УДК 004.02 DOI 10.33042/2522-1809-2023-3-177-2-9

**V. Harasymiv, T. Harasymiv, O. Moyseenko**

*Ivano-Frankivsk National Technical University of Oil and Gas, Ukraine*

# MATHEMATICAL MODELLING OF THE CENTRIFUGAL COMPRESSOR

*The paper is aimed to create the mathematical model of the centrifugal compressor based on the group method of data handling-type neural networks to determine the compressor volumetric flow rate as the dependence on the centrifugal compressor's technological parameters (the rotor's angular velocity, the compressor's inlet and outlet temperatures, the compressor's inlet and outlet pressures, the atmospheric pressure). It is the important scientific task, because most centrifugal compressors used in the process industry don't have equipment needed to measure the volumetric flow rate. It does not allow to estimate the compressor's technical state during its operation. Verification of the developed model has been performed, based on the 336 data points (collected from the field measurements) and with using the centrifugal compressor of natural gas (16ГЦ2-395/53-76С) of Dolyna linear production administration of gas transmittal pipelines. The test results have been showed the adequate efficiency of the mathematical model.*

***Keywords:*** *volume flow, centrifugal supercharger, mathematical model, method of group consideration of arguments, neural networks, technological parameters, correlation coefficient.*

## Introduction

The need of modelling of a centrifugal compressor is clearly established since the structural identification of the process of a gas compression become significant in control, prediction and analysis.

In the past, the well-known statistical methods were represented by researches to describe modelling algorithms based on a broad range of a priori assumptions, which could reflect only special states of the process and therefore might create inaccurate models.

The rapid development of artificial neural network (ANN) has improved the modelling algorithms. However, the demand of a significant amount of a priopi information about the model's structure (experts should decide on the number of hidden layers and neurons, the form of their activation function) tends to a subjective choice of the final model, which in the majority of the tasks will not approximate the ideal.

A new approach, which efforts to overcome the subjectiveness of a ANN is an inductive approach, based on the principle of self-organization. The group method of data handling (GMDH) refers to the class of inductive self-organization data driven approaches. It needs small data samples and has the opportunity to optimize model's structure objectively with using the external criteria. The GMDH method offers better accuracy and requires a fewer number of observations and therefore reduces a computation time [1].

The centrifugal compressor of natural gas can be considered as the dynamic system, which is formed by the combination of its parameters. Thermodynamics parameters (temperature, pressure, etc) and outlet parameters (compressor efficiency, polytrophic energy conversion efficiency, etc) are important information carries about the compressor technical state. The occurrence of any defect is connected with the change of compressor thermodynamics parameters. It leads to the corresponding changes of the outlet parameters (Fig.1). Compressor technical state recognition and prediction is performed by the technical state description, composed of the set of compressor thermodynamics and outlet parameters.

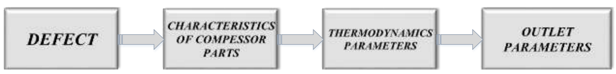


Fig. 1. Scheme of the information transfer about the compressor technical state

Therefore, thermodynamics and outlet parameters can be used for creating the centrifugal compressor mathematical model including all basic requirements (the adequacy, the model universality, the possibility of the model implementation) [2]. The influence of random and predictable processes (wear, external and exploitation conditions, etc) must be taken into consideration during the creating the compressor mathematical model [3-6].

The mathematical descriptions of centrifugal compressors are obtained in different ways. One of the first models was derived by Emmons and others [7]. The authors exploited the analogy between a self-excited Helmholtz resonator and the small oscillations associated with the onset of surge to develop a linearized compression system model. Proposed models based on the main physical laws [8-9] are too complex to implement for real systems. So the artificial intelligence methods are widely used for modelling the complex dynamic systems.

Today, compressor stations determine the integral impact of the whole existing faults set on the main compressor parameters [10]. The coefficient of the compressor technical state is determined for the estimation of compressor technical state [11]:

$$K_{\eta\, pol} = \frac{\sum_{i=1}^{s} \eta^{i}_{pol} \cdot \eta^{i}_{\mathrm{pol\ b}}}{\sum_{i=1}^{s} \left(\eta^{i}_{\mathrm{pol\ b}}\right)^2} = \frac{\sum_{i=1}^{s} \eta^{i}_{pol} \cdot f_{\mathrm{b}}\left(Q^{i}{}_{v}\right)}{\sum_{i=1}^{s} \left( f_b\left(Q^{i}{}_{v}\right)\right)^2}, \quad (1)$$

where $\eta^{i}_{pol}$ – the actual value of the compressor polytropic efficiency on the *i*-th control condition, $\eta^{i}_{\mathrm{pol\ b}} = f_{\mathrm{b}}\left(Q^{i}{}_{v}\right)$ – the value of the polytropic efficiency on its basic characteristic based on the resulted compressor volumetric flow rate received on the *i*-th control condition, *s* – the number of control conditions.

