SUA Slovak University of Agriculture in Nitra
SUA·FE Faculty of Engineering

DOI: 10.2478/ata-2026-0001

Acta Technologica Agriculturae 1
Nitra, Slovaca Universitas Agriculturae Nitriae, 2026, pp. 1–6

INVESTIGATION OF PV SYSTEM TILT ANGLE BY NEURAL NETWORK MODELLING OF ENERGY BALANCE

Vladimír MADOLA[1], Monika BOŽIKOVÁ*[2], Stanislav PAULOVIČ[3], Matúš BILČÍK[4]

[1, 4] Slovak University of Agriculture in Nitra, Faculty of Engineering, Information and Coordination Centre of Research, Nitra, Slovakia, vladimir.madola@uniag.sk (V.M.), matus.bilcik@uniag.sk (M.B.)
[2,3] Slovak University of Agriculture in Nitra, Faculty of Engineering, Institute of Electrical Engineering, Automation, Informatics and Physics, Nitra, Slovakia, stanislav.paulovic@uniag.sk
*correspondence: monika.bozikova@uniag.sk

This study presents a novel multidimensional computational framework for optimising the tilt angle of photovoltaic systems by utilising complex variable modelling, transfer function analysis, and artificial neural network modelling. A 35 kWp photovoltaic system was monitored continuously over one year at a fixed 25° tilt, and comprehensive statistical analyses were conducted to evaluate monthly and seasonal variations in energy output. The proposed methodology makes differential equations with constant coefficients and transfer function models to describe time-dependent energy balance, enabling robust dynamic system identification. Empirical relationships between tilt angle and produced energy yield were effectively quantified, with a negative correlation coefficient value of 0.95 observed between steady-state energy production and tilt angle. Comparative analysis demonstrated negligible differences in annual yield between the 25° and 35° tilt configurations. Validation by neural network, utilising various architectures, revealed that a single hidden layer with 12 neurons achieved optimal model prediction performance value of 99.15%. The results confirm the efficiency of combining complex variable models with AI-based validation for precise and practical PV system modelling. This integrated approach facilitates improved decision-making in PV design by providing accurate predictions of energy yield under varying operational conditions.

Keywords: AI; complex variable; modelling; photovoltaics; tilt

The energy output of photovoltaic (PV) systems is determined by various environmental factors, including solar irradiance, temperature, humidity, wind speed, dust accumulation, shading, and pollution (Jathar et al., 2023). The orientation and tilt angle of PV modules are significant installation parameters that have a direct effect on the system's yield (Hasan et al., 2021). The substantial effect of tilt angle and incident solar radiation intensity has also been validated in recent work (Aslam et al., 2022). Numerous mathematical procedures for optimal tilt calculation have been compiled in previous publications (Li and Lam, 2007). For instance, global calculations of optimal tilt angles were performed for every country using NREL's PVWatts program (Jacobson and Vijaysinh, 2018). Regionally specific studies have explored annual PV tilt variability using several predictive models (Hua et al., 2020).

Recent progress includes the application of computational methods for analysing the impact of tilt angle on PV system performance, employing algorithms based on diverse optimisation criteria (Zeeshan and Aized, 2023). For large-scale PV system evaluation, artificial intelligence techniques have been introduced to further model and analyse performance (Abubakar et al., 2022). Regression and statistical approaches assist in energy balance evaluation and provide quantitative tools for PV system modelling (Mostafavi et al., 2013). However, conventional models often focus on isolated tilt angle optimisation, rarely integrating dynamic system-level relationships.

This contribution presents a multidimensional optimisation approach founded on transfer function modelling and artificial neural networks to advance the characterisation of PV system energy balance. The methodology surpasses single-parameter models by enabling comprehensive system-level modelling and robust performance evaluation (Chinchilla et al., 2021). Comprehensive energy balance optimisation has been investigated by Libra et al. (2024).

