Advances in Engineering Research, volume 213
Proceedings of the International Scientific and Practical Conference "Young Engineers of the Fuel and Energy Complex: Developing the Energy Agenda of the Future" (EAF 2021)

Monitoring the Gas Balance in the Regional Gas Transmission Network Using Intelligent Methods

Aigul Petrova[1*]

[1] *Saint-Petersburg Electrotechnical University "LETI", Russian Federation*
[*]*Corresponding author. Email: ak72p@yandex.ru*

ABSTRACT
Improving the efficiency of balance control in the gas transmission system is an urgent task. Applying intelligent techniques such as artificial neural networks or adaptive hybrid neural fuzzy systems (ANFIS), combining the advantages of neural networks and fuzzy logic, could be such a solution. The article discusses a comparison of the use of intelligent methods for calculating gas reserves for data from one of the regional gas transmission networks of the Russian Federation.

Keywords: *Gas balance, Gas transmission network efficiency, Neural network, Fuzzy logic, Adaptive hybrid fuzzy inference system.*

1. INTRODUCTION

One of the problems of the gas metering system during its transportation in the system of main gas pipelines is the gas imbalance [1–3]. According to [4], the gas imbalance is the difference between the volume of gas supplied and taken from the system during the reporting period. The imbalance arises due to the influence of many changing factors, including such as nonlinearly dependent characteristics of the working environment (natural gas), equipment, pipeline, and environment [5, 6].

2. GAS STOCK IN THE MAIN GAS PIPELINE

One of the components of the imbalance is the value of the gas reserve in the main pipeline, which is influenced by the following factors [7]: absolute pressure and average temperature, the average gas compressibility factor in the pipeline, as well as the ambient temperature in which the gas pipeline runs.

The gas reserve in the section of the multi-line system of the main gas pipeline under standard conditions is determined by the Equation (1):

$$Q = \frac{V \cdot P_{av} \cdot 293.15}{1.033 \cdot z_{av} \cdot 10^6 (T_{av}+273.15)} \tag{1}$$

where V – the geometrical volume of a gas pipeline section, м3; P_{av} – average pressure in the gas pipeline section, kgf / cm2; z_{av} – average gas compressibility factor in the gas pipeline section; T_{av} – the average gas temperature in the gas pipeline section, °C.

The geometric volume of the pipe in the section is calculated by the Equation (2):

$$V_i = \frac{\pi \cdot D_{in}^2 \cdot L}{4} \tag{2}$$

where L, D_{in}^2 are the length and internal diameter of the trunk gas pipeline, respectively.

The average pressure of a trunk gas pipeline string, P_{av}, kgf / cm^2, is determined by the Equation (3):

$$P_{av} = \frac{2}{3} \cdot \left(P_b + \frac{P_e^2}{P_b+P_e}\right) \tag{3}$$

where P_b is the absolute gas pressure at the beginning of the gas pipeline section, kgf / cm^2; P_e – absolute gas pressure at the end of the gas pipeline section, kgf / cm^2.

The average temperature of a section of the main gas pipeline, T_{av},° C, is determined by the Equation (4):

$$T_{av} = T_{env} + \frac{T_b - T_{env}}{\alpha L}(1-e^{\alpha L}) - D\frac{P_b^2 - P_e^2}{2\alpha L P_{av}}\left(1 - \frac{(1-e\alpha L)}{\alpha L}\right) \tag{4}$$

where T_b is the gas temperature at the beginning of the gas pipeline section, ° C;

T_{env} is the ambient temperature, in the case of the pipeline laying in the ground –- T_{gr} , the ground temperature at the depth of the gas pipeline, is updated monthly according to statistical data; L is the length of the gas pipeline section; α – calculated coefficient (5).

$$\alpha = 0{,}225 \cdot \left(\frac{K_{av} d_o}{q \rho_{air} C_{av}}\right) \quad (5)$$

where K_{av} is the average overall coefficient of heat transfer from gas to the environment at the site, W / (m2 K); d_o – outer diameter of the pipe, mm; q – gas consumption, million m^3 / day; ρ_{air} – relative density of gas in air; C_{av} is the average isobaric heat capacity of the gas, kJ / (kg K).

