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Overcoming strain gauges limitation in the estimation of train load passing on a bridge through deep learning

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ABSTRACT

The estimation of trains weight could be useful under certain circumstances. For instance, in the field of structural health monitoring, some considerations can be derived from the evaluation of the load spectrum that an infrastructure has to withstand in its lifetime. One approach to estimate the train weight is based on the use of strain gauges mounted on the rail. The procedure allows to associate the local deformations with the load on an axle. However, strain gauges present several limitations: they are regarded as delicate sensors, and their replacement is burdensome and time-consuming. Moreover, their life is usually short when subjected to weathering and numerous load cycles. For these reasons, this paper proposes a novel methodology that relies on the use of more robust sensors mounted on a bridge structure for the estimation of the train load, alongside other information, such as the number of axles, the train speed, and the train class. The idea consists in the estimation of the train load starting from a network of sensors mounted on a bridge. A deep learning model is particularly suitable to achieve this task. The sensors network must consist of robust and easy-to-replace transducers (such as velocimeters mounted on the bridge structure). In this way, when the strain gauges are removed, the system is still able to estimate the loads passing on the bridge.

Keywords: Deep learning, Weigh in motion, Bridge monitoring, Sensors, Data Fusion

1. INTRODUCTION

Railway infrastructure is of paramount importance for the efficient flux of goods and people. According to a report on transportation in the European Union, in 2020, rail accounted for 11.5% of freight transport and 5% of passengers.[1] Within railway infrastructure, bridges and viaducts play an irreplaceable role. Lately, such elements have been growingly threatened by increasing loads and structural ageing, which are putting at risk their safety.[2,3] In this context, structural health monitoring of the railway infrastructure and accurate numerical modelling of the interaction between the train and the infrastructure underneath are essential tools to ensure safety, improve maintenance operations, and increase service quality.[4]

In this framework, relevant information resides in the identification of travelling loads, speed, and the number of axles.[5] In fact, knowledge of the dynamic loads acting on a structure is significant for its design, control, diagnosis and maintenance.[6] In regard, overloading represents a big issue, especially in the case of freight trains, both for the risk of derailment and possible damage caused to the infrastructure.[7,8] In parallel, such a characterisation of the crossing train is a fundamental ingredient for the realisation of reliable numerical models, aimed at testing the structural behaviour of a bridge in response to the travelling load.

The systems providing the information above are known by the name of weigh-in-motion (WIM).[5,9] According to the literature in matters, there are two approaches to perform the characterisation of the crossing train: a direct one, based on the measurements at the contact between wheel and rail, and an indirect one, which relies on a quantification of the forces applied by the vehicle to the infrastructure.[10] The former foresees the installation of sensors on the train, realising an onboard monitoring system; the latter, instead, takes the infrastructure viewpoint inferring the loads by monitoring the dynamic response of the infrastructure.[11] At this point, two cases onset, depending on whether the sensors are installed on the rail - a traditional WIM - or the bridge - so-called Bridge-WIM (or B-WIM).[5,12] A significant advantage of the latter is avoiding the use of sensors in

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the rails, an uncomfortable positioning that forces the installation and future maintenance to interfere with the circulation.

This aspect becomes even more critical considering that the most common sensors for WIM application are strain gauges[10,11] , which are extremely fragile and sensitive to external damage. Such characteristics motivated this research, whose aim is to design a new and more robust methodology for load estimation in correspondence with railway bridges. In particular, this work proposes a machine-learning-based approach to B-WIM that exploits measurements from velocimeters installed on the bridge deck. Once trained by using strain gauges on the rail, the neural network is able to correctly estimate the travelling load, speed, and the number of axles, only relying on signals from on-deck sensors. The methodology is tested on a real case study, a two-span Warren-truss bridge located in Italy. The popularity of this kind of structure in the worldwide railway realm renders the findings of this research even more valuable, since they could bring improvements to a relevant portion of the whole infrastructural network.[13]

The paper is organised as follows: Section 2 shows the experimental setup installed on the bridge; Section 3 explains the weigh-in-motion algorithm that exploits measurements from the strain gauges; Section 4 dives deep into the novelty content of the research by describing the machine-learning-based approach that enables performing Bridge-WIM with velocimeters. Results are presented in the same section; Section 5 presents the conclusions and summarises the study findings.