A novel stepwise computational framework is proposed for determining optimal tilt angle, utilising complex variable models for more straightforward identification of empirical relationships in experimental data. Modelling with complex variables offers an alternative to purely analytical or AI-based solutions, and their robustness can be further validated by artificial intelligence (Mellit and Kalogirou, 2021). Time-dependence in system response is described using a differential equation with constant coefficients. Functional similarities, such as shape resemblance at different steady states, are used to describe experimental results effectively. The resulting transfer function allows for testing models under varied boundary conditions to simulate experimental scenarios (Jacobson and Vijaysinh, 2018). Dynamic system identification and comparison of model predictions with experimental observations are also addressed (Benkaciali et al., 2016). The main aim of this research is the creation of a novel procedure for modelling the time dependency of PV system energy balance as a function of tilt angle. Quantitative indicators provide criteria for evaluating the validity of complex variable models, and a dedicated algorithm enables direct comparison between complex variable and regression-based models (Abubakar et al., 2022). The methodology focuses on crucial quantification parameters for characterising energy balance at specific tilt angles while preserving the practical simplicity of regression analysis.

This study presents a novel computational framework integrating complex variable modelling, transfer function analysis, and artificial neural networks for optimising photovoltaic system tilt angles. The principal innovation lies in developing a validation methodology for regression models using complex variable techniques, providing enhanced flexibility and precision through automated frameworks. The research demonstrates considerable novelty by achieving exceptional predictive accuracy with neural network confidence rates and establishing strong empirical relationships with high correlation coefficients.

Material and Methods

The description of experimental photovoltaic system and the methodology of data collection, data processing, creation and validation of the mathematical model is summarised in this section.

Description of experimental photovoltaic system

A 291.4 m^2 experimental photovoltaic installation occupies the infrastructure of Masaryk University, Brno, Czech Republic with a southwest azimuth (Fig. 1). The system consists of two segments:

- A 5 kWp building-integrated photovoltaic section (48 × SI 72-110 modules, vertical 90° inclination).
- A 30 kWp roof-mounted section (288 × identical modules, 25° tilt).

The SOLARTEC SI 72-110 photovoltaic modules are composed of 72 monocrystalline silicon cells, each with an active area of (10.16 × 10.16) cm^2. A single module provides a nominal peak power output of 110 W, with an open-circuit voltage of 21.6 V, a short-circuit current of 6.76 A, a maximum power point voltage of 17.4 V, and a maximum power point current of 6.32 A. The maximum system voltage of 760 V is reached at the level of a series-connected string of modules. Each module is internally configured as two parallel cell strings, with 36 cells connected in series in each string, which corresponds to the measured open-circuit voltage of approximately 21.6 V. Power conditioning employs FRONIUS IG40 (4100 W maximum output) and IG60HV (5000 W maximum output) inverters. These enable bidirectional grid interconnection via institutional switchgear.

Although the PV system consists of two parts, for the purposes of the presented model verification algorithm, the overall power and energy balance was taken into consideration. Energy balance data were obtained in 2021 year.

Data processing and creation of mathematical models

Data acquisition for the photovoltaic system encompassing temporal, energetic, and meteorological parameters sampled at five-minute intervals over a three-year period to capture seasonal variability. Data preprocessing and initial statistical analysis were conducted using MS Excel and Statistica software. Subsequent mathematical modelling employed regression analysis in MATLAB R2024b, revealing governing polynomial non-linear relationships for energy production. The resulting regression coefficients established an experimental-analytical modelling framework. The identification of seasonal representative days was performed through systematic assessment of daily operational parameter profiles. Model validation utilised an artificial neural network (ANN) implemented in Python 3.12.3, featuring a ReLU-activated neurons without standard normalisation. The ANN processed monthly segmented daily energy balance data as inputs, with modelled mean energy balance as output variable for comparative validation of PV data. For evaluation of the PV-system energy balance, a model day was computed from the average values of the produced energy. The model day was utilised as a reference value for energy production in time based on the best covariance on average values of produced electricity in analysed time range.

