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Neural network pressure observer for a turbomechanism electromechanical system powered by a wind generator

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ABSTRACT

Ecological and economic production of electrical energy through the use of alternative energy sources is an urgent direction due to the trend of increasing prices of energy carriers used in the electrical energy production and as a result of significant damage of the energy system of Ukraine in consequence of the war on the country territory. It is worth noting that in some areas it is possible to use only autonomous power generation systems, since the laying of electrical networks in these districts is impractical and unprofitable. Usually, the mentioned systems are based on a combination of a wind or hydro turbine - drive motor, and an electric generator. Such systems are characterized by high resource, reliability, low cost, and complexity of maintenance. Sometimes people's lives and the possibility of communication with the outside world depend on the operation of an autonomous electric power generation system, which is especially important in the conditions of martial law. At the same time, the lack of stabilization of the hydraulic network pressure of the water supply system can lead to the household conditions aggravation, the emergency situations occurrence, and the technological process disruption. In view of the mentioned factors, there is a need to measure the pressure of the hydraulic network, which is possible by using technological coordinates observers built on the basis of the artificial networks theory. In the paper a modern turbomechanism electromechanical control system powered by an alternative electrical energy source under the conditions of pressure stabilization of the hydraulic network when using a technological coordinates observer, namely a pressure estimator, is proposed. A mathematical description of the main elements of the investigated system is given. A hydraulic network pressure observer based on the artificial neural networks theory is built and studied. Features of design and training of technological coordinate estimators based on neural networks with feedback are described. The operation of the sensorless system during the pressure stabilization at a given level when the resistance of the hydraulic network changes within the typical daily cycle of water consumption is considered on a specific example. The results and analysis of the investigation of the developed observer in standard and sensorless control systems are shown.

Keywords: Pump unit; pressure stabilization; voltage regulation; induction generator; observer; neural network.

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INTRODUCTION

Today, taking into account the state of war in Ukraine and significant damage or destruction of the power system, which leads to long-term fan outages, the relevant task is to use autonomous power generation systems, such as wind turbines or solar panels, as an alternative way of powering the most important and necessary nodes of the power system or consumers. The use of alternative energy sources provides not only stable power supply for individual power consumers, but also provides an opportunity to release excess generated electrical energy and reduces the load on the main power system.

Now wind turbines are also used to pump water [1]. Wind generators, mechanically connected to water supply systems, are one of the most common methods of pumping water into agricultural arable land and to satisfy the needs of livestock on farms [2]. Since the connection in this case is only electrical, the wind turbine can be located at the optimal distance and in the area where the maximum amount of wind energy can be generated, while the pump is located nearby with water or a water tank [3], [4].

Devices for measuring coordinates and technological objects parameters are an integral part of the structure of electromechanical systems of turbomechanisms automatic control. In turn, sensors that provide information about the technological coordinates of pump units are quite expensive and in many cases, they cannot be installed or replaced without interfering with the hydraulic network. The theory of estimators is widely used to reduce sensors in the system. One of the ways of technical implementation of the latter is the use of artificial neural networks, which, on the basis of already known measured coordinates, allow to observe the values of other coordinates, for example, pressure, pump performance, its mechanical power, efficiency and others [5].

LITERATURE REVIEW

Controlling of water supply systems powered by alternative energy sources, such as wind turbines, is carried out using both systems with synchronous and induction wind generators [6].

Among water supply systems with a wind generator with variable speed, two main configurations can be distinguished. The first configuration is a direct connection between the generator and the motor stator, which allows maintaining a constant speed of both machines. The main disadvantage is that the components must be selected with such parameters that they are satisfactory for each individual case. This is due to the fact that to increase the efficiency of the system, it is necessary that the characteristic load curves formed by the pump at different speeds coincide with the optimal wind generator torque curve. The second configuration is two converters, which allows the pump and the turbine to be physically separated. In this case, there is no need to precisely match the parameters of the pump and the turbine, but the converters must have sufficient capabilities to control the pump at nominal power, which significantly increases the cost of the system [7].

Recently, systems using induction generators, especially double-feed machines, have been of great interest. Double-feed machines are an alternative to permanent magnet rotary machines in wind energy conversion systems. Due to the possibility of reducing or even removing the gearbox, its use in systems with autonomous wind generators increases the reliability and level of technical and economic indicators of the electromechanical system as a whole and reduces operating costs, which is of great importance [8]. In such systems, it is also possible to implement the auxiliary power supply of the double-feed through the stator of the generator, changing the frequency and voltage of its excitation using DC/AC and AC/DC frequency converters. The presence of two converters in the system allows to include in the system an additional source of energy from other types of alternative sources, such as solar batteries [9], the use of micro-organisms to obtain energy [10], which do not require additional management [11]. The DC bus connects the main and auxiliary stators through two converters so that the pump can be powered from both sources.

Wind turbines based on induction generators with self-excitation (IG) are becoming more and more common among modern alternative power generation systems. Voltage stabilization prevents the generator from tipping over when under heavy load. The problem of voltage stabilization is relevant and can be solved in many ways. Systems with voltage controlling using an electronic load regulator (ERN) and using a static compensator (STATCOM) have become the most widespread [12], [13].

Particular attention should be paid to the issues of measuring and estimation the main pump unit parameters, since the installation of sensors in the hydraulic network leads to an increase in the cost of the system and is difficult to maintain [14]. The use of sensorless control algorithms based on the theory of artificial neural networks allows to avoid the above-mentioned problems, as well as to increase the energy efficiency of the automatic control system of turbomechanisms [15]. It is worth noting that observation systems using the artificial neural networks theory are also widely used in other technological processes and systems [16].

