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Efficient electricity generation forecasting from solar power plants using technology: Integration, benefits and prospects

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Abstract. Accurate prediction of electricity generation from renewable sources is an essential element to ensure the stability of electricity systems and the transition to more sustainable energy production. The study aims to optimise the operation of Ukrainian power systems through the introduction of the required share of renewable energy sources to ensure the reliability of the power system. To study the accuracy of forecasting electricity generation by photovoltaic power plants in Ukraine, data analysis, a review of existing forecasting models and methods, and comparative analysis using satellite images and meteorological observations were used. Low accuracy of forecasting output is a feature of electricity generation from renewable energy sources, which is explained by the random nature of energy sources and related meteorological conditions. In Ukraine, the problem of qualitative forecasting of electricity generation from renewable sources is becoming more relevant. The importance of finding effective methods for forecasting electricity generation in Ukraine has increased with the emergence of the electricity market. This study addresses the issue of forecasting electricity generation by photovoltaic power plants for the day ahead in the conditions of the Ukrainian energy market. As part of the study, the issues of Ukrainian legislation regarding the requirements for the accuracy of electricity generation forecasting and the consequences of their failure were considered. The study also reviewed modern models and methods for forecasting electricity generation by photovoltaic power plants and explored the new "forecasting system market" in Ukraine. The study presents accepted forecasting metrics that allow estimating errors and comparing the effectiveness of different forecasting methods. Considering the dependence of electricity generation forecasting on meteorological parameters, a comparative analysis of forecasting accuracy using satellite images and meteorological observations was carried out. The study will determine the material presented in determining the model for forecasting electricity generation, thus increasing the efficiency of energy companies in the conditions of the Ukrainian energy market. The study will also reduce the negative impact of the energy sector on the environment and contribute to a more efficient and stable electricity system in the future

Keywords: capacity; generation; power system balance; renewable energy sources; energy market

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INTRODUCTION

Growing demand for electricity and the need to reduce emissions from traditional sources are becoming major challenges for the energy sector. Constant changes in meteorological conditions and technological innovations in the industry require the development of accurate methods for forecasting electricity generation using solar power plants. Research in this area will improve the reliability and efficiency of solar power plants, promote the development of renewable energy sources and ensure sustainable energy development in general. This study was important for improving the efficiency of Ukraine's electricity system by taking into account the introduction of the required share of renewable energy sources. The low accuracy of forecasting

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electricity output, especially with the use of photovoltaic power plants, has become an urgent problem that requires careful analysis and development of effective forecasting methods. Increasing the share of renewable energy sources in the electricity system requires accurate and reliable forecasting of electricity generation, which makes this study important for ensuring the stability and efficiency of the energy sector in the modern energy market.

The analysis of publications on effective forecasting of electricity generation from solar power plants revealed several problems that exist in the field. M. Konstantinou *et al.* (2021) determined that the problem is the insufficient accuracy of power generation forecasting in the face of significant changes in meteorological conditions. The study results highlighted the need to improve forecasting methods to ensure the stability and reliability of energy systems. T.M. Alabi *et al.* (2022) investigated the possibilities of integrating modern machine learning algorithms to improve power generation forecasting. They demonstrated the prospects of this approach in improving the accuracy and reliability of forecasting in the energy sector. A study conducted by F. Shaik *et al.* (2023) focused on the reliability of solar power plants and studied the impact of unpredictable factors on their efficiency. This study pointed out the significant impact of unforeseen factors on the operation of solar power plants and the need for further optimisation of control systems to ensure the stability and reliability of electricity production. L. Liu and L. Wu (2021) concentrated on the development of new mathematical forecasting models to reduce forecast errors. The results of this study showed a positive effect of using new mathematical models to improve the accuracy of power generation forecasting. A study conducted by K. Bandara *et al.* (2021) highlighted the need to improve data collection and analysis methods to improve the accuracy of electricity generation forecasts from solar power plants. The results of the study indicate the need to introduce new approaches in these processes to achieve more accurate and reliable forecasts.

V. Prema *et al.* (2021) focused on analysing the impact of the technical parameters of solar power plants on the results of power generation forecasting. The study identified key factors affecting forecasting accuracy and identified ways to optimise forecasts in the context of the technical characteristics of the plants. Ch. Chen *et al.* (2022) highlighted the challenges associated with improving forecast accuracy on a large scale, especially when tens or hundreds of solar power plants are considered. The results of their study identified key difficulties and suggested methods to improve forecasting in such conditions. D. Markovics and MJ. Mayer (2022) determined the optimal ratio between different data sources for power generation forecasting. The results helped to identify key aspects of using different sources of information and develop recommendations for improving the efficiency of electricity forecasting. The study by M. Sotnyk *et al.* (2023) analysed a general aggregation model in the electricity sector known as the Virtual Power Plant. This analysis provided insight into the key aspects of operation and the potential benefits of implementing such models in power systems.

M.O. Kyzym *et al.* (2022) conducted a study of global challenges and opportunities for the structural development of the electricity sector in Ukraine. The study identified the main trends in this area and suggested ways to optimise the development of the country's energy sector. V.Ya. Brych *et al.* (2022) analysed the development of technologies that are critical to ensuring Ukraine's energy security and increasing the stability and efficiency of the energy system. The study findings identified key areas of technology development that should be prioritised for implementation to ensure the reliability and optimisation of Ukraine's energy sector. While various studies already contributed to addressing these issues, gaps that still need to be explored include improving forecasting algorithms, increasing accuracy in the face of changing meteorological conditions, developing new models that incorporate technical parameters of power plants, and optimising the process of collecting and analysing large amounts of data for forecasting.

The study aim was to improve the efficiency of Ukraine's electricity systems by introducing an appropriate share of renewable energy sources to ensure the stability and reliability of the electricity grid. The objective of the study was to conduct a comparative analysis of the accuracy parameters of methods for forecasting electricity generation using satellite images and meteorological forecasts and meteorological observations, which would allow to identify the difference in accuracy between these methods.

