Short-term forecasting of photovoltaic energy production with short time series

KRASIMIRA STOILOVA[1,2], TODOR STOILOV[1,2], DENIS CHIKURTEV[1,2]
[1]Institute of Information and Communication Technologies – Bulgarian Academy of Sciences,
Acad. G. Bonchev str. bl.2, 1113 Sofia
BULGARIA

[2]Center of Competence for Mechatronics and Clean Technologies "Mechatronics, Innovation, Robotics, Automation and Clean Technologies" – MIRACLE,
1113 Sofia,
BULGARIA

Abstract: - The paper aims to develop a model for forecasting energy production from a photovoltaic (PV) system given a short range of data. Real data for a recently installed PV system is available. An analytical model based on time series analysis has been developed. A feature of modeling is the insufficient amount of available data needed to make predictions. This limitation necessitates the use of a relatively simple forecasting model, such as the linear autoregressive model AR(1). To achieve better forecasting accuracy, a set of technologies, such as optimization, the least squares method, model predictive control, and a sliding procedure for shifting the beginning of historical data, was used. A comparison between actual and forecasted values has been made where possible. The proposed innovative approach is a good tool for planning energy production from photovoltaic systems. This can be beneficial for the declared power generation of an energy supplier, which has a cost-effective result. In addition, the forecast of photovoltaic system generation can help in the correct design of the inverter and battery parameters of the PV system.

Key-words: -Analytical modeling, forecasting, linear regression models, optimization, photovoltaic energy production, time series.

Received: May 8, 2025. Revised: August 29, 2025. Accepted: October 11, 2025. Published: December 31, 2025.

1 Introduction

MODERN trends in the spread of alternative energy sources have led to the installation of photovoltaic systems to transform energy from the sun into electrical energy. This has sparked the interest of many scientists in modeling and studying these systems, [1], [2], [3]. The energy produced by photovoltaic systems depends on both the season and the duration of sunshine. It is important for the manager of an organization to plan the available resources well and, in particular, to know what energy is expected from the photovoltaic system. Several approaches, such as modeling, simulation, numerical estimation, and forecasting, are applied for the assessment and decision-making related to the planning and operation of the solar energy production and consumption. In [4], the modeling and simulation of a solar micro grid support proper energy management as a successful operation approach. Numerical estimates of the safety level of energy consumption are implemented in [5]. The solar irradiation forecast in [6], is used to plan the long-term horizon of electricity production and consumption. In [7], various forecasting methods and applications are summarized. Forecasting methods used in different fields are usually performed with different combinations of existing methods or with modifications of existing ones, [8]. A current and extensive review of forecasting theory and its application is given in [9]. Additional predictive estimates to quantify the uncertainty of predictive combinations are applied in [10]. When planning production, demand is forecasted using machine learning and statistical methods, [11]. An assessment of the effectiveness of statistical and predictive deep learning methods is given in [12].

This study applies a numerical forecasting approach to the evaluation and planning of photovoltaic generation in a micro grid system. Forecasting models are mainly based on statistical models. Statistical analysis is the process of collecting data and then using statistical and other data analysis techniques to identify trends. Statistical analysis is a widely applied mathematical apparatus for formalizing the process of predicting data, [13], [14], [15], [16], [17].

The study aims to create a model for predicting the energy produced by a real photovoltaic system that is installed at the end of 2024, and not much data is available on the energy produced. Since some problems arose in the initial months of installation of the system, it was not used continuously, which is why the data we will use is from the established mode of its operation, from the beginning of 2025. This limits the use of proven and complex mathematical forecasting models with a large base of accumulated data, [18], [19], [20], [21].

2 Materials and Methods

Here we will apply first-order linear regression analysis, through which we will create a forecasting model *AR*(1). The choice of the AR(1) model is justified based on insufficient data. Theoretical formal recommendations are suggested for analysis of the Autocorrelation Function (ACF) and the Partial Autocorrelation Function (PACF). A brief description of these functions and the necessary estimates is given below.

The Auto Correlation Function (ACF) estimates the correlation coefficients between data with a time delay lag x_t, x_{t-k}

$$\rho_{ACF}(k) = \frac{Cov(x_t, x_{t-k})}{\sqrt{Var(x_t).Var(x_{t-k})}} \, , \quad (1)$$

where $Cov(x_t, x_{t-k})$ is the covariance function between the real process x_t and its delayed series with lag *k*,

Var(.) are the corresponding variations of the real and delayed process,

x_t is the value of the real time series at time *t*,

x_{t-k} is the value of the time series at time *t*-*k*.

