

Blind PV temperature model calibration

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Abstract. The determination of module temperature in a photovoltaic (PV) system is a crucial factor in PV modelling and the assessment of system health status. However, the scarcity of on-site temperature measurements poses a challenge, and existing PV temperature models encounter difficulties in accurately estimating temperatures in systems characterized by unique structural or locational attributes. This paper introduces a novel approach that enables the calibration of PV temperature models without relying on direct temperature measurements. Referred to as blind calibration, this method eliminates the requirement for temperature measurements, thus offering a promising solution to the aforementioned challenges. The method is validated using three datasets, demonstrating accurate PV temperature (T_{PV}) estimation with mean absolute errors below 2 °C. The findings highlight the suitability of the proposed approach for various PV system types, while acknowledging limitations regarding certain system configurations.

Keywords: Photovoltaic systems / calibration / dynamic thermal model / DC voltage

1 Introduction

Accurate modelling of photovoltaic (PV) systems is vital for the design, operation, and optimization of solar power plants. The temperature of solar cells is a critical parameter that significantly impacts PV system performance [1]. It affects key electrical characteristics such as the open-circuit voltage (V_{OC}) and maximum power output (P_{MPP}), with a marginal impact on the short-circuit current (I_{SC}). To ensure accuracy, PV system modelling must account for temperature-induced changes in these characteristics. Thus, precise measurement and/or modelling of the PV temperature (T_{PV}) are essential for comprehending system behaviour under various environmental conditions and predicting performance with high accuracy.

Determining the temperature of a PV module is usually accomplished by either direct measurement from the module's rear side or using mathematical models developed for T_{PV} estimation [2,3]. However, even if single-module temperature measurements are reliable, concerns have been raised whether that temperature accurately represents the entire PV array or system temperature [4,5].

On the other hand, T_{PV} models rely on input data such as weather data obtained from nearby weather stations or satellites. These models require calibration to optimize their accuracy [6]. Furthermore, existing temperature

models assume temperature uniformity across the entire PV system, limiting their ability to capture temperature variations within individual arrays.

This paper proposes a novel method for calibrating temperature models without the need for module temperature measurements. Instead, this method uses inverter voltage measurements at the maximum power point (V_{MPP}). As V_{MPP} varies due to a variety of causes (clipping, curtailment, ...), it cannot be used continuously for system temperature monitoring. Therefore, it is combined with weather data (irradiance, ambient temperature, and wind speed), to calibrate thermal model coefficients of well-known models (Faiman, or Sandia, or Skoplaki) for subsequent use.

This approach therefore allows the array or system equivalent temperature to be found, instead of the single-module temperature. Moreover, this method can serve as a back-up to deal with faulty module temperature measurements, as well as provides the best estimate of the whole-of-system equivalent module temperature. This whole-of-system equivalent module temperature thus represents the average system temperature, and can be used for system performance evaluations.

2 Methodology

2.1 Filtering

The methodology relies on the linear relationship between maximum power point voltage and T_{PV} . Consequently, it is necessary to discard data points that do not conform to this linear relationship, such as those associated with low

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irradiance, clipping, noise, and other factors. The (near-) linear relationship between T_{PV} and V_{MPP} holds true when the plane of array irradiance (G_T) exceeds a threshold, typically around 50–100 W/m². However, due to limitations in capturing spatial shading using irradiance sensors, the maximum power point current (I_{MPP}), which is predominantly influenced by G_T , can serve as a filtering criterion. Empirical observations indicate that working with data where I_{MPP} falls within the range of 80–100% of the system's I_{MPP} under STC conditions yields more accurate outcomes.

$V_{MPP,STC}$ and the relative voltage temperature coefficient β or absolute voltage temperature coefficient θ may diminish over time due to degradation, resulting in increased thermal losses [7]. Consequently, the data period selected for model fitting should not exceed one year to account for these degradation-related effects.

