Neural network analysis of the productivity of biogas plants for small agricultural enterprises

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Abstract. The article is devoted to the problem of assessing the productivity of biogas plants. The aim of the work is to build intelligent tools for evaluating the performance of biogas plants by determining the output of biogas depending on the properties of raw materials based on the fuzzy inference method according to the Sugeno algorithm. First of all, the output of biogas is influenced by the chemical composition of the raw materials used. The chemical composition indicators were obtained by the authors in the framework of experimental studies. To carry out the analysis, a knowledge base was built on the following parameters: humidity, crude ash content, crude fat content, crude protein content, crude fiber content, nitrogen-free extractive substances content. The fuzzification of its vertices in the section of 2- and 3-term sets has been carried out. Membership functions of fuzzy sets for each parameter are constructed. The fuzzification of the root is defined in 5 categories. A system of rules was compiled based on experimental data, and the biogas yield was calculated depending on the initial parameters. The results obtained can be used in the organization of biogas plants.

1 Introduction

Currently, in the period of economic globalization, there are a number of problems. In particular, this is a decrease in energy reserves and climate change – global warming. Solving these problems is the main task of developing renewable (alternative) energy [1-4].

One of the promising directions for obtaining alternative energy on an industrial scale is the recycling of waste from the agro–industrial complex [5-7]. There are several directions of utilization, first of all, it is the use as organic fertilizers [8-10]. However, in some regions, in particular in the Belgorod region, the volume of organic matter exceeds the demand many times [11-13]. Because of this, the disposal of organic livestock waste is becoming an acute problem.

In particular, such an option may be processing in order to obtain biogas.

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This opens up new opportunities for the development of bioenergy in the regions, since complex organic compounds are formed from animal waste, in which a large amount of energy is accumulated [14-16]. Therefore, it is very important to investigate technologies for producing biogas to increase the volume of output of the final product, depending on the quality of the initial organic raw materials.

In this regard, the aim of the work is to build intelligent tools for evaluating the performance of biogas plants by determining the output of biogas depending on the properties of raw materials based on the fuzzy inference method according to the Sugeno algorithm.

2 Materials and methods

To analyze the performance of biogas plants and estimate the biogas yield, we used the fuzzy inference method according to the Sugeno algorithm [17].

The main stages of fuzzy modeling:

- Determination of the parameters of raw materials for biogas production.
- Building a knowledge base.
- Fuzzification of terminal vertices of the knowledge base.
- Fuzzification of the knowledge base root.
- Definition of transition rules.
- Calculation of the biogas yield from the chemical composition of the raw material.

3 Results and Discussion

The knowledge base for evaluating the effectiveness of biogas production is a system that includes a set of factors that affect its yield [18-19]. In our work, we used data on the chemical composition of raw materials produced from different sex and age groups of pigs (Table 1). Manure is a valuable source for biogas production compared to other components [20].

Table 1. Chemical composition of raw materials.

Animal category	Moisture, %	Crude ash content, %	Crude fat Content, %	Crude Protein Content, %	Crude fiber Content, %	Nitrogen-free extractive substances (NES), %
Manure of sow suppositories	4.32	20.75	5.84	12.84	22.97	33.31
Sow manure on suction	3.58	18.69	9.35	15.68	22.06	30.64
Manure is vilified	8.15	17.27	11.76	22.71	14.55	25.57
Pork manure	14.29	18.11	7.48	13.75	17.55	28.82

As can be seen from Table 1, six components of the chemical composition of the raw material have been identified, which significantly affect the output of biogas. Thus, the developed knowledge base consists of one root and six terminal vertices (Figure 1).

Terminal vertices are the main elements of the chemical composition of raw materials, and the volume of biogas produced is the root of the knowledge base. Therefore, the height of the knowledge base is 1, and its size is 7, all terminal vertices are nodes of the first level.

The next step is to define a universal set for each parameter. For this calculation, we use the data given in Table 1. The resulting universal set of values for the parameters of the chemical composition of raw materials is shown in Table 2.

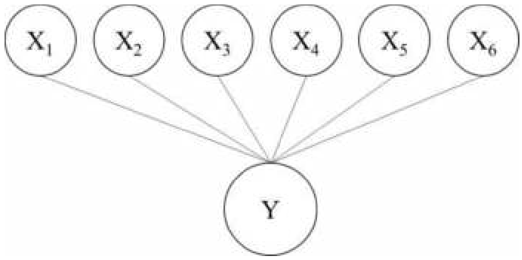


Fig. 1. Knowledge base.

