Probabilistic Models for Italian Road Traffic with Gross Vehicle Weight Limitations Based on Weigh-in-Motion Data

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ABSTRACT: Traffic load models provided by standard regulations play a major role in both design and management of road infrastructure. Considering the persistent change in the traffic load characteristics, a proper validation of code-based models with real traffic data becomes necessary, especially for their implementation in safety checks and monitoring of existing bridges. In this context, this study presents a comparative assessment of present Italian road traffic obtained from two weigh-in-motion stations located along European route E45 close to Naples, Italy, with existing European traffic. The traffic data was filtered to remove erroneous data and then classified based on the number and spacing of vehicle axles. Suitable unimodal and multimodal probabilistic models were then identified for major vehicle parameters such as gross vehicle weight, vehicle speed, axle weight, axle distance and relative axle weight. The paper ends with a preliminary comparison between measured traffic loads and existing traffic load models from bridge design standards. The results clearly indicate a significant variation in the available traffic load models with the present-day traffic. This comprehensive assessment considering different types of vehicles and traffic flow characteristics lay the basis for a future study to investigate the distribution of real traffic effects and its variation with respect to code-based traffic models.

1. INTRODUCTION

Traffic loads based on real traffic data are necessary for the proper construction and management of road infrastructures. The traffic load models (TLMs) provided by the standard codes are based on the traffic data obtained decades ago, like the TLMs of Eurocode 1 (EC1) which was developed based on the traffic data from various locations of Europe from 1980 to 1994 (Croce, 2020; EN1991-2, 2003). The recorded traffic data was associated with higher lorry flows with the recording time over a number of weeks and the motorway was considered one of the heaviest loaded infrastructures in Europe at that time (Bruls et al., 1996, Maljaars, 2020). In recent years, the frequency of heavy vehicles and traffic flow has changed considerably due to the circulation of long and heavy vehicles (LHVs) to reduce transportation costs. Studies that evaluated the effect of LHVs on the existing road infrastructure revealed 8% increase in lifetime maximum loading for European bridges (OBrien & Enright, 2011). The TLMs from the standard codes fail to consider the traffic load variation and the LHVs, leading to a major issue. Hence, the continuous update of TLMs of the current regulations from the traffic data obtained using weigh-in-motion (WIM) systems is necessary.

WIM systems are an advanced technology that yield highly useful information to study the traffic loads (Chen et al., 2014). Further, WIM systems are also helpful in semi-permanent monitoring for overload vehicles detection and fatigue assessment of bridges (Jacob & Cottineau, 2016). With recent advances in measurement technologies, the quality of traffic data obtained via WIM systems improved significantly (Burnos et al., 2021). However, a proper calibration and preliminary assessment of WIM systems are required to avoid errors on vehicle weights and axle distances (Tarefder & Ruiz, 2013).

Available WIM information on major parameters such as axle weights, inter-vehicle distance, vehicle length and vehicle speed are particularly useful in the simulation of traffic-dependent phenomena. Further, understanding variations in the statistical distribution of different vehicle classes is important for probabilistic evaluation of the traffic effects on existing bridges and roads (Tabatabai et al., 2017). The statistical analysis of road traffic and development of simulated traffic loading for numerical analysis would increase structural reliability of existing bridges (Caprani & O'Brien, 2010).

In this context, the present study aims at developing the probabilistic models for vehicle parameters based on the data collected by WIM systems installed in South Italy. WIM systems were installed to enforce a total weight limitation of 440 kN recently imposed according to safety assessment of critical road bridges located in-between the monitored stations (Cosenza & Losanno, 2021; Miluccio et al., 2023). The study involves the filtering of WIM data, followed by the classification of vehicles based on number of axles and axle distances. Statistics and probability distribution of traffic data of the classified vehicles and a comparison of the traffic data with code-based TLMs are presented.

