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ENERGY-EFFICIENT CONTROL OF PUMP UNITS BASED ON NEURAL-NETWORK PARAMETER OBSERVER

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An observer based on an artificial neural network was designed. The observer determines the pumping unit performance depending on the operating point. Determination is based on the measured technological coordinates of the system and the pressure of the turbomechanism. Three neural networks were designed for three types of the productivity observer. The developed observer was investigated by the simulation method within different variations of disturbing actions, such as hydraulic resistance of the hydraulic system and geodetic pressure. A comparative analysis of three types of the productivity observer, built with using the pressure and different signals of the system with arbitrary change of hydraulic resistance was given. By the use of the pump unit efficiency observer, in addition to the results presented earlier, the efficiency of the productivity observer, which built with using different sensors, in water supply systems with two series-connected pump units, operating for filling the large tank, is researched. In the water supply system one pump speed is regulated, the other is unregulated. References 14, Figure 5.
***Key words**:* pumping unit, neural network, observer, parameter, turbomechanism.

Introduction. The process of determining and observation the turbomechanisms' technological coordinates is an integral part of their automatic control systems design, however, the sensors, which provide information to the system, are expensive or the access for their installation is limited by the construction of the hydraulic network. Other parameters, such as pump efficiency, are impossible to be measured directly, only indirect determination with a certain number of sensors is possible. In [1], the authors propose a system with two temperature and pressure sensors on input and two on pump output to calculate its efficiency. To increase the water supply system energy efficiency, the forecasting method can be used [2]. The essence of this method is to determine the balance of supply productivity and water consumption, but there are many factors that affect the forecasting accuracy. The forecasting method can also be used to determine the optimal number of pumps in the system. Multi-pump systems are one of the main ways to improve energy efficiency. Multi-pump systems can be both single-drive and multi-drive [3]. The required number of working pumps can be determined based on monitoring the location of the operating point [4]. On the other hand, it is possible to use an optimal multi-pump head control system based on analytical characteristics and experimental efficiency distribution diagrams, the control algorithm of which is described [5]. Article [6] proposes performance control optimization of a multi-pump system by predicting the future state of the system. Reducing the number of pumps and starting or stopping them increases energy efficiency.

Another perspective way is artificial intelligence theory applying to obtain unknown coordinates [7]. Such observer based on artificial neural networks, which operates with already known measured coordinates, and allows to observe the other coordinates values, such as pressure, pump performance, mechanical power and others, is designed in [8]. The authors of article [9] proposed a heat pump direct heating system with real-time identification and the self-regulation principle, which has high observation values for the given values and the ability to deviate from perturbations. In [10], a multi-layer controller pump system with sliding-mode observer based on neural networks of the motion mode is developed and the system robustness

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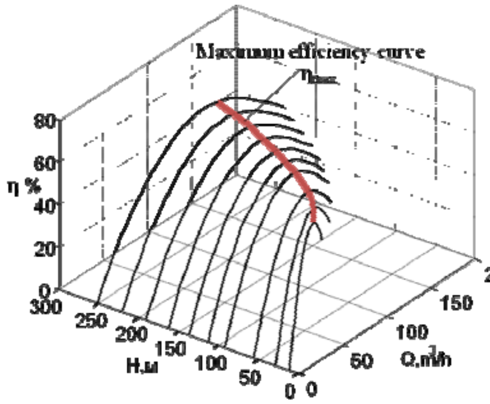
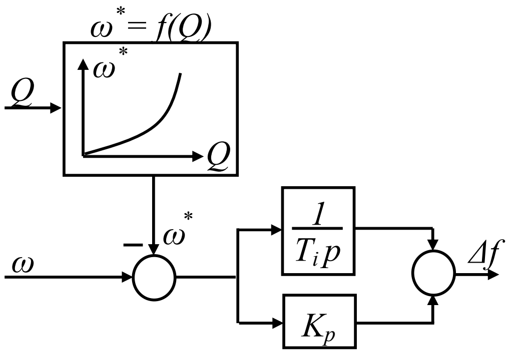
is investigated. Therefore, the task of building pump coordinate observer based on neural network and test of its performance is very relevant.