Fig. 1 Experimental PV system

A dedicated algorithm was implemented for the photovoltaic system analysis through sequential phases:
- data acquisition interfaces with photovoltaic installations to collect time series, energetic, and meteorological parameters for comprehensive operational characterisation;
- centralised processing converges data streams using designated computational tools, with mathematical computations executed in specialised software environments and statistical operations performed in standardised analytical platforms;
- the modelling framework implements parallel analytical and complex-variable methodologies to enable comparative analysis and enhance robustness;
- energy balance synthesis integrates model outputs into final quantifications, consolidating analytical procedures to comprehensively characterise photovoltaic energy processes while ensuring scientific validity and reproducibility.

The identification by transfer function in complex variable was used to evaluate experimental data from the PV system and validate the regression model. The transfer function analysis incorporated a steady-state value and rise time of transfer function to assess the dynamic behaviour of investigated data. The transfer function of the complex variable is given by Eq. (1).

$$G(s) = \frac{a_n s^n + a_{n-1} s^{n-1} + ... + a_1 s + a_0}{b_m s^m + b_{m-1} s^{m-1} + ... + b_1 s + b_0} \quad (1)$$

where: $G(s)$ – transfer function; a – constant coefficient of numerator; b – constant coefficients of denominator; n – number of zeros; m – order of dynamic system

The average values of the energy produced by the PV system were modelled using the transfer function.

Statistical analysis

The statistical significance of differences ($p \leq 0.05$) was evaluated by the non-parametric analysis of variance (ANOVA). Pearson's correlation coefficient quantified the characteristics of relationships. Model robustness was evaluated using the coefficient of determination (R^2) and mean absolute percentage error (MAPE). The ANN was used to predict system performance.

Results and discussion

Statistical evaluation of annual energy production

The photovoltaic system was evaluated continuously over an entire calendar year at a fixed tilt angle of 25°. Daily average energy production data were collected and processed to generate monthly mean values expressed in kilowatt hours (kWh). A month-to-month comparison using statistical analysis revealed a significant increase in energy yield between March and April ($p \leq 0.001$). This can be considered as good fit of experimental PV data like time series dependency. The comprehensive monthly energy production data are depicted in Fig. 2, which highlights the variations observed from January through December. The statistical significance of differences ($p \leq 0.05$) was evaluated by the non-parametric analysis of variance (ANOVA), whilst Pearson's correlation coefficient quantified the characteristics of relationships between temporal variables.

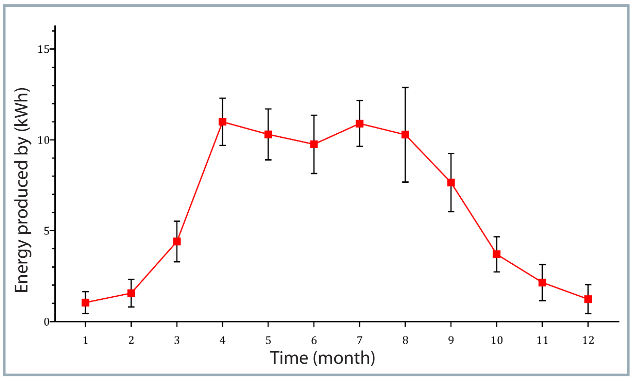

Fig. 2 Annual statistical evaluation of daily average energy produced by the PV system (kWh) (mean ± 95% confidence interval)

The statistical analysis employed a comprehensive methodology including confidence interval estimation, Pearson's correlation coefficients, and one-way ANOVA significance testing. Data are presented as mean ± standard error of mean (SEM), with statistical comparisons evaluated at a 95% confidence level ($p \leq 0.05$). The standard errors of the mean produced energy varied between months. The lowest standard error was identified in January (±286.26 kWh), indicating more stable data, and the highest in August (±1204.5 kWh), suggesting greater variability or fewer values. Higher errors in May, June, and September also point to less reliable averages. The experimental monthly averages range from approximately 0.7 kWh (winter months) to 7.8 kWh (summer months), which is consistent with the 35 kWp system's daily performance under Central European conditions.