2. EXPERIMENTAL SETUP

The railway bridge under analysis is a two-span Warren truss bridge, designed in 1946. The instrumented bridge is represented in figure 1, and is flanked by a twin structure consenting for train circulation in the opposite travel direction. The spans are simply supported, with hinge supports at the entrance and sliders at exit. The two spans are not directly connected one with each other, except for track system and the discontinuity pier.

Figure 1. A view of the bridge object of study, on the right, and its twin structure, on the left.

The permanent monitoring system installed includes strain gauges on the rail, to measure the shear stress, and velocimeters on the structure and on the pier, to measure the dynamic response. The strain gauges, as shown in figure 2, are placed at the entrance of the bridge, on the left rail. As depicted in figure 2, a total of twelve velocimeters are present on the bridge, six for each bridge span, and are positioned according to the following scheme: one-quarter and three-quarter length, and midspan, both sides. Such sensors produce data from ten acquisition channels: a vertical measure per each velocimeter, a lateral one from the upstream sensors

(1, 3, 5, 7, 9 and 11 in figure 2), and a longitudinal velocity from the upstream sensors at midspan (3 and 9 in figure 2). Finally, the velocimeter on the pier (13 in figure 2) acquires along all three measurement axes.

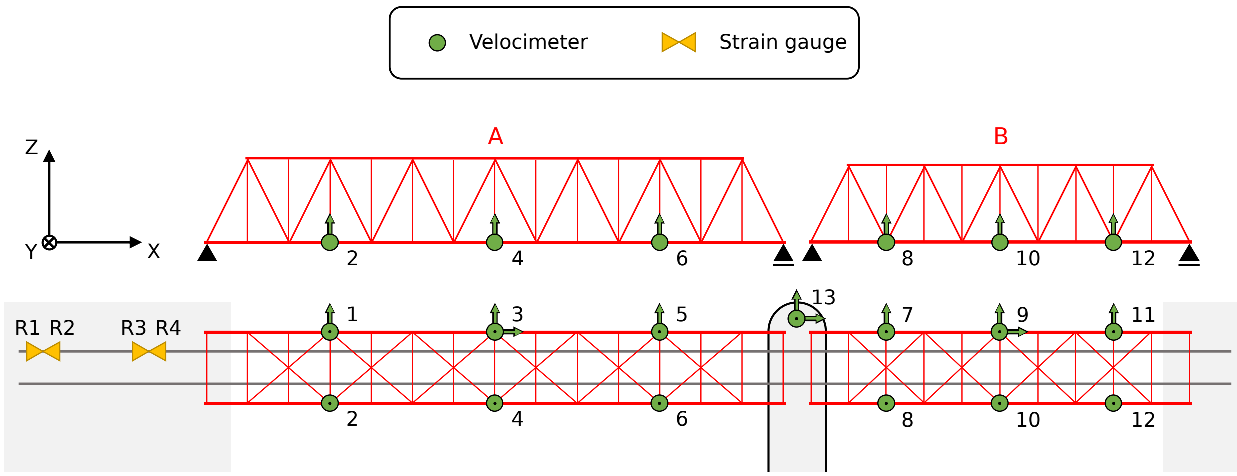

Figure 2. Positioning of sensing devices (strain gauges and velocimeters) along spans A and B.

All signals are acquired using a trigger logic, i.e. when the signal from any of the previous instruments exceeds a certain threshold, the signal is stored. A pre-trigger and a post-trigger are also set, so as not to interrupt the recorded event of interest.

3. STRAIN GAUGES APPROACH

This chapter describes the estimation of the average speed of the train and the axle load, by means of strain gauges measuring shear stress placed on the rail. This procedure is based on the technical specification *Sistema di misura dei carichi verticali dinamici dei rotabili*, draft by RFI.[14] To estimate the train speed and the axle load, two spans of measurement are instrumented and positioned at a distance $\boldsymbol{L}$ equal to 18 m (figure 3). This value corresponds to the distance between 24 railroad ties. The correct measurement of this distance is fundamental for the estimation of the train speed and the distance between the various railway axles. Each measurement span is placed symmetrically with respect to a pair of railroad ties, and thus the positioning coordinate of the span corresponds to the center line.
Moreover, each measuring span is composed of two measuring sections, each of which measures the shear stress acting on the rail at that specific coordinate, and the distance $\boldsymbol{D}$ between two measuring sections referring to the same span is approximately 0.55 m (figure 3). All measuring sections are oriented in the same way, so as to have consistent shear stresses measurements.

