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Predicting the military load class from bridge data with a multilayer perceptron

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ABSTRACT: Assessing the load bearing capacity of civilian bridges is a challenging task for routine reassessment jobs, especially in the military context. In order to ensure mobility of troops, the load bearing capacity of bridges needs to be assessed to make the safe crossing of military vehicles possible at home and abroad. For this reason, rapid assessment methods have been developed that allow for classification of civilian bridges after a quick visual reconnaissance. In the absence of verifiable calculations or drawings, the applied methods need to be based on geometrical data that is suspected to be correlated to the military load class of a structure. Current approaches are based on simplified assumptions such as correlations between dead loads and live loads or consist of simplified calculations assuming conservative material properties. In order to improve the current classification method, a Machine Learning (ML)-based methodology is given that classifies slab to a particular military load class without human intervention using a correlation between measured geometrical data and classification result. It is concluded that the usage of ML models is very promising for rough classifications of bridges with unknown military load class (MLC). However, the available training data is insufficient to train reliable models and an expanded amount of training data will be needed for deployment as a software package in the armed forces.

1 INTRODUCTION

1.1 *Importance of bridge assessment*

The assessment of the load bearing capacity of existing bridges is a challenging task when no verifiable calculations or as-built drawings are available. The development of methodologies to assess the maximum bearable traffic load is thus of special interest when the rapid assessment of the bridge geometry is the only source of information. For military bridge assessment, this is the case when convoys have to be guided through unknown terrains or when supply routes have to be planned. Use cases such as these have already been encountered in stabilization missions or similar military operations. (Haslbeck, Hertle & Braml, 2021; Haslbeck, Vallée & Braml, 2021).

Based on those experiences, bridge assessment codes have been developed independently by several nations to ensure a safe crossing of military vehicles over civilian bridges. The approach of most of these methods is to derive the maximum allowable Military Load Class (MLC) of a bridge from geometric parameters of the main structural parts. In order to enable soldiers to classify a bridge in the field, the tablet-based application BRASSCO-NG has been developed by the University of the Bundeswehr that allows for a rapid assessment on site.

For the application of BRASSCO-NG and the user interface please refer to (Haslbeck, Hertle & Braml, 2021; Haslbeck, Vallée & Braml, 2021).

1.2 *Introduction to military load classes and STANAG2021*

As the main output of the presented methodology using machine learning (ML) is the attribution of a military load class (MLC) to a specific bridge in the field, the system of matching vehicle MLC and bridge MLC needs to be discussed briefly.

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The framework of STANG2021 (NATO) describes a system of hypothetical vessels that shall reflect the true loading of military vehicles. Due to the different nature of the load distribution, each class comprises a load model for wheeled and for tracked vehicles. Due to reasons of brevity, the reader is referred to (Geissler, 2014) for further information on the MLC system and the attributed load models.

The system of load models describes the shape and the weight of the assumed vehicles both for structural analysis and the classification of the carrier to a certain MLC. Using the load scheme, each bridge can be sorted into a MLC class using the maximum bearable bending moment and shear force. Interpolation between different load classes is permitted, so intermediate MLCs are allowed. As the load bearing capacity for one-way and two-way traffic, the allowable load class is commonly split into a one-lane and a two-lane MLC.

As verifiable calculations are in many cases not available, the attribution of a MLC to a specific bridge often requires the assumption of a correlation between certain observable properties of a structure to its MLC class.

1.3 *Current approach*

Reconnaissance of civilian bridges is based on the recording of geometrical data using folding rules or laser distance meters. From this data, a correlation function is applied that exploits the assumed correlation of dead load and the ultimate load from military vehicles expressed by the capacity to resist a certain unit bending moment. This method for regression relies very much on engineering experience. The correlation function for the ratio of moment from dead load and moment from live load has been calibrated by a large number of verifiable calculations for bridges of different span length and construction types. However, the assumed relation might be improved by a more sophisticated regression using machine learning techniques.