MATERIALS AND METHODS

The study was conducted on actual data on electricity generation by the Petrivka photovoltaic power plant, which is located in the southern part of Ukraine, specifically in the Ivanivskyi district of the Odesa region. It was commissioned in 2019 and has a capacity of 8.85 MW (PV plant Petrivka, n.d.). After collecting this data, the forecasting results were compared with the actual data. To objectively assess the performance of each forecasting model, calculated accuracy indicators, such as mean absolute error (MAE), mean absolute percentage error (MAPE), mean absolute error concerning the base model (MASE), and root mean square error (RMSE), were used in the study. This highlighted the effectiveness of each model in predicting the electricity generation of the Petrivka PV (Photovoltaic) power plant during May 2021.

As part of the study, a detailed analysis of the accuracy of forecasting electricity generation by photovoltaic power plants was carried out. For this purpose, various forecasting models were used, which took into account various factors and methods. The analysis made it possible to assess the effectiveness of each model in predicting electricity generation using solar radiation. The results were processed and analysed to determine the most accurate and reliable forecasting model that can be used to improve the efficiency of photovoltaic power plants in electricity generation.

A real-time power generation forecasting model based on satellite imagery, supported by the Solcast satellite nowcasting system, used a global fleet of meteorological satellites to obtain information on cloud cover and other atmospheric phenomena. This model used satellite data to obtain up-to-date information on cloud cover and other atmospheric phenomena such as temperature, humidity, precipitation and other parameters. The information obtained from the satellites allowed to incorporate the dynamics of atmospheric conditions in real-time, which improved the accuracy of forecasting power generation from photovoltaic power plants.

Solargis Forecast Cloud Motion Vector-based power generation forecasting model depended on intensive monitoring and analysis of satellite imagery to get an accurate picture of cloud movement. This method was based on the systematic study and analysis of real-time changes in cloud location and movement. Using Cloud Motion Vector data, which described the speed and direction of cloud movement, the model could predict the impact of cloud cover on the generation of electricity from solar panels. This increased the accuracy of the forecasts, as it took into account specific dynamic changes in cloud cover that could affect the efficiency of solar power generation.

The Solcast Advanced PV model was developed specifically for photovoltaic installations, taking into account various system parameters and characteristics. This model addressed key aspects such as solar panel array geometry and tracking type, module and inverter parameters, horizon shading, dust and other losses including degradation, availability of tracking algorithms, and support for bifacial modules. This model enabled a more accurate consideration of the specifics of each PV installation, which helped to improve the accuracy of forecasting its efficiency and electricity production. Accounting for these parameters and characteristics in the model allowed for more accurate and realistic forecasts of electricity generation by photovoltaic installations, which was important for the effective management and planning of solar power plants.

A UTP (Univariate Time-series Prediction) forecasting model based on meteorological observation and weather forecast data was used as input to the neural network. This method was based on meteorological data and was used to predict the amount of solar radiation reaching the photosensitive surface, considering astronomical, geographical and topographical factors, as well as the absorption and scattering of solar radiation in the atmosphere. These meteorological parameters were used to build a neural network that analysed the input data and predicted the electricity generation by the photovoltaic plants. The UTP model allowed for forecasting based on actual meteorological conditions, which helped to improve the accuracy of forecasts and the efficiency of managing electricity generation in solar energy systems.

RESULTS

Software for efficiently forecasting power generation from solar power plants is critical in the modern energy industry, where the use of renewable energy sources is becoming increasingly important. Such software is used to predict the amount of electricity that solar power plants will be able to generate in the future based on various inputs. There are several well-known software solutions on the market for efficient forecasting of electricity generation from solar power plants. One of these solutions is Solcast, an online platform that provides accurate forecasts of solar radiation and electricity generation. It uses a variety of data, including satellite imagery and meteorological data, to improve forecasting accuracy. Another well-known software tool is PVsyst, which allows for the design, analysis, and forecasting of solar power plants, taking into account various factors such as geographic location and technical characteristics of the plants. In addition, HelioScope is an online platform that allows modelling and forecasting of power generation based on various inputs, helping solar power plant engineers and operators obtain reliable forecasts to optimise plant performance and plan efficient operations.

One of the main functions of forecasting software is to analyse information about weather conditions, including solar radiation, cloud cover, temperature, humidity, etc. The data is collected from weather stations, satellite images, meteorological models, and other sources. Based on this data, forecasting models are developed to determine the expected electricity generation for a certain period. Such software solutions can use a variety of forecasting methods, including statistical models, neural networks, machine learning algorithms, and other analytical techniques. They can accommodate factors that affect the operation of solar power plants, such as panel orientation, equipment specifications, energy losses, etc.

The main advantage of solar power generation forecasting software is that it allows energy companies, grid operators and other market participants to effectively plan electricity generation, optimise plant operating modes and avoid under- or overproduction. The continuous development of information and communication system technologies is making power generation forecasting software more accurate, reliable and accessible to various energy market players. In the future, these technologies may become the basis for the development of modern smart grids and the integration of distribution systems with renewable energy generation, which will contribute to the stability and efficiency of the energy infrastructure.

