, but it is a "black box" from a WIM data analyst's perspective. The NCSU/NCDOT approach, on the other hand, provides more flexibility and manual override capability, which is important for ensuring data accuracy. Ramachandran et al. (2011) also propose a new calibration algorithm that they believe can significantly increase the accuracy of vehicle weighing in WIM systems.

In a more recent study, Lin et al. (2022) report a spatiotemporal analysis by utilizing the spatial analysis function of a geographic information system. In addition, the weight of the overloaded vehicles was calculated using the overload rate. Furthermore, the clustering and concentration of the overloaded vehicles were obtained using the global spatial autocorrelation model. The kernel density estimation method was then used to identify areas with severe overloading and calculate the local probability of overloading in that area. The results revealed that the spatial distribution of the overloading severity was mainly influenced by the per capita income, density of highways, industry type, and freight policy in a given region, and that it was mainly concentrated in transportation hubs and areas with high traffic and complex logistics (e.g., municipal and provincial boundaries). Finally, the temporal aggregation of overloading was primarily affected by the level of law enforcement and freight policy because vehicles with high overload rates were mainly concentrated between 12:00 and 4:00 a.m.

Another trending method, proposed by Tahaei et al. (2021), involves using machine learning for Truck Traffic Classification groups from Weigh-in-Motion data. The pavement Mechanistic-Empirical (ME) design requires high-dimensional traffic feature inputs by categories, including Vehicle Class Distributions (VCD), Monthly Distribution Factors (MDF), Hourly Distribution Factors (HDF), and Normalized Axles Load Spectra (NALS). In simplifying the Pavement ME design practice, Truck Traffic Classification (TTC) groups are commonly used for characterizing traffic inputs. Thus, properly defining TTC groups is critical for state-specific pavement ME design practice. In this study, the truck traffic data from existing Weight-in-Motion (WIM) stations were mined to develop specific TTC groups to assist with pavement ME design practice in Georgia. An effective data analytics procedure was developed by leveraging unsupervised machine learning techniques to reduce the high-dimensional traffic features by stratified Principal Component Analysis (PCA), followed by K-means clustering to establish appropriate TTC groups. For a case study, the performance of two typical designs was evaluated using the AASHTOWare pavement mechanistic-empirical (ME) design software with respect to two scenarios of traffic inputs: (1) the derived cluster-based groups, and (2) the national default TTC groups. The results indicated that direct application of the national default TTC groups resulted in over-design of pavement structure in Georgia. Therefore, it is highly recommended that customized TTC groups should be developed using state-specific WIM data.

Despite all the advancements, traditional weigh-in-motion (WIM) systems still report that a significant portion of vehicles cannot be classified due to reasons such as tailgating, lane changing, traffic congestion, and equipment malfunction. Analysis of unclassified vehicles was performed with WIM-recorded data. Peng et al., (2021) proposed a neural network model to determine the appropriate allocations of unclassified vehicles to vehicle classes. Since the number of unclassified vehicles is often fairly high, the allocations will help to improve the accuracy of truck traffic data and thus improve pavement design. Video records of traffic streams on an interstate section and traffic data from a nearby WIM station were used to identify causes for vehicle misclassifications. The optimal model was developed through model algorithm design, data processing, model training, validation, robustness analysis, and verification of video records, and proven to be useful tool for properly classifying the unclassified vehicles; potentially increasing benefits and reducing the costs.

Haugen et al. (2016) describe the Norwegian Public Roads Administration's efforts to improve the quality of statistic weigh data. A key component of this project is the field testing of various Weigh-In-Motion (WIM) data collection techniques and equipment, including high-speed WIM equipment and V2I communication, in which the vehicle reports its own weight. The tests focus on data quality (WIM vs. static weight), user interface and usability, calibration procedures and requirements, and sensor lifetime. Another important aspect of the project is the use of WIM data to pre-select vehicles at control stations. WIM data is combined with license plate numbers from ANPR cameras, and the measured weight is compared to the permitted weight. If a vehicle is overloaded, a warning is displayed at the control station, allowing legal drivers to pass without being stopped. The authors conducted a series of tests over a three-year period, evaluating two distinct WIM sensor technologies from four different manufacturers. The tests focused on accuracy, sensor lifetime, calibration, and software and equipment usability. Additionally, the authors tested high-speed WIM equipment for pre-selecting vehicles at control stations. The results showed that lineas quartz sensors outperformed piezo electric cables. Calibration procedures were time-consuming and expensive, and sensor lifetime was very short. Deeper installation where possible can improve this. A significant challenge is the decrease in sensor accuracy over time. For one system, the average gross weight error increased to approximately 15% over a six-month period. The error in the other system increased to 15% in three months, and to 15% again in just over one month after calibration.

In February 2015, a full-scale, proof-of-concept V2I system was tested in Oslo as. A single instrumented vehicle was used to test the communication protocols. The information flow was consistent, so the focus shifted to the reported weight. The internal difference in the self-declared truck weight for each axle was minimal, with less than 1% variation between test runs. Compared to the static weight, the self-declared truck weight was approximately 5% too low. This was considered a promising start for the concept.

Full-scale tests with four vehicles are scheduled to begin in September. The trucks will be equipped with communication units to share their current weight for a two-month period. This configuration will provide a broader foundation for evaluating the system's data quality. The authors believe that WIM systems will be used in conjunction with V2I solutions in the future, which will further enhance vehicle weight control.

3. STAKEHOLDER PERCEPTIONS OF A WIM PROGRAM

This section reports an assessment of the needs of different stakeholders and how they use weigh-in-motion data. A survey was conducted of departments of transportation (DOTs), a survey of primary stakeholders, and a survey of enforcement personnel. Interviews with selected vendors are also used for case examples. Based on the feedback received on the pilot survey analysis, multiple surveys were designed to generate results and findings that are applicable to the following categories of participants

1) WIM System owners and data collectors (e.g. state DOTs, counties, municipalities, etc.)
2) First Tier WIM Data Users (i.e. organizations that have to use or report WIM data)
3) Second Tier WIM Data Users (i.e. organizations that would benefit from using WIM data)
4) WIM providers and others.

These four different participants received the following surveys:

1. DOT Survey
2. Primary stakeholder survey
3. Enforcement survey
4. Vendor Survey

3.1. Analysis of the DOT Survey

The **DOT survey** was sent to all 50 state DOTs in the United States, with response rate of was 70%, with 35 of the 50 DOTs responding. The DOT survey asked about WIM Availability and Responders Experience (9 Questions), Vendor information (2 Questions), WIM data (10 Questions), WIM Sensor Characteristics (6 Questions), WIM System Costs (10 Questions), and the Future WIM Technology (6 Questions).

The following analysis is based on the DOT survey responses:

- 32 DOTs (91% of the responding state DOTs) collect or have collected WIM data.
- The number of reported active WIM stations varies widely from state to state, with maximum of 44, average of 19.1 and median of 16 WIM stations.
- The average number of down, inactive or idle WIM stations reported is 8, and the average number of portable WIM stations is reported to be 4.
- 2020 NCHRC Synthesis survey indicated that more DOTs are contracting for maintenance and calibration services for WIM systems and considering pay-for-data solutions. However, our results show that DOTs are gaining capability in WIM system calibration, data processing and reporting.
    - The most common procurement model for WIM system installation and repair/replacement is 100% Vendor-managed (16 states), whereas only 7 states are relying on vendors for data processing. Namely, GA, IL, and WI DOTs have reported a 100% vendor-managed procurement model for all functions of the WIM system (installation, calibration, repair/replacement, data processing, reporting, and QA/QC).
    - Six states (AR, NC, WA, IA, MN, VT) reported 100% in-house capability for WIM system installation, calibration, repair/replacement, data processing, reporting, and QA/QC.
    - 11 state DOTs reported partially outsourced procurement models for installation, 7 for calibration and maintenance, 9 for repair and replacement, 10 for data processing, 6 for reporting, and 9 for QA/QC functions.
- On average 7 full-time DOT personnel are allocated to manage WIM systems across 26 states. The average number of full-time personnel allocated for WIM system maintenance is 2.5 per state DOT. WIM personnel is hosted in transportation planning (9), data collection/IT (10) or enforcement (7) departments or divisions.
- 68% of the survey participants expressed their expertise in data analysis, WIM systems and transportation planning. Only 2% identified themselves as bridge or pavement designers.
- 25 state DOTs reported to have high-speed WIM systems, 6 states reported to have low-speed WIM system and 3 states reported to have portable WIM systems.
- 13 state DOTs reported to have virtual weigh stations, 8 states reported tire safety screenings, 3 states (NC, WI, MO) reported automated weight enforcement, 2 states (NC, AZ) reported mobile speed enforcement, 3 states (NC, AZ, IL) reported industrial truck weighing, 3 states (NC, MO, VT) reported bridge protection, 12 states reported prescreening programs currently in place.
- A majority of the states are working with major vendors (17 states reported doing the work in-house)
- Average procurement lead time for WIM sensors and roadside equipment is reported to be 8 weeks (about 10 weeks for IRD and 7 weeks for Kistler)

WIM Data

- The top three WIM system installation purposes were 1) data analysis, 2) pavement design and maintenance, and 3) transportation planning. Law enforcement was selected by 15 states. 74% of the respondents indicated that WIM data was most useful for design and enforcement. The least valuable uses were for the design of ports, terminals, and airports and safety assessment.
- 11 states reported use of WIM data for bridge design, which is a significant increase compared to two states reported in 2020 NCHRP Synthesis Survey.
- Eight states (FL, IN, MN, WA, WI, GA, IL, SC) allow users to access WIM data through dashboard, while 21 other state agencies have various access formats.
- 52.94% of the WIM systems push data daily and38.24% of them push data continuously. Only a small number of systems push data annually, monthly, or weekly (2.94% each).
- 30% of the respondents indicate that the WIM stations are physically reviewed for data accuracy daily, 27.3% reports annually (27.3%) or weekly (15.2%). A small number of stations are physically reviewed monthly (21.2%) or quarterly (6.1%).
- In parallel with the 2020 NCHRC Synthesis study, our survey indicates that many DOTs are looking for ways to optimize WIM calibration. We found that almost half of the responding states had optimized their process. 17 respondents (47.2%) currently have auto-calibration capability. 28% do not have auto-calibration and indicate that they do not need it. 25% would like auto-calibration.
- 55% of the respondents reported having real-time data reporting capability. 42% would like to have automated data polling and automated data streaming capability.
- 44% of respondents reported having built-in QA/QC process and 33% reported that they would like to have this capability.

- The 2020 NCHRP Synthesis study indicated that states are working on new ways to use existing WIM data, or finding less costly ways to collect vehicle classification data. Our results support this statement in a more concrete way:
    - 12 states (AL, AZ, GA, IL, IN, MI, MO, ND, OH, OR, WA, WI) report satisfactory levels of WIM integration with weight stations for pre-screening.
    - 5 states (AL, AZ, IL, IN, WA, WI) report satisfactory levels of WIM integration with license plate readers.
    - 5 states (AL, AZ, GA, IL, ND, WI) report satisfactory levels of WIM integration with video recognition (e.g., speed and class)
    - 4 states (AZ, IL, ND, WI) report satisfactory levels of WIM integration with audio sensors (e.g., weight and speed assessment).
    - Only Wisconsin and Michigan DOTs report satisfactory levels of WIM integration with audio and video data.
    - 5 state DOTs (GA, ID, IN, SC, WI) report satisfactory levels of WIM calibration technology supported by Machine Learning algorithms.
    - 4 state DOTs (GA, IN, SC, WI) report satisfactory levels of WIM integration with interactive quality assurance dashboard and interactive analytics.
    - Only Wisconsin DOT report moderate level of satisfaction with LIDAR and four other DOTs reported dissatisfaction with LIDAR technology.

