XLVI CILAMCE
VITÓRIA - ES - BRAZIL - 2025
XLVI IBERO-LATIN AMERICAN CONGRESS ON COMPUTIONAL METHODS IN ENGENEERING

Pavement backcalculation using artificial neural networks

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Abstract. Pavement structural evaluation constitutes an essential component of management and maintenance routines. In this context, the precise determination of layer stiffness properties (elastic moduli) is fundamental for pavement backcalculation, enabling more accurate *in situ* assessments, supporting quality control in construction and rehabilitation, as well as an enhanced estimation of structural service life. Given the intrinsically nonlinear nature of the backcalculation problem, approaches based on Nonlinear Least Squares (NLS) minimization have been employed, utilizing optimization algorithms such as Gauss-Newton (GN) and Levenberg-Marquardt (LM), which demonstrate robustness in their application. However, it is observed in iterative methods the convergence speed of NLS optimization algorithms can be perceptibly influenced by the choice of initial estimates (seed moduli). In this context, Artificial Neural Networks (ANNs) represent a promising alternative, particularly due to their capacity to directly map deflections to moduli with notable computational speed and efficiency after training. Training a neural network necessitates a vast dataset, which can be synthetically generated using models such as the Finite Element Method. This study employs an Artificial Neural Network (ANN) to perform pavement backcalculation. The performance of the trained model is assessed using two distinct datasets: manufactured data from a Finite Element Model and in-situ field data from Falling Weight Deflectometer (FWD) tests. Furthermore, this research investigates the use of the ANN-predicted moduli as initial seed values for a traditional iterative optimization process to study potential gains in computational efficiency.

Keywords: Backcalculation, Gauss-Newton, Nonlinear Least Squares, Artificial Neural Networks.

1 Introduction

The structural assessment of pavements constitutes an essential activity for roadway maintenance. It assists in quality control of pavements in service, development of maintenance plans, and recommendation of necessary interventions for proper roadway functionality. Consequently, this area attracts significant investment and research as a means to develop methods that render this process efficient from both analytical and economic perspectives [1].

Testing procedures conducted on pavements, necessary to generate data enabling adequate analysis, can be destructive or non-destructive. Destructive testing involves the extraction of samples and laboratory testing, generating substantial costs and delays. Conversely, non-destructive testing presents a more rapid and effective means of generating data that enables the assessment process. For flexible pavements, the most widely utilized non-destructive test is the Falling Weight Deflectometer (FWD) [2].

Data obtained from FWD testing are employed to estimate the mechanical properties of pavements in service through a process termed backcalculation. Backcalculation is an iterative process that seeks to compare the responses of a pavement analysis model with deflections obtained by the FWD through an error function. The process aims to minimize this error to an acceptable value, determining a set of mechanical properties that best approximate the deflection basin obtained during testing.

The principal limitations of traditional backcalculation techniques include non-uniqueness of solutions, seed

modulus dependence, and convergence to local minima [1]. In their investigation of factors influencing pavement backcalculation, Torquato e Silva et al. [3] found that the choice of initial seed moduli did not significantly affect the final resilient moduli values, thereby demonstrating the robustness of the optimization algorithm employed in BackCAP software [4]. However, it should be noted that a seed modulus closer to the global solution can accelerate the convergence toward the optimum, improving the computational efficiency.

Neural networks constitute a computational technique that seeks to solve complex problems through machine learning, being extensively utilized in engineering applications, demonstrate efficiency in backcalculation applications but exhibit substantial dependence on training data quality and representativeness, particularly when applied to field conditions [5].

The literature has consistently showed the power of Artificial Neural Networks (ANNs) for pavement backcalculation. Meier and Rix [6] pioneered the approach, demonstrating significant gains in computational speed and objectivity by removing the need for seed moduli. Building on this, researchers like Goktepe et al. [7], Gopalakrishnan [1], and Beltrán and Romo [8] systematically refined ANN models, achieving near-perfect determination coefficients ($R^2 > 0.99$) through optimized algorithms and hybrid architectures. More recently, Al-Qaili et al. [9] advanced the field by showing that Recurrent Neural Networks (RNNs) can offer superior performance and faster convergence for heterogeneous data.

