SiliconPV 2023, 13th International Conference on Crystalline Silicon Photovoltaics

Module Reliability and Energy Yield

https://doi.org/10.52825/siliconpv.v1i.904

Published: 22 Feb. 2024

A Simple Approach for Module Temperature and Power Prediction

Andreas Schneider[1][https://orcid.org/0000-0003-3574-8265], Julia Chochollek[1][https://orcid.org/0009-0008-0017-8614], and Thomas Nierhoff[1]

[1]University of Applied Sciences Gelsenkirchen, Germany

Abstract. In this work a mathematical approach to calculate solar panel temperature based on measured irradiance, temperature and wind speed is applied. With the calculated module temperature, the electrical solar module characteristics is determined. A program developed in MatLab App Designer allows to import measurement data from a weather station and calculates the module temperature based on the mathematical NOCT and stationary approach with a time step between the measurements of 5 minutes. Three commercially available solar panels with different cell and interconnection technologies are used for the verification of the established models. The results show a strong correlation between the measured and by the stationary model predicted module temperature with a coefficient of determination R^2 close to 1 and a root mean square deviation (RMSE) of ≤ 2.5 K for a time period of three months. Based on the predicted temperature, measured irradiance in module plane and specific module information the program models the electrical data as time series in 5-minute steps. Predicted to measured power for a time period of three months shows a linear correlation with an R^2 of 0.99 and a mean absolute error (MAE) of 3.5, 2.7 and 4.8 for module ID 1, 2 and 3. The calculated energy (exemplarily for module ID 2) based on the measured, calculated by the NOCT and stationary model for this time period is 118.4 kWh, resp. 116.7 kWh and 117.8 kWh. This is equivalent to an uncertainty of 1.4% for the NOCT and 0.5% for the stationary model.

Keywords: Solar Modules, Performance Prediction, Field Measurement

1. Introduction

Modelling of PV (photovoltaic) system performance is todays key for pre-assessing the suitability of locations for the application of PV. Precise performance prediction depends on the quality level of existing, for the location specific, weather data, information on the electrical module performance such as temperature coefficients and characteristic current and voltage as well as underlying mathematical models used for the performance calculation. This is specifically important since PV modules operate most of the time under environmental conditions far from STC (Standard Test Conditions) to which the main information in the suppliers' datasheets refer. Existing variations in solar irradiation, ambient temperature and wind situation influence the solar module performances and its energy production. Only if thermal and electrical models precisely calculate the characteristics and performances of PV modules under various operating conditions installers can assess and maximize the cost effectiveness of the designed system before on-site installation.

Various models exist for calculating the individual module performance which in general can be calculated by knowing the modules temperature, irradiation in module plane, temperature coefficients and electrical module performance at STC [1]. For the calculation of the module temperature several mathematical approaches were published in the past [2], [3]. The model as proposed by Fuentes is one of the first developed models and can be easily applied in a stationary approach where the energy balance equation has been employed to construct the thermal model [4]. Non-stationary models use dynamic thermal approaches to calculate the module temperature [5], [6]. Nonetheless do most models neglect the structural setup of the module with stacked layers of different materials [7]. Novel models use back propagation artificial neural network to calculate the module temperature [8].

The main objective of this work is to apply the mathematical approach as given by Fuentes to calculate solar panel temperature based on ambient data such as irradiation, temperature and wind speed. With this information as input data on hand the electrical solar module characteristics is determined. A program developed in MatLab App Designer imports and processes the measurement data from a weather station and calculates the module temperature based on the mathematical NOCT and stationary approach and the electrical module performance with a time step between the measurements of 5 minutes. Three commercially available solar panels with different cell and interconnection technologies are used for the verification of the established models. In the statistical evaluation MAE is also stated due to its advantages for climatic and environmental evaluations over RMSE [9].

2. Mathematical approach

Various approaches exist to calculate the temperature of a solar panel based on environmental data [10]. The simplest is the NOCT approach:

$$T_{M_{NOCT}} = T_a + \frac{T_{NOCT} - 20^{\circ}C}{800\,\frac{W}{m^2}} * G_M \tag{1}$$

which allows the calculation based on the ambient temperature T_a, the NOCT temperature as given by the supplier T_{NOCT} (~ 45°C) and the irradiation G_M. This steady state model uses the linear relationship between the solar irradiance G_M and the difference between the module and the ambient temperature (T_M - T_a). This approach neglects various factors, such as for example wind and the mounting configuration and is hence less accurate.

