Short-Term Forecasting of Photovoltaic Solar Power Generation Based on Time Series: Application for Ensure the Efficient Operation of the Integrated Energy System of Ukraine

Alla Bosak, Dmytro Matushkin, Liudmyla Davydenko, Leonid Kulakovskyi, and Vadym Bronytskyi

Abstract Over the last decade, there has been a growing in the dependence of electricity production by solar power plants (SPPs) in Ukraine. Therefore, there is a need to optimize the structure of the energy balance of the state, based on the requirements of energy security and ensure the share of renewable energy at 25%. However, with the development of renewable energy sources (RESs) there is a problem of ensuring the appropriate maneuverability of the power system. This is due to the fact that the structure of generating capacity of the United Power System of Ukraine in terms of effective regulation of frequency and power in the power system is suboptimal. Among the reasons for this, the main ones are unregulated and variable operation of a SPP, which is exacerbated by the lack of tools and approaches for the power generation modes forecasting. That is why the issue of accurate forecasting of the possible electricity generation volume has become acute. However, solar energy forecasting is a rather difficult task, as it largely depends on climatic conditions that change over time. This study presents an analysis and application of the seasonal autoregressive integrated moving average (SARIMA) method to develop a model that can support and provide forecasting the amount of power produced by SPP. Data for the development of the model were obtained from the time series of electricity generation on the example of the SPP in the village of Velyka Dymerka, Kyiv region. The data consisted of more than 26 thousand samples collected from July 1, 2020, to December 31, 2020, which characterize the operating conditions of solar panels with a capacity of 9 MW. This led to the choice of the SARIMA model. The coefficient of determination (R^2) for the obtained model was 92%. This indicates the ability of the final model to accurately represent and give forecast based on data set of the SPP power generation.

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1 Introduction

Energy instability has led to the depletion of natural fuel and energy resources and the devastating effects of climate change. Thus, the priority of sustainable development of society is to ensure climate neutrality.

According to the Paris Agreement on Climate Change [1], the European Union had set a goal of reducing greenhouse gas emissions by 40% by 2030. In [2] established a new aim of reducing greenhouse gas emissions by at least 55% by 2030.

According to [3], more than 75% of all greenhouse gas emissions come from energy production and use. The decarbonisation of the energy system is an important step in meeting climate neutrality. Achieving these goals on the path to climate (carbon) neutrality "requires an energy transition to clean energy and a much larger share of RESs in the integrated energy system" [4]. According to [5], the share of renewable sources in the EU energy complex should be 32% by 2030, and according to the European Commission, this share should increase to 40% [6].

However, the decarbonisation of the economy requires coordinated planning and operation of the energy system, taking into account the links between different energy sources and consumption sectors [7]. This process involves the electrification of final consumption sectors and, as a consequence, increasing demand for electricity [7]. Solar and wind energy, as well as the production of renewable energy at sea are considered as sources of increased electricity needs [7]. At the same time, the intensive construction of solar and wind power plants, which have an unstable generation, causes a number of problems of both management and operation of the energy system [8]. For instance, the intermittent nature of generation causes uncertainty in energy supply and can lead to an imbalance of supply and demand [9, 10]. Therefore, in the context of the growing share of renewable energy, the issues of efficiency of integration of RESs into the electricity grid, monitoring of renewable energy generation, the coordination of operating modes of RESs and power systems to cover electricity load, etc. are becoming increasingly acute. Providing the planning of renewable energy generation and its control within the system of monitoring the modes of operation of RESs will increase the efficiency of the energy system and its economy and reliability. Creating a system for forecasting the generation of electricity from RESs is an important means of optimizing the modes of operation of energy infrastructure, management and ensuring the optimal functioning of the energy system.

2 Integration of Renewable Energy Sources into the Electricity System of Ukraine: Current Status, Tasks and Challenges

Ukraine has acceded to the Energy Community Treaty [11] and other European initiatives [12], in particular in the fields of energy production, transportation, supply and final consumption. By becoming a member of the Energy Community, Ukraine has committed itself to the implementation of basic acts of EU energy legislation on energy efficiency and the transition to clean energy [13–15]. Energy Strategy of Ukraine until 2035 [16] contains a number of tasks to meet Ukraine's commitments under the Energy Community Treaty, aimed at reforming the energy sector, optimizing and innovatively developing energy infrastructure, and ensuring sustainable development.

Among these tasks are the following [16]:

- further development of RES and growth of the share of renewable energy to the level of 12% of Total primary energy supply (TPES) and not less than 25%—by 2035;
- development of distributed generation and Smart Grid implementation;
- creation of a full-fledged electricity market in accordance with EU energy legislation, which provides for the introduction of a new model of electricity market operation. Launch of all market segments: the market of bilateral agreements; day-ahead market; intraday market; balancing market; ancillary services market.

Stimulating the construction of solar and wind power plants and the introduction of "green tariffs" contributes to the rapid development of renewable energy. As of August 1, 2021, the installed capacity of the renewable energy sector of Ukraine reached 8,877 MW (ed. including domestic SPPs) (Fig. 1) [17].

The reduction in the price of solar panels per unit, the cost of maintenance per installation compared to other renewable energy sources, as well as the expected service life of more than 20 years contributed to the growing share of PV-generation in the structure of RESs. The installed capacity of the industrial solar energy sector at the end of 2021 amounted to 6,351 MW [17]. At the same time, in 2021 the capacity of solar installations of private households increased by 156 MW. Thus, the cumulative installed capacity of domestic SPPs has increased to 933 MW (Fig. 2).

In 2021, the annual production of "green" electricity by all RESs power plants in Ukraine reached 10,023 million kWh, of which 230.5 million kWh accounted for wind farms in Ukraine (ed. which is 1,230 million kWh more than in 2020), and 6,053.9 million kWh were generated by national SSPs, including domestic SSPs (Fig. 3).