WIM Sensors

- Most states have piezo-electric (19), lineas quartz (14) or piezo-polymer (9) sensors in conjunction with inductive loop detectors. Only six states use quartz crystal-based sensors with a digital interface, which is the newest sensor technology. Eight states report planned future use of this technology. Piezo-ceramic sensors and infrared and magnetic detectors are reported to be in use by very few agencies.

- 11 state agencies report moderate or high sensitivity of sensors to temperatures potentially affecting WIM data quality especially in northern and southern states.

- The survey suggests that pavement type does not affect sensor selection. Piezo sensors are used more often with asphalt pavement. Bending plate sensors are used more often with PCC pavement.

- 70% of the state DOTs report full lane sensor configurations (e.g. PLP) whereas 30% report half lane configurations. 43% indicate sensor-loop-sensor array configuration, 38% reported loop-sensor-loop (LPL) and 19% reported loop-sensor-sensor-loop (LPPL or LQQL) configurations. In terms of the number of sensors per lane, 82% indicate double threshold sensors, 4% report single thresholds and 14% indicate “it depends”. Only AZ and MN DOTs report the installation of WIM arrays in all lanes at multilane sites.

- Lineas quartz sensors have been reported to have the long lifespan (>7 years) compared to piezo-electric and piezo-polymer with a life span of 4 to 7 years. Piezo-ceramic sensors seem to have a shorter life span (<4 years).

- 70% of the states say that rural freeways and rural major arterial corridors are important places for WIM installations. 62% say urban freeways and urban major arterials are most important while 35% say urban collectors and 30% say agricultural service highways.

WIM System Costs

- 13 states report funding WIMs (presumably for installation) using 20% state and 80% federal funds. 5 report the reverse: 80-100% state and 0-20% federal. 8 states reported using existing budgets for expansion of their WIM system, 20 states indicate using a combination of federal and other funding sources for expansion.

- KS, VA, MI and GA indicate the use of enforcement funds as part of funding source for their WIM systems. However, FL, IO, ND and WI indicated use of enforcement funds for potential expansion of the WIM system.

- A majority of the states (48%) believe that the cost of WIM sensors has remained the same since 2018. However, a significant minority of respondents (22%) believe that the cost of WIM sensors has increased. This suggests that there may be some variation in the cost of WIM sensors, depending on factors such as the manufacturer and the new sensor technologies. It is also worth noting that a small number of respondents (6%) report that the cost of WIM sensors has decreased. This suggests that there may be some competition in the WIM sensor market, which could be reducing prices. Finally, 23% of respondents reported that they had no opinion on the cost of WIM sensors. This suggests that they may not be familiar with the current market prices for WIM sensors, or that they do not believe that the cost of WIM sensors is a significant factor in their decision-making process.

- Based on the responses below, compared to 2018 FHWA report, sensor costs seem to be declined and sensor lifetimes have remained the same replacement costs seem to be stable.

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Sensor Type	Number of half-lane sensors	Range of costs for 1 lane of sensors		
		Life (years)	Sensor Installation	
			low	high
Polymer Piezo	4	2-3	4,000	6,400
Quartz Piezo	2	3-5	16,000	24,000
Strain Gauge Strip Sensor	2	3-5	16,000	24,000
Bending Plate	2	6-8	18,000	28,000
Load Cell*	2	10-12	44,000	53,000

*Includes cost of the pit.

WIM COMPONENT	LIFE (YRS)	LOW ($)	HIGH($)
Inductive Loop Detectors	10.8	994	2,006
Piezo-Electric	4.7	2,340	3,960
Piezo-Polymer	3.8	2,333	4,000
Piezo-Ceramic	3.25	2,667	4,333
Lineas Quartz	5.6	9,243	12,157
Bending Plate	6	12,000	15,000
Load Cell	11	25,250	45,000
Digital Quartz	8		
Strain Gauge Strip Sensor	4.5	2,650	7,250
Roadside Eq/Data Logger	11	13,360	26,000
Communication tools	7	650	1,290

WIM COMPONENT	AVG. INSTALLATION COST(S)
Controller	13,725
Infrastructure	26,500
Initial Calibration	4,114
Vendor Software	3,700

Based on the survey results, WIM Routine maintenance costs seem to be higher compared to 2018. Routine calibration and sensor replacement costs seem to be stable.

Element	Range of Annual Costs			
	2 lanes		4 lanes	
	low	high	low	high
1. Routine Maintenance	500	1,200	750	1,500
2. Routine Calibration*	2,500	6,000	4,000	7,500
3. Sensor Replacement**	Average Annual Cost per Lane***			
a. Polymer Piezo	4,300			
b. Quartz Piezo	10,600			
c. Strip Sensor	10,600			
d. Bending Plate	7,000			
e. Load Cell	9,000			

*Using one Class 9 truck (typically $90 to $135 per hour), maximum 20 runs per lane. Bending plates and load cells may be calibrated every 2 years.
** Includes parts, MOT and labor, but does not include mobilization.
*** Based on the number of sensors in each lane and the expected life of the sensor shown in Table 3.

Operating Element	Lower Cost ($)	Upper Cost ($)
Routine maintenance	1,700	4,263
Routine calibration	2,307	5,611
Sensor replacement		
» Inductive loop detectors	542	4763
» Piezo-electric	1,950	11,533
» Piezo-polymer	750	14,750
» Piezo-ceramic	1,500	2,667
» Lineas quartz sensor	1,950	7,333
» Digital Quartz		
» Strain gauge Strip sensor	1,500	2,000
» Bending plate	1,000	1,750
» Single load cell	1,333	3833.33
» Active infrared detection	500	12,000
Roadside eq./data logger	693	7,433
Alternative(e.q.optical fiber)	500	1,200
Communication tools	248	668

12 states indicate that the two main components of their WIM budget are sensor replacement (36.5%) and maintenance (32.25%). Calibration accounts for 15% and the remaining 15.5% is divided

between additional stations (10.83%) and other expenses such as IT (5.42%).

Futuristic Outlook

Most states (63%) expressed strong interest in establishing common standards for evaluating WIM system reliability. This suggests that there is a strong need and desire for standardized methods and criteria to assess the performance and reliability of WIM systems. The use of common standards would ensure consistency and comparability of WIM data across different jurisdictions or organizations, facilitating informed decision-making and resource allocation.

The state respondents chose responses of "Somewhat likely" and "Extremely likely" with regard to WIM systems. The response breakdowns are shown below. It seems state agencies are expecting further integration of WIM systems with enforcement. It is interesting to note that the respondents do not anticipate WIM systems to reduce the pavement investment.

Outcome	*Somewhat Likely*	*Extremely Likely*	*Extremely Unlikely*	*Total Likely*
Enforcement will increase	26.1%	30.4%	4.3%	56.5%
Less pavement investment	13.0%	8.7%	39.1%	21.7%
Tolls based on weight	21.7%	17.4%	34.8%	39.1%
Tickets for overweight trucks	26.1%	26.1%	4.3%	52.2%

- States indicate that the most significant factors in selecting a Weigh-In-Motion (WIM) technology are reliability, data accuracy and quality assurance, and system calibration effort. Maintenance effort, return on investment, and maintenance cost are indicated to be the next significant factors.

- Ohio, Arkansas, Illinois, Georgia, Rhode Island and South Carolina DOTs indicate interest in receiving WIM or freight data from North Carolina, whereas 16 states (KS, PA, AZ, WI, ND, MI, MN, WA, IA, MT, AK, ID, VT, OK, OR, and MS) indicated no interest because NC is not a bordering state.

- Ohio, Oklahoma, South Carolina, and Georgia DOTs (definitely), Arkansas, Illinois, Kansas and Minnesota DOTs (probably) are interested in all aspects of partnerships/collaborations with NC DOT.

3.2.Primary Stakeholder Survey Findings

The Primary Stakeholder survey divided into six blocks focused on organization and expertise (4 questions), WIM Data Usage (6 questions), WIM System Characteristics (2 question), WIM Data Cost (2 questions), WIM Technology (5 questions) and NCDOT Partnership (3 questions). The survey was sent to 100 individuals (by email). The response rate was 10%.

The following analysis is based on the Primary Stakeholder survey responses:

- The most common affiliation among the respondents was Freight/Logistics Operator/Provider (30%). The second most common affiliations were MPOs or COGs, Department of Defense or similar, and Other (Higher Education Institute and Public Policy Think Tank) (20% each). The least common affiliations were County, city or municipality, EPA or State equivalent, FHWA, Design engineer-pavement/bridge, Toll authority or operating agency, and Transportation planner (0% each). The only affiliation with a single respondent was rail and water transport operator.

- Most respondents reside in North Carolina, accounting for 70% of the total. This is followed by Tennessee and the District of Columbia, with 20% and 10% respectively.

- A significant portion of the respondents (60%) were not familiar with WIM Systems. 30% were and 10% were very familiar. This suggests that there is an opportunity to increase awareness of WIM Systems.

- The most common areas of expertise were asset management and freight logistics (15% each). The next most common areas were highway operations, inter-agency relations, planning and programming, research and development, and transportation planning (10% each). The least common areas of expertise were airports, freight planning, ports and terminals, and data analysis (5% each). The areas of expertise not selected by any respondents were bridge design, construction, highway maintenance, multi-modal transportation, pavement design, WIM provision, and law enforcement (0% each).

- 11% of the respondents indicated that their organization received WIM data quarterly. 89% indicated not receiving WIM data at all. One respondent reviews and uses WIM data quarterly, another reports using it annually, and eight (75%) indicate no use of WIM data for decision-making.

- The application areas that are most frequently rated as extremely useful for WIM data are freight planning and design (28.57% each). The application area that is most frequently rated as very useful for WIM data is multi-modal planning (42.86%). Those that are most frequently rated as not at all useful for WIM data are construction, design, enforcement (57.14% each), and crash analysis (42.86%). The area with the most diverse ratings for WIM data is operations, with respondents rating it from not at all useful to extremely useful.

- The locations that are most frequently rated as very important for placing a WIM station are urban freeway corridors, rural freeway corridors, port access highways, rail terminal access highways, and distribution center access highways. The locations that are most frequently rated as unimportant for WIM stations are urban collectors, rural freeway corridors, rural major arterial corridors, rural minor arterials, rural two-lane roads, agricultural service highways, logging service highways, and quarry service highways.

- Data accuracy and quality assurance are identified as the most significant factors for WIM data, with 50% of respondents rating these aspects as very significant, followed by installation cost and maintenance/calibration effort. Return on investment is the least significant factor, with only 16.67% of respondents rating it as very significant. Technology upgrades and reliability are evenly distributed, with respondents rating them from very insignificant to very significant.

