A bi-directional approach to building-integrated PV systems configuration

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Abstract. The configuration of local building-integrated photovoltaic (PV) installations can benefit from computational support. Especially in cases where a high degree of energy self-sufficiency is desired, it is important to optimally match the temporal profiles of the building's energy demand and the available solar radiation intensity. Typically, the building's demand profile is taken as given, which is treated as the basis for the sizing and configuration of the PV installation. The computational approach framework introduced in this paper is intended to offer additional functionalities. Specifically, it is conceived to facilitate a bi-directional approach to supporting the design and configuration of PV installations. This approach not only informs the configuration of PV system based on the building's demand profile, but also allows for the exploration of the consequences of the magnitude and temporal profile of the PV's energy supply potential for the values of relevant building design variables (e.g., building orientation, fraction of glazing in the envelope). The paper presents this computational approach and its functionality in terms of an illustrative case study.

1. Introduction
The configuration of local building-integrated photovoltaic (PV) installations can benefit from effective and reliable computational support. Especially in cases where a high degree of energy self-sufficiency is desired, it is important to optimally match the temporal profiles of the building's energy demand and the available solar radiation intensity. In many instances, such a matching is conducted in a mono-directional manner. As such, the building's demand profile is taken as given, which is treated as the basis for the sizing and configuration of the PV installation. The computational framework introduced in this paper facilities this type of matching, but it is intended to offer additional functionalities. Specifically, the developed computational platform is conceived to facilitate a bi-directional approach to supporting the design and configuration of PV installations meant to be integrated in new building projects. Thereby, the idea is to probe pertinent building design variables such as orientation, transparent envelope elements, thermal mass, daylight use, and indoor climate control systems (for heating, cooling, ventilation, and lighting) in terms of the magnitude and temporal distribution of the resulting building energy demand. The proposed bi-directional iterative approach not only informs the configuration of PV system based on the building's demand profile, but also allows for the exploration of the consequences of the magnitude and temporal profile of the PV's energy supply potential for the aforementioned relevant building design variables. In other words, the user can move from the direction of a given building's energy demand profile toward derivation of appropriate PV installation attributes, or from the opposite direction of a given PV-based energy supply profile to explore implications for optimized building design variables. We present this computational approach and its functionality in terms of an illustrative case study.
2. Elements of the computational framework
The computational platform for the aforementioned bi-directional configuration support of building-integrated PV systems entails three components. These components, which are briefly described below, serve the i) parametric computation of a building's energy demand profile, ii) parametric computation of a PV installation's electrical energy generation potential, iii) computation, visualization, and navigation of the values of a number of whole-system performance indicators.

2.1. Energy demand calculation
The computation of the building's energy demand (and its temporal profile) involves a number of steps. In a first step, the geometry of the case study building is modelled in the 3D modelling environment Rhino [1]. In a second step, the geometry model is augmented with required input assumptions by using the integrated visual scripting platform Grasshopper [1] together with the plug-ins Honeybee and Ladybug [2]. Thereby, information about the building with regard to the location, construction, occupancy, equipment load, lighting density, and the heating, cooling, and ventilation system is specified. After the required input data is defined in Honeybee, the building energy simulation are conducted using EnergyPlus [3].

2.2. Computation of PV-based energy generation
The computation of the PV-based electricity made use of the Python programming language. The pvlib-python library was relied on as the source of the simulation methods and models. This library entails a package of functions and classes for PV energy systems modeling [4, 5].

The modeling process requires input concerning the sun position, solar radiation intensity (and other microclimatic information), the orientation of PV panels, and further specifications regarding requisite equipment. EPW (EnergyPlus Weather) data files [6] provide the source of metadata regarding the candidate location's latitude, longitude, and altitude), incident solar radiation (direct normal, global horizontal, and diffuse horizontal), as well as air temperature and wind speed. This data is used to compute solar position [7], optimal tilts, incident irradiance, and generated electricity for each of the applicable location [8].

2.3. Data processing
To estimate the amount of time it takes to recover the cost of a solar PV system investment, one needs to look at two numbers, namely the estimated total system’s lifetime cost and the annual monetary gains from the energy generated by the system. The cost of the former consists of system’s initial purchase and installation price and the lifetime maintenance cost. The estimated purchase cost depends on the solar array size and is based on a market price kW peak (kWp) power (in Austria ca. 1650 €.kWp¹ [9]). The annual maintenance costs are assumed to be at a level of 1% of the initial PV system’s investment cost [10]. Over the assumed lifetime of the system (25 years), the maintenance costs should cover the renewal of the inverters, as well as panel servicing and cleaning. The annual financial gains depend on the energy usage profile of a building, energy generation profile of a PV system, and market electricity prices, both consumption and feed-in tariffs (roughly 0.21 €.kWh⁻¹ and 0.07 €.kWh⁻¹ in Austria [11, 12]). The annual gain is the sum of monetary value of the energy saved through the local coverage of the building’s energy demand and the sale of the surplus energy. Within the framework of a simple payback analysis adopted in the present study, the final payback duration is the ratio of a total lifetime solar PV system cost to the annual monetary gains generated by the PV system.
3. An illustrative case study