According to the Law of Ukraine №2019-VIII "On the Electricity Market" adopted in April 2017, in July 2019 a new wholesale electricity market was launched in Ukraine [13]. Thus, the country has moved from a pre-existing centralized single-buyer market model to a competitive liberalized model based on five distinct market

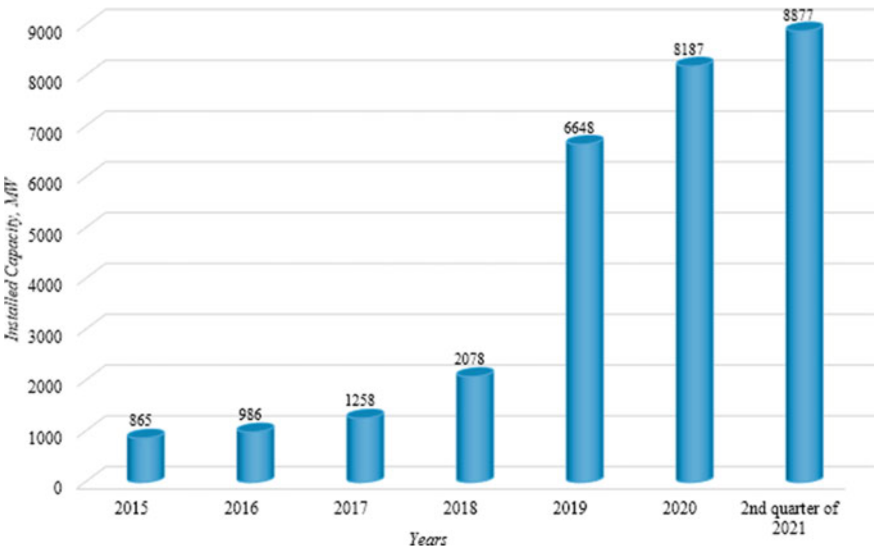

Fig. 1 Annual increase in the capacity of renewable energy sources in Ukraine

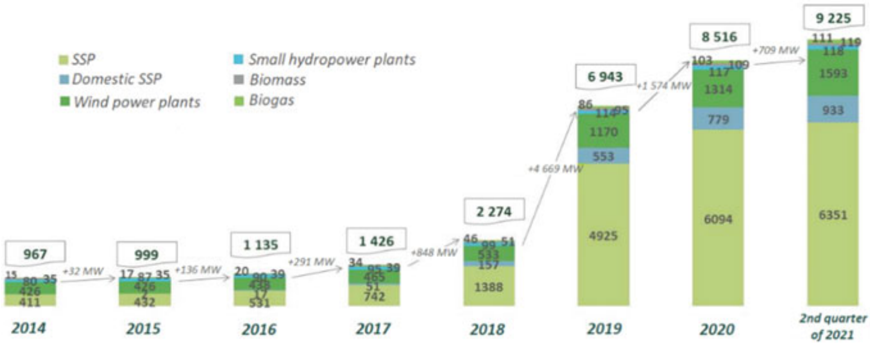

Fig. 2 Dynamics of growth of installed capacity of renewable energy facilities, MW (*Source* SAEE Ukraine, 2021)

segments: the market of bilateral agreements; day-ahead market; intraday market; balancing market; ancillary services market.

The use of RESs contributes to reducing the needs of the UES of Ukraine in the amount of balancing and regulatory capacity. The production of electricity by SPPs is quite flexible, which allows them to be adjusted to adapt to changing energy demand. At the same time, the growing share of solar energy sources, in particular solar installations of private households, causes a number of problems in terms of energy efficiency. The main reasons for the negative impact of solar generation on the electricity grid are interruptions and unpredictability due to dependence on solar

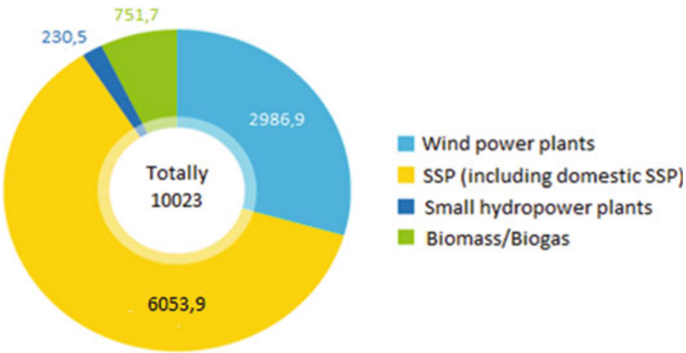

Fig. 3 Diagram of "green" electricity production in the renewable energy sector, by types, as of the end of 2021 in million kWh (source: The State Enterprise "Guaranteed Buyer")

radiation and weather conditions, as well as dispatching of generated energy [18, 19], and as a consequence of voltage fluctuations, low power quality and low stability [20]. To ensure the stable operation of the electricity system, it is necessary to plan the generation and demand of electricity, and forecasting the volume of renewable energy generation is an important step in this process. An energy production forecast, that provides information on how much energy a particular power plant will produce, can be useful for optimizing the marketing of renewable energy and, therefore, deploying system integration. Timely and accurate forecasts of solar electricity generation are necessary both for energy market participants engaged in the purchase or sale of energy, and for energy system operators who maintain the stability of the energy system [21]. The application of forecasting the volumes of photovoltaic generation at different time scales is the basis for achieving the balance of the grid [22], ensuring safe operation, efficient management and stability of the power system [9, 18]. As noted in [23], "reliable forecasting is key to several Smart Grid applications, such as optimal scheduling, demand response, grid regulation and intelligent energy management". The solar generation forecasting is an important part of the process of planning a sustainable power supply and covering the electrical load of power systems according to demand. The projected value of electricity generation volumes at the level of the SPP is necessary for coordination with the electricity network operator of the generation plan [8]. The solar generation forecast for the day ahead is an important point for placing proposals of the owner of the SPP on day-ahead market, as well as for optimizing electricity rates in day-ahead market and intraday market [8]. For small SPPs, solving the problem of generation forecasting is the cornerstone of sustainable development. As the contribution of green energy to the grid is constantly growing, the problem of building reliable models for forecasting energy production from such sources is becoming increasingly important. Accurate prediction of solar generation increases the reliability and cost-effectiveness of SPPs using.

