Stochastic Solar Irradiance from Deep Generative Networks and their Application in BIPV Design

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Abstract. Building Integrated Photovoltaics (BIPV) is a promising technology to decarbonize urban energy systems via harnessing solar energy available on building envelopes. Nevertheless, handling the trade-off between effort, speed and spatial-temporal resolution for 3D BIPV solar potential evaluation in a complex urban context has always been a challenging task. Existing physics-based solar simulation engines require significant manual modelling effort and computing time to obtain high-resolution deterministic results. Yet, solar irradiation is highly intermittent and representing its inherent uncertainty may be required for designing robust energy systems. Targeting these drawbacks, this paper proposes a data-driven model based on Deep Generative Networks (DGN) to efficiently generate high-fidelity stochastic ensembles of annual hourly urban solar irradiance time-series data with uncompromised spatial-temporal resolution at the urban scale. It requires only easily accessible data inputs, i.e., simple fisheye images as categorical masks, such as captured from Level of Details (LOD) 1 urban geometry models. Our validations exemplify the high fidelity of the generated solar time series when compared to the physics-based simulator. To demonstrate the model’s relevance for urban energy design, we apply it to the resilient design of a district multi-energy system (MES) with several hundreds of BIPV surfaces. Furthermore, we showcase the models’ potential for generative design by parametrically altering the urban environment and producing corresponding irradiation time-series in real-time.

Keywords: urban solar potential, data-driven model, BIPV, GAN, VAE

1. Background

Under the challenge of global urban population growth as well as the urgent necessity to tackle climate change, Photovoltaics (PV), including Building Integrated PV (BIPV), is considered as a pillar to decarbonize urban energy systems and bring affordable energy via harnessing solar energy available on building envelopes. Nevertheless, modern cities are formed with complicated mutual shading and reflections, and many building surfaces are not able to provide ideal conditions for solar application, which brings additional uncertainties to the intrinsically fluctuating and intermittent solar energy. Therefore, the evaluation of urban solar potential firstly requires to account for the temporal variations of solar irradiance specific to each building surface under various urban context conditions, i.e., to guarantee high spatio-temporal resolution. Ideally, the evaluation results should also reflect stochasticity.
due to fluctuating solar irradiance and uncertain urban context conditions to ensure the resilience of the BIPV location assessment and system design.

To predict time-resolved BIPV potential on the building surfaces, researchers usually divide the problem into different hierarchical steps and scales [1]. The core step is to obtain annual solar irradiance time-series data on the building surfaces. At the building scale, very accurate results with high spatio-temporal resolution can be obtained through 3D modeling and complex simulations, e.g., using industry-standard engine Radiance [2] and its interface Daysim [3], which requires significant modeling effort. Specifically, modelers need to retrieve local weather data and model the explicit geometries and surface properties of the building envelopes, to accurately calculate the solar beam and diffuse irradiance from the sky subject to the surrounding urban context as well as reflections from surrounding buildings, as shown in Fig. 1 (a). There are several recent studies aiming to speed up the computational process. The most common approach as deployed by Daysim (Radiance), EnergyPlus, or the model from Waibel et al. [4] is to only perform backwards raytracing on typical days and use interpolation to complete a year-long result, which still guarantees satisfactory accuracy. While currently the fastest commercial simulation engine, ClimateStudio [5], additionally exploits progressive path tracing and hardware acceleration to speed up Radiance. On the other hand, open-source GIS databases of urban morphology are released by more and more European cities in recent years. These Level of Detail (LOD) 1 models contain building footprint polygons and height information, i.e., minimally necessary geometric input for 3D solar potential evaluation, which has greatly eased the trouble of 3D modeling.