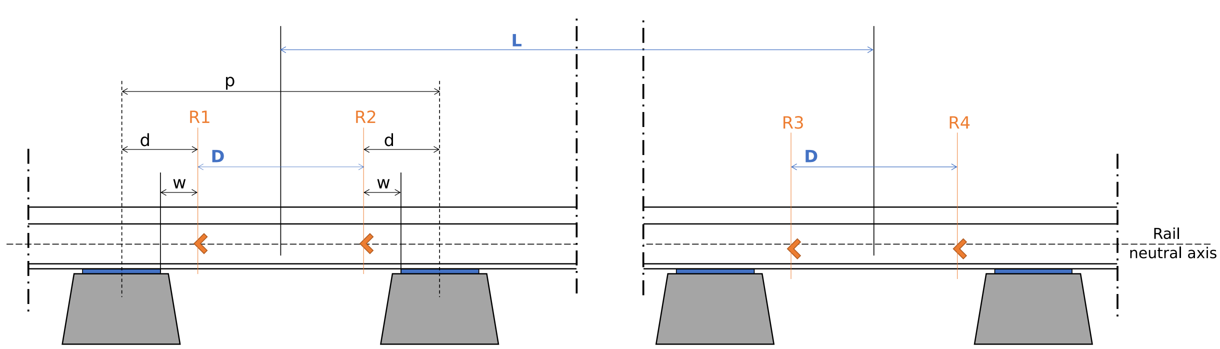

Figure 3. Schematic of strain gauges placement on the rail.

A measurement section is made up of two full-bridge strain gauge pairs, applied at 45° to the neutral axis of the rail, one on the inside and one on the outside of the track, so as to compensate for temperature, tension and bending. Using such instrumentation, with the distances described above, four strain gauge signals are therefore obtained, corresponding to the four measurement sections. By subtracting the signals from the same span ($R2$ - $R1$ and $R4$ - $R3$), a strain measurement is obtained that is directly correlated to the wheel load passing over the span, as depicted in figure 4.

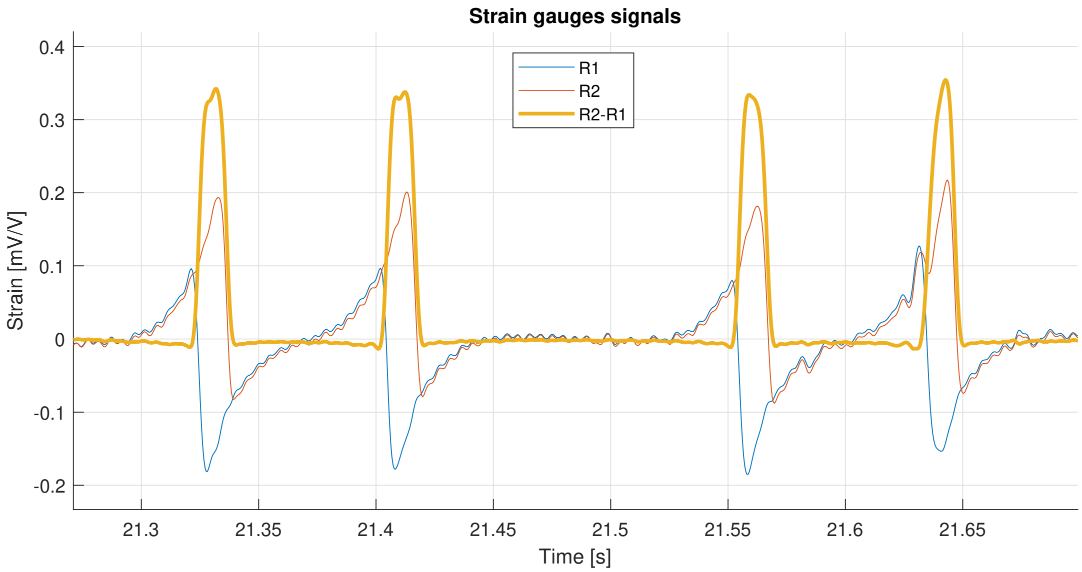

Figure 4. Example of the signals coming from the strain gauges (R1 and R2) and their combination, that leads to the measurement of the axle load. Four axles are represented in the plot.

