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Original Research

Multi-criteria assessment ranking of facade's alternatives using EDAS and CODAS combined MCDM system

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Abstract: In the field of building design, selecting the most suitable facade alternative is a complex decision-making task involving numerous conflicting criteria. This research aims to evaluate and rank facade options for public and commercial buildings using a structured decision-support framework. To address this problem, the study applies two well-established Multi-Criteria Decision-Making (MCDM) methods — Evaluation based on Distance from Average Solution (EDAS) and Combinative Distance-Based Assessment (CODAS). A total of twelve critical evaluation parameters were considered, encompassing economic, structural, environmental and aesthetic factors. The analysis identified the aluminium-glazing facade as the most preferred alternative, followed by sandwich panels, while rockwool plates with decorative plaster performed the worst. Furthermore, a sensitivity analysis was conducted to validate the consistency and robustness of the ranking results. The findings highlight the reliability of the proposed MCDM approach and its practical relevance in guiding sustainable facade selection decisions.

Keywords: MCDM, EDAS, CODAS, Facade, Alternatives, Buildings

1. Introduction

The selection of appropriate facade systems in building construction is a critical design decision that affects not only the aesthetics of a structure but also its energy performance, environmental sustainability, durability and economic feasibility. In both public and commercial construction projects, stakeholders are often faced with evaluating multiple, often conflicting criteria that influence the facade choice. This complexity necessitates a systematic and rational decision-making framework that can incorporate a wide array of qualitative and quantitative factors. Multi-Criteria Decision-Making (MCDM) methods have been widely employed in the construction sector to support complex evaluations where multiple factors must be considered simultaneously. These tools offer structured approaches to prioritize alternatives based on selected criteria, enabling more transparent and justifiable decisions. Recent studies have demonstrated that different MCDM methods may yield varying results depending on the approach used, prompting a need to compare and validate alternative techniques. This study focuses on evaluating facade alternatives for commercial and public buildings using two MCDM methods: Evaluation based on Distance from Average Solution (EDAS) and Combinative Distance-Based Assessment (CODAS). Twelve key parameters were used to assess four facade systems, covering economic, structural, environmental and user-experience aspects. The research includes a comparative analysis of ranking outcomes and

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a sensitivity analysis to test the stability of the results under varying weight conditions.

In recent years, MCDM methods have gained significant traction in the fields of construction and engineering as reliable tools for dealing with complex decision-making scenarios. These methods enable a systematic evaluation and prioritization of alternatives based on quantitative and qualitative criteria [1]. Xu and Li [2] proposed MOPSO combined with an unusual test variable of fuzzy concept tripling with permutation as an embedded analytical model to solve site layout spread planning problems. Bidding process selection can be considered as one of the best areas in which MCDM can be integrated. This scenario was adopted by Seydel and Olson [3]. Different criteria add value to each of the selected alternatives, which may be incompatible with the external environment, thus the bidding process can be very important to propose some of the important parameters that may affect outside boundary condition of the alternatives. Ustinovichius et al. [4] proposed CLARA (Classification of Real Alternatives) and UniComBOS (Unit Comparison for the Best Object Selection) for the variation of building constraints affecting the multi-attribute investment policy of the firms. Zavadskas et al. [5] distinguished the intensity available in the selection procedure using ARAS for the alternative installation of the base, otherwise different parameters need to be altered to secure the structural entity on iron and water rich soil. Pan [6] introduced the development of the α-cut design foremost to the other variants for the excavation on the triangular fuzzy numbers. This will help to create a more robust and error-free construction design. Nieto-Morote and Ruz-Vila [7] submitted a formal pre-qualification process based on the fuzzy set theory that only a qualified contractor can be accepted for tender. A number of different options are commonly considered in order to select the best building design. These can be qualitative for the cause of conversion into numeric values; furthermore, the quantitative values also deviate and attempt to converge at the critical point [1].

When it comes specifically to facade evaluation, several researchers have employed MCDM techniques. Zavadskas et al. [1] used the MOORA and WASPAS methods to rank facade alternatives based on parameters such as installation costs, structural characteristics and aesthetics. Šaparauskas et al. [8,9] further explored criteria weighting for facade systems using optimization-based ranking models. However, the existing studies primarily rely on traditional MCDM methods and there is a lack of research on the stability, consistency and robustness of newer methods such as EDAS and CODAS in this context. Building facades can be widely spread to numerous types of linguistic factors. The most critical question, however, is whether modern MCDM techniques such as EDAS and CODAS can provide a robust and stable ranking of facade alternatives based on economic, structural, environmental and user-focused criteria in public and commercial construction projects [8-10]. Four facade alternatives were assessed for prescribing alternative solution that may be encountered in daily life. There may be different parameters involves in the selection process. These may be economically supported by structural and physical performance properties. Additionally, environmental factors are also one of the important aspects that highly contribute in promoting green environment, thus environment is very essential for the selection of façade alternative. The parameters depend on the alternative decision theory using three optimization operation graded by Šaparauskas et al. [8, 9]. Zavadskas et al. [10] continued handling different MCDM problems, and a standard technique of the optimization model called WASPAS was proposed to handle facade ranking followed by Zavadskas et al. [1] who used MOORA method. This study is therefore motivated by the need to evaluate the performance and stability of EDAS and CODAS as decision-support tools for selecting optimal facade systems in building construction. In particular, the research investigated whether these methods can provide consistent and justifiable rankings of facade alternatives based on a wide range of performance criteria. The objective of this study is to apply EDAS and CODAS methods to evaluate four commonly used facade systems against twelve key criteria. The study also aims to validate the consistency of these methods through a sensitivity analysis and to compare the results with those obtained using other MCDM techniques reported in previous literature.

Recent advances in MCDM research have highlighted the integration of decision-making models with spatial analysis to address complex urban planning and justice issues. For example, Jamili et al. [11] proposed an integrated spatial and MCDM framework to evaluate the equity in the distribution of urban services in Tehran. Their study demonstrated how multi-criteria analysis can be extended beyond technical infrastructure decisions to support equity-oriented urban policy making. Such interdisciplinary applications underscore the relevance of MCDM tools in broader decision environments, including the evaluation of facade alternatives in urban settings. In a recent application, researchers used MCDM methods to assess the realization of spatial justice in a metropolis in northwestern Iran, demonstrating how multi-criteria analysis can serve as a vital tool in addressing urban equity challenges and informing policy decisions in spatially complex environments [12]. Moreover, recent research has also increasingly focused on integrating decision support tools into the early-stage building design to enhance energy efficiency and climate responsiveness. For example, Gaber et al. [13] developed a novel decision support system to optimize fixed shading systems in hot climates, demonstrating how MCDM techniques can be embedded into early design workflows to guide in making sustainable facade-related choices. Similarly, Gaber et al. [14] applied a hybrid MCDM approach to evaluate perforated shading systems in different case studies in hot regions, emphasizing the role of such tools in improving both daylighting and energy performance. These studies underscore the expanding relevance of MCDM models in facade-related decision making, particularly when applied to climate-responsive architecture and sustainable envelope systems. However, there is limited research applying newer MCDM techniques—such as EDAS and CODAS—to systematically evaluate complete facade alternatives considering structural, aesthetic, environmental and cost-related criteria, particularly in the context of commercial and public buildings. Previous publications and other research [1, 5, 8, 9] show that unique MCDM approaches can yield different methodological results. Further extensive research analysis is needed to find a reliable solution.

Numerous MCDM methods have been applied across various engineering disciplines to solve complex decision problems involving conflicting criteria. Traditional techniques such as TOPSIS, VIKOR and AHP have been widely used in construction management, material selection and infrastructure prioritization. For instance, TOPSIS has been employed to select green construction materials, while VIKOR has supported the selection of optimal construction method under conflicting constraints [15, 16]. In addition to stand-alone methods, researchers have increasingly adopted hybrid MCDM models that combine techniques such as AHP–TOPSIS, SWARA–MARCOS and Delphi–CRITIC–MABAC to enhance the decision robustness and reduce bias. For example, hybrid methods have been applied in evaluating sustainable construction technologies, selecting energy-efficient building components and optimizing transportation systems [17, 18]. In recent years, emerging methods such as MARCOS, MAIRCA and MABAC have gained traction due to their flexible data structures and adaptability to real-world engineering scenarios. Furthermore, combinations of fuzzy logic, rough sets and grey systems with MCDM tools have enabled more realistic modeling of uncertainty and linguistic judgments in engineering contexts [19, 20]. Despite these advances, little attention has been given to evaluating facade systems using newer methods such as EDAS and CODAS, especially in combination with objective weighting and sensitivity validation. This study contributed to filling this gap by applying EDAS and CODAS to assess facade alternatives and comparing their effectiveness with conventional methods.