1.4 *Potential of machine learning for bridge assessment and scope of this contribution*

In order to implement a regression for the maximum MLC depending on a set of geometrical input parameters, Artificial Intelligence (AI) can help to go beyond engineering experience and to find correlations that are not visible at first sight.

Using a limited data set available from a NATO database, the potential of machine learning techniques is revealed in this contribution using the example of slab bridges.

After a brief review on the theoretical background of the applied machine learning technique, the required input for the graphical user interface of BRASSCO-NG is depicted. Subsequent to the description of the implementation, several worked examples are given in order to present the results and to discuss the pros and cons of this new approach to military bridge assessment.

2 RELATED WORK

2.1 *Machine learning*

Neural Networks (NNs) are able to solve very complex problems more accurately than other algorithms in the field of machine learning, e.g. linear regression, decision tree (Wu et al., 2008) or random forest (Ho, 1995). The regression of tabular data can be a complex task, for the solution of which the NNs can be particularly suitable. The architecture of Neural Networks is inspired by biological neurons, in the ML context also called nodes. The special feature of NNs compared to other algorithms in the ML domain, is the contained weighted information in nodes forwarded to neighboring neurons. These weights (synapses) are trainable, whereby a transmitted signal can be amplified or attenuated (Goodfellow et al., 2018).

Figure 1 shows the sequence of the forward process that is carried out during inference of tabular data from a bridge. The model that will be used in this work is a multilayer perceptron (MLP), a neural network consisting of linear layers. Each input parameter is fed into the NN. Subsequently, the inputs are multiplied by weights. After having summarized all weighted inputs of one node, and biases were added, the activation function is applied. The aforementioned operations and the application of the activation function will be executed for all nodes in the hidden layer. For the nodes in the output layer, no activation is applied in order to obtain the result of the regression describing the military loading class.

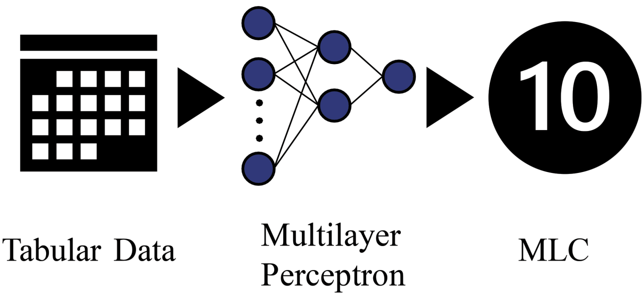


Figure 1. Feed-forward process of the MLP calculating MLC from tabular data.

2.2 *Machine learning models for load-carrying capacity*

Truong et al. (Truong et al., 2022) have analyzed the applicability of ML models for the estimation of the load-carrying capacity of semi-rigid connected steel structures. They evolved a dataset using the advanced analysis based on beam-column and zero-length elements. The model's input layer consists of member cross-sections and parameters of the high-order nonlinear functions characterizing the semi-rigid connection behaviors. They evaluated multiple ML methods: linear regression models, support vector machines, tree-based ensemble algorithms and models from the field of deep learning. The most performant model for solving the problem of depicting the load-carrying capacities of semi-rigid connected steel frames is XGBoost (Chen & Guestrin, 2016).

3 METHODOLOGY

3.1 *General*

The collection and preparation of data for later evaluation by AI represents a crucial step in the process chain of developing a military AI. The reliability of the trained model depends crucially on the data provided. For the model to be trained within the project, the collection of design drawings with associated MLC classification provided by the Military Engineering Centre of Excellence (MILENG-COE) will be used. In particular, the use of intermediate MLCs representing not only the load models depicted in STANAG 2021 (NATO) but also values representing interpolation between them, could find use in the training process. The geometric dimensions were taken manually from the design drawings.

The modeling of the neural network requires knowledge of the problem and the algorithms to be used as well as insight into the existing dataset. Especially the complexity of the regression model depends on the available data and the correlations. In the context of the investigations, a linear neural network is used, whose theoretical background is discussed in Section 3.2. For the training of the NN and the test of the regression, a MATLAB script has been used where the input is read directly from the NATO database provisioned for the testing of MLC classification methods.

