International Journal of Innovative Engineering Applications

Journal homepage: https://dergipark.org.tr/ijiea

MODELING A SOLAR POWER PLANT WITH ARTIFICIAL NEURAL NETWORKS

Seren Arslan[1], *Hikmet Esen*[*2] *Engin Avcı*[3] *Can Cengiz*[4]

[1]Marmara Private Education Institutions, 23200, Elazığ, Türkiye
[2]Fırat University, Faculty of Technology, Department of Energy Systems Engineering, 23119, Elazığ, Türkiye
[3]Fırat University, Faculty of Technology, Department of Software Engineering, 23119, Elazığ, Türkiye
[4]Vodafone, Technology Centers Operations Management, 06100, Ankara, Türkiye

Abstract

Original scientific paper

This study will enable us to estimate the power of the solar power plant with measurement data such as outdoor temperature-humidity, wind and precipitation amount, to protect the system from imbalance, and to determine the instant and daily effective energy trade more easily. By taking the data from the solar power plant installed in Samsun, Turkey, estimation was made with Artificial Neural Networks for electricity generation. In this study, Levenberg-Marguardt feed-forward backprop learning algorithm was used to find the best approach in the network. The best prediction results were obtained from the 2-layer and 5-neuron Artificial Neural Networks model, and it was observed that the system gave better training results as the number of iterations increased (multiple determination coefficient, R2, 0.99818).

Keywords: *Artificial neural network; solar; energy; power plant; electricity generation.*

GÜNEŞ ENERJİSİ SANTRALİNİN YAPAY SİNİR AĞI İLE MODELLENMESİ

Özet

Orijinal bilimsel makale

Bu çalışma, dış ortam sıcaklığı-nemi, rüzgar ve yağış miktarı gibi ölçüm verileriyle güneş enerjisi santralinin gücünü tahmin etmemizi, sistemi dengesizlikten korumamızı, anlık ve günlük efektif enerji ticaretini daha kolay belirlememizi sağlayacaktır. Samsun'da kurulu güneş enerjisi santralinden veriler alınarak elektrik üretimi için Yapay Sinir Ağları ile tahmin yapıldı. Bu çalışmada ağdaki en iyi yaklaşımı bulmak için Levenberg-Marguardt ileri beslemeli backprop öğrenme algoritması kullanılmıştır. En iyi tahmin sonuçları 2 katmanlı ve 5 nöronlu Yapay Sinir Ağları modelinden elde edilmiş olup, yineleme sayısı arttıkça sis-temin daha iyi eğitim sonuçları verdiği gözlemlenmiştir (çoklu belirleme katsayısı, R2, 0,99818).

Anahtar Kelimeler: *Yapay sinir ağı; güneş; enerji; enerji santrali; elektrik üretimi.*

1 Introduction

As the world population increases, the need for energy is increasing day by day in proportion to the population. From past to present, human beings have always needed energy. Energy needs can be met naturally. However, until now, countries have met their energy needs from fossil fuels. The fact that this huge energy deficit in the world could not be met with non-renewable energy sources, namely fossil fuels (coal, oil, natural gas) in the long term, naturally increased the need for renewable energy sources.

Predicting the production values of SPP maximizes the profitability of the plant. Renewable energy sources are built with long-term guarantees and this causes the production risk shares of power plants to decrease. In order for renewable power plants to operate in the market, production planning and estimations, like other energy sources, are very important for the manufacturer. In addition, determining the environmental conditions and predicting in advance while determining the efficient location and settlement will increase the profit rate.

