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Development of a Real-Time Wheel Load Quantification System for the Transit Environment

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Abstract

With recent (prepandemic) growth in both transit ridership and the number of passenger rail systems nationwide, researchers have been increasingly interested in quantifying the rail transit loading environment. Research that stemmed from this renewed interest provided engineers with greater insights into the loading demands placed on the track structure of heavy, light, and commuter rail systems. Although results from this earlier work were useful in a general manner, it was not possible to provide agencies with immediately actionable information on wheel loads, since the relevant data were analyzed and reported at a later date. As a result, agencies were unable to monitor their rolling stock wheel health in real time. In addition, trend analysis was not possible because it was not feasible to track specific wheels over time. To address these limitations, researchers at the University of Illinois have developed an economical system that both provides real-time notifications to transit agencies when it detects problematic loading conditions, and tracks specific wheels over time. This paper provides a framework for installing and launching this real-time wheel health monitoring system that transit agencies can replicate, as well as presents some preliminary data that have been collected. By receiving actionable wheel load data and better understanding the wheel deterioration trends present on their networks, agencies can remove bad actor wheels from service before they damage the track structure, improving the state of good repair. In addition, a more thorough understanding of the loading environment will allow them to plan maintenance and design more effectively.

Keywords

public transportation, commuter rail, heavy rail, public transportation, rail, track

From 1990 to 2016, both rail transit ridership and the number of rail transit systems in the United States almost doubled (*1*), prompting increases in investment for both new and existing transit systems. Policy makers at all levels of government have highlighted the role that rail transit can play in developing economically robust, healthy communities, as well as in mitigating climate change. This renewed national interest in rail transit has in some ways outpaced research on the environments that these systems operate in, with one of the shortcomings remaining a lack of understanding of the loading conditions present on transit networks (*2*, *3*). The lack of a firm grasp of the magnitudes and types of loads that rail transit vehicles impart on the track structure can generate inefficiencies in everything from design to maintenance.

Recent work by Edwards et al. (*3*) and Lima et al. (*4*) has improved this understanding by quantifying the loading environment of passenger rail systems through field instrumentation and data from existing Wheel Impact Load Detector (WILD) sites, which are wayside wheel load sensors that measure the force imparted by each wheel as it passes by the site (*5*). Models to predict dynamic loads were developed, allowing transit agencies

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and suppliers to design and maintain their systems more efficiently.

Nevertheless, the data used in this previous research were not analyzed in real time and did not include vehicle-identifying information, since WILD data were anonymized. This made it impossible to match recorded loads to specific wheels or axles. As a result, the findings presented were useful for engineering and maintenance purposes using total distributions and maximum loads but did not provide immediately actionable information for rolling stock maintenance needs. Further, it did not allow for long-term trend analysis of wheel health.

In the North American freight industry, rolling stock wheel maintenance is augmented by the widespread use of WILD sites. These sites are up to 50 ft long and capture multiple full wheel rotations, which ensures that wheel imperfections will immediately be detected (*3*). The main purpose of a WILD site is to flag wheels that generate high-impact loads, which are short-term, high-frequency forces created by irregularities in the track or wheel itself (*6*). Although rare, high-impact loads can damage the track structure or rolling stock because of their magnitude, as well as create high levels of noise and vibration (*7*, *8*). In the United States, interchange rules from the Association of American Railroads dictate that if a WILD site detects an impact load above 65 kips (kip = 1,000 lbf), the wheel in question may be flagged, and if it detects a load above 80 kips, the wheel may be condemned the next time the car is in a repair track. Wheels that generate impact loads of 90 kips or above may be condemned immediately (*9*). In addition, some railroads have set additional safety rules by which cars with wheels that generate impact loads greater than 140 kips must be immediately removed from the train and the wheel replaced (*10*). By detecting these problematic wheels and taking corrective action, freight railroads can minimize the damage that out-of-round wheels cause to the track structure and rolling stock (*11*).

Although WILDs are common in the freight industry, the nature of transit agencies often renders them economically unviable. On freight networks, the free interchange of railcars ensures that almost every car will periodically pass a WILD site, even if the frequency with which this occurs is low. Transit networks, on the other hand, are often organized such that each commuter or rapid transit line is a closed system, with rolling stock that does not move to other lines. As a result, to collect information on systemwide wheel health, the agency would have to install a WILD site on each line, which in many cases is neither an efficient use of resources nor economically feasible. Because of these limitations, many transit agencies' wheel maintenance programs are time- or mileage-based, allowing some damaged wheels to remain in service for extended periods of time.

