VIRTUAL WEIGH-IN-MOTION: THE USE OF ADDITIONAL DATASETS TO ENHANCE WIM



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Abstract
This paper reports on an investigation to enhance the current WiM systems to inform the credible risk-informed management of the bridge network. Based on a review of the WiM and complementary data, the concept of a virtual WiM (vWiM) emerged. vWiM integrates WiM, vehicle classifier, ANPR, OBM and bridge monitoring data to provide a richer dataset. This work focused on Class 1 heavy vehicles (including load platforms, low loaders and heavy mobile cranes) which have high axle loads and tend to occupy multiple lanes. The data demonstrated that by merging the datasets together it is possible to extend the coverage of WiM data by generating vWiM data at other locations. Different applications using the vWiM concept were investigated, with a prototype tool developed. The first application confirmed the feasibility of extrapolating WiM data to classifier sites (for some applications), through a site similarity statistic (Kolmogorov-Smirnov). The second prototype tool developed was the tracking of uncommon Class 1 heavy vehicles through the network, using only WiM and classifier data. These tools and approaches provide an opportunity to inform the risk management of the bridges and enhance the credibility of access management and compliance decisions through a database of the high-risk vehicles that have crossed these structures.

Keywords: Virtual WiM, vWiM, WiM, risk-informed decision making, data quality, Weigh-in-Motion, Virtual Weigh-in-Motion, ANPR, On-board Mass Management, OBM, vehicle classifiers, tracking, Class 1 heavy vehicles, load platforms, heavy mobile cranes, low loaders, bridge asset management, risk-informed management.

1. Introduction

The road network managed by the Department of Transport and Main Roads, Queensland (TMR), covers 33,000 km of roads and 3,300 bridges. There is a need to balance productivity with the risk to infrastructure. This requires an understanding of what is occurring on the network, as well as when this loading occurred, to aid credible decisions. This work (Karl et al. 2022) looked at enhancing the current Weigh-in-Motion (WiM) systems to identify opportunities for improvement and provide credible risk-informed management of the bridge stock. This is most important for the vehicles with large axle loads, including low loaders, load platforms and mobile cranes. This paper is based on the research outcomes of the National Asset Centre of Excellence (NACOE) Project S26: Virtual WiM – Enriching WiM and Enhancing Decisions (Karl et al. 2022), undertaken over four (4) years between 2018 to 2021. NACOE is a collaborative research agreement between the Queensland Department of Transport and Main Roads (TMR) and the Australian Road Research Board (ARRB), which is under NTRO. This work involved a review of the current WiM and classifier data, as well as datasets which would be complementary. Based on the WiM and complementary data the concept of a virtual WiM emerged, integrating WiM with vehicle classifiers, ANPR, on-board mass (OBM) and bridge monitoring data. This work focused on Class 1 heavy vehicles (load platforms, low loaders and heavy mobile cranes) which have high axle loads and tend to occupy multiple lanes.

2. Methodology

As the understanding of the vehicles operating on the network is invaluable, WiM and datasets considered to be complementary, were investigated. The data reviewed, included WiM, Classifiers, Authority to Operate data, OBM, ANPR data and bridge monitoring data. This started with a characterization of the datasets, to understand what information is recorded for each technology, and how this information can be utilised to enhance WiM. As part of this process, the confidence level of the dataset was identified utilising the steer axle mass of semitrailers (vehicles with a configuration of 123), with the confidence level based on the deviation of the median steer axle mass from the expected value of approximately 5.5 t (Karl et al. 2022).

Additionally, data filters were implemented on the WiM data to extract and investigate load platforms, low loaders and heavy mobile cranes from an Austroads class 6+ heavy vehicle dataset. This included a review of GVM, steer axle mass, WiM data confidence, speed, axle configuration axle spacing and vehicle count.

3. Virtual WiM Tools

The vWiM concept came out of the review of WiM and complementary datasets. By merging the datasets together it is possible to enhance quality and extend the coverage of WiM data by generating *virtual* WiM data at other locations, see Figure 1. The concept of vWiM in this paper should not be confused with other descriptions of virtual WiM as in Europe and the US, which act as a high-speed pre-selection system located upstream of a heavy vehicle checking station equipped with weighbridge and enforcement personnel.

Different applications using the vWiM concept were investigated, with prototype tools developed. The first application identified the feasibility of extrapolating WiM data to classifier sites, through a site similarity statistic (Kolmogorov-Smirnov), which assessed:

- similarity between vehicle configuration probability distributions indicating similar heavy vehicle traffic
- similarity between the axle spacing probability distributions for similar configurations indicating that the specific vehicles in traffic are similar
- similarity of the axle group mass probability distributions for similar configurations (where available) indicating that the vehicles are transporting similar loads.

