Surrogate model for predicting stresses of concrete slabs subjected to real vehicle loading using multilayer perceptron neural network

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Abstract. This work proposes an innovative method that uses machine learning with computational Finite Element Analysis simulations to optimize the design of concrete slabs for rigid pavements subjected to moving loads with different parameters. The objective is to create a surrogate model that takes into account the uncertainties of weight and shape of the vehicle loading on the concrete slabs, to predict the stresses in the concrete slabs. Based on the results of realistic finite element models that consider the three-dimensionality of the multilayer problem analyses, machine learning techniques are used to train and validate a surrogate model. This model allows the analysis of stresses in concrete slabs under different conditions of vehicle load and pavement geometric and mechanical properties. Based on these analyses, it is possible to optimize the shape and thickness of concrete slabs to cope with the effects of uncertainties, thus ensuring adequate performance of the structure under a wide range of operating conditions. This approach allows for a more precise and efficient optimization of concrete slabs, taking into account the stochastic variables involved in the process.

Keywords: finite element analysis, concrete slabs, surrogate model

1 Introduction

The Jointed Plain Concrete Pavement (JPCP) is the most commonly used type of rigid pavement, consisting of Portland Cement Concrete constructed slabs, typically laid upon layers of bases and subbases. The JPCP is a solution where the slabs are constructed with closely spaced contraction joints [1], with dowel bars being used for load transfer across them. It is the cheaper to construct than the other types of rigid pavements, being recommended for lower volume truck routes, ramps, urban streets.

Finite Element Analysis (FEA) is a computational numerical analysis method for obtaining approximate solutions for various engineering problems, its core idea being that any region can be modeled or analytically approximated by substituting it with an assembly of discrete elements [2]. By utilizing this tool, it is possible to create a model that simulates the passage of a vehicle axle load on constant speed over a 3 x 3 system of JPCP slabs, obtaining outputs such as stresses and displacements throughout the parts of the model.

Multilayer Perceptron Neural Network (MLP) is a machine learning technique, consisting of an artificial neural network composed of an input layer, one or more hidden layers, and an output layer, where each layer consists of interconnected neurons that process input data to produce an output [3]. A Surrogate Model is an approximation technique used to replicate the behavior and substitute a computationally expensive simulation. By training data generated from the FEA models, the surrogate model can provide rapid predictions, while significantly reducing computational costs.

In the present paper, a data set containing the outputs of stress in the traffic flow direction (σ_{yy}) at the bottom surface of the central slab was extracted from the results of 400 of the FEA simulations, where the input parameter for each model was randomly generated based on typical values distribution found in the literature. These parameters, such as geometric dimensions, load configuration, and material properties were stochastically varied to accurately represent a wide range of scenarios and conditions documented in existing studies. Afterwards, the data set was fed to a MLP Neural Network, building a MLP-based Surrogate Model, which can predict stresses in JPCP slabs in a less computationally complex way.

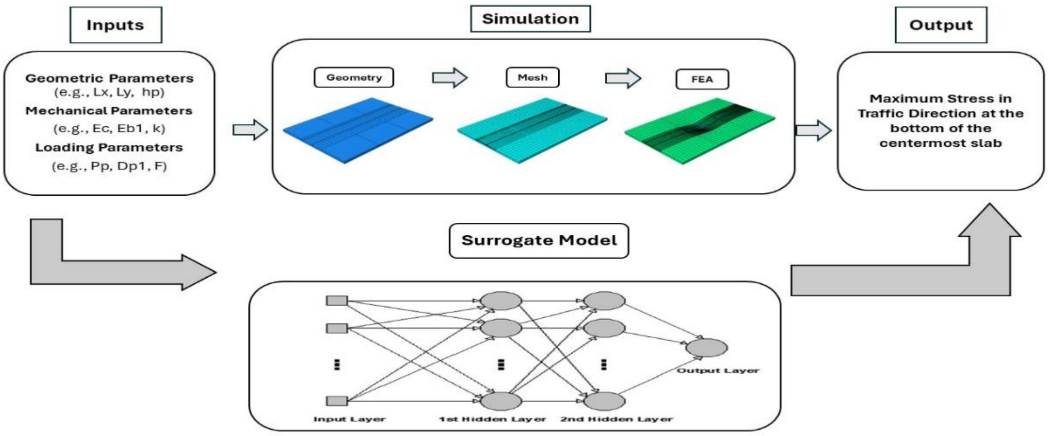

Figure 1. Surrogate Model Fluxogram

2 Methodology

2.1 Stochastic Variables

The input variables for each model were randomly generated to reflect a range of realistic conditions. All parameters are continuous variables following uniform distributions, except for the dowel diameter (ϕb) and number of dowel bars (nb), which are discrete variables following uniform distributions, and the lateral wheel wander (Dh), which is a continuous variable on normal distribution (sigma = 0.15 and u = 0.5) [4]. As it occurs in practicality, a subbase layer is not always utilized in rigid pavement design, so its respective variable varies between 0 and 1 as well. The interval for each parameter was defined based on typical values found in design manuals and rigid pavement literature, as summarized in Table 1.

