Fuzzy Rules Based System for Diagnosis of Stone Construction Cracks of Buildings

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ABSTRACT: This paper presents the fuzzy expert system for intelligent support of decision making about cause of stone construction crack of building. The system is based on some linguistic expert expressions formalised by 9 fuzzy knowledge bases. Tuning of fuzzy rules by genetic algorithms provided a good concordance between real causes of cracks and results of decision making by the system.

KEYWORDS: Stone Construction Crack, Diagnosis, Hierarchical Fuzzy Knowledge Bases, Tuning, Genetic Algorithms.

INTRODUCTION

Diagnosis (or determination of cause) of stone construction crack is an important task of building engineering. 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 large experience only. The number of such experts is lacking and in connection with this the design of intelligent system for crack of buildings diagnose is necessity.

This paper presents the fuzzy expert system for decision making support about cause of stone construction crack of building. The approach to the system design suggested in this paper is based on:

- description of the structure of diagnostic model by hierarchical decision making tree;
- presentation of state parameters in linguistic variable form;
- formalisation of linguistic terms by fuzzy sets;
- formalisation of expert nature language expressions about relationship «state parameters - diagnosis» by fuzzy knowledge bases;
- tuning of the knowledge bases by genetic optimization of membership functions parameters and weight of the rules.

The approach allows to use as expert linguistic information as experimental data reflecting interconnection between input and output parameters. The use of all available source information provides increasing of diagnostic model quality.

PROBLEM STATEMENT

Different causes of stone construction cracks was classified in the next 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 of building.

Suggested classification accords to maximal depth of diagnosis, which can be got for case of visual investigations. Source information, which need for decision making, is data of visual investigation of building. These are values of the next factors (parameters of object state): x_1 - construction type; x_2 - work condition; x_3 - thickness of horizontal junctions; x_4 - defects of junctions filling; x_5 - defects of bandaging system; x_6 - presence of unprovided 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 out 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} - present of water into basement; x_{30} - presence of capacity construction close; x_{31} - presence of new contiguity buildings; x_{32} - displacement of straight, beam; x_{33} - necessity of settle junction; x_{34} - presence of settle junction; x_{35} - presence of additional loads; x_{36} - presence of mechanical damage; x_{37} - quality of cushions under beams; x_{38} - insufficient size of beans bearing place; x_{39} - necessity of temperature junction; x_{40} - presence of temperature junction; x_{41} - execution work on winter; x_{42} - using of heterogeneous materials.

From cybernetic point of view, creation of the diagnostic model for cause (D) of crack determination is reduced to finding out the representation of this form:

$$X=\{x_1,...,x_{42}\} \to D\in\{d_1,...,d_6\},$$

where X is a vector of the sate parameters.

DECISION MAKING TREE

Hierarchical interconnection between state parameters (X) and cause of crack (D) is represented by Figure 1 in the form of decision making tree. Graph vertices are interpreted in the next way (Rotshtein, 1998):

- the root - cause of crack;
- terminal vertices - partial state parameters;
- nonterminal vertices (double circles) - fuzzy knowledge bases;

Enlarged state parameters, to which graph edges correspond, as going out of nonterminal vertices are interpreted in the following way:

y_1 - state of construction;

y_2 - destruction of brickwork;

y_3 - additional information;

y_4 - possibility of basis and foundation defects;

y_5 - possibility of static overload;

y_6 - demand to temperature junction;

y_7 - possibility of crack connected with breach of technological processes;

y_8 - demand to setle junction.

The tie between state parameters and diagnosis is defined by this system of relations:

$$D=f_D(x_1,x_2,y_1,x_{15},x_{16},x_{17},x_{18},x_{19},y_3);$$

$$y_1=f_{y_1}(x_3,x_4,x_5,x_6,y_2,x_7,x_8,x_9,x_{10});$$

$$y_2=f_{y_2}(x_{11},x_{12},x_{13},x_{14});$$

$$y_3=f_{y_3}(y_1,y_5,x_{20},x_{21},x_{22},x_{23},x_{24},y_6,y_7);$$

$$y_4 = f_{y_4}(x_{25}, x_{26}, y_8, x_{27}, x_{28}, x_{29}, x_{30}, x_{31}, x_{32});$$

