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ANALYSIS OF SOME PROBLEMS OF EXPERIMENTAL MECHANICS AND BIOMECHANICS BY MEANS THE ANFIS NEURO-FUZZY SYSTEM

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The Adaptive Neuro-Fuzzy Inference System (ANFIS) has been applied to the analysis of three problems: prediction of fundamental periods of vibrations of 5-storey prefabricated buildings, estimation of proximal femur strength, estimation of fracture toughness of dense concret. The results obtained by means of ANFIS are compared with those empirical formulae and forward neural networks. The ANFIS results have been proven to be superior.

Key words: neuro-fuzzy system, vibration of buildings, proximal femurs, fracture toughness, experimental mechanics

1. Introduction

Fuzzy Inference Systems (FIS), Artificial Neural Networks (ANNs) and Evolutionary Strategies (ES) create the background of the so called *soft computing* (cf Jang et al., 1997). A natural tendency is interaction and joining the components of the above mentioned approaches; e.g. fuzzy-networks are worth emphasising as a new efficient tool for the analysis of various simulation and identification problems. This concerns especially the problems with experimental evidence.

Applications of the Adaptive Neuro-Fuzzy Inference System (ANFIS) to the analysis of three problems are briefly discussed in the paper. ANFIS has been used to the analysis of experimental results obtained when solving the following problems of structural mechanics and biomechanics:

- fundamental period of vibration of 5-storey buildings

- strength of proximal femur
- fracture toughness of dense concrete.

The common feature of all these problems is that only one output variable is considered. The fundamental periods of vibrations were computed basing on the dynamic responses measured on real buildings. The strength of proximal femur and bone properties were measured during *in vitro* experiments. Laboratory tests were performed on special specimens made of dense concrete. One-to-one correspondence of the input and output data took place in the first two problems considered. It is not the case of fracture toughness estimation since, as usually in laboratory tests, the specimens made of the same concrete revealed various magnitudes of the fracture force. Another common feature is that a relatively small number of tests can be carried out.

The problems were briefly discussed in the contributions presented at the EANN'99 Conference, cf Waszczyszyn et al. (1999), Putanowicz and Waszczyszyn (1999), Ziemianski et al. (1999). In these papers the attention was focused on the results obtained by means the forward neural networks, i.e. Back-Propagation NN and Regularization NN.

2. Fuzzy Inference System (FIS) and ANFIS

The basic idea of FIS is to perform the mapping $f : \boldsymbol{x}' \to \boldsymbol{y}'$ using crisp values for the components of input and output vectors $\boldsymbol{x}'$ and $\boldsymbol{y}'$ without *a priori* given relationships between them and using intrinsic fuzzy inference rules. That means that looking from the outside we use crisp data but operations inside the system are performed on fuzzy sets.

In what follows we restricted our considerations to the mapping

$$\boldsymbol{x}'_p \in R^N \to y'_p \in R^1 \qquad \text{for} \quad p = 1, ..., P \tag{2.1}$$

where P – number of patterns. The components of input vector $\boldsymbol{x}'_p$ and scalar output y'_p are assumed to be crisp values.

In FIS we use the fuzzy sets according to the definition

$$A = \{(x, \mu_A(x)) |\ x \in X\} \tag{2.2}$$

where $\mu(x)$ – membership function. In what follows the following two membership functions are specified:

a) singleton

$$\mu_A(x;c) = \delta(x-c) = \begin{cases} 1 & \text{for} \quad x = c \\ 0 & \text{for} \quad x \neq c \end{cases} \tag{2.3}$$

b) Gaussian function

$$\mu_A(x;c,\sigma) = \exp\Big(-\frac{(x-c)^2}{2\sigma^2}\Big) \tag{2.4}$$

In Fig.1 a scheme of standard FIS is shown. Fuzzification of a crisp value x' to fuzzy set A' is usually performed by singleton, substituting $c = x'$ into Eq (2.3).

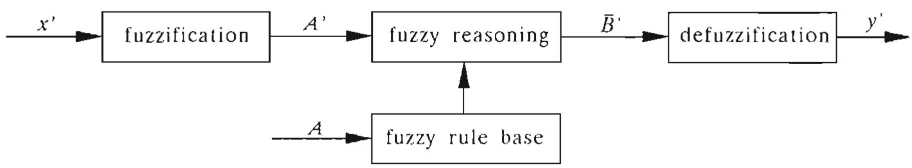

Fig. 1. Scheme of standard FIS

A fuzzy inference rule can be written in the following general form of fuzzy implication $\boldsymbol{A}^k \to B^k$

$$R^{(k)}: \quad \text{IF} \quad (\boldsymbol{x} \text{ is } \boldsymbol{A}^k) \quad \text{THEN} \quad (y \text{ is } B^k) \tag{2.5}$$

and fuzzy reasoning is performed according to the fuzzy composition of set $\boldsymbol{A}'$ and implication $\boldsymbol{A}^k \to B^k$

$$\overline{B}^k = \boldsymbol{A}' \circ (\boldsymbol{A}^k \to B^k) \tag{2.6}$$

Defuzzification is associated with the application of the formula for extracting a crisp value that best represents a union of the fuzzy sets $\overline{B}^k$.