It is seen that some studies that are considered important have come to the fore after a literature review on GES production estimation. SPP is a very popular energy production method in our country, as it is a clean and uninterrupted power source and in line with the incentives given. Due to Turkey's geographical location, the yield obtained from SPP also has a high potential. Electricity generation with solar energy has started to be recognized and applied more and more every day in the world and in Turkey [1]. Recently, when we examine these systems in terms of installation costs and turnaround times, troublesome processes come to mind. However, as

*Corresponding author.
E-mail address: hikmetesen@firat.edu.tr (H. Esen)
Received 02 August 2023; Received in revised form 22 November 2023; Accepted 05 December 2023
2587-1943 | Doi: https://doi.org/10.46460/ijiea.1336917

the technology and market conditions in solar energy systems get stronger day by day, it will be inevitable that the costs will decrease and become widespread [2].

In the last 15 years, electricity generation from wind power plants has increased from 39836.3 GWh to 129637.0 GWh with an average annual growth rate of 8.2%. These rates are 4.6%, 41.0%, 32.5%, 192.7% and 29.2% in hydro, geothermal, wind, solar and biomass, respectively. These rates are 12 years for wind and geothermal and six years for solar [3].

SPP's are one of the energy production facilities that are increasing in importance with their clean and renewable features. Photovoltaic SPPs are the most common technology for renewable energy generation today, and since 2016 PV solar has been the technology with higher growth [4, 5].

A system has been developed for a SPP production facility located in Kahramanmaraş, which can make a production estimation the day before. ANN is used in this system. Weather forecasts and past production values were used as inputs. It has been observed that the cloud estimation used structure has lower MSE and higher R values. In addition, it has been observed that the artificial neural network created using 10 neurons is more successful than the 5-neuron structure. The results obtained from the system were evaluated and it was seen that the system using cloud forecasting was much more successful [6].

Environmental factors (solar radiation, temperature, wind, humidity, PV panel temperature) and power values obtained from photovoltaic panels were measured and recorded for 1 year with the measurement stations established in three pilot regions (Adıyaman-Malatya-Şanlıurfa), which differ from each other in terms of environmental factors. The effects of humidity, wind speed and PV panel temperature on panel power generation were determined by making an estimation by passively training the relevant parameters in the general algorithm, and the effects of these parameters on the PV panel power. It was observed that the humidity parameter was 2.6%, the wind parameter was 0.8%, and the PV panel temperature parameter was 1.6% effective on the estimation of the PV panel power. With the trained ANN models, the PV panel power generation for any day was predicted and a high accuracy (99.34%) was determined when the actual values obtained from the measurement station for that day were compared with the ANN estimation results [7].

In another study [8], forward feedback propagation artificial neural networks and KNN (K-Nearest Neighbors) methods are used to estimate power values using the production data of photovoltaic panels (temperature, humidity, pressure, radiation). Panel values taken from an active site, whose installation was completed, were trained with both methods and the results obtained were compared. In the results obtained, the power values of the photovoltaic panels were classified using the ANN model developed with the highest accuracy of 98.7945%. As a result of the developed study, it was seen that the learning models used for power estimation had very high performance and the obtained data predicted results very close to the real field data. It was concluded that both estimation models developed in locations with different structural characteristics can be used according to the seasonally changing load demand.

He proposed a NARX model to estimate PV out put power using global solar radiation, sunlight intensity, hourly temperature, minimum temperature, maximum temperature, wind speed, relative humidity, air pressure and precipitation history data as inputs. The hour angle and the sun zenith angle of the mentioned place were also calculated and used in the modeling. In addition, the effects of increasing and decreasing the number of delays by changing the number of neurons in the hidden layer were also observed. The performance achieved by the NARX model is discussed using statistical evaluation parameters. The performance of the model is acceptably good and the power data can be predicted with errors of MAE, MAPE, MBE and n RMSE respectively 52.0815, 11.83%, 8.253 and 8.57% for the hourly forecast and 20.858. 4.60% for the daily forecast [9]. In this study, data were taken from the four 1 MW SPP fields in Samsun, based on June and July of 2022. Maximum, minimum, average temperature values, relative humidity, minimum, average, maximum wind speed and precipitation amount in these months were given to the forecast model as inputs. The daily production values of the SPP power plant were calculated as output. Very close results were obtained between the actual values obtained from the experiments and the estimated values.