A non-stationary approach is the in 1987 proposed thermal model by Fuentes. This approach is far more complex since it develops a detailed thermal energy balance between the module and the surroundings and evaluates the influence of external meteorological parameters on the module temperature and is given as a differential equation:

$$m * c * \frac{dT_M}{dt} = \varphi * G_M - h_c * (T_M - T_a) - \varepsilon_{back} * \sigma * \left(T_M^4 - T_{gr}^4\right) - \varepsilon_{top} * \sigma * \left(T_M^4 - T_{sky}^4\right) \tag{2}$$

where m is the mass of the specimen, c the heat capacity, φ is the absorptivity and h_c the convective coefficient of the module. The convective coefficient h_c can be divided in two kinds of convection. The free convection is independent from any other ambient data, where the forced convection is depending on the wind speed and can be sorted after laminar and turbulent convection. σ denotes to the Stefan-Boltzmann constant, ε_{top} and ε_{back} corresponds to the emissivity of the front resp. rear side of the module. T_{gr} and T_{sky} are the ground resp. sky temperature. Due to the relatively large heat capacity of the module leading to a time constant in the range of up to several minutes it is appropriate to convert and simplify formula (2) into a stationary approach as given by:

$$T_{M_{statio}} = \frac{\varphi * G_M + h_c * T_a + h_{r,sky} * T_{sky} + h_{r,gr} * T_{gr}}{h_c + h_{r,sky} + h_{r,gr}} \tag{3}$$

where $h_{r,sky}$ is the radiative coefficient to the sky and $h_{r,gr}$ the radiative coefficient to the roof or ground. Variables h_c, $h_{r,gr}$ and $h_{r,sky}$ are also functions of T_M and therefore equation (3) needs to be solved iteratively. For solving (3) iteratively all unknown variables needs to be determined which requires to solve >20 separate equations. The calculated module temperature finally allows to determine the voltage and current at maximum power point mpp, U_{mpp} and I_{mpp} by:

$$U_{mpp} = U_{mpp_{STC}} + \beta * U_{mpp_{STC}} * \left(T_{M_{statio}} - T_{a_{STC}}\right) + n * U_T * \log(\frac{G_M}{G_{M_{STC}}}) \tag{4}$$

$$I_{mpp} = I_{mpp_{STC}} * \frac{G_M}{G_{M_{STC}}} * (1 + \alpha * \left(T_{M_{statio}} - T_{a_{STC}}\right)) \tag{5}$$

where α and β are the modules current and voltage temperature coefficient, n is the ideality factor and U_T the thermal voltage. The temperature coefficients can be obtained by different ways. The first and simplest is to take the coefficients as given by the supplier in the datasheet as a constant value independent of irradiance. The more complex way is to determine the temperature coefficients from experimental outdoor data either as a constant value or in dependence of the irradiance.

3. Application and results

The previous section shows that the calculation of $T_{M,NOCT}$ is rather simple whereas the calculation of $T_{M,statio}$ requires a complex mathematical approach, specifically for determining the unknown variables. The proposed approach is novel this way that it uses measurement data from a weather station (G_M, T_a and wind speed) for re-calculating h_c, $h_{r,sky}$ and $h_{r,gr}$ every 5 minutes to determine $T_{M,statio}$. Larger calculating errors are specifically obtained in the early morning due to inhomogeneous illumination: The irradiation sensor covers a very small area in comparison to the solar module area hence is far less affected by shading which leads to power calculations not reflecting the reality on site. To compensate for this, the measured irradiance is compared with the calculated I_{mpp} and U_{mpp} and a fit applied, in case larger deviations occur. Accuracy is further improved by applying linear regression.

3.1 Metrological and specimen information

For this study a long-term outdoor measurement series has been consecutively started in April 2020 (still ongoing) on commercially available solar panels as shown in Table 1.

Table 1. Type of solar modules.

Module type	ID	Cell /module technology	P (W)	$T_{K,Pmpp}$ (%/K)	NOCT (°C)
Panasonic VBHN 340 SJ53	1	HIT / standard	340	-0.26	44
Sunpower P3 325 BLK	2	PERC / shingled	325	-0.36	45
REC-Alpha-Series 365 W	3	HJT / SmartWire	365	-0.26	44

Solar panels are permanently kept at P_{mpp} and the I/V-performance measured each minute by a calibrated Papendorf SOL.Connect® meter which comes with an (I/V) inaccuracy <1%. A PT1000 sensor measures the solar panel temperature at module rear side and an ISET sensor the irradiation in module plane. A Thies weather station in close proximity to the solar panels measures humidity, ambient temperature, wind speed, wind direction and horizontal as well as in-plane irradiation every five minutes.

