

1 **Modeling of partially shaded BIPV systems – model complexity selection for early stage**
 2 **design support**

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 4 **Ádám Bognár¹, Roel Loonen¹, Jan Hensen¹**

5 ¹Building Physics and Services, Eindhoven University of Technology, Eindhoven, the Netherlands
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Abstract

In the early stages of the building design process, when building energy simulations have the most potential to make an impact, a key role of the building energy modeler is decision-support, with fit-for-purpose lightweight models. As with other subdomains of building performance prediction, finding the right modeling complexity for Building Integrated Photovoltaic (BIPV) systems is challenging, considering that in the early stages of the investigation there is limited available input information, since the BIPV system has not yet been designed in detail. This work targets to aid the modeling decision, by determining in which cases simple (linearly responsive to partial shading) PV system models are applicable for early-stage building design support, and does this through the development and testing of new metrics calculated from high-resolution irradiance simulations as a pre-screening method.

Introduction

The increasing application of BIPV in urban environments goes together with the installation of PV on surfaces where shading caused by vegetation, other buildings or building parts, such as dormers or balconies regularly occurs (Zomer and Rüther, 2017a, 2017b). Considering the trend toward performance-based building design and operation, such new applications lead to a growing need to evaluate the influence of partial shading on PV system performance (Zomer et al., 2016). Depending on the architecture of the power system of a BIPV installation (e.g. stringing scheme and inverter types), the reduction in output due to (partial) shading may not be linearly related to the sunlit fraction or the average irradiance on the PV surface (Bognár et al., 2018; Killinger et al., 2018).

Table 1: Power generation simulation results for an unshaded solar array (ø) and the shading cases (a, b) shown in Figure 1.

Shading case	Sunlit fraction [%]	G _{AVG} [W/m ²]	P _{DC} [W]	P _{DC} [%]
ø	100	1000	5354	100
a	50	600	2581	48
b	50	600	3149	59

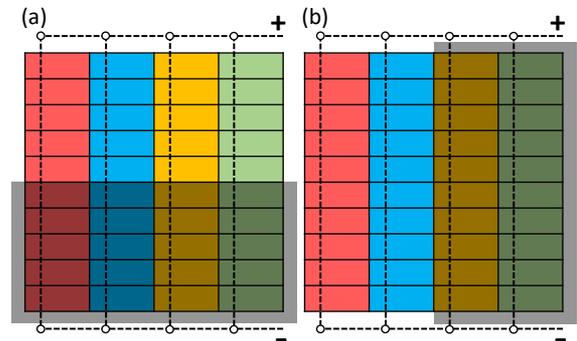


Figure 1: Example of a BIPV façade consisting of four vertical strings (ten modules connected in series) connected in parallel with different shadow arrangements (a) and (b).

Table 1 shows the result of simulations conducted with the tool PVMismatch (Mikofski et al., 2018) to illustrate the non-linear relationship between average irradiance and generated power. In this example, the irradiance is 1000 W/m² on the sunlit modules, and 200 W/m² on the shaded ones. While the sunlit fraction and the average irradiance on the two identical solar arrays (Figure 1a and 1b) are the same, the arrangement of the shadows is different, causing a different power loss.

Simulation tools, such as PVMismatch (Meyers and Mikofski, 2017) and PySpice (Salvaire, 2019) are available to accurately conduct detailed, cell-level electrical simulations for partially shaded PV systems. The biggest obstacles to conduct such detailed simulations – especially in the early stages of the building design – are simulation time, and input information availability about the PV system layout and geometry of the occurring shadow patterns. Moreover, often the building and the PV system model is simulated in separate tools, with separate CAD models, complicating the simulation workflow.

Studies have addressed the issue of simulation time by parametrizing the shade loss model (Dallapiccola et al., 2018; Meyers et al., 2016) aiding PV system designers to evaluate and optimize the stringing design of a PV system by enabling iterative testing of a large number of possible configurations. This approach requires detailed irradiance input, stringing design of the system and the parameters of the used modules, and provides predicted DC power as output. Others have addressed the issue of optimizing the PV system layout on the building surface and battery storage taking economic considerations into account (Lovati et al., 2018). The input in that research project consisted of solar irradiance, electric demand profiles and costs, and the output was the optimized battery capacity, size and position of PV modules on the building surface.