3.2 *Multilayer perceptron*

The operating principle of the neural network is explained in the following. The geometry information stored in the input variables is summed up in the neurons after the multiplication by their weighting factors to represent the importance of the information. To this, the bias b is added, which is trained as a parameter.

The nodes in the hidden layer are activated by the sigmoid function according to Equation 1.

$$y = \frac{1}{1 + e^{-\left(-\sum_j c_j x_j - b\right)}} \tag{1}$$

$$y = f(c_1 x_1 + c_2 x_2 + \ldots + c_n x_n + b) = f\left(\sum_j^n c_j x_j + b\right) \tag{2}$$

The multilayer perceptron includes one hidden layer with three nodes. The activation function in the hidden layer is the sigmoid function. During one training step all samples are fed into the network. Thus, the batch size corresponds to the number of data points in the training split. The default value of the learning rate of 0.001 is chosen. In total the training process is repeated for 100 epochs.

Table 1. Hyperparameters and architectural parameters of the network.

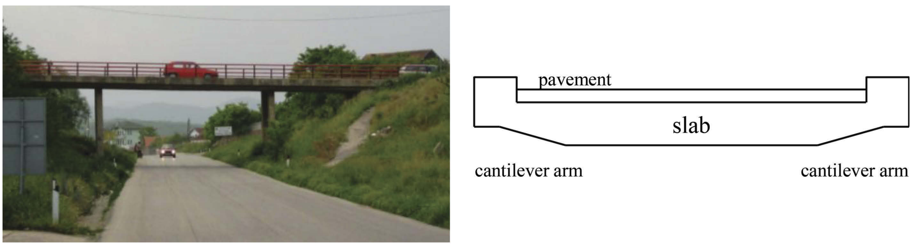
Parameters	Value
Hidden layers	1
Nodes in hidden layer	3
Activation function	Sigmoid
Batch size	37
Learning rate	$1e^{-3}$
Train epochs	100

4 IMPLEMENTATION OF A NEURONAL NETWORK FOR SLAB BRIDGES

4.1 *Engineering background*

For the purpose of this paper, the automatic evaluation of slab bridges shall be used as they are common on side roads with few heavy traffic to span over small and medium gaps.

The cross section of a slab bridge is formed by the slab itself and two cantilever arms at both outer faces. Figure 2 shows (a) a slab bridge as it has been found in the KFOR mission in Kosovo and (b) the schematic representation of the cross section with its major parts.



(a) (b)

Figure 2. (a) slab bridge in the regional road network in Kosovo from (KFOR) and (b) illustration of the cross section and its parts.

4.2 *Input values and dataset*

In order to exploit the assumed correlation of maximum load bearing capacity of a bridge and its physical dimensions, data from the cross section and the civil engineering system in longitudinal direction are part of the input into the BRASSCO-NG code. Figure 3 shows the GUI of the software package and the required dimensions. Especially challenging for the determination of the input was the need to choose a representation that corresponds to the various construction types for slab bridges in different regions. It should be noticed that the evaluation is based on a symmetrical cross section as the load bearing capacity is evaluated for the most unfavorable position of load, so only the weaker half of the superstructure's cross section is shown in the GUI. For the evaluations of this paper, only the height if the slab and the span length has been used as input because these values appear to be the most influential.

