Evaluating Carbon Payback Period in Parametric Facade Optimization Using Genetic Algorithms and Multi-Criteria Decision-Making

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Abstract

Facade shading systems can reduce cooling energy demand in office buildings located in tropical-humid climates, but the additional materials required may also increase embodied carbon emissions. Although many parametric facade optimization studies focus on operational energy and daylight performance, the temporal relationship between embodied carbon and operational carbon savings remains insufficiently explored. Carbon Payback Period (CPP) is therefore rarely integrated into parametric facade optimization and decision-making workflows. This study proposes an integrated framework combining Life Cycle Assessment (LCA), CPP, multi-objective optimization, and Multi-Criteria Decision-Making (MCDM) to support low-carbon facade design. A parametric facade model was developed for a medium office building in Taipei, Taiwan, with variations in window-to-wall ratio, glazing type, shading depth, and window configuration. Energy and daylight performance were simulated using Honeybee and Ladybug, while Wallacei was used to optimize Energy Use Intensity (EUI), Annual Sunlight Exposure (ASE), Whole-Life Carbon (WLC), Carbon Payback Period (CPP), and Spatial Daylight Autonomy (sDA). The resulting 20 Pareto-optimal alternatives were then evaluated using TOPSIS under multiple weighting scenarios. The results revealed clear trade-offs between operational efficiency and life-cycle carbon performance. Building Type 02 emerged as the most robust and balanced alternative, ranking first across the energy-priority, carbon-priority, and balanced scenarios and achieving a positive CPP of 8.95 years. These findings highlight the value of CPP as a complementary time-based indicator for verifying whether additional embodied carbon can be offset by future operational carbon savings in facade design decision-making.

Keywords –

Parametric facade design; Carbon payback period; Life cycle assessment; Genetic algorithms; Multi-criteria decision-making; Tropical-humid climate

1 Introduction

Global warming remains a major global challenge and has accelerated the use of life cycle assessment (LCA) to quantify emissions and support SDG 13 and long-term net-zero targets[1]. In the building sector, particularly in office buildings located in humid tropical climates, high cooling demand makes facade design a critical strategy for reducing operational energy use. In Taipei's hot-humid context, facade measures such as high-performance glazing and external shading can improve thermal and visual performance, but they may also increase embodied carbon.

Recent advances in parametric modeling, building performance simulation, and genetic algorithms have enabled the systematic exploration of facade alternatives based on indicators such as Energy Use Intensity (EUI), Spatial Daylight Autonomy (sDA), and Annual Sunlight Exposure (ASE)[2]. However, many studies still primarily focus on operational performance and give limited attention to embodied carbon throughout the building life cycle. Although LCA has increasingly been applied in building evaluation, aggregated carbon indicators often fail to reflect the temporal relationship between additional embodied carbon and future operational carbon savings. In this regard, the Carbon Payback Period (CPP), defined as the time required for operational carbon savings to offset additional embodied carbon, provides an important time-based perspective[3]. Yet CPP remains rarely integrated into parametric facade optimization workflows.

At the same time, multi-criteria decision-making (MCDM) methods such as TOPSIS are widely used to rank Pareto-optimal solutions under different decision priorities[4]. However, most facade-related MCDM studies still emphasize energy, cost, and daylight metrics, while time-based carbon indicators, such as CPP, receive limited attention. This gap is particularly relevant in humid tropical and subtropical climates such as Taipei, where the interactions among shading, glazing, daylight availability, and life-cycle carbon performance remain insufficiently explored.

Therefore, this study proposes an integrated LCA-CPP-MCDM framework that combines parametric facade modeling, Wallacei-based multi-objective optimization, and TOPSIS evaluation for an office building in Taipei. CPP is incorporated in the optimization stage as a time-based carbon objective, but it is excluded from the final TOPSIS ranking because negative CPP values represent no-payback conditions rather than stable and directly comparable ranking criteria. Instead, CPP is used as a post-evaluation indicator to verify whether the highly ranked alternatives also achieve meaningful carbon payback performance. This approach provides a more comprehensive and time-sensitive basis for low-carbon facade design in humid tropical climates.

