

DESIGNING A UNIVERSAL DIGITAL TWIN OF AN OBJECT BASED ON A HYBRID NEURO-FUZZY COMPUTER

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ABSTRACT

Designing a universal digital twin of an object based on a hybrid neuro-fuzzy computer is a topic that has been widely studied in recent years as it provides many benefits such as improving performance, reducing downtime, and increasing efficiency. This paper presents a method for creating a hybrid computational neuro-fuzzy double of an object. The goal is to create a digital twin of the object that can be used for monitoring, simulation, and prediction of the object's performance, while also utilizing the strengths of both neuro-fuzzy computation to improve the accuracy and robustness of the digital twin. The proposed method shows potential for improving the performance and efficiency of physical objects.

In the paper, the proposed method forms an electronic model - a digital double of the synthesized object. The proposed calculator is superior to a similar one in several advantages.

Keywords: *Digital Twin, A Hybrid Neuro-Fuzzy Calculator, Computer-Aided Design System, Neural Network Algorithms, Simulation, Neuro-Fuzzy Computer.*

1. INTRODUCTION

Digital twins are becoming increasingly important in various industries because they allow for the virtual replication of physical objects or systems, which can be used to simulate, analyze, and optimize their behavior in real-time. The development of a universal approach for designing digital twins based on a hybrid neuro-fuzzy computer is a real problem that needs to be addressed because current methods for designing digital twins are often specific to a particular object or system.

The concept of the digital twin was first introduced in the early 2000s by Dr. Michael Grieves, a professor at the Florida Institute of Technology [1]. Grieves developed the concept as part of his work on Product Lifecycle Management (PLM), which involved managing the entire lifecycle of a product from design to disposal. The

idea behind the digital twin was to create a virtual representation of a physical object that would mirror its behavior and performance in the real world, allowing for more accurate simulations, better design, and improved maintenance and operation. Since then, the concept has gained widespread adoption in various industries, including manufacturing, aerospace, and healthcare, among others [2-7].

In [8]-[11] focused on the construction of digital twins. More specifically, focus on methodologically of design, create and connect physical objects with their virtual counterpart.

There are researches considers the problem of digital twin engineering in organizational and technical systems. The theoretical and methodological basis is a fundamental scientific

work in the field of digital twins engineering and applied models [12]-[17].

Various devices and devices for designing objects (robots, cars, aircraft, etc.) are known and widely used [25-38].

The problems of risk and assumption lie in the limited functionality, not using information (objective, subjective) about the designed object and the low probability of designing (synthesis) of the object, as well as complexity of service and the impossibility of synthesizing the twin of the designed object.

A digital twin is a virtual representation of a physical object that can be used for monitoring, simulation, and prediction of the object's performance. The hybrid neuro-fuzzy computer is a powerful tool that can be used to create accurate and reliable digital twins of objects. This computer combines the strengths of neural networks and fuzzy logic to create a system that can handle complex and uncertain data. Therefore, the use of a hybrid neuro-fuzzy computer in designing digital twins can lead to more accurate and reliable results.

As a prototype lets view the invention of "CAD structure" (Computer-aided design systems) of IUS (Information Devices and Systems) in robotics and mechatronics, which consists of 3 stages of design: 1,2,3 design levels. This scheme is an iterative process. Design IUS is a set of tasks of synthesis (selection of the structure and calculated parameters of the systems being developed) and analysis (research of the synthesized system). The synthesis step IUS can be repeated if there are negative assay results. In the case of the corresponding result of the iterative process at the stage of development of the detailing project, performed at the next level of design [4]. This CAD structure is a specialized calculator.

This results in limited functionality - the impossibility of synthesizing a twin of any object due to not being able to utilize all of the information (objective, subjective) about the designed object and of a complete reliable assessment (synthesis) of the object.

The task is to create a hybrid computational neuro-fuzzy computation of the object's double with

improved functionality with complete information (objective, observed) about the designed object, the use of modern intelligent information technologies. and high accuracy observation of the object at hand.

The importance and significance of the issue under scrutiny, i.e., designing a universal digital twin of an object based on a hybrid neuro-fuzzy computer is very high. This is because digital twins are becoming increasingly important in various industries, including manufacturing, aerospace, and healthcare, to name a few. A digital twin is a virtual replica of a physical object or system that can be used to simulate, analyze, and optimize its behavior in real-time.

However, the current methods for designing digital twins are often specific to a particular object or system, and there is a lack of a universal approach. This creates a significant challenge for industries that need to develop digital twins for a wide range of objects and systems. Therefore, the development of a universal approach for designing digital twins based on a hybrid neuro-fuzzy computer is a real problem that needs to be addressed.

This paper has the potential to provide a valuable contribution to the field of digital twin design and can lead to more accurate and reliable digital twins for a wide range of objects and systems. Because the method includes gathering complete information about the object, training a neural network, integrating the neural network with a fuzzy logic system, creating a digital twin of the object, and validating the digital twin. The use of modern intelligent information technologies and high accuracy observation of the object is crucial for the success of this method [14], [15]-[23].

2. METHOD

We describe a method for creating a hybrid computational neuro-fuzzy digital twin of an object that physically consists of computer blocks. Figure 1 shows a block diagram of a hybrid neuro-fuzzy calculator of a digital twin of an object (hereinafter referred to as the Calculator).

