GLARE PREDICTION IN CHECK-IN HALLS OF AIRPORT TERMINALS USING INTEGRATED ALGORITHMS AND TRANSFER LEARNING STRATEGY

A Case Study of Guangzhou Baiyun International Airport

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Abstract. The construction process of large-scale spaces such as airport terminals is often carried out in several phases, so the environmental performance assessment and analysis of completed projects can provide effective reference information for new projects. On the other hand, the layout of large glass curtain walls and skylights in the check-in halls of terminals, while fully introducing natural light, also brings potential glare hazards, and therefore the influence of different design parameters on glare needs to be clarified. However, current research has not yet discussed in detail the prediction of glare performance of terminal buildings and its influencing factors. This study aims to develop a transfer learning strategy and a workflow for predicting glare performance in terminal buildings. The results have proved that the transfer learning strategy can help quickly predict the glare performance between projects with similar spatial characteristics with high accuracy, and the outcomes also help clarify the influencing factors of glare performance and provide designers or managers with support for performance prediction and optimization methods.

Keywords. Check-in Hall, Airport Terminal, Annual Glare, Performance Prediction, Transfer Learning, Integrated Algorithms

1. Introduction

1.1. BACKGROUND

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According to the 14th Five-Year Plan for the Development of Civil Aviation in China, the construction of civil airports in China will reach 270 by the end of 2025 (Yan S, 2022). Green and sustainable development goals are also receiving increasing attention during the progress of the civil aviation industry. During the design and construction of a terminal building, a phased approach is often used due to the complexity of the process and the long period it takes. For the same airport, terminals constructed in different periods often have certain similarities, mainly in terms of space and functional composition. This makes the assessment and analysis of the completed projects of the previous phase a high reference for the subsequent phases and other projects of the same type.

Large glass curtain walls combined with roof skylights are often used to ensure that natural light is fully introduced, which helps to reduce the need for artificial lighting and improve the indoor light environment while reducing energy consumption. However, the large lighting area inevitably brings a certain degree of glare hazard, and the glare will mainly affect passenger movement efficiency (Yi L et al., 2019). To adopt appropriate strategies to reduce the glare hazard at the design stage, it is important to investigate the annual glare-influencing factors and obtain the optimal solution.

1.2. RELATED WORKS

Due to the progress of computer simulation technology and artificial intelligence algorithms, building performance prediction has received widespread attention. In recent years, many researchers have realized rapid prediction of building environmental performance indicator values under different parameter combinations by establishing prediction models. For example, Aseel Hussien et al. used a random forest algorithm to predict the long-term energy performance of building envelopes (Aseel H et al., 2023), while He et al. integrated parametric design, performance simulation, image processing, and machine learning techniques to achieve rapid prediction and assessment of the wind environment of building clusters (Yi H et al., 2021). In a previous study, we also used integrated machine learning algorithms combined with a multi-objective optimization process to establish a prediction model between façade shading and indoor light environment and energy consumption for a typical corridor of a terminal building and proposed a preferred solution that could be screened by designers (Yinyi S et al., 2023).

However, the above studies on performance prediction and optimization are only available for specific buildings or certain types of datasets. Many design projects usually need to deal with various types of buildings and may also be constructed in different phases like terminal buildings, which puts a higher demand on the generalization and scalability of prediction models. The strategy of transfer learning has been proposed under such demands, which effectively adapts the training model by using a new building dataset and transferring the useful knowledge of the training model from the original dataset (Giuseppe P, 2022). For example, Fang et al. applied a hybrid deep transfer strategy to achieve the goal of assisting energy prediction of a target building with limited historical measurements (Xi F, 2021). Liu et al. applied the transfer learning strategy to energy systems in the field of data-driven fault detection and evaluation (Jiangyan L et al., 2021).

1.3. OBJECTIVE AND ORIGINALITY

Based on the above background and analysis of related literature, it is evident that the application of transfer learning in the performance prediction of such large public buildings or spaces as airport terminals has not been discussed in existing studies. The influencing factors of glare in airport terminals have also not been systematically compared. To bridge the existing research gap, the objective of this study is to develop a transfer learning strategy and workflow for modeling the prediction of annual glare in the check-in halls of different airport terminals, as well as to clarify the impact of different design factors on the glare performance, and Terminal 1 (T1, built in 2004) and Terminal 2 (T2, built in 2018) of Guangzhou Baiyun International Airport are proposed to be selected as demonstration cases.