2 Literature Review

2.1 Parametric Design and Multi-Objective Optimization for Facade Performance

Facade design strongly influences building performance by affecting solar heat gain, daylight availability, visual comfort, and energy use. In tropical office buildings, key variables such as window-to-wall ratio (WWR), glazing type, and shading depth must be carefully balanced because improving one aspect of performance may reduce another. Facade design should therefore be treated as a multi-criteria problem rather than a single-objective task[5].

Parametric design helps manage this complexity by defining geometric and performance-related properties as adjustable variables. When integrated with building performance simulation, it supports the rapid generation and evaluation of design alternatives during the early design stage. Because facade objectives are often conflicting, multi-objective optimization (MOO) is widely used to identify Pareto-optimal solutions rather than a single best design. In this context, Wallacei, which implements NSGA-II in Grasshopper-based workflows, has become a relevant tool for facade optimization[6].

However, most parametric multi-objective optimization studies still focus mainly on operational indicators, particularly energy use and daylight performance, with limited attention to embodied carbon and broader life-cycle carbon trade-offs. This limitation is also evident in tropical office building studies, where optimization frameworks often prioritize operational efficiency and indoor environmental quality over long-term carbon implications. As a result, life-cycle carbon indicators, especially time-based measures such as Carbon Payback Period (CPP), remain insufficiently integrated into facade optimization. To address this gap, the present study incorporates LCA-based metrics, including Whole-Life Carbon (WLC) and CPP, into facade optimization and design decision-making.

2.2 Life Cycle Assessment in Parametric Design Workflows

Life Cycle Assessment (LCA) is increasingly important in building evaluation because it captures environmental impacts beyond operational energy use[7]. In facade design, this is particularly relevant because strategies that improve energy and daylight performance may also increase embodied carbon through additional materials, such as glazing, framing, and shading systems.

To support early-stage design, parametric Life Cycle Assessment (pa-LCA) links parametric models with environmental impact calculations, enabling rapid comparison of design alternatives[8]. However, its application remains limited by data uncertainty, interoperability issues, and the computational burden of repeated quantity take-off and carbon calculations. Accordingly, this study adopts a partial life-cycle scope based on EN 15978, covering A1–A3 for embodied carbon and B6 for operational energy use[9]. This boundary is appropriate for early-stage facade evaluation, where detailed life-cycle data are still unavailable. Within this framework, Whole-Life Carbon (WLC) is used to assess combined embodied and operational emissions, while Carbon Payback Period (CPP) captures the time dimension of carbon performance[10].

2.3 Carbon Payback Period (CPP)

Carbon Payback Period (CPP) is a time-based indicator that measures how long it takes for the additional embodied carbon caused by a design intervention to be offset by annual operational carbon savings[11]. In facade design, CPP is particularly relevant because variables such as window-to-wall ratio (WWR), glazing type, and shading depth affect both embodied and operational carbon, thereby creating a trade-off between upfront and long-term environmental impacts. CPP is therefore useful for evaluating whether a facade strategy can deliver meaningful carbon benefits within a relevant time frame[12].

A key strength of CPP is its ability to introduce a temporal perspective into carbon assessment. A facade alternative may reduce operational energy use and even achieve lower Whole-Life Carbon (WLC), yet still require a long time to offset its initial embodied carbon burden when annual carbon savings are limited[13]. In this way, CPP helps distinguish between solutions that provide near-term carbon benefits and those whose advantages only emerge over longer time horizons. This distinction is important because earlier carbon reductions are generally more valuable for climate change mitigation than delayed ones[14].

Despite its relevance, CPP remains underused in parametric facade optimization studies, where most research continues to focus on energy use, operational carbon, or Whole-Life Carbon[15]. Therefore, this study adopts CPP as a complementary indicator to strengthen life-cycle carbon evaluation and support early-stage facade design decision-making. Positive CPP values indicate a valid carbon payback duration, meaning that the additional embodied carbon can be offset over time through annual operational carbon savings. Negative CPP values do not represent a valid payback duration; rather, they indicate that carbon payback is not physically meaningful under the given condition. This occurs when annual operational carbon savings are absent or insufficient to offset the initial embodied carbon increment.