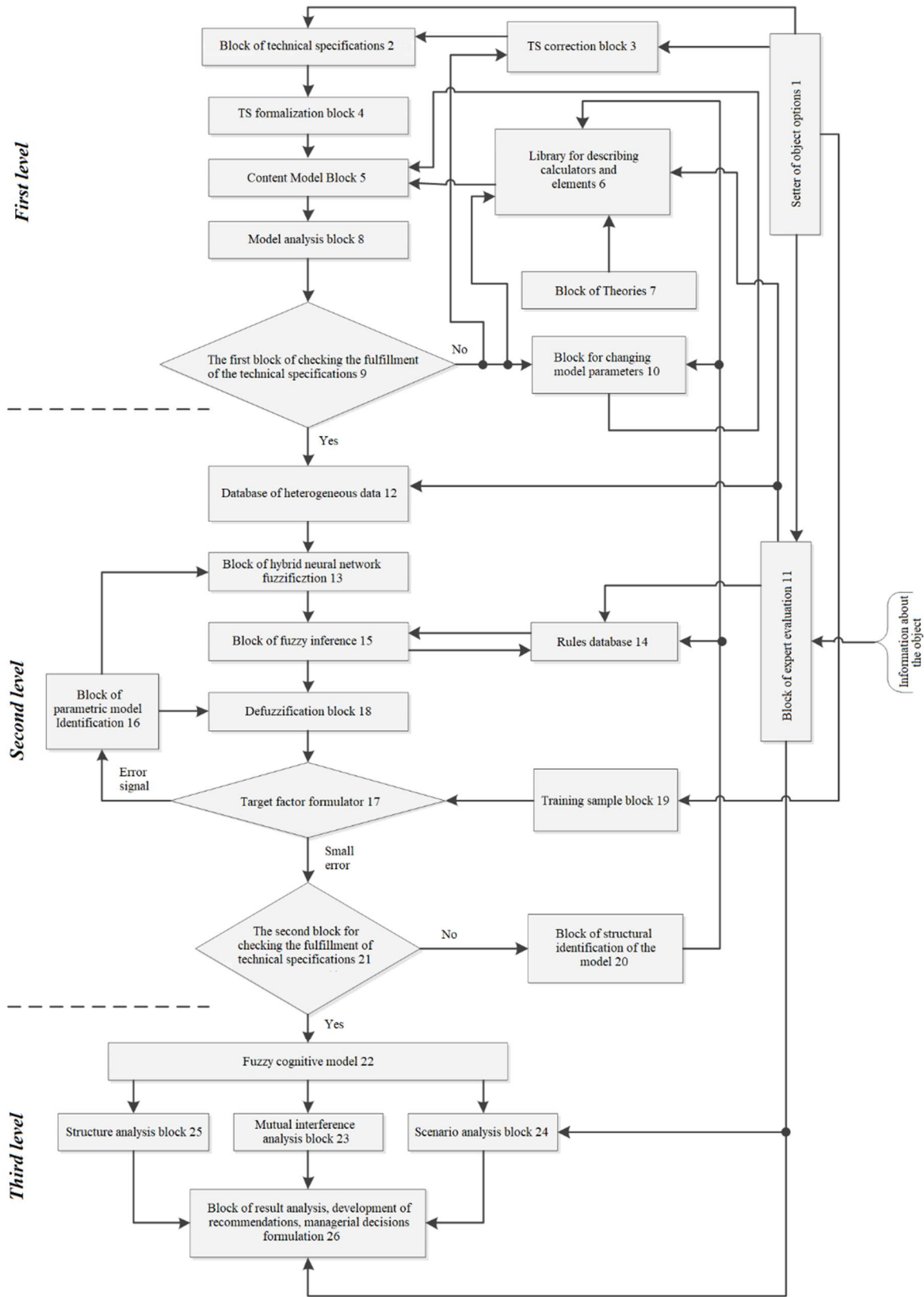


Figure 1. Structural diagram of the universal digital twin calculator

This scheme in Figure 1 contains the following blocks:

- 1 - Setter of object options (SOO);
- 2 - Block of technical specifications (TS), (BTS);
- 3 - TS correction block (TSCB);
- 4 - TS formalization block (TSBF);
- 5 - Content Model Block (CMB);
- 6 - Library for describing calculators and elements (LDCE);
- 7 - Block of Theories (BT);
- 8 - Model analysis block (MAB);
- 9 - The first block of checking the fulfillment of the technical specifications (FBCFTS);
- 10 - Block for changing model parameters (BCMP);
- 11 - Block of expert evaluation (BEE);
- 12 - Database of heterogeneous data (DHD);
- 13 - Block of hybrid neural network fuzzification (BHNN);
- 14 - Rules database (RD);
- 15 - Block of fuzzy inference (BFI);
- 16 - Block of parametric model Identification (BPMI);
- 17 - Target factor formulator (TFF);
- 18 - Defuzzification block (DB);
- 19 - Training sample block (TSB);
- 20 - Block of structural identification of the model (BSIM);
- 21 - The second block for checking the fulfillment of technical specifications; (SBCFTS);
- 22 - Fuzzy cognitive model (FCM);
- 23 - Mutual interference analysis block (MIAB);
- 24 - Scenario Analysis Block (SAB);
- 25 - Structure analysis block (SAB);
- 26 - Block of result analysis, development of recommendations, managerial decisions formulation (BRADRMDF).

The calculator includes three stages (levels) of work, which are described in the sections 2.1-2.4

2.1 Level 1. Formation of a content model of the object

At the first level, the setter of options for object 1 (technology, process) sets an object that has the features of a digital twin – a digital analog for a real object [18],[19]. SOO1 is designed as an automated system for selecting an object for producing a digital twin for [18],[19]. The next block of technical specifications 2 creates the specifications, while using information from the expert evaluation block 11, which is performed in

the form of an electronic questionnaire for the analysis of the object, electronic instructions for filling out the questionnaire, a smartphone application version of the website of the object's twin and experts [16],[17].

At the first level of development, a meaningful research model is compiled and calculated depending on the target occurrence on the basis of multidimensional information of the subject area (block Theories 7), which is characterized by quantitative and qualitative factors (Library of descriptions of the Calculator and elements 6), taking into account expert knowledge (block of expert evaluations 11). The process of generating the technical specifications (technical specifications block 2) is multi-stage, with the correction of the technical specifications (correction block of the technical specifications 3) and / or the parameters of the meaningful model 5 (block of parameters for changing the model 10) at each iteration, until the conditions of the technical specifications are reached.