The Adaptive Neuro-Fuzzy Inference System (ANFIS) is a modification of standard FIS. The modification consists in accepting the following assumptions (cf Jang et al., 1997):

- Partition of input space
- Sugeno fuzzy rule
- Hybrid learning.

In Fig.2 the two partitions are shown for the 2D input space (x_1, x_2). As an example four Sugeno first-order rules are written for the grid partitioning

$$R^{(k)} = R^{(k1,k2)} = \\ = \text{IF } (x_1 \text{ is } A_1^{k1} \text{ AND } x_2 \text{ is } A_2^{k2}) \text{ THEN } y_k = a_k + b_1^k x_1 + b_2^k x_2 \tag{2.7}$$

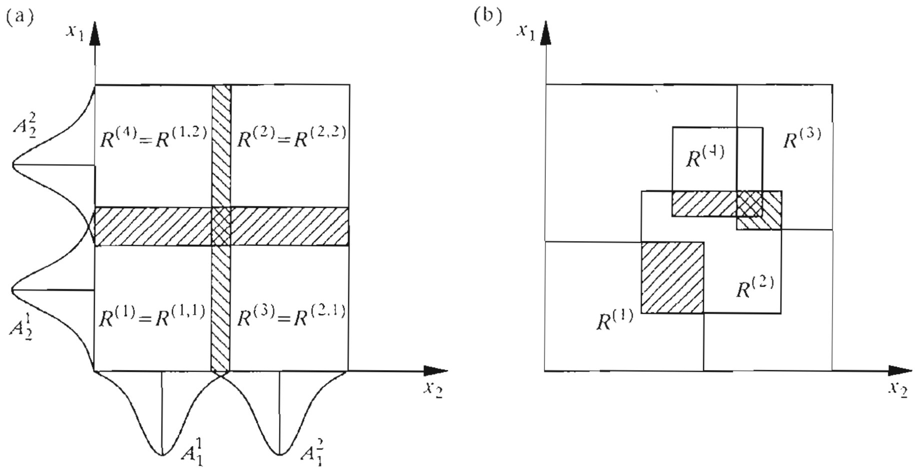

Fig. 2. Partitioning of input space: (a) grid partition, (b) scatter partition

In Fig.3 a scheme of ANFIS is shown. Fuzzy neurons correspond to the membership functions μ_{Ai} and weights w_k which are computed by means of the algebraic product

$$w_k = \mu_{A1}^{k1}(x_1')\mu_{A2}^{k2}(x_2')...\mu_{An}^{kn}(x_n') \tag{2.8}$$

The weighted centroid formula is used for computing the crisp output y'

$$y' = \frac{\sum\limits_{k=1}^{K} w_k y_k}{\sum\limits_{k=1}^{K} w_k} \tag{2.9}$$

Hybrid learning is associated with forward computation of consequence parameters a_k, b_1^k, b_2^k in (2.7). The error backpropagation method is used to compute the premise parameters of fuzzy-neurones (in Fig.3 the Gaussian membership function (2.4) is assumed so premise parameters are c_i and σ_i).

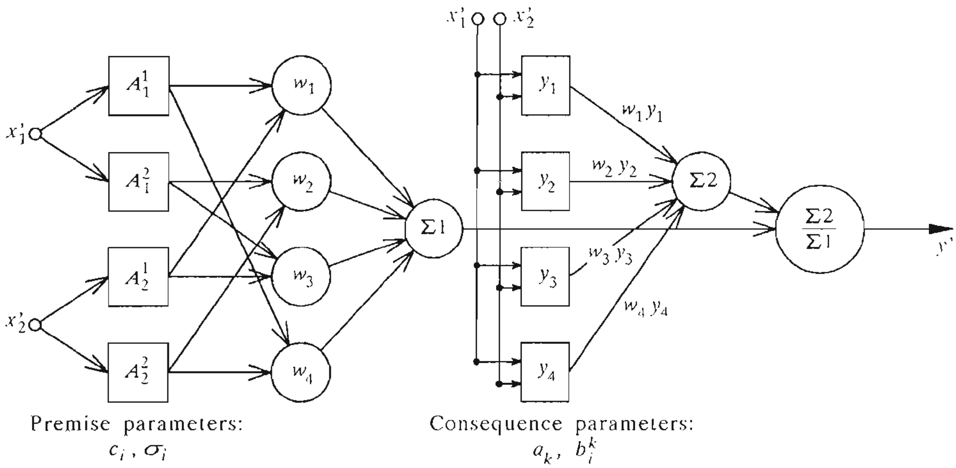

Fig. 3. Scheme of ANFIS

The analysis of the problems discussed in the following Sections has been carried out using the Fuzzy Logic Toolbox Matlab (1998). The corresponding computer program ANFIS enables us to select automatically the number of Sugeno's rules associated with the scatter partition of input space. Besides the Gaussian membership functions the first-order Sugeno rule (2.7) has been assumed.

