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Bridge's vehicular loads characterization through Weight-In-Motion (WIM) systems. The case study of Brescia

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Abstract

The growing traffic flow and the increase in transported masses negatively affect infrastructural safety. Several authors have characterized traffic loads on bridges in the American and Chinese context using Weigh-in-Motion (WIM) systems. Conversely, very few studies have been carried out in Europe and, as far as the authors know, none in Italy. This study covers this gap by providing a statistical analysis of raw WIM data collected on a main bridge near the city of Brescia (Italy). First, the traffic flow and the characteristics of vehicles were gathered by a WIM device. Second, some descriptive statistics were performed by computing the probabilistic distributions of numerous vehicular attributes. Third, as a novelty element, a K-means based Clustering technique was adopted on a wide set of vehicular features to detect heavy vehicle clusters. The results showed the existence of three main clusters: two predominately composed by lightly overloaded ordinary vehicles and construction machinery, respectively, and one by mass exceptional vehicles. This study considers a broader set of vehicular parameters than previous ones and then, provides a deeper understanding. Moreover, it shows that axle mass limits violations are noteworthy among mass exceptional vehicles in Italy highlighting the need of improving weight enforcement. These knowledges will be crucial for a rational organisation of the existing assets.

Keywords: Weight-In-Motion; Bridges; Exceptional vehicles; Overweighted vehicles

1. Introduction

Currently, in Italy, road transport plays a prominent role in the modal shift of goods handling. Indeed, in 2020, the road system has moved approximately the 84% of the land transported freight (MIMS, 2020). An essential condition for an efficient operation of this transport system is the presence of a safe and resilient road network. Originally, the concept of resilience was only proper to the science of materials: a material was resilient if it could absorb a shock without breaking. Nowadays, the concept of resilience has also

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been extended to complex systems, such as transport networks. More specifically, a resilient transport network is a system that can react to unexpected events in a timely manner.

An indispensable requirement for a resilient transport network is a capillary dotation of monitoring systems, which gathers real time data from vehicles on infrastructures, as vehicular traffic load is one of the main factors that could undermine the road network resilience. A particular concern is raised by mass exceptional vehicles, i.e., vehicles whose Gross Vehicle Mass (GVM) exceed the mass limits set by national Traffic Codes. Commonly, these mass limits are function of vehicle typology and axle number. Table 1 shows, as an example, the main mass limits prescribed by the Italian Traffic Code (Repubblica Italiana, 2015). In Italy, exceptional vehicles must comply with complex regulations and are subject to circulation authorizations issued by road management agencies. The only vehicles that can exceed these mass limits without specific authorizations are construction machinery up to 54,000 kg. However, these vehicles can only travel on specifically authorized roads and must pay a fee to compensate a greater infrastructural damage.

Table 1: Mass limits set by the Italian Traffic Code (Repubblica Italiana, 2015).

Vehicle Typology	*Number of axles*	*Mass limit [kg]*
Isolated trucks	2	18,000
	3 or more	25,000
Road trains	3	24,000
	4	40,000
	5 or more	44,000
Articulated trucks	3	30,000
	4	40,000
	5 or more	44,000

The growing flow of mass exceptional vehicles and the progressive increase in transported masses can negatively affect the infrastructures. Particularly, as for bridge deterioration, mass exceptional vehicles decrease service life by inducing fatigue damage (Lou et al., 2017). For limiting this phenomenon, some authors proposed to impose a compensation fee for overweight vehicles passing on bridges (Gungor et al, 2018). Moreover, extra heavy vehicles even can mine structural safety when the total applied load exceeds live load prescribed by design Codes. Particularly, it is a critical issue in Italy, as highlighted by the collapse of bridges built in XX century, designed to withstand lower vehicle loads than those currently flowing on road networks (Ventura et al, 2020).

As a result, the implementation of traffic and bridge monitoring systems is becoming indispensable for a safe road infrastructure management. The need of adopting permanent monitoring strategies is also recognized by the recent Italian guidelines for bridges risk management (MIT, 2020). As for traffic monitoring, that is the focus of this study, Weight-In-Motion (WIM) systems are an effective solution in preventing structural damage and warranting weight enforcement by measuring vehicular mass in a dynamic way. Potential, limitations, cost-effectiveness, and data usage were recently reviewed (Sujon & Dai, 2021). In addition to the whole vehicular mass, these systems can also record other attributes, such as total passing flow, passing datetime, transit speed, vehicular size, axle number, axle mass, axle type and interaxle distance. The main advantage of WIM systems is their capability of real time recording vehicular characteristics for all the passing flow, without the need for a human operator to randomly stop sample vehicles and to perform a manual weighing procedure.