Table 2. Parameters of raw materials for biogas production.

Parameters	Parameters	The universal set
Moisture, %	X_1	From 3 to 15
Crude ash content, %	X_2	From 17 to 21
Crude fat Content, %	X_3	From 5 to 13
Crude Protein Content, %	X_4	From 12 to 24
Crude fiber Content, %	X_5	From 14 to 23
NES, %	X_6	From 25 to 34

Next, we define a set of terms for each thermal value of the knowledge base. Traditionally, a classification from 2 to 5 terms is used [21]. Their number is determined conditionally, depending on how many regions the universal set of each parameter can be divided into. The calculated term sets are shown in Table 3. Graphs of the membership function of fuzzy sets of the parameter "Moisture" in Figure 2, for the rest of the parameters, the function was constructed in a similar way.

Table 3. Thermal properties of the chemical composition of raw materials.

Variables	Term sets and their evaluation
X_1	low (1), medium (3), high (5)
X_2	low (1), medium (3), high (5)
X_3	low (1), high (5)
X_4	low (1), medium (3), high (5)
X_5	low (1), medium (3), high (5)
X_6	low (1), medium (3), high (5)

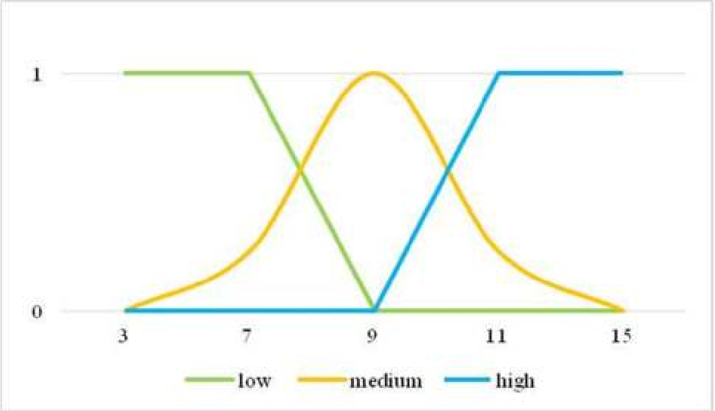


Fig. 2. The membership function of fuzzy sets according to the parameter "Moisture".

To fuzzify the knowledge base, we have increased the number of terms to five. The following values of the set of terms were used to determine the root of the knowledge base: "very low" (1), "low" (2), "medium" (3), "high" (4), "very high" (5).

Next, the transition from fuzzy values of terminal vertices to fuzzy was performed the value of the root. The calculation was performed using a fuzzy knowledge base:

$$\bigcup_{j=1}^{m}(\bigcap_{i=1}^{n} x_i = a_{j,i} \text{ with weight } w_j) \rightarrow y = d_j, 0 + b_{j,0} + b_{j,1} \cdot x_1 + \cdots + b_{j,n} \cdot x_n, \quad (1)$$

Where y is the output variable; $x = (x_1, x_2, x_3 \ldots x_n)$ – vector of input variables; $a_j = (a_{j,1}, a_{j,2}, a_{j,3} \ldots a_{j,n})$ – the values of the vector of input variables in the *j-th* rule, $j=0,1,2\ldots m$; $b_{j,0}$ – the coefficient for the output value in the *j-th* rule, $j=0,1,2\ldots m$; $b_{j,i}$ – the coefficient at the *i-th* term for the output value in the *j-th* rule, $j=0,1,2\ldots m$, $i=0,1,2\ldots n$; w_j – The weight of the *j-th* rule, $j=0,1,2\ldots m$.

In turn, the d_j rule is determined using a linear function from the input:

$$d_j = b_{j,0} + b_{j,1} \cdot x_1 + \cdots + b_{j,n} \cdot x_n. \quad (2)$$

The rules in Sugeno's fuzzy knowledge base are defined in the "IF..., THEN..." function, so they serve as switches from one linear law to another linear law. The boundaries of the parameters are fuzzy, which makes it possible to simultaneously execute several linear rules, but with varying degrees [22].

We introduce a new notation: $\mu_t(\upsilon)$ is the function of belonging of the input or output fuzzy variable υ to the fuzzy term t.