The present work proposes the use of an Artificial Neural Network (ANN) as a direct method for pavement backcalculation. The accuracy and robustness of this approach was evaluated using two distinct datasets: manufactured data from a Finite Element Model and in-situ field data from Falling Weight Deflectometer (FWD) tests. Furthermore, this research investigates a hybrid approach where the ANN-predicted moduli are used as initial seed values for the iterative, gradient-based optimization algorithm within the BackCAP software [4]. The effectiveness of this hybrid model was assessed by comparing its computational efficiency against the software's standard procedure, which relies on default seed moduli.

2 Pavement backcalculation using deflection testing

The Falling Weight Deflectometer (FWD) is a widely employed non-destructive test for evaluating in-service flexible pavements. It applies a transient dynamic load that simulates the impact of vehicle tires on the pavement surface. Immediately after the impulse, pavement deflections are recorded at predetermined radial offsets from geophone sensors, as illustrated in figure 1. The resulting deflection basin is subsequently analyzed through a backcalculation procedure to determine the pavement's mechanical properties.

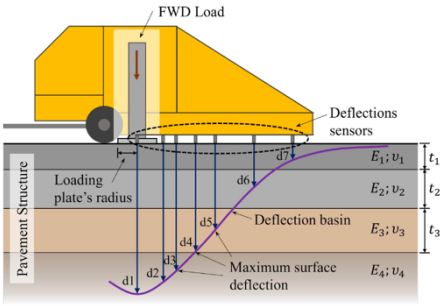


Figure 1. Falling Weight Deflectometer test [10]

Backcalculation constitutes an iterative computational procedure that seeks to match the predicted mechanical responses of the pavement structural model with the deflection measurements obtained through field testing protocols. The process is conventionally subdivided into two principal computational modules: the forward analysis module and the backward module.

The forward analysis module employs a representative structural model to compute theoretical pavement responses under specified loading conditions. The inverse analysis module estimates the unknown *in-situ* mechanical properties of the pavement layers by minimizing the discrepancies between the model-predicted responses and the experimentally measured deflection data.

The most prevalent metric for quantifying these discrepancies is the normalized root mean square error (NRMSE), expressed by the following mathematical formulation:

$$\text{NRMSE} = \sqrt{\frac{1}{m}\sum_{i=1}^{m}\left(\frac{\hat{y}_i - y_i}{\bar{y}_i}\right)} \tag{1}$$

where $\hat{y}_i$ and y_i are, respectively, simulated and measured deflections, $\bar{y}_i$ are deflection normalization factors and m is the number of FWD sensors.

Minimizing the NRMSE constitutes a nonlinear least squares (NLS) optimization problem, given that the mechanical properties of pavement layers exhibit inherently nonlinear relationships with the measured deflection responses. The optimization procedure seeks to determine the optimal set of material properties that minimizes the discrepancies between experimentally measured and computationally predicted deflection values. The objective function minimized in NLS formulations is expressed as:

$$\min_{\boldsymbol{x}\in\mathbb{R}^{\mathrm{n}}} \mathrm{f}(\mathbf{x}) = \frac{1}{2}\sum_{i=1}^{m}\left(\frac{\hat{y}_i - y_i}{\bar{y}_i}\right)^2, \ \mathrm{n} \leq \mathrm{m} \tag{2}$$

where n is the number of pavement layers. Generally, minimizing the NLS objective function is computationally more efficient than minimizing the NRMSE, as the square root operation is eliminated and gradient calculations are considerably simplified [10].

In conventional methodologies, pavement structural responses are typically computed using multilayer elastic theory or finite element analysis, while the error function is minimized through various optimization algorithms, including metaheuristic approaches, first and second-order derivative methods, or specialized algorithms tailored for NLS formulations and their corresponding derivatives.