3. Fundamental periods of vibrations of prefabricated buildings

Estimation of the fundamental periods of natural vibrations is usually required in assessment of real buildings by means of expert systems. The main approach is related to processing of the measurement results on buildings in natural scale in order to obtain the "experimental" periods of vibrations. The empirical formulae are formulated to establish the building fundamental periods for both structural and soil basement parameters.

In the paper by Ciesielski et al. (1995) the analysis results for a group of medium-height buildings were discussed. The group consisted of 13 Polish prefabricated, 5-storey flat buildings. In Fig.4 there are shown the plan and vertical cross-section of a building segment (tested buildings were made in large panel and large block technologies, cf Table 1). The tests consisted in measurements of horizontal vibration components in the x and y directions, i.e. transverse and longitudinal directions, respectively.

Kuźniar and Maciąg (1999) selected the following three representative inputs:

- elastic uniform vertical deflection of soil basement C_z
- building plan dimension b, cf Fig.4
- equivalent bending stiffness $k_b = \sum_i EI_i/a$, where E – building wall Young modulus, I_i – moment of inertia of the ith wall, a – length of the building segment, cf Fig.4.

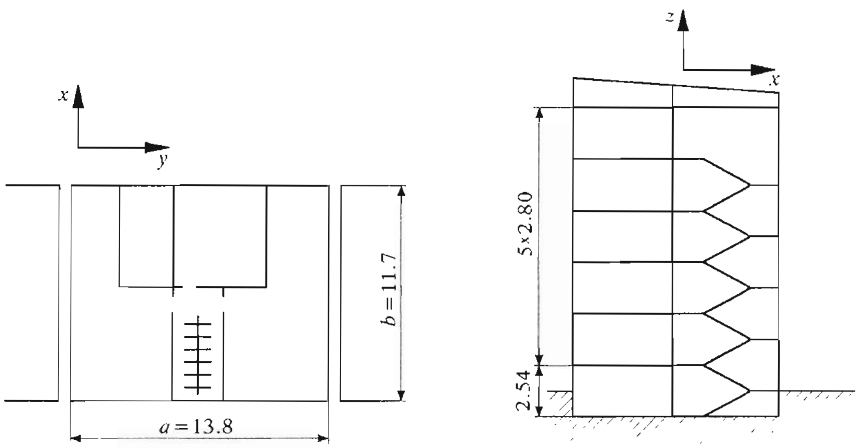

Fig. 4. Medium (5-storey) building, WBL type

The input vector $\boldsymbol{x}'$ and scalar output y' are

$$\boldsymbol{x}' = \{\overline{C}_z, \overline{b}, \overline{k}_b\} \qquad y' = T_1 \tag{3.1}$$

where all components $\overline{C}_z$, $\overline{b}$, $\overline{k}_b$ are transformed to the range $[0.1,\ 0.9]$.

The set of $P = 31$ patterns listed in Table 1 was split into $L = 22$ training(learning) patterns and $T = 9$ testing patterns. The selection of testing patterns (marked in Table 1 by the superscript T in column 3 was discussed by Kuźniar and Maciąg (1999). In Fig.5a the training and testing processes are visualised using the Root-Mean-Square-Error

$$\text{RMSE} = \sqrt{\frac{1}{V}\sum_{p=1}^{V}[T_{exp}^{(p)}(s) - T_{com}^{(p)}(s)]^2} \tag{3.2}$$

where

$V = L, T$	–	members of training and testing patterns
$T^{(p)}_{exp}, T^{(p)}_{com}$	–	experimental and computed fundamental periods of vibrations
s	–	number of epochs (one epoch corresponds to the subsequent presentation of all the training patterns L, one cycle of hybrid learning and checking of the testing error RMSE$(s;T)$ for all the testing patterns T without improving the network parameters).

The learning process was continued up to $S = 100$ epochs. It was stated that for $s* = 80$ epochs the testing error RMSE$(s*;T)$ was minimal. In Fig.5 the errors RMSE$(s;L)$ are related to the training process as well as the testing errors RMSE$(s;T)$ are shown.