THE PURPOSE OF THE ARTICLE

The purpose of this work is the development and research of a technological coordinates observer, such as pressure, of a turbomechanism electromechanical control system powered by an alternative energy source, which built on the basis of the artificial neural networks theory.

MAIN PART. RESEARCH RESULTS

The research was carried out using an electromechanical system, the functional diagram of which is shown in Fig. 1.

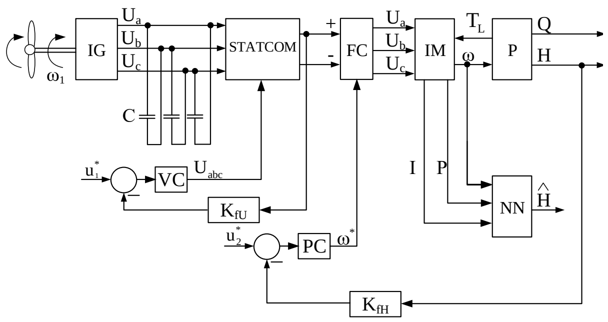

Fig. 1. **Functional diagram**
Source: **compiled by the authors**

The following designations are given in the diagram:

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IG – induction generator; STATCOM – static compensator; FC – frequency converter; IM – induction motor; P – pump unit; NN – pump pressure observer based on a neural network; u_1^*, u_2^* – tasks for voltage and pressure, respectively; VC – voltage regulator configured for the proportional-integral (PI) control law; PC – pressure regulator configured for the PI control law; K_{fU}, K_{fH} – feedback coefficients for voltage and head, respectively; ω_1 – angular velocity of the IG rotor; C – capacity of excitation capacitors; ω – pump velocity; T_L – load torque on the pump motor shaft; *P* – power of the pump drive motor; *I* – stator current module of the pump drive motor; *Q* – pump productivity; *H* – pump pressure; $\hat{H}$ – observed value of the pump pressure; ω^* – given speed; U_a, U_b, U_c – stator phase voltage; U_{abc} – given stator phase voltage.

The use of two frequency converters in the system provides an opportunity to place them optimally relative to each other and to ensure the maximum generation of electrical energy by the wind generator. The induction generator rotates by a turbine, the speed of rotation of which is assumed to be constant during the research.

The signals for controlling the keys of the STATCOM inverter come from the pulse width modulation (PWM) controller, which, depending on the value of the voltage received from the voltage regulator, gives a signal to close the keys. The voltage controller maintains a constant voltage of the IG, which leads to maintaining a constant value of the generated voltage. The output of the voltage controller is a vector containing three modulating signals used by the PWM generator to generate 6 IGBT pulses to control the inverter when the load on the generator output changes, which for the study is determined by a typical daily cycle of water consumption.

The mathematical model of an induction generator in an arbitrary coordinate system is described by the following system of nonlinear differential equations [17]:

$$\begin{aligned} \frac{d\Psi_S}{dt} &= U_S - R_S i_S - \omega_e J \Psi_S, \\ \frac{d\Psi_R}{dt} &= -R_R i_R + (p_n\omega_1 - \omega_e) J \Psi_R, \end{aligned} \tag{1}$$

where $J = \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix}$, $\Psi_S = \begin{bmatrix} \Psi_{SF} & \Psi_{SG} \end{bmatrix}^T$, $\Psi_R = \begin{bmatrix} \Psi_{RF} & \Psi_{RG} \end{bmatrix}^T$ – vectors of stator and rotor flux linkages; $i_S = \begin{bmatrix} i_{SF} & i_{SG} \end{bmatrix}^T$, $i_R = \begin{bmatrix} i_{RF} & i_{RG} \end{bmatrix}^T$ – vectors of stator and rotor currents; $U_S = \begin{bmatrix} U_{SF} & U_{SG} \end{bmatrix}^T$ – stator voltage vector; R_S and R_R – active resistances of the stator and rotor; p_n – number of pole pairs; ω_e – angular velocity of the arbitrary coordinate system F-G rotation.

A parallel battery of capacitors connected in a triangle is used for self-excitation of the IG. The capacitor battery, which is part of the static compensator, in such systems, is calculated in such a way that the IG is self-excited at the nominal load.

Excitation capacitors with capacity C are connected parallel to the stator windings, and parallel to them – the load caused by the change in the hydraulic resistance of the network in accordance with the daily cycle of water consumption by residential and communal enterprises.

Then, the equation for the voltage on the stator windings (on the excitation capacitors) is obtained on the basis of Kirchhoff's first law in the form,

$$-C\frac{dU_S}{dt} = i_S + i_L, \tag{2}$$

where $i_L = \begin{bmatrix} i_{LA} & i_{LB} \end{bmatrix}^T$ – load current vector.

To describe the drive induction motor of the pump, the classical model in the stator coordinates a-b is used [16]. The frequency converter of the pump unit is configured to work out the standard quadratic law of frequency control $U/f^2 = const$ [18]. To implement the system of pressure stabilizing of the hydraulic network at a given level, a pressure controller configured for the PI control law was used the mathematical description of which is presented in the paper [19].

Transient processes in the pump unit are described by the system of equations (3) and are presented in the structural diagram that is shown in Fig. 2.

