Multivariable Optimization of Dynamic Translucent Solar Screen on West-Facing Offices

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Abstract. Discomfort glare frequently occurs in the west-facing rooms of office buildings during the afternoon. Using conventional opaque and fixed solar screens can obstruct the direct solar radiation, and reduces the glare. However, they may considerably reduce indoor daylighting levels and block the view outside at the same time. Thus, dynamic translucent panels are proposed in this study as external solar shading screens on the west-facing facades. Most importantly, a systematic method is developed to optimize the positions of the panels, addressing both daylighting, glare and view. The optimization algorithm - Artificial Neural Networks, combined with daylighting performance simulations is used to determine the optimal design parameters of the proposed solar shading screens. An office room in Guangzhou is used as a case study to test and optimize the proposed method. The whole study process consists of three steps: simulation, regression, and optimization. The results show that the neural network regression results are very close to the simulation ones. It means that deep neural networks can achieve a relatable regression performance and reduce the optimization time significantly. The optimal positions of the solar screens effectively reduce the glare level and maintain a relatively high indoor daylighting level and a large view field. Furthermore, this study also discusses the different effects of the weights for evaluation indicators on the final optimization results.

1. Introduction
Solar shading devices are widely used on building envelopes. These consist of external and intermediate devices, covering both fixed and movable types [1]. As one of the typical shading devices, horizontal shading panel has its own strengths: it provides not only a high indoor daylighting level but also a continuous wider view outside for occupants. Yet for a west-facing office, uncomfortable glare often occurs in the afternoon, if the shading panel is located at an inappropriate place. To address this problem, movable translucent shading panel is proposed in this study. It can effectively reduce glare by adjusting its position according to the solar elevation, and its translucent material ensures a relatively even distribution of indoor illuminance. Nevertheless, determining the optimal position is still a challenge, as it considers the trade-off between the daylighting, glare and view field.

Though plenty of studies in optimization of shading devices have been conducted in the past few decades, most of them are still constrained in the enumeration method - searching for the better-performed results from a series of simulation cases [2] [3]. For instance, M. David et al. conducted a set of experiments to verify the thermal and visual efficacy in non-residential buildings [4]. Athanassios Tzempelikos et al. carried out a series of studies to investigate the how the design and control of a shading device influence the building cooling and lighting demand. [5].
With the development of parametric studies on building performance, the method that combines optimization algorithms and simulation tools become widely popularity in building performance evaluation [6][7][8][9][10]. Javier Gonzalez and Francesco Fiorito used the evolutionary solver Galapagos (Genetic Algorithms based) to optimize the external shadings in a typical office in Australia [11]. Yunsong Han et al. applied a multi-objective evolutionary algorithm to evaluate and optimize Timber-Glass residential buildings, considering daylighting, energy efficiency and economic performance [12]. Anxiao Zhang et al. used the evolutionary optimization component - Octopus to find out the trade-off between reducing the energy consumption and maximizing the useful daylight illuminance [13].

The methods mentioned above mainly rely on the grasshopper plug-in evolutionary solvers, which conduct the optimization and simulation sequentially. However, for the multi-objective optimization in this study, the simulation of the daylighting performance and glare normally involve a quite long simulation time, which leads to a considerably long optimization time using existing evolutionary solvers. Thus, a stable optimal method with high accuracy and efficiency is needed to be developed.

In this study, a developed optimization method is proposed, which adopts the deep neural networks and advanced machine learning approaches. The whole optimization consists of three individual processes: simulation, regression, and optimization. The most time-consuming process – simulation is able to conduct parallelly on different servers. Therefore, it will dramatically reduce the optimization time and increase the optimal accuracy. Moreover, this study investigates the effects of different weights in the optimization function on the optimization results, to give advice for users with distinguishing foci in their optimization.

2. Methods

2.1. Simulation

In this study, a typical west-facing office cell is chosen as the experiment subject. It is located in Guangzhou, China (latitude 23.23°N and longitude 113.26°E) and occupied on weekdays from 9 am to 5 pm. The dimensions of the room are illustrated in Figure 1. The room is shaded by two horizontal movable solar panels. The position height of each panel (called x or y) ranges from 0.8 m to 2.4 m.