The intensive development of renewable energy creates risks of disrupting the balance reliability of the power system, and this requires accurate forecasting of electricity generation. In many countries, scientists are working on this problem, as a new concept, "energymeteorology" has been introduced as a new scientific discipline, the subject of which is the quantitative assessment of electricity generation from renewable energy sources at time intervals from minutes to decades, and much attention is paid to the development of economic forecasting (forecasting losses/profits depending on the accuracy of forecasting power plant output) (Fiedler *et al.*, 2022). When choosing a forecasting method, it is necessary to take into account what data should be obtained as a result of calculations. The choice of methods for forecasting the operation of a photovoltaic power plant depends on the periods for which solar radiation forecasts are required. For short-term forecasting (up to 6 hours), physical forecasting methods such as Numerical Weather Prediction (NWP) or NWP models are used, i.e., the level of illumination, cloud cover, air temperature, wind speed and humidity in a particular area is considered (Schultz *et al.*, 2021). To predict energy generation for a short period (10-30 minutes) with high accuracy, sky view analysis is used. This includes obtaining an image of the sky, determining the type and condition of clouds, and analysing cloud movement to make a forecast of the future generation capacity of the plants compared to actual levels. In the global solar industry, short-term power generation forecasting does not have a proven and fully tested model. The generation forecast of a photovoltaic power plant is a forecast of the amount of solar insolation received by solar panels. All existing available methods for forecasting electricity generation by solar power plants can be divided into groups (Fig. 1).

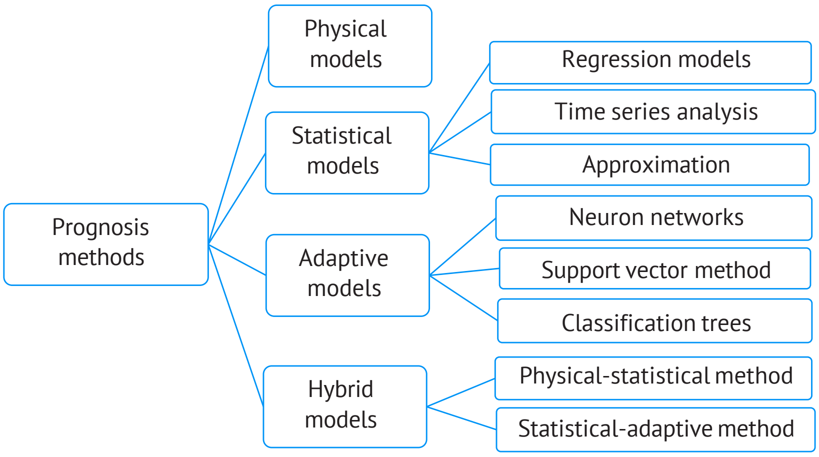

Figure 1. Classification of methods for forecasting electricity generation by solar power plants
Source: B. Yang *et al.* (2021)

Physical models are physical relationships between meteorological conditions and solar radiation, where the input data are: numerical weather forecasts; terrain; retrospective data on the power plant's output power; and the possibility of using satellite systems. The power output of a solar power plant is determined based on the predicted level of horizontal illumination and ambient temperature. Additional factors may include wind speed and air humidity, but their influence is generally negligible (Duan *et al.*, 2021).

Statistical (probabilistic) models determine the relationship between solar radiation density predicted by a numerical weather forecast and the power output of a solar power plant by analysing time series of past data, ignoring physical aspects. This dataset is used to train models, such as autoregressive or artificial intelligence models, that can predict the output of a solar power plant at a given point in time based on historical records. ARX methods (Autoregressive exogenous) are accurate methods for short-term forecasting (up to 2 hours) of solar radiation that incorporate both geographic location and time (Oliveira *et al.*, 2021). There are methods for forecasting solar energy generation that take into account historical data. Two common methods are ARIMA (Autoregressive Integrated Moving Average) and ARIMA-GARCH (Generalised Autoregressive Conditional Heteroskedasticity), which are suitable for stationary and non-stationary time series, respectively (Mboso, 2022). These methods are designed to process large amounts of data and identify patterns in it to build predictive models. They are widely used in short-term electricity forecasting due to the availability of a large amount of historical data on electricity generation at enterprises. However, the disadvantage of these methods is the lack of forecast accuracy.

Adaptive models use artificial intelligence systems to establish a link between predicted weather conditions and the power plant's production capacity. The learning process of these models is based on the analysis of historical data. The main factor that determines the accuracy of the forecast is the choice and structure of the input data used to create the model. Furthermore, the time required to train the network depends on the characteristics of the training sample. The advantage of the method is a fast training algorithm and the ability to work in the presence of noisy input signals.

According to studies on the use of electricity generation forecasting methods, the average forecast error is 21-26% for physical models, 20-24% for statistical models, 15-19% for adaptive models, 19-24% for hybrid physical-statistical models, and 5-10% for statistical-adaptive models (Bakay & Ağbulut, 2021). A study of the effectiveness of various methods shows that a linear autoregressive model is best suited for forecasting periods with predominantly sunny weather (e.g., spring or summer). Neural networks with the inclusion of exogenous parameters can be useful only during limited periods with high cloud cover, especially in autumn and winter. The improved results demonstrate a standard deviation of the error in solar radiation estimates of 16-18%, which is significantly higher than the low-performing constancy model of 30-50%. The effectiveness of short-term forecasts is determined by the criteria of accuracy, stability and validity of the results. Numerical indicators (metrics) are based on standardised values:

1. Mean Absolute Error (MAE) (1):

$$\mathrm{MAE} = {}^{1}/_{\mathrm{N}} \sum_{\mathrm{i-1}}^{\mathrm{N}} |\mathrm{x_i}|. \tag{1}$$

2. Mean Absolute Relative Error (MARE) (2):

$$\mathrm{MARE} = {}^{1}/_{\mathrm{N}} \sum_{\mathrm{i-1}}^{\mathrm{N}} \mathrm{x_i} \cdot 100. \tag{2}$$

3. Mean Absolute Scaled Error (MASE) (3):

$$\mathrm{MASE} = \frac{1}{\mathrm{N}} \sum_{\mathrm{i=1}}^{\mathrm{N}} (\mathrm{x_i} - \bar{\mathrm{x}}). \tag{3}$$

4. Root Mean Squared Error (RMSE) (4):

$$\mathrm{RMSE} = \sqrt{{}^{1}/_{\mathrm{N}} \sum_{\mathrm{i-1}}^{\mathrm{N}} \mathrm{x_i^2}}. \tag{4}$$

5. The Mean Squared Error (MSE) is used to determine the prediction error of the most possible (5):

$$\mathrm{MSE} = \frac{1}{\mathrm{N}} \sum_{\mathrm{i=1}}^{\mathrm{N}} (\mathrm{x_i} - \bar{\mathrm{x}})^2, \tag{5}$$

where x_i – the difference between the forecast and actual values; N – the size of the sample of values representing.