However, even with these advances, accurate simulations are still not obtainable in real-time, especially at the urban scale. In addition, the results of these simulations are often deterministic, whereas urban solar potential is often subject to uncertainties due to fluctuating solar irradiance and several unavailable urban context factors, e.g., windows, vegetations, etc. Regarding weather, a common strategy is to synthesize Typical Meteorological Year (TMY) weather files from weather data in the several past years. Urban building features are often parameterized as Window-Wall-Ratio (WWR), vegetation-coverage, etc., and multiple simulations under a series of settings of these parameters are executed. Peronato et al. [6] further propose a method to improve the design of TMY to synthesize both typical and extreme weather scenarios and conduct multiple simulations. However, as a single simulation is already rather time-consuming, strategies to cope with uncertainties by relying on multiple simulations are usually limited in practice as well.

Another alternative is to compensate for the simulation approaches via rapid data-driven surrogate models for large-scale applications. This approach usually exploits some machine-learning models trained on simulated ground truth. E.g., Assouline et al. [7] use a 2-stage Support Vector Machine regression model for weather data spatial interpolation and urban BIPV potential estimation. Nault et al. [8] present another workflow to exploit Gaussian Process models for the passive solar potential prediction using simulated results under both randomly generated building geometry blocks and realistic urban morphology for training. Except for the low computational cost, both models allow for prediction with empirical intervals, which is another advantage over the deterministic simulations. In addition, Walch et al. [9] conduct a principled benchmark study on 5 common machine-learning models for urban solar potential prediction and identify Random Forests to achieve the best accuracy.

Nevertheless, these surrogate models by nature lack spatio-temporal resolution. They usually predict the annual cumulative solar irradiation and have to rely on manually designed features to indicate urban context condition, e.g., street width, average building height, etc. These studies therefore generally focus on rooftop PV potential only while neglecting vertical surfaces. However, the BIPV potential on building facades, which could be several times larger in area than the roofs in modern cities, still lack focused data-driven studies due to their more complex and heterogeneous spatial distribution and temporal variations. To fill this gap, we need to develop a new approach that simultaneously ensures speed, accuracy, and spatial-temporal resolution at the urban-scale.

Fortunately, machine learning models continue to evolve, and recent Deep Neural Networks (DNN) can already handle complex and high-dimensional data, such as imagery and time-series data. Deep Generative Networks (DGN) can even create such kinds of data. Variational Autoencoder (VAE) [10]
and Generative Adversarial Networks (GAN) [11] are the most popular DGNs at the moment, both developed originally for computer vision tasks. GAN is specialized in generating very realistic images. VAE is usually behind in generation quality, but very good at compressing images and extracting representations from them. When combined [12], those DGN models can perform a variety of incredible tasks such as image editing, style transformation, etc.

In addition, GAN has also achieved appealing performance to generate synthetic time-series data [13, 14, 15], especially synthetic energy consumption or renewable yield time-series in our domain based on historical measurements or accurate simulated results. The temporal resolution of the generated time-series samples is thus identical to the ground truth. These time-series samples are stochastically sampled conditioned on given location, date, and weather condition, etc.. In addition, inspired by conventional simulation approaches based on shadow mask [4] and sky view factor [16, 17], we realize that a circular fisheye projection image can be an excellent form to represent the sky visibility and urban context conditions in the sunlit hemisphere of a test point on any building surface. Furthermore, such images can be easily captured from open-source urban LOD1 geometry databases. This enables the spatial resolution of our model to be equivalent to that of the simulation engines. Aply, VAE models are able to compress such images and extract low-dimensional representations from them, which can be fed into the downstream time-series GAN as generation conditions. This gives rise to the basic architecture of our proposed model.

The main objective of this research is to develop a data-driven surrogate model based on DGNs that generate high-fidelity stochastic urban solar irradiance time-series data without compromising the spatio-temporal resolution. In the following sections, we elaborate on how we design, train, and validate the model. We focus on how domain insights inspire us to design data pipelines and adapt well-established model architectures. Finally, we exhibit its application potential on district multi-energy systems (d-MES) and solar-driven geometry design. Due to space limitations, we provide details and specifics of the model architecture separately in a preprint [18] while focusing on the application potential here.