The goal of this research was to expand on previous work by developing a real-time wheel health monitoring system that is economical, easy to install, and that also has the capability of tracking specific wheels over time. Systems were installed at two transit agencies (one commuter and one heavy rail transit) to evaluate their performance and capability to provide the agencies with timely data on their rolling stock wheel health. If proven, this technology would help transit networks to increase the efficiency of their resource allocation by enabling them to target wheels that either currently create high-impact loads or are likely to create high-impact loads in the future, as well as to gain important insights into the specific loading conditions that the track is subjected to. This paper describes the developed system along with an analysis of the preliminary data generated by the technology. Additional work is ongoing to evaluate the integration of the system into the agencies' wheel maintenance practices and will be reported in subsequent papers.

Methodology

Transit networks' closed system design makes them unsuitable for typical WILD sites, but it also presents an advantage that can be exploited in the development of a transit-targeted wheel health monitoring system. In closed transit networks, the same trains pass a specific point several times per day, meaning that even if the system does not detect a wheel imperfection during one pass, statistically it is likely to be caught eventually. This could make it possible to efficiently identify tread imperfections with a significantly smaller system (i.e., one or two instrumented cribs) than a typical WILD site (i.e., 50 ft of instrumented cribs). Compact instrumentation design with a lower cost and simpler installation procedure could allow transit agencies to monitor a higher percentage of their rolling stock by installing such a system on multiple lines.

The real-time wheel health monitoring technology described in this paper is a complex system that involves several different components working in parallel. In essence, however, the process entails automatically quantifying wheel loads through track-mounted instrumentation, cleaning and analyzing the data, and notifying stakeholders if anomalies are detected. The next sections describe each of the components of the overall real-time monitoring system installed by the researchers, and the various ways in which they interface with each other.

Instrumentation Sites

To acquire the data necessary for wheel health monitoring, field sites were installed at two partner transit agencies, one commuter rail and one heavy rail transit. At

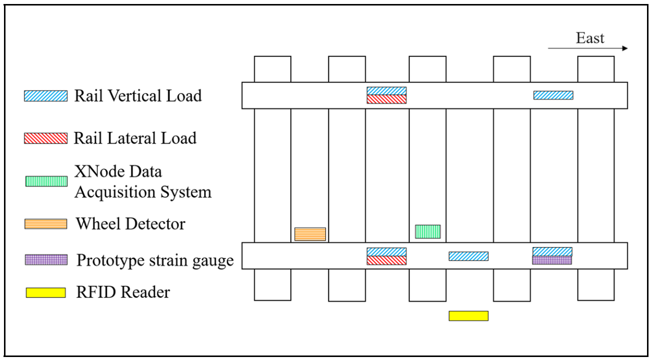

Figure 1. Layout of heavy rail instrumentation site.
Note: RFID = radio frequency identification.

these sites, a data acquisition system (DAQ) records data from various sensors each time a train passes by, creating the raw data used throughout the real-time reporting process.

This section describes the general layout of the instrumentation sites. For simplicity, only the commuter rail site is described in detail. However, it should be noted that the heavy rail site is similar, with only minor differences to the substantive components of the instrumentation. As shown in Figure 1, the commuter rail installation comprises eight total strain gauge bridges spread across three cribs. Vertical measurements are taken on both rails of two cribs, such that when a train passes the site there are two opportunities for the system to catch an imperfection on each wheel. It is important that the spacing of the instrumented cribs do not coincide with a full rotation of a passing wheel, so that multiple areas of the wheel tread can be captured during a pass. Although it is unnecessary to measure a full wheel rotation with every train pass, using two well-spaced cribs is likely to decrease the amount of time it takes to identify damaged wheels. In addition to the principal vertical strain gauge bridges, another vertical bridge was installed on the south rail of the center crib and connected to the XNode data acquisition system. A prototype vertical bridge was also overlaid with a traditional bridge on the eastmost crib of the south rail. Lastly, lateral strain gauge bridges were installed on both rails of one full crib. In addition to the strain gauge bridges, Figure 1 also shows the location of the radio frequency identification (RFID) reader, as well as the wheel sensor (i.e., trigger). The heavy rail site includes all the aforementioned sensors, as well as a microphone to measure train-pass sound pressures.