Table 1 shows the interpretation of the forecast error depending on MARE.

Table 1. Forecasting and interpretation of data

MARE, %	**Interpretations**
<10	High precision
10-20	Good precision
20-50	Satisfactory precision
>50	Unsatisfactory precision

Source: D. Chicco *et al.* (2021)

The reliability of the forecast is assessed using the ratio between the number of explained emissions and the total number of emissions. Extreme errors can be defined as those that fall outside the confidence interval. Since the assessment of validity requires a case-by-case analysis, in practice this indicator is calculated only in certain cases.

The forecasting model was created using a global fleet of meteorological satellites. Nowcasting is an ultra-short-range weather forecast with a 5-15-minute time step. This forecast is reduced to the task of extrapolating observed meteorological phenomena (Ozbek *et al.*, 2021) (6):

$$p(x_{t+1 \ldots t+k|} x_{1 \ldots t}) = \prod_{i=1}^{k} p(x_{t+i} | x_{1 \ldots t+I-1}), \tag{6}$$

where *x* – meteorological satellite image; *t* – the number of images used to make the forecast; *k* – number of projected images.

Assessment of solar resources and forecast data for illumination and photovoltaic power in the range of -7 days to +7 days – forecast of time horizons (Fig. 2).

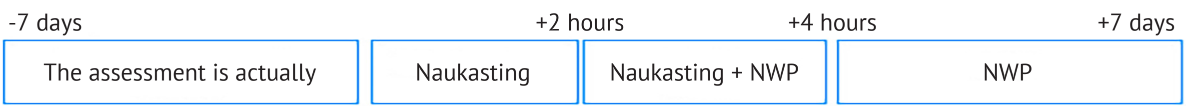

Figure 2. Forecasting time horizons

Source: compiled by the author

Forecast efficiency on the +3:45 time horizon the forecasting system uses mainly NWP numerical weather forecasts from several models. On the day-ahead horizon (which includes the +4 hour window), machine learning-based bias corrections are included, which are applied based on observed cloud opacity from satellite imagery. The performance in the first 0-3 hours will always be better than +4 hours, as it uses satellite forecasting of actual information with a fast update for 0-3 hours (individual clouds are tracked at a resolution of 1-2 km^2, with updates every 15 minutes).

The energy generation of photovoltaic converters depends on climatic conditions, and their power varies in proportion to changes in solar irradiation exposure of their working surface over time (Libra *et al.*, 2021). The amount of solar radiation that reaches a photosensitive surface at any given time depends on astronomical, geographical, and topographical conditions. This amount of radiation is determined by parameters such as the angle of incidence of the sun's rays on the earth's surface, as well as the processes of absorption and scattering of solar radiation in the atmosphere. Among the meteorological parameters that have the greatest impact on electricity generation are solar insolation, temperature, wind speed, humidity and sky conditions (cloud cover). The neural network "learns" to predict solar power generation based on meteorological parameters such as temperature, humidity, pressure and wind speed (Fig. 3).

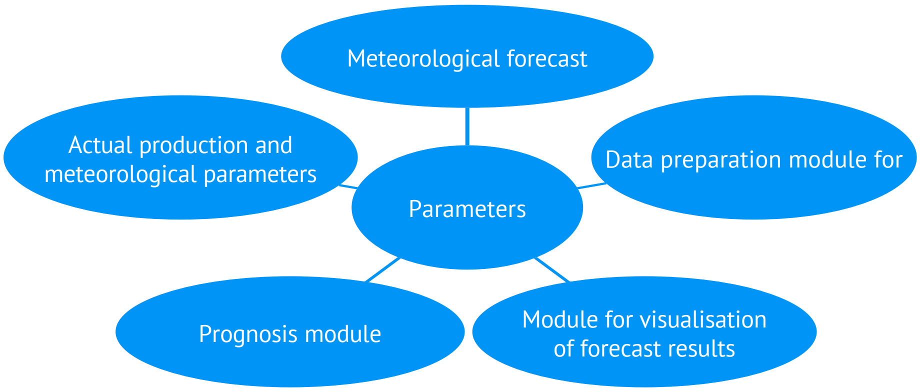

Figure 3. Generation forecasting model based on weather observation data
Source: X. Luo *et al.* (2021)

This method is a variation of the classical gradient descent method. Since neural networks need to adapt to geolocation and be able to retrain for other stations, the backpropagation algorithm is used for this purpose. The main concept of this method is to transmit error signals from the network outputs to its inputs in the opposite direction to the direct flow of signals during normal operation. The training sample is retrospective power generation data for an interval of one year before the forecast day. The number of neurons in the input layer is determined by the input parameters, and the output neuron is the forecast of the photovoltaic power plant generation. The forecasting method based on meteorological observations has advantages, such as the ability to use a wide range of input data (electricity consumption, air temperature, cloud cover, insolation, time of day) and the speed of the neural network. It is an effective tool for forecasting electricity generation, which is an alternative to traditional statistical methods.

