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Forecasting Solar Energy Production through Modeling of Photovoltaic System Data for Sustainable Energy Planning

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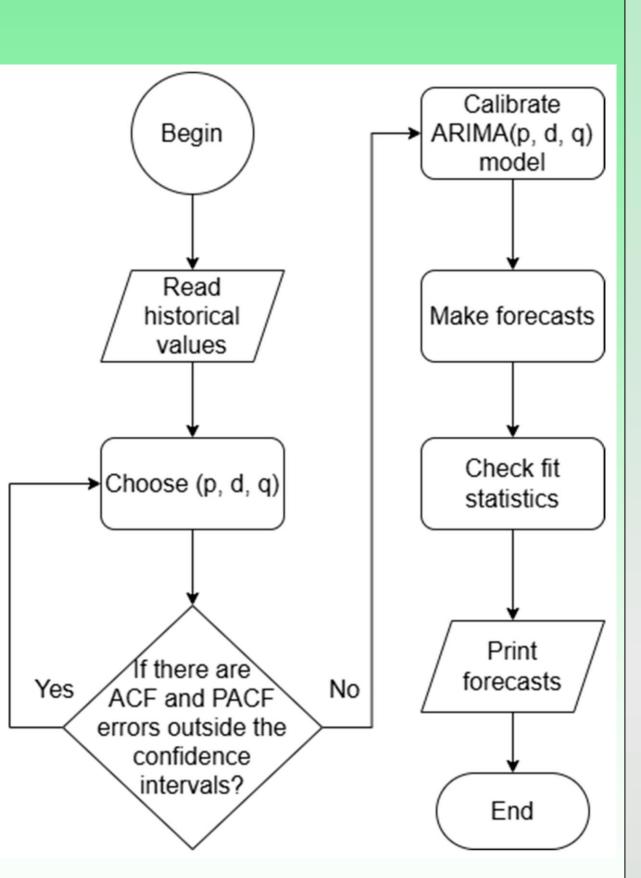
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Introduction

The use of photovoltaic energy is critical for supporting the transition to sustainable energy systems and for reducing dependence on fossil fuels. This study provides an analysis and forecast of the monthly electricity production of four 30kW photovoltaic (PV) power plants located in the Southwestern region of Bulgaria. We used five years of data to consider seasonal variations in solar energy production typical of temperate climates, as well as peak summer production and significant declines in winter.

The prediction was carried out using ARIMA algorithms, which are based on time series models. Analysis of the residuals involves applying different statistical approaches such as autocorrelation (ACF) and partial autocorrelation (PACF) for the determination of a suitable model. The reliability of the models was confirmed by calculating confidence intervals and by applying standard precision metrics, which provides a basis for reliable forecasting of future electricity production.

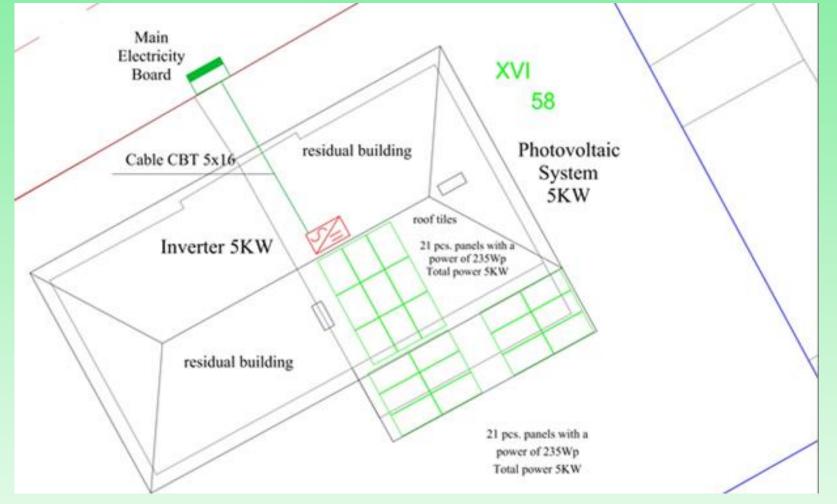
The study demonstrates that ARIMA models can successfully capture seasonal dynamics and long-term trends in photovoltaic production. Building forecasting models provides valuable information for decision-makers, helping them manage capacity, optimize costs, and plan strategically. According to the results, this approach is capable of improving the efficiency and sustainability of small-scale solar installations for business and personal use.

