A neural network model for short-term PV - energy forecasting

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Abstract. Nowadays, energy consumption in the world is growing becomes relevant to solve the problem of replacing traditional sources with alternative ones. The solution to this problem is impossible without preliminary forecasting of energy production by alternative sources. In this paper, we consider the problem of solving the problem forecasting electric energy by solar power plants, considering the influence of external factors (weather conditions) using a model implemented on the basis a neural network.

Keywords: data analysis, forecasting, alternative energy, electricity generation

1. Introduction
Currently, global energy consumption is growing. Traditional energy sources are becoming more efficient, but planetary population growth leads to a general increase in energy consumption. In this regard, to ensure the growth of global demands, the energy sector needs fundamental changes, namely decentralization of generation, introduction of smart grids (Smart Grid), and the use of alternative energy sources (solar energy and wind energy). Only in this case will it be possible to radically reduce the cost of electricity.

Nowadays, the Russian Federation operates a wholesale market for electric energy, which is divided into price zones. Until recently, traditional types of power plants, such as hydroelectric power stations, coal-fired thermal power plants and nuclear power plants, functioned in each such price zone. The system operator generates applications for the generation of electric energy at hourly intervals of the day. However, with the development of alternative energy sources, on the one hand, and the change in the global climate associated with the environmental situation on the planet, on the other hand, tasks arise related to the integration of alternative energy sources into electricity systems already created by man.

The research is aimed at solving the generation energy forecasting problem the by solar power plants in conditions of incomplete information about the electric power system. An electric power system is understood to mean a single electric grid with both traditional energy sources (combined cycle plants, heat and power plants (TPPs), nuclear power plants) and alternative energy sources, in particular solar power plants, as well as energy consumers with a priori undefined behaviour; operating in the wholesale market of electric energy, which is influenced by various environmental factors such as solar radiation, wind, ambient temperature, etc. The development of a mathematical model reflecting the structural organization and technological processes that occur in the predicted system, in order to create competitive algorithmic and software based on elements of artificial intelligence and machine learning technologies to increase the accuracy of forecasting the generation electric energy by solar power plants, which will allow more efficient loading of thermal power plants and gas turbines.
stations for generating electric energy increasing the economic component conductive due to fuel savings and improve environmental conditions by more effective use of alternative energy sources.

2. Existing methods

Currently, solar power plants are one of the most popular alternative energy sources considered in the world. There are a number of methods for short-term forecasting of electric energy generation applicable to these sources, which can be divided into 4 classes [1], as shown in Figure 1.

![Figure 1. Methods of short-term forecasting of electricity generation](image)

A two-stage method for forecasting electric energy by solar power plants, described in [2], which is divided into statistical and prognostic stages. In the first stage, statistical normalization of solar sources are carried out using the clear sky model, which was proposed in [3].

The next step involves forecasting already normalized solar energy using time-series models, such as an autoregressive model and an autoregressive model with an exogenous input, to which numerical weather forecast data are sent. The result of the work showed that using an autoregressive model with an exogenous input yields a 12% better result than a simple autoregressive model when forecasting a short horizon, and when making a forecast for the next day - by 23%.

In [4], the use of an artificial neural network, an adaptive network based on a fuzzy inference system and a generalized neural network is considered. The input parameters for the proposed model are: the level of solar radiation, ambient temperature, wind speed and temperature of the station module. As a result of the work, it was shown that the use of a generalized neural network gives the best result.

The methods considered above, as well as other methods [5–7], have different forecasting accuracy and a strong dependence on climatic conditions. The average forecast errors in the analysed research ranged from 5% under ideal climatic conditions for this model and from 20% in different cases. In this regard, at the first stage, it is necessary to analyse retrospective data on the generation of electric energy in order to search for patterns and significant components in them. At the second stage, develop a predictive model, taking into account the studies.

One of the main initial stages for constructing such prognostic models is to highlight the trend and cyclical components in the source data. It is obvious that the data of electric energy generation also have cyclic components.

To find them, as shown in [8], it is most expedient to use spectral analysis, in particular, construction of a periodogram based on retrospective data.

3. Spectral analysis

As the initial data for spectral analysis, we used data on the generation of electric energy by two solar power plants located on Hokkaido Island in Japan in 2016 and 2017, with a step of 30 minutes. A fragment of the source data is presented in Figure 2.
At the first stage of the study, a spectral analysis of the initial data was carried out on a two-year interval. The periodogram obtained for the first solar power station is shown in Figure 3.