This thermos-gas-dynamic model is suitable for compressor operation conditions, but accepted for its construction prerequisites (ignoring the actual compressor conditions and its real technical state, gas composition, etc) leads to significant errors in the determining of the centrifugal compressor power and fuel gas discharges.

In paper [12] a fractal time series is taken as the solution to a differential equation described the compression process, but authors of the paper [13] showed the better results of using a fractal time series in forecasting methods than in the modelling.

The mathematical modelling of centrifugal compressors based on the artificial intelligence methods is presented in the articles [14-15]. Some of the algorithmic approaches mentioned in these articles are possible to use for increasing the compressor efficiency and reducing the cost of its operation, but on the other side, they have low accuracy and convergence rate. The combination of several methods allows to get better results. Therefore, there are articles [16-18] proposed classical GMDH (group method of data handling) based on neural networks to get a high accuracy of the prediction or approximation.

Classical GMDH is discovered in the article [19]. It is based on the using of genetic algorithms and the parallel algorithm to improve the effectiveness of the computing process. The obtained model has the good accuracy, but the group method of data handling-type neural networks approach gives the opportunity to overcome the problem of a huge computing time.

## Material and methods

The research compressor parameters were taken during February of the year 2014. The operation of the gas pumping plant installed on KS-3 of Dolyna linear production administration of gas transmittal pipelines was investigated. The input matrix consists of 336 experiments for each technological compressor parameter. The output matrix, characterized the compressor volumetric flow rate, is changed during the research period. Input parameters are divided in testing and training sets, which are presented to inputs of each hybrid neural network. The best model is selected according to the criterion of a minimum displacement.

## Analysis of the centrifugal compressor as a control object

Centrifugal compressor of natural gas can be described as the control object with a set of parameters: input, output parameters and disturbances. The general structural scheme of the compressor automation system has been created to consider the influence of these factors on the compressor operation. It consists of the control object and the automated control system (Fig.2).

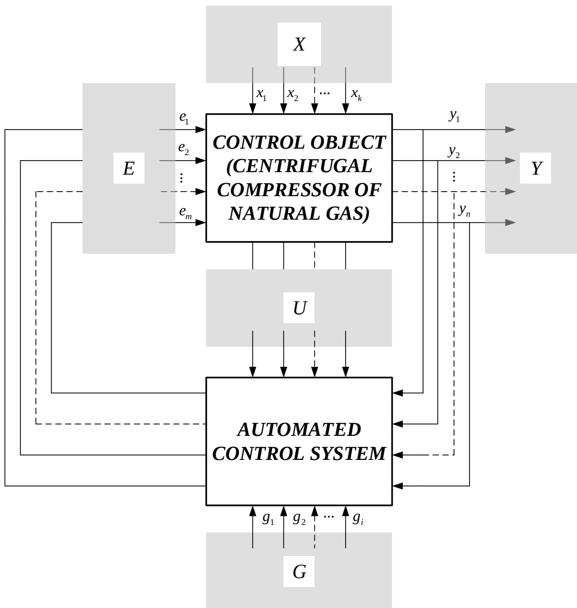


Fig. 2. Determining parameters in centrifugal compressor operation as the control object

Input values can be described by the group of parameters *X*, that are divided into two parts: the control parameters (the group *Z*) and no control parameters (the group *V*). For example, the group *Z* includes pressure, temperature, productivity, etc. The group *V* includes: the natural gas density, its chemical composition, the fuel gas heat of combustion, etc. In most cases, parameters of the group X have probabilistic features, which put a certain stochastic component to the natural gas compressing process.

Output values can be described by the group of parameters *Y*, which depends on the group of parameters *X* and compressor internal parameters (the geometric dimensions of the compressor wheels, the geometry of the bearings, etc).

In addition to parameters of the groups *X* and *Y*, centrifugal compressor as the control object can be described with parameters of the group *U*. The group *U* is formed by controlled input values, through which the natural gas compressing process is provided (the fuel gas rate, excess air ratio, etc).

Information about the current values of groups *U* and *Y* is received by the automated control system and compared with the corresponding values of the group *G* parameters (ccompressor values corresponding to operation of the new centrifugal compressor or after its overhaul, passport data, established limit values, etc.). As a result, the compressor automated control system realizes the influence (parameters of the group *E*) to control the operation of the centrifugal compressor. Estimations of the compressor technical state established by experts' groups are included to the group *E*.

Therefore, the estimation of the compressor technical state becomes particular important as the mathematical model is developed to improve the automated control system and define fault locations of the compressor station main equipment.