Several are the applications of these devices in the American and Chinese context, such as for bridge and infrastructure asset management, freight performance analysis, traffic forecasting, traffic flow simulation, weight enforcement and pavement design aiding (e.g., Huang et al, 2022; Hazlett et al., 2020; Fiorillo et al, 2014; Liao et al., 2014; Guo et al, 2011; Elkins & Higgins, 2008). Conversely, only a few studies have been carried out in Europe (e.g., Schmidt et al., 2016) and, as far as the authors know, none has analysed exceptional vehicles flows through WIM systems in Italy. Moreover, although other authors had already analysed WIM data through clustering algorithms (e.g., Huang et al, 2022; Fiorillo et al, 2014), they only considered a reduced set of vehicular characteristics (i.e., only axle configuration parameters).

This study covers these gaps by providing a statistical analysis of raw WIM data collected during a two-month observing period in a pilot station placed on a bridge along the heavy transited ring road of the city of Brescia (Italy). Specifically, the characteristics of vehicles with a gross vehicle mass (GVM) above a fixed threshold selected according to the legal limits set by the Italian traffic Code were investigated. First, the probability distributions of several vehicular parameters, such as GVM, passing speed, width, length, axle number, axle typology, axle mass, and axle distance were examined. Then, a K-means clustering technique was adopted to subdivide WIM observations into clusters basing on a wide set of vehicular features.

The results showed that the probability distributions of many parameters were characterized by a multimodal shape, indicating that these parameters were not normally distributed and suggesting the presence of different subsets composed by vehicles with similar characteristics. K-means analysis confirmed this hypothesis, as it showed the existence of three main vehicular clusters. Specifically, two clusters were predominately composed by lightly overloaded ordinary vehicles and construction machinery, while one cluster was mostly formed by exceptional vehicles.

The remaining paper is organized as follows. Section 2 presents material and methods to make the vehicular loads characterization through WIM systems. Section 3 shows and discusses the results. Finally, Section 4 draws conclusions and provides future perspectives.

2. Materials and method

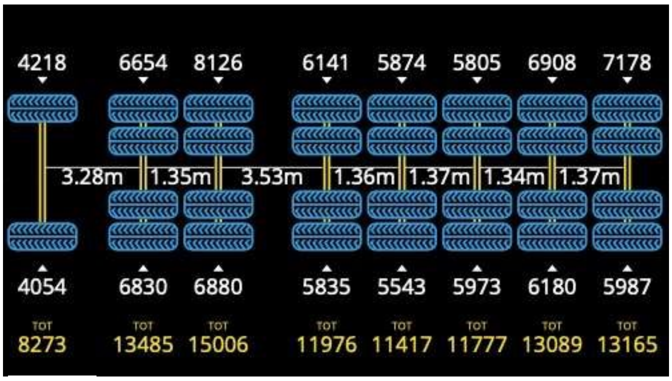
2.1 Research context

This research involved a pilot WIM station placed along the South Ring Road of city of Brescia (Italy) by the Local Road Authority (LRA), i.e., the Provincia of Brescia. South Ring Road belongs to the principal road network and constitutes one of the arterials with the highest traffic flow among those managed by the LRA, with an Average Daily Traffic (ADT) volume varying between 20,000 and 30,000 veh/day, and a high proportion of heavy vehicles (Provincia of Brescia, 2011). The LRA chose to collocate the WIM system near a bridge to monitor the vehicular live loads acting on it. This is simply supported overpass structure with a 17 m span length and a deck composed by 13 longitudinal precast concrete girders and a mid-span transversal cast-in-situ stiffening girder. At the monitoring station, the road section has two separate carriageways, with two lanes in each direction. The WIM device was installed on the north carriageway. Due to budget constraints, only on the right lane was instrumented, as heavy vehicle transit is forbidden in the left lane, according to the Italian Traffic Code.

