XLI CILAMCE
XLI Ibero-Latin American Congress on Computational Methods in Engineering
16-19 November, 2020 FOZ DO IGUAÇU PARANÁ - BRAZIL

Optimization of the concrete material parameters in numerical simulation of RC beams under shear failure by artificial neural networks

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Abstract. Three-dimensional nonlinear constitutive models for reinforced concrete (RC) often require an extensive number of material parameters. Some of these are evaluated through experimental tests, but most of them are estimated from empirical or semi-empirical expressions. The inherent limitations of representing real structures with mathematical models may introduce different constraints on the parameter calibrations that originally adjusted those expressions. That is one of the main reasons that lead to divergences between nonlinear finite element analysis (NLFEA) and reliable experimental data. In this study, we employ a method that adopts an artificial neural network (ANN) and Levenberg-Marquatd backpropagation method for calibrating material parameters in a numerical model of an RC member. The simulated experiment is an RC beam under a three-point bending scheme with shear failure. Finite element computations are carried out in ATENA software, and the goal of the calibration is to find the best adjustment of the experimental load-deflection curve at the center of the beam. The algorithm shows an excellent capability to fit the numerical curves, and it successfully automates a task that customarily would take several analyses and trial-and-error process to achieve the best fitting.

Keywords: reinforced concrete, material calibration, nonlinear analysis, neural networks.

1 Introduction

Nonlinear finite element analysis (NLFEA) is an excellent tool for the simulations of concrete structures, especially due to the cracking behavior of this material. The use of an appropriate constitutive model is necessary to reproduce the real response of the structures. However, due to the complexity of these models, they require an extensive number of material parameters.

Some of these parameters are evaluated through experimental measurements, but most of them are estimated from empirical or semi-empirical expressions. Even the values that can be measure by tests may be unknown in some cases and influenced by many factors such as characteristics of the environment and machinery. Also, there are limitations of representing real structures with mathematical models. That is one of the main reasons that lead to divergences between nonlinear finite element analysis (NLFEA) and reliable experimental data. Thus, a material calibration has to be performed, in which the values of parameters are iteratively modified, to better fit the structural behavior of these numerical models to the observed in the experimental tests.

Commonly, the correction of the parameters is made manually by the user, who changes parameter by parameter, processes the whole model, confronts the results with the experiments at every new change of values, and repeats this proceeding until obtain an acceptable results. This approach is excessively arduous, and there is no guarantee that the final parameters adopted by the user are the values that can provide the most agreeable results with the real structure.

This study aims to develop an algorithm for automatic identification of the material model parameters for concrete in numerical simulations. The proposed algorithm uses the Latin Hypercube Sampling (LHS) method to obtain values that form a set of training to an artificial neural network (ANN). After the training, the algorithm is capable to predict the best parameter values that fit the experimental results. This methodology is applied to a real experiment of shear beam failure. A similar approach is made in Obrzud, Vulliet and Truty [1], Novák and Lehký [2][3], and Pukl *et al.* [4].

2 Material calibration

The inverse analysis approach presented in this paper couples the statistical simulation method of the Monte Carlo (MC) simulation and artificial neural network (ANN). The technique is based on the work developed by Novák and Lehký [3]. The inverse analysis is divided into the following steps:

(i) Build a numericalmodel with initial estimated parameters.
(ii) Create a small sample using Latin Hypercube Sampling (LHS).
(iii) Run each sample.
(iv) Use the random realizations and the random responses to train the ANN.
(v) Use the trained ANN to estimate the best parameters that fit the model with the experimental data.
(vi) Perform the simulation with the estimated parameter and verify the results.

In this study, the base material model corresponds to the initial input parameters estimated by the finite element software based on the compressive strength of concrete. In the statistical analysis, the Latin Hypercube Sampling (LHS) method is used to generate random input parameters to the constitutive model. These values are replaced in the input base model to obtain random load x displacement curves, which form the set of training to the ANN.

The choice of the parameters that will be evaluated should be based on their influence on the global response of the numerical simulation. It must be said that the quantities of samples depend on the number of parameters and the type of problem.

The ANN is a type of machine learning model used in different fields and practical applications. The original idea was presented in the 1950s with the perceptron algorithm Rosenblatt [5]. The general ANN structure consists of several nodes (neurons) dispose in a vertical layer connected between them, refer to Figure 1. Each connection, like the synapses in a biological brain, can transmit a signal to other nodes. The ANN training consists of the adjusting of the values connections (also knowns as weights) between the nodes by analyzing the output and comparing it with the correct answers.