2. Methodology

2.1. OVERVIEW OF WORKFLOW

The overall workflow of this study is shown in Figure 1. The workflow can be divided into three main phases. Among them, the first phase involves the establishment of parametric models and the acquisition of different design parameters for both T1 and T2, which include the roofing system (including skylight, metal roof, and ceiling), glass curtain wall, floor, and building orientation, etc. The second phase involves obtaining annual glare performance data through batch simulation and completing the machine learning process for T1. The third stage is to transfer the trained model from T1 to T2 through the transfer learning strategy and then complete the adjustment and prediction.

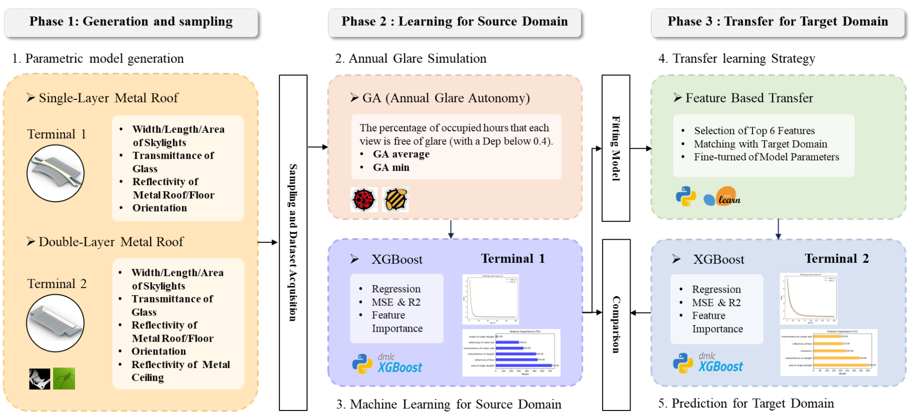

Figure 1. Overview of workflow

2.2. PARAMETRIC MODELLING AND SETTINGS

The determination of the design parameters of the terminal building check-in hall is based on the existing cases. After obtaining the original scheme design parameters, the study focuses on comparing the impact of skylights to simplify and improve the computational efficiency, so other geometric parameters are kept unchanged except for the skylights. In addition, the building orientation and the material parameters of each component will also be set parameter intervals. Figure 2 shows the parameterized model, the interior view, and the schematic of the sectional spatial forms of the selected two terminals. The main difference between them is that T1 has a single-layer roof combined with skylights, while T2 has a double-layer roof with the addition of metal ceilings, and the rest of the spatial forms of the two buildings are similar. Table 1 shows the parameter settings of each part of the model. Meteorological parameters are selected from typical year data of Guangzhou city in China.

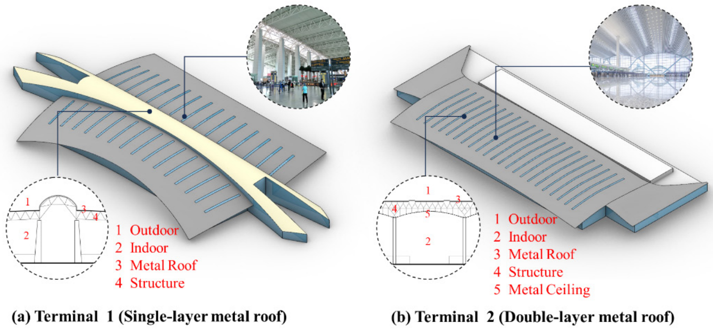

Figure 2. Parametric modeling of check-in halls in different airport terminals

Table 1. Summary of design parameters for terminal check-in hall.

Classification	Design parameter	Range	Baseline	Unit
Geometry	Skylight width	[3, 12]	3 (T2)	m
	Skylight length	[30, 125] (T2); [30, 60] (T1)	125 (T2)	m
	Orientation	[0, 360][a]	15	degree
	Number of skylight columns	16 (T1); 18 (T2)	18 (T2)	-
Glass	Skylight window transmittance	[0.3, 0.6]	0.3	-
	Curtain window transmittance	[0.4, 0.8]	0.5	-
General indoor wall	Reflectivity	-	0.2	-
Roof film (T1)	Transmittance	-	0.15	-
	Reflectivity	-	0.75	-
Floor	Reflectivity	[0.3, 0.6]	0.6	-
Metal roof	Reflectivity	[0.4, 0.8]	0.8	-
Metal ceiling (T2)	Reflectivity	[0.4, 0.8]	0.4	-

a. Interval of orientation will be set as 90°, which means the orientation includes N (north), E (east), W (west), and S (south).