Deviations due to module degradation are corrected by determining the T_K´s and verification of STC-data. In case of performance degradation, the experimentally determined STC-data is used. Both models were integrated into the source code of the MatLab program to calculate the module´s temperature based on ambient data and general module specification as delivered by the supplier or by conducting the designated measurements, either with a solar flasher in the laboratory or by outdoor measurements.

3.2 Comparison of the NOCT and stationary model

The first investigation evaluates the prediction accuracy for both models in terms of accuracy for different weather settings. Various weather settings with clear sky and casted conditions and varying maximum irradiances (e.g. by taking days from different seasons) were studied in depth. This study reveals that the stationary model performs excellent in terms of prediction accuracy specifically for clear sky and days with partly cloudy sky and outperforms the NOCT model tremendously. The NOCT model leads in general to higher deviations for clear sky conditions but typically comes with least deviations for very cloudy conditions which lead to sudden temperature and irradiation changes. The stationary model comes with a tendency to positive for clear sky and negative deviations for casted conditions.

Figure 1 shows exemplary the temperature difference between measured and predicted temperature for both models. The maximum temperature difference is 5.1 K for clear sky and -6.5 K for casted conditions for the stationary model whereas the NOCT model shows up to twice as high deviations. For the data as displayed in Figure 1 the mean of the temperature difference for the clear sky day is 1.16 ± 1.68 K for the stationary and 3.87 ± 2.67 K for the NOCT model. The mean for the casted day is -2.91 ± 1.15 K for the stationary and -1.08 ± 1.91 K for the NOCT model. The explanation why the simple NOCT model outperforms the stationary model at very cloudy conditions is the second term of the NOCT calculation in formula 1. The measured irradiance G_M follows instantaneously the actual irradiation level the module sees with no or only a very small time lag. The calculation of $T_{M,statio}$ as given in formula 3 is an iterative method of the assessment and requires various input parameters which all come with different time constants. This way the stationary model is less precise for very cloudy days if compared to the NOCT model. Nonetheless if all weather situations are carefully evaluated the stationary model outperforms the NOCT model and is therefore used in the consecutive chapters for the data evaluation.

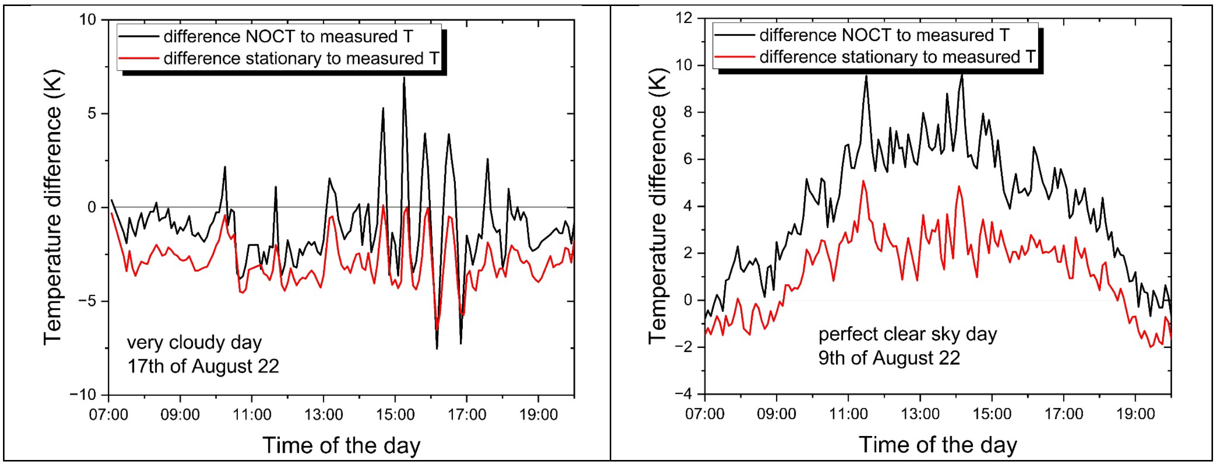

Figure 1. Temperature difference between measured and predicted (both models) for module ID 2 during a casted (left) and clear-sky day (right).