The average value of the compressibility factor is determined by the formula (6):

$$z_{av} = 10.0907 \cdot P_{av} \cdot \left(\frac{T_{av}}{200}\right)^{-3.668} \quad (6)$$

When analysing the expressions, it can be seen that each component of formula (1) is determined, in turn, by a mathematical formula that takes into account several nonlinear factors, which together can affect the correctness and speed of networks' calculating. So, according to [8], "the determination of one of the components for calculating α, K_{av} – the average in the area of the total heat transfer coefficient from gas to the environment, was recognized as impracticable. The procedure for calculating K_{av} from experimental data is carried out according to a modified formula."

Thus, it seems appropriate to investigate the application of other modern methods for calculating the gas reserve, in particular, intelligent methods such as artificial neural networks, fuzzy logic, or their combination. This article discusses the use of adaptive hybrid neuro-fuzzy and neural networks.

3. ADAPTIVE HYBRID NEURO-FUZZY NETWORKS

A hybrid neural fuzzy network is a multilayer neural network of a special structure. Information processing in a neuro-fuzzy network is carried out under the logic of the fuzzy system, and the parameters are set according to the rules for training neural networks. Thus, the advantages of fuzzy logic (in terms of clarity of presentation and simplicity of meaningful interpretation of the structure of inference rules) and neural networks are combined - in terms of the possibilities of constructing and learning the rules of fuzzy productions [9–11].

The most widespread in practice are hybrid networks implemented in the form of the so-called adaptive neuro-fuzzy inference systems ANFIS (Adaptive Neuro-Fuzzy Inference System) [12].

The work used statistical data on gas reserves for 5 months of the year at a section of the regional gas distribution network with the following parameters:

1) pressure in the pipeline P_{av}. (kgf / cm^2);

2) the average temperature of the gas in the pipeline T_{av}, ° C;

3) the average coefficient of gas compressibility in the pipeline z_{av};

4) gas stock in the pipeline, Q_{res}, thousand m^3;

The resulting output parameter is the gas reserve. The rest of the parameters are input.

The graph of the change in the resulting parameter depending on the index is shown in Figure 1.

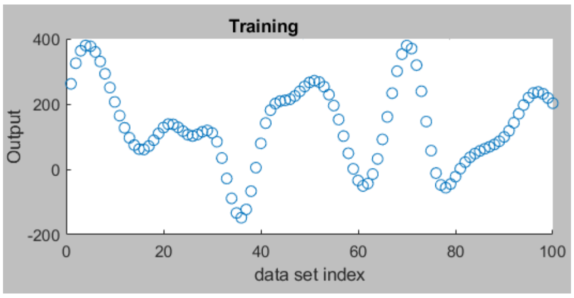

Figure 1 Graph of changes in gas reserves depending on the index.

Using the Matlab environment [13], various methods for constructing a hybrid adaptive neuro-fuzzy system were applied to the data, while the data set was divided into training and test samples in the proportion of 70 % and 30 % of the original dataset, respectively.

4. GENERATING FUZZY RULES OF THE GRID PARTITION METHOD

According to this method, the membership functions of fuzzy terms are evenly distributed within the range of data variation. The knowledge base contains all possible variations of the rules. The coefficients in the conclusions of the rules are taken equal to zero [14]. The structure of a neuro-fuzzy network based on the grid partitioning method is shown in Figure 2. In this model, the system formed 81 rules.

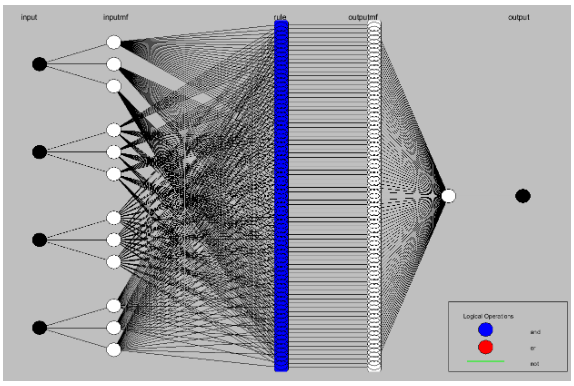

Figure 2 The structure of a neural fuzzy network, based on the grid partitioning method.