2.3. PERFORMANCE SIMULATION AND DATASET

To balance the performance simulation computation time with the availability of the actual scenarios, the simulation samples of the two terminals are set to 1408 and 3584 respectively. After completing the sampling of model parameters, the calculation of annual glare performance is completed by Ladybug and Honeybee performance calculation plug-ins of Rhina & Grasshopper, and the simulation calculation process is driven by algorithms. Finally, the model parameters and the performance simulation results are recorded in an Excel sheet.

Considering the characteristics of the terminal building's long-period operation mode, the glare performance simulation analysis metrics were determined as Daylight Glare Probability (DGP) and GA (Annual Glare Autonomy). According to the International Commission on Illumination (CIE), the range of DGP values corresponds to different levels of glare. GA, on the other hand, represents the percentage of glare-free time occupied by each viewpoint at each measurement point in the space, and in this study, if the annual average of DGP in the viewpoints is less than 0.4, it will be counted as the cumulative timeshare of GA. The final performance metrics for this study will be defined as the minimum and average values of GA among all measurement points for global considerations.

2.4. MACHINE LEARNING BASED DATA PREDICTION

2.4.1. XGBoost integrated algorithm

For structured data prediction, integrated machine learning algorithms based on decision trees have been proven to be superior by many studies, while XGBoost, as one of the models in this category, is executed recursively during training (Tianqi C and Carlos G, 2016). To further validate the advantages of XGBoost in this study, we also selected the T1 terminal dataset for validation to compare the performance difference between XGBoost and Random Forest as well as other ANN (Artificial Neural Network) algorithms such as MLP (Multilayer Perceptron) and SVM (Support Vector Machines), and the results show that the performance of XGBoost is better, and the specific results are detailed in Table 2. Therefore, the algorithm chosen in this study is the XGBoost integrated learning algorithm, which achieves the desired fitting effect by defining the model parameters in the regression task during training, and the main model parameters involved in this study include learning_rate, max_depth, n_estimators, etc.

For the evaluation of the training effect, this study selects Mean Squared Error (MSE) and R Squared as the evaluation indexes, in which the smaller the value of MSE and the closer the value of R Squared is to 1, the better the training effect of the model is, and the formulas for the calculation of MSE and R Squared are shown as follows. Root Mean Squared Error (RMSE) will be selected as the evaluation index in training loss analysis, which is the arithmetic square root of MSE.

$$MSE = \frac{1}{m}\sum_{i=1}^{m}(y_i - \breve{y}_i)^2$$

$$RMSE = \sqrt{MSE}$$

where m denotes the number of samples and $y_i - \breve{y}_i$ denotes the simulated value minus the predicted value.

$$R^2 = 1 - \frac{\sum_i(\breve{y}_i - y_i)^2}{\sum_i(\bar{y}_i - y_i)^2}$$

Where the numerator part represents the sum of the squared differences between the true and predicted values and the denominator part represents the sum of the squared differences between the true and predicted average values.

Table 2. Comparison of the different machine learning algorithms for the GA_average of T1

Algorithms	XGBoost	Random Forest	MLP	SVM
MSE	0.803	2.693	0.162	3.151
R Square	0.986	0.821	0.974	0.946

2.4.2. Transfer learning strategy

Transfer learning is the process of transferring knowledge from a learned related task to improve the new task from the similarity of data and task, and the two main concepts involved are domain and task. The domain is composed of feature space and probability distribution, and the task is composed of label space and predictive function. For this study, the feature space usually consists of the size of the skylight, the orientation of the building, the material parameter, etc., whereas the label space is the average and minimum values of GA.

The source domain is the dataset defined as T1, while the dataset of T2 is defined as the target domain. The transfer learning we define is as follows: given the source domain D_source and learning task T_source, the target domain D_target, and the target task T_target, the transfer learning aims to improve the target prediction function and D_source $\neq$ D_target but T_source = T_target. Specific transfer learning is divided into the following three steps: (1) Data acquisition and preprocessing. (2) Training in the source domain. (3) Using a small amount of data in the target domain to fine-tune and modify the pre-trained model in the source domain. (4) Completion of predicting in the target domain.

