IDENTIFICATION OF SHEAR WALL FAILURE MODE

V. ČERVENKA [1], D. NOVÁK [2], D. LEHKÝ [2] and R. PUKL [1]
[1] Červenka Consulting, Prague, Czech Republic
[2] Institute of Structural Mechanics, Faculty of Civil Engineering, BUT, Brno, Czech Republic

ABSTRACT

The paper is focused on identification of failure mode in a shear wall using advanced computational models and experiments. A problem arising from application of nonlinear fracture mechanics is discussed: a proper choice of material parameters in a computational model. The solution of such identification problem is presented. The approach is based on coupling of the stochastic nonlinear fracture mechanics analysis and the artificial neural network.

1 INTRODUCTION

A realistic modeling of structures made of quasi-brittle materials, such as concrete, is made possible due to advances in computational methods and nonlinear fracture mechanics. Computer code ATENA (Červenka [1], [2]) represents an efficient engineering tool for this purpose. It employs a set of advanced material models based on fracture mechanics, plasticity and damage. The models used in such analysis should be objective and thus should capture a sufficiently wide range of practical cases for a unique set of basic material parameters. This objectivity is tested through validation studies, where simulations done by computer program are compared with experiments. For such validations, we must first determine the basic material parameters, which can be used as input data for a simulation. However, in many practical cases some parameters needed for our theoretical models based on test data are lacking. In other cases we seek an inverse analysis of material parameters from complex experiments. In all such situations we are facing the problem of identification of model parameters. A most simple way of parameter identification, well known to all researchers, is the “trial-and-error” procedure, sometimes called “what-if-study”. However, this method is useful only in case when one parameter is most important and fails in general case of a multi-parameter model. This paper presents a rational method of model parameter identification.

The numerical analysis, such as the one with ATENA, can be considered as a virtual testing tool of concrete structures. The model needs a set of material parameters as input and provides a load-deflection curve as a response. The objective is to find such a set of material parameters, which gives the best agreement between the simulated and experimental load-deflection curves. The proposed identification strategy is based on a coupling of the stochastic nonlinear fracture mechanics analysis and the artificial neural network.

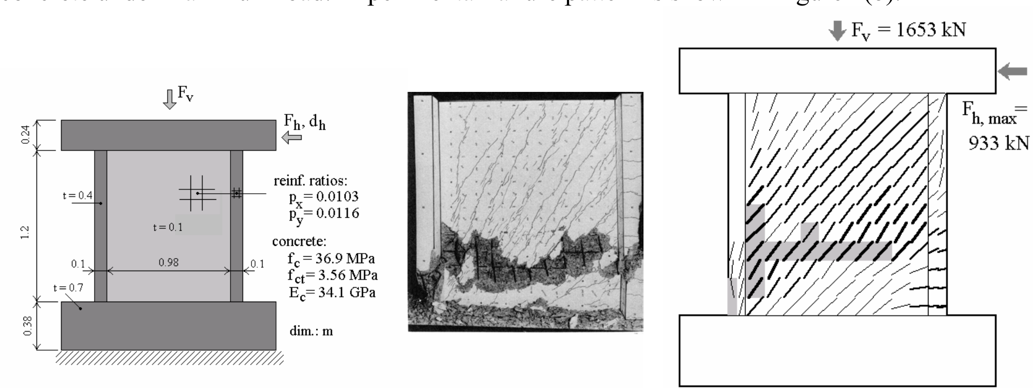
Identification parameters play the role of basic random variables with the scatter reflecting the physical range of possible values. The efficient Monte Carlo type simulation method Latin Hypercube Sampling (LHS) is used. The statistical simulation provides a set of response data, which can be considered as the results of virtual experiments. Generated basic random variables and consequently calculated load-deflection curves are used for training of a suitable type of neural network. Once the neural network is trained it can simulate the structural behavior, and can be utilized in an inverse way. For a given experimental load-deflection curve it can provide the best possible set of material model parameters.

