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Predicting the Power Generation from Renewable Energy Sources by using ANN

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Abstract—**This paper proposes power generation forecasting for photovoltaic power plants by using Adaptive Neuro-Fuzzy Inference Systems library in MATLAB and considering meteorological factors. Renewable energy sources (RES) introduce compensation instability problems in the grid hence forecasting methods are considered. Especially important for grid operators is a day ahead forecasting as it can reduce negative imbalance price. Means of ensuring the balance reliability of the power system in terms of RES integration are presented. The installation of charging stations for electric vehicles or use of hydrogen technologies and modern storage systems can provide grid balance. In addition, decreasing the deviation of the current (real) value from the predicted value of power generation is a way to compensate for power unbalance.**

Keywords-renewable energy sources; power grid; power balance; optimal control

I. INTRODUCTION

The main positive consequences of the active introduction of renewable energy sources (RES) in the electricity industry includes the reduction of the need for fossil resources during electricity production, which leads to a reduction in CO_2 emissions, in particular in thermal power plants [1]. A lot of companies research for a way to use RES, so goal of entering the clean energy space may also boost investment in renewables companies [2]. Authors in [2] noted a necessity for the CO_2 emissions to decrease by 85% between 2015 and 2050 due to global economic activity. One of the ways of achieving this proposal is the annual decline of energy-related CO_2 emissions by 2.6% on average, or 0.6 Giga tones (Gt) in absolute terms, resulting in 9.7 Gt of energy CO_2 emissions per year in 2050.

For Ukraine like other countries in the World, the problem of reducing CO_2 emission is a relevant one. The Ukrainian approach is by increasing electricity generation from RES power plants. So, in 2009, Ukraine made a guaranteed legal commitment to buy all electricity supplied by RES stations at a "green" tariff until 2030. In terms of electricity market impact, it should be noted that the mandatory buyout in the market segment "day ahead" supply from RES shifts the supply of other producers, stimulating a significant reduction in marginal prices for RES, which is an important component of the total cost of electricity to end consumers.

The urgency of the research of this paper is due to rapid increase in the share of RES in the overall balance of the electric power system of Ukraine, which, along with positive consequences, lead to a number of negative trends. Unregulated and abruptly changing schedules of electricity supply stations with RES reserves lead both to a reduction in supply and price increases in organized market segments, as well as to an increase in the tariff of the transmission system operator. The introduced RES additional imbalances cause an increase in the volume of balancing of the electric power system modes of Ukraine and the prices for balancing market, which leads to an increase in both the price of imbalances and their total value.

In addition, the stochastic nature of the generation levels of RES power plants due to meteorological factors demands additional reserves of generating capacity to regulate the current modes of the electric power system of Ukraine [3]. The aim of this work is to develop effective methods and tools for forecasting the supply of electricity coming from renewable sources, which will minimize the imbalance of electricity and their losses and compensate for those in today's market conditions.

II. COMPENSATION OF THE INFLUENCE OF INSTABILITY OF GENERATION ON THE MODE AND BALANCE RELIABILITY OF ELECTRICAL NETWORKS

The results of the research presented in [3, 4] show a significant instability of electricity generation in photovoltaic power plants (PPPs) and wind power plants (WPPs) caused by the stochastic nature of influential meteorological factors. Normally, the impact of the technical condition of RES equipment could be underestimated, which affects the amount

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of electricity generated, as well as the regime and balance reliability of electrical networks. Reducing the instability of RES generation will not ensure the mode and balancing reliability of electrical networks in full, as it is necessary to take into account the conditions of the distribution and transmission systems as well. The application of modern technologies of electricity storage and the use of RES, which have a relatively stable generation, will help to partially solve these problems.

A. Mode and balance reliability of electrical networks

The mode and balance reliability is the ability of the electrical network to maintain the stability of the steady-state in the event of random changes of its parameters and the ability of the micro-grid to continuously maintain its active power balance [3, 5].