The approach was validated by treating WiM sites as classifiers (removing the axle mass data) during the extrapolation, and comparing the accuracy of the resulting extrapolations with the actual mass data.

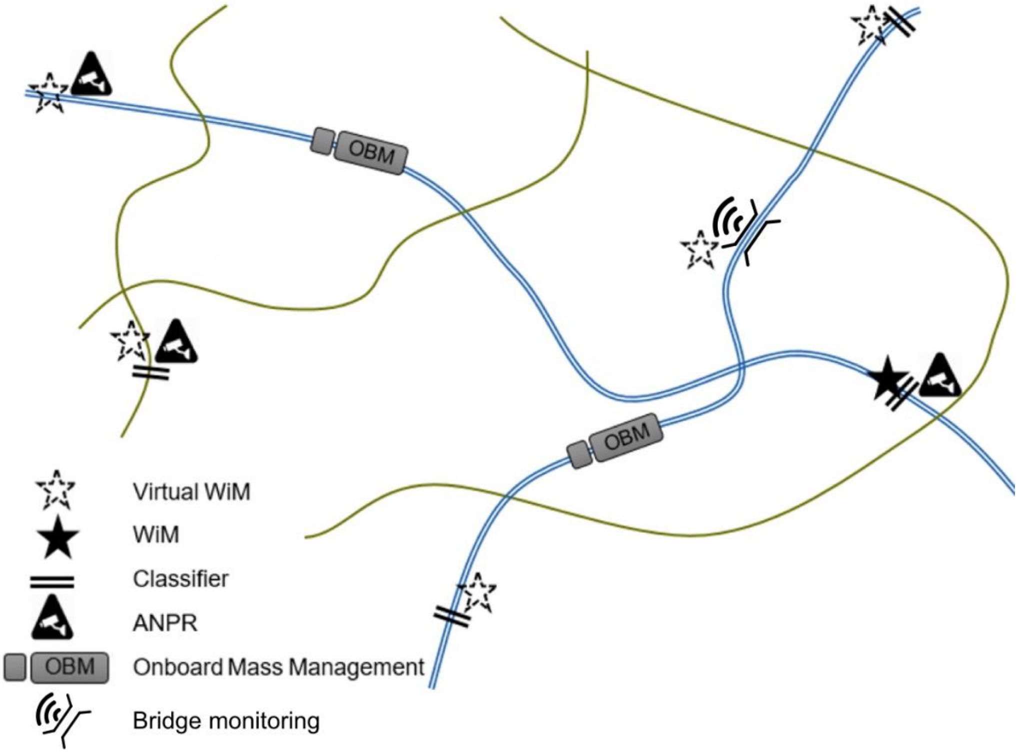


Figure 1 – Virtual WiM concept

The second prototype tool developed using the vWiM concept was the tracking of uncommon Class 1 heavy vehicles through the network, using only WiM and classifier data. These tools provide an opportunity to inform the risk management of the bridges and enhance the credibility of access management and compliance decisions through a database of the high-risk vehicles that have crossed these structures.

1.1. WiM to Classifier Extrapolation

Classifiers are cheaper to install and maintain than WiM, and provide information about the vehicle types, counts, configuration and axle spacing. The concept of vWiM enables the value of existing WiM infrastructure to be leveraged through the extrapolation of mass records from WiM to classifiers. The extrapolated vWiM data can provide estimates of mass distribution for vehicles of interest across Queensland, while maintaining the benefit of the reduced costs associated with the classifier sites.

To understand if the WiM data measured at one site is likely to be representative of the WiM data at a classifier site, a method was developed to assess the similarity between sites by comparing the data types available at both sites.

The method relies on an assumed correlation between the distributions of axle spacing and configuration to the gross vehicle mass (GVM). This correlation is evaluated using the site similarity objective function, detailed in Equation 1. The degree of similarity between the sites was compared using axle spacings, distributions of configurations and GVM. This was undertaken first at the WiM sites only, to allow for validation of the similarity. This assessed:

- similarity between vehicle configuration probability distributions indicating similar general traffic
- similarity between the axle spacing probability distributions for similar configurations indicating that the specific vehicles in traffic are similar
- similarity of the axle group mass probability distributions for similar configurations (where available) indicating that the vehicles are transporting similar loads.

