Досліджуються питання, що пов'язані з моделюванням та розробкою інтелектуальних систем для оцінки технічного стану будівельних конструкцій. Розглянуті математичні основи моделювання системи оцінки, в основу якої покладені нечітка база знань і одна з модифікацій нечіткої мережі Такаги-Сугено-Канга. Детально описані структура мережі та обґрунтовано вибір алгоритму її навчання. Основними критеріями вибору даної модифікації стали її здатність до розв'язання задачі класифікації в умовах невизначеності та можливість задавати правила функцією входів. Структуру мережі адаптовано до задачі оцінки технічного стану реальних будівельних конструкцій. Показано, що навчання мережі доцільно проводити за алгоритмом з вчителем. При цьому, для мінімізації похибки пропонується використовувати прямий метод випадкового пошуку, який адаптовано до розв'язання даної задачі. Для ідентифікації станів конструкцій запропоновано використовувати міри належності, що отримуються методом кластеризації. Реалізація та впровадження нейромережевих технологій в розв'язання задач оцінювання технічного стану будівельних конструкцій розширює та удосконалює можливості інтелектуальних систем, знижує ризики прийняття невірних рішень за рахунок підвищення надійності та швидкості моделювання

Ключові слова: база знань, будівельна конструкція, інтелектуальна система, нечітка імплікація, оцінка технічного стану

UDC 004.896:004.891.3

DOI: 10.15587/1729-4061.2018.132587

MODELING AN INTELLIGENT SYSTEM FOR THE ESTIMATION OF TECHNICAL STATE OF CONSTRUCTION STRUCTURES

S. Terenchuk
PhD, Associate Professor*
E-mail: terenchuksa@ukr.net

A. Pashko
Doctor of Physical and Mathematical Science
Research Sector of Problems of System Analysis
Taras Shevchenko National University of Kyiv
Volodymyrska str., 60, Kyiv, Ukraine, 01033

B. Yeremenko
PhD**

S. Kartavykh
Postgraduate student**

N. Ershova
Doctor of Technical Sciences, Professor
Department of Applied Mathematics and Information Technologies
Prydniprovs'ka State Academy of Civil Engineering and Architecture
Chernyshevskoho str., 24a, Dnipro, Ukraine, 49600

*Department of Architectural Structures***
Department of Information Technology Design and Applied Mathematics*
***Kyiv National University of Construction and Architecture
Povitroflotsky ave., 31, Kyiv, Ukraine, 03037

1. Introduction

Companies that develop construction objects are responsible for the reliability and safety of buildings and structures and for the identification of causes related to deviation of parameters of technical condition from normative values in the process of operation of these sites. The process of exploitation is long in time so they must process controlled parameters taking into consideration an accumulation of damage and changes in the parameters over time. Analysis of input information is considerably complicated due to a growth in the number of monitored parameters of technical state, which leads to an increase in the risk of the human factor at a rapid decision-making in emergencies.

In the course of integrated automation of lifecycle management of construction objects, automation of a decision-making process becomes more complicated because parameters of a technical state often have dependences between input and output data, which are difficult to formalize. This means that construction of a clear mathematical model of an object is not always possible. Artificial neural networks (ANN) solve such problems. Their development and implementation will make it possible to reproduce the logic of conclusions by the person who makes decisions under fuzzy conditions based on a knowledge base (KB), and to automate procedures for the estimation of technical state of construction structures. Specialized organizations develop such intelligent systems [1]. However, despite a considerable amount of work done, there is still no a unified technology for the estimation of structures with defects and damage of a different nature. This is explained by complexity of tasks associated with processing and analysis of large volumes of heterogeneous information on defects and damage, which influences differently the states of structures under different conditions. That is why automation of processes of observation, diagnosis and forecasting of technical state of building constructions using an intelligent system in the form of a fuzzy neural network remains relevant.

2. Literature review and problem statement

Definition 1. An intelligent system is a knowledge-based system for supporting decision-making and acquring of new knowledge based on the knowledge engineering methods.

It is the knowledge engineering system that defines methods for representation and acquisition of knowledge and an architecture of expert systems due to the unique organization of a knowledge base and management of data by an interpreter (Fig. 1).