Conventional backcalculation methodologies are inherently constrained by fundamental challenges including solution non-uniqueness, seed modulus dependency, and convergence to local optima[1]. To address these computational limitations, numerous alternative approaches have been developed, notably the implementation of artificial neural network techniques. Halil Ceylan et al. [5] developed a comprehensive review of neural network applications in pavement engineering over three decades, demonstrating that neural networks consistently outperformed traditional modeling counterparts in solving complex engineering problems, while acknowledging their inherent limitations in practical applications.

An artificial neural network constitutes a computational framework inspired by the operational mechanisms of biological nervous systems, comprising interconnected artificial neurons organized in hierarchical layers for processing complex information patterns. The typical architecture of a multilayer neural network encompasses three fundamental components: the input layer, responsible for receiving the problem's input data, where each neuron represents an independent system variable; the hidden layer, composed of intermediate neurons that process information through nonlinear activation functions, enabling the learning of complex patterns and nonlinear relationships among variables; and the output layer, which generates the final network predictions following the computational processing of information.

3 Sampling, training and evaluation of the machine learning model

For artificial neural network training, the *scikit-learn* library in Python was employed using the MLPRegressor (Multi-layer Perceptron Regressor), a fully connected feedforward implementation for regression problems with continuous outputs. This model utilizes backpropagation for synaptic weight adjustment and is suitable for complex nonlinear mapping, such as pavement backcalculation, where relationships between deflections and elastic moduli exhibit intrinsically nonlinear behavior.

Training samples consist of virtual tests conducted using CAP3D software [11], employing an axisymmetric finite element model with mesh composed of quadratic finite (Q8) and infinite (L6) elements [4]. The pavement structure was kept fixed, utilizing 4 layers: surface course (6.5 cm), base (20 cm), subbase (15 cm), and subgrade (infinite). Input variables consist of applied load (40-50 kN) and deflections measured at seven radial positions of the geophones, totaling 8 input features for predicting 4 elastic moduli as output variables.

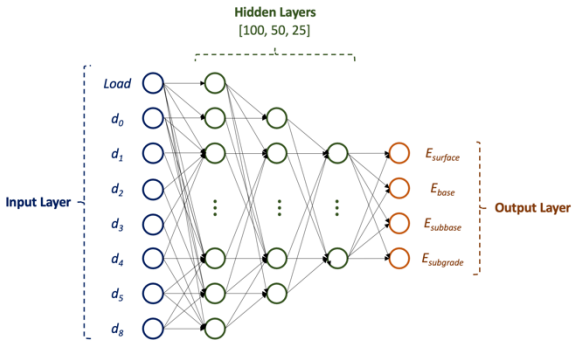
The dataset was initially partitioned into training (80%) and validation (20%) sets. For hyperparameter optimization, the RandomizedSearchCV method from the *scikit-learn* library was employed on the training data, exploring 50 candidate combinations through a random search in the hyperparameter space, which included hidden layer architectures, activation functions, learning rates, and regularization parameters. To ensure a robust performance evaluation and mitigate overfitting, a K-fold cross-validation procedure with 5 splits was systematically applied to all candidate models, resulting in 250 training fits for each configuration.

In a first attempt, simulations were performed by simultaneously varying elastic moduli and Poisson's ratios, as it was expected that the trained network would generate adequate initial estimates for both parameters. The employed neural network featured an architecture with three hidden layers (100, 50, 25 neurons), tanh activation function, learning rate of 0.005, and alpha regularization of 0.0001, trained with 15,000 samples. However, results were unsatisfactory (global R^2 = 0.6027), demonstrating that simultaneous prediction of Poisson's ratio significantly compromises model performance.

Therefore, for virtual tests in the second approach, Poisson's ratios were fixed according to characteristic values per layer: 0.35 for surface course and base, and 0.40 for subbase and subgrade. Elastic moduli were varied

according to ranges presented in Table 1, based on typical mechanical property values for pavements as suggested by Torquato e Silva [12]. The artificial neural network was configured to generate initial estimates (seeds) exclusively for elastic moduli, significantly simplifying the optimization problem. Data were preprocessed using StandardScaler for statistical normalization), essential for efficient neural network training.

