

INVESTIGATION OF A SENSORLESS WATER SUPPLY SYSTEM FOR EXCESS ENERGY REDISTRIBUTION FROM WIND TURBINE

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Environment-friendly and cost-effective generation of electricity from alternative sources is becoming particularly relevant in the context of rising energy prices for electricity generation, as well as due to the significant damage to Ukraine's energy system caused by the war. In certain areas, only stand-alone power generation systems can be used, as it is impractical and unprofitable to lay power grids in these areas. Such systems are usually based on a combination of wind or hydro turbines, drive motors and electric generators. It is characterised by high reliability, long service life, low cost and ease of maintenance. In times of military emergency, the operation of autonomous systems can be critical for people's lives and communication with the outside world. In addition, in such systems, the main consumers of electricity do not use the entire resource of energy generated by the wind turbine. Therefore, the issue of redistributing excess energy is relevant and can be solved by connecting a water supply system to provide additional potable water to consumers. At the same time, pressure instability in the hydraulic water supply network can worsen living conditions and lead to accidents and disruptions in technological processes.

In connection with these challenges, there is a need to measure and stabilise the pressure in the hydraulic network, which can be done using observers of technological coordinates developed on the basis of the theory of artificial neural networks. The paper proposes a modern electromechanical control system for a turbomechanism powered by an alternative source of electrical energy, with a focus on stabilising the pressure in a hydraulic network using a pressure observer.

A mathematical description of the main elements of the investigated system is given. The pressure estimator of the hydraulic network is built on the basis of artificial neural networks with a modified structure with feedback. The paper considers the operation of a sensorless pressure stabilisation system during changes in hydraulic resistance within the daily water consumption cycle with redistribution of excess energy generated by a wind turbine. The results and analysis of the developed estimator in sensorless control systems powered by a wind turbine with an electronic load controller are presented.

Key words: pump unit, sensorless control, wind turbine, artificial neural network, pressure stabilisation, pressure observer.

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ДОСЛІДЖЕННЯ БЕЗДАВАЧЕВОЇ СИСТЕМИ ВОДОПОСТАЧАННЯ ПРИ ПЕРЕРОЗПОДІЛІ НАДЛИШКОВОЇ ЕНЕРГІЇ ВІД ВІТРОУСТАНОВКИ

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Екологічні та економні способи отримання електричної енергії з використанням альтернативних джерел набувають особливого значення з огляду на зростання цін на енергоносії, які використовуються для виробництва електрики, а також через значні пошкодження енергосистеми

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України внаслідок війни. В окремих районах можливе застосування лише автономних систем генерування електричної енергії, оскільки прокладання електричних мереж у цих місцевостях є недоцільним і нерентабельним. Такі системи зазвичай базуються на поєднанні вітро- або гідротурбін, при-водних двигунів та електричних генераторів. Вони характеризуються високою надійністю, тривалим терміном експлуатації, низькою собівартістю та простою обслуговування. В умовах воєнного стану робота автономних систем може бути критично важливою для життя людей і забезпечення зв'язку з зовнішнім світом. Також в таких системах основними споживачами електричної енергії використовується не весь ресурс виробленої вітроустановкою енергії. Тому питання перерозподілу надлишкової енергії є актуальним та може вирішуватися підключенням системи водопостачання для забезпечення додаткових потреб споживачів. Водночас нестабільність тиску в гідравлічній мережі водопостачання може погіршити побутові умови, призвести до аварій і збоїв у технологічних процесах.

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Через ці виклики виникає потреба у вимірюванні та стабілізації тиску в гідромережі, що можливо здійснити за допомогою оцінювачів технологічних координат, розроблених на основі теорії штучних нейронних мереж. У роботі запропоновано сучасну електромеханічну систему керування турбомеханізмом, що живиться від альтернативного джерела електричної енергії, з акцентом на стабілізацію тиску в гідравлічній мережі за допомогою оцінювача тиску.

Наведено математичний опис основних елементів досліджуваної системи. Оцінювач тиску гідровлічної мережі побудовано на основі штучних нейронних мереж із модифікованою структурою зі зворотнім зв'язком. Розглянуто роботу бездавачевої системи стабілізації тиску під час змін у гідровлічному опорі протягом добового циклу споживання води при перерозподілі надлишкової енергії, отриманої внаслідок живлення від вітроустановки. Презентовано результати та аналіз роботи розробленого оцінювача в системах бездавачевого керування, що живиться від вітроустановки з електронним регулятором навантаження.