2.4 Facade Optimization in Tropical-Humid Climates

Facade optimization in tropical-humid climates requires climate-specific evaluation because high solar radiation, temperatures, humidity, and daylight availability create performance conditions distinct from those in temperate regions[11]. In Taipei, facade design influences cooling demand, glare risk, and daylight distribution, making variables such as window-to-wall ratio (WWR), glazing type, and shading geometry critical to performance. These trade-offs are commonly assessed using metrics such as sDA, ASE, and DGP, which reflect daylight adequacy, excessive sunlight exposure, and visual comfort. Although previous studies in hot-humid climates have emphasized operational energy and comfort performance, life-cycle carbon and carbon payback remain less explored. Therefore, this study extends climate-responsive facade optimization by integrating energy, daylight, glare, and life-cycle carbon metrics for an office building in Taipei.

2.5 Research Gap

The reviewed literature demonstrates substantial progress in parametric facade optimization, life-cycle assessment integration, and multi-criteria decision-making. However, three critical gaps remain:

(1) First, CPP is rarely integrated into parametric optimization workflows and is typically applied only as a post-evaluation metric.

(2) Second, existing LCA-based facade studies rely heavily on aggregated carbon indicators, overlooking the temporal relationship between embodied and operational emissions.

(3) Third, tropical-humid climates remain underrepresented in integrated LCA–optimization studies, particularly those addressing facade shading systems.

To address these gaps, there is a clear need for an integrated framework that embeds CPP within parametric facade optimization and decision-making processes, enabling designers to evaluate not only energy and daylight performance but also the time-dependent carbon effectiveness of facade interventions. This study responds to this need by proposing a combined LCA–CPP–MCDM framework applied to a tropical-humid office building case study.

3 Method

This study adopts an integrated, multi-stage framework (see Figure 1) combining parametric facade modeling, life cycle assessment (LCA), carbon payback period (CPP) analysis, genetic algorithm optimization, and multi-criteria decision-making (MCDM). The overall workflow is structured into four sequential stages: (1) literature review and framework setup, (2) parametric modeling and simulation, (3) multi-criteria decision-making, and (4) validation and final decision support.

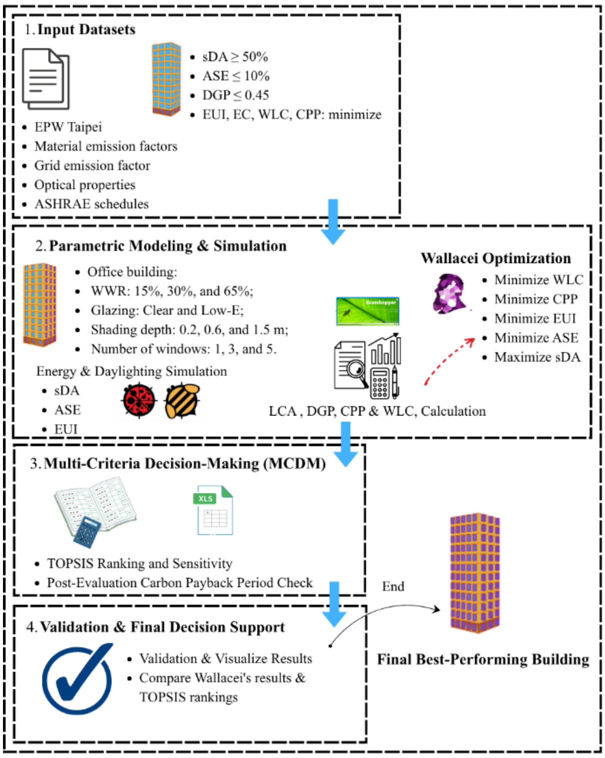

Figure 1. Research Workflow

3.1 Stage 1: Input Datasets

In the first stage, the study defines the input datasets, analytical boundaries, and performance targets for the integrated facade optimization framework. The case study is a medium office building in Taipei, where solar radiation, cooling demand, and daylight availability strongly influence facade performance. The main inputs include the Taipei EPW weather file, material emission factors, grid emission factors, optical properties, and ASHRAE schedules, which together support energy, daylight, and carbon assessment. The facade is defined by four key variables: window-to-wall ratio (WWR), glazing type, shading depth, and number of windows. At this stage, the performance criteria are established as sDA ≥ 50%, ASE ≤ 10%, and DGP ≤ 0.45, while EUI, embodied carbon (EMB), WLC, and CPP are treated as indicators to be minimized.