2. PRELIMINARY DATA ASSESSMENT

WIM data sets were collected from two stations with different traffic conditions, which are named 'Fratte' and 'Pontecagnano' as shown in Figure 1. The stations are located on two motorways in Southern Italy, which are a part of E45 European road and were installed in 2021 after safety checks of some existing bridges which required traffic load limitations. Fratte WIM system was installed on A3 Napoli–Salerno motorway to prevent vehicles having total mass higher than 44 t passing on critical bridges, with a proper derailment system involving signalling and traffic police. Pontecagnano WIM system was installed 15 km south on A2 Salerno–Reggio Calabria motorway (also called 'Mediterranean motorway') where allowable legal mass is 44 t without systematic overload traffic derailment. The WIM data at the selected locations contains information on vehicle crossing time, license plate number (for illegal vehicle tracking), vehicle acceleration, gross vehicle weight (GVW), vehicle speed (*V*), vehicle length (*L*), number of axles, axle weight, axle distance (*d*) and vehicle width. The WIM data measured in the slow lane at the selected locations was considered for the study. Traffic data includes both low-weight vehicles and heavy-weight trucks. To avoid a hefty pool of data in traffic load analysis, the traffic data was broadly classified in two categories based on GVW. Vehicles with GVW < 75 kN were considered as low-weight vehicles.

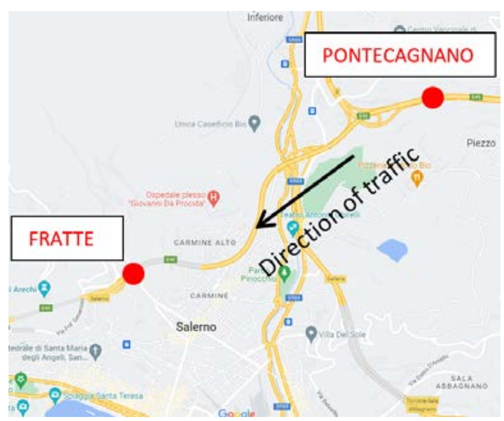


Figure 1: Location of WIM stations along A2 (Pontecagano) and A3 (Fratte) motorways, Italy

The WIM data was filtered as per the conditions listed below, to remove erroneous data that arises due to uncertainties on electromagnetic interference and extreme weather conditions:

- Minimum axle distance = 0.92 m
- Maximum axle weight = 392 kN
- Maximum vehicle length = 18.75 m
- Maximum gross vehicle weight = 1500 kN
- Maximum vehicle speed (*V*) = 170 km/h
- Number of axles = 2 to 7

The major representative traffic parameters (such as GVW, and *V*) at the selected locations are listed in Table 1. As seen from the traffic data, the maximum GVW measured at Pontecagnano is 9.80% larger than that at Fratte. At Fratte, 3.23% of total vehicles (i.e. 112) were found to be heavier than 40 t. In case of Pontecagnano, 5.53% of recorded vehicles (i.e. 102) were found to be heavier than 44 t. The minimum vehicle speed of 3.00 km/hr was observed at the Fratte station during a traffic jam condition.

Table 1: Main traffic characteristics at Pontecagnano and Fratte.

Vehicle Parameters	*Pontecagnano*		*Fratte*	
	Min	*Max*	*Min*	*Max*
GVW (kN)	*1.9*	*558.6*	*1.9*	*503.7*
V (km/h)	*6.0*	*152.0*	*3.0*	*159.0*

The comparison of the GVW distribution of the vehicles at Pontecagnano and Fratte for low-weight and heavy-weight vehicles are shown in Figures 2 and 3, respectively. The GVW distribution of heavy trucks at the selected locations follows a trimodal distribution with mean values of unimodal distributions (assumed to be normal) generating the multimodal distribution of GVW approximately equal to 99 kN, 198 kN, and 327 kN at Pontecagnano, and 128 kN, 183 kN, and 308 kN at Fratte. In case of low-weight vehicles, the mean values were around 18.81 kN, 32.22 kN, and 98.36 kN at Pontecagnano, and 16.29 kN, 23.88 kN, and 70.54 kN at Fratte.