2. **SolarGAN - The Proposed Generative Model**

2.1. **Method**

![Figure 1. Comparison of (a). the physics-based simulation workflow and (b). the proposed DGN-based workflow.](image-url)
To develop such a data-driven model, we propose a workflow that contains three steps from data acquisition, processing, to the model design based on several state-of-the-art DGNs, as shown in Fig. 1(b).

We use the open-source whole-city LOD1 building geometry models of Zurich [19] and weather files from five European cities as the simulation input data. All these cities belong to the temperate climate region in the Köppen climate classification system. Thus, we can examine whether our model has sufficient capacity to handle multiple cities with similar weather patterns. We simulate the ground-truth dataset for randomly sampled test points on building facades via the solar simulation engine ClimateStudio, which is also used to generate those aforementioned circular fisheye categorical masks for each test point as an essential input to our proposed model. As Fig. 1(b) shows, such a fisheye image compactly contains the spatial relations of the sky, ground, as well as surrounding obstacles and reflective surfaces to the given test point, comprehensively providing its urban context conditions. We also generate a triplet of ground-truth solar irradiances and paired fisheye images for each test point with three WWR levels for the surrounding buildings during simulation. An example of such a triplet is shown in Fig. 5(a). This intentional design of the dataset enables our model to learn the influence of windows, which is usually an unavailable urban context factor that should be accounted for via parametric study.

| # test points | # image samples | # annual time-series | # train / # test | Weather files                       |
|---------------|-----------------|----------------------|-----------------|-------------------------------------|
| 5000          | 15000 (3 WWRs)  | 75000 (5 locations) | 4:1             | Geneva, Milan, Paris, Berlin, Zurich |

As shown in Fig. 1(b), these fisheye categorical mask images are further reprojected to unfolded semi-cube-maps, with one-hot-encoded (multiple binarized channels) pixel-wise categories. Such image formats are concise while the image features remain identifiable after shifting and scaling, which is preferred by Convolutional Neural Networks (CNN) that are specialized to deal with images. As per the weather time-series data input, i.e., Direct Normal Irradiance (DNI) and Diffuse Horizontal Irradiance (DHI), we note that only drawing some statistics, e.g., peak and average values, could be a simple but effective way that avoids model complexity [14] and allows for more flexible generation that do not strictly follow the deterministic weather patterns in the weather file. As a time-series with 8760 steps is too long for any time-series DGN, we experimentally let the model generate patches by weekly sliding windows. Therefore, the weather statistics are also drawn in weekly segments. As shown in Fig. 1, except for images and weather statistics, auxiliary conditional input of a test point for generation also includes longitude and latitude of the weather file location, as well as height and surface normal vector of the test point. Both are easily acquirable from the LOD1 model.

Finally, we design the model architecture of the SolarGAN, which consists of two main components, as shown in Fig. 1(b). The first component combines a VAE with a GAN, which both are CNN-based, as proposed in [12], to deal with images. The image encoder within the VAE extracts low-dimensional image representations of the urban context condition from the high-dimensional fisheye categorical masks. It also informs the combined GAN, which "edits" the original fisheye image accordingly when the values of some extracted low-dimensional representations are changed. This enables an auxiliary functionality, i.e. providing visual aids to the user's parametric input and finding the proper value ranges, when performing some parametric studies, e.g., adjusting the WWR of the surrounding context. In Section 3.2 this capability will be illustrated in detail. The second component is a conditional time-series GAN, which is designed based on [13], a Recurrent Neural Networks (RNN)-based GAN model. It fuses the VAE-extracted urban context low-dimensional representations together with other conditions for each test point and generates an ensemble of annual solar irradiance time-series for each one, which are
consistent with the given conditions while exhibiting stochasticity in terms of weather patterns. The details and specifics of the SolarGAN model architecture are provided in another preprint [18].