Both instrumentation sites were installed under traffic using appropriate track protection provided by the partner agencies. Most of the necessary equipment was mobile enough to simply remove it from the right of way when the team was notified of an approaching train, allowing the installation to be performed in a single shift, with minimal disturbance to traffic. The only activity requiring dedicated track occupancy was the calibration of the bridges, since the calibration frame attaches to the rail head and may also shunt the track (*3*).

Data Collection

All data captured at the site is collected by a compact DAQ (cDAQ), which consists of a National Instruments^{TM} (NI) chassis and associated modules. The cDAQ at the commuter rail site records data at 2 kHz, whereas the heavy rail location uses a much higher 25 kHz rate because of the need to accurately capture sound pressure data. In total, there are three signals that are monitored and recorded at both sites: voltage data from the strain gauge bridges, which the NI system converts to strain; voltage data from the wheel sensor that are used to trigger data collection; and RFID data that are brought into the cDAQ using an RS-232 serial port. In addition, the system at the heavy rail site also records sound pressure data and ambient temperature.

Incoming data are continuously monitored by the system, but only saved to a file when a train passes the site. To trigger data collection, the sites employ a Frauscher RSR110 induction wheel sensor. The sensor is also used to calculate the speed of the trains by dividing the known wheel spacing by the elapsed time between two adjacent wheels, as recorded by the sensor.

Once the data have been recorded by the cDAQ, a Sierra Wireless RV55 AirLink LTE modem uploads each train-pass file over the LTE cellular network to a cloud folder for further processing and offsite analysis. Owing to inconsistent cellular coverage at the commuter rail site, external high-gain antennas were also used to ensure a reliable network connection.

Wheel Load Quantification

The loading data that are captured at the instrumentation sites are generated by strain gauges attached to the rail (Figure 2*a*). Both vertical and lateral loads are measured by strain gauges arranged into a Wheatstone bridge pattern, as described in Cook et al. (*12*).

A portable strain gauge welding unit was used to attach the gauges to the rail. Once the gauges were affixed, silicone caulk and aluminum tape were applied to provide environmental protection. A detailed description of the installation process can be found in Edwards et al. (*3*). The final installed system at the commuter rail site is shown in Figure 2*b*.

All sensors were calibrated by applying known loads to the track through a self-reacting calibration device known as the delta frame (*3*), and recording the response

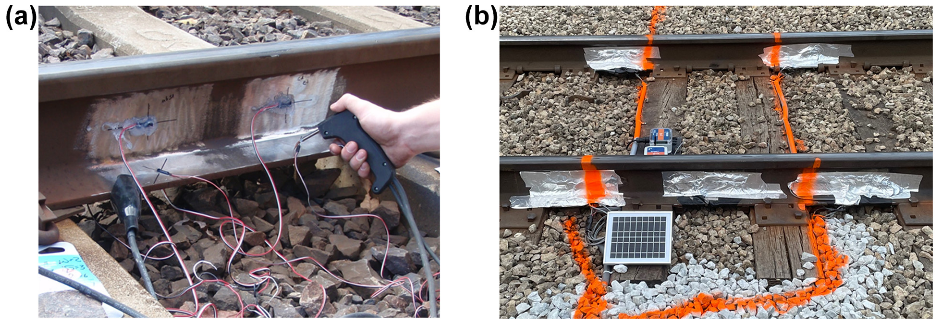

Figure 2. (*a*) Strain gauge bridges attached to rail and (*b*) the commuter railroad instrumentation site, as installed.

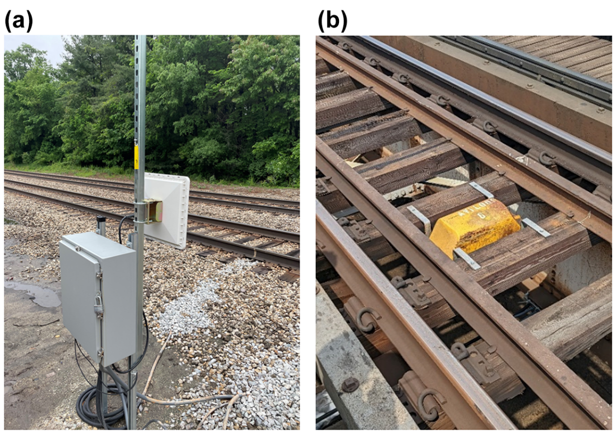

Figure 3. (*a*) RFID readers as installed at the commuter rail site and (*b*) the heavy rail site.
Note: RFID = radio frequency identification.

generated in the strain gauge bridges. Using the applied load magnitude and the strain gauge bridge response, a calibration factor was calculated for each sensor that relates any raw strain measurement to a wheel–rail applied load.