2.2 Estimation of voltage parameters and transformation to equivalent PV temperature

After surpassing the cut-in irradiance values, the V_{MPP} values on the DC side of the inverter are expected to follow (1).

$$\begin{aligned} V_{MPP} &= V_{MPP,STC} * (1 + \beta(T_{PV} - T_{STC})) \\ &\equiv V_{MPP,STC} + \theta * (T_{PV} - T_{STC}). \end{aligned} \quad (1)$$

Typically, V_{MPP} and β for PV modules are provided by manufacturers. However, these values may differ in PV setups with multiple modules or undergo changes due to degradation, necessitating reapproximation. Expanding (1), we obtain:

$$V_{MPP} = V_{MPP,STC} + \theta * T_{PV} - \theta * T_{STC}. \quad (2)$$

Since $V_{MPP,STC}$, T_{STC} and θ are constants, they can be substituted by the term V_1 as in (3)

$$V_1 = V_{MPP,STC} - \theta * T_{STC}, \quad (3)$$

$$V_{MPP} = \beta * T_{PV} + V_1. \quad (4)$$

A first estimation of T_{PV} can be accomplished using the Ross equation (3) provided in (5).

$$T_{PV} = T_{amb} + k * G_T, \quad (5)$$

where T_{amb} denotes the ambient temperature and k represents the Ross heating coefficient, which is multiplied with the plane of array irradiance G_T .

Substituting T_{PV} from (5) in (4) gives

$$V_{MPP} = \theta * k * G_T + \theta * T_{amb} + V_1. \quad (6)$$

Hence, V_{MPP} has been transformed into a function of weather parameters. Since (6) is linear in the three-dimensional space, the values of θ , k , and V_1 can be determined by applying multiple linear regression, with V_{MPP} as the dependent variable and G_T and V_1 as features. Considering that V_{MPP} signals often contain outliers, it is

recommended to use Huber regression [8], which is more robust in the presence of outliers, for model development. The resulting model will take the form of equation (7),

$$V_{MPP} = s_1 * G_T + s_2 * T_{amb} + intercept. \quad (7)$$

Consequently,

$$s_1 = \theta * k, \quad (8)$$

$$s_2 = k, \quad (9)$$

$$intercept = V_1 = V_{MPP,STC} - \theta * T_{STC}. \quad (10)$$

It should be noted that if enough data are available after the filtering, instead of performing a single linear regression for all the data at once, several regressions can be applied to different batches of wind speed in order to achieve a better fitting for k . In such cases, the final values of θ and V_1 should be the median of all regressions.

Once θ and V_1 have been found, the PV temperature can be estimated from (11), in the linear range between voltage and PV temperature:

$$T_{PV,estimate} = \frac{V_{MPP} + V_1}{\theta}. \quad (11)$$

This PV temperature estimate is thus obtained without the need for module temperature data, i.e. a blind estimation.

2.3 Calibration of weather-based estimation model

With $T_{PV,estimate}$, and weather data (G_T , T_{amb} and WS), any equation-based thermal model that uses these values can be calibrated. This extrapolation to all weather conditions and associated V_{MPP} values is wider than the range of weather conditions used to determine $T_{PV,estimate}$, and avoids issues that may be seen in the inverter voltage data, such as clipping, curtailment, partial shading, ...

The model that has been selected to be calibrated for the evaluation, is Faïman's model, described in [2].

To make the thermal model data dynamic at 1-minute resolution and therefore reduce model errors, an exponentially weighted mean (EWM) filter is applied to the G_T and wind speed data as proposed in [9].

$$T_{Faïman,dyn} = \frac{G_{EWM}}{U_0 + U_1 * WS_{EWM}} + T_{amb}. \quad (12)$$

Figure 1 presents a visual depiction of the sequential steps undertaken to estimate T_{PV} in this paper.

3 Datasets used

The validation of the proposed method will be conducted using three distinct datasets. The first two datasets originate from the ground and rooftop PV systems of NIST located in Maryland, USA [10]. These datasets have been obtained from the NIST open datasets [11], where T_{PV} has been measured using RTD sensors attached to the PV