2.2 Data collection

Traffic measurements were carried using a WIM system (Figure 1 a)) consisting in two stainless steel plates placed on the road surface, equipped with fibre optic sensors, and connected to a data logger. The device exploits induced photo-elastic properties in glass fibre. A data acquisition unit processes and stores the detected information in a database. The main parameters that were acquired by the WIM system for each passing vehicle were GVM, speed, length, width, axle number, axle type (single or twin wheel), axle masses and axle distances. Figure 1 b) provides an example of vehicular configuration acquired by the WIM device.

a)



b)

Figure 1: a) Illustration of the WIM device adopted to carry traffic measurements (iWiM BISONTE, 2022); b) Example of a vehicular configuration acquired by the WIM device.

2.3 Data processing and analysis

Since WIM data are automatically collected, the dataset was first pre-processed to remove outliers as happen in other fields (e.g., Barabino et al. 2017). These outliers could be observations in which the WIM system was unable to determinate vehicular parameters for various reasons, such as out of range passing speed, excessive vehicular acceleration, and tyre passage out plates borders. Moreover, those observations in which one or more determined vehicular parameters values were judged inconsistent were classified as outliers. Outliers were automatically recognized and labelled by the WIM system. Then, the data were filtered on the GVM parameter imposing a minimum threshold of 44,000 kg to exclude the lightest vehicles from the analyses, as the extra-heavy vehicles were the focus of this research. This threshold was selected considering that it is the highest mass limit imposed by the Italian Code for ordinary trucks.

Next, GVM, speed, width, length, axle mass and axle distance parameters were assumed as random continuous variables and their Probability Density Functions (PDFs) were determined to investigate their statistical distributions.

More precisely, let:

- I be the set of observations obtained after pre-processing and filtering procedures, and $i \in I$ an individual observation.
- x be the considered vehicular parameter and x_i the value assumed from this parameter on the observation $i \in I$.
- Z be the set of frequency bin for the considered parameter and $z \in Z$ an individual bin.
- Δy be the amplitude of the frequency bin for the considered parameter.

Then, the PDF_z of the considered parameter, which represents the probability that an observation belongs to a specific frequency bin $z \in Z$, was numerically computed as follows:

$$PDF_z = \frac{Count(x_i)_z}{|I| \cdot \Delta y} \qquad \forall i \in I, \forall z \in Z \tag{1}$$

Likewise, axle number and axle type parameters were assumed as random discrete and categorical variables respectively, and their Probability Functions (PFs) were determined. Specifically, the PF_z, which represents the probability that an observation belongs to a specific frequency bin $z \in Z$, was numerically computed as follows:

$$PF_z = \frac{Count(x_i)_z}{|I|} \qquad \forall i \in I, \forall z \in Z \tag{2}$$

The probability distributions determined through eqns. (1) and (2) refer to a dataset of several vehicular typologies, each of those was characterized by different parameters configurations. Therefore, to individuate these typologies, a cluster analysis was performed by applying the K-means algorithm. To perform this task, a fixed set of factors (Table 2) were preliminary extracted for each individual observation and arranged into a matrix.

Table 2: Factors extracted for each individual observation and assumed as input for running the K-means algorithm.

Name	*Symbol*	*Unit*	*Type*	*Description*
Gross Vehicle Mass	GVM	kg	Continuous	Total vehicular mass (tare plus net load)
Speed	v	km/h	Continuous	Mean passing speed among all vehicular axes
Width	w	m	Continuous	Mean width among all vehicular axles
Length	l	m	Continuous	Distance from the first and the last axle
Axles number	$axle\_num$	$axles$	Discrete	Total number of vehicular axles
Ordinary axle number	ord_axle_num	$axles$	Discrete	Number of vehicular axles with single wheels
Twin axle number	$twin\_axle\_num$	$axles$	Discrete	Number of vehicular axles with twin wheels
Mean axle mass	$mean\_axle\_mas$	kg	Continuous	Mean of the masses acting on all vehicular axles

Name	*Symbol*	*Unit*	*Type*	*Description*
Min axle mass	min_axle_mass	kg	Continuous	Minimum of the masses acting on vehicular axles
Max axle mass	max_axle_mass	kg	Continuous	Maximum of the masses acting on vehicular axles
Std. dev. axle mass	std_axle_mass	kg	Continuous	Standard deviation of the masses acting on vehicular axles
Mean axle distance	$mean\_axle\_dist$	m	Continuous	Mean of the vehicular axle distances
Min axle distance	min_axle_dist	m	Continuous	Minimum of the vehicular axle distances
Max axle distance	max_axle_dist	m	Continuous	Maximum of the vehicular axle distances
Std. dev. axle distance	std_axle_dist	m	Continuous	Standard deviation of the vehicular axle distances

This procedure was indispensable as the K-means algorithm requires, as input, an equal number of variables for each observation $i \in I$, whereas the number of parameters acquired by the WIM system vary among the observations set (I) due to the different vehicular axle number.