It turns out that the first block for checking the fulfillment of the conditions of TS 9 evaluates the compliance of the content model and directs the process to re-create the content model (output signal "no") or to the second level of design (output signal "Yes").

In the process of forming a library of descriptions of the calculator and elements 6, methodological issues of qualitative representation of experts' knowledge in the course of multi-stage surveys and expert seminars are studied, taking into account their professional identity. For the purpose of a deeper theoretical justification of the content model, the areas of coverage, limitations and assumptions, as well as the principles for the formation and selection of parameters and indicators of the subject area are investigated and determined.

At the initial stage, the content model includes a set of quantitative and qualitative indicators identified by experts. At the next stages, it can be modified by other features, depending on the target factors. For example, BEE11, using information about the state of the synthesized object, provides the necessary information to LDCE6, DHD12, RD14, SAB24 and BRADRMDF26 to make changes to the model.

2.2 Level 2. Adaptive multicriteria neuro-fuzzy model

The second level of design is associated with the formation of an information base of multidimensional features (DHD12) based on the results of a meaningful research model built at the

1st level, the solution of calculated multi-criteria problems of classification (regression), with the derivation of fuzzy diagnostic decision rules (RD14). For this, an adaptive neuro-fuzzy binary classifier was developed based on a modified Wang-Mendel fuzzy production network in Figure 2 with the generation of parameters of membership

function based on self-organizing Kohonen networks [16], [17]:

$$\mu_A^{(1)}(x_i), \dots, \mu_A^{(M)}(x_i), \quad (1)$$

where for each variable $x_i, i=1, \dots, N$.

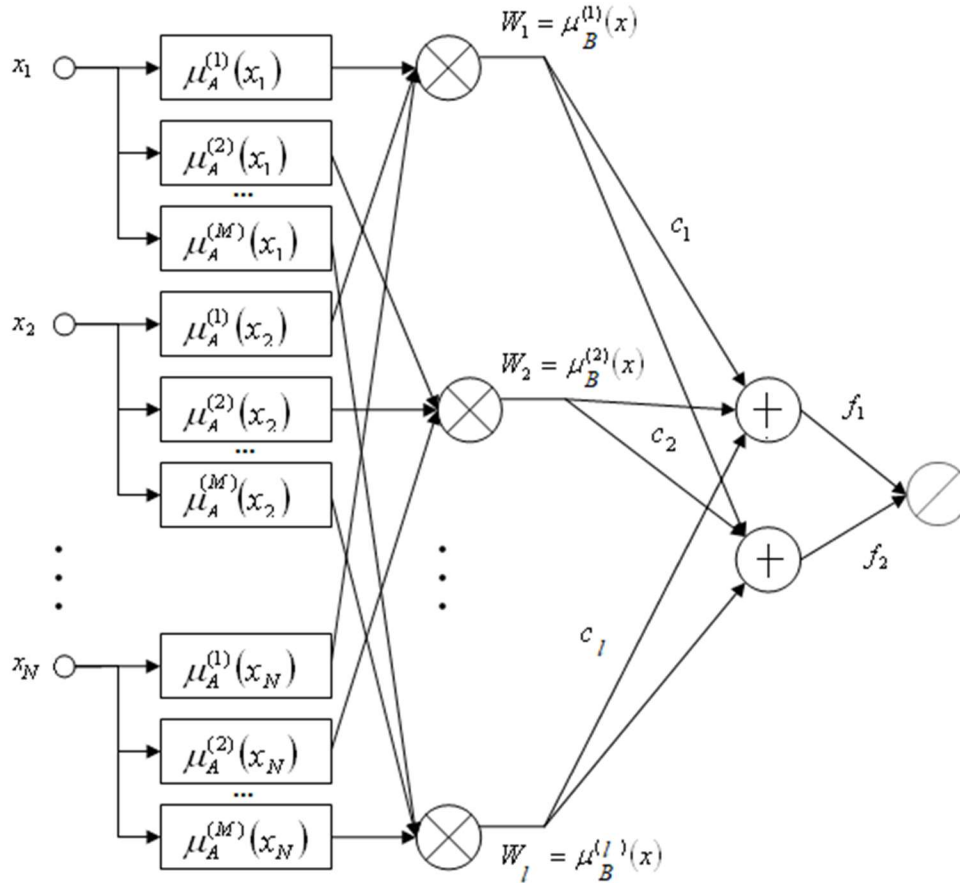


Figure 2. Adaptive neuro-fuzzy binary classifier based on Wang-Mendel fuzzy production network

The structure of the fuzzy inference circuit includes BHNN13, BFI15, BD18 and BD14 (Figure 1).

The hybrid neural fuzzification block 13 transforms a clear set of input data $x = (x_1, \dots, x_N)^T \in X$ into a fuzzy set $A \subseteq X$, defined using specific membership functions (1).

Defuzzification unit 18 converts several fuzzy sets $B_k, k=1, \dots, l$, into specific values of output variables f_1, f_2 corresponding to classes, based on fuzzy inferences generated by the decision output module (with pre-normalization) with weight parameters c_1, \dots, c_l (rule consequents) and in accordance with the chosen defuzzification method

(the symbols X and Y denote the spaces of input and output variables).

The construction of adaptive fuzzy inference systems involves the formalization of initial data, including the experts data, in the form of interval values (fuzzy interval), falling into each interval of which is characterized by a degree of uncertainty. Based on the initial information, experience and intuition, experts can often quite confidently quantitatively characterize the boundaries (intervals) of possible (permissible) parameter values and the areas of their most possible (preferred) values. For example, triangular fuzzy numbers can be used as initial data. These numbers model the following statement: "parameter A is

approximately equal to b and is uniquely in the range $[a, c]$ ".

