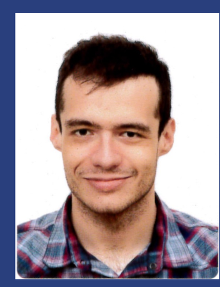
Forecasting the severity of design traffic loads exceeding on road's bridges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1.Introduction

Trucks frequently overcome the **mass limits** prescribed by **Traffic Codes**, sometimes leading to road's **bridge failures** when the traffic design loads of bridges are surpassed (Zhang et al. 2022).

The **severity** of design traffic load exceeding events is a key component of traffic load hazard risk assessment procedures, being a concise **driver of failure consequences** (Ventura et al., 2023).

Thus, forecasting the severity of these events is fundamental to **preserve the safety** of the road transport system by driving effective **traffic management actions** aimed at preventing bridge failure occurrences.

2.Literature gaps and research aim

On the one hand, **previous research** mainly focused on estimating (direct and indirect) failure consequences, by carrying out detailed cost analyses and calibrating refined traffic models accounting for the road network topology (e.g., Abarca et al., 2022; Fiorllo and Ghosn, 2022). However, these procedures are **time-consuming** and require **resource-consuming** elaborations that frequently hinder their applicability among Road Authorities.

On the other hand, only a recent study assessed the severity of design traffic load exceeding events as a driver of failure consequences (Ventura et al., 2023). **Econometric models** by **Binomial Logistic Regressions (BLRs)** were applied achieving good results. Conversely, **Machine Learning Models** by **Artificial Neural Networks (ANNs)** were never explored for this purpose despite their well-recognized performance in prediction (e.g., Hegde & Rokseth, 2020).

This research aims to **cover this gap**.

3.Materials and methods

Two different models are specified, calibrated, and validated to predict the severity metric (denoted as $\widetilde{V_s}$) as function of **several predictors** (denoted as f_s) measured during each temporal slot (denoted as $s \in S$).

The former is based on a **BLR** trained with an automated stepwise technique:

$$\widetilde{V_s} = \frac{e^{\alpha+\sum_{f\in F}\beta_f f_s}}{1+e^{\alpha+\sum_{f\in F}\beta_f f_s}};\ \forall\, s \in S;$$

where α and β_f are the coefficients of the model.

The latter is based on a **two-layer feedforward ANN** trained with the scaled conjugated gradient algorithm:

$$\widetilde{V_s} = \widetilde{\omega}(\{f_s \in F\}, \theta_0);\ \forall\, s \in S;$$

where $\widetilde{\omega}$ is the function describing the ANN structure and θ_0 is the vector of the ANN parameters.

These models are compared by **Confusion Matrixes (CMs)**, some **Performance Indicators (PIs)** and the **Cross Entropy (CE)** parameter to evaluate their fitting and forecasting performance.

More than **7.4M raw vehicular records** acquired by **Weigh-In-Motion system** on a bridge (simply supported overpass structure, 23.5 m span length) along a main road in the city of **Brescia (Italy)** are elaborated to set up the two models.

4.Results

Confusion Matrixes on the training dataset.

Parameter	Typology	BLR model Training	BLR model Test	ANN model Training	ANN model Validation	ANN model Test
II comparison strategy						
True positive rate ($\mathcal{TPR}$)	+	99.4%	100%	99.4%	100%	97.0%
True negative rate ($\mathcal{TNR}$)	+	100%	99.9%	100%	100%	99.9%
Positive predictive value ($\mathcal{PPV}$)	+	100%	97.0%	100%	100%	97.0%
Negative predictive value ($\mathcal{NPV}$)	+	100%	100%	100%	100%	99.9%
False negative rate ($\mathcal{FNR}$)	−	0.6%	0.0%	0.6%	0.0%	3.0%
False positive rate ($\mathcal{FPR}$)	−	0.0%	0.1%	0.0%	0.0%	0.1%
False discovery rate ($\mathcal{FDR}$)	−	0.0%	3.0%	0.0%	0.0%	3.0%
False omission rate ($\mathcal{FOR}$)	−	0.0%	0.0%	0.0%	0.0%	0.1%
Accuracy ($\mathcal{ACC}$)	+	100%	99.9%	100%	100%	99.8%
III comparison strategy						
Cross Entropy (CE)	−	0.0202	0.0435	0.0059	0.0042	0.0096

+ : Positively oriented score (more is better)
− : Negatively oriented score (less is better)

Comparison among the fitting and prediction performances of BLR and ANN models.

Traffic flow characteristics, interaction between vehicular and bridge characteristic, and compliance with Traffic Code load limit prescriptions resulted the **factors having the stronger influence** on severity predictions.

Moreover, on the one hand, findings indicated a **similar (and strong) fitting and predictive power** for BLR and ANN models when **CMs** and **PIs** were considered.

On the other hand, the ANN model showed **a CE value an order of magnitude lower** than the BLR model, implying that the former predicted severity records with **higher confidence** than the latter.

5.Conclusions

This research provides the **first empirical contribution** into the potentialities of **Machine Learning Models** in predicting the severity of **design load exceeding events** brought on by traffic load hazard on a road's bridge.

The results could **support Road Authorities** to implement effective traffic management strategies to increase the safety of bridges against traffic load hazards.

An investigation on the impact of Artificial Neural Network modelling approaches in **assessing the risk** of traffic load on bridges is recommended as **future development**.

Learn more:

References

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