

*Розв'язано задачу оцінювання технічного стану гідрогенератора в умовах нечіткої інформації. Для цього розроблено ряд моделей комплексного оцінювання технічного стану гідрогенератора за даними про стани його локальних вузлів. Технічні стани локальних вузлів визначаються за раніше розробленими нечіткими моделями типу Мамдані і представляють собою нечіткі величини, що враховано в моделі оцінювання технічного стану гідрогенератора.*

*Для розроблення моделей було використано нечіткі методи Мамдані, Сугено, Заде та спрощеного нечіткого виводу. Нечітка модель Мамдані має тільки якісну базу правил, що спрощує її побудову експертом. Моделі, побудовані за нечітким алгоритмом Сугено, передбачають базу правил з ваговими коефіцієнтами, які визначаються за методом Сааті. Спрощений метод та метод Заде потребують мінімальної участі експерта при побудові нечіткої моделі. Розглянуто приклади оцінки технічного стану гідрогенератора за п'ятьма розробленими нечіткими моделями та перевірено чутливість моделей до якості та достовірності вхідної інформації.*

*Визначено що найбільш достовірний результат оцінки стану гідрогенератора з похибкою 1,5–2 % дають моделі, побудовані за методом Заде та за спрощеним нечітким виводом, оскільки вони мають найменшу залежність від нечіткості вхідних даних про стани локальних вузлів, які самі отримані за нечіткими моделями. Висока точність цих моделей та низька залежність від якості вхідної інформації пояснюється мінімальною участю експерта під час її налагодження. Нечіткі моделі, побудовані за алгоритмами Мамдані та Сугено, дають більшу похибку 3–4 %. Отримані результати можуть бути використані для оцінювання залишкового або спрацьованого ресурсу гідрогенераторів, імовірності їхньої відмови на інтервалі часу та організації ризик-орієнтованого управління електроенергетичною системою та її підсистемами*

*Ключові слова: гідрогенератор, нечітка логіка, модель Мамдані, модель Сугено, метод Заде, спрощений метод*

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## 1. Introduction

Modern operating conditions of electric power systems (EPS) require a comprehensive approach to the assessment of the technical condition (TC) of equipment in real time without disconnecting them from a power grid. The main requirements to diagnostic parameters are their informativeness and the possibility to measure and monitor them on-line [1].

One of the most important objects in EPS is a hydraulic generator. Assessing its TC is a complex task, since a hydro-generator is a multilevel object consisting of separate nodes and subsystems [2].

# CONSTRUCTION OF MODELS FOR ESTIMATING THE TECHNICAL CONDITION OF A HYDROGENERATOR USING FUZZY DATA ON THE STATE OF ITS LOCAL NODES

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Under these conditions, it is important to build an integrated approach to assessing the operability of hydro-generators and their nodes. Such an approach should take into consideration the real state of a generator, the probabilistic character of its damage, as well as possible consequences of damage [2].

To assess the reliability of hydraulic generator operation, it is necessary to have an adequate model for the comprehensive assessment of its TC, which would take into consideration the following factors:

- structural complexity of the hydrogenerator as an object;
- significant number of dissimilar diagnostic attributes;

- fuzzy data on TC of a hydrogenerator's local nodes, which are determined according to fuzzy models;
- the absence of analytical relations between separate diagnostic attributes of the state of a hydrogenerator and its individual nodes.

The above factors indicate that the task on the integrated estimation of the state of a hydrogenerator contains a significant number of uncertainties in its statement. Solving problems with such uncertainties is in the field of fuzzy models and algorithms that are capable of taking them into consideration.

The relevance of this task is defined by that the lack of reliable quantitative assessment of the technical condition of a hydraulic generator makes it impossible to assess the reliability of EPS operation and to determine the risk of an emergency in it. At the same time, the generating equipment, specifically hydrogenerators, are the most complicated objects within EPS in terms of assessing their condition and a probability of failure over a time interval. When compared with other EPS elements, hydrogenerators remain insufficiently studied in terms of their TC and reliability.

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## 2. Literature review and problem statement

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Papers [2, 3] estimated TC of the local nodes in a hydrogenerator by employing a fuzzy algorithm by Mamdani [4], which produces satisfactory results at a small number of diagnostic attributes and uses a rule base composed of quality rules «IF-THEN», which are convenient for an expert to compile in the absence of analytical relations between diagnostic attributes. The use of a given algorithm in solving the task on the comprehensive evaluation of a generator state is difficult due to a considerable number of its nodes, which causes difficulties for experts when forming a qualitative rule base for decision making.

A series of other approaches to assessing the TC of hydrogenerators and its nodes have been analyzed. Thus, paper [5] proposes using, in order to assess the magnetic properties of the machine, a method to control the synchronous resistances of a generator  $X_d$  and  $X_q$  involving a finite element method. The advantage of this method is the possibility to check and control values of the machine's synchronous resistances under an on-line mode. The disadvantage is that at the same time one controls the state of stator «hardware» and the magnetic gap between the rotor and the stator. A more efficient solution to this problem is the method for diagnosing the eccentricity of a synchronous generator's rotor, suggested in [6]. This method employs the functional dependence of inductance of the stator winding on air gap eccentricity, which is constructed based on the comparison of characteristics for the same-type machines, which have different values of eccentricity. The disadvantage of this method is the need to have a large number of similar generators to build a functional dependence.