## Algorithm description

Centrifugal compressors can be described by a large number of different parameters varied within their limits. However, the compressor volumetric flow rate and its pressure ratio have the greatest influence on the compressor efficiency. The compressor volumetric flow rate $Q_i$ can be written as the dependence on compressor technological parameters (the compressor rotor angular velocity $\omega$, inlet $T_1$ and outlet temperatures $T_3$, the compressor inlet $P_1$ and outlet pressures $P_3$, the atmospheric pressure $P_a$). This equation can be written in the multidimensional nonlinear model form:

$$Q_i = f\left(\omega, T_1, T_3, P_1, P_3, P_a\right). \qquad (2)$$

Matrix of the compressor technological parameters can be written as:

$$X = \begin{vmatrix} x_{11} & x_{21} & \dots & x_{n1} \\ x_{12} & x_{22} & \dots & x_{n2} \\ \dots & \dots & \dots & \dots \\ x_{1m} & x_{2m} & \dots & x_{nm} \end{vmatrix}, \qquad (3)$$

where *n* – the number of input parameters, *m* – the number of investigations.

So, matrix of the compressor volumetric flow rate values is follow one:

$$\bar{Y} = \left[ y_1 \quad y_2 \quad \dots \quad y_m \right]^T. \qquad (4)$$

The equation (2) can be expressed by the following form:

$$\bar{Y} = f(X). \qquad (5)$$

GMDH is used to synthesis the mathematical model of a centrifugal compressor (5). The classical GMDH has its disadvantages: the possibility of losing some or all of informative parameters, if they are excluded at the beginning of a selection; output vectors of the best models become more correlated due to an increase in the amount of series. So, above all, systems of equations are often ill-conditioned or ill-posed for parameter estimation. It is proposed a neural network approach to prevent mentioned disadvantages. Its main advantage is a variable structure of the GMDH network, which can be changed during a learning process.

The implementation of the GMDH type neural networks involves the selection of the partial models at the selection levels *k (k=n)* and can be divided into three steps:

*Step 1*. Formation of teaching sets and preparation of the partial models structures.

The formation of teaching sets includes the creating the partial teaching matrices *i*, containing various columns *k* combinations of the original matrix. Its dimension is $m \times n$. This procedure is implemented with using the structural vector:

$$P = \left[ p_1 \quad p_2 \quad \dots \quad p_n \right]^T. \qquad (6)$$

If an element of the vector (6) takes the value 1, then the corresponding argument *n* is included in the partial model, if we have 0, then the corresponding argument *n* is not included. The obtained partial samples can be written as the dependence:

$$X_{m \times n}^{(i,k)} = X_{m \times n} \cdot P. \qquad (7)$$

The matrix $X^{(i,k)}_{m\times n}$ columns, contained non-zero values, are included in the resulting sample $X^{(i,k)}_{m\times k}$.

When the partial model structure $i$ of the level $k$ is being determined, it is assumed that the resulting model can be written as the set of the fuzzy rules:

$$\begin{cases} if\left[\left(x_1 \in A_{11}\right) i \left(x_2 \in A_{21}\right) i \ldots \left(x_k \in A_{k1}\right)\right] \\ than\left(y \in B_1\right), \\ if\left[\left(x_1 \in A_{1j}\right) i \left(x_2 \in A_{2j}\right) i \ldots \left(x_k \in A_{kj}\right)\right] \\ than\left(y \in B_j\right), \\ \qquad\qquad \ldots \\ if\left[\left(x_1 \in A_{1h}\right) i \left(x_2 \in A_{2h}\right) i \ldots \left(x_k \in A_{kh}\right)\right] \\ than\left(y \in B_h\right), \end{cases} , \quad (8)$$

where $h$ – the number of rules; $A_{kj}$ – the membership function of the variable $x_k$, reffered to the certain fuzzy set in the rule $j$, $n = 1 \ldots k$; $B_j$ – the membership function of the output $y$ reffered to the fuzzy set in the rule $j$, $j = 1 \ldots h$. Variables $x_k$ are indexed according to the basis of the partial sample $X^{(i,k)}_{m\times k}$.

*Step 2*. Partial models generation based on the hybrid neural network.

Hybrid neural network is proposed to generate partial models.

The first layer realizes fuzzification with using given input membership functions. Neuron outputs of this layer are the membership functions values for corresponding values of input parameters.

The second layer includes the set of fuzzy rules (8). The number of rules is equal to the number of this layer neurons.

Neurons of the third layer provide the implication operation. The number of rules is equal to the number of this layer neurons as in the second layer. The outputs of this layer are defined as:

$$\begin{aligned} &\tilde{y}_1 = B_1^{-1}\left(\beta_1\right); \\ &\tilde{y}_2 = B_2^{-1}\left(\beta_2\right); \\ &\ldots \\ &\tilde{y}_h = B_h^{-1}\left(\beta_h\right), \end{aligned} \quad (9)$$

where $B_h\left(\beta_h\right)$ – the membership function of output parameters, $\beta_h$ – the outputs of the third layer.