3 Analysis of Factors Influencing Solar Generation

Solar photovoltaic energy is a function of solar radiation [25]. However, other environmental factors (temperature and relative humidity, wind speed, rainfall, length of daylight, cloudiness and amount of solar radiation) have a significant impact on the production of electricity by solar power plants. Changes in temperature and solar radiation can reduce solar energy generation by more than 20% [24]. In addition, different weather variables have different nature and significance of the impact on PV generation [19]. Moreover, the correlation of each variable with the amount of generated energy is different for different days [19]. The influence of various factors on the efficiency of solar panels and electricity generation of a SPP is considered in many studies. In particular, in [26, 27] the effect of changes in humidity on the performance of the solar panel was studied. In [28], the authors investigated the interdependence of dust accumulation, humidity and air velocity and their combined effect on photovoltaic performance. In [29] the influence of weather factors was studied, as well as fluctuations in radiation, which is strongly influenced by the shadow of the cloud. For this purpose, the spatial characteristics of clouds and the concentration of solid particles in the atmosphere moving in the wind direction were taken into account.

Factors influencing the efficiency of hourly forecast of the SSP generation include forecast horizon, local weather conditions, geographical location, data availability (e.g. volume, location, methods of obtaining and reliability of information), data quality (e.g. time consistency, accuracy, breakdown and correction of the territory coverage), etc.

Investigations of the dynamics of weather parameters (such as temperature, solar radiation, humidity, atmospheric pressure, wind direction and speed) and the SSP generation (Fig. 4) were performed to identify the relationship between them. The data set contained samples of measurements of the amount of electricity generation and weather parameters, which were recorded from July 1, 2020 to December 31, 2020. The measurements were performed for SSP in the village of Velyka Dymerka, Kyiv region.

Mainly the amount of generation is affected by *solar radiation*, W/m^2. The voltage of the solar cell depends on the light flux incident on it, namely: with increasing light, the voltage increases to a certain limit. In turn, the intensity of solar radiation depends on the *air temperature*, which directly affects the amount of heating panels. Most panels are designed to operate in temperatures from −40 to + 80 °C, and the lower the temperature, the higher the level of conversion. For instance, considering the 270 W panel, in hot summer at + 35 °C it‘s power will be approximately 257 W, and in winter at −20 °C may be 298 W. This is due to the fact that as the temperature increases, the flow of electrons inside the cell increases, which causes an increase in current and voltage drop. The voltage drop is more than the increase in current. Therefore, the total power ($P = UI$) decreases, which reduces the efficiency of the panel. To numerically characterize the decrease in electricity generation with increasing solar panel temperature, manufacturers specify the value of the temperature coefficient. The temperature coefficient is a parameter that indicates how much the efficiency of

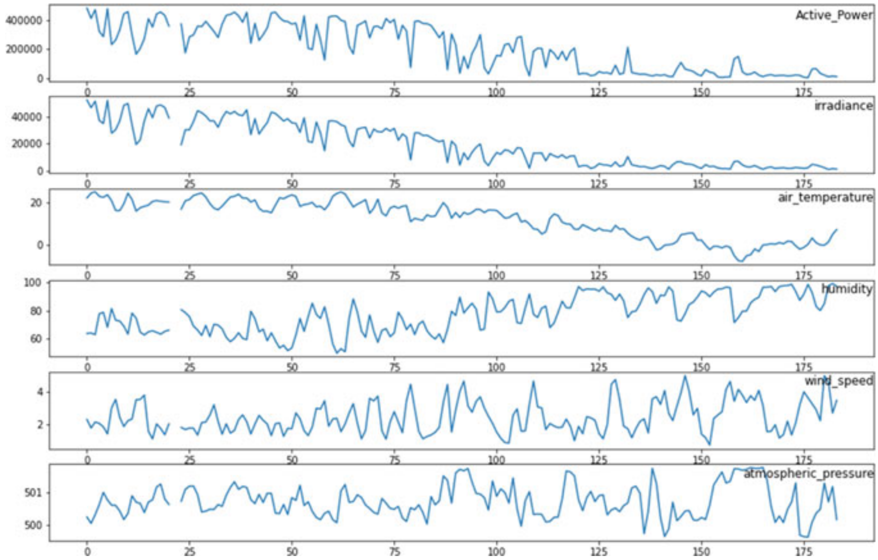

Fig. 4 Dynamics of changes in the active power of the Dymer solar power plant and influencing weather factors

the solar panel decreases with increasing air temperature by each degree. The value of this coefficient is obtained by the manufacturer experimentally and specified in the specifications. In summer, the own temperature of the panel can rise to 60−70 °C. On average, when the temperature rises by 20 °C, the power loss is about 10%.

Humidity has a great influence on the efficiency of solar panels. The generation of electricity from solar panels can be reduced to 15–30% depending on how high the humidity level is, as high humidity can form a layer of water on their surface. In this case, the probability of cloud formation, fog and scattering radiation also increases.

The next parameter that affects the amount of electricity generation is *wind speed*. By increasing the wind speed, more heat can be removed from the surface of the photocells. Also, higher air velocity reduces the relative humidity, which in turn leads to improved efficiency. Conversely, the wind raises dust and disperses it into the environment, which can lead to shading and poor performance of photovoltaic cells [30].