The plot of the output variable, depending on the two input variables, is shown in Figure 3.

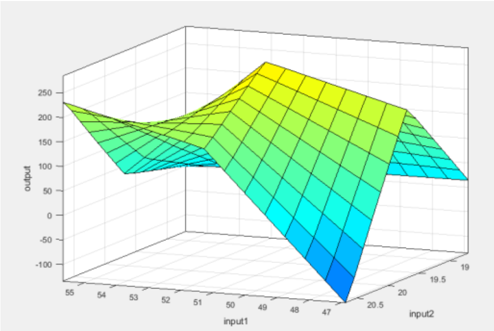

Figure 3 Image of the output variable of the fuzzy inference system, for the model generated by the grid partitioning method.

In this graph, input1 = P_{av}, pressure in the pipeline; input2 = T_{av}, average gas temperature in the pipeline, output = Q_{res}, gas reserve in the pipeline.

Next, the model was trained. To train a fuzzy system with ANFIS, Matlab software uses a backpropagation algorithm either alone or in combination with a least squares algorithm. Here, a hybrid method was used, consisting of backpropagation of the parameters associated with the input membership functions and the least-squares estimation for the parameters associated with the output membership functions. The number of eras was chosen to be 50.

Next, the trained model was tested on a test sample. The graph of the test results is shown in Figure 4. On this graph, larger markers (snowflakes) show the values of the test sample, smaller markers (plus signs) – the result of the trained model.

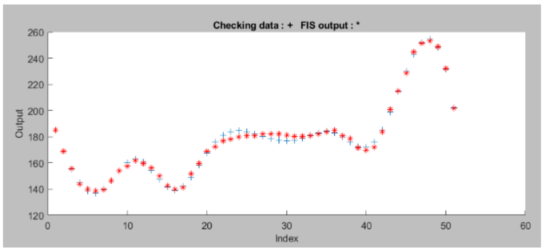

Figure 4 Result of testing the trained model generated by the grid partitioning method.

5. APPLYING THE RULES SPECIFIED BY THE SUB. CLUSTERING METHOD

The algorithm is based on the proposition that each experimental point can be the centre of a cluster, while first for each point the likelihood measure of this assumption ("point potential") is calculated, based on the density of points in a given neighbourhood of the considered one. Further calculations are performed iteratively [15].

1) The point with the highest potential is declared the centre of the first cluster;

2) All other points are removed from the marked neighbourhood of this point;

3) From the remaining points, the centre of the next cluster is announced, etc., until all points have been considered (excluded or declared as centres).

The structure of a hybrid network based on subtractive clustering is shown in Figure 5. In this model, the system generated 28 rules.

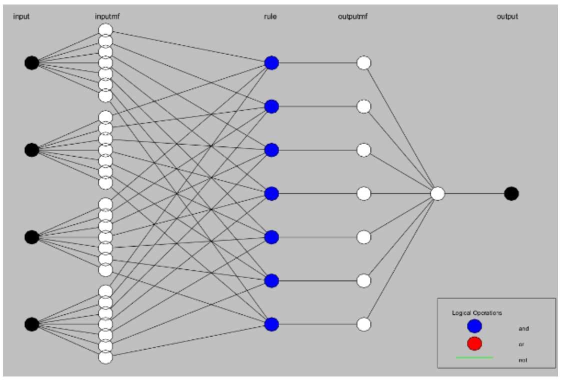

Figure 5 The structure of a neural fuzzy network, based on subtractive clustering.

The plot of the output variable, depending on the two input variables, is shown in Figure 6.

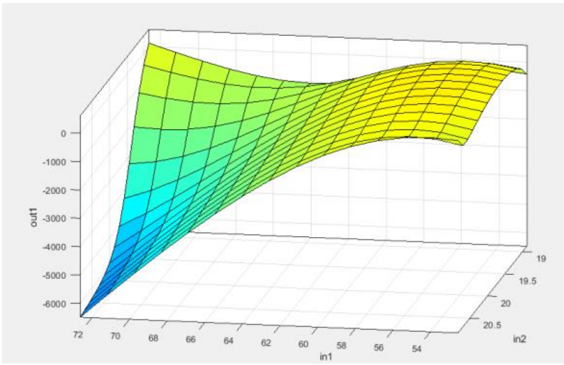

Figure 6 Image of the output variable of the fuzzy inference system, for the model generated by the subtractive clustering method.