3. CLASSIFICATION OF VEHICLES

The vehicles are classified based on the GVW as low weight and heavy weight vehicles. Based on such classification, the total number of low-weight vehicles recorded at Pontecagnano and Fratte were 100,656 and 162,966, respectively for a sampling period of two weeks. The total number of heavy vehicles measured at Pontecagnano and Fratte were 1846 and 3472, respectively. The frequency of heavy trucks (GVW > 75 kN) at Pontecagnano and Fratte was respectively about 1.8% and 2.1% of the vehicles measured in the slow lane. The low-weight vehicles at Pontecagnano and Fratte were about 98.2% and 97.9% of the total vehicle traffic recorded in the slow lane. The average GVW of the low-weight vehicles at Pontecagnano and Fratte was around 25.04 kN and 18.82 kN, and their average speed was around 92.74 km/h and 74.84 km/h, respectively.

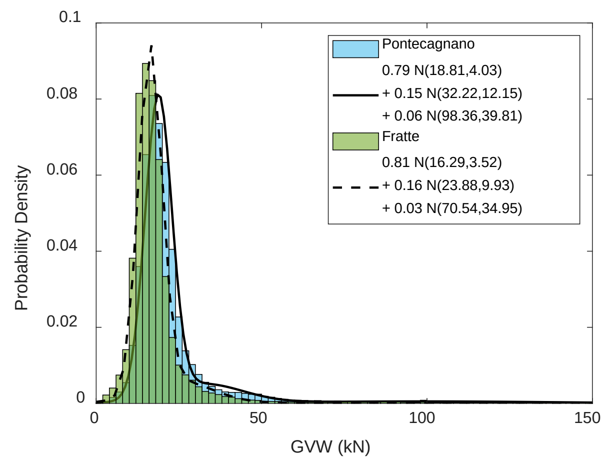


Figure 2: GVW distribution of low-weight vehicles

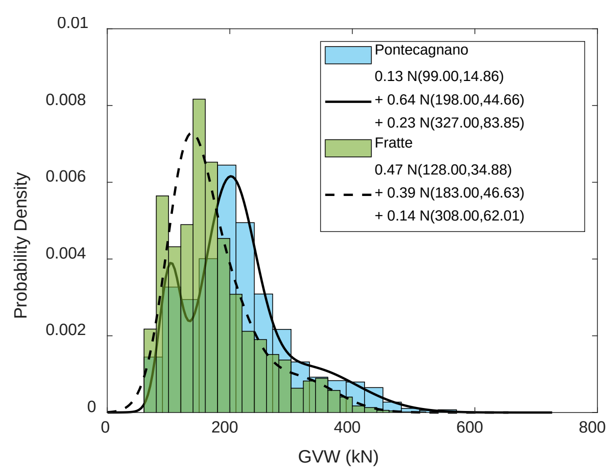
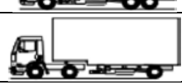
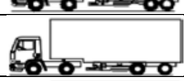
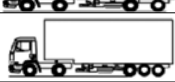
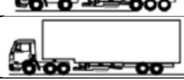
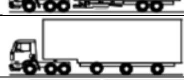
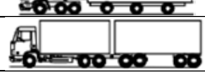


Figure 3: GVW distribution of heavy-weight vehicles

Commonly, the vehicles are classified based on the number of axles and axle distance. Based on the standard vehicle classification groups reported in the literature (Guo et al., 2012; Tabatabai et al., 2017), the vehicles at the selected locations were classified into nine vehicle classes as listed in Table 2. The most frequent vehicle classes with a frequency greater than 20% at both stations were found out to be 2A and 5F. The vehicle classes 2A, 3B, 4D and 5F constitute about 94% and 92% of total vehicles at Pontecagnano and Fratte, respectively. Average GVW values at Fratte are lower than those measured at Pontecagnano for all vehicle classes, further remarking the effects of traffic restrictions. In the same trend, the average speed range of 2A and 5F vehicles at Pontecagnano were found to be [82.6 km/h, 88.3 km/h], which is higher than that associated with Fratte (i.e. [55.6 km/h, 73.2 km/h]) due to influence of urban traffic and port area in the latter case.

Table 2: Classification of vehicles at Pontecagnano and Fratte.

