UDC 621.311.26:622.532
DOI: 10.15587/1729-4061.2022.267034

DETERMINING OPTIMAL RATED POWER OF A PHOTOVOLTAIC STATION FOR MINE DEWATERING

Sviatoslav Vasylets
Corresponding author
Doctor of Technical Sciences, Professor*
E-mail: svyat.vasilets@gmail.com
Kateryna Vasylets
Senior Lecturer*
*Department of Automation, Electrical Engineering and Computer-Integrated Technologies
National University of Water and Environmental Engineering
Soborna str., 11, Rivne, Ukraine, 33028

The object of the study is the main dewatering system of the mine. Climate change has stimulated the refusal to use coal in many countries. In conditions of massive closure of mines, there is a need to pump out mine waters to avoid flooding. A significant water influx determines the high cost of electricity consumed by pumps. It is proposed to increase the efficiency of the mine dewatering system due to the introduction of a smart power supply grid with photovoltaic generation. The relative value of the annual balance of payment for energy consumption is chosen as an optimization parameter. The rated capacity of the photovoltaic station is optimized according to the criterion of approaching, with accuracy up to the permissible mismatch, the absolute value of the optimization parameter to zero. The relationship between the optimization parameter and the rated capacity of the photovoltaic station is represented by a parabolic regression. Regression parameters are estimated in the case study for a specific mine based on the results of a single-factor simulation experiment conducted using a computer model of a smart power grid. The randomness of natural, technical and economic factors is taken into account. Based on the prediction intervals for the regression, the optimal rated capacity of the photovoltaic station for the selected mine is estimated at 3.164 MW with a pump capacity of 1.732 MW. It was found that the annual energy savings for the case study conditions reach 3,745 MWh. Equipping the power supply grid of the main dewatering system with a photoelectric station of optimal configuration will reduce the cost of consumed electricity to several percent. This will make it possible to avoid financial costs for maintaining the balance of underground water and reduce the flooding probability of coal regions being transformed

Keywords: pumping unit, dewatering system, photovoltaic module, rated capacity, optimization criterion

Received date 01.09.2022
Accepted date 09.11.2022
Published date 30.12.2022

How to Cite: *Vasylets, S., Vasylets, K. (2022). Determining optimal rated power of a photovoltaic station for mine dewatering. Eastern-European Journal of Enterprise Technologies, 6 (8 (120)), 6–15. doi: https://doi.org/10.15587/1729-4061.2022.267034*

1. Introduction

The efforts of the world community to combat climate change provide for the reduction of greenhouse gas emissions, as defined by the Paris Agreement [1]. Countries are gradually abandoning fossil hydrocarbons, in particular, hard coal, since the coal industry's contribution to the greenhouse effect is significant [2]. The liquidation of coal mining enterprises is accompanied by the appearance of abandoned territories. Only in the USA, there are about 67,000 abandoned hardrock mine features, which pose a physical danger to humans, and about 22,500 objects that worsen the environmental situation in the long term [3].

The liquidation of coal mining enterprises exacerbates the problem of maintaining the underground water balance. For example, the mass closure of mines in the territory of the Upper Silesian Coal Basin (Poland) significantly affected the level and quality of mine water [4]. Such changes in hydrological conditions can lead to buildings damage and soil subsidence due to flooding, uncontrolled release of explosive methane into basements, and waterlogging of agricultural lands. These negative factors can, in the long term, disrupt the normal life of urbanized areas where coal has been mined for many decades, such as the Donetsk Coal Basin (Ukraine).

One way to maintain the balance of underground mine waters in coal regions is to ensure the functioning of the main dewatering facilities of closed mines. The total electric power of pump unit drives in most cases exceeds several MW, the height of the water rise averages from 500 to 1,000 m. The operation time of pumps can exceed ten hours a day. Such circumstances cause a significant cost of electricity for pumping out mine waters. In particular, in the structure of electricity consumption by mining enterprises in India, more than 40 % are the needs of dewatering pumps [5]. The above factors determine the expediency of research aimed at reducing costs for the pumping units operation of closed mines.

Thus, the need to increase the energy efficiency of maintaining the underground water balance of coal-mining regions during the mass liquidation of mines determines the relevance of the revealed scientific issues.

2. Literature review and problem statement

The energy efficiency of dewatering installations of mines that do not produce coal can be increased in several ways.

First, it is possible to reduce the cost of consumed electricity by turning on pumps in hours when the market price of electricity is minimal. This method makes it possible to reduce payments for the dewatering system operation by 20–25 % [6]. However, the duration of pumps operation at the minimum electricity price may not be sufficient to pump out the entire volume of water that arrives during seasonal increases in water inflow. This reduces the effectiveness of this method. Such difficulties can be partially overcome using energy storages, which give previously stored cheap electricity to pumping units during peak load hours of the power system. There are proposals to equip the shafts of closed mines with gravity storages [7]. The possibility of using the infrastructure of abandoned mines in Poland for the equipment of energy storage on compressed air was also considered [8]. However, the energy intensity of such installations is too low compared to the consumption of dewatering pumps.

Secondly, there is a theoretical possibility to compensate for part of the cost of electricity consumed by pumps by selling the thermal energy of mine waters. It is known about the introduction of pilot thermal systems at two former coal mines in England, Yorkshire/Derbyshire [9]. However, this technology involves the deployment of heat exchangers in flooded shafts and is not suitable when it is necessary to constantly pump out mine waters.

The most promising way to increase the energy efficiency of mine dewatering is the introduction of a power supply grid with renewable sources of electricity [10]. There is a known method of building power supply grids for water pumping units using photovoltaic modules [11]. However, this approach is focused on pumps with a power of several kW and does not take into account the significantly greater power and operation time of mine dewatering systems. The autonomous system for the power supply of pumps from photovoltaic modules equipped with batteries [12] cannot be scaled for use in mine conditions. The reason lies in the high cost of batteries of suitable, for the mine dewatering system, capacity, which eliminates the economic effect. There are known proposals to use a floating photovoltaic station (PVS) to power mine consumers. In particular, in the conditions of mines in Northern Ontario, Canada, the possibility of using such generation to reduce the consumption of diesel fuel has been determined [13]. In Anhui Province, China, a floating PVS with a capacity of 70 MW was installed in a flooded area once used for coal mining [14]. Placing photovoltaic modules on the water surface is a promising solution, as the generation efficiency increases due to improved cooling. At the same time, the use of mine settling ponds for this purpose requires additional technical solutions to protect structural elements from corrosion due to the aggressive nature of groundwater pumped to the surface.