The site similarity statistic is determined through a weighted ratio of the difference in axle spacing θ_{AS} and configuration θ_{VC} between sites, with the weights balanced.

$$\theta_{1,2} = \frac{W_{VC}\theta_{VC,1,2} + W_{AS}\theta_{AS,1,2}}{W_{VC} + W_{AS}} \tag{1}$$

where

$\theta_{1,2}$	=	multi-objective assessment between the reference and comparison datasets
1	=	the reference dataset (from a WiM site that has data that can be extrapolated elsewhere)
2	=	the comparison dataset (from a classifier site that records axle spacing data but not mass)
W_{VC}	=	the vehicle configuration objective function weight
$\theta_{VC,1,2}$	=	the objective value for vehicle configuration distribution between the reference and comparison datasets
W_{AS}	=	the axle spacing objective function weight
$\theta_{AS,1,2}$	=	the objective value for axle spacing between the reference and comparison datasets.

Using this statistic, the similarity of WiM or classifier sites is calculated using axle spacing and configuration frequencies. The similarity statistic combines discrete distributions of vehicle configuration with the continuous distribution of axle spacing grouped by configuration. Due to the primary purpose of this statistic being a means of comparing the similarity in the WiM and classifier data, the mass is not considered. However, the mass is used to validate the methodology, by comparing WiM sites. The viability of the statistic in choosing the WiM data which may be extrapolated to classifier sites was then assessed for

similarity utilising the D-statistic of the two sample Kolmogorov-Smirnov test. For this test a high site similarity objective function value should yield a low D-statistic value. The hypothesis was tested utilising data from WiMs which were within confidence of class B or greater, utilising data from 20 sites between January 2019 to February 2020. The data confidence level is based on the deviation of measured steer axles for 123 vehicle configurations against a set 123 steer axle mass (Karl et al. 2022).
Using the site similarity statistic, WiM sites with a high degree of similarity were identified and the relationship between the similarity statistic and the difference in GVM distributions was considered utilising the Kolmogorov-Smirnov two sample test. This process acted as ground truth for the predicted similarity score calculated between WiM and classifiers. The regression statistics of this relationship has a reasonably high R^2 value of 0.75. Site pairs with high similarity correlate well with the D-statistic, however medium scores for site similarity were found to be less well correlated. This may indicate that the site similarity statistic can be further optimised. In its current form, the site similarity statistic is unable to be used as a continuous predictor of how representative a WiM site is of a classifier.
The population of interest shown in the red box in Figure 2 has high site similarity and low D-statistic, indicating that the site pairs within this area may be suitable for extrapolation. This is due to the much higher degree of correlation (closeness to the 45-degree line) and the very low difference in GVM distributions between the sites (low values in the y-axis or D-statistic) This population can be numerically defined as site pairs with a similarity statistic greater than 0.85. Alternatively, this population can also be defined as those pairs with a D-statistic of less than 0.2, however this definition is not useful when comparing WiM to classifier sites, as the D-statistic between GVM distributions cannot be calculated.