Table 1. Parameters description and variation

Parameters	Description	Variation
Lx	Slab Width (m)	[3.00 - 5.00]
Ly	Slab Length (traffic flow direction) (m)	[5.00 - 7.00]
hp	Slab Thickness (m)	[0.15 - 0.30]
hb1	Base Thickness (m)	[0.12 - 0.40]
hb2	Subbase Thickness (m)	[0, 0.12 - 0.40]
Dh	Lateral Wheel Wander (m)	[0.00 - 1.00]
ϕb	Dowel Bar Diameter (mm)	[32, 33, 34, 35, 36, 37, 38]
nb	Number of Dowel Bars per Joint	[12, 13, 14, 15, 16, 17, 18]
Ec	Concrete Young Modulus (GPa)	[20.00 - 40.00]
Eb1	Base Young Modulus (GPa)	[7.00 - 20.00]
Eb2	Subbase Young Modulus (GPa)	[0, 7.00 - 20.00]
k	Modulus of Subgrade Reaction (MPa/m³)	[20.00 - 70.00]
Axle	Type of Axle	[Single, Tandem]
Dp1	Horizontal Spacing between Tires (m)	[1.50 - 2.20]
Dp2	Vertical Spacing between Tires (only Tandem Axle) (m)	[1.00 - 1.50]
Pp	Tire Pressure (kPa)	[200.00 - 700.00]
F	Load on Each Tire (kN)	[23.00 - 67.00]

2.2 Area of Contact

The loadings are considered to be distributed loads acting along a defined area of contact of each tire. Such area of contact (Ac), as suggested by Huang (2004), can be obtained by dividing the load on each tire (F) by its pressure (Pp). Its shape is assumed to be a rectangle with its length being equal to 1.205Ac (direction of traffic flow) and width 0.83Ac.

2.3 FEA Models

The FEA Model consists of a 3 x 3 JPCP system, with dowel bars placed throughout the transverse joints of the 3 central slabs (2, 5 and 8). Every slab is laid upon a base (and a subbase, in some cases), and the lowermost layer is considered to rest on a Winkler foundation. Tie constraint interactions were created to simulate the interaction properties between bottom surface of the slabs and top surface of the base, and to restrain relative movement along the longitudinal joints. The top surfaces of the slabs 2, 5 and 8 were partitioned as to represent the passage of the calculated Ac of the tire, and the loads were applied in sequential steps of the analysis. All the outputs (σ_{yy}) were extracted from bottom of surface of the slab 5. The software ABAQUS 2020 was utilized to create and analyze every model.