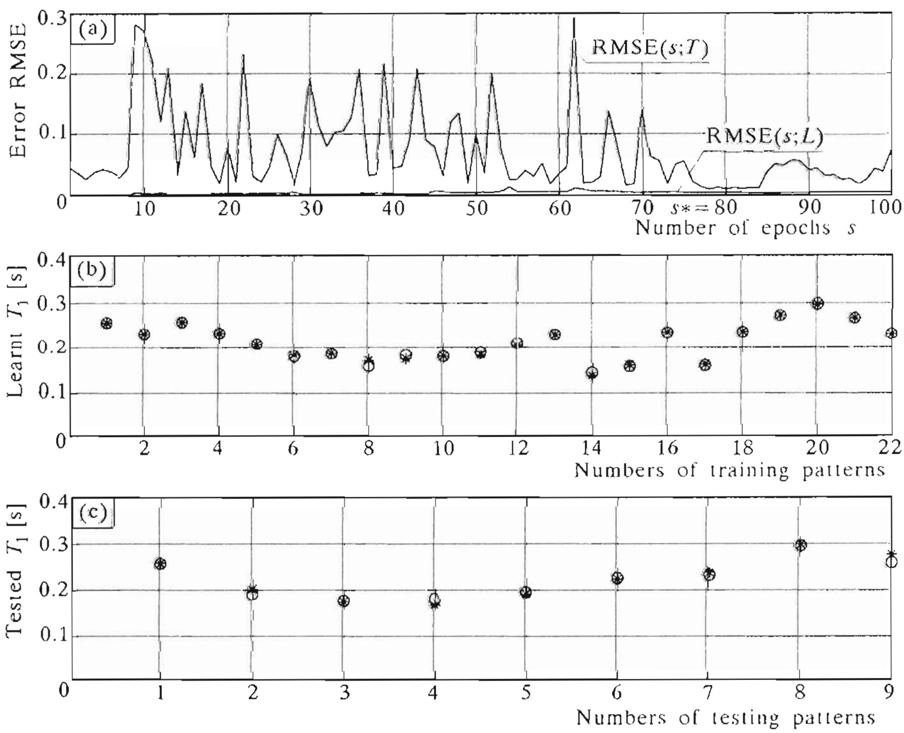

Fig. 5. Errors for the patterns listed in Table 1: (a) training(learning) errors RMSE$(s;L)$ and testing errors RMSE$(s;T)$, (b) fundamental periods of vibrations $T^{(p)}_{exp}$ and $T^{(p)}_{com}$ for the training patterns, (c) $T^{(p)}_{exp}$ and $T^{(p)}_{com}$ for the testing patterns

Table 1. Relative errors $e_{rel}^{(p)}$ for the fundamental periods of 5-storey building vibrations

Building		Direction of vibration	Pattern number	Measured periods T_{exp} [s]	$e_{rel} = \|1 - T_{exp}/T_{com}\|100\%$				
					BPNN	RBF	ANFIS	Formula	
								(3.5)	(3.6)
1		2	3	4	5	6	7	8	9
DOMINO-68 (I)		transverse	1	0.256	6.0	1.9	0.1	2.6	17.4
		longitud.	2	0.230	0.6	4.1	0.0	11.6	20.4
DOMINO-68 (II)		transverse	3	0.256	6.0	1.9	0.1	2.6	17.4
		longitud.	2	0.230	0.6	4.1	0.0	11.6	20.4
WUF-T-67-S.A./V		transverse	5^T	0.253	7.0	3.1	0.4	5.0	17.6
		longitud.	6	0.240	3.5	1.0	0.0	22.4	14.0
WUF-GT 84 (I)	seg.(I)	transverse	7	0.175	4.3	2.5	1.5	3.5	14.4
		longitud.	8^T	0.185	4.5	3.5	5.9	5.4	9.9
	seg.(II)	transverse	9	0.180	1.8	0.4	0.2	9.3	11.9
		longitud.	10^T	0.169	2.3	3.2	1.0	0.0	0.9
WUF-GT 84 (II)	seg.(I)	transverse	11	0.157	7.8	9.4	7.7	3.1	20.5
		longitud.	–	–	–	–	–	–	–
	seg.(II)	transverse	12	0.180	5.6	4.6	4.5	10.7	5.7
		longitud.	13	0.177	6.8	5.0	0.0	8.8	8.5
C/MBY/V (I)		transverse	14^T	0.172	6.8	4.9	8.0	13.8	4.5
		longitud.	15	0.192	9.3	8.8	2.6	26.9	3.6
C/MBY/V (II)		transverse	16^T	0.185	5.2	5.6	2.2	1.9	12.5
		longitud.	17	0.213	3.4	6.3	1.6	17.0	2.4
C/MBY/V (III)		transverse	18^T	0.227	1.7	5.8	1.0	11.4	1.6
		longitud.	19	0.223	0.4	3.3	0.1	13.9	5.7
BSK (I)	seg.(I)	transverse	20	0.155	4.2	10.5	4.3	1.5	14.2
		longitud.	21^T	0.233	2.0	9.3	2.3	53.5	20.0
	seg.(II)	transverse	22	0.155	5.8	10.8	2.2	1.5	15.5
		longitud.	23	0.233	1.1	10.4	0.5	53.5	20.0
BSK (II)	seg.(I)	transverse	–	–	–	–	–	–	–
		longitud.	–	–	–	–	–	–	–
	seg.(II)	transverse	24	0.156	5.1	10.1	1.5	3.1	14.6
		longitud.	25	0.233	1.1	10.4	0.5	53.5	20.0
WWP		transverse	26	0.270	1.7	2.4	0.4	5.4	4.9
		longitud.	27^T	0.294	6.2	14.9	0.9	14.7	5.2
WBL		transverse	28	0.294	10.6	10.1	0.2	14.7	7.7
		longitud.	29	0.263	2.9	0.0	0.0	2.6	14.7
WK-70		transverse	30^T	0.256	3.7	2.9	6.6	0.0	10.5
		longitud.	31	0.227	0.1	1.3	0.0	11.4	13.0
				e_{avr}	4.1	5.6	1.8	12.8	11.9
				e_{max}	9.3	14.9	7.7	53.5	20.5
				r	0.967	0.876	0.987	0.768	0.793