2.2. Model Validation
A typical generated ensemble of annual hourly solar irradiance time-series on a test point is shown in Fig. 2. It can be observed that each individual sample within the generated ensemble differs in detail from the ground truth, but the trend of the whole ensemble is consistent.

We further quantitatively validate the fidelity of the generated samples on a population basis using some common statistical metrics. We consider the fidelity mainly from the following two aspects:

1. **Value distribution**: similar to [14] we measure the similarity of solar irradiance value distribution between ground truth and generated samples using Jensen-Shannon Divergence (JSD) for both raw hourly values and annual cumulative values. As a rule of thumb, when the JSD is lower than 0.1, then two distributions could be considered as very similar [14].

2. **Temporal trend**: including both short-term and long-term trends. For short-term, we consider the daily peak hour characterize the specific location and urban context for each test point, we could still use JSD to measure the distribution similarity between ground truth and generated samples, respectively. For the long-term trend, annual autocorrelation curve on daily cumulative irradiation is a classic indicator [20], which ranges from -1 to 1. We use Mean Absolute Error (MAE) to calculate the discrepancy between the autocorrelation curves of generated samples and that of the ground truth. The lower the MAE, the better the consistency.

![Figure 2](image)

**Figure 2.** A typical generated ensemble of annual hourly solar irradiance time-series, with local zoom in on a monthly segment and weekly segment, in comparison to the ground truth.

Table 2 summarizes the statistical validation results. It can be seen that for raw hourly irradiance values and temporal trends, the fidelity of generated samples is good. In case of long-term cumulation, the fidelity with respect to value distribution seems to be compromised, but is still satisfactory. These results prove the basic feasibility and effectiveness of our model. The weaker performance for long-horizon predictions (i.e., annual) however suggests that longer generation windows, e.g., monthly, should also be explored. The results do not show obvious variation across cities, suggesting that one model is able to account for several cities as long as they share similar weather characteristics.
Table 2. Statistical validation results on the fidelity of the generated time-series samples using weather files from 5 different cities

| City   | Value distribution | Temporal trends |
|--------|--------------------|-----------------|
|        | Hourly-JSD         | Annual-JSD      | Peak hour-JSD | AC-MAE |
| Geneva | 0.047              | 0.161           | 0.120        | 0.044  |
| Milan  | 0.040              | 0.152           | 0.083        | 0.040  |
| Paris  | 0.048              | 0.153           | 0.071        | 0.041  |
| Berlin | 0.044              | 0.173           | 0.070        | 0.041  |
| Zurich | 0.053              | 0.176           | 0.054        | 0.040  |

2.3. **Computing Time**

We also conduct a simple test of the computing time, as speed is one of the major advantages of data-driven approaches. Specifically, we sample 10 new test points scattered over the LOD1 model and repeat all the necessary workflows in our model to generate solar time-series ensemble and modifying context WWR, as shown in Table 3. We also let ClimateStudio simulate solar irradiance for these 10 test points for comparison.

Table 3. Computing time evaluation (seconds), in comparison with the performance of ClimateStudio.

| Operations in ClimateStudio | Operations in SolarGAN | Data acquisition & processing |
|-----------------------------|------------------------|-------------------------------|
| Full simulation             | Extracting image       | Rendering fisheye*            |
|                             | representations         | Reproject to cube-map         |
|                             | Generating time-series |                                |
|                             | ensemble (ensemble size: 10) |                                |
|                             | Editing images (4 WWRs) |                                |
|                             |                        | 5.12                          |
|                             |                        | 0.02                          |
|                             |                        | 0.48                          |
|                             |                        | 0.49                          |
|                             |                        | 63.72                         |
|                             |                        | 0.59                          |

* Rendering complicated fisheye image in ClimateStudio is not necessary in the deployment stage.