3.2 Stage 2: Parametric Modeling and Simulation

In the second stage, a parametric facade model was developed in a visual programming environment by varying the window-to-wall ratio (WWR), shading depth, glazing type, and number of windows within predefined ranges, as summarized in Table 1.

Table 1. Building Geometry & Simulation Setup

No	Category	Value
1.	Building Type	Medium Office Building
2.	Location & Climate	Taipei, Taiwan; Tropical-Humid
3.	Geometry	15 × 15 m plan, 12 floors, floor height 4.0 m
4.	Spatial Model	Single zone per floor
5.	Orientation	North, East, South, and West
6.	Facade Variables	WWR: 15% / 30% / 65%; Glazing: Clear / Low-E; Shading depth: 0.2 / 0.6 / 1.5 m; Number of windows: 1 / 3 / 5
7.	Simulation Platform	Rhino + Grasshopper + Honeybee/Ladybug
8.	Weather Data	EPW (Taipei)
9.	Energy Simulation	Honeybee Energy (Energy Plus)
10.	Daylight Standards	EN 17037, LEED v4.1
11.	Energy Metric	EUI (kWh/m²·yr)
12.	Daylight Metrics	sDA, ASE, DGP
13.	Carbon Metrics	Embodied Carbon, CPP, WLC
14.	LCA Data Source	QTO and EF-based carbon coefficients
15.	Grid Emission Factor	Taiwan electricity grid
16.	Optimization Method	Wallacei Genetic Algorithm (GA)
17.	Optimization Objectives	Maximize sDA; minimize ASE, EUI, WLC, and CPP
18.	Decision-Making Method	TOPSIS (MCDM) with DGP as a supporting visual comfort criterion
19.	Facade Final Output	Optimal facade parameters

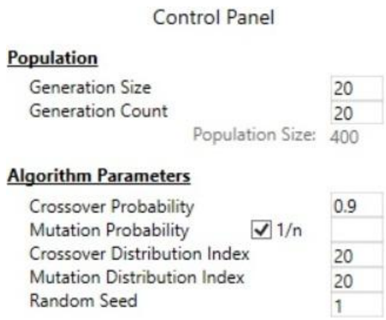

Figure 2. Wallacei optimization settings

Multi-objective optimization was then performed using the Wallacei genetic algorithm to minimize EUI, ASE, WLC, and CPP while maximizing sDA. The optimization settings are shown in Figure 2. During the evolutionary search, a simplified embodied carbon proxy was adopted to represent carbon sensitivity within the optimization loop, while Daylight Glare Probability (DGP) was evaluated separately at the post-optimization stage. For the selected Pareto-optimal alternatives, embodied carbon was recalculated using quantity take-off (QTO)-based geometry and emission-factor-based carbon coefficients. These recalculated embodied carbon values were then combined with annual operational carbon emissions to determine Whole-Life Carbon (WLC) and Carbon Payback Period (CPP), enabling an integrated assessment of energy, daylight, and carbon performance.

Accordingly, this study used two embodied carbon representations with distinct roles. QTO-based embodied carbon was used for the final calculation of WLC and CPP, whereas the simplified embodied carbon proxy in Wallacei served only as a surrogate indicator to test the influence of carbon sensitivity during the evolutionary search. Although the proxy may affect which solutions are explored and retained in the Pareto set, the final carbon assessment of the selected alternatives was based entirely on the more detailed QTO-derived embodied carbon values.

3.3 Stage 3: Multi-Criteria Decision-Making (MCDM)

In the third stage, the 20 Pareto-optimal facade alternatives generated by Wallacei were evaluated using TOPSIS to identify the most balanced final design. Four weighting scenarios were defined: energy-priority, carbon-priority, comfort-priority, and balanced.

TOPSIS ranked the alternatives using six criteria: sDA, ASE, DGP, EUI, WLC, and embodied carbon (EMB). Carbon Payback Period (CPP) was excluded from the final ranking because negative CPP values do not represent a valid payback duration but rather indicate a no-payback condition. This occurs when a design fails to generate sufficient annual operational carbon savings to offset the additional initial embodied carbon, meaning that the carbon payback mechanism is not achieved in physical terms. Therefore, CPP was not used as a primary ranking criterion, but was instead treated as a post-evaluation indicator to verify whether the highly ranked alternatives also demonstrated meaningful carbon payback performance. A post-evaluation CPP check was also applied to all Pareto-optimal solutions. Together, these analyses provided a stronger basis for selecting the final facade design for validation and interpretation.