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Ключові слова: насосна установка, бездавачеве керування, вітроустановка, штучна нейронна мережа, стабілізація напору, оцінювач тиску.

The list of used symbols and abbreviations:

ELC – electronic load controller

PU – pump unit

SEG – self-excited induction generator

Background. Modern technologies in the field of electricity generation provide an extremely important contribution to the sustainable development of society and its infrastructure. Electricity is a key resource for the functioning of various sectors of the economy, including industry, transport, agriculture, services and household consumers. A stable supply of electricity is essential for the smooth operation of both small businesses and large production complexes. In addition, electricity powers critical infrastructure facilities, including medical institutions, water and heat supply systems, transport networks, and information and communication systems. Thus, the stability of these facilities directly depends on the reliability of electricity generation and supply systems [1].

Electricity generation systems can be based on the use of various energy sources, which can be divided into two main categories: non-renewable and renewable. The first category includes fossil fuels such as coal, natural gas and oil. These sources have historically been the main ones for electricity generation, as they have high energy density and can provide a stable and constant supply of energy [2], [3]. However, they also have significant disadvantages, including high levels of environmental pollution due to green-

house gas emissions, which contribute to global climate change.

At the same time, renewable energy sources, such as wind, solar, hydropower and biomass, are becoming increasingly widespread due to their environmental friendliness. They do not cause significant emissions of harmful substances and do not deplete natural resources, making them a more sustainable choice for the future [4], [5]. However, their efficiency depends on many factors, including natural conditions (wind or sunlight), which can affect the stability of electricity supply. The choice of a specific source for an electricity generation system depends on factors such as geographical location, resource availability, economic costs of installation and operation, and environmental impact.

Typical power generation systems, regardless of the source used, have a number of common components. These include energy sources, energy conversion devices (e.g. turbines or photovoltaic panels), power generators, management and control systems, and electricity distribution and transmission systems. Depending on the type of system, it may include a variety of technical components, such as internal combustion engines, wind turbines, solar panels,

batteries and other devices that convert energy from a primary source into electricity.

In recent years, alternative power generation technologies, including wind turbines, have gained special attention as one of the most promising forms of renewable energy. Wind turbines using self-excited induction generators (SEGs) provide efficient electricity generation using the kinetic energy of the wind. However, one of the main challenges associated with their operation is the need to stabilise the voltage in the system to prevent failures during heavy loads [6]. In the case of unstable voltage, there may be problems with generator shutdowns, which in turn leads to interruptions in electricity supply.

Various technical solutions are proposed to solve the problem of voltage stabilisation, among which the use of electronic load controllers (ELCs) is particularly effective [7], [8]. These devices allow adjusting the voltage in the system by automatically adjusting electrical parameters, which ensures stable operation of the generator even under variable loads. One of the important advantages of such solutions is the ability to use excess electricity to power auxiliary systems, such as water supply systems, which can use this energy for irrigation, water injection or other needs. Thus, the introduction of such solutions not only improves the efficiency of wind turbines, but also contributes to a more rational use of available energy resources.

Meanwhile, ensuring high-precision and efficient control of the parameters of process facilities is a critical task in modern electromechanical automation systems, in particular in the field of turbo-mechanism control. In many cases, the installation of traditional sensors to measure various parameters can be technically difficult and financially burdensome [9]. For example, in hydraulic systems, where parameters such as pressure, fluid flow, rotational speed, and other coordinates need to be monitored, a large number of sensors significantly increases the cost of the system and complicates its installation and operation. To optimise such processes and reduce costs, parameter estimators are widely used [10]. Estimators allow determining certain coordinates based on information that is already available and accessible in the system or values from other measuring devices [11].

One of the promising approaches to the implementation of observers is the use of artificial neural networks [12], [13]. They are capable of learning from a large amount of input data, which makes it possible to estimate parameters that cannot be directly measured. Low- and medium-level logic controllers can be used for their implementation, which makes this approach flexible and affordable [14].

In turbomechanism control systems, neural networks can be used to estimate parameters such as pressure, performance, mechanical power, and efficiency based on a limited number of input signals [15]. This can significantly improve the efficiency of control, monitoring and optimisation of turbo-mechanisms, while reducing the cost of installing and maintaining sensors.