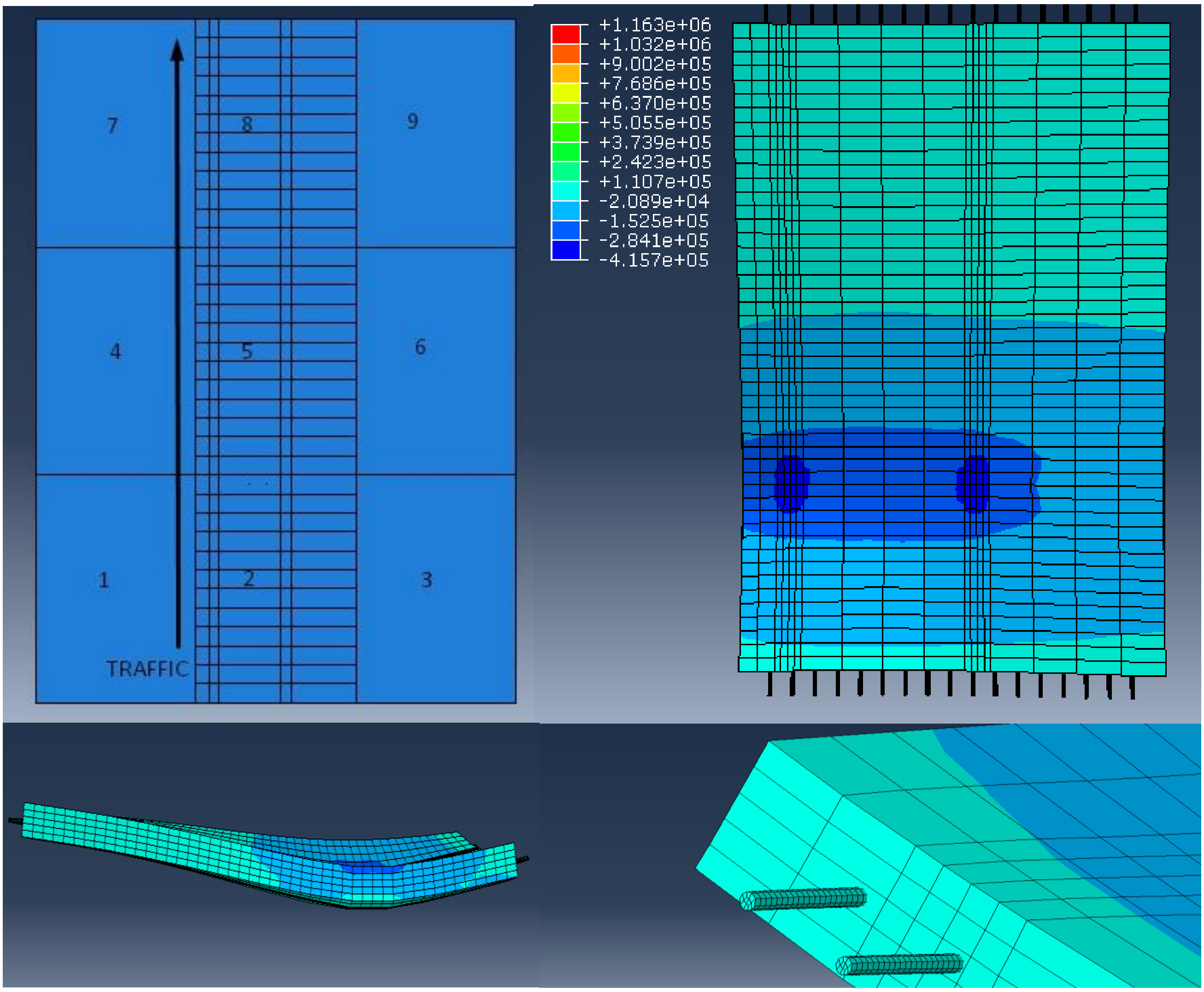

Figure 2. Example of a FEA Model. a) Assembly of the Model and Slabs numeration; b) Top view of deformed slab 5; c) Left view of deformed slab 5; d) Dowel Bar embedded into slab

2.4 Multilayer Perceptron Neural Network (MLP)

The data set was split in 80% for training and 20% for testing, the input data set consisting of a 400 x 18 matrix and the output consisting of a 400 x 1 vector. For the training set, a k-fold cross validation was done with k = 5. For the hyperparameters optimization, the technique utilized was Bayesian Optimization, being the loss function the mean of Mean Squared Error (MSE) from each fold. The activation function for the hidden layers was the Rectified Linear Unity (ReLU). The gradient-based optimizer utilized to determine the optimal parameters of the MLP is a variant of Adam [5] called AMSGrad [6]. Some regularization techniques were implemented: Early Stopping, Weight Decay and Batch Normalization [7]. With the model fitted, the Permutation Feature Importance technique was utilized to evaluate the importance of each feature with n = 1000 permutations.

3 Results

The metrics obtained for the model are R^2 test: 0.82, RMSE (Root Mean Squared Error) test: 35.111, MSE test (Mean Squared Error): 1232.795, MAPE (Mean Absolute Percentage Error) test: 37.70 %, SD (Standard Deviation) of APE (Absolute Percentage Error): 45.29 %, Mean MSE - Validation: 1954.00, SD MSE - Validation: 460.17. The importance of each feature in the model is presented in Table 2, where the second column indicates the Mean of the increase of MSE after the permutation. The graphic is displayed in Fig.3, the horizontal axis being the observed value and the vertical axis predicted by the surrogate model.

Table 2. Results of the Permutation Feature Importance

Parameters	Mean	SD
hb2	4449.26	41.79
hb1	3227.59	43.05
F	1112.6	48.05
Ec1	1026.05	49.74
Eb1	791.87	60.18
k	481.45	68.59
Single_Axle	352.43	80.17
Tandem_Axle	327.03	95.16
Dh	267.91	110.57
Ly	203.6	116.3
Dp2	147.77	119.8
Pp1	75.87	122.64
Lx	58.58	178.96
Eb2	44.67	248.9
db	26.42	262.47
nb	11.11	300.84
Dp1	-3.2	733.61
hp	-27.44	963.59

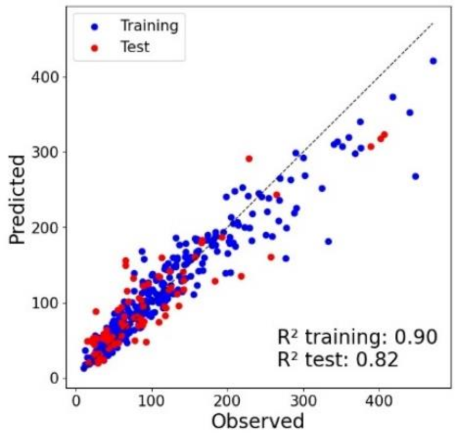

Figure 3. Graphic representing Observed x Predicted for the output Variable

4 Conclusions

It is observed that the model could attain 0.82 as a value for R^2, indicating an acceptable level of accuracy in its predictions, which makes the model, even though still partial, effective as a Surrogate Model for the analysis of stresses in traffic flow direction for concrete pavement slabs. In future works, it will be possible to further improve the model by increasing the numerical data set or by creating surrogate models for other outputs, such as vertical displacements or stresses in other directions.

After the implementation of the Permutation Feature Importance technique, it was expected that the slab thickness (hp) would be a much more important parameter, with a lesser SD, but as the results are still partial, it is possible to assume that, with a higher number of FEA simulations, it will be possible to obtain a more satisfactory result.

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