Researchers have demonstrated the potential in linking ray-tracing simulations with detailed electrical and thermal simulation of PV cells in order to conduct accurate simulations of complex BIPV systems (Sprenger, 2013). Others have developed an irradiance-electrical-thermal co-simulation design tool with a planned inclusion of a database of pre-defined BIPV products to bridge the gap between BIPV system manufacturers and building designers (Alamy and Nguyen, 2018).

The scope of the challenge that is being addressed in this paper is slightly different, as it intends to support building energy modellers instead of PV system designers in the early stages of the building design, when only the geometry of the available built surfaces, location and shading environment of the current building design iteration tends to be known. In these situations, the lack of information on the architecture of the BIPV system with the diverse distribution of shadows on it, can induce a high degree of uncertainty in the simulated effect of partial shading on the performance of the BIPV system. Most currently available building energy software, such as IDA ICE, IES VE, Trnsys and EnergyPlus have the capability to model PV yield, however, the power output of the PV models tend to be modeled in a lumped way in these software. The system and module level electrical interconnections cannot be modeled. As a result, the effect of partial shading is taken into account in a simplified, linear way (U.S. Department of Energy, 2018). When simple models are used in a complex case of partial shading, significant overprediction of PV performance is likely to occur, possibly leading to wrong building design decisions or too optimistic return-on-investment estimates. On the other hand, simple models should be used when applicable, to avoid unnecessary modelling work and errors introduced due to assumed model input (Gaetani et al., 2016; Trčka and Hensen, 2010).

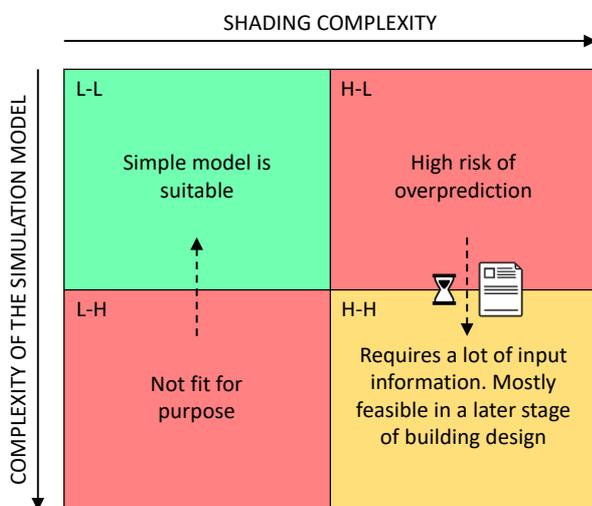


Figure 2: Simplified complexity matrix of BIPV system simulations.

Deciding on the complexity of the applied (irradiance, electrical, thermal) model needs to be done “a priori” and

is therefore a challenging task. The decision is highly case-dependent and although it should be made on the basis of (i) the available input, (ii) the aim of the investigation, and (iii) the complexity of the investigated problem. There is currently no guidance available to assist building modellers during this process.

The current work aims to quantify the *complexity of the investigated problem* for the case of performance predictions of BIPV systems. Figure 2 shows the possible cases of matching the complexity of the modelled problem, and the complexity of the simulation model. Once the complexity of the shading situation is determined, the modeller can make an informed decision to simplify the model - move from L-H to L-L at no cost – or make it more detailed – move from H-L to H-H, which often requires additional input and time. The model pre-screening method that is proposed in this paper aims to support such modelling decisions, leading to models that are fit-for-purpose and can effectively support building design decisions in the early stages of building design. In the Approach section simulation tools are described, which can be used for calculation of the model complexity indicators, which are defined in the following Shade complexity metrics section.