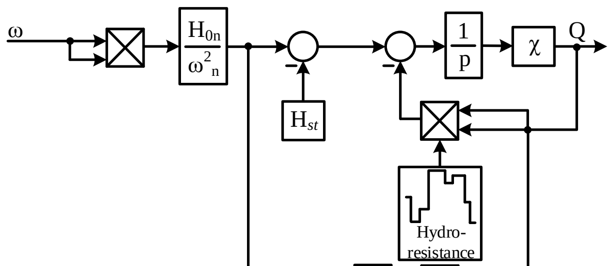

Fig. 2. **Structural diagram of the investigated pump unit**
Source: **compiled by the authors**

$$\chi \frac{dQ}{dt} = \frac{H_{0n}\omega^2}{\omega_n^2} - H_{st} - (a_n + a)Q^2,$$
$$H = \frac{H_{0n}\omega^2}{\chi\omega_n^2} - a_n Q^2, \tag{3}$$
$$T_L = \frac{\rho g Q H}{\eta\omega},$$

where: H_{0n} – nominal pressure at zero supply at the nominal speed; ω_n – nominal speed of the pump; χ – pump integration time constant; H_{st} – geodetic height of the water level; a_n – nominal hydraulic resistance of the pump; a – hydraulic resistance of the network; ρ – density of water; g – free fall acceleration; η – pump efficiency; t – time.

The work of consumers in this model is approximated by the specified hydraulic resistance in accordance with the typical water consumption graph, which is selected depending on the operating conditions and scope of application of the electromechanical system.

To work with neural networks, special attention should be paid to their mathematical description.

In the general case, the equation of neurons is described by the following expression:

$$y_i = \lambda_i \left(\sum_{j=1}^{m} x_j w_{ij} + b_i\right), \tag{4}$$

where: x_1, x_2,… x_m – neuron inputs; w_{i1},w_{i2}, …, w_{im} – weight coefficients of synaptic connections; b_i – displacement of the neuron; $\lambda_i(.)$ – activation function of the neuron.

The equations describing each neuron in the case of a two-layer neural network with 10 neurons with three inputs and feedback are written as follows:

$$\begin{aligned} &y_1 = th((Pw_{11} + \omega w_{12} + Iw_{13} + b_1 + y_1)/a_1) \\ &y_2 = th((Pw_{21} + \omega w_{22} + Iw_{23} + b_2 + y_2)/a_2) \\ &\ldots \\ &y_{10} = th((Pw_{101} + \omega w_{102} + Iw_{103} + b_{10} + y_{10})/a_{10}) \end{aligned}, \tag{5}$$

where: P, ω, I – neuron inputs; w_{i1},w_{i2}, w_{i3}, …, w_{im} – weight coefficients of synaptic connections; b_i – displacement of the neuron; a_1 – coefficient of inclination of the hyperbolic tangent function tansig.

Thus, the general equation describing the operation of the neural network for observing the pump unit pressure is written as follows:

$$\begin{aligned} \hat{H} = c(&th((Pw_{11} + \omega w_{12} + Iw_{13} + b_1 + \hat{H})/a_1)w_1 + \\ &+th((Pw_{21} + \omega w_{22} + Iw_{23} + b_2 + \hat{H})/a_2)w_2 + \\ &+th((Pw_{31} + \omega w_{32} + Iw_{33} + b_3 + \hat{H})/a_3)w_3 + \\ &+th((Pw_{41} + \omega w_{42} + Iw_{43} + b_4 + \hat{H})/a_4)w_4 + \\ &+th((Pw_{51} + \omega w_{52} + Iw_{53} + b_5 + \hat{H})/a_5)w_5 + \\ &+th((Pw_{61} + \omega w_{62} + Iw_{63} + b_6 + \hat{H})/a_6)w_6 + \\ &+th((HPw_{71} + \omega w_{72} + Iw_{73} + b_7 + \hat{H})/a_7)w_7 + \\ &+th((Pw_{81} + \omega w_{82} + Iw_{83} + b_8 + \hat{H})/a_8)w_8 + \\ &+th((Pw_{91} + \omega w_{92} + Iw_{93} + b_9 + \hat{H})/a_9)w_9 + \\ &+th((Pw_{101} + \omega w_{102} + Iw_{103} + b_{10} + \hat{H})/a_{10})w_{10} + b), \end{aligned} \tag{6}$$

where c – coefficient of inclination of the linear activation function.

Based on the above mathematical description of the electromechanical system main elements, models were implemented within the MATLAB SimPowerSystems and Simulink application package for the investigation of the pressure observer of the water supply system under conditions of pressure stabilization in the hydraulic system when powered by a wind turbine.

In general, the procedure for designing an artificial neural network is quite simple, using the Matlab2014b application package with the Neural Network editor (nntool) and Simulink. This toolbox allows to create more common neural networks.

In general, the procedure for artificial neural networks designing consists of the following steps [20]:

1. Selection of the number of hidden layers of the artificial neural network, that is, those layers located between the input of the neural network and the output layer of neurons.
2. Selection of the number of neurons in each layer.
3. Selection of the neuron activation function.
4. Network training (learning).

However, the Neural network time series tool (ntstool) is in Matlab2018b that allows to create two-layer feed-forward networks. The interface for choosing the type of the necessary neural network is presented in Fig. 3.