The solution to the problem of ensuring the mode balance is proposed in the scientific work [6, 7] in which the authors focus on local electrical systems (LES), and emphasize that guaranteeing the real-time balance of LES modes in the generation, distribution, and consumption of electricity is needed. In addition, powerful communication capabilities of the distributed control system requires appropriate approaches to the formation of control effects and laws of control for individual sources of electricity, taking into account the specifics of their controllability and observation [8].

Hydrogen production during periods when RES generates more than planned and electricity generation from accumulated hydrogen during periods when RES electricity generation volumes are less than those of declared volume. RES operating on hydrogen can become a full member of the balancing group and it can help reduce the losses of companies caused by penalties due to the deviation of current generation values from the forecasted ones. The use of hydrogen technology has a promising future, as shown by the launch of Hydrogen for Climate Action in Europe according to which eleven hydrogen technology projects have been announced, aiming at preserving the climate on our planet and preventing ecological catastrophe. These projects are aimed at hydrogen use in transportation, its use in the central heating systems, construction of large vessels operating on hydrogen as well as infrastructural development. Hydrogen is a renewable energy source. Its chemical properties are such that when it combines and separates with other chemical elements, a large amount of thermal and electrical energy is indirectly released [9]. Europe expects 10 GW of hydrogen production from Ukraine, of which 2.5 GW is aimed at local market development and 7.5 GW - should ensure cross-border trade with the EU in the future until 2025. Decarbonization is part of DTEK's development strategy, which has set itself the ambitious goal of becoming a carbon-neutral company by 2040. The end of July 2020, almost 23,000 electric cars and slightly more hybrids were registered in Ukraine, which together make up about 46,000 cars. The National Transport Strategy until 2030 provides stimulation for the use of electric vehicles. The agency also initiated and actively participated in the development of key changes in state building codes regarding the placement of gas stations on the roads.

The situation with COVID-19 [10], namely the reduction of energy consumption by 8%, and the location of electric vehicle charging stations changed the load structure. Authors in [3] proposed to update the graphical interpretation of the power balance in the local electrical system, presented in [7] (see Fig. 1). Fig. 1 presents one interpretation of the creating a power balance process in a power network with a combined power supply. According to the scenario presented in [3, 4, 11], electricity is supplied from internal sources of PPPs, WPPs and small hydroelectric power plants (sHPPs), cogeneration power plants (CPPs) and biogas power plants (BPPs) installations and centralized power sources. A load of transformer substations consists of a load of consumers and the generation of power sources that are in their balance. Modern conditions for the operation of RES are characterized by stricter conditions of liability for imbalances, increasing use of new technologies such as hydrogen units (HU), reducing total consumption, as well as the introduction of a new type of consumer such as electric vehicle charging stations (EVCSs) (see Fig. 1) [12, 13].

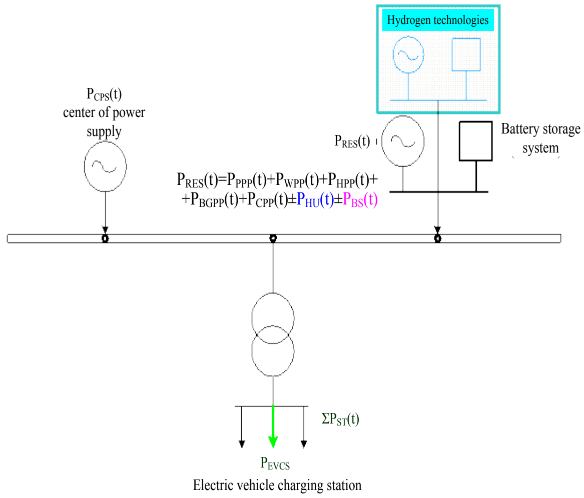


Figure 1. The power balance in power grid taking into account modern trends: installation of charging stations for electric vehicles and the use of hydrogen technologies and modern storage.

