ARTIFICIAL NEURAL NETWORKS FOR IDENTIFICATION OF FIBRE–REINFORCED CONCRETE

David Lehký [1]

Abstract: The aim of the paper is to introduce methodology of parameters identification of material models for fibre-reinforced concrete. Such model often contains number of parameters which has to be correctly identified in order to carry out accurate numerical analysis. One of the possibilities is to use identification technique based on artificial neural networks in combination with stochastic analysis. Nonlinear numerical analysis of structures made of fibre-reinforced concrete is very often time demanding. For that reason the emphasis is on utilization of effective simulation technique which is needed for training set preparation.

1. Introduction

For numerical modeling of quasi-brittle failure of structures made of fibre-reinforced concrete (FRC) it is necessary to know parameters of utilized material model, especially fracture parameters. For that reason development of identification techniques using results of laboratory testing is important task of research in the field of fracture and computational mechanics. Considering fibre-reinforced concrete the significant factor for modeling and design of structures made of this material is higher variability

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[1] LEHKÝ David, Ing., Ph.D., Ústav stavební mechaniky, Fakulta stavební, VUT v Brně, lehky.d@fce.vutbr.cz.

of its parameters (e.g. modulus of rupture). This can be observed from experimental results and it is due to the higher heterogeneity of the FRC-material and fibre content in comparing with “normal” concrete. In such a case it is essential to identify material parameters not only as deterministic values but as random variables or random fields (Lehký & Novák, 2005).

2. Material models for fibre-reinforced concrete

For modeling of structures made of fibre-reinforced concrete an appropriate material model should be used, e.g. SBETA model or bending fracture model, see below.

2.1 SBETA model

SBETA model implemented in ATENA software (Červenka et al., 2005) is powerful material model for modeling of structures made of quasi-brittle materials such as fibre-reinforced concrete. In this model tensile behavior of concrete is modeled by non-linear fracture mechanics combined with the crack band method and smeared crack concept. Main material parameters are tensile strength f_t, fracture energy G_f and shape of the stress-crack opening curve. A real discrete crack is simulated by a band of localized strains. The crack strain is related to the element size (localization limiter). Consequently, the softening law in terms of strains for the smeared model is calculated for each element individually, while the crack-opening law is preserved. This model is objective due to the energy formulation and its dependency on the finite element mesh size is negligible.

SBETA model consists several stress-crack opening laws. One of these laws is fibre-reinforced concrete law, see equation (1) and Fig.1. The shape of the stress-crack opening curve is linear with slips c_1 and c_2 which corresponds to proportion between stresses f_1 or f_2 and tensile strength f_t. First slip is realized when ultimate tensile strength is reached, second one is realized when maximal crack width is achieved. Parameters which have to be correctly identified when this model is used are modulus of elasticity E, tensile strength f_t, slips c_1 and c_2 and fracture energy G_f.

$$c_1 = \frac{f_1}{f_t}, c_2 = \frac{f_2}{f_t}, w_c = \frac{2G_f}{f_1 + f_2}. \qquad (1)$$

