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AN INTEGRATED GRAPH-BASED IFC DECISION SUPPORT FRAMEWORK FOR SUSTAINABLE BUILDING COMPONENT SELECTION

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ABSTRACT

Decision-making in the selection of sustainable building components remains one of the most persistent challenges in the construction industry. Projects involve numerous conflicting objectives and highly interdependent variables, yet the rich semantic and relational data embedded in IFC-based BIM models is rarely fully exploited for advanced analytical support. Existing approaches typically suffer from fragmented workflows, inefficient data extraction, and poor integration between modelling, optimisation, and decision-making processes. This study proposes a comprehensive, integrated data-driven decision-support framework that directly addresses these limitations. The framework transforms IFC-based BIM data into a scalable graph database using Neo4j and connects it seamlessly with multi-objective optimisation, Data Envelopment Analysis (DEA), and multi-criteria decision-making (MCDM) within a single coherent pipeline. The framework was implemented and validated on a residential building case study, considering four key sustainability objectives. Results demonstrate that the graph-based representation improves data accessibility and efficient retrieval, while the integrated pipeline effectively reduces the solution space and delivers transparent, high-quality recommendations that balance technical performance with stakeholder preferences. Compared with conventional fragmented methods, the proposed framework offers a more coherent, practical, and potentially scalable solution for complex multi-criteria decision-making problems across the Architecture, Engineering, and Construction (AEC) industry.

Keywords: Building Information Modeling; Industry Foundation Classes; Graph Database; Multi-objective Optimisation; Data Envelopment Analysis; Multi-criteria Decision-making; Sustainable Building Components.

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1. INTRODUCTION

Optimal decision-making continues to be one of the most persistent challenges in the construction industry. This challenge has intensified as projects increase in scale, complexity, and the number of interdependent variables influencing their outcomes. The sector has long been characterized by relatively low returns on investment compared to other industries, along with persistent issues such as cost overruns, managerial inefficiencies, unforeseen expenditures, and the financial consequences of design and execution changes [1,2]. These systemic issues highlight the urgent need for robust, data-driven decision-support frameworks that can handle multi-dimensional trade-offs [3,4]. In this context, optimisation serves as a critical mechanism bridging engineering practice and strategic planning [5]. However, conventional approaches become inadequate when faced with the growing number and interdependency of decision variables, necessitating advanced computational and data-centric methodologies [6].

Recent advancements in digital construction technologies have created new opportunities to address some challenges across Architecture, Engineering, and Construction (AEC) domains. Among them, Building Information Modeling (BIM) has emerged as a transformative paradigm by integrating geometric, semantic, and relational information within a unified digital environment, thereby enhancing coordination, information exchange, and lifecycle management [7].

The Industry Foundation Classes (IFC), as the standard data schema underpinning BIM, provide a rich, object-oriented, and platform-independent representation of building data. Nevertheless, the complex hierarchical and highly interconnected structure of IFC models poses significant limitations for data extraction and advanced analytics. Therefore, attention has been paid to the effective exploitation of IFC-based data for decision support [8–12].

Traditional relational databases struggle to query and process data efficiently. To address these limitations, graph-based representations of IFC data have been proposed and shown to deliver substantial improvements in query performance, data accessibility, and relationship traversal [13–15]. Graph databases provide substantial advantages for managing and analyzing BIM-derived data [16].

Concurrently, the selection of building materials and components has evolved into a complex decision-making problem. Beyond traditional criteria such as cost and quality, stakeholders must now consider energy performance, environmental impact, recyclability, and local sourcing. Therefore, material selection constitutes a multi-objective problem requiring the integration of diverse and often conflicting objectives within a unified decision-making framework [17,18].

While previous studies have explored BIM-enabled decision support, multi-objective optimisation, and multi-criteria decision-making (MCDM) individually, these approaches are typically developed in isolation and lack a seamless data-to-decision pipeline. In particular, the potential of IFC-based data when structured within graph databases to support end-to-end optimisation and decision-making remains largely underexplored.

To bridge these gaps, this study develops a comprehensive, integrated decision-support framework. The proposed framework transforms IFC-based BIM data into a graph-based representation and seamlessly integrates it with multi-objective optimisation, data envelopment analysis (DEA), and MCDM techniques. By establishing a coherent pipeline

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from raw data extraction to final decision-making, the framework enhances computational efficiency, transparency, and robustness in selecting optimal sustainable building components.

2. LITERATURE REVIEW

The selection of building materials and components has been investigated, particularly in the context of sustainability, lifecycle performance, and decision-support systems. Existing studies can be broadly categorized into three primary streams: (i) BIM-based decision-support frameworks, (ii) optimisation-driven approaches, and (iii) multi-criteria decision-making (MCDM) models and efficiency analysis. Some studies are common between the two categories.

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2.1. BIM-based Decision Support

A substantial body of recent research has leveraged BIM as a data-rich platform for supporting decision-making in sustainable material and component selection. For example, Jalaei et al. [18] developed a BIM-integrated decision-support system that incorporates Life Cycle Cost (LCC) analysis and employs TOPSIS together with pairwise comparison to reflect stakeholder preferences. Liu et al. [19] integrated BIM with Particle Swarm Optimisation (PSO) to balance lifecycle cost and environmental performance, while Akanmu et al. [20] combined a modified Harmony Search algorithm with supplier performance evaluation in material selection.

