THE USE OF NEURO-FUZZY MODELS IN EXPERT SUPPORT SYSTEMS FOR FORENSIC BUILDING-TECHNICAL EXPERTISE

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A R T I C L E I N F O

A B S T R A C T

The paper is focused on solving the problem of assessing the impact of repair-building works on the technical condition of objects near which these works were or are being carried out. Particular attention is paid to the analysis of the problems that accompany the creation of expert systems for supporting forensic building-technical expertise.

The main aim of the work: conceptual modeling of an expert system for supporting forensic building-technical expertise.

Object of research: the process of execution of forensic building-technical expertise and expert research.

Solved problem: automation of a system capable of functioning in conditions of fuzzy uncertainty caused by the non-uniformity of the logic of the process of performing forensic building-technical expertise and the ambiguity and inconsistency of the information provided for research.

Main scientific results: a model of a knowledge-based system is proposed and the use of neuro-fuzzy networks is justified to solve the problem of supporting the decision to assess the impact of repair-building works on the technical condition of the object, which has become the subject of expertise.

Field of practical use of research results: forensic activities in the framework of building-technical expertise to determine the possible causes of deterioration in the technical condition of structural elements of buildings and their individual premises.

Innovative technological product: a support system for forensic building-technical expertise based on knowledge and neuro-fuzzy models.

Scope of application of an innovative technological product: forensic and investigative practice in resolving issues requiring the use of special knowledge in assessing the impact of repair-building works on the technical condition of nearby facilities.

1. Introduction
1. 1. The Object of Research
The object of research is the process of conducting forensic building-technical expertise and expert researches. At the same time, special attention is paid to the analysis of the problems that accompany the creation of expert systems (ES) for supporting forensic building-technical expertise (FBTE).

Definition 1. Expert system is a system that uses expert knowledge in the subject area to effectively solve problems in this area.

1. 2. Problem Description
Fuzzy uncertainty is considered to be one of the main problems, making it difficult for FBTEs and expert researches (ER) to establish a possible connection between the deterioration of

the technical condition (TC) of the facilities and repair-building works (RBW) that were carried out nearby [1].

Definition 2. Objects in this work are the structural elements of buildings, which became the subject of forensic building-technical expertise.

The primary information contained in the materials presented for the researches may be characterized by such fuzzy factors as [2, 3]:

– inconsistency;

– incompleteness or failure to provide all necessary input data;

– ambiguity of interpretation of textual and geometric information.

To overcome this uncertainty, additional materials are provided for the expert's application.

After processing received in the manner prescribed by law from conflicting participants in the case, new facts and descriptions of events, it may become clear that the information provided refutes the conclusions reached earlier. As a result of such a transformation of knowledge, there is a need to acquire and study additional information on the repeated application of the expert, since the expertise is complicated by the uncertainty that makes it impossible to make the right conclusions [2].

This non-uniformity of logic is one of the main reasons for the delay in the conduct of FBTE expertise, since set of current alternatives can repeatedly change.

Definition 3. Nonmonotonic logic is a fuzzy factor, manifested in the inconsistency of new knowledge with knowledge that was obtained earlier [4].

Another significant reason for the delay in the implementation of FBTE is a considerable increase in the volume of RBW in the context of compacted urban development [5].

In the described conditions, in order to facilitate and accelerate the work of experts, there is a need to automate their activities by introducing specialized software into the process of conducting expertise. It should be borne in mind that the ES can be used as intelligent databases.

Thus, the execution and implementation of computerized expert systems in the process of assessing the impact of RBWs on the TC of objects in the zone of influence of these works is an urgent and justified task. But the use of such systems involves the development of appropriate models and methods for formalizing, processing and testing the knowledge of experts.

1. 3. Suggested Solution to the Problem

The development of models and methods, which is the ES basis, is based on the expert knowledge described by the expert, which forms the application logic and fills the system knowledge base. This knowledge allows to solve the problem of determining a partially observable environment.

Definition 4. A partially observable environment is an environment which individual state characteristics are absent and there is no possibility to gain access to complete information [6].

The solution to the problem of determining a partially observable environment consists in interpreting fuzzy knowledge and choosing alternative search directions in the space of possible solutions.

In this paper, the subject environment is set of:

– geometric and physical parameters of damage that determine the TC of the object;

– environmental factors of technological and natural origin, which could affect the TC of the facility;

– expert conclusion.