The aim of the paper is to increase the energy efficiency of a pump unit by applying an energy-efficient control algorithm using neural networks to observe technological coordinates.

Materials and results of the research. Ways to increase the turbomechanism energy efficiency are almost always deal with the decreasing the drive angular speed and, as a consequence, reduction the consumed power. However, it does not mean that energy efficiency will be maximized, as there is only one point with maximum efficiency at each speed characteristic of the pump. In order to get to the maximum efficiency point it is necessary to have an array of speeds and productivity at which the maximum efficiency is obtained. This dependence is called the "maximum efficiency curve" and is shown in Fig. 1, *a* on the Q-H-efficiency characteristics of the pump of 160 kW power.



a



b

Fig. 1

For the implementation of the rotation speed search algorithm with the maximum pump efficiency the PI controller, which corrects the actual motor rotation speed, and the block ω*= f(Q), which determines the required speed by the measured performance signal, are used. The structural scheme is presented in Fig. 1, *b*, it is described with following equations:

$$\omega^* = k_1Q^2 + k_2Q + k_3, \tag{1}$$

$$\Delta f = (\omega - \omega^*)(K_p + 1/T_i p), \tag{2}$$

where Q is the actual pump productivity; ω* is the desired rotation speed at which maximum efficiency is achieved at the desired productivity value; ω is the actual measured motor speed; k_1, k_2, k_3 are the approximation coefficients of the maximum efficiency curve; Δf is the increment of the frequency reference; K_p is the proportional component of the controller; T_i is the time constant of the controller integral part.

The application of energy efficient control algorithms for pump units involves measurement of the technological system coordinates required for its operation. The main problem with this is the high cost of productivity sensors, and the absence of speed sensors on pump units drive motors. To solve the problems of required coordinates measuring, it is advisable to use the artificial neural networks apparatus (NN) [11], which has ability to self-study. This approach allows design technological coordinate observers of pump units based on the coordinates that are available for measurement.

The procedure for NN design consists the selection of the number of hidden layers of neurons, determination the number of neurons in the hidden layers, selection the activation function of neurons, and training the network, which determines the numerical values of its internal connections parameters.

To create the productivity observer for the 160 kW pump, a two-layer NN was formed with 10 neurons in the first and 1 in the output layer. Two signals can be used as network inputs, one of which is pressure, which is easy to measure, the other one could be speed or active power or one of the stator currents. The observation accuracy changes from choosing of this coordinate. Angular velocity and hydraulic resistance arrays were used for the network training as perturbations; their transients are shown in Fig. 2. The training error was 0.034, the regression coefficient – 0.999.

While working with neural networks, their adequate mathematical description is important. In the general case, the neuron equation is described by the following expression:

$$y_i = \lambda_i\left(\sum_{j=1}^{m} x_j w_{ij} + b_i\right), \qquad (3)$$

where $x_1, x_2, \ldots x_m$ are the inputs of the neuron; $w_{i1}, w_{i2}, \ldots, w_{im}$ are the weight coefficients of synaptic bonds; b_i is the displacement of the neuron; $\lambda_i(.)$ is the activation function of the neuron.