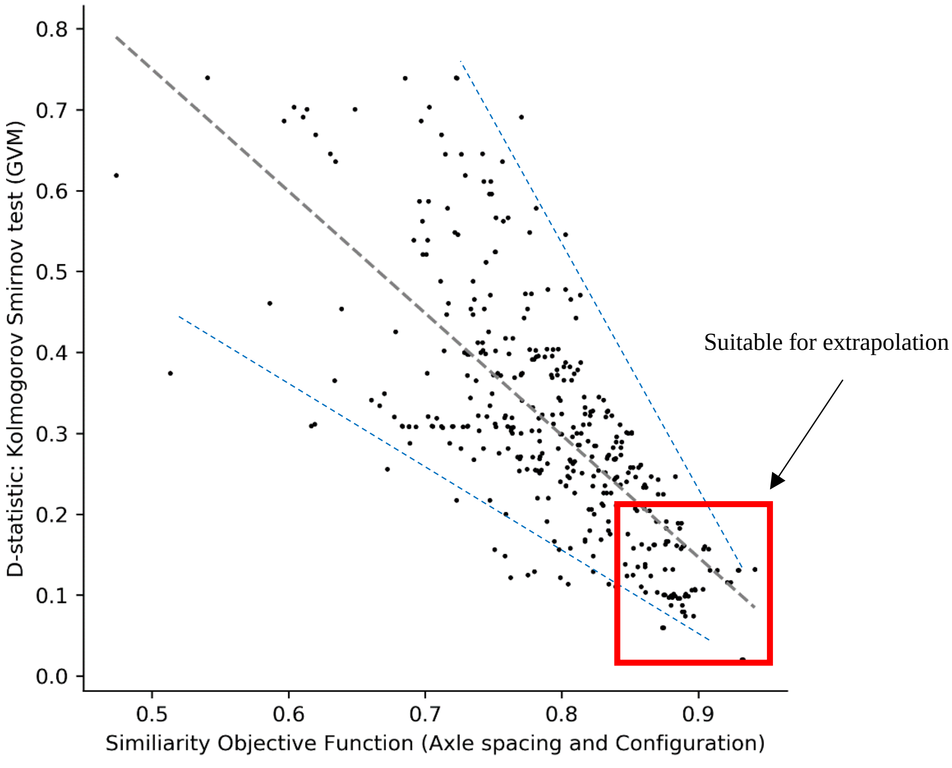
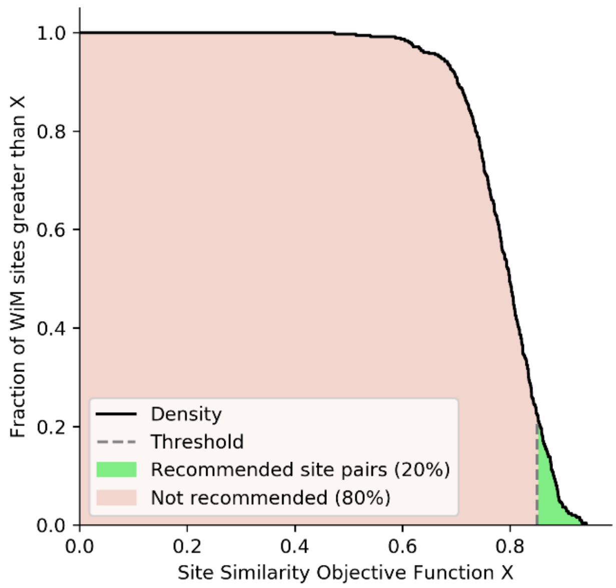


Figure 2 – Site similarity statistic against KS statistic two sample test

Based on the correlation between GVM similarity and the site similarity objective function ($R^2 = 0.75$), approximating GVM profiles to classifier sites was concluded to be viable. This statistic can predict how similar a site's GVM profile is without GVM data.
Extrapolating dissimilar WiM data to classifier sites will result in unrepresentative GVM profiling. The minimum similarity index was set at a lower bound of 0.85 based on a reduced correlation to the D-statistic below this threshold. When the similarity score is higher than 0.85, the observed low D-statistic values show that the GVM distributions between the sites are similar, which is a key criterion for extrapolation, as the source of data should match the targeted or missing data's GVM distribution, below 0.85 and the correlation diminishes. Approximately 20% of WiM site pairs have a similarity objective function value greater than 0.85 as seen in Figure 3. Based on these results alone it is believed that at least 20% of WiM to classifier site pairs could benefit from extrapolated WiM data. A systematic analysis of the relationship between the acceptable level of error in the extrapolated GVM and the true GVM could result in an updated lower bound which may increase the volume of classifier sites for which mass can be extrapolated without introducing substantial error.

