Fuzzy Technology-Based Cause Detection of Structural Cracks of Stone Buildings

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Abstract. The article presents a hierarchical fuzzy rule base for intelligent support of decision making about cause of structural crack of stone building. According to civil engineering practice the causes of structural cracks are classified by the followings diagnoses: static overload; dynamic overload; especial overload; defects of basis and foundation; temperature influence; breach of technological process during the building. Source information needed for decision making is the data of visual investigation of building, icluding simple measuremnts. For decision making we take into account 42 input attributes. The hierarchical system ties 9 fuzzy knowledge bases, which contain 151 rules in total. Cause detection of the crack is carrying out by max-min fuzzy inference with hierarchical knowledge base. Learning of fuzzy rules by genetic algorithms provided a good matching between real causes of cracks and modeling results.

Keywords: fuzzy technology, fuzzy inference, fuzzy rule, hierarchical knowledge structure, diagnosis, structural crack, stone construction.

1 Introduction

Instant and correct diagnosis of the stone construction cracks makes further investigations, design and reconstruction of buildings successful. The task of diagnosis may be solved correctly by high qualification engineers with huge experience. The number of such experts is lacking, hence the creation of decision making model for diagnosis of structural cracks of buildings is necessity.

One of the most promising ways to processing uncertain expert information is fuzzy sets theory [12]. Application of fuzzy sets for diagnosis of building constructions was started in 1982 [6]. It used a fuzzy inference for assessment of structural damages after an earthquake. Later, articles showed the successful applications of fuzzy inference for diagnosis the cracks in reinforced concrete structures [3], for assessment of building damage and safety after an earthquake [4], for damage identification in Timoshenko beam-type structures with cracks [2], and for concrete bridge damage diagnosis and prediction which aims to provide bridge designers with valuable information about the impacts of design factors on bridge deterioration [13]. In building diagnosis also is accepted and other kind of a fuzzy information processing, for example, a fuzzy signature rule base for hierarchical decision making on renovating or replacing the historical buildings [9], and fuzzy integrals and fuzzy arithmetic for seismic resilience assessment of bridges [1].

This paper presents a hierarchical fuzzy rule base and corresponding technology for decision making support about the cause of stone construction crack of building. The used approach to fuzzy diagnosis model design is based on a conception of creation and learning the hierarchical fuzzy rule base. The general conception of identification of multifactor dependences with hierarchical fuzzy rule base is described in article [9]. The conception consists of carrying out the following stages: 1) description of decision making process in form of inference tree; 2) presentation of input attributes in linguistic variable form; 3) formalisation of linguistic terms by fuzzy sets; 4) formalisation of expert nature language expressions about "attributes – diagnosis" relationship by fuzzy rule bases; 5) learning the hierarchical fuzzy rule base by genetic optimization.

2 Formalisation of the Diagnosis Problem

According to civil engineering practice different causes of structural cracks of stone building are classified by the followings diagnoses:

d_1 – static overload;
d_2 – dynamic overload;
d_3 – especial overload;
d_4 – defects of basis and foundation;
d_5 – temperature influence;
d_6 – breach of technological process during the building.

The suggested classification accords to maximal depth of diagnosis, which can be got for case of visual investigation of the building. The input attributes are as follows:

x_1 – construction type;
x_2 – work condition;
x_3 – thickness of horizontal junctures;
x_4 – defects of junctures filling;
x_5 – defects of bandaging system;
x_6 – unforeseen holes;
x_7 – defects of reinforcing;
x_8 – curve of construction;
x_9 – deflection from vertical line;
x_{10} – moistening of brickwork;
x_{11} – peeling of brickwork;
x_{12} – weathering of brickwork;
x_{13} – leaching of brickwork;
x_{14} – crumbling of brickwork;
x_{15} – crack location;
x_{16} – crack direction;
x_{17} – opening of crack;