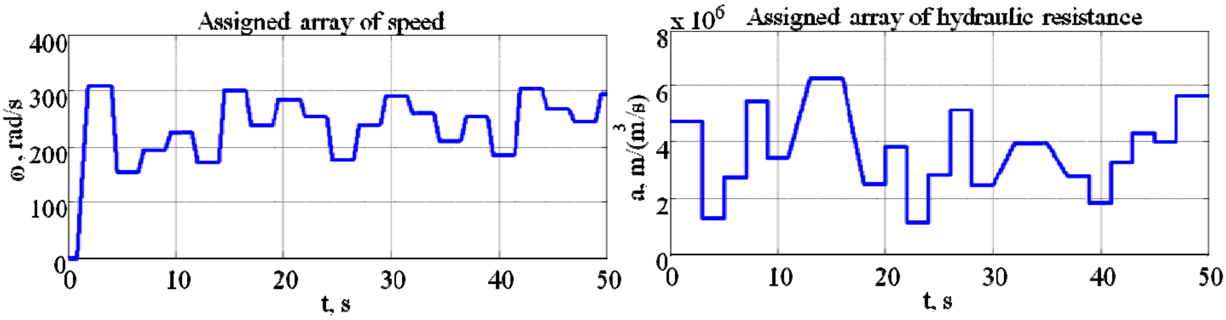


Fig. 2

In the case of a two-layer neural network of 10 neurons, the equations describing each neuron are defined according to the following expressions:

$$\begin{aligned} y_1 &= \mathrm{th}((Hw_{11} + \omega w_{12} + b_1)/a_1), \\ y_2 &= \mathrm{th}((Hw_{21} + \omega w_{22} + b_2)/a_2), \\ &\ldots \\ y_{10} &= \mathrm{th}((Hw_{101} + \omega w_{102} + b_{10})/a_{10}), \end{aligned} \qquad (4)$$

where H, ω are the neuron inputs; $w_{i1}, w_{i2}, \ldots, w_{im}$ are the weight coefficients of synaptic bonds; b_i is the displacement of the neuron; a_1 is the coefficient of inclination of the function of the tangential hyperbolic tangent tansig.

The general equation describing the neural network operation has the following form:

$$\begin{aligned} \hat{Q} = c(&\mathrm{th}((Hw_{11} + \omega w_{12} + b_1)/a_1)w_1 + \mathrm{th}((Hw_{21} + \omega w_{22} + b_2)/a_2)w_2 + \\ &+\mathrm{th}((Hw_{31} + \omega w_{32} + b_3)/a_3)w_3 + \mathrm{th}((Hw_{41} + \omega w_{42} + b_4)/a_4)w_4 + \\ &+\mathrm{th}((Hw_{51} + \omega w_{52} + b_5)/a_5)w_5 + \mathrm{th}((Hw_{61} + \omega w_{62} + b_6)/a_6)w_6 + \\ &+\mathrm{th}((Hw_{71} + \omega w_{72} + b_7)/a_7)w_7 + \mathrm{th}((Hw_{91} + \omega w_{92} + b_9)/a_9)w_9 + \\ &+\mathrm{th}((Hw_{101} + \omega w_{102} + b_{10})/a_{10})w_{10} + b). \end{aligned} \qquad (5)$$

where c is the slope factor of linear activation function.

To evaluate the performance of the developed observer, the mathematical simulation was performed and comparisons were made with the results that were obtained through experimental research.

For the simulation, a structural scheme of an electromechanical automatic control system of two series-connected pumps, operating for filling the large tank was developed. One pump speed is regulated, the other is unregulated. The structural scheme is presented in Fig. 5. Herewith the parameters of the hydro system are unknown and may arbitrarily change. The algorithm uses the observed performance value to determine the required rotation speed. Also in the system the efficiency observers, which are developed on the basis of artificial neural networks, for each pump are used [12].