3.4 Stage 4: Validation and Final Decision Support

In the fourth stage, the optimization outcomes from Wallacei were compared with the TOPSIS ranking results to assess the consistency between search-based and decision-based evaluation. This stage also included visual validation and post-evaluation CPP verification to support the final selection of the best-performing facade alternative. Through this process, the final design was assessed not only on ranking performance but also on its practical balance among daylight, visual comfort, operational energy, and life-cycle carbon performance.

4 Optimization Results: Pareto Front Analysis

4.1 Multi-Objective Optimization Outcomes

The Wallacei optimization generated a range of facade design alternatives that balance energy, daylight, and life-cycle carbon objectives. Building Type 00 served as the baseline reference case, and 20 Pareto-optimal solutions were identified as non-dominated alternatives.

Figure 3 shows the distribution of these solutions in the objective space, and Figure 4 summarizes the facade parameters and performance values of the baseline and optimized cases. Together, these results define the feasible trade-off space among the main optimization objectives.

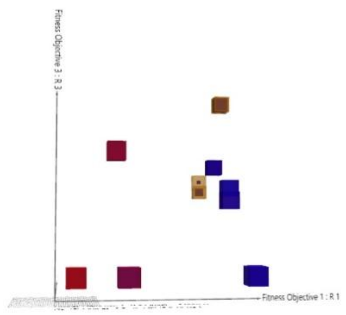

Figure 3. Wallacei Objective Space Results

Building Type	Number of Windows (N/E/S/W)	WWR (N/E/S/W)	Shading depth (m) (N/E/S/W)	Glass Type (N/E/S/W)	sDA (%)	ASE (%)	DGP	EUI (kWh/m²·yr)	WLC ($kgCO_2e$)	EMB ($kgCO_2e$)
00.	2/2/2/2	0.5/0.5/0.5/0.5	0.0/0.0/0.0/0.0	0/0/0/0	95.76	1.00	0.20	273.26	2.029E+07	3.089E+05
01.	1/5/5/2	0.3/0.3/0.2/0/2	0.4/0.3/1.2/0.8	1/1/0/0	94.71	0.94	0.40	278.78	2.111E+06	3.267E+05
02.	3/2/4/2	0.3/0.3/0.2/0.2	0.3/0.6/1.2/1.2	0/0/0/0	94.70	0.94	0.40	242.27	1.889E+06	3.385E+05
03.	3/2/5/2	0.3/0.3/0.2/0.2	0.4/0.4/1.2/1.2	1/1/0/0	94.69	0.94	0.40	278.78	2.119E+06	3.347E+05
04.	1/2/4/2	0.3/0.3/0.3/0.2	0.5/0.6/1.1/1.1	1/0/1/1	94.89	0.98	0.36	273.70	2.105E+06	3.540E+05
05.	3/2/2/1	0.6/0.3/0.2/0.3	0.5/0.4/1.2/1.5	1/0/0/0	95.34	0.96	0.28	273.75	2.150E+06	3.978E+05
06.	3/5/2/2	0.6/0.3/0.2/0.3	0.5/1.4/1.2/1.5	1/0/0/0	95.34	0.96	0.28	273.75	2.162E+06	4.097E+05
07.	3/5/3/2	0.3/0.3/0.2/0.2	0.5/1.3/0.4/1.4	0/0/1/0	94.70	0.94	0.40	252.51	1.964E+06	3.485E+05
08.	4/3/4/2	0.3/0.4/0.2/0.2	0.4/0.3/0.5/1.2	0/0/0/0	94.87	0.97	0.36	250.79	1.929E+06	3.242E+05
09.	1/2/4/2	0.3/0.3/0.3/0.2	0.5/0.6/0.5/1.1	1/0/1/0	94.88	0.98	0.36	273.7	2.089E+06	3.376E+05
10.	2/3/3/2	0.3/0.3/0.2/0.2	0.4/0.3/0.5/1.2	1/0/0/0	94.69	0.94	0.4	252.93	1.935E+06	3.161E+05
11.	3/4/2/2	0.3/0.3/0.2/0.4	0.5/1.4/1.2/0.8	0/1/1/0	95.08	0.97	0.31	274.45	2.131E+06	3.744E+05
12.	3/2/4/4	0.3/0.3/0.3/0.2	0.5/0.6/1.2/1.1	1/0/1/0	94.87	0.98	0.36	273.69	2.103E+06	3.516E+05
13.	1/5/5/2	0.3/0.3/0.2/0.3	0.4/0.3/1.1/1.2	1/1/0/0	94.89	0.96	0.35	275.85	2.110E+06	3.448E+05
14.	5/2/1/4	0.2/0.3/0.6/0.3	1.1/1.2/0.5/0.8	0/0/1/0	95.34	0.96	0.28	273.75	2.150E+06	3.984E+05
15.	2/1/4/4	0.3/0.6/0.3/0.2	1.2/0.5/0.8/1.2	0/1/0/0	95.08	0.97	0.31	274.45	2.103E+06	3.470E+05
16.	1/4/4/2	0.6/0.3/0.2/0.3	0.5/0.8/1.2/1.5	1/0/0/0	95.34	0.96	0.28	273.75	2.138E+06	3.857E+05
17.	4/4/2/3	0.3/0.2/0.3/0.3	0.8/1.2/1.5/0.3	0/0/0/0	94.89	0.96	0.35	275.85	2.104E+06	3.389E+05
18.	4/2/3/4	0.2/0.3/0.3/0.3	1.2/1.5/0.3/0.6	0/0/0/1	95.34	0.96	0.28	273.75	2.121E+06	3.693E+05
19.	2/3/4/3	0.3/0.3/0.3/0.2	1.5/0.3/0.6/1.2	0/0/1/1	94.87	0.98	0.36	273.69	2.100E+06	3.485E+05
20.	3/4/3/2	0.3/0.3/0.2/0.4	0.3/0.6/1.2/0.8	0/1/1/0	94.88	0.96	0.35	275.67	2.129E+06	3.649E+05

