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A Data-Driven Optimization Control Framework for Adaptive Solar Façades Balancing Photovoltaic Performance and Indoor Environment

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Abstract. Global warming and increasing urban density highlight the necessity of adaptive solar façades (ASF), yet challenges persist in achieving a balance between photovoltaic performance and indoor comfort. This study proposes a novel optimization control framework for ASF based on the vertical mobility of solar-tracking units. In the research case, the ASF system is divided into seven rows in an office setting, with photovoltaic irradiance, indoor irradiance, and daylight glare probability (DGP) as performance metrics. Batch sampling uncovers dynamic correlations between façade positions and performance metrics, providing references for open-loop control strategies. A machine learning-based surrogate model (XGBoost), trained on simulation data and paired with NSGA-II optimization, supports real-time control. Results show that façade unit positions significantly correlate with performance metrics, with vertical angles varying by unit height, season, and time. Higher-positioned units are generally more effective for indoor control. The XGBoost model achieved high precision ($R^2 = 0.999$) and reduced simulation time by 99.9%, enabling real-time predictions. Optimization results demonstrated a 5% increase in photovoltaic irradiance, a 19% improvement in indoor irradiance, and a 5% reduction in DGP, validating the effectiveness of the control framework.

Keywords. Adaptive solar façades, Photovoltaic performance, Natural lighting, Machine learning, Multi-objective optimization

1. Introduction

With the intensification of global warming and the increasing frequency of extreme heat events, building energy consumption and carbon emissions are on the rise. In this

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context, green buildings have garnered widespread attention as a key measure for sustainable development. Simultaneously, there is a growing demand for enhanced comfort in residential and workplace environments. Adaptive Façades (AF), which can dynamically respond to environmental changes by adjusting light and thermal parameters, demonstrate significant potential for improving occupant comfort and reducing energy consumption (Aelenei et al., 2016). As urban density increases and roof areas become limited, the role of vertical façades in solar energy generation has gained prominence. Against this backdrop, the concept of Adaptive Solar Façades (ASF) has emerged as an innovative solution that integrates renewable energy generation with dynamic environmental adaptability (Rossi et al., 2012).

However, several challenges remain in the development of ASF:

(1.) ASF systems rely solely on simple solar tracking mechanisms, and that is insufficient to significantly enhance indoor comfort. A critical research question lies in how to develop refined control strategies that balance power generation efficiency with multiple indoor thermal and visual comfort metrics.

(2.) The temporal complexity of ASF control strategies presents substantial challenges during design and operational phases, as different control states can have varying impacts on performance indicators.

(3.) Existing methods for evaluating indoor thermal and visual performance heavily count on computational simulations, making it hard to achieve real-time optimization. This leads to potential underutilization of ASF performance and limits their application in practical engineering contexts (Shan & Junghans, 2018, p. 270).

This study mainly contributes on the following aspects:

(1.) Proposing a novel ASF motion strategy: A new ASF motion strategy is introduced, with its feasibility validated through practical experimentation.

(2.) Unveiling the relationship between façade positioning and performance metrics: Based on simulation data, the relationship between façade motion within segmented regions and three critical performance indicators would be analyzed, providing researchers with more detailed insights for further refinement.

(3) Developing performance prediction models and multi-objective optimization (MOO): Machine learning models are trained on simulation datasets to enable rapid prediction of performance metrics under specific climatic conditions and façade states, significantly reducing simulation time. MOO is conducted using the dataset to validate the feasibility and effectiveness of the proposed framework.

This research offers a comprehensive approach to improving the design, optimization, and implementation of ASF systems, advancing their potential for sustainable architectural applications.

2. Related Work

2.1. ADAPTIVE SOLAR FAÇADES

Transitioning from rooftop to façade applications, BIPV systems are increasingly tied to occupant comfort. ASF require sophisticated intelligent control strategies to balance multiple performance objectives, including energy efficiency, thermal comfort, and visual comfort (Loonen et al., 2013). Recent advancements in ASF optimization have yielded significant progress: optimizing indoor lighting and BIPV irradiance (Biloria et al., 2023), balancing occupant views and glare (Valitabar et al., 2021), employing biomimetic designs to enhance PV efficiency, indoor lighting as well as energy performance (Anzaniyan et al., 2022). The research group at ETH has implemented full-scale ASF prototypes in actual buildings, optimizing power gains and energy consumption (Svetozarevic et al., 2019).