The use of artificial neural networks in turbomechanism control systems is a relevant and promising area of research, as it not only provides more accurate control and management, but also significantly reduces the cost of traditional measurement and maintenance equipment.

Research objective. The aim of the paper is to investigate a sensorless water supply system with a modified pressure observer with feedback, powered by excess electrical energy generated by a wind turbine using an electronic load controller.

The research methods are mathematical modelling in the MATLAB application package, namely the use of Simulink and ntstool.

Presenting of main materials. In general, the SEG voltage stabilisation system using an ELC includes a ballast resistor that acts as a ballast load [16].

The functional diagram of a sensorless turbomechanism control system that uses a pressure observer based on a modified neural network with feedback, powered by a wind turbine generator through an electronic load controller, is shown in Fig. 1.

In Fig. 1, an induction generator is connected to a load that can vary from 0 % to 100 % of its rated value during operation. In parallel with the generator and the load, the ELC is connected, which consists of a rectifier, a filtering capacitor (C_{ELC}), and a ballast load, which is represented by the water supply system under the condition of stabilising the pressure in the network.

The SEG rotor is driven by the wind turbine at a constant velocity, regardless of changes in wind speed. At the same time, the wind velocity can vary from the nominal to the critical one. A capacitor bank connected in parallel according to the 'delta' scheme is used to ensure self-excitation of the SEG. The capacity of this battery is calculated in such a way that the self-excitation process is guaranteed when the rated load is connected to the generator. For a more accurate determination of the required capacity, a preliminary calculation of the SEG self-excitation limits in the coordinates 'capacity - rotational speed - load' is performed, as well as an analytical determination of the static voltage characteristics of the generator [17].

In Fig. 1. the following notations are introduced: IG – induction generator; FC – frequency converter; IM – induction motor; PU – pump unit; NN – pump pressure observer based on a neural network; u_2^* – task for pressure; PC – pressure regulator configured for the PI control law; K_{fh} – feedback coefficient for and pressure; 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; $\hat{H}$ – observed value of the pump pressure; ω^* – given speed; U_a, U_b, U_c – stator phase voltage; U_{abc} – given stator phase voltage.

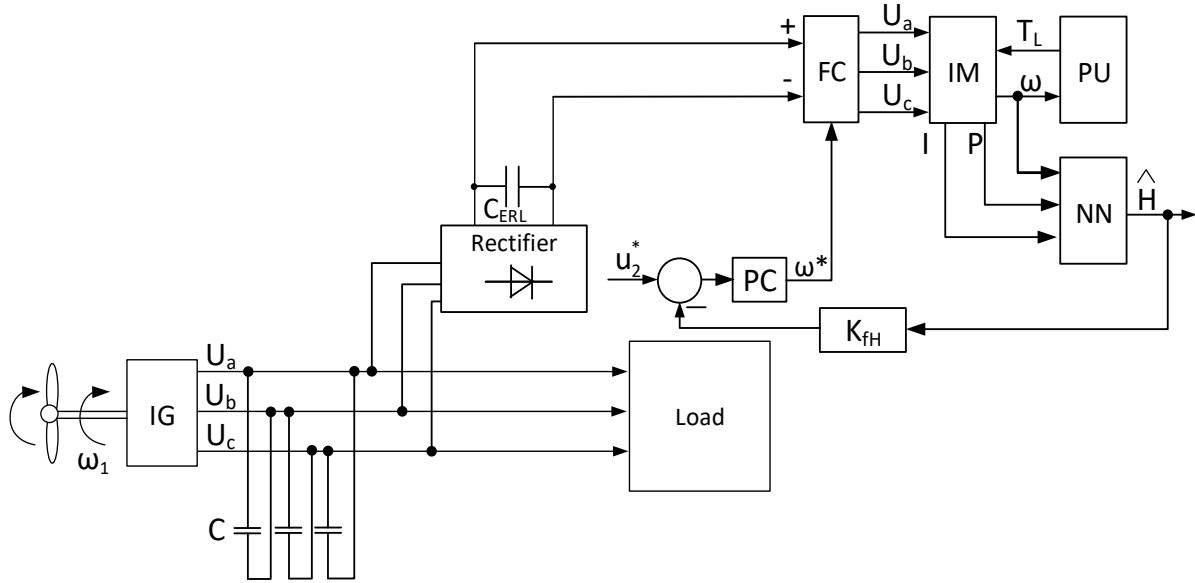


Fig. 1. Functional diagram for the investigation of a sensorless control system for the turbomechanism

