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An interactive assessment framework for residential space layouts using pix2pix predictive model at the early-stage building design

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Abstract

Purpose – In this study, a novel framework based on deep learning models is presented to assess energy and environmental performance of a given building space layout, facilitating the decision-making process at the early-stage design.

Design/methodology/approach – A methodology using an image-based deep learning model called pix2pix is proposed to predict the overall daylight, energy and ventilation performance of a given residential building space layout. The proposed methodology is then evaluated by being applied to 300 sample apartment units in Tehran, Iran. Four pix2pix models were trained to predict illuminance, spatial daylight autonomy (sDA), primary energy intensity and ventilation maps. The simulation results were considered ground truth.

Findings – The results showed an average structural similarity index measure (SSIM) of 0.86 and 0.81 for the predicted illuminance and sDA maps, respectively, and an average score of 88% for the predicted primary energy intensity and ventilation representative maps, each of which is outputted within three seconds.

Originality/value – The proposed framework in this study helps upskilling the design professionals involved with the architecture, engineering and construction (AEC) industry through engaging artificial intelligence in human–computer interactions. The specific novelties of this research are: first, evaluating indoor environmental metrics (daylight and ventilation) alongside the energy performance of space layouts using pix2pix model, second, widening the assessment scope to a group of spaces forming an apartment layout at five different floors and third, incorporating the impact of building context on the intended objectives.

Keywords Artificial intelligence, Human–computer interactions, Computer vision, Deep learning, Pix2pix model, Space layout

Paper type Research paper

1. Introduction

Globally, the buildings and the construction industry account for 36% of final energy demand and almost 40% of energy- and process-related emissions, of which the share of residential buildings corresponds to 22 and 17%, respectively (IEA, 2019). Accordingly, measures have been taken to reduce the energy demand of this building type mostly by modifying the building orientation, envelope characteristics, passive heating and cooling mechanisms, shading and glazing, particularly during the design phase (Pacheco *et al.*, 2012). The early-stage decisions in the building design process, including the building orientation, allocation of spaces and window-to-wall ratio (WWR) highly affect the building performance in the subsequent design steps. Therefore, making proper early design decisions is integral to a high-performance and sustainable

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building design. One of the main steps in the "schematic design" and "design development" stages of the building design process is the selection of space layout (i.e. the allocation of space, the interior collocation of different rooms, the interior layout and the placement of interior partitions) (AIA ETN, 2022). The decisions made in this step should address the architectural, energy-related and environmental requirements of each space. In a broader perspective, the orientation of the building, the exterior walls boundary and the envelope characteristics such as windows' dimension and location have also been reported to be related to the space layout design (Du *et al.*, 2020). At the early stage of the design process, the designer faces numerous space layout alternatives, all of which should be evaluated based on several quantitative metrics. This makes the decision-making process challenging and once the decision is made, any further change in the space layout is not conveniently feasible in the subsequent design steps.

Several previous studies have investigated the impact of architectural space layout on the building's energy performance, daylight condition and thermal comfort. Combining the variations of space layout and WWR (Yi, 2016), compared a base case design of an office building in Seoul with four optimized space layout cases. As a mixed result of space layout and WWR change, results showed the reduction in the annual intensity for the summed heating and cooling loads up to 30% and also a drop in the daylight illuminance in the same case compared to the baseline design up to 68%. By coupling daylight and thermal simulation in an office building in the Netherlands (Du *et al.*, 2019), compared eleven variants of space layout based on energy performance. Results showed that in the worst layout case compared to the best one, lighting energy, heating demand and cooling demand increased up to 65%, 12% and 10%, respectively. Authors later compared the energy performance of the same office building space layout variants in three cities representing temperate (Amsterdam), cold (Harbin) and tropical (Singapore) climatic contexts (Du *et al.*, 2021). The comparison showed that lighting demand is affected the most by the layout variance, resulting in a maximum difference of up to 46% in the case of Harbin. Energy demand and daylight analysis of different space layouts were also assessed in a library case (Dino and Üçoluk, 2017). Comparing four different layouts and WWRs for the same geometry and orientation of the library, results showed an increase of 25%, 23% and 11% in cooling, heating and lighting demand in the worst cases of each metric compared to the best cases. Moreover, the best case in daylighting analysis satisfied the illuminance set-point 731 h (27%) more than the worst case. In a review paper, the isolated effect of space layout on energy- and comfort-related metrics was investigated by Du *et al.* (2020). Among the reviewed cases, authors reported variations in annual space heating and cooling demand up to 52 and 57%, respectively. In addition, variations up to 11 and 65% were reported in illuminance level and air volume in natural ventilation mode for different space layout alternatives. Thus, a high discrepancy in energy demand and environmental metrics can be detected when various space layout design options are compared to one another. This shows the vital role of space layout decision-making at the early stage of the design process. In the mentioned previous studies, the physics-based simulations were performed using EnergyPlus (Du *et al.*, 2019, 2021; Dino and Üçoluk, 2017), Ecotect (Yi, 2016), Thermal Analysis Software (TAS) (Musau and Steemers, 2008) and IDA ICE (Poirazis *et al.*, 2008) for energy assessment, Ecotect (Yi, 2016) and DAYSIM (Du *et al.*, 2019, 2021; Dino and Üçoluk, 2017) for daylighting simulations, and Ecotect (Yi, 2016) for the thermal comfort assessment. It is important to note that almost all BES tools require numerous inputs, and the process of simulation could be considerably time-consuming. This issue would be even more noticeable when many early-stage design alternatives are to be compared.