Approach

The work in this paper uses as assumption that the complexity of the irradiance distribution on a PV surface is affecting the linearity of the losses due to partial shading. There is a strong linear correlation between the power output of a PV system and the mean incident irradiance, if the irradiance on the active surface is uniform. On the other hand, the linear correlation is weaker, in the case of a more complex, uneven irradiance distribution. Surface irradiance distributions, which are relatively easy to obtain with state-of-the-art irradiance simulation tools, are the only input necessary to determine the shading complexity of a BIPV system. The discrete, numerically specified solar irradiance function on a building surface can be formalized as:

$$G = f(x, y, t), \quad (1)$$

where the solar irradiance at a given point on the surface (G) is a function of the position (x and y coordinates on the surface) and time (as the solar position and irradiance conditions change at every timestep). The irradiance function is discrete in the spatial domain, because the number of sensor points is finite, and discrete in time, because the simulations are conducted at distinct timesteps of the used weather file. To generate the irradiance function the ray-tracing method of DAYSIM/Radiance (DS/Rad) is used (Reinhart and Walkenhorst, 2001). The necessary inputs are:

- Geometry of the surface in question
- Geometry and reflectance properties of the potentially shadow-casting surfaces of the surroundings
- Weather data for the given location
- Desired density (pts/m²) of the irradiance sensor points
- Irradiance simulation parameters required by DS/Rad

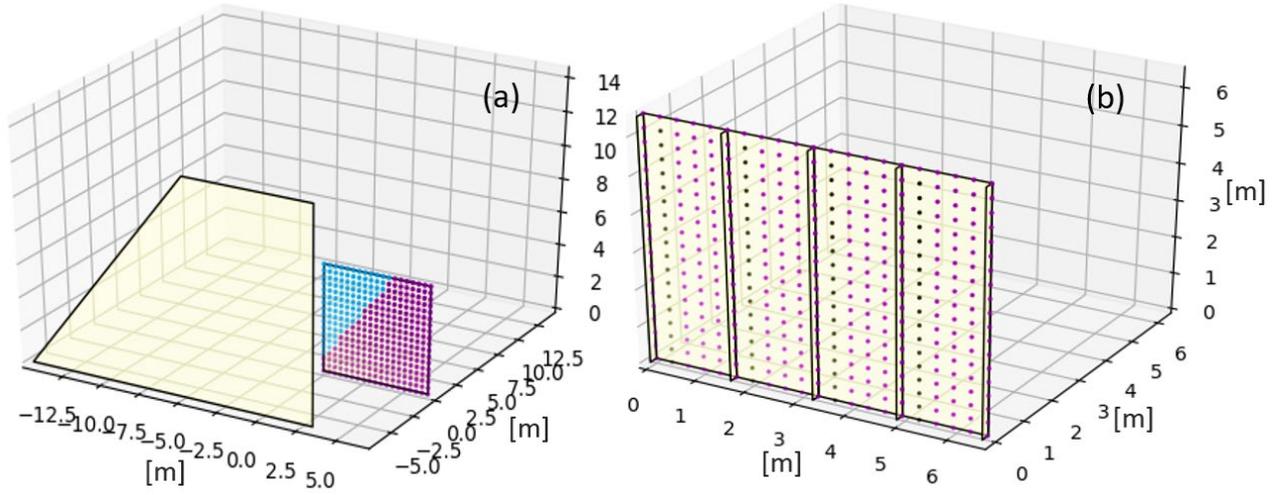


Figure 3: Irradiance simulations of a BIPV facade for an (a) external obstruction, (b) fins on the façade.

To preprocess and execute the irradiance simulations, Daypym (Bognár and Loonen, 2018) was used, which is a Python package developed to:

- Translate EnergyPlus geometry to DS/Rad readable .rad files
- Generate irradiance sensor points based on the desired sensor point density and write the .pts file
- Write the .hea file, that contains DS/Rad simulation parameters
- Manage the file structure and execute the DS/Rad simulations
- Postprocess and visualize the results

Daypym builds on Eppy (Philip et al., 2019) and GeomeEppy (Bull, 2019), and was designed to smoothen the linking of building energy simulations (EnergyPlus) with high resolution irradiance simulations (DS/Rad) and electrical simulations of PV systems (PVMismatch). DS/Rad-PVMismatch simulations are used to emulate reality, and the performance of EnergyPlus' irradiance and simple PV system model is compared to this to quantify the complexity of different shading conditions. The aim is to develop a model pre-screening method, that is capable of determining the applicability of linear PV models for early-phase design support by only analysing the irradiance distribution on the PV system. Three types of geometries were investigated. Two of them are shown in Figure 3 and a third is discussed in more detail in the Case study section.