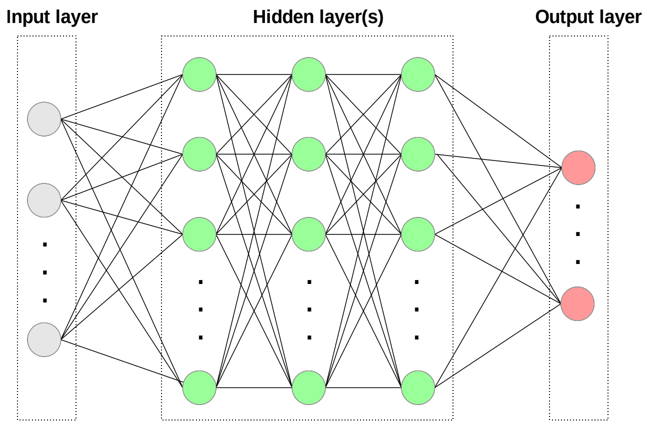

Figure 1. General ANN architecture.

3 Implementation

The methodology is carried out by the integration of the programs GiD, ATENA, and MATLAB. GiD is a graphical interface, use for the preprocessing phase which consists of generating geometry, define initial material, specify of boundary conditions, and assign mesh. Subsequently, a script developed in MATLAB performs the LHS method. This script is used to modify the original data file (*.inp) to create the sample with the random input generated by LHS. The finite element simulations of each file are made in ATENA (version 5), a software for reinforced concrete nonlinear numerical analysis, developed by Cervenka Consulting company. The input and output results are used as a training set for an ANN created in MATLAB using the Neural Network Toolbox [6]. The workflow between the programs is depicted in Figure 2.

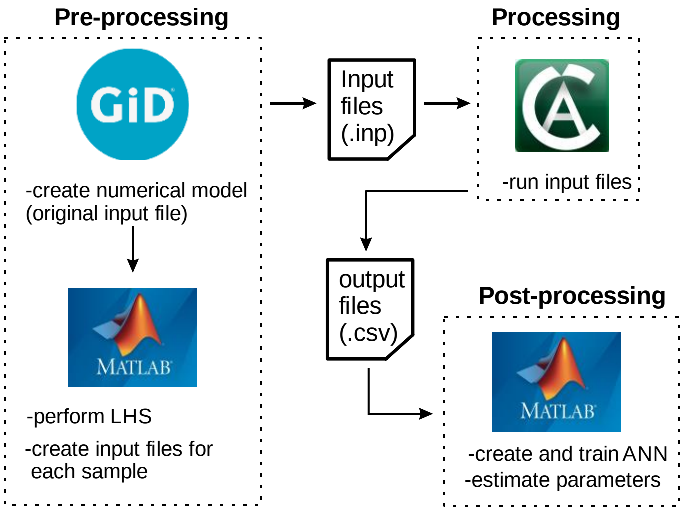

Figure 2. Integration of programs used for the proposed inverse analysis methodology.

4 Applications

4.1 Modeling of concrete

A finite element simulation of a concrete prism and a shear failure beam is carried out in ATENA (version 5). The material model for concrete in ATENA is a three-dimensional constitutive model, which combines fracture and plasticity to represent the nonlinear behavior of concrete (Cervenka, and Papanikolaou [7]). A more detailed description can be found in Cervenka, and Papanikolaou [7], on which the following brief description is based.

The fracture model refers to the tension behavior and is based on smeared crack formulation. In tension is implemented the Rankine criterion for cracking and the exponential softening curve from Hordijk [8], which relates tensile strength (f_t) and crack opening (w_t). Also, the stress softening is determined using the crack band theory proposed by Bažant and Oh [9].

According to Cervenka *et al.* [10], the plasticity model refers to the compressive behavior and use the Menétrey-Willam failure criterion for the plasticity of concrete in a multiaxial stress state. Futhermore, the shear strength, is considered according to the Modified Compression Theory proposed by Vecchio and Collins [11].

The material models used are *SBeta* and *Cementitious2*, available in ATENA software. A great number of parameters are required for these models, but only five are evaluated in this study: compressive strength, tensile strength, Young’s module, and fracture energy.

