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Modifications of self-learning FEM/NMM approach to identification of equivalent material models for plane stress problems

*** Ewa Pabisek[1] and Zenon Waszczyszyn[2]**

[1] Institute for Computational Civil Engineering, Cracow University of Technology
ul. Warszawska 24, 31-155 Kraków, Poland
E-mail e.pabisek@l5.pk.edu.pl
URL www.L5.pk.edu.pl

[2] Chair of Structural Mechanics, Rzeszów University of Technology
ul. W.Pola 2, 35-935 Rzeszów, Poland
E-mail zewasz@prz.edu.pl

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Identification of material models in real structures is a difficult problem of solid mechanics because of material changes during the structure life. The identification corresponds to the analysis of an inverse, homogenisation problem in which an equivalent material model is searched.

It was shown in many papers (cf. references in [4]) that neural networks can be efficiently used for implicit formulation of Neural Material Models (NMMs). Using NMMs in FEM codes leads to hybrid FEM/NMM programs in which NMM is a numerical material procedure. The main problem of such an approach is formulation of patterns for NMM training. In case of a known material the patterns can be computed by means of assumed constitutive equations and then the NMM is trained in the 'off line' mode [3]. In case the material model is 'a priori' unknown J. Ghaboussi proposed to apply the 'on line' method, which he called the autoprogressive method [1]. In this method the patterns are formulated at each increment of the loading process using a two stage Newton-Raphson method for the correction of displacements at control points. The NMM is retrained at each incremental load by means of an updated set of patterns computed by the hybrid FEM/NMM program.

The autoprogressive method is very sensitive to the patterns selection since only a part of them can be updated. Another question is formulation of input and output data in order to take into account the history of the loading process. In case of plane stress problems the output vector is $\boldsymbol{y}_{(3x1)} = \{_{n+1}\boldsymbol{\sigma}\}$, where n is a quasi time number instant. Corresponding input vectors can be adopted in the form:

$$\boldsymbol{x}_{(9\times1)} = 1) \quad \{_{n+1}\boldsymbol{\varepsilon},\ _{n}\boldsymbol{\varepsilon},\ _{n}\boldsymbol{\sigma}\}, \quad 2) \quad \boldsymbol{x}_{(3x1)} = \{_{n+1}\boldsymbol{\varepsilon}\}, \tag{1}$$

where: $_{k}\boldsymbol{\varepsilon} =_{k} \{\varepsilon_x,\ \varepsilon_y,\ \gamma_{xy}\},\ _{k}\boldsymbol{\sigma} = {}_{k}\{\sigma_x,\ \sigma_y,\ \tau_{xy}\}$ for $k = n, n+1$.

The form 1) in (1) was suggested in [2] but in the present paper the form 2) was explored, since the vectors $_{n}\boldsymbol{\varepsilon}$ and $_{n}\boldsymbol{\sigma}$ are stored in the program FEM/NMM, out of the NMM model. The NMM input and output variables and those stored in the program FEM/NMM enable the computation of the consistent stiffness matrix components $k_{ij} = \partial\Delta\sigma_i/\Delta\varepsilon_j$.

Another modification is related to the initial formulation of NMM and its training. The first cycle of the computation starts from an isotropic, elastic linear model of a material but for the subsequent steps of the initial cycle the autoprogressive method is applied. The network architecture is formulated in the first loading cycle and then only network parameters are updated.

The introduced modifications were verified on boundary value problems analysed in [3], see Figures 1 and 2. The equilibrium path $u_A(\lambda)$ of a tension perforated strip shown in Fig. 1a, computed for elastoplastic material, was assumed to be a measurement curve at the control point A, see Fig. 1b. The network 3-15-15-3 was trained using two loading cycles. Then this network was retrained on the same structure shown in Fig. 1a adding patterns corresponding to compression of the perforated strip. A more general identified equivalent NMM-ret was applied to the simulation of displacements in the notched beam shown in Fig. 2a. The loading paths computed for the elastoplastic material by the FEM program is shown in Fig. 2b vs. the paths computed by the hybrid FEM/NMM-ret program.

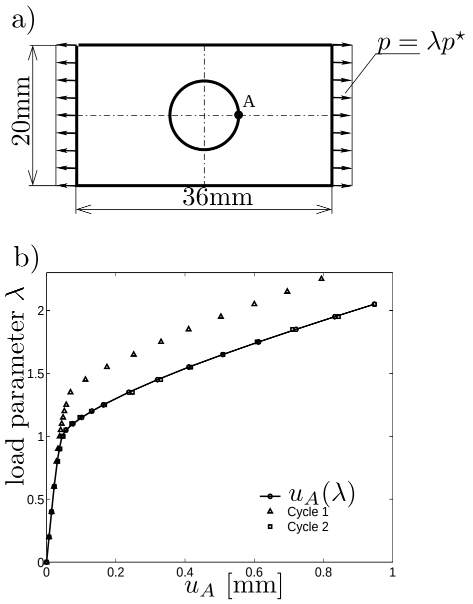

Fig.1: a) Tension perforated strip, b) Equilibrium path $\lambda(u_A)$

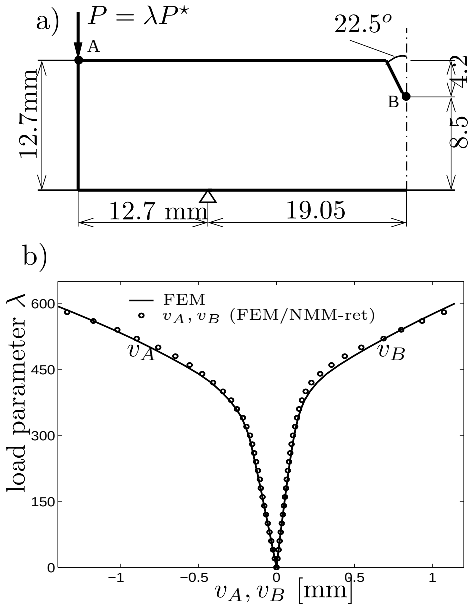

Fig.2: a) Notched beam, b) Equilibrium paths $\lambda(v_A)$ and $\lambda(v_B)$

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