Table 1. Pavement layer properties and ranges



Layers	E (MPa)	ν
Surface	500 - 6000	0.35
Base	100 - 800	0.35
Subbase	100 - 800	0.40
Subgrade	100 - 800	0.40

Figure 2. Schematic representation of artificial neural network components applied to a fixed 4-layer pavement structure

The optimized configuration of the second approach resulted in an architecture with three hidden layers (100, 50, 25 neurons) Illustrated in Figure 2, hyperbolic tangent (tanh) activation function, Adam optimizer, learning rate of 0.001, L2 regularization (alpha = 0.0001), early stopping with tolerance of 10^{-6} and patience of 15 epochs. This decreasing neuron configuration allows progressive feature refinement, suitable for the complexity of the backcalculation problem. To evaluate training sensitivity to sample size, training sessions were executed for datasets with 2,000, 5,000, 10,000, and 15,000 samples. Results demonstrate progressive performance evolution: global R^2 increased from 0.9905 (2,000 samples) to 0.9994 (15,000 samples), while RMSE decreased from 0.0797 to 0.0185. K-fold cross-validation confirmed model robustness, with R^2 standard deviation reducing from 0.0028 to 0.0002 with increasing samples.

Table 2. Neural network performance evaluation as a function of training dataset size

Samples	R^2 Model	RMSE Model	R^2 Cross-Validation	RMSE Cross-Validation
2000	0.9905	0.0797	0.9916 ± 0.0028	0.0904 ± 0.0161
5000	0.9988	0.0278	0.9970 ± 0.0028	0.0506 ± 0.0206
10000	0.9993	0.0197	0.9992 ± 0.0002	0.0283 ± 0.0032
15000	0.9994	0.0185	0.9992 ± 0.0002	0.0290 ± 0.0026

Performance improvement saturation is observed from 10,000 samples onward, where gains become marginal (R^2 = 0.9993 versus 0.9994 for 15,000 samples). The results demonstrate that starting from 2,000 samples, it was possible to achieve R^2 values exceeding 99%, which constitutes exceptional performance and suggests that extensive datasets are not required for obtaining a robust and consistent model.

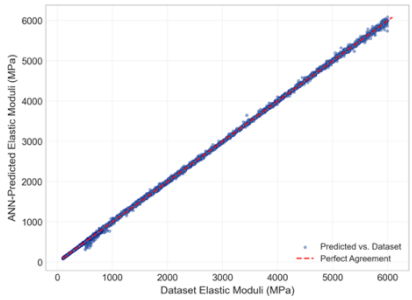


Figure 3. Experimentally measured versus predicted elastic moduli

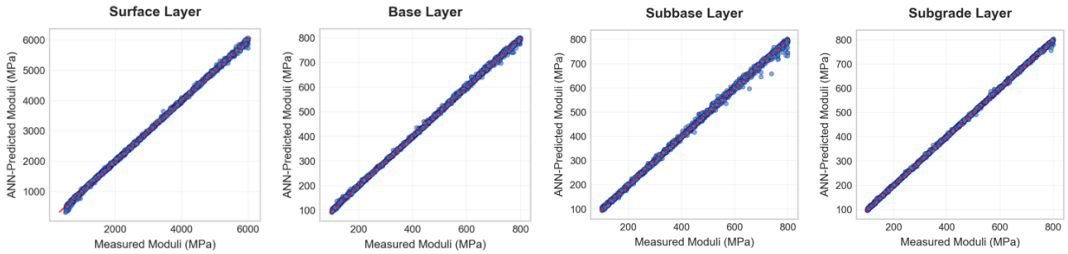


Figure 4. Layer-specific performance evaluation of ANN predictions

Therefore, it can be concluded that the proposed methodology is highly effective for generating initial elastic moduli estimates, achieving accuracy superior to 99.9% with moderate datasets, making it a computationally efficient tool for initializing nonlinear optimization algorithms in pavement backcalculation, as illustrated in Figures 3 and 4.