4.2 Concrete prism

Initially, we verify the validity of the inverse analysis approach by a three-point bending test on a plain concrete beam simulation. The analyzed beam geometry and support conditions are shown in Figure 3. A sample of 30 (random) inputs was generated using the LHS method, according to the statistical parameters presented in Table 1. Correlations between parameters are taken into account to avoid unrealistic combinations (e.g., a high value of compressive strength with a low value of tensile strength). The material model used in ATENA is the *SBeta* material. The concrete prism is model as a 2D element plane stress, using quadrilateral eigth-nodes element with mesh size of 20 mm.

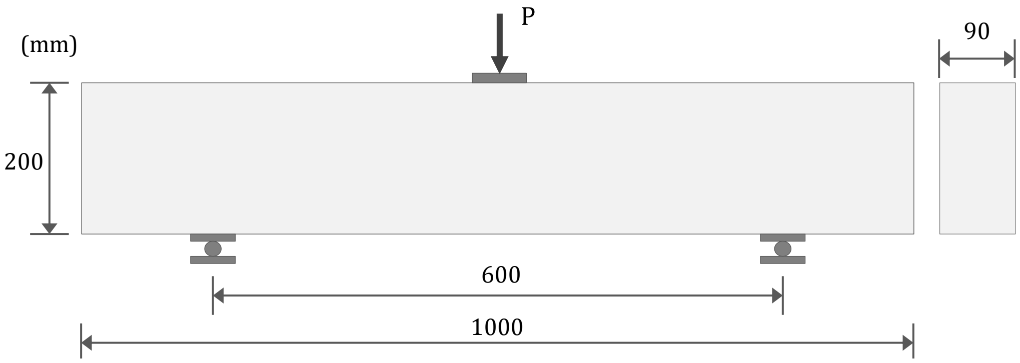

Figure 3. Geometry of the validation model

Table 1. Summary of statistical parameters used for LHS

Parameter	Distribution	Mean	CoV
Compressive strength (f_c)	Normal	32.31 MPa	0.15
Tensile strength (f_t)	Normal	3.04 MPa	0.18
Young modulus (E_c)	Normal	31850.00 MPa	0.15
Fracture energy (G_f)	Normal	96.00 N/m	0.15

Figure 4 shows the response variability within the 30 analyses performed. Each blue line corresponds to a random input obtained from the LHS method. The black line is also a random realization, but it was chosen as a 'target' curve to validate the inverse analysis algorithm. For the inverse analysis, a multi (MLPN) with three layers were employed. The input layer had 30 neurons, corresponding to the load x displacement curves of each input. The hidden layer had also 30 neurons, and the output layer had 4 neurons, corresponding to the concrete parameters. The Levenberg-Marquadt backpropagation, implemented in MATLAB, was used as a training algorithm. Using the described procedure, we obtained the results depicted in Figure 5. The red curve corresponds to the predicted ones by the algorithm. The comparison between the input and the predicted values is presented in Table 2, confirming a good agreement.

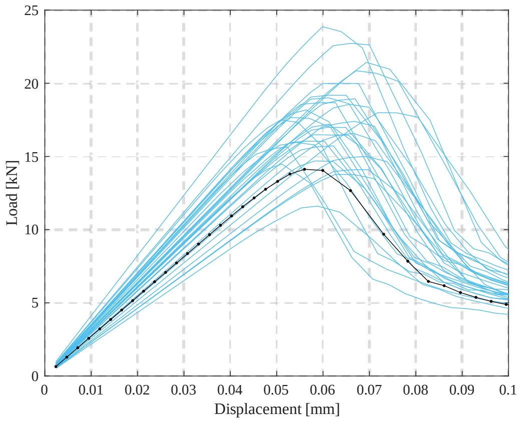

Figure 4. Load x Displacement curves from the random values of material parameters for the ANN training and the target curve (black line)

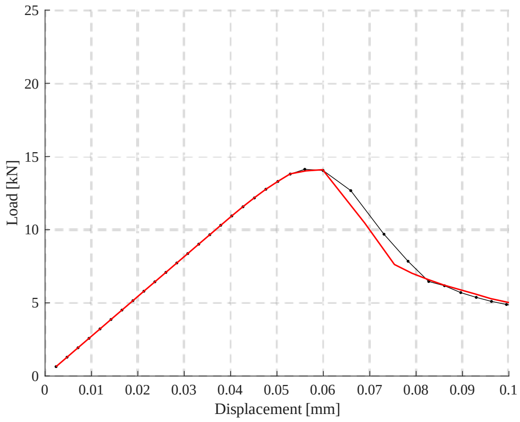

Figure 5. Comparison of Load x Displacement curves between the predicted curve (red line) and the target curve (black line)