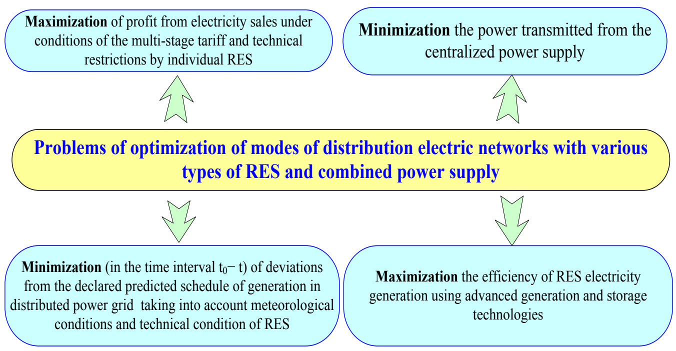


Figure 2. Optimization problems for microgrids with different types of RES

Considering the latest trends in the development of advanced technologies for consumption and generation of RES, new optimization problems may arise for power grids with combined power supply (see Fig. 2).

Studies conducted in the introduction show a steady trend of increasing RES generation, and the article [14] states that this trend will continue until 2024. With the growth of RES generation in electrical networks, the problem becomes relevant, which is formulated as follows:

$$\int_{t_0}^{t_k} \frac{1}{2}\left(P_{RES}(t) - \sum_{i=1}^{n} P_i(t)\right) dt \to min \tag{1}$$

where $P_{RES}(t)$ is the declared (set) schedule of total RES generation in the power grid; $\sum_{i=1}^{n} P_i(t)$ is current total generation of controlled RES in the power grid; n is the number of controlled RES in the power grid. The power balance in the network can be represented by equation (2):

$$P_{CPS}(t) + \sum_{i=1}^{n} P_i(t) + \sum_{j=1}^{m} P_{STj}(t) - \Delta P(t) = 0, \tag{2}$$

where $P_{CPS}(t)$ is power transmitted to the power grid from centralized power sources; $P_{STj}(t)$ is loading of transformer substations taking into account charging stations for electric cars; $\Delta P(t)$ is technological losses of electricity (TLE) in the power grid.

Then the power of the centralized power supply of the power grid is determined by expression (3) obtained from (2):

$$P_{CPS}(t) = -\sum_{i=1}^{n} P_i(t) + \sum_{j=1}^{m} P_{STj}(t) + \Delta P(t), \tag{3}$$

Ideally, the power grid should operate in the mode for which the conditions in (4) for all RES are controlled and provide the full load needs and their generation is predictable with sufficient accuracy:

$$\begin{cases} P_{RES}(t) - \sum_{i=1}^{n} P_i(t) = 0 \\ P_{RES}(t) = \sum_{i=1}^{m} P_{ST_j}(t) \end{cases} \tag{4}$$

However, to ensure such conditions, in addition to data on meteorological conditions for RES, which are non-guaranteed energy sources, we also need data for RES, which are conditionally controlled and used to quickly control the parameters of normal power grid, taking into account their technological limitations.

B. *The balance reliability of the electric power system in terms of RES integration*

Currently, there is a need to develop new generating capacity with the necessary dynamic characteristics for the power system, in particular - highly maneuverable generation, which will ensure reliable operation of the power system and ensure the balance of renewable energy with unguaranteed electricity supply schedule. The main technologies for ensuring the balance reliability of electric power system in terms of integration of DESs (distributed energy sources) with unguaranteed capacity as of 2021 are shown in Fig. 3.

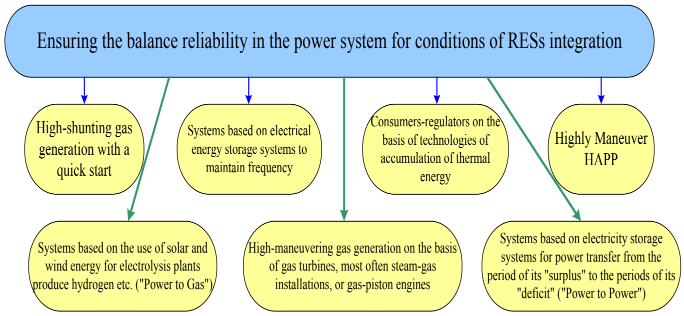


Figure 3. Ensuring the balance reliability of the UES in terms of RES integration

To implement the proposed ways to compensate for the instability of RES generation, it is necessary to adapt the known problem of optimal control of the parameters of distribution networks with different types of renewable generation sources to modern conditions.