Vehicle class	*Silhouette*	*Frequency (%)*	
		Ponte-cagnano	*Fratte*
2A		*32.3*	*41.4*
3B		*15.9*	*11.9*
3C		*1.3*	*1.0*
4D		*20.2*	*16.1*
4E		*2.9*	*2.6*
5F		*25.5*	*22.9*
5G		*1.3*	*0.8*
6H		*0.3*	*0.9*
7I		*0.1*	*0.2*

4. PROBABILISTIC MODELS FOR MAJOR TRAFFIC PARAMETERS

A detailed statistical analysis of traffic data was thus carried out to understand the different load conditions and dependency upon traffic restrictions at the selected locations. The vehicle parameters may follow different probability distributions due to the variation in the type of vehicles and the carrying load (Lan et al., 2011; Obrien et al., 2009). Hence, the different vehicle parameters assumed as random variable are analysed to identify the suitable probability distribution. Comparison was made using various statistical models, namely normal (N), lognormal (Logn), logistic (Log), loglogistic (Loglog), kernel (K), and Weibull (W), using maximum likelihood estimation to estimate model parameters in case of unimodal distributions. In addition, multimodal distribution is also considered. The model parameters were estimated using the expected maximum (EM) algorithm which is one of the most frequently used methods for the estimation of model parameters with required accuracy (Xia et al., 2012). The validation of the unimodal and multimodal distributions was carried out using Kolmogorov-Smirnov (K-S) test with significance level of 0.05.

4.1. Gross vehicle weight

The GVW distribution of the vehicle classes associated with heavy-weight vehicles tend to follow loglogistic, lognormal and multimodal distributions. The comparison of the probability density functions (PDFs) of GVW of one of the most frequent vehicle classes 5F at Pontecagnano and Fratte are shown in Figure 4. GVW distribution of vehicle class 5F follows loglogistic distribution with the mean weight around 268 kN at Pontecagnano and the multimodal distribution with the mean values around 167 kN and 285 kN at Fratte. In case of low-weight vehicles, GVW can be described by trimodal distributions at both WIM stations. Similar to heavy-weight vehicles, the mean GVW at Pontecagnano was found to be comparatively larger than that related to Fratte.

4.2. Vehicle speed

In most cases, vehicle speed was found to be described by logistic and loglogistic distributions. The PDF of vehicle speed for the same vehicle class is shown in Figure 5. Both GVW and V measured at Pontecagnano tend to be larger than those at Fratte. A similar trend was confirmed by other vehicle classes. Vehicle speed of low-weight vehicles follows loglogistic distribution with mean value around 92.76 km/h and 73.70 km/h at Pontecagnano and Fratte, respectively.

