Calibrating Perez Model Coefficients Using Subset Simulation

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Abstract. The Perez sky diffuse model has been validated in many locations, however, studies have shown that the precision of estimation can be improved through localization of the model coefficients. This paper studies the effect of tuning Perez irradiance coefficients based on local information for estimating the incident solar radiation on tilted surfaces. The added value of a calibrated Perez model is highlighted by evaluating the heating and cooling energy needs of an office building. Calibration is performed by using Subset Simulation, i.e. a sampling technique based on Markov Chain Monte Carlo. The versatility of the Subset Simulation technique allows for handling multivariant calibration problems and is therefore suitable for finetuning Perez irradiance coefficients. Measurements of global horizontal, direct normal and diffuse horizontal solar irradiation, as well as the global solar irradiation on 90°, 30° and 15° tilted surfaces form the basis of the calibration. It is found that in the studied location, the default Perez model overestimates the incident solar radiation on vertical surfaces facing south. The calibrated coefficients are then embedded in the source code of EnergyPlus. Simulations with a reference office show that the effect of calibrating Perez coefficients can be significant, because it leads to approximately 12% difference in predicted annual cooling energy use and 9% difference in peak cooling loads, respectively.

Keywords: Perez model; Calibration; Subset Simulation; Building energy

1. Introduction

Solar radiation has a significant influence on a building's energy balance, as it affects both the potential for on-site energy generation (e.g. PV or solar thermal) and the indoor contribution of solar heat gains and daylighting. While solar irradiation on horizontal surfaces is measured in numerous locations around the world, the incident solar irradiation on tilted surfaces is mostly calculated through white-box models [1]. Specifically, the diffuse component of global solar radiation on tilted surfaces is calculated by models that transpose the diffuse horizontal solar radiation to diffuse solar irradiation on tilted surfaces, generally referred to as diffuse solar irradiation models. Solar models are mainly developed based on the data available in a few selected locations, which are then extrapolated to the entire globe [2]. The increasing availability of incident solar irradiation measurements on tilted surfaces, especially at PV farms, creates the opportunity to assess the accuracy and performance of solar models in different locations [3–7]. Comparing solar models in different studies reveals that for obtaining more accurate estimations of solar irradiation on inclined surfaces, each location may perform better with a specific (or even a hybrid) solar model [4]. Therefore, finding the best model for a site is not easy since the mismatch between measurements and calculations can come from either the model or the measurements [8].

Among solar models, the Perez Model is frequently used in building energy simulation [9]. The model calculates diffuse irradiation on tilted surfaces based on estimations of the brightness and clearness of the sky [10]. Different approaches have been proposed to calibrate the Perez model to a specific location. Sun et al. proposed an uncertainty quantification of Perez parameters through fitting regression on a selection of parameters [11], resulting in an improved version of the Perez model for the intended location. As an alternative approach, Yang et al. used a "Least Square Method" to optimize the Perez irradiance coefficients for tropical sky conditions, stressing that the intended location was not among the original experimental data used to develop the Perez model [12].

In this study we propose a new method to tune the Perez model for a specific location. This process involves Subset Simulation, which is based on Markov Chain Monte Carlo and Importance Sampling. The effect of using a calibrated Perez model is evaluated on the incident solar irradiance on vertical surfaces, as well as cooling and heating loads of a building. The method proposed in this study can successfully adapt Perez coefficients to local measurements and is easy to implement in building energy simulation models.

2. Calibration method

2.1 Subset Simulation

In this study, we opt for Subset Simulation (SuS) to calibrate Perez solar coefficients. The application of SuS for calibration of different models has previously been adopted by Gong et al. [13]. This technique is specifically useful for complex models with high dimensions of uncertain variables and can reduce the computational time of the process. The method shifts rare probabilities to more frequent events, by resorting to Markov Chain Monte Carlo sequence, i.e. rejecting unwanted samples that have higher errors [14]. The SuS framework adopted in this study is presented in Figure 1.
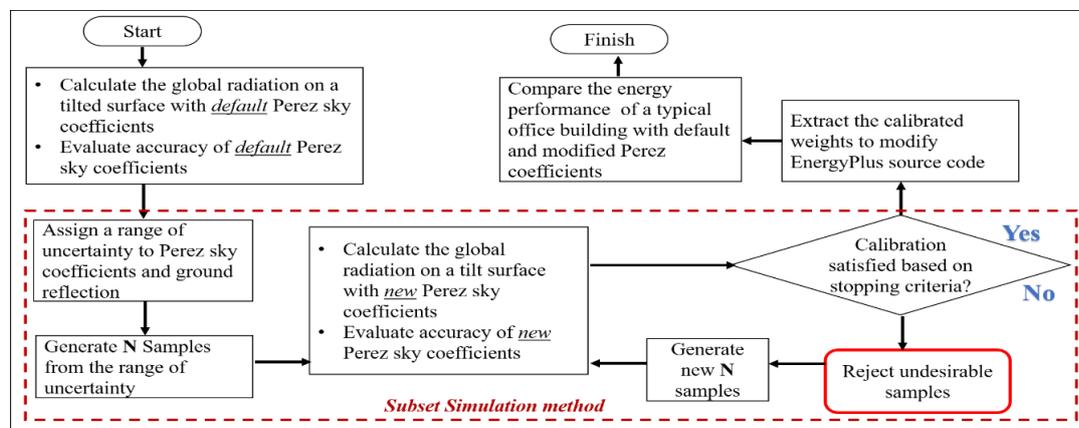