All the operations in the DGNs are almost real-time and take less than one second, even though we enable ensemble time-series generation as well as traversing several times in the latent dimension of WWR. Nevertheless, the speed of the entire data pipeline is impacted by rendering the fisheye image. However, as we only need simple categorical masks, as shown in Fig. 1(a), fully raytraced high-quality renderings would not be necessary. Instead, simple screenshots from the geometries would be sufficient, and these could be captured in real-time. Under these assumptions, our proposed workflow is ~3.5x faster than simulations using ClimateStudio. Additionally, it creates stochastic ensembles and is capable of generative parametric alterations of the urban scenery.

3. **Applications of the Proposed Model**

After demonstrating the fundamental viability of the approach, we introduce two application scenarios to demonstrate how it can support multiple downstream tasks and why it has great potential to effectively incorporate uncertainties inherent to solar irradiance. First, our model can provide fast and stochastic boundary conditions for simulating and optimizing design algorithms of urban multi-energy systems (MES) from the community to the district scale. Due to the intermittent nature, urban BIPV systems have to be designed together with other energy generation, conversion and storage systems to maximize self-consumption of PV generation. The stochastic ensemble of solar irradiance created by our model is thus able to support resilient decision-making for integrated d-MES design. Additionally, our model’s capabilities of editing urban context conditions represented by fisheye images and generating
corresponding solar time-series allows new solar-driven parametric geometry building design approaches without explicit 3D representation. In the following section, we elaborate on these two potential applications to exhibit both potentials and limitations that need to be explored in depth in future work.

![Figure 3](image-url)

**Figure 3.** LOD1 geometries of “Suurstoffi” for the 2 application cases: (a) District-level MES design, 4 test points (green dots) sampled per building surface. (b) Example sensor-point for the building-level parametric design. (c) Deterministic solar potentials of the district (from [22]).

### 3.1. Application 1: Resilient Optimal d-MES design

Since proposed by Geidl et al [21], the Energy-hub (E-hub) approach has been developed as a concept for MES design. In this approach, several critical sub-tasks, e.g., technology selection and equipment sizing, annual hourly energy flow, as well as the economic payback and emission abatement performance of the MES are modelled together as a standard Mixed-Integer Linear Programming (MILP) problem and solved at one stop. Nevertheless, E-hub still requires high-resolution energy demand and site environmental condition data as input. Solar irradiance data on building envelopes via simulation represents an existing bottleneck. Our model could address this limitation, especially for stochastic scenario analysis. Compared to conventional deterministic solar profiles that are derived from weather data, our stochastic ensemble accounts for more fluctuation and alternating cloudy and sunny periods, which is expected to facilitate the optimization model to cope with the intermittent nature of solar irradiance and to make more resilient decisions.

To demonstrate this, we modify the case study based on a d-MES E-hub from [22], which investigates a community with mixed residential, commercial, and educational buildings, called “Suurstoffi”, which locates near the lake of Lucerne in Switzerland, as shown in Fig. 3(a). These buildings possess 170,000 m² of total floor area as well as 193 roof and façade surfaces for BIPV (42,325 m²). This time, for the 160 façade surfaces (each divided into 4 patches with 4 test points sampled correspondingly, as Fig. 3(a) shows), we simulate solar irradiance using ClimateStudio and generate the stochastic ensemble using our model for comparison. The ensemble size is set to 40 (i.e., 40 stochastic solar irradiance time series per test point). All the energy demand data and candidate technology settings remain unchanged, as described in [22].