In addition to conventional and hybrid MCDM techniques, fuzzy-MCDM methods have gained increasing popularity in recent years due to their ability to model uncertainty and imprecise linguistic assessments. These methods are particularly useful in architectural and construction-related decision problems where expert judgments play a central role, and crisp numerical data may be unavailable or subjective. For instance, fuzzy AHP, fuzzy TOPSIS, and fuzzy VIKOR have been applied to tasks such as contractor selection, green material assessment, and HVAC system prioritization [21, 22]. More advanced models such as fuzzy-DEMATEL and fuzzy-MARCOS have also been proposed to evaluate the dependencies between criteria and incorporate qualitative expert input into multi-layered decision frameworks. These advancements reflect an emerging trend toward integrating human-centric reasoning with computational MCDM tools to provide more adaptive and realistic solutions in complex environments such as facade selection.

The goal may be stated as to find the optimal critical point to access the entire alternative based on economic and physical matters. However, a valid decision has been made to contribute some elements to the design solutions for commercial buildings. The popular EDAS and CODAS method [23] is presented and implemented for the case study on the highly consistent observed phenomenon. The results of the implemented approaches are compared and suggestions for the most preferred one by the basic MCDM algorithm of alternative facade are given [1].

Facade systems significantly influence the functional, environmental and aesthetic performance of buildings, particularly in the commercial and public sectors where occupant comfort, sustainability and visual identity are critical. However, selecting the most suitable facade requires evaluating diverse and conflicting criteria, making it a complex decision-making challenge [9]. While several studies have employed MCDM methods—such as MOORA, WASPAS and WSM—for facade assessment, few have explored the use of EDAS and CODAS techniques in this context. Furthermore, previous research often lacks comprehensive sensitivity validation or relies heavily on subjective weighting schemes without systematically investigating the impact of different evaluation parameters on the final rankings [9, 23]. This study addresses these gaps by applying the EDAS and CODAS methods to an existing set of facade alternatives, recalculating the weights using the Entropy method, and validating the outcomes through sensitivity analysis. The research is motivated by the need for robust and replicable decision-support frameworks that can support the selection of facade for both conventional and sustainability-oriented building projects.

The novelty of this study lies in the application of two relatively underutilized but robust MCDM techniques—EDAS and CODAS—to the problem of facade selection in the construction industry [24]. While several prior studies have employed traditional methods such as MOORA, WSM and WASPAS for similar evaluations, this study distinguishes itself by testing the consistency, stability and ranking behavior of EDAS and CODAS using both performance analysis and sensitivity validation [4, 5]. This dual-method comparative approach not only broadens the methodological scope of facade selection studies, but also contributes to the literature by demonstrating the reliability and applicability of EDAS and CODAS in addressing real-world architectural decision problems [18, 19]. The flow diagram of the entire MCDM model is shown in Figure 1. The rest of this article is structured as follows: Section 2 presents the methodology and the rationale for selecting

EDAS and CODAS; Section 3 describes the evaluation process and the results of the analysis; Section 4 compares the findings with previous studies; Section 5 validates the robustness of the ranking through a sensitivity analysis; and Section 6 concludes with key insights and potential directions for future research.

2. Materials and methods

This study fulfills the purposes of choosing preferred façade alternative that can be installed in commercial or public buildings based on a broad variety of qualitative and quantitative criteria. The economic aspect associated with decisions is the primary factor reflecting the nature of the criteria. The statement is also supported by other factors and efficient criteria such as the environmental effects of particular facade systems, structural and physical properties. The criteria considered by the previous researchers [1] are as follows: IH 1 = Installation and handling cost (Lt/m^2); LA 2 = intensity of labor by assembling (days); SW 3 = Structural weight (Kg/m^2); ST 4 = Structural thickness (mm); UF 5 = user and economic friendliness (points); DP 6 = durability peroid (points); WG 7 = warranty given (points); EF 8 = Environmental and eco friendliness (points); RT 9 = Recovery time (points); AE 10 = Aesthetic values (points); SI 11 = Sound insulation (points); FR 12 = Fire resistance (points). Out of these 12 criteria, IH 1 to ST 4 are non-beneficial criteria, whereas, UF 5 to FR 12 are beneficial criteria [1].

Four facade alternatives for buildings considered by previous researchers [1] were evaluated and graded on the basis of the above parameters, namely rockwool plates coated with cellular concrete fixed on masonry and a thin layer of plaster surrounded by decorative fusion concrete layer (ATV 1), façade looking like "sandwich" mounted on panels (ATV 2), Rockwool fused with silicate releasing vapor mixed with masonry fumes and panels mounted on "minerit" (ATV 3) and façade glazed vitrified with aluminium powder (ATV 4). Table 1 clearly portrays the significance of the 12 selected criteria and the 4 alternatives for the ongoing decision analysis. The relative importance of the parameters (criteria weights) wj was calculated by the entropy method [1, 24] and is shown in Table 2. Calculations of the relative significance for the current case study were provided in [1, 8-9]. The criteria weights used in this study were taken directly from Zavadskas et al. [1] where they were originally calculated using the entropy method. While the dataset remains unchanged, the current study provides new insights by using EDAS and CODAS—two robust and less commonly used MCDM methods—to analyze the same facade alternatives. This comparative approach enables a methodological evaluation of the consistency and stability of different ranking techniques, which was not the focus of the original study.

In this study, the entropy method was used to derive the criteria weights due to its objectivity and reliance on data variability rather than subjective judgment. However, it is important to recognize certain limitations of this approach. The entropy-based weights depend solely on the distribution of values in the decision matrix. Therefore, criteria that exhibit little variation across alternatives are assigned less importance, regardless of their actual practical significance. This may inadvertently downplay the role of uniformly critical criteria such as fire resistance or environmental friendliness if their scores do not fluctuate significantly among alternatives. Furthermore, the entropy method does not incorporate expert opinions or stakeholder preferences, which can be crucial in the real-world facade selection, particularly for projects driven by aesthetic, safety or sustainability goals. Subjective weighting techniques such as the Analytic Hierarchy Process (AHP) or the Delphi method allow for the inclusion of expert judgments, while CRITIC (Criteria Importance Through Intercriteria Correlation) balances both contrast intensity and correlation between criteria, offering a more nuanced perspective. Future research should explore a comparative analysis using both objective (e.g., Entropy, CRITIC) and subjective (e.g., AHP, BWM) methods to determine how weight variations influence the final rankings. This would enhance the robustness and generalizability of the proposed MCDM framework and support more flexible applications in diverse construction environments.

All computational analyses, sensitivity tests, tabulations of results and graphical visualizations were performed using Microsoft Excel. The built-in formula functions and data visualization tools available in Excel were used to implement the EDAS and CODAS methods, apply the entropy weighting technique, and generate comparative ranking figures. The choice of Excel ensures accessibility and ease of replication for practitioners and researchers without specialized programming skills.

The selection of the EDAS in this study is driven by its proven stability, simplicity and effectiveness in evaluating both beneficial and non-beneficial criteria [25]. In contrast to classical methods such as TOPSIS, which rely on ideal and anti-ideal solutions and may lead to a reversal of ranking with certain normalization techniques, EDAS evaluates the alternatives based on their distance from the average solution, offering better interpretability and less sensitivity to outliers [23]. CODAS, on the other hand, incorporates both Euclidean and Taxicab distance to allow for a more nuanced distinction between alternatives, making it particularly robust in differentiating closely ranked options [26]. Although methods such as MABAC, MARCOS and MAIRCA have shown promising results in the context of construction and material selection, they often involve complex normalization and utility-based calculations, which may introduce unnecessary computational burden without significantly improving decision quality for small to medium sized alternatives such as those considered here [27]. Additionally, MARCOS depends on the extended utility function, which may not perform well with hybrid (qualitative and quantitative) data, while MAIRCA relies on matching between theoretical and real assessments, which is more appropriate in preference-driven environments. EDAS and CODAS were thus chosen for their balance of accuracy, transparency and computational simplicity, as well as their ability to validate results through parallel analysis and sensitivity testing [28, 29]. These features make them particularly well-suited for the current study, where a reliable, replicable ranking of facade alternatives is needed for practical architectural and engineering decision making.