At the same time, the technical condition of objects often depends on hidden defects, which significantly complicates the interpretation of the input data. Hidden defects are internal factors that influence the formation of a complete group of possible causes for the deterioration of the TC of an object under the influence of various external factors and complicate the application of the Bayesian approach [7].

The interpretation of the input data is complicated by the fact that there is no clear boundary between measures of external environmental and technological factors impact on the object. This leads to the fact that the relationship between input and output data is difficult to formalize. In such cases, estimates of the probabilities of hypotheses about the possible causes of the

object TC deterioration can be contradictory, since they are based on personal knowledge and experience of experts.

Thus, subjectivity and inconsistency are characteristic features of forensic and investigative practice, and set of current alternatives may appear due to:

– formation by different experts of different groups of hypotheses about the causes of the deterioration of the technical condition of the object;

– various estimates of the probabilities of a priori hypotheses about the causes of the deterioration of the technical condition of the object.

In addition, as conflicting parties provide additional conflicting information, not only current decisions, but also the space of possible alternatives can repeatedly change.

Experienced specialists are able to make the right decisions in the described conditions thanks to the use of heuristics. However, the use of heuristics in the ES requires formalizing the heuristic activity of specialists in a form acceptable for machine processing.

Definition 5. Heuristic activity is the organization of the process of productive thinking, using the totality of mechanisms inherent in man by means of which procedures for solving problems are generated [4].

The use of fuzzy rules in a fuzzy logical basis allows to formalize the process of performing FBTEs and create a system of fuzzy production models that reproduce fuzzy logical reasoning by experts. Subsequently, these models form the ontology of the system.

The choice of models and methods for the presentation and processing of special knowledge determines the architecture of the ES, the organization of the knowledge base and control schemes for the withdrawal mechanism. Moreover, in knowledge-based systems, the knowledge base is separated from the rest of the system [8, 9].

This separation of the knowledge base greatly simplifies the process of replenishing knowledge in the conditions associated with changes:

– a full group of hypotheses about the causes of the TC deterioration of the object;

– current alternative findings.

A lot of work has been devoted to the issues of using fuzzy logic and fuzzy conclusions that allow to create expert systems for various purposes. A systematic presentation of the mathematical foundations and methods for processing fuzzy knowledge is contained in [10]. It is noted that output systems with fuzzy logic is a convenient tool for explaining conclusions, but these systems are not able to automatically acquire knowledge for use in output mechanisms. Artificial neural networks (ANNs), on the contrary, can automatically gain knowledge, but a trained ANN is a "black box" for the user, and the introduction of expert (a priori) knowledge is usually a complex process [11].

Neuro-fuzzy models are systems in which the output is performed on the basis of a fuzzy logic apparatus, and membership functions are configured using ANNs, but iterative methods for their learning are considered too slow. Therefore, it is urgent to develop models that allow non-iterative mode to take into account a priori information on sample learning [12].

The aim of this research is the conceptual modeling of an expert system for supporting forensic building-technical expertise, which is able to function in the conditions of uncertainty that accompanies the process of conducting FBTE.

To achieve this aim, it is necessary to solve the following objectives:

– to implement the adaptation of the fuzzy inference system to the task of assessing the influence degree of repair-building works on the TC of the object, which has become the subject of FBTE;

– to propose a conceptual model of an expert system for supporting FBTE with an integrated ANN.

2. Materials and Methods

Materials:

– support system for forensic building-technical expertise (SSFBTE);

– process of fuzzy inference.

Methods:

– fuzzy logic to formalize the heuristic activity of experts in the formation of the system rules base;

– structural modeling of the system.

2. 1. SSFBTE Model

Fig. 1 shows the support scheme for making expert decisions on assessing the impact of repair-building works on the technical condition of objects that have become the subject of FBTE [3].
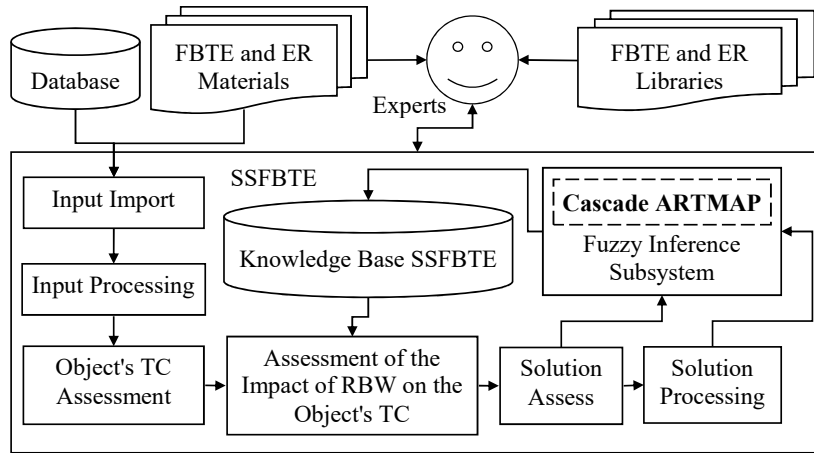