Train Identification

RFID systems are used at both sites to identify individual train cars. Using this information, problematic wheels can be flagged, and specific wheels can be tracked over time for trend analysis. The RFID system used at the commuter rail site is a TransCore Encompass 4 RFID reader, installed trackside as shown in Figure 3*a*. The heavy rail site uses a TagMaster S1569 Heavy Duty Track Reader, mounted in the gauge, as depicted in Figure 3*b*. As trains pass the instrumentation, the RFID reader collects information that uniquely identifies each car equipped with an RFID tag and relays this information to the data acquisition system.

Experimental Data Collection Methods

In addition to the established methods and systems described, this study also deployed and evaluated two novel forms of instrumentation at the commuter rail installation site with the goal of further reducing costs and increasing the ease of installation.

Prototype Strain Gauge. The prototype gauge (Figure 4) has the same purpose and functionality as a traditional strain gauge bridge (Figure 2*a*) but is smaller and more compact. As shown in Figure 4, the prototype gauge covers 6.5 in. of the crib, whereas the traditional gauge spans 10 in. To verify that the prototype does not react differently when subjected to the same wheel load as the traditional gauge, both gauges were tested using a simulated wheel pass in the laboratory. The two gauges registered similar responses to the wheel load, suggesting that the prototype gauge would perform satisfactorily in the field. It should be noted that, although the response was similar, the total distance over which a high-impact load can be recorded remained shorter in the case of the prototype gauge (i.e., 6.5 in. as opposed to 10 in.).

The principal advantage of the prototype gauge is that the two individual strain gauges stemming from the terminal connector are constrained laterally, which makes locating their correct position on the rail much easier. In addition, the prototype gauge uses fewer connecting wires than a traditional gauge. The compact size and simpler design results in a sensor that is both quicker to install and easier to protect from the elements. These features are important on transit systems for which work windows are extremely constrained. Experience from the commuter railroad site suggests that ease of installation was improved.

XNode. The XNode is a proprietary device developed at the University of Illinois specifically for remote monitoring of infrastructure (*13–15*). As shown in Figure 5, it

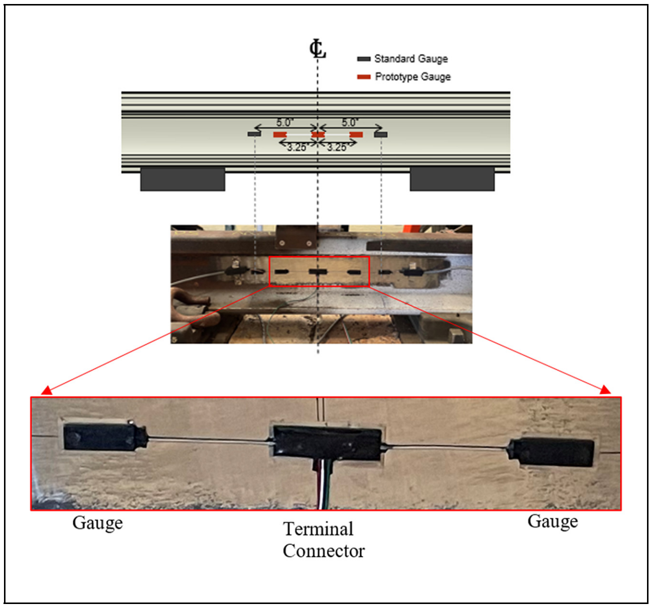

Figure 4. Prototype gauge overlaid on traditional strain gauge.