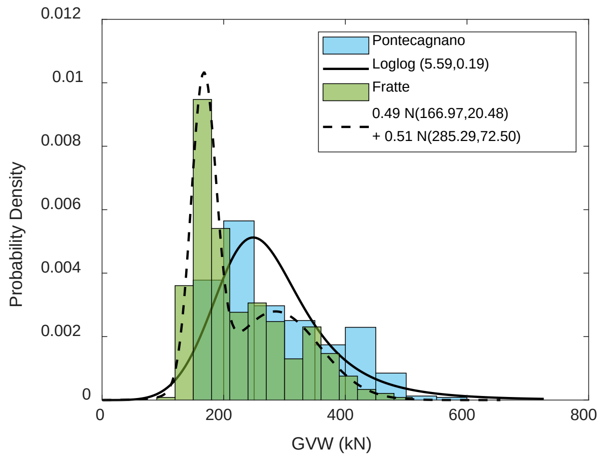


Figure 4: Probability density functions of GVW for vehicle class 5F

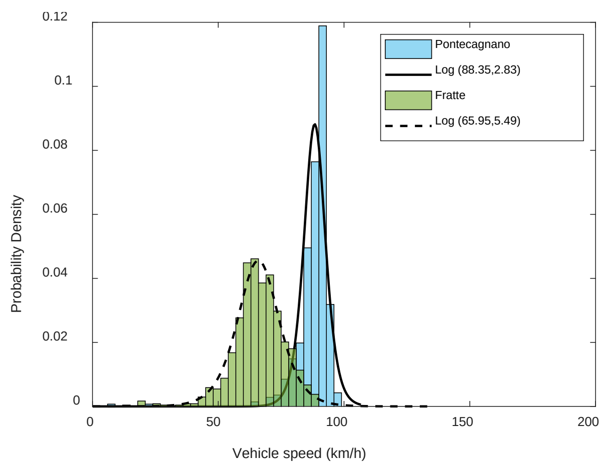


Figure 5: Probability density functions of vehicle speed for vehicle class 5F

4.3. Axle weight and axle distance

The axle weight was represented as w_i, where the subscript denotes the number of the axle from front to rear. The axle distance was represented as d_{ij}, where the subscripts denote the number of the axles between which the distance was measured. The axle weight in most of the vehicle classes follows the normal and loglogistic distributions. Few axle weight distributions from Fratte stations were found to follow bimodal distribution. While comparing the axle weight distributions of all the vehicle classes, the average axle weight recorded in Pontecagnano is larger than Fratte over all the axle weights. The axle weight of low-weight vehicles follows a trimodal distribution at both WIM stations, with the major proportion of the axle weight approximately equal to 9.38 kN and 8.16 kN at Pontecagnano and Fratte, respectively. The PDFs of axle weight w_1 for vehicle class 5F are shown in Figure 6. For heavy-weight vehicle classes, the axle distance distribution tends to follow normal, logistic, loglogistic and bimodal distributions. The PDFs of axle distance d_{23} for vehicle class 5F are shown in Figure 7.

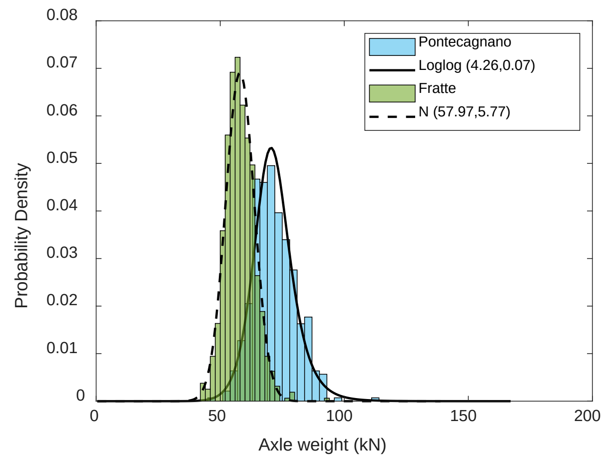


Figure 6: Probability density functions of axle weight (w_1) for vehicle class 5F

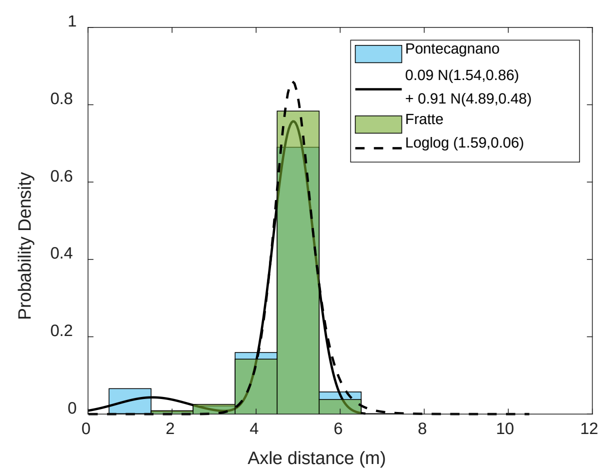


Figure 7: Probability density functions of axle distance (d_{23}) for vehicle class 5F

In case of low-weight 2-axle vehicles, the axle distance was found to follow a trimodal distribution at both locations. The major proportion of the axle distance at Pontecagnano were concentrated around 1.70 m and 1.72 m. In case of Fratte, the axle distances of 1.78 m and 2.16 m constitute the major proportion of the recorded vehicles.

