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

Please check the document version of this publication:

Modeling of partially shaded BIPV systems – Model complexity selection for early stage design support

Ádám Bognár[1], Roel C.G.M. Loonen[1], Jan L.M. Hensen[1]
[1]Unit Building Physics and Services, Department of the Built Environment
Eindhoven University of Technology, Eindhoven, the Netherlands

Abstract

Finding the fit-for-purpose modeling complexity for Building Integrated Photovoltaic (BIPV) systems in the early stages of building design is challenging, because typically at this stage the BIPV system is not yet designed in detail, which limits the applicability of detailed simulation models. This work targets to aid determining in which cases simple (linearly responsive to partial shading) PV system models are applicable for early-stage building design support. To achieve this, a pre-screening method is being developed using new metrics calculated from high-resolution irradiance simulations. The method was tested on different geometries and was proven to be able to predict, under what conditions the linear model would overestimate the PV performance.

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 (Freitas et al., 2015; Moraitis, 2018; 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).

BIPV systems consist of electrically interconnected set of components: the smallest components are the *PV cells*, which convert light to electric current at a specific voltage. Cells are interconnected in series (and sometimes in parallel) to form a *PV module*. Modules are series-connected to form *PV strings*, and strings are often connected in parallel to form a *PV array*. Then the array is connected to power electronics, such as Maximum Power Point (MPP) trackers, inverters and transformers to convert the direct current generated by the PV array to alternating current in a usable voltage range. In this paper we regard the power electronics as ideal systems, that is, we do not consider inverter and MPP tracking losses, as we want to investigate the modeling uncertainties due to non-uniform irradiance on the PV array in their purest form.

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

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

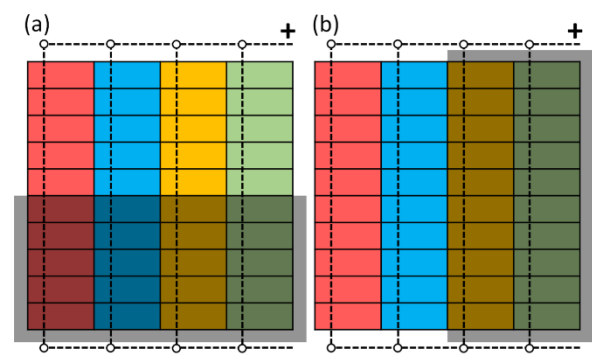| Shading case	Sunlit fraction [%]	G_{AVG} [W/m2]	P_{DC} [W]	P_{DC} [%]
Ø	100	1000	5354	100
A	50	600	2581	48
B	50	600	3149	59

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

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 modelers 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 of the 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 tools, not considering that the elements of the system affect each-other's performance during operation. 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, module-level 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 mean incident irradiance on the PV system. Similar losses can occur on the system level, where the interconnected modules affect each other's performance in case of a non-uniform irradiance distribution. Such system and module level electrical interconnections cannot be modeled in building

performance simulation tools such as EnergyPlus, and as a result, the effect of partial shading is taken into account in a simplified, linear way. When simple models are used in a complex case of partial shading, significant overprediction of PV performance is likely to occur (U.S. Department of Energy, 2018), 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 modeling work and errors introduced due to assumed model input (Gaetani et al., 2016; Trčka and Hensen, 2010).

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 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 modelers 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 modeled problem, and the complexity of the simulation model. Once the complexity of the shading situation is determined, the modeler 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 modeling decisions, leading to models that are fit-for-purpose and can effectively support building design decisions in the early stages of building design.