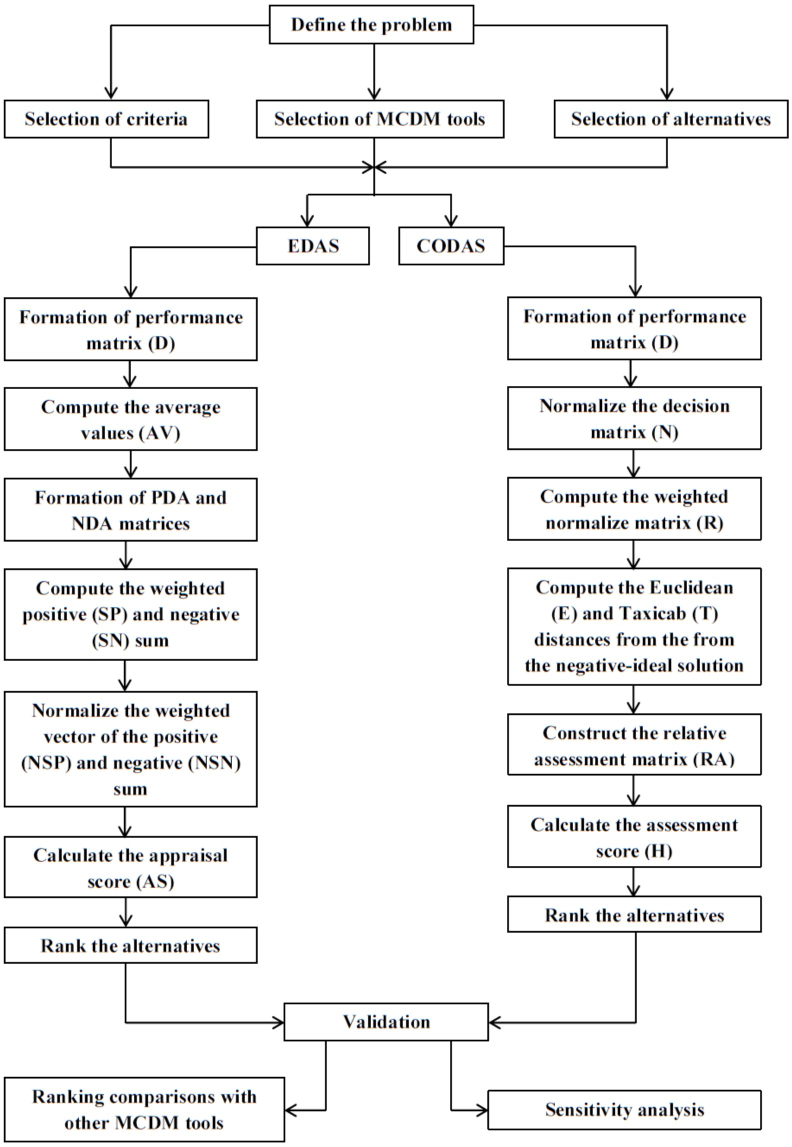


Figure 1. Flow diagram of the MCDM model

Table 1. The significance of the selected criteria and alternatives

Criteria				
Criteria Code	**Criteria Name**	**Significance**	**Relevancy to Research Problem**	**References**
IH 1	Installation and handling cost	Reflects direct capital expenditure associated with facade installation.	Crucial for cost-effective project planning in both public and commercial construction.	[1,4,5]
LA 2	Intensity of labor by assembling	Indicates manpower requirements and time investment for setup.	Affects scheduling, labor management, and overall project efficiency.	[1,2,8]
SW 3	Structural weight	Measures the load imposed on the structural frame by the facade.	Important for structural integrity, especially in high-rise or retrofit applications.	[1,7,9]
ST 4	Structural t hickness	Determines space utilization and thermal performance.	Influences energy efficiency, interior layout, and structural compatibility.	[1,8,9]
UF 5	User and economic friendliness	Assesses usability, maintenance, and cost-effectiveness from the end-user perspective.	Vital for long-term performance and user satisfaction in commercial/public buildings.	[1,4,9]
DP 6	Durability period	Indicates expected service life of the facade without major repair.	Impacts lifecycle cost and long-term maintenance planning.	[1,11,12]
WG 7	Warranty given	Reflects manufacturer's confidence in product reliability.	Enhances decision certainty for stakeholders concerned with risk and liability.	[1,3,10]
EF 8	Environmental and eco-friendliness	Measures the ecological impact and sustainability credentials of the facade.	Essential for green building certifications and compliance with sustainability goals.	[1,5,11]
RT 9	Recovery time	Indicates how quickly the facade can be restored or serviced after damage.	Relevant for post-disaster recovery planning and serviceability.	[1,11,12]
AE 10	Aesthetic values	Represents the visual appeal and architectural contribution of the facade.	Influences urban context fit, client preference, and public perception.	[1,3,8]
SI 11	Sound insulation	Measures the facade's ability to block external noise.	Important for comfort in urban, commercial, or institutional environments.	[1,8,12]
FR 12	Fire resistance	Assesses the ability to withstand and slow down fire propagation.	Critical for safety compliance and occupant protection in multi-use and high-occupancy buildings.	[1,12,13]
Alternatives				
Alternative Code	**Facade Description**	**Significance**	**Relevancy to Research Problem**	**References**
ATV 1	Rockwool plates with cellular concrete on masonry, coated with decorative fusion concrete and plaster	Traditional solution offering basic insulation and fire resistance.	Serves as a baseline alternative with moderate cost and minimal architectural appeal.	[1,11,14]
ATV 2	Sandwich-type panel facade	Pre-engineered, prefabricated solution offering good thermal insulation and installation speed.	Preferred for rapid construction and modern commercial facilities demanding balanced performance.	[1,13,14]
ATV 3	Rockwool fused with silicate vapor, mounted on masonry with "Minerit" panels	Advanced composite system offering enhanced fire safety and moisture resistance.	Suitable for environments requiring durability and regulated indoor climates.	[1,6,8]
ATV 4	Glazed aluminium vitrified facade	High-performance, aesthetically premium system with superior weathering and thermal control.	Best fit for high-end commercial buildings demanding elegance, durability, and long-term sustainability.	[1,5,6]

3.Results

3.1 Evaluation based on distance from average solution (EDAS)

Ghorabaee et al. [23] stated that this approach may help the researchers to get rid of contradictory decisions that are hybrid with contemporary thinking. VIKOR and TOPSIS [17] are the compromise based decision making tools that help to replace the best alternative with new alternatives and rank them lower with the best alternative on the top place. In these MCDM approaches, the optimal superior alternative has a lower specific distance from the pure solution ideal in nature and a higher relative distance from the base bounded by nadir superimposed solution. However, the optimum can be estimated from the average solution (AV) based on the practical decision made by the decision maker. The calculation of the epitome and the base solution is not required at all in these approaches, which are higher priority decision tools. Two steps need to be performed for the succession of the priority value towards the desired alternative. The first step, PDA making it close towards the optimal solution and the second step is NDA make it far away from the solution optimized with the fuzzy theory. By specifying these measures, the optimal conditions can be included in the list of rating proposed with these analyses. These differences hold the main rational index to sort the distance between the alternatives and the average optimized route theory. A higher PDA represents the comparison of the selected alternatives with respect to the higher and lower values. The NDA values are generally lower than the PDA, which represents the best condition of the alternatives. The intensity of PDA and NDA helps to distinguish the best and the worst choice from the list. Higher PDA values and/or lower NDA values signifies the ideal choice is very close to the optimal condition. The steps of EDAS, as explained in [23], are as follows.

Step 1: Performance matrix was created according to equation 1 below. The matrix in Table 2 is taken from [1] for the analysis purposes.

$$D\,(m_i \times n_j) = \begin{bmatrix} d_{11} & d_{12} & \cdots & d_{1n} \\ d_{21} & d_{22} & \cdots & d_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ d_{m1} & d_{m2} & \cdots & d_{mn} \end{bmatrix} \tag{1}$$

Table 2. Performance matrix (EDAS and CODAS)

	Nature	Min				Max							
	Weights (wj)	0.0627	0.0508	0.053	0.1417	0.1114	0.0874	0.0625	0.1183	0.0784	0.0984	0.0798	0.0557
	Alternatives	IH 1	LA 2	SW 3	ST 4	UF 5	DP 6	WG 7	EF 8	RT 9	AE 10	SI 11	FR 12
	ATV 1	370	11	88	410	2.69	2.75	5	1.63	1.47	7.11	2.93	1.98
	ATV 2	314	7	12.6	100	2.37	3.27	35	1.72	2.07	5.6	2.13	3.21
	ATV 3	480	10	94	410	3.09	3.67	30	1.87	1.38	7.82	2.87	2.94
	ATV 4	850	16	23	65	3.17	4.1	50	1.91	2.22	8.25	1.1	4.37
EDAS	Average	503.5	11	54.4	246.25	2.83	3.4475	30	1.7825	1.785	7.195	2.2575	3.125
CODAS	Max	850	16	94	410	3.17	4.1	50	1.91	2.22	8.25	2.93	4.37
	Min	314	7	12.6	65	2.37	2.75	5	1.63	1.38	5.6	1.1	1.98