One of the key functions of the ELC is to maintain a constant load on the generator set, which ensures a constant output voltage. In case of load changes in the system, the ballast load, which is realised through the pumping system, is automatically connected, keeping the total power supplied to the generator unchanged. This avoids voltage fluctuations and ensures stable operation of the generator [18], [19].

$$P_{\text{total}} = P_L + P_{\text{bal}}, \quad (1)$$

where P_{total} – the total electrical power at the generator; P_L – the electrical power consumed by the load connected to the SEG; P_{bal} – the electrical power consumed by the ballast load.

For further research, the method of mathematical modelling based on a mathematical description of the main elements of the system was used.

The mathematical model of SEG, represented in an orthogonal coordinate system rotating at an arbitrary velocity, is described by a system of nonlinear differential equations [20]:

$$\begin{aligned} \frac{d\Psi_1}{dt} &= U_1 - R_1 i_1 - \omega_e J \Psi_1, \\ \frac{d\Psi_2}{dt} &= -R_2 i_2 + (p_n \omega_1 - \omega_e) J \Psi_2, \end{aligned} \quad (2)$$

where

$$J = \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix}, \Psi_1 = [\Psi_{1d} \quad \Psi_{1q}]^T, \Psi_2 = [\Psi_{2d} \quad \Psi_{2q}]^T -$$

vectors of stator and rotor flux linkages; $i_1 = [i_{1d} \quad i_{1q}]^T$,

$i_2 = [i_{2d} \quad i_{2q}]^T$ – vectors of stator and rotor currents;

$U_1 = [U_{1d} \quad U_{1q}]^T$ – stator voltage vector; R_1, R_2 – active

resistances of the stator and rotor; p_n – number of pole pairs; ω_e – angular velocity of rotation of an arbitrary coordinate system d-q.

The mathematical model of the induction pump motor is based on the classical system in the stator a-b coordinates [21]. The frequency converter of the PU is configured in accordance with the quadratic frequency control law [22]. To maintain a stable pressure in the hydraulic network, a pressure regulator is used that implements the PI control law; details of the mathematical description of this regulator can be found in [23].

The dynamics of transient processes in a single-unit PU, taking into account the hydraulic network, is described by the system of equations [24]:

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

where Q – pump productivity; H – pump pressure; 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.

In the model of a water supply system, the operation of consumers is approximated by a given hydraulic resistance determined on the basis of a typical water flow curve,

which is selected depending on the operating conditions and the scope of the electromechanical system.

When modelling neural networks, special attention should be paid to their mathematical description. In general, the neuronal equation is described as follows [12]:

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

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

To solve the problem of estimating technological parameters in a continuous conveying system, the NARX neural network with feedback was chosen. The modified structure

$$\begin{aligned} \hat{H} = & c(\text{th}((Pw_{11} + \omega w_{12} + lw_{13} + b_1 + \hat{H})/a_1)w_1 + \text{th}((Pw_{21} + \omega w_{22} + lw_{23} + b_2 + \hat{H})/a_2)w_2 + \\ & + \text{th}((Pw_{31} + \omega w_{32} + lw_{33} + b_3 + \hat{H})/a_3)w_3 + \text{th}((Pw_{41} + \omega w_{42} + lw_{43} + b_4 + \hat{H})/a_4)w_4 + \\ & + \text{th}((Pw_{51} + \omega w_{52} + lw_{53} + b_5 + \hat{H})/a_5)w_5 + \text{th}((Pw_{61} + \omega w_{62} + lw_{63} + b_6 + \hat{H})/a_6)w_6 + \\ & + \text{th}((HPw_{71} + \omega w_{72} + lw_{73} + b_7 + \hat{H})/a_7)w_7 + \text{th}((Pw_{81} + \omega w_{82} + lw_{83} + b_8 + \hat{H})/a_8)w_8 + \\ & + \text{th}((Pw_{91} + \omega w_{92} + lw_{93} + b_9 + \hat{H})/a_9)w_9 + \text{th}((Pw_{101} + \omega w_{102} + lw_{103} + b_{10} + \hat{H})/a_{10})w_{10} + b), \end{aligned} \quad (5)$$

where c – coefficient of inclination of the linear activation function; P, ω, l – neuron inputs (power, velocity, stator current module); $w_{i1}, w_{i2}, w_{i3}, \dots, w_{im}$ – weight coefficients of synaptic connections; b_i – displacement of the neuron; a_1 – coefficient of inclination of the hyperbolic tangent function.