Figure 1. Framework of calibration method using Subset Simulation

2.2 Uncertain parameters

Global irradiation on tilted surfaces is calculated from direct, sky diffuse and ground reflected irradiation. Among the three components, sky diffuse irradiation has been reportedly associated with the largest amount of uncertainty [11]. In the Perez model, sky diffuse radiation is calculated through a series of predefined irradiance coefficients (See Table 1 in [10]). Irradiance coefficients in Perez model are presented for eight sky categories (e-Bins), which vary from overcast to clear sky conditions. To decrease the number of uncertain parameters and avoid multi-modality, second order curves are fitted to e-Bins values. Converting the bins to curve equations reduces the number of uncertain parameters from 48 to 18. Therefore, instead of using the actual values of Perez coefficients, the coefficients of polynomial equations are used in the SuS calibration. The total radiation incident on a tilted surface is also affected by the reflected solar radiation from the ground. Since the ground reflected radiation is

composed of both direct and diffuse radiation and considering that the diffuse component is the subject of the study, the albedo of ground is also associated with uncertainty and subject to calibration.

2.3 Gaussian Mixture Model

Ground reflection and Perez irradiance coefficients are the parameters that are associated with uncertainty for calibration. Therefore, the study deals with a multivariate distribution of uncertain variables, composed of 19 different parameters in total. To represent the covariation of all uncertain parameters within a single matrix, we opted for a Gaussian Mixture Model (GMM). The GMM creates a k multivariant distribution, where k is the number of random (or uncertain) parameters [15]. In this study, MATLAB scripting is used to create a pipeline of functions for implementing the SuS.

3. Case study

3.1 Data description

This study is developed based on sub-hourly measurements of solar irradiation, which are provided by SEAC/SolarBEAT. The measurement site is located at Eindhoven University of Technology with 51.4° N, 5.5° E latitude and longitude, respectively. All measurements are performed with secondary class pyranometers from EKO Instruments B.V., which are installed perfectly due south. Table 1 provides an overview of datasets utilized in this study. It should be noted that for performing building energy simulations, we used measured horizontal diffuse irradiation rather than the traditional diffuse irradiation in typical weather data files. Therefore, the global, direct and diffuse horizontal solar irradiation in the TMY file are replaced with that of measured data. This is important as we want to assess the specific effects of calibrating Perez with real measurements.

Table 1. Availability of measured data

Quantity	Tilt	Time steps	Period of data
Global, diffuse and direct irradiation	0°	15 minutes	2015-2017 / 24 months
	0°	1 minute	2017-2018 /10 months
Global irradiation	90°	15 minutes	2016-2017 /15 months
	30°	15 minutes	2015-2016 /12 months
	15°	1 minute	2017-2018 /10 months

3.2 Model implementation

Prior to performing the calibration, measured solar irradiation datasets are divided in two portions; a training set and a test set. The training data consists of 70% of the measurements which are randomly selected from the entire dataset. The remaining 30% are used solely for testing the performance of the model after calibration. To increase the probability of sampling from the "area of interest" with smaller errors, it is necessary to define a threshold, based on which unwanted samples are rejected. In this study the performance of the MCMC is evaluated based on the Euclidean distance between absolute zero and a custom measure dubbed the "Threshold", i.e. equation (Eq.2). The Threshold is calculated from the CV_RMSE (%) and MAE of all datasets with various tilts.

$$Threshold = \begin{bmatrix} (CV\_RMSE_{Tilt\,90})^2 + (MAE_{Tilt\,90})^2 + (CV\_RMSE_{Tilt\,30})^2 + \\ (MAE_{Tilt\,30})^2 + (CV\_RMSE_{Tilt\,15})^2 + (MAE_{Tilt\,15})^2 \end{bmatrix}^{1/2} \quad \text{(Eq.2)}$$