Although these studies demonstrate the practical value of BIM in material selection, they remain constrained by conventional data management mechanisms. Most approaches rely on manual or semi-automated extraction from BIM models and relational databases, which limits scalability and efficient traversal of the complex relational and hierarchical structures inherent in IFC files.

Recent efforts have explored graph-based and semantic approaches to address these limitations. Graph-based BIM frameworks enable more efficient handling of relationships and support advanced querying mechanisms compared to relational models [21]. In parallel, semantic web and linked data approaches—such as Linked Building Data (LBD)—have been introduced to improve interoperability and machine readability [22–24]. Nevertheless, these solutions are primarily focused on data representation and rarely integrate directly with optimisation or decision-making modules.

2.2. Optimisation-Based Approaches

Metaheuristic algorithms have been widely adopted to tackle the complex, multi-objective nature of building design and material selection. Dawood [25] proposed a Genetic Algorithm (GA) framework supported by parametric programming to link BIM with optimisation modules. Also, the integration of multi-objective optimisation with BIM for balancing embodied and operational energy is examined [26]. Subsequent studies applied GA [27,28], PSO [19,29], and other evolutionary algorithms to optimise façade design, prefabricated systems, and window parameters under energy, cost, and sustainability objectives.

While most optimisation-driven studies have achieved notable improvements in specific performance metrics, they generally suffer from two major limitations [30]. First, they depend on predefined or manually extracted data structures rather than directly exploiting rich IFC models. Second, they lack seamless integration with advanced data management paradigms such as graph databases [31]. Consequently, the full potential of real-time, relationship-rich IFC data remains underutilised in the optimisation loop.

2.3. Multi-Criteria Decision-Making (MCDM) and Efficiency Analysis

MCDM techniques have been extensively used to handle the conflicting objectives inherent in sustainable material selection. Notable examples include the hybrid DANP–TOPSIS framework by Govindan et al. [32] and BIM-based sustainability assessment incorporating objective and subjective indicators [33]. VAHP has also been applied within BIM environments to prioritise façade alternatives based on expert judgment [34]. In addition, the effectiveness of MCDM techniques in sustainable construction and material evaluation is widely examined in the literature [31,35,36].

Despite their strengths in capturing stakeholder preferences and trade-offs, MCDM approaches are frequently applied as post-processing tools rather than being embedded within an integrated data-to-decision pipeline. They often rely heavily on subjective weighting schemes and rarely incorporate advanced BIM data structures [18,26,34].

Data Envelopment Analysis (DEA) has emerged as a powerful non-parametric method for assessing relative efficiency of decision-making units under multiple inputs and outputs [37]. In the construction domain, DEA has been widely applied [38,39] such as to benchmark the eco-efficiency of building materials and components by integrating life-cycle environmental impacts with economic performance [17]. However, existing DEA applications in AEC have not yet been linked with IFC-based graph databases and multi-objective optimisation within a unified framework.

2.4. Critical Analysis and Research Gap

Although the three research streams—BIM-based decision support, optimisation-driven approaches, and MCDM—have made significant contributions to sustainable material and component selection, they remain largely fragmented. Most studies rely on conventional data extraction methods and relational databases that fail to exploit the full relational and hierarchical complexity of IFC models. Even recent advances in IFC-Graph, which substantially improve query performance and relationship traversal, have not yet been systematically linked with multi-objective optimisation, DEA, or MCDM.

A critical shared limitation is the lack of an integrated data-to-decision pipeline. Consequently, existing frameworks suffer from fragmented workflows, reduced computational efficiency, and limited transparency.

To address these gaps, this study develops a unified, data-driven decision-support framework. The proposed framework transforms IFC-based BIM data into a graph-based representation and seamlessly integrates it with multi-objective optimisation, data envelopment analysis (DEA), and MCDM techniques, thereby establishing a coherent end-to-end pipeline from raw data extraction to final decision-making.

In doing so, this research contributes to the literature in two important ways. First, it bridges the gap between advanced IFC-Graph modelling and integrated optimisation–decision

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processes. Second, it operationalises this integration to provide practical, transparent, and computationally efficient decision support for sustainable building component selection under multiple conflicting sustainability objectives

3. PROPOSED DECISION SUPPORT FRAMEWORK

This study proposes an integrated, data-driven decision-support framework for the optimal selection of sustainable building components. The framework establishes a coherent end-to-end pipeline consisting of five sequential phases: (1) data preparation, (2) graph database construction, (3) multi-objective optimisation, (4) efficiency evaluation using DEA, and (5) multi-criteria decision-making. These phases collectively transform raw IFC-based BIM data into actionable decisions. The overall structure of the framework is illustrated in Figure 1.