The technical condition of the stator winding was estimated in paper [7] based on the results from measurements of its electrical characteristics. An important advantage of this model is the use of a fuzzy model to assess its state. At the same time, the paper failed to pay enough attention to the technique for constructing a base of decision-making rules and for justifying the output value of state assessment. The main drawback of this model is that it does not account for the thermal and vibrational influences on the winding of the stator, which could provide preventive information on its condition.

Authors of [8] diagnosed partial discharges in the stator windings of powerful generators using a permanent monitoring system, which makes it possible to control condition of insulation without removing the generator for repair. The disadvantage of this method is the high price of diagnostic equipment and the monitoring system, as well as the lack of a decision-making system based on data from monitoring.

In [9], authors perform the fuzzy identification of parameters for a synchronous generator when it is included in the network; in this case, its technical condition is disregarded. A given approach should be used not only to determine the actual parameters of the generator, but to assess its TC as well.

Fuzzy approaches to the identification of interturn damage to the generator's rotor windings are proposed in [10–12]; these methods, however, were not adapted to the comprehensive estimation of a hydrogenerator TC.

In [13], the same methods are used to assess the TC of powerful electric motors; however, there are no defined approaches to assessing the state of an electric machine in general, and the model is not adapted for synchronous generators.

It should be noted that the considered models make it possible to run an analysis of the electric part of a hydraulic generator. The condition of mechanical nodes of the hydrogenerator [3] is not evaluated in this case. The issue on the integrated estimation of the state of a hydrogenerator also remains insufficiently considered in this case.

Our analysis of the scientific literature has revealed that the reliable models of the comprehensive estimation of technical state of powerful synchronous machines, specifically hydrogenerators, have remained insufficiently investigated up to now. At the same time, when analyzing the reliability of an electricity energy system, one should consider the hydrogenerator to be a single subsystem, which is impossible if a reliable comprehensive model for assessing its state is missing.

Resolving this task is a complex and multifactorial problem because of the fuzzy information on the TS of local nodes in a hydrogenerator, obtained from fuzzy models, as well as the absence of analytical dependences between these states.

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## 3. The aim and objectives of the study

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The aim of this study is to construct a model for the comprehensive assessment of the technical condition of a hydraulic generator under conditions of fuzzy output data on the TS of local nodes in the hydrogenerator and the absence of analytical relations between these states.

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

- to construct fuzzy models for evaluating the technical condition of a hydrogenerator based on the methods by Mamdani, Sugeno, Zadeh, and the simplified method of fuzzy inference;
- to carry out the assessment of a hydrogenerator's TC based on the constructed models under conditions of fuzzy input information on the state of nodes in a hydrogenerator;
- to perform a comparative analysis of the obtained results and to determine the models that are the least sensitive to the quality of input information.

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## 4. Construction of fuzzy models for evaluating the technical condition of a hydrogenerator

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The hydrogenerator consists of a large number of nodes; each is characterized by a set of dissimilar diagnostic attri-

butes. Given this, it is advisable to represent it as a multi-level object composed of separate nodes and subsystems. According to statistical data [2], the most damage-prone generator nodes are:

- stator core (8 % of the total amount of damage);
- stator winding (18 % of the total amount of damage);
- excitation winding (6 % of the total amount of damage);
- excitation system (11 % of the total amount of damage);
- control system (9 % of the total amount of damage);
- bearings (13 % of the total amount of damage);
- thrust bearing (17 % of the total amount of damage – for vertical hydrogenerators);
- rotor (5 % of the total amount of damage);
- cooling system (10 % of the total amount of damage);
- other (3 % of the total amount of damage).

Since the generator is considered to be a multilevel object in solving the set problem, a fuzzy model that describes its TC has a hierarchical structure as well, shown in Fig. 1.

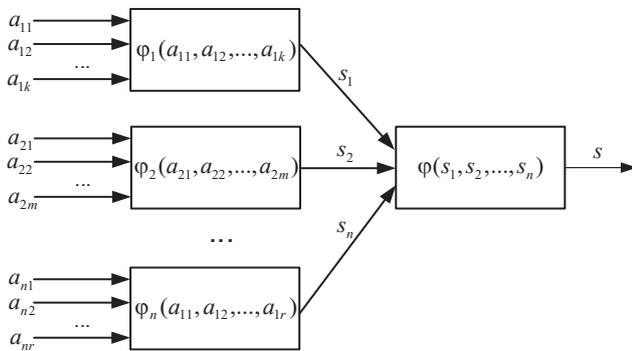


Fig. 1. A hierarchical fuzzy model for estimating the TC of a hydrogenerator:  $a_{ij}$  – the  $j$ -th input attribute of the state of the  $i$ -th node in a hydrogenerator;  $\varphi_i$  – fuzzy function of TC estimation of the  $i$ -th node in a hydrogenerator;  $s_i$  – TC of the  $i$ -th node of a hydrogenerator;  $\varphi$  – fuzzy function of the general TC estimation of a hydrogenerator;  $s$  – general TC of a hydrogenerator

In the synthesis of the model based on the proposed structure, there is a task to determine the fuzzy functions of the state of local nodes in a generator  $\varphi_i$  and the general state  $\varphi$ . Papers [2, 3] applied, when estimating the TC of local nodes of a hydrogenerator, the fuzzy Mamdani algorithm, which produces satisfactory results at a small number of diagnostic attributes and uses the rule base composed of qualitative rules «IF-THEN», which are convenient for an expert to form in the absence of analytical relations between diagnostic attributes.