![Figure 1. Dimensions of the office geometry](image)

Tools used for the daylighting simulation are Grasshopper, DIVA and Python. DIVA plug-in is used for Daylight and Glare analyses. Python in Grasshopper integrates a series of customized programs to automatically control the changing of the input variables in loops. The surface materials are shown in Table 1.

| Table 1. Room surface materials and parameters. |
In this study, the evaluation indicator for the daylighting performance, glare and view are Daylight Factor (namely, $u$), Daylight Glare Probability (namely, $v$), and view field (namely, $z$), respectively. To simulate the Daylight Factor, a horizontal grid surface is placed at a height of 800 mm above the floor with a grid size of 10 mm. To simulate the DGP, a viewpoint is set at a height of 1200 mm, and 500 mm away from the window. The view field is the distance between the lower shading panel and window sill. The simulation time for glare is 16:00 on 22nd December, which is reveals the worst glare conditions for the west-facing office during working hours.

### 2.2. Multi-objective optimization analysis

#### 2.2.1 Neural network regression

The regression network aim to fit the $u$ and $v$ values for each combination of $x$ and $y$ based on the limited simulation results. It is a four-layer fully connected network, and each layer consists of 256 nodes. The activation function is RELU (Rectified Linear Unit). The hyperparameters of this network are achieved by a series of experiments, which considering the trade-off between the efficiency and accuracy. The loss function of this network is defined as the MSE (Mean Square Error) loss between the predicted value and the simulated one, shown as Function 1.

$$\text{Regression loss} = (U_{\text{pred}} - U_{\text{true}})^2 + (V_{\text{pred}} - V_{\text{true}})^2$$  \hspace{1cm} (1)

Where, $U_{\text{pred}}$ and $U_{\text{true}}$ are the predicted value of $u$ by using the regression network, and the simulated value of $u$ by using DIVA, respectively. $V_{\text{pred}}$ and $V_{\text{true}}$ are the predicted value of $v$ by using the regression network, and the simulated value of $v$ by using DIVA, respectively. SGD (Stochastic gradient descent) is used as the optimization algorithm. The learning rate is 0.01, and the learning rate decay is set to 0.9 per 10,000 steps. The training ends when the training loss descends below $1e^{-4}$.

In this study, order does not count, when counting the combinations of the $x$ and $y$. Thus, the inputs of $x$ and $y$ are transferred into another two equivalent values, which are $\min(x,y)$ and $\max(x,y)-\min(x,y)$. Then, each of them is normalized to a value between 0 and 1, using Function 2 and 3.

$$\tilde{x} = \frac{(\min(x,y) - 800)}{700}$$  \hspace{1cm} (2)

$$\tilde{y} = \frac{(\max(x,y) - \min(x,y))}{(2400 - \min(x,y))}$$  \hspace{1cm} (3)

Where, 800 is the minimum value of $x$, and 700 is the span of $x$. Similarly, the output values of $u$ and $v$ are normalized to values between 0 and 1 as well. The simulation results are the base for the regression. 80% of them are randomly selected as the training set, 5% of them as the validation set, and 15% of them as the test set.

#### 2.2.2 Neural network optimization

The neural network is also used for the optimization, applying the same network structure and weights as those for the regression. The optimization consists of two processes: inference and back propagation. During the inference process, the optimal values from the simulation results are selected as the input values, and the output values are calculated through the network. By comparing the calculated output
values with the simulated ones, the corresponding score can be calculated by using an optimization function. During the back propagation, the gradient for the descending direction of target function is calculated. Then based on the back propagation algorithm, the error gradient of each layer network output is propagated. Unlike the backward process for the network training, for the optimization, the weights of the network are fixed, while only the input values are updated in each step. It is expected that the input values would be closer to the optimum value gradually. The preprocess and normalization methods used for the network input and output in optimization are the same with those in regressive training. The optimization function is as follows (Function 4):

\[
\text{Score}_{\text{overall}} = w_v \text{Score}_v + w_u \text{Score}_u + w_z \text{Score}_z
\]

\[
\text{Score}_v = \left( \frac{v - v_{\text{min}}}{v_{\text{max}} - v_{\text{min}}} \right)^2, \quad \text{Score}_u = \left( 1 - \frac{u - u_{\text{min}}}{u_{\text{max}} - u_{\text{min}}} \right)^2, \quad \text{Score}_z = \left( 1 - \frac{z - z_{\text{min}}}{z_{\text{max}} - z_{\text{min}}} \right)^2.
\]

The lower the score is, the better optimization result is achieved. To avoid getting stuck into the local optimum at the early stage of optimization, the sgd algorithm with momentum is used in the optimization. The learning rate is set to 0.001, and the momentum is 0.9.