C. *Analysis of distributed power grid parameters optimal control with different types of RES*

The task of optimal control is to minimize the control function, which is represented by the expression (4) [15]:

$$F(u) = \int_{t_0}^{t_k} \left[\mathbf{x}_t(t)\mathbf{H}\mathbf{x}(t) + \mathbf{u}_t(t)\mathbf{L}\mathbf{u}(t)\right] dt \to min \tag{5}$$

in the space of system conditions

$$\frac{dx}{dt} = \mathbf{A}\mathbf{x}(t) + \mathbf{B}\mathbf{u}(t); \qquad \mathbf{x}(t_0) = \mathbf{x}_0; \tag{6}$$

$$\mathbf{y}(t) = \mathbf{C}\mathbf{x}(t) + \mathbf{D}\mathbf{u}(t), \tag{7}$$

where **x** (t), **u** (t), and **y** (t) are the vectors of condition, control and observation, respectively; A, B, C, D, H, L are matrices of constant coefficients representing the physical content of generalized parameters of electric power grid; t_0, t_k are the beginning and the end of the time interval at which the control function is minimized (for electric power grid it is usually 15 minutes); x_0 is the initial value of the condition vector;

$$\mathbf{x}(t) = \begin{bmatrix} \dot{\mathbf{J}}(t) \\ \dot{\mathbf{U}}_{\Delta}(t) \\ U_{\delta} \end{bmatrix}; \mathbf{y}(t) = \begin{bmatrix} \dot{\mathbf{S}}_b(t) \\ \dot{\mathbf{I}}_b(t) \\ \mathbf{U}(t) \\ \dot{\mathbf{S}}_{RES\_plan}(t) \end{bmatrix}; \ \mathbf{u}(t) = \begin{bmatrix} \mathbf{k}(t) \\ \mathbf{Q}_{SRP}(t) \\ \dot{\mathbf{S}}_{RES}(t) \\ \mathbf{P}_{BSS}(t) \\ \mathbf{S}_{HU,Bio}(t) \end{bmatrix}$$

Where $\dot{\mathbf{J}}(t) = \hat{\mathbf{U}}_d^{-1}(t)\ \hat{\mathbf{S}}(t)$ is vector of currents in nodes; $\dot{\mathbf{U}}_d\ (t)$ is diagonal matrix of nodal voltages; $\dot{\mathbf{S}}(t) = \mathbf{P} + j\mathbf{Q}$ is power vector in nodes; $\dot{\mathbf{U}}_\Delta(t)$ is the voltages vector of the nodes relative to the basis node; U_δ is basis node voltage; $\dot{\mathbf{S}}_b(t)$ is $\dot{\mathbf{I}}_b(t)$ are vectors representing total power and branch currents, respectively; $\mathbf{U}(t)$ represents a vector of node voltages; $\dot{\mathbf{S}}_{RES\_plan}(t)$ is a vector of predicted (planned) generated power of RESs; $\mathbf{k}(t)$ is a vector containing transformation coefficients of transformers with regulators under load, $\mathbf{Q}_{SRP}(t)$ is a vector of reactive power sources load; $\dot{\mathbf{S}}_{RES}(t)$ is a vector of total power of renewable energy sources (partially controlled); $\mathbf{P}_{BSS}(t)$ is a vector of power battery storage system; $\mathbf{S}_{HU,Bio}(t)$ is a vector of total power hydrogen utilities and biogas/biomass power plants (fully controlled).

So, optimality criterion uses normal mode of electric power system for control of parameters and it can be presented by flow-chart [16]. We propose to add new component value of power, equivalent to energy loss due to unstable power generation RES and caused by meteorological factors (Fig.4).