x_{18} – crack width;
x_{19} – crack length;
x_{20} – consequences of fair;
x_{21} – information about earthquakes, explosions;
x_{22} – presence of dynamic load;
x_{23} – splitting under straight;
x_{24} – crack depth;
x_{25} – displacement of breast-wall;
x_{26} – damage of water-supply system;
x_{27} – quality of drains;
x_{28} – presence of loose soils;
x_{29} – presence of water in cellar;
x_{30} – presence of capacitevy construction close;
x_{31} – presence of new adjacent buildings;
x_{32} – displacement of straight, beam;
x_{33} – necessity of sedimentary juncture;
x_{34} – presence of sedimentary juncture;
x_{35} – presence of additional loads;
x_{36} – presence of mechanical damages;
x_{37} – quality of cushions under beams;
x_{38} – insufficient size of beans bearing place;
x_{39} – necessity of temperature juncture;
x_{40} – presence of temperature juncture;
x_{41} – execution of works on winter;
x_{42} – using of heterogeneous materials.

Creation of the diagnostic model for crack cause detection is reduced to finding out the mapping of this form:

$$X = (x_1, x_2, ..., x_{42}) \rightarrow D \in \{d_1, d_2, d_3, d_4, d_5, d_6\},$$

where X denotes a vector of the input attributes and D denotes a cause of the crack.

3 Fuzzy Inference Tree

Hierarchical interconnection between input attributes (X) and cause of crack (D) is represented in the form of a fuzzy inference tree (Figure 1). Graph vertices are interpreted in the following way: the squares – possible causes of the crack; the circles – input attributes; the double circles – fuzzy rule bases. Enlarged attributes, to which edges correspond, as going out of nonterminal vertices are interpreted as followings:

y_1 – state of construction;
y_2 – destruction of brickwork;
y_3 – extra support for some cause;
y_4 – support for basis and foundation defects;
y_5 – possibility of static overload;
y_6 – demand to temperature juncture;

y_7 – support for of crack connected with breach of technological processes;

y_8 – demand to sedimentary juncture.

The hierarchical structure of decision process makes the diagnostic model more interpretable and more compact. The hierarchical structure reflects expert knowledge and information from a lot of special books and articles about crack dynamics.

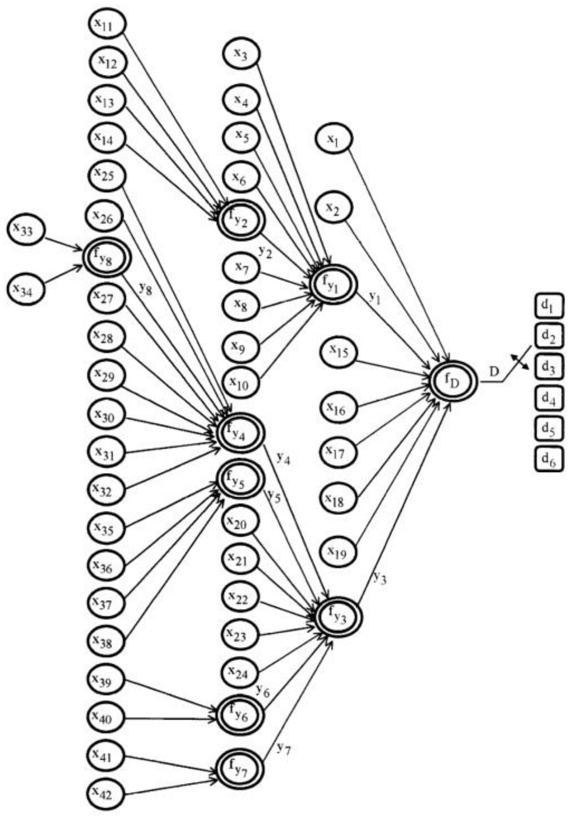

Fig. 1. Fuzzy inference tree

4 Fuzzy Rules

The attributes are represented as linguistic variables. The following 117 terms are used for linguistic assessment of input attributes:

x_1 – {deaf wall (DW), wall with pilaster (WP), pier (P), deaf partition (DP), pier with aperture (PA), wall with aperture (WA)};

x_2 – {holding (H), self-holding (SH), non-holding (NH)};

x_3 – {normal (N), excessive (E), very excessive (VE)};

x_4, x_7, x_9 – x_{14} – {absence (A), minor (M), significant (S)};

x_5, x_6 , x_8, x_{20} – x_{23}, x_{25}, x_{26}, x_{29}, x_{31}, x_{32}, x_{35}, x_{36}, x_{38} – {absence (A), present (P)};