Neurons of the forth layer define the influence power of each fuzzy rule on the system output. The neurons number is equal to the rules number too. The outputs of the third layer are determined as:

$$\begin{aligned} &\delta_1 = \frac{\beta_1}{\beta_1 + \beta_2 + \ldots + \beta_h}; \\ &\delta_2 = \frac{\beta_2}{\beta_1 + \beta_2 + \ldots + \beta_h}; \\ &\ldots \\ &\delta_h = \frac{\beta_h}{\beta_1 + \beta_2 + \ldots + \beta_h}. \end{aligned} \quad (10)$$

The fifth layer consists of the one neuron. It is used to define the output value:

$$\hat{y} = \delta_1 \cdot \hat{y}_1 + \delta_2 \cdot \hat{y}_2 + \ldots + \delta_h \cdot \hat{y}_h. \quad (11)$$

The training process is ended, when the error $E$ satisfies the following condition:

$$E < \frac{1}{2}\left(\hat{y}_h - \hat{y}_{h-1}\right). \quad (12)$$

Training $X^{(i,k)}_{mA\times k}$ and testing $X^{(i,k)}_{mB\times k}$ sets, obtained as the result of the set $X^{(i,k)}_{m\times k}$ dividing, are presented to inputs of each hybrid neural network, built on the rules system (8). A criterion of a minimum displacement or sequence is performed to estimate obtained models on mentioned above sets. The criterion requires the maximum coincidence of the two models original values, obtained from training $X^{(i,k)}_{mA\times k}$ and testing $X^{(i,k)}_{mB\times k}$ sets.

The criterion of a minimum displacement uses the following distribution of experimental data: $X^{(i,k)}_{mA\times k} = 0.5 X^{(i,k)}_{m\times k}$ and $X^{(i,k)}_{mA\times k} = 0.5 X^{(i,k)}_{m\times k}$. Models, obtained with using sequences $X^{(i,k)}_{mA\times k}$ and $X^{(i,k)}_{mB\times k}$, are indicated as $f_A^{(i,k)}$ and $f_B^{(i,k)}$ respectively.

*Step 3*. The best models selection according to the selected criterion.

The best models are selected according to the external criterion, which is performed by using information obtained from outside the clustering process.

The sample $X^{(i,k)}_{m\times k}$ is presented to inputs of each training neural fuzzy network $f_A^{(i,k)}$ and $f_B^{(i,k)}$ to estimate models of the level *k*. The output evaluations are calculated as follows:

$$Y_A^{(i,k)} = f_A^{(i,k)}\left(X^{(i,k)}_{m\times k}\right), \quad (13)$$

$$Y_B^{(i,k)} = f_B^{(i,k)}\left(X_{m\times k}^{(i,k)}\right). \qquad (14)$$

The value of the minimum displacement criterion is calculated based on the obtained evaluations. It can be written as follows [18]:

$$\Delta_{dis}^{2\ (i,k)} = \frac{1}{m}\cdot\left(Y_A^{(i,k)} - Y_B^{(i,k)}\right)^T\cdot\left(Y_A^{(i,k)} - Y_B^{(i,k)}\right). \qquad (15)$$

Using this criterion, the best models selection of the level $k$ is performed according to the following rules:

- if $k > 1$, then the selection condition can be written as

$$\Delta_{dis}^{2\ (i,k)} \le \max_{i=1...L}\left(\Delta_{dis}^{2\ (i,k-1)}\right). \qquad (16)$$

- if $k = 1$, then the models are selected for which the indicator $\Delta_{dis}^{2\ (i,k)}$ is minimal.

The selection process is completed and the optimal model, contained the input variable $k-1$, is selected. Otherwise, the selected models number is fixed and the finding process of the optimal complexity model is continued.

The average value of the minimum displacement criterion for the level $k$ is calculated on the selected models set as:

$$\Delta_{dis}^{2\ (k)} = \frac{1}{L_k}\cdot\sum_{i=1}^{L_k}\Delta_{dis}^{2\ (i,k)}, \qquad (17)$$

where $L_k$ – the number of selected models.

The condition is also checked:

$$\Delta_{dis}^{2\ (k)} \ge \Delta_{dis}^{2\ (k-1)}. \qquad (18)$$

If the condition (18) is done, the selection is stopped and the model of the optimal dimension $k_{opt} = k-1$ is selected.

The iterative process is completed at this point. Only one model is selected among all other models of the level $k_{opt}$. This model satisfies the following accuracy criterion [20-21]:

$$i_{opt} = \min_{i=L...L_k}\left\{\frac{1}{m}\left(Y - Y^{(i)}\right)^T\cdot\left(Y - Y^{(i)}\right)\right\}. \qquad (19)$$

The structure of the obtained hybrid neural-fuzzy networks is preserved to estimate the accuracy of the unbiased partial models of the level $k_{opt}$. Their training is performed on the whole set $X_{m\times k}^{(i,k)}$.