The structure of the paper is as follows: The used simulation tools are described in the Approach section. Calculation of the model complexity indicators is defined in the following Shade complexity metrics section. The Case study section demonstrates the use of the pre-
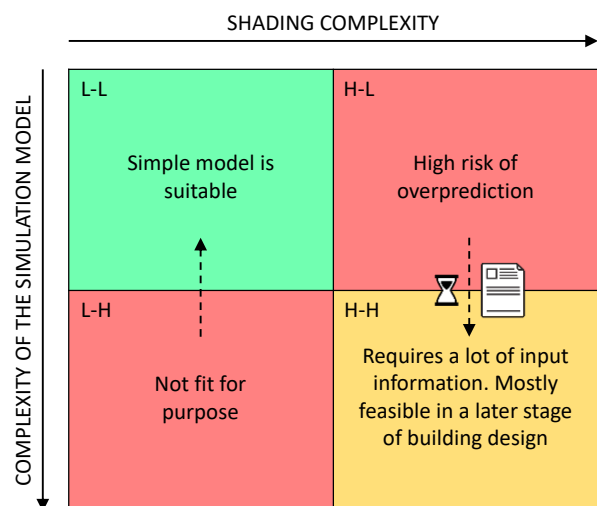

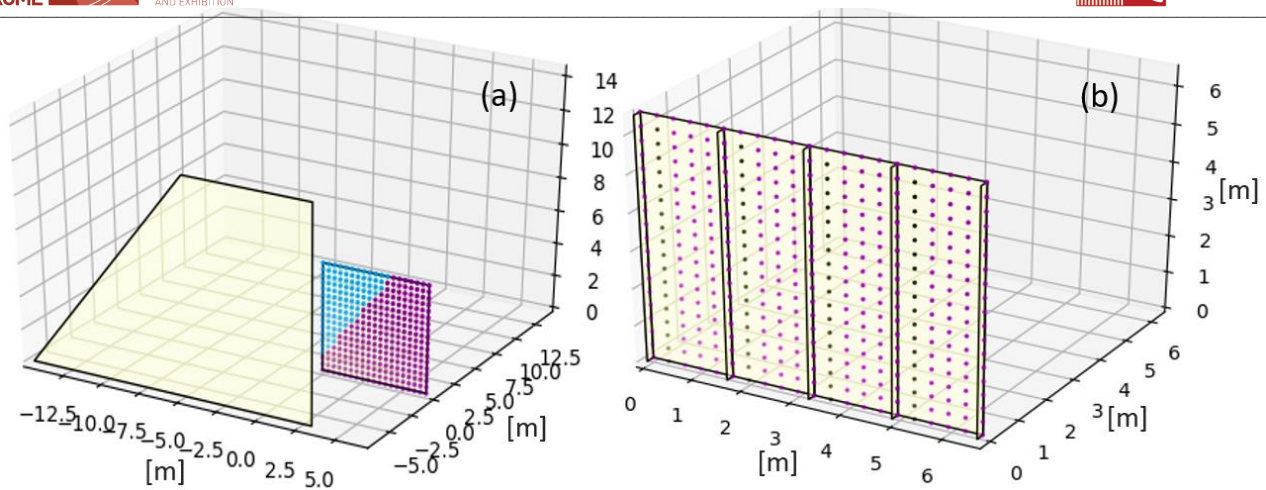*Figure 2: Simplified complexity matrix of BIPV system simulations.*

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

screening method, then conclusions are drawn and plans for future work are described in the last 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:

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

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. 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/m^2) of the irradiance sensor points
- Irradiance simulation parameters required by DS/Rad

To preprocess and execute the irradiance simulations, Daypym (Bognár and Loonen, 2018) was used, which is a Python module 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 GeomEppy (Bull, 2019), and was designed to smoothen the linking of building energy simulations (EnergyPlus) with high resolution irradiance simualtions (DS/Rad) and electrical simulations of PV systems (PVMismatch). In this paper DS/Rad-PVMismatch simulations are used to emulate reality, and the performance of EnergyPlus' irradiance and linear *PhotovoltaicPerformance: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):

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

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 simulations, 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:

$$C = \frac{G_{max} - G_{min}}{G_{max}}, \tag{3}$$

where G_{max} is the highest and G_{min} is the lowest irradiance on the surface. The contrast metric is useful to investigate whether bypass diodes are being activated in the PV system, which might lead to module- or system-level mismatch losses that can only be captured with more detailed PV system models.

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.