4.4. Relative axle weight

A relative axle weight (*RW*) is defined for the *i*th axle as the ratio of the axle weight (W_i) to GVW for every vehicle class. The statistical distributions of vehicle class 5F tend to follow unimodal and multimodal distributions. The *RW* distributions of vehicle class 5F at Pontecagnano are shown in Figure 8. The mean *RW* of axles 3, 4 and 5 were found to be close to each other at both locations, with the mean *RW* varying between 0.16 and 0.17. While comparing the distribution of RW_1 between stations, the mean values of the multimodal distribution were almost similar with a slight variation in the standard deviation and the proportions. In case of RW_2, the mean values of the multimodal distribution were found to be between 0.26 and 0.28 at both stations. The cumulative distribution functions (CDFs) of the relative axle weights for vehicle class 5F are shown in Figure 9.

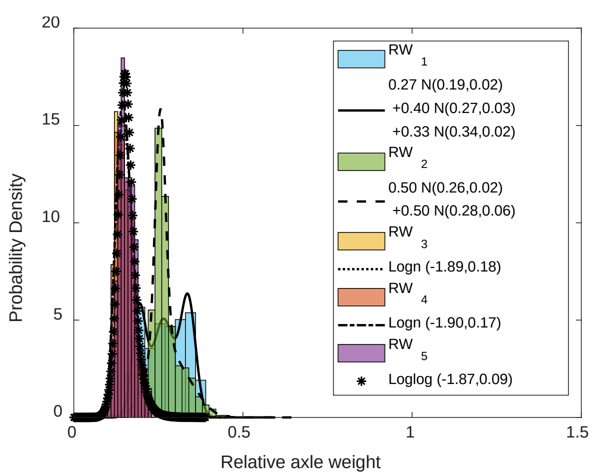


Figure 8: Probability density functions of the relative axle weights of vehicle class 5F at Pontecagnano

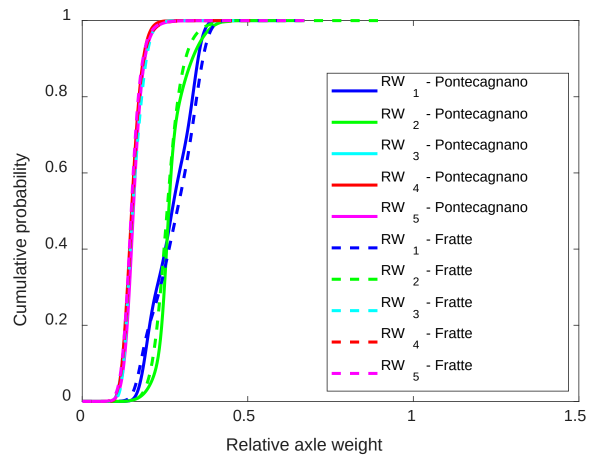


Figure 9: Cumulative probability functions of the relative axle weights of vehicle class 5F

5. COMPARISON OF LOAD MODELS

Even if according to modern reliability criteria TLMs are established based on given return periods for limit state verifications, a preliminary comparison is proposed between WIM collected data and most common TLMs. Structural analyses will have to be developed for an effective comparison between different models and calibration of WIM-based TLMs.

5.1. Fatigue load models in Eurocode 1

As per Eurocode 1 (EC1; EN1991-2, 2003), the fatigue load model 2 (FLM2) was represented by a set of five idealized “frequent” lorries. The vehicle classes 2A, 3B, 4D and 5F considered in the present study are similar to the first four frequent lorries mentioned in EC1. It is also important to point out that these vehicle classes represent about 94% and 92% of the total traffic at Pontecagnano and Fratte, respectively. Only a slight variation in the axle distance was observed between traffic data considered in the present study and EC1 recommended values. However, considerable differences arise in terms of axle loads for all vehicle classes. The fatigue load model 4 (FLM4) is represented by sets of standard lorries which together produce equivalent effects to those of typical traffic on European roads. Similar to FLM2, a significant variation in the axle loads between EC1 and the different vehicle classes at both WIM stations was observed.