So, the proposed algorithm can be used not only for the model creation, but for the search of the most influence parameters on the system output.

## The approbation results

The algorithm of the centrifugal compressor mathematical model, based on the group method of data handling type neural networks, was tested using the experimental data, taken during operation of the centrifugal compressor of natural gas 16ГЦ2-395/53-76С of Dolyna linear production administration of gas transmittal pipelines, which compression ratio is 1,44 and power 16MW. The research consists of $m = 336$ experiments and $n = 6$ input parameters.

So, the input data matrix is obtained, which has the dimension $[336\times 6]$. It contains information about the change of the centrifugal compressor input parameters $n$ during February 2014.

The output matrix $\overline{Y}$ is the matrix characterized the compressor volumetric flow rate change. It can be determined by the following formula:

$$Q_{вс} = A_к\cdot\sqrt{\frac{\Delta P\cdot Z_1\cdot R\cdot T_1}{P_1}}, \qquad (20)$$

where $A_к$ – confuser coefficient (passport data), $\Delta P$ – confuser pressure drop, $Z_1$ – gas deviation factor correspond to the compressor input, $R$ – gas constant, $T_1$ – compressor inlet temperature, $P_1$ – compressor inlet pressure.

Gas deviation factor $Z_1$ was determined by the Benedict-Webb-Rubin equation [22]:

$$Z_1^3 - Z_1^2 - a\cdot Z_1^3 - b = 0, \qquad (21)$$

where $a$ and $b$ – coefficients, which are calculated by the following formulas:

$$a = \left(\frac{0{,}1237}{\tau_1} - \frac{0{,}3468}{\tau_1^2} - \frac{0{,}1188}{\tau_1^4}\right)\cdot\pi_1, \qquad (22)$$

$$b = \left(\frac{0{,}0291}{\tau_1^2} - \frac{0{,}0273}{\tau_1^3} - \frac{0{,}039}{\tau_1^5}\right)\cdot\pi_1^2, \qquad (23)$$

where $\pi_1$ – calculated pressure at the compressor inlet, $\tau_1$ – calculated temperature at the compressor inlet. These values are calculated by the following formulas:

$$\pi_1 = \left(P_1 + 1{,}33 \cdot 10^{-4} \cdot P_a\right) / P_{cr}, \qquad (24)$$

$$\tau_1 = T_1 / T_{cr}, \qquad (25)$$

where $P_{cr}$ – the value of critical pressure, $T_{cr}$ – the value of critical temperature.

The values of critical pressure and critical temperature are calculated by the following formulas:

$$P_{cr} = 4.67 - 0.1\Delta, \qquad (26)$$

$$P_{cr} = 4.67 - 0.1\Delta, \qquad (27)$$

where $\Delta$ – relative gas density.

Results of the mathematical model, obtained on the training data set $X_{mA\times k}^{(i,k)}$ are shown in Fig.3. So, results of the mathematical model, obtained on testing data set $X_{mB\times k}^{(i,k)}$ are shown in Fig.4.

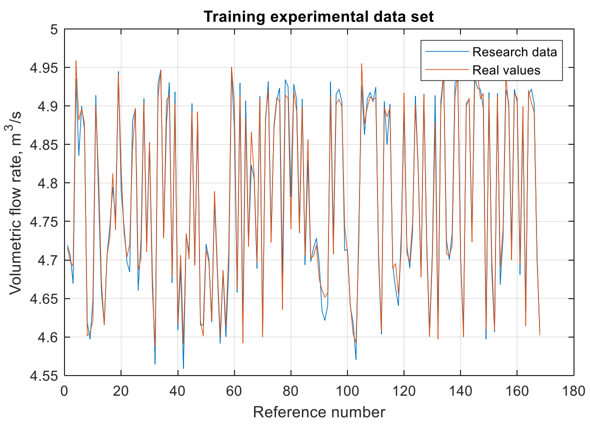


Fig. 3. Results of the mathematical model, obtained on the training data set

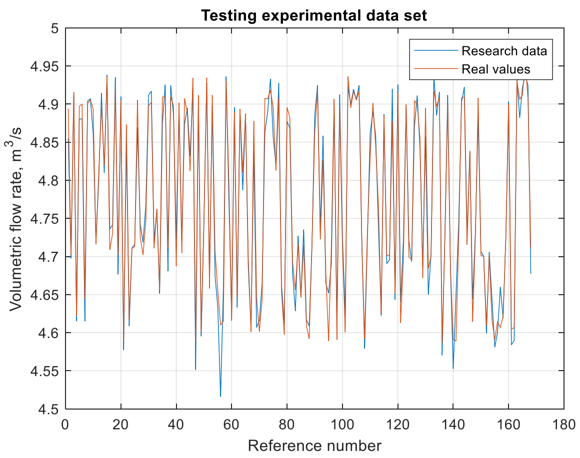


Fig. 4. Results of the mathematical model, obtained on the testing data set

The approbation result of the proposed synthesis algorithm of the centrifugal compressor mathematical model based on the group method of data handling type neural networks is shown in Fig. 5.