3. Results and discussion

After the simulation of 289 models. The simulated DF and DGP values are used for the regression and optimization.

1. Regression results

The regression results are presented in Figure 2. The horizontal axis represents the iterations step, and the vertical axis represents the loss. Logarithmic coordinates are plotted along the vertical axis, while linear coordinates along the vertical axis. It can be seen that the training ends after 150,000 steps, where the training loss is 7e-4(less than1e-5). Table 2 shows part results of the test set. As can be seen from the results that the difference between the simulation and neural network regression results are less than 0.01, which indicates a relatable regression performance.

![Figure 2. Curves of the test and training loss](image)

| x     | y     | u\text{true} | v\text{true} | u\text{pred} | v\text{pred} |
|-------|-------|--------------|--------------|--------------|--------------|
| 1600  | 800   | 3.24         | 0.327722     | 3.246204     | 0.328659     |
| 1800  | 800   | 3.19         | 0.33509      | 3.196169     | 0.334877     |
| 1900  | 800   | 3.26         | 0.336288     | 3.269616     | 0.33596      |
| 900   | 900   | 6.01         | 0.336429     | 6.057541     | 0.337187     |
| 1600  | 900   | 3.35         | 0.324133     | 3.3598       | 0.324065     |

the difference between the simulation and neural network regression results are less than 0.01, which indicates a relatable regression performance.
2. Optimization results

Based on the optimization function, 13 sets of optimal solutions are achieved based on the different combinations of \( w_u, w_v, \) and \( w_z \). Tables 3 - 7 show part of the optimal results for a detailed analysis and discussion.

**Table 3. Optimization result of case 1.**

| Weight | Optimum results | Performance | Score |
|--------|-----------------|-------------|-------|
| \( w_u \) | \( w_v \) | \( w_z \) | \( x \) | \( y \) | \( u \) | \( v \) | \( z \) | \( u \) | \( v \) | \( z \) | overall |
| 5 | 1 | 10 | 1399.54 | 2199.56 | 6.29 | 0.38 | 599.5 | 0.6 | 0.64 | 0 | 3.68 |

Visualization and simulation verification

Simulated DGP=0.37

In the optimization of this case, the greatest weight value (10) is given to \( z \). The weight for \( u \) is 5 and is only 1 for \( v \). Accordingly, the view field (z) is the major concern in the optimization of this case. The results in Table 3 show that the optimized \( z \) is 599.5 mm, and the score\( z \) is as lowest as 0. Meanwhile, as the weight for \( u \) is also relatively high, the optimal DF is as large as 6.29, which indicates a pretty high daylighting level. As a very small weight is assigned to \( v \), the optimal DGP is relatively high, which is 0.38, within the range of a “perceptible” glare based on the classification of DGP levels.

**Table 4. Optimization result of case 2.**

| Weight | Optimum results | Performance | Score |
|--------|-----------------|-------------|-------|
| \( w_u \) | \( w_v \) | \( w_z \) | \( x \) | \( y \) | \( u \) | \( v \) | \( z \) | \( u \) | \( v \) | \( z \) | overall |
| 10 | 5 | 1 | 1206.8 | 2006.84 | 6.12 | 0.32 | 406.8 | 0.63 | 0.05 | 0.54 | 7.07 |

Visualization and simulation verification

Simulated DGP=0.31

In the optimization of the case 2, the greatest weight value is assigned to \( u \), while the smallest one is assigned to \( z \). Thus, DF (\( u \)) is considered to be the most important factor in this optimization. The results in Table 4 show that the optimized DF value is 6.12, and the corresponding score is 0.63, which is one of the lowest score\( u \) out of all the score\( u \) values. Because glare is considered as the second important factor, the optimal DGP is quite low. It is only 0.32, which is within the range of “imperceptible” glare.