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

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

and for the y direction:

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

See figure 4 for interpretation of $G_{i,j}$ in the sensor point grid.
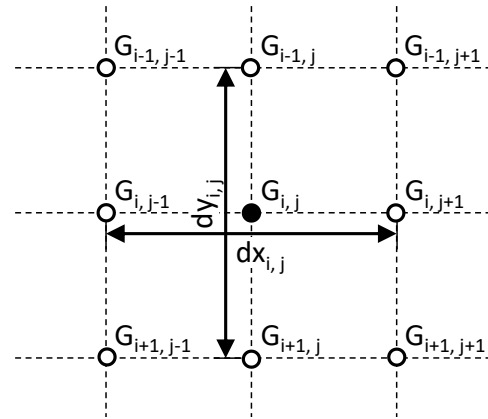
Figure 4: Irradiance sensor points in a grid.

The resultant irradiance gradient for each point can then be calculated as:

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

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

(a)

(b)

Figure 5: DS/Rad simulation of irradiance marked with color, and the calculated gradients marked with arrows for a surface with (a) no hard shadows on it, and (b) with the shadow of a pole.

16th IBPSA
INTERNATIONAL
CONFERENCE
AND EXHIBITION
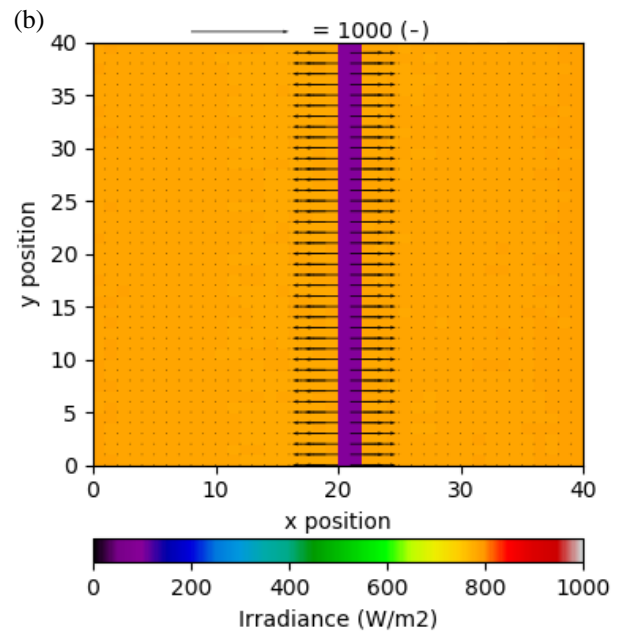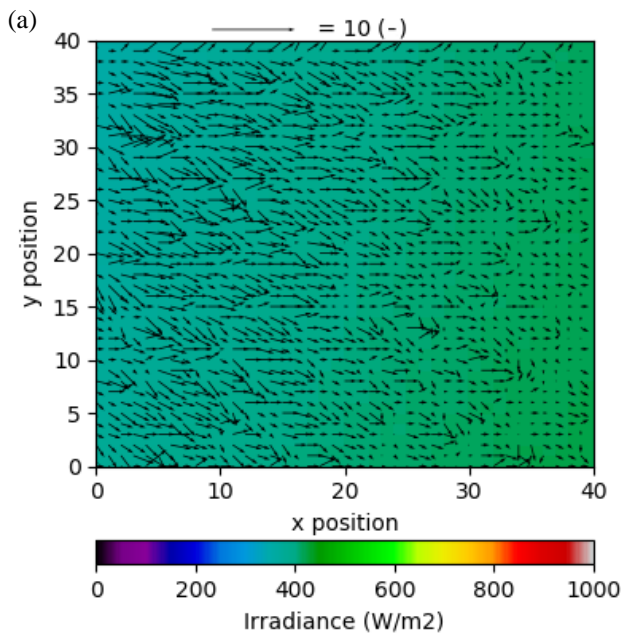
INTERNATIONAL
BUILDING
PERFORMANCE
SIMULATION
ASSOCIATION

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

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

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

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 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 errors 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:

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

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
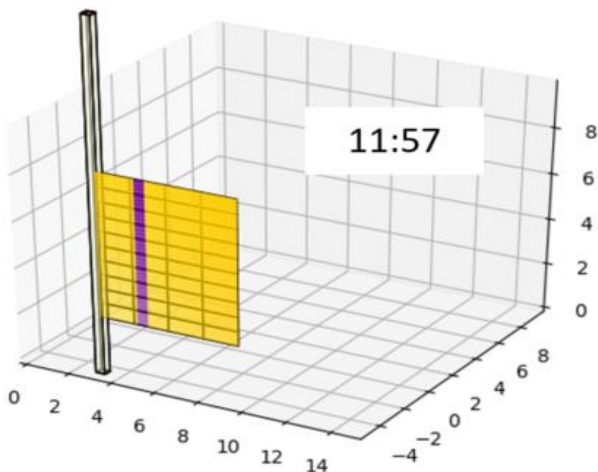

Figure 6: Shadow of the pole on 6th of Mar. at 11:57

(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 7a 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 (one irradiance sensor point for each PV cell) 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 modeled. The weather input is an hourly IWEC weather file for Amsterdam, the Netherlands.

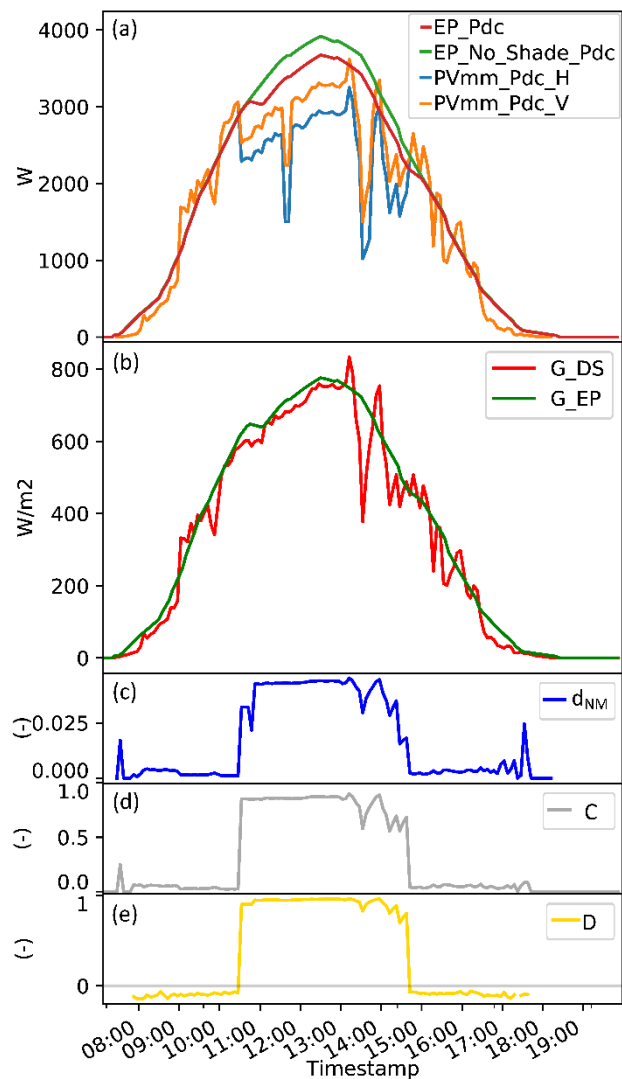**Results – unshaded period**

Figure 7: (a) Simulated power with the EnergyPlus PV model and PVMismatch, (b) Simulated irradiance with EnergyPlus and DS/Rad, (c) Normalized mean gradient, (d) Contrast, and (e) Directionality on the 6th of March.

16th IBPSA
INTERNATIONAL
CONFERENCE
AND EXHIBITION

INTERNATIONAL
BUILDING
PERFORMANCE
SIMULATION
ASSOCIATION

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. 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 (similar to the stringing shown in Figure 1) instead of a horizontal scheme, leads to smaller mismatch losses on a yearly level due to partial shading.