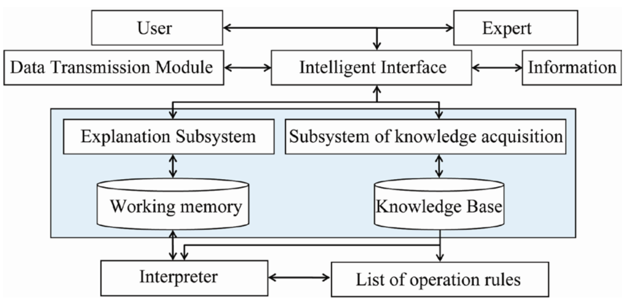


Fig. 1. System of knowledge engineering of an intelligent system for the estimation of technical state of construction structures

A base of the development of models for estimation is the fact that an expert forms knowledge, which describes application and compiles a knowledge base. Based on the available knowledge and a given target function, metaprocedures of a system generate and execute a procedure for solving a problem and formulate an explanation of the logic of a system according to its internal model [1, 2]. Thus, an intelligent system is an information system that uses a knowledge base and a developed system of software for its processing.

Knowledge's location is in the application program and it forms a single database with an application program when using traditional programming structured languages. However, such an approach makes it possible to draw conclusions provided by the processing program only [3, 4].

Advantages of artificial neural networks include their capability to learn and to transfer knowledge of experts to the knowledge base of a system in an automated mode (Fig. 2).

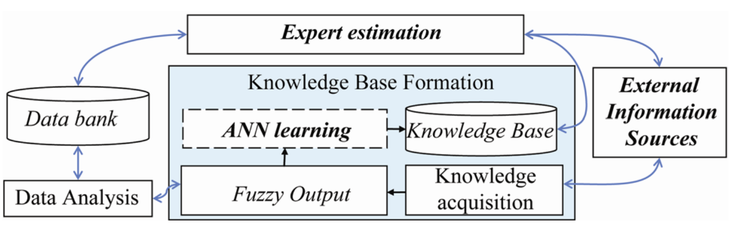


Fig. 2. Scheme of functioning of an intelligent system for the estimation of technical state of construction structures

Analysis of learning algorithms and results of operation of artificial neural networks of different architecture used in diagnosing the construction structures and materials revealed the following advantages and disadvantages of each of them [5–9]:

1) a Kohonen network (SOM) solves problems of cluster analysis without a trainer, but the quality of a classifier decreases significantly in cases of linearly inseparable spaces of input data, and it is usually impossible to build a linearly separable set of signs of degradation of construction structures [5];

2) radially basic functions (RFB-networks) developed to solve classification problems based on the restoration of mixtures of distributions are suitable for conditions where it is difficult to determine a degree of influence of each of environmental factors, but the application of RFB-networks requires organization of a large sample of data for learning [6];

3) advantages of networks of adaptive resonance theory (ART) include the capability to perceive new abnormal objects while preserving information on known classes and ability to perform analysis of signals with constraints predetermined by degradation of building materials, provided that a number of essential factors and corresponding coefficients are determined accurately in the process of testing ART model [7];

4) a classifier based on a multilayered perceptron is a universal means of approximation of functions, however, a perceptron is not capable of adapting to the appearance of objects from unknown classes and operates with binary values only (0 or 1), since the function of a single jump forms outputs of its neurons [8];

5) one can use Hopfield recurrent networks as associative memory in problems of image recognition by geometric parameters, but memory capacity compared with the number of standards limits the application of networks of a given architecture for identification of defects and damage to construction structures [8];

6) using fuzzy functions at an input/output of a system provides for the capability of fuzzy neural (hybrid) networks to split linearly inseparable data, but the correct division depends strongly on building a fuzzy set of features for diagnosing an output decision [9].

Definition 2. A fuzzy knowledge base is a set of fuzzy rules ***if*** <condition of a rule> ***then*** <conclusion of a rule>, which define the relationship between inputs and outputs of the examined object [8].

In the field of engineering sciences, a knowledge base is informational tool, which contains all links between all variables of an object and makes it possible [1]:

– to calculate values of some variables through other variables;

– to determine the first and second derivatives of experimental dependencies;

– to solve both direct and inverse tasks;

– to forecast characteristics and properties of unexplored objects;

– to forecast parameters of a process to obtain an object with predetermined characteristics.

One of the main directions for obtaining the knowledge about dynamics of loss of operational qualities of construction structures due to an influence of various factors is analysis and processing of statistical data obtained in the process of monitoring and diagnosis of technical state [10, 11]. However, several problems associated with collection, processing, and accumulation of useful data in the form we obtain them during a survey limits the introduction of a fuzzy knowledge base to the construction industry [10].