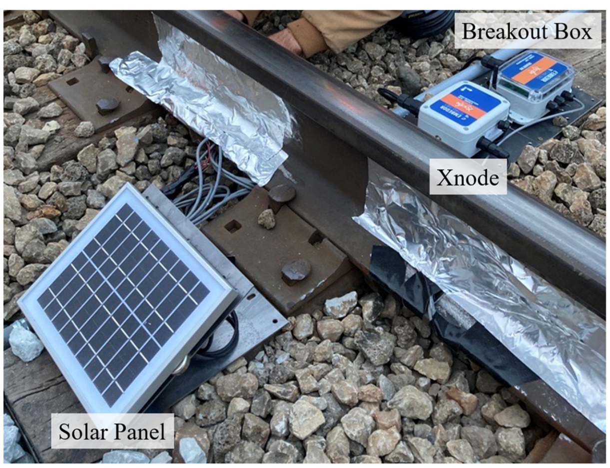

Figure 5. XNode data acquisition system as installed at the commuter railroad.

consists of the XNode and breakout box installed on track, and a gateway installed trackside (not pictured). All three components are compact and easily installed. The system is powered by internal batteries and a solar panel, though the gateway was hard-wired for this trial installation. The breakout box allows up to five external analog sensors to be connected to the XNode without the need for a custom cable, through several terminal block connections built into the box. In contrast to the cDAQ system, the XNode system is woken up from power-saving sleep mode by a built-in, low-power trigger accelerometer that senses the vibration of incoming trains. The XNode then collects and records incoming strain gauge data from the breakout box, transfers the data to the gateway via Zigbee radio, and then returns to deep-sleep mode. After receiving the data, the gateway uploads them to the cloud using a cellular connection. Owing to its compact and wireless design, the XNode data acquisition system can further increase ease of installation while reducing the footprint of the data acquisition system. In addition, the wireless design makes it easier to troubleshoot and maintain the site since the gateway can be installed in an accessible location without the need for wired connections to the sensors.

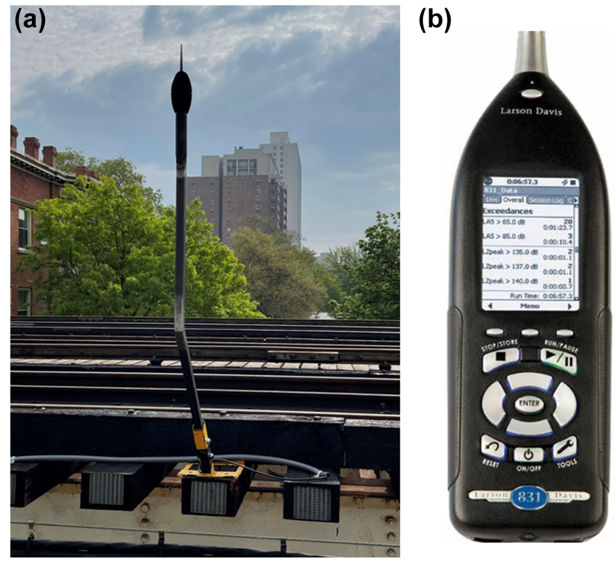

Figure 6. Sound pressure measurement equipment: (*a*) as installed in the heavy rail site and (*b*) sound level meter.

Sound Level Monitoring

Sound pressure data were also collected at the heavy rail site to investigate the frequency of the noise generated by passing trains, as well as the relationship between load magnitude (vertical and lateral) and the associated sound pressure level. Instrumentation to measure the sound pressure is depicted in Figure 6. The system includes a precision condenser microphone (PCB 377B02), preamp (PCB PRM2103-FF), and sound level meter (Model 831C). The sound level meter is used to run environmental protection features in the microphone/preamp system and it outputs sound pressure readings as proportional voltage, which is then read by the NI cDAQ. The sound pressure data analysis is still underway and will be presented in a future paper.

Real-Time Processing and Data Visualization

Because of the volume of data that the system collects and the desire to provide timely exception reporting to agencies, it is vital that all components of the real-time monitoring system be automated. Once the data have been collected at the field site, the cDAQ uploads them to the cloud via a cellular connection, from which the files are downloaded to a local server. A series of Python scripts automatically run to clean (i.e., filter) and calibrate the data as well as identify train characteristics such as number of axels, speed, and, for commuter trains, the division between locomotives and coaches. Lastly, the code then identifies each wheel load peak and records the values in a separate file.

After the wheel loads have been extracted, the program examines each peak load and compares it with a threshold value that is set by the agencies. If any of the wheel loads on a given train exceed that threshold, the system automatically generates a notification email that is sent to selected stakeholders within the agency so that the wheel can be flagged for inspection, repair, or removal. The generated email includes the time the impact load was detected, as well as the train, car, and axle numbers, so that the exact wheel can be easily identified by maintenance personnel.