Satellite images provide highly accurate data on solar radiation and atmospheric conditions (Nespoli *et al.*, 2022). Forecasting models based on these images are used to predict electricity generation by solar power plants. The main advantage of such models is their ability to respond quickly to changes in weather conditions and accurately predict electricity generation for several hours or even days in advance. Solcast nowcasting system is one of the most advanced platforms for predicting solar activity and power generation. It uses data from satellites and meteorological stations to calculate and forecast solar radiation. The artificial intelligence technologies used in Solcast improve the accuracy of forecasts and ensure the stability of electricity generation from solar sources. One of the key advantages of using forecasting models based on satellite imagery is the ability to manage the operating modes of solar power plants. Operators can adapt their power generation to the forecasted weather conditions, maximising the use of solar energy and maintaining the stability of the grid. The scheme for forecasting electricity from solar power plants is shown in Figure 4.

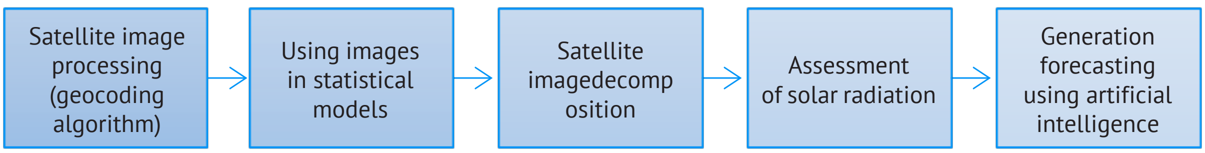

Figure 4. Generation forecasting algorithm based on real-time satellite imagery data with the support of the Solcast satellite nowcasting system
Source: Q. Paletta *et al.* (2023)

Solargis Forecast, a power generation forecasting model based on the Cloud Motion Vector model, is one of the most advanced forecasting systems in the solar industry. This model uses sophisticated intensive monitoring algorithms based on satellite image analysis to obtain accurate data on cloud movement and other atmospheric phenomena. The main advantages of the Solargis Forecast model are its ability to predict the dynamics of cloud movement and changes in the direction and speed of their movement. This provides a clear, high-quality view of the weather conditions at the location of solar power plants. For example, by analysing changes in cloud positions over a short time interval, it is possible to determine whether solar panels will be shaded shortly, which is important for accurate forecasting of electricity generation. Cloud Motion Vector technology allows taking into account various factors such as wind speed, humidity, temperature, atmospheric pressure, and others that affect cloud movement and the overall weather situation (Aicardi *et al.*, 2022). Integration of these data into a forecasting model allows for more accurate results in predicting electricity generation by solar power plants. One of the key advantages of such a model is its ability to respond to changes in weather conditions in real-time. This allows for prompt adjustments to solar power plant operation plans, minimising losses and maximising electricity generation in the face of weather uncertainty.

The Solcast Advanced PV model is an important tool in the field of photovoltaic installations that allows for more accurate forecasting of electricity generation. This model was developed for use in installations where system characteristics are known, which means that it takes into account the various parameters and conditions that affect the operation of PV systems. One of the key features of the model is its ability to exploit installation specifications such as array geometry and solar panel tracking type (Zohner *et al.*, 2023). For example, the size and orientation of solar panels can have a significant impact on solar energy collection efficiency, and these parameters are important to consider when predicting electricity generation. In addition, the model also considers other factors that affect the efficiency of a photovoltaic system, such as module and inverter information, horizon shading, dust losses, and other losses, including panel degradation over time. This data creates more accurate forecasts of electricity production and scheduling of photovoltaic installations. The model also supports tracking algorithms that optimise the position of solar panels to maximise solar energy collection throughout the day. The support for a double-sided module is also important, allowing the use of sunlight reflection for additional power generation.

The model for predicting UTP (installed capacity) from meteorological observation and meteorological forecast data plays an important role in predicting the generation of electricity by photovoltaic power plants (PVPPs). Astronomical, geographical, and topographical conditions are among the main factors that affect the amount of solar radiation reaching a photosensitive surface (Kitamura *et al.*, 2022). The amount of solar energy that reaches the earth's surface depends on the angle of the sun's rays and atmospheric processes such as absorption and scattering. The proposed meteorological parameters, such as temperature, humidity, precipitation, and wind, are used as input to neural networks in the UTP forecasting model. These parameters allow taking into account the dynamics of changes in weather conditions, which affect the generation of electricity by solar power plants. The study of the parameters of the accuracy of forecasting electricity generation by a photovoltaic power plant was carried out based on actual data from the PV power plant in May 2021. The results of this study help to improve the UTP forecasting model and assess its accuracy and reliability in a real operating environment. This approach is important for ensuring the efficiency of solar power plants and planning their operations taking into account the forecasted weather conditions (Table 2; Table 3).

Table 2. Forecast data based on real-time satellite imagery with the support of the Solcast satellite science system, the Solcast Advanced PV model and the actual generation of the Petrivka PV plant for May 2021

	Solcast				Solcast_Update			
	Actual, MWh	Forecast, MWh	Remainder	Square	Actual, MWh	Forecast, MWh	Remainder	Square
01.05	45.641	50.124	4.483	20.097	45.641	50.359	4.718	22.26
04.05	54.989	55.782	0.793	0.629	54.989	55.308	0.319	0.102
05.05	52.656	54.069	1.413	1.997	52.656	54.495	1.839	3.382
06.05	40.996	30.976	10.02	100.4	40.996	31.768	9.228	85.156
07.05	33.471	33.614	0.143	0.02	33.471	34.431	0.96	0.922
08.05	33.959	21.685	12.274	150.651	33.959	23.28	10.679	114.041
11.05	51.88	45.907	5.973	35.677	51.88	45.266	6.614	43.745
12.05	41.816	43.798	1.982	3.928	41.816	43.495	1.679	2.819
13.05	29.792	30.625	0.833	0.694	29.792	29.718	0.074	0.005
14.05	51.571	41.979	9.592	92.006	51.571	43.214	8.357	69.839
15.05	49.637	57.682	8.045	64.722	49.637	58.114	8.477	71.86
19.05	15.89	19.661	3.771	14.22	15.89	19.702	3.812	14.531

Continued Table 2.