When compared with conventional BES approaches, data-driven models present the intended output in a significantly shorter amount of time and acceptable accuracy as well, resulting in quick analysis. Accordingly, implementing data-driven approaches using machine learning (ML) method for predicting the energy and environmental performance of buildings has attracted considerable attention. Authors have investigated the data-driven approach in the field of building energy consumption, retrofit techniques, energy flexibility as well as daylight optimization. The distribution of studies focusing on data-driven methods in predicting building energy consumption was reviewed by Amasyali and El-gohary (2018). It was reported that 46%, 31%, 20% and 2% of the investigated studies focused on predicting overall, cooling, heating and lighting energy consumption, respectively. In another review study (Bourdeau *et al.*, 2019), emphasized on the impact of occupant behavior modeling when using data-driven models to predict energy efficiency of buildings, considering different building typologies and the properties of the input data to the predicting models. Highlighting the time series property of energy related data (Sun *et al.*, 2020), covered the whole data-driven process, namely feature engineering, models and outputs. Authors also proposed different strategies for updating multi-step building energy prediction using data-driven models. The application of data-driven energy modeling approach with a focus on building retrofit was investigated by Deb and Schlueter (2021). As a result, authors proposed a framework integrating data collection, data-driven hybrid modeling and cost-optimal retrofit analysis. In another study (Kathirgamanathan *et al.*, 2021), reviewed the implementation of the data-driven predictive control strategies in buildings with the focus on energy flexibility. Authors highlighted the significance of the data-driven predictive control approach in the integration of buildings with the grid and also carbon footprint reduction at the single building level. With the aim of finding an optimal residential building design (Saryazdi *et al.*, 2022), implemented the data-driven performance analysis using artificial neural networks (ANNs). Results showed the potential of reduction in energy consumption, discomfort hours and carbon emission up to 39.3%, 62.8% and 40.5% compared with the base case, respectively. The data-driven ML-based approach in optimizing daylight metrics at the building design and operation phases was investigated by Ngarambe *et al.* (2022). In addition to pointing out the various limitations of this approach, authors reported that supervised ANN algorithms have been mostly used for the daylight analysis in buildings.

While in the all the above-mentioned research the numerical data type has been predicted by ML algorithms, studies with the focus on predicting image type data as the output is relatively scarce. For instance, AlOmani and El-Rayes (2020), implemented image processing using Python programming to generate nature-inspired plan layouts. Based on the presented methodology in this study, the required rooms' adjacency and areas alongside the nature-based image are defined as input, and the output is an image of a floor-plan, fulfilling the designer's requirements. In another study (Sharma, 2017), used convolutional neural networks (CNN) for image processing of architectural floor plans to automatically analyze and retrieve similar floor plan images from a repository. The proposed deep learning framework in this research is able to extract features from the query layout and retrieve the top five ranked similar layouts accordingly. Nevertheless, the image-to-image translation tasks using specific group of ML techniques called generative adversarial networks (GANs) has been the most applied method in the built environment data (Wu *et al.*, 2022). The following sub-section is dedicated to this particular topic.

1.1 Background

GANs are considered as a class of machine learning frameworks working with the image-type data and have a wide application in the image processing field. Also, GANs are useful in floor plan image processing with many energy-related and environmental metrics that are available as maps (e.g. daylight maps). The GAN architecture is composed of two models which are trained simultaneously, a generative model to capture the data distribution, and a discriminative model to estimate the probability that a sample came from the training data rather than the generative model (Goodfellow *et al.*, 2020).

The application of GANs in the field of floor plan image generation or evaluation has been investigated in several previous studies. An image-to-image translation is performed by a model of GANs, called the pix2pix model, which was first presented by Isola *et al.* (2017). The pix2pix model has been tested in many applications, from generating a textured image from a linear sketch to converting street images to equivalent Google maps (Isola *et al.*, 2017). The application of the pix2pix model in automating building performance simulation was investigated by Yousif and Bolojan (2021). Five different datasets, each containing 3,000 paired images of architectural floor plans and their daylight simulation metrics were used to train the model. The accuracy of the trained pix2pix model was then evaluated by the test set containing 300 unseen floor images, resulting in an average structural similarity index measure (SSIM) of 0.94. In another study conducted on daylight maps prediction using the pix2pix model (He *et al.*, 2021), developed the predictive GAN model using a dataset containing 575 real-case examples of different residential space layouts. The performance of the trained predictive model in generating daylight maps for unseen test set spaces was reported by SSIM close to 0.90 in one second. The applicability of the pix2pix model to predict daylight maps of a given geometry at the early-stage design was also evaluated by Jia (2021). Using 300 building geometry samples from 6 different areas of Manhattan, New York as the dataset, the average similarity between the predicted daylight autonomy maps and simulated results as ground truth was reported to up to 91.51%. The pix2pixHD network is a refined version of pix2pix (2048×1024 vs. 256×256 image resolution), proposed by Luo *et al.* (2018). Implementing this network (Huang and Zheng, 2018), developed a framework for recognition and generation of floor plan images. The proposed model was trained by 100 paired images of floor plan drawings and corresponding labeled maps showing each space with a unique color code. Afterward, the trained model's performance was evaluated by the test set containing 15 images to determine how accurate the predicted drawings are. The authors reported that the network has the potential to learn the rules of design effectively.

The computer vision application in extracting information from architectural image-type data can be categorized into two classes, namely generation and analysis. The studies focusing on space layout analysis using the pix2pix model are brought and compared in Table 1, due to the higher relevance to the scope of the current study. In the mentioned studies, space layout parameters include exterior boundaries of the space, WWR, shape of rooms, doors location and floor height. Although both energy performance and environmental requirements of space layout design alternatives are necessary to be taken into account in the early-stage design, the focus of the mentioned previous studies is only on the former in terms of daylight analysis. It can be also seen that the building context, inclusion of grouped spaces and floor height variations are covered in the previous studies, but there is no single research comprising all of them simultaneously.

Although there is considerable amount of image-type data in architecture documents, less attention has been attracted to utilize ML models to assess building design performance, particularly in terms of space layout analysis. Using images in forms of floor plans, sections and also perspectives is an effective way of representing architectural data. In addition, the simulation results of many energy and environmental assessments of buildings are in form of maps, rather than numbers. These types of data, particularly when classified, are more convenient to be comprehended at a glance; and therefore are more useful in the decision-making process of the early-stage design. Accordingly, a novel framework is proposed in this study to implement deep learning (DL) models for evaluating the architectural image-type data, namely space layout representations. The analysis of the residential building space layouts using the presented methodology is based on the pix2pix model and includes the assessment of the energy and environmental related indicators (i.e. daylight and natural ventilation). Given the high number of design alternatives at the early-stage design process, this approach would help designers gain quicker feedbacks of theirs design with acceptable accuracy.

