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Multicriteria fuzzy statistical analysis of biogas energy systems dependability

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Abstract. The work is devoted to the problems of assessing the dependability of autonomous energy systems with biogas type of electrical generation. The purpose of the work is to develop an intelligent tool for multi-criteria dependability assessment, taking into account the statistical uncertainty of individual indicators. A three-level hierarchy (according to the degree of generalization) of dependability indicators, represented by statistical (at the lower level) and fuzzy linguistic (starting from the second level) variables, has been developed. It is proposed to implement the transition from statistical values of lower-level indicators to numerical values of second-level indicators using an artificial neural network. Fuzzification of second-level indicators was carried out using L. Zadeh's z-number apparatus, which allows taking into account statistical uncertainty. To determine the integral dependability indicator (top of the hierarchy) based on second-level indicators, it is proposed to use the Mamdani fuzzy inference algorithm. The constructed procedure for determining the level of dependability allows us to obtain data for making scientifically based decisions when operating biogas energy systems.

1 Introduction

The use of autonomous energy systems is relevant for sparsely populated rural areas and significantly contributes to their socio-economic development [1-2]. Biogas energy, using agricultural waste as raw materials, occupies a special place within nuclear power plants, since (due to the integrated nature of biogas technologies) it allows solving several important problems at once [3]:

- Generation of electrical energy for domestic and industrial needs.
- Heat supply for residential and industrial premises, as well as providing thermal energy for technological processes for processing agricultural products.
- Production of environmentally friendly organic fertilizers.
- Recycling of waste from livestock (poultry), crop production and processing of agricultural products.

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However, it is the complexity of the tasks being solved that makes the problem of ensuring the dependable operation of biogas energy systems (BGES) particularly relevant: a disruption of the normal operation of the system associated with solving at least one of the listed tasks can negatively affect the agricultural enterprise operating the BGES.

When assessing the dependability of BGES, it is necessary to keep in mind that this property, understood as the ability to maintain the ability to perform the required functions in given modes and conditions of use, is determined by several indicators and is largely of a qualitative nature, which makes it advisable to use expert technologies.

The purpose of this work is to build a toolkit for assessing the dependability of biogas energy systems based on multi-criteria fuzzy statistical analysis.

2 Materials and methods

2.1 Hierarchy of dependability of BGES

Analyzing the dependability of BGES (in accordance with [4]) , taking into account the complexity of this indicator, we can consider:

- Functional dependability analysis, consisting of the study of a set of dependability indicators in relation to solving problems of the BGES (production of thermal and electrical energy, production of fertilizers, waste disposal).
- Structural dependability analysis, consisting of determining the reliability indicators of individual devices as part of the BGES (device for receiving and initial preparation of raw materials, system for transporting a heterogeneous multicomponent mass inside the installation, bioreactor, substrate mixing device, raw material loader, gas holder, pumping station for pumping manure and removing substrate and etc.).
- Semantic analysis of dependability, consisting of the study of individual properties included in the concept of reliability.

Due to sufficient knowledge of the issues of functional and structural dependability of BGES ([5-7]), we will limit ourselves to the study of semantic analysis of dependability including the main (from the point of view of the specificity of BGES) properties measured by sub-indicators Ind_i ($i=1,2,\dots,5$) :

- Ind_1 – reliability (maintaining the ability of BGES to perform the required functions for some time or operating time in specified modes and conditions of use).
- Ind_2 –recoverability (ability of BGES to recover from failure without repair).
- Ind_3 –maintainability (adaptability to maintain and restore the state in which the BGES is capable of performing required functions through maintenance and repair).
- Ind_4 –durability (ability of BGES to perform the required functions under specified modes and conditions of use, maintenance and repair until the limiting state is reached).
- Ind_5 – availability (ability of the BGES to be in a state in which it can perform the required functions under specified modes and conditions of use, maintenance and repair, assuming that all necessary external resources are provided).

Each of sub-indicators corresponds to primary statistical numerical indicators that allow direct measurement. For example, the reliability indicator Ind_1 corresponds to the primary indicators:

- Ind_{11} – reliability function (probability of failure-free operation).
- Ind_{12} – mean (expected value) operating time to failure.
- Ind_{13} – failure rate (conditional probability density of the occurrence of an object failure, determined under the condition that the failure did not occur before the considered point in time), etc.

In general, the system of reliability indicators of BGES (the determination of which is the purpose of the analysis) can be presented in the form of a hierarchy (Figure 1).

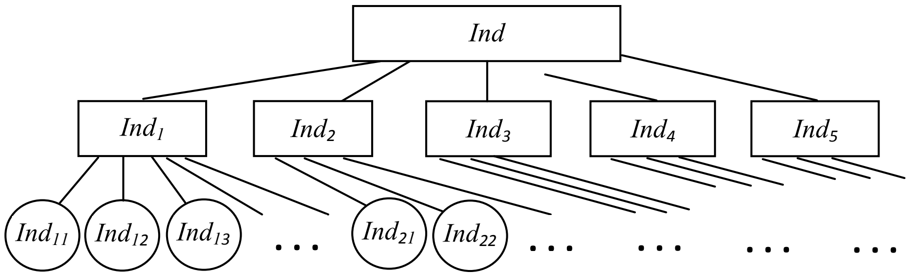

Fig. 1. Hierarchy of dependability indicators of a biogas energy system.