In this graph, also input1 = P_{av}, pressure in the pipeline; input2 = T_{av}, average gas temperature in the pipeline, output = Q_{res}, gas reserve in the pipeline.

Next, the trained model was tested on a test sample. The graph of the test results is shown in Figure 7. In this graph, larger markers (snowflakes) show the values of the test sample, smaller markers (plus signs) – the result of the trained model.

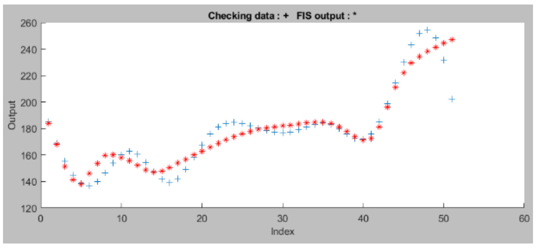

Figure 7 Result of testing the trained model generated by the subtractive clustering method.

The results of applying the two methods for generating rules show that the grid partitioning method works more correctly. The results of comparing the application of methods for generating rules are shown in Table 1.

6. APPLICATION OF AN ARTIFICIAL NEURAL NETWORK

For a more complete comparison, training was carried out on the same statistical data of an artificial neural network [16–18]. The learning error is shown in Figure 8.

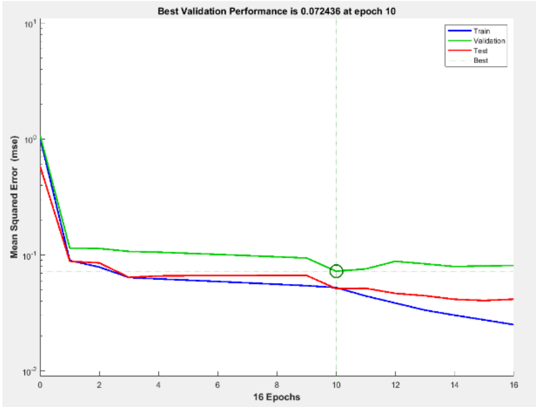

Figure 8 Graph of the error of training a neural network model.

Table 1. Results of comparing the application of intelligent methods to calculate gas reserve

Models	Models' parameters		
	Learning error	**Test error**	**Number of model rules**
Grid Partitioning Method	1.7	2.59	81
Subtractive clustering method	2.9	3.14	7
ANN	0.01	0.28	-

The results of applying the trained neural network to the validation and test samples, as well as comparison with the results of the training set, are shown in Figure 9.

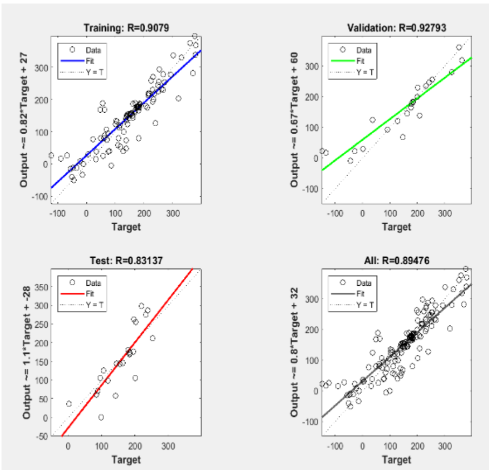

Figure 9 The results of applying the trained neural network to the validation and test samples, in comparison with the results of the training sample.

The results show that the artificial neural network more accurately describes the dependence of the amount of gas supply on the input factors, in comparison with hybrid adaptive neuro-fuzzy networks.

The results of the comparison of the application of intelligent methods are shown in Table 1.

7. CONCLUSION

As part of the work, a study was carried out of the possibility of determining the value of the gas reserve using an adaptive hybrid neuro-fuzzy network. A comparison of the methods for generating fuzzy rules by the methods of grid partitioning and subtractive clustering is carried out. The results showed that of the hybrid networks, the network obtained based on the grid partitioning method is more accurate, but the most accurate was the artificial neural network.