The implementation of the proposed identification method was made by integrating several software tools: Nonlinear analysis software ATENA (Červenka [1], [2]), probabilistic software package FREET (Novák et al. [3]), reliability shell SARA (Pukl et al. [4], Bergmeister et al. [5])

and neural network software DLNNET recently developed (Lehký [6]). The method is illustrated on the example of a shear wall tested by Maier and Thürliman [7], for which promising good results have been achieved and indicate that efficient techniques have been combined at all three basic levels: deterministic nonlinear modeling, probabilistic stratified simulation and neural network approximation.

2 SHEAR WALL FAILURE MODE: EXPERIMENT AND MODELING

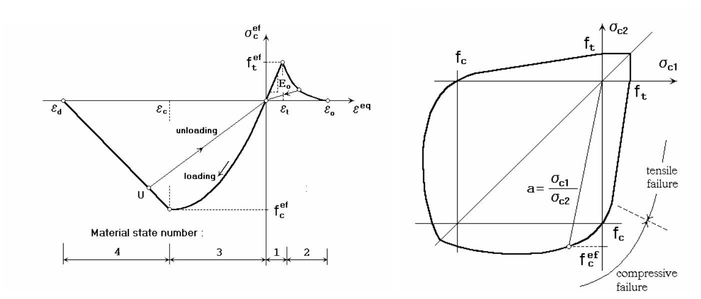
The shear wall shown in Figure 1 was tested by Maier and Thürliman [7] as a part of an research project on structural systems of high rise buildings. The square panel was orthogonally reinforced and provided with stiffening flanges. Loading by the vertical force was applied first representing a dead load. Then a horizontal force was applied and increased to failure. Behavior during the experiment reported extensive diagonal cracking prior to failure followed by explosive crushing of concrete under maximum load. Experimental failure pattern is shown in Figure 1(b).



(a) Geometry, material data. (b) Experimental failure (c) Failure simulated by ATENA

Figure 1: Shear wall tested by Maier and its ATENA simulation.

The analysis was done by ATENA using plane-stress isoparametric finite elements with the composite reinforced concrete material. This material consists of two phases, concrete and smeared reinforcement. Concrete constitutive law is based on damage-based concept, in which



(a) Stress-strain law. (b) Failure function based on Kupfer.

Figure 2: Concrete model SBETA.

the stress-strain law, Figure 2(a), covers the whole range of behavior including the post-peak softening in tension as well as in compression. The peak stresses in compression and tension are defined by the strength envelope according to Kupfer, see Figure 2(b). This relation is used for stress response in two orthogonal material axes within the concept of otrhotropic damage model. Fixed crack model is adopted. The strain-localization due to softening is controlled by the crack band, which is related to the element size. Strain localizes into a displacement, which represents a failure discontinuity in tension, or compression. Within the crack band model these displacements can be calculated as

$$w_c = L_t \varepsilon_t, \quad w_d = L_d \varepsilon_d \tag{1}$$

where in tension w_c is the crack width, ε_t is a tensile strain (or in case strain decomposition a fracture strain) within the crack band L_t. Similarly, w_d is the compression slip of the crush zone, ε_d is compressive strain (or in case strain decomposition a plastic strain), L_d is the localization band in compression. The values of bands L_t (tension), L_d (compression), measured in perpendicular directions, are element projections oriented parallel and normal to the orientation as shown in Figure 3. The constitutive laws in softening ranges, denoted by numbers 2 and 4 in Figure 2(a), are formulated in terms of stress-displacement variables. In tension the exponential softening law according to Hordijk is accepted, which is fully defined by two parameters, the fracture energy G_f and tensile strength f_t. In compression a linear approximation of Van Mier softening is used, with the parameter w_d. Details of these formulations can be found in the references Červenka [1], [2].