Known technical solutions to reduce the energy consumption of pumping units through the introduction of PVS are focused on installations of a small, compared to the mine dewatering system, capacity. This does not solve the problem of increasing the energy efficiency of underground pumping units, which leads to significant financial costs for maintaining the balance of underground water in coal-mining regions being transformed.

All this suggests that it is appropriate to determine the optimal, in terms of reducing the financial costs of electricity consumed, rated capacity of the photovoltaic station for the mine dewatering system. This will decrease the cost of water pumping from operating and liquidated mines due to the consumption of electricity from renewable sources.

3. The aim and objectives of the study

The aim of the study is to increase the efficiency of the mine dewatering system due to the introduction of a smart power grid with photovoltaic generation. This will make it possible to significantly reduce the annual financial costs of a coal mining enterprise (especially closed mines operating in the dewatering mode) for pumping out mine water. Additional profit can be brought by greenhouse gas emissions trading, since powerful underground consumers will mainly be powered by ecologically clean energy.

To achieve the aim, the following objectives were accomplished:

– to justify the optimization parameter and criterion when determining the rated capacity of the photovoltaic station as part of a smart power grid for the mine dewatering system;

– to define a mathematical model that links the optimization parameter with the rated capacity of the photovoltaic station;

– to estimate the optimal rated capacity of the PVS for the main dewatering system using a specific mine as a case study.

4. Materials and methods

The object of the study is the main mine dewatering system. For numerical modeling, a dewatering system of 500 m horizon of the Bilytska Mine in the State Enterprise «Dobropillyavugillya» (Donetsk region, Ukraine) was chosen. The normal water inflow on the specified horizon is 200 m^3/h, the maximum – 250 m^3/h. The simultaneous operation of two TsNS300-600 centrifugal multistage pumps (Ukraine) is considered. VAO2-560LA4 induction motors with a capacity of 800 kW and supply voltage of 6 kV (Ukraine) are used as drives. The inner diameter of each of the pressure pipes is 303 mm. The total volume of the two branches of the water collector is 1250 m^3. The bottom area of an equivalent cylindrical collector with a depth of H_w=5 m is S_w=250 m^2.

The main dewatering system in a steady state is characterized by the active power P_c, consumed by the motors of a group of simultaneously operating pumping units, and the total water flow Q_c through the pumps. The specified parameters are estimated using the Simulink model (MATLAB, USA) (Fig. 1).

Induction motors (M1, M2) are powered by a 6 kV three-phase symmetrical power source U through a power cable laid in the mine shaft. The cable is represented by active-inductive impedance RL. The rotors of the motors rotate centrifugal pumps (P1, P2). Two pressure pipelines (PP1, PP2) are connected to the pressure nozzles of the pumps through valves (V1, V2). The power P_c is measured by the PW wattmeter and displayed on the display Disp1 in kW. Sensors FS1, FS2 are used to measure the flow rate Q_c, the sum of readings of which is displayed on the display Disp2 in m^3/h. Using this model, the values of the operating parameters for the system of the given configuration are determined (Fig. 1): P_c=1732 kW; Q_c=731 m^3/h.

The subject of the study is the energy consumption of the main mine pumping units. This parameter is estimated for each hour during the year using a Simulink model, the block diagram of which is shown in Fig. 2.

Input parameters of the model are (Fig. 2): H_0 – water level in the collector at the beginning of the hour; H_{up}=4.8 m – upper water level at which the pumps are turned on; H_{down}=0.4 m – lower water level at which the pumps are turned off; Q_{fjk} – water inflow during the current day,

$k=\overline{1,12}$ – month number, $j=\overline{1,m_k}$ – day number of the month, including m_k days. The output values are the hourly electricity consumption W_{cijk}, where $i=\overline{1,24}$ is the hour number during the day, the water level and the state of the pumps at the end of the hour.

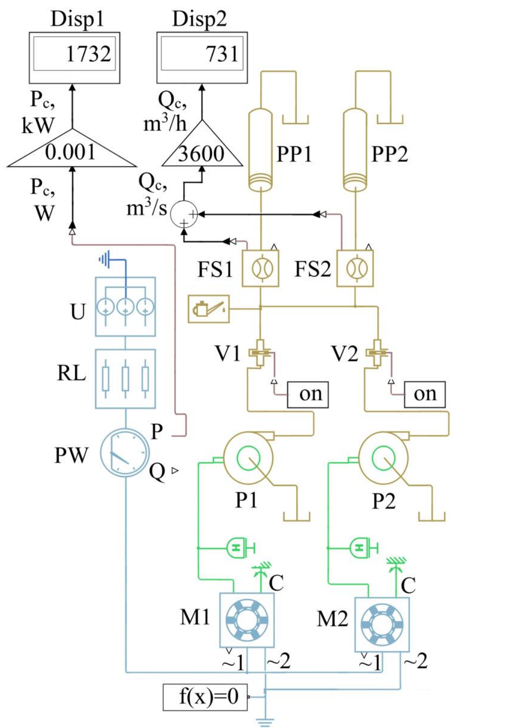

Fig. 1. Computer model for determining the steady-state operating parameters for a group of pumping units of the main mine dewatering system

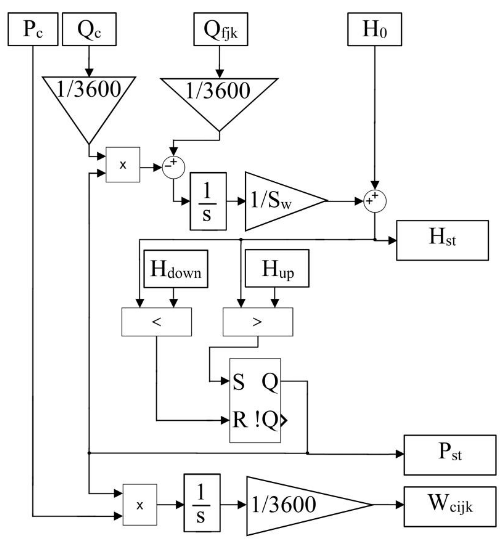

Fig. 2. Computer model for estimating the hourly energy consumption of the main pumping units of the mine

The water inflow Q_{fjk} for the current day is determined by the implementation of a random process (Fig. 3). The mean value, as a non-random characteristic of such a process, for a specific day is determined by cubic spline interpolation of reference values corresponding to the average monthly water inflow. The standard deviation of such a random process is 5 m^3/h.