5.2. Design load model in Eurocode 1

According to EC 1 – Part 2 (EN1991-2, 2003), the traffic load model 1 (LM1) describes the concentrated and uniformly distributed loads (UDL) including dynamic amplification factors of traffic for global and local verifications having a return period of 1000 years. The equivalent uniformly distributed loads (eUDL) for the different vehicle classes at Pontecagnano and Fratte were calculated from the mean GVW considering a conventional width of 3.0 m and a total length equal to the sum of the axle distances. In case of vehicle class 2A, the eUDL value was close to 11 kN/m^2 at both the WIM stations, which is about 18% to 20% higher than that of the code recommended value. In case of vehicle class 5F, the eUDL values at Pontecagnano and Fratte were 9.68 kN/m^2 and 7.69 kN/m^2, respectively.

5.3. Heavy load traffic model of the new Italian guidelines for existing bridges

In 2020, new guidelines for safety assessment of existing bridges were issued by the Italian Ministry of Infrastructures and Transportation including standard vehicles (i.e. based on actual traffic vehicles as per Italian road code) for novel TLMs (Cosenza & Losanno, 2021) to be adopted in case of non-compliant bridges with respect to LM1. The heaviest 5% range (H5P) GVW of the vehicle class 5F at Pontecagnano (452.8 kN) is close to the GVW suggested by the Italian guidelines with a variation of +2.82% which is also within 5% tolerance to maximum legal value of 440 kN. In case of vehicles at Fratte, H5P GVW of vehicle 5G is 415.1 kN (i.e. the peak H5P value among different vehicle classes) close to 440 kN with –5.65% variation but higher than legal limit of 400 kN by 3.78%.

5.4. Design load model of AASHTO guidelines

As per the AASHTO-LRFD regulations, the design vehicular load is represented by three load types such as design truck, design tandem and design lane load. The design lane load is represented by a uniform distributed load of 0.64 klf (corresponding to 9.34 kN/m) in the longitudinal direction (AASHTO, 2010). The load is assumed to spread for 10 ft (i.e. 3.05 m) width transversely. The transverse width is very close to the width of the notional lane (equal to 3.0 m). By considering the eUDL values multiplied by the notional lane width (equal to 3.0 m), a significantly higher distributed load is obtained, i.e. approximately 2.5 and 4.0 times higher in terms of average and H5P values, respectively.

The design truck provided by AASHTO guidelines consists of three axles with axle weights. The GVW of the design truck is 320 kN, with the axle weights of 8 kips (36 kN), 32 kips (142 kN) and 32 kips (142 kN) each. The spacing between the first two axles is 14 feet (4.27 m), and spacing of next two axles varies from 14 feet (4.27 m) to 30 feet (9.14 m) to be selected to achieve the maximum effect. Usually, the minimum axle distance of 4.27 m controls design and values greater than 4.27 mm are selected in case of continuous short-span bridge where the maximum negative moment at the pier is being computed.

The H5P values of the vehicle classes 3B and 6H were found to be closer to that the GVW of the design truck load by AASHTO, with the variation of 2.82% and 3.56%, respectively. In case of Fratte, smaller variations with the AASHTO design truck load were observed with that of the vehicle classes 4D (3.71%) and 6H (3.56%). Further, the design truck axle weights were compared with the axle weights of the vehicle classes 4D and 5F representing 40–45% frequency of total traffic.

6. CONCLUSIONS

The probabilistic models of the traffic parameters of the current Italian traffic, along with the comparison of the traffic load models of standard regulations is presented in this study. The WIM data were obtained from two stations on the E45 European highway close to Naples, Italy, over a period of two weeks. The data was filtered initially, followed by the classification of vehicles based on GVW, number of axles and axle distances. Based on the results, the two-axle vehicle class 2A and five-axle vehicle class 5F were identified as the most frequent vehicles with frequency greater than 20% at both the stations.

The statistical distribution of major vehicle parameters, such as axle weight, axle distance, GVW, and vehicle speed, were then identified. The vehicle parameters tend to follow unimodal and multimodal distributions. The traffic data was then compared with the traffic load models and design vehicles provided by the standard regulations. While comparing EC1-conforming fatigue load models, a significant variation in the axle loads of the frequent lorries (fatigue load model 2) and standard lorries (fatigue load model 4) were identified at both WIM stations selected in this study. Considerable variation is also observed between the H5P GVW of the most frequent vehicle class 5F and the GVW suggested by the Italian guidelines. Based on collected WIM data, a traffic load simulation procedure will be developed for structural analysis.