Despite these advancements, challenges remain. The complexity of ASF designs and control strategies can pose difficulties for construction, maintenance and even compromise photovoltaic efficiency. Additionally, ASF designs vary significantly, and findings from a single optimization case often fail to generalize the relationships between façade placement and performance metrics, limiting broader applicability. Furthermore, current approaches rely on qualitative, intuition-driven analyses of these relationships, lacking the precision of quantitative methodologies.

2.2. MACHINE LEARNING (ML) & OPTIMIZATION

Building performance metrics often exhibit trade-offs; for instance, energy consumption, natural lighting, and thermal comfort may show negative correlations. The NSGA-2 algorithm (Deb and Goel, 2001), widely applied in the field of building technologies, is a multi-objective optimization method commonly used to balance potential conflicting performance objectives. However, MOO relies a lot on extensive simulation data, which can be computationally intensive and time-consuming. This limitation not only reduces efficiency during the early design stages but also poses significant challenges for real-time optimization and adjustments of ASF in complex, dynamic environments.

Artificial intelligence has demonstrated its potential to significantly accelerate prediction processes in computational thermal and daylight simulations. Machine learning (ML) algorithms, such as XGBoost, have shown outstanding performance in predicting and optimizing DGP values, enabling real-time feedback for ASF adjustments (Takhmasib et al., 2023). Similarly, artificial neural networks (ANNs) have been employed to optimize operational strategies for BIPV/T façades, improving their performance while reducing computation time by 92.6% (Wang et al., 2022). These findings underscore the transformative potential of ML techniques in building performance optimization, enhancing prediction accuracy and efficiency while providing faster and smarter solutions for complex architectural environments.

3. Methods

The overall research framework is illustrated in Figure 1. After introducing the research case and boundary conditions in Section 3.1, the subsequent sections will demonstrate the following content: Section 3.2 (ASF Design), Section 3.3 (Performance Evaluation), Section 3.4 (Correlation Analysis), Section 3.5 (Machine Learning & Optimization).

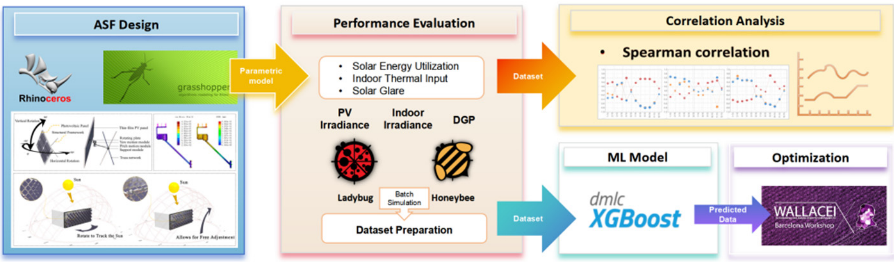

Figure 1. Overall research framework

3.1. RESEARCH CASE AND BOUNDARY CONDITIONS

This study selected a small office space as the research object. The building façade features a south-facing glass curtain wall design, with an indoor net dimension of 8m × 4m × 3m. The study site is Hangzhou, China, which falls into Light Climate Zone IV and Hot-summer & Cold-winter Zone. The specific information about the location and parametric room is shown in Figure 2.

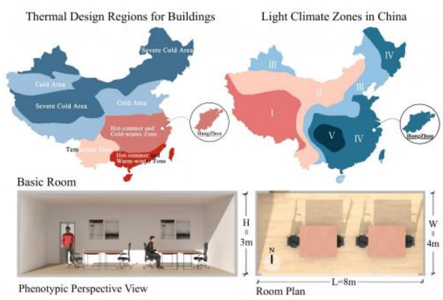

Figure 2. Case study

3.2. ASF DESIGN

The ASF units in this study adopt a simple square design with a side length of 0.4 meters, facilitating standardized manufacturing and assembly of solar panels. Sixty-seven units are arranged in seven rows, staggered in front of the curtain wall and mounted on an X-shaped truss network. Each unit is designed to rotate independently on two axes: one for tracking the solar azimuth and another for pitch adjustment ranging from 0° to 90° in 10° increments. The pitch angles for all units in each row are identical. This design accounts for the wider range of solar azimuth angles compared

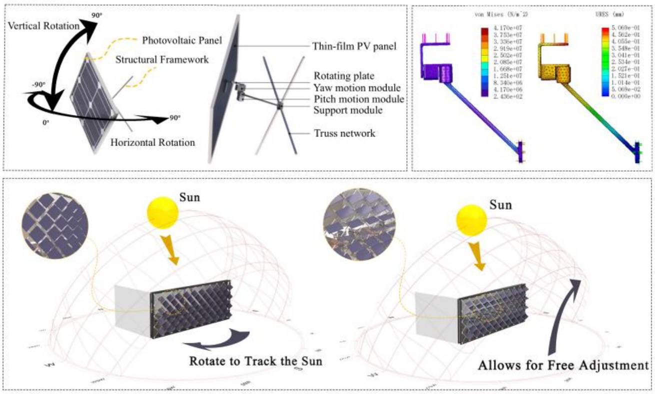

Figure 3. ASF movement strategy and drive design

to altitude angles, enabling effective solar tracking and optimizing indoor solar radiation.