In relation to the studied BGES, the primary indicators Ind_{is}, that make up the lower level of the hierarchy, can be determined as a result of statistical tests. Indicators of the second level of the hierarchy Ind_i ($i=1,2,...,5$) are, generally speaking, qualitative in nature, but can be expressed quantitatively in points or (as is assumed in the work) in numbers belonging to the interval $[0, 1]$. Numeric values of the second level sub-indicators can be determined using a neural network trained on the basis of a dataset compiled by experts.

We will also assume that the probabilistic nature of these indicators (inherent both in the occurrence of various types of faults and in the neural network method of calculation [8]) can be reflected by setting the probabilities P_i that the indicators Ind_i actually take the considered values. The parts of P_i associated with the calculation method are determined by analyzing statistics comparing the control sample and the results obtained using a trained neural network:

$$P^*_i = N^+_i / N_i \qquad (i=1,2,...,5) \tag{1}$$

Where N_i is the total number of comparisons, and N^+_i is the number of comparisons where the calculated Ind_i values coincide (with a given accuracy) with the control values.

2.2 Fuzzy description of BGES dependability

It must be borne in mind that Ind_i indicators are qualitative in nature and their numerical values cannot fully reflect the significance in relation to a particular situation. For example, the same numerical value of the reliability indicator may be high for one BGES and at the same time be average (or even low) for another BGES operating under different conditions.

One of the ways to solve this problem is to use expert assessment methods and the apparatus of the theory of fuzzy linguistic variables by L. Zadeh [9-11]. Let's build for indicators Ind, Ind_i and probabilities P_i linguistic variables $LingInd$, $LingInd_i$ и $LingP_i$, defined by a common universal set $U= [0, 1]$, sets of linguistic terms $T_{Ind}= \{ t_1=$ "*low*", $t_2=$"*medium*", $t_3=$ "*high*"$\}$ и $T_P = \{ t_4=$ "*unlikely*", $t_5=$"*likely*", $t_6 =$ "*highly likely*"$\}$, the semantics of which is determined by the membership functions $\mu_{ij}(\cdot)$, $\eta_{ijk}(\cdot)$ with Gaussian type (common to Ind, Indi and Pi, but with different parameters)

$$\mu_j(x)= exp(-a_j(x-b_j)^2), \quad \mu_{ij}(x)= exp(-c_{ij}(x-d_{ij})^2), \quad \eta_{ijk}(x)= exp(-g_{ijk}(x-h_{ijk})^2),$$
$$i=1,2,...,5, \quad j=1,2,3, \quad k=4,5,6 \tag{2}$$

The general view of the membership functions $\eta_{ij}(\cdot)$ is presented in Figure 2.

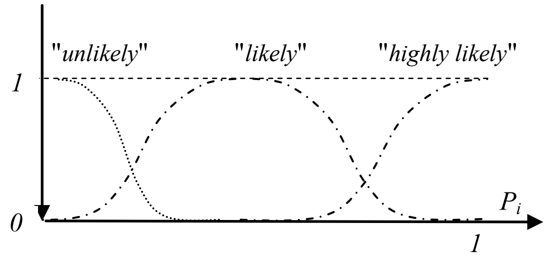

Fig. 2. Graphical representation of membership functions of *terms* "*unlikely*", "*likely*", "*highly likely*".

Z-numbers corresponding to sub-indicators of the second level of the hierarchy have the representation:

$$<((\,LingInd_i - t_j),\, \mu_{ij}),\, ((LingP_i - t_k\,),\, \eta_{ijk}\,)> \tag{3}$$

For example, $<((\,LingInd_1 - t_2),\, m_{12}),\, ((LingP_1 - t_5\,),\, h_{125}\,)>$ characterizes the case when the level of reliability has the value "*medium*" with a degree of compliance m_{12} and the probability of this (a measure of confidence) has the value "*highly likely*" with a degree of compliance h_{125}.

In accordance with [12-13], the confidence measure l is taken into account by moving to normalized weighted Z-numbers that have a membership function:

$$m^{l*}(x)= m\,(x/(l)^{0.5}) \tag{4}$$

This makes it possible to make a recalculation that takes into account the statistical uncertainty of sub-indicators by moving to linguistic variables $LingInd_i^*$.

In general, a system of fuzzy production rules connecting a linguistic variable *LingInd* with linguistic variables $LingInd_i^*$ can be represented in the form of relationships

$$\textbf{if } F^s(LingInd_i^* - t_j\,;\, j=1,2,3;\, i=1,2,\ldots,\, I) \textbf{ then } LingInd - t_s;\ s=1,2,3 \tag{5}$$

Where F^s are fuzzy propositional formulas regarding fuzzy statements $LingInd_i^* - t_j\,;$ $j=1,2,3;\ i=1,2,\ldots,\, I$. The form of these formulas is specified by experts.