Fig. 1. Support scheme for making expert decisions on assessing the impact of repair-building work on the technical condition of objects

The structure of an expert system, the purpose of its structural units, the processes of formalizing the geometric parameters of damage to an object and the formation of fuzzy rules that reflect the process of productive thinking of experts during FBTE are described in detail in [3].

But in [3] it is not shown:

– how the fuzzy inference subsystem can be adapted to solve the problem of assessing the degree of influence of RBWs on the technical condition of an object;

– as a SSFBTE will function with the integrated Cascade Adaptive Resonance Theory Mapping (ARTMAP).

2. 2. System and process of fuzzy inference

The model of the fuzzy inference system, which is one of the subsystems of the expert system for supporting FBTE, is shown in **Fig. 2**.
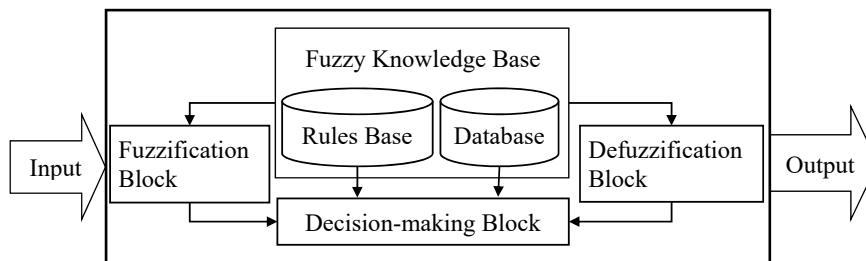

Fig. 2. Fuzzy Inference System

The fuzzy inference system consists of [9, 10]:

– a rule base that contains a system of fuzzy rules "if $x \in A$, then $y \in B$", where: x and y are the input and output variables defined on the domain of definition of the fuzzy rule X and the domain of definition of output Y; A and B are statements that are defined on X and Y with membership measures $\mu_A(x) \in [0, 1]$ and $\mu_B(y) \in [0, 1]$, respectively;

– database in which membership functions of fuzzy sets used in fuzzy rules are stored;

– fuzzification block with their membership functions;

– decision-making block, in which the membership measures of fuzzy implications $\mu_{A \rightarrow B}(x, y)$ are determined using operations on fuzzy sets from the fuzzification block and fuzzy sets from the corresponding rules;

– defuzzification block, which implements the procedure for converting fuzzy output results to clear values for measures of their belonging.

In [9, 13], the feasibility of using fuzzy Mamdani implications in solving the problem of assessing the technical condition of building structures was substantiated:

$$\mu_R(x, y)=\min\{\mu_A(x), \mu_B(y)\}, \tag{1}$$

where $R:R=A\rightarrow B$ is a fuzzy causal relationship between premise A and conclusion B, which reflects the knowledge of experts, and the operation min corresponds to calculating the degree of truth of the premise of the rule.

However, in this work, another problem is solved, which requires the formation of fuzzy production models that can adequately reproduce the process of associative thinking of experts.

3. Result
3. 1. Formalization of heuristic activity of experts

A formalized expert conclusion on the possible connection between the deterioration of the technical condition of the facilities and the repair and repair-building works that was carried out nearby is reproduced in a linguistic assessment of the initial variable in the form of a list with an explicit list of sets (2):

$$y=\{(d_1, \mu^k_B(d_1)),\ldots, (d_j, \mu^k_B(d_j)),\ldots, (d_J, \mu^k_B(d_J)\}, \tag{2}$$

where $d_j (j=1,\ldots, J)$ is the fuzzy term of the linguistic estimation of the output variable (**Table 1**); $J=4$ is the number of terms used for linguistic evaluation of y; $\mu^k_B(d_j)$ is the measure of membership of the k-th damage ($k=1,\ldots, K$) of the j-th expert conclusion on the impact of RBWs on the development of this damage.