Determining a fuzzy function  $\varphi$  of the general condition of a hydrogenerator is a more complicated task due to a considerable number of hydrogenerator nodes that are used to assess its general state, and due to the fuzzy estimations of local states derived from fuzzy models. Under these circumstances, it is advisable to consider other fuzzy inference algorithms and assess their effectiveness.

According to [9], the most effective methods of fuzzy inference, if there is a large number of diagnostic attributes and fuzzy input data, are:

- the Sugeno algorithm «AND»;
- the Sugeno algorithm «OR»;
- the scheme of fuzzy inference by Zadeh;
- the simplified fuzzy inference.

Below are the constructed fuzzy models for the comprehensive estimation of a hydrogenerator TC, built in line with the above three methods; their effectiveness was tested under conditions of fuzzy values for the input diagnostic attributes.

*The Mamdani model.* Consider a hierarchical fuzzy model by Mamdani for the comprehensive assessment of a hydrogenerator TC (Fig. 1). The first level of this model consists of 4 models for assessing the state of its local nodes. The input values of the second level in such a model are:

- 1)  $S_1$  = «stator TC»;
- 2)  $S_2$  = «thrust bearing TC»;
- 3)  $S_3$  = «guiding bearing TC»;
- 4)  $S_4$  = «rotor TC».

The linguistic variables corresponding to the input attributes of the generator nodes state are described by the following fuzzy terms:

- $S_1$ :  $\{s_{11}$  = «Satisfactory»,  $s_{12}$  = «Unsatisfactory»};
- $S_2$ :  $\{s_{21}$  = «Satisfactory»,  $s_{22}$  = «Unsatisfactory»};
- $S_3$ :  $\{s_{31}$  = «Satisfactory»,  $s_{32}$  = «Unsatisfactory»};
- $S_4$ :  $\{s_{41}$  = «Satisfactory»,  $s_{42}$  = «Unsatisfactory»}.

The membership functions of fuzzy terms for values  $S_i$ ,  $i = 1, \dots, 4$  are shown in Fig. 2.

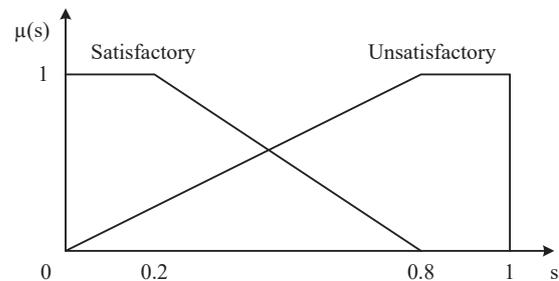


Fig. 2. Membership functions of fuzzy terms for input value

The output value is the general TC (spent resource) of a generator. The output linguistic variable is described by five fuzzy terms.

- $S$ :  $\{s_1$  = «Very good»,  $s_2$  = «Good»,  $s_3$  = «Average»,  $s_4$  = «Poor»,  $s_5$  = «Bad»}.

The membership functions of output linguistic variables are determined along the Harrington interval (Fig. 3).

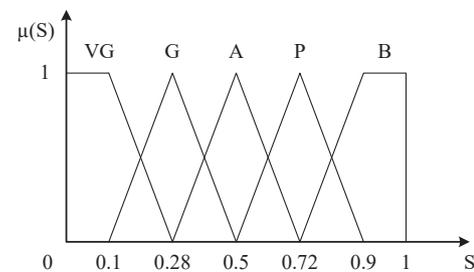


Fig. 3. Membership functions of output value

A base of decision-making rules is built by an expert and takes the form given in Table 1.

Table 1

A rule base for the fuzzy Mamdani model

$S_1$	$S_{11}$			$S_{12}$		
$S_2$	$S_3$	$S_{31}$	$S_{32}$	$S_3$	$S_{31}$	$S_{32}$
$S_{21}$	$S_4$	VG	G	$S_4$	G	A
	$S_{41}$	G	A	$S_{41}$	A	P
$S_{22}$	$S_3$	$S_{31}$	$S_{32}$	$S_3$	$S_{31}$	$S_{32}$
	$S_4$	G	A	$S_4$	P	B
	$S_{41}$	A	P	$S_{41}$	B	B
	$S_{42}$	A	P	$S_{42}$	B	B

Defuzzification is performed based on the centroid method for continuous sets.

$$s = \frac{\int \mu(s) \cdot s \cdot ds}{\int \mu(s) ds} \tag{1}$$

The Sugeno model. The fuzzy inference by Sugeno is organized based on the following algorithm [14, 15]:

– a base of decision-making rules is formed, which consists of the rules in the following form:

$$\text{IF } \langle b_1 \in s_1 \rangle, \langle b_2 \in s_2 \rangle, \dots, \langle b_n \in s_n \rangle \text{ THEN } w = b_1 \cdot w_1 + b_2 \cdot w_2 + \dots + b_n \cdot w_n$$

where  $w_1, w_2, \dots, w_n$  are the weight coefficients;

– the fuzzification of input values is performed using the membership functions of fuzzy terms, constructed according to expert estimations;

– aggregating of subconditions in fuzzy rules is executed according to the logical operation of conjunction: those rules whose conditions' membership functions are different from zero are considered active and are involved in the fuzzy inference;

– the accumulation of a conclusion based on fuzzy rules is performed using real numbers  $w_i$  and  $\mu(s_i)$ ;

– defuzzification is performed in the form of the centroid method for point sets.