In Fig.5b,c the experimental values $T_{exp}^{(p)}$ are marked as $\circ$ and the results of training and testing are marked by $\star$ as corresponding to $s* = 80$.

In Table 1 the following relative errors are put together

$$e_{rel}^{(p)} = \left|1 - \frac{T_{exp}^{(p)}}{T_{com}^{(p)}}\right| 100\% \qquad e_{avr} = \frac{1}{P}\sum_{p=1}^{P} e_{rel}^{(p)} \qquad e_{max} = \max_{P} e_{rel}^{(p)} \tag{3.3}$$

where $p = 1, ..., P$ and $P = L + T$ – total number of patterns used for learning(training) and testing. In order to compare better the networks used for the estimation of natural periods of vibrations the linear correlation coefficient was computed

$$r = \min(r_L, r_T) \tag{3.4}$$

where r_L, r_T – coefficients of correlation of the measured and computed periods of vibrations $T_{exp}^{(p)}$, $T_{com}^{(p)}$ for the training and testing sets of patterns L and T, respectively.

In Table 1 also the relative errors corresponding to the results yielded by two forward neural networks are given. In column 5 the results are referred to the Back- Propagation Neural Network (BPNN) of structure 3-4-1. In column 6 the results correspond to a simple regularization network with the Radial Basis Functions (RBF), discussed by Putanowicz and Waszczyszyn (1999).

Columns 8 and 9 of Table 1 present the results obtained by means of two empirical formulae:

— according to Ciesielski et al. (1995)

$$T_1 = 0.98/\sqrt[3]{C_z} \tag{3.5}$$

— according to Kuźniar and Maciąg (1999)

$$T_1 = 1.2/\sqrt[3]{C_z + 0.003(k_b + k_s)/b} \tag{3.6}$$

where: $k_b = \sum_i EI_i/a$, $k_s = \sum_i GA_i/a$ – equivalent bending and shear stiffnessses of partition walls of the segment shown in Fig.4.

The comparison of results points out that the neural predictions are much better than those yielded empirical formulae. The ANFIS estimation is superior to the estimation by neural networks.

4. Strength of proximal femur

In the scope of cooperation with KU Leuven, Belgium the neural networks were applied to estimation of the strength of proximal femur. The strength is defined as an input load which causes cracking of the femur. The experiments were performed *in vitro* using the setup shown in Fig.6. Bone tissue properties were estimated by DXA (Dual X-ray Absorptiometry) and QCT (Quantitative Computer Tomography) techniques.

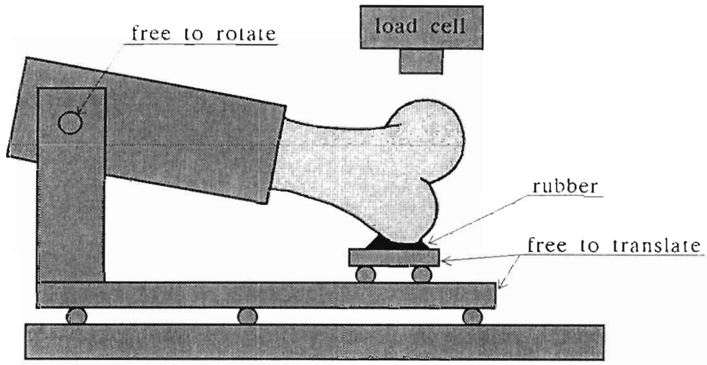

Fig. 6. Experimental setup for the bone strength measurement

From among the tests described by Druys (1998) only a group of 36 male femur specimens is considered. On the base of linear regression analysis Druys formulated the following formula

$$\begin{aligned} P_M &= -0.9 + 8.83 \cdot \text{Troch BMD} + 1.9 \cdot \text{Ward BMD} + 3.79 \cdot Pq \text{ densT} + \\ &+ 0.00015 \cdot \text{BMOIC} - 0.33 \cdot Pq \text{ areaC} - 0.000022 \cdot \text{BMOIT} \end{aligned} \tag{4.1}$$

where: Troch BMD, Ward BMD – bone mineral densities evaluated using the DXA and other inputs were evaluated by means of the QCT.