Figure 4 shows a periodogram for the source data of the second solar power plant.
As can be seen from Figure 3, the periodogram has three main peaks at a frequency of 0.0001, 0.0208, 0.0416, which indicates three main cycles in the initial data equal to days, 12 hours and a year. Moreover, the daily cycle is the most pronounced, and the annual one is the least.

The periodogram shown in Figure 4 shows that there are two main peaks at a frequency of 0.0208, 0.0416, respectively, the data have daily and 12-hour cycles.

Taking into account the study of two solar power plants, we can conclude that the annual cycle of generating electricity by solar power plants is of little importance and will focus on the daily and 12-hour cycles.

4. Construction of forecast model

At the second stage of constructing a short-term prognostic model, it was decided to carry out a correlation analysis of the initial data on the generation of electric energy and meteorological data. The results of the correlation analysis are shown in Figure 5.
Based on the results of correlation analysis, we can conclude that there is no linear relationship between the parameters. In this connection, the parameters were selected empirically.

To build a prognostic model, a mathematical model was proposed for predicting the volume of electric energy production based on an artificial neural network - this is a function of the following variables:

\[ V(t) = \{D, s, sH, tS, w, v, uv, T, p, c\} \]  

where \( V \) is the volume of electricity generation, which must be predicted in the format for the day ahead, MW; \( D \) is the date; \( t - 30 \) minute interval; \( s \) - a sign indicating whether the sun has risen (with \( s = 1 \) - the sun has risen, \( s = 0 \) - the sun has not risen); \( sH \) is the length of a sunny day, hour; \( tS \) - snow level, cm; \( w \) - type of weather (clear, partly cloudy, fog, etc.); \( v \) - visibility, km; \( uv \) - the UV index; \( T \) - ambient temperature, °C; \( p \) - the amount of precipitation, mm; \( c \) - cloud cover, %.

When creating a training sample, the input signals of the neural network are represented by the parameters \( D, t, s, sH, tS, w, v, uv, T, p, c \), and the reference values are represented by the parameter \( V \). A fragment the training sample of data on the generation electric energy is shown in Table 1.
Table 1. Fragment of a neural network training sample

| Label | V | D | t | s | sH | tS | w | v | uv | T | p | c | V |
|-------|---|---|---|---|----|----|---|---|----|---|---|---|---|
| 0     | 1 | 1 | 2017 | 0 | 0 | 6.5 | 0.05 | 113 | 10 | 2 | -7 | 0 | 35 | 0 |
| 0     | 1 | 1 | 2017 | 0 | 30 | 6.5 | 0.05 | 113 | 10 | 2 | -7 | 0 | 35 | 0 |
| 0     | 1 | 1 | 2017 | 1 | 00 | 6.5 | 0.05 | 113 | 9.5 | 2 | -6 | 0 | 30 | 0 |
| 65.2  | 1 | 1 | 2017 | 12 | 00 | 6.5 | 0.05 | 116 | 9.5 | 2 | 0 | 0.01 | 50 | 110.13 |
| 52.7  | 1 | 1 | 2017 | 12 | 30 | 6.5 | 0.05 | 116 | 9.5 | 2 | 0 | 0.01 | 50 | 131.09 |
| 54.7  | 1 | 1 | 2017 | 13 | 00 | 6.5 | 0.05 | 116 | 9 | 2 | 0 | 0 | 65 | 65.69 |

The structure of the neural network for short-term forecasting of the generation electric energy in the "day ahead" mode is presented in Fig. 6. It consists of 15 input neurons of the first layer, 13 neurons of the hidden layer and 1 output neuron. The activation function of the neuron is ReLU [9]. To set up the neural network weights, a learning algorithm with a teacher, known as the error back propagation algorithm, is used [10, 11].

The number of neurons in the input network layer is determined by the input parameters presented in table 1. The method for determining the number of neurons of the hidden layer is considered in detail in [12]. In fig. 7 shows a UML diagram for constructing a forecast for generating electric energy.

As a training sample, retrospective data on the generation of electric energy at the annual interval preceding the predicted day are used.

In Figures 8 and 9 show the forecast data for 1 and 2 solar power plants located on Hokaydo Island.
Figure 6. The scheme of the neural network to build a forecast for the production of electric energy.
Figure 7. UML diagram of the method for predicting the generation of electric energy
5. Conclusion
As can be seen from the data presented in Figures 8 and 9, the technique used gives an average deviation in the predicted interval of about 20 MW; however, peak discrepancies can reach 100 MW. The standard error of the model (RMSE) is 19 MW. Based on the data obtained, it can be concluded that it is necessary to refine the prognostic model in order to reduce peak discrepancies.

6. References
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