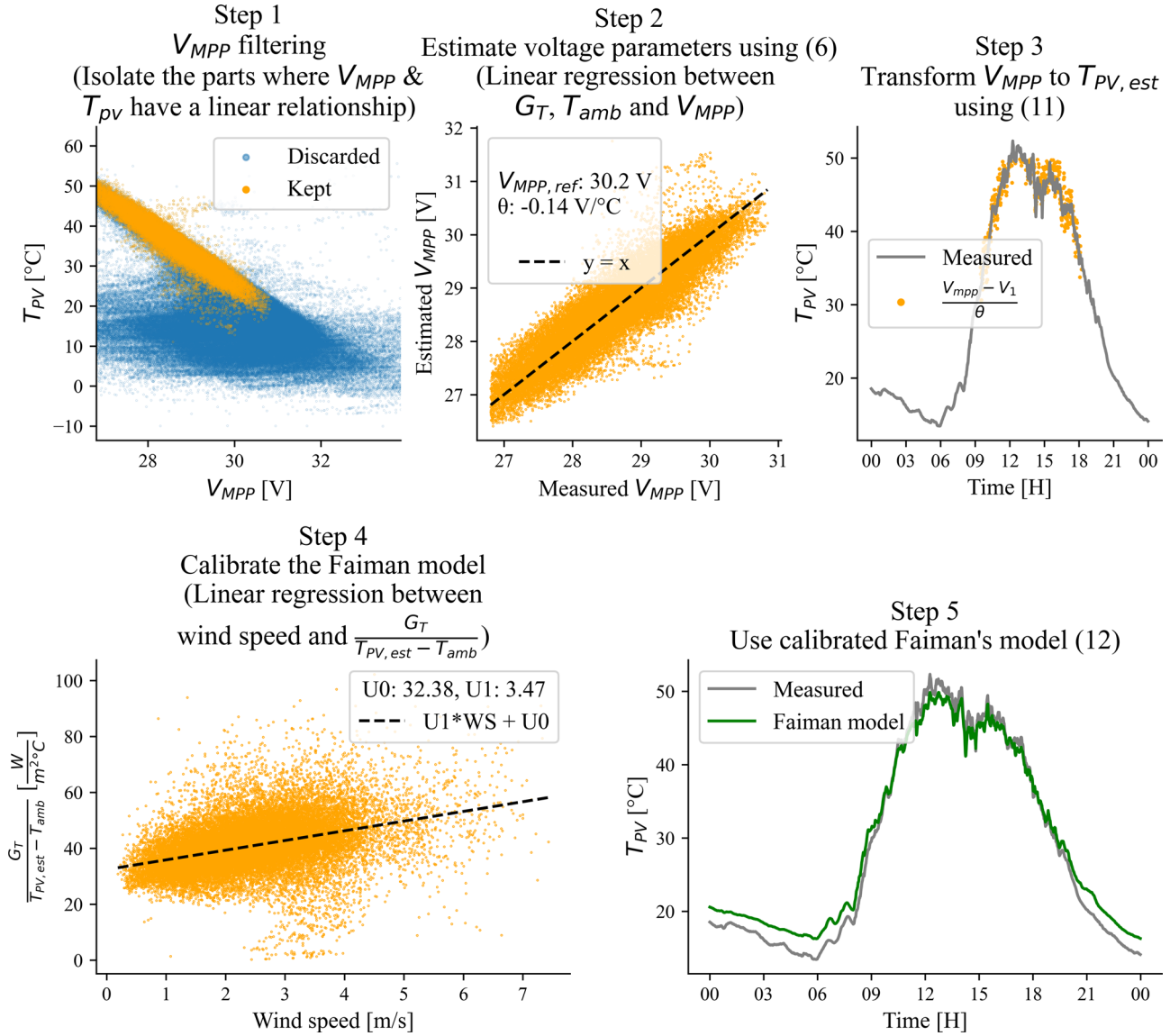


Fig. 1. Demonstration of the steps taken to estimate PV temperature in this paper. The data used in this plot are from the KUL data set and the time series plots (steps 3 & 5) are from the 11th of July 2015. It is worth mentioning that the figure of step one can be reproduced using the estimation of a given T_{PV} model (even if the coefficients are not optimized) to check the filtering result.

module backsheet. Notably, the rooftop PV system at NIST is equipped with metal deflectors on the back of the PV modules, serving to mitigate wind forces. However, these deflectors also impede wind cooling, resulting in higher operating temperatures compared to neighbouring installations without such deflectors.

The third dataset corresponds to a PV system comprising a single PV module connected to a micro-inverter, situated on the tallest building of the KU Leuven campus in Ghent, Belgium [1]. For this particular system, the reference T_{PV} is measured using an RTD sensor laminated against the cell of the module. This system exhibits periodic fluctuations in V_{MPP} every 10 min due to the inverter performing a periodic I - V curve sweep to verify its MPP values.

All three datasets are used at a resolution of one minute average values; the KUL data is measured and stored at 1 s resolution, whereas NIST has data measured at 1 and 10 s and stored at 10 s or 1 min resolution averages. Additional information regarding the systems can be found in Table 1.