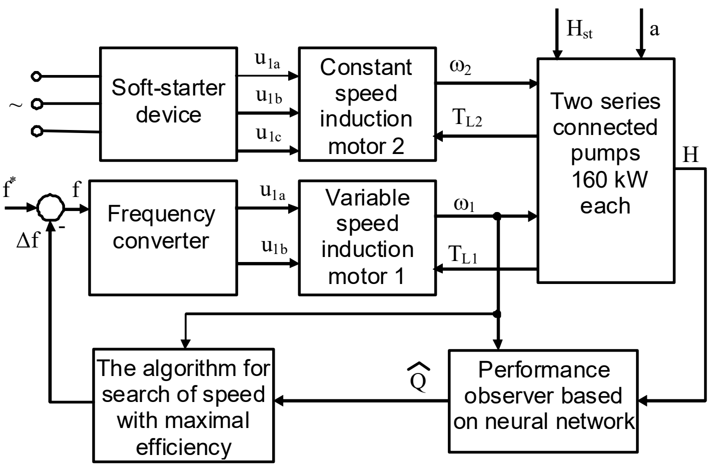


Fig. 3

In Fig. 3 the following notations have been used: u_{1a}, u_{1b}, u_{1c} are the phase stator voltage; T_{L1}, T_{L2} are the loading torque of first and second pumps respectively; ω_1, ω_2 are the speed of first and second motors respectively, f^* is the frequency reference.

Classic induction motor models in stator coordinates a-b are used in the system [13]. A frequency converter implements a quadratic scalar control law u/f^2=const. A mathematical model of two sequentially operating pumps and a hydraulic network is described by the following equations (6)-(9) [14]:

$$\frac{d\hat{Q}}{dt} = \frac{H_{01n}}{\chi\omega_{n1}^2}\omega_1^2 + \frac{H_{02n}}{\chi\omega_{n1}^2}\omega_2^2 - \frac{H_{st}}{\chi} - \frac{1}{\chi}\left(a_{n1} + a_{n2} + a\right)\hat{Q}^2, \tag{6}$$

$$H_1 = \frac{H_{01n}}{\omega_{n1}^2}\omega_1{}^2 - a_{n1}\hat{Q}^2,\ H_2 = \frac{H_{02n}}{\omega_{n1}^2}\omega_2{}^2 - a_{n2}\hat{Q}^2, \tag{7}$$

$$T_{L1} = \frac{\rho g \hat{Q} H_1}{\hat{\eta}_1\omega_1},\ T_{L2} = \frac{\rho g \hat{Q} H_2}{\hat{\eta}_2\omega_2}, \tag{8}$$

$$H = H_1 + H_2, \tag{9}$$

where H is the total pressure; H_1, H_2 are the the pressure of the first and second pumps respectively $\hat{Q}$ is the observed value of the productivity; H_{01n}, H_{02n} are the nominal pressures at zero feeds of the first and second pumps at nominal speeds; ω_{n1}, ω_{n2} are the nominal speeds of the first and second pumps respectively; χ is the integration time constant; $\hat{\eta}_1$, $\hat{\eta}_2$ are the observed value of the pumps efficiency; a_{n1}, a_{n2} are the nominal hydraulic resistance of the first and second pumps respectively; a is the hydraulic resistance of the hydraulic system; H_{st} is the geodetic height of water level; ρ is the water density; g is the free fall acceleration; t is the time.

The research results of the operation of dynamic modes with a hydraulic resistance arbitrary change, under the presence of two disturbing actions: a hydraulic resistance and geodetic pressure, and a smooth change of hydraulic network parameters are shown in Fig. 4, respectively.