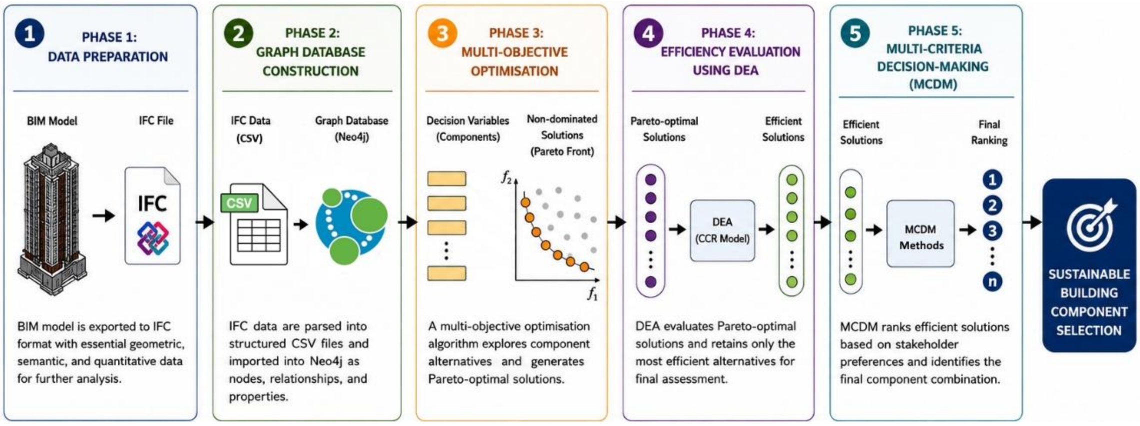

Figure 1: Pipeline of the proposed decision support framework

3.1 Phase 1: Data Preparation

In the first phase, a three-dimensional building model is developed in a BIM authoring tool (e.g., Autodesk Revit) at an appropriate Level of Development (LOD). Decision variables are defined as the building components selection that are subject to optimisation. For each selected component, a set of feasible alternatives is established based on technical specifications and project requirements.

To ensure data consistency and relevance, the BIM model is exported to the Industry Foundation Classes (IFC) format using appropriate export settings, including the selection of IFC schema version and Model View Definition (MVD). This step retains only the necessary geometric, semantic, and relational information while eliminating redundant data, thereby preparing a clean and structured input for the subsequent phases.

3.2 Phase 2: Graph Database Construction

The IFC file exported in Phase 1 serves as the primary input for this phase. This phase establishes a critical link between raw BIM data and downstream analytical processes by converting the IFC-based representation into a graph-structured data model. Through this transformation, complex hierarchical and relational information embedded in the BIM model becomes explicitly accessible, queryable, and computationally tractable. The resulting graph database acts as the core data layer for all subsequent optimisation and decision-making processes.

From a methodological perspective, this transformation enables the reinterpretation of IFC data as a computation-ready network structure, facilitating its direct integration with optimisation algorithms and decision-support models.

This phase consists of two main steps: (1) IFC parsing and (2) graph database development.

Step 1: IFC Parsing

Each IFC file is parsed to systematically extract entities, relationships, and their attributes. The parsing process is implemented using custom scripts that interpret the IFC schema (defined in EXPRESS language and stored in STEP Physical File format or XML-based formats). Key IFC classes relevant to this study are extracted, including:

- *IFCRELATIONSHIP* (for connectivity, aggregation, and dependency relations),
- *IFCSPATIALSTRUCTUREELEMENT* (for hierarchical spatial organisation such as IfcSite, IfcBuilding, IfcBuildingStorey, and IfcSpace),
- *IFCBUILDINGELEMENT* (representing physical components such as walls, slabs, and beams that constitute the decision variables), and
- *IFCPHYSICALQUANTITY* (providing quantitative attributes such as area, volume, and length required for objective function evaluation).

For a comprehensive understanding of the IFC schema, reference [40] can be consulted. The output of this step is a set of structured data files (e.g., CSV) containing explicit entities, relationships, and attributes while preserving both semantic meaning and topological structure.

Step 2: Graph Database Development

The parsed data are imported into a graph database using Neo4j. In this representation, IFC entities are modelled as nodes, relationships as directed edges, and attributes as node or edge properties. The database is populated and queried using the Cypher query language, which enables efficient traversal of complex relationships and rapid retrieval of parameters needed for optimisation.

This graph-based approach overcomes the limitations of traditional relational databases by providing a natural and scalable representation of the inherently interconnected BIM data. The resulting graph database serves as a flexible, high-performance foundation for the multi-objective optimisation phase.

3.3. Phase 3: Multi-Objective Optimisation

In this phase, the graph database constructed in previous Phase is utilised to support the generation and evaluation of alternative design combinations. A population-based

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metaheuristic algorithm can be employed to efficiently explore the large combinatorial design space defined by the building components and their feasible alternatives.

Each candidate solution represents a unique combination of building components, where decision variables correspond to the selection of specific alternatives for each component. The required parameters, such as geometric quantities are retrieved from the Neo4j graph database using Cypher queries and used for evaluating each solution.

The optimisation process is performed iteratively, with the population evolving according to the search mechanism of the selected metaheuristic algorithm. Multiple objective functions are considered simultaneously, reflecting key sustainability criteria such as cost, environmental impact, etc.

Given the multi-objective formulation, the outcome of this phase is a set of non-dominated solutions forming the Pareto front. These solutions represent optimal trade-offs among conflicting objectives and provide a reduced yet representative set of feasible alternatives for subsequent evaluation.

3.4. Phase 4: Efficiency Evaluation Using DEA

Although the Pareto front generated in Phase 3 contains a set of non-dominated solutions representing optimal trade-offs, it may still include a large number of alternatives. To further reduce the number of candidate solutions before applying multi-criteria decision-making (MCDM), Data Envelopment Analysis (DEA) is employed as a powerful non-parametric technique for assessing the relative efficiency of decision-making units.

Each Pareto-optimal solution is treated as a Decision-Making Unit (DMU). The values of the objective functions are classified as inputs and outputs. This approach enables a relative efficiency assessment without requiring predefined subjective weights. The Charnes-Cooper-Rhodes (CCR) model [41] is adopted to calculate efficiency scores by determining the optimal weights that maximise the relative efficiency of each DMU. Solutions with low efficiency score are systematically eliminated, retaining only the most efficient configurations from the Pareto set.