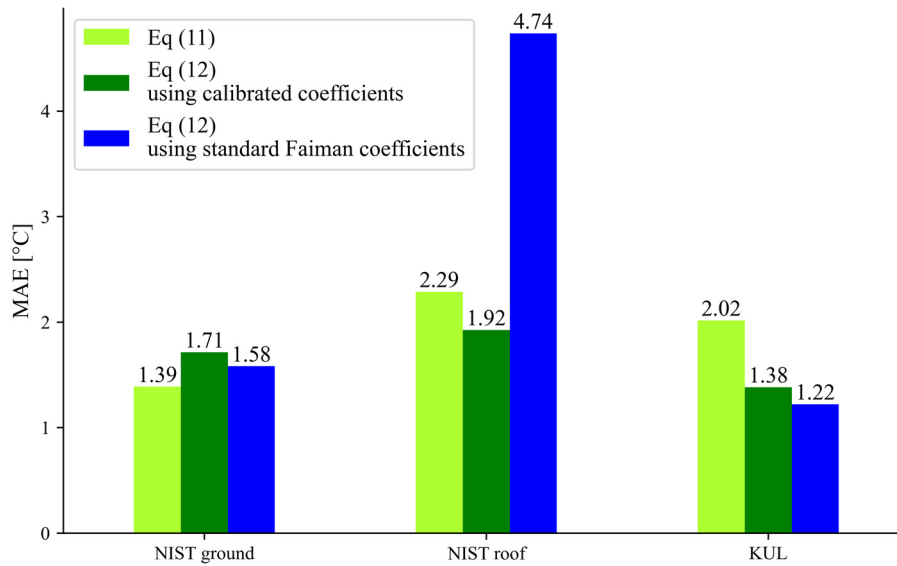
4 Results

The entire process of data analysis and modelling was conducted within a Python environment, utilizing various libraries such as pandas, NumPy, matplotlib, SciPy, and scikit-learn.

The criterion employed to assess the outcomes of the proposed methodology was the mean absolute error (MAE) between the estimations obtained using the suggested

Table 1. Description of the PV systems from which the datasets used in this paper were derived.

Measurement set up	KUL	NIST roof	NIST ground
Location	Ghent, Belgium	Maryland, USA	Maryland, USA
Data period	2015 (one year)	2017 (one year)	2018 (one year)
Number of modules per system	1	321	1152
P_{STC}	245 W	271 kW	73 kW
Measurements	T_{amb} (4-wire RTD), G_T (CMP11), WS (cup anemometer), T_{CELL} (RTD), V_{MPP} (dedicated inverter)	T_{amb} (4-wire RTD), G_T (CMP11), WS (Vaisala WMT52 ultrasonic anemometer), T_{BS} (RTD), V_{MPP} (central inverter)	T_{amb} (4-wire RTD), G_T (CMP11), WS (Vaisala WMT52 ultrasonic anemometer), T_{BS} (RTD), V_{MPP} (central inverter)

**Fig. 2.** MAE comparison between the TPV measurements and estimations obtained through three different approaches for each of the studied datasets. Note that the MAE for the transformed V_{MPP} coefficients using (11) was determined using the data retained after the filtering process, which results in fewer data points, compared to MAE calculation using Faiman's model.

coefficients proposed by the authors in the respective publication, the estimations derived from the method's results and the estimations after the transformation of V_{MPP} to T_{PV} using the equation (11). These results are visually depicted in Figure 2.

The findings of this study demonstrate that the Mean Absolute Error (MAE) for all cases utilizing Faiman's model consistently remains below 2°C. These results closely align with the outcomes achieved by Herteleer et al. [9] during their application of the EWM approach to Faiman's model. More specifically, when utilizing PV temperature measurements as a reference for model calibration, the MAE values attained in their work are 1.14 and 1.63 for the KUL and NIST ground sites, respectively. This outcome yields a small discrepancy in power estimation, amounting to less than 1%, even when assessing PV systems characterized by a large power

temperature coefficient (around $-0.5\%/^{\circ}\text{C}$). However, it should be noted that the MAE using the standard coefficients for Faiman's model ($U_0 = 25.0$, $U_1 = 6.84$) exhibited a slightly smaller magnitude for the PV installations with easy wind access to the modules, while it was significantly higher for the NIST roof array, where the wind deflectors significantly affect convective cooling. This situation arises due to the origin of Faiman's work, which found the coefficients for ground-mounted PV modules with open back. It is important to acknowledge that the newly estimated coefficients are based on the equivalent temperature of the examined system, which may deviate from the measurements acquired from individual panels. Consequently, utilizing temperature sensor measurements as a reference from individual PV modules may deviate from the array equivalent temperature. The system equivalent temperature determined as

presented in this work, can serve to quantify the temperature deviations within an array, and help quantify mismatch errors, when individual module measurements are available.