The six variables used in Eq (4.1) were assumed to be inputs in ANFIS. In Fig.7 the experimental strength loads P_{exp} versus the computed loads P_{com} are shown. The computed loads were obtained for $s* = 39$ epochs corresponding to the minimal value of error RMSE$(s*; T)$, where $T = 6$ is the number of selected testing patterns.

Table 2. Comparison between male femur estimations

Estimator	r	$St\varepsilon$
Linear regr. (4.1)	0.971	0.509
BPNN: 6-4-1	0.989	0.236
RBF: 6-30-1	0.973	0.412
ANFIS: 6-F-1	0.991	0.142

In Table 2 there are put together the values of linear coefficients of correlation r and standard error $St\varepsilon$ for various estimators. The statistical parameters r and $St\varepsilon$ were computed for all the patterns $P^{(p)}_{exp}$ versus $P^{(P)}_{com}$

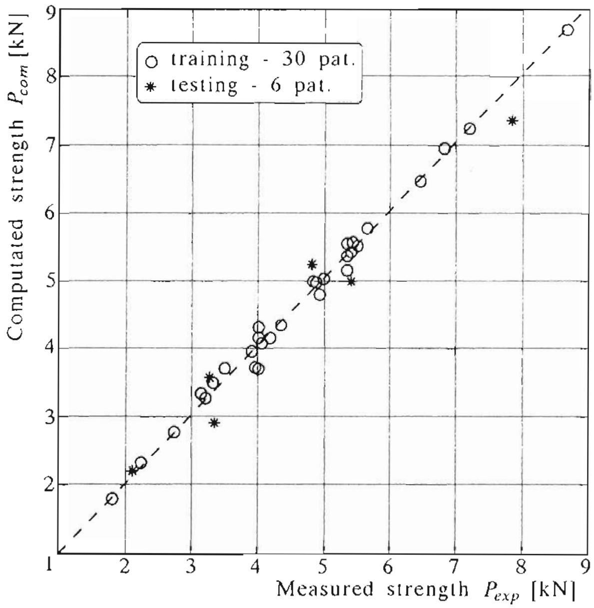

Fig. 7. ANFIS prediction of male femur strength P_{com} versus the measured strength P_{exp}

for $p = 1, ..., P$, where $P = 36$. Besides the regression formula (4.1) the BP network of structure 6-4-1 and RBF regularization network were used, cf Ziemianski et al. (1999).

The comparison between the results shows a superiority of ANFIS over forward networks and regression estimators.

5. Estimation of dense concrete fracture toughness

Dense concrete (of $\rho > 2600\,\mathrm{kg/m^3}$) used in special structures have brittle properties. Estimation of the fracture toughness of concrete is performed by means of laboratory tests on especially prepared specimens. In Fig.8a the so called Model II specimens is shown, cf Rawicki and Wojnar (1992). The tests on such specimens were made at the Cracow University of Technology, cf Kopta and Niziórski (1991), Prejzar (1998).

From among the experimental evidence the results corresponding to the two groups of tests (test I performed in 1998, test II in 1991) are used as a

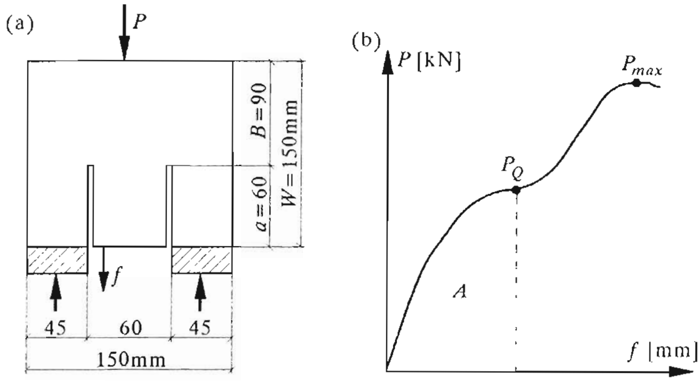

Fig. 8. (a) Model II of concrete specimens, (b) force-displacement relation for Model II

background to compute the stress intensity factor

$$K_{IIc} = \frac{5.11 P_Q}{2BW} \sqrt{\pi a} \quad [\mathrm{MN/m^{3/2}}] \tag{5.1}$$

where the specimen parameters and the force value P_Q are shown in Fig.8. In Table 3 the values of factor K_{IIc} are put together for two concrete mixtures (concrete A and B). For the fixed values of concrete strength f_c six tests I were carried out on the specimens with notches. 60 specimens of this group were used for learning by ANFIS. 8 average values of the factor K_{IIc} computed for tests II were explored for testing.