More formally, let:

- K be the set of clusters into which the set of observations (I) should be subdivided and $k \in K$ an individual cluster.
- F be the set of factors considered for the cluster analysis, $f \in F$ an individual factor and $f_{k,i}$ the value assumed by the factor f on observation $i \in I$ belonging to $k \in K$ cluster.
- $c_{k,f}$ be the coordinate of the $k \in K$ cluster centroid along the generic factor f.
- $d_{k,i} = \left(\sum_{f\in F}\left(f_{k,i} - c_{k,f}\right)^2\right)^{1/2}$ (3) be the Euclidean distance in the $|F|$-dimensional space between the observation $i \in I$ belonging to $k \in K$ cluster and the corresponding cluster centroid.
- $WCSD = \sum_{k\in K}\sum_{i\in I} d_{k,i}$ (4) and $WCSS = \sum_{k\in K}\sum_{i\in I} {d_{k,i}}^2$ (5) be the Within-Cluster Sum of Distances and the Within-Cluster Sum of Squares, respectively.

Selected a fixed number of clusters ($|K|$), the K-means algorithm partitioned the set of observations into $|K|$ sets to minimize the WCSS. More formally, the goal was to find:

$$\arg\min_{K} \sum_{k\in K}\sum_{i\in I} {d_{k,i}}^2 \tag{6}$$

The optimal number of clusters ($|K|_{opt}$) was determined by adjusting the Elbow method (e.g., Nainggolan et al., 2019). This consisted in plotting the $WCSD$ as a function of $|K|$ and picking the Elbow of the curve as the optimal number of clusters to use. It differs from the classical Elbow method, that considers the WCSS instead of $WCSD$. This choice was motivated by the best ability showed by $WCSD$ parameter in discerning the dissimilarities among similar observations if compared with WCSS. Indeed, WCSS tended to exacerbate within cluster distances when the observations were strongly different and to smooth them when observations were similar.

3. Results and discussion

A two-month observation period (from 1 January 2022 to 28 February 2022) was considered as case study and a total of 1,005,782 vehicles were recorded. After the pre-processing procedure, a total of 665,090 observations were preserved. Subsequently, a set of 14,861 heavy vehicles (I) was obtained performing the weight filtering procedure. Therefore, PDFs were computed for continuous parameters by applying eqn. (1). Similarly, PFs were determined for discrete and categorical parameters by applying eqn. (2). Results are shown in Figure 2.