(Source: Zavadskas et al., 2013 [1])

Step 2: The parameters are measures from the average solution using equation 2. The average values were calculated and are shown in Table 2.

$$AV_j = \frac{\sum_{i=1}^{m} d_{ij}}{m} \tag{2}$$

Step 3: Calculate the positive distance that exceeds the expert opinions from the PDA matrix and the negative distance that lags behind the judgmental verdicts from the NDA matrix according to the nature of the parameters as shown in equations 3-8.

$$PDA = \left[PDA_{ij}\right]_{m\times n} \tag{3}$$

$$NDA = \left[NDA_{ij}\right]_{m\times n} \tag{4}$$

If the jth criteria is beneficial,

$$PDA_{ij} = \frac{\max\{0, (d_{ij} - AV_j)\}}{AV_j} \tag{5}$$

$$NDA_{ij} = \frac{\max\{0,(AV_j - d_{ij})\}}{AV_j} \quad (6)$$

if the jth criteria is non-beneficial

$$NDA_{ij} = \frac{\max\{0,(d_{ij} - AV_j)\}}{AV_j} \quad (7)$$

$$PDA_{ij} = \frac{\max\{0,(AV_j - d_{ij})\}}{AV_j} \quad (8)$$

Step 4: Determine the corresponding potential active weighted sum of the positive interacting solution PDA and the negative interacting solution NDA for all alternatives using equation 9 and equation 10.

$$SP_i = \sum_{j=1}^{n} w_j PDA_{ij} \quad (9)$$

$$SN_i = \sum_{j=1}^{n} w_j NDA_{ij} \quad (10)$$

'SP_i' and 'SN_i' are the weighted positive and negative sum of the ith alternative and the jth criterion, respectively.

Step 5: Normalize the values of SP_i and SN_i for all alternatives using equation 11 and equation 12.

$$NSP_i = \frac{SP_i}{\max_i(SP_i)} \quad (11)$$

$$NSN_i = 1 - \frac{SN_i}{\max_i(SN_i)} \quad (12)$$

'NSP_i' and 'NSN_i' are the normalized vectors of weighted positive and negative sum, respectively. The potential positive and negative sums and their normalized values are determined and displayed in Table 3 and Table 4.

Table 3. Weighted sum and its normalized values of PDA (EDAS)

	IH 1	LA 2	SW 3	ST 4	UF 5	DP 6	WG 7	EF 8	RT 9	AE 10	SI 11	FR 12	SP_i	NSP_i
ATV 1	0.0166	0	0	0	0	0	0	0	0	0	0.0238	0	0.0404	0.1492
ATV 2	0.0236	0.0185	0.0407	0.0842	0	0	0.0104	0	0.0125	0	0	0.0015	0.1914	0.7071
ATV 3	0.0029	0.0046	0	0	0.0102	0.0056	0	0.0058	0	0.0085	0.0217	0	0.0594	0.2196
ATV 4	0	0	0.0306	0.1043	0.0134	0.0165	0.0417	0.0085	0.0191	0.0144	0	0.0222	0.2707	1
												Max	0.2707	

Table 4. Weighted sum and its normalized values of NDA (EDAS)

	IH 1	LA 2	SW 3	ST 4	UF 5	DP 6	WG 7	EF 8	RT 9	AE 10	SI 11	FR 12	SN_i	NSN_i
ATV 1	0	0	0.0327	0.0942	0.0055	0.0177	0.0521	0.0101	0.0138	0.0012	0	0.0204	0.2478	0
ATV 2	0	0	0	0	0.0181	0.0045	0	0.0041	0	0.0218	0.0045	0	0.0531	0.7858
ATV 3	0	0	0.0386	0.0942	0	0	0	0	0.0178	0	0	0.0033	0.1539	0.3789
ATV 4	0.0431	0.0231	0	0	0	0	0	0	0	0	0.0409	0	0.1072	0.5675
												Max	0.2478	

Table 5. Appraisal score (AS) of the alternatives (EDAS)

Alternatives	NSP	NSN	AS	Rank
ATV 1	0.1492	0	0.0746	4
ATV 2	0.7071	0.7858	0.7465	2
ATV 3	0.2196	0.3789	0.2992	3
ATV 4	1	0.5675	0.7838	1

Step 6: Calculate the appraisal score (AS_i) for all the alternatives using equation 13. The appraisal scores of the alternatives are shown in Table 5.

$$AS_i = \frac{(NSP_i + NSN_i)}{2} \tag{13}$$

Decreasing values indicate the most superior properties of the alternatives, so a corresponding ranking has been established. The alternative that gets popular with the appraisal values showing the highest determines the strongest alternative candidates. Based on this rating, we may identify and classify the alternatives.

3.2 Combinative distance based assessment (CODAS)

In this section, a new approach for dealing with multiple factors associated with any situations is presented, which is called CODAS [26]. Desirability is one of the important factors dealing with the measures by CODAS. The key and primary calculation is related to the distance between the Euclidean and the negative-ideal alternatives. The application of CODAS in practical field of study involves the normalization of L2 indifference space for optimization of parameters. There is a secondary measure that quantifies the distance between the taxicab and the Euclidean space. It is obvious that an alternative that is further away from the desired negatively impact alternatives. In this approach, if we consider two alternatives incomparable in terms of physical distance in the case of Euclidean distance, the taxicab distance is readily applied as a secondary measure. CODAS prefers modular L2 normalization triviality, since different types of indifference space may establish a relationship between two or more alternatives. For 'm' alternatives and 'n' parameters involved in the present analysis, they help to build interrelationship among the factors. The steps of the CODAS method as proposed by [26] are presented as follows.

Step 1: The same performance matrix is again used for CODAS analysis to evaluate the interrelationship among the factors shown in equation 1, which was already done in the case of EDAS. The decision matrix is taken from [1] as shown in Table 2.

Step 2: Normalize the decision matrix using equation 14 according to the nature of the criteria. The normalized values are shown in Table 6.

$$N_{ij} = \begin{cases} \dfrac{d_{ij}}{\max\limits_{i} d_{ij}} & \text{if } j \in N_b \\ \dfrac{\min\limits_{i} d_{ij}}{d_{ij}} & \text{if } j \in N_c \end{cases} \tag{14}$$

'd_{ij}' and 'N_{ij}' are the performance quantification and normalized orientation. 'N_b' and 'N_c' represents the beneficial and non-beneficial criteria, respectively.

Step 3: The standardized decision matrix weighted from the normalized values can be determined using equation 15 as displayed in Table 7.

$$R_{ij} = w_j \times N_{ij} \tag{15}$$

'R_{ij}' denotes the standardized weighted values that involve the prioritization of the alternatives. The negative ideal point (ns_j) is determined and indicated in Table 7 as the minimum values.

Table 6. Normalized matrix (CODAS)

Weights	0.0627	0.0508	0.053	0.1417	0.1114	0.0874	0.0625	0.1183	0.0784	0.0984	0.0798	0.0557
Alternatives	**IH 1**	**LA 2**	**SW 3**	**ST 4**	**UF 5**	**DP 6**	**WG 7**	**EF 8**	**RT 9**	**AE 10**	**SI 11**	**FR 12**
ATV 1	0.8486	0.6364	0.1432	0.1585	0.8486	0.6707	0.1000	0.8534	0.6622	0.8618	1.0000	0.4531
ATV 2	1.0000	1.0000	1.0000	0.6500	0.7476	0.7976	0.7000	0.9005	0.9324	0.6788	0.7270	0.7346
ATV 3	0.6542	0.7000	0.1340	0.1585	0.9748	0.8951	0.6000	0.9791	0.6216	0.9479	0.9795	0.6728
ATV 4	0.3694	0.4375	0.5478	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.3754	1.0000

Table 7. Weighted matrix (CODAS)

Alternatives	IH 1	LA 2	SW 3	ST 4	UF 5	DP 6	WG 7	EF 8	RT 9	AE 10	SI 11	FR 12
ATV 1	0.0532	0.0323	0.0076	0.0225	0.0945	0.0586	0.0063	0.1010	0.0519	0.0848	0.0798	0.0252
ATV 2	0.0627	0.0508	0.0530	0.0921	0.0833	0.0697	0.0438	0.1065	0.0731	0.0668	0.0580	0.0409
ATV 3	0.0410	0.0356	0.0071	0.0225	0.1086	0.0782	0.0375	0.1158	0.0487	0.0933	0.0782	0.0375
ATV 4	0.0232	0.0222	0.0290	0.1417	0.1114	0.0874	0.0625	0.1183	0.0784	0.0984	0.0300	0.0557
Min (nsj)	0.0232	0.0222	0.0071	0.0225	0.0833	0.0586	0.0063	0.1010	0.0487	0.0668	0.0300	0.0252