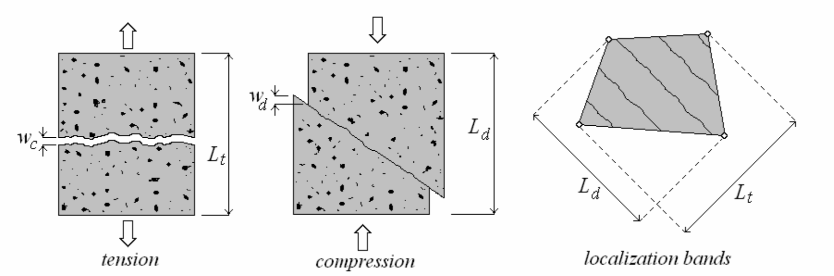


Figure 3: Localization bands in tension and compression.

A low mesh sensitivity of the model and its objectivity was published in the paper by Červenka et.al. [8]. The concrete constitutive model described above includes some additional features for cracked concrete (shear retention, etc.), which can be found in paper by Červenka [1].

The simulation of the load-displacement response of this shear wall revealed, that the quality of the failure mode can be well captured with the above model. As shown in Figure 1(c) the crack directions and locations of crushed concrete agree with experiment. However, the maximum load and ductility of the model was significantly underestimated. This is likely due to the simplification of the constitutive model. The stress-strain curve, Figure 2(a), is based on uni-axial experiments of cylinders and is only slightly modified to account for the bi-axial stress action. There is no ductility in compression in such model.

However, in reality, there are some locations in the shear wall, in which a three-dimensional stress state can develop. Then a confinement effect can increase the strength and ductility of concrete. This is expected near the joints of panel with flanges and with the foundation slab. If we restrict our model to a plane stress formulation, there is no rational way for modeling confinement. However, in 2D model we have a simple tool for this by adjusting the compressive parameter w_d. This was done by "trial-and-error" method and results are compared with experiment in Figure 4.

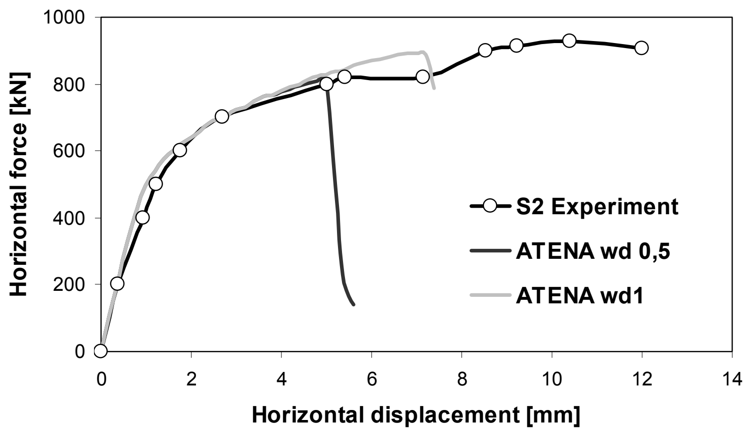


Figure 4: Comparison of simulations with experiment (without identification).

A more rational method for determination of parameters is proposed in the following part.

3 IDENTIFICATION OF MATERIAL MODEL PARAMETERS

The new identification technique is based on combination of statistical simulation and training of neural network (Lehký & Novák [9]). Several software tools had to be combined in order to make the identification possible. The whole procedure can be itemized as follows (software relevant to individual steps is referenced):

1. Computational model hast to be first developed using the appropriate FEM software which enables modeling of both pre-peak and post-peak behavior. Initial calculation uses a set of initial material model parameters. Software: ATENA (Červenka & Pukl [10]).
2. Parameters of material model to be identified are considered as random variables described by a probability distribution, rectangular distribution is a "natural choice" as lower and upper limits represent the bounded range of physical existence. But other distributions can be also used, eg. Gaussian (in spite of the fact that it is not bounded). These parameters are simulated randomly based on Monte Carlo type simulation, small-sample simulation LHS is recommended. Statistical correlation between some parameters can be taken into account. Software: FREET (Novák et al. [3]).
3. A multiple calculation of deterministic computational model using random realizations of material model parameters is performed resulting in "a bundle" of load-deflection curves (usually overlapping experimental curve). Software: SARA (Pukl et al. [4], Bergmeister et al. [5]).
4. Random load-deflection curves serve as basis for training of an appropriate neural network. Such training can be called a stochastic training due to the stochastic