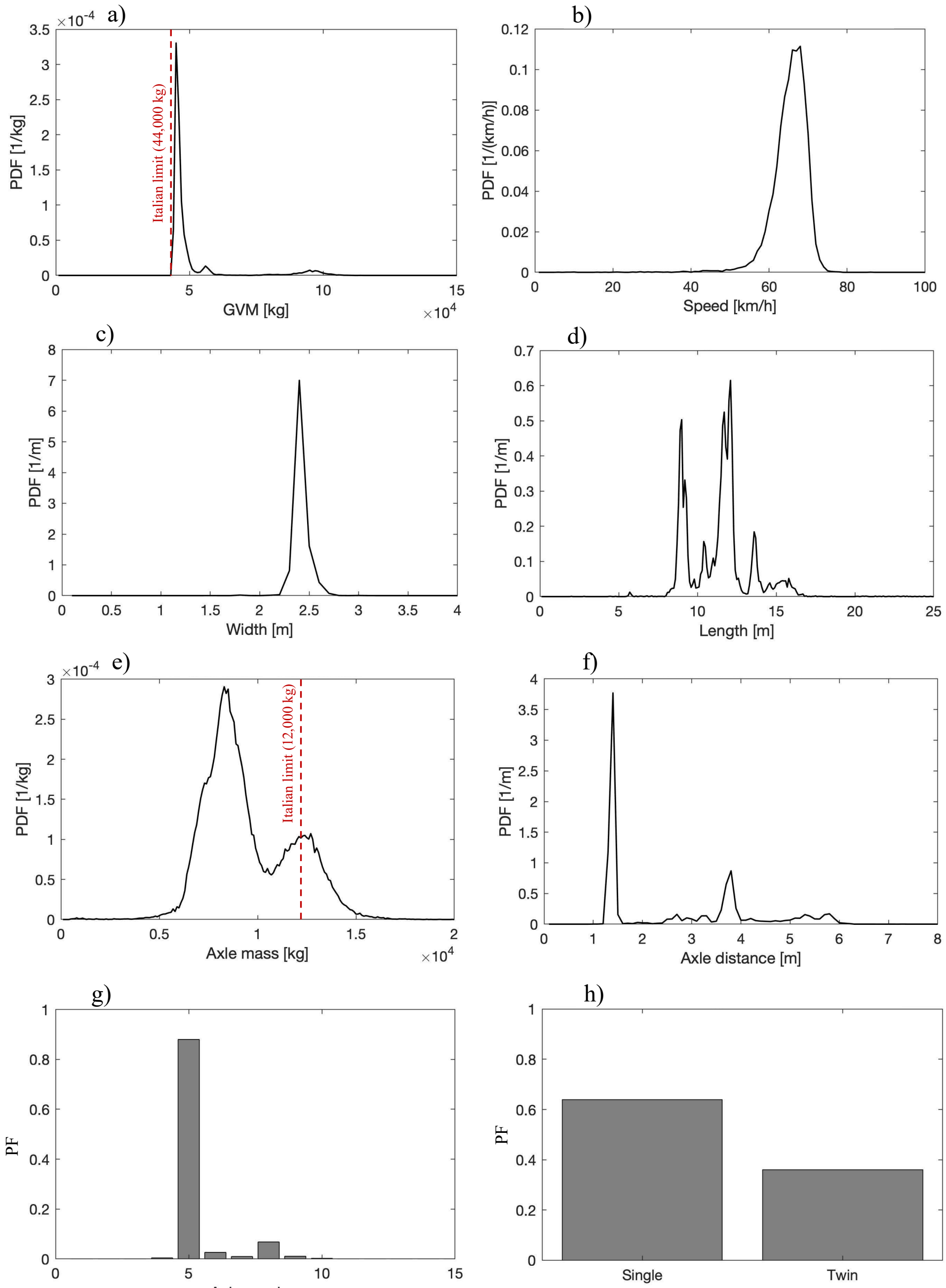


Figure 2: a) PDF for GVM parameter; b) PDF for speed parameter; c) PDF for width parameter; d) PDF for length parameter; e) PDF for axle mass parameter; f) PDF for axle distance parameter; g) PF for axle number parameter; h) PF for axle type parameter.

As for continuous parameters, according to a general perspective, many PDFs showed a multimodal shape, indicating that the associated parameters were not normally distributed. The only exceptions were speed and width distributions, which showed a monomodal pattern. Focusing on each parameter separately, the following considerations result. As for GVM, the distribution exhibited a trimodal shape, with a high peak around 45,000 kg and two significantly lower peaks around 56,000 kg and 96,000 kg approximately. Similarly, length parameter PDF showed multiple peaks, with the three highest peak near 9 m, 12 m, and 13.5 m. Moreover, axle mass distribution showed a bimodal form, with a first maximum around 8,300 kg and a second one near 12,500 kg. Likewise, axle distance PDF presented bimodal profile, with a high peak near 1.4 m, and a lower peak near 3.8 m. These outcomes are consistent with the findings of previous studies (e.g., Guo et al, 2011) and could indicate the presence of different subsets composed by vehicles with similar characteristics. Conversely, speed parameter showed a monomodal shape with a single peak around 66 km/h. This is an expected result, as it is well known that vehicular speed tends to be normally distributed (e.g., Martinelli et al., 2022a; Martinelli et al., 2022b). Similarly, width parameter presented a monomodal form and was densely distributed around 2.4 m value, indicating a likely low variability of this vehicular characteristic among the different subsets.