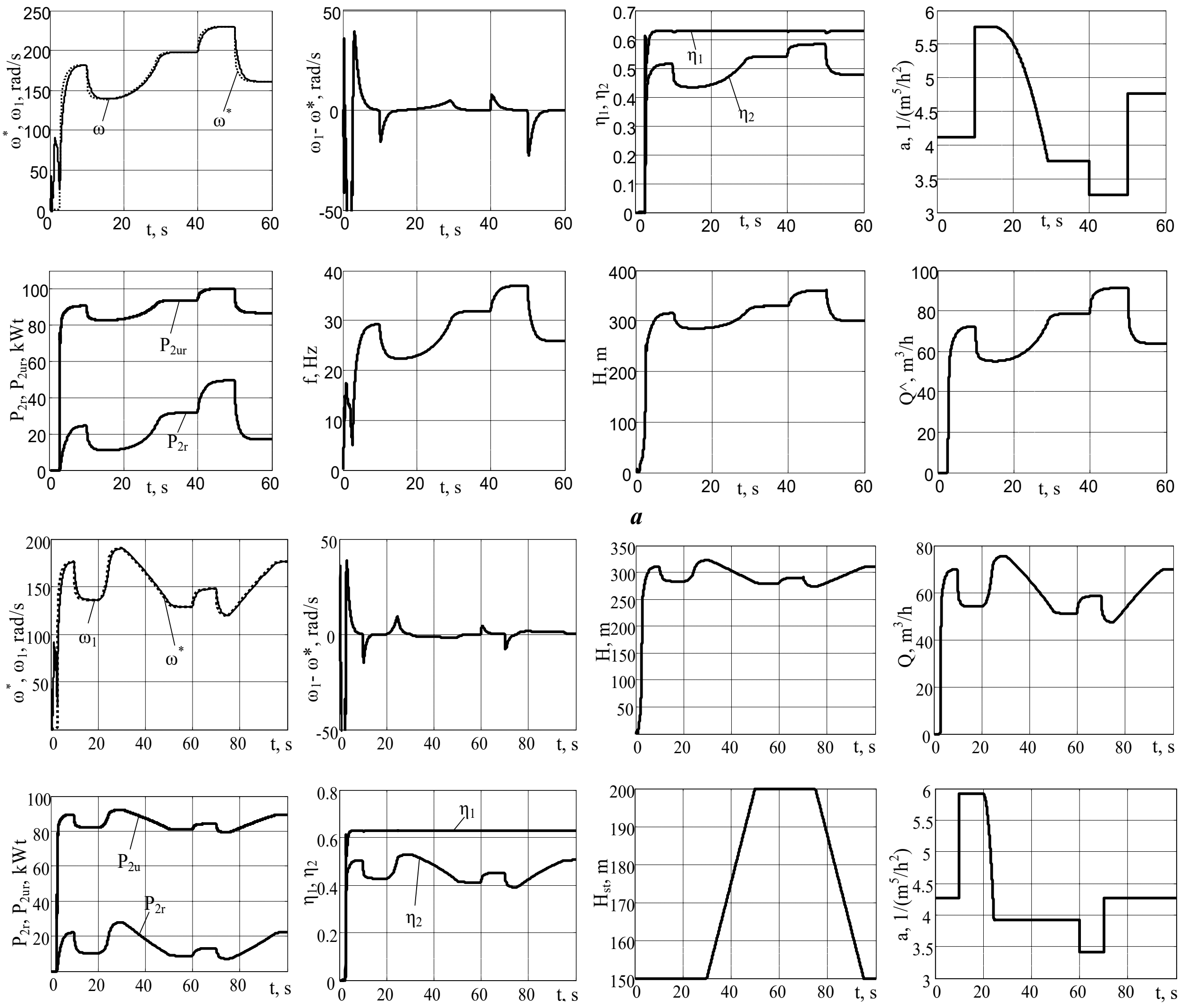


Fig. 4

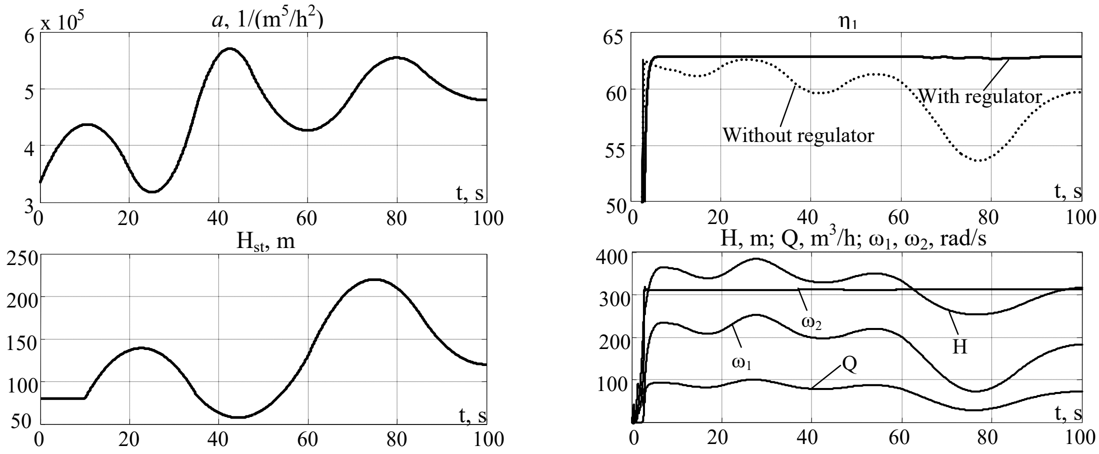


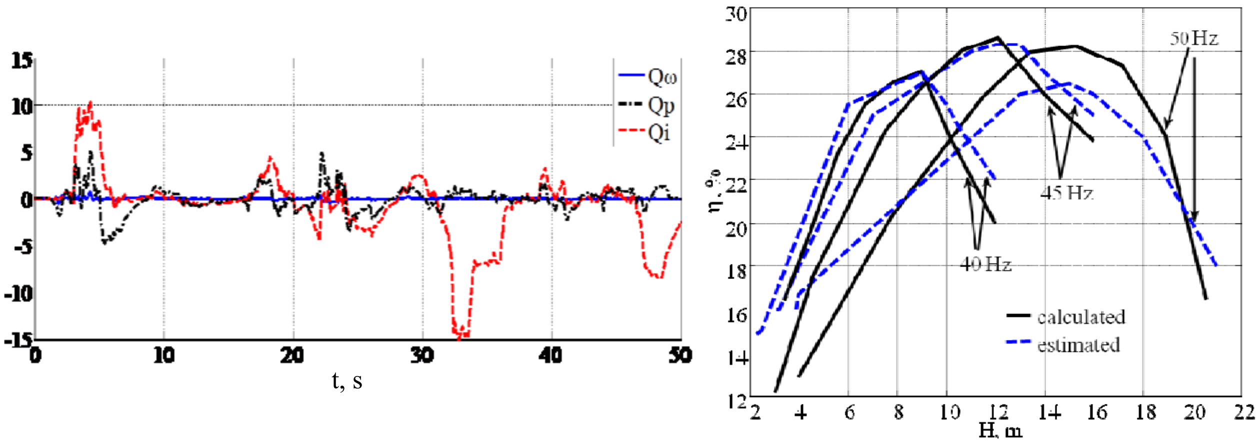
Fig. 4, *c*

The transients of hydraulic resistance (Fig. 4, *a*) show that the efficiency of the regulated pump due to the speed change is constantly at the maximum value, the efficiency of the second pump varies depending on the operating point position. Herewith, the consumed power of the regulated pump is reduced by 30-40% depending on the operating point position. The pump efficiency is kept maximum even with two perturbations in the hydro system (Fig. 4, *b*). With a hydraulic resistance and geodetic pressure smooth changing (Fig. 4, *c*), the pump efficiency is increased by a maximum of 8% depending on the operating point.

The productivity observer can be built using different sensors or coordinates. In Fig. 5, *a* a comparison of three types of observers is presented. The observers constructed using: pressure and velocity (Qω), pressure and active power (Qp), pressure and stator current (Qi) with a hydraulic resistance arbitrary change are presented. The maximum productivity difference from the standard pump model is obtained for the pressure array and stator current. The minimum is for pressure and speed.

For the observation of the pump efficiency, the arrays of the pressure and the consumed active power, which were obtained from the analog frequency converter output, were used as the NN input signals. The technical implementation of the efficiency observer was made on the basis of the ALTERA DE1-SoC developer's board [12].