3.3 Predicted versus measured module temperature

In order to qualify the prediction accuracy for the stationary model in terms of modelled module temperature one week with only cloudy days and one week with only clear sky days is used. Figure 2 shows the difference between predicted (modelled) and measured module temperature for both scenarios, exemplarily for module ID 2. The prediction accuracy for clear sky days shows a mean for the distribution of 0.71 ± 1.48 K and -2.48 ± 1.64 K for cloudy days. More interesting is the maximum deviation which is ± 5 K for clear sky and -8 K resp. +4 K for cloudy conditions. The data proves that specifically for clear sky situation the prediction accuracy is very high. For cloudy days mainly the time lag between the measured module temperature and the instantaneously updated irradiance leads to larger deviations. On the mathematical site only few approaches exist to enhance the prediction accuracy specifically since the module temperature as measured does not match the cell temperature, neither in a matter of time nor in a matter of precision since changes in cell temperature propagate not one-dimensional. Any cell temperature change will propagate over the whole module volume with time.

Furthermore, is the temperature profile over the module area not homogenous, typically it is 2-4 K higher at the center compared to the edge area. For this reason, any comparison between the measured module temperature on the panels back side and the predicted module temperature comes with an uncertainty. The accuracy can be increased by applying a wind filter which takes out data for larger wind situations leading to larger convective flow of heat at the modules rear side and hence reduce the prediction accuracy. It must be noted that the available amount of data is the more reduced the smaller the threshold for the wind filter is.

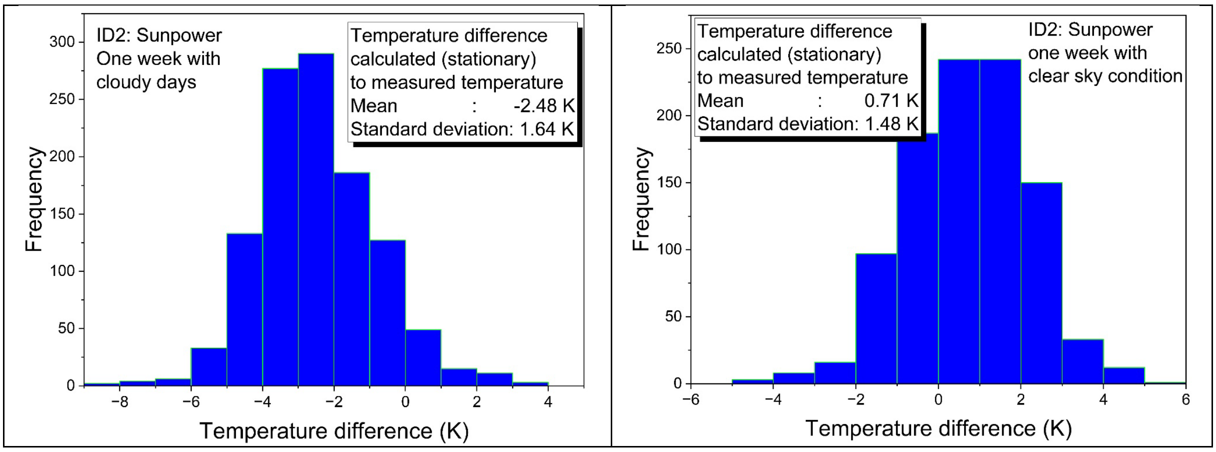

Figure 2. Histogram of temperature difference between modelled (stationary) and measured temperature for one week with cloudy days (left) and clear sky (right) for module ID 2.

3.4 Predicted versus measured module power

In the following the predicted module temperature as calculated by the stationary approach is used – in combination with the experimentally determined module parameters (e.g. temperature coefficients and in case performance degradation is seen the STC module parameters) to calculate the modules current and voltage values and hence power $P_{mpp,statio}$ and fill factor as well as efficiency. In a first step the accuracy of the model is evaluated on single days of the year, representing completely different weather situations. As Figure 3 quantitatively shows, measured power $P_{mpp,measured}$ and calculated power $P_{mpp,statio}$ for module ID 2 at casted (here the 13th of March 2022) and clear sky conditions (here the 9th of August 2022) is modelled with only small deviations hence high accuracy.