4 Case study

To validate the proposed methodology, a comprehensive case study was conducted encompassing both synthetic datasets and field measurements. The CAP3D software served as the structural analysis framework for generating reference data and validating computational results. In both scenarios, the pavement structural configuration remained consistent with that employed during neural network training, as detailed in the preceding section. Initially, synthetic numerical experiments were randomly generated to assess the performance of the trained artificial neural network in conducting pavement backcalculation analyses. The accuracy assessment of the ANN predictions was conducted using the normalized root mean square error (NRMSE), which provides a dimensionless error metric through normalization with a constant factor of 1000 μm. The corresponding deflection basins are presented in Table 3.

Table 3. Synthetic deflection data generated for artificial neural network validation

Stations	F (kN)	Deflections (μm)						
		d0	d20	d30	d45	d60	d90	d120
1	41.443	300.04	193.02	141.70	97.22	71.55	45.37	33.23
2	40.028	413.59	282.87	219.02	164.03	130.56	90.28	67.30
3	42.705	396.13	211.27	157.27	117.69	93.20	63.39	46.72
4	46.664	350.66	157.98	84.61	46.24	33.55	22.61	17.03

Backcalculation analyses were conducted employing both the ANN and BackCAP software [4]. The Poisson's ratios remained consistent with those employed during ANN training. For the BackCAP analysis, a standardized set of initial seed moduli E = [3500, 345, 345, 350] MPa was employed.

Table 4. Comparative performance assessment for synthetic deflection data

Stations	Time (s)		RMSE		E (MPa)			
	ANN	BackCAP	ANN	BackCAP	Surface (E_{ANN}/E_{BCAP})	Base (E_{ANN}/E_{BCAP})	Subbase (E_{ANN}/E_{BCAP})	Subgrade (E_{ANN}/E_{BCAP})
1	8.47E-03	3.00	3.70E-04	2.00E-04	3217.24 (0.998)	692.77 (1.016)	232.62 (1.003)	274.95 (0.996)
2	2.07E-03	3.45	1.62E-03	1.00E-04	3221.91 (1.006)	440.68 (0.993)	288.52 (0.981)	136.31 (0.995)
3	8.64E-03	2.18	2.68E-03	2.00E-04	465.67 (0.880)	530.23 (1.010)	511.86 (1.016)	216.80 (1.027)
4	3.41E-03	2.09	8.41E-04	7.00E-04	1948.69 (1.017)	285.57 (0.985)	503.79 (1.018)	604.60 (1.003)

The comparative results, presented in the table 4, shows a significant trade-off between computational efficiency and numerical precision. The ANN demonstrated a substantial speed advantage, delivering predictions in an average of 5.65 milliseconds, whereas the iterative BackCAP procedure required approximately 2.68 seconds per station—a difference of nearly three orders of magnitude.

While the BackCAP software consistently achieved a lower Root Mean Square Error (RMSE), indicative of a more accurate fit to the deflection basin, the ANN's predicted elastic moduli showed remarkable agreement with

the final optimized values. This concordance is evidenced by the E(ANN)/E(BCAP) ratio, which remained close to unity (typically within ±2%) for many layers across all stations. The overall analysis confirms the ANN's capability to provide rapid and highly reliable estimates of pavement layer moduli.

Field measurements were conducted using Falling Weight Deflectometer (FWD) equipment on a Brazilian highway [4]. The resulting deflection basin data are presented in Table 5.

Table 5. Field deflection measurements obtained through FWD testing on Brazilian highway

Stations	F (kN)	Deflections (μm)						
		d0	d20	d30	d45	d60	d90	d120
1	46.383	290	159	107	68	47	29	23
2	45.851	843	517	342	209	143	73	44
3	45.693	1047	665	454	279	195	113	74
4	45.545	354	192	130	85	62	38	27

The comparative analysis, presented in the Table 6, reveals critical insights into the performance of the ANN when confronted with the inherent complexities and variability of real-world pavement conditions. Computationally, the ANN maintained its significant speed advantage, delivering predictions with an average processing time of approximately 8.8 milliseconds per station. This is nearly three orders of magnitude faster than the BackCAP software, which required an average of 4.82 seconds. The ANN's Root Mean Square Error (RMSE) was consistently higher than that of BackCAP, indicating that the iterative method achieves a better fit to the measured deflection data. Unlike the near-perfect agreement observed with synthetic data, the results from field data show significant variability. These results indicate that while the ANN can provide highly accurate estimates under certain conditions (Station 1), its reliability diminishes when faced with field deflection bowls.