1.2 Research scope

This study aims to present a novel framework using image-based pix2pix model to predict energy and environmental performance of a given building space layout in the early-stage

Ref.	Parameters	Metrics	Building type	Number of storeys	Building context	Space type	Dataset number
Yousif and Bolojan (2021)	External wall boundary, WWR	spatial daylight autonomy (sDA), direct, daylight access (DLA) and useful daylight illuminance ranges of UDLI(0-100), UDLI(100-2000) and UDLI(2000-more) maps	Office	3	Not included	Single space	Five sets of 3,000
He *et al.* (2021)	Shapes of rooms, WWR, doors location	illuminance distribution maps	Residential	1	Not included	Grouped spaces	Two sets of 575
Jia (2021)	Floor height, WWR	daylight autonomy, maps	Not mentioned	Various	Included	Single space	One set of 300
The present study	Orientation, floor level, WWR, Floor plan type	annual primary energy usage intensity (EUI), illuminance map, spatial daylight autonomy map, air change rate per hour (ACH)	Residential	5	Included	Grouped spaces	Four sets of 300

Table 1.
The summary of recent studies implementing pix2pix model in space layout analysis

design. The term "space layout" in this study is considered as the allocation of spaces, building orientation, floor level and WWR. The pix2pix predictive models make use of image-type input and output data, thereby providing a more visually integrated analysis. The specific novelties of this research are: first, evaluating indoor environmental metrics (daylight and ventilation) alongside the energy performance of space layouts using pix2pix DL model, second, widening the assessment scope to a group of spaces forming an apartment layout at five different floors, as opposed to a single space located on the ground and third, incorporating the impact of building context on the intended objectives, rather than considering only a single building.

The rest of the paper is organized as follows: In Section 2, the proposed framework, the characteristics of the case study, the process of generating data sets and the intended DL model are presented. Section 3 contains the results and validation of DL model predictions. In Section 4 the overall performance of the presented framework is discussed and the future work potential is presented. And finally, Section 5 provides a summary of the presented work and the main conclusions.

2. Research method

The proposed framework in this study to incorporate DL method into daylight, energy and ventilation evaluation of space layouts involves five main steps (Figure 1): (1) 3D modeling of

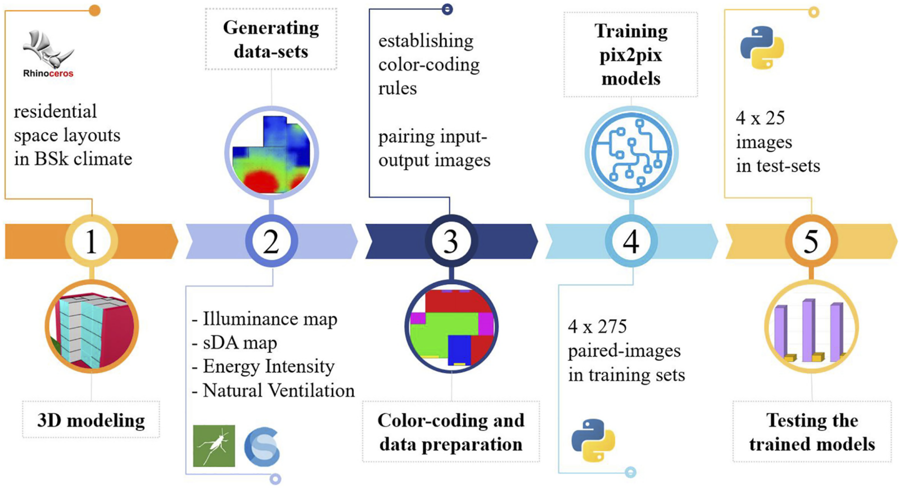


Figure 1.
The research workflow

case buildings to be further used in developing data-sets, (2) generation of data sets in four parts (daylight simulation including illuminance and sDA maps, primary energy intensity simulation and ventilation rate simulation), (3) the process of color-coding and data preparation to make the image-type data suitable for training the pix2pix model, (4) development and training process of the pix2pix models and (5) the testing process of the trained models. The test case application and the first four steps are discussed in the following sub-sections, and the last step is presented in Section 3.

2.1 Test-case application

The application of the proposed framework is investigated for different space layouts of apartment units in mid-rise (five-story) residential buildings in the BSk climatic context of Tehran, Iran. Due to the lack of prepared data-set for training pix2pix models, the data-sets have been manually modeled in the Rhinoceros program and developed for this research. The test-case buildings are modeled in a way to be suitable representatives of typical apartment buildings in Tehran, having one to three bedrooms and orienting toward either north or south. Four main variables to be investigated are orientation, floor level, WWR and floor plan types (Table 2). Function allocation, space and boundary dimension and form, besides interior partitions have been included as sub-variables of “floor plan types” (Figure 2). Each case building corresponds to a distinct floor plan type modeled in five stories. This results in 300 distinct space layout alternatives. The boundary condition of surfaces not having external windows and the floor area of ground floor is considered as adiabatic and ground, respectively (Figure 3). The space interconnections and local building design constraints has also been considered in generating different space layout alternatives. The selected metrics for energy and environmental performance assessment are as follows: the apartment unit annual primary energy usage intensity (EUI) as a sum of energy required for heating, cooling, lighting, water heating and electric appliances (in kWh/ m^2.a), illuminance map (150–2000 lux), spatial daylight autonomy map (in %) and air change rate per hour (ACH) in the natural ventilation mode. The first three metrics were simulated for all spaces at the building level, while the natural ventilation was only captured for the living room area. This space is the most occupied area in an apartment unit and more critical to be evaluated in terms of ventilation.

2.2 Generating data sets

To train the pix2pix models for predicting energy and environmental performance of different space layouts, four data sets were generated, each containing 300 maps as a result of illuminance, sDA, primary energy intensity and ventilation rate simulations. Rhinoceros program was used for 3D modeling of the building case and its context. ClimateStudio (Solemma, 2020) program was used for energy, daylight and ventilation simulations.