2 Field Data

It has been determined that the production of the facilities varies periodically in the examinations made on a real solar power plant of the same size, installed in the province of Samsun, located in the Black Sea region of Turkey, for about 2 years.

What we think is valuable for academic study in the part of the established facility is that the power plant is located in the Black Sea Region of Turkey and was established in four different directions. The facility was established on the roofs of a chicken farm located within the borders of the Bafra district of Samsun province, and the roof slopes were established as 12 degrees. In the established facility, 1 MW system was installed in the North, South, East and West directions. Since the number of roofs is low in the North and South directions, 1283 kWp can be placed on 10 roofs by tight placement. Since there are 14 roofs on the east and west directions, 1308 kWp has been placed with a more comfortable layout. The top view of the facility is given in Fig.1 [1].

Figure 1. Top view of the SPP facility in Samsun [1].

Data from the established SPP systems continued to be collected in 2022. The 3-year production values of our

SPP systems installed in 2020 are given in Table 1. As a result of the data received, the production value in 2022 was 5.899.187 kWh. In 2022, the production was very close to the previous year and realized as 5.938.120. The production difference between 2021 and 2022 was around 1%. The target value in 2020 is the values predicted by the programs and the installation companies. In 2021, the value was taken to the highest value that can be produced by the company officials. This turned out to be a lack of overproduction. In 2022, the most obvious and appropriate target value was determined by taking the arithmetic average of two years, and it was seen that a production value very close to this value was realized at the end of the year.

Table 1. Comparisons by year of production [1].

Years	Target Production (kWh)	Actual Production (kWh)	Difference (%)
2020	5.624.888	6.409.125	13.9
2021	6.270.165	5.899.185	-5.9
2022	5.988.762	5.938.120	-0.8

The daily, monthly and annual data obtained in the system were recorded and the system efficiency was calculated with analyzes from different parameters. The efficiency of solar panels is calculated by using Eq. 1 [1].

$$n_{max}=P_{max}/(I.A) \quad (1)$$

here, η_{max} is the maximum efficiency, P_{max} is the maximum power output (W), I is the amount of radiant flux from the sun (W/m^2), and A is the panel area (m^2). If we give an example from the panel we use; The area of our 310W panel is 1.64 m^2 and its efficiency was calculated as in Eq. 1 under test environment conditions. As can be seen from the process below, the efficiency value of our panel, which was preferred for 1000 W/m^2 radiation value, was 18.9%.

$n_{max}=(310\text{ W})/(1000\text{ W/m}^2.\ 1.64\text{ m}^2) = 0.189$

System reviews have been advanced over two main scopes. It was made in the form of daily reviews and monthly reviews. Different evaluations were made by taking into account other factors (temperature, wind speed, pollution, etc.) by collecting the same radiation values by creating special data sets in daily examinations. In the monthly evaluation, the systems were examined by creating data sets over the monthly average factor values. Values were evaluated on days with irradiance values of >1000W/m^2 at full efficiency in the daily reference examinations. Since the number of days when the panel works at full capacity in terms of solar panels operating inefficiently in the Black Sea region except summer months, the evaluations were made by taking daily data in May, June, July and August. In Table 2, the sunshine duration of Turkey as a region and the amount of energy per square meter per year are given.

Table 2. In Turkey, the duration of sunshine by region and the amount of energy per square meter per year [4].