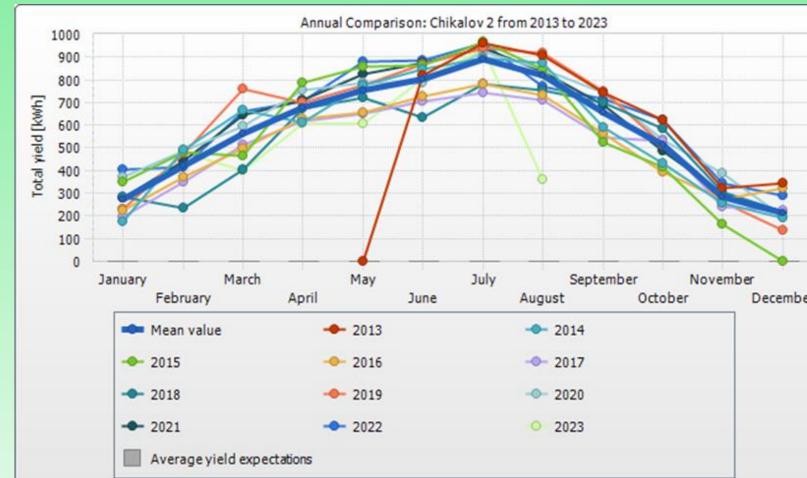


Materials and methods

In the current study a photovoltaic system – 5KW is considered, installed on the roof of a residential building in Simitli, Blagoevgrad, south-western Bulgaria.

The generated power (kW) from the PV system between 2013 and 2023 for ten years.





In this study we use ARIMA method, a fundamental approach for time series forecasting. The core goal of the ARIMA technique is to forecast future trends in PV yields by focusing on the changes between successive values within the series rather than solely on the observed values themselves. ARIMA models are constructed using three key parameters: p, d, and q [1]. The autoregressive parameter, p, accounts for the influence of observations from the preceding p time points. The integrated parameter, d, reflects the underlying trend of the data by incorporating the necessary differencing to achieve stationarity. The moving average parameter, q, smooths short-term fluctuations by incorporating q lagged forecast errors into the model.

Results

| Year | January | February | March | April | May | June | July | August | September | October | November | December |
|---------|---------|----------|--------|--------|--------|--------|--------|--------|-----------|---------|----------|----------|
| 2013 | | | | | | 146.00 | 171.68 | 161.72 | 132.68 | 110.88 | 58.04 | 61.49 |
| 2014 | 31.65 | 87.52 | 118.98 | 108.92 | 138.09 | 151.58 | 160.45 | 156.00 | 104.94 | 77.15 | 45.63 | 34.10 |
| 2015 | 62.70 | 86.11 | 82.99 | 140.85 | 153.54 | 154.39 | 173.15 | 150.95 | 93.76 | 74.60 | 29.47 | 0.00 |
| 2016 | 39.79 | 66.73 | 88.79 | 112.51 | 116.88 | 130.07 | 139.19 | 130.35 | 100.63 | 70.39 | 48.79 | 57.76 |
| 2017 | 35.56 | 62.21 | 91.37 | 110.31 | 116.50 | 125.54 | 132.34 | 126.99 | 97.33 | 94.60 | 43.19 | 40.31 |
| 2018 | 50.57 | 41.85 | 71.84 | 119.55 | 128.41 | 113.32 | 139.06 | 134.24 | 125.16 | 103.93 | 55.10 | 39.42 |
| 2019 | 40.79 | 85.28 | 135.16 | 125.36 | 138.68 | 154.70 | 167.48 | 164.31 | 133.98 | 91.34 | 46.58 | 23.99 |
| 2020 | 66.51 | 87.28 | 106.36 | 134.69 | 140.61 | 140.40 | 164.45 | 150.94 | 132.92 | 95.18 | 69.45 | 34.75 |
| 2021 | 49.80 | 79.06 | 115.22 | 126.79 | 147.20 | 156.39 | 167.90 | 149.59 | 122.80 | 87.26 | 53.96 | 39.28 |
| 2022 | 72.07 | 73.75 | 118.38 | 125.76 | 157.30 | 158.20 | 171.33 | 137.63 | 127.55 | 111.38 | 61.42 | 51.41 |
| 2023 | 40.95 | 86.34 | 71.58 | 108.37 | 108.78 | 143.79 | 166.43 | | | | | |
| Mean | 49.04 | 75.61 | 100.07 | 121.31 | 134.60 | 143.12 | 159.41 | 146.27 | 117.17 | 91.67 | 51.16 | 42.50 |
| value | | | | | | | | | | | | |
| Year | 3.98% | 6.14% | 8.12% | 9.85% | 10.93% | 11.62% | 12.94% | 11.87% | 9.51% | 7.44% | 4.15% | 3.45% |
| portion | | | | | | | | | | | | |