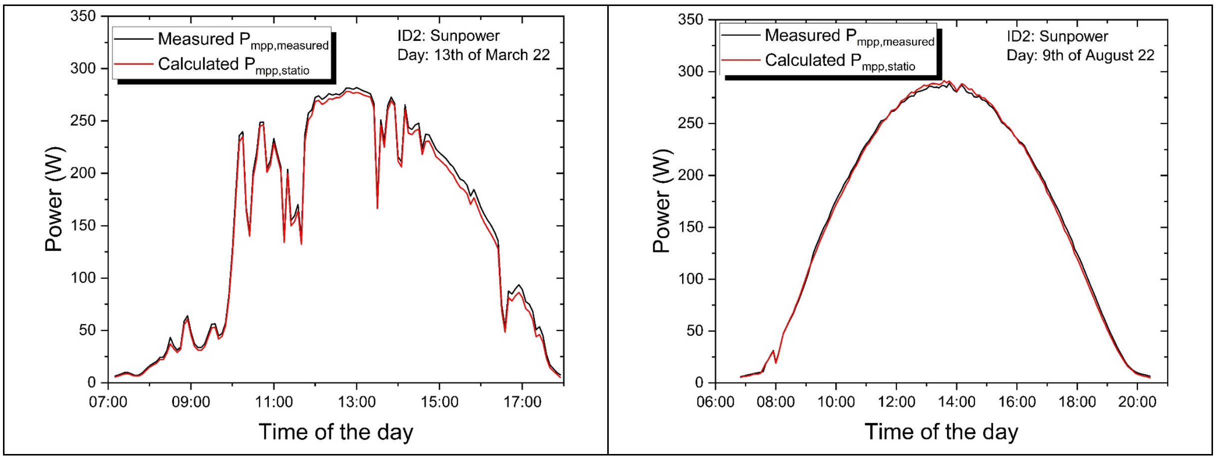

Figure 3. Power (measured and predicted) for module ID 2 during a casted (left) and clear-sky day (right).

Mean and standard deviation of the difference between measured and modelled power and temperature is ΔP_{avg} = -0.03 ± 3.43 W and ΔT_{avg} = 2.39 ± 1.89 K for clear-sky, resp. ΔP_{avg} = 4.52 ± 2.22 W and ΔT_{avg} = 0.50 ± 2.07 K for casted conditions. The devolution for measured and predicted power over the course of the day also matches which can specifically be seen for the casted day. Even sudden module power changes as measured are precisely predicted.

Figure 4 shows $P_{mpp,statio}$ as calculated based on data from the stationary model versus $P_{mpp,measured}$ for one week with only clear sky (right) and only casted (left) condition. The linear regression analysis shows a slope of 1.022 and an R^2 of 0.999 for clear sky and a slope of 1.020 and an R^2 of 0.999 for casted conditions. The data shows no larger deviations in the plot $P_{mpp,statio}$ versus $P_{mpp,measured}$.

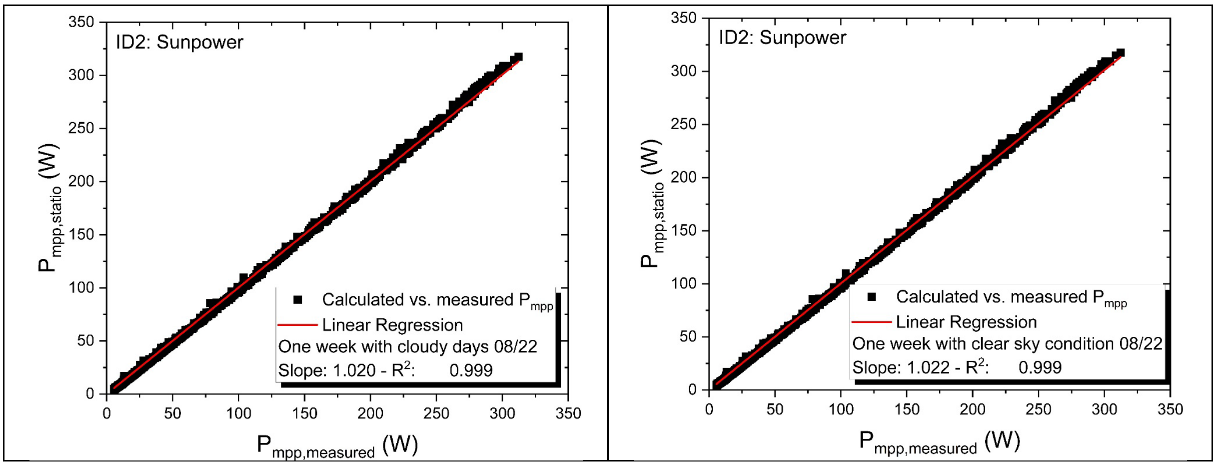

Figure 4. Modelled (stationary) versus measured P_{mpp} for one week with cloudy days (left) and clear sky condition (right) for module ID 2.