Region	Sunshine Duration (hours/year)	Total Solar Energy (kWh/ m²year)
Southeastern Anatolia	2.993	1.460
Mediterranean	2.956	1.390
Eastern Anatolia	2.664	1.365
Central Anatolia	2.628	1.314
Aegean	2.738	1.304
Marmara	2.409	1.168
Black Sea	1.971	1.120

3 Modeling

Several different power estimation model studies have been published in recent years related to PV plants. The solutions in these studies can be classified as physical, statistical and hybrid methods. A few of these models used for PV plants were aimed at estimating the amount of solar radiation [10–12]. Some studies offer models dedicated to hourly power generation forecasting, especially in PV plants [13–16]. The intelligent method calculation technique known as Artificial Neural Networks (ANN) is the most applied technique in the different prediction models obtained, but different from this, simpler methods have been used in a few articles [17-21].

ANN is machine learning developed with the aim of automatically performing the human brain's advanced learning function, such as the ability to generate, create and explore new information on its own. It mimics the structure of biological neural networks in the human brain, learning, remembering and generalizing properties. The learning process in ANN is carried out by using different examples and making many trials. During learning, some rules are set by giving input and output information.

Artificial nerve cells come together to form the ANN. The coming together of nerve cells is not random. Nerve cells come together in three layers and in each layer parallel to each other to form the network. These layers are:

Input layer: It is called the layer in which the samples that come as input to a network are given as input. There should be input neurons up to the number of features of the examples to be taught in the input layers.

Hidden layers: The layer between the input layer and the output layer is called. In this layer, forward comprehensive calculations and backward comprehensive error propagation are performed. It is possible to have more than one middleware within a network. Having many layers causes computational complexity and computational processes to increase.

Output layer: The processing elements in this layer receive the data from the middleware and produce the output that the network should produce for the input set (sample) presented from the input layer. Each cell can have multiple inputs, but only one output. This output can be linked to any number of cells.

An image showing the network structure of the ANN is given in Fig. 2 [21].

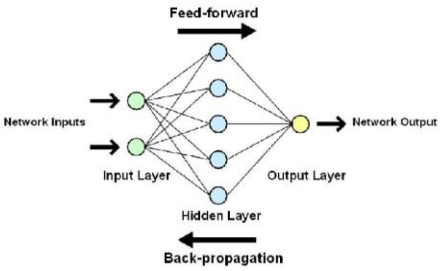

Figure 2. Artificial Neural Network Structure.

Just as biological neural networks have nerve cells, ANN has artificial nerve cells. Artificial nerve cells are also called processing elements in engineering science. Each processing element has 5 basic components. These; inputs, weights, summation function, feedforward neural network and backward computation [22].

In this study, it was tried to estimate the daily production values of a SPP using ANN. The data we use are the daily values for July and June from an established SPP. Maximum, minimum, average temperature values, relative humidity, minimum, average, maximum wind speed and precipitation amounts for the months of June and July were taken as input values to the ANN.

Evaluation was made on a total of 62 data taken daily for the months of July and June. Daily production values were estimated as output value. After completing the ANN training, the program that calculates the best prediction values was obtained by changing some structural features of the ANN in the next stages.

In the designed ANN system, the feed forward back propagation model was used as the network type by assigning the input and output values. In the system, there are 8 inputs as minimum, average and maximum temperature values, relative humidity, minimum, average, maximum wind speed and precipitation amount. The daily values of June and July were recorded over the SPP field of 2022. The image of the designed ANN model is given in Fig. 3.

In the designed MATLAB model, "TRAINLM and TRAINGDX" functions were tested separately as training functions. “LEARNGDM” is used for Adaptation Function, MSE as performance function and “TANSIG” as transfer function.

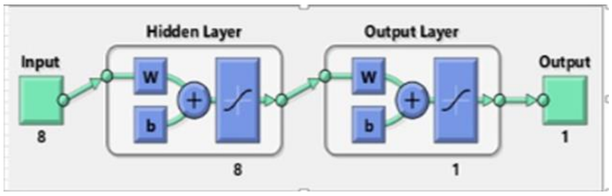

Figure 3. ANN model image used in the study.