7. ACKNOWLEDGEMENTS

This study was developed within INSIST project (Grant No. ARS01_00913) and FIRMITAS project (Grant No. 2020P5572N), which were funded by the Italian Ministry of University and Research. The authors would like to acknowledge MOVYON s.p.a., Società Autostrade Meridionali s.p.a. and SIS s.c.p.a. for providing WIM data.

8. REFERENCES

AASHTO. (2010). *AASHTO LRFD Bridge Design Specifications*.

Bruls, A., Calgaro, M., & Mathieu, P. M. (1996). ENV 1993 part 3: The main model of traffic loads on road bridges - Background studies. *IABSE Colloquium on the Basis of Design and Action of Structures*.

Burnos, P., Gajda, J., Sroka, R., Wasilewska, M., & Dolega, C. (2021). High Accuracy Weigh-In-Motion Systems for Direct Enforcement. *Sensors*, *21*(23), 8046.

Caprani, C.C., & OBrien, E.J. (2010). The use of predictive likelihood to estimate the distribution of extreme bridge traffic load effect. *Structural Safety*, *32*(2).

Chen, B., Zhong, Z., Xie, X., & Lu, P. (2014). Measurement-Based Vehicle Load Model for Urban Expressway Bridges. *Mathematical Problems in Engineering*, *2014*, 1–10.

Cosenza, E., & Losanno, D. (2021). Assessment of existing reinforced-concrete bridges under road-traffic loads according to the new Italian guidelines. *Structural Concrete*, *22*(5), 2868–2881.

Croce, P. (2020). Impact of Road Traffic Tendency in Europe on Fatigue Assessment of Bridges. *Applied Sciences*, *10*(4), 1389.

EN1991-2. (2003). Eurocode 1: Actions on Structures – Part 2: Traffic Loads on Bridges. *CEN: Brussels, Belgium*.

Guo, T., Frangopol, D. M., & Chen, Y. (2012). Fatigue reliability assessment of steel bridge details integrating weigh-in-motion data and probabilistic finite element analysis. *Computers & Structures*, *112–113*, 245–257.

Jacob, B., & Cottineau, L.-M. (2016). Weigh-in-motion for Direct Enforcement of Overloaded Commercial Vehicles. *Transportation Research Procedia*, *14*, 1413–1422.

Lan, C., Li, H., & Ou, J. (2011). Traffic load modelling based on structural health monitoring data. *Structure and Infrastructure Engineering*, *7*(5), 379–386.

Maljaars, J. (2020). Evaluation of traffic load models for fatigue verification of European road bridges. *Engineering Structures*, *225*.

Miluccio, G., Losanno, D., Parisi, F., & Cosenza, E. (2023). Fragility analysis of existing prestressed concrete bridges under traffic loads according to new Italian guidelines. *Structural Concrete*, 24(1), 1053–1069.

OBrien, E.J., & Enright, B. (2011). Modeling same-direction two-lane traffic for bridge loading. *Structural Safety*, *33*(4–5), 296–304.

OBrien, E.J., Rattigan, P., González, A., Dowling, J., & Žnidarič, A. (2009). Characteristic dynamic traffic load effects in bridges. *Engineering Structures*, *31*(7).

Tabatabai, H., Titi, H., & Zhao, J. (2017). WIM-based assessment of load effects on bridges due to various classes of heavy trucks. *Engineering Structures*, *140*.

Tarefder, R., & Rodriguez-Ruiz, J.I. (2013). WIM data quality and its influence on predicted pavement performance. *Transportation Letters*, *5*(3), 154–163.

Xia, H.W., Ni, Y.Q., Wong, K.Y., & Ko, J.M. (2012). Reliability-based condition assessment of in-service bridges using mixture distribution models. *Computers & Structures*, *106–107*.