**Table 5. Optimization result of case 3.**

| Weight | Optimum results | Performance | Score |
|--------|-----------------|-------------|-------|
| \( w_u \) | \( w_v \) | \( w_z \) | \( x \) | \( y \) | \( u \) | \( v \) | \( z \) | \( u \) | \( v \) | \( z \) | overall |
| 5 | 10 | 1 | 1191.42 | 1991.46 | 6.1 | 0.32 | 391.4 | 0.63 | 0.05 | 0.57 | 4.18 |

Visualization and simulation verification

Simulated DGP=0.31
In the optimization of the case 3, the weights of u and v are exchanged compared with the settings for the case 2 settings. DGP (v) is considered to be the most important factor in this optimization. It can be seen from Table 5 that the optimal DF is slightly lower than the one for the case 2, while the optimal DGP stay the same. The view field is 15.4 mm less than the one for the case 2, due to the effect of DF.

| Weight | Optimum results | Performance | Score |
|--------|-----------------|-------------|-------|
| w_u   | w_v  | w_z | x    | y    | u   | v   | z   | u   | v   | z   | overall |
| 1     | 10   | 5   | 1244.06 | 2312.43 | 3.3 | 0.32 | 444.1 | 0.89 | 0.05 | 0.45 | 3.64 |

Visualization and simulation verification

Simulated DGP=0.32

In the optimization of the case 4, DGP (v) is considered as the most important factor, which is the same as 3. However, different weights for u and z lead to big differences in the optimization result. It can be seen from Table 6 that the optimal DF is almost half of the value for the case 3, which is only 3.3. The view field is much larger than the value for case 3, reaching 444.1 mm. The DGP value stays the same in these two optimizations, which is 0.32, within the range of the “imperceptible” glare.

Table 7 presents the optimization results of the case 5. It shows that when all the weights are set to 1, the optimal values of u, v, z are 6.18, 0.34, 474.23 respectively. Though none them reaches the best value, each of them achieves a relatively good performance, and thus lead to the best overall performance taking all the aspects into account.

| Weight | Optimum results | Performance | Score |
|--------|-----------------|-------------|-------|
| w_u   | w_v  | w_z | x    | y    | u   | v   | z   | u   | v   | z   | overall |
| 1     | 1    | 1   | 1274.23 | 2074.27 | 6.18 | 0.34 | 474.2 | 0.62 | 0.18 | 0.38 | 1.17 |

Visualization and simulation verification

Simulated DGP=0.33

Table 7 presents the optimization results of the case 5. It shows that when all the weights are set to 1, the optimal values of u, v, z are 6.18, 0.34, 474.23 respectively. Though none them reaches the best value, each of them achieves a relatively good performance, and thus lead to the best overall performance taking all the aspects into account.

Overall, when the value of w_u is set to 10 or 5, the optimal DF values range from 6.29 to 6.11 regardless the w_v and w_z values. This DF value indicates a high daylighting level. Under this condition, the optimal DGP ranges from 0.32 to 0.38. However, when the w_v and w_u values are set to 10 and 1, respectively, the optimal DGP values decrease to 0.32 or 0.31. The DF value drops dramatically to the range from 3.3 to 4.29. If w_z is set to 10, the z value is 599.54, no matter what value w_u or w_v takes.

4. Conclusion and implications
This study investigates a multi-objective parametric optimization method for the dynamic translucent solar screen panels on west-facing offices. Deep neural networks are used for the regression and optimization. Such method significantly reduces the optimization time, as the simulation is conducted in several servers parallelly. The results show that the differences between the simulation and neural network regression results are less than 0.01. It indicates that deep neural networks can achieve a relatable regression performance. Moreover, the optimization results show that, for a west-facing office using horizontal movable shading panels, if the DGP is controlled into the “perceptible” range (DGP...
<0.4), pursuing a lower DGP excessively has a great influence in the DF and view field, but has little effect in glare reduction. Therefore, an overall optimal result can be achieved, if all weights are set to 1.

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