A feature of this toolbox is that it is possible to create a neural network with feedback in it. This form of observation is called nonlinear autoregressive with exogenous (external) input, or NARX. It can be used to identify or estimate the parameters of systems, in which models are developed to represent dynamic systems, such as chemical processes, manufacturing systems, robotics, etc.

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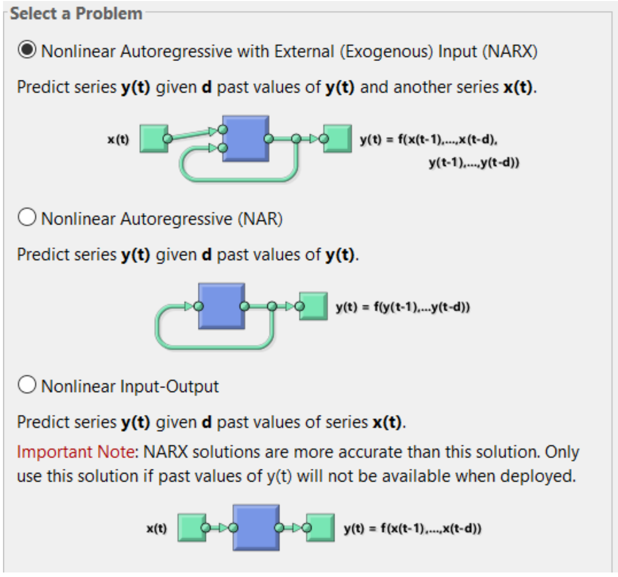


Fig. 3. **Neural network time series app**
***Source:* compiled by the authors**

The training of the neural network was based on the drive motor coordinates, such as power, current and velocity. The input and output (reference) data for neural network training were formed during the research of a closed electromechanical system by pressure. The simulation was performed with a clock frequency of 2 kHz and a basic sampling time of $1 \cdot 10^{-5}$ s. Increasing the parameters of the system simulation will increase the accuracy of the training arrays, but will lead to an increase in the training time and, as a result, the subsequent possible overflow of the computer's random access memory. After selecting the input and output arrays for training the system, it is necessary to configure the distribution of data for training, validation and testing. Settings are presented in Fig. 4.

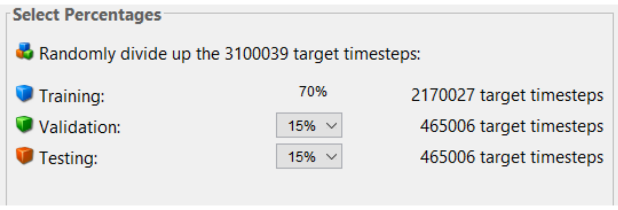


Fig. 4. **Validation and test data**
***Source:* compiled by the authors**

The validation and test data sets are each set to 15 % of the original data.

With these settings, the input vectors and target vectors will be randomly divided into three sets as follows:

• 70 % will be used for training;

• 15 % will be used to validate that the network is generalizing and to stop training before overfitting;

• the last 15 % will be used as a completely independent test of network generalization.

The next step is the formation of the neural network structure. As practice shows, the more neurons are selected per layer, the higher the accuracy of the neural network. However, the system becomes much more complex as the level required for layer description increases. An important step is to determine the optimal number of neurons and delays for creating a specific neural network.

The standard NARX network is a two-layer feedforward network with a sigmoid transfer function in the hidden layer and a linear transfer function in the output layer. This network also uses tapped delay lines to store previous values of the x(t) and y(t) sequences. However, for efficient training this feedback loop can be opened.

Because the true output is available during the training of the network, it is possible to use the open-loop architecture shown in Fig. 5, in which the true output is used instead of feedback to the estimated output. This has two advantages. The first is that the inputs to the feedforward network are more accurate. The second is that the resulting network has a purely feedforward architecture, and therefore a more efficient algorithm can be used for training.

The default number of hidden neurons is set to 10. The default number of delays is 2. It is possible to adjust these numbers if the network training performance is poor.

The network of 2 layers of 10 neurons in the first layer and 1 in the output layer was formed for investigation. The architecture of the neural network is presented in Fig. 5.

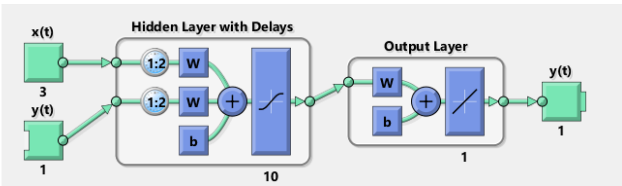
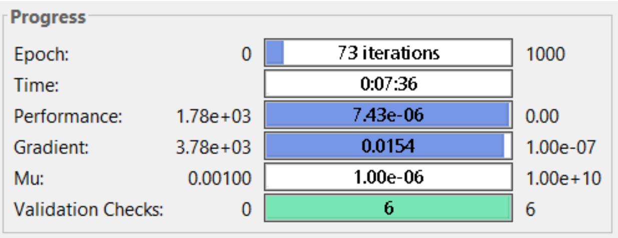


Fig. 5. **Neural network architecture**
***Source:* compiled by the authors**

The next step is choosing a neural network training method. The Levenberg-Marquardt training method (trainlm) was chosen to implement the pressure observer. This algorithm typically requires more memory but less time. Training automatically stops when generalization stops improving, as indicated by an increase in the mean square error of the validation samples. The training progress is shown in Fig. 6.