The signal coming from the difference of the measurements of two strain gauges that belong to the same span is called s, and is measured in mV/V. Having two measuring spans in this system, we will have two strain signals, s_1 and s_2, that are defined in the following way:

$$s_1[n] = R_2[n] - R_1[n] \qquad\qquad s_2[n] = R_4[n] - R_3[n] \tag{1}$$

where n is the discrete coordinate representing the acquisition points. Since the same acquisition frequency of 2048 Hz was always used and the trigger activation is synchronous on all the sensors, the total number of acquisition points making up the signals is the same, and is indicated by N_s.

3.1 Speed estimation

For the estimation of the speed, the maximum of the cross-correlation between s_1 and s_2 and the corresponding delay is evaluated (not considering the delay values which would produce excessively high speeds). The cross-correlation between the two signals is defined as:

$$R_{s_1-s_2}[\Delta n] \overset{\text{def}}{=} \sum_{n=0}^{N_s-1} s_1[n]\ s_2[n+\Delta n] \qquad -N_s \leq \Delta n \leq N_s \tag{2}$$

Consequently, the maximum of the cross-correlation occurs in:

$$\begin{gathered} \Delta n^* = \underset{|\Delta n|<\Delta n_{lim}}{\arg\max}\ R_{s_1-s_2}[\Delta n] \\ \Delta n_{lim} = \Delta t_{lim}\ f_s = \frac{L f_s}{v_{lim}} \end{gathered} \tag{3}$$

where L is the distance between the two measuring spans, f_s is the sampling frequency of strain gauge signals and v_{lim} represents the maximum allowable speed for a train; a value of 300 km/h was chosen for this work. This choice was due to the fact that higher speed values would most likely be attributable to signal irregularities, and would have no physical meaning, given the speed limit in force on the Italian railway network. The delay Δn^*, corresponding to the cross-correlation maximum, divided by the sampling rate, becomes a time delay:

$$\Delta t^* = \frac{\Delta n^*}{f_s} \tag{4}$$

Finally, the ratio of the distance between two measurement spans and the time delay produces the estimate of the average speed of the train under consideration:

$$\bar{v}_{est} = \frac{L}{\Delta t^*} \tag{5}$$

3.2 Axle load estimation

For the load measurement currently used, strain gauges are employed to measure the shear stress acting on a single rail at a given longitudinal coordinate. The shear stress, in fact, integrated on the rail section allow to find the vertical load that generated it, that is, the load exerted by a wheel on the rail. As described above, after initial processing, two strain signals, s_1 and s_2, measured in mV/V, are obtained. Using the Gauge Factor of the strain gauge G_f, the expression of the physical strain can be obtained:

$$\varepsilon_{xy}\ [m/m] = \frac{s\ [mV/V]}{1000\ G_f} \tag{6}$$

This strain, being measured by a strain gauge, is axial. To calculate the shear stress to which the section is subjected, the corresponding angular strain must be calculated, through the well-known relationship:

$$\gamma = 2\varepsilon_{xy} \tag{7}$$

Now that the angular strain is known, the shear stress can be calculated as follows:

$$\tau_{max} = \gamma G = 2\varepsilon_{xy}\frac{E}{2(1+\nu)} \tag{8}$$

This stress value is associated with the application point of the strain gauges, located on the neutral axis of the rail, and represents the maximum value of the shear stress. The value of the traveling load, on the other hand, is related to the average stress acting on the rail section, which can be calculated by reducing the maximum stress with a multiplicative coefficient:

$$\bar{\tau} = c\tau_{max} \tag{9}$$

Once the average shear stress is known, the value of the vertical force causing this stress is:

$$T = \bar{\tau}A \tag{10}$$

The axle load value is:

$$M = 2\frac{T}{g} \tag{11}$$

where g is the gravitational acceleration and the factor 2 is due to the fact that, since only one rail is instrumented, the load due to only one wheel is measured, with the load due to the entire axle simply being twice that value. Now that the raw measurements of the load associated with each axle has been obtained, it needs to be regularized. Given the similarity between the peaks representing the load of the various axles and the Tukey window,[15] this type of window will be used to normalize the peak value of the loads associated with the various axles. To do this, the cross-correlation between a reference Tukey window and the signal M containing the series of the loads is calculated. The peaks of this cross-correlation function will be directly correlated with the axle loads values. The reference Tukey window represents the transit of an axle on the measurement span, so it consists of a number of points equal to:

$$N_p = \frac{D}{\bar{v}_{est}} f_s \tag{12}$$

where D is the distance between two measurement sections (for this work = 0.55 m), $\bar{v}_{est}$ is the average train velocity, and f_s is the sampling frequency of strain gauge signals. The other parameter characterizing a Tukey window is the cosine fraction, and this value depends on the geometry of the measurement span. For this work, a value of 0.6 was found to fully respect the shape of the individual peaks of the M signal. A key assumption for the proper use of the Tukey window to regularize the load measurement is that the speed of the train as it passes across the two measurement spans does not vary excessively.
The Tukey window thus characterized has maximum value 1; conversely, the signal M consists of a sequence of N_{ax} peaks (with N_{ax} total number of axles). If the assumption of relatively constant velocity is met, the peaks of the M signal will have a similar shape to the reference Tukey window, rescaled for the single axle load. At this point, denoting the reference Tukey window as $win[n]$, the expression of the signal M evaluated around a peak corresponds to:

$$M_k[n] = m_k win[n] \tag{13}$$

where m_k represents the height of the k-th peak, and thus the load of the k-th axle. Thus, using eq. 13, the cross-correlation between the reference window $win[n]$ and the signal $M_k[n]$ results in the following expression:

$$\begin{aligned} R_{win-M_k}[\Delta n] &= \sum_{n=0}^{N_p-1} win[n]\ M_k[n+\Delta n] = \sum_{n=0}^{N_p-1} win[n]\ m_k\ win[n+\Delta n] = \\ &= m_k \sum_{n=0}^{N_p-1} win[n]\ win[n+\Delta n] \qquad -N_s \le \Delta n \le N_s \end{aligned} \tag{14}$$

This expression, evaluated in its maximum, will be directly proportional to the k-th axle load:

$$\max R_{win-M_k}[\Delta n] = R_{win-M_k}[\Delta n]\big|_{\Delta n=0} = m_k \sum_{n=0}^{N_p-1} win^2[n] \Longrightarrow m_k = \frac{\max R_{win-M_k}[\Delta n]}{\sum_{n=0}^{N_p-1} win^2[n]} \tag{15}$$

Evaluating the cross-correlation between $win[n]$ and $M[n]$ will simply result in a function with N_{ax} peaks, and denoting the value of the k-th peak as $\langle \max R_{win-M_k}[\Delta n]\rangle_k$, the value of the k-th axle load will simply be:

$$m_k = \frac{\langle \max R_{win-M_k}[\Delta n]\rangle_k}{\sum_{n=0}^{N_p-1} win^2[n]} \tag{16}$$

Lastly, the full load of the train will simply be:

$$M_{TOT} = \sum_{k=1}^{N_{ax}} m_k \tag{17}$$

Through this procedure, it is possible to estimate the train of loads traveling on the bridge, and thus the total load of the convoy under analysis. Given the uncertainty about the values of the various physical constants used, especially the one used to calculate the maximum shear stress from the average stress on the rail section (see eq. 9), following this procedure, a calibration of the load measurement algorithm was performed. Using passages with known loads passing over the bridge, the value of the correction coefficient c has been estimated, such that a reliable load measurement was obtained. After this operation, the maximum deviation between known and measured loads is 3%.

4. DEEP LEARNING APPROACH

Once the train parameters (velocity, load for each axle and number of axles) are computed with the approach described in section 3, a deep learning architecture is taken into account for estimating them starting from velocimeter measurements. As described in section 2, the bridge is equipped with different multi-axial or mono-axial velocimeters for a total number of measurement channels equal to 23. For developing the algorithm able to estimate the train parameters, only channels that measures the velocity in Z-direction (vertical) are taken into account, leading to a number of 12 channels.
During the period of acquisition, a total number of 1020 passages are obtained. The dataset is splitted in training-validation-test partitions according to 75-15-10 rule.
Two different approaches (hereafter described) are adopted for developing a regressor to estimate train parameters.