Shade complexity metrics

In this section, metrics are proposed that attempt to capture the non-uniformity of the irradiance over the investigated façade on a timestep level. The long-term aim is to find a connection between the irradiance distribution and the simulation error of linear PV system models. The first two metrics (SF and G_{AVG}) are commonly used, and can be calculated with EnergyPlus. Calculating the rest of the metrics requires irradiance simulation with a higher spatial resolution, e.g. irradiance simulated with DS/Rad over a sensor point grid, as can be seen in Figure 3.

Sunlit fraction

Sunlit fraction is the ratio of the sunlit surface area (A_{sl}), and the whole surface area (A):

$$SF = \frac{A_{sl}}{A}. \quad (2)$$

This metric can be calculated with EnergyPlus. Its value is 1 in case of a fully sunlit surface and 0 in case of a fully shadowed one. A value of 0 or 1 indicates, that no shadow edges are present on the surface, therefore the irradiance distribution is very close to uniform, however, in reality, some non-uniformity of irradiance might be caused by diffuse shading or reflection from other surfaces, which can only be captured by high-resolution irradiance simulations.

Mean irradiance

Mean irradiance is the most commonly used metric to describe irradiance on a surface. EnergyPlus calculates it from the sunlit fraction and the direct, sky- and ground-diffuse irradiance for a given surface. In the case of DS/Rad simulation, it is the mean of the calculated irradiance values over the sensor point grid. Mean irradiance does not provide information about the distribution of the irradiance, but it is useful for weighting, when calculating aggregated yearly values of other metrics.

Contrast

Contrast is calculated as:

$$C = \frac{G_{max} - G_{min}}{G_{max}}, \quad (3)$$

where G_{max} is the highest and G_{min} is the lowest irradiance on the surface. Most PV modules include built-in bypass diodes, that prevent damage of shaded cells caused by hotspots. When a PV module is partially shaded, the shaded cells act as a resistance, and dissipate energy by heating up. To protect the cells from overheating, the bypass diodes activate and bypass the shaded cells. (Silvestre et al., 2009). As a result, mismatch losses occur in the PV system, and the irradiance incident on the shaded cells is not utilized, which leads to power output that is not linearly proportional to the average incident irradiance on the PV system. Bypass diodes only