The triangular membership function is defined by three numbers (a, b, c) , and its value at the point x is calculated by the formula (2):

$$\mu(x) = \begin{cases} 1 - \frac{b-x}{b-a}, & a \leq x \leq b, \\ 1 - \frac{x-b}{c-b}, & b \leq x \leq c, \\ 0, & \text{in other cases} \end{cases} \quad (2)$$

One of the most important stages in data fuzzification (Hybrid Neural Network Fuzzification Block 13) is the initial selection of the type and parameters of the membership function (MF) of the corresponding fuzzy sets, because how accurately the MF reflects the qualitative component of information - descriptive data and the accumulated knowledge of an expert in the subject area, the adequacy of the fuzzy production model largely depends. Membership functions of fuzzy sets can be constructed both by direct and indirect methods.

Direct methods (block of expert evaluation 11) are characterized by the fact that the expert directly sets the rules for determining the values of the membership function. Direct membership function methods are used for measurable concepts such as speed, time, etc., or when polar values are highlighted. In this case, it is possible to directly set the membership function by a table, graph or formula. Varieties of direct methods include group methods, when, for example, a group of experts is presented with a specific object, and each expert must give one of two answers: does this object belong to a given set or not. Then the ratio of the number of affirmative answers to the total number of expert answers, and gives the value of the object's belonging function to this fuzzy set. In the case of polling and agreeing on the opinions of a group of experts, as a rule, a direct method of constructing membership functions that are approximately equal to some fuzzy number, as well as the method of approximate interval estimates, is used. From the analysis of research results and the solution of practical problems presented in the literature, it is known that direct methods are mainly used as auxiliary methods, since they are characterized by a large amount of subjectivity.

Indirect methods for constructing MF values are used in cases where there are no measurable properties of the object through which

fuzzy sets are defined. In this case, the values of the membership function are chosen in such a way as to satisfy the previously formulated conditions. Additional conditions may be imposed both on the type of information received and on the procedure for processing it. These methods include the statistical method, the method of paired comparisons, and the method of expert assessments.

In the proposed architecture of the neuro-fuzzy analyzer, self-organizing Kohonen maps (hybrid neural network fuzzification block) are used as an indirect method for determining the MF centers.

As a MF, either a triangular MF or a Gaussian MF is used.

A set of rules is generated based on possible combinations of fuzzy statements in the prerequisites and conclusions of the rules (Fuzzy Inference Block), according to which the maximum number of rules in the base is determined by the following ratio (3):

$$l = l_1 \cdot l_2 \dots l_n \cdot l_y, \quad (3)$$

where l_1, l_2, \dots, l_n is the number of membership functions for setting variables x_1, x_2, \dots, x_n ; l_y is for the output variable y .

The procedure for bringing to clarity (Defuzzification block 18) for each accumulated output variable is to convert the fuzzy values of the output variables into clear ones. At the same time, methods for obtaining a clear value of the output variable can be divided into 2 groups:

1. Methods for defuzzification of the output variable accumulated at the previous stage (from the activated conclusions of all rules of the base):

1.1. Center of gravity (Figure 3a).

1.2. Center of area (Figure 3b).

1.3. Membership function maximum (Figure 3c).

1.4. The first maximum, also called the leftmost maximum (Figure 3d).

1.5. Right most maximum (Figure 3e).

1.6. Middle-of-maxima (Figure 3f).

1.7. Max-criterion).

1.8. Height defuzzification.

2. Methods of defuzzification of the output variable without preliminary accumulation of the activated conclusions of individual rules:

2.1. Center average defuzzification.

2.2. Center of sums defuzzification).

2.3. Fuzzy mean.

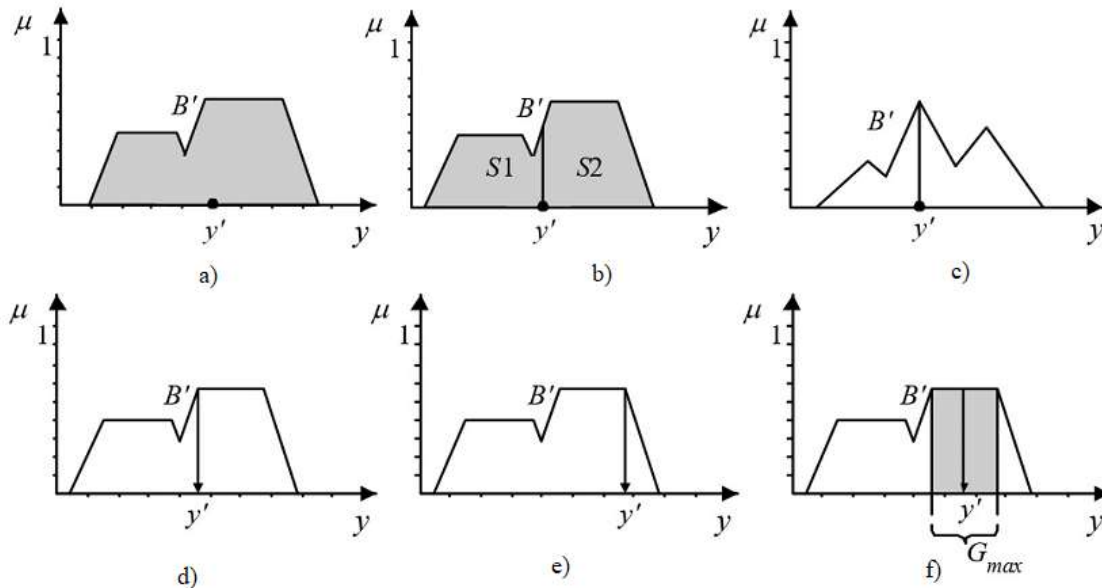


Figure 3. Methods for defuzzifying an accumulated output variable

Parametric model identification (Parametric model identification block 16) includes parametric optimization of the parameters of the centers and width of the MF and the parameters of rule conclusions using a training sample (Training sample block 19) until the root-mean-square error (Target factor shaper 17 or the Error function block) is reached in advance of a predetermined small value. For each example from the training sample, the value of the output variable is determined, the error function is calculated for all examples of the training sample, and the optimization of the parameters minimizes the error function. Both gradient algorithms (backpropagation) and genetic algorithms can be used.