Table 2. Variable and constant parameters assumed in generating data sets

Parameters		Number of options	Description
Variable	Orientation	2	North/South
	Floor level	5	Floor numbers: 1/2/3/4/5
	WWR percentage	3	25/35/45
	Floor plan type	10	apartment units with one/two/three bedroom(s)
Constant	Building context	1	a group of three buildings with the same height as the case building, located 10 meters in front of faces having external windows (an example is brought in Figure 3)
	Envelope characteristics	1	described in Table 3

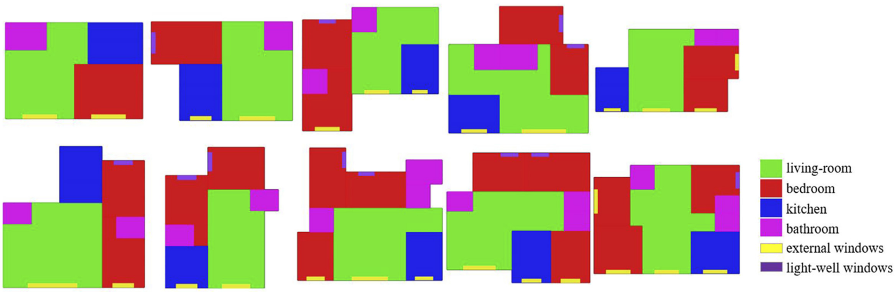


Figure 2. Floor plan alternatives assumed in generating data sets

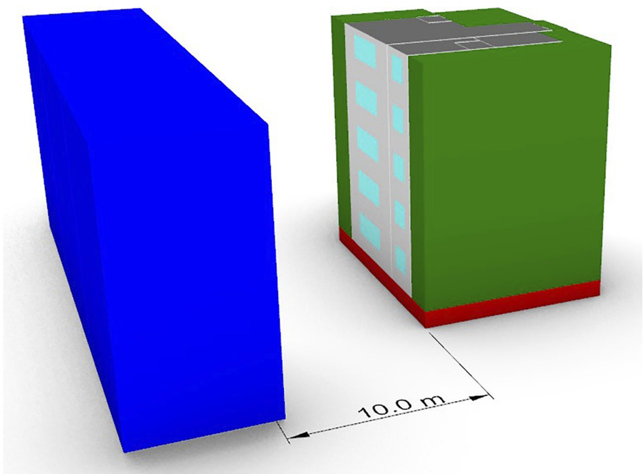


Figure 3. Building context (blue boxes), adiabatic (green surfaces) and ground (red surfaces) boundary conditions representation for one of the space layouts

The daylight simulations of application case buildings located in Tehran, Iran were performed with a grid resolution of 0.6 m and at 0.76 m working plane height. The resulting illuminance maps corresponding to the date-time of September 21st at 12:30 were captured for daylight data set under the sky type of Perez from Weather Data. The date was selected based on LEED rating system (U.S. Green Building Council, 2021) requirements of daylight assessment in buildings, and the time was set to be near the solar noon so that the effect of the building's context is represented more accurately, and southern and northern units are more comparable. The illuminance targets in each space were considered based on the recommended values by DiLaura *et al.* (2013). These values are specified in Table 3 alongside the lighting and equipment power densities of each space based on ASHRAE 90.1 standard. The dynamic metric of sDA has also been simulated and captured for all space layouts to make the comparison of different layouts more comprehensive. The required illuminance level during the occupancy hours in each space is fulfilled by either daylight or electric lighting, considering the continuous dimming type. The electric lighting availability in each space was selected based on the schedules provided for prototype building models by the US Department of Energy (DOE) for mid-rise residential buildings located in 3B ASHRAE climate zone.

The energy and ventilation simulations were performed in an annual period. It is assumed that the apartment unit can be naturally ventilated when the outdoor dry-bulb temperature is within the range of 21–25°C. Accordingly, the heating and cooling systems are assumed to be available when the outdoor dry-bulb temperature is less than 21 or more than 25°, respectively. As a result, the ACH metric is simulated monthly for the living room area during occupancy hours in natural ventilation mode. Each space layout is assigned one ACH value by averaging monthly ACH values over a year. It is also assumed that the infiltration rate is constant through the year and is equal to 0.5 ACH. The COP (coefficient of performance) and EER (energy efficiency ratio) of heating and cooling systems were considered equal to 3.41 and 3.02, respectively. The occupancy and domestic hot water use profiles are considered as such in typical residential buildings. Moreover, the height of the windows is about 1.35 meters with one meter sill height, and the change in WWR is directly related to the change in external windows' lengths. The light-well windows have a constant length of 1.35 meters in all cases, and the aperture of external windows is equal to 30% with the discharge coefficient of 0.65. The thermal and optical characteristics of the test case building's components are presented in Table 4.

2.3 Color-coding and data-preparation process

To represent each variable option in a floor plan image, a color-coding rule was established using different color hues and distinct saturation to show areas with different functions and positions. According to this rule, the living room, bedroom, kitchen and bathroom spaces are presented with green, red, blue and pink (RGB: 0.255,0; 255,0,0; 00.255; 255,0,255), respectively. Moreover, as the floor number increases from 1 to 5, the color saturation of each space changes from 100 to 255. The variations in the percentage of external windows are also represented as the change in length of the representative yellow strip. The dimensions of light-well windows are constant in all cases, so there is no change in the length of the purple strips. Finally, the orientation of the

Table 3. Simulation parameters of spaces regarding lighting condition and power

Space	Target illuminance (lux)	Lighting power Density (W/ m^2)	Equipment power Density (W/ m^2)
Living room	100	7.85	3.06
Bedroom	100	11.94	3.58
Kitchen	300	10.65	30.28
Bathroom	100	10.54	1.61

apartment unit is assumed to be "Southern" or "Northern" if the external windows are oriented toward south or north, respectively (Figure 4).

The color-coding rules for turning numerical results of energy and ventilation into representative colored maps were also created to classify the floor plans into three classes of energy and ventilation. The three energy classes are as follows: (1) low (cyan), (2) acceptable (lime green) and (3) high (purple) primary energy intensity. The acceptable value for primary energy intensity is considered based on Iran National Buildings' Legislation. The three ventilation classes are only assessed in living room space, as the most occupied area in an apartment unit and crucial in terms of ventilation, and are categorized as (1) less than 1.5 ACH (red), (2) from 1.5 to 3 ACH (yellow) and (3) more than 3 ACH (blue). Accordingly, only the living room area is colored in the output images of the natural ventilation. Each labeled floor plan image and corresponding daylight, energy and ventilation maps were after all saved in a 600 × 600 pixels image. Then, 300 paired floor plan-daylight, floor plan-energy and floor plan-ventilation images with the dimension of 1200 × 600 pixels were generated to be used as training and test sets in the following steps. A sample paired image of each daylight (illuminance and sDA), energy and ventilation map is presented in Figure 5.