The ACF is a linear relationship between a time series and its lagged values. A positive ACF at lag *k* indicates a positive correlation between the current observation and observation *k*.

The Partial Autocorrelation Function (PACF) takes into account the direct correlation between x_t and x_{t-k} removing the influence of intermediate lags. The PACF at lag *k* is estimated by conditional values.

$$\rho_{PACF}(k) = \frac{Cov(x_t, x_{t-k} | x_{t-1}, x_{t-2}, \dots, x_{t-k+1})}{\sqrt{Var(x_t | x_{t-1}, x_{t-2}, \dots, x_{t-k+1}).Var(x_{t-k} | x_{t-1}, x_{t-2}, \dots, x_{t-k+1})}} \, , \quad (2)$$

where

$Cov(x_t, x_{t-k})$ is the conditional covariance between x_t and x_{t-k} for given values of the intermediate lags,

$Var(x_t | x_{t-1},\ x_{t-2}, \dots, x_{t-k+1})$,

$Var(x_{t-k} | x_{t-1},\ x_{t-2}, \dots, x_{t-k+1})$ are the corresponding conditional variances.

The use of ACF and PACF insists relatively long range of data for the time series. Therefore, the increasing value of the lag *k* requires an increase in the set of initial data, which can be decomposed in time in both time series x_t and x_{t-k} for the evaluation of the corresponding covariance and variances.

The PACF function is recommended for identifying the Moving Average (MA) process of order *q*. The ACF function is recommended for identifying the Autoregressive (AR) process of order *p*.

To identify the scale *p* (the Autoregressive part value**)** of ACF(*p*), the ACF function must decay (decrease gradually). The corresponding PACF must break after lag *p*. Accordingly, if Moving Average (MA) components are required for this case, the lag value *q* is evaluated when the ACF breaks after lag *q* and the PACF is decayed. Since in our case the photovoltaic dataset is very short in time, our approach to identify the lag *p* for the AR(*p*) model was evaluated based on the internal estimates of the Least Squares Method and the application of the sliding forecasting procedure. The analysis performed on the Least Squares Method determines that an inverse matrix must be defined and numerically calculated.

The available time series components are indicated by $x(t=1), x(t=2),\dots, x(t=9)$. As such, for the case of AR(1), the forecasting process is formalized as

$$x(t+1)=a_0+a_1x(t) \quad (3)$$

Two unknown coefficients, a_0 and a_1, must be evaluated. The application of the Least Squares Method requires the use of at least n=2 equations:

$$\begin{aligned} x(t+1)&=a_0+a_1x(t) \\ x(t+2)&=a_0+a_1x(t+1) \end{aligned} \quad (4)$$

Therefore, the values of $x(t=1)$, $x(t=2)$, $x(t=3)$ from the short range of available photovoltaic data should be used for the AR(1) formal estimation and prediction. The Least Squares Method estimates an inverse matrix of dimension $n\times n$ or in this case, 2×2. Since the values of the photovoltaic production are stochastic in nature, the $n\times n$ quadratic matrix may be irregular, and its inverse matrix may not exist. To overcome such potential irregularity, system (4) is augmented with an additional equation:

$$\begin{aligned} x(t+1)&=a_0+a_1x(t) \\ x(t+2)&=a_0+a_1x(t+1) \\ x(t+3)&=a_0+a_1x(t+2). \end{aligned} \quad (5)$$

Therefore, (5) is an overdetermined system for estimating the coefficients a_0 and a_1, and the Least Squares Method is suitable for solving (5).

The estimation of a_0 and a_1 from (5) requires four data: $x(t)$, $x(t+1)$, $x(t+2)$, $x(t+3)$. The reason for choosing AR(1) is the need for a small set of available data to estimate the necessary parameters of the forecasting system (5). The limited set of available data does not allow for the estimation of covariances with increasing lag values. To achieve better approximation accuracy, we will use the closest consecutive data.