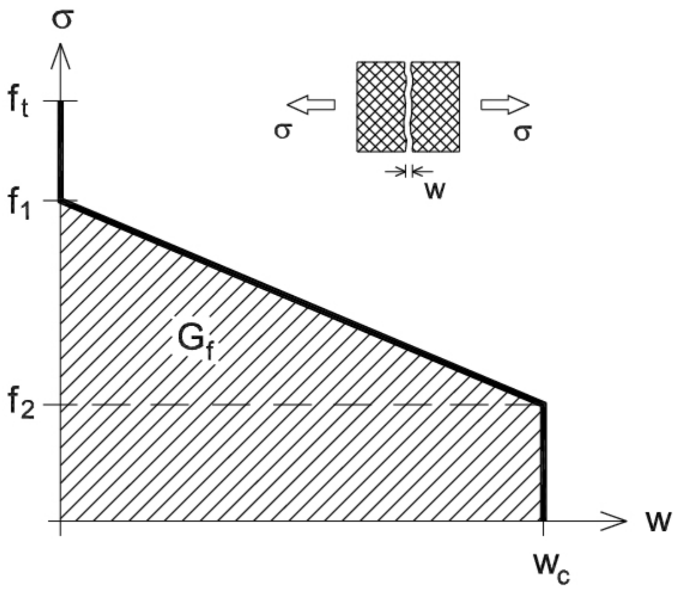

Fig. 1: Stress–crack opening law for fibre-reinforced concrete

2.2 Bending fracture model

Bending fracture model (Keršner et al., 2005) was developed for simple modeling of three-point bending tests which are often carried out in laboratory to evaluate fracture-mechanical parameters. The scheme of the model is as follows (Fig.2): rigid slab which represents one half of a beam is fixed to rigid wall using hinge and tensile fibres that are decisive for model behavior. Stress function of one fibre is fully determined by three local parameters: initial stiffness $k_{incr,i}$, maximum tensile force $F_{peak,I}$ and coefficient of strain energy c_i, which is defined as ratio between total strain energy which is needed for fibre rupture and strain energy which is needed for maximal force achievement in fibre.

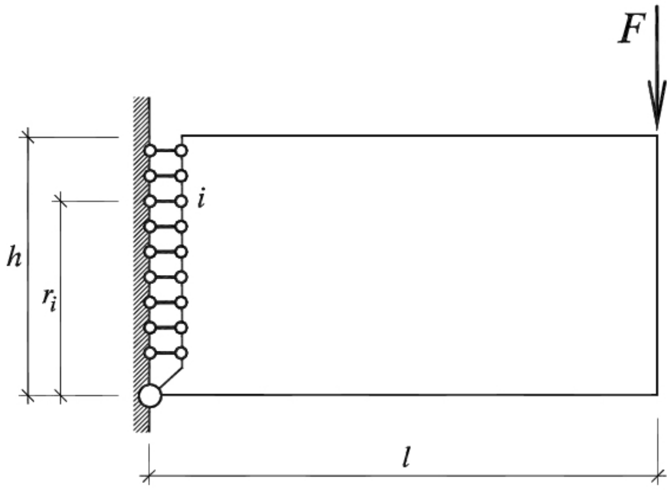

Fig. 2: Simplified model of beam fracture under three-point bending [adopted from Keršner et al., 2005]

Because of the discrete character of model it is much more convenient to define global model parameters instead of local ones: tensile strength *ft*, tensile stiffness k_t, coefficient of strain energy *c* and amplitudes $A_{ft,j}$ and phases $\phi_{ft,j}$ of base functions. All these parameters are then subject of identification.

3. Methodology of identification technique

Proposed identification method is based on the coupling of a stochastic simulation and an artificial neural network (ANN), Novák & Lehký (2005, 2006), Lehký & Novák (2005). The identification parameters (mentioned in previous section) play the role of basic random variables with a scatter reflecting the physical range of possible values. Here, an efficient small-sample simulation method Latin Hypercube Sampling (LHS) is used for the stochastic preparation of the training set utilized in training the neural network. Once the network has been trained, it represents an approximation consequently utilized in a following way: To provide the best possible set of material parameters for the given experimental data.

In ANN based identification technique a classical feed-forward neural network, multi-layer-perceptron (MLP), is used (e.g. Cichocki and Unbehauen, 1993). A keystone of this network is McCulloch–Pitts's perceptron. All neurons in one layer are connected with all neurons in the following layer. The connecting paths among neurons are weighted, which models their conductivity. At the level of neuron the bias is added to the sum of the weighted impulses from each neuron of the preceding layer. Then an activation function is applied. Synaptic weights, biases and the activation functions determine the behavior of neurons and the whole artificial neural network. Output from a single neuron can be calculated as:

$$y = f(x) = f\left(\sum_k (w_k \cdot p_k) + b\right), \tag{2}$$

where k is number of input impulse (1,...,*K*), w_k is synaptic weight of connecting path from *k*-th neuron of previous layer , p_k is impulse from *k*-th neuron of previous layer, *b* is bias of neuron and *f* is transfer function of neuron. If the output vector of whole neural network is required, output vectors have to be calculated layer by layer from the input layer to the output layer of network. Output of *u*-th layer of network is:

$$y_k^u = f^u\left(\sum_{j=1}^{J} \left(w_{kj}^u \cdot y_j^{u-1}\right) + b_k^u\right), \tag{3}$$

where k is number of component in output vector in u-th layer (1,...,K = number of neurons in u-th layer), j is number of component in output vector in (u-1)-th layer (1,...,J = number of neurons in (u-1)-th layer), y_k^u is one component of output vector, w_{kj}^u is synaptic weight and it is connecting k-th neuron of u-th layer with j-th in (u-1)-th layer , y_j^{u-1} is one component of output vector in previous layer, b_k^u is bias of k-th neuron in u-th layer and f^u is transfer function in u-th layer. If u is the number of the last layer then y^u is the output vector.