Where:

$$RMSE = \left[\frac{1}{n}\sum_1^n (GI_{Measured} - GI_{Simulated})^2\right]^{1/2} \quad \text{(Eq.3)}$$

$$CV\_RMSE = RMSE \left(\frac{1}{n}\sum_1^n GI_{Measured}\right)^{-1} \quad \text{(Eq.4)}$$

$$MAE = \frac{1}{n}\sum_1^n |GI_{Meas} - GI_{Simulated}| \quad \text{(Eq.5)}$$

The output of SuS are the calibrated parameters i.e. ground albedo and Perez sky coefficients. The calibrated ground reflectance returns a value of 0.1, which is notably smaller than the default value (0.2) but can be explained by the fact that a black rubber mat is placed below the pyranometers in the experiment. The Perez sky clearness coefficients fitted to Eindhoven sky conditions are presented in Table 2. The performance of the calibration process is reported in Table 3. The improvement of estimation using a calibrated model, is evaluated on the test dataset. The highest improvement was observed for 30° of tilt, reducing the RMSE from 57.6 W/m^2 to 36.6 W/m^2. This improvement was slightly smaller for the 90° estimations with the calibrated model.

Table 2. The numeric value of Perez irradiance coefficients before and after calibration for Eindhoven sky. Default coefficients (left) and calibrated coefficients (right).

e-Bin	F11	F12	F13	F21	F22	F23
1	-0.008	0.588	-0.062	-0.06	0.072	-0.022
2	0.13	0.683	-0.151	-0.019	0.066	-0.029
3	0.33	0.487	-0.221	0.055	-0.064	-0.026
4	0.568	0.187	-0.295	0.109	-0.152	-0.014
5	0.873	-0.392	-0.362	0.226	-0.462	0.001
6	1.132	-1.237	-0.412	0.288	-0.823	0.056
7	1.06	-1.6	-0.359	0.264	-1.127	0.131
8	0.678	-0.327	-0.25	0.156	-1.377	0.251

e-Bin	F11	F12	F13	F21	F22	F23
1	0.2437	0.7074	-0.1881	0.0966	0.4489	-0.0015
2	0.2895	0.6334	-0.2001	0.1138	0.4253	0.0046
3	0.3733	0.4996	-0.2221	0.1453	0.3824	0.016
4	0.5033	0.2962	-0.2567	0.1944	0.3166	0.0345
5	0.7094	-0.0111	-0.3127	0.2737	0.2153	0.0665
6	1.0058	-0.3888	-0.3988	0.3932	0.0816	0.124
7	1.2305	-0.5363	-0.4759	0.4957	0.0063	0.1924
8	0.9992	0.4676	-0.469	0.4632	0.2442	0.2741

Table 3. Statistical analysis

	Training set						Test set		
	Original Perez			**Calibrated Perez**			**Calibrated Perez**		
	South 90°	South 30°	South 15°	South 90°	South 30°	South 15°	South 90°	South 30°	South 15°
RMSE	37.56	57.67	55.46	32.15	36.62	40.17	32.93	36.17	40.49
CV-RMSE (%)	13.95	13.91	21	11.93	8.83	15.21	12.38	8.87	15.67
MAE (W/m^2)	27.17	40.07	40.37	22.33	25.67	28.07	22.3	25.42	27.74

4. Result and discussion

The effects of opting for a calibrated Perez model and how it impacts building's estimated energy performance is discussed in this section. Therefore, the original sky clearness coefficients from Perez are replaced with the calibrated coefficients in EnergyPlus software, and both the original and calibrated sky models are tested on a typical building energy model. In this study, we perform the comparisons on an energy model that is characterized based on ASHRAE's large office reference building. To have a more robust observation of the calibration's impact, a single thermal zone oriented due south is selected. The area of the studied zone is 340.72 m^2 and the studied zone is preserved from the adjacent indoor spaces by considering internal boundary conditions as adiabatic. In this study, the term "Base-EP" refers to the default EnergyPlus code with original Perez coefficients, and a ground reflection of 0.2. The term "Modified-EP" refers to the modified EnergyPlus code with calibrated Perez parameters and a ground reflectance of 0.1.

Figure 2 (Left) indicates that the calibrated implementation of the Perez model returns different estimations of incident solar irradiation on vertical surfaces. It is understood that the Base-EP overestimates incident solar irradiation on south facade. Also, it can be clearly observed how the calibrated model Perez shifts the estimations of solar irradiation with Modified-EP to real measurements. In free-floating conditions, indoor comfort is strongly correlated by the building's boundary conditions, and therefore, any changes in the surrounding environment can affect the indoor comfort conditions.