- One respondent indicated that funding was divided into 13% state funds, 5% enforcement, and 8% private funding sources.
- Other data being used in conjunction WIMs included occupancy counts for express lanes, speed estimates, and pressure gauge readings. None of the respondents indicated a use of license plate readers, vehicle classifiers, toll collectors, and direct enforcement.

- Respondents indicated a high interest in using WIM data in conjunction with weigh stations (pre-screening), license plate readers, video recognition, and interactive analytics.

- Interactive QA dashboards and LIDAR were the sensor technologies respondents would be interested in using. These technologies are relatively new, and they have the potential to significantly improve the efficiency and accuracy of WIM systems. The sensor technologies with the lowest ratings were audio sensors, audio and video with WIM, and real time data from low power edge computing and wireless communications.

- 80% of the respondents indicated an interest in standards for assessing WIM system reliability.

- System calibration and data accuracy were reported to be the most critical factors for using WIM data. Real-time, low latency data and data management and permissions were also reported to be important. WIM data sharing was indicated to be valuable for using WIM data. Transportation agencies should consider all these factors when planning and implementing WIM systems.

- Respondents anticipated that WIM systems will result in increased tickets for overweight trucks. There was a consensus that WIM systems will increase enforcement, decrease pavement investments and enable weight-based tolling.

- The most common ways identified to access or obtain WIM data or statistics were “obtain reports by request” and “summary data is accessible through the dashboard, but more detailed data must be requested” (33.33% and 22.22%, respectively).

- The respondents reported following WIM-based statistics used for the selected application areas:
    - Freight Planning: Fleet capacity planning and allocation, DOT SAFERWEB
    - Multi-Model Planning: DOT SAFERWEB
    - Crash Analysis on Arterials: Number of instances caused by overweight, DOT SAFERWEB
    - Crash Analysis on Freeways: Number of instances caused by overweight, DOT SAFERWEB
    - Environmental: Emission as a function of actual weight and vehicle class
    - Enforcement: Number of over-weight penalties

- Five participants were interested in partnering and receiving WIM or freight data from North Carolina.

3.3.Analysis of the Enforcement Survey

The Enforcement survey contained six blocks including organizational information (3 questions), WIM Technology Usage (5 questions), WIM Data (3 questions), WIM System Costs (1 question), Technology Integration (4 questions) and NCDOT Partnership (3 questions). The survey was sent to 15 enforcement contacts and shared with academics with an interest in enforcement. Five respondents to the DOT survey, from MI, WI, VT, MA, and SD, identified themselves as law enforcement experts. However, we have not included their responses here since the focus of this survey was on enforcement agencies outside of DOTs.

Although 11 responses were obtained, none contained answers beyond the third question. Hence, we scheduled a meeting with the enforcement representatives, namely Traffic Safety Systems Engineer and North Carolina Transportation Mobility and Safety Division staff, research team as well as NCDOT Steering Committee.

The meeting resulted in new information regarding the current inventory of the WIM sites in NC. The Table 5 and map below show where these are located and their outfitting. The sensors are installed only in the shoulder lane and all but 2 of them are located immediately upstream of a permanent weigh station. The meeting proved useful in encouraging future collaboration and data sharing conversations to maximize the output of the current and future WIM systems.

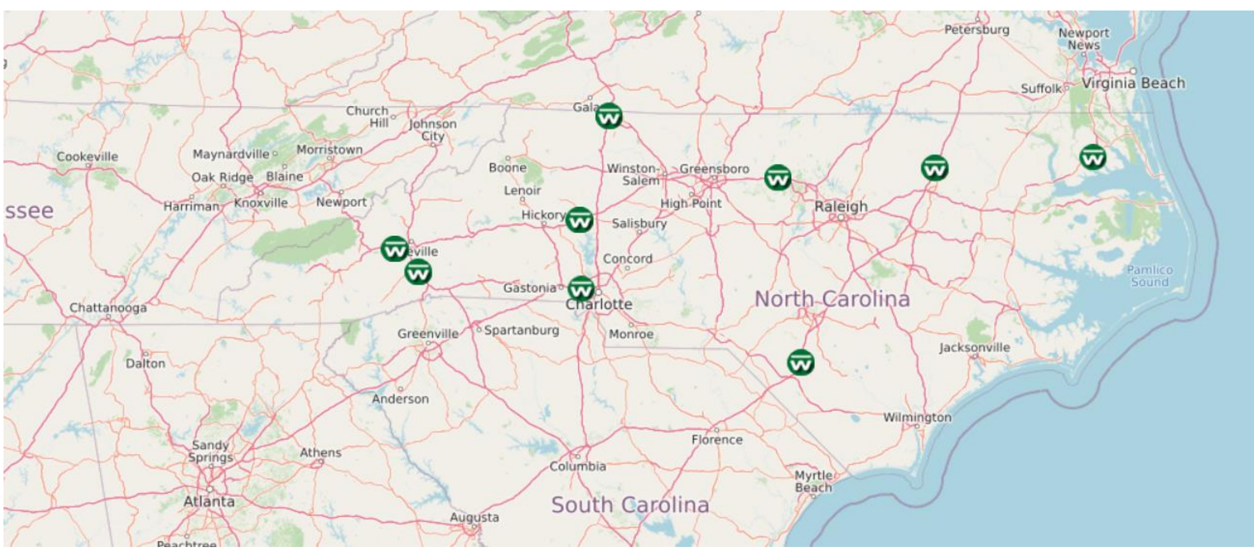

Figure 4 Map of Weigh Stations in North Carolina

Table 5 Current WIM Stations Maintained by Enforcement

County	City (vicinity)	Route	Dir.	Location	Drive Wyze'	Pre Pass [1]	DOT Reader'	Thermal Imaging'	License Plate Reader'	Tire Screening Device [1]	WIM Ramp Screening [1]	WIM Mainline Screening	Fiber[1]	Dynamic Message Sign	Over Height Detector•	Sort Signals•
Buncombe	Asheville	I-40	EB	Approx. 12 miles w of Asheville	A	A		A	A	A		A	A	X		
Buncombe	Asheville	I-40	WB		A		F		F	F		F	A	X	X	
Gaston	Gastonia	I·85	NB	Approx. 2 miles SW of Gastonia	A	A			A	A	A	A	A	X	X	X
Halifax	Enfield	I-95	NB	Approx. 18 miles S of Roanoke Rapids	A	A	A		A	A			A	X		X
Halifax	Enfield	I·95	SB		A	A			F		A		A			
Henderson	Hendersonville	I-26	EB	Approx. 7 miles N of Hendersonville	A	x'			F							
Henderson	Hendersonville	I·26	WB		A	A			F						X	X
Iredell	Statesville	I-40	EB	Approx. 6 miles w of Statesville	A	A			F	F		A		X		
Iredell	Statesville	I-40	WB		A	A	A		A	F		A	A	X		
Mecklenburg	Charlotte	I·85	SB	Approx. 10 miles SW of Charlotte	A				A	A		A	A	X	X	X
Montgomery	Seagrove	I-74	NB	Approx. 3 miles S of Seagrove								A				
New Hanover	Wilmington	US 421	NB	Approx. 3 miles E and N of Belville					A			A				
Orange	Hillsborough	I-40/85	EB/NB	Approx. 15 miles W of Durham	A	A			A	A	A	A	A	X	X	X
Orange	Hillsborough	I-40/85	WB/SB		A	A			A	F	A	A	A	X		
Robeson	Lumberton	I-95	NB	Approx. 10 miles N of Lumberton	A	A			F					X		
Robeson	Lumberton	I·95	SB		A				F	County				X		X
Surrv	Mount Airy	I-77	NB	Approx. 3 miles S of the Virginia state line	A	A			A	A		A		X		X
Surry	Mount Airy	I·77	SB		A	A			A		A			X		X
Total Stations:	18			Total Items:	16	13	3	1	18	10	5	11	9	13	5	8

A = Active F= Funded X= Present

' *Source: Weigh Station Feasibility Study" prepared by HNTB for the NCDOT Transportation Mobility and Safety Division (September 2022) unless otherwise specified.*

' *Source: Weigh Station Static Scale Assessment prepared by HNTB for the NCDOT Transportation Mobility and Safety Division (June 2023).*

3.4.Vendor Survey

The Vendor survey was sent to 25 different vendors operating in the United States. The response rate was 4%. The survey contained seven blocks including Vendor information (5 questions), WIM Data/Usage (8 questions), WIM Sensor Technology (5 questions), WIM System Characteristics (6 questions), WIM System Costs (8 questions), Technology Integration (3 questions) and Partnership with NCDOT (2 questions).

Because of the low response rate and lack of cost and technology information, our analysis limited.

- The major vendors, especially manufacturers, are providing worldwide services.
- They are not necessarily providing portable WIM solutions, but they are providing various other services calibration, such as virtual weigh stations, tire safety screening, automated wright enforcement, weight-based tolling and prescreening.
- Their WIM systems are installed for various purposes including bridge and pavement design, highway operations and maintenance, R&D, data analysis, transportation planning and law enforcement.
- Their systems can push WIM constantly (lineas quartz and digital quartz) and suggest an annual review for data accuracy.
- WIM data seems to be used for crash analysis, bridge and pavement design and maintenance, enforcement, and safety assessments. WIM data is reported to be relatively less useful for freight and multi-modal planning, construction, and environmental assessments.
- The life cycle of the WIM sensors is 1 year at a minimum and 15 years at a maximum with an average of 7 years. The lineas quartz sensor technology is reported to have the longest life span, while piezo-electric, piezo-polymer and piezo-ceramic sensors are reported to have the shortest life spans. Bending plates strain gauges, digital quartz, magnetic and other sensor types are reported to have moderate (4-7) life times.
- The average procurement lead time is reported to be 2-3 weeks.
- Temperature sensitivity is reported to be unimportant, and the preferred pavement type is asphalt.
- Only manual calibration is possible, with automated data polling. Auto-calibration, automated data streaming, built-in QA/QC, real-time reporting capabilities are not available.
- WIM technicians, state QA personnel, district or resident engineers, and enforcement personnel are reported as being the people responsible for checking the quality of WIM data.
- Although rural freeways and arterials as well as urban freeway and arterials are the best locations for WIM stations; clients seem to mostly chose rural freeway or rural major arterial corridors.
- Initial installation cost, maintenance and calibration effort, reliability, data accuracy and QA, technology upgrade and ROI are very significant factors regarding WIM system installation.
- The most common WIM sensor configuration is single threshold - staggered, with one sensor in each wheel path. Contrary to the state DOT survey results, one vendor indicates that the single threshold configuration is the one most often specified.
- Installation of WIM arrays in all lanes at multilane sites is most often preferred.
- One respondent avoided the cost-related questions, possibly viewing those details as proprietary.
- One respondent may have bypassed the technology-related questions, likely due to confidentiality concerns.

We feature a few specific vendors below.

Kistler
The advanced and certified Weigh In Motion (WIM) systems from Kistler collect and process traffic data without impact to traffic flow. KiTraffic and its Lineas quartz sensors reach an accuracy of up to 2.5 % GVW and feature an extremely high lifetime. The measurement technology experts' portfolio includes comprehensive measurement systems that range from sensors to software. Reliable data on traffic volume, axle load and total weight facilitate the identification of overloaded vehicles, thus helping to reliably protect

road infrastructure, increase road safety and effectively charge traffic originators. Additional services, such as Site Selection and calibration, round off the Weigh In Motion (WIM) system portfolio from Kistler.