Further training of the neural network for the implementation of the pressure observer was carried out using the Levenberg-McWardt method (trainlm) to solve the problem of function approximation [25], using the MATLAB ntstool application package.

Based on the above mathematical description of the key elements of the electromechanical system, a model was created in the MATLAB SimPowerSystems and Simulink environments. The model is used to study a water supply system with a modified structure of the pressure estimator under conditions of stabilisation of the head in the hydraulic system when powered by excess energy generated by a wind turbine (Fig. 1). The modelling was carried out for an installation with the following parameters: the power of the SEG was 5.5 kW, the induction drive motor was 4 kW, and the pump was 3.7 kW.

One of the typical water consumption patterns during the daily cycle in residential water supply systems was chosen for the research [23], [26]. The graph of changes in the hydraulic resistance of the network is shown in Fig. 2. The start of the daily cycle is 5 s earlier, as the generator and engine must first be accelerated. Conventionally, the cycle is divided into four main phases: morning (6:00-12:00), daytime (12:00-17:00), evening (17:00-21:00) and nighttime (21:00-6:00). The highest load on the system occurs in the morning and evening, when the hydraulic resistance of the network is minimal. The gradual nature of the resistance

of the coordinate estimator improves the accuracy of determining the output parameter under conditions of variable dynamic influences, in particular, the hydraulic resistance of the network. Neural networks with feedback can function with incomplete or noisy data, efficiently processing large amounts of information and performing distributed processing on multiple nodes, which makes them suitable for working with large-scale data sets.

For investigation, a neural network consisting of two layers was used: the first layer with 10 neurons and the output layer with 1 neuron. The equations describing the functioning of neurons in a two-layer network with 10 neurons, three input signals and feedback for the tasks of estimating the pressure in a pumping unit are as follows:

change is explained by the fact that processes in liquid transport systems are subject to minor fluctuations. This helps to improve the accuracy of training sets for the neural network that estimates pressure, although there is no significant impact on other system parameters. The increase in the amount of training data, however, complicates the modelling of such processes both in the time dimension and in terms of memory usage of computing devices [27].

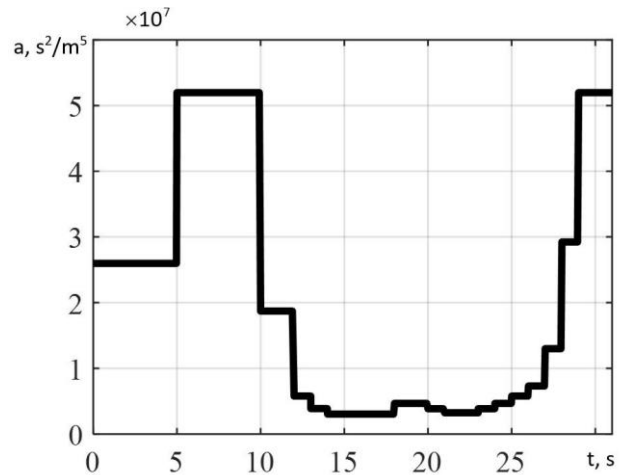


Fig. 2. Graph of changes in hydraulic resistance in the hydraulic network of the system

Further studies were carried out for the following values of electric power P_{bal} and the level of pressure stabilisation in the hydraulic network to meet the needs of consumers:

- from 0 s to 7 s (morning cycle period) $P_{bal} = 1.65$ kW, which corresponds to 30% of the total generator power P_{total} ; pressure stabilisation level – 5 m

- from 7 s to 15 s (daytime period of the cycle) $P_{bal} = 2.75$ kW, which corresponds to 50% of P_{total} ; pressure stabilisation level – 10 m.
- from 15 s to 22 s (evening period of the cycle) $P_{bal} = 0$ kW, which corresponds to 0% of P_{total} .
- from 22 s to 30 s (night period of the cycle) $P_{bal} = 4.95$ kW, which is 90% of P_{total} ; pressure stabilisation level – 40 m.

The results of the investigation are shown in Figs. 3–5.