In some trials, the number of iterations was increased and the number of neurons and layers was kept constant. In some trials, the best results were tried to be obtained with different trials by increasing or decreasing the number of neurons and layers and keeping the number of iterations constant. The results of training, accuracy, test and mean (all) values obtained in different trials are given in Table 3.

Table 3. General data obtained as a result of the analysis.

Iteration	Neuron	Layer	Training	Validation	Test	Average
250	5	1	0.687	0.540	0.765	0.664
500	5	2	0.722	0.571	0.536	0.640
1000	5	2	0.510	0.955	0.923	0.647
1000	3	1	0.820	0.757	0.896	0.822
1500	3	1	0.754	0.998	0.880	0.822
2000	10	1	0.847	0.855	0.811	0.832
2000	10	2	0.815	0.798	0.801	0.792
2000	5	2	0.835	0.916	0.996	0.879
2500	5	2	0.985	0.860	0.781	0.740
2500	5	1	0.844	0.901	0.940	0.875
3000	5	2	0.830	0.980	0.810	0.870
3000	10	2	0.886	0.812	0.986	0.887
3500	5	1	0.980	0.761	0.881	0.871
3500	8	1	0.764	0.938	0.914	0.817

When the experimental results are compared with the numerical analysis made using different trials, different neuron and layer numbers; The best results were obtained using 2 layers - 5 neurons. The results obtained under these conditions are shown in Table 4.

Table 4. The best results obtained in the study.

Iteration	Neuron	Layer	Training	Validation	Test	Average
2000	5	2	0.83519	0.91677	0.99632	0.8792
3000	5	2	083164	0.99818	0.94475	0.89333

Model validation is the process by which the input vectors from the input/output datasets on which the ANN is not trained are presented to the trained model to see how well the trained model predicts the corresponding dataset output values. In order to compare the estimated and actual values for model validation, the multiple determination coefficient (R^2) statistical method was found and interpreted.

The multiple determination coefficient (R^2) was obtained from Equation 2 below [21].

$$R^2 = 1 - \frac{\sum_{m=1}^{n}(y_{est,m} - t_{mea,m})^2}{\sum_{m=1}^{n}(t_{mea,m})^2} \tag{2}$$

where n is the number of data patterns in the independent data set, $y_{est,m}$ indicates predicted, $t_{mea,m}$ is the measured value of a data point (m).

In Fig. 4, the program results obtained in the study are given according to 2000 iterations. The R^2 value is shown according to the combination of training, accuracy, test and average values specified in Table 4. R^2 value was calculated as 0.91 according to 2000 iterations. In Fig. 5, the program results obtained in the study are given according to 3000 iterations. The R^2 value is shown according to the combination of training, accuracy, test and average values specified in Table 4. The R^2 value was calculated as 0.99 according to the number of 3000 iterations.

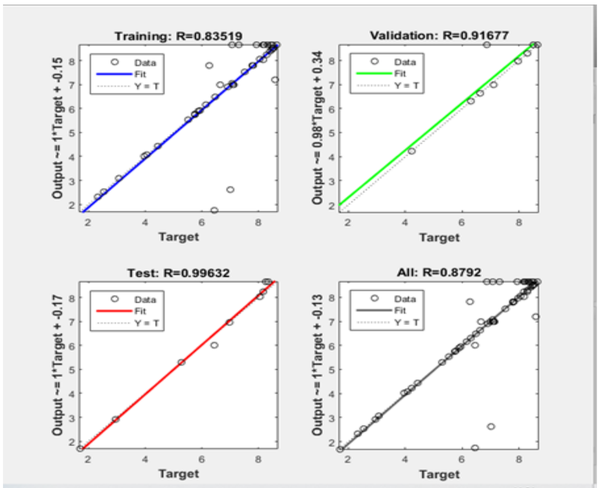

Figure 4. Training, validation, test and average values for 2000 iterations.