Let us consider a hierarchical fuzzy model for the integrated assessment of a hydrogenerator TC, whose first level (Fig. 1) consists of 4 models for assessing the state of its local nodes. The input values of the second level in such a model are:

- $b_1 = \langle \text{stator TC} \rangle$ ;
- $b_2 = \langle \text{thrust bearing TC} \rangle$ ;
- $b_3 = \langle \text{guiding bearing TC} \rangle$ ;
- $b_4 = \langle \text{rotor TC} \rangle$ .

The linguistic variables corresponding to the input values for the generator nodes state are described by the following fuzzy terms:

- $b_1$ :  $\{s_{11} = \langle \text{Satisfactory} \rangle, s_{12} = \langle \text{Unsatisfactory} \rangle\}$ ;
- $b_2$ :  $\{s_{21} = \langle \text{Satisfactory} \rangle, s_{22} = \langle \text{Unsatisfactory} \rangle\}$ ;
- $b_3$ :  $\{s_{31} = \langle \text{Satisfactory} \rangle, s_{32} = \langle \text{Unsatisfactory} \rangle\}$ ;
- $b_4$ :  $\{s_{41} = \langle \text{Satisfactory} \rangle, s_{42} = \langle \text{Unsatisfactory} \rangle\}$ .

The membership functions of the fuzzy terms for values  $b_i, i = 1, \dots, 4$  are similar to the membership functions of the fuzzy model by Mamdani (Fig. 2).

The fuzzy inference is executed according to the rules in the following form:

– rule No. 1:

$$\text{IF } b_1 = s_{11} \text{ AND } b_2 = s_{21} \text{ AND } b_3 = s_{31} \text{ AND } b_4 = s_{41} \text{ THEN } w = b_1 \cdot w_{1-1} + b_2 \cdot w_{2-1} + b_3 \cdot w_{3-1} + b_4 \cdot w_{4-1}$$

– rule No. 2:

$$\text{IF } b_1 = s_{12} \text{ AND } b_2 = s_{21} \text{ AND } b_3 = s_{31} \text{ AND } b_4 = s_{41} \text{ THEN } w = b_1 \cdot w_{1-2} + b_2 \cdot w_{2-1} + b_3 \cdot w_{3-1} + b_4 \cdot w_{4-1}$$

– rule No. 3:

$$\text{IF } b_1 = s_{12} \text{ AND } b_2 = s_{22} \text{ AND } b_3 = s_{31} \text{ AND } b_4 = s_{41} \text{ THEN } w = b_1 \cdot w_{1-2} + b_2 \cdot w_{2-2} + b_3 \cdot w_{3-1} + b_4 \cdot w_{4-1}$$

– ...

– rule No. 16:

$$\text{IF } b_1 = s_{22} \text{ AND } b_2 = s_{22} \text{ AND } b_3 = s_{32} \text{ AND } b_4 = s_{42} \text{ THEN } w = b_1 \cdot w_{1-2} + b_2 \cdot w_{2-2} + b_3 \cdot w_{3-2} + b_4 \cdot w_{4-2}$$

It is obvious from the formed rules that obtaining a reliable quantitative assessment of the general state of a hydrogenerator requires the substantiated determination of vectors for weight coefficients  $w_1$  and  $w_2$ :

$$w_1 = \{w_{1-1}; w_{2-1}; w_{3-1}; w_{4-1}\}; \tag{2}$$

$$w_2 = \{w_{1-2}; w_{2-2}; w_{3-2}; w_{4-2}\}. \tag{3}$$

To determine the vectors for weight coefficients  $w_1$  and  $w_2$ , the Saaty method is applied for determining the largest eigenvalue and processing information based on primary scales with the use of expert assessments [15].

According to the results from expert polling on the importance of TC of local nodes in a hydrogenerator, when determining its general condition, we obtained the ratios given in Tables 2, 3.