x_{15} – {across whole wall (AW), between walls (B), borders of wall (BW), from monolithic inclusion (MI), at supports (S), top of construction (TC), free field (FF), bottom of construction (BC)};

x_{16} – {vertical (V), oblique (O), horizontal (H)};

x_{17} – {up, slanting (S), down (D)};

x_{18} – {hair (H), small (S), average (A), large (L), very large (VL)};

x_{19} – {short (S), average (A), long (L), very long (VL)};

x_{24} – {one-sided (OS), through (T)};

x_{27} – {low (L), excellent (E)};

x_{28}, x_{30}, x_{41}, x_{42} – {absence (A), uncertainly (U), present (P)};

x_{33}, x_{39} – {unnecessary (UN), necessary (N)};

x_{34}, x_{40} – {absence (A), low quality (LQ), quality (Q)};

x_{37} – {low (L), high (H)}.

The following 24 terms are used for linguistic assessment of enlarged attributes:

y_1 – {normal (N), weak (W), very weak (VW)};

y_2 – {absence (A), medium (M), heavy (H)};

y_3 – {absence (A), static overload (SO), dynamic overload (DO), especial overload (EO), defects of basis and foundation (BF), temperature influence (T), breach of technological process of building (TP)};

y_4 – {absence (A), low (L), high (H)};

y_5, y_7 – {absence (A), present (P)};

y_6, y_8 – {observed (O), ignored (I)}.

Formalisation of linguistic terms of input attributes is carried with bell-shaped membership function with 2 parameters: b – core of the fuzzy set and c – concentration of membership curve.

Natural language expert expressions, which tie up the attributes and output variable, are formalised in fuzzy rule base form. Tables 1 – 9 show some fragments of the rule bases. In the tables the symbol "–" is equal to membership function *"Do not care"* [5]. We use 49 rules in D-base, 31 rules in y_1-base, 15 rules in y_2-base, 16 rules in y_3-base, 20 rules in y_4-base, 6 rules in y_5-base, 4 rules in y_6-base, 6 rules in y_7-base, and 4 rules in y_8-base. Total number of rules of all the bases is 151.

Table 1. Fragment of fuzzy rule base about diagnoses

x_1	x_2	y_1	x_{15}	x_{16}	x_{17}	x_{18}	x_{19}	y_3	D
–	H	–	S	–	up	–	–	SO	d_1
WP	H	W	S	O	up	H	–	A	d_1
–	–	VW	AW	O	–	–	–	SO	d_1
WA	H	W	AW	O	S	H	VL	DO	d_2
–	–	–	BW	V	up	H	–	DO	d_2
DW	H	–	B	O	up	–	–	EO	d_3
–	H	–	S	V	up	A	L	EO	d_3
WA	H	–	AW	V	up	L	VL	A	d_4
–	–	VW	AW	O	–	–	–	BF	d_4

x_1	x_2	y_1	x_{15}	x_{16}	x_{17}	x_{18}	x_{19}	y_3	D
–	SH	W	B	V	up	H	–	A	d_4
DW	H	–	BC	V	D	L	–	BF	d_4
–	–	–	TC	V	up	–	–	BF	d_4
–	–	–	TC	V	up	–	–	BF	d_4
DW	–	W	BC	O	–	–	–	BF	d_4
DP	NH	W	AW	H	S	A	VL	BF	d_4
–	SH	N	TP	O	up	S	L	T	d_5
WA	SH	–	FF	O	S	H	–	T	d_5
P	H	–	MI	O	up	H	A	TP	d_6
PA	NH	VW	TC	O	up	S	A	TP	d_6

Table 2. Fragment of fuzzy rule base about enlarged attribute y_1

x_3	x_4	x_5	x_6	y_2	x_7	x_8	x_9	x_{10}	y_1
N	A	A	A	A	A	A	A	A	N
N	H	P	A	A	A	A	A	A	W
VE	H	A	A	A	A	A	A	A	W
N	M	A	A	M	A	A	A	M	W
VE	–	P	P	–	–	–	–	–	VW
E	S	P	–	–	S	P	–	S	VW
–	S	–	–	–	M	P	M	–	VW