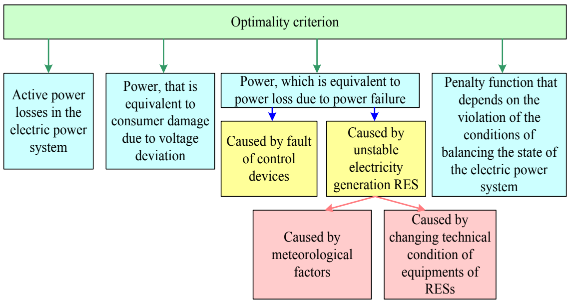


Figure 4. Criterion optimality

III. PREDICTION OF RES GENERATION

Starting January 1, 2021 Ukrainian government is imposing financial liability affecting producers of RESs that cannot provide forecasted electricity supply with minimal error of less than 5%.

A. Forecasting of electricity supply

Forecasting is becoming a key tool for the cost-effective integration of RES power plants, such as wind and solar, into local, regional and national energy systems. Even though, the large number of prediction algorithms exist, the issue of reliable and accurate forecasting still requires careful study and research due to constant weather change and its effects on the forecasting process. The problems of predicting the RES generation can be classified depending on the purpose of the usage of predicted data, as shown in Fig. 5. That is, the generation can be predicted for different time series, with different time periods, and the classification of the forecast execution time is individual. As RESs are becoming more represented in the share of global energy production, improving the accuracy of RES generation forecasting is critical to the planning, control, and operation of power systems. However, this is a difficult task due to the volatile and chaotic nature of data characterization of the RES operation. To date various methods have been developed, including physical models, statistical methods, artificial intelligence methods and their hybrids to improve the accuracy of RES prediction.

Forecasting methods are used to study system connections and patterns of operation and development of objects and processes using modern methods of information processing and are an important tool in the analysis of complex application systems, in working with information (electricity generation, precipitation, solar radiation, temperature), in the purposeful influence of the person on objects of research for the purpose of increase of efficiency of their functioning [17].

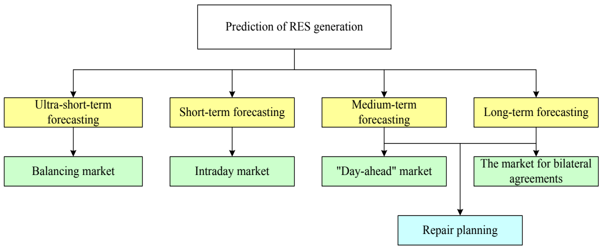
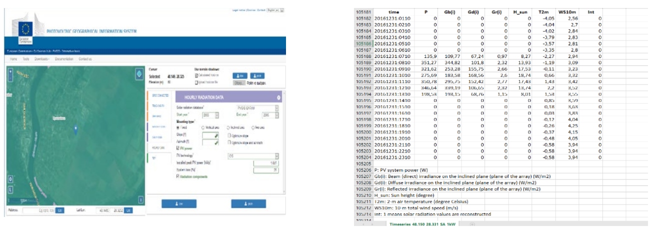


Figure 5. Classification of forecasting tasks depending on the purpose of using the forecast data

Combining the technical condition of RES and the predicted value of RES electricity generation we can determine the criterion of optimality with greater accuracy. Furthermore, we can obtain the vector of parameters of control devices with more accuracy (for example calculate transformation coefficients of transformers with regulators under load) and provide more efficient operation of power grids with RES.

B. Determination of RES generation using ANN

We use the platform developed by the European Commission – Photovoltaic Geographical Information System which shows the hourly generation of Photovoltaic stations to obtain training set for ANN. In order to use this service we needed to know the coordinates (Latitude/Longitude), the type of panels, the power that the photovoltaic module can generate under standard conditions, the installed power of the station, and the percentage of system losses in the station (Fig. 6). The actual installed capacity for PPP "Tsekinivska-2" Ukraine 4-5 is 1045.44 kW.



a) b)

Figure 6. Window screensaver of the service for obtaining hourly meteorological data Photovoltaic Geographical Information System a) and an example of the obtained data b).