Table 8. Euclidean and Taxicab distances of the alternatives (CODAS)

Alternatives	IH 1	LA 2	SW 3	ST 4	UF 5	DP 6	WG 7	EF 8	RT 9	AE 10	SI 11	FR 12	T_i	E_i
ATV 1	0.0300	0.0101	0.0005	0.0000	0.0112	0.0000	0.0000	0.0000	0.0032	0.0180	0.0498	0.0000	0.1229	0.0629
ATV 2	0.0395	0.0286	0.0459	0.0696	0.0000	0.0111	0.0375	0.0056	0.0244	0.0000	0.0281	0.0157	0.3059	0.1119
ATV 3	0.0179	0.0133	0.0000	0.0000	0.0253	0.0196	0.0313	0.0149	0.0000	0.0265	0.0482	0.0122	0.2091	0.0768
ATV 4	0.0000	0.0000	0.0219	0.1192	0.0281	0.0288	0.0563	0.0173	0.0297	0.0316	0.0000	0.0305	0.3634	0.1503

Table 9. Relative Assessment Matrix (CODAS)

	ATV 1	ATV 2	ATV 3	ATV 4	Sum	Rank
ATV 1	0.0000	-0.2321	-0.0139	-0.3279	-0.5739	4
ATV 2	0.2321	0.0000	0.1319	-0.0959	0.2681	2
ATV 3	0.0139	-0.1319	0.0000	-0.2278	-0.3458	3
ATV 4	0.3279	0.0959	0.2278	0.0000	0.6516	1

Step 4: Euclidean and Taxicab measure the farthest distances from the negative-ideal point (ns_j) using equation 16 and equation 17, respectively.

$$E_i = \sqrt{\sum_{j=1}^{n} \left(R_{ij} - ns_j\right)^2} \tag{16}$$

$$T_i = \sum_{j=1}^{n} \left|R_{ij} - ns_j\right| \tag{17}$$

'E_i' and 'T_i' are the Euclidean and Taxicab distances, respectively, calculated in Table 8. 'ns_j' is the negative ideal point.

Step 5: A relative assessment matrix is constructed according to equation 18 to equation 20 and shown in Table 9.

$$RA = [h_{ik}]_{m \times m} \tag{18}$$

$$h_{ik} = (E_i - E_k) + \{\Psi(T_i - T_k)\} \tag{19}$$

Where, k ϵ {1, 2…, m}. 'Ψ' denotes the threshold function and is defined by equation 20.

$$\Psi = \begin{cases} 1 & \text{if } |E| \geq \tau \\ 0 & \text{if } |E| < \tau \end{cases} \tag{20}$$

In this contradictive function, τ is the threshold optimality index that can be set by the experts after thorough research. The range of this threshold parameter can be set between 0.01 and 0.05. Based on previous experiences and extensive knowledge in this field, the decision makers have chosen the most optimal value of τ. The differences of the Euclidean distances between two chosen alternatives may be larger, in such cases the taxicab distance helps to measure the degree of ability. In this analysis, τ = 0.02 is taken for calculations.

In this study, the threshold parameter τ = 0.02 was selected based on the recommendations from the original CODAS method proposed by Ghorabaee et al. [26], where it was demonstrated that τ values between 0.01 and 0.05 typically provide optimal discrimination sensitivity between alternatives. A value of 0.02 was chosen as a moderate threshold, commonly used in previous literature to provide a balance between excessive sensitivity (at very low values) and over-smoothing (at higher values). This selection ensures meaningful differentiation between closely ranked alternatives without introducing excessive instability or noise into the ranking process. Future studies may experiment with varying τ values to investigate their influence on decision robustness in different problem contexts.

Step 6: Calculate the assessment score (H_i) of each alternative using equation 21.

$$H_i = \sum_{k=1}^{m} h_{ik} \tag{21}$$

The ranking of the alternatives is established on the basis of the optimality scores obtained by securing the highest position in both cases. The decreasing assessment scores of the alternatives signify the conversion from superior to inferior. The alternative with highest assessment score is always the best choice in respect to quality and importance, etc. Table 9 shows the relative assessment matrix with the assessment scores and the ranking of the alternatives.

To evaluate the robustness of the ranking results derived from the EDAS and CODAS methods, a single-dimensional weight sensitivity analysis was performed [23, 26]. In this approach, the weight of a critical criterion was systematically changed, while the remaining weights were proportionally adjusted to maintain the normalization condition. The maximum potential weight (wj^*) for a criterion is calculated using the following equation 22.

$$w_j^* = [w_j^{max} + (n-1) \times w_j^{min}] \tag{22}$$

Where, w_j^{max} and w_j^{min} represent the upper and lower limits of the weight variation for the criterion and 'n' is the total number of criteria. This formulation ensures that the adjusted weights remain within acceptable limits while testing the impact of varying importance levels on the final ranking. The application of this equation and the resulting variations in ranking are presented in the Results and Discussion section.

4. Discussion

The rankings for EDAS and CODAS are proposed accordingly in Table 5 and Table 9. This problem has already been solved by many researchers using MOORA, WSM, WPM, WASPAS method [1, 8-10], etc. and the present ranking was compared with the previously proposed rankings in Table 10. It can be seen from Table 10 that the third and fourth ranked alternatives are exactly the same in all cases. However, there are some confusions regarding the first and second position. The comparison of the rankings is also shown graphically in Figure 2.

The methods selected for the comparative ranking analysis—MOORA, WSM, WPM and WASPAS—were chosen based on their widespread application in previous studies related to construction materials, facade systems, and architectural decision making. These techniques represent a combination of simple, weighted-sum-based approaches (e.g., WSM, WPM) and more advanced methods that incorporate normalization and ratio-based evaluations (e.g., MOORA, WASPAS). Furthermore, these methods have been specifically applied to similar facade evaluation problems in previous work by Zavadskas et al. [1], making them ideal benchmarks for validating the performance of EDAS and CODAS in this study. Other methods such as MARCOS, MAIRCA and MABAC, although methodologically robust, were not included in the current comparison either due to their recent emergence in the literature or limited prior application to facade systems. Future research could extend the comparative framework to include these newer techniques and examine their compatibility with sensitivity analysis and data-driven weighting strategies.

The results obtained through the application of EDAS and CODAS methods confirm that aluminium-glazed facades (ATV 4) consistently outperform other alternatives, followed by sandwich panel facades (ATV 2). These findings align closely with those derived using WSM and WASPAS methods in previous studies [1], thereby reinforcing the robustness and reliability of the selected MCDM tools. However, the MOORA and WPM methods yielded slightly different rankings, indicating that methodological variance can influence decision outcomes in multi-criteria environments. Despite the strong consistency observed between EDAS, CODAS and some previous methods, several limitations must be acknowledged. First, the dataset and criteria weights were derived from a previously published research by Zavadskas et al. [1], which limits the originality of the input data. Secondly, only four facade alternatives and twelve criteria were considered in the study, which may not capture the full complexity of real-world projects. Third, the entropy method used for weighting, although objective, does not take into account stakeholder preferences or expert judgments, which could be crucial in practical scenarios.

To address these limitations, future research should aim to generate original datasets through industry surveys or field studies. Additionally, integrating subjective weighting methods such as AHP, SWARA or the Best–Worst Method (BWM) can reflect expert input, thereby enhancing the practical relevance of the model. Moreover, expanding the range of alternatives and criteria allows for a more comprehensive evaluation of facade performance in diverse urban contexts. Finally, future studies could explore hybrid approaches that combine MCDM with geographic information systems (GIS), building information modelling (BIM) or life cycle assessment (LCA) tools. These integrations would offer spatial and environmental insights and create a more holistic decision-making framework that can be used for smart and sustainable urban development.