2.3 Backpropagation Algorithm

With N training examples (X(j), dj), j=1,...,N (training sample block), we write the network output signal as a system of expressions:

$$\begin{cases} y_1^* = \bar{w}_{11}r_1 + \dots + \bar{w}_{l1}r_l, \\ \dots \\ y_N^* = \bar{w}_{1N}r_1 + \dots + \bar{w}_{lN}r_l, \end{cases} \quad (4)$$

where w_{ij} is the degree of truth of the prerequisites of the i-th rule in the j-th example of the training sample, it is calculated as the product of membership functions for all variables x_k that are reflected in the i-th rule:

$$w_{ij} = \prod_k \mu_{ki}(x_{kj}) = \prod_k \frac{1}{1 + \left| \frac{x_{kj} - c_{ki}}{\sigma_{ki}} \right|^{2b_{ki}}}, \quad i=1, \dots, l \quad (5)$$

where i – rule number, $i=1, \dots, l$;
l - number of rules,
 $c_{ki}, \sigma_{ki}, b_{ki}$ – membership function parameters.

The resulting system of expressions can be represented in matrix form:

$$\begin{bmatrix} y_1^* \\ y_2^* \\ \dots \\ y_N^* \end{bmatrix} = \begin{bmatrix} \bar{w}_{11} & \bar{w}_{21} & \dots & \bar{w}_{l1} \\ \bar{w}_{12} & \bar{w}_{22} & \dots & \bar{w}_{l2} \\ \dots & \dots & \dots & \dots \\ \bar{w}_{1N} & \bar{w}_{2N} & \dots & \bar{w}_{lN} \end{bmatrix} \begin{bmatrix} c_1 \\ c_2 \\ \dots \\ c_l \end{bmatrix} \quad (6)$$

Abbreviated: $y^* = \bar{W}r$.

The dimension of the matrix is $\bar{W} = N \times l$.

After calculating the actual outputs of the network as a vector y^* , then the error is calculated:

$$\varepsilon = y^* - d \quad (7)$$

The differentiable objective error function f is minimized as the standard deviation E [25]:

$$E = \frac{1}{2} \sum_{j=1}^N (y_j^* - d_j)^2 \rightarrow \min \quad (8)$$

where y_j^* – are network outputs;
 d_j – are the output values of the examples from the training set.

A necessary condition for minimizing the error function is the equality of its derivatives with respect to the parameters c_{ki} , σ_{ki} , b_{ki} k -th input variable ($k \in [1, n]$) in the i -th rule to zero.

According to the error backpropagation algorithm, error signals are sent to the network fuzzification layer (hybrid neural network fuzzification block 13), where the gradient components of the objective function are calculated. After the gradient vector is formed, the parameters are refined based on steepest descent learning:

$$c_{ki}(t+1) = c_{ki}(t) - \eta_c \frac{\partial E(t)}{\partial c_{ki}} \quad (9)$$

$$\sigma_{ki}(t+1) = \sigma_{ki}(t) - \eta_\sigma \frac{\partial E(t)}{\partial \sigma_{ki}} \quad (10)$$

$$b_{ki}(t+1) = b_{ki}(t) - \eta_b \frac{\partial E(t)}{\partial b_{ki}} \quad (11)$$

The process is repeated in a cycle until the error signal reaches a smaller value of a predetermined small value.

In the case of obtaining learning results that do not satisfy the TS, an additional structural identification of the model is performed (Structural identification block of the model 20) with a change in the library of descriptions of the system and elements.

2.4 Level 3. Neutrosophic Cognitive Model

The third level is associated with fuzzy cognitive modeling, which solves a number of problems of a predictive nature (Structure analysis block 25, mutual influence analysis block 23, scenario analysis block 24). Currently, cognitive modeling is developing as one of the areas of cognitive sciences (lat. cognitio - knowledge) - an interdisciplinary scientific direction that combines the theory of knowledge, cognitive psychology, neurophysiology, cognitive linguistics and the

theory of artificial intelligence. The results of such a synthesis, for example, in the form of the described intelligent decision support system, have a pronounced synergistic effect.

The traditional cognitive model is based on the concept of a cognitive map in the form of a signed directed graph (digraph) $G = \langle V, E \rangle$, in which:

V is a set of concepts (vertices), $V_i \in V$, $i=1, 2, \dots, k$, are elements of the system under study;

E is a set of arcs, arcs $e_{ij} \in E$, $i, j=1, 2, \dots, N$ reflect the relationship between concepts.

Such an apparatus allows one to work with data of both qualitative and quantitative types, and the degree of use of quantitative data can increase depending on the possibilities of quantifying the interacting factors in the iterative cycle of modeling. The goal of cognitive modeling is to generate and test hypotheses about the functional structure of the observed situation until a functional structure is obtained that can explain the behavior of the observed situation (Structure Analysis block 25). An adequately built block diagram of cause-and-effect relationships will make it possible to understand and analyze the behavior of the calculator.

To build a complex system of factors interacting with each other based on data on the nature and intensity of these interactions, cognitive research has recently often used fuzzy cognitive maps (FCMs). They were proposed by B. Kosko in 1986 and are used to model the causal relationships identified between the concepts of a certain area. Unlike classical cognitive maps, fuzzy cognitive maps are a fuzzy directed graph whose nodes are fuzzy sets. The directed edges of the graph not only reflect the causal relationships between concepts, but also determine the degree of influence (weight) of the associated concepts in the interval $[0;1]$ (Figure 4).

Thus, two possible types of relationships between factors are admissible in the FCM:

- lack of relationship;
- the presence of relationships with a certain degree of influence.

The work [17] describes the third possible variant of relations between the elements of real systems - uncertainty. It corresponds to those cases when it is not possible to establish mutual influence between concepts, but, at the same time, there are no grounds to deny its existence. Edges indicating such relationships are denoted by dotted lines, interaction intensity values are denoted as I , and such cognitive maps are called neutrosophic cognitive maps (NeutKK).