Mettler Toledo

The staggered WIM sensor configuration eliminates the need for costly, maintenance-intensive axle sensors or the use of additional WIM sensors. Their exclusive Auto-Calibration of the WIM sensors via a static scale interface eliminates costly regular calibration. Full system integration capabilities provide maximum flexibility in real-world applications, from communication with state-wide or National data networks, to combining weighing operations with other vehicle safety and credential-checking technologies. Designed to comply with ASTM E1318 requirements. Range of peripheral devices includes:

- Over-height and off-scale detection
- Variable Messaging Signs to sort vehicles and control traffic flow
- Image capturing with LPR (License Plate Reader) and USDOT number readers using OCR (Optical Character Recognition) technology
- In-motion vehicle dimensioning

Vehicle Weigh-in-Motion software is provided in three configurations to match the WIM application:

- **WIMenforce™** provides a weigh station user interface that is easy to interpret and assures efficient operation. It includes a reporting feature to generate a variety of truck volume reports with graphical elements and the option to export the reports to different formats.

- **WIMplan**™ makes vehicle data collection simple. Data includes counts, length, weight, classification, and speed. When multiple sites are linked, WIMplan can collect planning information and send it to a central computer for analysis. The software is also able to display real-time traffic information from one lane or any combination of lanes, and to produce a graphical representation of the vehicles by lane.

- Web-based **WIMvirtual™** can monitor commercial vehicle traffic at strategic remote Weigh-In-Motion sites. Sites typically combine weigh-in-motion sensors with imaging technology – overview and license plate cameras – to generate vehicle weight information and vehicle identification. The WIMVirtual record gives enforcement officers the information they need to monitor commercial vehicle compliance.

- Web-based **WIMvirtual™** can monitor commercial vehicle traffic at strategic remote Weigh-In-Motion sites. Sites typically combine weigh-in-motion sensors with imaging technology – overview and license plate cameras – to generate vehicle weight information and vehicle identification. The WIMVirtual record gives enforcement officers the information they need to monitor commercial vehicle compliance.

Cardinal – Vendor

Cardinal Scale offers a full line of in-motion vehicle scales utilizing strain gauge load cell, piezoelectric, and Kistler LINEAS® technologies. These scales meet or exceed ASTM E1318-02 performance requirements and can be used with a variety of peripherals like over-height detectors, off-scale sensors, image capture cameras, DOT and ALPR readers and others. Custom software allows the WIM-based system to fit your exact requirements while modular hardware design ensures the ability to upgrade in the future.

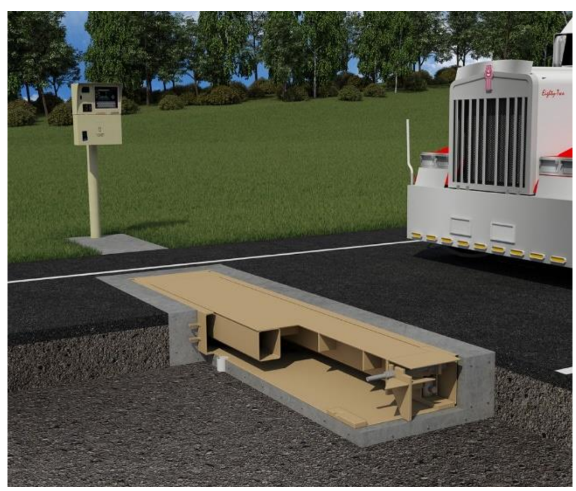

Figure 5 Slow-Speed In-Motion Load Cell-Based Scales

The Cardinal SWIM Series of Slow Speed In-Motion Vehicle Scale offers the ideal combination of accuracy and speed. The SWIM In-Motion Scale uses a single weighbridge contained in a solid lower frame. Each platform is supported by four Cardinal SCA Series Stainless Steel Compression Load Cells to weigh each axle end of a vehicle as it travels across the scale. The weighing platform is approximately 12 feet in width and 30 inches in length and is constructed of smooth steel plate. The welded steel structure is designed with performance and longevity in mind. The extremely stiff and rigid weighbridge, coupled with four 50,000-pound capacity Cardinal strain gauge load cells, results in a higher resonant frequency allowing more efficient filtering of spurious weight signals.

Cardinal's QWIM Series uses Kistler Lineas Quartz Sensors, and Cardinal's CVW Series WIM controller. QWIM series scales have a fifteen-year history in traffic monitoring, ramp sorting, and virtual weigh station application.