	Solcast				Solcast_Update			
	Actual, MWh	**Forecast, MWh**	**Remainder**	**Square**	**Actual, MWh**	**Forecast, MWh**	**Remainder**	**Square**
21.05	35.825	28.308	7.517	56.505	35.825	27.806	8.019	64.304
24.05	50.033	46.733	3.3	10.89	50.033	46.92	3.113	9.691
26.05	54.059	56.58	2.521	6.355	54.059	55.757	1.698	2.883
27.05	54.497	54.046	0.451	0.203	54.497	53.881	0.616	0.379
28.05	50.223	47.865	2.358	5.56	50.223	48.551	1.672	2.796
29.05	42.612	34.586	8.026	64.417	42.612	33.981	8.631	74.494
31.05	34.375	25.891	8.484	71.978	34.375	26.107	8.268	68.36
Average value	41.976	39.348			41.976	39.264		

Source: PV plant Petrivka (n.d.)

Table 3. Forecast data from the Solargis Forecast model based on the Cloud Motion Vector model, the UTP forecast model based on weather observation data using neural networks and the actual generation of Petrivka FES for May 2021

	Solargis Forecast				UTP			
	Actual, MWh	**Forecast, MWh**	**Remainder**	**Square**	**Actual, MWh**	**Forecast, MWh**	**Remainder**	**Square**
01.05	45.641	0	45.641	2083.101	45.641	32.487	13.154	173.028
04.05	54.989	0	54.989	3023.79	54.989	41.346	13.643	186.131
05.05	52.656	0	52.656	2772.654	52.656	45.267	7.389	54.597
06.05	40.996	0	40.996	1680.672	40.996	33.106	7.89	62.252
07.05	33.471	27.027	6.444	41.525	33.471	29.477	3.994	15.952
08.05	33.959	33.679	0.28	0.078	33.959	33.889	0.07	0.005
11.05	51.88	51.081	0.799	0.638	51.88	38.131	13.749	189.035
12.05	41.816	40.771	1.045	1.092	41.816	28.678	13.138	172.607
13.05	29.792	28.266	1.526	2.329	29.792	34.987	5.195	26.988
14.05	51.571	48.556	3.015	9.09	51.571	39.714	11.857	140.588
15.05	49.637	54.474	4.837	23.397	49.637	44.716	4.921	24.216
19.05	15.89	22.827	6.937	48.122	15.89	30.122	14.232	202.55
21.05	35.825	25.586	10.239	104.837	35.825	49.025	13.2	174.24
24.05	50.033	47.545	2.488	6.19	50.033	39.401	10.632	113.039
26.05	54.059	49.398	4.661	21.725	54.059	42.861	11.198	125.395
27.05	54.497	53.808	0.689	0.475	54.497	38.956	15.541	241.523
28.05	50.223	48.937	1.286	1.654	50.223	25.895	24.328	591.852
29.05	42.612	43.4	0.788	0.621	42.612	37.42	5.192	26.957
31.05	34.375	30.5	3.875	15.016	34.375	32.722	1.653	2.732
Average value	41.976	40.39			41.976	36.4		

Source: PV plant Petrivka (n.d.)

Based on the actual and forecasted electricity generation of Petrivka SPP for May 2021, a comparative graph was built, which is shown in Figure 5. This graph shows a comparison of actual and forecast electricity generation during this period. The graph shows how the forecast values differed from the actual values on different days in May 2021. This comparison helps to evaluate the efficiency and accuracy of electricity forecasting at Petrivka PVP by using the appropriate forecasting model (Table 4).

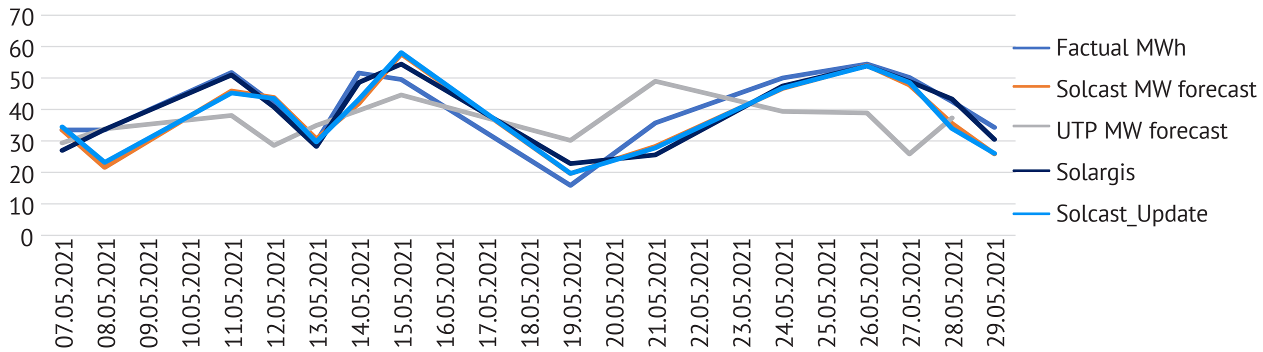

Figure 5. Graph of actual and forecast electricity generation at Petrivka PVP in May 2021
Source: compiled by the author

Table 4. Comparison of the calculated data of the PV power generation forecasting accuracy indicators by the studied generation forecasting models

Indicators	Solcast	Solcast_Update	UTP	Solargis
MAE	5.018	4.845	9.927	3.261
MAPE, %	11.95	12.31	23.65	8.07
MASE	0.11954	0.11541	0.23648	0.07767
RMSE	6.207	6.004	11.684	4.296

Source: compiled by the author

Analysing the calculated indicators of forecasting errors of PV power generation by different forecasting models that were the subject of the study, based on the graph of actual and forecast generation, some important conclusions can be drawn. Based on the results of the analysis, it is possible to emphasise that the most accurate method is forecasting using the Solargis Forecast model, which is based on the Cloud Motion Vector model. This method demonstrates a MARE of 8.07%, which is close to a high level of accuracy. The Solcast and Solcast_Update models also show good accuracy results with MAREs of 11.95 and 12.31%, respectively, which indicates that they are suitable for practical use. The worst performer among the analysed methods is the UTP model based on weather forecast and weather observation data, which demonstrates a MARE of 23.65%. This indicates that this method may be less accurate and will require further development to improve forecasting results. Thus, it can be reasonably stated that in the context of the considered forecasting models, the Solargis Forecast model based on the Cloud Motion Vector model is the most accurate and efficient for forecasting the electricity generation of PV power plants.