Collection of data on the state of structures during operation period and compiling a knowledge base based on experimental studies and knowledge of experts requires the following diagnosis procedures [12]:

– obtaining and specification of characteristics of materials, structures, assemblies and foundations, changes in which lead to changes in the technical state of a construction object;

– determination of essential factors of loads and influences;

– analysis of deformations, defects and damages of structures and foundations;

– estimation of the degree of influence of degradation parameters on the state of structures;

– calculations that are necessary for the estimation of technical state.

We should assign a data bank to accumulate data (Fig. 2).

The data bank contains information arrays and data streams on structures necessary for forecasting using artificial neural networks, finding templates that reflect dynamics of the behavior of input parameters adequately.

Here:

– experts have a possibility to receive information for fuzzy output and formation of a fuzzy knowledge base [10, 12];

– trained neural networks are capable of performing functions of experts [9].

The base to train a system is the analysis of data and estimates of changes in structures constructed at different times, which have defects and damage of different nature and operate under different conditions, and hybrid technologies combine advantages of fuzzy systems and artificial neural networks [2, 13].

We apply a “fuzzy inference” module (Fig. 2) for the engineering of rules, according to which we estimate the technical state of structures. The module works as a “white box”, a human expert guarantees its reliability under conditions of uncertainty (Fig. 1). Paper [10] describes expert support for operation of the “fuzzy inference” module, the algorithm for formation and implementation of a fuzzy knowledge base in the process of estimation of the technical state of building structures with a use of the *Fuzzy Logic Toolbox* of *Matlab* environment in detail [10].

Fuzzy implication plays an important role in fuzzy production models that reproduce fuzzy logical considerations of experts.

Definition 3. We call a binary logical operation, the result of which is a false statement, a fuzzy implication (the implication of fuzzy statements) A and B [8].

A fuzzy cause-effect relationship **«*R:A→B*»** takes the form of a fuzzy implication: «**if** $\boldsymbol{x \in A}$, **then** $\boldsymbol{y \in B}$», where: x is the input variable given in the field of definition of a fuzzy rule X; y is the output variable given in the output definition area Y; A and B are the statements defined on X and Y with measures of membership $\mu_A(x)$: $X \to [0,1]$ and $\mu_B(y)$:$Y \to [0,1]$, respectively.

The truth of a fuzzy implication can take a value determined by one of the formulas [8]:

– *Zadeh* fuzzy implication:

$$\mu_{A\to B}(x,y)=\max\left\{\min\left\{\mu_A(x),\mu_B(y)\right\},1-\mu_A(x)\right\}; \tag{1}$$

– *Gyodel* fuzzy implication:

$$\mu_{A\to B}(x,y)=\begin{cases}1, & \mu_A(x)\le\mu_B(y);\\ \mu_B(y), & \mu_A(x)>\mu_B(y);\end{cases} \tag{2}$$

– *Mamdani* fuzzy implication*:*

$$\mu_{A\to B}(x,y)=\min\left\{\mu_A(x),\mu_B(y)\right\}; \tag{3}$$

– *Larsen* fuzzy implication:

$$\mu_{A\to B}(x,y)=\mu_A(x)\cdot\mu_B(y); \tag{4}$$

– *Lukasievitch* fuzzy implication:

$$\mu_{A\to B}(x,y)=\min\left\{1,\ 1-\mu_A(x)+\mu_B(y)\right\} \tag{5}$$

or

$$\mu_{A\to B}(x,y)=\max\left\{0,\ \mu_A(x)+\mu_B(y)-1\right\};$$

– *Gogen* fuzzy implication:

$$\mu_{A\to B}(x,y)=\begin{cases}1, & \mu_A(x)\le\mu_B(y);\\ \dfrac{\mu_B(y)}{\mu_A(x)}, & \mu_A(x)>\mu_B(y).\end{cases} \tag{6}$$

There are also other methods for identification of fuzzy implications. In particular, there are measures of membership, which we obtain by the expert method and the method of clustering used [8, 13].

There are examples of fuzzy implications based on expert assessments of technical states of various building structures constructed based on models of Mamdani and Sugeno published in [11, 12]. Papers [9, 10] investigate the system of fuzzy output and the algorithm of fuzzy output based on the models of Mamdani and Sugeno [9, 10].