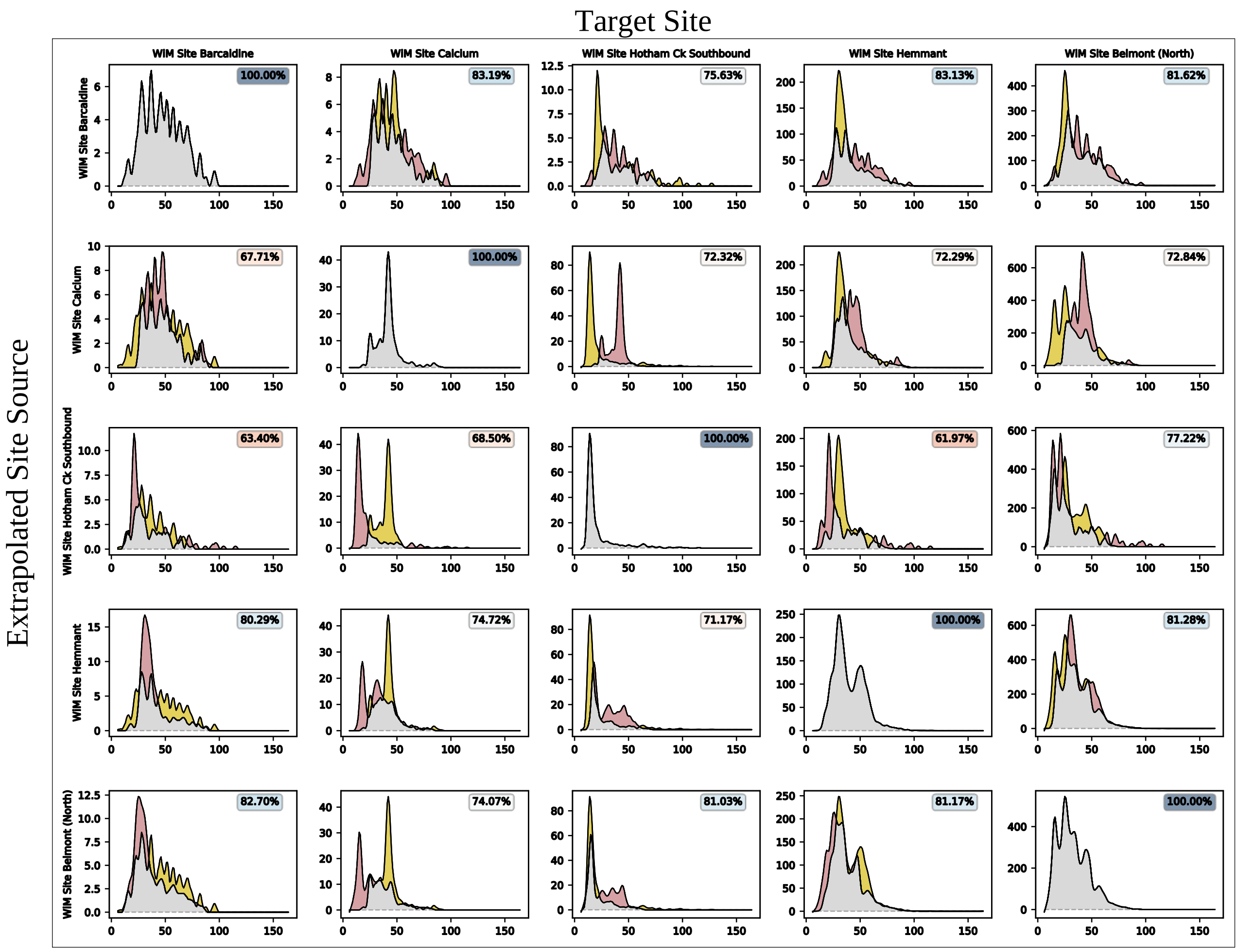


Note: The green population is the same as that in the red box shown in Figure 2.

Figure 3 – Volume of WiM site pairs with an acceptable level of site similarity

Based on the similarity achieving an appropriate level of similarity (use case dependent) can be used to generate measured distributions of parameters of interest by vehicle configuration. The measured distributions can then be extrapolated based on vehicle counts (by configuration) at a classifier site with similar traffic. In other words, distributions of vehicle characteristics from an origin site are scaled by the ratio of the number of vehicles at the origin site to the number of vehicles with the same configuration at the target site.
This gives an estimate of the expected mass at the classifier site without additional capital expenditure. While the objective is to extrapolate WiM data to classifier data, the accuracy of this procedure cannot be directly assessed as the GVM profile is unknown at the classifier site. The effectiveness of the extrapolation from WiM to classifier can therefore be inferred from the results of extrapolation from WiM to WiM.

Figure 4 shows the extrapolation of the multi-objective function for five sites based on the similarity of WiM sites. The columns show mass distribution for the target site, while the rows show the site which was used to extrapolate the data from. For example, the top right figure shows the target site of Belmont (north) WiM - Barcaldine WiM was used to extrapolate for Belmont (north). Similarly, the bottom left figure shows the target site of Barcaldine WiM, for which the mass from the Belmont (North) WiM was used to extrapolate for Barcaldine. The distribution matrix shows how similar the extrapolated (dashed line) and true (solid line) GVM distributions are. Over-estimates are shaded red, and underestimates yellow. The higher the similarity between the sites, as shown in the top right of each chart, the less shaded area is expected.



Note: X-axis provides the GVM of the vehicle in tonnes.