4.1 Pre-processing

When considering a single passage of train acquired and stored in a triggered file, it is necessary to isolate the part of the signals related to the "forced motion" of the bridge response. To do so, velocimeter mounted on the pier placed in the middle of the bridge (velocimeter 13) is considered and two moving averages of the absolute value of the signal are computed, one with a window of 1 seconds (short), and the other with a window of 20 seconds (long). The short moving window represents an envelope of the signal, capable of following it also when its intensity goes rapidly up, as in the case of a train passage. The long moving window, instead, represents the average power of the signal, varying only slightly when a train passage happen. When the value of the fast moving window is the higher, the train is actually on the bridge: that portion of the signal represents the forced motion (as shown in fig. 5).

The different sensors present a time shift due to the different position along the bridge and the window is

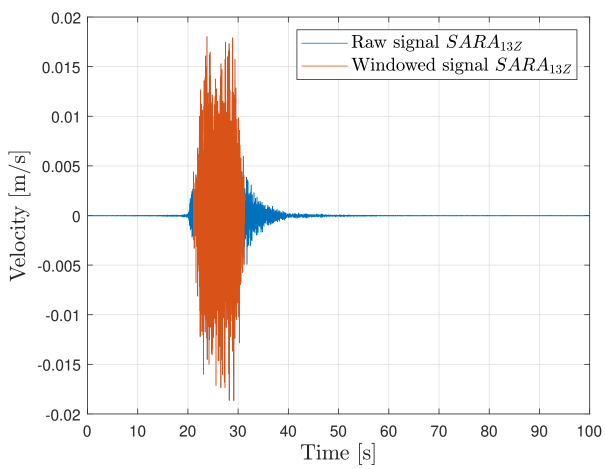

Figure 5. Isolation of forced motion.

computed on a sensor placed in the middle of the bridge. Since the minimum velocity acquired for a train passage is equal to 60 km/h and the bridge length is around 60 meters, to be sure to acquire in each velocimeter the entire forced motion, it is necessary to consider a "pre-window" and a "post-window" to be added to the force motion computed on velocimeter 13. These two windows are considered with a length equal to the time for travelling half bridge length (30 m) at the minimum velocity (60 km/h):

$$T_{pre\&post} = \frac{L/2}{v_{min}} = 1.8\ s \tag{18}$$

In this way, all velocimeter measurements are "trimmed" by adopting the same window, leading to have signals with equal length and that consider the entire train passage. For the next steps of the approach, the velocimeter 13 is not considered since it is not mounted on the bridge deck, but on the pile.

4.2 Feature-based approach

The first approach relies on the computation of different time domain features starting from the raw velocity signals. These features are reported in fig 6 and they are computed for each signal. In this way a total number of $n_{features} X n_{signal}$ features are obtained; in particular for this bridge 144 features are computed. // In this case,

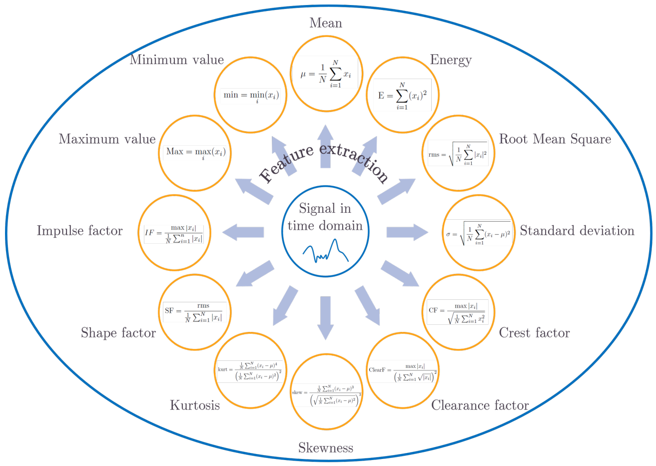

Figure 6. Time-domain features extracted from signals

the features represent the neural network inputs and a simple architecture (shown in figure 7) is adopted for estimating velocity, total load and number of axle of the train. The number of inputs and outputs are respectively 144 (total number of features) and 3 (number of parameters to estimate). All layers in this case are dense with ReLU activation function, except for the last one where linear activation function is adopted. Furthermore, a dropout layer is considered in the middle of the network.