The driver uses a micro servo, achieving dual-axis motion through the series connection of two servos. The finite element analysis results of the actuator indicate that this actuator can stably support photovoltaic panels and drive their rotational motion.

3.3. PERFORMANCE EVALUATION

Performance simulations were conducted using Ladybug and Honeybee plugins in the Grasshopper platform. The simulation times were set at 9:00, 12:00, and 15:00 on the 15th day of each month, representing typical office hours. Weather data were downloaded and extracted from EnergyPlus EPW files to construct CIE skies. The indoor simulation grid size was set to 0.5 meters, with a glass transmittance of 0.85.

Three metrics were used to evaluate photovoltaic energy gain, indoor solar radiation gain, and occupant glare: PV Irradiance, Indoor Irradiance, and DGP. The selection of these metrics considered the generalizability of the study. Specific definitions and explanations are provided in Table 1.

Table 1. Performance objectives and metrics

Objective	Metric	Unit	Instruction
Solar Energy Utilization	PV Irradiance	W/m²	Directly reflects the potential for energy harvesting while remaining independent of the specific performance of photovoltaic panels, offering high generalizability.
Indoor Thermal Input	Indoor Irradiance	W/m²	Exclusively quantifies solar irradiance as an indicator of thermal input, unaffected by other heat sources or material properties.
Solar Glare	DGP	%	The average DGP value of 128 grids at an indoor height of 1.2 meters.Reflects the overall glare level within the indoor environment.

Batch simulations were performed using Colibri, with 360 completely random combinations of the pitch angles of the seven rows of façade units at each of the 36-time points, resulting in 12,960 simulation results. The simulation results were saved using the TT toolbox, and Accelerad (Nathaniel Jones, 2019) was used to speed up the simulations.

3.4. CORRELATION ANALYSIS

Spearman's rank correlation coefficient was used to analyze the relationship between façade position and performance metrics at different times. Different regions of the façade have varying influences on performance goals; for example, the middle zone may focus more on daylighting and visual comfort, while upper and lower zones may prioritize energy collection and thermal gain (Svetozarevic et al., 2019, p. 672). To summarize the relationship between façade regions and performance metrics and provide generalized references for regional control logic design, the seven rows of ASF units were divided into three zones based on façade position: Rows 1-2 (Zone 1), Rows 3-5 (Zone 2), and Rows 6-7 (Zone 3). The average pitch angle of the units in each zone was calculated, and the correlation coefficients with the three performance metrics were obtained based on iterative simulation results. Finally, the trends of the correlation coefficients at 12 × 3 time points throughout the year were plotted for in-depth analysis.

3.5. MACHINE LEARNING & OPTIMIZATION

XGBoost (Extreme Gradient Boosting) is an efficient gradient boosting algorithm that builds trees incrementally, handling non-linear data and providing strong generalization capabilities. In this study, XGBoost was used to establish non-linear relationships between input features and multi-objective variables. The input features included the pitch angles of the seven rows of façade units and the solar position vector. The output labels were PV Irradiance, Indoor Irradiance, and DGP.

The data were divided into 80% training and 20% testing sets, and the input features were standardized. Model performance was evaluated using the coefficient of determination (R^2), mean squared error (MSE), and mean absolute error (MAE). Optimal models were determined through model comparison and hyperparameter tuning, providing support for subsequent multi-objective optimization.The Wallacei engine (Makki et al., 2018), which is based on the NSGA-II evolutionary algorithm, was selected as the multi-objective optimization plugin. The ASF state at 9:00 AM on December 15th was chosen as the optimization condition. The optimization parameters comprised the pitch angles of seven rows of ASF units. The optimization objectives were to maximize PV Irradiance and Indoor Irradiance while minimizing DGP.