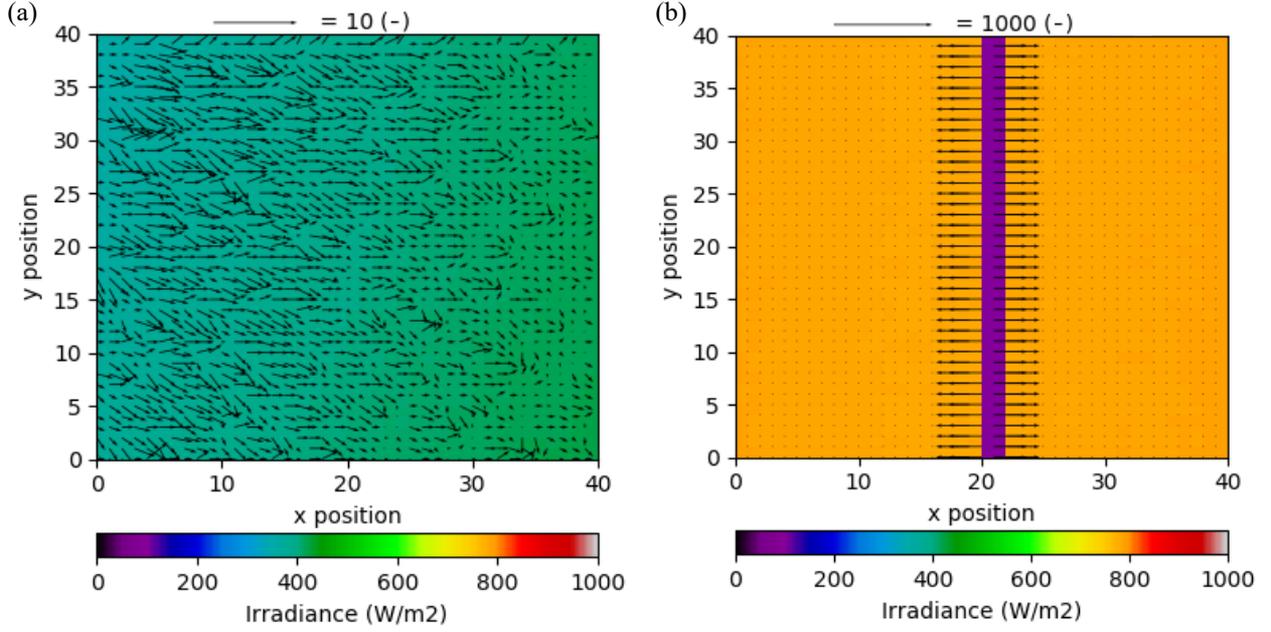


Figure 5: Simulated irradiance values and gradients for a surface with (a) no hard shadows on it, and (b) with the shadow of a pole.

activate, if the irradiance difference between the shaded and non-shaded cells is larger than a certain value (usually around 20% (Solaredge, 2010)). The contrast metric is useful to investigate, whether bypass diodes are being activated in the PV system.

Normalized mean gradient

For this metric, the simulated irradiance values for a grid of sensor points over the PV system is required, (see Figure 3 and 4) to capture the variability of the irradiance on the surface.

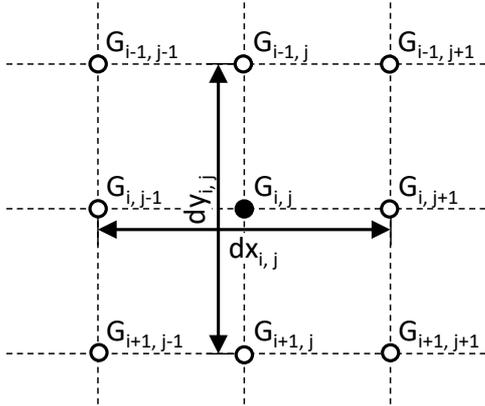


Figure 4: Irradiance sensor points in a grid.

As a first step, for each sensor point, the central differences of the simulated irradiance are calculated for the x direction:

$$dx_{i,j} = \frac{|G_{i,j+1} - G_{i,j-1}|}{2}, \quad (4)$$

and for the y direction:

$$dy_{i,j} = \frac{|G_{i+1,j} - G_{i-1,j}|}{2}. \quad (5)$$

See figure 4 for interpretation of $G_{i,j}$ in the sensor point grid. The resultant gradient for each point can then be calculated as:

$$dxy_{i,j} = \sqrt{\left(\frac{dx_{i,j}}{dx_{max}}\right)^2 + \left(\frac{dy_{i,j}}{dy_{max}}\right)^2}. \quad (6)$$

For an $m \times n$ grid of sensor points, the result is an $n \times m$ matrix of gradients. Note, that we normalized the gradient components with the maximum possible gradient for a given timestep:

$$dx_{max} = dy_{max} = \frac{G_{max}}{2}, \quad (7)$$

to make it independent of the value of irradiance. The normalized mean gradient for a given timestep is calculated as:

$$d_{NM} = \sum_{i=1}^m \sum_{j=1}^n \frac{dxy_{i,j}}{m * n}. \quad (8)$$

Figure 5 shows the calculated dxy for each sensor point represented with an arrow, and the irradiance values with color (note, that the scale of the arrows is different for Figure 5a and 5b). Figure 5a shows the gradient for a surface that is relatively uniform. There are no hard shadows on it. Some non-uniformity is caused by diffuse shading and reflection from the ground causing small gradients between the sensor points. Figure 5b shows a case, when a shadow from a pole casts a hard shadow on the surface, causing a large gradient at the shadow edges. The hypothesis is that if the normalized mean gradient for all sensor points in the matrix for a given timestep is small, then the irradiance distribution is uniform, leading to small simulation error with linear PV system models.