In the future, it is planned to improve the quality of the model through the use of expanding and processing the training sample and improving the base of fuzzy rules, building a controller model based on fuzzy logic, as well as comparing the results of using neuro-fuzzy models with the results of building regression models based on artificial neural networks.

REFERENCES

[1] E.M. Clarke, E.A. Emerson, Design and synthesis of synchronization skeletons using branching time temporal logic, in: D. Kozen (Eds.), Workshop on Logics of Programs, Lecture Notes in Computer Science, vol. 131, Springer, Berlin, Heidelberg, 1981, pp. 52–71. DOI: https://doi.org/10.1007/BFb0025774

[1] Ignatiev A.A. “Assessment of the reasons for the imbalance in gas volumes in the “supplier – consumer” system,” Gas Industry. 2010. No. 6. P. 20–22.

[2] Salikov A.R. “Imbalance in gas distribution networks,” Gas of Russia. 2015. No. 4. P. 36–41.

[3] F. Arpino, M. Dell'Isola, G. Ficco, P. Vigo, “Unaccounted for gas in natural gas transmission networks: Prediction model and analysis of the solutions,” J. of Natural Gas Science and Engineering. 2014. Vol. 17. P. 58–70.

[4] Information letter of the Federal Tariff Service (FTS) dated June 28, 2005, Ref. SN-3923/9 “On the accounting of gas losses”.

[5] Zh.A. Daev, A system for automatic control of imbalances in the volume of natural gas based on a neuro-fuzzy model: Automation, telemechanization and communication in the oil industry 3 (548) 2019, pp. 37-40.

[6] Khvorov G.A., Kozlov S.I., Akopova G.S., Evstifeev A.A. “Reduction of natural gas losses during transportation through the main gas pipelines of OAO Gazprom,” Gas Industry. 2013. No. 12. P. 66–69.

[7] STO GAZPROM 2-3.5-051-2006 Standards for technological design of gas trunklines.

[8] Slobodchikov K.Yu. “Method of generating design examples for dispatching tasks of gas transportation,” Gas Industry 2018; 3: 78-86

[9] Zade L.A. “Fundamentals of a new approach to the analysis of complex systems and decision-making processes,” Mathematics today: Collection of articles; trans. from English. Moscow: Knowledge Publ., 1974. Pp. 5-49.

[10] S.D. Shtovba Introduction to the theory of fuzzy sets and fuzzy logic -http: //matlab.exponenta.ru/fuzzylogic/book1/index.php

[11] PL Yarushkina, Fundamentals of the theory of fuzzy and hybrid systems: textbook. allowance Moscow: Finance and Statistics Publ., 2009. 320 p.

[12] AV Nazarov, AA Loskutov, “Neural network algorithms for forecasting and optimization of systems: Science and Technology,” St. Petersburg, 2003, 384 p.

[13] Dyakonov V.P., Kruglov V.V. MATLAB 6.5 SP1 / 7/7 SP1 / 7 SP2 + Simulink 5/6. Artificial intelligence and bioinformation tools. Moscow: SOLON-PRESS Publ., 2006.

[14] Uskov A.A., Kuzmin A.V. Intelligent control technologies. Artificial neural networks and fuzzy logic. Moscow: Hot line - Telecom, 2004. 143 p.

[15] Chiu S., “Fuzzy Model Identification Based on Cluster Estimation,” Journal of Intelligent & Fuzzy Systems, Vol. 2, No. 3, Sept. 1994.

[16] Diligensky N.V., Dymova L.G., Sevastyanov P.V. “Fuzzy modeling and multicriteria optimization of production systems in conditions of uncertainty: technology, economics, ecology,” Moscow: “Publishing house Mashinostroenie”, 2004.

[17] A. Vellidoa, P.J.G. Lisboaa, J. Vaughanb Neural networks in business: a survey of applications (1992–1998): Expert Systems with Applications 17 (1999) 51-70.

[18] Khaikin S. Neural networks. Complete course. Williams, 2018.