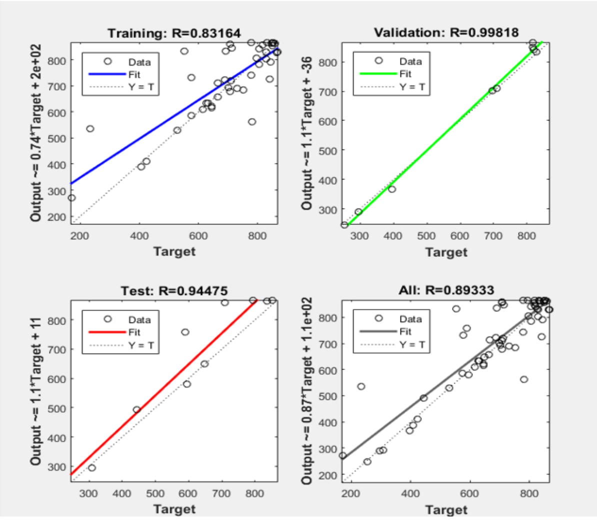

Figure 5. Training, validation, test and average values for 3000 iterations

As a result of the comparison, the best values were obtained in double-layered trials. It was observed that learning increased as the number of iterations and neurons increased. In the best ANN model we obtained, different values that we did not use in education were used as test data. The estimated results obtained by the ANN and the actual values measured over the SPP system are given in Fig. 6.

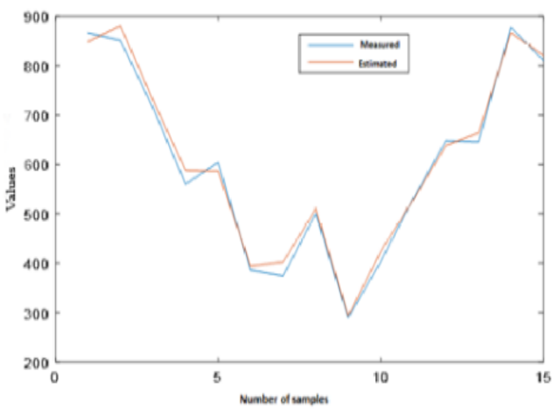

Figure 6. Image of comparison of estimated values with measured values.

4 Conclusion

In this study, which we have done using ANN, a system has been developed to estimate the production values of a SPP facility. In this developed system, minimum-maximum-average temperature, wind, relative humidity and precipitation values were used as input data. The results obtained by changing the structural features of the ANN (neuron-layer-iteration number) were evaluated. The best prediction results were obtained using 2 layers and 5 neurons. In addition, it was observed that the system gave better training results as the number of iterations increased (R^2= 0.99818). Thanks to this study, it will help to interpret the real field data for the SPP to be established in future studies.

Declaration

Ethics committee approval is not required.

References

[1] Cengiz, C. (2023). *Comparison of the parameters of solar power plants with the same characteristics installed in four different directions.* (Master's Dissertation, Fırat University).

[2] International Energy Agency (2023). Solar PV Global Supply Chains – Analysis 2023. Retrieved March 2, 2023 from https://www.iea.org/reports/solar-pv-global-supply-chains/executive-summary

[3] Sahin, H., Esen, H. (2022). The usage of renewable energy sources and its effects on GHG emission intensity of electricity generation in Turkey. *Renew Energy* 192:859–69.

[4] Republic of Turkey Ministry of Energy and Natural Resources. Electricity (2023). Retrieved March 2, 2023 from https://enerji.gov.tr/infobank-energy-electricity

[5] Alvara, R.R. (2018). Design and Modelling of a Large-Scale PV Plant. *Escola Tècnica Superior d'Enginyeria Industrial de Barcelona*.

[6] Gök, A. O., Yıldız, C., & Şekkeli, M. (2019). Yapay sinir ağları kullanarak kısa dönem güneş enerjisi santrali üretim tahmini: Kahramanmaraş örnek çalışması. *Uluslararası Doğu Anadolu Fen Mühendislik ve Tasarım Dergisi,* 1(2), 186-195.