Fig.9a depicts the processes of ANFIS learning and testing. The minimal value of testing errors RMSE$(s;T)$ is obtained for $s* = 4$. The testing errors RMSE$(s;T)$ were computed for the average values of $K_{IIc}(f_c)$ listed in Table 3 for tests II.

For each concrete strength f_c average values of K_{IIc} are computed according to regularization properties of ANFIS, cf Fig.9b. The results of testing are shown for $s* = 4$, cf Fig.9c. In Fig.10a the linear correlation coefficients for tests I are computed separately for concrete A and B. The maximal relative errors for average values of K_{IIc} for tests II, computed by ANFIS trained on tests I, are about 3.5% for concrete A and 6.5% for concrete B. These results are slightly better than those obtained by means of the RBF regularization network, cf Putanowicz and Waszczyszyn (1999). In this paper the linear correlation coefficients $r_A = 0.877$ and $r_B = 0.897$ were computed versus $r_A = 0.870$ and $r_B = 0.924$ by ANFIS.

Table 3. Stress intensity factor K_{IIc} [$\mathrm{MN/m^{3/2}}$] for concrete A and B taken from Tests I and Tests II

Type of concrete	Tests I					Tests II			
f_c [MPa]	25.8	30.1	35.1	36.6	40.2	27.2	30.2	35.5	41.0
	2.36	2.70	2.84	3.00	3.32	2.38	2.71	2.94	3.29
	2.48	2.82	2.92	3.35	3.72	2.19	3.20	2.89	3.20
A	2.62	3.00	2.97	3.30	3.25	3.25	3.12	3.12	3.86
	2.52	2.65	3.10	3.12	3.82	2.66	3.37	2.85	4.35
	2.48	2.90	3.05	3.05	3.42	2.55	2.05	3.04	3.29
	2.63	2.69	3.00	3.46	3.35	2.34	2.79	2.96	3.20
average values	2.52	2.79	2.82	3.21	3.48	2.56	2.87	2.97	3.53
f_c [MPa]	19.8	21.9	28.1	32.7	37.7	19.6	22.5	28.9	28.4
	2.31	2.36	2.46	3.15	4.12	2.30	2.79	2.38	2.96
	2.42	2.30	2.84	3.66	3.65	2.38	2.46	2.88	4.27
B	2.70	2.63	2.56	2.82	4.02	2.71	2.55	2.46	2.79
	2.63	2.56	3.02	3.62	3.85	2.22	2.38	2.46	4.11
	2.29	2.96	2.92	3.26	4.17	2.30	–	2.96	4.68
	2.58	2.89	2.70	3.02	4.00	2.79	–	–	4.19
average values	2.49	2.62	2.75	3.26	3.99	2.45	2.55	2.63	3.83

In Fig.10b the relations $K_{IIc}(f_c)$ are depicted. The curves $K_{IIc}(f_c; A)$ and $K_{IIc}(f_c; B)$ are closer both to the empirical estimation, cf Kopta and Niziórski (1991) and to the results yielded by BP networks, cf Dąbrowski et al. (1996), than to the curves computed by means of the RBF network, cf Putanowicz and Waszczyszyn (1999).

6. Conclusions and final remarks

On the basis of the results discussed in the paper the following conclusions seem to be justified:

- Neuro-fuzzy system ANFIS can be efficiently applied to the analysis of simple problems of experimental mechanics and biomechanics.