This two-stage evaluation process significantly reduces the solution space while preserving optimality and incorporating performance efficiency considerations. The resulting efficient solutions form the input for the final multi-criteria decision-making phase.

3.5. Phase 5: Multi-Criteria Decision-Making

The efficient solutions obtained from the DEA-filtered Pareto set are subjected to a final decision layer to identify the most suitable configuration under project-specific priorities and stakeholder preferences.

A multi-criteria decision-making (MCDM) model is applied to rank the remaining combinations based on their performance across the defined objective space. The criteria used in this phase are directly aligned with the objective functions employed in the optimisation stage, ensuring methodological consistency across the framework.

Unlike the previous phases that focus on feasibility, optimality, and efficiency, this final stage introduces a preference-driven selection mechanism. The integration of multi-objective optimisation, DEA-based efficiency filtering, and MCDM thus establishes a hierarchical decision structure that balances technical optimality, performance efficiency, and stakeholder

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requirements, delivering a single implementable solution for sustainable building component selection.

4. IMPLEMENTATION OF THE PROPOSED FRAMEWORK

To demonstrate the practicality and effectiveness of the proposed framework, a 33-storey residential building with a gross floor area of 36,856 m² was selected as the case study. The decision problem was formulated with four sustainability-oriented objectives: minimising total cost, maximising energy efficiency, maximising material recyclability, and prioritising locally sourced materials.

The framework was implemented through an integrated computational environment combining BIM, data processing, and graph-based data management. The building model was developed in Autodesk Revit, from which an IFC file was exported and subsequently utilized as the primary data source. The IFC data were processed using MATLAB for parsing and structuring and then transformed into a graph-based representation within the Neo4j database using the Cypher query language. The outputs corresponding to each phase of the framework are reported in the following sections.

4.1. Results of Phase 1: Data Preparation

The case study building was modelled in Autodesk Revit at LOD 300, providing sufficient geometric and semantic detail for subsequent analysis. Representative three-dimensional and plan views of the developed model are presented in Figure 2.

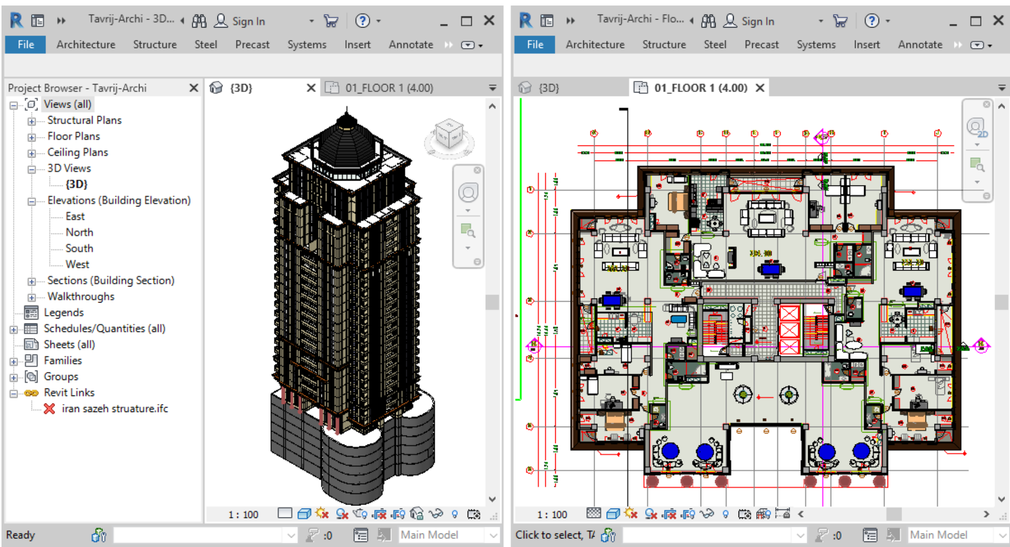

Figure 2: A view of case study modeling in BIM environment

The model was exported to IFC format using the IFC2x3 Coordination View 2 schema, with the “Export Base Quantities” option enabled to include essential quantitative attributes. Due to the size and complexity of the IFC file, only a partial excerpt is shown in Figure 3.

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```
ISO-10303-21;
HEADER;
/****************************************************************************************
* STEP Physical File produced by: The EXPRESS Data Manager Version 5.02.0100.07 : 28 Aug 2013
* Module:                          EDMstepFileFactory/EDMstandAlone
* Creation date:                   Tue Mar 30 12:34:41 2021
* Host:                            Rastegar
* Database:                             C:\Users\Ehsan\AppData\Local\Temp\8a304c5d-dae1-4b95-952b-
f476090f3eec\8d563b16-ce1c-4074-9437-82165888e6ef\ifc
* Database version:                5507
* Database creation date:          Tue Mar 30 10:49:35 2021
* Schema:                          IFC2X3
.
.
.
****************************************************************************************/
FILE_DESCRIPTION(('ViewDefinition[CoordinationView_V2.0,QuantityTakeOffAddOnView]'),'2;1');
FILE_NAME('0001','2021-03-30T12:34:42',(''),(''),'The EXPRESS Data Manager Version 5.02.0100.07 :
28 Aug 2013','21.0.0.383 - Exporter 21.0.0.383 - Alternate UI 21.0.0.383','');
FILE_SCHEMA(('IFC2X3'));
ENDSEC;