Table 6. Comparative performance assessment for FWD field measurements

Stations	Time (s)		RMSE		E (MPa)			
	ANN	BackCAP	ANN	BackCAP	Surface (E_{ANN}/E_{BCAP})	Base (E_{ANN}/E_{BCAP})	Subbase (E_{ANN}/E_{BCAP})	Subgrade (E_{ANN}/E_{BCAP})
1	2.06E-02	2.54	1.13E-03	6.00E-04	1748.88 (1.037)	709.03 (1.023)	295.11 (1.003)	457.23 (0.972)
2	4.59E-03	7.60	1.87E-02	5.60E-03	631.53 (0.484)	338.11 (1.391)	42.11 (0.877)	178.66 (0.973)
3	5.50E-03	4.24	1.72E-02	4.00E-03	1414.64 (0.826)	187.43 (1.191)	47.64 (0.893)	113.51 (0.934)
4	5.26E-03	4.90	1.99E-03	7.00E-04	865.23 (0.753)	654.12 (1.116)	252.20 (0.926)	364.56 (1.000)

Table 7. Computational efficiency using ANN-generated initial seed moduli versus standard default values

Station	Time (s)			Iterations		
	Standard	ANN Seed	Δ (%)	Standard	ANN Seed	Δ (%)
1	2.34	1.11	-52.40	4	2	-50.00
2	7.60	6.53	-14.10	11	10	-9.09
3	4.24	2.83	-33.40	7	5	-28.57
4	4.90	1.66	-66.15	6	3	-50.00

Finally, the computational performance of the BackCAP solution was evaluated using both the software's default initial seed moduli and the ANN-predicted elastic moduli as starting parameters. The findings presented in Table 7 demonstrate that the initial seed moduli predicted by the artificial neural network significantly enhance the computational efficiency of the backcalculation procedure.

5 Conclusions

The artificial neural network model for pavement backcalculation demonstrated a very good performance on synthetic datasets, exhibiting excellent predictive capability for elastic moduli within the established training domain. Model validation under field conditions was conducted using deflectometric data acquired from four stations along a Brazilian highway through Falling Weight Deflectometer (FWD) testing protocols. Direct application of

the ANN on field measurements revealed substantial limitations when compared to results achieved by the Back-CAP software. The increased variability, noise in real-world FWD measurements, and the divergence between the underlying backcalculation assumptions and the actual mechanical behavior of the pavement layers led to a noticeable degradation in the ANN's predictive accuracy, with moduli ratios deviating by as much as 52%. This decline in ANN performance was expected, given well-documented limitations in the literature, including the pronounced dependency on training dataset quality and representativeness, as well as the inherent complexity associated with nonlinear material behavior of pavement layers under field conditions. The hybrid approach, employing ANN-predicted moduli as initial seed values for the Gauss-Newton iterative algorithm, yielded substantial reductions in computational time and iteration requirements without compromising solution accuracy. The proposed methodology of using neural networks as intelligent seed moduli generators demonstrated considerable promise, significantly enhancing the computational efficiency of conventional backcalculation procedures. The findings indicate that the hybrid framework is well-suited for optimizing structural assessment protocols through deflectometric backcalculation analyses, effectively combining the computational speed of neural networks with the numerical robustness of traditional iterative optimization methods.

Acknowledgements. The authors gratefully acknowledge the financial support provide by CNPq (Conselho Nacional de Desenvolvimento Científico e Tecnológico) and FUNCAP (Fundação Cearense de Apoio ao Desenvolvimento Científico e Tecnológico).

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