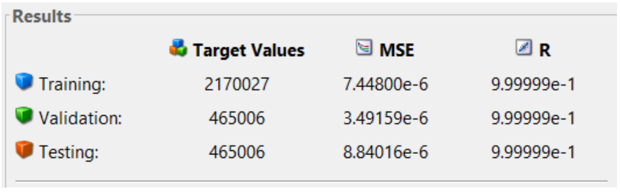


Progress

Epoch:	0	73 iterations	1000
Time:		0:07:36	
Performance:	1.78e+03	7.43e-06	0.00
Gradient:	3.78e+03	0.0154	1.00e-07
Mu:	0.00100	1.00e-06	1.00e+10
Validation Checks:	0	6	6

Fig. 6. **Training progress**
Source: **compiled by the authors**

The maximum training errors and regression coefficients, which indicate the performance of the neural network and the possibility of using it as a pressure observer for the selected pump, are presented in Fig. 7. Additional training outcomes that can be generated using the selected tools are shown in Fig. 8, Fig. 9 and Fig. 10.



Results

	Target Values	MSE	R
Training:	2170027	7.44800e-6	9.99999e-1
Validation:	465006	3.49159e-6	9.99999e-1
Testing:	465006	8.84016e-6	9.99999e-1

Fig. 7. **Results of neural network formation**
Source: **compiled by the authors**

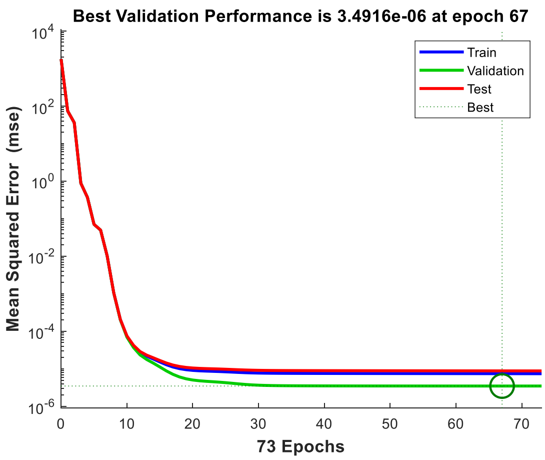


Fig. 8. **Neural network training performance**
Source: **compiled by the authors**

Fig. 10 displays the error autocorrelation function. The graph describes how the prediction errors are related in time. For a perfect prediction model, there should only be one nonzero value of the autocorrelation function, and it should occur at zero lag (mean squared error). If there is significant correlation in the prediction errors, then it should be possible to improve the prediction – perhaps by increasing the number of delays in the tapped delay lines being reproduced. If more accurate results are desired, the network can be retrained.

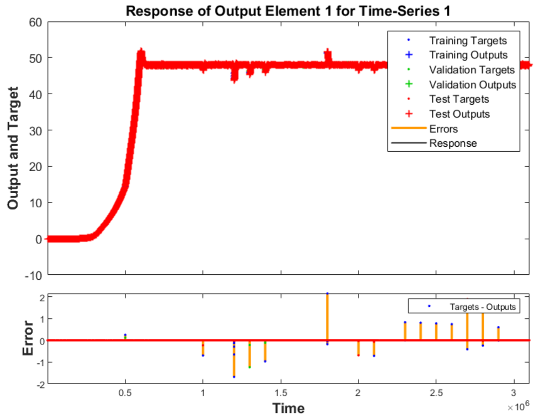


Fig. 9. **Neural network training time-series response**
Source: **compiled by the authors**

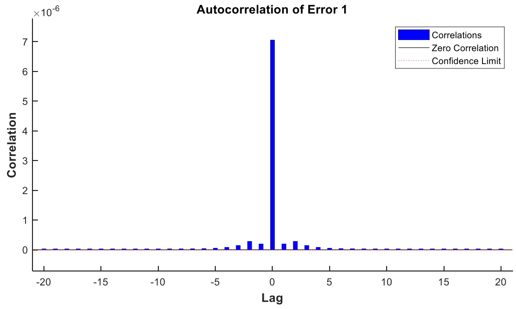


Fig. 10. **Neural network training error autocorrelation**
Source: **compiled by the authors**

One of the typical schedules of water consumption within the daily water supply cycle of residential buildings was adopted for research [19], [20]. The schedule of changes of the network hydraulic resistance is shown in Fig. 11. The daily cycle begins with 5 s, since it is necessary to accelerate the generator and the motor first. The daily cycle is conventionally divided into 4 main periods: morning (6-12) hours, daytime (12-17) hours, evening (17-21) hours and night (21-6) hours. The morning and evening periods are the busiest, so the value of the network hydraulic resistance is the lowest. The gradual nature of the network hydraulic resistance change is due to the fact that the processes in fluid transportation systems have minor fluctuations, which leads to an increase in the accuracy of training arrays for the neural network of the pressure estimator, but does not have a significant effect on other system parameters. The increase in training arrays, in turn, leads to an increase in the complexity of modelling such processes, both in terms of time and the use of memory of the computing device [22].