The proposed mathematical model (5) is estimated by the correlation coefficient and the standard deviate determined by the following formulas [21]:

$$K_{Yy} = \frac{\sum_{i=1}^{N} Y \cdot y}{\sqrt{\sum_{i=1}^{N} (Y)^2 \cdot \sum_{i=1}^{N} (y)^2}}, \qquad (28)$$

where $y = Q_i$, $i = 1...336$ – values of the volumetric flow rate with using synthesized algorithm, $Y = Q_{вс}$ – values of the volumetric flow rate with using formula (20), $N$ – the number of reference points.

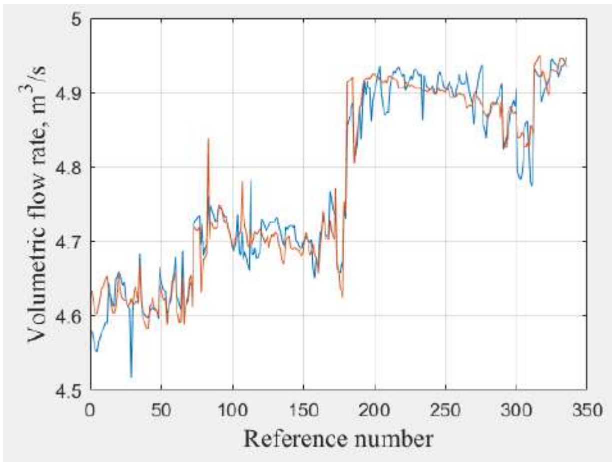


Fig. 5. Compressor volumetric flow change on the training data set

$$\sigma_{Yy} = \sqrt{\frac{\sum_{i=1}^{N} (Y - y)}{N-1}}. \qquad (29)$$

The correlation coefficient $K_{Yy}$ = 0,9867 and the standard deviation $\sigma_{Yy}$ = 0,0523 have been obtained. This results shows sufficient correlation between obtained values of the volumetric flow rate and calculated ones.

The testing results of the proposed model are showed in Fig.6.

The regression line equation between the values $y = Q_i$ and values $Y = Q_{вс}$ is obtained by the following formula:

$$y = a_0 + a_1 \cdot Y, \qquad (30)$$

where $a_0 = 0{,}0981$; $a_1 = 0{,}9792$.

The regression line, constructed by using the method of least squares, indicates a rather small deviation of the values $y = Q_i$ and values $Y = Q_{вс}$. So, the compressor mathematical model, obtained by using synthesized algorithm, has the sufficient adequacy.

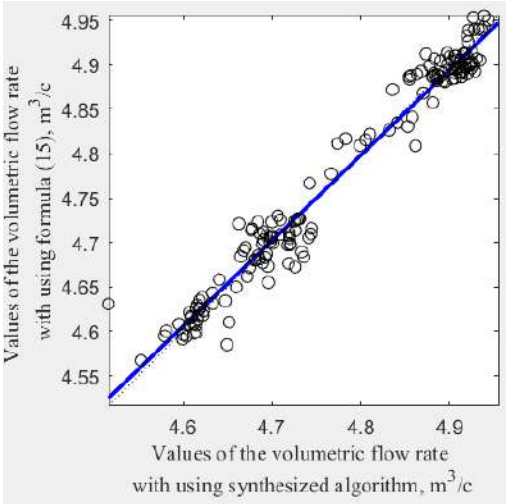


Fig. 6. Testing results of the centrifugal compressor model

## Conclusions

There is a trend in the creation of new algorithms for predicting and determining variable malfunctions, which include the failure of equipment. This is the reason for developing and improving new compressor mathematical models, which should be exact enough and suitable for typical compressor station equipment. The compressor volumetric flow rate should be monitored frequently during its operation to prevent the problems, related to any changes in the compressor operation. There is the dependence for determining the compressor volumetric flow rate at the compressor stations, but obtained values are different from real ones, so in this paper and for the first time we introduced new model to determine the compressor volumetric flow rate in real time. The algorithm of the centrifugal compressor mathematical model is developed, which is based on the weights, biases and the transfer functions used in the group method of data handling type neural networks. It is can be used for decision support system for complex control objects.

The developed compressor model was tested on the experimental data set obtained during compressor operation at the Dolyna compressor station. The correlation coefficient $K_{Yy} = 0{,}9867$ and the standard deviation $\sigma_{Yy} = 0{,}0523$ have been calculated. Obtained results confirm the operability and possibility of the compressor model implementation.