Alternatively, transformed V_{MPP} exhibits a propensity to yield reasonably precise outcomes in instances where PV systems operate beyond the threshold values of irradiance, encompassing a linear range of T_{PV} – V_{MPP} . However, it is imperative to acknowledge that the presence of elevated voltage fluctuations and unmitigated factors such as spatial shading can induce deviations from the established reference values.

5 Discussion

The proposed methodology demonstrates its efficacy in adapting T_{PV} models to diverse types of PV systems, leveraging inverter voltage data. However, it is advised that the calibration of the models, if temperature sensors are suitably incorporated within the system, should rely on the readings obtained from these sensors. This method can be effectively employed in systems lacking temperature measurements but possessing accessible electrical and weather data. This broadens the scope for coefficient extraction from a wider range of PV systems, which can subsequently be utilized in the modelling of new, analogous systems.

Furthermore, the method proves beneficial in enhancing the accuracy of prior systems that lack wind measurements. In such cases, the Ross model can be employed for temperature estimation. Nonetheless, the inadequacy of the Ross model in accounting for wind cooling often results in diminished accuracy. However, by utilizing the proposed method, the parameters $V_{MPP,ref}$ and V_1 can be calculated, enabling temperature estimation through equation (11). It is important to note, however, that this approach does not facilitate temperature estimations based on weather forecasting.

While the Faïman model is utilized in this paper, alternative models can also be employed. Nevertheless, based on our experience, there is no single equation that can provide a perfect fit for all PV systems. Hence, more flexible approaches such as machine learning or deep learning can be utilized. The development of such models for T_{PV} estimation, based on the V_{MPP} will be presented in future work.

Extracting the temperature, as well as the $V_{MPP,ref}$ and β , from the PV systems can provide valuable insights into the degradation of the system.

However, it should be noted that this method may not be applicable to all PV systems.

The V_{MPP} collected from power optimizers is not suitable for this method, as these devices optimize the maximum power point to achieve current uniformity across the PV array. Consequently, this disrupts the linearity between V_{MPP} and T_{PV} , when assessed from the inverter. The use of optimisers thus challenges the ability to rapidly determine the system equivalent temperature.

Permanent spatial shading on a specific area of the system can modify the voltage levels, leading to inconsistencies in the data. If such shading events occur frequently, they can result in inaccurate outcomes.

Clipping events in power or voltage need to be filtered out, as they disrupt the linearity between V_{MPP} and T_{PV} . Therefore, PV systems with frequent clipping events may not be suitable for this method, as the data that remains after filtering might not be sufficient for an accurate fit.

The data utilized in this method should originate from a PV system without any significant faults that could alter the voltage and current levels of the system.

6 Conclusions

Accurate estimation of T_{PV} is crucial for the optimal design and operation of solar power plants. This paper presented a novel methodology for calibrating temperature models without the need for module temperature measurements. By utilizing the equivalent T_{PV} of the PV array, derived from the V_{MPP} , a weather-based T_{PV} estimation model was calibrated.

The methodology involved filtering data points based on the linear correlation between V_{MPP} and T_{PV} , discarding outliers and low irradiance data. The resulting models exhibited accurate T_{PV} estimation across various PV system types, with mean absolute errors below 2 °C.

The findings indicate that the proposed method can be applied to various PV system types, including specialized installations. However, it is recommended to calibrate the model based on temperature sensor measurements if available within the system. Future work may explore the use of alternative models or more flexible approaches, such as machine learning or deep learning, for T_{PV} estimation based on the transformed V_{MPP} .

Overall, the proposed methodology offers a valuable contribution to PV system modelling, enabling accurate estimation of T_{PV} without the need for direct temperature measurements while providing insights about system's degradation.

Author Contribution Statement

Introduction, Methodology, Results writing—original draft preparation, A.K.; Review and editing, supervision, B.H.; supervision, funding acquisition J.C.; all authors have read and agreed to the published version of the manuscript.

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