4. Results

4.1. CORRELATION ANALYSIS RESULTS

Based on the data in Figure 4, the average tilt angles of panels in different zones (Zone 1, Zone 2, Zone 3, referred to as Z1, Z2, and Z3 in this section) exhibit dynamic correlations with the three performance indicators—PV Irradiance (PV), Indoor Irradiance (IR), and Daylight Glare Probability (DGP, referred to as PV, IR, and DGP). Overall, the correlations between panel angles in Z1 and Z2 and the performance indicators show significant fluctuations throughout the year, while the variations in Z3 are relatively smaller, particularly with weaker impacts on IR and DGP.

Specifically, Z1 exhibits a negative correlation with PV Irradiance during spring, particularly in early spring, while showing a positive correlation in other seasons. In

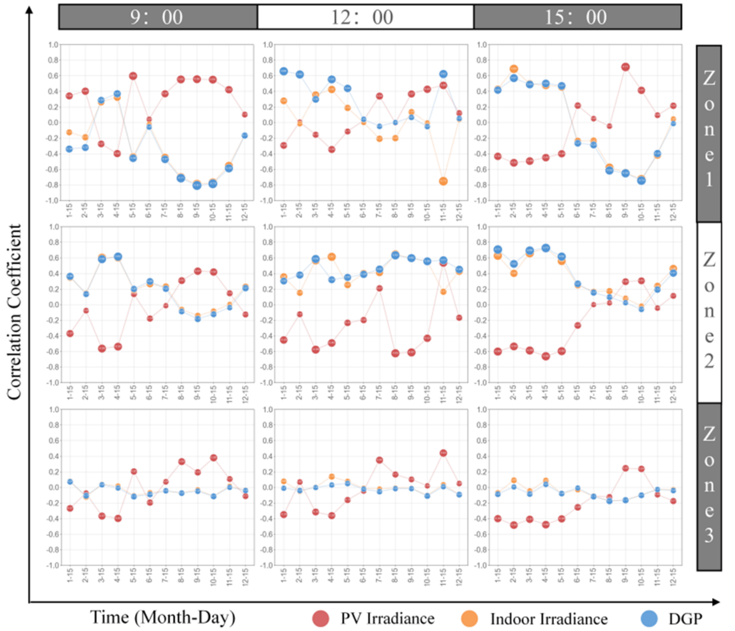

Figure 4. The correlation between the pitch angles of ASF zones and performance metrics over time.

contrast, its correlation trends with IR and DGP are generally opposite. This may be attributed to Z1's position at the top of the façade, making it more sensitive to variations in solar altitude. The combined effects of time and seasonal changes further amplify the dynamic fluctuations in these trends.

Similarly, Z2 exhibits an almost consistent negative correlation with PV Irradiance throughout the day during winter and spring. In contrast, during summer and autumn, the correlation transitions dynamically from positive in the morning to negative in the afternoon and back to positive later in the day, reflecting a time-dependent characteristic. Its correlations with IR and DGP remain predominantly positive throughout the year and across the day, although they weaken in the mornings and afternoons of autumn while strengthening around midday. This pattern may be influenced by the east-to-west trajectory of sunlight.

Z3 shows a pronounced negative correlation with PV Irradiance throughout the day during winter and spring, while the correlation reverses in summer and autumn, though less prominently. This is likely due to Z3's position at the lower part of the façade, where it is partially shaded by upper panels. Its correlations with IR and DGP remain negligible throughout the year, likely because its lower position has minimal influence on indoor comfort metrics. However, it retains the potential for solar energy capture.

In addition, there are inherent correlations among the performance indicators. For instance, PV and IR often exhibit a negative correlation, while IR and DGP tend to show a synergistic relationship. During summer (cooling season), the objectives of reducing indoor heat gains, minimizing glare, and maximizing photovoltaic energy yield can be simultaneously achieved by optimizing the panel tilt angles. Conversely, in winter (heating season), achieving these goals involves a more complex balance among conflicting objectives, requiring trade-offs to be carefully optimized.

Based on the correlation analysis, this study proposes the following control strategies:

(1.) In spring, adjust the Zone 1 panels to a more horizontal angle so that they can mitigate the negative correlation with PV Irradiance and optimize the indoor light and thermal environment. In other seasons, setting the panels to a more vertical angle enhances power generation efficiency while limiting excessive heat gains indoors.

(2.) Especially during summer and autumn, dynamically adjust the panel angles in Zone 2 to adapt to the solar path throughout the day. This enables flexible control to balance PV Irradiance, Indoor Irradiance, and DGP.