## References

1. Anastasakis,L. Mort, N. (2001) The development of self-organization techniques in modelling: a review of the group method of data handling (GMDH), *Research Report*, Department of Automatic Control & Systems Engineering, October, 38 Retrieved from https://gmdhsoftware.com/GMDH_%20Anastasakis_and_Mort_2001.pdf

2. Schmitz, D., Paige, R. F., Hartman, A., Rensink, A. (2009, June) Mapping Requirement Models to Mathematical Models in Control System Development. *5th European Conference on Model Driven Architecture – Foundations and Applications, Enschede*, 253-264. DOI:10.1007/978-3-642-02674-4_18

3. Zanoli, Z. M., Astolfi, G., Marczyk, J. (2012, June 20-22) Complexity-based methodology for Fault Diagnosis: application on a centrifugal machine. *IFAC Conference on Analysis and Control of Chaotic*, *Mexico*, 51-56. DOI:10.3182/20120620-3-MX-3012.00060

4. Lomario, D., Fattore, L., De Poli, Marczyk, J. (2007, May 14-17) A complexity-based approach to robust design and structural assessment of aero engine components. *ASME Turbo Expo Conference, Mexico*, 67-71. https://doi.org/10.1115/GT2007-27205

5. Higham, E., Perovic, S. (2001) Predictive maintenance of pumps based on signal analysis of pressure and differential pressure (flow) measurements. *Trans. Of the Institute of Measurement and Control, vol. 4, 23*, 226-248. DOI:10.1177/014233120102300402

6. Apstein, A. H., Williams, J. E., Fowcs, F., Greitzer, E. M. (2012, May 23) Active suppression of aerodynamic instabilities in turbomachines. *Proc. 10th AIAA Aeroacoustics Conf, Seattle*, USA, 86-94. https://doi.org/10.2514/3.23137

7. Albertson, F., Boden, H. (2006) Comparison of different methods to couple nonlinear source descriptions in the time domain to linear system descriptions in the frequency domain —Application to a simple valveless one-cylinder cold engine. *Journal of Sound and Vibration, vol. 291, issue 3-5*, 963-985. https://doi.org/10.1016/j.jsv.2005.07.046

8. Hrudz, V. Y., Hrudz, Y. V., Kostiv, V. V., Mykhalkiv, V. B., Tarayevskyy, O. S., Tymkiv, D. F. (2012) Technical diagnostics of pipeline systems: monograph, Liliya-NV, Ivano-Frankivsk.

9. Wood, B. M., Olsen, C. L., Hartzo, G. D., Rama, J. C., Szenasi, F. R. (1997) Development of an 11,000 r/min, 3500 hp induction motor and adjustable speed drive for refinery service. *IEEE Transactions on Inustry Applications, vol. 3, 33*, 815-825. DOI: 10.1109/28.585875

10. Galerkin, Y., Rekstin, A., Soldatova, K., Drozdov, A., Solovyeva, O., Semenovskiy, V., Marenina L. (2020) The Current State of the Engineering Method for the Optimal Gas-Dynamic Design and Calculation of Centrifugal Compressor. *Energies, vol. 13, 21*, 1-18. DOI:10.3390/en13215651

11. Kotowicz, J., Marcin, J., Brzeczek, M., Nawrat, K., Medrych, J. (2016) The methodology of the gas turbine efficiency calculation. *Archives of Thermodynamics, vol. 37, 2016*, 19-35. DOI:10.1515/aoter-2016-0025

12. Ortigueira, M. D. (2009) Comments on Modelling fractional stochastic systems as non-random fractional dynamics driven Brownian motions. *Applied Mathematical Modelling, vol. 33, 5*, 2534-2537. https://doi.org/10.1016/j.apm.2008.05.018

13. Kropyvnytska, V., Kopystynskyy, L., Sementsov, G. (2017) Development of a set of methods for preforecasting fractal time series analysis to determine the level of persistence. *Eastern-European Journal of Enterprise Technologies, vol. 3/4 (87)*, 10-17. https://doi.org/10.15587/1729-4061.2017.104425