It is also necessary to note the possibility of the influence of *wind direction.* Depending on the angle and side of the wind blows the panels, the effect of wind speed on the efficiency of the panels may increase or decrease. The direction of the wind can also affect the shading of the panels from the deposition of dust or snow. If the wind blows in the direction of the panel, the snow will settle better on the surface than if it blows opposite to the slope of the panel.

It is a known that before bad weather (precipitation) the atmospheric pressure drops, and before clear (dry) weather—the pressure increases [10]. Short-term precipitation has small effect on efficiency. However, significant rainfall is usually character in cloudy weather when radiation and, accordingly, generation in this situation are reduced. Atmospheric pressure by itself is not a factor that directly affects the level of electricity generation. But it has an indirect effect on the main factors. In general, depending on the increase or decrease of atmospheric pressure, the influence of temperature, wind and humidity on energy production can increase or decrease.

The study of the degree of influence of weather parameters on SSP generation was performed using correlation analysis. The cross-correlation coefficient was used to estimate the degree of relationship between the parameters [31]:

$$r_{xy} = \frac{\sum_{i=1}^{n}(x_i - \overline{x})(y_i - \overline{y})}{(n-1)s_x s_y} = \frac{\sum_{i=1}^{n}(x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \overline{x})^2 \sum_{i=1}^{n}(y_i - \overline{y})^2}}, \tag{1}$$

where $\overline{x}$, $\overline{y}$—the average values for the sample x and y, s_x and s_y—unbiased (adjusted) estimate of the standard deviation for x and y.

Graphs of correlations between weather factors and the active power of the solar power plant are shown in Fig. 5.

Three parameters have positive correlations with the active power generation. Such parameters are solar radiation, air temperature and wind speed. And relatively humidity has negative correlation. It should be noted that the wind direction correlates directly with atmospheric pressure. This means that the value change of one parameter almost completely depending on the value of another. In other words, these factors in the model will be duplicated. And this will increase the complexity of the model, may increase the error of the model and increase the possibility of retraining. Therefore, the "wind speed" parameter is excluded from the model.

4 Methodological Bases of Solar Generation Forecasting

4.1 Solar Photovoltaic Generation Forecasting Methods: A Review

Many solutions have been proposed to solve the problem of solar generation forecasting. According to the length of the forecast period, there are methods of short-term, medium-term and long-term forecasting of solar generation. In terms of forecasting strategies, there are three groups of methods [21, 23, 32–34]: physical; statistical and hybrid.

Physical methods for estimating the generated power include the construction of a physical model of the photovoltaic module, or PV performance model, taking into account the models of radiation and temperature of photovoltaic modules in combination with weather forecast data. The main advantage of these methods is

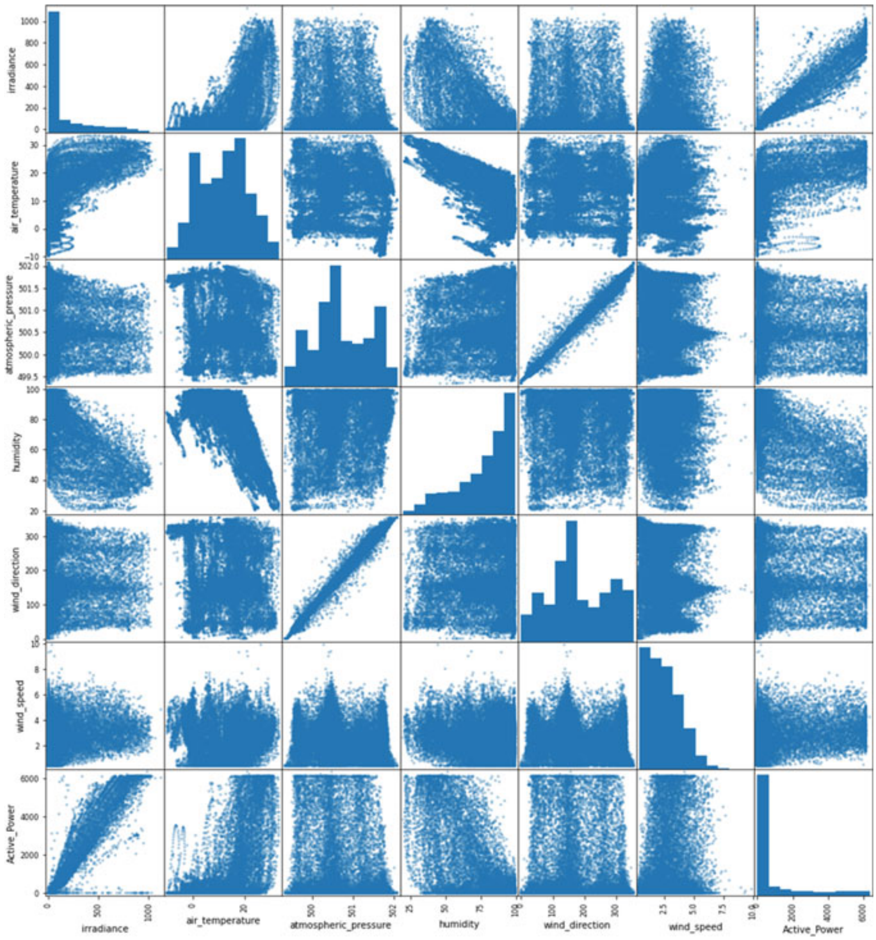

Fig. 5 Correlation of weather factors and solar generation

independence from historical data [23, 32]. However, the efficiency of the predictive model of PV performance significantly depends on the efficiency of numerical weather forecasting [32], and the process of physical modeling is complex [21].

Statistical methods are based on the use of large sets of historical data on weather factors and the generation of solar electricity to identify certain patterns and relationships in these data sets. They do not require internal information about the state of the system to build a model [33]. Statistical methodologies are better and easier to implement [23], they can have higher forecasting accuracy [32] than physical models. Statistical approaches are widely used for short-term forecasting of solar electricity generation [23].