Table 10. Ranking comparisons

Alternatives	ATV 1	ATV 2	ATV 3	ATV 4
MOORA (Ratio system)	4	1	3	2
MULTIMOORA	4	1	3	2
WSM	4	2	3	1
WPM	4	1	3	2
WASPAS (λ = 0.5)	4	2	3	1
EDAS	4	2	3	1
CODAS	4	2	3	1

(Source: Zavadskas et al., 2013 [1]; Author himself)

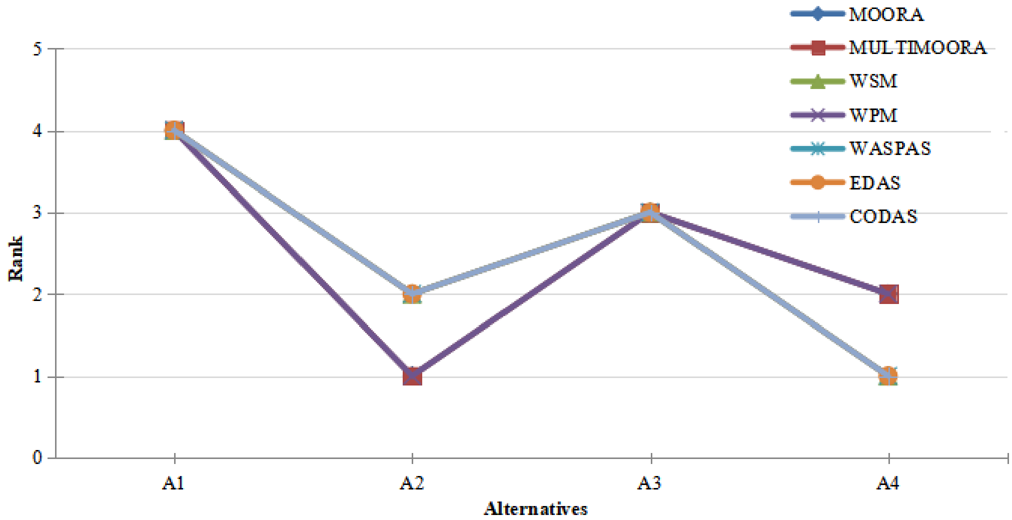


Figure 2. Graphical ranking comparisons of the applied methods

The use of EDAS and CODAS in this study offers a structured and robust approach to multi-criteria facade evaluation. These methods provide simple calculations, consider both beneficial and non-beneficial criteria, and demonstrate high ranking stability under sensitivity testing. Unlike traditional methods such as WSM or WPM, which rely on simple aggregation, or methods such as TOPSIS, which are sensitive to definitions of ideal solutions and normalization techniques, EDAS and CODAS evaluate alternatives based on their distance from a mean or reference solution, leading to more nuanced rankings and better outlier management. Furthermore, their compatibility with objective weighting methods such as entropy supports neutral, data-driven evaluations. However, the proposed methodology also has its limitations. Unlike hybrid frameworks (e.g., fuzzy-AHP, BWM-CRITIC) that integrate expert judgment or model uncertainty in qualitative assessments, EDAS and CODAS rely on crisp input data and assume stable, well-defined criteria. This could limit their applicability to projects with high levels of ambiguity or expert-driven variation. Additionally, this study focuses exclusively on performance-based evaluation in terms of structural, environmental, economic and aesthetic dimensions, without taking into account geographic or climatic conditions, which are known to significantly influence facade performance. For example, a facade that performs well in a temperate region may underperform in hot, humid or arid climates. The absence of region-specific thermal behavior, solar gain, humidity resistance or local environmental impacts in the evaluation matrix limits the generalizability of the findings to broader climatic contexts. Future research should aim to integrate geographic and climate-responsive parameters—such as solar heat gain coefficients, U-values, daylight penetration and wind resistance—into the criteria set. Additionally, applying this model in regionally distinct case studies would help assess its flexibility and enhance its value for globally relevant applications.

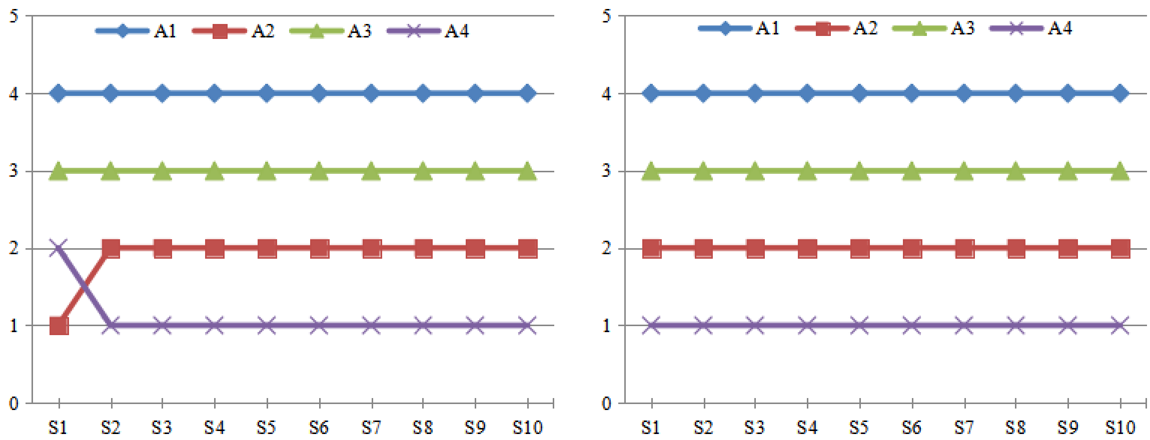
4.1 Validation using sensitivity analysis

On the basis of above calculation analysis, a validation needs to be executed to confirm the results. Therefore, single dimensional weight sensitivity analysis [17] was applied to the ongoing problem. The sensitivity analysis was performed to address the any changes occurs in the proposed rankings.The single dimensional analysis dealt with the weight variation within a specific range. The maximum potential parametric weight (wj^*) was calculated using equation 22. The weight adjustment calculations based on equation 22 described earlier in the methodology, were applied to perform a sensitivity analysis using ten weight scenarios. The value of wj^* was found to be 0.7005. To begin with the analysis, the value of the most important parameter, i.e. ST 4, was altered within range $0 \leq wj^* \leq 0.7005$, keeping an interval of 0.1, however any interval can be chosen, as for example, 0.05, 0.2, etc. The range of the weights variation is shown as 0, 0.1, 0.1417, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.7005. Hence, total 10 sets of criteria had been obtained. Now, the rests of the weights were distributed proportionally among the other criteria adjusted accordingly to comply with the weight constraint rule. The following EDAS and CODAS were further applied utilizing these 10 new sets to detect any changes in the rankings. Thus, there were 10 alternatives rankings for each CODAS and EDAS. 10 sets of criteria weights are presented in Table 11. The ranking deviations for 10 different sets are also shown graphically in Figure 3 [17].

$$w_j^* = [w_j^{max} + (n\text{-}1) \times w_j^{min}] \tag{22}$$

Table 11. 10 sets of parameter weights

Criteria	IH 1	LA 2	SW 3	ST 4	UF 5	DP 6	WG 7	EF 8	RT 9	AE 10	SI 11	FR 12
Actual weights	0.0627	0.0508 Min	0.053	0.1417 Max	0.1114	0.0874	0.0625	0.1183	0.0784	0.0984	0.0798	0.0557
SET 1	0.0756	0.0637	0.0659	0	0.1243	0.1003	0.0754	0.1312	0.0913	0.1113	0.0927	0.0686
SET 2	0.0665	0.0546	0.0568	0.1	0.1152	0.0912	0.0663	0.1221	0.0822	0.1022	0.0836	0.0595
SET 3	0.0627	0.0508	0.0530	0.1417	0.1114	0.0874	0.0625	0.1183	0.0784	0.0984	0.0798	0.0557
SET 4	0.0574	0.0455	0.0477	0.2	0.1061	0.0821	0.0572	0.1130	0.0731	0.0931	0.0745	0.0504
SET 5	0.0483	0.0364	0.0386	0.3	0.0970	0.0730	0.0481	0.1039	0.0640	0.0840	0.0654	0.0413
SET 6	0.0392	0.0273	0.0295	0.4	0.0879	0.0639	0.0390	0.0948	0.0549	0.0749	0.0563	0.0322
SET 7	0.0301	0.0182	0.0204	0.5	0.0788	0.0548	0.0299	0.0857	0.0458	0.0658	0.0472	0.0231
SET 8	0.0210	0.0091	0.0113	0.6	0.0697	0.0457	0.0208	0.0766	0.0367	0.0567	0.0381	0.0140
SET 9	0.0119	0.0000	0.0022	0.7	0.0606	0.0366	0.0117	0.0675	0.0276	0.0476	0.0290	0.0049
SET 10	0.0119	0.0000	0.0022	0.7005	0.0606	0.0366	0.0117	0.0675	0.0276	0.0476	0.0290	0.0049



a) EDAS b) CODAS

Figure 3. Validation of EDAS and CODAS

From the graphs shown, it can be seen that EDAS and CODAS have only very minor variations in the ranking, almost none. In the case of EDAS, only one set of weights, i.e. the first and the foremost set, leads to a different ranking, but from the weight value 0.1 onwards, the ranking is uniform, stable and results in exactly the same ranking in all cases. In the case of CODAS, not a single weight sets proposed a different ranking. The rating remains consistent throughout. Hence, based on this scenario, it can be stated that the adopted tools EDAS and CODAS are robust and very stable MCDM tools. These two tools are able to produce much more consistent results than the previously applied methods. As we can see from Table 10 that MOORA, MULTIMOORA and WPM produced a different ranking of alternatives, therefore these tools are not so superior tools. The most challenging aspect being addressed by these two tools is the consistency of the rating order, which remains the same throughout the analysis.

