Analysis of photovoltaic power station (PPS) modeling using artificial neural network and PVsyst software

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Abstract. The possibility of using the method of artificial neural networks to analyze the modes of complex electric power systems with integrated large photovoltaic stations is considered. Based on the correlation analysis, the main factors influencing the energy parameters of photovoltaic power plants were selected and the boundary conditions for the Pearson coefficient were determined. The algorithm of the developed program for calculating the modes of electric power systems using neural networks is described, which makes it possible to more accurately predict generation, taking into account climatic conditions. On the example of calculations of the modes of the South-Western part of the energy system of Uzbekistan, taking into account the change in power flows as the generation of the Navoi photovoltaic plant with a capacity of 100 MW changes, a comparative analysis of the results obtained by calculation with real measurements was carried out.

1. Introduction

It is known that, based on the concept of supplying the Republic of Uzbekistan with electricity in 2020-2030, special attention has been paid to the production of electricity from renewable energy sources in 2020-2030, especially the development of solar energy. In order to achieve the development indicators of renewable energy, in 2020-2030 it is envisaged to build 3 GW of wind and 5 GW of solar power plants [1, 2, 3], for this, the decisions of the President of the Republic of Uzbekistan on the construction of solar Photovoltaic power station (PPS) in 4 regions of our Republic were signed. Based on these decisions, 4 solar PPSs with a total capacity of 1 196.6 MW will be commissioned by the end of 2023.

In order to enforce these decisions, it is important to forecast the amount of active power produced in solar power plants. It is important to take into account the factors affecting solar panels in order to increase the accuracy of forecasting the active power generated in solar power plants [4]. Taking into account the influencing factors ensures an increase in forecasting accuracy.

In the article, the results of modeling in the PVsyst program and the method of the classical method of correctly oriented one-layer artificial neural network are analyzed in forecasting the electricity produced in solar power plants. Many problems of science and technology are based on finding a function that has an extreme value of a given function. During its development, artificial intelligence has moved to new ways of representing and processing knowledge that are closer to human thinking. In this regard, a new computing paradigm was established with many developments and applications - artificial neural networks [5]. An artificial neural network or simple neural network can be considered as a biologically inspired computational model composed of artificial neurons, consisting of a network architecture [6, 7, 8].

Neural networks can provide high accuracy in forecasting the active power generated in solar power plants. Artificial neural networks can be used in the production of forecasting models of active power produced in solar power plants in all periodic (short, medium and long-term) types of forecasting [9, 10]

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2. Methodology

The idea behind the algorithm of the neural network is the cascading processing of data. Once the input data is obtained, this data is propagated to different layers that make up the model, and in each of these layers, a transformation is applied to the data to extract certain features. Layers are made up of nodes or neurons, which is where the computation happens. This computation contains a variable called weight (w_i) that multiplies the input value and gives the output value to the next layer.

A typical model of a neural network is shown in Figure 1, which consists of an input layer, multiple hidden layers, and an output layer.

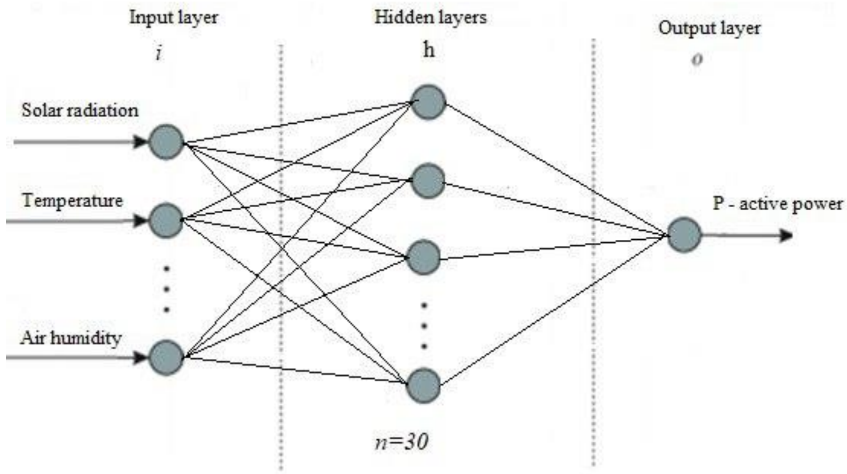

Fig. 1. A typical model of a neural network

The purpose of forecasting the active power produced by PPS is to compare the actual power produced by them and the forecasted results and to analyze the error between them.

Technological (slope of installation of panels) and meteorological factors affecting the forecasting model of active power produced in PPSs [the angle of sunlight falling on the solar panels, i.e. at a certain time of the day (hours), solar radiation (W/m^2), temperature (^{0}C), air humidity (%), wind speed (m/s) and sky openness index it is necessary to determine the factors and select the main ones among them.