- ARIMA approaches have been applied to forecast the data from the 5KW photovoltaic system for the following 17 months. These ARIMA approaches were implemented using the IBM SPSS Statistics software product [1-5].
- The autocorrelations and partial autocorrelations are calculated, several ARIMA(p,d,q) models with fixed values of the parameters p, d, and q are proposed, as well as their characteristics and predictions.
- In this study, we proposed a quantitative approach to forecast the future values of both the specific PV system yield and the total yield using ARIMA models.
- Our suggested models demonstrated the ability to produce reliable and robust forecasts, making them applicable in various practical scenarios, such as energy management and planning for grid-connected solar photovoltaic systems.

Residual ACF

Table: Autocorrelations. Series: Specific PV System Yield

| T | A . 1 | C(1 F * | Box-Ljung Statistic | | | | |
|----------|-----------------|-------------|----------------------------|----|---------|--|--|
| Lag | Autocorrelation | Std. Error* | Value | df | Sig. ** | | |
| 1 | 0,789 | 0,089 | 77,881 | 1 | 0,000 | | |
| 2 | 0,437 | 0,089 | 101,949 | 2 | 0,000 | | |
| 3 | 0,000 | 0,089 | 101,949 | 3 | 0,000 | | |
| 4 | -0,405 | 0,088 | 122,993 | 4 | 0,000 | | |
| 5 | -0,670 | 0,088 | 181,058 | 5 | 0,000 | | |
| 6 | -0,760 | 0,088 | 256,444 | 6 | 0,000 | | |
| 7 | -0,666 | 0,087 | 314,849 | 7 | 0,000 | | |
| 8 | -0,387 | 0,087 | 334,680 | 8 | 0,000 | | |
| 9 | 0,001 | 0,086 | 334,680 | 9 | 0,000 | | |
| 10 | 0,409 | 0,086 | 357,330 | 10 | 0,000 | | |
| 11 | 0,720 | 0,086 | 427,926 | 11 | 0,000 | | |
| 12 | 0,819 | 0,085 | 520,136 | 12 | 0,000 | | |
| 13 | 0,689 | 0,085 | 585,935 | 13 | 0,000 | | |
| 14 | 0,381 | 0,084 | 606,274 | 14 | 0,000 | | |
| 15 | -0,026 | 0,084 | 606,367 | 15 | 0,000 | | |
| 16 | -0,365 | 0,084 | 625,335 | 16 | 0,000 | | |