The known value of electricity energy produced from the PV system is denoted at moment t by $x(t)$, and the unknown forecasted value at moment t+1 by $x^p(t+1)$. The forecasted value at time t+1 depends on the value at the previous time t. The linear autoregressive model AR(1) in the case of m linear equations is

$$x_i^p(t+1) = a_0 + a_1x_i(t), \quad i=1,\dots, m, \quad (6)$$

where the coefficients a_0, a_1 are unknown and must be estimated. In this research, three equations are used for the evaluation of the coefficients a_0, a_1 of the AR(1) model or m=3. For the case of m=3 it is necessary to use four initial historical data points. Therefore, the first forecast can be made for the fifth data point. We denote the first point of historical data $x_i(t) = x_1$, and the subsequent ones are $x_i(t+1) = x_2$, $x_i(t+2) = x_3$ and $x_i(t+3) = x_4$ The AR(1) model (6) is analytically implemented with the linear system with m=3 equations

$$\begin{aligned} x_2 &= a_0 + a_1x_1 \\ x_3 &= a_0 + a_1x_2 \\ x_4 &= a_0 + a_1x_3 . \end{aligned} \quad (7)$$

The system (7) uses four data x_1, x_2, x_3, x_4 to estimate the coefficients a_0, a_1 of AR(1). The first forecasted value is x_5^p according to the equation

$$x_5^p = a_0 + a_1x_4 \quad . \quad (8)$$

The estimate of the parameters a_0, a_1 of the AR(1) model is found from the matrix relation

$$Y = \gamma\overline{Y} \quad , \quad (9)$$

where the matrices are

$$\mathrm{Y} = \begin{vmatrix} x_2 \\ x_3 \\ x_4 \end{vmatrix}; \ \gamma = \begin{vmatrix} a_0 \\ a_1 \end{vmatrix} \quad \overline{Y} = \begin{vmatrix} 1 & x_1 \\ 1 & x_2 \\ 1 & x_3 \end{vmatrix}. \quad (10)$$

The estimation of the unknown coefficients $\gamma = \begin{vmatrix} a_0 \\ a_1 \end{vmatrix}$ is performed according to the Least Squares Method. Such an estimate aims to minimize the difference between the actual and analytically estimated values from (8) in the time series. Analytically, the error is given by the difference

$$\delta_i = y_i - y_i^p . \quad (11)$$

The optimization problem for the evaluation of the AR(1) coefficients is of the form

$$\min_{a_0,a_1} \delta = \sum_{i=1}^{3}(y_i - y_i^p)^2 \quad (12)$$

or

$$\min_{\gamma} \delta = \left(Y - \overline{Y}\gamma\right)^T \left(Y - \overline{Y}\gamma\right) = Y^TY - Y^T\overline{Y}\gamma - \gamma^T\overline{Y}^TY + \gamma^T\overline{Y}^T\overline{Y}\gamma . \quad (13)$$

The solution of the AR(1) parameters $\gamma = \begin{vmatrix} a_0 \\ a_1 \end{vmatrix}$ is given by the equation

$$\gamma = (\overline{Y}^T\overline{Y})^{-1}\overline{Y}^T Y \quad . \tag{14}$$

The AR(1) parameters are estimated as solutions to the optimization problem (12). Therefore, the error between the actual and the forecasted values should be minimal, or the accuracy of the forecast should be maximal.

3 Simulations and results

The chosen optimization approach for forecasting has been applied to a recently installed photovoltaic system in central Bulgaria. The data we have on the electricity produced by this system were for only 9 months, Table 1 (Appendix).

This short range of data on green energy production is the main reason for using a relatively simple AR(1) forecasting model. The choice of parameter p=1 of the AR(1) model was justified by the necessary data for the application of the Least Squares Method, with a combination of a sliding forecasting procedure.

The forecasts can be evaluated after the 9th month (September). Therefore, for the analytic definition and solution of the optimization problem (12), for the forecast of the photovoltaic production for the month 10, x_{10}^p (October), four real historical time series data, x_6, x_7, x_8, x_9 will be used.