DISCUSSION

The analysis demonstrated that the introduction of modern technologies in the process of forecasting electricity generation does indeed improve the accuracy of forecasting and optimisation of electricity production. Analysing the research results, it can be noted that the integration of the latest technologies into power generation forecasting allows obtaining more accurate forecasts of electricity generation from solar power plants. This is because modern technologies allow for a more detailed consideration of various input data, such as meteorological parameters, equipment characteristics and other factors that affect the efficiency of solar power plants. The use of advanced data analytics and artificial intelligence methods in the process of power generation forecasting is becoming particularly important. These methods allow automating the process of processing and analysing large amounts of data, which in turn improves the quality of forecasts and allows for a prompt response to changes in electricity generation from solar power plants.

When analysing the results of the study, the effectiveness of forecasting models for electricity generation from solar power plants is important to consider. One of the key aspects that was considered was the effectiveness of specific forecasting models. For example, when analysing the results, the Solargis Forecast model, which is based on the Cloud Motion Vector model, was found to be highly accurate in predicting electricity generation. This shows that the use of modern cloud and weather analysis technologies can significantly improve forecasting efficiency. In addition, other models, such as Solcast and Solcast_Update, also demonstrated positive results in terms of forecasting accuracy. This confirms the wide range of possibilities in choosing an effective model for forecasting electricity generation from solar power plants.

Effective forecasting has several significant advantages, the most important of which are the ability to respond quickly to changes in weather conditions and ensure the stable operation of power plants. This advantage is crucial for planning and managing electricity systems. One of the main advantages of effective forecasting is the ability to respond to changes in weather conditions in real-time. For example, with an accurate forecast of solar radiation and cloud cover, solar power plants can be scheduled to operate optimally, increasing their efficiency and overall power generation. Forecasting meteorological conditions also help ensure reliable and stable operation of power plants. Considering the intensity of solar radiation, the presence of clouds and other meteorological factors, it is possible to effectively regulate the operation of equipment to ensure optimal performance and maximum use of solar energy. In the future, the development of forecasting methods will focus on the use of artificial intelligence, big data analysis and improved algorithms. It is also important to pay attention to the integration of data from IoT (Internet of Things) systems and the expansion of data sources to improve the accuracy and reliability of forecasting. In general, effective forecasting of power generation from solar power plants plays an important role in modern energy systems and contributes to the development of renewable energy sources.

According to the results of recent studies by E. Kim *et al.* (2023), the development of methods for predicting solar power generation is a key research area in the relatively young field of solar energy. With a large increase in the number of installed solar power plants around the world, the need for accurate forecasting of electricity generation is becoming increasingly important. Accurate forecasting of solar power generation allows for an increase in the efficiency of solar power plants, optimises their operation and ensures a stable electricity supply. These data are consistent with the theses presented in this paper. One of the key aspects in the development of forecasting methods is the use of modern technologies and data analysis methods, such as artificial intelligence, machine learning, and big data analysis. These methods account for numerous factors affecting solar energy production, such as weather conditions, geographical location, types of panels, etc. This approach improves forecasting accuracy and ensures the reliable operation of solar power plants in different conditions.

Referring to the definition of M. Elsaraiti and A. Merabet (2022), solar power generation forecasting using deep learning techniques is one of the ways to improve forecasting accuracy and optimise the efficiency of solar power plants. Deep learning methods, such as neural networks, combine many layers and nodes, which allows them to effectively learn complex dependencies in data, factoring in various factors that affect solar power generation. It is worth noting that neural networks can automatically detect and adjust for various patterns and trends in the data, which allows for more accurate and reliable solar power generation forecasts. The use of deep learning in solar energy forecasting opens up prospects for further improving the efficiency of solar power plants and increasing their contribution to clean energy production.

Yu. Natarajan *et al.* (2021) determined that forecasting energy production at large PV power plants is an important task in the management and optimisation of solar power plants. Especially on a large scale, where numerous panels and plant components make it difficult to manage and forecast power generation. Accurate forecasting allows for efficient production planning, resource management and stable operation of power plants. These results support the above study, as a variety of methods and technologies are used to forecast power generation at large-scale PV plants. This includes the use of meteorological data, analysis of solar panel performance, and consideration of the impact of weather conditions and other factors on power generation efficiency.

L. Fara *et al.* (2021) demonstrated that forecasting energy production for PV systems is a key task in the optimisation and planning of solar power plants. This is especially true in the modern environment when the use of alternative energy sources is increasingly important and the scale of solar PV systems is expanding. To achieve effective forecasting, advanced models such as ARIMA and ANN (Artificial Neural Networks) are used. The ARIMA model is a popular method in time series forecasting and is used to analyse and predict the relationships between previous time series values. In the context of solar power generation forecasting, ARIMA can handle seasonality, tendencies, and other regular patterns that affect power generation. Also, ANNs have become a powerful tool in forecasting, especially in the energy sector. ANNs can effectively account for complex relationships between input parameters, such as weather conditions, geographical factors, system characteristics, and others. Their ability to learn from a large amount of data allows them to create accurate and reliable models for predicting electricity production from solar PV systems. This opinion can be agreed that the application of such advanced methods in power generation forecasting helps energy companies and plant operators to ensure stable and efficient operation of the grid. Consideration of power generation forecasting is a key element for optimising electricity production and planning the operation of power companies, considering variable weather conditions and other factors affecting solar energy production.