DATA;
#1= IFCORGANIZATION ($,'Autodesk Revit 2021 (ENU)',$,$,$);
#5= IFCAPPLICATION (#1,'2021','Autodesk Revit 2021 (ENU)','Revit');
#6= IFCCARTESIANPOINT ((0.,0.,0.));
.
.
.
#119=IFCPROJECT('111xWWhzjGT4NpoX5Ha',#41,'0001',$,$,'ProjectName','ProjectStatus',(#111),#106);
#125= IFCPOSTALADDRESS ($,$,$,$,('Enter address here'),$,'','Boston','','MA');
#129= IFCBUILDING('111xWWhzj7NPGT4NpoX5Hb',#41,'',$,$,#32,$,'',.ELEMENT.,$,$,#125);
.
.
.
#2652026=    IFCDOOR('0jZ9iYE5z50uzg6xEVelsD',#41,'Doors_Barausse_Rei-HTBS3:Int_Door_Barausse_TN-
inverso_1100x2150_Wall_Min-100:1339382',$,'Doors_Barausse_Rei-HTBS3:Int_Door_Barausse_TN-
inverso_1100x2150_Wall_Min-100',#7187397,#2652020,'1339382',2.14999999999998,1.1);
#2652029= IFCMATERIALLIST ((#1584682,#1584692));
#2652031= IFCPROPERTYSET('0jZ9iYE5z50uzg44EVelsD',#41,'Pset_DoorCommon',$,(#451,#146507));
#2652033= IFCPROPERTYSINGLEVALUE('Category',$,IFCLABEL('Doors'),$);
#2652034= IFCPROPERTYSET('2NcH6lZc11QPgZOLlHUjk4',#41,'Pset_ProductRequirements',$,(#2652033));
#2652036= IFCPROPERTYSET('34c7n3_1n1POCdpfvy_JSd',#41,'Pset_QuantityTakeOff',$,(#146507));
#2652038= IFCRELDEFINESBYPROPERTIES('38_vumdG98hQj74Pvk3A7x',#41,$,$,(#2652026),#2652031);
#2652042= IFCRELDEFINESBYPROPERTIES('1QJ9mCxrHAqR_j7tspGnHK',#41,$,$,(#2652026),#2652034);
#2652045= IFCRELDEFINESBYPROPERTIES('3g$IiqD1f38uukWx5gUY9B',#41,$,$,(#2652026),#2652036);
#2652048= IFCQUANTITYLENGTH('Height','',$,2.15);
#2652049= IFCQUANTITYLENGTH('Width','',$,1.1);
.
.
.
#6984656 =IFCRELASSOCIATESMATERIAL('1XynYq73T7NActKlq_OIUg',#41,$,$,(#155893),#155910);
#6984659 =IFCRELASSOCIATESMATERIAL('3e8IA$CBT5r9Z2mNxXNiJF',#41,$,$,(#155963),#156015);
#6984662= IFCRELASSOCIATESMATERIAL('0F7ZKsFLP6xh1hl$c_KdY6',#41,$,$,(#156083),#156100);.
.
.
.
ENDSEC;
END-ISO-10303-21;
```

Figure 3: A partial excerpt of IFC file

Seven building component categories were defined as decision variables: windows, internal doors, flooring systems, internal walls, external walls, curtain wall systems, and roof covering elements. For each category, five feasible alternatives were identified. Technical, economic, and environmental characteristics of the alternatives were obtained from publicly available manufacturer catalogues and technical datasheets. Therefore, the decision space consists of 5^7 = 78,125 possible combinations. Technical specifications and environmental characteristics of these alternatives were extracted and structured for use in the optimisation and evaluation phases.