Energetic balance of representative model day

Energy yield comparison between summer-optimised 25° tilt angle (678.9 kWh July; 685.4 kWh June; 616.6 kWh August; 5230.3 kWh annual) and year-round 35° tilt (656.4 kWh July; 665.7 kWh June; 611.6 kWh August; 5254.9 kWh annual) showed statistically insignificant differences (up to 3.5% monthly). A model day was selected by the maximal covariance between experimental 25° tilt PV data and seasonal analytical models to ensure representative system performance characterisation (Poncelet et al., 2017; Cereghetti et al., 2003). The selection process incorporated automated correlation coefficient calculations for all candidate days, identifying the representative day exhibiting the highest statistical correlation with seasonal mean behaviour.

The regression analysis demonstrated that PV energy output follows a non-linear polynomial trend, with the experimental regression spanning from the second to fourth-degree polynomic functions. The fourth-degree polynomial (Eq. 2) was selected for its optimal fit to

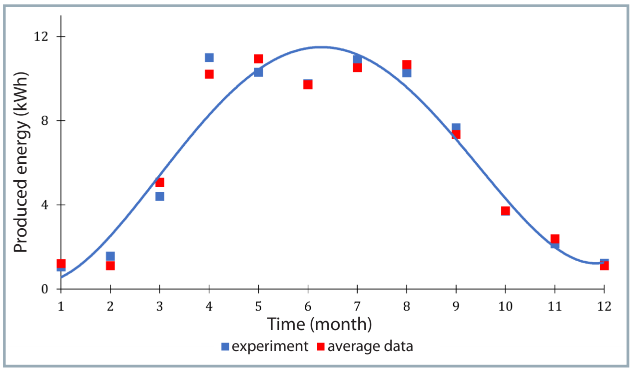

Fig. 3 Annual PV daily average energy data (kWh) with comparison of average energies produced by the PV system (blue solid line is related to the fourth order polynomial regression of produced energy by Eq. 2)

Fig. 3 experimental data (Eq. 4). The model robustness was evaluated using the coefficient of determination (R^2) and mean absolute percentage error (MAPE), with a comprehensive validation assessment conducted through cross-validation techniques. The function dependence for the average data of energy produced by the PV system depicted in Fig. 3 is represented by the regression relationship (Eq. 3). These parameters were incorporated to enable accurate total energy balance calculations for the PV system. Annual experimental data (Fig. 3) demonstrate comparable morphology between empirical observations and theoretical transfer functions. Statistical processing yielded 95% confidence intervals quantifying estimation uncertainty (p >0.05) and considered as insignificant differences between energy data. Given the continuous tendency of the investigated parameter, regression modelling was applied to describe photovoltaic energy generation throughout the annual cycle. The nature of data distribution was verified by Kolmogorov-Smirnov test for goodness-of-fit to a normal probability distribution (p >0.05).

$$E = a_4 t^4 + a_3 t^3 + a_2 t^2 + a_1 t + a_0 \tag{2}$$

$$E = 0.011\, t^4 - 0.26\, t^3 + 1.77\, t^2 - 1.66\, t + 0.71 \tag{3}$$

$$E = 0.011\, t^4 - 0.26\, t^3 + 1.77\, t^2 - 1.67\, t + 0.73 \tag{4}$$

where: E – daily average energy produced by the PV system (kWh); t – time value (month)

The polynomial coefficients in Eq. 3 have the following dimensional units to ensure dimensional consistency: a_4 = 0.011 (kWh·month^{-4}); a_3 = -0.26 (kWh·month^{-3}); a_2 = 1.77 (kWh·month^{-2}); a_1 = -1.66 (kWh·month^{-1}); and a_0 = 0.71 (kWh). Similarly, for Eq. 4: a_4 = 0.011 (kWh·month^{-4}); a_3 = -0.26 (kWh·month^{-3}); a_2 = 1.77 (kWh·month^{-2}); a_1 = -1.67 (kWh·month^{-1}); and a_0 = 0.73 (kWh).