![Figure 4](image-url)

**Figure 4.** MES design results comparison: deterministic ground-truth data vs. stochastic ensemble. (a): Pareto front curves. (b): distributions of façade patch activation for BIPV integration.
Fig. 4(a) shows the Pareto front curve(s), i.e., optimal system performances under different trade-offs between minimizing emission and cost, which are obtained using simulated ground truth and stochastic ensembles, respectively. As can be seen, the clusters of curves corresponding to the stochastic ensemble almost cover the curve of the ground truth, which proves that the generated ensemble is generally credible. Fig. 4(b) further compares both scenarios with respect to the distributions of activation for BIPV integration of each patch on the 160 facades, decided by the optimization model. It can be seen that a single deterministic ground-truth input obtains only a binarized 0/1 indicator. While being fed with the stochastic ensemble, the optimization model yields 40 solutions accordingly, and by calculating the frequency of each patch being activated in the entire ensemble, we can obtain a probabilistic distribution. This can more effectively quantify the BIPV potential of these patches under fluctuating solar irradiance. However, it is still important to point out that some of the facade patches that were activated with the ground-truth input are not activated at all under the 40 ensemble inputs. Such a discrepancy implies that the fidelity of the generated samples could still be improved.

### 3.2. Application 2: Design with Parametric Urban Context Factors

![Figure 5](image_url)

**Figure 5.** Parametrically changing urban context factors via fisheye image editing (left) and the corresponding solar time-series outputs (right), taking one test point as an example. For clarity, the generated images are recoloured and only one-week patches of the solar time-series under 2 extreme parametric inputs are plotted with ensemble size setting to 1. (a). Traversing in the latent dimension of WWR with zoom-in during one peak period, ground truth (above) vs. generated samples (below). (b) Traversing latent dimensions related to vertical (above) and horizontal (below) viewpoint shifting.
Finally, we would like to qualitatively exhibit our model's potential to conduct solar-driven parametric geometry design without 3D representation. First, the WWR of the surrounding buildings is the intentionally considered parametric urban context variability when designing the dataset. Compared to the ground-truth image triplet and solar time-series, Fig. 5(a) demonstrates that the model is able to add windows and adjust WWR given a fisheye categorical mask, via traversing one of the latent representations. This means that the model has learnt to align the underlying variability of WWR in the dataset to one latent dimension without any supervision. Then, the time-series GAN is also able to generally capture the specific effects of changing the latent WWR in terms of magnitude and trend.

In addition, although not intentionally designed, our model also associates some latent dimensions with viewpoint coordinates, another underlying and prevailing variability in the dataset. As shown in Fig. 5.(b), via traversing in specific latent dimensions, we are able to shift the view from a given test point location vertically or horizontally. The time-series generator can also make reasonable responses, e.g., in overall generating larger solar irradiance data when moving above or away from the surrounding obstacles. By doing parametric studies on one or several test point(s) of an individual building, we can therefore learn how this building’s solar potential is impacted by this its own form and shape as well as by the surrounding urban context conditions. Note that since the model is generating scenarios that do not exist in the dataset, therefore there is no ground truth for comparison. Additionally, it can also be observed that, comparing to the case of WWR editing, the generated solar irradiance data compromises more details and becomes more random in the case of viewpoint shifting, which indicates the variability of viewpoint locations and orientations within the dataset should also be controlled for improvements.

4. Discussion

By validating the fidelity of the generated samples, we can confirm that the proposed data-driven solar irradiance time-series generation model based on DGNs and open-source urban geometry data is a feasible and promising solution as a fast surrogate model for time-consuming simulation. Unlike other data-driven models that usually compromise on resolution, the spatio-temporal resolution of our model is consistent with that of a simulation engine, thanks to the apt input forms of urban context as fisheye categorical mask images inspired by previous urban solar studies, as well as appropriate DGN model architectures following the state-of-the-art deep-learning research.