The forecast for the 11th month, x_{11}^p (November) again requires four historical data. In this case, the actual historical data are x_7, x_8, x_9 and the last one is the forecast x_{10}^p. Therefore, the estimate of x_{11}^p will contain an internal prediction error resulting from the last prediction x_{10}^p. That is why continuing with long-term forecasting is not recommended, as any new forecast based on previous forecasts may contain accumulated and propagated error. Since the real dataset is limited, simulations were done in the MATLAB environment until the 11th month (November). The beginning of the forecast estimates starts with historical data from the first to the fourth month, and a forecast is estimated for the fifth month. The beginning of the historical period is then shifted forward one month for subsequent forecast estimates. The new optimization problem (12) is defined using shifted historical data. The solution to problem (12) gives new parameters for AR(1), and new parameters for estimating the sixth forecast x_6^p. This sliding procedure with a sequential shift of the beginning of historical data was applied until the 9th month for which real data is available.

The forecast for October 2025 allows the use of real data from June 2025, x_1 (June), x_2 (July),...,x_4 (September**).** A forecast for October is estimated, but no real error can be estimated for this forecast. For the next month, November, the forecast can be made, but using the previously received forecast and a set of real historical data. Forecasting procedures were suspended until November, as continuing the procedure could lead to an accumulation of errors, and the forecasts may not be accurate.

The assessment of the accuracy of the AR(1) model applied to the forecasts of months x_{10}^p , x_{11}^p is performed by evaluating the errors between the actually available data from x_5^p and x_9^p. Figure 1 (Appendix) graphically presents the differences between the values of the actual data x_{i} and the estimated forecasts x_i^p , i=5, …, 9. Figure 2 (Appendix) illustrates the change in forecast error for the period May-September.

- The numerical assessment of the accuracy of the forecast model can be made based on commonly used indicators:

Mean Absolute Error (MAE)

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |x_{i-}x_i^p | \tag{15}$$

Root Mean Square Error (RMSE)

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - x_i^p)^2} \tag{16}$$

Mean Absolute Percentage Error (MAPE)

$$MAPE = \frac{1}{n}\sum_{i=1}^{n} \frac{|x_i|}{|x_i - x_i^p|} \, . \, 100 \tag{17}$$

These indicators have their own characteristics for interpreting forecast accuracy. MAE gives a clear assessment of forecast accuracy. RMSE is similar to MAE, but it gives greater weight to large errors, due to the square differences between the actual and forecasted values. RMSE is useful for estimates where large errors are unacceptable. MAPE can be unstable if the actual values are close to zero. All of these metrics should be applied based on the specific needs and characteristics of the time series.

Our case is with the application of the MAE metric, because this criterion gives clear, easily understandable, and good results.

4 Results and Discussion

The available data from the time series of photovoltaic production allows two forecasts to be made for October and November. The short-term data period is the primary reason for applying AR(1) forecasting modeling, given the limited historical data available. This study presents the derivation of an optimization model and an algorithm for its application, along with a sliding procedure for generating forecast estimates. The numerical estimate of the average production and the mean of the forecasts for the data sets: $[x_5, \ldots, x_9]$ and $[x_5^p, \ldots, x_9^p]$ are:

Average real data $[x_i, i=5,\ldots,9] = 1079.3$ kWh (18)

Average forecast data $[x_i^p, i=5,\ldots,9] = 1174.7$ kWh (19)

The differences $(x_i - x_i^p)$, $i=5,\ldots,9$ are presented graphically in Figure 2 (Appendix). Using the MAE criterion, it gives the value

$$\text{MAE}(x_i - x_i^p),\ i=5,\ldots,9 = 95.4 \text{ kWh}. \quad (20)$$

The average value of 95.4 kWh is an acceptable accuracy for photovoltaic production for one month. Therefore, if we assume the accuracy of AR(1) for the forecast values for October and November, the numerical forecast can be in the range of

Average (photovoltaic production /per month) ± MAE.

From the initial data, it is estimated:

Average (photovoltaic production /per month) = 908.18 kWh

The real value x in the future months could be in the range of

$$908.18 - 95.4 = 812.78 \leq x \leq 908.18 + 95.4 = 1003.6 \quad (21)$$

or

$$812.78 \leq x \leq 1003.6. \quad (22)$$

Our assessment of these results is satisfactory for short-term planning of energy and cost estimates. A relative increase in forecasting accuracy can be expected with increasing time series data, with a longer time interval. The increase in available data allows the application of more sophisticated forecasting methods compared to the current study. The peculiarity in our case is that we have very few available data (only 9). To compensate for this lack of data, several techniques have been applied to increase accuracy: linear regression modeling, the least squares method, optimal determination of the approximation coefficients for minimal approximation error, and a sliding procedure for shifting the beginning of the historical interval. The resulting model was developed to take into account the limited set of available data, with a recommendation to apply short-term forecasts.