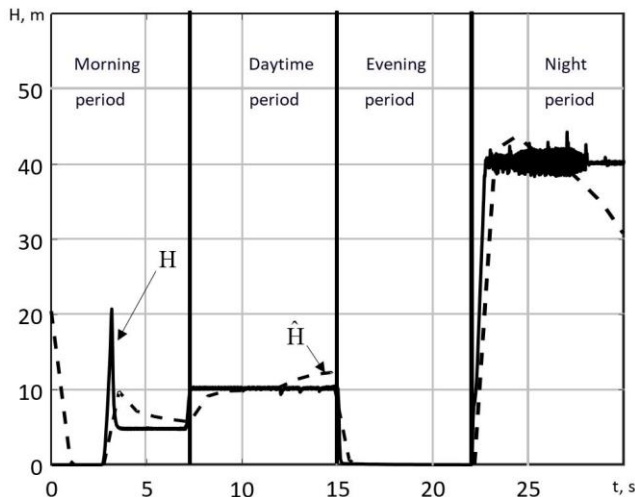


Fig. 3. Transients in a sensorless control system: actual H and observed $\hat{H}$ pump pressure

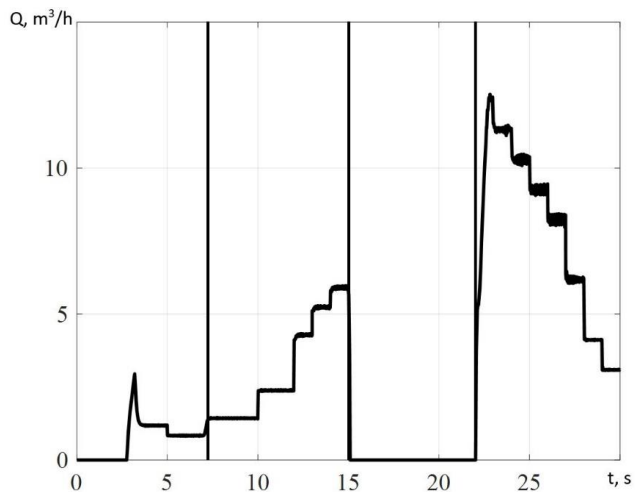


Fig. 4. Transients in a sensorless control system: pump performance

From the graphs in Figs. 3–5, it can be seen that in the process of investigating the sensorless control system of the turbomechanism with a modified pressure estimator and feedback, which is powered by a wind turbine using an electronic load controller to redistribute excess electrical energy, the system successfully stabilises the pressure in the hydraulic network within the daily cycle with high accuracy at the corresponding specified levels. When comparing the estimated pressure value in the sensorless control system

with the actual pressure value obtained using a pressure sensor, the estimation error varies from 0% to 14%. Such errors are caused by abrupt changes in the hydraulic resistance of the network. At night, oscillatory processes are observed due to the low resistance of the hydraulic network. Since the pump acts as a ballast load, the developed system can be used for additional tasks in water supply systems, such as irrigation or pumping water into tanks.

The results of the investigation have confirmed that the developed pressure observer can be effectively used in sensorless pressure stabilisation systems in hydraulic networks powered by wind turbines when redistributing excess energy.

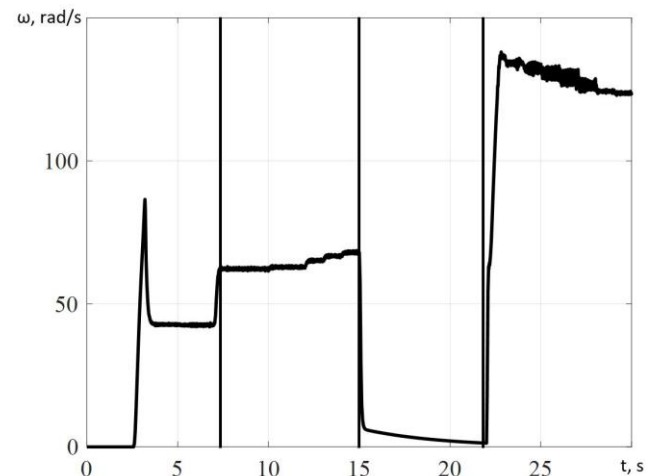


Fig. 5. Transients in a sensorless control system: velocity of the pump drive motor

Conclusions. Based on the research, the following conclusions have been formulated:

A sensorless water supply system with a modified feedback pressure estimator was developed, which is powered by a wind turbine using an electronic load controller under conditions of stabilising the pressure of the hydraulic network. This system allows the pumping unit to be used as a ballast load in an autonomous network, which makes it possible to consume excess energy and meet the needs of consumers, such as pumping water into reservoirs and irrigation.