In a next step the modelled temperature, power and energy is calculated from 27th of June 2022 to 5th of September 2022 hence reflecting three months with various changing weather situations. Table 2 shows the statistical analysis results for measured vs. predicted temperature, power and energy for all three modules for three months. For the evaluation R^2, RMSE and MAE are determined. Results prove the high prediction accuracy of the approach if ambient data is used to calculate the required parameters for the stationary temperature model in real time. One of the main reasons for larger deviations between predicted and measured module temperature is shading by clouds which leads to sudden module current and cell temperature changes which are only reflected with a time lag in the module temperature as measured by the PT1000 at the outside of the module.

Table 2. Statistical analysis results for all modules calculated between 27.06.22-05.09.22.

ID	**Temperature**			**P_{mpp}**			**Energy**		
	R^2	**RMSE (K)**	**MAE**	**R^2**	**RMSE (W)**	**MAE**	**R^2**	**RMSE (kWh)**	**MAE**
1	0.959	2.421	2.055	0.998	4.085	3.500	0.998	0.031	0.025
2	0.966	2.539	2.069	0.999	3.138	2.688	0.999	0.029	0.027
3	0.971	2.147	1.729	0.997	5.437	4.814	0.998	0.052	0.050

Based on the measured and calculated module power the energy is calculated by performing an integration over the individual days between 27th of June 2022 and 5th of September 2022. Therefore, days with cloudy, clear sky and mixed weather conditions are included. The produced energy as an example for the Sunpower module (ID 2) based on the measured, calculated by the NOCT model and stationary model power is 118.4 kWh, resp. 116.7 kWh and

117.8 kWh. This is equivalent to an uncertainty of 1.4% for the NOCT model and only 0.5% for the stationary model.

3.5 Proposal for optimization measures

To further increase the accuracy of the module temperature calculation by the stationary model several measures can be named:

- Application of a wind filter to neglect data for situations with larger wind speeds leading to larger convective flow of heat at the modules rear side
- Increase of the number of temperature sensors on the rear side and distributing the location of the sensors at the outer and inner module area
- Replacing the static temperature by irradiance dependent temperature coefficients
- Optimization of parameters as given in formula 3

4. Conclusion

This paper presents results on the application of the stationary temperature model by using weather data as measured by a weather station to calculate the module temperature, module power and generated energy. For this, a software tool was programmed in MatLab App Designer which is able to import and process data from a weather station as well as from high accuracy module performance measurement devices from single days up to several months. It is found that the source for larger deviations between modelled and measured temperature mainly stems from the time lag between instantaneously measured irradiation and module temperature on the rear side of the module which is used to compare the predicted temperature. This leads to larger uncertainties specifically for days with casted sky conditions. A comparison of the module temperature as calculated by the stationary and the simple NOCT model shows that the simplicity of the formula behind the NOCT model comes with advantages for casted days where the prediction accuracy of the NOCT model is more accurate if compared to the stationary model. For specific days the mean for the clear sky day is 1.16 ± 1.68 K for the stationary and 3.87 ± 2.67 K for the NOCT model. The mean for the casted day is -2.91 ± 1.15 K for the stationary and -1.08 ± 1.91 K for the NOCT model. Based on the predicted module temperature the module power is calculated. A linear regression, performed for the stationary approach for one week with only clear sky and one week with only casted conditions reveals a slope of 1.022 and an R^2 of 0.999 for clear sky and a slope of 1.020 and an R^2 of 0.999 for casted conditions for the relation between predicted versus measured module power. Furthermore, shows the data no larger deviations or outliers. Finally, the stationary model is applied for a longer time period from 27th of June 2022 to 5th of September 2022 hence reflecting three months with various changing weather situations for three commercially available solar modules with different cell and interconnection technologies. A statistical evaluation for the stationary model shows an RMSE for the calculated temperature ≤ 2.5 K for all three modules and an RMSE for the calculated power ≤ 4.1 W for module ID1 and ID2 and ~5.4 W for module ID3. The mean absolute error (MAE) for the power is 3.5, 2.7 and 4.8 for module ID 1, 2 and 3. The produced energy for the Sunpower module based on the measured, calculated by the NOCT model and stationary model power is 118.4 kWh, resp. 116.7 kWh and 117.8 kWh. This is equivalent to an uncertainty of 1.4% for the NOCT model and only 0.5% for the stationary model. Results prove the high accuracy of the modelling approach if big measurement data for modelling plus precise module performance data for the calculation and verification of the individual modules is used.