Artificial neural network works in two phases – *active* and *adaptive*. In active phase signal passes through the connecting paths from the input layer to the output layer of the network. To obtain correct results of that process, weights and biases must have appropriate values. To assign those values, adaptive phase must be used. This process is called training of neural network. For network training a set of training parameters is needed. This set consists of ordered pairs [$\mathbf{p}_i$, $\mathbf{y}_i$] (Fig.3), where $\mathbf{y}_i$ are expected output vectors (identified parameters), which yields from simulation of network with input vectors $\mathbf{p}_i$ (e.g. points on load-deflection diagram, etc.). The main aim during training is to minimize following criterion:

$$E = \frac{1}{2} \sum_{i=1}^{N} \sum_{k=1}^{K} \left(y_{ik}^{v} - y_{ik}^{*} \right)^2 , \qquad (4)$$

where N is number of ordered pairs input–output in training set, $y_{ik}*$ is required output value of k-th output neuron at i-th input and y_{ik}^v is real output value (at same input).

The well-known backpropagation algorithm (gradient descent method with the momentum, Levenberg–Marquardt method, etc.) or optimization methods based on artificial intelligence (genetic algorithms, simulated annealing, etc) are used to minimize criterion E.

As it is mentioned above the basic step of the whole procedure is to generate the training set for the neural network training (based on a certain number of random simulations) which can be time consuming. The utilization of LHS appeared to be very useful as the whole multi-dimensional space of IP is covered perfectly by relatively small number of simulations (McKay et al., 1979, Novák et al. 1998).

The first step of whole identification procedure is development of computational model. It can be any analytical formulation as well as numerical model created using FEM software. Material parameters of the model have to be roughly adjusted based on testing, engineering judgment and virtual computational simulation. Second step is consideration of identified material parameters as random variables described by probability distribution. Then, random realizations of parameters are obtained based on the Monte Carlo type simulation, the small-sample simulation LHS is recommended. With these realizations the stochastic analysis of structure is carried out and random responses are obtained. At this stage it is convenient to perform sensitivity analysis to find out which parameters don't affect structural response thus it is useful to omit them in identification process.