Table 3. Fragment of fuzzy rule base about enlarged attribute y_2

x_{11}	x_{12}	x_{13}	x_{14}	y_2
A	A	A	A	A
S	A	A	A	M
A	A	A	M	M
S	M	M	–	H
M	M	M	M	H
S	S	S	S	H

Table 4. Fragment of fuzzy rule base about enlarged attribute y_3

y_4	y_5	x_{20}	x_{21}	x_{22}	x_{23}	x_{24}	y_6	y_7	y_3
A	A	A	A	A	A	OS	O	A	A
–	P	–	–	–	–	–	–	–	SO
–	–	–	–	P	–	–	–	–	DO
–	–	–	P	–	–	–	–	–	EO
H	–		–	–	–	–	–	–	BF
L	A	P	A	A	P	T	O	A	BF
–	–	–	–	–	–	–	I	–	T
–	–	–	–	–	–	–	–	P	TP

Table 5. Fragment of fuzzy rule base about enlarged attribute y_4

x_{25}	x_{26}	y_8	x_{27}	x_{28}	x_{29}	x_{30}	x_{31}	x_{32}	y_4
A	A	O	E	A	A	A	A	A	A
A	A	O	E	A	A	P	A	A	L
P	–	–	–	–	–	–	–	–	H
–	P	–	–	–	–	–	–	–	H
–	–	I	–	–	–	–	–	–	H
–	–	–	L	–	–	–	–	–	H
–	–	–	–	P	P	–	–	–	H
–	–	–	–	U	P	–	–	–	H
–	–	–	–	–	P	P	–	P	H
–	–	–	–	–	–	–	P	P	H

Table 6. Fuzzy rule base about enlarged attribute y_5

x_{35}	x_{36}	x_{37}	x_{38}	y_5
A	A	A	A	A
P	–	–	–	P
–	P	–	–	P
–	–	P	–	P
–	–	–	P	P
P	P	P	P	P

Table 7. Fuzzy rule base about enlarged attribute y_6

x_{39}	x_{40}	y_6
N	Q	O
UN	–	O
N	A	I
N	LQ	I

Table 8. Fuzzy rule base about enlarged attribute y_7

x_{41}	x_{42}	y_7
P	–	P
–	P	P
A	A	A

Table 9. Fuzzy rule base about enlarged attribute y_8

x_{33}	x_{34}	y_8
UN	–	O
N	Q	O
N	A	I
N	LQ	I

5 Decision Making

Decision making about diagnosis is carried out according to the following algorithm:

1. Fix the input attributes of the diagnosis object.
2. Make up a fuzzification i.e. find input attributes membership degrees to linguistic terms and present results in form of bifuzzy sets. Adjective "bifuzzy" [7] emphasizes that fuzzy set support consists of fuzzy sets. In our case, support of the bifuzzy set equals the term-set.
3. Make up a fuzzy inference for all fuzzy rule bases.
4. Choose the decision from set $\{d_1, d_2, d_3, d_4, d_5, d_6\}$ with the maximum membership degree.

During the fuzzification the membership degrees of input attributes to terms from rule base are calculated taking into account crisp and fuzzy values. For crisp source data, membership degree is calculated by the substitution of the current value of the input attribute into membership function. It is possible to use the linguistic values for input attributes. In this case the linguistic values is taken from the term-set of relevant variable. Hence, the linguistic value became equals to some fuzzy set. For fuzzy source data, the membership degree of one fuzzy set (the value of an input attribute) to another fuzzy set (a term from a rule base) must be calculated. According to [10], the membership degree equals the height of intersection of these fuzzy sets (Figure 2). If the both fuzzy sets are represented bell-shaped membership functions with coefficients (b_1, c_1) and (b_2, c_2), then the height of their intersection may be calculated by following fast formulae:

$$height = \frac{1}{1 + \min\left(\frac{b_1 - b_2}{c_2 \pm c_1}\right)^2}.$$

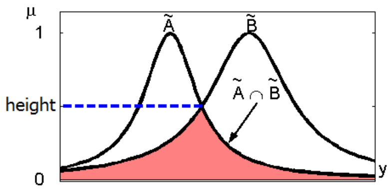

Fig. 2. Calculation of membership degree of fuzzy set $\tilde{A}$ to fuzzy set $\tilde{B}$

Fuzzy inference is carried according to tree from Figure 1. Operations fuzzification – defuzzification are not employed for enlarged attributes (Figure 3). The result of fuzzy inference on the lower level in form of fuzzy set is passed directly into inference machine at higher level. Fuzzy output value at lower hierarchical level is considered as input fuzzy value at higher hierarchical level. In this case, membership functions for terms of the conjuncted variables (enlarged attributes) are unnecessary. We have selected the following inference options: minimum as t-norm and single winner rule [5] as aggregation.