Table 1
Formalization of the linguistic assessment of the initial variable

No.	Expert opinion	Fuzzy semantics	Term	Measure of membership
1	Repair and RBW *did not affect* the technical condition of the facility	did not affect	d_1	$\mu^k_B(d_1)$
2	Repair and RBW *may affect* the technical condition of the facility	may affect	d_2	$\mu^k_B(d_2)$
3	Repair and RBW *affects* the technical condition of the facility	affect	d_3	$\mu^k_B(d_3)$
4	*It is impossible to determine* or repair and RBW have affected the technical condition of the facility	It is impossible to determine	d_4	$\mu^k_B(d_4)$

In the case of this choice of the complete terminal space Y, the full scope of premises X should be divided into:

– set of damage characteristics indicating a deterioration in the technical condition of the object ($Q=\{x_1;\ldots; x_n\}$);

– set of characteristics of environmental factors that could lead to this deterioration, ($Z=\{x_{n+1};\ldots; x_I\}=\{z_1;\ldots; z_I\}$).

In this case, $X=Q\cup Z$, and the fuzzy relationship between X and Y $R:(X\times Y)$, which reflects the process of productive thinking of experts, is determined through R_1 and R_2 by the expression $R=R_1\bullet R_2$, where [10]:

– $R_1:(Q\times Z)\rightarrow[0, 1]$;

– $R_2:(Z\times Y)\rightarrow[0, 1]$;

– "•" is operation of logical multiplication.

Fuzzy inference is based on a fuzzy knowledge base (**Fig. 2**).

The rules for a fuzzy knowledge base take the form $R:(A\times B)$.

A fragment of the fuzzy rule l ($l=1,\ldots, L$) according to the research [3] is formalized as follows:

if «type of defect = crack ($k=1$)
and characteristic (x_1) = longitudinal ($\mu^1_{Aj1}(x_1)$)
and position in the structure (x_2) = vertical ($\mu^1_{Aj2}(x_2)$)
and direction of development (x_3) = up ($\mu^1_{Aj3}(x_3)$)
and location (x_4) = in the load-bearing wall ($\mu^1_{Aj4}(x_4)$)
and opening width (x_5) = large ($\mu^1_{Aj5}(x_5)$)
and length (x_6) = critical ($\mu^1_{Aj6}(x_6)$)
and depth (x_7) = through ($\mu^1_{Aj7}(x_7)$)
and influence factor (z_1) = settlement of the base of the house ($\mu^1_{Aj8}(z_1)$)
and influence factor (z_2) = change in the stress-strain state
soil foundation of the house as a result of pits
the new construction of the <address, type, time and duration of work> ($\mu^1_{Aj9}(z_2)$)
then RBW <addresses, type, time and duration of work>
did not affect the technical condition of the facility (y) = impact assessment
$\{(d_1, \mu^1_B(d_1)); (d_2, \mu^1_B(d_2)); (d_3, \mu^1_B(d_3); (d_4, \mu^1_B(d_4)\}$, for
$\mu^1_B(d_1) < \rho_{11}$ or $\mu_{1B}(d_1) - \mu^1_B(d_3) \geq \rho_{13}$ or $\mu^1_B(d_1) - \mu^1_B(d_4) \geq \rho_{14}$» with the weight w^j_{11}
or repair and RBW <address, type, time and duration of work>
possible impact on the technical condition of the facility (y) = impact assessment
$\{(d_1, \mu^1_B(d_1)); (d_2, \mu^1_B(d_2)); (d_3, \mu^1_B(d_3); (d_4, \mu^1_B(d_4)\}$, for
$\mu^1_B(d_2) - \mu^1_B(d_1) \geq \rho_{21}$ or $\mu^1_B(d_2) - \mu^1_B(d_3) \geq \rho_{23}$ or $\mu^1_B(d_2) - \mu^1_B(d_4) \geq \rho_{24}$» with weight w^j_{12}
or repair and RBW <addresses, type, time and duration of work>
impact on the technical condition of the facility (y) = impact assessment
$\{(d_1, \mu^1_B(d_1)); (d_2, \mu^1_B(d_2)); (d_3, \mu^1_B(d_3); (d_4, \mu^1_B(d_4)\}$, for
$\mu^1_B(d_3) > \rho_{31}$ or $\mu^1_B(d_3) - \mu^1_B(d_2) \geq \rho_{32}$ or $\mu^1_B(d_3) - \mu^1_B(d_4) \geq \rho_{34}$» with weight w^j_{13}
or it is impossible to install or RBW
<address, type, time and duration of work> impact on the technical condition
object (y) = impact assessment $\{(d_1, \mu^1_B(d_1)); (d_2, \mu^1_B(d_2)); (d_3, \mu^1_B(d_3); (d_4, \mu^1_B(d_4)\}$
attached to $|\mu^1_B(d_1) - \mu^1_B(d_4)| < \rho_{44}$ with weight w^j_{14}»   (3)