(3.) Prioritize optimizing Zone 3's contribution to PV Irradiance throughout the year to enhance its solar energy capture potential.

4.2. MACHINE LEARNING MODEL

The final configuration of the XGBoost parameters was set as follows: the number of trees (n_estimators) = 100, learning rate (learning_rate) = 0.1, and tree depth (max_depth) = 6. Scatter plots show a high degree of alignment between the predicted values and actual values for the three target variables, with R^2 scores approaching 0.999, indicating excellent model fit. Residual distribution is concentrated around zero without significant bias, showcasing the high precision and stability of the model (Figure 5).

Moreover, the computation time for single performance metric calculations has been drastically reduced from 56 seconds to 0.009 seconds, representing a reduction of approximately 99.9%. The prediction outcomes suggest that the constructed performance prediction model is reliable and can significantly shorten the duration required for performance simulations.

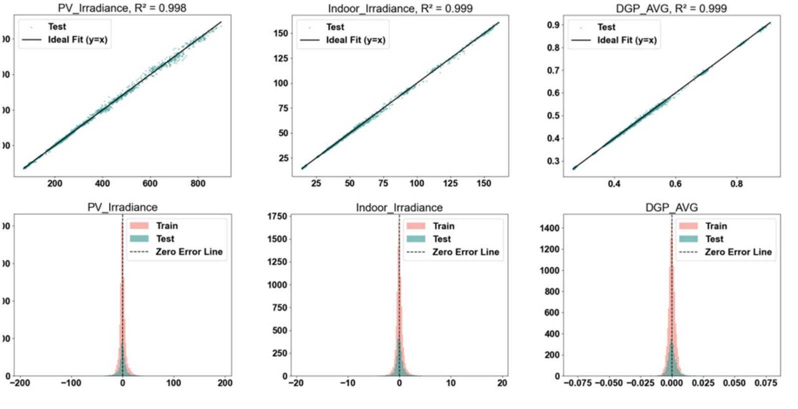

Figure 5. Model Training: Scatter Plot and Residual Distribution Analysis

4.3. MULTI-OBJECTIVE OPTIMIZATION RESULTS

For the optimization of AFS, the Wallecei Engine was used to generate parameter combinations, with the GA solver settings and optimization visualization results shown in Figure 6. By integrating the machine learning model from Section 4.2 into GHPython, individual solution optimization time was significantly reduced and can be generated within 3 seconds. The overall optimization trend indicates that the algorithm has essentially converged, achieving favorable outcomes.

To evaluate the advantages of the optimization results, the optimal solutions for three key metrics were compared against the first test gene sets. The results showed an increase of 5% and 19% in PV Irradiance and Indoor Irradiance, respectively, and a 5% reduction in DGP. This also indirectly highlights the strong trade-offs among the three metrics, further emphasizing the necessity of multi-objective optimization. These outcomes demonstrate that incorporating machine learning models into multi-objective optimization enables efficient performance enhancement within a short timeframe, offering support for the optimization of complex systems.

Parameter name	Setting details
Generation Size	50
Generation Count	50
Crossover Probability	0.9
Mutation Probability	1/r
Crossover Distribution Index	20
Mutation Distribution Index	20

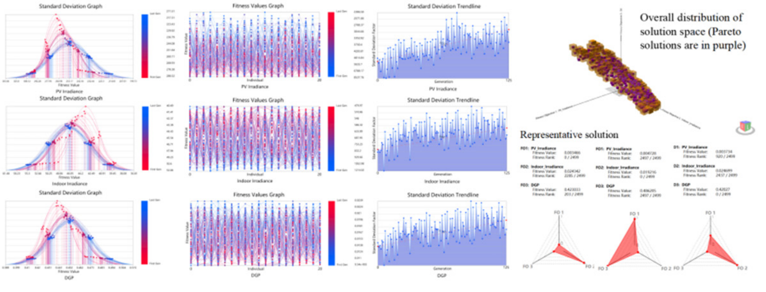

Figure 6. GA Solver Settings and Optimization Visualization Results

5. Conclusion

This study proposes a new paradigm for optimizing the performance of ASF. By employing a dual-axis motion control strategy, the research reveals the dynamic temporal relationships between façade regions and performance metrics and introduces generalized seasonal and regional control guidelines. The integration of machine learning with the NSGA-2 algorithm significantly reduces optimization time, demonstrating the engineering applicability of the proposed framework. Future work will extend this framework to various climatic conditions and complex environments to enhance its applicability and promote the practical implementation of ASF in engineering projects, including the construction and validation of physical models.

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