Directionality

If we examine Figure 5a and 5b, we can notice, that the gradients generally have a horizontal direction in both

cases. This means, that the change in irradiance in the horizontal direction is generally larger, than in the vertical one. According to the example shown in the Introduction section, this can provide useful information for PV system design, to determine the direction of module wiring in a way, that the irradiance of a substring is more uniform. For example, in Figure 1a the directionality is negative (horizontal shadows), and in 1b the directionality is positive (vertical shadows). Directionality is calculated as:

$$D = \frac{dx_{i,j} - dy_{i,j}}{dx_{i,j} + dy_{i,j}}. \quad (9)$$

Case study

A case study of a BIPV façade made out of 40 40-cell modules with 134 W_p nominal power each is investigated (see Figure 6). The system with 5354 total DC W_p is shadowed by a pole, to demonstrate if the proposed metrics can predict the usability of linear PV models for performance prediction.

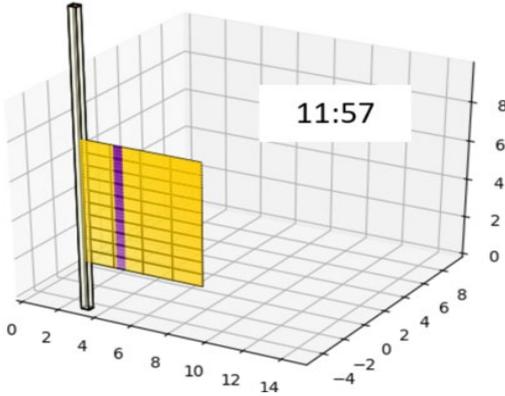


Figure 6: Shadow of the pole on 6th of Mar. at 11:57

Figure 7 shows the results of DC power output simulations with EnergyPlus and with PVMismatch on the 6th of March. In the case of EnergyPlus, the irradiance and PV models are built-in EnergyPlus models, while for the detailed simulations the irradiance is calculated with DS/Rad over a 40*40 sensor point grid and the PV power output is calculated with PVMismatch. Moreover, for the detailed case, stringing information is also provided for a horizontally and a vertically strung PV system case (for the EnergyPlus model, stringing is invariant; it cannot be modelled). The weather input is an hourly IWEC weather file for Amsterdam, the Netherlands.

Results – unshaded period

We can observe in Figure 7a, that when no shadows are present, like at 09:00, (i) there is no difference between the horizontal and vertical stringing case for PVMismatch, and (ii) the difference between the linear EnergyPlus, and the more complex DS/Rad-PVMismatch simulations is small. Most of this small difference comes from the different irradiance model of EnergyPlus and DS/Rad. The simulation was ran with a 5-minute timestep in both cases. While EnergyPlus linearly interpolates the hourly weather file solar data for sub-hourly irradiance

calculations, DS/Rad uses a stochastic model to introduce variation in the upsampled data (see Figure 7b).

Results – shaded period

In the period, when a shadow is present on the surface, like at 11:57, (i) stringing arrangement causes a difference in the power output of the detailed PVMismatch models, and (ii) there is a significant difference between the EnergyPlus and the PVMismatch models. The performance drop of the EnergyPlus model is linearly proportional to the irradiance loss due to shading (i.e. mean irradiance), while in reality and in the case of the detailed model, the performance drop is dependent on the size, shape and position of the shadow, and the PV system layout. It can be observed in Figure 7c, that when d_{NM} is close to zero (low shading complexity), the linear PV model performs similarly to the more complex one, while at high d_{NM} (high shading complexity), the results deviate. The same can be observed in Figure 8, where it is demonstrated, how d_{NM} can be used for predicting the applicability of linear models. Figure 8a shows the result of the linear EnergyPlus simulation, with the d_{NM} values marked with colour. Each dot on the scatter plot represents the simulated power as a function of surface average irradiance for each timestep on the 6th of March. As a result of the analysis of the irradiance distribution, each point was marked with the d_{NM} value. High d_{NM} values indicate that, at the given timestep, the linear model will overpredict the performance. In Figure 8b, results of the simulation with PVMismatch show that, indeed the points with high d_{NM} fell off the linear irradiance-power curve.