Table 1. PPS influencing factor and actual PPS active power (10.09.2021)

V aqt, (Hours)	Solar radiation, (W/m^2)	t , Temperature (°C)	U, Moisture (%)	Ff, Wind speed (m/s)	Openness Index (%)	Active power (W)
18:00	0.01	19.65	13.38	4.7	0.001	8
17:00	29.09	22.48	12.06	5.53	0.3	22
16:00	164.23	24.9	11	6.81	0.46	33
15:00	366.94	26.44	10.44	7	0.62	42
14:00	577.43	27,48	9.94	7.03	0.72	49
13:00	746.01	28.05	9.31	6.93	0.77	51
12:00	826.59	28,18	8.62	6.69	0.78	50
11:00	855.56	27.65	8.19	6.42	0.79	34
10:00	796.96	26.65	8.5	6.23	0.76	24
9:00	718.55	25,16	9.62	6.24	0.77	25
8:00	551.65	23.1	11.5	6.55	0.71	10
7:00	360.45	19.89	14.25	6.34	0.64	3

For this purpose, the information on the 1 day act and power produced at the PPS in the Karmana district of the Navoi region (Table 1) was obtained from JSC "National Electric Networks of Uzbekistan". The factors affecting it are solar radiation from September 9, 2021 to March 31, 2022. The rest of the factors from the "Construction Norms and Regulations" 2.01.01-94 were obtained based on Internet information [11, 12, 13, 14].
Here, a classically directed one-layer Artificial Neural Network type is used. Despite the complexity of extracting knowledge in a neural network system, it is often successfully used in management and forecasting issues. The period from September 2021 to March 2022 was taken as the incoming data base.
In an artificial neural network model, 70% of this data is trained and the remaining 30% is left for testing. Using the correlation matrix, we analyzed which of the factors affecting the active power of PPSs have a general effect. Determination of the main influencing factors is determined based on the algorithm presented in Figure 2.

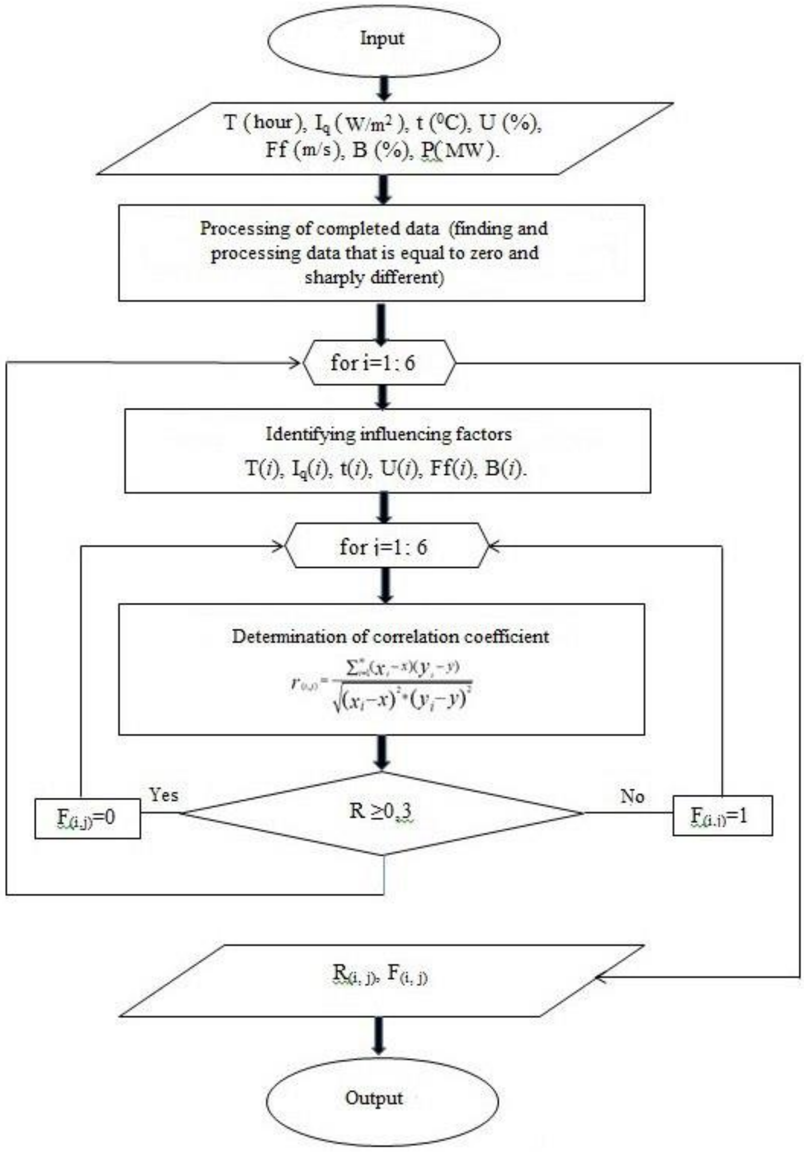

Fig. 2. Extraction of factors using correlation analysis

Each of the identified factors is subjected to regression analysis, and those with a correlation coefficient greater than 0.3 are singled out.