Table: Partial Autocorrelations. Series: Specific PV System Viold

| - | System Yield. | | | | | | | |
|----|---------------|--------------------------|--|--|--|--|--|--|
| | LagPartial Au | tocorrelation Std. Error | | | | | | |
| 1 | 0,789 | 0,091 | | | | | | |
| 2 | -0,493 | 0,091 | | | | | | |
| 3 | -0,441 | 0,091 | | | | | | |
| 4 | -0,299 | 0,091 | | | | | | |
| 5 | -0,149 | 0,091 | | | | | | |
| 6 | -0,174 | 0,091 | | | | | | |
| 7 | -0,151 | 0,091 | | | | | | |
| 8 | 0,080 | 0,091 | | | | | | |
| 9 | 0,169 | 0,091 | | | | | | |
| 10 | 0,257 | 0,091 | | | | | | |
| 11 | 0,239 | 0,091 | | | | | | |
| 12 | 0,067 | 0,091 | | | | | | |
| 13 | -0,013 | 0,091 | | | | | | |
| 14 | 0,000 | 0,091 | | | | | | |
| 15 | -0,076 | 0,091 | | | | | | |
| 16 | 0,202 | 0,091 | | | | | | |

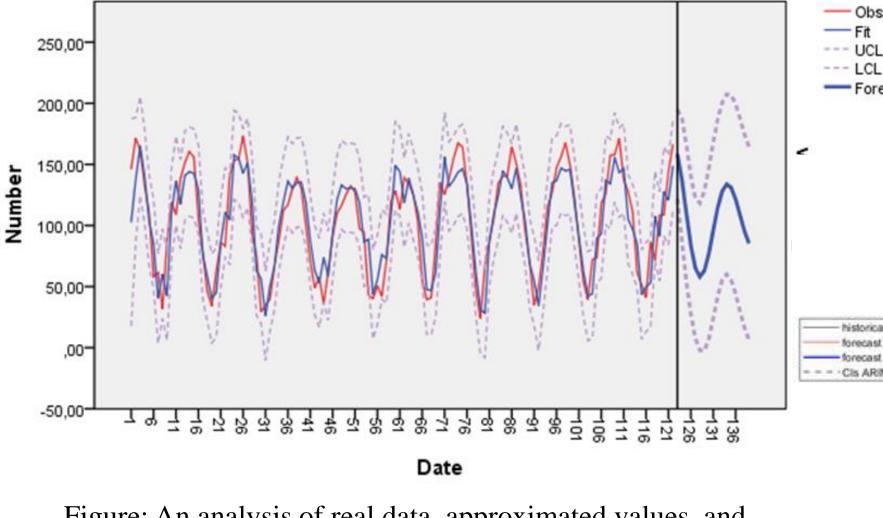
| | System Hera: | | | | | | | | |
|----------------|-----------------|------------------------|--|--|--|--|--|--|--|
| | LagPartial Auto | correlation Std. Error | | | | | | | |
| $\overline{1}$ | 0,789 | 0,091 | | | | | | | |
| 2 | -0,493 | 0,091 | | | | | | | |
| 3 | -0,441 | 0,091 | | | | | | | |
| 4 | -0,299 | 0,091 | | | | | | | |
| 5 | -0,149 | 0,091 | | | | | | | |
| 6 | -0,174 | 0,091 | | | | | | | |
| 7 | -0,151 | 0,091 | | | | | | | |
| 8 | 0,080 | 0,091 | | | | | | | |
| 9 | 0,169 | 0,091 | | | | | | | |
| 10 | 0,257 | 0,091 | | | | | | | |
| 11 | 0,239 | 0,091 | | | | | | | |
| 12 | 0,067 | 0,091 | | | | | | | |
| 13 | -0,013 | 0,091 | | | | | | | |
| 14 | 0,000 | 0,091 | | | | | | | |
| 15 | -0,076 | 0,091 | | | | | | | |
| 17 | 0.202 | 0.001 | | | | | | | |

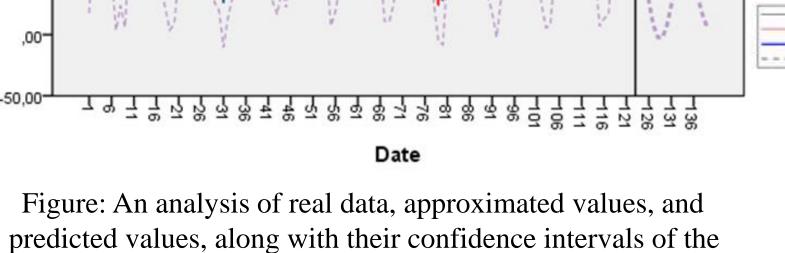
Residual Figure: The values and confidence interval of ACF and PACF errors of the ARIMA (3,0,4) model.