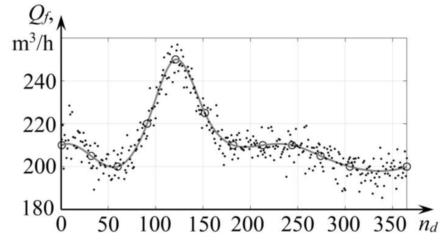

Fig. 3. One of the implementations of a random process describing the water inflow Q_f, m^3/h, to the main water collector versus the through number n_d of the day during the year: the circles correspond to the reference values of the monthly water inflow; the solid line – the mean of a random water inflow process; the dots indicate the daily water inflow Q_{fjk}

The model (Fig. 2) calculates the hourly energy consumption of the main pumping units as:

$$W_{cijk}=\int_0^{t_h} P_c\cdot z\mathrm{d}t, \tag{1}$$

where t_h=3,600 s – duration of an hour; z – logical state variable of the pumps determined by the current water level H in the collector, taking into account the operation algorithm of the automation equipment of the mine dewatering system (for example, AAV type, Ukraine):

$$z=\begin{cases}1, & \text{if } H>H_{up} \text{ or} \\ & H_{down}<H<H_{up} \text{ while } dH/dt<0; \\ 0, & \text{if } H<H_{down} \text{ or} \\ & H_{down}<H<H_{up} \text{ while } dH/dt>0.\end{cases} \tag{2}$$

The current water level H in the collector is determined taking into account the operation of the pumps:

$$H(t)=\frac{1}{S_w}\int_0^t\left[Q_f-Q_c\cdot z\right]\mathrm{d}t+H_0. \tag{3}$$

The main hypothesis of the study consists in the possibility of bringing the annual payment balance for the energy consumption of the main mine dewatering system closer to zero by optimizing the rated capacity of the photovoltaic station as part of a smart power grid.

The System Advisor Model (SAM) software developed by the National Renewable Energy Laboratory (NREL, USA) was used to calculate the hourly generation of the PVS during the year. The Photovoltaic Geographical Information System (PVGIS, European Commission) data were used to determine weather conditions at the PVS site (town of Biletske, Donetsk region, Ukraine, latitude 48.407 DD, longitude 37.171 DD, altitude 189 m). Hourly values of solar irradiance I during the year are taken into account (Fig. 4). The mean value of this parameter is $m[I]$=141.2 W/m^2 with a standard deviation of $s[I]$=230.9 W/m^2. Average annual indicators are: global horizontal irradiance 3.39 kWh/m^2/day; average temperature 8.9 °C; average wind speed 3.1 m/s.

The engineering five-parameter model «CEC Performance Model with Module Database» [15] was used to simulate photovoltaic modules. Such a model was developed by the California Energy Commission (CEC) and is available in the SAM program. The SunPower SPR-P19-405-COM type module is selected (design – USA, manufacture – China). The maximum power of this module is P_{mp}=405.122 W, the voltage and current at the maximum power point are equal to 44.5 V and 9.1 A, respectively.

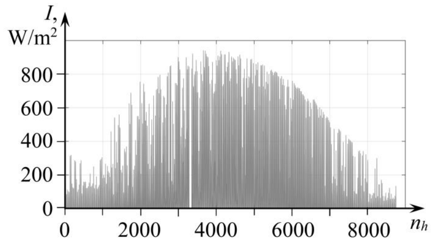

Fig. 4. Solar horizontal irradiance I, W/m^2, versus the through hour number n_h during the year at the photovoltaic station site, data averaged over 2005–2020

The inverter model «Inverter CEC Database» is used, which includes a system of equations for calculating the output power of an AC inverter, corresponding to the power from DC photovoltaic modules. The PVS-166-TL-POWER-MODULE-1-US multi-string inverter (ABB, Switzerland) is selected for the PVS construction. The maximum AC power of the inverter is 165,950 W.

The number of modules per string N_{ms}=22 is determined taking into account the minimum and maximum values of the inverter DC voltage. When determining the number of parallel strings N_{mp}=21 connected to one inverter, the maximum power of the photomodule and the presence of the required number of inputs are taken into account. This ensures that the value of the inverter DC to AC ratio K_{dcac}=1.13 falls within the recommended range of 0.9–1.25. It is assumed that the PVS includes several inverters with arrays of photovoltaic modules of the selected configuration.

The hourly electricity purchase and sale prices throughout 2021 were determined according to the data of the Joint Stock Company «Market Operator» (Ukraine). The weighted average feed-in tariff for excess electricity obtained from the PVS, according to the data of the State Enterprise «Guaranteed Buyer» (Ukraine) for 2021, is T_{PV}=0.16772 c.u./(kWh).

Optimization of the PVS rated capacity for the main dewatering system of the mine is carried out under the following assumptions:

1) switching on a group of pumping units is not related to a certain time of day and is carried out as the water in the collector reaches the upper level;

2) the tariff for the excess energy generated by the PVS transmitted to the power system in accordance with the monthly balance (feed-in tariff) is unchanged throughout the year;

3) losses in power transformers are not taken into account.

Processing of the results of the simulation experiment to optimize the PVS rated capacity as part of a smart power grid of the mine dewatering system involves the use of the following statistical methods. The Kolmogorov-Smirnov test is used to check the hypothesis about the normality of the optimization parameter samples. The Cochran's C test is used to check the homogeneity of sample variances. The significance of the calculated sample values of the linear correlation coefficient and the correlation ratio is evaluated using the Student's t-test. The hypothesis of a linear type of regression is checked according to Fisher's test. The least squares method is used to calculate the parameters of the regression line, and the numerical minimization of the sum of residuals squares is performed using the Nelder-Mead simplex method.

5. Results of the study of the photovoltaic station optimal capacity for the mine dewatering system

5. 1. Justification of the parameter and criterion for optimizing the photovoltaic station rated capacity

Let's assume that the pumping units of the main mine dewatering system are powered by the power system PS through the power transformer TV1 of the main step-down substation (Fig. 5). Electric motors (M) of the pumps are fed from the 6 kV buses of this substation. The PVS can be connected to the 6 kV buses using a TV2 transformer.