The design and training of a pumping unit pressure observer is based on artificial neural networks, which ensures the implementation of the principle of sensorless control of turbomechanisms. Removing pressure sensors from the system reduces its cost. The use of a neural network with feedback allows for accurate modelling of dynamic processes with an error of up to 15% in estimating process coordinates. Dynamic errors are associated with abrupt changes in the hydraulic resistance of the network.

Research was conducted on a sensorless control system for a turbomechanism with a modified pressure estimator with feedback, which is powered by a wind turbine while redistributing excess energy. When comparing the estimated pressure values obtained in the sensorless system with the

actual pressure measured by the sensor, it was found that the estimation error ranges from 0% to 14%.

The results of the investigation can be recommended for use in the design of new or reconstruction of existing control systems for pumping systems powered by a wind turbine with a self-excited induction generator, provided that the wind turbine velocity is constant.

REFERENCES

1. Zamulko A., Veremiichuk Y., Mahnitko A. Assessment of potential electricity demand aggregation at ukrainian electricity market. In: 2020 IEEE 7th International Conference on Energy Smart Systems (ESS). IEEE, 2020. p. 377-381. DOI: 10.1109/ESS50319.2020.9160194
2. Furlan C.; Mortarino C. Forecasting the impact of renewable energies in competition with non-renewable sources. *Renewable and Sustainable Energy Reviews*, 2018, 81: 1879-1886. DOI: 10.1016/j.rser.2017.05.284
3. Ragazzi M., Ionescu G., Cioranu S. I. Assessment of environmental impact from renewable and non-renewable energy sources. *International Journal of Energy Production and Management*, 2017, 2.1: 8-16. DOI: 10.2495/EQ-V2-N1-8-16
4. Karpchuk H., Budko V., Lysenko O. Technical achievable potential of photovoltaic conversion of solar radiation for the conditions of Ukraine, *EPJ Photovoltaics* 15, 30 (2024) <https://doi.org/10.1051/epjpv/2024027>
5. Owusu P. A., Asumadu-Sarkodie S. A review of renewable energy sources, sustainability issues and climate change mitigation. *Cogent Engineering*, 2016, 3.1: 1167990. DOI: 10.1080/23311916.2016.1167990
6. Sang S., Zhang C., Zhang J., Shi G., Deng F. Analysis and stabilization control of a voltage source controlled wind farm under weak grid conditions. *Frontiers in Energy*, 2022, 1-13. DOI: 10.1007/s11708-021-0793-5
7. Kiselychuk O., Bodson M., Wang J. Model of a self-excited induction generator for the design of capacitor-controlled voltage regulators. In: 21st Mediterranean Conference on Control and Automation. IEEE, 2013. p. 149-154. DOI: 10.1109/MED.2013.6608713
8. Roodsari B. N., Nowicki E. P. Analysis and experimental investigation of the improved distributed electronic load controller. *IEEE Transactions on Energy Conversion*, 2018, 33.3: 905-914. DOI: 10.1109/TEC.2018.2823334
9. Cattaert A. E. High pressure pump efficiency determination from temperature and pressure measurements. In: 2007 IEEE Power Engineering Society Conference and Exposition in Africa-PowerAfrica. IEEE, 2007. p. 1-8. DOI: 10.1109/PESAfr.2007.4498076
10. Robles-Velasco A., Cortés P., Muñizuri J., Onieva L. Prediction of pipe failures in water supply networks using logistic regression and support vector classification. *Reliability Engineering & System Safety*, 2020, 196: 106754. DOI: 10.1016/j.res.2019.106754
11. Tchórzewska-Cieślak B., Szpak D., Żywiec J., Rożnowski M. The concept of estimating the risk of water losses in the water supply network. *Journal of environmental management*, 2024, 359, 120965. DOI: 10.1016/j.jenvman.2024.120965
12. Burian S. O., Zemlianukhina H. Y. Neural Network Pressure Observer for a Turbomechanism Electromechanical System Powered by a Wind Generator. *Applied Aspects of Information Technology*, 2022, 5(4): 303-314. DOI: 10.15276/ahait.05.2022.20
13. Pechenik M. V., Burian S. O., Zemlianukhina H. Y., Pushkar M. V., Teriaiev V. I. Investigation of energy efficiency of water supply system when powered by an alternative energy source. *Tekhnichna Elektrodynamika*, 2022, 5: 77-81. DOI: 10.15407/technd2022.05.077
14. Vineetha K. V., Reddy M. M. S., Ramesh C., Kurup D. G. An efficient design methodology to speed up the FPGA implementation of artificial neural networks. *Engineering Science and Technology, an International Journal*, 2023, 47: 101542. DOI: 10.1016/j.jestch.2023.101542
15. Burian S. O., Kiselychuk O., Pushkar M. V., Reshetnik V. S., Zemlianukhina H. Y. Energy-efficient control of pump units based on neural-network parameter observer. *Technical Electrodynamics*, 2020, 1: 71-77. DOI: 10.15407/technd2020.01.071
16. Chilipi R. R., Singh B., Murthy S. S., Madishetti S., Bhuvaneshwari G. Design and implementation of dynamic electronic load controller for three-phase self-excited induction generator in remote small-hydro power generation. *IET Renewable Power Generation*, 2014, 8(3): 269-280. DOI: 10.1049/iet-rpg.2013.0087
17. Pushkar M., Krasnoschapka N., Pechenik M., Burian S., Zemlianukhina H. Approximation of magnetizing inductance curve of self-excited induction generator for investigation of steady-state operation modes. In: 2020 IEEE 7th International Conference on Energy Smart Systems (ESS). IEEE, 2020. p. 301-305. DOI: 10.1109/ESS50319.2020.9160143
18. Karmakar S. Artificial Neural Network-Built Electronic Load Controller for Three-Phase Self-Excited Induction Generator Feeding Single-Phase Load," Michael Faraday IET International Summit 2020 (MFIIS 2020), Online Conference, 2020, pp. 185-190. DOI: 10.1049/icp.2021.1073.
19. Ion C. P. A comprehensive overview of single-phase self-excited induction generators. *IEEE Access*, 2020, 8: 197420-197430. DOI: 10.1109/ACCESS.2020.3034291
20. Bodson M., Kiselychuk O. Analysis of triggered self-excitation in induction generators and experimental validation. *IEEE transactions on energy conversion*, 2012, 27(2): 238-249. DOI: 10.1109/TEC.2012.2182999