The data, both raw and processed, are compiled and uploaded to a cloud-based SQL database. The contents of this database are then displayed in an online interactive dashboard interface that gives agencies real-time access to their data through a secure login. The website uses visualization techniques such as tables, charts, and graphs to display information on both aggregate and individual train passes. This system will also allow for tracking of individual wheels over time and the evaluation of trends once sufficient data have been amassed.

Preliminary Data

The following section presents several examples of preliminary data that have been processed by the system to-date. This section focuses on data from the commuter rail instrumentation site, however, all analysis and features discussed are also applicable to the heavy rail agency's site. Although long-term trend analyses remain to be performed once enough data have been accumulated, an analysis of the preliminary results will provide a general sense of the data that have been captured by the instrumentation and will offer insights into the value of the collected data. Through the web portal, a subset of the graphs displayed in the following figures will be available to the agencies and updated automatically.

Figure 7 presents a time-history of the vertical loads from a representative train pass captured by a single strain gauge bridge, in which each vertical spike represents an individual wheel. Here, a four-axle locomotive leads the train followed by eight coaches, each with four axles. As expected, the locomotive displays much higher average wheel loads than the coaches, given the difference in gross static weight (i.e., 260,000 lb and between 102,000 and 126,000 lb, respectively). The average locomotive wheel load during this train pass was 33.9 kips, compared with an average coach wheel load of 16.1 kips. Note that the second wheel on the last coach generated a high-impact load of 35.2 kips, which is greater than the average coach wheel load by a factor of 2.2. This impact load would even exceed the static maximum passenger capacity load (i.e., AW3), as defined by FTA (*16*) and explored by Lin (*2*), by a factor of 1.7. These elevated dynamic factors suggested an imperfection was likely present on this wheel's tread, and that it should be inspected and repaired if confirmed. Since locomotives regularly impart loads of similar magnitude onto the track structure, immediate concern is not warranted, but the real-time notification system would allow the commuter railroad to flag the wheel for repair the next time that the coach is in the yard.

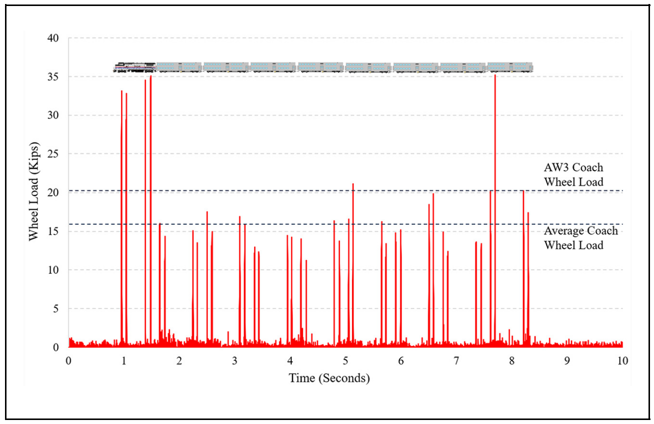

Figure 7. Example commuter rail train-pass.
Note: AW3 = static weight of a railcar at its maximum passenger capacity.

Figure 8 presents a distribution of around 17,000 coach wheel loads recorded at the commuter rail site to-date. On the X-axis, a bracket indicates that the associated value is included in the bin, whereas a parenthesis indicates that it is not. The identified AW0 loading represents the weight of a static, empty passenger railcar. This commuter railroad employs several different coach models, therefore, the shading represents the range of empty weights of these coaches. Wheel loads that fall under the lower limit of the AW0 range are likely to be the result of dynamic rocking caused by track geometry imperfections and the rolling stock's suspension system, showing one of the disadvantages of the smaller instrumentation. Likewise, the AW3 shading represents the

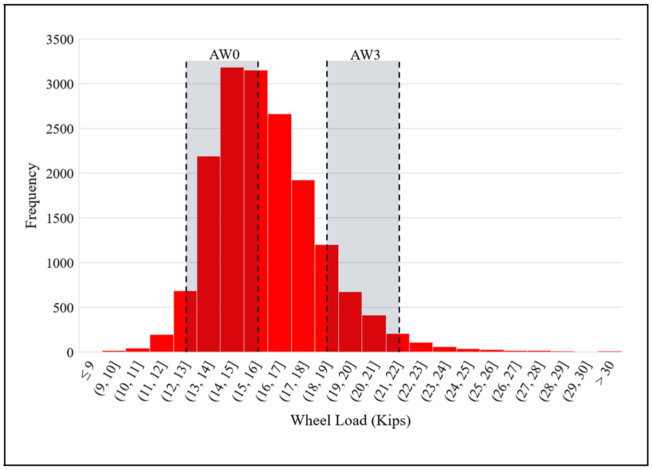

Figure 8. Distribution of 17,000 commuter rail coach wheel loads.