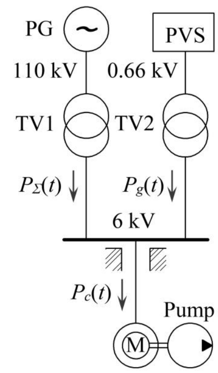

Fig. 5. Conditionally positive directions of power in the power supply grid of the mine dewatering system equipped with the photovoltaic station

The pumping units consume active power $P_c(t)\geq 0$ at time t, the PVS produces power $P_g(t)\geq 0$. The total power consumption from the power system is:

$$P_\Sigma(t)=P_c(t)-P_g(t). \quad (4)$$

For the time interval (t_1, t_2), the values of the active energy consumed by the pumping units, as well as the energy generated by the PVS, are equal to the specified integrals of the respective capacities:

$$W_c\big|_{t_1,t_2}=\int_{t_1}^{t_2} P_c(t)\mathrm{d}t, \quad (5)$$

$$W_g\big|_{t_1,t_2}=\int_{t_1}^{t_2} P_g(t)\mathrm{d}t. \quad (6)$$

The active energy consumed from the power system during the time interval (t_1, t_2) is defined as the energy difference according to expressions (5) and (6), which corresponds to the dependence (4), namely:

$$W_\Sigma\big|_{t_1,t_2}=W_c\big|_{t_1,t_2}-W_g\big|_{t_1,t_2}. \quad (7)$$

Assume that the price T_{ijk} of electricity at the time of purchase is market-based and is set every hour. Then the cost of electricity consumed for the k-th month can be calculated as:

$$B_k=\begin{cases} W_{\Sigma k}\cdot B_{ck}/W_{ck}, & \text{if } W_{ck}>W_{gk}; \\ 0, & \text{if } W_{ck}=W_{gk}; \\ W_{\Sigma k}\cdot T_{PV}, & \text{if } W_{ck}<W_{gk}, \end{cases} \quad (8)$$

where $W_{\Sigma k}$ – active energy consumed from the power system for the k-th month, determined according to (7); W_{ck} – active energy consumed by pumping units per month, calculated according to (5); W_{gk} – active energy generated by the PVS for the k-th month, according to (6); B_{ck} – the cost of electricity consumed by pumping units for the k-th month at market-based prices (without taking into account PVS generation):

$$B_{ck} = \sum_{j=1}^{m_k} \sum_{i=1}^{24} W_{cijk} \cdot T_{ijk}, \quad (9)$$

and W_{cijk} – consumption of active energy by pumping units for the i-th hour of the j-th day of the k-th month.

If the value calculated by (8) is positive $B_k>0$, the mine pays the determined sum to the energy supply company. A negative value ($B_k<0$) indicates a reverse flow of funds. The algebraic sum of monthly costs (8) is equal to the annual balance of payment for the energy consumption of the main mine dewatering system, namely:

$$B = \sum_{k=1}^{12} B_k. \quad (10)$$

The annual balance B is measured in monetary units and is a sign variable. In particular, a positive value of $B>0$ indicates that the consumer paid more for the year to the energy supplier than he received, while a negative value corresponds to the opposite case. Let's take as a base value the annual total cost of electricity consumed by pumping units at market prices without taking into account the PVS generation, which is determined considering (9) as follows:

$$B_c = \sum_{k=1}^{12} B_{ck}. \quad (11)$$

Then the optimization parameter y (annual balance in relative units) is defined as:

$$y = B / B_c. \quad (12)$$

According to the formulated research hypothesis, it should be possible to select such a rated capacity of the PVS that, under certain natural conditions and electricity prices, the optimization parameter approaches zero. Denoting the rated power of the PVS as P_r and the optimal rated power as P_o, the optimization criterion can be formulated as follows:

$$\lim_{P_r \to P_o} y(P_r) = 0. \quad (13)$$

The rated power of real PVS varies discretely due to the finite capacity of parallel strings of photovoltaic modules. In addition, disturbances (solar irradiance, water inflow, electricity prices) vary randomly. Therefore, for practical use, the permissible value of mismatch ε can be introduced:

$$-\varepsilon < \lim_{P_r \to P_o} y(P_r) < \varepsilon. \quad (14)$$

Dependence (14) provides for finding the optimal value of the PVS rated capacity, in which the relative value of the annual balance in monetary units does not exceed ±100·ε %.

5. 2. Mathematical model relating the optimization parameter to the rated capacity of the photovoltaic station

The mathematical model $y(P_r)$ relating the optimization parameter to the rated capacity of the PVS can be determined by a regression dependence as a result of a single-factor simulation experiment. The PVS DC rated power P_r is considered as an influence factor. Assuming the same size of the photomodule matrix connected to each inverter, the value of P_r is determined by the number N_{inv} of the latter as:

$$P_r = N_{inv} \cdot N_{ms} \cdot N_{mp} \cdot P_{mp}. \quad (15)$$

Since the boundaries of P_r variation near the zero value of the optimization parameter y are not known a priori, three trial simulation experiments were conducted at N_{inv}={10; 15; 20}, which corresponded to P_r={1.8717; 2.8075; 3.7433} MW. The following optimization parameter values are obtained: y={5.2512·10^{-1}; 1.6786·10^{-1}; –3.2654·10^{-1}} p.u. Based on this, l=4 evenly distributed factor levels were adopted for the simulation experiment (Table 1). The selected levels correspond to 15–18 inverters, i.e., the rated capacity of the PVS is 2.8075–3.3690 MW. In this case, encoding of the factor levels is carried out according to the dependence: x=3.5615·P_r–11. The values of the optimization parameter for the final levels of the selected range of factor variation are approximately symmetric relative to the optimal value y=0.

The following disturbances are considered: specific solar irradiance I_{ijk}, water inflow Q_{jk}, market price of electricity T_{ijk}. The value of I_{ijk} is predicted on the basis of long-term meteorological observations with accuracy up to the i-th hour of the j-th day of the k-th month. Within a year, when conducting a simulation experiment, this value can be considered as the implementation of a random process. The daily water inflow Q_{jk} is considered as a random normally distributed quantity. The statistical characteristics of this value for a specific mine are determined on the basis of long-term observations. The electricity market price T_{ijk} is also considered as an implementation of a random process.

The block diagram of the model illustrating the determination of the optimization parameter during the simulation experiment is shown in Fig. 6. Subsystem 1 corresponds to the model of pumping units (Fig. 2). The water inflow Q_{fjk} is the disturbance for such a subsystem, the output value is the electricity consumption W_{cijk} for a specified hour. Subsystem 2 implements the PVS model. The rated capacity P_r of the PVS is the input value controlled by changing the configuration of the photovoltaic station (in particular, by changing the number of inverters). The solar irradiance I_{ijk} is the disturbance. The monthly generation W_{gk} is the output value. Subsystem 3 provides calculation of the optimization parameter value according to (12) taking into account (8)–(11).