Furthermore, we also investigate the application of our model in two scenarios, exhibiting that the generated stochastic solar irradiance ensemble can support the downstream urban MES optimal design to capture the fluctuating and intermittent nature of the solar irradiance when assessing BIPV locations. Our model’s capability of image editing and conditional time-series generation also allows for the parametric design of several urban context factors without explicit 3D representation. Considering that uncertainty in urban solar potential assessment consists of aleatory uncertainty due to the intermittent nature of the solar irradiance and epistemic uncertainty due to unavailable urban context factors, our approach allows to obtain a probabilistic score for the solar potential of each building surface and thus to better address both types of uncertainty, as demonstrated in Fig. 4(b). This could fundamentally change the common practice of solar potential screening based on a minimal threshold of annual cumulative irradiation. The probabilistic score could facilitate more informative risk quantification and more resilient decision-making. However, as this work is an initial study, we also found that the current workflow reveals several challenges that need to be studied systematically in the future;

The comprehensiveness of potential variabilities reflected in the dataset should be improved, especially for urban context factors other than WWR, such as surface inclination, vegetation and tree, and surface albedo settings. This is decisive for the generalization of the model. As demonstrated in Fig. 5, although our model is capable to capture some implicit variabilities within the dataset, its performance in this aspect is not as good as that for the intentionally introduced variabilities. Hence, It is necessary to propose a principled guideline to cover comprehensive scenarios within the dataset, based on the domain knowledge of solar radiation mechanics and PV system dynamics. In this case, it is relevant to follow closely the advances in physics-based urban PV studies, especially regarding sensitivity and uncertainty analysis based on simulations and real-world experiments.
Also, although viable, the current model architecture offers room for improvement. This includes a more exhaustive study to select appropriate backbone network architectures and determine some important hyperparameters, e.g., time-series patch length in generation, dimension of the latent image representation, etc. There is also a need to qualitatively evaluate the model’s response to parametric input of urban context factors when a more comprehensive dataset is available.

The acquisition of data, especially the way to capture the fisheye categorical mask images, although this is not the focus of this paper, can be significantly streamlined. In the future, alternative approaches similar to [16, 17], which are based on taking real-time screenshots from multiple directions on a GIS platform, need to be investigated. Even so, reading, writing, and transferring images can be time-consuming in practice. To mitigate this issue, we could leverage the model’s capabilities of extracting image representations and editing images. Specifically, some representative test points could be selected beforehand, with their corresponding images captured and fed into the model. Then, the model yields and only saves their low-dimensional image representations as GIS data. For other test points in adjacent regions, their image representations could be obtained via interpolating the latent dimensions associated with viewpoint coordinates. This is similar to the parametric design workflow shown in Fig. 4(b) but will be established as a spatial 3D interpolation method.

5. Conclusion
In this work, we introduce SolarGAN, an approach that combines multiple state-of-the-art DGNs to generate stochastic ensembles of solar irradiance time-series, while requiring only simple images, such as from LOD 1 urban geometries. At the urban scale, the resulting model can function as a fast and high-resolution surrogate for time-consuming solar simulation engines. We identify that the fisheye categorical masks can be utilized effectively as image-based inputs representing urban context information in data-driven models. We also demonstrate that combining image VAE with time-series GAN could enable the model to extract low-dimensional representations of the urban context condition from fisheye and generate corresponding solar time-series.

We further showcase the models’ practical relevance and potential capabilities for, e.g., ensemble generation, image editing, and conditional time series generation in two application scenarios: (i) resilient optimal design of district MES, which potentially provides the energy system designers with a simple approach to introduce stochasticity into the simulated deterministic solar irradiance results to ensure the robustness of urban MES design against uncertain PV generation; and (ii) convenient parametric solar-driven urban geometry design, which potentially offers the urban morphology designers with a generic alternative to quickly assess the impacts of building geometry without operating complicated 3D representations in a CAD environment. In addition, the proposed model is only based on open-source data, operates in real-time, and can be easily integrated with other GIS web applications, which will also provide local municipalities, residents, and other non-professional stakeholders with a barrier-free and accurate solution to help them evaluate the local BIPV potential and promote their engagement to the BIPV adoption. While we acknowledge the models’ current limitations, particularly for precisely reconstructing the deterministic profiles, but also in terms of model generality and usability, we are optimistic that there is potential to improve on these aspects in future research.

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