2.4 Training four deep learning models

The pix2pix GAN is an approach to training a deep CNN for image-to-image translation tasks, which is a type of conditional GAN (cGAN) (Isola *et al.*, 2017). The pix2pix model in this research has been developed using Keras Deep Learning Framework, and it is designed in the way that the input and output images are the size 256 × 256 pixels. The architecture is comprised of the discriminator and the generator models. The 70 × 70 PatchGAN discriminator is a CNN that performs conditional image classification. The model takes two input images that are concatenated together and predicts a patch output of predictions, and it

Component	Thermal characteristics U-value (W/ m^2.k)	Optical characteristics Reflectance/transmittance (%)
Ceiling	0.364	70
External walls	0.472	50
Internal walls	2.338	50
Floor	1.577	20
Windows	2.69	77.4
Context buildings	Not applicable	13.8

Table 4. Thermal and optical characteristics of test case building's components

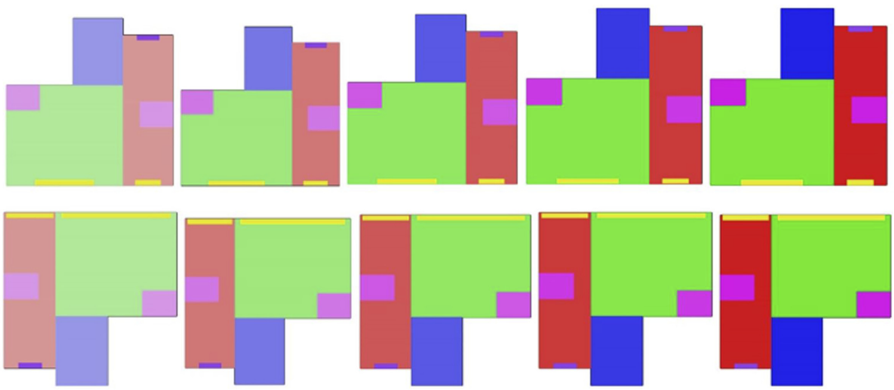


Figure 4. The color-coding rule – first row of images represents southern orientation and WWR of 25% and the second row corresponds to northern orientation and WWR of 45% (left to right: floor numbers 1 to 5)

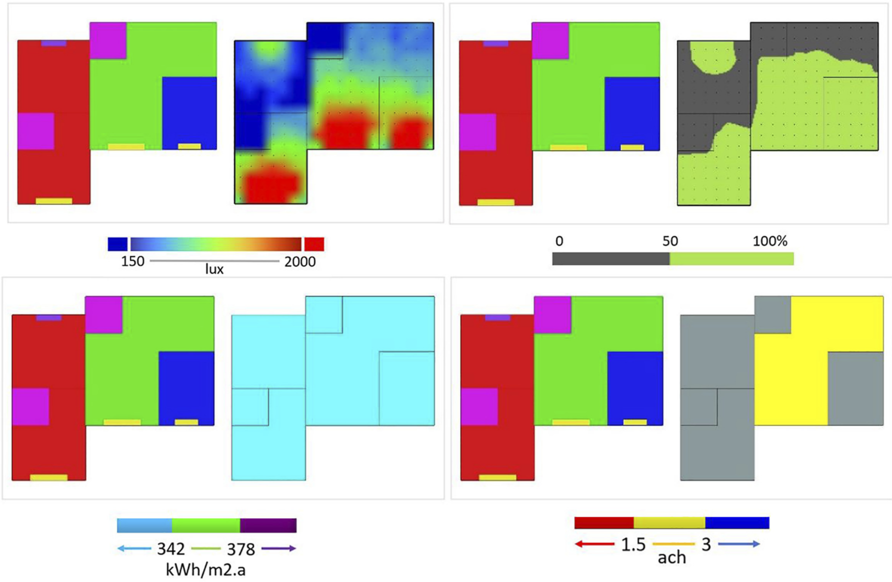


Figure 5.
Paired-image samples (top: paired illuminance (left) and sDA (right) maps, down: energy intensity (left), and natural ventilation (right) maps)

is optimized using binary cross-entropy. The generator is an encoder-decoder model using a U-Net architecture, in which skip-connections are added between the encoding layers and the corresponding decoding layers (Navab *et al.*, 2015). The encoder and decoder of the generator are comprised of standardized blocks of convolutional, batch normalization, dropout and activation layers. The tanh activation function is used in the output layer, meaning that pixel values in the generated image will be in the range [−1, 1].

The discriminator model is trained directly on real and generated images, whereas the generator is trained via the discriminator model. It is updated to minimize the loss predicted by the discriminator for generated images marked as "real." Therefore, it is encouraged to generate more real images. The generator is also updated to minimize the L1 loss or mean absolute error between the generated image and the target image. It is updated via a weighted sum of both the adversarial loss and the L1 loss. The discriminator is updated in a standalone manner, so the weights are reused in this composite model but are marked as not trainable. Adam optimizer was used with an initial learning rate of 0.0002 and the exponential decay rate for the first moment of the gradient equal to 0.5.

Four individual models were trained for the four main objectives of this research (i.e. illuminance, sDA, energy intensity and natural ventilation maps of input space layouts). Each model was trained using 275 paired images in training set by 100 epochs and a batch number of one, resulting in a total of 27,500 training steps. The generator was saved and evaluated every 10 epochs or every 2,750 training steps, in order to find the best predictive model of each objective. Accordingly, 10 different models were developed for each of four metrics.

3. Results

3.1 Simulation results

As reported by previous researches, space layout highly affects the energy performance of buildings. The simulation results of EUI in this research also confirm this fact. As it is shown in Figure 6, various floor plan types lead to different ranges of EUI and ACH, depending on their orientation, WWR and floor level. The highest EUI and ACH differences among the 300 space layouts were 117.5 kWh/m^2 (ranging from 291 to 408 kWh/m^2 with a percentage difference of 33.4%) and 5.3 ACH (ranging from 0.4 to 5.7 ACH with a percentage difference of 173.7%), respectively. Generally, apartment units with less access to daylight (either low WWR or low floor level) resulted in higher EUI values, and those with deeper living rooms and non-rectangular shapes led to lower ACH values. Moreover, units with southern orientation corresponded to higher amounts of EUI and ACH due to the higher cooling demand and prevalent wind direction in Tehran, respectively. It is also worthwhile to mention that since units located in higher floor levels could benefit from daylight and natural ventilation more, they generally resulted in lower EUI and higher ACH. Despite increasing ACH, the higher percentage of WWR did not show high discrepancy in EUI values, since increasing thermal loads were approximately equal to decreasing lighting demand.