Figure 4. Pareto Dataset of Optimized Designs

4.2 Characteristics of Pareto-Optimal Facade Solutions

The 20 Pareto-optimal facade solutions show variations in WWR, shading depth, glazing type, and window configuration that affect energy, daylight, and carbon performance. However, daylight performance remains consistently high across the Pareto set, with all solutions satisfying the applied sDA, ASE, and DGP criteria. This indicates that daylight primarily serves as a compliance condition rather than as the main source of variation among the final alternatives.

The main differences among the Pareto solutions are observed in EUI, WLC, and embodied carbon. Lower EUI does not always correspond to lower WLC, showing that operational energy savings may be accompanied by higher facade-related carbon impacts. These results reflect the trade-off between operational efficiency and life-cycle carbon performance in the optimized facade set.

4.3 Pareto Trade-Offs between Energy, Daylighting, and Carbon Performance

The Pareto set shows that the main trade-off lies between EUI and WLC rather than between acceptable and unacceptable daylight performance. Because all solutions meet the applied daylight and glare criteria, the final comparison is mainly driven by differences in energy use and carbon impact.

CPP provides an additional layer of interpretation in this trade-off. Although it is included in the optimization stage, it is used only as a post-evaluation indicator in the final analysis, as negative CPP values indicate no-payback conditions and are not suitable for direct MCDM comparison. CPP, therefore, helps verify whether alternatives with favorable energy and carbon performance also achieve meaningful carbon payback.

4.4 Selection of Pareto Dataset for Decision Analysis

The 20 Pareto-optimal facade alternatives were retained as the input dataset for the subsequent TOPSIS analysis, while Building Type 00 was treated as a separate baseline reference case. For each alternative, facade parameters and performance indicators were compiled into a unified evaluation table. At this stage, final embodied carbon values were calculated using detailed QTO-based results from the optimized facade geometries. These values were then used to derive WLC and support the post-evaluation assessment of CPP. This data set provides the basis for transparent multi-criteria comparison of the optimized facade alternatives.