Figure 4 – Extrapolation of GVM from a WiM site to a classifier

The closest WiM site (as the crow flies) deemed suitable for extrapolation to a classifier site was calculated using the method shown in the pseudo code in Figure 5. As per the pseudo code, the similarity score was calculated for each WiM to classifier pair in the dataset.

```
FOR each classifier site C_i
    FOR each WiM site W_j
        Similarity: S = L1(C_i,W_j)
        Distance D  = Geodetic_distance (C_i,W_j)
        IF S > 0.85 :
            Set Covered_by_WiM[C_i] = TRUE
        IF D < Minimum_distance_to_WiM[C_i]
            Set Minimum_distance_to_WiM[C_i]= Distance(C_i,W_j)
            Set Best_WiM_site[C_i] = W_j
FOR each classifier site C_i
     If Covered_by_WiM[C_i] is TRUE
        Plot classifier site C_i
        Plot best_WiM_Site[C_i]
        Plot line between site C_i and Best_WiM_site[C_i]
```

Figure 5 – Pseudo code for finding the closest WiM site to extrapolate data

To see how many WiM to classifier pairs were viable (similarity > 0.85), 95 classifiers were compared against 20 WiM stations. 93 classifier sites had a similarity score of greater than 0.85 for at least one of these WiM sites. This indicates 97% of classifier sites have enough similarity to WiM sites to allow for extrapolation from at least one site. Previously, the likelihood of one WiM matching with another classifier was inferred to be ~20%, but because there are multiple WiM sites across the network the likelihood that at least one has a similarity score greater than 0.85 for any given classifier is much greater than 20%.

1.2. Prototype Tracking Tool

Tracking Class 1 heavy vehicles across the Queensland network enhances the value of WiM data by allowing the investigator to know where a vehicle of interest has been before. Not only can multiple records be attributed to the same vehicle, but the trip and destination of the vehicle can also be inferred. The data can be used in real-time predictive and monitoring applications as well as retrospective analysis.

In contrast to an isolated WiM record, a vehicle trip can be used to confirm all infrastructure crossings even if these assets are far from any WiM or classifier sites. Knowing the source of a WiM record at different sites can also be used to improve confidence in the axle spacing and mass data for the vehicle, for retrospective mass calibration at the site, particularly when the vehicle is known to have a consistent weight, as in the case of cranes and load platforms transporting indivisible loads.

WiM and classifier records do not contain a unique vehicle identifier unless they are integrated with additional technology. This limits applications of WiM for tracking to the use on vehicles with uncommon ‘axle spacing footprint' during the travel window. This is the case for the specific vehicles of interest to this project, such as low loaders, load platforms and heavy mobile cranes.

By merging WiM and classifier data, the density of sites collecting data is effectively increased, improving the odds of identifying the trips taken by vehicles of interest. If, for example, a vehicle tracked across multiple classifier sites also crosses a WiM site, the data from the WiM site becomes ‘virtually’ known at the other sites. It is possible that a vehicle may only be laden for part of a trip or may change loads, however, because the vehicles are permitted to carry indivisible loads, it is less likely. When it is possible to track a vehicle in this way, periods where data are inaccurate or lost at individual sites becomes less mission critical – value and redundancy are increased.

Matching records were identified by comparing the records of a reference vehicle of interest’s axle spacing to all records of the same vehicle configuration within 10 days of the initial observation. Vehicle mass was not chosen for use in the matching algorithm, due to mass not being included in the classifier dataset. The performance of the algorithm was benchmarked using a representative dataset of WiM and classifier records in combination with a small sample of IAP data which contains unique vehicle identifiers. Lastly, the vehicle trips and the infrastructure crossings were inferred and presented as an application of WiM Class 1 heavy vehicle tracking.

The likelihood of matching WiM records originating from the same vehicle is dependent on variation in axle spacing and configuration, referred to as the vehicle footprint. To investigate the general characteristics of low loader and load platform WiM records, a test dataset of Class 1 heavy vehicle configurations from January 2019 to February 2020 was used.

In the dataset 142 sites contained a minimum of 1,000 WiM record events and 293 different vehicle configurations were observed. Ninety-seven vehicle configurations had less than 1,000 records across all sites. While this indicates that for some vehicle types matching could be done solely with the vehicle configuration, between 10,000 and 200,000 records were found for the 5 most common configurations. Vehicles with these configurations are indistinguishable from each other using configuration alone. Therefore, to increase the uniqueness of the WiM records for matching purposes, the additional characteristics identified as likely candidates to be used as a pseudo-identifier included axle spacing, time between records and location of records.

Vehicle records were identified as a potential match if they had the same configuration, were less than 10 days between records and all the matching axle spacings were within ± 200 mm. For potentially matching records, the average variation between axle spacings for two records with matching configurations was evaluated to assess fitness of the match using Equation 2. If Δ_s is less than 200 mm, then the pair of records was considered a match. Pairs which shared a common record were then collected into trips which were sorted by time.

$$\Delta_s = \frac{\sum_{i=1}^{S} |s_{r,i} - s_{c,i}|}{S} \tag{2}$$

where

Δ_s	=	the average variation in axle spacings between the comparison and reference vehicle
S	=	the number of axle spacings in the vehicle configuration
$s_{c,i}$	=	the ith axle spacing of the comparison vehicle
$s_{r,i}$	=	the ith axle spacing of the reference vehicle

To explore the value of the matching algorithm, a best-case scenario was created. Over the one-year period, records with configuration classes observed more than 1,000 times were excluded. The remaining 97 configurations are so unique that they are expected to originate from a small number of vehicles, significantly decreasing the chance of false positives. Using this filtered dataset matched records identified using the algorithm became WiM records pairs and were predicted to have the same vehicle source.