After analyzing the data for 2012-2015 for the location of PPP "Tsekinivska-2" 4-5 (Tsekynivka, Yampilskyi raion, Vinnytska oblast (Lat/Lot 48.1490/ 28.3251)), a training sample was obtained. When forming the sample of training data, only those hourly data were taken into account when the station generates electricity and the output is hourly value of RES electricity generation in kWh. Input features used in this study are: Gb(i), Gd(i), and Gr(i) representing solar (direct), diffuse and reflected irradiation on an inclined plane (W/m^2) respectively; H_sun represents the height of the sun (degrees); T_{2m} represents the air temperature measured at 2m above the ground (C◦); WS_{10m} represents total wind speed at 10m above the ground (m/s).

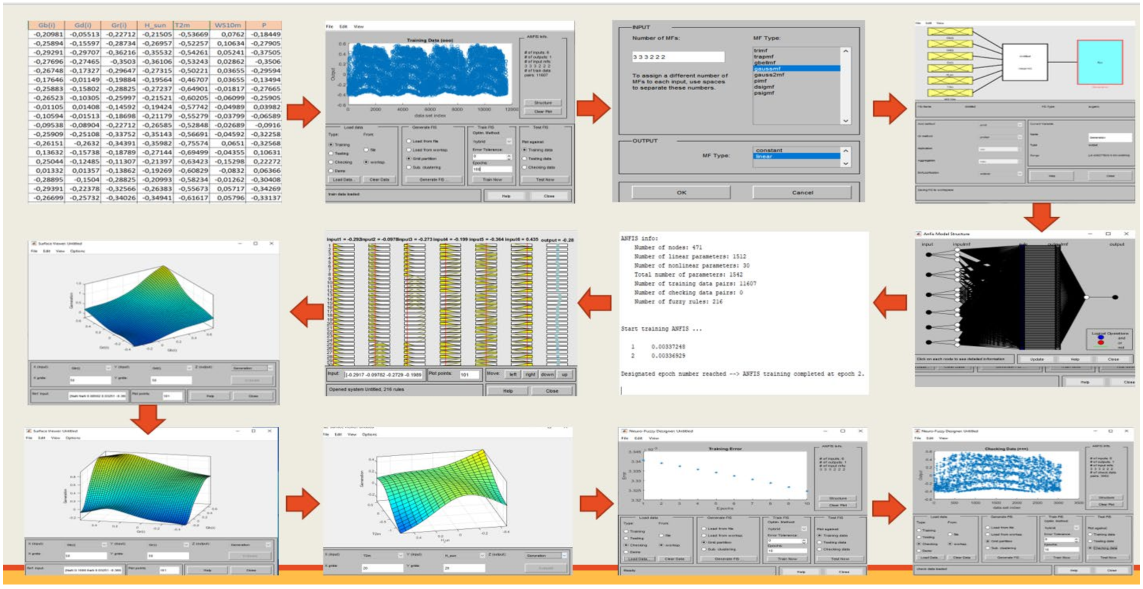
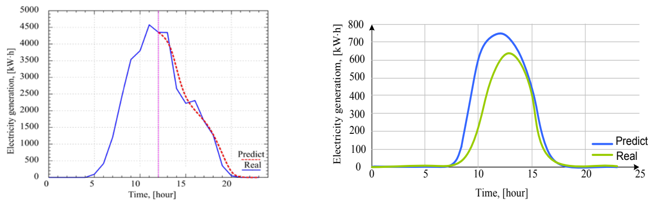


Figure 7. Determination of the hourly value of RES generation using the Neuro Fuzzy Designer module (ANFIS – Adaptive Neuro-Fuzzy Inference System)

Process of determination of the hourly value of RES generation using the Neuro Fuzzy Designer module and Adaptive Neuro-Fuzzy Inference System (ANFIS) is presented in Fig. 7. Proposed ANN can be used to predict hourly day-ahead generation. ANFIS network is a neural network with a single output and multiple inputs representing the fuzzy linguistic variables. The terms of the input linguistic variables are described by standard membership functions (as a result of searching for all possible membership functions and the best result for the problem was obtained with bell-shaped and Gaussian membership functions (gaussmf)), and the terms of the output variable are linear or constant membership functions. On the other hand, the ANFIS network is a fuzzy output system in which each of the fuzzy product rules has a constant weight of 1. This type of network can be successfully used to configure membership function parameters and configure the rule base in a fuzzy expert system. Proposed ANN has 6 inputs of gaussmf type: Gb(i), Gd(i), Gr(i), H_sun, T2m, WS10m. The output of mf is linear. We used gridpartion method for fuzzy inference system: (i) one rule for each input membership function combination and the consequent rule corresponding to a different output membership function and (ii) one output membership function for each fuzzy rule. We used 10 epochs for training ANN and hybrid method.