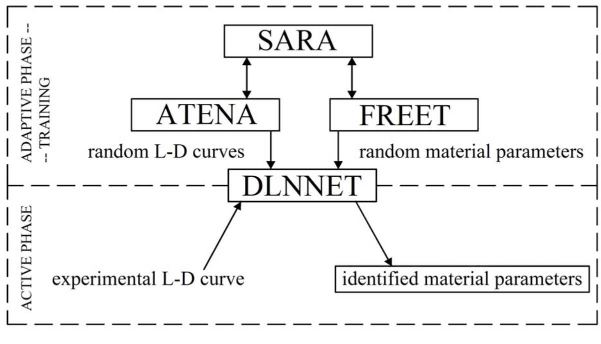


Figure 5: Identification software communication scheme.

origin of load-deflection curves. After training the neural network is ready to answer the opposite task: To select the material model parameters which can capture the experimental load-deflection curve as close as possible. Software: DLNNET (Lehký [6]).

5. Final calculation using identified material model parameters should verify how well parameters were identified (ATENA).

The complexity of program communication and necessary interfaces are shown in Figure 5.

All 10 shear wall parameters of material models (both concrete and steel reinforcement) were identified here. Mean values of parameters used for stochastic simulation and consequent identification are as follows: for concrete (SBETA model) – modulus of elasticity E_c = 30 GPa, compressive strength f_c = 35 MPa, tensile strength f_t = 2.5 MPa, fracture energy G_F = 75 N/m, compressive strain in the uniaxial compressive test ε_c = 0.0025, critical compressive displacement w_d = 0.003 m; for steel (bilinear law) – yield strain x_1 = 0.0027, yield stress f_{x1} = 574 MPa, ultimate strain x_2 = 0.015 and ultimate stress f_{x2} = 764 MPa.

For stochastic training, randomness was introduced using coefficient of variation 0.10 for E_c, f_t and f_c, 0.2 for G_F and ε_c, 0.3 for w_d and 0.1 for all steel parameters. Rectangular probability distribution for all random variables is used. 20 simulations of LHS resulted in load-deflection curves presented in Figure 6. This input-output information serves for training of selected neural network: network with 24 inputs (24 points on load-deflection curve for every simulation is utilized for training), two hidden layer consisting of 12 and 10 neurons with nonlinear transfer functions and one output layer of 10 neurons with linear transfer function. Trained neural network provided the material model parameters: E_c = 33 GPa, f_c = 35.3 MPa, f_t = 2.47 MPa, G_F = 77.85 N/m, ε_c = 0.0026, w_d = 0.0031 m, x_1 = 0.0028, f_{x1} = 570.7 MPa, x_2 = 0.0147 and f_{x2} = 768.8 MPa.

Final calculation using ATENA resulted in a very good agreement with experimental load-deflection curve, Figure 7.

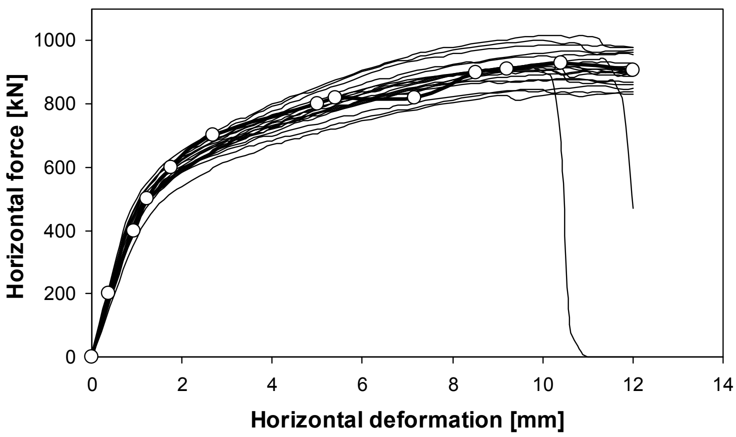


Figure 6: Random load-deflection curve realizations – 20 simulations of LHS.