The annual energy balance analysis across tilt angles (0° ÷ 90°) revealed optimal performance at a 35° inclination, yielding (8.59 ±4.70) kWh. However, long-term system performance must also consider reliability characteristics and actual operational lifetime of PV panels, which may differ significantly from manufacturer declarations (Poulek et al., 2024). Validation through 12-month operational data confirmed predictive accuracy, with measured versus predicted correlations achieving R^2 = 0.929 ±0.017. The energies produced in the annual seasons are statistically insignificantly different (p >0.05) to the model day (Fig. 4). Statistical validation incorporated Student's t-tests for paired comparisons. Statistical metrics demonstrate the robustness of the analytical approach under real-world operational conditions. Multiple recent sources indicate that tuning regression setup and the selection of input variables – especially weather data – critically influence forecast accuracy (Markovics and Mayer, 2022; Starke et al., 2021). This aligns with global studies finding high correlation between sunlight and PV power during these daily periods (Starke et al., 2021; Senger et al., 2024).

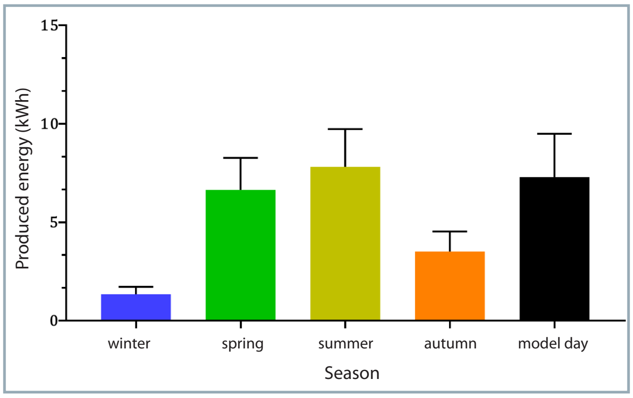

Fig. 4 Statistical evaluation of daily average energy (kWh) produced by the PV system in annual seasons with comparison to a model day (mean value ± standard error of mean)

Results of PV data comprehensive modelling

The dynamic behaviour of the PV system in the complex variable plane was described using a fourth-order transfer function with one zero, incorporating a time-derivative term as outlined in relevant literature (Farooq et al., 2025).

Transfer function parameters were systematically analysed across different tilt angles. Table 1 summarises the dependence of the steady-state value and rise time of transfer function (Eq. 5) on the panel tilt angle.

Table 1 Characteristics of transfer function dynamic markers on different tilt angles of the PV system

Tilt angle (°)	Steady-state value	Rise time of transfer function (s)
0	7300	1884
25	6808	1880
30	6861	1083
35	6638	2059
45	6150	2529
90	5811	3180
Coefficient of correlation on tilt angle	-0.95	0.74

A strong negative nonlinear correlation was identified between the steady-state value and tilt angle, indicating that the system's long-term output decreases as the tilt increases. In contrast, rise time showed a strong positive linear correlation with tilt, reflecting slower system response at higher angles.

For the representative case of 25°, modelling was based on monthly averages of the energy balance. The fitted transfer function (Eq. 5) for this configuration achieved R^2 = 89.20%. Table 1 provides the parameter values across the different tilt angles.

$$G(s) = \frac{s^3 - 2.159\, s^2 + 8.713\, s + 1.6640}{0.000933\, s^4 + 0.0002055\, s^3 + 0.00268\, s^2 + 0.0001527\, s + 0.000404} \quad (5)$$

where: $G(s)$ – transfer function of average modelled case; s – Laplace's operator

Table 2 Dynamic characteristics of average modelled energy by the PV system

Characteristic parameter	Average produced energy (25°)	Significance (vs. other tilt angles)
Steady-state gain	4119	$p \leq 0.01$
Rise time (s)	1.15	$p \leq 0.05$

Recent adaptive and interval-based forecasting approaches, as promoted in new research (Wang et al., 2023; Ni et al., 2017), permit dynamic adjustment for shifting weather or operation, notably improving prediction reliability.