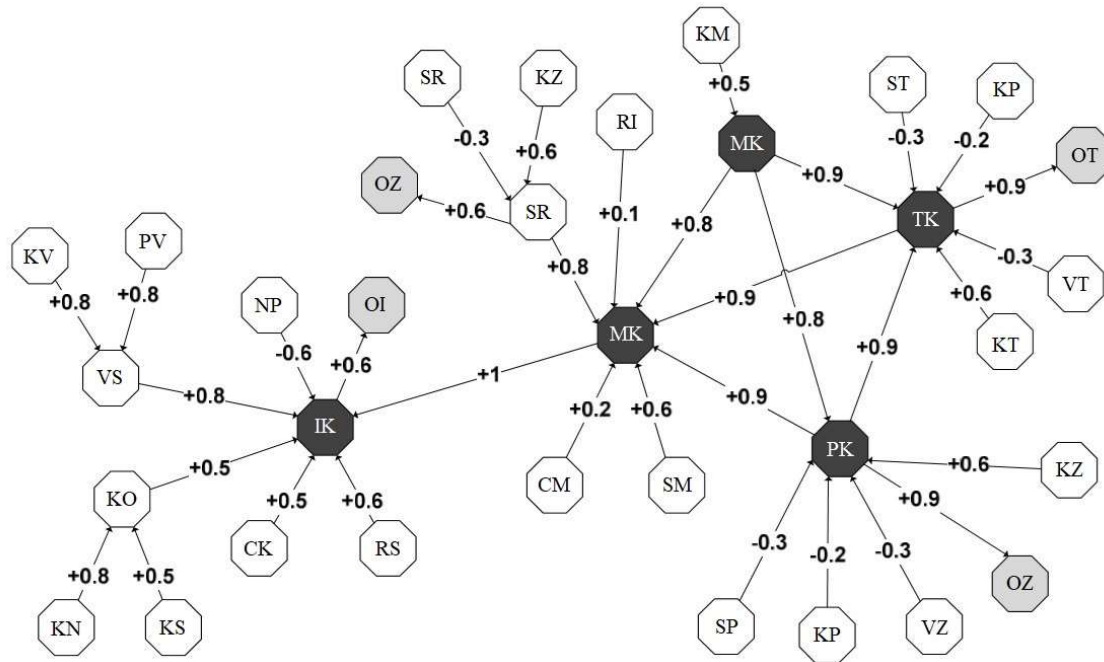


Figure 4. An example of a fuzzy cognitive map

The result, carried out in [20], comparing FCM and NeutKK indicates that NeutKK allows more accurate modeling of complex systems in real conditions, as well as:

- there is no need for preliminary specification of concepts and influence relations;
- there is a possibility of visual representation of the modeled subject area within the system;
- constructiveness, clarity and relative ease of interpretation with their help of cause-and-effect relationships (relationships) between concepts;
- integration with methods for evaluating the results of analysis.

Within the framework of this approach, at the 3rd level of the analyzer, a fuzzy cognitive model of mutual influence and conjugation of technologies was developed based on neutrosophic cognitive maps [19].

To form a NeutKK on the basis of a meaningful research model containing an information base of features, a list of factors (concepts) of the analyzed system is compiled, and the direction of the links between them is established (structural analysis block 25). Part of the relationship between factors can be established by statistical methods [26].

At the same time, the use of NeutKK allows you to effectively supplement the existing map with other concepts and relationships through the use of expert methods. In other words, under conditions of

insufficient statistical data to form a reliable conclusion, it becomes possible to supplement the input data space with expert data, thereby increasing the grounds for generating a potentially more reliable conclusion.

For a more correct description of the methodology of neutrosophic cognitive modeling, we present several basic definitions [27].

Definition 1.

A NeutKK with edge weights taking the values $\{-1, 1, I\}$ is called a complex NeutKK.

Definition 2.

Let C_1, C_2, \dots, C_n be NeutKK nodes, then the Neutrosophic matrix of this map is defined as $N(W)=(w_{ij})$, where w_{ij} are the weights of the directed edges $C_i \rightarrow C_j$, taking the values $w_{ij} \in \{-1, 1, I\}$. In this case, $N(W)$ is called the Neutrosophic adjacency matrix.

Definition 3.

Let $A=(a_1, a_2, a_3, \dots, a_n)$, where $a_i \in \{0, 1, I\}$, then A is called the instantaneous neutrosophic state vector, denoting the on, off or indefinite state of the node at a given moment, i.e.:

- $a_i=0$, if the node is off (no impact on it),
- $a_i=1$, if the node is enabled (it has a single impact),
- $a_i=I$, if the node is not defined (impact is not defined).

Definition 4.

A NeutKK is said to be cyclic if its edges form directed cycles. If the causality goes through

the whole cycle, then NeutKK is called a dynamic system.

Definition 5.

Let the edges C_1, C_2, \dots, C_n form a cycle, then if the node C_i is turned on and the causality, passing through the cycle, returns back to C_i , then we say that the dynamic system goes in a circle. If this is true for any node C_i with $i=1,2,\dots,n$, then this situation is called the equilibrium position of the dynamical system or the hidden pattern NeutKK (hidden pattern).

The state vector, which is the equilibrium position, is called a fixed point.

From the point of view of cognitive modeling, all factors can be divided into 3 types: amenable to influence, not amenable to influence and target. NeutKK analysis allows to determine the degree of impact of one or a group of concepts on other concepts of the system and thereby predict the degree of implementation of the target indicator (scenario analysis block 24). At the same time, the analysis takes into account the mutual influence of concepts on each other, including the multiplicative effect, when an increase in influence on one node of

the graph generates an increase in influence on the next node of the causal chain (mutual influence analysis block 23).

3. RESULT AND DISCUSSION

In the course of the foresight study, the experts were asked on a 10-point scale to assess the degree of interaction w_{ij} technologies in terms of the impact on the process of conjugation and the formation of carrier industries and clusters of the economy of the new TS (assessment of the impact of technology T_i on technology T_j in terms of their conjugation for the formation of carrier industries may differ from the assessment of the impact of technology T_i on technology T_j).