Out of 97 configurations and 11,095 WiM records, 723 unique trips were found. The best-case dataset of rare vehicle configurations represents 2.6% (11,095 out of 420,737) of all WiM and classifier records in the Class 1 heavy vehicle categories. Of these records, 34% were assignable to unique trips. Based on the characteristics of the WiM data, a lower bound of 34% of Class 1 heavy vehicle WiM activities can be tracked effectively using the vehicle footprint algorithm when not considering accuracy.

To determine the most likely trip of these matched records, map matching, in combination with a routing algorithm which was developed in NACOE R103 (Hore-Lacey et al. 2020) was used. The most likely trip is always considered to be the shortest trip by time when travelling at the speed limit. As the vehicles of interest are low loaders and load platforms, the networking was restricted to within 100 m of the 'Heavy Vehicle Routes' network (Queensland Department of Resources 2021). By determining the vehicle's trip, infrastructure crossings of interest can be detected. Using the tracking algorithm and routing methodology, bridge crossings can be inferred for individual vehicles based on the order of the movements.

To understand if matched sets returned by the algorithm all originate from the same vehicle, a separate IAP WiM merged dataset was used. It should be noted that this dataset did not include low loaders or load platforms. IAP data is provided per vehicle over the entire network. By comparing IAP records from the same vehicle at WiM sites to vehicle trips generated via the tracking algorithm, the accuracy of the algorithm can be determined.

One month of IAP tagged vehicle records were matched to WiM movements at the Nudgee site. IAP records were aligned with WiM movements using geospatial and temporal alignment. By synthesising the IAP and WiM data, unique vehicle identifiers were associated with WiM records. These identifiers were then used to validate the accuracy of the vehicle tracking algorithm. If a vehicle trip is accurate, then all records within the trip should have the same vehicle identifier. The matching algorithm was used to find pairs of records which crossed the Nudgee site and were predicted to be from the same vehicle. For each pair, a pass was assigned if the IAP vehicle IDs were identical. The average accuracy of the matching algorithm was 38%. Based on these results, an accuracy statistic for the more common Class 1 heavy vehicle configurations is expected to be at most 38%. This is based on the average rate of successful vehicle matches with the same IAP vehicle identifier. It is noted that the rarer the configuration, the higher the accuracy. With an average accuracy of 38**%** it is expected that if all vehicle configurations were processed ~12.8% of all Class 1 heavy vehicle movements could be tracked using this methodology.

This adjacent IAP validation demonstrates that vehicle matching using WiM footprints is only feasible when the vehicle configuration and axle spacings are significantly rare. For most vehicles, and even some low loader configurations, this is not the case. While low loaders and load platforms are relatively unique, the consistency of axle spacing and configuration measurements between sites was lower than expected. This resulted in fewer matches than what is possible using a vehicle footprint alone.

Two possible reasons for a lower-than-expected match volume and accuracy are:

- Variance in the axle spacing measurements between sites is greater than variance between different unique axle spacings.
- Vehicle configurations are not being classified in the same way or the classification windows are unsuitable for vehicle tracking.

4. Discussion

The developed WiM to classifier extrapolation considers the site similarity statistic for pairing, the correlation was seen to be relatively strong with a D-statistic value greater than 0.85. Optimisation of the similarity score formula could greatly improve the accuracy of this proposed multi-site extrapolation by better distinguishing between different sites with similar similarity scores. It is noted that this task may be optimised to tune to the weighted effects of axle spacing and configuration differences.

Furthermore, it may be possible to extrapolate WiM data to locations where neither a WiM site, nor a classifier is present through integrating several classifiers and WiM sites. Song et al. (2019) proposes a geospatial extrapolation methodology to predict traffic volumes of heavy vehicles across a road network based on point data sources. This methodology interpolates traffic count data between points in the network through using a regression model known as kriging (Song et al. 2019). One primary advantage of kriging methods over WiM to classifier site extrapolation is that the GVM distribution of any road segment in Queensland could be predicted. Previous attempts to perform kriging with the existing WiM network were significantly limited by the rate of coverage of WiM across the network (Hore-Lacey et al. 2020). While not impossible to perform kriging interpolation when network coverage is low, confidence intervals over resultant predictions are so wide they offer little value relative to guess work. Additionally, the use of inductive loop and WiM signatures as a footprint of vehicles (SBIR N.D.) may be considered in the future for investigation as a means of refining the matching of vehicles. The use of ground contact width, currently not collected within Queensland, may also be used as an additional means of improving the footprint of the vehicles of interest.