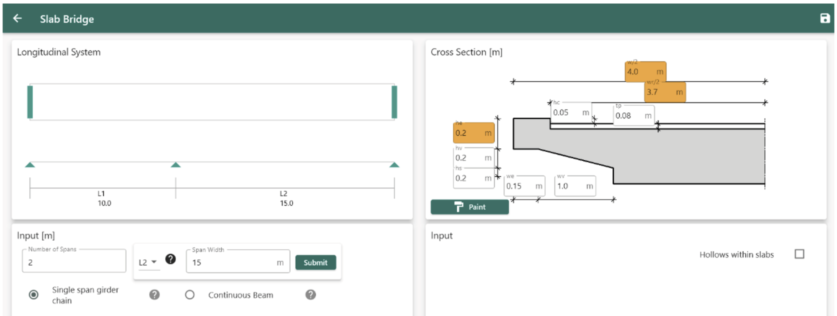


Figure 3. GUI of BRASSCO-NG for slab bridges with the required input L1, L2, …, he, hv, hs, we, wv, hc, tp, w/2, wr/2.

In order to achieve the best possible result from the training of the neuronal network, a set of data has been chosen that represents a large spectrum of bridges. Figure 4 shows a histogram of the set of MLC for single lane crossing of wheeled vehicles in the training data of size 37.

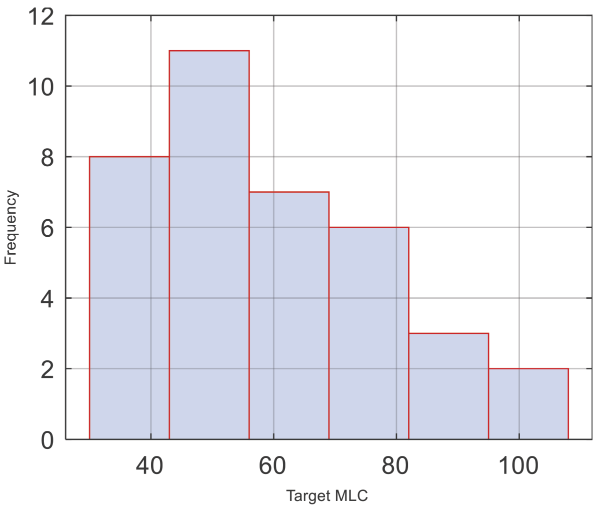


Figure 4. Histogram of the target MLC for the classification of slab bridges for single lane traffic of wheeled vehicles.

The bridges' heights range from 3.7 to 25 meters while the widths and spans range from 0.20 to 0.80 and 4 to 17 meters (Table 2). Generally, the variety in geometries indicates a strong heterogeneity of the underlying data.

Table 3 shows the sample distribution over the data splits. In total the dataset includes information of 40 bridges. The size of the dataset can be considered as small compared to others,

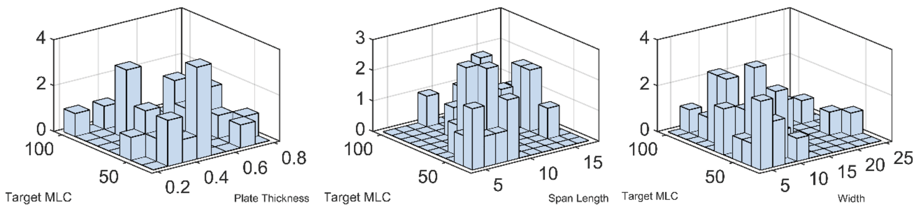


Figure 5. Histograms for the input parameters.

Table 2. Minimum, median and maximum for the input parameters of slab bridges, demensions in in [m].

Parameter	Min	Median	Max
Height	3.7	7.4	25
Width	0.20	0.44	0.80
Span	4	8.8	17

such as the ones named in chapter 2.1. Therefore, the data was split in into two packages, the training and validation split. The validation split also represents the test data. Usually, datasets consist of a training, validation and test split. The three samples included in the test package approximately describe the whole range of bridges in the dataset regarding the MLC.

Table 3. Train and validation splits for the MILENG plate dataset.

Split	Count
Train	37
Validation/Test	3
Total	40

4.3 *Results and discussion*

In order to show the applicability and the advantages of machine learning techniques to the subject of military bridge classification, the results of the process of training are presented and discussed.

Figure 6 shows the progress of the loss during training. It can be stated that the loss continually decreases without significant variability and the patterns in the training data are well recognized by the network.