Table 2. Comparison between input and predicted parameters for the concrete prism application

Parameter	Input	Predicted
Compressive strength (f_c)	27.95 MPa	27.77 MPa
Tensile strength (f_t)	2.39 MPa	2.41 MPa
Young modulus (E_c)	28022.00 MPa	28027.00 MPa
Fracture energy (G_f)	80.00 N/m	80.00 N/m

4.3 Shear failure concrete beam

The simulated experiment is an RC beam under a three-point bending scheme with shear failure tested by Sarkhosh [12] (Figure 6). Sarkhosh [12] tested 42 RC beams divided into five series. In this paper, only the first series is simulated, formed by six beams with the same geometrical and mechanical properties tested until failure. The specimen were a rectangular beams 200 x 450 mm, 3000 mm of length, and shear span of 1200 mm. For the flexural reinforcement was used three steel bars of 20 mm diameter and a yield strength of 500 MPa. The cube compressive strength of concrete is 38.2 MPa and corresponds to the average of three samples at 28 days.

The beam is model as a 2D element plane stress as a simplification for the 3D model. The symmetry boundary condition is used in the half of the specimen. A quadratic finite element with eight nodes is used and mesh of 25 mm (Figure 7). The load is applied as displacement in a plate with elastic material in top of the beam, the same plate is used in the support condition. For the reinforcement bars is used the *1D Reinforcement* material model with the default parameters of the software.

The input parameters for the initial simulation of the concrete material *Cementitious2* were based in the experimental cubic mean compressive strength. The rest of parameters were estimated by the software, based on the compressive strength and the *fib* Model Code 2010 [13]. They are the compressive strength f_c = 33.7 MPa, tensile strength f_t = 2.61 MPa, Young's module E_c = 32224.5 MPa and fracture energy G_f = 137 N/m.

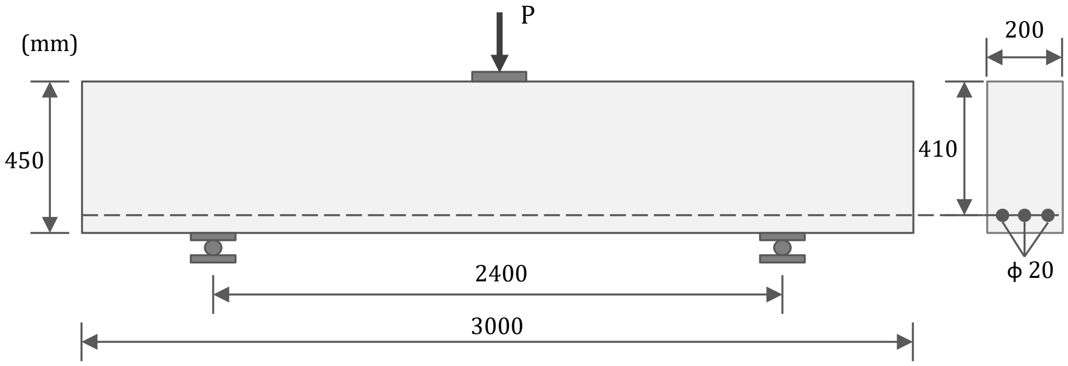

Figure 6. Beam tested by Sarkhosh [12]

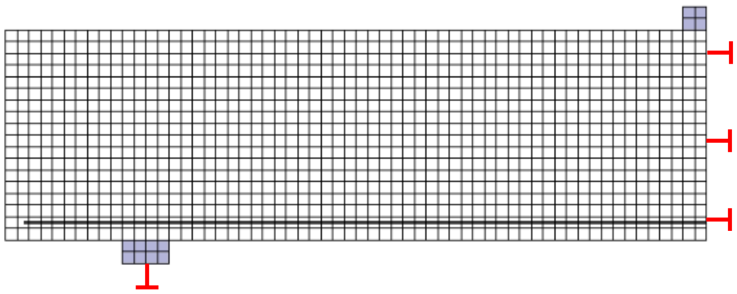

Figure 7. Numerical model.

Similarly to the concrete prism application, the LHS method is used to generate 30 (random) inputs. Figure 8 shows the set of load x displacement curves and the average experimental curve. Then, the concrete parameters are predicted using the implemented ANN of the previous example. The comparison between the load x displacement curve from the initial model, the predicted, and the average experimental one are shown in Figure 9. The input and predicted parameter values are described in Table 3.