Strong correlations between axle spacing and GVM distribution that became evident as part of this investigation can contribute to future extrapolation and interpolation investigations. While the methodology focused chiefly on extrapolating WiM data to classifiers, if traffic data is available, this methodology can be extended to other datasets, such as ANPR, segmented IAP and telematics data. The site similarity and extrapolation procedures required aggregated data on vehicle type and axle spacing. Where this data is available the methodology can be repurposed. Combining the point-to-point based methods documented here with kriging interpolation could greatly improve the geospatial coverage of GVM profiling.

5. Conclusions

The project demonstrated that there are increasing opportunities for WiM and related technologies to support evidence-based decisions. Enhancements to WiM, utilising data fusion or added technology would provide road agencies with better data more often, aiding in credible decision making based on the risk to the infrastructure.

Internal engagement, national and international reviews also found that the value proposition for WiM data is not well articulated because the focus is on collecting data to inform compliance rates rather than the optimal management of the road and bridge network and the heavy vehicles that provide transport services for the community.

The vehicles posing the greatest risk to bridges across the network were investigated to understand their characteristics and enable them to be tracked through the network. The applications of vWiM expand with increasing data quality and data coverage.

While it is possible to extract value from imperfect data, it is also the case that some applications require improved quality and reliability of data. It was concluded that there are

many means for improving data quality, including updating specifications for WiM and classifiers (improving axle spacing measurement accuracy), continuous improvement of data post processing with a network-level focus, and live calibration of existing WiM sites using vehicles of known and consistent mass, identified in the traffic stream.
Data coverage can be improved through strategic maintenance of existing WiM systems, identifying and addressing data black spots, using the WiM data extrapolation methods developed as part of this project to provide virtual WiM data at classifier sites, combining complementary datasets, incorporating the connection between WiM and other heavy vehicle data sources, including bridge monitoring, ANPR, IAP, ATO, OBM, and classifier data. The more independent complementary data sources that can be effectively combined, the more opportunities that will arise.

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7. References

- Eskew, E, Ward, D, Heldt, T, Heywood, R, Karl, C, Lewis, K & Dann, E 2021, ‘S26: review of TMR WiM systems and strategies: virtual WiM & heavy vehicle tracking: feasibility & value (year 3 2019/20)’, contract report 014932, prepared for Queensland Department of Transport and Main Roads under the NACoE program, ARRB, Brisbane, Qld.
- Hore-Lacey, W, Germanchev, A, Eastwood, B & Shackleton, D 2020, R103: virtual weigh-in-motion and Queensland freight movement study, contract report 015302, prepared for Queensland Department of Transport and Main Roads under the NACOE program, ARRB, Brisbane, Qld.
- Karl, C, Lewis, K, Heywood, R, Ward, D and Dann, E 2022, *NACOE S26: virtual WiM – enriching WiM and enhancing decisions (2018-21)*, contract report 015696, prepared for Queensland Department of Transport and Main Roads under the NACoE program, ARRB, Brisbane, Qld, accessed 14 June 2023, <https://www.nacoe.com.au/wp-content/uploads/2022/03/S26-Applications-of-Virtual-WiM-2018-21.pdf>.
- Small Business Innovation Research N.D., Tracking of heavy vehicles for estimating heavy load distributions across the highway system and weigh-in-motion calibration, SBIR, accessed 22 March 2023, <https://www.sbir.gov/sbirsearch/detail/691236>.
- Song, Y, Wang, X, Wright, G, Thatcher, D, Wu, P & Felix, P 2019, ‘Traffic volume prediction with segment-based regression kriging and its implementation in assessing the impact of heavy vehicles’, IEEE Transactions on Intelligent Transportation Systems, vol. 20, no. 1, pp. 232-43.
- Queensland Department of Resources 2021, Queensland spatial catalogue: state controlled roads bridges, catalogue, DoR, Brisbane, Qld, accessed 24 March 2023, <https://qldspatial.information.qld.gov.au/catalogue/custom/detail.page?fid={14D6B946-F361-4CE7-B156-EA8C324866DC}>.