The results of the observer work were tested on an experimental setup with a Calpeda pump of 0.33 kW power [12]. The efficiency static characteristics for the three frequencies of 50, 45 and 40 Hz, built according to the calculated data and taken with using of a neuro-observer, are shown in Fig. 5, *b*. Their difference does not exceed 2.1%.



a ***b***

Fig. 5

Conclusions. In this paper the actual task of increasing the energy efficiency of the electromechanical system of pump unit with the use of technology of neuro-observation of technological coordinates was solved. The methods of observation of technological coordinates of pump units, their advantages and disadvantages have been analyzed, the most promising method of evaluation based on neural networks was cho-

sen. A detailed methodology for evaluating technological parameters has been developed, which will enable the creation of sensorless control systems and increase the energy efficiency of pump units. Three artificial neural networks were designed, using the motor speed data, active power of the motor and the stator current, based on which the performance observers of the pump unit were constructed. Training of developed networks and comparison of their operation were conducted. According to simulation results the designed energy-efficient controller of pump performance based on the neural-network observer provides a 33% energy savings for the series connection of two water pumps, one of which is variable speed, and the other in a constant speed pump. It is shown that high energy efficiency is achieved in the presence of system disturbances such as a variation of hydraulic network resistance, hydrostatic pressure variation and consumers' activity. The results for pump units can be extended to other turbomechanisms, including fans, air conditioners and the mechanisms that operate in continuous modes, such as conveyors etc.

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ЕНЕРГОЕФЕКТИВНЕ КЕРУВАННЯ НАСОСНИМИ УСТАНОВКАМИ НА ОСНОВІ НЕЙРОМЕРЕЖЕВОГО ОЦІНЮВАЧА КООРДИНАТ

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На базі штучної нейронної мережі розроблено оцінювач, який на основі виміряних технологічних координат системи та напору турбомеханізму, визначає продуктивність насосної установки в залежності від розташування робочої точки. Спроектовано три нейронні мережі для трьох типів оцінювача продуктивності. розроблений оцінювач досліджено методом моделювання при різних варіаціях збурюючих дій таких, як гідравлічного опору мережі та геодезичного тиску. Наведено порівняльний аналіз трьох типів оцінювачів продуктивності, побудованих з використанням напору та різних сигналів системи при довільній зміні гідравлічного опору. Використовуючи оцінювач коефіцієнта корисної дії насосної установки у додаток до результатів, що були представлені раніше, вивчено ефективність застосування оцінювача продуктивності, побудованого з використанням різних датчиків в системах водопостачання з двома послідовно з'єднаними насосними агрегатами, один з яких – керований по швидкості, інший – некерований та які працюють в режимі наповнення великого резервуара. Бібл. 14, рис. 5.

Ключові слова: насосна установка, нейронна мережа, оцінювач, координати, турбомеханізм.

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ЭНЕРГОЭФФЕКТИВНОЕ УПРАВЛЕНИЕ НАСОСНЫМИ УСТАНОВКАМИ НА ОСНОВЕ НЕЙРОСЕТЕВОГО ОЦЕНЩИКА КООРДИНАТ

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Разработано оценщик на базе искусственной нейронной сети, который, на основе измеренных технологических координат и напора турбомеханизма, определяет производительность насосной установки в зависимости от расположения рабочей точки. Спроектировано три нейронные сети для трех типов оценщика производительности. Исследовано методом моделирования разработанный оценщик при различных вариациях возмущающих воздействий, таких как гидравлического сопротивления сети и геодезического давления. Приведен сравнительный анализ трех типов оценщиков производительности, построенных с использованием напора и различных сигналов системы при произвольном изменении гидравлического сопротивления. Используя оценщик коэффициента полезного действия насосной установки в дополнение к результатам, которые были представлены ранее, изучена эффективность применения оценщика производительности, построенного с использованием различных датчиков в системах водоснабжения с двумя последовательно соединенными насосными агрегатами, один из которых – управляемый по скорости, другой – неуправляемый и которые работают в режиме наполнения большого резервуара. Библ. 14, рис. 5.

Ключевые слова: насосная установка, нейронная сеть, оценщик, координаты, турбомеханизм.

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