3.1. The building
To demonstrate the working of the proposed approach, consider the simple case of a building design project involving a set of eight identical row houses located in a site in the city of Vienna, Austria (see Figure 1). For the purpose of the present illustrative case study, certain attributes of these houses are assumed to be fixed, including overall shape and geometry, the U-value of external walls (0.26 W.m⁻².K⁻¹) and windows (1.21 W.m⁻².K⁻¹), the occupancy density, and the heating, cooling, and ventilation system (electricity based). Other aspects were considered to be open for parametric analysis in conjunction with the PV installation options. Specifically, the façade glazing fraction could be varied (from 20% to 40%), the row of buildings could be rotated to face different orientations, and the ventilation rates could vary from a basic constant rate (0.4 h⁻¹) to options involving summer-time ventilative cooling.

3.2. The PV installation
The technical specification of the solar PV system under consideration corresponds to a typical residential installation quality. The solar panels are considered to have nominal power of 300 W and an efficiency of 17.8%. They are to be connected inverter units with a maximum efficiency of 97.5%. Three aspects of the PV panels array were opened for parameterization, namely the system size (18, 36, 54 kWp), the inclination of the panels (15°, 30°, 45°) and the alignment of the panels (SE, S, SW).

3.3. Illustrative results
As stated previously, the proposed platform allows for the concurrent parametric modelling of both building configurations and PV system configurations. To demonstrate the working of the platform, the illustrative case of a building design project involving eight row houses was considered. This building was to be equipped with a roof-top PV installation. Both building and installation could be subjected to parametric analyses. Given the demonstrative nature of the present treatment, a rather reduced set of both the building and the PV systems was considered for parametric variation. These variables included, in the case of the building block, the orientation of the building, the fraction of glazing in the façade, and the ventilation rates. In case of the PV system, its overall size, as well as the tilt and azimuth (orientation) of the PV panels were considered for parametric analysis. Starting from a base case involving no PV system, it was possible to navigate through the design-performance space with the overall objective of reducing the payback time for the PV installation investment, or to increase the return on investment on such a PV system. Note that, this payback time is focused on the PV installation only, and does not address the expenditures for the building itself. Certain changes in design variables (such as the glazing to wall ratio), however, may influence the building construction investment. Whereas the present case study did not consider the global payback time for both building and PV-system investments as the designated performance indicator, this can be implemented in the system, given the availability of pricing information concerning various building design options. These simplifications notwithstanding, the prototypical implementation of the proposed approach displayed a promising capacity to support the navigation of option space and the convergence toward increasingly high-performance solutions. Note that the proposed navigation strategy is distinct from a one-time optimization approach meant to identify the optimal solution within the design-performance space. Rather, the idea is to support an open user-driven iterative and bi-directional search, thereby exploring different constellations of the building and PV-system attributes in view of their implications for the designated performance indicator.

To exemplify the characteristics of such navigation processes, Figure 2 illustrates a sequence of successive changes to either building or PV systems variables leading to steady reduction of the value of the selected performance indicator, that is, in this case, the payback time for the investment costs of the PV systems and their maintenance expenditures. Note that, due to the difference in the electricity buying and selling prices, the magnitude of the performance indicator, namely payback time, is influenced by the level of matching between the temporal profiles of the building's electricity demand and the PV installation's supply. Obviously, given the assumed pricing scheme, variants that maximize the coverage of electricity demand via PV-based electricity are advantageous. Similarly, building design
solutions that increase electricity demand during low-supply periods lead to the need for increased purchase of high-price electricity and are thus disadvantageous in view of the selected performance indicator. The data set generated through the aforementioned navigation process and depicted in Figure is rather extensive. As such, Figure 2 shows the evolving – continuously improving – value of the performance indicator (payback time, y-axis) over the entire course of the convergence process (x-axis) in terms of the successive states of the designs.

For visualization and analysis purposes, this data can be disaggregated in different ways. For instance, Figure 3 shows the data in terms of three distinct sets, each corresponding to a different overall PV system size. As mentioned before, the various positions in these functions represent different design states (i.e., different concrete constellations of variable values pertaining to the building and the PV system). As such, the changes in the individual variable values cannot be directly observed form this Figure 3. Specifically, Figures 2 and 3 also do not explicitly display the interesting and dynamic back and forth in the evolution of the evolving building-related variables and the PV system-related variables.

To pursue this matter further, we randomly selected a smaller number of design states spread over the trajectory depicted Figure 4. This Figure entails again, for the smallest PV size class (18 kWp) and natural ventilation option, the trajectory of the design variants. The selected instant cases highlighted in Figure 4 are further specified in Table 1, which includes variables related to both the building and the PV system. Thereby, building design variables pertain to the building (orientations E-W, SE-NW, S-N, SW-NE; glazing fraction of the façade in %) and the PV system (PV panel tilt; PV panel azimuth SE, S, SW).