In the past, learning algorithms for adaptive fuzzy systems were considered time-consuming compared to learning algorithms for neural networks. This is not a problem anymore with modern computer capabilities. Training consists of two stages: (i) Generation of linguistic rules and (ii) Adjustment of membership functions. The first stage is the task of searching for all possible variants of the membership function and the second task is optimization in continuous space. Following implementation steps referring to the construction, configuration and use of the neuro-fuzzy Sugeno model was used to determine the hourly value of RES generation by given meteorological factors: (i) standardized sample of data required for training; input of initial data for network training, (ii) selection of parameters of the neural fuzzy network Sugeno, (iii) the structure of the created network, (iv) information about the created network, (v) network learning error, (vi) the results of the work of the network with an illustration of the created rules, (vii) the dependence of the normalized value of the photovoltaic plant generation on the normalized hourly value of diffuse irradiation and the normalized hourly value of solar (direct) irradiation on an inclined plane, (viii) dependence of the normalized value of photoelectric station generation on the normalized hourly value of the reflected irradiation and the normalized hourly value of solar (direct) irradiation on an inclined plane, (ix) dependence of the normalized value of the height of the sun normalized on the value of the photovoltaic station generation and the normalized hourly value of the solar (direct) radiation on the inclined plane, (x) dependence of the normalized value of the photovoltaic station generation on the normalized value of diffuse irradiation on an inclined plane and the normalized hourly value of the sun height, (xi) dependence of the normalized value of the photovoltaic station generation on the normalized value of air temperature at a height of 2 m and the normalized hourly value of the sun height, and (xii) the dependence of the change in the learning error of the network depending on the number of the learning epochs. After 12 steps are performed the performance check of the created network is done. ANN was trained on the data from the year 2012 to 2015, and tested on the unseen generation data from year 2016. The relative error of predicting RES generation contributes to 1.5%. So, a day ahead prediction is very important for grid operators and a big mismatch between predicted and actual production causes a negative imbalance in price. Taking this into account, we predicted generation for the day ahead using meteorological data from Meteonor and used ANN model. We obtained prediction error between 2-5 %. During February 2021 (see Fig. 8) the weather in Ukraine was with heavy snow conditions hence, some days prediction error increased up to between 10-15 %. Prediction errors are shown in Fig.9.

Figure 8. PPP Vinnytska during winter in Ukraine at different times in a day



(a) (b)

Figure 9. The result of solving the task of forecasting the time series of electricity generation RES: (a) PPP "Dymerskaya" May 28, 2019: red curve – forecast; blue curve – real values; purple curve – the beginning of forecasting, (b) PPP "Tsekinivska-2" 4-5 February 15, 2021.

Conclusions

At present, certain peculiarities of the power grid functioning have appeared in Ukraine, such as problems of balancing production/consumption in electric power systems caused by an increase in the number of wind farms and solar power plants. There are also power balancing problems caused by insufficient maneuverability for balancing. This situation in electrical networks versus the annual increase in installed capacity and electricity generation RES poses new challenges and issues. For the Ukrainian energy sector, the problem is current as starting from January 1, 2021 a resolution was adopted on financial liability for power imbalance in the electricity system. Energy supply companies that generate electricity through RES will pay a financial penalty for electricity imbalances. One way to compensate for the instability of RES generation is to forecast electricity generation with minimal error and minimize possible compensation for inaccurate forecasts. Forecasting is becoming a key tool for the cost-effective integration of RES, such as WPPs, HPPs, small HPPs, into micro, local, regional, and national energy systems. In this paper a forecasting method using ANN is proposed for reducing the system imbalance for RES power generation.

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