The fuzzy output algorithm used in [10–12] makes it possible to build fuzzy implications based on the rules given by fuzzy terms. The study proposes using a fuzzy Takagi-Sugeno-Kang network [8, 14], which calculates the output result using the Takagi-Sugeno-Kang input function [8, 14] for the evaluation of technical state of construction structures.

3. The aim and objectives of the study

The objective of this study is to model an intelligent system for the estimation of technical state of construction structures based on one of the modifications of a Takagi-Sugeno-Kang (TSK) fuzzy network.

To accomplish the aim, the following tasks have been set:

– to propose a model of structure of TSK fuzzy neural network;

– to adapt the learning algorithm of TSK network to the task of the estimation of technical state of construction structures;

– to substantiate the identification of categories of the technical state of structures.

4. Modeling an intelligent system for the estimation of technical state of construction structures

4. 1. Designing a Takagi-Sugeno-Kang fuzzy network

A number of rules and a number of input variables determine the structure of Takagi-Sugeno-Kang network [8]. We selected an option where an output parameter y takes the value, which expresses the technical state of construction structures, to evaluate the technical state (Table 1).

Table 1

Categories of the technical state of construction structures

TS category	Level of suitability	Appropriate measures (excerpts from estimations) [9, 13]
1	Normal (N)	–
2	Satisfactory (S)	Restoration of a protective layer of concrete overlay with a use of repair and regenerative mixture, pre-cleaning of the surface of concrete and reinforcement and application of a layer of first coat on concrete and a solution of an inhibitor on the reinforcement
3	Unsuitable for normal operation (Un)	Replacement of the reinforcing rods with new ones and fastening them to the grid and overlap when a cross-section of the reinforcement rods is reduced by more than 10 % from the damage to the corrosion. The strength of a protective layer of concrete should be at least CE5 / 20 class. Using of the construction object under the limited operation program, which is designed taking into consideration the technical state and load of the structure till the end of activities
4	Emergency (E)	Immediate restriction of the access for people in the area of possible collapse and application of measures that make collapse impossible till repair, reinforcement or replacement of the structure

An output parameter of a fuzzy output system is a coordinate of the vector, which determines the level of suitability of structures:

$$\vec{y} \in Y = \{y_1\}(l = 1,\ 2,\ ...,\ L,\ L = 4).$$

For input variables x_j (j=1, 2,..., N) and the i-th rule (i==1, 2,..., M), the output circuit takes the form [8]:

$$if\ (x_1\ \ is\ A_1^{(i)}\ )(x_2\ \ is\ A_2^{(i)})\ldots(x_N\ \ is\ A_N^{(i)}),$$

then

$$y_i = p_{i0} + \sum_{j=1}^{N} p_{ij}\, x_j, \qquad (7)$$

where p_{ij} are the unknown parameters (i=1, 2,..., M, j=1, 2,..., N).

The phase function realizes the condition (x_i is A_i):

$$\mu_A(x_i) = 1 / \left(1 + \left((x_i - c_i) / \sigma_i\right)^{2bi}\right). \qquad (8)$$

The aggregated output result of the network takes the form:

$$y(x) = \sum_{i=1}^{M} \omega_i y_i(x) / \sum_{i=1}^{M} \omega_i,\ \ y_i(x) = p_{i0} + \sum_{j=1}^{N} p_{ij}\, x_j. \qquad (9)$$

Thus: for L=4 values of an output variable, N input variables and M rules, the multilayer Takagi-Sugeno-Kang neural network takes the form (Fig. 3).

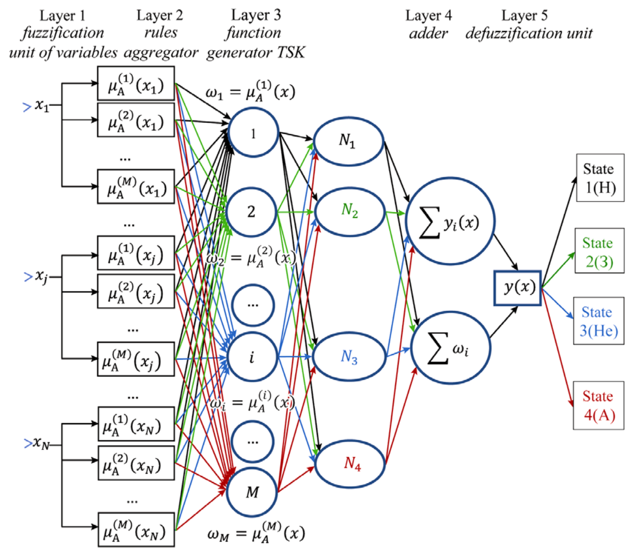


Fig. 3. Model of structure of the Takagi-Sugeno-Kang fuzzy neural network

Takagi-Sugeno-Kang network, in which ω_i weights are interpreted as significance of components $\mu_A^{(i)}(x)$, has 5 layers.