3 Results and Discussion

The main result of the work is the procedure for determining the dependability indicator of BGES, the main stages of which are presented in Figure 3.

At the first stage of the procedure, data is collected and statistically processed regarding equipment failures of the BGES in question. In this case, both available reference data and the results of specially planned experiments can be used [14-15].

An artificial neural network is used as a tool for moving to indicators of the second level of the hierarchy. Given the presence of a sufficiently large number of development tool platforms [16-18], the questions of choosing a configuration and constructing a dataset for training a neural network remain, the solution of which is the second stage of the procedure.

At the third stage, the artificial neural network constructed (at the second stage of the procedure) is used to calculate the numerical values of sub-indicators (based on the primary data obtained at the first stage).

At the fourth stage, fuzzification is carried out, within which the degree of compliance with the terms of the numerical values of sub-indicators is determined.

The fifth stage consists of implementing the Mamdani fuzzy inference algorithm ([19]) based on fuzzy production rules using recalculation of fuzzified sub-indicator values, which allows taking into account the probabilistic aspect of these values. The result of the algorithm is to obtain a fuzzified value of the integral indicator dependability of BGES.

At the sixth stage, the integral indicator dependability of BGES is defuzzified, as a result of which the numerical value of this indicator is determined.

At the seventh stage of the procedure, the numerical values of primary statistical indicators, numerical and fuzzy values of sub-indicators, as well as the integral indicator of dependability of BGES are documented.

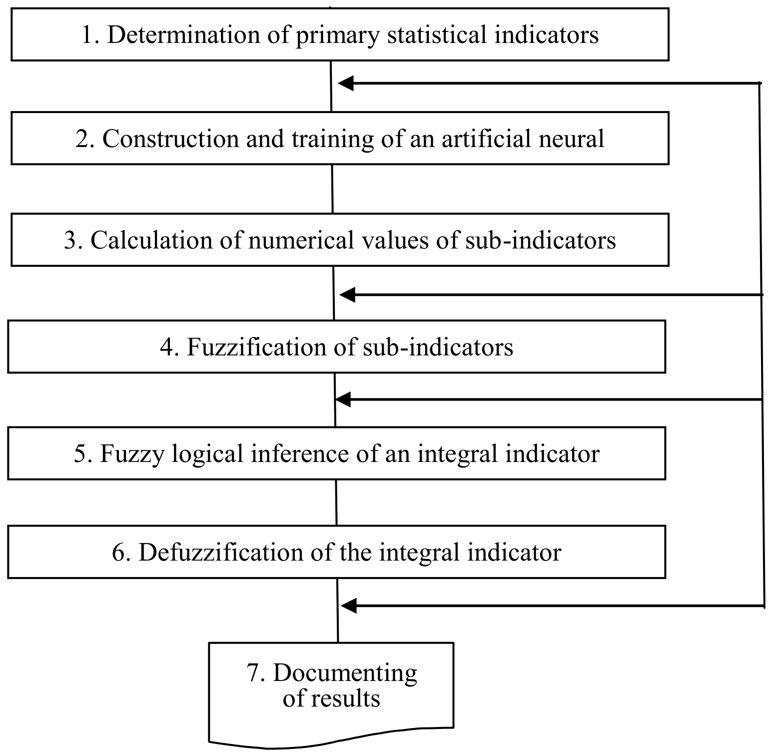

Fig. 3. Scheme of dependability indicators of a biogas energy system determining.

It seems important to provide the decision maker in the operation of BGES with not only the final decision in the form of a numerical or fuzzy value of the integral dependability indicator, but also other dependability-related indicators. This approach (along with the use of a linguistic description of indicators, a system of intuitive fuzzy production rules and the Mamdani fuzzy inference algorithm with a high degree of interpretability) complies with the general principles of Explainable artificial intelligence (XAI [20]) and allows increasing confidence in the result obtained.

4 Conclusion

Ensuring the dependable functioning of biogas energy systems is of high importance both from the point of view of supplying technological and social facilities with heat and electricity, and from an environmental point of view. At the same time, it is necessary to keep in mind not only the undoubted environmental benefits of green energy, but also waste disposal and the production of high-quality organic fertilizers, which to a certain extent closes the cycle of agricultural production.

The proposed approach to assessing the dependability of biogas energy systems is based on the use of a constructed hierarchy of indicators and the application of methods from the theory of artificial intelligence (neural networks, representation of knowledge in the form of fuzzy production rules). The constructed procedure for determining dependability indicators (from primary statistical indicators to an integral indicator) allows us to formalize the analysis process and can be used as part of decision support (in accordance with [21]) when choosing design solutions and subsequent operation of biogas energy, taking into account local (regional) specifics.

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