Therefore, the degrees of belonging of the input vector to fuzzy d_j terms from the knowledge base can be calculated as follows:

$$\mu_{d_j}(x) = \bigvee_{j=1}^{m} w_j \cdot \bigwedge_{i=1}^{n} \left[\mu_{b_{j,i}}(x_i)\right]. \quad (3)$$

The above function (3) shows the result of evaluating the *j-th* rule from the knowledge base, where ∨ (∧) is an operation from the *s*-norm (*t*-norm), i.e. from a set of options for implementing logical operators OR (AND).

As a result, we get *m* new membership functions, the totality of which forms a new fuzzy set which corresponds to the input vector *x*:

$$\tilde{y} = \frac{\sum_{i=1}^{m} \mu_{d_1}(x) \cdot f_i(x)}{\sum_{i=1}^{m} \mu_{d_1}(x)}. \quad (4)$$

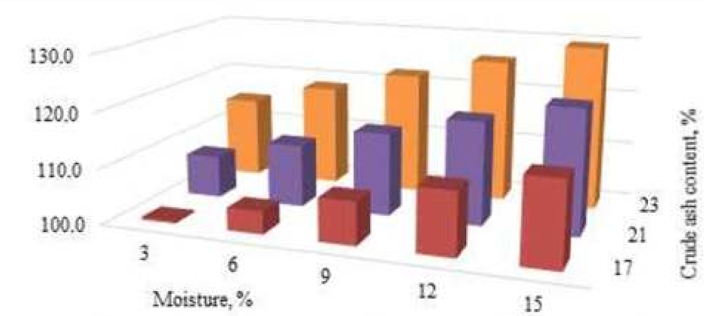
To calculate the potential output of biogas, a number of rules were created with two changing variables – humidity and crude ash content, the remaining parameters were fixed at average values:

$$\begin{cases} \text{if } (\mathrm{x}_1 = \mathrm{A}_{min}) \text{ and } (\mathrm{x}_2 = \mathrm{A}_{min}), \text{then } (\mathrm{y}_1 = Y_{min}) \\ \text{if } (\mathrm{x}_1 = \mathrm{A}_{min}) \text{ and } (\mathrm{x}_2 = \mathrm{A}_{max}), \text{then } (\mathrm{y}_1 = Y_{average}) \\ \text{if } (\mathrm{x}_1 = \mathrm{A}_{max}) \text{ and } (\mathrm{x}_2 = \mathrm{A}_{min}), \text{then } (\mathrm{y}_1 = Y_{average}) \\ \text{if } (\mathrm{x}_1 = \mathrm{A}_{max}) \text{ and } (\mathrm{x}_2 = \mathrm{A}_{max}), \text{then } (\mathrm{y}_1 = Y_{max}) \end{cases} \quad (5)$$

Thus, the calculated biogas yield, depending on the chemical composition of the raw material with fixed parameters of protein, fat, fiber and NES content, was:

$$Y = \frac{402.5+\mu_1 \cdot x_1+\mu_2 \cdot x_2}{3.5+\mu_1+\mu_2} = 115.0 \pm 14.5\ m^3/t.$$

The graphical dependence of the biogas yield on the above parameters, obtained using the Sugeno neural network, is shown in Figure 3. The dataset, including training and control samples, was formed on the basis of experiments conducted by the authors at a laboratory biogas plant.



	3	6	9	12	15
■17	100.5	104.1	107.7	111.4	115.0
■21	107.7	111.4	115.0	118.6	122.3
■23	115.0	118.6	122.3	125.9	129.5

Fig. 3. Dependence of biogas yield on the chemical composition of manure.

According to the calculation results, it was found that when analyzing these two parameters, the differences in the Y value are not high and do not reach the designated limits. Therefore, in the future it is planned to explore other pairs of parameters to assess the biogas yield.

4 Conclusion

Thus, the use of the fuzzy inference method according to the Sugeno algorithm is a promising area of neural network analysis for predicting the efficiency of biogas plants for small agricultural enterprises. Despite the large number of fuzzy data on the chemical composition of raw materials, it expands the possibilities of existing forecasting methods and its choice is justified in the management of biogas plants at agricultural enterprises.

Further use of the proposed neuro-fuzzy forecasting algorithm may be related to the organization of biogas plants to support decision-making in the implementation of energy projects in agriculture.

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