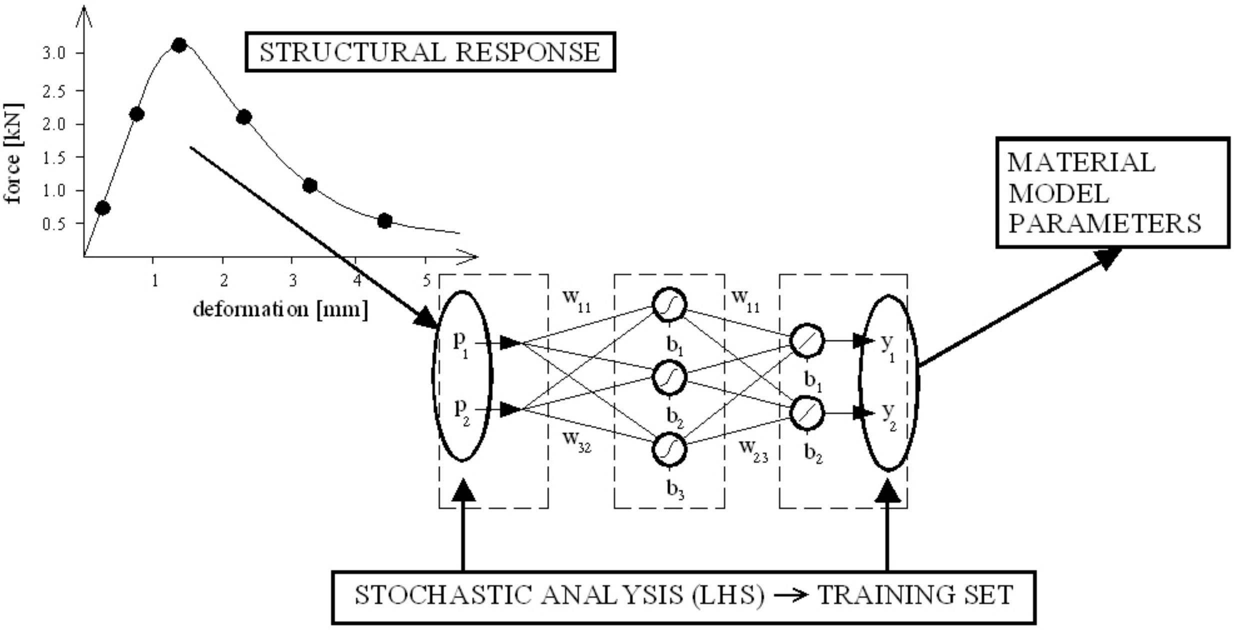

Fig. 3: A scheme of stochastic training of the neural network

Random realizations of material parameters and random responses from the computational model serve as the basis for the training of an appropriate artificial neural network. This key point of the whole procedure is illustratively sketched in Fig.3 (here for the FEM model response in the form of a nonlinear load-deflection curve including both pre-peak and post-peak behavior). The trained neural network is ready to give an answer to the key task: To select the best parameters so that the calculation may result in the best agreement with experimental response, which is performed by means of the network simulation using experimental response as an input. This results in an optimal set of material parameters for fibre-reinforced concrete.

The last step is the results verification – the calculation of the computational model using optimal parameters. A comparison of numerical and experimental response will show to what extent the inverse analysis was successful.

4. Software tools

Multi-purpose software for artificial neural network based identification has been developed. This program system is based on the integration of software for statistical, sensitivity and reliability analyses FReET (Novák et al., 2007), and a neural network software DLNNET (Lehký, 2008). The problem which is being solved can be implemented at two levels: an ‘‘equation editor’’ can be used for simple functions representing computational model (the integral part of FReET program); for comprehensive models (existing codes in a programming language, C++, Fortran, etc.) *.DLL function according to prescribed rules has to be created first. The software for the inverse analysis simply calls for this function.

5. Conclusions

A new efficient inverse analysis methodology is proposed, parameters of a computational model can be identified based on the experimental response. The methodology is based on the stochastic training set preparation for the neural network using the small-sample statistical simulation method LHS. The methodology and the developed software tools are general and can easily be used for almost any inverse analysis problem.

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References

[1] Červenka, V., Jendele, L., Červenka, J.: *ATENA Program Documentation – Part 1: Theory*. Červenka Consulting, Prague, Czech Republic, 2005.

[2] Cichocki, A., Unbehauen, R:. *Neural Networks for Optimization and Signal Processing*. Wiley, & B.G. Teubner, Stuttgart, Germany, 1993.

[3] Keršner, Z., Frantík, P., Řoutil, L., Veselý, V.: Approximation of bending fracture model by load-deflection diagrams. *National conference Engineering mechanics 2005*, Svratka, Czech Republic, 2005, 151-152, (in Czech).

[4] Lehký , D., Novák, D.: Probabilistic inverse analysis: Random material parameters of reinforced concrete frame. *Ninth International Conference on Engineering Applications of Neural Networks, EAAN2005*, Lille, France, 2005, 147–154.

[5] Lehký, D.: *DLNNET – program documentation, Theory and User's Guides*, Brno, Czech Republic, 2008, (in preparation).

[6] McKay, M.D., Conover, W.J., Beckman, R.J.: A comparison of three methods for selecting values of input variables in the analysis of output from a computer code. *Technometrics*, 21, 1979, 239–245.

[7] Novák, D., Teplý, B., Keršner, Z.: The role of Latin Hypercube Sampling method in reliability engineering. *Proceedings of ICOSSAR-97*, Kyoto, Japan, 1998, 403–409.

[8] Novák, D., Lehký, D.: Inverse analysis based on small-sample stochastic training of neural network. *Ninth International Conference on Engineering Applications of Neural Networks, EAAN2005*, Lille, France, 2005, 155–162.

[9] Novák, D., Lehký, D.: ANN Inverse Analysis Based on Stochastic Small-Sample Training Set Simulation. *Engineering Application of Artificial Intelligence*, 19, 2006, 731-740.

[10] Novák, D., Vořechovský, M., Rusina, R.: *FReET v.1.5 – program documentation, User´s and Theory Guides*. Brno/Červenka Consulting, Czech Republic, 2007, http://www.freet.cz.