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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