This said, the estimations of solar irradiation are among the parameters that affect the solar heat gains, and therefore the indoor temperature as displayed in Table 4. The Modified-EP reported a smaller frequency of temperatures in the comfort bound while the frequency of heating hours (T < 20 °C) is increased.

Table 4. Indoor temperature frequency in free-floating conditions

Indoor air temperature (℃)	Base-EP (hours)	Modified-EP (hours)
T < 20	5805	6067
20 ≤ T ≤ 26	2715	2522
T > 26	240	171

We also compared the building's heating and cooling loads using both default and modified EnergyPlus models. The results of annual heating and cooling loads reveal that the overestimation of solar irradiation by EnergyPlus mostly affects the cooling loads (Table 5). Consequently, the default Perez model overestimates the annual cooling load by approximately 12%, in the considered climate context. Moreover, the difference in the peak cooling loads obtained by the two models is significant (9%). On the other hand, it can be argued that the variation of annual heating energy use and peak heating load are negligible.

Table 5. Effect of calibrated Perez model on the estimations of heating and cooling loads

Case	Annual energy (MWh)		Peak load (kW)	
	Heating	Cooling	Heating	Cooling
Base-EP	21.72	15.52	37.82	11.83
Modified-EP	22.48	13.75	37.87	10.85

Since the frequency of peak loads can affect the system sizing process, a cumulative distribution of all cooling loads is provided in Figure 2 (Right). It is observed that when opting for a 90% reliability, the Base-EP returns a cooling load of 5569 W, which corresponds to a cooling system with at least 5500 W of capacity. Meanwhile, the Modified-EP returns a cooling of 4933 W for the same level of reliability (90%), which corresponds to a smaller system with capacity of 5000 W.
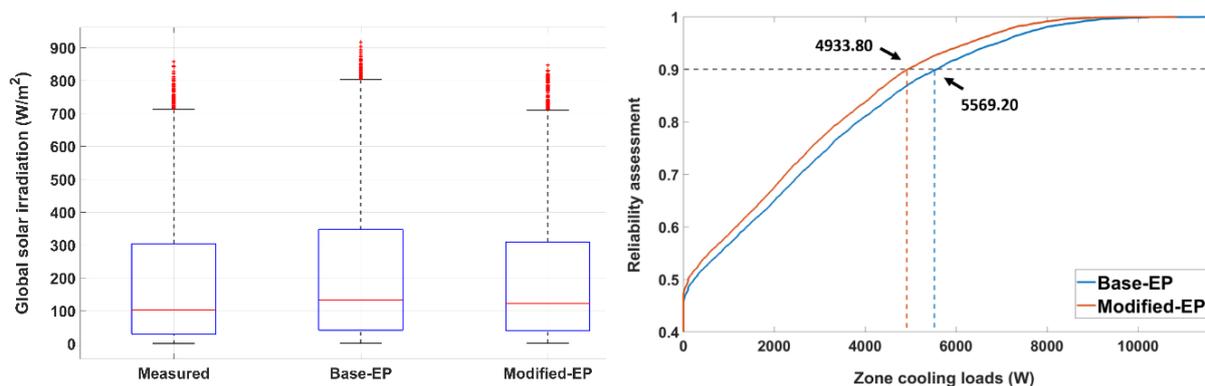

Figure 2. Comparison of incident solar irradiation on vertical surface (Left), Reliability assessment of the proposed cooling system (Right).

5. Conclusion

In this study, we proposed a method for calibrating the Perez sky diffuse model using Subset Simulation. The calibration method focused on ground reflection and Perez irradiance coefficients, by using measured global solar irradiance obtained from three different tilts and a horizontal surface. Also implementing the calibrated Perez model into building energy simulation tool EnergyPlus, revealed an

overestimation of incident radiation on vertical walls where annual mean absolute error is reduced from 14 to 4 W/m^2. This resulted in overestimating the cooling loads by approximately 12 % for Eindhoven climate. More accurate calculation of solar irradiations in the context of building energy performance can also be important in estimating the performance of BIPVs, and therefore expanding this study to the envelope's solar potential can further underline the importance of using calibrated solar models.

Since in this study the measured data were only available for the south orientation, concluding about the numerical effect of calibration on building's energy performance is not finalized. Therefore, the proposed framework can be adapted to other case studies with measured data in all orientations and is a potential for future studies.

Acknowledgment

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