1. The first (parametric) layer with c_j^i, σ_j^i, b_j^i, parameters, which should be adapted in the learning process, performs fuzzification of variables.

2. The second (nonparametric) layer performs *aggregation* of individual variables that determine a resulting value of a weight of the rule $\omega_i = \mu_A^{(i)}(x)$ for x vector.

3. The third layer calculates the value $y_i(x)$ according to (9) and multiplies $y_i(x)$ by ω_i, formed in the previous layer. Weights p_{ij} (i=1, 2,..., M, j=1, 2,..., N) are subject to adaptation.

4. The fourth (nonparametric) layer consists of two neurons-adders, one of them calculates the weighted sum of signals $y_i(x)$, and the other one - the sum of weight coefficients ω_i (i=1, 2,..., M).

5. The fifth (normalizing) layer of one neuron performs aggregation of an output signal of a network by the formula (7).

We can divide parameters to be adapted into two groups:

– the first group consists of p_{ij} parameters of the third (linear) layer;

– the second group consists of parameters of the membership function of the first (nonlinear) layer.

A network refines the parameters of the first and third layers only in the process of learning.

We set settings in two stages.

Stage 1. Calculation of parameters of TSK polynomial.

Solution of systems of linear equations for calculation of parameters of TSK polynomial TSK – p_{ij} (i=1,..., M, j=1,..., N) at fixed values of the membership function parameters.

Stage 2. Calculation of actual values of output signals.

Calculation of actual values of output signals y_k (k==1,..., P) at fixed linear parameters p_{ij}.

Paper [8] describes the algorithm for learning of the artificial neural network of Takagi-Sugeno-Kang in general.

4. 2. Adaptation of the learning algorithm of TSK network to the task of the estimation of technical state of construction structures

We selected an option where an output parameter of a network takes a value that expresses the technical state of constructions to adapt the learning algorithm of Takagi-Sugeno-Kang network to the task of the estimation of technical state of construction structures (Table 1).

$$y_i(x) = y_{i0},\ \ y = \sum_{i=1}^{m} \omega_i y_{i0}, \qquad (10)$$

where m is the number of different values (different membership functions) for each variable x_j.

We can train a fuzzy network:

– by an algorithm with a trainer;

– by an algorithm of self-organization.

We investigate a learning algorithm with a trainer in this study. It minimizes the function:

$$E = \frac{1}{2}\sum_{i=1}^{k}\left(y(x^{(i)}) - d^{(i)}\right)^2, \qquad (11)$$

where k is the number of pairs (x, d) for learning, $d^{(l)}$ is the value of an output signal of a network, which exists at the output at values of components $\mu_A^{(i)}(x)$.

Stage 1. Adaptation of linear parameters.

There are values $\{x_i\}$ given to the network input.

To interpret significance of components $\mu_A^{(i)}(x)$, we obtain a system of linear equations of $W \cdot \vec{Y} = \vec{d}$, type, where: $W = \left(\omega'_{ij}\right)$; ω'_{ij} is the level of activation of the j-th rule for the input vector $\vec{x}^{(k)} = (x_1^k, x_2^k, ..., x_N^k)$, and $\vec{Y}^{(k)} = (y_{10}^k, y_{20}^k, ..., y_{M0}^k)$ and $\vec{d}$ are the output values.

The dimension $\vec{Y}$ is equal to M, the dimension $\vec{d}$ is equal to K, and the dimension W is equal to $K \cdot M$.

We can find values ω'_{ij} from formula:

$$\omega'_{ij} = \frac{\Pi_{j=1}^{N}\mu_A^{(i)}(x_j^{(k)})}{\sum_{r=1}^{M}\left[\Pi_{j=1}^{N}\mu_A^{(i)}(x_j^{(k)})\right]}. \qquad (12)$$

We as $\mu_A(x_i)$ propose to consider a measure of membership in the form:

$$\mu_A(x_i) = \frac{1}{1+\left(\frac{x_j - c_i}{\sigma_i}\right)^2}. \qquad (13)$$

And a number of K lines is greater than a number of columns (variables).