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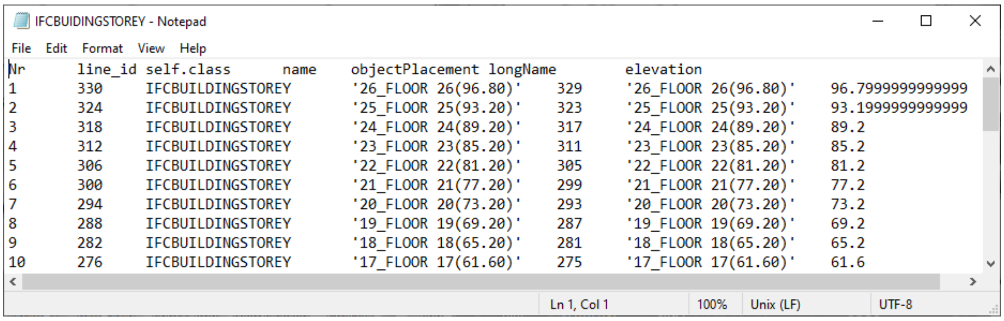
4.2. Results of Phase 2: Graph Database Construction

The IFC file exported from the BIM model was parsed to generate structured CSV files corresponding to the selected IFC entity classes as depicted in Figure 4. These files were subsequently imported into the Neo4j graph database using Cypher queries.


IFCBUIDINGSTOREY - Notepad

File Edit Format View Help

Nr	line_id	self.class	name	objectPlacement	longName	elevation
1	330	IFCBUILDINGSTOREY	'26_FLOOR 26(96.80)'	329	'26_FLOOR 26(96.80)'	96.7999999999999
2	324	IFCBUILDINGSTOREY	'25_FLOOR 25(93.20)'	323	'25_FLOOR 25(93.20)'	93.1999999999999
3	318	IFCBUILDINGSTOREY	'24_FLOOR 24(89.20)'	317	'24_FLOOR 24(89.20)'	89.2
4	312	IFCBUILDINGSTOREY	'23_FLOOR 23(85.20)'	311	'23_FLOOR 23(85.20)'	85.2
5	306	IFCBUILDINGSTOREY	'22_FLOOR 22(81.20)'	305	'22_FLOOR 22(81.20)'	81.2
6	300	IFCBUILDINGSTOREY	'21_FLOOR 21(77.20)'	299	'21_FLOOR 21(77.20)'	77.2
7	294	IFCBUILDINGSTOREY	'20_FLOOR 20(73.20)'	293	'20_FLOOR 20(73.20)'	73.2
8	288	IFCBUILDINGSTOREY	'19_FLOOR 19(69.20)'	287	'19_FLOOR 19(69.20)'	69.2
9	282	IFCBUILDINGSTOREY	'18_FLOOR 18(65.20)'	281	'18_FLOOR 18(65.20)'	65.2
10	276	IFCBUILDINGSTOREY	'17_FLOOR 17(61.60)'	275	'17_FLOOR 17(61.60)'	61.6

Ln 1, Col 1 100% Unix (LF) UTF-8

Figure 4: Example CSV file for class *IFCBUILDINGSTOREY*

As shown in Figure 5, *IFCBUILDINGSTOREY* entities were generated from the corresponding CSV data. Furthermore, based on sample code as illustrated in Figure 6, the entity *IFCELEMENTQUANTITY* was linked to *IFCWINDOW* through the *IFCRELDEFINESBYPROPERTIES* relationship, ensuring the correct association of quantitative attributes with building elements.

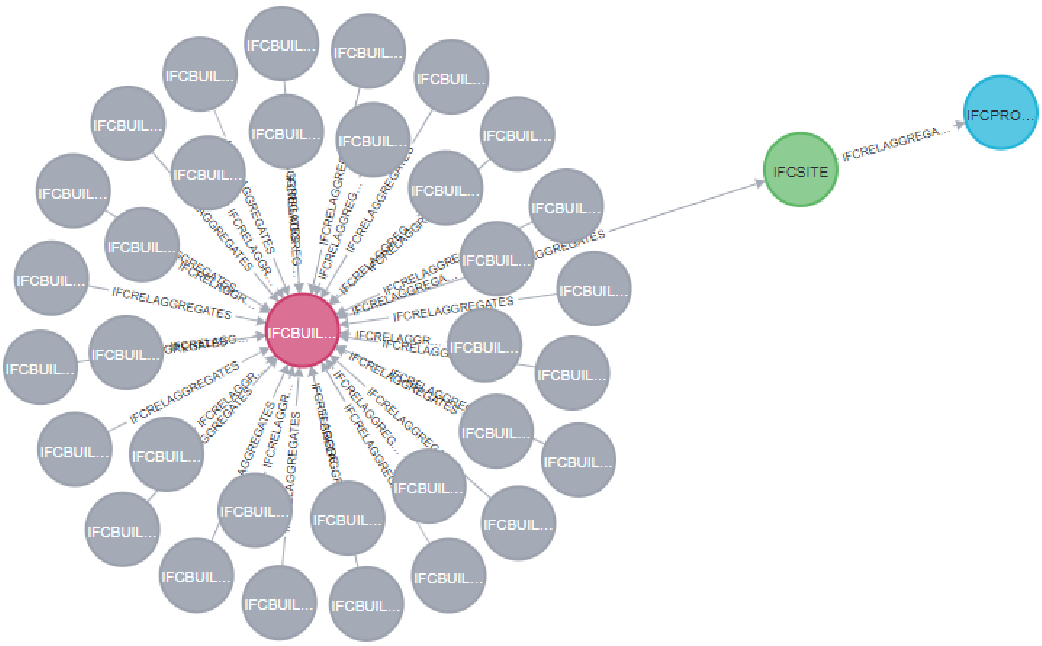


Figure 5: Nodes and connections created for the *IFCBUILDINGSTOREY* class CSV file

Due to visualisation limitations in large models, Figure 7 presents a partial view of the extended graph, including elements associated attributes.

[DOI: 10.22068/ijoce.2026.16.2.676]