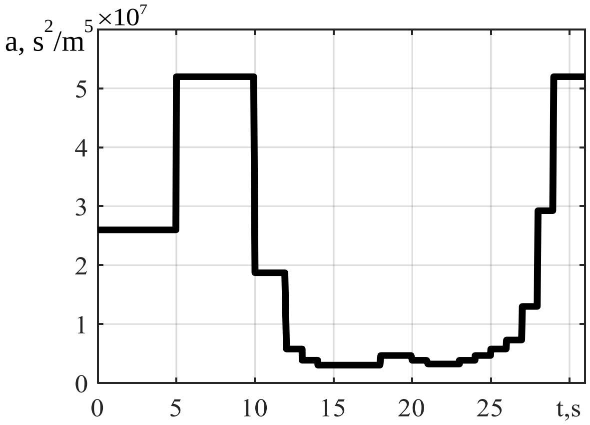


Fig. 11. **Graph of hydraulic resistance of the system**
Source: **compiled by the authors**

The investigations were conducted for a specific unit, in which the power of the induction generator is 5.5 kW, the induction drive motor is 4 kW, and the pump is 3.7 kW. The given pressure stabilization level is 48 m, which is the nominal pressure for the pump selected for the research.

Simulation were carried out for the following algorithm of operation of an induction generator with self-excitation and a pump unit motor:

– from 0 s to 0.1 s, the IG accelerates to a speed of 157 rad/s, with a full nominal load of 5.5 kW connected to the system outputs;

– from 0.1 s to 5 s, the drive motor of the pump accelerates to the nominal speed of 157 rad/s at the nominal load value of the hydraulic network;

– from 4.5 s to 5 s, the water, which rising to the given pressure level, overcomes the amount of load caused by the static pressure H_{st}, which presses from top to bottom;

– from 5 s to 30 s, the load changes corresponding to the daily cycle of water consumption, according to the hydraulic resistance change schedule (Fig. 11).

The investigation results of the pump unit and drive motor are shown in Fig. 12 and Fig. 13.

From the graphs of the transient processes of the pump unit (Fig. 12) it is seen that the pressure controller works out the set value with a dynamic error of no more than 1 % while the hydraulic resistance changes. This value of the dynamic error satisfies the requirements of technological and residential and communal consumers. However, the character of the error of working out the given pressure is due to the discrete hydraulic resistance change. The pump unit and the drive motor operate in nominal modes in the morning and evening periods, when the pump productivity reaches its maximum value.

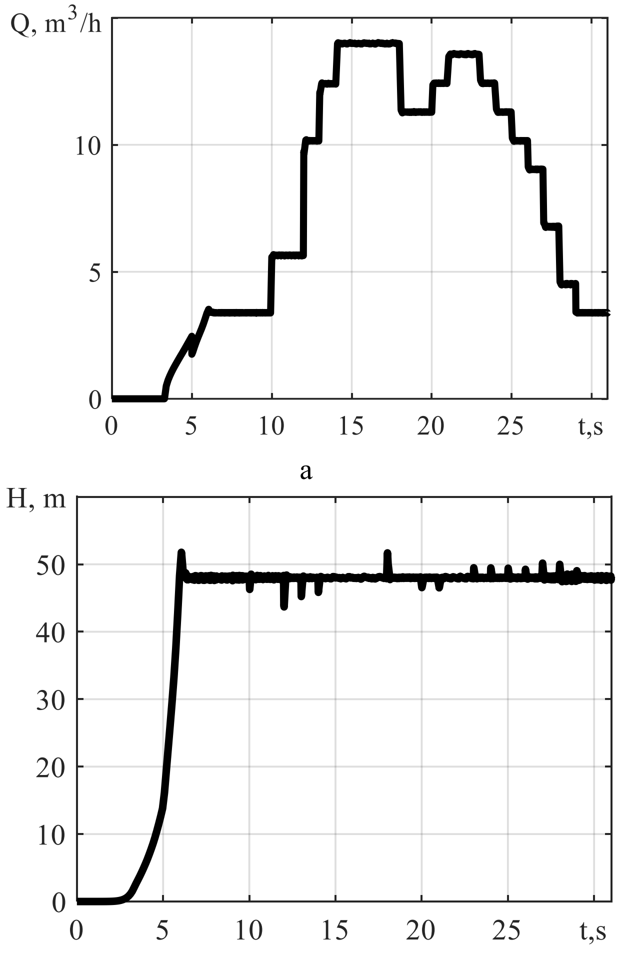


Fig. 12. **Transient processes of the pump unit without the pressure observer: a – productivity; b – pressure**
Source: **compiled by the authors**

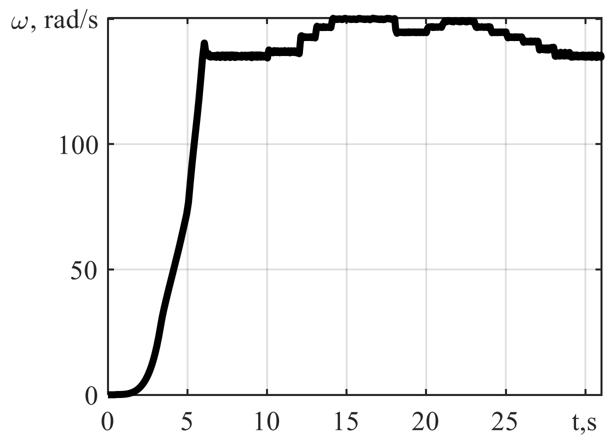
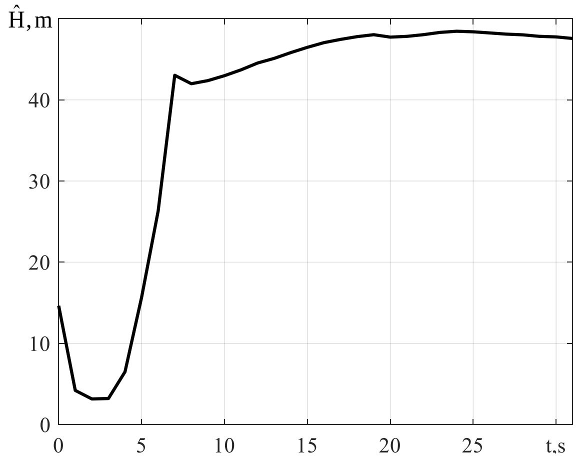