Note: AW0 = static weight of an empty passenger railcar; AW3 = static weight of a railcar at its maximum passenger capacity.

range of possible weights of the cars at maximum carrying capacity. The data revealed that coach wheel loads were concentrated, with the vast majority (i.e., 97%) of wheel loads falling within a 10-kip range from 12.0 to 22.0 kips. Only 139 wheel loads were observed in this data set that were greater than 24.0 kips, or about 1.5 times the average coach wheel load, and only eight wheel loads exceeded the average coach wheel load by a factor of two or greater. Because RFID tracking was not fully operational at the commuter rail site, it was not possible to identify how many different wheels generated this set of eight impact loads, but given the frequency with which every car passed the site and the size of the data set, it is plausible that the majority of these loads were caused by only one or two wheels.

That most of the data were concentrated within a relatively narrow load range, coupled with the very low number of wheel loads that exceeded twice the average coach wheel load, suggested that the rolling stock in question had good wheel health. The commuter railroad's current wheel maintenance program was successfully removing damaged wheels from service or maintaining them before they deteriorated to unacceptable levels. Figure 8 also serves as a preliminary check on the accuracy of the data generated by the system. The measured wheel loads conformed well with the known static loads, and the shape of the frequency distribution was characteristic of loading data. For example, the longer right-hand tail represents rare impact loads, whereas the shorter left-hand tail represents the improbability of recording wheel load magnitudes smaller than those associated with static loading. Similar wheel load distributions were observed by Edwards et al. (*3*) and Lima et al. (*4*).

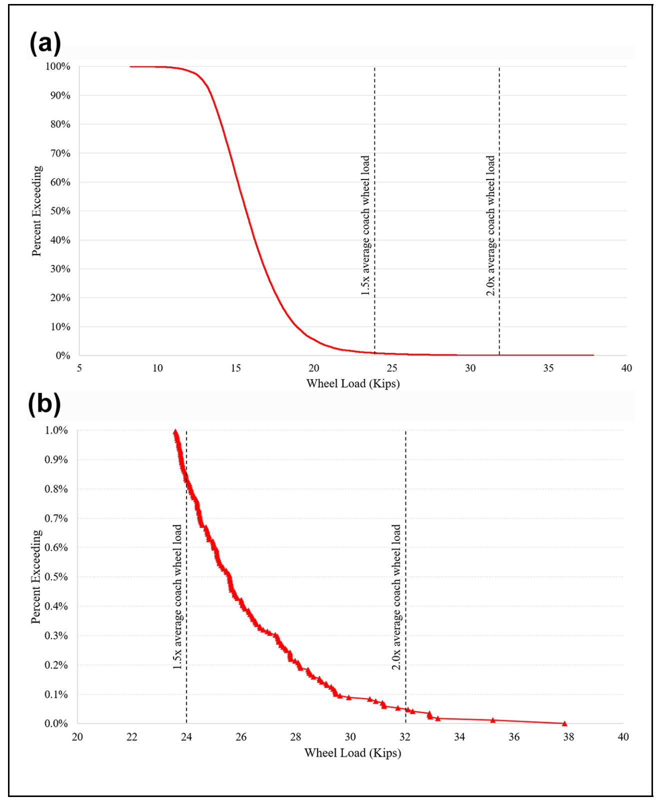

Figure 9. Percent exceeding graphs of (*a*) all commuter rail coach wheel loads and (*b*) top 1%.

Lastly, Figure 9*a* shows the same data but as a percent exceeding graph. The shape of the curve is consistent with the data displayed in Figure 8: the 97% of wheel loads that fell between 12.0 and 22.0 kips is represented by the steep portion of the graph, where a small increase in the wheel load corresponds to a large decrease in the percent of data points in exceedance. The less common high-impact loads are embodied in the flat right-hand tail. Given the significance of the high-impact loads, Figure 9*b* provides a closer view of the top 1% of wheel loads. By using this percent exceeding graph, the agency can directly relate a given threshold level to the approximate number of wheels that the system will flag. With the limited capacity of maintenance departments, the agency must select a threshold that identifies problematic wheels without overwhelming the shop with maintenance requests. This threshold can be dynamically updated once the overall health of wheels in circulation is improved to continue flagging a consistent number of wheels.