Table 1

Encoding of factor levels and statistical characteristics of optimization parameter samples

Number of factor level ζ	1	2	3	4
PVS rated capacity P_r, MW	2.8075	2.9947	3.1818	3.3690
Number of inverters N_{inv}	15	16	17	18
Encoded factor levels x_ζ°, p.u.	–1	–0.3333	0.3333	1
Sample mean of the optimization parameter $\bar{y}_\zeta$, p.u.	1.6999·10^{-1}	7.9023·10^{-2}	–1.3050·10^{-2}	–1.1257·10^{-1}
Sample variance of the optimization parameter s_ζ^2, p.u.	5.3806·10^{-6}	5.2777·10^{-6}	6.7281·10^{-6}	9.0622·10^{-6}

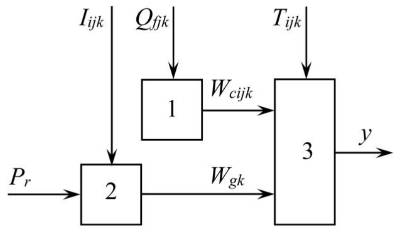

Fig. 6. The general structure of the model for calculating the optimization parameter, including subsystems: 1 – modeling of pumping units; 2 – PVS modeling; 3 – calculation of the optimization parameter value

The minimum sample volume of the optimization parameter values, which provides an estimate of the standard deviation with an accuracy of d=0.25 with a statistical reliability of γ=0.95, is $s=1+0.5(z_{1-\gamma}/d)^2\approx30$, where $z_{1-\gamma}$=1.96 – standardized normally distributed variable. Taking this into account, 30 experiments were conducted using a simulation model for each level of the factor, the statistical characteristics of the obtained samples are shown in Table 1.

The statistical parameters of the mathematical model are estimated at the significance level α=0.05 [16]. Each of the obtained samples was checked for normal distribution using the Kolmogorov-Smirnov test. The critical value of the criterion $K_c=2.4173\cdot10^{-1}$ exceeds the empirical values for each of the samples: $K=\{1.3550\cdot10^{-1}$; $1.5566\cdot10^{-1}$; $7.6244\cdot10^{-2}$; $1.0322\cdot10^{-1}\}$. This does not give grounds for rejecting the null hypothesis about the normal distribution of empirical data for each sample. Cochran's C test is used to check the hypothesis of homogeneity of sample variances. The value of the criterion G=0.3426 calculated from sample variances is smaller than the critical value $G_c(\alpha;\ s-1;\ 4)=G_c(0.05;\ 29;\ 4)=0.3978$: $G<G_c$. Accordingly, there are no grounds for rejecting the hypothesis of sample variances homogeneity at the accepted significance level.

To test the hypothesis that there is no correlation between the investigated values, the values of the linear correlation coefficient $\hat{r}=-9.9948\cdot10^{-1}$ and the correlation ratio $\hat{r}=-9.9948\cdot10^{-1}$ are calculated. As a result of checking the significance of the calculated values, it was found that: $|\hat{r}|\sqrt{(s\cdot l-2)/(1-\hat{r}^2)}=3.3774\cdot10^2$, which exceeds the Student's distribution point $t_\alpha(s{\cdot}l-2)$= =1.6600; $\hat{\rho}\sqrt{s\cdot l-2\,/\,1-\hat{\rho}^2}=1.8776\cdot10^4$ is also significantly larger than $t_\alpha(s{\cdot}l-2)$. This confirms the statistical significance of the investigated correlation. To test the hypothesis of a linear type of dependence, the W^2 criterion is used:

$$W^2=\frac{l(s-1)\left(\hat{\rho}^2_{y/x}-\hat{r}^2\right)}{(l-2)\left(1-\hat{\rho}^2_{y/x}\right)}. \tag{16}$$

The calculated value of the criterion $W^2=4.5626\cdot10^1$ exceeds the critical point of the Fisher's distribution $F(\alpha;\ l-2;\ s{\cdot}l-l)$= $=F(0.05;\ 2;\ 116)=3.0744$. This allows considering the hypothesis of a linear type of regression dependence as statistically unfounded. Then we assume a parabolic form of dependence:

$$\hat{y}(x)=\hat{a}_0+\hat{a}_1x+\hat{a}_2x^2. \tag{17}$$

Estimates of parameter values:

$$\hat{a}_0=3.3520\cdot10^{-2},\ \hat{a}_1=-1.4098\cdot10^{-1},\ \hat{a}_2=-4.8080\cdot10^{-3}$$

were found by the least squares method using the Nelder-Mead simplex method. In this case, the minimized standard deviation of the observation results is $s_{std}=2.6508\cdot10^{-3}$, which confirms the possibility of using the parabola (17) as a regression dependence (Fig. 7).

Confidence intervals $C_{1,2}(x)$, which estimate the deviation of the average values of the optimization parameter by empirical regression $\hat{y}(x)$ from the true average values with a probability of (1–α), for parabola (17) are calculated as (Fig. 7):

$$C_{1,2}(x)=\hat{y}(x)\pm t_{\alpha/2}(s\cdot l-3)\cdot\frac{s_{std}}{\sqrt{l}}\times$$

$$\times\sqrt{c+\frac{(x-\bar{x})^2}{s_x^2}+\frac{l\cdot\varphi_2^2(x)}{\sum\limits_{\zeta=1}^{l}\varphi_2^2\left(\overset{\circ}{x}_\zeta\right)}}, \tag{18}$$

where c=1; $t_{\alpha/2}(s{\cdot}l-3)$ – the Student's distribution point at the α/2 significance level and with $(s{\cdot}l-3)$=117 degrees of freedom, which is $t_{0.025}(117)=1.9804$; $\bar{x}=0$ – the mean of the factor values; $s_x=7.4528\cdot10^{-1}$ – standard deviation of factor levels from the mean. Expression (18) also indicates:

$$\varphi_2(x)=x^2-d_1(x-\bar{x})-d_2; \tag{19}$$

$$d_1=\frac{\sum\limits_{\zeta=1}^{l}\left(\overset{\circ}{x}_\zeta\right)^3-\bar{x}\cdot\sum\limits_{\zeta=1}^{l}\left(\overset{\circ}{x}_\zeta\right)^2}{\sum\limits_{\zeta=1}^{l}\left(\overset{\circ}{x}_\zeta\right)^2-k\cdot\bar{x}^2}; \tag{20}$$

$$d_2=\frac{1}{k}\sum_{i=1}^{k}\left(\overset{\circ}{x}_i\right)^2, \tag{21}$$

and for the case of the simulation experiment d_1=0, $d_2=5.5544\cdot10^{-1}$.