The predicted curve had a good fit along with the experimental one until a load of 163 kN, a value 12% lower than the average ultimate load obtained in the tests (184 kN). The divergence in the last load steps can be attributed to some simplification included in the numerical model, such as the assumption of plaine stress state and the no consideration of the dowel effect provided by the reinforcement. Thus, the results are quite satisfactory for this study. Furthermore, the rupture mode observed in the test was accurately simulated (Figure 10 and Figure 11).

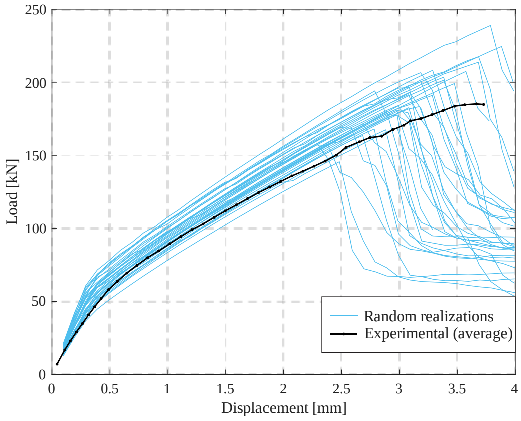

Figure 8. Load x Displacement curves from the random values of material parameters for the ANN training

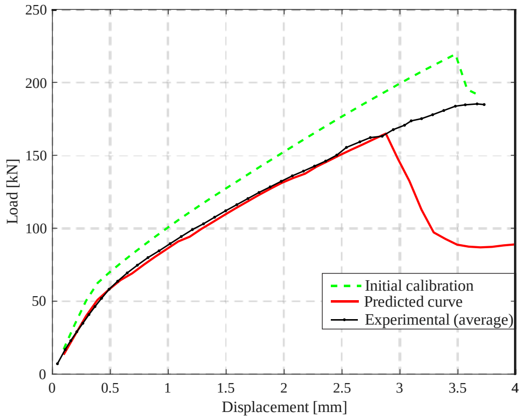

Figure 9. Comparison of Load x Displacement curves of the initial model, final model, and experimental average.

Table 3. Comparison between input and predicted parameters for the shear beam failure application

Material parameter	Initial	Predicted
Compressive strength (f_c)	33.70 MPa	32.66 MPa
Tensile strength (f_t)	5.61 MPa	2.34 MPa
Young's module (E_c)	32224.50 MPa	24307.00 MPa
fracture energy (G_f)	137.00 N/m	91.96 N/m

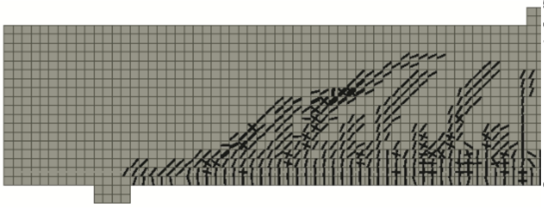

Figure 10. Crack pattern from the final numerical model

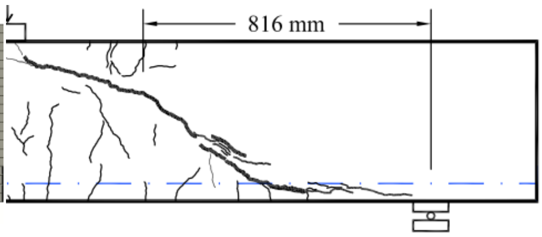

Figure 11. Crack pattern from the S1B4 of Sarkhosh [12] (Adaptad from Sarkhosh [12])

5 Conclusions

Nonlinear fracture constitutive models for quasi-brittle materials such as concrete are complex. Therefore, they demand a higher number of parameters. The determination of the mechanical parameters in numerical analysis presents a hard task for the simulations of these structures. Hence this difficult, this study developed an algorithm for the identification of parameters to reinforce concrete constitutive material. The methodology uses artificial neural networks to create an automatic tool for the proceeding of calibration, which shows an excellent capability to fit the numerical in the experimental results, as is noticed in the application on the shear failure beam tested by Sarkhosh [12]. The automatic identification is also a better strategy for the correction of parameter values in comparison with the classical trial-and-error approach that demands more time and effort of the user.

Acknowledgments. This research is supported by the National Council for Scientific and Technological Development (CNPq) and the Coordination for the Improvement of Higher Education Personnel (CAPES).

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