$$r_{(i,j)} = \frac{\sum_{i=1}^{n}(x_i - x)(y_i - y)}{\sqrt{(x_i - x)^2 * (y_i - y)^2}}$$

As a basis for this, the value of Pearson's correlation coefficient varies in the range [–1 +1], that is $-1 \leq r \leq 1$. The sign (+) indicates a direct relationship and (-) indicates an inverse relationship. To obtain conclusions on the quantitative assessment of the Pearson correlation coefficient (connection dependence), the Chaddock scale is used in absolute value [15, 16, 17] (Table 2).

Table 2. Pearson correlation coefficient limits

R Value	Correlation Sign (Connection)
R = 0	No correlation (no connection)
0 < R < |0.2|	Very little correlation (very low correlation)
|0.2| ≤ R < |0.3|	Weak correlation (low connection)
|0.3| ≤ R < |0.5|	Average correlation (trivial link)
|0.5| ≤ R < |0.7|	Average correlation (important relationship)
|0.7| ≤ R < |0.9|	High correlation (strong association)
|0.9| ≤ R < |1|	Very high correlation (very strong relationship)
R = |1|	Complete correlation (functional relationship)

If the correlation coefficient differs from unity by less than 1% (0.99 or more), then in this case we are talking about establishing a functional relationship. If it differs from zero by less than 10%, it indicates that there is no significant relationship between the studied variables.

3 Results and Discussion

There is a coefficient of determination D, which is equal to the square of the correlation coefficient, which indicates what proportion of the variance (or variability) of the resulting attribute determines the variation of the factor attribute. If we square a value that does not exceed 0.1, we get a number less than 0.01 - and if the change in the factor explains less than 1% of the variation in the result, such an "interaction" is usually due to observation error and other errors.

Table 3. General correlation matrix

Factors	Power	Time	Solar radiation	Temperature	Moisture	Wind speed	Sky openness index
X_{ij}	**P**	**T**	**R**	**t**	**SHE IS**	**Ff**	**B**
September	1	0.1137	0.8645	0.3767	-0.3194	0.0110	-0.0075
October	1	-0.0446	0.8219	0.3881	-0.3988	-0.0129	-0.2017
November	1	-0.0509	0.8328	0.2684	-0.2798	-0.0028	-0.1128
December	1	0.0114	0.7277	0.2994	-0.3620	0.1663	-0.4078
January	1	0.0656	0.5720	0.0996	-0.3676	0.0456	-0.3857
February	1	0.1224	0.6845	0.3053	-0.3960	-0.0464	-0.3199

As can be seen from the table of correlation matrices (Table 3), we can see that among the factors affecting the active power produced in PPS, the factors with a correlation coefficient higher than 0.3 are three and in some cases four. It is definitely related to the season, i.e. the influencing factors are those with a correlation coefficient higher than 0.3:

R - Solar radiation (W/m^2);
U-air humidity (%);
t-Air temperature (^{0}C);
B-Weather Openness Index.

Forecasting of active power in solar power stations for September, October and November, an artificial network model was created in Matlab, and as initial information for the autumn season, the factors affecting the solar power station are solar radiation (W/m^2), temperature (^{0}C) and air humidity (%) are included.

Construction of PPS from the database of the weather station or from its own database (Meteo File), the coordinates of the outer regions are determined (for example, Karmana 40.14° N, 65.35° E).The optimal tilt angle of the photocell relative to the horizon is set (for example: 30°), and the direction to the sun is the azimuth (for example, 0°). The program automatically calculates deviations as a percentage of optimal values.

Specifies the installed capacity of the solar power plant in kW or the available m^2 area for the plant. The selected parameters in this section serve as the basis for the following automatic calculations (the number of photocells, the number of modules connected in series, the number of rows, the number of inverters, the operating frequency of the inverter is selected, etc.). The user can select the type of photocell and inverters from the database of the software package (the user can also create his own in the database of PVSyst software and add new components).

The user selects the possible losses given in the program, if necessary, enters the values of his experimental data shows information about the main parameters of the system entered according to the program. A dual solar module: JA Solar JAM72D20-455 / MV, 455-based photovoltaic cell was used in PPS [18, 19, 20].

The main parameters of the PPS are the photocell power - 455 W, the number of photocells - 270,000, the total power of the PPS - 120.2 MW, the number of panels in one module - 20, the total number of modules in the PPS is 13,500, and information about inverters is given.Calculations show that the PPS with a capacity of 120.2 MW produces 255.9 GWh/year of energy per year, but due to system losses (15.8%), the production is 192 GWh/year. The biggest PPS losses depend on temperature. In PPS, the loss due to heating is 9.86%.