The sensitivity analysis conducted in this study was limited to the single-dimensional weight variation of one criterion (ST4: Structural Thickness), which was selected due to its high initial entropy weight. Ten alternative weight sets were generated by increasing and decreasing the weight of ST4, while the remaining weights were proportionally adjusted to preserve the normalization condition. The results showed that CODAS produced stable rankings across all scenarios, while EDAS exhibited a ranking deviation in the first case, after which it stabilized. These findings demonstrate that both methods exhibited strong robustness to changes in the weights of individual criteria—particularly EDAS and CODAS, whose rankings remained mostly unaffected by moderate shifts in ST4. A more cautious interpretation is that EDAS and CODAS are suitable and robust methods for this decision problem, as they offer consistent rankings under the chosen criteria and weight variation strategy. Moreover, the observed consistency of their top- and bottom-ranked alternatives with those identified using WSM and WASPAS strengthens confidence in their applicability. Nonetheless, to evaluate comparative superiority more rigorously, future work should conduct multi-parameter sensitivity analysis and apply statistical measures of rank consistency (e.g., Kendall's tau or Spearman's rho) across different MCDM models. Extending the analysis to test the influence of other criteria (not just ST4) would also help to identify the most influential parameters and validate the reliability of the rankings under broader decision scenarios.

Figure 2 illustrates the consistency of the ranking of facade alternatives in ten different weight scenarios generated through a single-dimensional sensitivity analysis. For each case, the weight of the most critical parameter (ST4: Structural Thickness) was varied within a defined range and the rankings were recalculated using both the EDAS and CODAS methods. The graphical output shows that the CODAS maintained 100% ranking consistency, while the EDAS showed only one minor deviation in the first scenario, after which the rankings stabilized completely. This demonstrates the strong robustness and insensitivity to weight perturbation of both methods, particularly CODAS. To further support this conclusion, a simple statistical analysis reveals that in the 10 EDAS runs, the modal ranking (ATV 4 > ATV 2 > ATV 3 > ATV 1) occurred 9 out of 10 cases, indicating a 90% ranking stability rate. For CODAS, all 10 weight sets produced identical rankings, confirming 100% consistency. These results reinforce the claim that both methods are suitable for real-world decision environments where input uncertainty or shifting stakeholder priorities are common. Nevertheless, this form of sensitivity analysis has its limitations. First, it only takes into account changes in the single-criterion weight in a deterministic manner, not accounting for inter-criterion correlations or the simultaneous uncertainty of multi-parameters. Secondly, it does not consider probabilistic or fuzzy variations that could more realistically reflect variations in expert judgment in construction settings. Future research could apply Monte Carlo simulation, interval analysis or fuzzy weight distributions to model uncertainty in a more comprehensive and statistically rigorous manner.

Overall, the analysis confirms that EDAS and CODAS are highly stable MCDM tools that can maintain consistent rankings even under varied assumptions, with CODAS slightly outperforming EDAS in resistance to early-stage fluctuations.

4.2 Practical implications

The stability and consistency demonstrated by the EDAS and CODAS rankings in this study have important implications for real-world construction and architectural decision making. By identifying aluminium-glazed facades (ATV 4) and sandwich panel systems (ATV 2) as the top-performing alternatives across multiple evaluation scenarios, the findings offer project stakeholders—such as developers, architects, engineers and public authorities—a reliable, data-driven foundation for selecting facade systems that meet performance expectations while being cost-effective and environmentally friendly. In large-scale commercial and institutional construction, where design decisions can have long-term financial and operational consequences, the ability to robustly evaluate alternatives under varying criteria weights is particularly valuable. In addition, the use of transparent and replicable methods such as EDAS and CODAS supports collaboration among multi-stakeholders by providing defensible outcomes that reduce bias and foster consensus. This is critical in public procurement and sustainable development projects where decisions must be justified to regulatory bodies, clients and community stakeholders. Additionally, by incorporating both objective and subjective evaluation parameters—such as aesthetics, fire resistance, environmental friendliness and installation costs—the model accommodates the complex trade-offs inherent in facade selection.

These insights can also aid in risk mitigation, as the validation of rankings through sensitivity analysis ensures that the preferred facade options remain viable even if project priorities shift or certain parameters (e.g. labor availability, material costs) fluctuate. Ultimately, the findings contribute to evidence-based construction management that enables faster and more confident design approvals, optimizes resource allocation and aligns project outcomes with broader goals such as energy efficiency, occupant comfort and life cycle value.

4.3 Practical recommendations and case study applications

The results of this study yield several practical recommendations for construction professionals and industry stakeholders involved in facade selection and architectural decision making. Firstly, it is advisable to integrate multi-criteria evaluation methods such as EDAS and CODAS in the early design stages of a project. This allows for a balanced assessment of facade alternatives that takes into account aesthetics, cost, sustainability and technical performance, thereby minimizing the risk of redesign and inefficiencies during execution. Secondly, the use of objective weighting techniques such as the entropy method can significantly enhance transparency and reduce subjectivity in the evaluation process. This is particularly important in public-sector projects or collaborative environments where decision accountability and traceability are essential. Furthermore, incorporating sensitivity analysis into the decision model enables practitioners to assess how changes in key parameters—such as material costs, labor intensity or environmental standards—might affect the final ranking. This capability supports more resilient planning and facilitates risk mitigation. The intuitive structure of EDAS and CODAS also makes them accessible for use in multidisciplinary teams, enabling stakeholders with diverse priorities to interpret the results, understand trade-offs and reach a consensus more efficiently. These methods can also be integrated into digital platforms such as Building Information Modelling (BIM) systems, allowing real-time updates and seamless integration into broader project workflows.

In terms of case study applications, the proposed framework can be adapted to various real-world scenarios. For example, in the construction of public schools, where fire resistance, acoustic insulation and long-term durability are essential, the model can guide cost-effective and regulation-compliant facade choices. In commercial office projects, the methodology supports the selection of solutions that optimize energy efficiency and life cycle costs while meeting aesthetic expectations. The approach is also compatible with green building certification systems such as LEED or BREEAM by aligning evaluation criteria with sustainability benchmarks. Future applications may involve the use of stakeholder-specific weighting schemes or the extension of this framework to projects located in different climatic or regulatory contexts, thus broadening its practical impact across the building industry.

5. Conclusion

This study applied two robust Multi-Criteria Decision-Making (MCDM) methods—EDAS and CODAS—to evaluate and rank four facade alternatives for use in public and commercial buildings. Based on twelve critical evaluation criteria, the aluminium-glazed facade (ATV 4) was found to be the most suitable option, closely followed by the sandwich-type panel system (ATV 2), while Rockwool with decorative plaster (ATV 1) was ranked the least favorable. The consistency of the rankings produced by both methods, validated by a single-dimensional sensitivity analysis, demonstrates the reliability and stability of the proposed approach. Furthermore, comparisons with previous studies using MOORA, WASPAS and WSM confirm the effectiveness of EDAS and CODAS in the context of architectural material selection.

Although this study contributes to the advancement of facade evaluation using EDAS and CODAS methods, it is not without limitations. First, the analysis was based on a previously published dataset, which, while useful for benchmarking, limits the originality and real-time contextual relevance of the input values. Second, the study relied exclusively on objective weighting through the entropy method, without incorporating expert-driven or stakeholder-based weighting systems that may better reflect practical preferences. Third, only four facade alternatives and twelve criteria were considered in the analysis, which may not fully reflect the diversity of modern facade technologies and emerging sustainability factors. Additionally, the geographic and climatic context was not included, although these factors significantly influence the facade performance in real-world scenarios. Another assumption was the use of deterministic (crisp) data without modeling uncertainty or imprecision, which limits the flexibility of evaluation under vague or subjective conditions.

Future research could address these gaps by incorporating hybrid weighting schemes (e.g., AHP–Entropy, CRITIC–SWARA), expanding the dataset with real-world industry inputs, and integrating fuzzy logic or probabilistic models to handle uncertainty. Moreover, by integrating fuzzy logic, grey systems or Monte Carlo simulations, the model would better reflect uncertainty in the real world. Applying the model in actual case studies, including different climate zones, regulatory environments and building types, would further validate its practical utility and adaptability. Additionally, developing a user-friendly software tool or plugin—perhaps within BIM environments—could further improve its utility among construction professionals and decision-makers.