Table 2

Expert benefits based on the Saaty scale to determine vector  $w_1$

Parameter	$b_1$	$b_2$	$b_3$	$b_4$
$b_1$	1	1/2	3	4
$b_2$	2	1	3	2
$b_3$	1/3	1/3	1	1/4
$b_4$	1/4	1/2	4	1

Table 3

Expert benefits based on the Saaty scale to determine vector  $w_2$

Parameter	$b_1$	$b_2$	$b_3$	$b_4$
$b_1$	1	3	1/2	1/4
$b_2$	1/3	1	2	3
$b_3$	2	1/2	1	2
$b_4$	4	1/3	1/2	1

Let us determine a vector of weight coefficients  $w_1$ . According to the obtained expert estimates, there is a matrix of paired comparisons:

$$B_1 = \begin{bmatrix} 1 & 0.5 & 3 & 4 \\ 2 & 1 & 3 & 2 \\ 0.333 & 0.333 & 1 & 0.25 \\ 0.167 & 0.143 & 3 & 1 \end{bmatrix} \tag{4}$$

The matrix eigenvalues are derived:

$$B_1 - \lambda E = \begin{bmatrix} 1-\lambda & 0.5 & 3 & 4 \\ 2 & 1-\lambda & 3 & 2 \\ 0.333 & 0.333 & 1-\lambda & 0.25 \\ 0.167 & 0.143 & 3 & 1-\lambda \end{bmatrix} = 0. \quad (5)$$

This equation has four roots:

$$\lambda_{1,2} = 0.1874 \pm j1.1818; \lambda_3 = 3.9984; \lambda_4 = -0.3733. \quad (6)$$

The largest eigenvalue of the matrix is a real positive root  $\lambda_3=3.9984$ ; substituting it in the original equation and replacing the last equation with the normalizing condition  $\sum_{i=1}^6 \omega_{i-1} = 1$  forms a system of equations to determine the weight coefficients of the importance of optimization criteria:

$$\begin{cases} -2.9984\omega_{1-1} + 0.5\omega_{2-1} + 3\omega_{3-1} + 4\omega_{4-1} = 0; \\ 2\omega_{1-1} - 2.9984\omega_{2-1} + 3\omega_{3-1} + 2\omega_{4-1} = 0; \\ 0.333\omega_{1-1} + 0.333\omega_{2-1} - 2.9984\omega_{3-1} + 0.25\omega_{4-1} = 0; \\ \omega_{1-1} + \omega_{2-1} + \omega_{3-1} + \omega_{4-1} = 1. \end{cases} \quad (7)$$

A solution to the system of equations is the vector of weight coefficients  $\omega_1$ :

$$\omega_1 = \{0.348; 0.419; 0.096; 0.137\}. \quad (8)$$

Let us determine a vector of weight coefficients  $\omega_2$ . According to the obtained expert estimates, there is a matrix of paired comparisons:

$$B_2 = \begin{bmatrix} 1 & 3 & 0.5 & 0.25 \\ 0.333 & 1 & 2 & 3 \\ 2 & 0.5 & 1 & 2 \\ 4 & 0.333 & 0.5 & 1 \end{bmatrix}. \quad (9)$$

The matrix eigenvalues are derived:

$$B_2 - \lambda E = \begin{bmatrix} 1-\lambda & 3 & 0.5 & 0.25 \\ 0.333 & 1-\lambda & 2 & 3 \\ 2 & 0.5 & 1-\lambda & 2 \\ 4 & 0.333 & 0.5 & 1-\lambda \end{bmatrix} = 0. \quad (10)$$

The equation has four roots:

$$\lambda_{1,2} = -0.6903 \pm j2.8125; \lambda_3 = 5.5528; \lambda_4 = -0.1722. \quad (11)$$

The largest eigenvalue of the matrix is a real positive root  $\lambda_3=5.5528$ ; substituting it in the original equation and replacing the last equation with the normalizing condition  $\sum_{i=1}^6 \omega_{i-2} = 1$  forms a system of equations to determine the weight coefficients of the importance of optimization criteria:

$$\begin{cases} -4.5528\omega_{1-2} + 3\omega_{2-2} + 0.5\omega_{3-2} + 0.25\omega_{4-2} = 0; \\ 0.333\omega_{1-2} - 4.5528\omega_{2-2} + 2\omega_{3-2} + 3\omega_{4-2} = 0; \\ 2\omega_{1-2} + 0.5\omega_{2-2} - 4.5528\omega_{3-2} + 2\omega_{4-2} = 0; \\ \omega_{1-2} + \omega_{2-2} + \omega_{3-2} + \omega_{4-2} = 1. \end{cases} \quad (12)$$

A solution to the system of equations is the vector of weight coefficients  $\omega_2$ :

$$\omega_2 = \{0.228; 0.285; 0.24; 0.247\}. \quad (13)$$

Determining the general TC of a hydrogenerator (Defuzzification) is performed by the centroid method as a superposition of linear laws. To this end, the weighted average is derived:

$$s = \frac{\sum_{i=1}^n \mu(s_i) \cdot \omega_i}{\sum_{i=1}^n \mu(s_i)}. \quad (14)$$

*The Zadeh method.* Let there be a set of  $Y$  states of the local nodes in a hydrogenerator. Since the hydrogenerator is a complex system, the number of sub-systems  $N$ , of which it consists, in a general case, can be quite large:

- $y_1$  – stator technical condition;
- $y_2$  – thrust bearing technical condition;
- $y_3$  – bearing technical condition;
- $y_4$  – rotor technical condition;
- $y_5$  – excitation system technical condition;
- $y_6$  – control system technical condition;
- $y_7$  – cooling system technical condition;
- ...
- $y_N$  – technical condition of the  $N$ -th node.