14. Lahoida, A., Kropyvnytska, V., Humenuik, T. Sementsov, G. (2018) Modeling of dynamic stability of the well deepening process based on the catastrophe theory. *Eastern-European Journal of Enterprise Technologies, vol.4/3 (94)*, 36-46.
15. Huang, S. (2011) Immune Genetic Evolutionary Algorithm of Wavelet Neural Network to Predict the Performance in the Centrifugal Compressor and Research. *Journal of Software, vol. 6, issue 5*, 908-914.
16. Chowdhury, F. N. (2000) Input-output modeling of nonlinear systems with time-varying linear models. *IEEE Trans. on Automatic Control, 7*, 1355-1358. DOI:10.1109/9.867047
17. Onwubolu, G. C. (2008) Design of hybrid differential evolution and group method of data handling networks for modeling and prediction. *Information Sciences, vol. 178, 18*, 3616-3634. https://doi.org/10.1016/j.ins.2008.05.01
18. Jain, A., Kumar, A. (2006) An evaluation of artificial neural network technique for the determination of infiltration model parameters. *Applied Soft Computing, vol. 6, issue 3*, 272-282. https://doi.org/10.1016/j.asoc.2004.12.007
19. Gorbiychuk, M. I., Medvedchuk, V. M., Lazoriv, A. N. (2016) Analysis of Parallel Algorithm of Empirical Models Synthesis on Principles of Genetic Algorithms. *Journal of Automation and Information Sciences, vol. 48, 2*, 54-73. DOI: 10.1615/JAutomatInfScien.v48.i2.60
20. Samsudin, R., Saad, P., Shabri, A. (2011) A hybrid GMDH and least squares support vector machines in time series forecasting. *Neural Network World, vol. 21, issue 3*, 251-268. DOI:10.14311/NNW.2011.21.015
21. Korenberg, M. J. (1998) A robust orthogonal algorithm for system identification and time-series analysis. *Biological Cybernetics, vol. 60, issue 4*, 267-276.
22. Vestfálová, M. (2015) Thermodynamic properties of real gases and BWR equation of state. Retrieved from https://www.epj-conferences.org/articles/epjconf/pdf/2015/11/epjconf_efm2014_02106.pdf

**Рецензент:** д-р техн. наук проф. В.І. Шекета, Івано-Франківський національний технічний університет нафти і газу, Україна.

**Автор:** ГАРАСИМІВ Віра Михайлівна
*кандидат технічних наук, доцент кафедри*
*Івано-Франківський національний технічний університет нафти і газу*
*E-mail – Viraharasymiv78@gmail.com*
*ID ORCID: https://orcid.org/0000-0002-6613-3549*

**Автор:** ГАРАСИМІВ Тарас Григорович
*асистент кафедри*
*Івано-Франківський національний технічний університет нафти і газу*
*E-mail – tarikksm@gmail.com*

**Автор:** МОЙСЕЄНКО Олена Володимирівна
*кандидат технічних наук, доцент, доцент кафедри*
*Івано-Франківський національний технічний університет нафти і газу, Україна.*
*E-mail – olena.moiseienko@nung.edu.ua*
*ID ORCID: https://orcid.org/0000-0002-7995-2949*

## МАТЕМАТИЧНЕ МОДЕЛЮВАННЯ ЦЕНТРОБІЖНОГО КОМПРЕСОРА

В.М. Гарасимів, Т.Г. Гарасимів, О.В. Мойсеєнко
Івано-Франківський національний технічний університет нафти і газу, Україна.

*На сьогоднішній день спостерігається тенденція збільшення потужності, продуктивності та ступеня підвищення тиску газу промислових відцентрових нагнітачів разом із врахуванням зниження металоємності їхньої конструкції. Більшість відцентрових нагнітачів, які використовуються в нафтогазовій промисловості, не мають обладнання, необхідного для вимірювання об'ємної витрати, що унеможливлює оцінити їхній технічний стан під час роботи. Створення математичної моделі відцентрового нагнітача, яка дозволить оцінити його технічний стан під час експлуатації, являється актуальною науковою задачею. В роботі запропонована математична модель відцентрового нагнітача на основі методу групового врахування аргументів із використанням нейромережевого підходу. Основною його перевагою є те, що відмінно від традиційних нейронних мереж з визначеною архітектурою типу класичного багатошарового персептрона, нейронна мережа, яка побудована на основі методу групового врахування аргументів, має структуру, яка здатна змінюватись в процесі навчання. Дана модель дозволяє визначити об'ємну витрату відцентрового нагнітача як функцію його технологічних параметрів (кутова швидкість ротора, вхідний отвір компресора, і температури на виході, тиск на вході та виході компресора, атмосферний тиск).*

*Виконано верифікацію розробленої моделі на основі 336 точок даних, зібраних в робочих умовах відцентрового нагнітача природного газу (16ГЦ2-395/53-76С) Долинського лінійного виробничого управління магістральних газопроводів. Визначено структуру та параметри моделі із використанням навчальної множини експериментальних даних, поступовим генеруванням ускладнених моделей та селекції найбільш правдоподібних з них із використанням принципу зовнішнього доповнення, яке виражається у вигляді похибки отриманих моделей, одержаних з використанням перевірочної множини експериментальних даних.*

*Побудовано пряму лінії регресії з використанням методу найменших квадратів, яка показала досить мале відхилення експериментальних значень до розрахункових. Обчислено коефіцієнт кореляції та середнє квадратичне відхилення, які доводять достатню ефективність запропонованої математичної моделі.*

***Ключові слова:*** *об'ємна витрата, відцентровий нагнітач, математична модель, метод групового врахування аргументів, нейронні мережі, технологічні параметри, коефіцієнт кореляції.*