5 Multi-Criteria Decision-Making Results

5.1 TOPSIS Evaluation under Different Priority Scenarios

Following the Pareto front analysis, the 20 Pareto-optimal facade alternatives were evaluated using TOPSIS to support final decision-making. The decision matrix included six criteria: sDA, ASE, DGP, EUI, WLC, and embodied carbon (EMB). All criteria were normalized using vector normalization, and benefit and cost criteria were treated accordingly, as shown in Table 2. Four weighting scenarios were defined: energy-priority (EUI, ASE), carbon-priority (WLC, EMB), comfort-priority (sDA, DGP), and balanced. TOPSIS then produced a closeness coefficient for each alternative under each scenario.

Table 2. TOPSIS Normalization

Building Type	sDA	ASE	DGP	EUI	WLC	EMB
1	0.223	0.219	0.258	0.231	0.227	0.205
2	0.223	0.219	0.258	0.201	0.203	0.212
3	0.223	0.219	0.258	0.231	0.227	0.210
4	0.223	0.228	0.232	0.227	0.226	0.222
5	0.224	0.223	0.181	0.227	0.231	0.250
6	0.224	0.223	0.181	0.227	0.232	0.257
7	0.223	0.219	0.258	0.209	0.211	0.219
8	0.223	0.226	0.232	0.208	0.207	0.203
9	0.223	0.228	0.232	0.227	0.224	0.212
10	0.223	0.219	0.258	0.209	0.208	0.198
11	0.224	0.226	0.200	0.227	0.229	0.235
12	0.223	0.228	0.232	0.227	0.226	0.221
13	0.223	0.223	0.226	0.228	0.226	0.216
14	0.224	0.223	0.181	0.227	0.231	0.250
15	0.224	0.226	0.200	0.227	0.226	0.218
16	0.223	0.223	0.181	0.227	0.229	0.242
17	0.223	0.223	0.226	0.228	0.226	0.213
18	0.224	0.223	0.181	0.227	0.228	0.232
19	0.223	0.228	0.232	0.227	0.225	0.219
20	0.223	0.223	0.226	0.228	0.228	0.229

Table 3 presents the weighting scenarios used in the TOPSIS evaluation, including the energy-, carbon-, and comfort-priority settings.

Table 3. TOPSIS Weighting Scenarios

Scenario	sDA	ASE	DGP	EUI	WLC	EMB
Energy	0.05	0.15	0.05	0.55	0.10	0.10
Carbon	0.03	0.02	0.02	0.08	0.75	0.10
Comfort	0.20	0.10	0.40	0.10	0.10	0.10
Balanced	0.050	0.100	0.050	0.400	0.300	0.100

5.2 Ranking Results and Identification of the Optimal Facade Design

The TOPSIS results in Figures 5–8 indicate that the preferred facade alternative changes with the weighting scenario, confirming that the final ranking is highly dependent on decision priorities. Building Type 02 ranked first in the energy-priority, carbon-priority, and balanced scenarios, demonstrating robust performance across multiple evaluation contexts. In contrast, Building Type 18 ranked first only in the comfort-priority scenario, indicating stronger performance when daylight and visual comfort are emphasized. These findings suggest that no single facade alternative is universally optimal under all weighting scenarios. Overall, Building Type 02 can be regarded as the most robust option, whereas Building Type 18 is preferable when comfort is prioritized.