[7] İçel Y. (2019). Güneş enerji sistemlerinin performans tahmini için yapay sinir ağları ile modellenmesi ve verimliliğin incelenmesi (Master's Dissertation, Inonu University)

[8] Dinçer, A., & İlhan, U. (2022). Fotovoltaik Panellerde Güç Tahminlenmesi için Yapay Zekâ Yöntemlerinin Kullanılması. *Tekirdağ Ziraat Fakültesi Dergisi,* 19(2), 435-445.

[9] Nkuriyingoma, O., & Selçuklu S. B. (2021). Solar power plant generation forecasting using NARX neural network model: *A case study, I. J. of Energy Applications and Technologies*, 8(3), 80-92.

[10] Wang, F., Mi, Z., Su, S., & Zhao, H. (2012). Short-term solar irradiance forecasting model based on artificial neural network using statistical feature parameters. *Energies*, 5, 1355–1370.

[11] Mellit, A., & Pavan, A. M. (2010). A 24-h forecast of solar irradiance using artificial neural network: Application for performance prediction of a grid-connected PV plant at Trieste, *Italy. Sol. Energy*, 84, 807–821.

[12] Hocaoglu, F. O., Gerek, O. N., & Kurban, M. (2008). Hourly solar radiation forecasting using optimal coefficient 2-D linear filters and feed-forward neural networks. *Sol. Energy*, 82, 714–726.

[13] Pedro, H. T. C., & Coimbra, C. F. M. (2012). Assessment of forecasting techniques for solar power production with no exogenous inputs. *Sol. Energy*, 86, 2017–2028.

[14] Izgi, E., Öztopal, A., Yerli, B., Kaymak, M. K., & Sahin, A. D. (2012). Short-mid-term solar power prediction by using artificial neural networks. *Sol. Energy*, 86, 725–733.

[15] Shi, J., Lee, W.J., Liu, Y., Yang, Y., & Wang, P. (2012). Forecasting power output of photovoltaic systems based on weather classification and support vector machines. *IEEE Trans. Ind. Appl.,* 48, 1064–1069.

[16] Alamsyah, T., Sopian, K., & Shahrir, A. (2004). Predicting average energy conversion of photovoltaic system in Malaysia using a simplified method. *Renew. Energy*, 29, 403–411.

[17] Monteiro, C., Fernandez-Jimenez, L. A., Ramirez-Rosadoc, I.J., Muñoz-Jimenez, A., & Lara-Santillan, P. M. (2013). Short-term forecasting models for photovoltaic plants: Analytical versus soft-computing techniques. *Math. Problems Eng.*

[18] Ulbricht, R., Fischer, U., Lehner, W., & Donker, H. (23–27 September 2013). First steps towards a systematical optimized strategy for solar energy supply forecasting. In Proceedings of the European Conference on Machine Learning and Principles and Practice of Knowledge Discovery in Databases (ECMLPKDD 2013*), Prague, Czech Republic*.

[19] Ogliari, E., Grimaccia, F., Leva, S., & Mussetta, M. (2013). Hybrid predictive models for accurate forecasting in PV systems. *Energies*, 6, 1918–1929.

[20] Dolara, A., Grimaccia, F., Leva, S., Mussetta, M., & Ogliari, E. (2015). A physical hybrid artificial neural network for short term forecasting of PV plant power output, *Energies,* 8:1138–53.

[21] Abdelhak K., Razika I., Ali B., Abdelmalek A., Müslüm A., Nacer L., & Nabila I. (2023). Solar photovoltaic power prediction using artificial neural network and multiple regression considering ambient and operating conditions, *Energy Conversion and Management*, Volume 288.

[22] Rocha Vaz, A.G.C. (2014). Photovoltaic Forecasting with Artificial Neural Networks, (Master's Dissertation, *Lisboa University.)*