Hybrid models involve a combination of physical and statistical modeling strategies.

Existing approaches to solar energy forecasting based on statistical methods belong to two groups [20, 21]: (1) methods based on a structural approach and (2) methods based on a time approach. The first group includes methods that apply the principle of "indirect forecasting", which is based on historical data on weather factors that affect the performance of the photovoltaic battery. These are the so-called multivariate forecasting methods. The forecast of an endogenous variable is based on exogenous variables (one or more) that have a significant impact on the endogenous variable. The second group includes methods based on the principles of "direct forecasting", which directly predicts the power of PV based on historical data from the generation of solar energy. These are the so-called one-dimensional forecasting methods. The forecast of an endogenous variable is based on previous values of the same variable (i.e. time series).

It should be noted that forecasting energy production is a dynamic process. Forecasting for the next 48 h requires constant updating of information on weather factors, pre-production of energy to ensure proper calibration of the system. However, the control of solar power plant energy production depends not only on the uncontrolled energy resource, but also on the management strategies of the power plant. The implementation of management strategies depends on technical constraints, price volatility, user demand and etc. It should be noted that all the necessary information is not always available, which makes forecasting renewable energy difficult to control. In addition, to forecast production taking into account weather conditions, it should be performed a weather forecast, the error of which affects the final result. One-dimensional methods are simpler and cheaper. For their implementation it is enough to have only the value of the time series of solar energy and do not need to perform additional measurements of weather factors that require maintenance of weather stations or other measuring instruments (except solar meters) [35]. Also, according to the authors [23, 35], one-dimensional methods of solar energy forecasting work better and are more efficient, especially in conditions of dynamic control, which requires short-term forecasting of solar energy generation [35].

4.2 Application of Time Series for Solar Generation Forecast

Time series forecasting methodology has wide practical application in the energy field [21]. There are many examples in the literature of the use of time series models for predicting solar generation [18, 21, 24, 25, 35].

The approach to time series forecasting is based on the following assumption: some knowledge can be obtained from a series that describes the initial process, and based on this knowledge to build a process model to predict future process behavior. The primary objective of time series analysis is to develop mathematical models that provide plausible descriptions from sample data.

The time series forecasting is solved using classical methods, such as autoregression and moving average methods [18, 36–38], and methods of machine learning and artificial intelligence [10, 24, 38].

Among the classical methods of time series forecasting, the moving average autoregression model (ARMA) is widely used [36, 37]. The moving average model uses current and previous white noise values for forecasting. ARMA contains two parts, autoregressive (AR) and moving average (MA). White noise is created from forecast errors or residuals when observations become available. The ARMA model requires a lot of preliminary data. The main requirement for the application of the ARMA model is the requirement of stationary time series.

However, the time series of solar electricity generation have seasonal and non-seasonal variations and are non-stationary [24, 25]. One of the most commonly used methods for predicting nonstationary time series is the Box-Jenkins model—ARIMA (integrated model of autoregression-moving average). In the ARIMA model, the predicted value is defined as a linear combination of past values (simulated by AR autoregression) and noise (simulated by the moving average (MA)), and the number of differences to convert the time series into a stationary simulated integrated (I) part [35]. The advantage of the ARIMA model is its simplicity. To apply the ARIMA model to non-stationary time series, the conversion of time series data into a stationary series is performed by taking the difference of some order from the original values of the time series. This approach was used in [24, 36] to predict the generation of solar energy.

In [39] the method of forecasting for several months ahead (one, two and three months) the average monthly time series of global solar generation and forecasting based on solar radiation data is presented. ARMA and ARIMA models are used to predict the nearest values of the global time series of solar radiation. Both models are applicable to stationary and non-stationary time series of solar radiation data.

To identify and take into account trends and seasonality that occur in the time series of solar generation, use the seasonal extension of the ARIMA model—the seasonal model of autoregressive integrated moving average (SARIMA). SARIMA models have received considerable attention for the formation of time series forecasts for RES due to their good ability to identify seasonality [21].

The SARIMA model is used to predict the production of energy from solar power plants, both small [18] and large installed capacity [38].

4.3 Methodology of Construction of Seasonal Model of Moving Average Autoregression

Time series models are data-driven models, ie, learn or obtain useful information from a set of historical data to predict the outcome [20]. The purpose of the forecasting process is to determine the amount of solar energy generation one step ahead based on a sample of historical data. Assume that there is a function that can be applied to both past and future data [35]:

$$\hat{p}(t) = f(p(t-1),\ p(t-2), \ldots), \tag{2}$$

where $p(t)$ is the actual power generated by the solar power plant at the time t, $\hat{p}(t)$ is a forecast of energy produced by a solar power plant at a time t, $p(t-1)$ indicates the power output for the previous time $(t-1)$.

Time series consist of four components: seasonal, trend, cyclical and random. Seasonal components are the result of systematic and calendar effects and are defined as repetitive or predictable fluctuations over a period of time that include natural conditions such as weather fluctuations. Due to components such as trend and seasonality, real time series are usually non-stationary. Non-stationary time series data cause errors and unsatisfactory forecasting results. Because seasonal components can affect some off-season characteristics of a time series and some trends in it, seasonal adjustments are applied to the process. Seasonal adjustment is the evaluation and then the removal of seasonal components.

The SARIMA model is the introduction of seasonal terms into the ARIMA model, which are denoted as SARIMA (p, d, q) (P, D, Q) s, where p, d, and q represent the parameters of the non-seasonal part of the model. P, D and Q represent the parameters of the seasonal part of the model, and s is the seasonal period. Values (p, d, q) (P, D, Q) s are used to parameterize the model. The parameters p and P characterize the autoregressive part of the model (respectively non-seasonal and seasonal components) and allow us to take into account in the model the effect of past values in our model. Parameters d and D characterize the integral part of the model and take into account the amount of differentiation (i.e. the number of moments of the past time that must be subtracted from the current value) to apply to the time series. Parameters q and Q characterize the part of the moving average model and allow to establish the error of the model as a linear combination of error values observed in previous moments in the past.