The model accuracy was further assessed by the coefficient of determination and mean absolute percentage error (MAPE). The artificial neural network (ANN) model trained on average daily energy balance values achieved the best coefficient of determination value of 99.15% and MAPE value of 5.99% with one hidden layer and 12 neurons, confirming robust agreement with observed data.

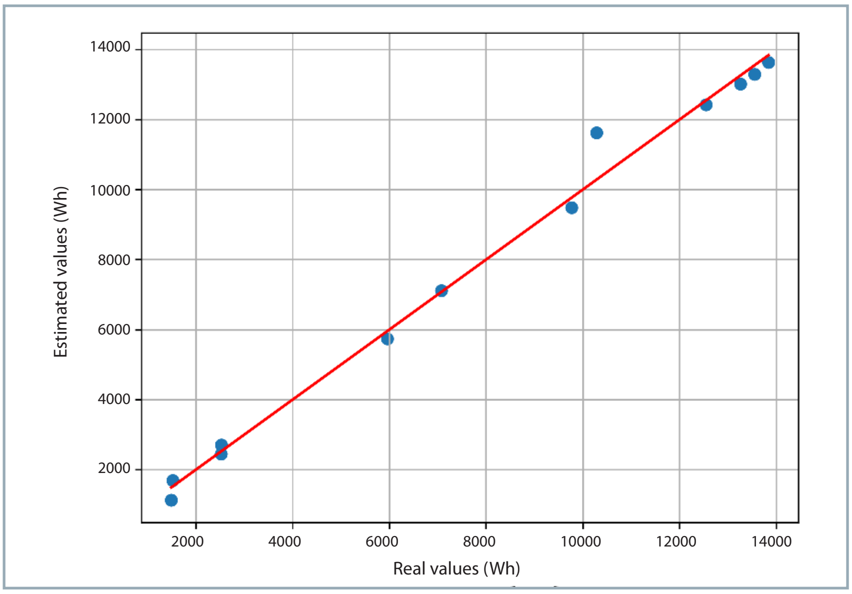

Fig. 5 Best correlation between real and estimated energies produced by the PV system via ANN modelling (1 hidden layer with 12 neurons)

As shown in Fig. 5, the case yielded optimal results when the network architecture was configured with one hidden layer including 12 neurons, reflecting the strongest confidence with experimental values and the minimum value of MAPE. At two hidden layers, the model was already overtrained (MAPE value of 22.75%).

Recent advances in artificial intelligence have enabled the development of highly accurate models for predicting and optimising photovoltaic system performance under diverse environmental conditions (Ma et al., 2022; Dimovski et al., 2020).

Conclusion

The photovoltaic system performance is influenced by environmental and installation-specific factors, demanding advanced modelling for reliable predictions. This study introduces a key novelty: a validation method for regression models using complex variable modelling, which significantly enhances the flexibility and precision of PV analysis.

A principal benefit of the proposed approach is its dynamic framework that incorporates statistical comparison, transfer function analysis, and neural networks. This methodology achieves high reliability in energy balance predictions, in case of 25° tilt angle with confidence rates of 93.9% for the regression model which is validated by ANN on confidence reliability up to 99.15% and 89.20% for the complex variable model. The benefits also include streamlined data processing, robust model verification, and the ability to accurately capture both long-term energy trends and detailed system dynamics. Future research should focus on leveraging these novelties and benefits for smart energy management and the scaling of the approach to larger photovoltaic installations.