5 Conclusions

A forecasting approach with limited volumes of data points has been derived as presented in (1) – (22). The forecast is performed using first-order linear regression analysis in order to use the most recent data as the forecast history. To increase the accuracy of the forecast, an optimization problem is defined and solved sequentially. The optimization problem estimates the optimal values of the parameters of the applied AR(1) forecasting model. The Least Squares Method is applied sequentially with an offset for the beginning of the historical interval used to estimate the AR(1) parameters. Therefore, each forecast is performed on new and actual data sets. The available data set was used to train the AR model. Then, two forecasts were made based on the trained model. Future forecasts are only made for two consecutive months to avoid the accumulation of errors when real data is not used.

The forecast estimates were necessary for planning the energy consumption of a private company. Accordingly, this was used to reduce the required electricity from suppliers, which had a cost-effective result. Forecasting the electricity production from a photovoltaic system supports the production and exploitation of green energy. A practical result of such forecasting is the quantitative assessment of the required battery resources in the photovoltaic system. Therefore, predicting the need for electricity consumption can help in the correct selection of battery capacity and inverter power of a photovoltaic system. Limited photovoltaic generation can help select a lower capacity battery, as the generated photovoltaic energy will not be sufficient to charge it. This can save on photovoltaic system design and operation costs.

Possible shortcomings of the forecasting results are due to the stochastic nature of solar radiation. Therefore, it is recommended to make appropriate forecasts with average data to estimate solar radiation in different months of the year.

References

[1] S. Karabanov, Y. Kukhmistrov, B. Miedzinski, and Z. Okraszewski, "Photovoltaic systems," Modern Electric Power Systems, 2010, https://ieeexplore.ieee.org/abstract/document/6007207 (Accessed on November 25, 2025).

[2] J. Siecker, K. Kusakana, B. P. Numbi, "A review of solar photovoltaic systems cooling technologies," Renewable and Sustainable Energy Reviews, vol. 79, pp.192-203, 2017. https://doi.org/10.1016/j.rser.2017.05.053

[3] S. Ahmed, A. Ali, J. A. Ansari, S. A. Qadir, and L. Kumar, "A Comprehensive Review of Solar Photovoltaic Systems: Scope, Technologies, Applications, Progress, Challenges, and Recommendations," IEEE Access 13:69723-69750, 2025. https://doi.org/10.1109/ACCESS.2025.3558539

[4] F. Alam, T. H. Chowdhury, Md. H. Akbar, Md. T. Islam, A. Bhowmick, "Modelling and Analyzing of Solar Microgrid System for Rural Area using Simulink," WSEAS Transactions on Power Systems, vol. 20, pp. 309-315, 2025. https://doi.org/10.37394/232016.2025.20.24

[5] J. Bilbao, "Application of Numerical Methods in the Study of the Power Blackout of April 28, 2025, in Spain," WSEAS Transactions on Power Systems, vol. 20, pp. 289-296, 2025. https://doi.org/10.37394/232016.2025.20.22

[6] V. D. Gil-Vera, C. Quintero-López, "Solar Irradiation Prediction Level," WSEAS Transactions on Power Systems, vol. 19, pp. 409-416, 2024. https://doi.org/10.37394/232016.2024.19.35

[7] C. Beaumont, "Forecasting: Methods and Applications," J. of the Operational Research Society, vol. 35(1), 79, 1984. https://doi.org/10.1057/jors.1984.11

[8] X. Wang, R. J. Hyndman, F. Li, and Y. Kang, "Forecast combinations: An over 50-year review," International Journal of Forecasting, vol. 39(4), pp. 1518-1547, 2022. https://doi.org/10.1016/j.ijforecast.2022.11.005

[9] F. Petropoulos, D. Apiletti, V. Assimakopoulos, M. Z. Babai, D. K. Barrow, S. B. Taieb, C. Bergmeir, R. Bessa, J. Bijak, J. E. Boylan, J. Browell, C. Carnevale, J. L. Castle, P. Cirillo, M. C. Clements, C. Cordeiro, F. L. C. Oliveira, S. D. Baets, A. Dokumentov, J. Ellison, F. Ziel, "Forecasting: theory and practice," International Journal of Forecasting. vol. 38(3), pp. 705-871, 2022. https://doi.org/10.1016/j.ijforecast.2021.11.001