As for discrete or categorical parameters, PFs indicated that five-axle configuration was the most common among heavy vehicles (approximately 88% of the total), followed by the eight-axle configuration (approximately 7% of the total). Moreover, singe wheel was the most widespread axle typology (approximately 64% of the total) although double wheel axle was quite common (approximately 36% of the total).

Subsequently, to individuate vehicular subsets, a cluster analysis was performed by applying the K-means algorithm, as described in section 2.3. Different instances were run by varying the number of clusters ($|K|$) from 1 to 10. Therefore, the WCSD as a function of $|K|$ was calculated applying eqn. (4) and then analyzed to determine the optimal number of clusters ($|K|_{opt}$), according to the adjusted Elbow method. It was observed that WCSD decreasing rate was very low over $|K| = 3$. Hence, the optimal number of clusters was assumed equal to three. Consequently, three cluster, i.e., Cluster 1, Cluster 2 and Cluster 3, were obtained. They are composed by 12,745 (85.8 % of total), 1,175 (7.9 % of total) and 941 (6.3 % of total) observations, respectively. Table 3 shows the centroids coordinates of each cluster. Exploiting the mechanical analogy, centroids can be interpreted as the cluster centers of gravity, when each observation is assumed as a point of the $|F|$-dimensional space.

Table 3: Cluster centroids coordinates.

Factor [unit]	*Clust. 1*	*Clust. 2*	*Clust. 3*	*Factor [unit]*	*Clust. 1*	*Clust. 2*	*Clust. 3*
Gross Vehicle Mass [kg]	44,093	53'091	93,535	Min axle mass [kg]	6,923	7,014	7,592
Speed [km/h]	64.87	64.80	62.39	Max axle mass [kg]	11,959	13,454	14,093
Width [m]	2.36	2.41	2.43	Std. dev. axle mass [kg]	2,014	2,567	2,114
Length [m]	11.33	10.50	13.73	Mean axle distance [m]	2.82	2.50	1.93
Axles number [$axles$]	5.01	5.18	8.14	Min axle distance [m]	1.31	1.34	1.33
Single axle number [$axles$]	3.61	2.50	2.50	Max axle distance [m]	4.97	4.07	3.65
Twin axle number [$axles$]	1.40	2.68	5.94	Std. dev. axle distance [m]	1.79	1.33	0.99
Mean axle mass [kg]	8,819	10,327	11,513				

From a general viewpoint, the larger set of vehicular characteristics considered in this analysis enables a deeper insight on the main features of the heavy vehicles in each cluster if compared with previous research.

More precisely, concentrating on each factor separately, the subsequent considerations follow. As for GVM factor, Table 3 clearly shows that Cluster 1, which is the most populated, is composed by vehicles whose mean GVM is slightly above the 44,000 kg threshold. Considering the mass limits imposed by Italian Traffic Code, these vehicles are likely lightly overloaded road trains and articulated trucks. Adopting similar considerations, Cluster 2 is probably constituted by construction machinery, for which the Italian Traffic Code allows to extend the GVW threshold up to 54,000 kg by paying a compensation fee. Therefore, Cluster 1 and Cluster 2 seem predominately composed by lightly overloaded ordinary vehicles or construction machinery. Conversely, as for Cluster 3, the high mean GVM (that is far above traffic code limits) suggests that it is mostly formed by mass exceptional vehicles. These considerations could explain the meaning of the three peaks showed in Figure 2 a) for the GVM distribution. As for speed factor, the outcomes indicates that exceptional vehicles (i.e., Cluster 3) have a slightly lower average passing speed than other vehicles, that is an expected result. As for width factor, no relevant difference emerges among the clusters. Conversely, as for length factor, centroids reveal that Cluster 3 vehicles are significantly longer than Cluster 1 and Cluster 2 vehicles. This is a consistent result as the heavier vehicles are more likely longer than light ones to distribute the higher load along a larger space. Moreover, Cluster 3 vehicles are characterized by a higher axle number than Cluster 1 and Cluster 2. This is an expected outcome, as a higher GVM require to allocate vehicular load among many axes. Particularly, Cluster 1 and Cluster 2 are predominantly of single wheel typology while for Cluster 3 vehicles prevails the twin one, as double wheels can bear a higher load. This evidence reinforces the hypothesis that while Cluster 1 and Cluster 2 are mainly composed of lightly overloaded ordinary vehicles or construction machinery, in Cluster 3 exceptional vehicles prevail. As for the mass acting on each single axis, Table 3 clearly indicates that exceptional vehicles axes are characterized by heavier loads, as confirmed by Cluster 3's higher mean, minimum and maximum axle masses than Cluster 1 and Cluster 2. Particularly, the maximum mass acting on Cluster 3 vehicles axes is largely above the 12,000 kg threshold imposed by the Italian Code. Although the latter is a somewhat an expected result due to the low surveillance along the road network, as far the authors know, this is the first research that proves the axle mass limit violation is a remarkable phenomenon among exceptional vehicles in the Italian context. This highlights the need of improving weight enforcement by the authorities responsible for road surveillance to safeguard the safety and the lifetime of infrastructures. Finally, as for axle distance, centroids show significantly lower mean and maximum values for Cluster 3, suggesting that exceptional vehicles have closer axles than ordinary vehicles. This evidence is likely correlated to the need of provide exceptional vehicles with a higher number of axles and it could have a negative impact on road structures when the presence of many axles over a reduced length leads to an excessive load concentration.