We find the solution to the system from equation $\vec{Y} = W^+ \cdot \vec{d}$, where W^+ is the pseudo inversion of W matrix [8].

Stage 2. Clarification of non-linear parameters.

After calculation of values y_i (i=1, 2,..., K), we calculate an error $\vec{E} = \left|\vec{d} - \vec{y}\right|$. We can use methods of gradient descent and random search to minimize an error.

We can mark out a method of "annealing imitation" and a direct method of random search among methods of random search for this task. However, the task of diagnostics of building constructions involves a very large number of input parameters N. An optimal number of rules $M = m^N$ is also very large under such conditions, and a use of gradient descent methods and the method of "annealing imitation" requires more computational resources and time costs than the direct method of random search. Paper [8] describes the gradient descent method for Takagi-Sugeno-Kang network [8].

We propose a direct method of random search for network learning.

For parameters $\{c_l\}$ and $\{\sigma_l\}$:

– we determine acceptable limits $\left\{\left[c_i^H, c_i^B\right]\right\}$ and $\left\{\left[\sigma_i^H, \sigma_i^B\right]\right\}$;

– we model random values

$$\xi_i \in \left\{\left[c_i^H, c_i^B\right]\right\} \text{ and } \eta_i \in \left\{\left[\sigma_i^H, \sigma_i^B\right]\right\},$$

evenly distributed in these intervals;

– we find an error vector $\vec{E}$.

Learning lasts as long as an error reaches an acceptable value. After refining of nonlinear parameters, the process of adaptation of linear parameters of TSK (first stage) restarts.

4. 3. Identification of categories of the technical state of construction structures

A fragment of a fuzzy production knowledge base, which is a system of fuzzy rules for estimation of the technical state of structures with various signs of degradation, consists of fuzzy implications of the form [10–12]:

Rule 1: ***if*** <type of defect = signs of soakage ***and*** size of area = in*significant* ***and*** shape of area = ellipsoid, ***and*** position = *on areas of wall overlap* ***and*** temperature influence = absent ***and*** humidity influence = *absent* ***and*** soakage influence = *slow* ***and*** vibration influence = *absent*> ***then*** <state = normal>.

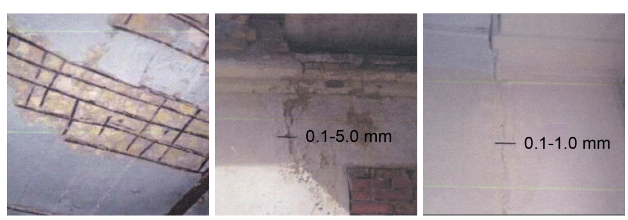
Rule 2: ***if*** <type of defect = *destruction of finishing layer* ***and*** size of area = *insignificant* ***and*** shape of area = *spherical*, ***and*** position = *on ceiling areas* ***and*** temperature influence = absent ***and*** humidity influence = *slow* ***and*** soakage influence = *insignificant* ***and*** vibrations influence= *absent*> ***then*** <state = satisfactory>;

Rule 3: ***if*** <type of defect = *crack* ***and*** characteristic = *longitudinal* ***and*** width of opening = *large* ***and*** length = *critical* ***and*** depth = *critical* ***and*** location = *along reinforcement* ***and*** humidity influence = *significant* ***and*** soakage influence = *significant* ***and*** vibrations influence = *significant* ***and*** temperature influence = *significant*> ***then*** <state = *emergency*>;

Rule 4: <type of defect = *corrosion of reinforcement* ***and*** characteristic = *solid surface* ***and*** shape of area = *incorrect* ***and*** position = *in joints between plates* ***and*** humidity influence = *average* ***and*** soakage influence = *absent* ***and*** vibration influence = *significant* ***and*** temperature influence = *average*> ***then*** <state = *unsuitable for normal operation*>.

We performed inference of fuzzy rules based on estimations of the technical state of various structures, which operate in different modes and under different conditions.

Fig. 4 shows examples of photographic registration of defects and damage observed during surveys of various objects.



a *b* *c*

Fig. 4. Photographic registration of defects and damages: *a* — destruction of protective layer of concrete, exposure and corrosion of reinforcement on the area of 1.5 m^2; *b* — a crack with a width of opening of 0.1—5.0 mm, signs of soakage, wall saltpeter, fungus on walls and ceilings on areas of 1.0 m^2; *c* — a crack in adjoining of a wall and partition of the length of 3.0 m and the width of the opening of 0.1—1.0 mm

Text information accompanies pictures and drawings. It contains clear and fuzzy characteristics of defects and damage parameters recorded during the survey of the building in general and its individual constructions.