```
MATCH (window:IFCWINDOW)
MATCH (rel:IFCRELDEFINESBYPROPERTIES)
MATCH (quantity:IFCELEMENTQUANTITY)
WHERE rel.relatedObjects = window.id AND rel.relatingPropertyDefinition = quantity.id
CREATE (quantity)-[r:IFCRELDEFINESBYPROPERTIES]->(window)
```

Figure 6: Sample cypher code to link the entity *IFCELEMENTQUANTITY* to *IFCWINDOW*

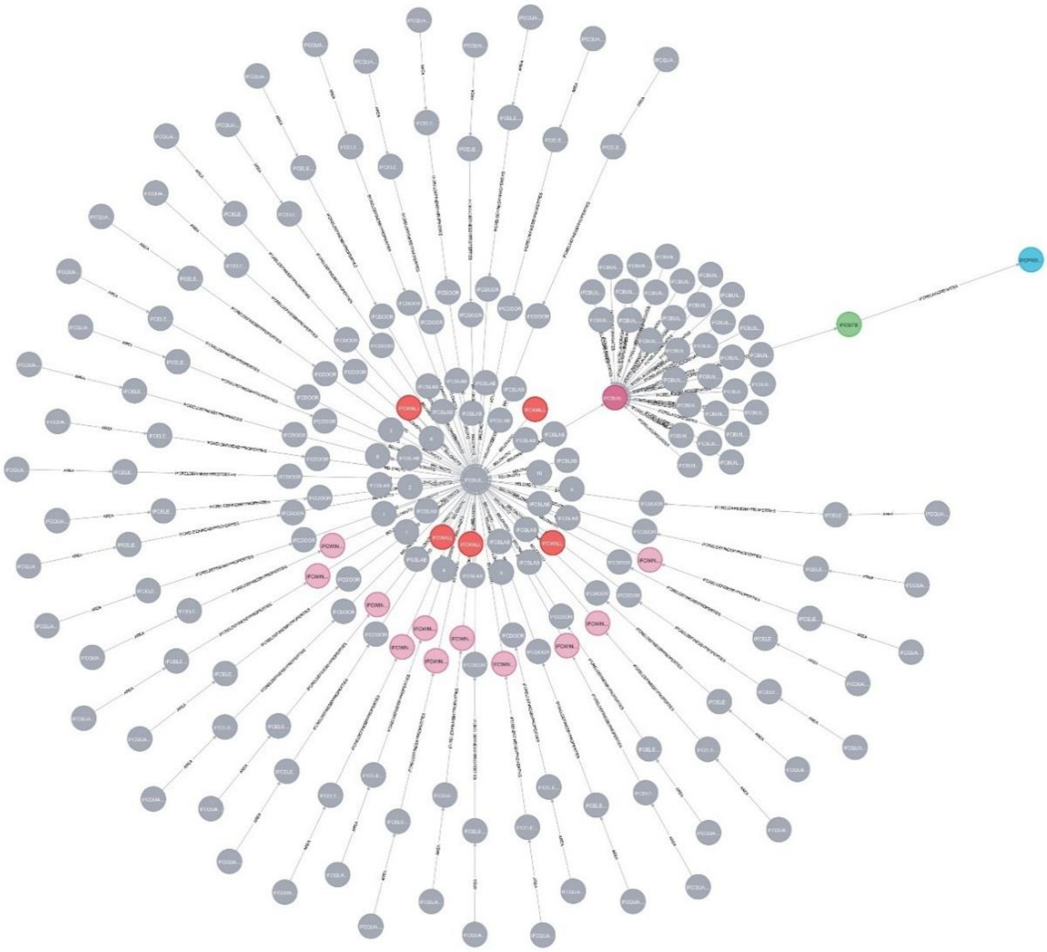


Figure 7: A partial view of the generated graph model

To demonstrate the analytical capability of the graph database to support the optimization phase, a Cypher query was developed to calculate the total area of window elements on a specific storey based on constructing a path-type subgraph. The query implementation is illustrated in Figure 8.