where $\mu^1_{Aji}(x_i)$ – the measure of membership of the input crack characteristic in the j-th term of the output variable; $\mu_A = \{\mu_A(x_1); \ldots ; \mu_A(x_i); \ldots; \mu_A(x_I)\}$ – vector membership function for input data; ρ – decision support threshold; $w^j_l \in [0, 1]$ – the weight of the j-th conjunction of the l-th ($l=1,\ldots, L$) rule, which is characterized by the expert's confidence measure.

The determination of the parameters of the membership function, the weights of the rules and the decision support threshold at this stage of research is carried out by the expert method [1, 4].

To formalize the associative thinking of experts when establishing a possible connection between RBW and the deterioration of the technical condition of objects that have become the subject of FBTE, it is advisable to use the max-min composition [10, 13]:

$$\mu_{R_1 \cdot R_2}(x, y) = \max_y \left[\min\left(\mu_{R_1}(q, z), \mu_{R_2}(z, y)\right) \right].$$ (4)

When applying the composition max, all the fuzzy subsets intended for each output variable in all rules are combined into one fuzzy subset for all output variables. Such a union provides the conclusion of a fuzzy subset; it is constructed as a point maximum for all fuzzy subsets.

Thus, associative rules (4) allow to identify patterns between related events, and max-min composition is one of the tools to extract knowledge from data arrays due to properties such as:

– associativity: $Y \bullet (Z \bullet Q) = (Y \bullet Z) \bullet Q$;
– distributivity with respect to the union $Q \bullet (Z \cup Y) = (Q \bullet Z) \cup (Q \bullet Y)$;
– non-distributivity with respect to the intersection $Q \bullet (Z \cap Y) \neq (Q \bullet Z) \cap (Q \bullet Y)$;
– if $Y \subset Z$, then $Q \bullet Y \subset Q \bullet Z$.

One of the significant drawbacks of fuzzy inference systems is the dependence of membership functions and rule weights on a priori knowledge of experts.

In integrated neuro-fuzzy systems, ANNs are used to determine the parameters of fuzzy inference.

3. 2. Integrated neuro-fuzzy system

The knowledge base of a neuro-fuzzy system is implicitly set by the ANN structure.

At the same time [12, 14]:

– input nodes perform the function of phasing;

– hidden nodes reflect the rules;

– the output node performs the function of defuzzification.

To preserve the fuzzy rule, reflects the heuristic of associative thinking of an expert, the neuro-fuzzy network Kosko Fuzzy Associate Memory (FAM) can be used. In this case, the rules for N variables that are connected using conjunctions (2) in the antecedent can be represented using N FAM networks. In addition, each network retains one rule. Combining the outputs of all N FAM networks ends with the operation of maximum and defuzzification of the result.

Thus, the work of FAM is based on the interpretation of a fuzzy rule as an association between antecedent and consequent. The weights of the rules can be determined during learning of the ANN or can be replaced by equivalent modifications of membership functions.

Two methods can be used to learn a neuro-fuzzy system:

– training with increasing count of rules;

– training with reducing count of rules.

Considering the number of rules that need to be formalized and reflected on the initial ANN map, it is advisable to use the learning method with building up rules for the tasks of supporting FBTE.

Papers [15, 16] describe in detail the architecture and learning algorithm of Cascade ARTMAP, which is one of the modifications of Fuzzy ARTMAP.