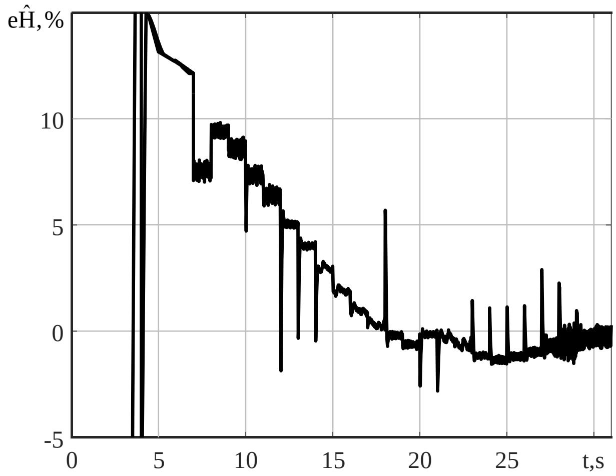
Fig. 13. **Transient processes of the drive motor: angular velocity of the motor**
Source: **compiled by the authors**

With the help of a voltage controller, the output linear load voltage is stabilized at 510 V. This justifies the fact that the implementation of the proposed system allows maintaining the value of the output voltage at a constant nominal level, despite the change of the network hydraulic resistance.

The results of the work of the pump installation pressure observer, built on the basis of an artificial neural network with feedback, are presented in Fig. 14, where $\hat{H}$ – value of the observed pump pressure; $e\hat{H}(\%) = H - \hat{H}$ – pressure observation error.



a



b

Fig. 14. **Transient processes of the pressure observer:**
a – value of the observed pressure of the pump; b – pressure observation error
***Source:* compiled by the authors**

Fig. 14 shows that the pressure estimator works with quite high accuracy.

At the time when the self-excitation of the wind generator occurs and during periods of low loading of the hydraulic network, the observer works with insufficient accuracy. However, at the moment of time from 7 s to 30 s, when the load changes corresponding to the daily cycle of water consumption, the error of the head estimation reaches a value of up to 10 %, which is acceptable in such systems. Dynamic observation errors are caused by a sudden change in load. This estimator of pump parameters can be used in the future to implement sensorless control systems for turbomechanisms powered by an alternative source of electricity.

To investigate the possibility of implementing sensorless control through the use of a pressure observer, a system was used, the functional diagram of which is shown in Fig. 15. The results of the research are shown in Fig. 16, where $\hat{H}$ – value of the observed pressure of the pump; $\tilde{\hat{H}}(\%) = H - \hat{H}$ – pressure observation error.

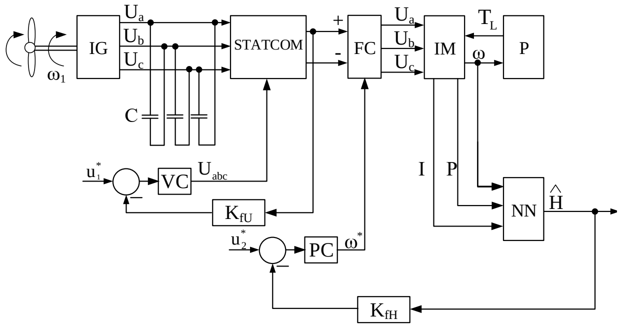


Fig. 15. **Functional diagram for the investigation of the sensorless control**
***Source:* compiled by the authors**

From Fig. 16, it is seen that when investigating the head stabilization system using the pressure estimator signal as feedback, the error of working out the set pressure does not exceed 5 %, which may be acceptable for some technological process requirements. Comparing the sensorless control system and when using a pressure estimation, the pressure observation error ranges from 0% to 8%. Dynamic errors are caused by a discrete change on the network hydraulic resistance. When the generator is self-excited, the estimator does not work, so the observation error exceeds the permissible 10 %. It is recommended not to use this data. Therefore, the conducted research showed that the developed pressure observer can be used in pressure stabilization systems of hydraulic networks of an electromechanical turbomechanism control system powered by an alternative energy source, to implement sensorless control systems. To increase the accuracy of the estimation of technological coordinates, additional retraining of the neural network or search for the optimal number of neurons and delays during network formation is possible, while the pressure stabilization system will work more accurately and reliably.