For the source domain, 80% of the data will be used for training and 20% for testing. Whereas in the target domain, only 20% of the data will be selected for fine-tuning and the remaining data will be used for testing.

3. Results and Discussion

3.1. DISTRIBUTION OF GLARE PERFORMANCE DATASET

In Figure 3, we show a comprehensive dataset of the glare performance of the check-in halls of the terminals obtained from the batch performance simulation. Overall, the distribution trends of the datasets for the two terminals are somewhat similar, i.e., the average values of GA are all higher while the minimum values are lower, and the distribution of the minimum values is more dispersed. Specifically, for the average value of GA, T2 generally has values higher than 75%, reaching 90% on average, with the highest even approaching 100%. T1, on the other hand, is mainly concentrated in the range of 20%-40%, with an average of only 30%, which shows that the double-layer roof system with a ceiling is more conducive to controlling the generation of uncomfortable glare. For the minimum value of GA, the lower limit of both terminals is lower than 20%, which shows that although uniformly arranged roof skylights are set up, there still exists a greater risk of glare hazard in some specific spaces, which requires the consideration of certain control strategies.

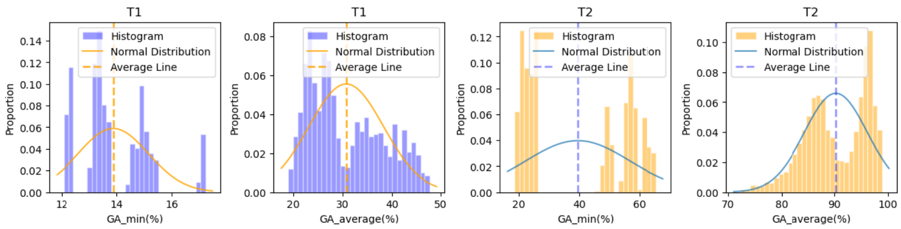

Figure 3. Histogram of GA distribution

The results of the correlation analysis for the two terminals are shown in Figure 4. Among them, the correlation between the glass curtain wall, floor parameter, and area of skylight and the glare performance is higher and shows a negative correlation, indicating that the glare hazard increases as the values of these parameters increase. It is worth noting that the correlation between the design parameters and the average value of GA is higher than the minimum value, which shows that the variation of the design parameters has a lower impact. In addition, the increase in building orientation angles in T1 leads to an increase in the potential hazard of glare.

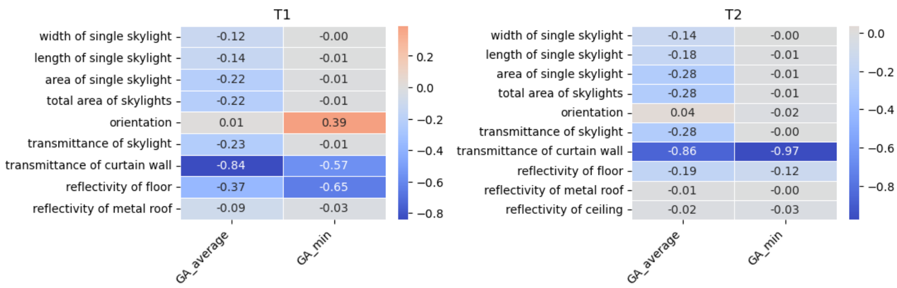

Figure 4. Correlation analysis between model parameters and glare indicators

3.2. EVALUATION AND VALIDATION OF TRANSFER LEARNING

Figure 5 depicts the machine learning in the source domain and the transfer learning training process in the target domain. During the training process, the training set and test loss show a monotonically decreasing trend, implying that the optimization process is stable and converges after 20 and 75 generations, respectively. In addition, we also compared the training effects of different methods or strategies to the transfer learning strategy, and the summary results are shown in Table 3.

Table 3 records the values of R Squared and MSE in the source and target domains by the three strategies of only source, data combination, and transfer learning, and although the different strategies show better training effects in the source domain, the prediction effects of the first two strategies in the target domain are weaker. The R Squared in the target domain under the data combination strategy is only 0.514, while the R Squared in the target domain and the source domain under the transfer learning strategy are 0.986 and 0.921, respectively. Therefore, we believe that the transfer learning strategy developed in this study can effectively improve the prediction effect in the target domain, and thus assist in the prediction of glare.