[10] X. Wang, Y. Kang, F. Petropoulos, and F. Li, "The uncertainty estimation of feature-based forecast combinations," Journal of the Operational Research Society, vol. 73(5), pp. 979–993, 2022. https://doi.org/10.1080/01605682.2021.1880297

[11] C. Vithitsoontorn, and P. Chongstitvatana, "Demand Forecasting in Production Planning for Dairy Products Using Machine Learning and Statistical Method," 2022 International Electrical Engineering Congress (iEECON), Khon Kaen, Thailand, pp. 1-4, 2022 https://doi.org/10.1109/iEECON53204.2022.9741683

[12] B. G. Hansen, Y. Li, R. Sun, I. Schei, "Forecasting milk delivery to dairy – How modern statistical and machine learning methods can contribute," Expert Systems with Applications, vol. 248, pp. 123475, 2024. https://doi.org/10.1016/j.eswa.2024.123475

[13] V. Kumar, "Predictive Analytics: A Review of Trends and Techniques," International Journal of Computer Applications, vol. 182(1), pp. 31-37, 2018. https://doi.org/10.5120/ijca2018917434

[14] X. Bai, F. Zhang, I. Lee, "Predicting the citations of scholarly paper," Journal of Informetrics, vol. 13(1), pp. 407-418, 2019. https://doi.org/10.1016/j.joi.2019.01.010

[15] S. Bakken, "Predictive models: important problems and innovative methods," J Am Med Assoc vol. 29(1), pp. 1-2, 2022. https://doi.org/10.1093/jamia/ocab274

[16] C. Starbuck, "Predictive Modeling," In The Fundamentals of People Analytics. Springer, Cham. 2023, pp. 239-260. https://doi.org/10.1007/978-3-031-28674-2_13

[17] C. Saksupawattanakul and W. Vatanawood, "Predictive Modeling of Software Behavior Using Machine Learning," IEEE Access vol. 12, pp. 120584-120596, 2024. https://doi.org/10.1109/ACCESS.2024.3451012

[18] J. Muñoz, A. M. Felicisimo, "Comparison of statistical methods commonly used in predictive modelling," Journal of Vegetation Science, vol. 15,

pp. 285-292, 2004. https://doi.org/10.1111/j.1654-1103.2004.tb02263.x

[19] L. Duponchel, C. Fabre, B. Bousquet, V. Motto-Ros, "Statistical comparison of predictive models for quantitative analysis and classification in the framework of LIBS spectroscopy: A tutorial," vol. 208, pp. 106776, 2023. https://doi.org/10.1016/j.sab.2023.106776

[20] P. A. Alvizuri-Tintaya, J. Lora-Garcia, J. I. Torregrosa-López, V. G. Lo-Iacono-Ferreira, "A Comparative Analysis of Statistical Models and Mathematics in Reverse Osmosis Evaluation Processes as a Search Path to Achieve Better Efficiency," Water, vol. 14(16), pp. 2485, 2022. https://doi.org/10.3390/w14162485

[21] D. Koska, D. Oriwol, C. Maiwald, 2023. "Comparison of statistical models for characterizing continuous differences between two biomechanical measurement systems," J Biomech. Vol. 149, pp. 111506, 2023. https://doi.org/10.1016/j.jbiomech.2023.111506

Contribution of individual authors to the creation of a scientific article (ghostwriting policy)

Krasimira Stoilova carried out the modeling and optimization.

Todor Stoilov has integrated the different technologies in the proposed approach.

Denis Chikurtev was responsible for the Simulation and Statistics.

Sources of funding for research presented in a scientific article or scientific article itself

This work was accomplished by the Center of Competence for Mechatronics and Clean Technologies "Mechatronics, Innovation, Robotics, Automation and Clean Technologies" – MIRACle, with the financial support of contract No. BG16RFPR002-1.014-0019-C01, funded by the European Regional Development Fund (ERDF) through the Program "Research, Innovation and Digitalization for Smart Transformation" (PRIDST) 2021–2027.

Conflict of Interest

The authors have no conflicts of interest to declare that are relevant to the content of this article.