3.2 Performance of Pix2pix predictive models

In the testing phase, the performance of the trained pix2pix models was evaluated by introducing 25 unseen space layout images. The test was run on a computer with Intel(R) Core (TM) i7-4700HQ CPU @ 2.80 GHz and memory of 12 GB. The trained model was saved every 10 training epochs and used to generate sample image-to-image translations periodically during training. Then, the generated images at the end of the training process were reviewed and the image quality determined the final predictive model. Predicted illuminance and sDA maps by the model were compared to the actual simulated results (i.e. ground truth) by the SSIM. SSIM is a widely used metric for measuring the similarity between two images and its formula is based on three comparison measurements of luminance, contrast and structure (Abu-Srhan *et al.*, 2022). To reveal the learning process of the daylight predictive model, three illuminance and sDA map predictions corresponding to 10, 50 and 100 epochs for the same space layout input are brought in Table 5. It can be seen that the predicted daylight maps at the earlier epochs are relatively vague and represent poor accuracy. The comparison between each predicted map and ground truth image shows more accurate predictions of the last model, as the increasing of the SSIM validates this claim.

The predicted EUI maps of 10, 50 and 100 epochs are brought in Figure 7. The last energy predictive model with 100 epochs presents more accurate results, while the predicted results of earlier models are whether unclear or wrong.

Although the daylight and energy predictive models performed better with 100 epochs, the third to last ventilation predictive model with 80 epochs outperformed the others. As it is

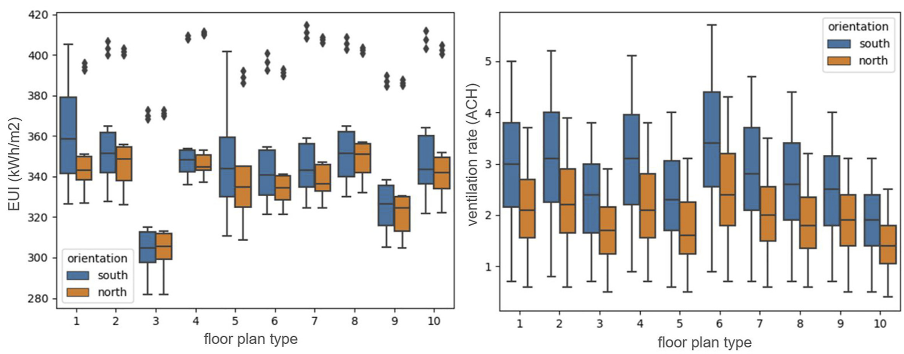
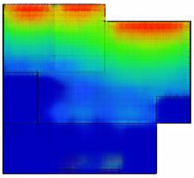
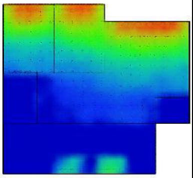
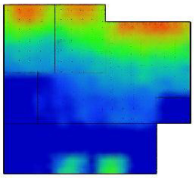
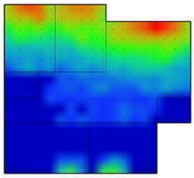
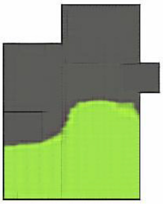
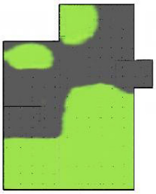
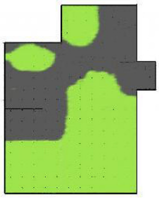
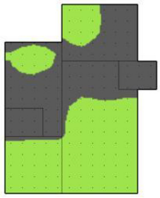
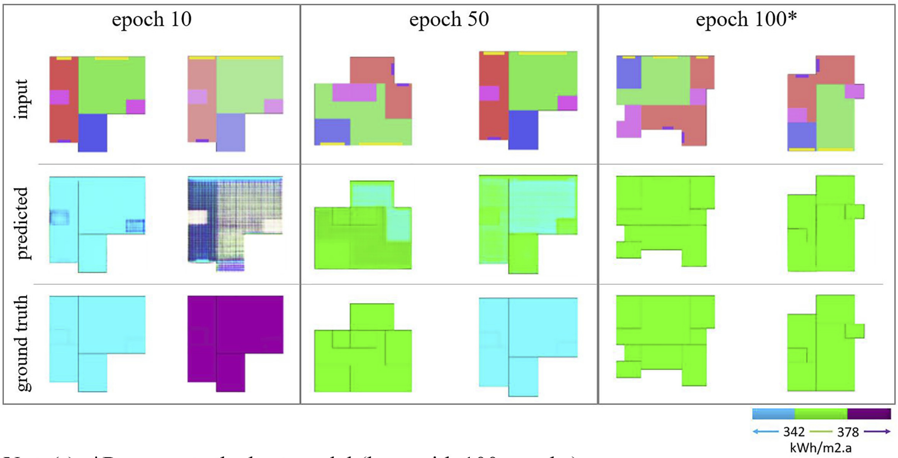


Figure 6.
EUI (left) and ACH (right) box plots of different space layouts in the data set

	epoch 10	epoch 50	epoch 100*	ground truth
Illuminance map				
SSIM	0.7795	0.8014	0.8234	- 150 lux 2000
sDA map				
SSIM	0.7061	0.7989	0.8086	- 0 50 100%

Note(s): *Represents the best predicted result

Table 5.
The learning process of the daylight predictive model for two random samples in test set



Note(s): *Represents the best model (here with 100 epochs)

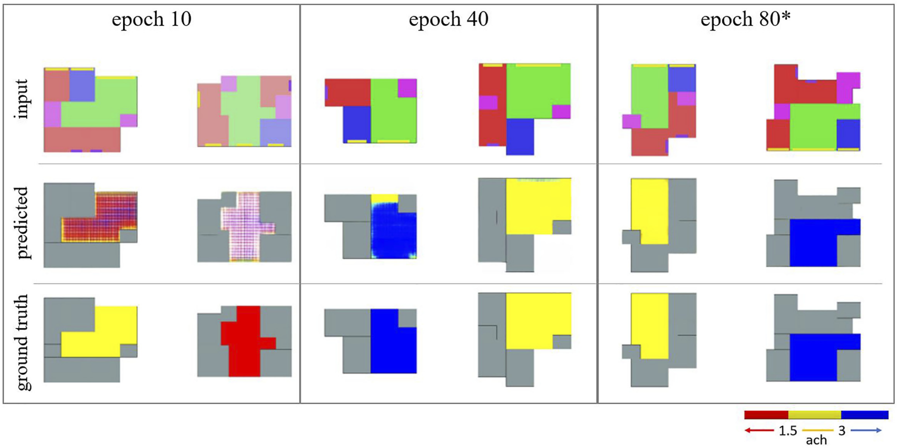
Figure 7.
The learning process of the energy predictive model

shown in Figure 8, the predicted ACH maps of earlier models do not either contain a single color or present the wrong color to represent the ventilation rates. The trained model with 80 epochs predicts clear ACH maps with almost no inconsistency in the texture. It is also important to mention that the performance of the ACH predictive model degraded after 80 epochs due to the nature of GANs, in which the model trained by more epochs does not always perform more accurately than earlier ones with less number of epochs.