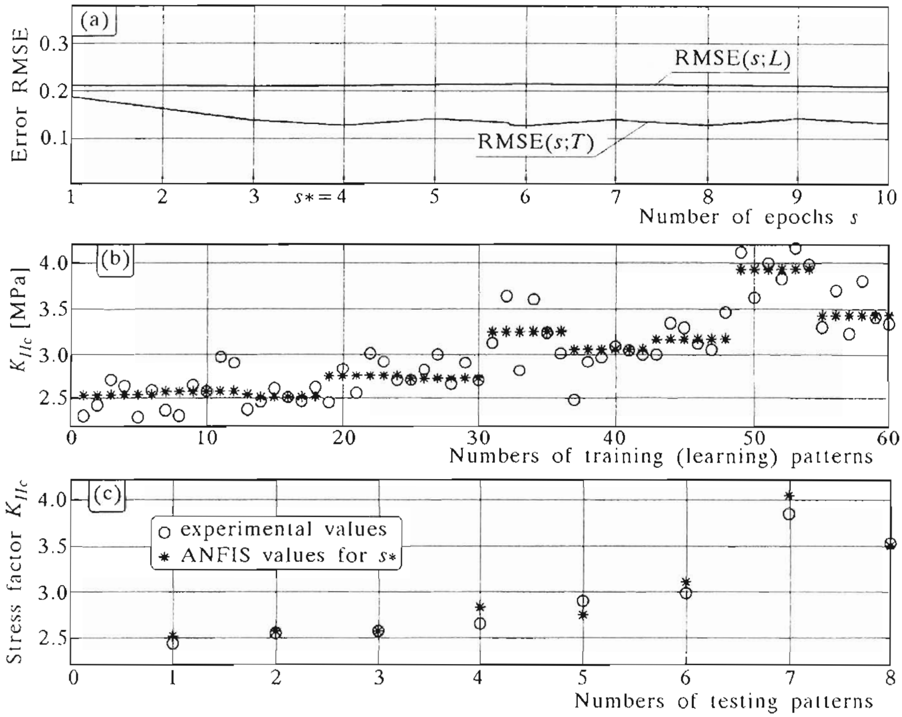

Fig. 9. (a) Training errors RSME($s;L$) and testing errors RSME($s;T$) for the concrete patterns, (b) stress intensity factors K_{IIc} for the training patterns, (c) K_{IIc} for the testing patterns

- In the considered problems the results yielded by ANFIS are superior to those emerging from empirical formulae and those obtained by means of forward neural networks (Back-Propagation NN and simple version of Regularization NN with Radial Basis Functions).

- MATLAB version of ANFIS is fully automated so it makes it easier into use for special applications.

The paper is treated by the authors as their first step towards recognition of new possibilities of soft computing in the field of experimental mechanics and biomechanics. Application of ANFIS to the analysis of more complicated problems is planned to be continued in the near future.

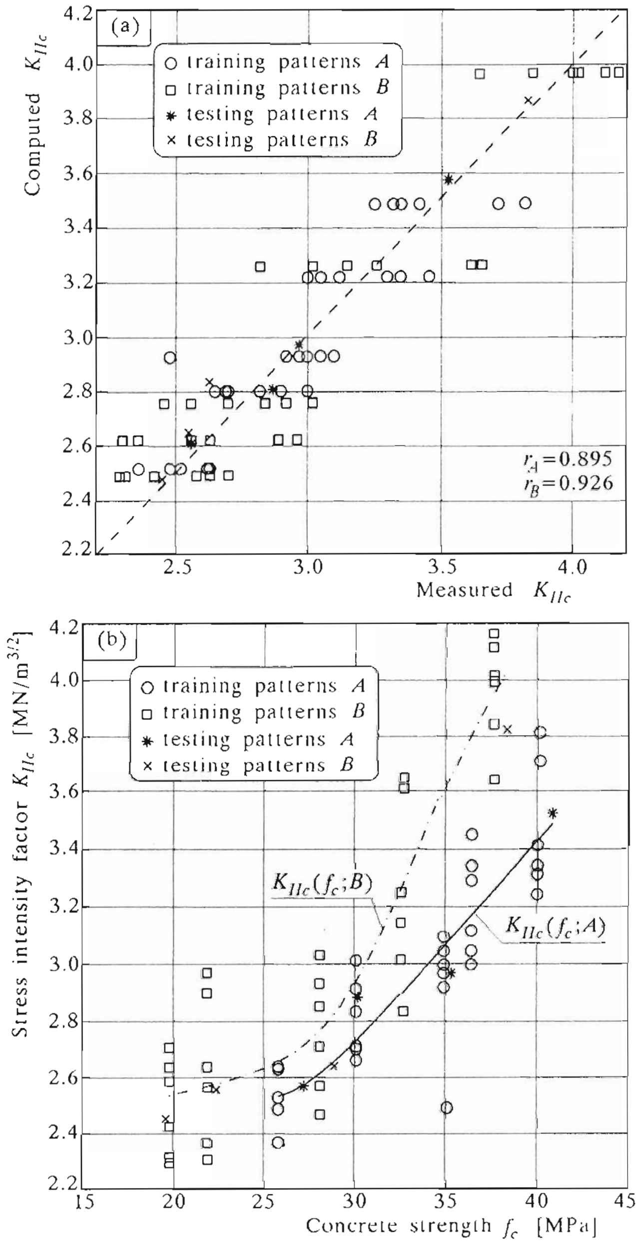

Fig. 10. (a) ANFIS estimation of stress intensity factors (computed K_{IIc}) versus the measured K_{IIc}, (b) measured factors K_{IIc} versus the concrete strength f_c and ANFIS relationships $K_{IIc}(f_c)$ for concrete A and B

Dedication and acknowledgement

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Analiza wybranych zagadnień doświadczalnej mechaniki i biomechaniki za pomocą neuro-rozmytego systemu ANFIS

Streszczenie

Adaptacyjny neuro-rozmyty system ANFIS został zastosowany do analizy trzech problemów: określenie podstawowych okresów drgań 5-piętrowych budynków prefabrykowanych, określenie wytrzymałości górnej części kości udowych oraz oszacowanie odporności na zniszczenie betonów ciężkich. Wyniki otrzymane za pomocą systemu ANFIS porównano z wynikami, jakie dają wzory empiryczne i jednokierunkowe sieci neuronowe. Wykazano, że najlepszą dokładność daje system ANFIS.

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