From the list of technologies for the purposes of the experiment, 13 technologies (concepts) T_i of thematic orientation were selected, according to which the cognitive model was built.

In Figure 5 shows the Neutrosophic cognitive map of the mutual influence and conjugation of the selected technologies (concepts) T_i .

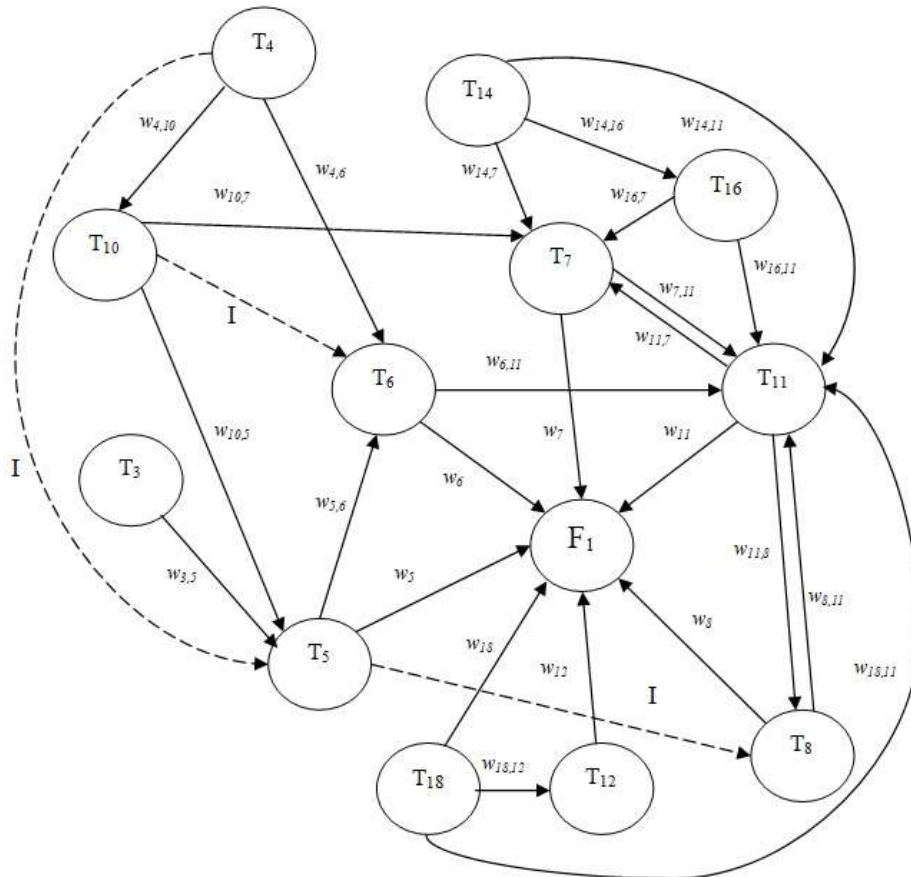


Figure 5. Neutrosophic cognitive map of mutual influence and conjugation of concepts (technologies)

The Neutrosophic adjacency matrix obtained from NeutKK has the form:

$$\begin{matrix}
 0 & 0 & w_{3,5} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
 0 & 0 & I & w_{4,6} & 0 & 0 & w_{4,10} & 0 & 0 & 0 & 0 & 0 & 0 \\
 0 & 0 & 0 & w_{5,6} & 0 & I & 0 & 0 & 0 & 0 & 0 & 0 & w_5 \\
 0 & 0 & 0 & 0 & 0 & 0 & 0 & w_{6,11} & 0 & 0 & 0 & 0 & w_6 \\
 0 & 0 & 0 & 0 & 0 & 0 & 0 & w_{7,11} & 0 & 0 & 0 & 0 & w_7 \\
 0 & 0 & 0 & 0 & 0 & 0 & 0 & w_{8,11} & 0 & 0 & 0 & 0 & w_8 \\
 0 & 0 & w_{10,5} & I & w_{10,7} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
 0 & 0 & 0 & 0 & w_{11,7} & w_{11,8} & 0 & 0 & 0 & 0 & 0 & 0 & w_{11} \\
 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & w_{12} \\
 0 & 0 & 0 & 0 & w_{14,7} & 0 & 0 & w_{14,11} & 0 & 0 & w_{14,16} & 0 & 0 \\
 0 & 0 & 0 & 0 & w_{16,7} & 0 & 0 & w_{16,11} & 0 & 0 & 0 & 0 & 0 \\
 0 & 0 & 0 & 0 & 0 & 0 & 0 & w_{18,11} & w_{18,12} & 0 & 0 & 0 & w_{18} \\
 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0
 \end{matrix}$$

The purpose of the NeutKK analysis is to calculate the degree of impact of one or more concepts (technologies), taking into account their state, on the target indicator.

Let us consider the impact on the system, for example, of the T5 concept, which corresponds to genomic, proteomic, and postgenomic technologies. Based on Definition 5, we will show how the fixed point is found under the influence of the state vector $A1 = (0\ 0\ 1\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0)$ on the system. To do this, we multiply the vector A1 by the Neutrosophic adjacency matrix W, and, based on the result of the multiplication, construct a new state vector. Then we multiply the vector A2 obtained in the course of the previous step by the neutrosophic adjacency matrix W, after adding one to the third component of the vector (in order to take into account the initial single impact), and also write down the state vector for the multiplication result. Iterations are carried out until the state vector at step n is equal to the state vector at step n-1. This means that the fixed point has been reached:

$$\begin{aligned}
 A1W &= (0\ 0\ 0\ w_{5,6}\ 0\ 1\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ w_5) \\
 \rightarrow A2 &= (0\ 0\ 1\ 1\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 1)
 \end{aligned}$$