Table 3 Performance of energy production by the PV system via selected ANN architectures

Model case	ANN architecture	R^2 (%)	MAPE (%)
Average produced energy (tilt angle 25°)	1 hidden layer with 2 neurons	72.77	57.29
	1 hidden layer with 12 neurons	99.15	5.99
	2 hidden layers, each with 12 neurons	95.90	22.75

Acknowledgement

This publication was supported by the Operational Programme Integrated Infrastructure within the project Drive4SIFood 313011V336, cofinanced by the European Regional Development Fund, project VEGA 1/0221/25, and project KEGA 020SPU-4/2023.

References

Abubakar, M., Che, Y., Ivascu, L., Almasoudi, F.M., Jamil, I., 2022. Performance analysis of energy production of large-scale solar plants based on artificial intelligence (machine learning) technique. Processes 10(9), 1843. https://doi.org/10.3390/pr10091843

Aslam, A., Ahmed, N., Qureshi, S.A., Assadi, M., Ahmed, N., 2022. Advances in solar PV systems; a comprehensive review of PV performance, influencing factors, and mitigation techniques. Energies 15(20), 7595. https://doi.org/10.3390/en15207595

Benkaciali, S., Haddadi, M., Khellaf, A., Gairaa, K., Guermoui, M., 2016. Evaluation of the global solar irradiation from the artificial neural network technique. Journal of Renewable Energies 19(4), 617–631. https://doi.org/10.54966/jreen.v19i4.599

Cereghetti, N., Bura, E., Chianese, D., Friesen, G., Realini, A., Rezzonico, S., 2003. Power and energy production of PV modules statistical considerations of 10 years activity. Proceedings of the 3rd World Conference on Photovoltaic Energy Conversion 3, 2105–2108. https://doi.org/10.1109/WCPEC.2003.1305194

Chinchilla, M., Santos-Martín, D., Carpintero-Rentería, M., Lemon, S., 2021. Worldwide annual optimum tilt angle model for solar collectors and photovoltaic systems in the absence of site meteorological data. Applied Energy 281, 116056. https://doi.org/10.1016/j.apenergy.2020.116056

Dimovski, A., Moncecchi, M., Falabretti, D., Merlo, M., 2020. PV forecast for the optimal operation of the medium voltage distribution network: A real-life implementation on a large scale pilot. Energies 13(20), 5330. https://doi.org/10.3390/en13205330

Farooq, U., Mushtaq, M.F., Ullah, Z., Ejaz, M.T., Akram, U., Aslam, S., 2025. Time series analysis of solar power generation based on machine learning for efficient monitoring. Engineering Reports 7(2), e70023. https://doi.org/10.1002/eng2.70023

Hasan, K., Yousuf, S.B., Tushar, M.S.H.K., Das, B.K., Das, P., Islam, M.S., 2021. Effects of different environmental and operational factors on the PV performance: A comprehensive review. Energy Science & Engineering 10(2), 656–675. https://doi.org/10.1002/ese3.1043

Hua, Y., He, W., Liu, P., 2020. Optimum tilt angles of solar panels: A case study for Gansu Province, Northwest China. Applied Solar Energy 56, 388–396. https://doi.org/10.3103/S0003701X20050060

Jacobson, M.Z., Jadhav, V., 2018. World estimates of PV optimal tilt angles and ratios of sunlight incident upon tilted and tracked PV panels relative to horizontal panels. Solar Energy 169, 55–66. https://doi.org/10.1016/j.solener.2018.04.030

Jathar, L.D., Ganesan, S., Awasarmol, U., Nikam, K., Shahapurkar, K., Soudagar, M.E.M., Fayaz, H., El-Shafay, A.S., Kalam, M.A., Bouadila, S., Baddadi, S., Tirth, V., Nizami, A.S., Lam, S.S., Rehan, M., 2023. Comprehensive review of environmental factors influencing the performance of photovoltaic panels: Concern over emissions at various phases throughout the lifecycle. Environmental Pollution 326, 121474. https://doi.org/10.1016/j.envpol.2023.121474