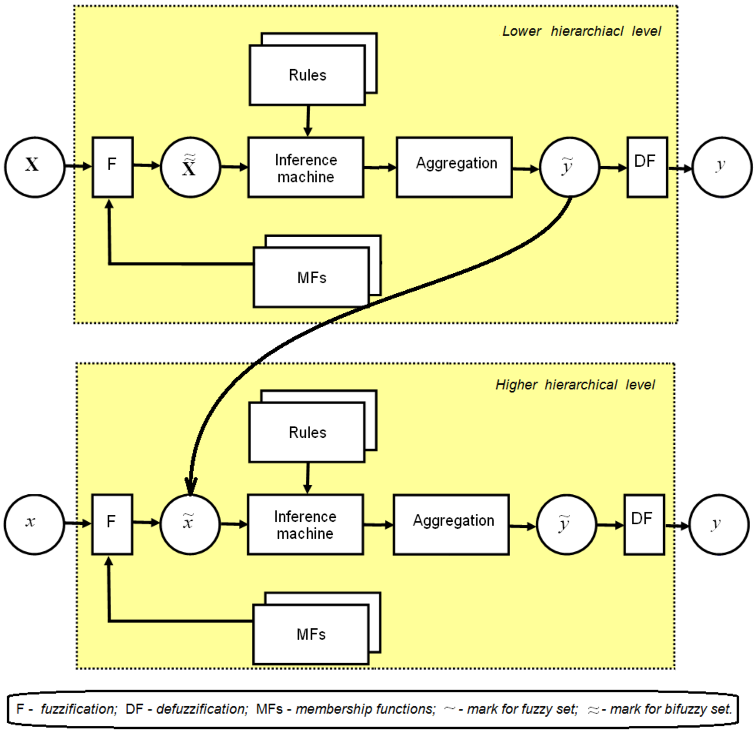

Fig. 3. Hierarchical fuzzy inference

6 Learning the Hierarchical Fuzzy Rule Base

Learning is the process of finding out such values of model parameters which provide shortest distance between results of modeling and experimental data. The tuning parameters are membership functions coefficients (*b* and *c*) and weight factors of fuzzy rules. The total number of these parameters is 2*117+151=385. For reducing the learning complexity we will not change weight factors for 23 absolutely-reliable rules. According to interpretability saving scheme in [11] we will not change coefficients *b* for membership functions extreme terms such as *Low* and *High*. There are 2*42=84 extreme terms for input attributes $x_1 - x_{42}$. Hence, total number of the tuning parameters becomes equal to 385–23–84=278. The quantity of the tuning parameters is large, because of for solving this nonlinear optimization task we employed genetic algorithms. For overfitting prevention we setup the narrow changing bounds of membership functions coefficients.

After learning, the misclassification rate is about 4.5%. There are 4 wrong inferred decisions out 89 testing cases. Note, that for these 4 cases the inferred decision with the second rank is correct.

7 Conclusions

We described the hierarchical fuzzy rule base for decision making support about cause of structural crack of stone building. Different causes of structural cracks are classified by the followings diagnoses: static overload; dynamic overload; especial overload; defects of basis and foundation; temperature influence; breach of technological process during the building. For decision making we use 42 input attributes. The hierarchical system ties 9 fuzzy knowledge bases, which contain 151 rules. The hierarchical structure of decision making process makes the diagnostic model more interpretable and more compact. Learning of fuzzy rules by genetic algorithms provided a good concordance between real causes of cracks and modeling results with misclassification rate at level of 4.5%. The design of our inferring model for stone construction crack diagnosis suggests a general approach to expert systems design in other diagnostic fields.

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