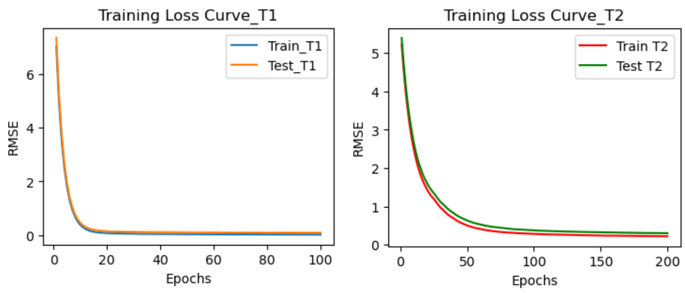

Figure 5. Training loss of source domain (T1) and target domain (T2)

Table 3. Comparison of prediction model evaluation in source and target domains under different strategies

Strategy	Source Domain (T1)		Target Domain (T2)	
	R Squared Score	MSE Loss	R Squared Score	MSE Loss
Only source	0.986	0.803	-56.510	2356.807
Data combination	0.955	23.05	0.514	28.577
Transfer learning	0.986	0.803	0.921	2.758

3.3. FEATURE IMPORTANCE ANALYSIS

Figure 6 shows the results of the feature importance analysis conducted after completing the training in the target and source domains, demonstrating the extent of the influence of different features on glare performance. Overall, the area of a single skylight has the greatest impact on the glare performance of both terminals, which shows that the reasonable design of skylight forms and sizes is important for reducing the glare hazard. Secondly, the material parameters of the skylight and glass curtain wall are also the key features affecting the glare performance, and these features play an important role in the glare control of both terminals.

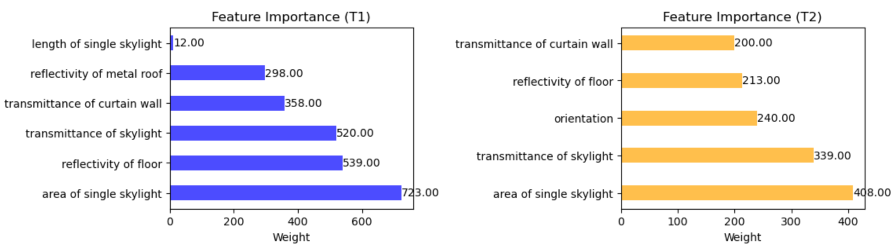

Figure 6. Feature importance analysis in the source and target domain

It is also worth noting that some parameters in the target and source domains have a low impact on glare performance, such as the length, width, and total area of skylights, so it is recommended that the design process focuses on the form and area of individual skylights, as well as the material parameters of the key envelope. Besides, the reflectivity of the floor will also have a certain impact on the glare performance, which is consistent with the results of a previous study (Xingyue H et al., 2021).

3.4. CONTRIBUTION AND APPLICATION

The results of this study demonstrate the feasibility of a machine learning model using a transfer learning strategy for predicting the glare performance of different terminals, which will provide an important reference for the new construction and expansion of other airports in the future. In the practical application of other projects, designers only need to adjust the relevant procedures of parametric modeling, while the batch simulation, machine learning models and transfer learning strategies applied in this study can be referred to directly.

The steps and process of this study can also be referred to when conducting prediction studies for other performance metrics. Meanwhile, the predictive models can be applied directly to the performance optimization process in the next step, which will reduce simulation time driven through the optimizer, and the data can be saved and recalled more flexibly.

3.5. LIMITATION AND FUTURE WORKS

This study also has some limitations. Firstly, the acquisition of design parameters failed to take into account the variation of the overall geometry, and only the skylight parameters were selected as variables. Therefore, in the subsequent study, we will enrich the design parameters to obtain a more complete and representative dataset. Secondly, in the selection of environmental performance targets, the annual glare indicator (GA) was selected in this study, and in terms of future works, we will consider other lighting indicators and combine deep learning to establish an image-based glare prediction study. Thirdly, the T1 and T2 in the study have similar spatial and structural characteristics, and if differentiated spatial types are involved, special attention needs to be paid to the accuracy of the results after transfer learning, and further comparisons can be attempted in conjunction with different transfer learning strategies.