$$\begin{aligned}
 A2W &= (0\ 0\ 0\ w_{5,6}\ 0\ I\ w_{4,10}\ w_{6,11}\ 0\ 0\ 0\ 0\ (w_5+w_6)) \\
 \rightarrow A3 &= (0\ 0\ 1\ 1\ 0\ 0\ 1\ 1\ 0\ 0\ 0\ 0\ 1)
 \end{aligned}$$

$$\begin{aligned}
 A3W &= (0\ 0\ w_{10,5}\ (w_{5,6} + I)\ (w_{10,7} + w_{11,7})\ (I + w_{11,8})\ 0\ w_{6,11}\ 0\ 0\ 0\ 0\ (w_5 + w_6 + w_{11})) \\
 \rightarrow A4 &= (0\ 0\ 1\ 1\ 1\ 1\ 1\ 0\ 1\ 0\ 0\ 0\ 1)
 \end{aligned}$$

$$\begin{aligned}
 A4W &= (0\ 0\ 0\ w_{5,65}\ w_{11,7}\ (I + w_{11,8})\ 0\ (w_{6,11} + w_{7,11} + w_{8,11})\ 0\ 0\ 0\ 0\ (w_5 + w_6 + w_7 + w_8 + w_{11})) \\
 \rightarrow A5 &= (0\ 0\ 1\ 1\ 1\ 1\ 0\ 1\ 0\ 0\ 0\ 0\ 1) = A4
 \end{aligned}$$

In this case, the fixed point is reached in 4 iterations. The A4W value is a system state vector, each of whose elements characterizes the influence transferred to the corresponding concept as a result of a single impact on T5.

From a practical point of view, the case of simultaneous action of several concepts T5, T7, T8, is very important, i.e. influence on the vector system

$$B1 = (0\ 0\ 1\ 0\ 1\ 1\ 0\ 0\ 0\ 0\ 0\ 0\ 0)$$

$$\begin{aligned}
 B1W &= (0\ 0\ 0\ w_{5,6}\ 0\ I\ 0\ (w_{7,11} + w_{8,11})\ 0\ 0\ 0\ 0\ (w_5 + w_7 + w_8)) \\
 \rightarrow B2 &= (0\ 0\ 1\ 1\ 1\ 1\ 0\ 1\ 0\ 0\ 0\ 0\ 1)
 \end{aligned}$$

$$\begin{aligned}
 B2W &= (0\ 0\ w_{10,5}\ w_{5,6}\ w_{11,7}\ (I + w_{11,8})\ 0\ (w_{6,11} + w_{7,11} + w_{8,11})\ 0\ 0\ 0\ 0\ (w_5 + w_6 + w_7 + w_8)) \\
 \rightarrow B3 &= (0\ 0\ 1\ 1\ 1\ 1\ 1\ 0\ 1\ 0\ 0\ 0\ 1) = B2
 \end{aligned}$$

Thus, when analyzing the results, it is not difficult to see a significant change in the impact on the target, depending on which concepts were affected.

By combining the impact on different groups of concepts, it is possible to form various scenario analyzes of the change in the impact of the impact on the target indicator (scenario analysis block 24).

The use of neutrosophic cognitive modeling in combination with neuro-fuzzy inference models makes it possible to qualitatively conduct a deep analysis of semi-structured problems. On the other

hand, the calculator allows the possibility of introducing additional expert data, which in the general case can help increase the reliability of the conclusions for the manager making the decision.

Based on the results of neuro-fuzzy and neutrosophic cognitive modeling at the 3rd level of design, the final generalization of the results and the development of recommendations for the manager who makes the decision to form text documents, drawings and program listings (block Generalization of results, development of recommendations, management decisions 26) are consistent with the works [22-25].

As a result, an electronic model is formed - a digital twin of the synthesized object, which physically consists of calculator blocks.

Thus, the proposed calculator is superior to the analogue due to the following advantages:

1. High functionality due to the ability to form a digital twin of a wide range of objects (robotic complex, information system for forecasting the development of a territory (state), hardware and software complex for predicting the development of medical diseases, etc.).

2. High accuracy characteristics of the synthesis of a digital model of an object with objective (various theories and computer programs) and subjective (involvement of knowledge of highly qualified experts).

3. High functionality and high accuracy of the synthesis of the digital twin of the object due to the constant monitoring of the functioning of the synthesized object (by using information about the state of the physical object).

4. CONCLUSION AND FUTURE WORKS

The article described a hybrid neuro-fuzzy calculator of the digital twin of an object with improved functionality due to the use of complete information about the designed object. The advantages and disadvantages of the calculator are given.

Three levels of creating "Digital twins" based on the synthesis of a hybrid neuro-fuzzy computer are given: level 1 - the formation of a meaningful object model, level 2 - adaptive multi-criteria neuro-fuzzy model, level 3 - neutrosophical cognitive model. The article discusses in detail the principles of creating "Digital Twins" based on a hybrid neuro-fuzzy computer, as an example of deep neural network algorithms. As a result, an electronic model is formed - a digital twin of the synthesized object, which physically consists of calculator blocks.

Among other things, a hybrid neuro-fuzzy computer, as a type of artificial intelligence, can be used in computer X-ray microtomography for segmentation and classification of material defects. The authors actively apply artificial intelligence methods in the tasks of designing and working with microtomograph images [16,17,18].

Suggestions for development studies next using digital twins could be conducted with Integration of AI and machine learning to enable automated decision making and real-time optimization. Currently, digital twins are mainly focused on modeling and monitoring individual systems or components. However, there is a need to develop multi-domain digital twins that can model and optimize the interaction between different systems such as energy systems, transportation systems and communication networks.

As digital twins become more complex and interconnected, there is a need to develop scalable and interoperable architectures that can support large-scale modeling and data exchange between different digital twins and data protection.

There are currently no generally accepted standards or rules for digital twins, which can lead to inconsistencies and compatibility issues. The development of common standards and regulatory frameworks can help ensure the reliability and consistency of digital twin technologies.

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