For the best daylight model, the results of the validation in test set data showed an average similarity value of 0.86 and 0.81 with an overall similarity value range of 0.78–0.91 and 0.72–0.85 for illuminance and sDA maps, respectively. Less accuracy occurred in upper-floor units with light-well windows, which made the prediction of the illuminance distribution more challenging. To examine the performance of the model in predicting the EUI and ACH representative maps, a color detection procedure in Python was followed. For each true prediction in the color of EUI and ACH representative maps, one score was given to the corresponding model. The best models of energy and ventilation also predicted the EUI and ACH representative maps with the total score of 88%, i.e. 22 true predictions out of 25 data in the test set. The four corresponding predicted maps for three sample floor plans in test set compared to their ground truth simulated maps are brought in Table 6. The first sample represents a low-energy space layout, with acceptable ACH in its living room and good daylighting condition in its living room, kitchen and northern bedroom. The second one represents a space layout that most probably requires glare-protecting strategies on its Southern façade, but its performance in energy is acceptable and shows high ACH in its living room. The third one is the worst space layout with high EUI, low ACH and unpleasant illuminance distribution. Using these energy and environmental representative maps, designers can get quick feedback on their space layout alternatives.

4. Discussion and future perspectives

The predicted results of the trained pix2pix models for assessing the daylight maps (illuminance and sDA), primary energy intensity and natural ventilation condition of the space layout images can provide designers quick feedback with acceptable precision. The



Note(s): *Represents the best model (here with 80 epochs; Note that only the living room area is colored in the output due to the scope of evaluation; accordingly, the natural ventilation is not predicted in other spaces as they are colored in gray

Figure 8. The learning process of natural ventilation predictive model in the living room area

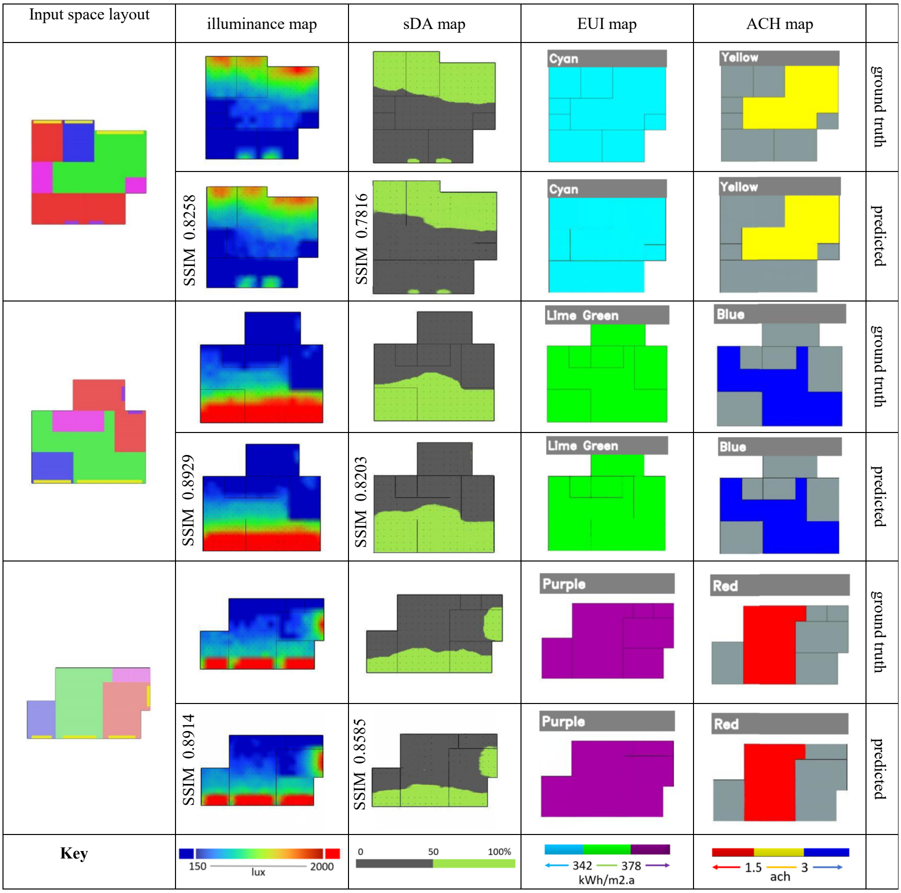


Table 6.
Three samples of the best daylight, energy, and natural ventilation predictive models

proposed framework in this study assists the decision-making process in the early-stage space layout design when the designer faces a comparative process of choosing between many design options. Precise numerical outputs are out of the scope of this study due to the comparative nature of the decision-making process in this stage of design. Accordingly, the simplified color-coded maps instead of numerical results for annual primary energy intensity and natural ventilation rate were established alongside the daylight maps. The main challenge of this work was to represent each attribute of the space layout, namely space allocation, floor level, WWR and orientation through a single input image. Space layout images with several distinct colors for each space and with different saturations to represent different floor levels were utilized to combat this challenge.

The application of the presented framework was investigated by a data-set containing 300 space layouts from five-story residential buildings in BSk climate and mid-latitude city of Tehran, Iran. The daylight metrics in this study were selected in a way that can represent both point in time (illuminance map at 12:30 21st September) and annual (sDA) daylight performance of different space layouts. The annual primary energy intensity was selected to represent the energy performance of the layouts due to the fact that it gives a more holistic vision of energy consumption rather than final energy intensity. Also, the natural ventilation metric was only assessed in the living room area, which is the most occupied space in an apartment unit and has a higher demand of fresh air accordingly. The predicted illuminance and sDA maps were compared to those resulting from the daylight simulations and showed the SSIM of 0.86 and 0.81, respectively. Also, the average accuracy of both energy and ventilation models was 88%. The test-case application of the pix2pix predictive models showed promising predicted results, with each of the metrics' being predicted within three seconds. This time duration is calculated based on the prediction time of the models on the computer with the mentioned properties in Section 3.2, when the input color-coded image of the space layout is given to the trained model.