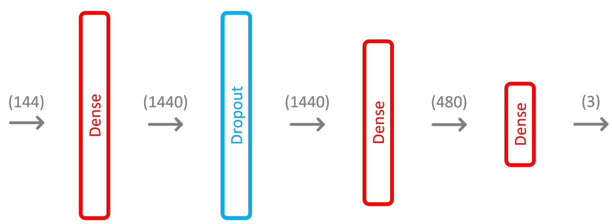

Figure 7. Neural network architecture for feature-based approach

4.3 Signal-based approach

The second approach directly feed the neural network with trimmed signals. In this case a completely different architecture (shown in figure 8), composed by convolutional and long short-term memory layers, is adopted. The

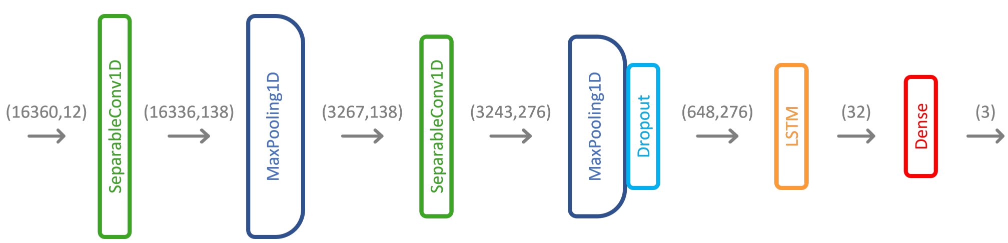

Figure 8. Neural network architecture for signal-based approach

main issue that has to be faced concern the fact that the input shape for the neural network has to be fixed and the different signals has a different length due to the nature of the acquisition performed with a constant

sampling frequency. So far, with reference to image processing, two solutions have been studied to cope this issue: *resizing*, which operates a bi-linear interpolation, and *padding*, that fill the remaining values with zeros. However, with resizing, slightly better performances have been achieved.[?] For this reason, a resampling procedure based on the longest signal available is applied.[16,17] In this way, all the signals will have a number of samples equal to the ones in the longest acquisition (16360 samples).
The last step concerns the data scaling by means of a max-min scaling technique. For each signal, all the samples in the training set are concatenated in a single vector, and then max (M) and min (m) values are computed. Hence, all the samples belonging can be normalized by computing the Z-score:

$$x_{scaled} = \frac{x}{M - m} \tag{19}$$

Then all the signals coming from the different velocimeters are arranged as column of a matrix of $n_{samples} X n_s ignals$ dimensions.

4.4 Results

Performances of the two approaches are evaluated on the test set in order to validate the ability of the network to generalize results for data that are not present in the training set. The metrics adopted for computing the performance are the mean absolute error in percentage (MAE (%)) and standard deviation of errors in percentage (σ_E (%)). Before deriving these quantities, it is necessary to compute the error in percentage for each observation in the test set and for each predicted parameter:

$$E_{i,\%} = \frac{y_i - \hat{y}_i}{y_i} * 100 \tag{20}$$

where y_i is the real value of the parameter and $\hat{y}_i$ is the predicted value. The two metrics are now defined as:

$$MAE(\%) = \frac{\sum_{i=1}^{N} |E_{i,\%}|}{N} \tag{21}$$

$$\sigma_E(\%) = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(E_{i,\%} - \mu_{Ei,\%})^2} \tag{22}$$

being N the total number of observation in the test set and $\mu_{Ei,\%}$ the mean percentage error. The result obtained are summarized in table 1.

	Feature based network			**Signal based network**		
	Total load	Speed	N° axles	Total load	Speed	N° axles
MAE (%)	7.31	5.01	7.02	5.89	4.95	6.38
σ_E (%)	31.2	25.4	36.7	11.1	8.2	6.3

Table 1. Metrics evaluated on test set.

5. CONCLUSION

This study proposed a machine-learning-based methodology to perform weigh-in-motion (WIM) by exploiting signals from velocimeters installed on a Warren-truss railway bridge in Italy. Two algorithms have been designed and tested by comparing the results to a standard WIM technique based on strain gauges placed on the rail track. In both cases loads, speed, and the number of axles have been estimated. The algorithm based on extracting some features from the velocity signals provided worse accuracy compared to the one which takes in input the raw time histories. The best-performing technique estimated the parameters of interest with a mean average error lower than 6.5% and a maximum standard deviation of 11.1%, related to the load estimation. Such promising results encourage using the proposed methodology as an alternative to strain gauges, which are fragile and placed in a position - the rail track - hard to reach for installation and maintenance purposes without interfering with the traffic circulation. Further developments foresee testing the methodology to other case studies, with the aim to increase its generality.

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