$$y_5 = f_{y_5}(x_{35}, x_{36}, x_{37}, x_{38});$$

$$y_6 = f_{y_6}(x_{39}, x_{40});$$

$$y_7 = f_{y_7}(x_{41}, x_{42});$$

$$y_8 = f_{y_8}(x_{33}, x_{34}).$$

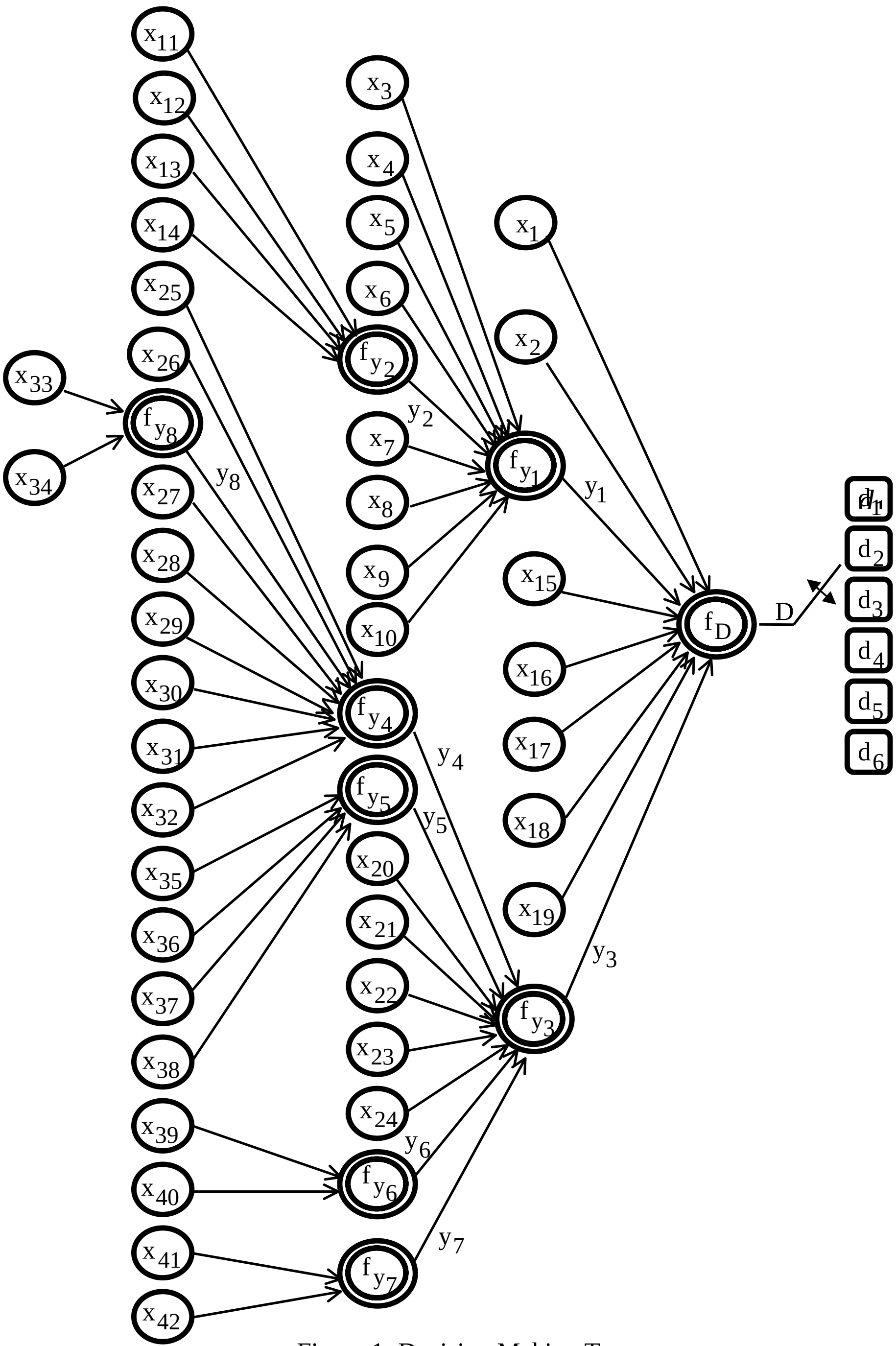

Figure 1: Decision Making Tree

LINGUISTIC VARIABLES AND FUZZY KNOWLEDGE BASES

According to our approach the state parameters was represented as linguistic variables (Zimmerman, 1996). There were 118 terms, which used for linguistic assessment of partial state parameters and 24 - for enlarged state parameters. For formalisation of linguistic terms have been employed the next membership function model (Rotshtein and Katelnikov, 1998):

$$\mu^{t}(x)=\frac{1}{1+\left(\frac{x-b}{c}\right)^{2}},$$

where $\mu^{t}(x)$ - membership function of variable x to term t;

b and c - tuning parameters - coordinate of maximum and concentration coefficient.