The following formula is used to build the model:

$$\begin{cases} \phi(B)\nabla^d X_t = \Theta(B)\varepsilon_t; \\ E(\varepsilon_t) = 0,\ Var(\varepsilon_t) = \sigma^2,\ E(\varepsilon_t \varepsilon_x) = 0,\ s = 24; \\ E(X, \varepsilon_t) = 0,\ \forall s < t, \end{cases} \tag{3}$$

where $\nabla^d = (1-B)^d$, B is the delay operator, $\nabla^d X_t$ is time series after the difference of the final order, ε_t is the sequence of white noise, $\Theta(B)$ is a stable and reversible polynomial of the moving smoothing coefficient of the ARMA (p, q) model, $\phi(B)$ is the polynomial of the autoregression coefficient of the stationary and reversible ARMA (p, q) model.

Preliminary observations are described by a polynomial:

$$X^t = \varepsilon_t + \psi_1\varepsilon_{t-1} + \psi_2\varepsilon_{t-2} + \ldots = \varphi(B)\varepsilon_t, \tag{4}$$

where ψ_1, ψ_2 are determined by the equation:

$$\phi_B(1-B)^d\psi(B) = \theta(B). \tag{5}$$

If $\phi^*(B)$ defined as a generalized autocorrelation function, we have

$$\phi^*(B) = \psi(B)(1-b)^d = 1 - \phi_1 B - \phi_2 B - \ldots \quad . \tag{6}$$

Values ψ_1, ψ_2 satisfy the equation:

$$\begin{cases} \psi_1 = \phi_1 - \theta_1; \\ \psi_2 = \phi_1\psi_1 + \phi_2 - \theta_2; \\ \ldots, \\ \psi_j = \phi_1\psi_{j-1} \ldots + \phi_{p+d}\psi_{j-p+d} - \theta_j. \end{cases} \tag{7}$$

In this formula:

$$\psi_j = \begin{cases} 0, & j < 1; \\ 1, & j = 0, \end{cases}$$

where j is the autoregression coefficient, θ_j is the moving average coefficient.

Then the forecast value of SSP generation can be written as follows:

$$X_{i+1} = (\varepsilon_{i+1} + \psi_i\varepsilon_{i+l-1} + \ldots + \psi_{l-1}\varepsilon_{t+1}) + (\psi_i\varepsilon_t + \psi_{l+1}\varepsilon_{i-1} + \ldots). \tag{8}$$

Therefore, the SARIMA model is expressed by the formula:

$$\nabla^d \nabla_s^D x_t = \frac{\Theta(B)\Theta_s(B)}{\phi(B)\phi_s(B)}\varepsilon_t, \tag{9}$$

where

$$\phi_s(B) = 1 - \varphi_1 B^s - \cdots - \varphi_{\mathrm{p}}\mathrm{B}^{\mathrm{ps}}, \ \Theta(\mathrm{B}) = 1 - \theta_1\mathrm{B} - \cdots - \theta_{\mathrm{q}}\mathrm{B}^{\mathrm{q}}$$
$$\Theta_s(B) = 1 - \theta_1 B^s - \cdots - \theta_{\mathrm{p}}\mathrm{B}^{\mathrm{QS}}$$

Choosing the optimal model is one of the problems that arise during forecasting. The choice of the optimal structure of the model is performed on the basis of analysis of the values of the information criterion Akaike (AIC), Schwartz Bayes test (VIC), the residual sum of squares (RSS) [24]. The choice is based on determining the quality of the statistical model on the data set to determine which set of model parameters provides the best performance.

The constructed model should be tested for adaptability. This step is to check the compliance of the remnants of the model with white noise. If the residuals of the model are a sequence of white noise, then the construction of the model fully reflects the information contained in the data. In this case, the seasonal model is adaptive. Otherwise, the model must be optimized and these model parameters reconfigured.

The forecasting process involves finding an estimate of p(t) that optimizes the performance criterion (or forecast error). The effectiveness of the forecast model is measured by various indicators associated with forecast error. The following key indicators are used to assess the performance of the model [21, 35]: Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and R-squared. These criteria are useful for comparing the predictive power of models of different structures.

5 Results of Modeling and Verification of Forecast Accuracy

5.1 SARIMA Models for Short-Term PV Generation Forecasting

Seasonality can be determined by regularly located peaks of the curve or flatness with the same value during this period. The change in the value of the time series may also be associated with a change in the component of the time series trend. In some cases, the trend (or irregular components) may dominate over the seasonal components, and then it is impossible to detect the small seasonality that is represented in the time series (Fig. 6).

The model will be presented in the form of SARIMA (p, d, q) × (P, D, Q) s, where (p, d, q) are non-seasonal parameters, respectively, autoregressive part of the model, integral part of the model and part of the moving average model; (P, D, Q) are the same in terms of part of the model, but apply to the seasonal component of the time

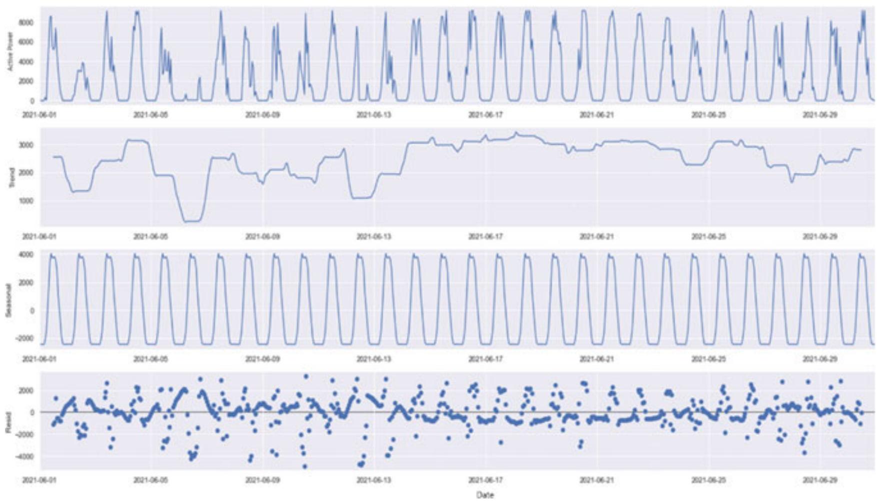

Fig. 6 Annual solar power plant generation with seasonal time series decomposition