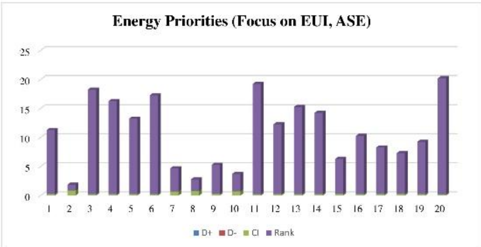

Figure 5. TOPSIS Results: Energy-Priority

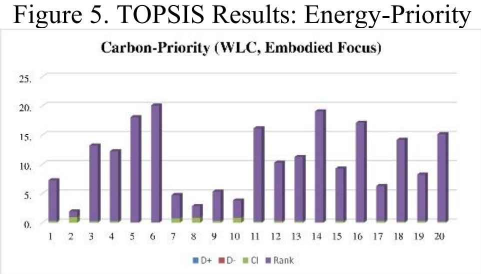

Figure 6. TOPSIS Results: Carbon-Priority

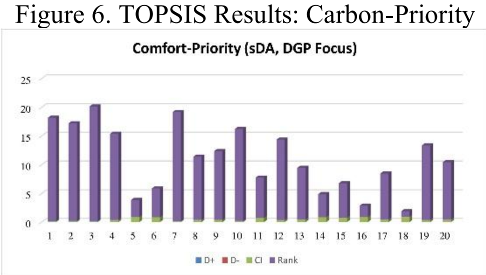

Figure 7. TOPSIS Results: Comfort-Priority

Figure 8. TOPSIS Results: Balanced

Table 4. Post-Evaluation Carbon Payback Period Check

BUILDING TYPE	CPP (YEARS)	CPP STATUS
1	-30.24	No payback
2	8.95	Achieved
3	-43.80	No payback
4	-953.39	No payback
5	-1670.47	No payback
6	-1893.55	No payback
7	17.92	Achieved
8	6.39	Achieved
9	-606.39	No payback
10	3.31	Achieved
11	-514.18	No payback
12	-914.38	No payback
13	-129.70	No payback
14	-1681.97	No payback
15	-299.12	No payback
16	-1444.11	No payback
17	-108.48	No payback
18	-1135.95	No payback
19	-847.28	No payback
20	-217.64	No payback

As shown in Table 4, positive CPP values indicate a valid carbon payback duration, meaning that the additional embodied carbon can be offset over time through annual operational carbon savings. By contrast, negative CPP values do not represent a valid payback duration; instead, they indicate a no-payback condition in which annual operational carbon savings are absent or insufficient to offset the initial embodied carbon increment.

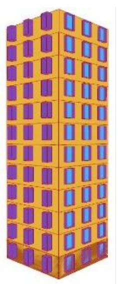

Figure 9. Final Selected Facade Design

Figure 9 presents the final selected facade design for Building Type 02. The figure visualizes the overall facade composition of the selected alternative, highlighting the arrangement of windows and shading features across the building form. This design was chosen as the final recommendation because it showed the most stable overall performance across the TOPSIS scenarios and also achieved a positive CPP value, indicating acceptable carbon payback performance over the building life cycle.

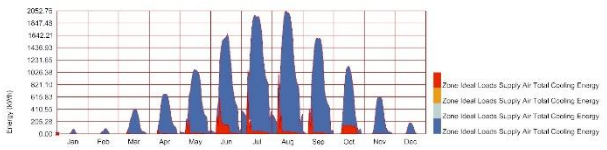

Figure 10. Monthly Cooling Energy Profile (HB-Energy)

Figure 10 presents the monthly cooling energy profile of the selected facade design. A pronounced seasonal variation can be observed, with cooling demand remaining minimal during the winter months, increasing steadily through spring, and peaking in July and August before declining again toward the end of the year. This distribution is consistent with Taipei’s hot-humid climatic context, in which cooling loads are primarily driven by elevated summer air temperatures and increased solar exposure. The figure therefore highlights the strong seasonal dependence of cooling energy use in the evaluated office building.

6 Conclusion

This study developed an integrated LCA–CPP–MCDM framework combined with parametric modeling and Wallacei-based multi-objective optimization for office facade design in Taipei’s hot-humid climate. The results revealed clear trade-offs among energy use, daylight availability, glare performance, and life-cycle carbon outcomes. Shading strategies were found to reduce cooling demand, but they could also increase embodied carbon, making the Carbon Payback Period (CPP) an important indicator for evaluating long-term carbon effectiveness. The optimization process generated 20 Pareto-optimal solutions, and the TOPSIS analysis identified Building Type 02 as the most robust and balanced alternative across the evaluated weighting scenarios. Building Type 02 also achieved a positive CPP of 8.95 years, indicating that its additional embodied carbon can be offset by annual operational carbon savings within a measurable period. This result was therefore classified as Achieved. However, CPP was not included as a direct TOPSIS criterion because negative CPP values are not physically interpretable as valid payback durations in a conventional ranking process. Therefore, CPP was treated as a post-evaluation indicator to verify whether the selected alternatives also achieved meaningful carbon payback performance.

This study was tested on a single office-building case in Taipei, which limits the direct generalizability of the findings. Nevertheless, the proposed workflow remains adaptable to other tropical and subtropical contexts through adjustment of weather data, grid emission factors, and building geometry inputs. Future work should extend the framework to multiple building types and climatic conditions to further examine the robustness of facade design trade-offs under different environmental and carbon scenarios.

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