Natural language expert expressions, which tie up the state parameters and output variable, were formalised in fuzzy knowledge base form. Table 1 shows a fragment of fuzzy knowledge base of top level. Total number of rules of all knowledge bases is 151.

x_1	x_2	y_1	x_{15}	x_{16}	x_{17}	x_{18}	x_{19}	y_3	D
-	holding	-	at support	vertical	up	-	-	static overload	d_1
wall with aperture	holding	relax	across all construc-tion	slanting	uniform	hair	very long	dynamic overload	d_2
deaf wall	holding	-	between walls	slanting	up	-	-	especial overload	d_3
wall with aperture	holding	-	across all construc-tion	vertical	up	large scale	very long	absence	d_4
-	holding itself	normal	upper part	slanting	up	small	long	influence of tempe-rature	d_5
pier	holding	-	from mo-nolithic inclusion	slanting	up	hair	middle	property of materials	d_6

Table 1: Fragment of knowledge base about cause of crack

Definite cause of crack will be determined by way of solving the system of fuzzy logical equations, which is isomorphic to decision making tree and fuzzy knowledge bases (Rotshtein, 1998). Fuzzy logical evidence is carried out according to the following algorithm (Rotshtein, 1998):

Step 1. Fix partial state parameters.

Step 2. Find partial state parameters membership degrees to linguistic terms.

Step 3. Weaken found membership degrees in fuzzy logic equations and calculate decision membership degrees to terms $d_1,d_2,...,d_6$.

Step 4. Choose the term from set $\{d_1,d_2,...,d_6\}$ with the maximum membership degree as the diagnosis.

Execution of step 2 according to (Rotshtein and Shtovba, 1998) allows to use as quantitative as qualitative values of state parameters.

SOFTWARE REALISATION AND CHECK EXAMPLE

The models and algorithms suggested here are realised in expert system which provides intelligent support in decion making about cause of stone construction cracks of buildings. The system is realised on base of FuzzyExpert shell (Rotshtein, 1998).

Illustration of proposed model and algorithms application is showed below. Let us consider the crack in wall of Mogiliv-Podilsky Machine Works building. The next state parameters corresponding to the object: x_1=deaf wall; x_2=holding; x_3=normal; x_4=absence; x_5=sacred; x_6=absence; x_7=absence; x_8=absence; x_9=absence; x_{10}=absence; x_{11}=absence; x_{12}=absence; x_{13}=absence; x_{14}==absence; x_{15}=between walls; x_{16}=vertical; x_{17}=up; x_{18}=2, mm;

x_{19}=2, m; x_{20}=absence; x_{21}=absence; x_{22}=absence; x_{23}=available; x_{24}=two-sides; x_{25}=absence; x_{26}=available; x_{27}=available; x_{28}=available; x_{29}=absence; x_{30}=available; x_{31}=absence; x_{32}=absence; x_{33}=not necessary; x_{34}=absence; x_{35}=absence; x_{36}=absence; x_{37}=absence; x_{38}=absence; x_{39}=not necessary; x_{40}=absence; x_{41}=uncertainly; x_{42}=absence. As the results of the fuzzy logic evidence we obtain the following degrees of membership:

$\mu^{d_1}(D) = 0.083$; $\mu^{d_2}(D) = 0.01$; $\mu^{d_3}(D) = 0.022$; $\mu^{d_4}(D) = 1$; $\mu^{d_5}(D) = 0.038$; $\mu^{d_6}(D) = 0.027$.

what correspond to solution d_4 - defects of basis and foundation.

TUNING OF FUZZY DECISION MAKING MODEL

Tuning or parametrical identification is finding out such values of model parameters which provide the best results of modeling. According to (Rotshtein and Katelnikov, 1998) the tuning parameters of fuzzy decision making model are membership functions parameters and weights of fuzzy rules. For our model the total number of this parameters (controlled variables) is 2x(118+24)+151=435. The number of the one is large, because of for solving this nonlinear large scale optimization task we employed genetic algorithms. After tuning, the results of decision making by the system is good concordant with real causes of cracks - the diagnostic error is less than 4%.

CONCLUSION

Fuzzy expert system which provides intelligent support in decision making about cause of stone construction crack of buildings is proposed in this paper. The system can be useful also for the students corresponding subject apart from it being employed by practising building engineering. Suggested approach for the expert system design may be used for creation diagnostic system in other fields.

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