Table 1 Seasonal ARIMA parameter combinations

ARIMA (p, d, q) combinations considered	Seasonal parameters (P, D, Q, S) considered
(0, 0, 0)	(0, 0, 0, 24)
(0, 0, 1)	(0, 0, 1, 24)
(0, 1, 0)	(0, 1, 0, 24)
(0, 1, 1)	(0, 1, 1, 24)
(1, 0, 0)	(1, 0, 0, 24)
…….	……….

series; s is the periodicity of the time series (s = 4 for quarterly periods, s = 12 for annual periods, s = 24 for daily periods).

The forecast was made for two days ahead.

The study used the "grid search" method to iteratively investigate different combinations of parameters. A new seasonal ARIMA model with SARIMA function was selected for each combination of parameters. After researching the full range of parameters, the optimal set of parameters was the one that gave the best performance for the criteria of interest. Table 1 shows the different combinations of parameters that needed to be evaluated: it was now possible to use the triplets of parameters defined above to automate the learning process and evaluate ARIMA models on different combinations.

When evaluating and comparing statistical models with different parameters, each of them can be ranked against each other based on how it corresponds to the data or its ability to accurately predict future data points. The choice of a more efficient model was based on the assessment of the quality of the model on the data set according to the information criterion Akaike (AIC) [24]. The AIC (Akaike Information Criterion) value was used, which is convenient to rotate with ARIMA models installed using the statsmodels Python 3.8 module. The AIC measures how well the model matches the data, taking into account the overall complexity of the model. A model that matched the data very well using a large number of functions was assigned a higher AIC score than a model that had fewer functions to achieve the same match. Therefore, there was interest in finding the model that gives the lowest AIC value (Table 2).

The modeling results are shown in Figs. 7 and 8. The best model with parameters SARIMA (1, 0, 1) × (2, 1, 0, 24) is presented in Fig. 8.

After selecting the model with the best parameters, the residual graphs were checked to verify the correctness of the model. The best forecasting method has a minimum of information that will remain in the residuals, if any.

At this stage, residual diagnostics, standard residue, histogram plus estimated density, normal Q−Q and correlogram were checked for model analysis (Fig. 9).

The coincidence of the residual points with the normal on the graph "Normal Q−Q" indicates the absence of systematic deviation. In addition, the Correlogram shows that there is no autocorrelation in the residues, so they are actually white noise. Therefore, these residues are uncorrelated and have a zero average. This suggests that the model is adaptive and the model's relevance to historical data is sufficient.

Table 2 Seasonal ARIMA parameter combinations with AIC

ARIMA (p, d, q) combinations considered	Seasonal parameters (P, D, Q, S) considered	AIC
(0, 0, 0)	(2, 1, 0, 24)	13,105.512
(2, 0, 0)	(1, 1, 0, 24)	12,954.057
(0, 0, 0)	(0, 1, 0, 24)	13,388.464
(1, 0, 1)	**(2, 1, 0, 24)**	**12,826.840**
(0, 0, 0)	(2, 1, 0, 24)	13,104.847
…….	……….	

Bold represents the best ARIMA model according to the AIC criterion

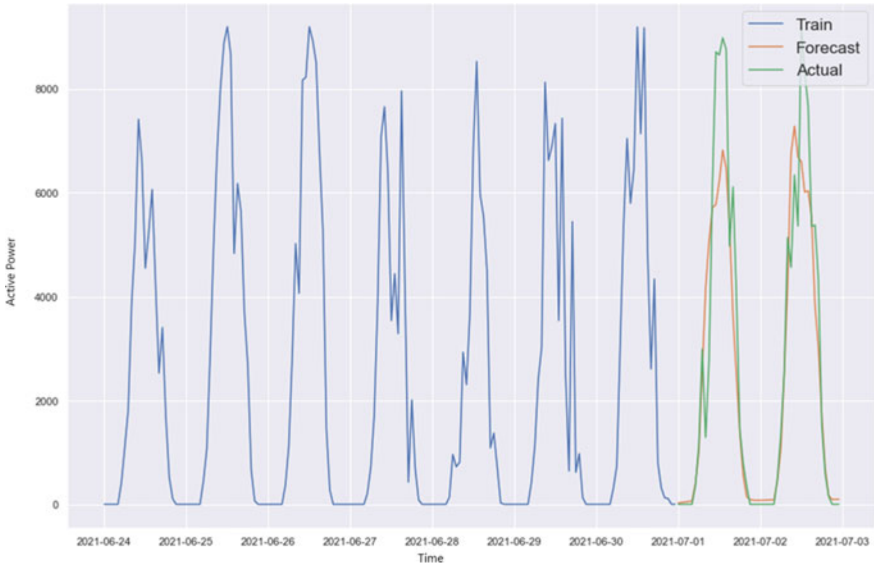

Fig. 7 Model with SARIMA parameters: (1, 1, 2) × (2, 1, 2, 24)

5.2 *Verification of the SARIMA Model Forecast Accuracy*

The following equations were used to evaluate the effectiveness of each model:

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|\hat{y}_i - y_i\right|; \tag{10}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(y_i - \hat{y}_i\right)^2}; \tag{11}$$