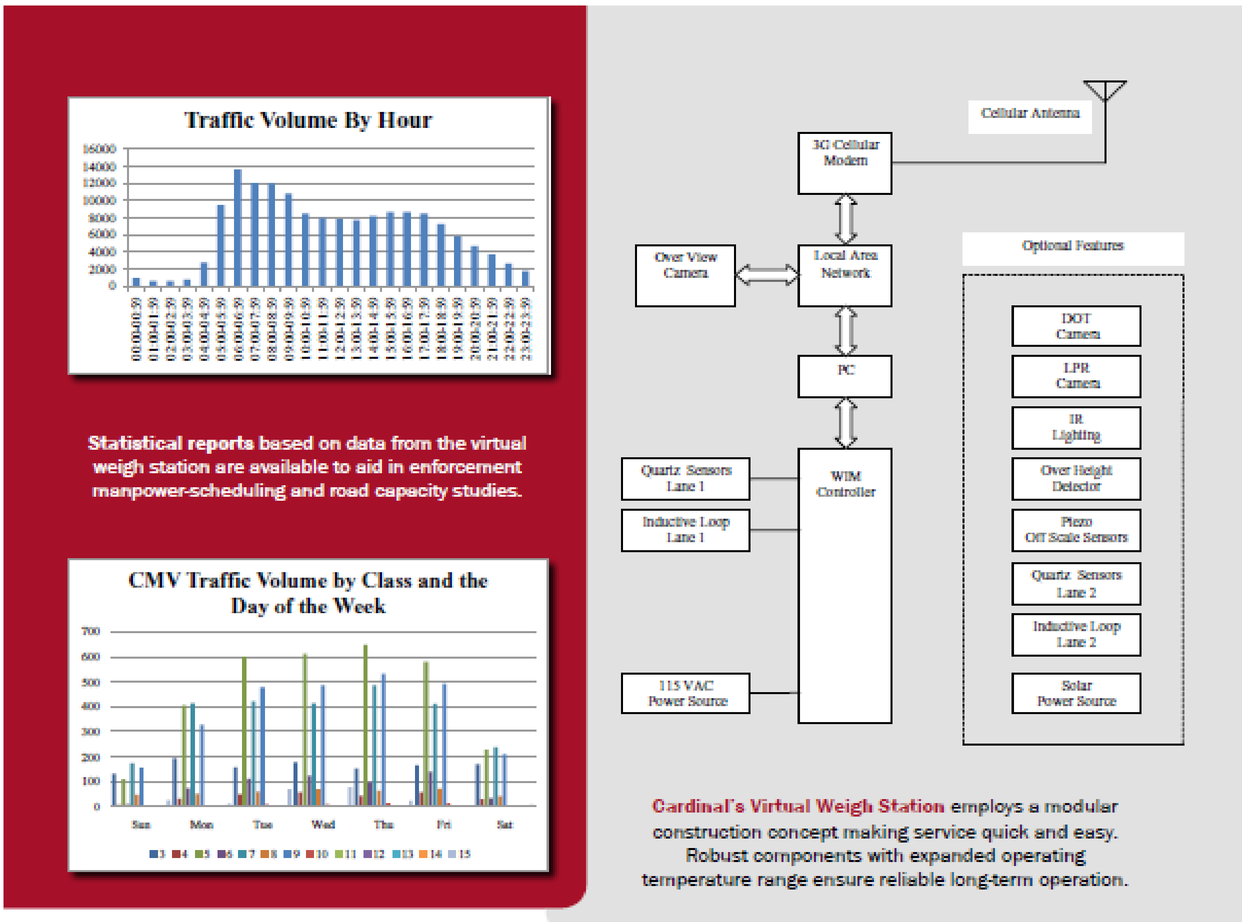

Figure 6a Cardinal Virtual Weigh Station Configuration and Statistical Report

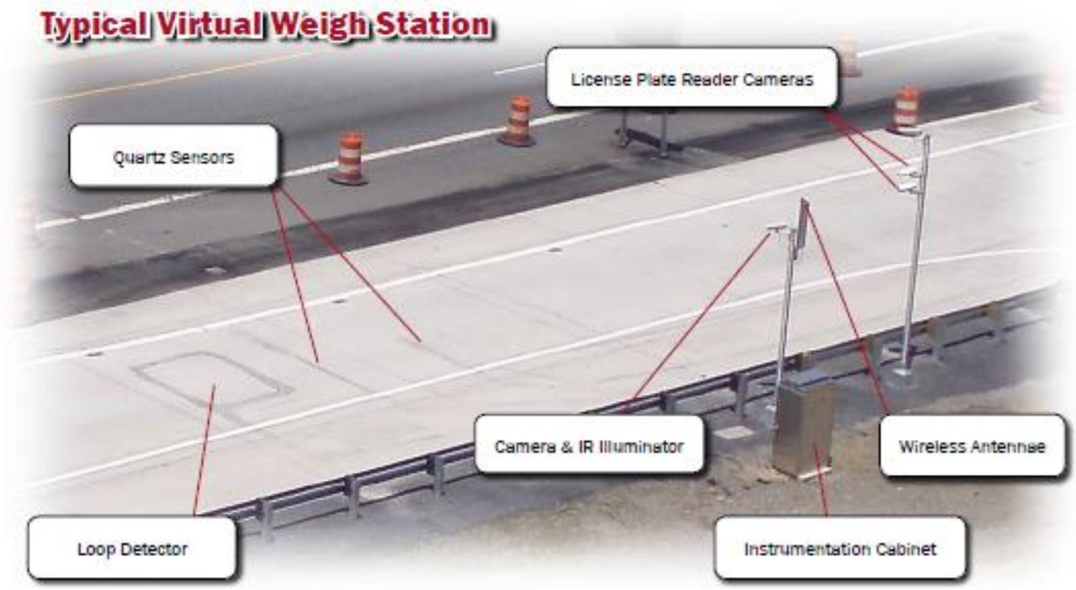

Figure 7b Cardinal Virtual Weigh Station Installation Configuration

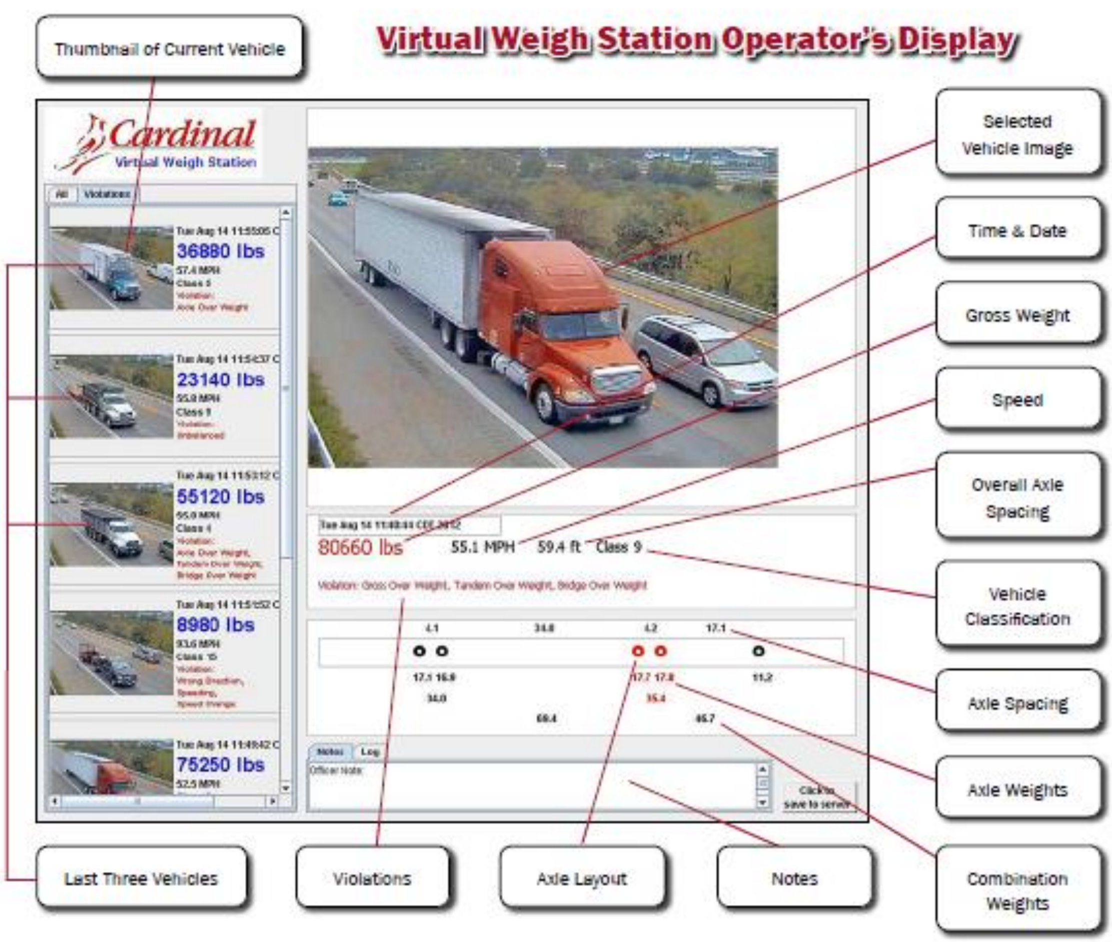

Figure 8 Cardinal Virtual Weigh Station Operator's Display

4. DESIGN SUGGESTIONS FOR A WEIGHT MONITORING PROGRAM

Vehicle weight monitoring is a critical component of transportation safety and infrastructure management. Overweight vehicles can damage roads and bridges, reduce their lifespan, and create safety hazards for other road users. By monitoring vehicle weights, transportation agencies can identify and address overweight vehicles, protect infrastructure, and improve safety.

Weigh-in-motion (WIM) technology is a non-invasive way to measure the weight of vehicles while they are in motion. WIM systems can be installed on roads and bridges and they can collect data on vehicle weights, axle loads, and other vehicle characteristics. WIM technology offers several advantages over static weigh stations, portable scales, and other traditional methods of vehicle weight monitoring. WIM systems can collect data on many vehicles without disrupting traffic flow. They can also monitor vehicle weights in remote or inaccessible locations.

WIM technology is increasingly being used by transportation agencies worldwide to implement vehicle weight monitoring (VWM) programs. VWM programs can achieve a variety of objectives, such as:

- Ensuring the safety and durability of roads and bridges
- Identifying and addressing overweight vehicles
- Collecting data on vehicle weights, axle loads, and other vehicle characteristics
- Informing transportation planning and decision-making

4.1. Designing a Comprehensive VWM Program

When designing a comprehensive VWM program, transportation agencies should consider several factors. These include:

- *Program goals and objectives*: What are the specific goals and objectives of the program? For example, does the agency want to focus on identifying and addressing overweight vehicles, or does it want to collect data on vehicle weights for transportation planning purposes?
- *Target populations*: What types of vehicles will be targeted by the program? For example, will the program focus on all vehicles on a particular road or bridge network, or will it focus on commercial vehicles?
- *Data collection methods*: What data collection methods will be used? WIM technology is the most common method for collecting vehicle weight data, but other methods, such as portable scales and static weigh stations, may also be used.
- *Data analysis and dissemination*: How will the data collected from the program be analyzed and disseminated? The data should be analyzed to track vehicle weights over time, identify overweight vehicles, and inform transportation planning and decision-making. The data should also be disseminated to the public and other stakeholders.
- *Integration with WIM technology*: How will WIM technology be integrated into the program? WIM data can be used to identify overweight vehicles, develop targeted enforcement strategies, and inform transportation planning and decision-making.
- *Program implementation and evaluation*: How will the program be implemented and evaluated? The program should be implemented in a phased approach, and it should be evaluated on a regular basis to assess its effectiveness in meeting its goals and objectives.

Moreover, there are WIM-related design considerations that should be considered when designing and implementing a comprehensive VWM program. These include:

- *Technology*: Several WIM technologies are available, each with its own advantages and disadvantages. Transportation agencies should carefully consider their specific needs when selecting a WIM system.
- *Calibration and maintenance procedures*: It is important to properly calibrate and maintain WIM systems to ensure that they are providing accurate data.
- *Data analysis procedures*: The data collected from the WIM system should be analyzed using sound statistical methods. This will help to ensure that the data is accurately interpreted and used to make informed decisions.

- *Dissemination processes*: It is important to communicate the findings of the VWM program to the public and other stakeholders. This can be done through reports, websites, and other communication channels.

A VWM program is an essential component of transportation safety and infrastructure management. By integrating WIM technology into a comprehensive VWM program, transportation agencies can identify and address overweight vehicles, protect infrastructure, and improve safety. Transportation agencies should carefully consider the design issues discussed above when implementing a comprehensive VWM program. VWM technology is rapidly evolving; new technologies are constantly emerging. For example, some transportation agencies are exploring the use of artificial intelligence (AI) to analyze WIM data and identify overweight vehicles. Other agencies are developing new ways to integrate WIM data with other transportation data sources, such as traffic data and weather data. As VWM technology continues to evolve, transportation agencies will have new opportunities to design and implement VWM programs that are more effective and efficient. NCDOT can use AI to:

- *Improve the accuracy of WIM systems*: AI can be used to develop new algorithms for WIM systems that can more accurately measure vehicle weights, especially in challenging conditions such as high traffic volumes or bad weather. It can also help better detection of irregularities and discarding of invalid measurements.
- *Automate the identification of overweight vehicles*: AI can be used to develop systems that can automatically identify overweight vehicles from WIM data. AI can help in accurately classifying vehicles, even in uncommon situations involving vehicles towing other vehicles. This can help to improve the efficiency and effectiveness of weight enforcement programs.
- *Support predictive maintenance*: AI can be used to analyze WIM data to identify potential problems with WIM systems before they occur. AI can compensate for sites where missing or broken in-ground sensors lead to compromised data collection. This can help to reduce downtime and ensure that WIM systems are always operating at peak performance.
- Integration with Other Systems: AI can be used for re-identification of commercial vehicles allowing WIM systems to operate with fewer intrusive sensors.
- *Support research on vehicle weight and its impact on transportation infrastructure and safety*: AI can be used to analyze WIM data to identify trends and patterns in vehicle weight and traffic flow. This information can be used to support research on vehicle weight and its impact on transportation infrastructure and safety.
- *Develop new algorithms for calibrating and maintaining WIM systems*: Enabling continuous calibration can help to ensure that WIM systems are providing reliable real-time data over time.
- *Develop new WIM data analysis tools customized for different stakeholders*: This information can be used to identify trends and patterns in vehicle weight data to improve transportation planning and decision-making.

Some specific examples of how AI is being integrated with WIM technology today include:

- FHWA (the Federal Highway Administration) is developing an AI-based system for identifying overweight vehicles from WIM data. The system is expected to be able to identify overweight vehicles with greater accuracy and efficiency than current methods.
- The European Union-funded Horizon 2020 project Weigh-in-Motion for Smart Transport (WIM4ST) is developing a new generation of WIM systems that are integrated with AI. The WIM4ST systems are expected to be more accurate and reliable than current WIM systems, and they will be able to collect a wider range of data on vehicle weights, axle loads, and other vehicle characteristics.
- Weighbridge Systems, an Australian company, is developing an AI-based system for predictive maintenance of WIM systems. The system is expected to be able to identify potential problems with WIM systems before they occur, which can help to reduce downtime and ensure that WIM systems are always operating at peak performance.

Overall, AI has the potential to significantly improve the performance and capabilities of WIM technology. AI-powered WIM systems will be more accurate, reliable, and efficient than current WIM systems, and they will be able to collect a wider range of data on vehicle weights, axle loads, and other vehicle characteristics. This data can be used to improve the safety and durability of roads and bridges, to identify and address overweight vehicles, and to support research on vehicle weight and its impact on transportation infrastructure and safety.

For the success of any new initiative, selecting the right product through the right vendor is particularly important. To that end, we explored various technologies that are currently available in this industry and the vendors that provide these systems.

4.2. WIM Vendor Selection Model

NCHRP (2023) provides a detailed guideline for WIM sensor selection (Tools for Assuring WIM Data Quality: Practical Guide). However, this guide does not cover the vendor selection process.
Based on the procurement recommendations presented in WIM Guidebook, Part 1 (dot.gov) and the survey results presented above, and using the analytical hierarchy process and multi-objective decision making models, the research team developed a methodology that should help agencies optimize their vendor selection process.

Assign Weights to the Selection Criteria: A Multi-Expert Approach: Effectively selecting the most suitable vendor requires a thorough evaluation process that considers various factors and prioritizes their relative importance. Assigning weights to selection criteria is a critical step in this process, as it allows decision-makers to quantify the significance of each factor in determining the optimal vendor. However, relying solely on the judgment of a single individual can introduce biases and potentially lead to inaccurate results. To mitigate this risk and enhance the robustness of the decision-making process, employing a multi-expert approach using pairwise comparison matrices and the Analytic Hierarchy Process (AHP) is recommended.

Create a Pairwise Comparison Matrix: A pairwise comparison matrix is a structured tool used to quantify the relative importance of different criteria. In this matrix, each criterion is compared against every other criterion, and a numerical value is assigned to indicate the degree of preference. For instance, if you are comparing the criteria of "price" and "quality," a value of 2 for "price" in the corresponding cell would indicate that you consider price to be twice as important as quality. This numerical representation allows for a more objective and consistent assessment of relative importance.