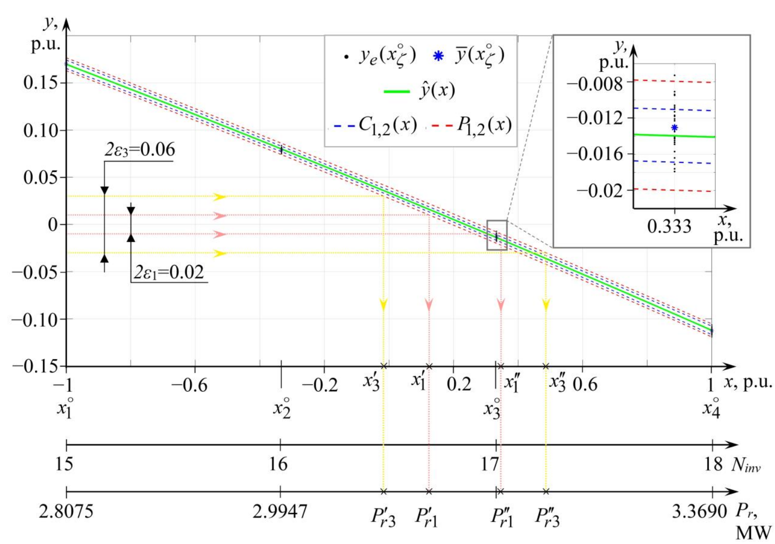

Fig. 7. The regression line of the relative annual balance y, p.u., versus the value of the factor x, p.u., the number of inverters N_{inv} and the rated capacity of the photovoltaic station P_r, MW, with confidence intervals $C_{1,2}(x)$ and prediction intervals $P_{1,2}(x)$, plotted on the y_e points obtained in the simulation experiment at the selected factor levels $\overset{\circ}{x}_\zeta$ with the observed sample means $\bar{y}$ of the optimization parameter

The boundaries of the prediction intervals $P_{1,2}(x)$, including sample values of the optimization parameter with probability $(1-\alpha)$, are estimated by a dependence similar to (18) at $c=1+l=5$ (Fig. 7).

5. 3. Energy consumption of the mine dewatering system when powered by a smart grid of an optimal configuration

Using the estimated boundaries of the prediction interval $P_{1,2}(x)$ for three values of the permissible mismatch ε, the boundaries of the intervals (P_r', P_r'') of the PVS rated capacity were estimated (Table 2). Such intervals, shown in Fig. 7, with a 0.95 probability include the optimal value.

With a mismatch of $\varepsilon_1=0.01$, according to the boundaries $P_{r1}'=3.1235$ MW and $P_{r2}'=3.1861$ MW, the boundaries for the total strings number of series-connected photoelectric models were calculated: $\sum N_{mp}'=351$, $\sum N_{mp}''=358$. The mean value of the total number of parallel strings can be taken at the level of 355. Let's leave the number of strings connected to one inverter unchanged ($N_{mp}=21$). Then the optimal PVS configuration for the given conditions involves 16 inverters, each of which is connected to 21 strings of modules, and an additional inverter with 19 strings. Under such conditions, the optimal rated PVS capacity is estimated at 3.1640 MW.

As a result of 30 simulation experiments of the operation of optimally configured PVS, it was found that the generation of active energy by photoelectric models per year is equal to 3.745 MWh (Fig. 8).

Table 2

The interval boundaries of the PVS rated capacity, which with a 0.95 probability include the optimal value, estimated based on the results of simulation experiments for the permissible mismatches of the optimization parameter

Number of estimation		1	2	3
Permissible mismatches of the optimization parameter with a probability of $(1-\alpha)=0.95$	ε, p.u.	0.01	0.02	0.03
Boundaries of the factor interval	x', p.u.	$1.2438\cdot10^{-1}$	$5.3963\cdot10^{-2}$	$-1.6862\cdot10^{-2}$
	x'', p.u.	$3.4722\cdot10^{-1}$	$4.1671\cdot10^{-1}$	$4.8593\cdot10^{-1}$
Boundaries of the PVS rated capacity	P_r', MW	3.1235	3.1038	3.0839
	P_r'', MW	3.1861	3.2056	3.2250

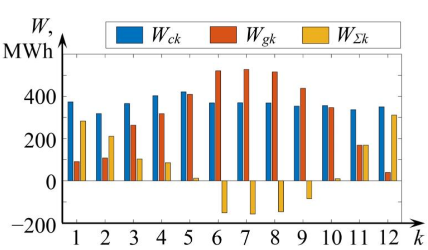

Fig. 8. Implementation of random values of energy consumption by pumping units, W_{ck}, kWh, photovoltaic station generation W_{gk}, kWh, and energy balance $W_{\Sigma k}$, kWh, by months k during the year in one of the simulation experiments

At the same time, the financial indicators are:

– annual total cost of electricity consumed by pumping units at 2021 market prices, excluding PVS generation: mean $m[B_c]=288.9$ thousand c.u., standard deviation $s[B_c]=877.1$ thousand c.u.;

– annual balance of payment for electricity consumed by the main dewatering system of the mine: $m[B]=-1138.7$ c.u.; $s[B]=674.4$ c.u.;

– the relative value of the annual balance: $m[y]=-3.9458\cdot10^{-3}$ p.u.; $s[y]=2.3431\cdot10^{-3}$ p.u.

Graphs in Fig. 8 show the relationship between the monthly energy consumption W_{ck} by pumping units and the monthly generation W_{gk} of the PVS. At the same time, positive values of the energy balance $W_{\Sigma k}$ correspond to the predominant consumption of electricity from the power system during the k-th month, and negative values indicate the predominant supply of energy to the power system.

6. Discussion of the results of configuration optimization of the smart power supply grid of the main dewatering system

The relative value of the annual balance (12) of payment for electricity consumed by the main dewatering system was considered as an optimization parameter. The reason is its integral nature, since it is necessary to take into account factors of various etiologies. This optimization parameter considers natural factors: the random character of water inflow and the stochastic solar irradiance. Technical factors are also taken into account: the volume of the water collector, the electric power of the drive motors of pumping units, the total flow of water through the pumps (considering the pumping height), the operation algorithm of the automation equipment of the mine dewatering system. In addition, economic factors are taken into account: the market hourly price and the feed-in electricity tariff. The selected optimization parameter allows determining what part of the total annual electricity consumption (11) by pumping units is the annual balance of payment for the consumed energy (10) when using the PVS. Characteristic points of the optimization parameter definition area ($y\le1$) are the values 0 and 1, which is explained as follows.

At $y=0$, the PVS fully compensates for the financial costs of powering the main dewatering system, but power flows are not excluded. The value $y=1$ corresponds to the absence of PVS. The proposed optimization criterion (13) provides the selection of suitable PVS rated capacity for specific conditions, which ensures that the optimization parameter approaches zero based on the results of the year. At the same time, monthly financial calculations (8) of both directions between the coal mining enterprise and the energy supply company are allowed. The minimization of the optimization parameter absolute value with accuracy up to the permissible mismatch (14) is explained by the discrete change in the PVS rated capacity (15) when the number of inverters or strings of modules changes. Also, the introduction of ε is explained by the random nature of water inflow (Fig. 3) and solar irradiance (Fig. 4) as natural factors, as well as the market price of electricity as an economic factor.