Results – directionality

The shadow of the pole in this example is very prominently vertical, causing two sudden transitions in the horizontal direction. This can be observed in Figure 5b, 6 and 7e. When the shadow of the pole is present, D is close to 1, indicating, that almost all change in the irradiance is in the horizontal direction. Using the surface average irradiance (G_{mean}) for weighting, the yearly irradiance weighted D for the BIPV façade is 0.44, indicating that using vertical stringing (as can be seen in Figure 1) instead of a horizontal scheme, leads to smaller mismatch losses on a yearly level due to partial shading.

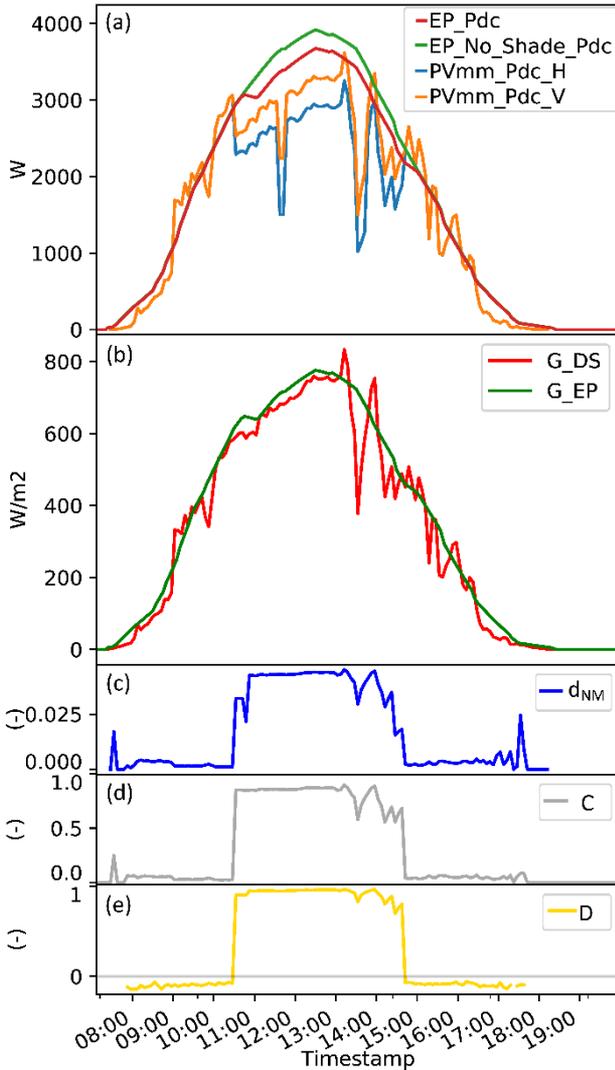


Figure 7: (a) Simulated power with the EnergyPlus PV model and PVMismatch, (b) simulated irradiance with EnergyPlus and DS/Rad, (c) d_{NM} , (d) C and (e) D on the 6th of March.

Conclusions

With the goal of assisting building energy modellers to select the appropriate complexity level of BIPV performance prediction models, this paper has shown the development and testing of indicators that can estimate the occurrence of PV mismatch losses on the basis of irradiance simulations only. The results of the presented case study simulations have demonstrated that the normalized mean irradiance gradient (d_{NM}) can be a good predictor of the applicability of linear PV system models. Moreover, it was shown that the directionality of irradiance/shading patterns can provide relevant input for the purpose of detailed BIPV system design.

Conducting high spatial resolution irradiance simulations only requires model input that is typically available in an early stage of the building design (e.g. PV stringing schemes or inverter types are not needed as input). As such, the approach has potential to be used as a pre-screening method, to verify the validity of assumptions of preliminary linear models, namely that linear PV models

predict the performance well, when the incident irradiance is uniform over the whole surface of the PV system. High values of d_{NM} signal the occurrence of non-uniform irradiance distributions, warning the modeller that the linear PV model is likely to overpredict the performance of the system. Often, design decisions can still be made with such a model. For example if reaching a certain yearly PV yield is required for including BIPV to the design, and this limit is not reached even with the “optimistic” model, the modeller can be certain, that increasing the model complexity will just reduce the predicted yield, therefore the decision can already be made to exclude the BIPV system from the design. On the other hand, if a linear early-stage model predicts that the system just reaches the required yield limit, and the d_{NM} over the year is low, the decision can be made to include BIPV to the building design, as the risk of overprediction with the linear model is low.