Specific PV system yield: (a) residual ACF; (b) residual PACF.

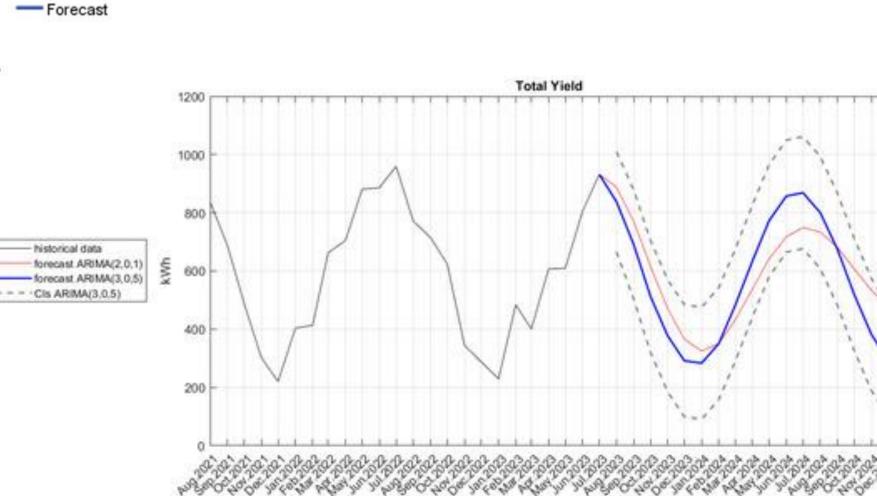
* The underlying process assumed is independence (white noise). ** Based on the asymptotic chi-square approximation.

| | | | | Mod | lel Fit | | | | | | |
|----------------------|---------|----|---------|---------|------------|---------|---------|---------|---------|---------|---------|
| Fit Statistic | Mean | SE | Minimum | Maximum | Percentile | | | | | | |
| | | | | | 5 | 10 | 25 | 50 | 75 | 90 | 95 |
| Stationary R-squared | 0,802 | • | 0,802 | 0,802 | 0,802 | 0,802 | 0,802 | 0,802 | 0,802 | 0,802 | 0,802 |
| R-squared | 0,802 | • | 0,802 | 0,802 | 0,802 | 0,802 | 0,802 | 0,802 | 0,802 | 0,802 | 0,802 |
| RMSE | 18,929 | • | 18,929 | 18,929 | 18,929 | 18,929 | 18,929 | 18,929 | 18,929 | 18,929 | 18,929 |
| MAPE | 18,591 | • | 18,591 | 18,591 | 18,591 | 18,591 | 18,591 | 18,591 | 18,591 | 18,591 | 18,591 |
| MaxAPE | 107,196 | • | 107,196 | 107,196 | 107,196 | 107,196 | 107,196 | 107,196 | 107,196 | 107,196 | 107,196 |
| MAE | 14,703 | • | 14,703 | 14,703 | 14,703 | 14,703 | 14,703 | 14,703 | 14,703 | 14,703 | 14,703 |
| MaxAE | 45,534 | • | 45,534 | 45,534 | 45,534 | 45,534 | 45,534 | 45,534 | 45,534 | 45,534 | 45,534 |
| Normalized BIC | 6,039 | • | 6,039 | 6,039 | 6,039 | 6,039 | 6,039 | 6,039 | 6,039 | 6,039 | 6,039 |





ARIMA(2,0,1) model.



Residual PACF

Figure. A comparison between the real data, predicted values, and their confidence intervals of the ARIMA (2,0,1) and ARIMA (3,0,4) models: specific PV system yield.

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- 5. Bulgarian Photovoltaic Association: https://www.bpva.org/en/index

References 1. Sapundzhi F, Chikalov A, Georgiev S, Georgiev I. Predictive Modeling of Photovoltaic Energy Yield Using an ARIMA Approach. Applied Sciences. 2024; 14(23):11192. https://doi.org/10.3390/app142311192