It is instructive to consider the scope of reshuffling in the values of the different variables as represented in Table 1. Both the building's energy demand profile and the PV system's electricity generation profile change with each iteration, and these changes are reflected in the evolving value of the performance indicator (in this case, the payback time for the PV system). Consideration and analysis of this interdependency makes sense, if we consider a building-integrated PV system as a lasting component of a building project. Concurrent consideration of the designs of building and PV system does not mean that strict and undue constraints are imposed on the freedom in the selection of building design features. Interestingly, Figure 4 and Table 1 demonstrate that, for a certain fairly narrow value range of the performance indicator, multiple and diverse configurations of building design variables can provide similar levels of performance.
Figure 2. Estimated payback time for PV system's installation and maintenance cost plotted across the trajectory of the building and PV system variants.

Figure 3. Estimated payback time for PV system's installation and maintenance cost plotted across the trajectory of the building and PV system variants shown for three distinct classes of PV installation sizes.
Table 1. State descriptions of the design variables regarding the building (orientations E-W, SE-NW, S-N, SW-NE; glazing fraction of the façade 20, 30, and 40 %) and the PV system (PV panel tilts 15, 30, 45 degrees; PV panel azimuth values SE, S, SW) for a selected number of design states along the trajectory shown in Figure 4. As with Figure 4, the states in this Table are arranged in descending order of the respective computed payback times in month.

| Building Orientation | Glazing | PV Tilt | PV Azimuth |
|----------------------|---------|---------|------------|
| E-W                  | ✓       | ✓       | ✓          |
| SE-NW                | ✓       | ✓       | ✓          |
| S-N                  | ✓       | ✓       | ✓          |
| SW-NE                | ✓       | ✓       | ✓          |
| Glazing Fraction    | 20%     | 30%     | 40%        |
| Payback time [months]|         |         |            |
| 236                  | ✓       | ✓       | ✓          |
| 228                  | ✓       | ✓       | ✓          |
| 224                  | ✓       | ✓       | ✓          |
| 221                  | ✓       | ✓       | ✓          |
| 217                  | ✓       | ✓       | ✓          |
| 215                  | ✓       | ✓       | ✓          |
| 212                  | ✓       | ✓       | ✓          |
| 211                  | ✓       | ✓       | ✓          |
| 208                  | ✓       | ✓       | ✓          |
| 207                  | ✓       | ✓       | ✓          |
| 206                  | ✓       | ✓       | ✓          |
| 204                  | ✓       | ✓       | ✓          |
| 203                  | ✓       | ✓       | ✓          |
| 202                  | ✓       | ✓       | ✓          |
| 201                  | ✓       | ✓       | ✓          |
| 200                  | ✓       | ✓       | ✓          |
| 199                  | ✓       | ✓       | ✓          |
| 198                  | ✓       | ✓       | ✓          |
| 197                  | ✓       | ✓       | ✓          |
| 196                  | ✓       | ✓       | ✓          |
| 196                  | ✓       | ✓       | ✓          |
| 195                  | ✓       | ✓       | ✓          |
| 194                  | ✓       | ✓       | ✓          |
| 193                  | ✓       | ✓       | ✓          |
| 192                  | ✓       | ✓       | ✓          |
| 191                  | ✓       | ✓       | ✓          |
| 187                  | ✓       | ✓       | ✓          |
Figure 4. Estimated payback time for PV system's installation and maintenance cost plotted across the trajectory of the building and PV system variants shown for smallest PV installation size class and natural ventilation options. Shown are also the positions of a set of randomly selected states with the corresponding payback time expressed in months (see Table 1).

4. Conclusion
We introduced a bi-directional computational approach to the concurrent performance analysis of building designs and respective building-integrated PV system installations. The computational method allows not only for the exploration of the implications of buildings' energy demand profile for the configuration of the PV system, but also the other way around: The PV installation options can be explored in view of their potential implications for buildings' design features. As such, the proposed approach facilitated the parametric and iterative analysis of the both building design and PV configuration variables. Hence, those aspects of the building design could be identified, for which the temporal structure of energy demand and profile may be of relevance.

The key features of this approach were realized in terms of a prototypical computational framework, whose functionality was presented using an illustrative case study. Thereby, a building complex comprising of eight identical row houses was considered, which was to be equipped with a building-integrated PV system. The values of both the building design variables and the PV system variables could be adjusted within certain ranges. The results of operation of this computational framework verified its utility toward the concurrent exploration of the option space pertaining to building and PV system variables. Thereby, it could be demonstrated that a high level of overall performance (expressed, for instance, in terms of the payback time for the PV system) can be achieved with very different constellations of both building design aspects and PV system options. Currently, work is under way to further develop and improve the utility of the computational platform, particularly in view of the ease of data exchange between various components as well as enhanced user-interface for the navigation of the solution space.
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