Obtaining a mathematical model that relates the optimization parameter to the PVS rated capacity by conducting a one-factor simulation experiment is explained by the large number of disturbances taken into account. This complicates the use of analytical methods for mathematical modeling of the research object. The need to conduct trial simulation experiments (Table 1) is due to the lack of a priori information about the boundaries of the influence factor variation. The use of the computer model, which structurally includes pumping units and PVS (Fig. 6), ensures the calculation of the optimization parameter value for specific implementations of random variables. Samples of optimization parameter values obtained as a result of repeated experiments with a statistical reliability of 0.95 for each of the selected factor levels became the basis for developing the desired mathematical model. The application of the Kolmogorov-Smirnov test did not give grounds to reject the hypothesis of the normality of the sample distribution at a significance level of 0.05. Also, as a result of applying the Cochran's C test, the hypothesis of homogeneity of sample variances was not rejected. The significance check of the sample correlation coefficient and correlation ratio confirmed the significance of the correlation between the PVS rated capacity and the annual balance of payment for electricity consumed by the mine dewatering system. A negative $r_{\vdots}$ value indicates an inverse relationship between the studied parameters. Since the hypothesis of a linear type of dependence was statistically unfounded according to criterion (16), the assumption of a parabolic type of dependence was confirmed. The regression coefficients (17), which are the desired mathematical model, were estimated using the least squares method. The nonlinearity of the regression can be considered insignificant during engineering calculations, since the coefficient $\hat{a}_2 = -4.8080 \cdot 10^{-3}$ at the second order summand of the regression polynomial is two orders of magnitude smaller than the coefficient $\hat{a}_1 = -1.4098 \cdot 10^{-1}$ at the first order summand. The regression graph (Fig. 7) illustrates a decrease in the optimization parameter with an increase in the PVS rated capacity. This is explained by the growth in the amount of energy generated by the modules, respectively, a decrease in the cost of electricity consumed at market prices. From the point of view of the averaged y values, the confidence intervals (18) are of interest, and from the perspective of the sample values of the optimization parameter – the wider prediction intervals $P_{1,2}(x)$, plotted in Fig. 7. In particular, at the factor level of 0.333 p.u., corresponding to the presence of 17 inverters in the PVS with a total capacity of modules of 3.1818 MW, the mean value of the optimization parameter is $-1.3050 \cdot 10^{-2}$ p.u. In this case, the width of the confidence intervals is $5.7839 \cdot 10^{-3}$ p.u., and of the prediction intervals is $1.1987 \cdot 10^{-2}$ p.u. Some expansion of the mentioned intervals in the areas of the minimum and maximum values of the factor is explained by a decrease in the accuracy of prediction compared to the central area of the factor change.

An increase in the value of the permissible mismatch (0.01–0.03) expands the range of changes in the PVS optimal power, estimated according to the boundaries of the prediction interval for sample values of the optimization parameter (Table 2). Each percent of the mismatch corresponds to an expansion of the power range by approximately 40 kW. From the point of view of PVS design, this provides an opportunity to choose an optimal configuration of the modules matrix and number of inverters, taking into account the number of physical DC inputs of the latter. In particular, for the Bilytska Mine conditions, the optimal PVS rated capacity is estimated at 3.1640 MW, which is 1.8 times higher than the 1.7320 MW capacity of two simultaneously operating pumping units. When interpreting such a capacity ratio, it is necessary to take into account the statistical characteristics of solar irradiance and water inflow during the year. Most of the time, the actual PVS capacity does not reach the rated value, which is determined under normal conditions, in particular, the solar irradiance of 1.000 W/m^2. Since $m[I] = 141.2$ W/m^2 and $s[I] = 230.9$ W/m^2 at the PVS site, the probability of reaching the rated power by photoelectric modules is low. It is also necessary to take into account the discrete nature of the operation of the main dewatering system. The analysis of the statistical indicators of the PVS operation in case of the optimal configuration allows determining an insignificant level of financial calculations between the coal mining enterprise and the energy supply company. On average, the annual balance is about 1.1 thousand c.u. in favor of the mine, with a total cost of electricity for the operation of the main dewatering system of 288.9 thousand c.u. Monthly generation of PVS exceeds consumption from June to September (Fig. 8). Photoelectric modules generate the least amount of energy from December to February. Accordingly, in these months most electricity is purchased at market prices.

The advantage of the founded method of determining the optimal PVS rated capacity for the mine dewatering system, in comparison with [10], is the consideration of the operating mode of pumping units when the intensity of the water inflow changes. This is ensured by dependencies (1)–(3). Compared to [11], the advantage of the obtained regression (17) is the consideration of weather conditions at the PVS site (Fig. 4). In contrast to [12], the cost of the proposed power supply grid of the main dewatering system is significantly reduced due to the absence of storage batteries and the presence of energy exchange with the power system. The latter is estimated by dependence (8). Due to the implementation of criterion (14), a reduction in the payment for energy consumption of the main dewatering system by 98–99 % of the full cost is achieved. This is much more effective than a 20–25 % reduction by implementing the measures developed in [6].

Implementation of the proposed power supply grid for the dewatering system with a PVS of optimal capacity solves the issue of increasing the energy efficiency of underground pumping units. This will reduce the payments for consumed electricity to a negligible amount (within a few percent of the total cost). Accordingly, the coal mining company, and ultimately the communities of the coal regions, which are transformed after the mines closure, will avoid unproductive financial costs for maintaining the groundwater balance. The probability of territories flooding where the natural water regime has been disturbed due to coal mining and other negative consequences of increased levels of underground water will decrease.

The use of the proposed methodology for optimizing the PVS rated capacity is limited to a fixed number of working pumping units. In the case of changes in the number of simultaneously operating pumps, when the water inflow changes, the optimal PVS rated capacity estimated by the model may be slightly overvalued. In addition, the estimated optimal capacity is correct in the absence of restrictions on the operation of the main dewatering system during peak hours of power system loads. The presence of such limits leads to underestimates of the PVS capacity.

The disadvantages of the study include the lack of reliable methods of forecasting market prices for electricity and the size of the feed-in tariff. A significant increase in prices and a decrease in the feed-in tariff can increase the payback period of the project and the risks of the PVS construction. Also, the proposed methodology for estimating the optimal rated capacity does not provide for the minimization of power flows between the power system and the power supply grid of the dewatering system. This prevents the dewatering system from switching to the autonomous mode of operation in case of external emergency situations.