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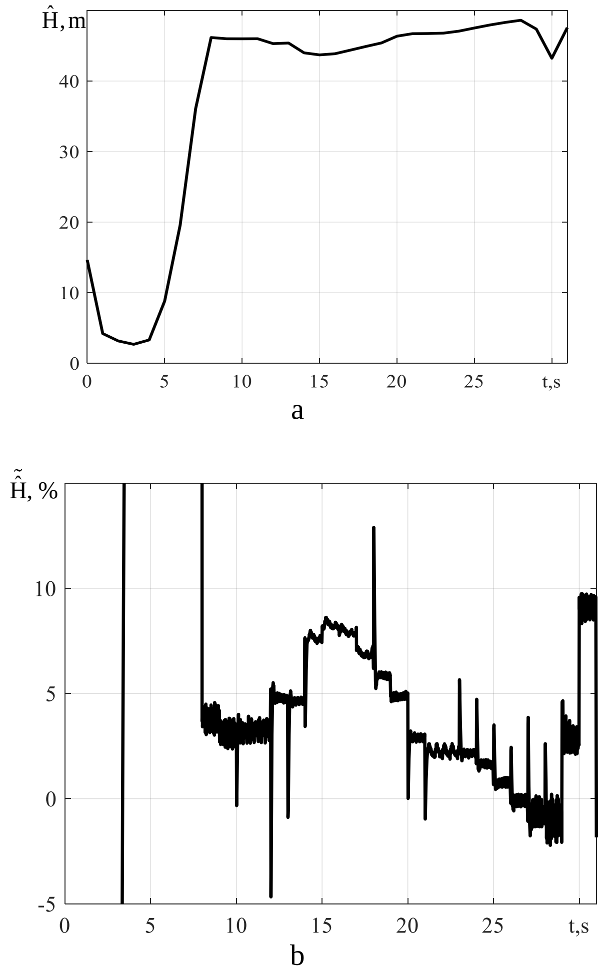

Fig. 16. **Transient processes of the sensorless control system:**
a – value of the observed pressure of the pump; b – pressure observation error
Source: **compiled by the authors**

CONCLUSIONS

Based on the results of the research, the following conclusions can be drawn:

1. The developed system allows to stabilize the hydraulic network pressure and the value of the input voltage at the given levels when the hydro resistance changes within the daily cycle of water consumption. At the same time, the dynamic error of working out the system pressure does not exceed 1 %.

2. The design and training of the pump unit pressure observer was carried out on the basis of the theory of artificial neural networks, which makes it possible to implement the principles of sensorless control of turbomechanisms. The use of such an estimator will reduce the cost of the system because of removing pressure sensors from the system. The chosen method of forming a neural network using feedback allows investigating dynamic processes with high accuracy. The observation error of technological coordinates does not exceed 10 %. The dynamic error of estimation is caused by a step-like change of the hydraulic resistance of the network.

3. The use of a pressure observer for the implementation of a sensorless water supply system in conditions of head stabilization is possible for technological processes that allow an error of working out the pressure at a given level of up to 5 %. The pressure observation error in the sensorless control system ranges from 0% to 8 %, which is admissible both for satisfying technological requirements and for measuring network parameters when using control measuring devices.

4. In view of the analysis of the conducted researches, it is possible to recommend using the obtained results both in the design of new and in the reconstruction of existing control systems of pump units powered by a wind turbine with an induction generator with self-excitation, provided that the wind turbine velocity is unchanged.

5. The developed neural network can be implemented programmatically on the basis of a field-programmable gate array, such as the FPGA Cyclone V, which has an extremely high speed compared to other controllers, which in turn will allow evaluating technological coordinates in real time, even in dynamic processes, without significant time delays. Such a solution will increase the speed and accuracy of working out the given pressure level.

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Нейромережевий оцінювач тиску для електромеханічної системи турбомеханізмів з живленням від вітрогенератора

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АНОТАЦІЯ

Екологічне та економічне отримання електричної енергії за рахунок використання альтернативних джерел енергії є актуальним напрямом у зв'язку з тенденцією подорожчання енергоносіїв, які використовуються при виробництві електричної енергії, та у наслідок значних пошкоджень енергосистеми України у результаті війни на території країни. Варто зазначити, що в деяких районах можливим є використання лише автономних систем генерування електричної енергії, оскільки прокладання електричних мереж в цих місцевостях є недоцільним та нерентабельним. Зазвичай згадані системи базуються на поєднанні вітро-, або гідро- турбіни – привідного двигуна, та електричного генератора. Такі системи відзначаються високим ресурсом і надійністю, низькою собівартістю і складністю обслуговування. Іноді від роботи автономної системи генерування електричної енергії залежить життя людей та можливість зв'язку із зовнішнім світом, що є особливо важливим в умовах воєнного стану. Разом з тим відсутність стабілізації напору гідравлічної мережі системи водопостачання може призвести до погіршення побутових умов, виникнення аварійних ситуацій, зриву технологічного процесу. З огляду на зазначені фактори, виникає необхідність вимірювання тиску гідромережі, що можливе за допомогою використання оцінювачів технологічних координат, побудованих на базі теорії штучних мереж. У роботі запропоновано сучасну електромеханічну систему керування турбомеханізмом, що живиться від альтернативного джерела електричної енергії, в умовах стабілізаційї напору гідравлічної мережі при використанні оцінювача технологічних координат, а саме оцінювача тиску. Наведено математичний опис основних елементів досліджуваної системи. Побудовано і досліджено оцінювач тиску гідравлічної мережі на основі теорії штучних нейронних мереж. Описано особливості проєктування та навчання оцінювачів технологічних координат на базі нейронних мереж із зворотними зв'язками. Розглянуто на конкретному прикладі роботу бездавачевої системи при стабілізації напору на заданому рівні при зміні опору гідравлічної мережі в межах типового добового циклу споживання води. Показано результати та аналіз дослідження розробленого оцінювача в системах стандартного та бездавачевого кервуваннях.

Ключові слова: насосний агрегат; стабілізація тиску; регулювання напруги; асинхронний генератор; оцінювач; нейронна мережа

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