Sameer	Automatic scale calibration	Automated weight enforcement	Turnkey systems(Outsourcing 100% service)	License plate readers	Check weight, dimensions at highway speeds.	Expert installation, configuration, and start-up
Automatic scale calibration	1.00	0.50	0.11	2.00	2.00	0.80
Automated weight enforcement	2.00	1.00	0.11	4.00	0.11	2.00
Turnkey systems(Outsourcing 100% service)	9.00	9.00	1.00	9.00	0.33	9.00
License plate readers	0.50	0.50	0.11	1.00	0.11	0.25
Check weight, dimensions at highway speeds.	0.50	0.50	3.00	9.00	1.00	9.00
Expert installation, configuration, and start-up	1.25	1.25	0.11	4.00	0.11	1.00
User training for accurate, safe, and effective operation	2.00	2.00	2.00	3.00	0.33	0.50
Seamless data acquisition and integration	0.33	0.33	0.33	2.00	0.33	4.00
Optimized uptime and equipment life	0.33	0.33	0.50	5.00	1.00	0.11
Compliance with regulations	9.00	9.00	9.09	9.09	1.00	9.09
Cost-effective maintenance	0.33	0.33	0.25	2.00	0.33	4.00
Vendor location	0.33	0.33	0.50	2.00	0.33	0.20
Traffic data collection	0.25	0.25	0.50	2.00	0.50	0.20
Bridge protection	9.00	9.00	9.00	9.00	1.00	9.00
Tire safety screening	0.20	0.20	0.20	2.00	0.11	4.00
Weight-based tolling	0.20	0.20	0.20	0.20	0.11	0.20
Experience in the WIM field	0.50	0.50	0.50	2.00	0.20	4.00
Life of instruments	2.00	2.00	2.00	2.00	1.00	1.00
User-friendly user interface (UI), integration using REST API,	0.50	0.50	0.50	2.00	0.20	1.00
Ability to withstand extreme conditions	9.00	9.00	9.00	9.00	1.00	9.00
Response time/lead time	2.00	2.00	4.00	4.00	0.25	4.00
Granularity or frequency of data collection	0.25	0.25	0.25	2.00	0.25	0.50
System availability	9.00	9.00	9.00	9.00	1.00	9.00
A variety of solutions are available and upgrade options.	0.33	0.33	0.50	2.00	0.20	0.50
Data Accuracy	9.00	9.00	9.00	9.00	1.00	9.00
Price-to-performance ratio	9.00	9.00	9.00	9.00	0.20	9.00
Energy consumption	0.25	0.25	0.25	0.25	0.13	0.25
Technology used	0.20	0.20	0.25	9.00	0.13	0.50
Permit checker	0.11	0.11	0.11	0.11	0.11	0.11
System warranty	9.00	9.00	9.00	9.00	1.00	9.00

Figure 9 Sample Pairwise Comparison Matrix

Use the Analytic Hierarchy Process (AHP): The Analytic Hierarchy Process (AHP) is a multi-criteria decision-making framework that helps prioritize different criteria and evaluate alternative options. By decomposing complex decisions into smaller, more manageable hierarchies, AHP allows for a systematic and transparent approach to decision-making. In the context of vendor selection, AHP can be used to structure the evaluation process, decompose the overall selection decision into smaller sub-decisions, and prioritize the various selection criteria.

To effectively gather weights from multiple experts and ensure a comprehensive assessment of relative importance, follow these steps:

1. *Identify Experts*: Carefully select individuals who possess relevant expertise and experience in the procurement process and the specific domain of the vendor selection.
2. *Construct Pairwise Comparison Matrices*: Provide each expert with a pairwise comparison matrix and ask them to compare the relative importance of each pair of selection criteria. Ensure that the experts have a clear understanding of the criteria and the context of the vendor selection process.
3. *Calculate Individual Weights*: For each expert's pairwise comparison matrix, calculate the normalized weights using the eigenvector method. The eigenvector method is a mathematical technique that identifies the relative weights of the criteria based on the pairwise comparisons provided by the expert.
4. *Aggregate Individual Weights:* Average the normalized weights from all experts to obtain a collective set of weights. Averaging the individual weights allows for the incorporation of diverse perspectives and helps mitigate potential biases.

Use Average Weights for Vendor Selection: Once the average weights have been identified for each selection criterion, the vendor evaluation process can proceed as follows:

1. *Establish the Rating Scale*: Define a common rating scale for each criterion, such as a numerical scale from 1 to 10, where 1 represents the lowest rating and 10 represents the highest rating. Ensure that the rating scale is appropriate for the nature of each criterion and provides a clear differentiation between different levels of performance.
2. *Evaluate the Vendors:* Assess each vendor against each selection criterion using the established rating scale. Perform a thorough evaluation of each vendor's qualifications, experience, and proposed solutions, ensuring that the ratings are objective and consistent.
3. *Calculate the Weighted Scores*: For each vendor, multiply each rating by the corresponding criterion weight and sum the products to obtain the vendor's weighted score. The weighted score reflects the overall performance of each vendor, considering both the ratings and the relative importance of the criteria.
4. *Compare the Vendors:* Rank the vendors based on their weighted scores, with the highest score indicating the most preferred vendor. The vendor with the highest weighted score has been identified as the most suitable choice based on the specified selection criteria and the collective expertise of multiple experts.

By incorporating the collective expertise of multiple experts through pairwise comparison matrices and AHP (as shown in Table 6 below), you can ensure a more objective, reliable, and well-informed approach to assigning weights and selecting the most suitable vendor. This approach helps mitigate biases, enhances transparency, and leads to a more robust and defensible decision-making process.

Table 6 WIM Vendor Selection Criteria

Criteria	**Weight**	**Vendor A**	**Vendor B**	**Vendor C**
Compliance with regulations	11.7%	10	10	10
Built-in QA/QC process	8.9%	9	8	8
Ability to withstand extreme conditions	8.5%	8	8	8
System warranty	8.2%	9	9	9
Data Accuracy and reliability	6.9%	6	6	6
Price-to-performance ratio	6.7%	6	6	6
Check weight, dimensions at highway speeds.	5.8%	10	10	10
System availability	5.7%	5	5	5
Response time/lead time	4.3%	6	7	7
Life of instruments	4.1%	6	8	7
Optimized uptime and equipment life	3.1%	8	8	8
Tire safety screening	3.0%	8	8	7
Turnkey systems (Outsourcing 100% service)	2.6%	10	8	7
Automatic scale calibration	2.1%	7	7	6
Automated weight enforcement	1.9%	8	8	8
Seamless data acquisition and integration	1.8%	8	7	6

User training for accurate, safe, and effective operation	1.8%	6	6	7
Cost-effective maintenance	1.7%	8	8	7
Experience in the WIM field	1.5%	9	7	7
Traffic data collection	1.5%	9	8	8
User-friendly user interface (UI), integration using REST API, etc.	1.5%	8	8	7
Expert installation, configuration, and start-up	1.5%	9	8	8
Technology used	1.0%	8	8	7
Granularity or frequency of data collection	0.9%	9	9	7
License plate readers	0.8%	8	8	8
Weight-based tolling	0.8%	8	8	7
Availability of integrated solutions and upgrade options	0.6%	6	6	6
Permit checker	0.5%	6	6	6
Vendor location	0.5%	9	9	9
Energy consumption	0.4%	5	5	5
	1.00	**7.9**	**7.8**	**7.7**

As illustrated in the vendor selection evaluation table above, the best decision is to select Vendor A as the sole-source provider. Awarding the contract to this vendor will give NCDOT a highly accurate and relatively easy to maintain system while eliminating the problems and cost associated with compatibility issues that arise from the integration of multiple systems. In the awarding contract NCDOT should clearly state the requirements for its WIM BI Dashboard (data collection and real time processing requirements) to include what is required for law enforcement.

For law enforcement data collection, contract road maintenance should be included for 140-yard stretches (100 prior and 40 after each WIM station) . A pairwise comparison matrix can be used to generate average weights for each selection criteria. Use of technology and different visualization tools to effectively monitor traffic data and enforce weight and other dimension restrictions. A fully functioning WIM system in North Carolina will improve NC's highway planning, pavement and bridge design, freight movement studies, motor vehicle enforcement, and legislative and regulatory studies associated with traffic flow, movement, and weight.

5. EMERGING TECHNOLOGIES & CONCEPTUAL SYSTEM DESIGN

The emergence of intelligent transportation systems (ITS) represents a paradigm shift in managing vehicle traffic and infrastructure health. Traditional weigh-in-motion (WIM) systems, pivotal in these efforts, have long been constrained by their reliance on contact-based, mechanical measurement techniques. These methods, while effective, suffer from inherent limitations such as high maintenance costs, limited lifespan, and susceptibility to environmental factors.

Artificial Intelligence (AI) and Computer Vision (CV) are technologies that have revolutionized various fields with their ability to interpret and analyze complex data. The research team advocates for the integration of AI and CV into WIM systems, aiming to transcend the constraints of traditional methods. By harnessing the power of AI algorithms and the analytical capabilities of CV, we propose a non-intrusive, more accurate, and cost-effective approach to vehicle weight measurement. This novel system is poised to redefine traffic load monitoring and infrastructure maintenance, aligning with the evolving needs of modern ITS.

This section proposes a cutting-edge Weight-in-Motion (WIM) system using advanced Artificial Intelligence (AI) and Computer Vision (CV). This system aims to deliver a non-contact, highly accurate vehicle weight measurement method, improving traditional WIM systems. Key goals include developing an AI algorithm for precise visual data analysis to determine vehicle weights, integrating CV technology for processing real-time data from moving vehicles, creating a cost-effective and low-maintenance system adaptable to different traffic conditions, and ensuring the system supports efficient traffic load monitoring and infrastructure health assessment. This innovative approach aspires to transform traffic management and infrastructure maintenance with a reliable, efficient, and technologically sophisticated solution.

5.1 Technology Overview

The proposed Weight-in-Motion system integrates two cutting-edge technologies: Artificial Intelligence (AI) and Computer Vision (CV).

- *Artificial Intelligence (AI)*: AI algorithms, particularly machine learning and deep learning models, form the core of the system. These algorithms are trained on vast datasets to accurately predict vehicle weights from visual data. They are capable of adapting to different vehicle types and environmental conditions, ensuring consistent performance.
- *Computer Vision (CV):* CV technology is employed to capture high-resolution images of vehicles in motion. This includes advanced camera systems and image processing techniques. The system analyzes visual indicators such as tire deformation to estimate vehicle weight. This non-contact method offers a significant advantage over traditional methods, reducing wear and tear on equipment.

Together, AI and CV enable a highly accurate, efficient, and non-intrusive approach to measuring vehicle weights, marking a significant leap forward in WIM technology.

5.2 System Design

The proposed AI and CV-based Weight-in-Motion system comprises several key components and functionalities:

- *Sensors and Cameras*: High-resolution cameras and specialized sensors are strategically positioned to capture real-time data of vehicles in motion. These devices are designed to work in various lighting and weather conditions.
- *Data Processing Unit:* This unit is equipped with powerful processors and adequate storage to handle large volumes of data. It runs the AI algorithms and processes the visual data captured by the cameras.
- *AI and Machine Learning Models*: The heart of the system, these models are trained to analyze the captured data, focusing on parameters such as tire deformation, to accurately estimate vehicle weight.
- *User Interface and Reporting Software*: A user-friendly interface allows operators to monitor the system, view real-time data, and generate reports. This includes weight estimations, traffic flow analysis, and system diagnostics.
- *Existing Infrastructure Integration*: The system is designed for easy integration with current traffic management systems, ensuring seamless operation and data sharing.
- *Maintenance and Support System*: A comprehensive maintenance plan ensures the longevity and reliability of the system, including regular software updates and hardware checks.