Limitations and future work

The current paper is the presentation of an ongoing effort to quantify the complexity of the irradiance distribution on PV surfaces, thus aiding modelling decisions in the early stage of building design. Therefore, the following issues will be addressed in future work:

- What threshold should be used for d_{NM} to accept a linear as model applicable with low risk of overprediction? Based on the presented case study, a $d_{NM} = 0.02$ seems a reasonable threshold, nevertheless, this value can be specific for this geometry and PV system architecture. Therefore, in future work investigation of other case studies, with various geometries will be conducted in order to generalize these findings.
- Is d_{NM} the best metric to evaluate the complexity of irradiance distribution on a surface? According to Figure 7, C and to some extent D can also be a suitable indicator. The correlation between the various indicators, and their potential divergence, will be investigated further by exploring other case studies with various shading scenarios.
- PV system performance is usually evaluated on a yearly level. Therefore, the applicability of linear models should also be evaluated based on yearly performance. While at each timestep the d_{NM} metric can be calculated, it is normalized with the maximum irradiance on the surface. Timesteps with lower irradiance have smaller impact on the annual yield, which should be addressed with a robust irradiance-weighting method for calculating the yearly d_{NM} .

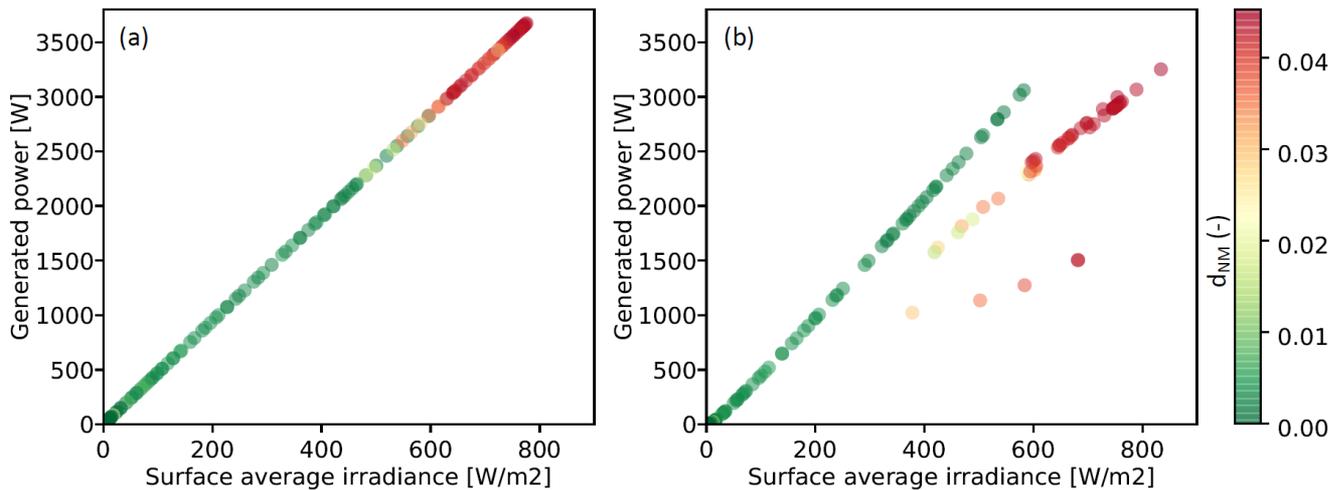


Figure 8: EnergyPlus (a) and PVMismatch (b) PV power simulation results as a function of average surface irradiance on the 6th of March, with d_{NM} marked for each timestep.

Acknowledgements

This work has been supported by the project “PV OpMaat”, financed by the cross-border collaboration program Interreg V Flanders-Netherlands with financial support of the European Regional Development Fund (CCI 2014TC16RFCB046).

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