Conclusions

With the goal of assisting building energy modelers 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, without the need of conducting high-resolution electrical simulations. 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 concluded that the proposed indicator for quantifying directionality of change in the simulated irradiance on the surface 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 the 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
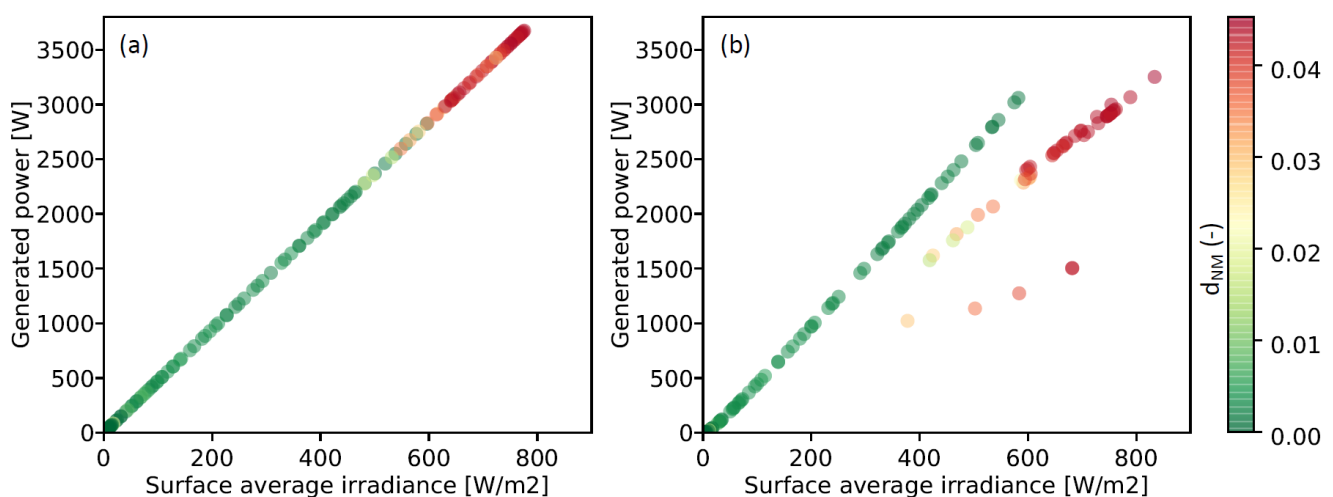

Figure 8: (a) EnergyPlus and (b) PVMismatch PV power simulation results as a function of average surface irradiance on the 6th of March, with d_{NM} marked for each timestep. High d_{NM} indicates that the linear model will overpredict.

modeler 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 modeler 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

Current paper is the presentation of an ongoing effort to quantify the complexity of the irradiance distribution on PV surfaces, thus aiding modeling decisions in the early stage of building design. Future work will address the following issues:

- What threshold should be used for d_{NM} to accept a linear model as applicable with low risk of overprediction? Based on the presented case study, a $d_{NM} = 0.02$ seems to be 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 and SF 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}.

Acknowledgements

References

Alamy, P., Nguyen, V.K., 2018. PVSITES software tools for BIM-based design and simulation of BIPV systems, in: Advanced Building Skins, Bern, Switzerland. Bern, pp. 799–805.

Bognár, Á., Loonen, R.C.G.M., 2018. Daypym Project [WWW Document]. URL https://gitlab.tue.nl/bp-tue/daypym

Bognár, Á., Loonen, R.C.G.M., Valckenborg, R.M.E., Hensen, J.L.M., 2018. An unsupervised method for identifying local PV shading based on AC power and regional irradiance data. Sol. Energy 174, 1068–1077. https://doi.org/10.1016/j.solener.2018.10.007

Bull, J., 2019. GeomEppy project [WWW Document]. URL https://github.com/jamiebull1/geomeppy

Dallapiccola, M., Ingenhoven, P., Moser, D., Stein, J.S., 2018. Simplified Method for Partial Shading Losses Calculation for Series Connected PV Modules with Experimental Validation. 35th Eur. Photovolt. Sol. Energy Conf. Exhib. 1609–1614. https://doi.org/10.4229/35thEUPVSEC20182018-6CO.3.1