The output parameter $y(x)$ takes its value from a segment [1, 4].

To identify conditions of construction structures, one can use measures of membership obtained by the expert method [10] and measures of membership obtained by the method of clustering [8, 13]:

$$\mu_1(x)=\begin{cases} e^{-\frac{(x-1)^2}{2}}, & x\in[1,4], \\ 0, & x\overline{\in}[1,4]; \end{cases}$$
$$\mu_2(x)=\begin{cases} e^{-\frac{(x-2)^2}{2}}, & x\in[1,4], \\ 0, & x\overline{\in}[1,4]; \end{cases}$$
$$\mu_3(x)=\begin{cases} e^{-\frac{(x-3)^2}{2}}, & x\in[1,4], \\ 0, & x\overline{\in}[1,4]; \end{cases} \qquad (14)$$
$$\mu_4(x)=\begin{cases} e^{-\frac{(x-4)^2}{2}}, & x\in[1,4], \\ 0, & x<1, \\ 1, & x>4. \end{cases}$$

A user can choose the method for obtaining a membership measure by himself.

5. Discussion of modeling results and prospects for the introduction of ANN to the system for the estimation of technical state of construction structures

The tasks related to the problem of automated estimation of technical state of construction structures become widespread not only due to the growing need to ensure operational suitability of construction structures. Modern design practice shows an increase in the number of tasks associated with execution of construction works and reconstruction works in the densely populated urban development. To solve such problems, there is typically a wide set of alternatives for the allocation of combined resources and issues, and decision-making is associated with modeling of fields of random loads and influences in construction structures of surrounding facilities (Fig. 5).

a *b*

Fig. 5. Construction objects of "DIM group" in Kyiv and the surrounding facilities: *a* – "A52" Residential complexes; *b* – "Autograph" Residential complexes

The fact that construction objects have the property to accumulate damage complicates the task of risk management. Transition of a structure from one state to another goes with accumulation of damage, and the accumulation period can be long-term and not always clearly defined. In addition, a number of input parameters is very large, but not all defects and damage affect the technical state of a construction equally. In such circumstances, traditional monitoring and testing methods lose their effectiveness.

The intelligent system for estimation of the technical state of building structures, designed in this study, takes into consideration a fuzzy and non-linear nature of dynamics in damage development through the use of a nonlinear input layer. Applying the nonlinear adders provides another possibility to solve the task of classification of a very large number of data in a network of a smaller dimension.

Automation of monitoring and estimation of technical state of structures using intelligent systems in the form of a neural network ensures significant advantages, however, it requires an information base capable of responding promptly to changes in the technical state of structures and variability of operation conditions. Therefore, there are plans for further study into development of methods for the organization of data collection using modern information technology, into choosing the input variables for a Takagi-Sugeno-Kang network, into construction of fuzzy sets of signs of degradation of structures and development of models of accumulation of damage.

6. Conclusions

1. We substantiated the topology of the Takagi-Sugeno-Kang fuzzy neural network. Specifically: we defined the network architecture, we defined the rule, according to which a number of elements is determined at the input and the output, we showed the structure of links and described designation of elements of each layer in detail. Building standards determine belonging of a construction to one of the states at the output.

2. We can use results of modeling of random loads, accumulation of damage and forecasting of dynamics of defects in structures in the input data in the process of learning of an intelligent system. An analysis of rules used by experts to identify categories of technical states of building structures showed that Mamdani or Larsen fuzzy implications are best suited for engineering rules according to which it is possible to estimate the technical state.

An amount of computing resources and time necessary for processing of a very large amount of data determined the choice of the learning method.

3. Introduction of the fuzzy neural network by Takagi-Sugeno-Kang to the task of the estimation of technical state of construction structures makes it possible to compare parameters of the technical state with reference values and to make informed decisions regarding identification of technical state categories, which helps to reduce risks of development of uncontrolled defects under conditions of accumulation of damage and analysis of a very large amount of data.

Acknowledgements

Underlying this study is the analysis of scientific-and-technical reports and expert assessments [11, 12]

used by the investment construction company of the full cycle "DIM group" (Development Investment Management) in the design and construction of residential complexes in Kyiv (Fig. 5). Authors express their gratitude to the management of the company for the informational support to the study aimed to introduce the latest, scientifically grounded, technologies and systems to the processes that would ensure reliable and safe operation of buildings and structures.