Thus, the following conclusions can be drawn: The annual production of mono-crystalline PPS will decrease by 16%, and 10% of them will depend on the effect of temperature.

Table 4. Prediction results in the artificial neural network model with real active power produced in PPSs (10.09.2021)

Solar radiation, (W/m^2)	t , Temperature (°C)	U, Moisture (%)	Active power using SNT model, MW	PVsyst, MW	PPS real asset capacity, MW
360.45	19.89	14.25	13.72	0	14
551.65	23.1	11.5	61.00	13.56	58
718.55	25,16	9.62	88.73	30.64	82
796.96	26.65	8.5	79.87	57.26	86
855.56	27.65	8.19	96.01	72.32	92
826.59	28,18	8.62	101.97	77.35	94
746.01	28.05	9.31	100.04	100.45	93
577.43	27,48	9.94	97.70	77.35	95
366.94	26.44	10.44	95.44	72.32	89
164.23	24.9	11	82.40	57.26	80
29.09	22.48	12.06	59.67	30.64	57
0.01	19.65	13.38	30,45	13.56	30

PR=85.38%, the annual production volume of PPS was 192 GW*h. It should be noted that the values of the measured operating parameters may differ from the values obtained by modeling the PPS performance in PVSyst due to the intensity of solar radiation and the increase in ambient temperature in summer. PVSyst calculates average values of ambient temperature based on long-term meteorological data from ground-based meteorological stations and satellites. The maximum temperature included in the PVSyst software package database is 43 $^{0\ C.}$ There are summer days with high temperature in the republic. For example, on July 27, 2018 in the city of Tashkent, the

ambient temperature reached 53 ^{0}C with the intensity of solar radiation of 1050 W/m ^{2}. In 2020, there were 10 days (average 1 hour) of summer with temperatures above 43°C. In 2 days of them, the air temperature exceeded 45 ^{0}C (2 hours) [2, 21].
One-day average hourly asset value was found based on the average values obtained in the PVSyst program, and the value of the artificial neural network model and the true values of Karmana PPS were compared.
If we analyze the results of active power in the forecasting results of the artificial neural network model with the real active power produced in PPSs (Table 4), we can see that the difference between them in both cases does not exceed 8-10%.

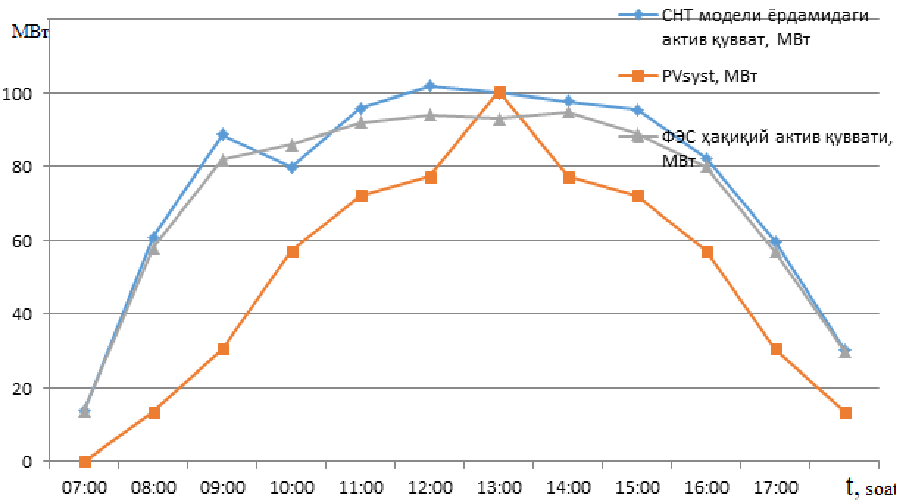

Fig. 3. Active power diagram in real, artificial neural network model and PVsyst program generated in PPSs

4 Conclusions

From the actual active power produced in PPS, the results obtained using the artificial neural network program and the active power diagram obtained from the PVsyst program, we can conclude that if we accurately include the factors affecting PPS in the artificial neural network program, we will be able to more accurately forecast the active power of PPS.

1. Such as Time (hours), Solar radiation (W/m^2), Temperature (^{0}C), Air humidity (%), Wind speed (m/s) and Sky openness index, which affect PPS, were analyzed by regression analysis, and the correlation coefficient was 0. Those older than 3 were separated.
2. An artificial neural network model and algorithm were developed for forecasting the active power produced in PPSs.
3. Taking into account average hourly, average daily actinometric and climatic data indicators, a model for determining PPS power was developed using the PVsyst program.
4. The real active power produced in PPSs was analyzed and the error between them was analyzed in the prediction results of the artificial neural network model.

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