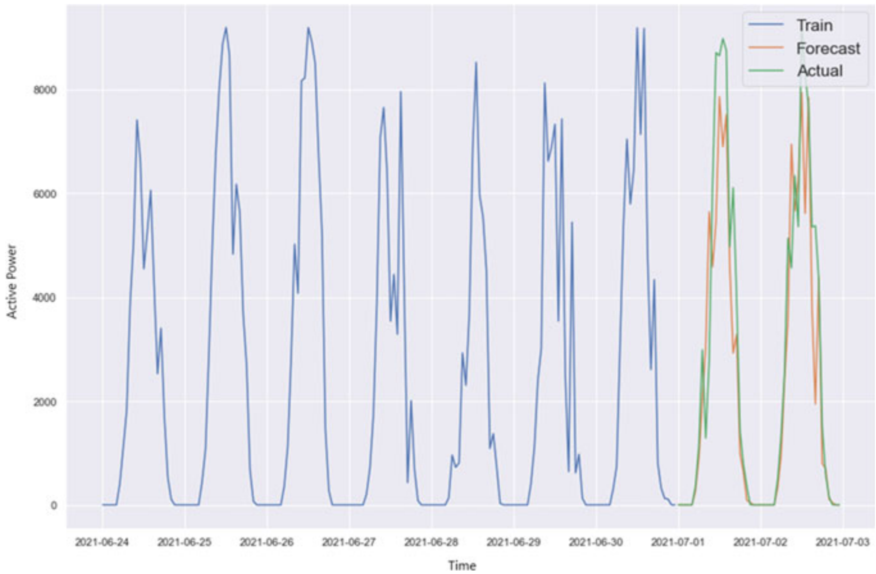

Fig. 8 Model with SARIMA parameters (1, 0, 1) × (2, 1, 0, 24)

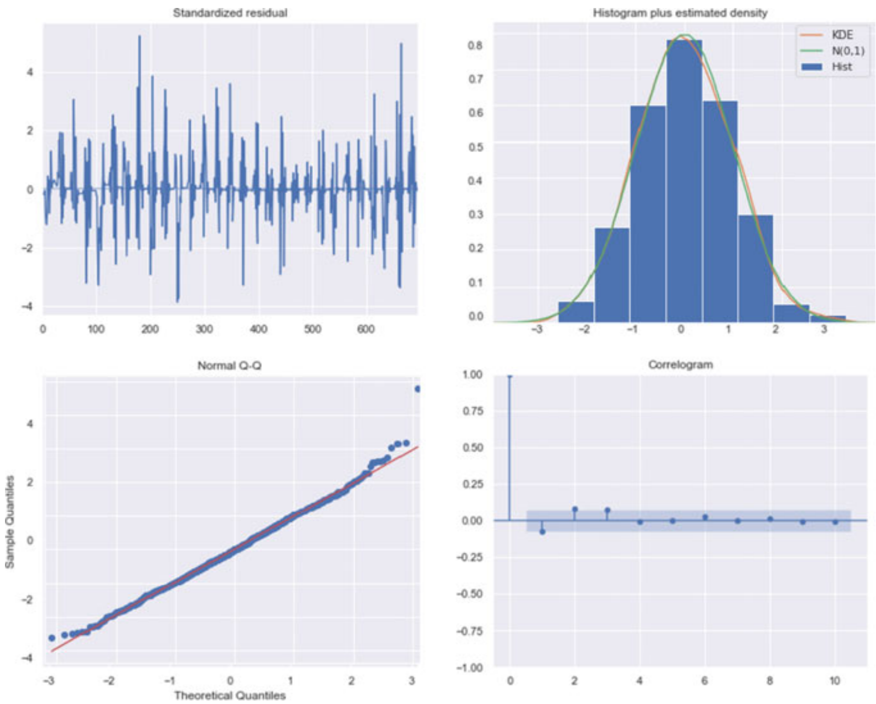

Fig. 9 Residual graphs of the SARIMA model (1, 0, 1) × (2, 1, 0, 24)

Table 3 Comparison of errors criteria for the results obtained for each of the test from the solar radiation forecast

Model	MAE, W	RMSE, W	R^2, abs. un
SARIMA (1, 1, 2) × (2, 1, 2, 24)	315.12	1245	0.87
SARIMA (1, 0, 1) × (2, 1, 0, 24)	258.57	1259	0.92

$$R^2 = 1 - \left(\sum_{i=1}^{N} \left(y_i - \hat{y}_i\right)^2 / \left(y_i - \overline{y}_i\right)^2 \right), \tag{12}$$

where N is the sample size; y_i is the actual value; $\hat{y}_i$ is the predicted value; $\overline{y}$ is the sample mean.

The results of the comparison of the best selected SARIMA models based on the values of MAE, RMSE and R^2 are shown in Table 3.

The results show that the SARIMA (1, 0, 1) × (2, 1, 0, 24) model performed better than SARIMA (1, 1, 2) × (2, 1, 2, 24) in data prediction, with the value of R^2 of 0.92, the value of MAE of 258.57 W and the value of RMSE of 1259 W. Lower the value of MAE and the value of R^2 closer to 1, indicate a correlation between observed and predicted dataset.

6 Conclusions

This chapter proposes a time series approach for forecasting the generation of solar power plants. The dynamic series of solar energy generation is characterized by rigid seasonality, so the optimal solution is to use an autoregressive model with a seasonal component—SARIMA. This model allows us to take into account trends and identify seasonal fluctuations in day-ahead generation, which perfectly meets the needs of the electricity day-ahead market.

The use of the proposed model SARIMA (1, 0, 1) × (2, 1, 0, 24) reduces the average forecast error for the day ahead to 2.58% from 3.15% and has a correlation coefficient R2 of 0.92. The developed mathematical models are implemented in the form of a computer program.

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