The development of this research is possible in the direction of increasing the accuracy of estimating both technical and economic parameters. In particular, it is expedient to justify the algorithm of turning on pumping units depending on the time of day, taking into account the PVS generation, which optimizes power flows with the power system.

7. Conclusions

1. The relative value of the annual balance of payment for electricity consumed by the mine dewatering system is substantiated for use as an optimization parameter when determining the rated capacity of the photovoltaic station as part of a smart power supply grid. The integral character of the indicator, unlike the known ones, is ensured by taking into account natural, technical and economic aspects. The selection of the rated capacity of the photovoltaic station, which approaches the optimization parameter, within the permissible mismatch, to zero, is considered as an optimization criterion. The implementation of the optimization criterion makes it possible to reduce the cost of electricity for pumping mine water to an insignificantly small value, which considerably reduces the annual financial operating costs of a coal mining enterprise, including closed mines.

2. The possibility of representing the regression dependence of the annual balance of electricity payments on the rated capacity of the photovoltaic station for the mine dewatering system by a parabola has been confirmed. The methodology for estimating the parameter values of such a mathematical model is substantiated. The methodology involves setting disturbance values for specific mine conditions (solar irradiance, water inflow, parameters of pumping units, etc.), carrying out simulation experiments and statistical processing of the results. For the given conditions, the small width of the confidence intervals (does not exceed 1 %) and prediction intervals (up to 1.5 %) makes it possible to use the obtained regression dependence directly in the optimization of the photovoltaic station configuration.

3. Simulation studies of the energy consumption of the mine dewatering system when fed by a smart power supply grid of an optimal configuration confirmed the presence of a significant economic effect from the PVS introduction. Annual electricity savings for the Bilytska Mine conditions (Ukraine) reach 3,745 MWh. At market prices for electricity in Ukraine in 2021 and at the weighted average value of the feed-in tariff of 0.16772 c.u./(kWh), savings in monetary terms exceed 288 thousand c.u.

Conflict of interest

The authors declare that they have no conflict of interest in relation to this research, whether financial, personal, authorship or otherwise, that could affect the research and its results presented in this paper.

Financing

The study was conducted without financial support.

Availability of data

The manuscript has no associated data.

References

1. Adoption of the Paris Agreement. FCCC/CP/2015/L.9/Rev.1 (2015). Available at: http://unfccc.int/resource/docs/2015/cop21/eng/l09r01.pdf
2. Wang, B., Cui, C.-Q., Zhao, Y.-X., Chen, M., Yuan, X.-C. (2018). Climate change mitigation in the coal mining industry: low-carbon pathways and mine safety indicators. Natural Hazards, 95 (1-2), 25–38. doi: https://doi.org/10.1007/s11069-018-3438-1
3. Abandoned hardrock mines. Information on number of mines, expenditures, and factors that limit efforts to address hazards (2020). GAO-20-238. United States Government Accountability Office. Available at: https://www.gao.gov/assets/gao-20-238.pdf
4. Janson, E., Gzyl, G., Banks, D. (2009). The Occurrence and Quality of Mine Water in the Upper Silesian Coal Basin, Poland. Mine Water and the Environment, 28 (3). doi: https://doi.org/10.1007/s10230-009-0079-3
5. Sahoo, L. K., Bandyopadhyay, S., Banerjee, R. (2014). Water and energy assessment for dewatering in opencast mines. Journal of Cleaner Production, 84, 736–745. doi: https://doi.org/10.1016/j.jclepro.2014.07.072
6. Razumnyi, Yu. T., Rukhlova, N. Yu., Rukhlov, A. V. (2015). Energy efficient work of a coal mine dewatering plant. Naukovyi visnyk Natsionalnoho hirnychoho universytetu, 2, 74–79. Available at: http://nvngu.in.ua/index.php/uk/component/jdownloads/finish/53-02/8298-2015-02-razumnyi/0
7. Morstyn, T., Chilcott, M., McCulloch, M. D. (2019). Gravity energy storage with suspended weights for abandoned mine shafts. Applied Energy, 239, 201–206. doi: https://doi.org/10.1016/j.apenergy.2019.01.226
8. Saigustia, C., Robak, S. (2021). Review of Potential Energy Storage in Abandoned Mines in Poland. Energies, 14 (19), 6272. doi: https://doi.org/10.3390/en14196272
9. Banks, D., Athresh, A., Al-Habaibeh, A., Burnside, N. (2017). Water from abandoned mines as a heat source: practical experiences of open- and closed-loop strategies, United Kingdom. Sustainable Water Resources Management, 5 (1), 29–50. doi: https://doi.org/10.1007/s40899-017-0094-7

10. Sinchuk, O. M., Boiko, S. M., Minakov, I. A. (2018). Aspects of Smart Grid Concept Introduction in the Complex of Electrical Supply and Electricity Supply of Hydrogen Industry Enterprises. Visnyk of Vinnytsia Politechnical Institute, 2, 27–32. Available at: https://visnyk.vntu.edu.ua/index.php/visnyk/article/view/2206
11. Sharma, U., Singh, B., Kumar, S. (2017). Intelligent grid interfaced solar water pumping system. IET Renewable Power Generation, 11 (5), 614–624. doi: https://doi.org/10.1049/iet-rpg.2016.0597
12. Mishra, A. K., Singh, B. (2018). Stage Solar PV Powered Water Pump with a Storage System. 2018 8th IEEE India International Conference on Power Electronics (IICPE). doi: https://doi.org/10.1109/iicpe.2018.8709497
13. Trapani, K., Millar, D. L. (2015). Floating photovoltaic arrays to power the mining industry: A case study for the McFaulds lake (Ring of Fire). Environmental Progress & Sustainable Energy, 35 (3), 898–905. doi: https://doi.org/10.1002/ep.12275
14. Pouran, H. M. (2018). From collapsed coal mines to floating solar farms, why China's new power stations matter. Energy Policy, 123, 414–420. doi: https://doi.org/10.1016/j.enpol.2018.09.010
15. Dobos, A. P. (2012). An Improved Coefficient Calculator for the California Energy Commission 6 Parameter Photovoltaic Module Model. Journal of Solar Energy Engineering, 134 (2). doi: https://doi.org/10.1115/1.4005759
16. Montgomery, D. C. (2017). Design and analysis of experiments. John Wiley & Sons, 752. Available at: https://www.wiley.com/en-ie/Design+and+Analysis+of+Experiments,+9th+Edition,+EMEA+Edition-p-9781119638421