This design ensures that the WIM system is not only accurate and efficient but also robust and user-friendly, meeting the needs of modern traffic management and infrastructure maintenance.

5.3 Benefits and Applications

AI and CV technologies provide a more precise weight measurement compared to traditional systems. The system's reliance on visual data eliminates the need for physical contact, reducing wear and tear. Lower maintenance and operational costs due to the non-contact nature and advanced analytics. Capable of handling various vehicle types and environmental conditions. Offers immediate weight estimations, aiding in efficient traffic management.

Applications: Optimizes traffic flow by providing accurate vehicle weight data. Assists in predicting and preventing infrastructure damage by monitoring vehicle weights. Useful for ensuring compliance with vehicle weight regulations. Provides valuable data for ongoing improvements in transportation technology and infrastructure planning.

5.4 System Design & Implementation Plan

The system should be designed as a three-tier architecture:

- *Presentation tier*: The presentation tier will consist of a web-based user interface that will allow users to access the weight data and generate custom reports.

- *Application tier*: The application tier will contain the business logic of the system, including the AI-based WIM system, the weight monitoring system, and the custom reporting module.
- *Data tier*: The data tier will store the weight data in a relational database management system (RDBMS).

System Components

The system would be comprised of four components:

1) *Imaging System***:** one or more high-resolution cameras that are capable of capturing clear images of vehicles at high speeds. The cameras should be installed in strategic locations to ensure that all vehicles are captured.
2) *AI-based WIM System***:** a deep learning model that measures the weight of vehicles in real time. The deep learning model will be trained on a large dataset of images of vehicles with known weights. Once trained, the deep learning model will be able to accurately measure the weight of vehicles in new images.
3) *Weight Monitoring System*: a relational data base management system (RDMS) that stores the weight data collected by the AI-based WIM system. The weight monitoring system will also provide users with access to the weight data through a web-based interface. The web-based interface will allow users to view the weight data in real time, as well as generate reports on the weight data.
4) *Custom Reporting Module***:** an application that allows users to generate custom reports on the weight data. The custom reporting module will allow users to filter the weight data by date, time, vehicle type, and other criteria. The custom reporting module will also allow users to export the weight data to a variety of formats, such as CSV, PDF, and Excel.

The following are the system requirements for the imaging AI-based WIM and weight monitoring system:

- Hardware:
  - One or more high-resolution cameras
  - A server with a powerful CPU and GPU

- Software:
  - A web server
  - A programming language such as Python or Java
  - A deep learning framework such as TensorFlow or PyTorch
  - A database management system such as PostgreSQL or MySQL
  - A streaming platform such as Apache Kafka

System Security The system should be designed with security in mind. The following security measures should be implemented:

- Data encryption: The weight data will be encrypted at rest and in transit.
- User authentication and authorization: Users will be authenticated and authorized before they are allowed to access the weight data.
- Regular security audits: The system will be regularly audited for security vulnerabilities.

System Maintenance The system will be maintained on a regular basis to ensure that it is operating properly and that the AI-based WIM system is still accurate.

Reporting Capability for Different Stakeholders

The custom reporting module will be designed to meet the reporting needs of different stakeholders. For example, the system could generate reports for the following stakeholders:

- Transportation agencies: Transportation agencies could use the system to generate reports on the weight of vehicles on their roads and bridges. This information could be used to identify overweight vehicles and to monitor the impact of heavy vehicles on infrastructure.
- Law enforcement agencies: Law enforcement agencies could use the system to generate reports on the weight of vehicles to identify overweight vehicles that may be violating traffic laws.
- Freight companies: Freight companies could use the system to generate reports on the weight of their vehicles to ensure that they are not overweight and to track their fuel efficiency.

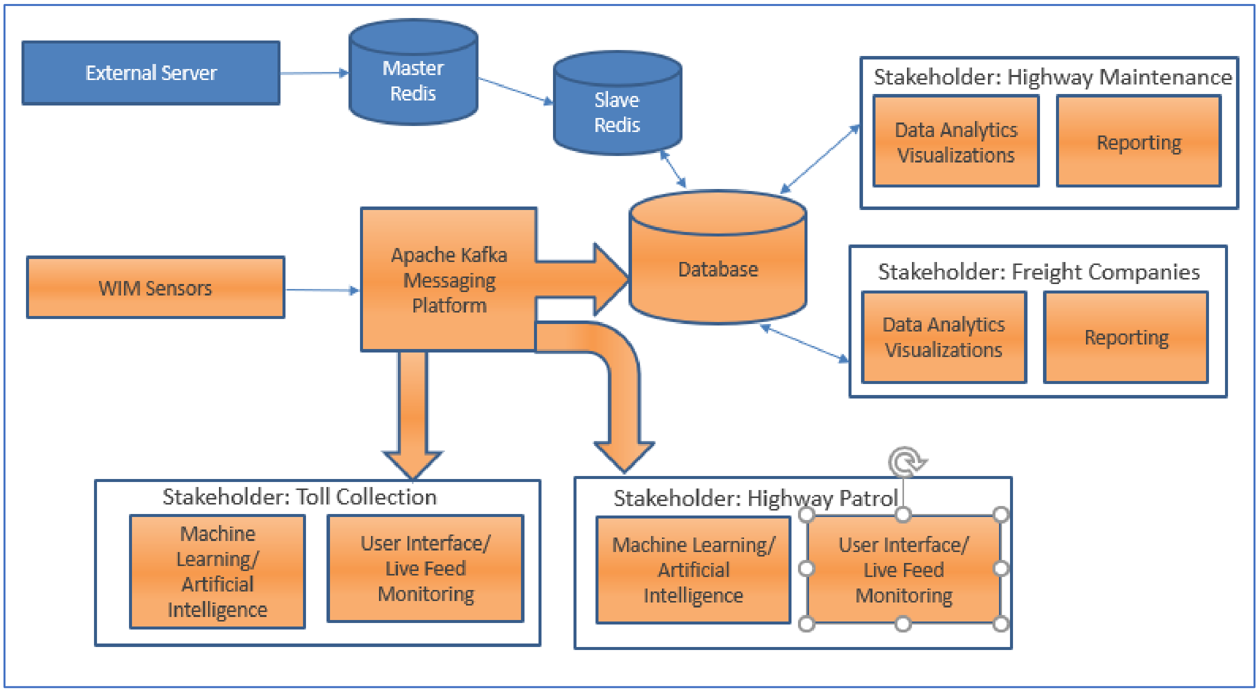

Figure 10 Illustration for Low Latency Architecture

Figure 9 presents an example low latency architecture. For illustration purposes, we assume that the traffic and vehicle data is collected by various WIM sensors. The data that has been collected is then published to our dedicated topics. Consumer clients can be developed wherever there is a need to utilize the data in real time. The data can be read by some consumer clients and displayed in a monitoring dashboard for real time usage. Any trained machine learning models can also be fed with the collected data to generate necessary alerts, notifications, or meaningful insights. The data can be fed to a persistent database by another consumer. MongoDB or some data warehouse can be used for that. The stored data can be used for reporting and visualization purposes. If there is a need to train any machine learning or AI model, the data from this persistent data source can be used. The user interface from a stakeholder's point of view is represented by the different boxes. A cache layer (like Redis cache) can be installed to prevent any bottleneck situation if there is a need to connect this system with other external data sources.

The major components of our architecture (besides Kafka and Database) are as follows.

- *Live Feed (Web User Interface)* for monitoring live traffic and vehicles in real time.
- *Machine learning and Artificial Intelligence* for predicting the traffic pattern, overloaded vehicles, and accidents.
- *Data cube (MONGO DB or data warehouse)* for archiving the traffic data.
- *Data analytics and Visualization (Visualization software)* to deal with analysis, visualization, and reporting.

We propose considering the following variables for a low latency architecture.

- License Plate ID
- Speed
- Vehicle Length
- Gross Vehicle Weight / Classification
- Direction and lane
- Axle Weight & Distance to determine the vehicle class.
- Tire pressure detection
- Lane Number
- Whether liquid material is transported
- Height of the vehicle
- Timestamp

6. PROPOSED VEHICLE WEIGHT MONITORING PROGRAM

Based on the research literature and survey responses, the research team proposes that NCDOT develop a vehicle weight monitoring program with the following characteristics:

6.1 Overall Program Design

- Use a sample-based methodology for identifying the types of seasonal class volume and vehicle loading patterns experienced on NC routes.
- Sampling should incorporate all types of facilities including those in urban areas, rural areas, designated truck routes, non-truck routes, arterials, collectors, and local routes.
- Employ state of the art weigh in motion technologies to collect vehicle class and weight data.
- Support dual use of the sample sites for traffic monitoring and real time enforcement purposes.
- Use the existing Traffic Count Database System (TCDS) software to manage the processing and QC/QA of WIM data.
- Identify WIM data-based stakeholder products to be supported by the program.
- Customize the TCDS software and/or procure additional software to support generation of stakeholder data products.

6.2 Weigh In Motion Standards

- Use the ASTM E1318-09 specification “Standard Specification for Highway Weigh-In-Motion (WIM) Systems with User Requirements and Test Methods” as the standard for weigh in motion data.
- Comply with the Type I and Type II systems as defined in ASTM E1318-09WIM systems for traffic monitoring.
- Comply with the Type III system as defined in ASTM E1318-09WIM systems for both traffic monitoring and real time enforcement.
- Use WIM system calibration procedures consistent with those specified in ASTM E1318-09.

6.3 Weigh In Motion Technology

The WIM technologies recommended can support meeting the standards specified above, are the lower cost technologies, and have a reasonable life cycle. Recommendations are:

- Sensor Technology – the piezo type sensor is recommended for WIM technology; recommended piezo technologies are:
  - Quartz piezo
  - Digital quartz piezo
  - Strain gauge piezo

  These types of piezo sensors are currently in use on the mainline WIM enforcement sites. Other types of piezo sensors are not suitable for weight measurements but can be used for axle based classification; the bending plate and load cell technologies are suitable for weight measurements but would add substantial cost for installation and maintenance

- WIM Array configuration recommendation:
  - Use a double threshold piezo array for weight measurements (two full lane width sensors or 4 wheel path sensors); this configuration is in use for enforcement at the existing mainline WIM sites.
  - Use piezo spacing based on the formula developed by Cebon in Chapter 8 of the Handbook of Vehicle-Road Interaction (2000)
  - Place inductance loop sensors based on the recommendations of WIM sensor vendors and WIM controller equipment vendors.

  Use a triple threshold array as it provides slightly more accurate weight measurements and would provide some redundancy so that a double threshold array would still be operational if one of the sensors fails.

- Dual Use WIM Sites – these types of sites must be configured to meet both traffic monitoring and real time enforcement requirements; it is recommended:

- All lanes be instrumented for weight measurements to meet traffic monitoring requirements.
- Enforcement lanes be instrumented with additional technologies that support generating information required for real time enforcement.
- Due to the more complex requirements of enforcement sites, these sites should be designed, maintained, and operated with the other enforcement WIM sites.
- The enforcement systems should be designed based on the virtual weigh station (VWS) model.