Data availability statement

The data that support the findings of this study are available from the corresponding author, [A.S.], upon reasonable request.

Author contributions

This study was designed, directed and coordinated by A.S. as the principal investigator. A.S designed the experiments, planned and performed the data analysis. J.C. designed and programmed the evaluation software for the study, implemented supporting algorithms and performed evaluation tasks. J.C. suggested and commented on the design of experiments. T.N. performed the indoor measurements, maintained the measurement tools and provided the ambient measurement data. The manuscript was written by A.S. and J.C. and commented on by all authors. All authors read and approved the final manuscript.

Competing interests

The authors declare no competing interests.

Funding

This work was supported by the SOLAR-ERA.NET funding scheme under contract no. FKZ EFO0007 (AmBiPV).

References

1. A. Migan-Dubois, J. Badosa, F. C. Obaldía, O. Atlan, V. Bourdin, M. Pavlov, D. Y. Kim, Y. Bonnassieux, “Step-by-step evaluation of photovoltaic module performance related to outdoor parameters: evaluation of the uncertainty,” 44th IEEE Photovoltaic Specialists Conference (IEEE-PVSC), Jun 2017, Washington, United States. pp.626-631, 10.1109/PVSC.2017.8366615. hal-01630076
2. P. Mora Segado, J. Carretero, M. Sidrach-de-Cardona, “Models to predict the operating temperature of different photovoltaic modules in outdoor conditions,” Prog. Photovolt: Res. Appl.2015;23:1267–1282, DOI: 10.1002/pip.2549
3. M. Zouine, M. Akhsassi, N. Erraissi, N. Aarich, A. Bennouna, M. Raoufi, A. Outzourhit, “Mathematical models calculating PV module temperature using weather data: Experimental study,” Lecture Notes in Electrical Engineering 519:630-639, DOI:10.1007/978-981-13-1405-6_72, April 2018
4. M. K. Fuentes, “A Simplified Thermal Model for Flat-Plate Photovoltaic Arrays,” Tech. rep., Sandia National Labs, USA, SAND-85-0330 ON: DE87009386, 1987.
5. J. Barry, D. Böttcher, K. Pfeilsticker, A. Herman-Czezuch, N. Kimiaie, S. Meilinger, C. Schirrmeister, H. Deneke, J. Witthuhn, F. Gödde, “Dynamic model of photovoltaic module temperature as a function of atmospheric conditions,” Adv. Sci. Res., 17, 165–173, 2020, https://doi.org/10.5194/asr-17-165-2020
6. B. Tuncel, T. Ozden, R.S. Balog, B.G. Akinoglu, “Dynamic thermal modelling of PV performance and effect of heat capacity on the module temperature,” Case Studies in Thermal Engineering 22 (2020) 100754
7. A. K. Abdulrazzaq, B. Plesz, G. Bognár, “A Novel Method for Thermal Modelling of Photovoltaic Modules/Cells under Varying Environmental Conditions,” Energies 2020, 13, 3318; doi:10.3390/en13133318
8. H. Zhu, W. Lian, L. Lu, P. Kamunyu, C. Yu,, S. Dai, Y. Hu, “Online Modelling and Calculation for Operating Temperature of Silicon-Based PV Modules Based on BP-ANN,” Hindawi International Journal of Photoenergy Volume 2017, Article ID 6759295, https://doi.org/10.1155/2017/6759295
9. C. J. Willmott*, K. Matsuura, “Advantages of the mean absolute error (MAE) over the root mean square error (RMSE) in assessing average model performance,” Climate Research 30 (1): 79, DOI:10.3354/cr030079
10. J. R. G. Ross and Smokler, M. I., “Flat-Plate Solar Array Project Final Report,” pp. 86-31, 1986