21. Marino R., Peresada S., Tomei P. Exponentially convergent rotor resistance estimation for induction motors. *IEEE Transactions on Industrial Electronics*, 1995, 42(5): 508-515. DOI: 10.1109/41.464614
22. Osadchyy V., Nazarova O., Olieinikov M. The research of a two-mass system with a PID controller, considering the control object identification. In *2021 IEEE International Conference on Modern Electrical and Energy Systems (MEES)*, 2021: 1-5. DOI: 10.1109/MEES52427.2021.9598542
23. Pechenik M., Burian S., Pushkar M., Zemlianukhina H. Analysis of the Energy Efficiency of Pressure Stabilization Cascade Pump System. In *2019 IEEE International Conference on Modern Electrical and Energy Systems (MEES)*, 2019: 490-493. DOI: 10.1109/MEES.2019.8896588
24. Pechenik M., Burian S., Pushkar M., Zemlianukhina H. Electromechanical system of turbomechanism when using an alternative source of electric energy. *Natsional'nyi Hirnychiy Universytet. Naukovyi Visnyk*, 2022, 2: 61-66. DOI: 10.33271/nvngu/2022-2/061
25. Yuzer E. O., Bozkurt A. Instant solar irradiation forecasting for solar power plants using different ANN algorithms and network models. *Electrical Engineering*, 2024, 106(4): 3671-3689. DOI: 10.1007/s00202-023-02067-z
26. Yan-juan L., Yi Y., Hai-qin G., Ye Z. Identification and self-tuning control of heat pump system based on neural network. *Chinese Control and Decision Conference (CCDC)*, 2016: 6687-6691. DOI: 10.1109/CCDC.2016.7532200
27. Tamminen J., Ahonen T., Ahola J., Kestilä J. Sensorless flow rate estimation in frequency-converter-driven fans. In *Proceedings of the 2011 14th European Conference on Power Electronics and Applications*, 2011: 1-10. URL: <https://ieeexplore.ieee.org/document/6020153>