Suppose there is a matrix vector of fuzzy ratios (the reference matrix of states)  $R$ , built by experts, which determines the influence of the state of the  $i$ -th node on the overall TC of a generator:

$$R = [r_1 \ r_2 \ \dots \ r_n]^T. \quad (15)$$

Each element from the matrix  $r_i$  is determined as follows:

$$r_i = \frac{m_i}{M}, \quad (16)$$

where  $m_i$  is the number of experts who recognized the influence of the state of the  $i$ -th node on the general state to be «substantial»,  $M$  is the total number of experts.

The set of states of local nodes also takes the form of a matrix vector:

$$Y = [y_1 \ y_2 \ \dots \ y_n]. \quad (17)$$

The hydrogenerator TC  $S$  is determined by means of composite multiplication of two matrix vectors:

$$S = Y \circ R, \quad (18)$$

where  $\circ$  is the maxmin composition.

-  $M=10$  experts assessed the material impact of the state of each local node on the overall utilized resource:

- $m_1=9$  experts recognized significant influence of the stator state on the general condition of a hydrogenerator;
- $m_2=8$  experts recognized significant influence of the saddle state on the general condition of a hydrogenerator;
- $m_3=7$  experts recognized significant influence of the bearing state on the general condition of a hydrogenerator;
- $m_4=9$  experts recognized significant influence of the rotor state on the general condition of a hydrogenerator.

Based on the assessments obtained, the fuzzy ratios matrix elements were determined:

$$r_1 = \frac{m_1}{M} = \frac{9}{10} = 0.9, \tag{19}$$

$$r_2 = \frac{m_2}{M} = \frac{8}{10} = 0.8, \tag{20}$$

$$r_3 = \frac{m_3}{M} = \frac{7}{10} = 0.7, \tag{21}$$

$$r_4 = \frac{m_4}{M} = \frac{9}{10} = 0.9. \tag{22}$$

Matrix column  $R$  takes the form:

$$R = [0.9 \ 0.8 \ 0.7 \ 0.9]^T. \tag{23}$$

*The simplified method of fuzzy inference.* The algorithm for the simplified method of fuzzy inference is given in [16]. Let a hydrogenerator enter one of five states:

- $S_1$  – very good;
- $S_2$  – good;
- $S_3$  – average;
- $S_4$  – poor;
- $S_5$  – bad.

The condition of a hydrogenerator is estimated based on the TC of its main nodes. The main nodes of the hydrogenerator are: stator, rotor, saddle, and bearings. These four local states form the input attributes of the hydrogenerator state:

- $\beta_1$  = «stator TC»;
- $\beta_2$  = «thrust bearing TC»;
- $\beta_3$  = «guiding bearing TC»;
- $\beta_4$  = «rotor TC».

Each input attribute is described by two fuzzy terms ( $i=1, \dots, 4$ ):

- $\beta_{i1}$  = «Satisfactory»;
- $\beta_{i2}$  = «Unsatisfactory»;

which are determined by the membership functions  $\mu(\beta)$ , shown above in Fig. 2.

Based on the set of the hydrogenerator state attributes  $\beta$ , we formulated the rules of fuzzy inference, which define the matrices of reference states of a hydrogenerator. The number of reference matrices equals the number of the adopted states of the hydrogenerator.

Reference matrices of states are given in Table 4.

The result of estimating the state of local nodes of a hydrogenerator (stator, rotor, saddle, bearing) is the determined vector of object's states  $\beta_K = \{\beta_{1K}, \beta_{2K}, \beta_{3K}, \beta_{4K}\}$ . Based on the membership functions of the fuzzy terms, values for the membership of each attribute to its fuzzy terms are determined and a matrix of the actual state of a hydrogenerator  $S_K$  is constructed (Table 5).

To determine which reference state the actual state belongs to, the following algorithm of fuzzy inference is implemented:

1) one performs the operation of logical association based on a minimization rule for matrix  $S_K$  and for each reference matrix  $S_1 \dots S_5$ ;

2) one determines a comparison index  $I_i, i=1, \dots, 5$ , which determines the proximity of matrix  $S_K$  to each of the reference matrices  $S_1 \dots S_5$ :

$$I_i = \frac{\sum_{j=1}^4 \mu_{S_K \cap S_j}(\beta_{iK})}{\sum_{j=1}^4 \mu_{S_j}(\beta_{ij})}; \tag{24}$$

3) comparison index with the maximum value determines which reference state the actual state of the hydrogenerator belongs to:

$$S_K \in S_E = \{S_i | \max I_{ij}\}. \tag{25}$$

Table 4

Reference matrices of hydrogenerator states

$S_1$ – very good				
$\mu(\beta_i)$ \ $\beta_i$	$\beta_1$	$\beta_2$	$\beta_3$	$\beta_4$
$\mu_1(\beta_i)$ = «Satisfactory»	1	1	1	1
$\mu_2(\beta_i)$ = «Unsatisfactory»	0	0	0	0
$S_2$ – good				
$\mu(\beta_i)$ \ $\beta_i$	$\beta_1$	$\beta_2$	$\beta_3$	$\beta_4$
$\mu_1(\beta_i)$ = «Satisfactory»	1	1	1	0
$\mu_2(\beta_i)$ = «Unsatisfactory»	0	0	0	1
$S_3$ – average				
$\mu(\beta_i)$ \ $\beta_i$	$\beta_1$	$\beta_2$	$\beta_3$	$\beta_4$
$\mu_1(\beta_i)$ = «Satisfactory»	0	1	1	0
$\mu_2(\beta_i)$ = «Unsatisfactory»	1	0	0	1
$S_4$ – poor				
$\mu(\beta_i)$ \ $\beta_i$	$\beta_1$	$\beta_2$	$\beta_3$	$\beta_4$
$\mu_1(\beta_i)$ = «Satisfactory»	0	1	0	0
$\mu_2(\beta_i)$ = «Unsatisfactory»	1	0	1	1
$S_5$ – bad				
$\mu(\beta_i)$ \ $\beta_i$	$\beta_1$	$\beta_2$	$\beta_3$	$\beta_4$
$\mu_1(\beta_i)$ = «Satisfactory»	0	0	0	0
$\mu_2(\beta_i)$ = «Unsatisfactory»	1	1	1	1