Discussion

In addition to the quality of the final data that the system produces, which was addressed in the previous section, there are additional considerations that factor into the viability of the system. The three most important of these are cost, ease of installation, and reliability.

In relation to cost, the initial stages of this project have proven to be relatively economical. The instrumentation is much more compact than a typical freight wheel health monitoring system, and as a result demonstrated the expected cost savings. Although the system did not analyze a full rotation of every wheel that passed the site, its placement on closed systems allowed for this more targeted approach. Transit agencies with limited resources will be able to track their wheel health across multiple lines for a fraction of the cost of commercially available systems, even if multiple train passes are required to detect a particular wheel imperfection.

The sites have also shown promising results for ease of installation, although it remains clear that there are areas for improvement. On the one hand, the installations took a single shift to complete, and both sites were successfully installed by researchers and transit employees, as opposed to trained technicians. In addition, the sites were installed under traffic, demonstrating the value of this system to the transit industry, in which track time is extremely limited. On the other hand, preparing for the installations took considerable time and coordination, involving many hours of developmental lab work and meetings. The research team believes that it is possible to further streamline both the field installation and preparation work by using the described prototype strain gauge and the XNode data acquisition system. The compact and easy-to-install designs of these new tools could lessen the amount of time needed to both assemble the instrumentation and install it in the field.

Lastly, although both systems are now recording accurate data, the overall reliability of the system could be improved. Noise in the data has been a persistent issue at both sites, especially at the commuter rail site where multiple strain gauge bridges became unusable. Digital filters have helped mitigate this issue, but future work should attempt to further isolate the source. In addition, the commuter rail cDAQ experienced a failure soon after installation that required multiple site visits to rectify. In general, further simplification of the equipment used at the sites should improve both ease of installation, as discussed, as well as site reliability.

Conclusion

This study has built on previous load quantification research to create a new real-time wheel health monitoring system specifically designed for transit agencies. This technology will allow agencies to monitor their rolling stock wheel health across multiple lines and modes, as well as perform predictive analytics on the data, helping them target problematic wheels as or before the issue occurs. In addition, it can provide agencies with important insights into the specific loading conditions that their track is subjected to. Both advancements should improve track and rolling stock state of good repair. The following conclusions can be drawn from this research:

- Wheel load quantification instrumentation was successfully deployed under traffic on a commuter railroad and heavy rail rapid transit system, demonstrating the ease of installation of the system. Novel forms of instrumentation, including a prototype strain gauge and the XNode data acquisition system, are being tested and have shown promising performances, which should further improve the ease of installation of future systems.
- Despite the complex nature of the system, this technology has proven to be economical owing to its compact design, which uses only one to two instrumented cribs to gather loading data. This design makes the system ideal for closed transit networks, though unsuitable for the North American freight environment.
- Both instrumentation sites have performed satisfactorily to-date, though minor reliability issues were observed. Technological improvements such as the prototype gauge and XNode data acquisition system should mitigate some of these problems.
- Preliminary data from the commuter railroad instrumentation site displayed characteristics typical of aggregate wheel load data, such as concentrated frequency distributions with longer right-hand tails resulting from the presence of impact loads. In addition, the data corresponded well to known AW0 and AW3 coach wheel loads.

All told, these initial observations suggest that the transit-specific real-time wheel health monitoring system was economical, feasible, and accurate. Future papers will elaborate further on the data analytics, including sound data analysis, and discuss how this wheel health monitoring system has affected the maintenance and engineering procedures at the partner transit agencies. Ultimately, this study and system serve as a proof-of-concept of the value of a compact, transit-specific wheel health monitoring system, which the industry can develop into a commercial product that meets the needs of transit agencies.

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Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: J. Riley Edwards, A. de O Lima, M. Dersch; data collection: D. Mueller, A. de O Lima, J. Riley Edwards; analysis and interpretation of results: D. Mueller, A. de O Lima, J. Riley Edwards, M. Dersch; draft manuscript preparation: D. Mueller, A. de O Lima, J. Riley Edwards. All authors reviewed the results and approved the final version of the manuscript.

Declaration of Conflicting Interests

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Data Accessibility Statement

The data used in this study can be made available on reasonable request from the authors.

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