4 CONCLUSION

A method for rational identification of material parameters from structural experiments is proposed. It combines numerical tools for nonlinear analysis, stochastic processes and neural networks. The method allows an efficient inverse analysis of material parameters based on experimental load-displacement response. It gives better much results then the heuristic “trial-and-error” approach. Such well-identified parameters based on an experiment can be then used for simulation of a real structure.

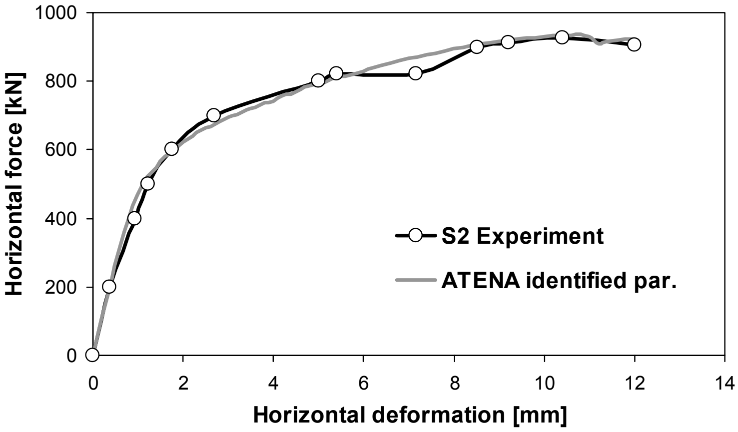


Figure 7: Load deflection curves – experiment and simulation using identified parameters.

ACKNOWLEDGEMENT

The financial support by grant of the Grant Agency of Czech Republic (GACR) No. 103/04/2092 is greatly appreciated.

REFERENCES

[1] Červenka, V. Simulating a response. Concrete Engineering International, 4 (4): 45-49, 2000.

[2] Červenka, V. Computer simulation of failure of concrete structures for practice. 1st fib Congress 2002 Concrete Structures in 21 Century, Osaka, Japan, Keynote lecture, 289-304, 2002.

[3] Novák, D., Vořechovský, M. & Rusina, R. Small-sample probabilistic assessment – software FREET. 9th International Conference on Applications of Statistics and Probability in Civil Engineering – ICASP 9, San Francisco, USA, 91-96,Rotterdam: Millpress, 2003.

[4] Pukl, R., Červenka, V., Strauss, A., Bergmeister, K. & Novák, D. An advanced engineering software for probabilistic-based assessment of concrete structures using nonlinear fracture mechanics. 9th International Conference on Applications of Statistics and Probability in Civil Engineering (ICASP9), San Francisco, California, USA, Rotterdam: Millpress, 1165-1171, 2003.

[5] Bergmeister, K., Novák, D., Strauss, A., Eichinger, E.M., Kolleger, J., Pukl, R., & Červenka, V. Structural analysis and safety assessment of existing concrete structures. In Proc: 1st fib Congress Concrete Structures in 21st Century, Osaka, Session 11, 47–54, 2002.

[6] Lehký, D. DLNNET – Program documentation, theory and user's manual. Institute of Structural Mechanics, Brno University of Technology, 2004, (in preparation).

[7] Maier, J. & Thürliman, B. Bruchversuche an Stahlbetonscheiben, Institut für Baustatik und Konstruktion ETH Zürich, Bericht Nr.8003-1, 1985.

[8] Červenka V., Pukl R., Ožbolt, R. & Eligehausen R. Mesh Sensitivity Effects In Smeared Finite Element Analysis Of Concrete Fracture, FraMCoS-2, Second International Conference on Fracture Mechanics of Concrete and Concrete Structures, Zürich, Switzerland, 1387-1396, 1995.

[9] Lehký, D. & Novák, D. Identification of material model parameters using stochastic training of neural network. 5th International PhD Symposium in Civil Engineering, Delft, Netherlands, 2004.

[10] Červenka V. & Pukl R. ATENA Program documentation – theory. Červenka Consulting, Prague, Czech Republic, 2003.