4. Conclusions

The rising spread of mass exceptional vehicles can adversely affect road network efficiency and safety. Indeed, extra heavy vehicles can accelerate bridge structures degradation phenomena. Moreover, extra heavy vehicles can even induce a structural collapse when the applied load on the bridge exceeds design load prescribed by Codes. Consequently, the installation of traffic and bridge monitoring systems is becoming essential for the safe management of road infrastructure. WIM systems, which measure vehicular mass in a dynamic manner, are an effective solution for preventing structural damage by promoting weight enforcement.

Although there are several applications of these devices in the American and Chinese context, much less studies have been carried out in Europe and, particularly, in Italy. Furthermore, while other authors had previously analysed raw WIM data using clustering algorithms, they only considered a subset of vehicular parameters.

This study filled these gaps by providing a statistical analysis of raw WIM data collected during a two-month observation period in a pilot station located on a bridge along Brescia's heavily travelled ring road (Italy). Specifically, the characteristics of vehicles with a gross vehicle mass (GVM) greater than 44,000 kg threshold were investigated. The probability distributions of several vehicular parameters were determined, and a K-means based clustering technique was adopted to subdivide WIM observations into clusters basing on a wide set of vehicular features. The outcomes revealed that the probability distributions of many parameters had a multimodal shape, implying the presence of different subsets made up of vehicles with similar characteristics. This result was confirmed by K-means analysis, which revealed the existence of three major vehicular clusters. Precisely, two clusters were predominately composed by ordinary or lightly overloaded vehicles, while one cluster was mostly formed by exceptional vehicles. Particularly, the outcomes indicated that exceptional vehicles were characterized by an average GVM of approximately 94,000 kg, were longer than ordinary vehicles and were provided with a higher number of axles. Moreover, while for lightly overloaded ordinary vehicles or construction machinery the single wheel axle typology was dominant, in exceptional vehicles twin wheel axle typology prevailed. Finally, the masses acting on exceptional vehicle's axes were significantly higher than for lightly overloaded ordinary vehicles, and the maximum values exceeded the 12,000 kg prescribed by the Italian Traffic Code. This last outcome is particularly relevant, as it confirms that exceptional vehicles have stronger contribute to infrastructure degradation, being the damaging proportional to axle load.

The proposed method can be regarded as an enhancement of previous research since a wider set of vehicular parameters were considered (e.g., Huang et al, 2022; Fiorillo et al, 2014). The main advantage of this study is to provide a deeper understanding of the main features that enables to distinguish among ordinary, overloaded, and exceptional vehicles. Additionally, although data from only one WIM pilot station were analysed, as far as the authors know, this is the first research that quantitative shows the violation of axle mass limits is a remarkable phenomenon in Italian context.

Finally, the results of this study lay the groundwork for two lines of future research. The former concerns the development of models for predicting GVM as a function of small set of vehicular characteristics (e.g., width, length, passing speed, axle number and axle distance) to enable a rapid estimate of vehicular loads with more cost-effective monitoring systems, such as traffic cameras. The latter regards the definition of a framework for a real time assessment and management of the risk related to the transit of heavy loaded vehicles on bridges.

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