Regarding the differences between predictions and targets in Figure 7 an acceptable performance is observed. Only six predictions differ more than 10 MLC from the target. Most prognosticated samples have a difference, compared to the target, of less than five MLC.

The neuronal network was tested using three examples of bridges that were not part of the training data. To show the applicability, the test set of bridges was chosen such that the lower, medium and higher range of the MLC spectrum is covered. The target values for the three examples can be given by MLC 55, 95 and 20. Table 4 gives the design values, the result from the approach currently implemented in BRASSCO-NG and the result gained from the regression done by machine learning. The results of this small control sample indicate that the application of neuronal networks might be a significant advance for the classification of civil bridges. Even though the classification result does not show perfect agreement to the target values of the structural analysis, the results fit better than the currently implemented approach using the bending moment from dead load or the linear fit of the parameters to the target

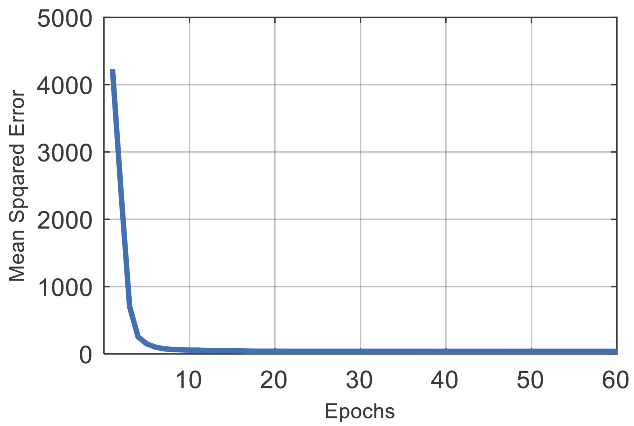


Figure 6. Loss during the training process for slab bridges.

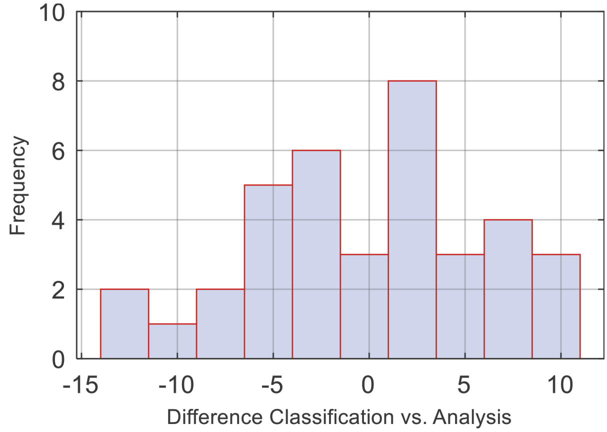


Figure 7. Differences between predictions and targets for slab bridges.

values. However, a larger sample set and a wider range of MLCs is required to improve the regression. This is especially true for the lower part of the MLC spectrum (test sample #3).

Table 4. Comparison of the results for slab bridges (single lane, wheeled vehicles).

Test Bridge no.	Structural analysis (target)	Current approach	ML-approach	Linear regression
#1	55	100	76	86
#2	95	150	81	140
#3	20	80	50	47

5 CONCLUSIONS

In this contribution, a new approach for the classification of civil bridges for military purposes is presented utilizing Machine Leaning techniques instead of state-of-the-art engineering approaches. The results show that the methodology is superior both to the current method and a simple least squares regression that was performed for reasons of comparison. It can be reasoned that the application of the presented approach is very promising. However, the data set used for training is not yet sufficient for application in the field and needs further enlargement. What is more, an analysis of sensitivities for the applied input as well as the amplification of the studied input parameters may give further insights into the correlation of certain features and the load bearing capacity. Supplementary to the measurable geometrical dimensions, the inclusion of the material strength, the percentage of reinforcement or the design load model are very promising for further investigations. Further improvement may also be made when other Machine Learning methods are applied and compared to the implemented linear neuronal network, e.g. decision tree, support vector machines or random forest.

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