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Authors' contribution

All authors contributed substantially to the development of this research article. AB contributed to the data curation, software implementation and formal analysis of the MCDM methods. SSG conceptualized the study, developed the methodology, and led the writing of the original draft manuscript. SM was responsible for the literature review, validation of results, and preparation of visualizations. DKB was responsible for supervising, reviewing and editing of the article. All authors participated equally in preparation of this manuscript, approved the final version, and agreed to be accountable for all aspects of the work.

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Availability of data and materials

The data presented in this study are available in this article.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used ChatGPT to restructure sentence formation and paraphrasing and to refine the language. We confirm that no initial ideas were adopted from any AI-generated tools. AI tools were used just to increase the depth and clarity of the text. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

Informed consent statement

Not applicable

Conflict of interest

The authors declare no conflict of interest.

References

[1] Zavadskas EK, Antucheviciene J, Šaparauskas J, Turskis Z. Multi-criteria assessment of facades' alternatives: peculiarities of ranking methodology. Procedia Engineering. 2013; 57: 107-12. doi:10.1016/j.proeng.2013.04.016.

[2] Xu J, Li Z. Multi-objective dynamic construction site layout planning in fuzzy random environment. Automation in construction. 2012; 27: 155-69. doi: 10.1016/j.autcon.2012.05.017.

[3] Seydel J, Olson DL. Multicriteria support for construction bidding. *Mathematical and Computer Modelling*. 2001; 34(5-6): 677-701. doi:10.1016/S0895-7177(01)00091-7.

[4] Ustinovichius L, Shevchenko G, Barvidas A, Ashikhmin IV, Kochin D. Feasibility of verbal analysis application to solving the problems of investment in construction. *Automation in construction*. 2010; 19(3): 375-84. doi: 10.1016/j.autcon.2009.12.004.

[5] Zavadskas EK, Turskis Z, Vilutiene T. Multiple criteria analysis of foundation instalment alternatives by applying Additive Ratio Assessment (ARAS) method. *Archives of civil and mechanical engineering*. 2010; 10(3): 123-41. doi: 10.1016/S1644-9665(12)60141-1.

[6] Pan NF. Selecting an appropriate excavation construction method based on qualitative assessments. *Expert Systems with Applications*. 2009; 36(3): 5481-90. doi: 10.1016/j.eswa.2008.06.097.

[7] Nieto-Morote A, Ruz-Vila F. A fuzzy multi-criteria decision-making model for construction contractor prequalification. *Automation in construction*. 2012; 25: 8-19. doi: 10.1016/j.autcon.2012.04.004.

[8] Šaparauskas J, Zavadskas EK, Turskis Z. Evaluation of alternative building designes according to the three criteria of optimality. *10th International Conference Modern Building Materials, Structures and Techniques*. 2020; 1. Available from: https://etalpykla.vilniustech.lt/handle/123456789/127507 [Accessed 25th March 2025].

[9] Šaparauskas J, Kazimieras Zavadskas E, Turskis Z. Selection of facade's alternatives of commercial and public buildings based on multiple criteria. *International Journal of Strategic Property Management*. 2011; 15(2): 189-203. doi: 10.3846/1648715X.2011.586532.

[10] Zavadskas EK, Turskis Z, Antucheviciene J, Zakarevicius A. Optimization of weighted aggregated sum product assessment. *Elektronika ir Elektrotechnika*. 2012; 122(6): 3-6. doi: 10.5755/j01.eee.122.6.1810.

[11] Jamili A, Imani Shamloo J, Dargahi F. Spatial analysis and integrated multi-criteria decision making methods; a model to evaluate justice in the distribution of urban services in Tehran. *International Journal of Urban Sciences*. 2024; 1-26. doi:10.1080/12265934.2024.2438184.

[12] Dargahi F, Shamloo JI. Investigating the realization of spatial justice based on multi-criteria decision-making methods in a metropolis in northwest Iran. *Sustainable Cities and Society*. 2023; 99: 104986. doi: 10.1016/j.scs.2023.104986.

[13] Gaber B, Zhan C, Han X, Omar M, Li G. A novel decision support system for designing fixed shading systems in the early design stage: A case study in Egypt. *Journal of Building Engineering*. 2024; 96: 110453. doi: 10.1016/j.jobe.2024.110453.

[14] Gaber B, Zhan C, Han X, Omar M, Li G. Enhancing Daylight and Energy Efficiency in Hot Climate Regions with a Perforated Shading System Using a Hybrid Approach Considering Different Case Studies. *Buildings*. 2025; 15(6): 988. doi:10.3390/buildings15060988.

[15] Chen CH. A new multi-criteria assessment model combining GRA techniques with intuitionistic fuzzy entropy-based TOPSIS method for sustainable building materials supplier selection. *Sustainability*. 2019; 11(8): 2265. doi:10.3390/su11082265.

[16] Cai J, Li Z, Dou Y, Teng Y, Yuan M. Contractor selection for green buildings based on the fuzzy Kano model and TOPSIS: A developer satisfaction perspective. *Engineering, Construction and Architectural Management.* 2023; 30(10): 5073-108. doi: 10.1108/ECAM-01-2022-0054.

[17] Zhuang H, Zhang J, CB S, Muthu BA. Sustainable smart city building construction methods. *Sustainability*. 2020; 12(12): 4947. doi:10.3390/su12124947.

[18] Dagdougui H, Minciardi R, Ouammi A, Robba M, Sacile R. Modeling and optimization of a hybrid system for the energy supply of a "Green" building. *Energy Conversion and Management*. 2012; 64: 351-63. doi: 10.1016/j.enconman.2012.05.017.

[19] Antucheviciene J, Kala Z, Marzouk M, Vaidogas ER. Solving civil engineering problems by means of fuzzy

and stochastic MCDM methods: current state and future research. *Mathematical Problems in Engineering*. 2015; (1): 362579. doi: 10.1155/2015/362579.
[20] Vafadarnikjoo A, Scherz M. A hybrid neutrosophic-grey analytic hierarchy process method: Decision-making modelling in uncertain environments. *Mathematical Problems in Engineering*. 2021; (1): 1239505. doi:10.1155/2021/1239505.
[21] Ramavandi B, Darabi AH, Omidvar M. Risk assessment of hot and humid environments through an integrated fuzzy AHP-VIKOR method. *Stochastic Environmental Research and Risk Assessment*. 2021; 35(12): 2425-38. doi: 10.1007/s00477-021-01995-1.
[22] Taylan O, Alamoudi R, Kabli M, AlJifri A, Ramzi F, Herrera-Viedma E. Assessment of energy systems using extended fuzzy AHP, fuzzy VIKOR, and TOPSIS approaches to manage non-cooperative opinions. *Sustainability*. 2020; 12(7): 2745. doi: 10.3390/su12072745.
[23] Keshavarz Ghorabaee M, Zavadskas EK, Olfat L, Turskis Z. Multi-criteria inventory classification using a new method of evaluation based on distance from average solution (EDAS). *Informatica*. 2015; 26(3): 435-51. doi: 10.3233/INF-2015-1070.
[24] Shannon CE. A mathematical theory of communication. *The Bell system technical journal*. 1948; 27(3): 379-423. doi:10.1002/j.1538-7305.1948.tb01338.x.
[25] Opricovic S, Tzeng GH. Compromise solution by MCDM methods: A comparative analysis of VIKOR and TOPSIS. *European journal of operational research*. 2004; 156(2): 445-55. doi:10.1016/S0377-2217(03)00020-1.
[26] Ghorabaee MK, Amiri M, Zavadskas EK, Hooshmand R, Antuchevičienė J. Fuzzy extension of the CODAS method for multi-criteria market segment evaluation. *Journal of Business Economics and Management*. 2017; 18(1): 1-9. doi: 10.3846/16111699.2016.1278559.
[27] Karande P, Zavadskas EK, Chakraborty S. A study on the ranking performance of some MCDM methods for industrial robot selection problems. *International Journal of Industrial Engineering Computations*. 2016; 7(3): 399-422. doi:10.5267/j.ijiec.2016.1.001.
[28] Antuchevičienė J, Zakarevičius A, Zavadskas EK. Measuring congruence of ranking results applying particular MCDM methods. *Informatica*. 2011; 22(3): 319-338. doi: 10.15388/Informatica.2011.329.
[29] Pamučar D, Badi I, Sanja K, Obradović R. A novel approach for the selection of power-generation technology using a linguistic neutrosophic CODAS method: A case study in Libya. *Energies*. 2018; 11(9): 2489. doi:10.3390/en11092489.