Freitas, S., Catita, C., Redweik, P., Brito, M.C., 2015. Modelling solar potential in the urban environment: State-of-the-art review. Renew. Sustain. Energy Rev. 41, 915–931. https://doi.org/10.1016/j.rser.2014.08.060

Gaetani, I., Hoes, P., Hensen, J.L.M., 2016. Occupant behavior in building energy simulation : Towards a fit-for-purpose modeling strategy. Energy Build. 121, 188–204. https://doi.org/10.1016/j.enbuild.2016.03.038

Killinger, S., Lingfors, D., Saint-Drenan, Y.-M., Moraitis, P., van Sark, W., Taylor, J., Engerer, N.A., Bright, J.M., 2018. On the search for representative characteristics of PV systems: Data collection and analysis of PV system azimuth, tilt, capacity, yield and shading. Sol. Energy 173, 1087–1106. https://doi.org/10.1016/j.solener.2018.08.051

Lovati, M., Adami, J., Moser, D., 2018. Open source tool for better design of BIPV + Battery system: an applied exemple, in: 35th European Photovoltaic Solar Energy Conference and Exhibition. pp. 1641–1646. https://doi.org/10.4229/35thEUPVSEC20182018-6CO.4.1

Meyers, B., Mikofski, M., 2017. Accurate Modeling of Partially Shaded PV Arrays, in: 2017 IEEE 44th Photovoltaic Specialist Conference (PVSC). IEEE, pp. 3354–3359. https://doi.org/10.1109/PVSC.2017.8521559

Meyers, B., Mikofski, M., Anderson, M., 2016. A fast parameterized model for predicting PV system performance under partial shade conditions. Conf. Rec. IEEE Photovolt. Spec. Conf. 2016–Novem, 3173–3178. https://doi.org/10.1109/PVSC.2016.7750251

Mikofski, M., Meyers, B., Chaudhari, C., 2018. PVMismatch Project [WWW Document]. URL https://github.com/SunPower/PVMismatch

Moraitis, P., 2018. Urban Environment and Solar PV Performance : https://doi.org/10.3390/en11061333

Philip, S., Tran, T., Youngson, E.A., Bull, J., 2019. Eppy project [WWW Document]. URL https://github.com/santoshphilip/eppy

Reinhart, C.F., Walkenhorst, O., 2001. Validation of dynamic RADIANCE-based daylight simulations for a test office with external blinds. Energy Build. 33, 683–697. https://doi.org/https://doi.org/10.1016/S0378-7788(01)00058-5

Salvaire, F., 2019. PySpice [WWW Document]. URL https://pyspice.fabrice-salvaire.fr

Silvestre, S., Boronat, A., Chouder, A., 2009. Study of bypass diodes configuration on PV modules. Appl. Energy 86, 1632–1640. https://doi.org/10.1016/j.apenergy.2009.01.020

Sprenger, W., 2013. Electricity yield simulation of complex BIPV systems. Delft University of Technology.

Trčka, M., Hensen, J.L.M., 2010. Overview of HVAC system simulation. Autom. Constr. 19, 93–99. https://doi.org/10.1016/j.autcon.2009.11.019

U.S. Department of Energy, 2018. EnergyPlus Input Output Reference.

Zomer, C., Nobre, A., Reindl, T., Rüther, R., 2016. Shading analysis for rooftop BIPV embedded in a high-density environment: A case study in Singapore. Energy Build. 121, 159–164. https://doi.org/10.1016/j.enbuild.2016.04.010

Zomer, C., Rüther, R., 2017a. Simplified method for shading-loss analysis in BIPV systems – part 1: Theoretical study. Energy Build. 141, 69–82. https://doi.org/10.1016/j.enbuild.2017.02.042

Zomer, C., Rüther, R., 2017b. Simplified method for shading-loss analysis in BIPV systems – part 2: Application in case studies. Energy Build. 141, 83–95. https://doi.org/https://doi.org/10.1016/j.enbuild.2017.02.043