Table 5

Hydrogenerator actual state matrix

$\mu(\beta_i)$ \ $\beta_i$	$\beta_1$	$\beta_2$	$\beta_3$	$\beta_4$
$\mu_1(\beta_i)$ = «Satisfactory»	$\mu_1(\beta_{1K})$	$\mu_1(\beta_{2K})$	$\mu_1(\beta_{3K})$	$\mu_1(\beta_{4K})$
$\mu_2(\beta_i)$ = «Unsatisfactory»	$\mu_2(\beta_{1K})$	$\mu_2(\beta_{2K})$	$\mu_2(\beta_{3K})$	$\mu_2(\beta_{4K})$

To determine a quantitative value for output variable  $S_{out}$ , we assume that the ratio of comparison index  $I_{out}$  to the sum of maximal comparison indexes of output terms defines a degree of trust to the conclusion drawn. For the case of a large number of comparison indexes, a degree of distrust to be taken is the arithmetic mean from all distrust indexes.

Under a such approach, the quantitative value for output variable  $S_n$  is determined from the following expression:

$$S_{out} = S_{out-l} + \Delta S_{out} \frac{I_{out}}{I_{out} + \frac{\sum_{i=1}^n I_i}{n}}, \tag{26}$$

where  $S_{out-l}$  is the lower limit of the output term interval, which was defined as a solution;  $\Delta S_{out} = S_{out-h} - S_{out-l}$  is the width of the output term interval, defined as the solution.

### 5. Estimating the TC of a hydrogenerator based on the designed fuzzy models

It is necessary to assess technical condition of the vertical hydrogenerator at Dnipro HPP-2, type SV-1230/140-56, based on the results from the assessment of state of 4 local nodes:

- $B_1=0.68$  – stator TC (utilized resource);
- $B_2=0.45$  – thrust bearing TC (utilized resource);
- $B_3=0.82$  – guiding bearing TC (utilized resource);
- $B_4=0.38$  – rotor TC (utilized resource).

Based on the membership functions of fuzzy terms (Fig. 2), we determine:

- $b_1: \{ \mu(s_{11})=0,21, \mu(s_{12})=0,79 \}$ ;
- $b_2: \{ \mu(s_{21})=0,58, \mu(s_{22})=0,42 \}$ ;
- $b_3: \{ \mu(s_{31})=0, \mu(s_{32})=1 \}$ ;
- $b_4: \{ \mu(s_{41})=0,71, \mu(s_{42})=0,29 \}$ .

According to the above methods, we estimated the overall hydrogenerator TC. The results are given in Table 6.

**Table 6**  
Results from estimating a hydrogenerator TC based on five methods

Mam-dani	Sugeno «OR»	Sugeno «AND»	Zadeh	Simplified
0.611	0.632	0.655	0.7	0.746

The results obtained have a significant difference from each other. To determine the most accurate and effective method of evaluating a hydrogenerator TC, we shall employ a random number generator to find out which method is the least sensitive to the quality of input information on the state of local nodes in a hydrogenerator.

### 6. Comparative analysis of sensitivity of the constructed fuzzy models to the quality of input information

To assess the sensitivity of each of the five models to the quality of input information, which in turn was obtained from the fuzzy models for assessing the state of local nodes, each input value is randomly changed in a range of  $\pm 10\%$ . Employing a random number generator, 20 pairs of values for input values were obtained. For each set of values  $B_1...B_4$ , we determined the hydrogenerator general condition  $S$  based on each synthesized model. The modeling results are given in Table 7.

Based on the results obtained, one can define the following:

- 1) The mathematical expectation of the value for a hydrogenerator TC over 20 implementations of the fuzzy-statistical algorithm corresponds to those solutions that were

obtained at the discrete values for input values for all five fuzzy models (Tables 6, 7);

- 2) the standard deviation of value for the technical condition of a hydrogenerator over 20 implementations of the fuzzy-statistical algorithm is within 3–4 % for the Mamdani and Sugeno models and within 1.5–2 % for the models built according to the simplified method and the Zadeh method. This makes it possible to conclude that the fuzzy models for estimating the integrated TC of a hydrogenerator, built in line with the simplified method and the Zadeh method, due to their inherent fuzzy inference algorithms, have the smallest dependence on the interval variability of input values for the local states of a hydrogenerator’s nodes.