Li, D.H.W., Lam, T.N.T., 2007. Determining the optimum tilt angle and orientation for solar energy collection based on measured solar radiance data. International Journal of Photoenergy 2007, 85402. https://doi.org/10.1155/2007/85402

Libra, M., Kozelka, M., Šafránková, J., Belza, R., Poulek, V., Beránek, V., Sedláček, J., Zholobov, M., Šubrt, T., Severová, L., 2024. Agrivoltaics: dual usage of agricultural land for sustainable development. International Agrophysics 38(1), 121–126. https://doi.org/10.31545/intagr/184133

Ma, M., He, B., Shen, R., Wang, Y., Wang, N., 2022. An adaptive interval power forecasting method for photovoltaic plant and its optimization. Sustainable Energy Technologies and Assessments 52(D), 102360. https://doi.org/10.1016/j.seta.2022.102360

Markovics, D., Mayer, M.J., 2022. Comparison of machine learning methods for photovoltaic power forecasting based on numerical weather prediction. Renewable and Sustainable Energy Reviews 161, 112364. https://doi.org/10.1016/j.rser.2022.112364

Mellit, A., Kalogirou, S., 2021. Artificial intelligence and internet of things to improve efficacy of diagnosis and remote sensing of solar photovoltaic systems: Challenges, recommendations and future directions. Renewable and Sustainable Energy Reviews 143, 110889. https://doi.org/10.1016/j.rser.2021.110889

Mostafavi, E.S., Ramiyani, S.S., Sarvar, R., Moud, H.I., Mousavi, S.M., 2013. A hybrid computational approach to estimate solar global radiation: An empirical evidence from Iran. Energy 49, 204–210. https://doi.org/10.1016/j.energy.2012.11.023

Ni, Q., Zhuang, S., Sheng, H., Wang, S., Xiao, J., 2017. An optimized prediction intervals approach for short term PV power forecasting. Energies 10(10), 1669. https://doi.org/10.3390/en10101669

Poncelet, K., Höschle, H., Delarue, E., Virag, A., D'haeseleer, W., 2017. Selecting representative days for capturing the implications of integrating intermittent renewables in generation expansion planning problems. IEEE Transactions on Power Systems 32(3), 1936–1948. https://doi.org/10.1109/TPWRS.2016.2596803

Poulek, V., Aleš, Z., Finsterle, T., Libra, M., Beránek, V., Severová, L., Belza, R., Mrázek, J., Kozelka, M., Svoboda, R., 2024. Reliability characteristics of first-tier photovoltaic panels for agrivoltaic systems – practical consequences. International Agrophysics 38(4), 383–391. https://doi.org/10.31545/intagr/192173

Senger, G., Chtirkova, B., Folini, D., Wohland, J., Wild, M., 2024. Persistent extreme surface solar radiation and its implications on solar photovoltaics. Earth's Future 12(8), e2023EF004266. https://doi.org/10.1029/2023EF004266

Starke, A.R., Lemos, L.F.L., Barni, C.M., Machado, R.D., Cardemil, J.M., Boland, J., Colle, S., 2021. Assessing one-minute diffuse fraction models based on worldwide climate features. Renewable Energy 177, 700–714. https://doi.org/10.1016/j.renene.2021.05.108

Wang, L., Mao, M., Xie, J., Liao, Z., Zhang, H., Li, H., 2023. Accurate solar PV power prediction interval method based on frequency-domain decomposition and LSTM model. Energy 262(B), 125592. https://doi.org/10.1016/j.energy.2022.125592

Zeeshan, S., Aized, T., 2023. Design and analysis of a solar energy system for a fruit harvesting robot in Pakistan. Acta Technologica Agriculturae 26(4), 185–193. https://doi.org/10.2478/ata-2023-0025