Fuzzy ARTMAP hybridization elements may include FAM networks, which are capable of performing the function of internal associative memory (**Fig. 3**).
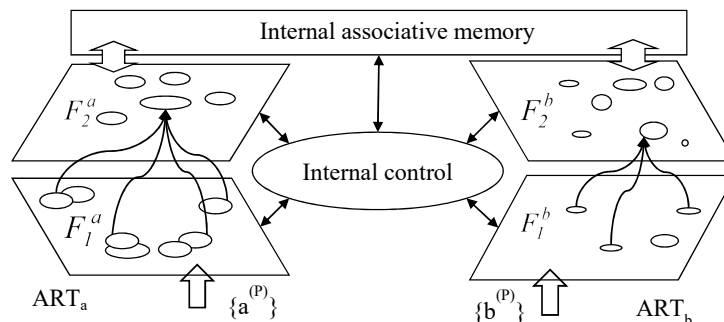

Fig. 3. ARTMAP structure model

The structure of the (Fa) and (Fb) ARTMAP layers and the process of forming an associative image are described in detail in [12, 16] and are determined by the pairs $\{a^{(P)}, b^{(P)}\}$, $(p=1, 2,...)$.

It is noted that the cascade method of learning provides Cascade ARTMAP with a significant advantage in [15]:

– a large number and variety of input images $\{a^{(P)}\}$;

– lack of a reference $\{b^{(P)}\}$ the ANN memory card.

In [14], a scheme for acquiring knowledge by reflecting a priori expert knowledge on an integrated Cascade ARTMAP memory card is shown.

These works also investigate such properties of a neuro-fuzzy model as:

– training plasticity (adjustment of knowledge);

– training stability (preservation of knowledge).

It is these properties that became decisive when choosing a neuro-fuzzy model for a support system for forensic construction and technical expertise.

Studies in this paper substantiate the ability of Cascade ARTMAP to form associative pairs, since the internal memory function in Cascade ARTMAP is performed by FAM networks.

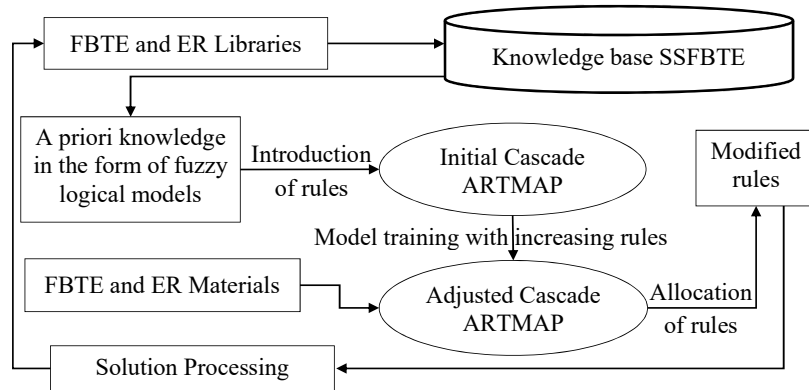The operation diagram of Cascade ARTMAP in SSFBTE is shown in **Fig. 4**.

Fig. 4. Cascade ARTMAP operation scheme in the SSFBTE

4. Discussion

When constructing recognizing models, especially in diagnostic problems, situations may arise when individual signs have little effect on the initial sign, and their combined effect is very significant. This can be explained by the fact that features that are available for observation and measurement are indirect manifestations of significant factors that are not available for observation [17, 18]. In such cases, models based on indirect features are inconvenient for further analysis, since they do not always adequately reflect the real relationships between the features or highlight the factor implicitly. This is precisely the situation that arises when the measures of influence of various environmental factors on the technical condition of objects with hidden defects are evaluated.

In [19], for such cases, it is recommended to use hierarchical logically transparent neuro-fuzzy networks and neuro-fuzzy networks with a grouping of features.

In this paper, this feature of the influence of rules by light weight is taken into account by maintaining these rules, as a result of which the comparative layer contains a large number of FAM networks and a large number of connections between neurons. The consequence of this approach is a significant complication of Cascade ARTMAP. Therefore, in the future, it is planned to conduct a comparative analysis of Cascade ARTMAP and hierarchical logically transparent ANN [12, 15].

5. Conclusions

As a result of the research:

– fuzzy inference system has been adapted to the task of assessing the degree of influence of repair-building works on the technical condition of objects, which has become the subject of forensic building-technical expertise;

– conceptual model of an expert system for supporting forensic building-technical expertise with Cascade ARTMAP integrated artificial neural network is proposed.

The main attention is paid to the substantiation of the ability of the integrated neuro-fuzzy model to form associative pairs.

Acknowledgments

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