**Table 7**  
Fuzzy-statistical evaluation of hydrogenerator state

No.	$B_1$	$B_2$	$B_3$	$B_4$	$S_{Mamd}$	$S_{SugOR}$	$S_{SugAND}$	$S_{Zadeh}$	$S_{Simple}$	
1	0.638	0.457	0.741	0.342	0.588	0.599	0.626	0.7	0.721	
2	0.63	0.42	0.776	0.394	0.633	0.611	0.630	0.7	0.73	
3	0.715	0.465	0.875	0.406	0.65	0.677	0.711	0.715	0.753	
4	0.703	0.498	0.745	0.414	0.628	0.649	0.682	0.703	0.745	
5	0.619	0.444	0.745	0.405	0.557	0.609	0.627	0.7	0.725	
6	0.709	0.48	0.803	0.342	0.594	0.642	0.675	0.709	0.755	
7	0.623	0.493	0.785	0.4	0.622	0.633	0.653	0.7	0.732	
8	0.669	0.467	0.891	0.378	0.643	0.661	0.688	0.7	0.739	
9	0.622	0.44	0.767	0.408	0.567	0.615	0.634	0.7	0.733	
10	0.651	0.432	0.772	0.402	0.601	0.621	0.643	0.7	0.736	
11	0.637	0.442	0.791	0.366	0.585	0.615	0.636	0.7	0.744	
12	0.668	0.454	0.802	0.4	0.632	0.639	0.665	0.7	0.741	
13	0.637	0.446	0.838	0.365	0.619	0.629	0.650	0.7	0.729	
14	0.734	0.439	0.841	0.371	0.587	0.656	0.692	0.734	0.75	
15	0.743	0.481	0.784	0.378	0.635	0.656	0.695	0.743	0.759	
16	0.716	0.472	0.773	0.39	0.64	0.647	0.681	0.716	0.748	
17	0.642	0.409	0.869	0.409	0.612	0.640	0.661	0.7	0.741	
18	0.62	0.483	0.897	0.414	0.597	0.664	0.684	0.7	0.731	
19	0.727	0.404	0.821	0.373	0.645	0.639	0.673	0.727	0.758	
20	0.711	0.472	0.82	0.364	0.596	0.651	0.684	0.711	0.747	
Mathematical expectation					$M(S)$	0.612	0.638	0.665	0.708	0.741
Standard deviation					$\sigma(S)$	0.027	0.021	0.026	0.015	0.011
					%	4.4	3.3	3.9	2.1	1.5

### 7. Discussing the results from studying a hydrogenerator TC

The constructed fuzzy models for estimating a hydrogenerator’s technical condition according to the Mamdani, Sugeno, Zadeh methods, as well as the simplified method of fuzzy inference, provide a possibility to quantify the estimation of a hydrogenerator state under conditions of fuzzy input information about the state of nodes in the hydrogenerator. In contrast to previous suggestions, these models use the input information, which was also derived from fuzzy models and algorithms under an «on-line» mode. Application of the proposed models makes it possible to obtain a quantitative assessment of the state of a hydrogenerator with the accuracy defined by the employed method of model construction. The highest accuracy in the assessment of a hydrogenerator’s state (1.5 %) is demonstrated by the simplified method of fuzzy inference. This is because the construction of reference matrices requires a minimum amount of subjective expert

information. The result's high accuracy (2.1 %) is also produced by the model built in line with the Zadeh method, which is explained by the use of expert assessments from several experts, which reduces subjectivity in the configuration of the model. Other models yield a state assessment error greater than 3 % and are more sensitive to the quality of input information due to the considerable subjectivity of expert assessments in building decision-making rule bases.

The advantages of the models constructed in the current research include a possibility to use fuzzy data on the state of the local nodes of a hydrogenerator and to obtain at the same time a quantitative assessment of the condition of a hydrogenerator as an object with an accuracy of 1.5–2 %. The disadvantage of the approach is the complexity of forming the bases of decision-making rules and the reference matrices given a large number of input attributes (local nodes in a hydrogenerator).

Further advancement of our study implies the adaptation of the constructed models to include turbogenerators and other large alternating current machines that exist within EPS.

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## 8. Conclusions

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1. The fuzzy models for estimating a hydrogenerator's TC, constructed in this work, make it possible to deter-

mine, with an accuracy of 1.5–2 %, the overall condition of a hydrogenerator. In this case, only the «on-line»-available parameters of the state of an assembly are employed, as well as expert estimations to determine the relations between individual diagnostic attributes and conditions of the generator's local nodes.

2. Assessment of the overall TC of a hydrogenerator is performed under conditions of fuzzy output data, which are obtained from fuzzy models for evaluating the states of local nodes in a hydrogenerator. Our analysis of sensitivity of the developed models to the quality of input information has revealed that the slightest influence is exerted by the interval variability of input values for local states of a hydrogenerator's nodes in the models built in line with the Zadeh methods and the simplified method of fuzzy inference, which have simple algorithms and minimal dependence on the subjectivity of expert knowledge in their construction.

3. The comprehensive estimates of the overall state of hydrogenerators, obtained from the constructed fuzzy models, make it possible to consequently determine the probability of failure of a hydrogenerator over a time interval taking into consideration the individual characteristics of its state. The derived values of probabilities should be used in problems on estimating the reliability of hydrogenerators, planning their repairs, and implementing risk-oriented control over EPS.

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