4. Conclusion

This study develops and demonstrates a glare performance prediction and transfer learning strategy for check-in halls in terminals of different spatial types. It aims to obtain the glare performance impact characteristics of different spaces and provide methodological support for future glare performance prediction and transfer learning studies of similar spaces. The main conclusions of the study are summarized as follows.

- Double-layer roofing systems with evenly spaced ceilings are more conducive to less glare hazards and a comfortable indoor light environment.
- The application of transfer learning to glare performance prediction of terminal buildings has good practical value, and in this study, the prediction accuracy in the source domain (R Squared= 0.986) and the application of the XGBoost model to the performance prediction task in the source domain by utilizing transfer learning

is also able to achieve good prediction accuracy (R Squared= 0.921).

- For the case of this study, the area of a single skylight is the most critical feature affecting glare performance. Secondly, skylight glass, curtain wall glass, and floor material parameters are also important features affecting glare performance, and the design process should rationalize skylight forms and sizes to control direct and floor reflectivity to reduce reflected glare.

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References

Aseel, H, Wasiq K, Abir, H, Panos, L, Ahmed, AL-S & Dhiya, AL-J. (2023). Predicting energy performances of buildings' envelope wall materials via the random forest algorithm. *Journal of Building Engineering,* 69, 106263. https://doi.org/10.1016/j.jobe.2023.10626.

Giuseppe, P, Zhe, W, Abhishek, R, Tianzhen, H & Alfonso, C. (2021). Transfer learning for smart buildings: A critical review of algorithms, applications, and future perspectives. *Advances in Applied Energy,* 5, 100084. https://doi.org/10.1016/j.adapen.2022.100084.

Jiangyan, L, Qing, Z, Xin, L, Guannan, L, Zhongming, L, Yi, X, Kuining, L & Bin, L. (2021). Transfer learning-based strategies for fault diagnosis in building energy systems. *Energy and Buildings,* 250, 111256. https://doi.org/10.1016/j.enbuild.2021.111256.

Tianqi, C & Carlos, G (2016). XGBoost: A Scalable Tree Boosting System. In *22nd International Conference on Knowledge Discovery and Data Mining, ACM SIGKDD 2016* (pp. 785-794). Association for Computing Machinery (ACM).

Xi, F, Guangcai, G, Guannan, L, Liang, C, Weiqiang, L & Pei, P. (2021). A hybrid deep transfer learning strategy for short term cross-building energy prediction. *Energy,* 215, 119-208. https://doi.org/10.1016/j.energy.2020.119208.

Xinyue, H, Xiaoxiao, Z, Junming, L, Yuanjie, P & Xiaopeng, M. (2021). Subjective Evaluation Experiment of Ground-Reflected Glare in Tall and Large Spaces of Airport Terminals. *China Illuminating Engineering Journal,* 32 (5), 130-137. http://10.3969j.issn.1004-440X.2021.05.020.

Yan, S. (2022).The 14th Five-Year Plan for the Development of Civil Aviation. Civil Aviation Administration of China (CAAC). Retrieved November 20, 2023, from http://www.gov.cn/xinwen/2022-01/07/content_5667004.htm.

Yi, H, Xiaohui, H, Hongliang, Z, Wei, Z, Fuyun, Z, Marc, A. S & Yi, M. (2021). Hybrid framework for rapid evaluation of wind environment around buildings through parametric design, CFD simulation, image processing and machine learning. *Sustainable Cities and Society,* 73, 103092. https://doi.org/10.1016/j.scs.2021.103092.

Yi, L, Lin, Z & Rongfeng, C. (2019). Design Research on Spatial Comfort and Green Energy Saving of Airport Terminals. *Architectural Journal,* 09, 18-23.

Yinyi, S., Jinhui, C., Guangzhi, H., & Cunyuan, W. (2023). Prediction and Optimisation of the Typical Airport Terminal Corridor Façade Shading Using Integrated Machine Learning and EvolutionaryAlgorithms. In *28th International Conference on Computer-Aided Architectural Design Research in Asia: Intelligent and Informed, CAADRIA 2023* (pp. 59-68). The Association for Computer-Aided Architectural Design Research in Asia (CAADRIA).