Despite the usefulness of the proposed framework in providing a quick and acceptable design feedback on the daylighting, energy and natural ventilation performance of the space layouts, the need for implementing the conventional building energy performance tools would not be completely vanished. There is still the need for precise modeling of the selected space layout and simulation procedure at the following stages of the design process, namely design development. Although the time consumed for the training process of each model is not negligible, the use of the proposed framework would be broader with the expansion of generating the related dataset in the built environment area. There are other limitations to consider, which can be listed as follows:

(1) *Climatic context:* climatic characteristics, particularly global horizontal and direct normal illuminance and radiation, air temperature and wind conditions highly influence the daylight accessibility, energy demand and ventilation performance, respectively. Therefore, the predicted results of the trained pix2pix model in this research are exclusively applicable for the climatic context of BSk, in mid-latitude locations. However, the same framework can be implemented for other data sets in which the simulations are performed for other climatic contexts.

(2) *Building and its context:* the five-story buildings modeled in this study are reasonable representatives for a considerable share of residential buildings in Tehran, Iran, although buildings with different height would be modeled for other cities with dissimilar prevailing building heights. Despite the undeniable role of building context on the environmental and energy performance of buildings, particularly daylight access, less attention has been given to it in the previous studies (Jia, 2021). In this study, the building context was considered as a group of three buildings with the same height as the case building, and the distance of these three buildings was set to 10 meters in front of the building faces having external windows. Given that obstructions have a huge impact on daylight accessibility, incident radiation and ventilation rate, the predicted results of the trained pix2pix model in this research would not be very accurate for other low-rise or high-rise building contexts or with different obstruction distances. Meanwhile, the same framework would be still applicable when the pix2pix model is trained by data from intended building contexts.

(3) *Data set generation:* due to the manual process of daylight and thermal modeling and the floor plans labeling in this research, the total number of paired images for training the model is relatively limited (300 paired images for each of the four metrics, and a total of 1200). Although the pix2pix model showed an acceptable performance when being trained by fewer images as in Huang and Zheng (2018), researchers gained higher precisions with a greater number of images in the training set (Yousif and Bolojan, 2021) and (He *et al.*, 2021). It is important to consider that the data sampling of a group of spaces with meaningful connections and adjacency is time- and effort-consuming process. Thus, if the data generation and labeling process would be automated, the chance of getting higher precisions will enhance as a result of an increase in generated data.

In addition to the main points above, there are other factors that were considered as constant in all simulations, namely the type and efficiency of HVAC systems, heating and cooling set-points and occupancy, appliances and domestic hot water usage schedules. Even though these parameters are irrelevant to the space layouts, they have considerable effects on the amount of building energy consumption and therefore must be chosen properly. The implementation of the proposed framework in this study is demonstrated on a test case with given assumptions, yet the transfer performance of the model is still to be evaluated by applying the trained models on different datasets.

There are multiple future perspectives that can be integrated into the presented framework to develop it more comprehensively. The presented framework can be applied to other building types such as educational, office, or commercial buildings. It is only required that each space layout with different attributes would be distinctly identifiable from the other options. While the thermal and optical characteristics of the building envelope were considered as constant values in all different space layouts in this research due to the weaker relevancy to the space-layout, they can also be considered as variables. This requires thorough investigations to tackle the complexity of representing the change in envelope characteristics in image-type data. Various building contexts including low-rise and high-rise with different corresponding sky view factors can be included in simulations and be represented in image-type data with distinct alterations, such as a change in the pattern of images. Also, the proposed method would be more accurate in predicting the metrics if more comprehensive parametric studies in building scale could be conducted to form a larger dataset. Besides the energy- and environmental-related metrics conducted in this study, other objectives such as spatial thermal comfort and glare probability, which can be conveniently represented in maps, would be also be assessed in future studies for various space-layouts by the same proposed framework. Ventilation can also be evaluated in the whole unit rather than a single space.

5. Conclusion

Through engaging artificial intelligence in human–computer interactions, a framework using pix2pix deep learning model is proposed in this research to assist designers with the energy and environmental evaluation of space layout design alternatives. The proposed framework encompasses four predictive models which take a single color-coded image of a space layout as the input and then deliver the corresponding daylight, energy and ventilation maps as the outputs. The research workflow is developed in five main stages: (1) 3D modeling of case buildings for thermal and daylight simulations, (2) generating four data sets containing simulation results of illuminance maps, sDA maps, primary energy intensity and natural ventilation rate, (3) preparing the image-type data using the color-coding process, (4) training the predictive pix2pix model using training-sets and (5) testing the performance of the trained models by test sets. The presented framework was also applied to a test case including 300 various residential space layouts in which the variables are orientation, floor level, WWR percentage and floor plan type. Also, the selected metrics for energy and environmental performance assessment of these space layouts are annual primary energy intensity, illuminance and sDA maps of the apartment unit and air change rate per hour in the living room area when it is naturally ventilated. The predictive pix2pix model, which was trained using four sets of 275 paired-image, showed acceptable performance in predicting the results of daylight (SSIM of 0.86 and 0.81 in illuminance and sDA maps, respectively), annual primary energy intensity (score of 88%) and ventilation rate (score of 88%) maps. The primary contribution of this research is the implementation of a novel framework to present corresponding energy, daylight and ventilation maps of input space layout in a few seconds. Also, the distinct novelties of this research include (1) incorporating energy and ventilation metrics in the DL predicting process by presenting them as representative maps, which has not been addressed in the related previous studies, (2) performing the energy and environmental assessment for a group of spaces in form of an apartment unit at different floors and (3) incorporating building context to show its impact on the mentioned metrics. The presented framework would help designers to assess multiple early design space layout alternatives more quickly, compared to implementing the conventional BEP tools, making the decision-making process more convenient in the early-stage design. The main limitations of this study include generalization of the predictive models on different climatic and building contexts, and the process of data generation.

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