As noted by R. Tawn and J. Browell (2022), very short-term solar energy forecasting is an important component of solar power plant management. This type of forecasting is typically focused on a time frame of several minutes to several hours ahead. Its main goal is to provide operational data to adjust the operation of power plants to take into account instantaneous changes in weather conditions. Analysing the results and conclusions obtained, algorithms and models based on fast processing of meteorological and power generation data are often used for very short-term solar energy forecasting. Such models can accommodate cloud dynamics, solar radiation intensity, temperature changes and other factors that have an immediate impact on solar energy generation. However, it is not only the accuracy of the forecast that is important but also the speed of its preparation and processing to respond to changes in energy production promptly.

S.C. Lim *et al.* (2022) determined that solar energy forecasting is a key task for the efficient use of solar power plants. One advanced approach is to use hybrid models, such as a convolutional neural network with LSTM (CNN-LSTM (Convolutional Neural Network, Long Short-Term Memory)). This combined model combines the advantages of both architectures and provides more accurate solar power generation forecasts. The hybrid CNN-LSTM model allows for the efficient use of spatial and temporal information obtained from meteorological and energy generation data. The CNN enables the model to detect spatial dependencies in meteorological data, such as cloud cover and solar radiation intensity at different locations. At the same time, the Long Short-Term Memory (LSTM) layer allows for time dependencies and trends in energy production, which is critical for accurate forecasting, as noted by C.M. Zohner *et al.* (2023).

This approach to solar energy forecasting is quite promising and can be widely used in modern solar power plant control systems. The use of hybrid models can improve forecasting accuracy and optimise the operation of energy systems, considering variable weather conditions and other factors affecting solar energy generation.

CONCLUSIONS

Effective forecasting of electricity generation from solar power plants is an important aspect of optimising production and ensuring the stability of the electricity supply. This report discusses the key aspects of effective forecasting, its benefits and prospects. The use of modern technologies, such as the integration of data from meteorological stations and satellite imagery, allows for more accurate and timely power generation forecasting data. This reduces energy losses and optimises the operation of solar power plants. An important aspect is the ability to respond quickly to changes in weather conditions. Integrated forecasting systems allow power plants to plan operations based on predictable changes, such as cloud cover, solar radiation intensity and temperature changes. This improves the reliability and stability of the energy supply. In particular, the integration of deep learning and artificial neural networks can improve forecasting accuracy by analysing large amounts of data and identifying complex relationships between various factors affecting electricity generation.

Analysing the calculated errors in forecasting PV power generation by different forecasting models, it can be noted that the results highlight important trends and performance indicators. The study confirmed that the Solargis Forecast forecasting model based on the Cloud Motion Vector model is the most accurate among the methods considered, which is confirmed by the low average absolute percentage error (MARE). Other models, such as Solcast and Solcast_Update, also demonstrated positive accuracy results, but still require some attention to detail to optimise and improve their performance in practical applications. In general, effective forecasting is an important step towards optimising the use of solar energy, which contributes to resource conservation, reducing CO2 emissions and improving the sustainability of energy supply for consumers. An additional area for research is the development of more accurate and reliable forecasting models, considering the impact of climate change and the technological development of solar energy.

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CONFLICT OF INTEREST

None.

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Ефективне прогнозування електрогенерації від сонячних електростанцій за допомогою технологій: інтеграція, переваги та перспективи

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Анотація. Точне прогнозування виробітку електроенергії з використанням відновлюваних джерел є важливим елементом для забезпечення стабільності електричних систем та переходу до більш сталого енергетичного виробництва. Метою цього дослідження є оптимізація роботи електричних систем України з урахуванням впровадження необхідної частки відновлювальних джерел енергії для забезпечення надійності електричної системи. Для дослідження точності прогнозування генерації електроенергії фотогальванічними електростанціями в Україні використовувалися аналіз даних, огляд сучасних моделей та методів прогнозування, а також порівняльний аналіз за допомогою супутникових знімків та метеорологічних спостережень. Низька точність прогнозування відпуску є особливістю виробництва електроенергії з відновлюваних джерел енергії, що пояснюється випадковим характером джерел енергії та супутніми метеорологічними умовами. В Україні стає більш актуальною проблема якісного прогнозування виробітку електричної енергії з використанням відновлюваних джерел. Значення пошуку ефективних методів прогнозування генерації виробництва електроенергії в Україні зросло з появою ринку електроенергії. Дана дослідницька робота скерована на вирішення проблемного питання щодо прогнозування генерації електроенергії фотогальванічними електростанціями на добу наперед в умовах енергетичного ринку України. У рамках роботи були розглянуті питання законодавства України щодо вимог до точності прогнозування генерації електроенергії та наслідки їх невиконання. Також було проведено огляд сучасних моделей та методів прогнозування генерації електроенергії фотогальванічними електростанціями та досліджено новий «ринок систем прогнозування» в Україні. У дослідженні були представлені прийняті метрики прогнозів, які дозволяють оцінити похибки і порівняти ефективність різних методів прогнозування. З урахуванням залежності прогнозування генерації електроенергії від метеопараметрів, був проведений порівняльний аналіз точності прогнозування за допомогою супутникових знімків та метеорологічних спостережень. Запропоноване дослідження дозволить враховувати викладений матеріал при визначенні моделі прогнозування генерації електроенергії, таким чином підвищуючи ефективність роботи енергетичних компанії в умовах енергетичного ринку України. Дослідження також сприятиме зменшенню негативного впливу енергетичного сектору на навколишнє середовище та сприятиме створенню більш ефективної та стабільної електричної системи у майбутньому

Ключові слова: потужність; генерація; баланс енергосистеми; відновлювані джерела енергії; енергетичний ринок