References

1. Baza znaniy: eksperiment, intellektual'nyy analiz dannyh, iskusstvennye neyronnye seti / Abrukov V. S., Abrukov S. V., Smirnov A. V., Karlovich E. V. // Sb. trudov II Vserossiyskoy nauchnoy konferencii «Nanostrukturirovannye materialy i preobrazovatel'nye ustroystva dlya solnechnoy energetiki». 2014. doi: 10.13140/2.1.4926.2400
2. Hybrid metaheuristics in combinatorial optimization: A survey / Blum C., Puchinger J., Raidl G. R., Roli A. // Applied Soft Computing. 2011. Vol. 11, Issue 6. P. 4135–4151. doi: 10.1016/j.asoc.2011.02.032
3. Zaitseva E., Levashenko V., Kostolny J. Importance analysis based on logical differential calculus and Binary Decision Diagram // Reliability Engineering & System Safety. 2015. Vol. 138. P. 135–144. doi: 10.1016/j.ress.2015.01.009
4. Sarycheva L. V. Objective Cluster Analysis of Data Based on GMDH // Journal of Automation and Information Sciences. 2008. Vol. 40, Issue 4. P. 28–48. doi: 10.1615/jautomatinfscien.v40.i4.30
5. Hybrid Self-Organization Based Facility Layout Planning / Potočnik P., Berlec T., Sluga A., Govekar E. // Strojniški vestnik – Journal of Mechanical Engineering. 2014. Vol. 60, Issue 12. P. 789–796. doi: 10.5545/sv-jme.2014.1748
6. Performance of multi layer feedforward and radial base function neural networks in classification and modeling / Sánchez M. S., Swierenga H., Sarabia L. A., Derks E., Buydens L. // Chemometrics and Intelligent Laboratory Systems. 1996. Vol. 33, Issue 2. P. 101–119. doi: 10.1016/0169-7439(95)00089-5
7. Yeremenko V. S., Pereidenko A. V., Monchenko O. V. Zastosuvannia neiromerezhevykh tekhnolohiyi u systemakh neruinivnoho kontroliu // Tekhnicheskaya diagnostika i nerazrushayushchiy kontrol'. 2012. Issue 1. P. 35–41.
8. Osowski S. Sieci neuronowe do przetwarzania informacji. Warszawa, 2000. 342 p.
9. Terenchuk S. A., Yeremenko B. M., Pashko A. O. Otsiniuvannia tekhnichnoho stanu budivelnykh konstruktsiy na osnovi nechitkoho vyvedennia // Budivelne vyrobnytstvo. 2016. Issue 61. P. 23–31.
10. Terenchuk S., Yeremenko B., Sorotuyk T. Implementation of intelligent information technology for the assessment of technical condition of building structures in the process of diagnosis // Eastern-European Journal of Enterprise Technologies. 2016. Vol. 5, Issue 3. P. 30–39. doi: 10.15587/1729-4061.2016.80782
11. Application of fuzzy mathematics methods to processing geometric parameters of degradation of building structures / Terenchuk S., Yeremenko B., Kartavykh S., Nasikovskyi O. // EUREKA: Physics and Engineering. 2018. Issue 1. P. 56–62. doi: 10.21303/2461-4262.2018.00554
12. Zastosuvannia ekspertnykh znan dlia formuvannia bazy znan systemy otsiniuvannia tekhnichnoho stanu budivelnykh konstruktsiy / Yeremenko B. M., Terenchuk S. A., Kartavykh S. M., Nasikovskyi O. V. // Nauka ta budivnytstvo. 2017. Issue 4. P. 63–69.
13. Hammah R. E., Curran J. H. Fuzzy cluster algorithm for the automatic identification of joint sets // International Journal of Rock Mechanics and Mining Sciences. 1998. Vol. 35, Issue 7. P. 889–905. doi: 10.1016/s0148-9062(98)00011-4
14. A Sum-of-Squares Approach to Modeling and Control of Nonlinear Dynamical Systems With Polynomial Fuzzy Systems / Tanaka K., Yoshida H., Ohtake H., Wang H. O. // IEEE Transactions on Fuzzy Systems. 2009. Vol. 17, Issue 4. P. 911–922. doi: 10.1109/tfuzz.2008.924341