APPENDIX

Table 1. Energy Production from PV system [kWh]

Month	1	2	3	4	5	6	7	8	9	10	11	12
2025	394.3	570	966.1	1183.5	1130.4	1481.4	1549.2	680.6	554.7			

Source: created by the authors.

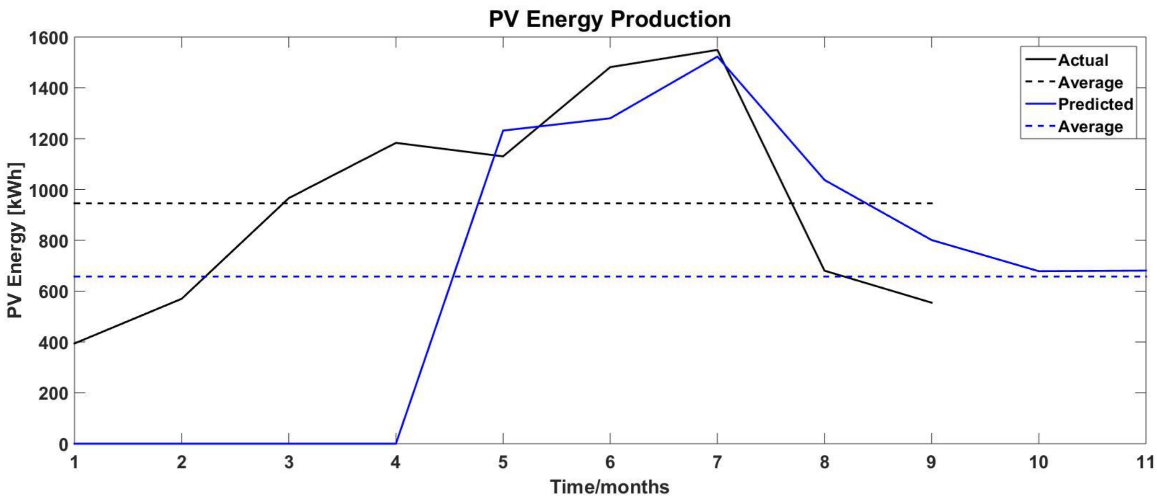

Fig. 1. Comparison between actual and predicted values of energy produced by the PV system
Source: created by the authors

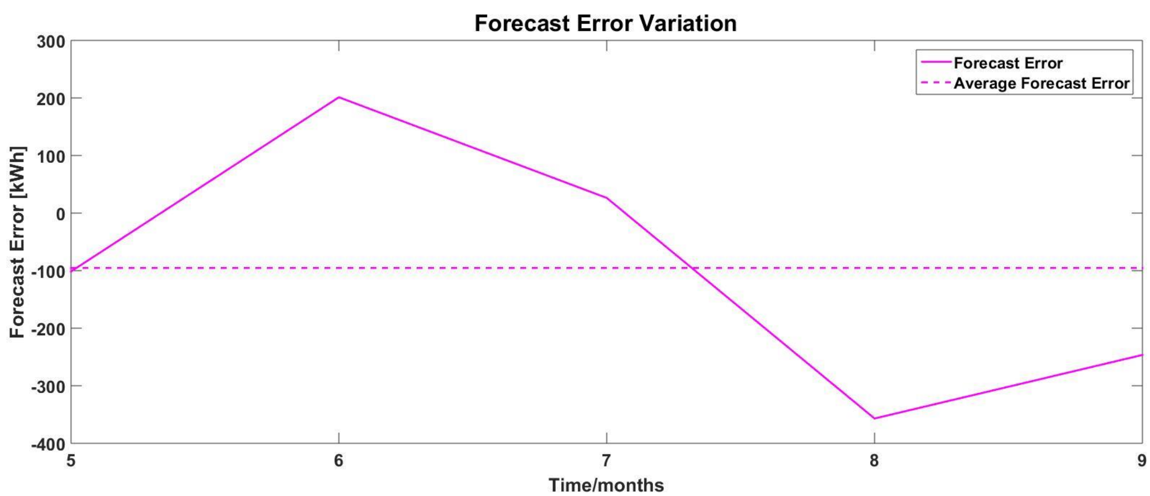

Fig. 2. Estimation of errors between the actual and forecast data
Source: created by the authors