6.4 WIM Data Products

There are many potential uses of statistics generated from data collected by WIM systems. NCDOT should meet with agency staff in each specialty area to identify the specific uses, the statistics required, and any standards specified for that data. Potential uses are:

- Traffic Monitoring – systems need to support meeting the federally mandated traffic monitoring requirements, support the generation of Highway Performance Monitoring System (HPMS) data, and the submittal of WIM data in the FHWA TMAS reporting system.
- Enforcement – requirements for enforcement include:
    - Real time screening of trucks for potential violations
    - Support enforcement planning activities
    - Support evaluation of the impact of enforcement activities (performance measures)
- Pavement design statistics (MEPDG and AASHTO methods)
- Pavement monitoring
- Bridge design
- Bridge monitoring
- Freight and logistics
- Regulatory

6.5 WIM Program Size

The size of the program should be dependent upon the required number of WIM sites needed to meet the data needs of the intended products. The size should be consistent with the number of unique patterns occurring in North Carolina and the number of sites required to characterize each of those patterns reliably.

This type of analysis was performed in a previous NCDOT research project (RP 2008-11) that supported the generation of design statistics for the MEPDG pavement design method. This report recommended the required number of WIM sites to meet the precision standards specified in the Traffic Monitoring Guide for the 4 Axle Load Distribution Factor groups (ALDF) should be 53 WIM sites. Due to the operational processes of managing continuous traffic monitoring, a few additional WIM sites are recommended to avoid inadequate sampling due to older sites being retired and the time it takes for new sites to have adequate data to be grouped. A total of 60 WIM sites are recommended as the target for planning WIM program development. The final number required should be determined based on the data collected at new WIM sites implemented in the program. Our recommendations are:

ALDF	WIM Sites
1	26
2	8
3	5
4	14

6.6 WIM Program Costs

Our cost estimates are based on the 60 WIM sites recommended above and the costs identified in the survey for the technologies recommended previously. A range is provided for each type of expense due to the ranges of costs gathered in the surveys for those technologies. Cost estimates are provided for initial installation of new WIM sites and annual maintenance (including calibration). The cost estimates for program infrastructure are:

Activity	Frequency	Low Estimate	High Estimate
Installation	One Time	$18,000,000	$24,000,000
Maintenance	Annual	$2,000,000	$3,000,000

Other major costs associated with managing the program are software and staffing. It is anticipated the TCDS software currently used for managing traffic monitoring data sets will require customizations to generate some of the required data products. Other software may be required to generate and manage some data products.

The Traffic Survey Group has staffing to support the current level of traffic monitoring. Adding 60 WIM sites will require additional staffing to effectively support the management of data processing, QC/QA, and generation of data products. Regardless of whether this activity is performed in house or outsourced, the staffing requirements must be funded. Estimated costs associated with these requirements are:

Activity	Frequency	Low Estimate	High Estimate
TCDS Customizations	One Time	$400,000	$800,000
Other Software Licensing	One Time	$200,000	$400,000
Software Maintenance	Annual	$100,000	$200,000
Staffing (1 engineer, 3 technicians)	Annual	$400,000	$600,000
Overall WIM program costs are estimated to be:			
Activity	**Frequency**	**Low Estimate**	**High Estimate**
Program Implementation	One Time	$18,600,000	25,200,000
Program Management	Annual	$2,500,000	3,800,000

These cost estimates are intended to provide the relative level of funding required from the NCDOT for implementation and management of the recommended WIM program. They exclude the costs associated with additional enforcement technologies at WIM sites.

6.7 WIM Program Benefits

In general, the benefits associated with the use of North Carolina vehicle weight data are related to those processes that employ the data products. Additional enforcement sites will support more effective detection of violators resulting in a higher level of compliance with weight limits and safety regulations. Improving safety on NC highways and preserving infrastructure. Using NC based statistics for planning and design of highways will result in facilities that meet the needs of the traveling public and businesses. Better designs result in more predictable life cycles for infrastructure, improving the management of maintenance and replacement activities. Given the high cost of WIM systems it is critical to leverage the use of that data for those processes that require vehicle weight-based statistics. Many of these processes rely on national defaults as inputs today. Which often results in overly conservative designs. Use of NC based data will support better designs and more effective use of limited funding.

6.8 Funding Sources

The prior WIM program was supported through funds from Statewide Planning and Research (SPR). The bulk of it came from planning funds but some funding was provided from the research portion for the LTPP pavement research sites. The SPR funding source is very limited and the legacy program was substantially impacted by this ultimately leading to its discontinuation. The proposed program is intended to leverage the WIM data to support many processes and other funding sources should be considered to support an effective vehicle weight monitoring program. Potential funding sources are:

- *STIP Funding*: design statistics generated from vehicle monitoring data can be used for design processes for highway improvements; a portion of funding could come from STIP funds to support the design of these improvements.
- *SPR Funding*: The Traffic Survey Group can use vehicle class data to generate seasonal factors for annualizing short term class counts; vehicle class and weight data will be reported to FHWA in TMAS; SPR funds can be used for this traffic monitoring activity.
  Enforcement Funding: For the dual use sites, the WIM systems needed could be funded by NCDOT as this supports the data needs of the agency; for the instrumentation of enforcement lanes with additional technologies to support real time enforcement we recommend use of enforcement funding sources.

A cost sharing approach would reduce the impact on any individual funding source and ensure there are adequate funds to manage an effective vehicle weight monitoring program.

6.9 Sourcing Options

For the previous monitoring program, a hybrid approach was used to manage the WIM installations and supporting systems. New WIM sites were installed, and initial calibration was performed by contractors. All major maintenance activities were also contracted. Inspections of contractor work were performed by the Traffic Survey Group (TSG). For recurring calibrations, a trucking services contract provided a calibration truck, but calibration of the equipment was performed by TSG staff. Operation and polling of WIM sites and basic maintenance were performed by TSG staff. All data processing, QC/QA, and reporting activities were performed by TSG staff.

For the revived monitoring system, a few options can be considered, such as:

- *Fully In House*: This would require a substantial commitment of staff and equipment that many agencies find difficult to maintain. Few state agencies use this approach.
- *Hybrid Contracted and In House*: This would be similar to the legacy sourcing method where major activities were contracted and operation and management of the systems were performed in house.
- *Fully Contracted*: The WIM systems would be installed, calibrated, maintained, and operated by contractors but owned by NCDOT.
- *WIM Data as a Service*: The WIM systems would be installed, calibrated, maintained, operated, and owned by contractors. NCDOT would pay for the data provided.

6.10 Vehicle Weight Monitoring Implementation Plan

A high-level plan for addressing the major requirements of a WIM program and the progression of implementation steps are provided below.

1) Design Phase

- Identify WIM data uses and prepare data specifications for each
- Identify design resources and prepare design and contracting templates
- Identify funding sources and setup funding mechanisms
- Evaluate software needs, software options, and procure software
- Evaluate sourcing options and select sourcing method
- Identify corridors for WIM site selection and evaluate WIM locations
- Develop and implement WIM data QC/QA methods

2) Site Installation Phase 1 – Install 20 WIM sites

3) Evaluate data from new WIM sites to identify patterns and group assignments

4) Site Installation Phase 2 – Install 20 WIM sites

5) Evaluate data from new WIM sites to identify patterns and group assignments

6) Site Installation Phase 3 – Install 20 WIM sites

7) Evaluate data from new WIM sites to identify patterns and group assignments

8) Implement production of data products

It is critical to evaluate new WIM sites after each installation phase to determine the ALDF they group with so that the next set of WIM sites can be selected to meet the sampling requirements of each group.

6.11 Emerging Technology Assessment

As presented in Section 5, the research team recommends integrating emerging technologies in establishing a new weight monitoring system, which may require another project prior to the implementation phase. Integrating AI and CV technologies would require a separate implementation plan as outlined below.

Research and Development Phase (0-6 Months):
- Conduct thorough research on current AI and CV technologies.
- Develop the initial AI algorithms and CV models.

Prototype Development (6-12 Months):
- Create a prototype system integrating AI, CV, and necessary hardware.
- Begin initial testing in controlled environments.

System Testing and Refinement (12-18 Months):
- Deploy the system in a real-world environment for testing.
- Collect data, analyze performance, and refine the system accordingly.

Final System Development (18-24 Months):
- Finalize the design based on test results.
- Prepare for full-scale production and deployment.

Deployment and Training (24-30 Months):
- Install the system in selected locations.
- Conduct training sessions for operators and maintenance personnel.

Post-Deployment Review and Support (30-36 Months):
- Monitor the system's performance.
- Provide ongoing support and updates.

This plan is designed to ensure a thorough and efficient development process, leading to a reliable and effective AI and CV-based WIM system.

In conjunction with this effort, a cost analysis of the options should be conducted:

- *Research and Development*: Estimated to involve significant investment primarily for AI and CV technology research, software development, and prototype testing
- *Hardware Acquisition*: Costs for high-resolution cameras, sensors, and data processing units. Bulk purchases and long-term supplier agreements could reduce costs.
- *Software Licensing and Development*: Expenses related to AI algorithm development, CV software, and system integration.
- *Installation and Deployment*: Costs for installing the system at designated locations, including labor and materials.
- *Training and Education*: Budget for training personnel in system operation and maintenance.
- *Maintenance and Upgrades*: Ongoing costs for software updates, hardware maintenance, and system improvements.
- *Operational Expenses*: Regular expenses for system operation, including power and data management.
- *Contingency Funding*: Allocation for unforeseen expenses and challenges during implementation.

The total cost will depend on the scale of deployment and specific technology choices, but investments in AI and CV technologies typically yield long-term savings and efficiency gains.

Finally, a risk assessment should be conducted, including strategies to minimize any risk identified.

Technological Failure: Risk of system malfunction due to software or hardware issues.
- Mitigation: Regular system maintenance, having backup systems, and robust software testing.

Data Inaccuracy: Potential errors in AI and CV data analysis.

- Mitigation: Continuous algorithm refinement, use of redundant systems for verification.

Adverse Weather Conditions: Impact on system's ability to accurately capture and process data.

- Mitigation: Use weather-resistant equipment and incorporate algorithms adaptable to various environmental conditions.

Cybersecurity Threats: Risk of data breaches or system hacking.

- Mitigation: Implement strong cybersecurity protocols and regular security audits.

Cost Overruns: Budgetary constraints leading to project delays or reduced functionality.

- Mitigation: Careful financial planning, regular budget reviews, and contingency funds.

User Acceptance: Resistance to new technology from operators or stakeholders.

- Mitigation: Comprehensive training programs and demonstrating the system's benefits.

Each risk should be accompanied by strategic measures to mitigate its impact, ensuring the smooth operation and reliability of the WIM system. This report presents a visionary approach to modernize Weight-in-Motion (WIM) systems by integrating Artificial Intelligence (AI) and Computer Vision (CV). This innovative solution promises to enhance accuracy, efficiency, and cost-effectiveness in traffic management and infrastructure maintenance. The implementation plan, backed by a detailed risk assessment and mitigation strategy, paves the way for a seamless integration into existing traffic systems. Embracing this technology not only aligns with current ITS advancements but also sets a new standard for future transportation infrastructure monitoring and management.

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