```
MATCH p=(win_area:IFCQUANTITYAREA)-[r:AREA]->(:IFCELEMENTQUANTITY)-
[s:IFCRELDEFINESBYPROPERTIES]->(:IFCWINDOW)-[t:BELONGTO]->(:IFCBUILDINGSTOREY{floor:'1'})-
[u:IFCRELAGGREGATES]->(:IFCBUILDING)-[v:IFCRELAGGREGATES]->(:IFCSITE)-
[w:IFCRELAGGREGATES]->(:IFCPROJECT)
RETURN sum(apoc.convert.toInteger(win_area.areaValue))
```

Figure 8: Query the total area of the first-floor windows of the project

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These results confirm that the constructed graph database provides a structured, queryable, and scalable representation of the BIM model, enabling efficient data retrieval for the subsequent multi-objective optimisation phase.

4.3. Results of Phase 3: Multi-Objective Optimisation

Four sustainability-oriented objective functions were defined for the optimisation problem:

- Minimisation of total component cost:

$$\text{Minimize} \qquad TC = \sum(Q_i \times C_i) \tag{1}$$

where C_i denotes the unit cost of component i, Q_i represents its quantity, and TC is the total cost index.

- Maximisation of energy efficiency:

$$\text{Maximize} \qquad ES = \frac{1}{H} = \frac{1}{\sum(A_i \times K_i)} \tag{2}$$

where K_i is the thermal conductivity of component i, A_i is its surface area, and ES represents the energy-saving index.

- Maximisation of material recyclability:

$$\text{Maximize} \qquad RC = \sum(W_i \times R_i) \tag{3}$$

where R_i is the recyclability ratio of component i, W_i is its weight, and RC denotes the recyclability index.

- Minimisation of non-local material usage (using Haversine distance):

$$\begin{gathered} \text{Minimize} \qquad LC = \sum(W_i \times D_{i.s}) \\ a_{i.s} = \sin^2\left(\frac{\Delta\varphi_{i.s}}{2}\right) + \cos\varphi_i \cos\varphi_s \sin^2\left(\frac{\Delta\lambda_{i.s}}{2}\right) \\ C_{i.s} = 2\arctan 2\left(\sqrt{a_{i.s}}, \sqrt{1 - a_{i.s}}\right) \\ D_{i.s} = R \times C_{i.s} \end{gathered} \tag{4}$$

where φ_i and λ_i denote the latitude and longitude of supplier i, φ_s and λ_s represent the project location, R is the Earth's radius (6,371 km), and LC is the locality index.

The Multi-Objective Particle Swarm Optimisation (MOPSO) algorithm was implemented using a population size of 50. The inertia weight (w) was set to 0.7, while the cognitive and social acceleration coefficients (c1 and c2) were both assigned a value of 1.5. An external repository with a capacity of 100 solutions was employed to preserve non-dominated solutions throughout the optimisation process. In addition, a mutation rate of 0.1 was adopted to enhance solution diversity and reduce the risk of premature convergence. The selected parameter values were based on commonly adopted settings reported in the literature and preliminary trial runs. Several preliminary trial runs were conducted to verify the stability of the selected

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values. The parameter settings for MOPSO are summarized in Table 1.

Table 1: Parameter configuration of the MOPSO algorithm

Parameters	Value
Population size	50
Iterations	1000
Inertia weight	0.7
C1	1.5
C2	1.5

The algorithm converged to a Pareto front consisting of 40 non-dominated solutions after 1000 iterations, visualised using a pairwise comparison chart (Figure 9). Required data for each candidate solution evaluation were retrieved from the Neo4j graph database via Cypher queries. These solutions represent the best possible trade-offs among the four conflicting objectives and provide a reduced yet representative set of alternatives for the subsequent efficiency evaluation phase.

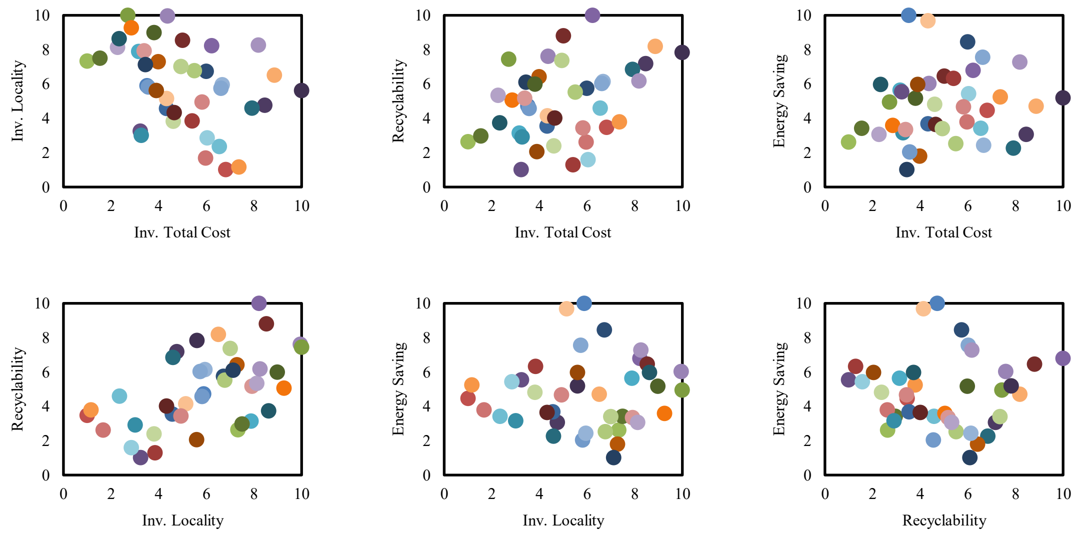

Figure 9: Pairwise Comparison of Normalized Objective Function Values Obtained by MOPSO

4.4. Results of Phase 4: Efficiency Evaluation

The 40 non-dominated solutions obtained from the Pareto front were evaluated using Data Envelopment Analysis (DEA). Each solution was treated as a Decision-Making Unit (DMU), with cost and locality index considered as inputs and energy efficiency and recyclability as outputs.

The Charnes-Cooper-Rhodes (CCR) model was applied to compute relative efficiency scores. Figure 10 presents the efficiency scores of all Pareto-optimal solutions. A subset of high-efficiency solutions with scores greater than 0.90 was retained for the final multi-criteria decision-making phase.

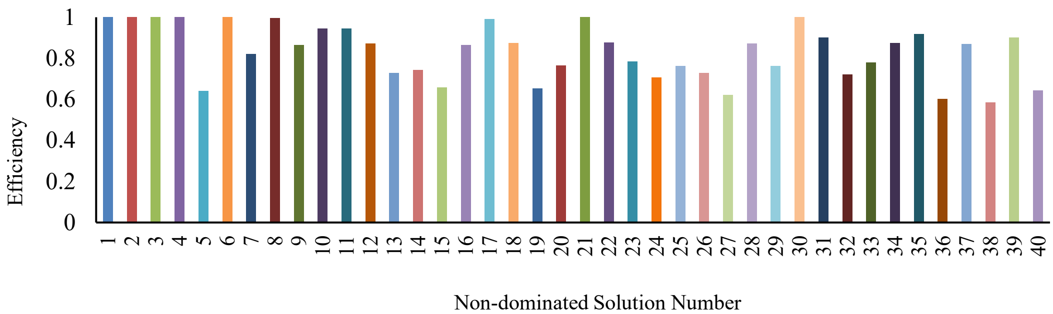

Figure 10: Efficiency scores of all Pareto-optimal solutions

The characteristics of these efficient solutions are summarised in Table 2. A comparative chart of the selected high-efficiency solutions is shown in Figure 11, highlighting the performance differences across the four objectives.

Table 2: The characteristics of these efficient solutions

Combination No.	Efficiency	Normalized Index				Windows	Doors	Flooring	Int. wall	Ext. wall	Curtain wall	Roof covering
		1/TC	1/LC	RC	ES							
1	1	2.84	1.7	4.72	10	5	2	3	2	3	1	2
2	1	1.47	10	3.46	4.45	3	5	3	2	1	4	5
3	1	10	1.36	2.63	2.62	2	5	3	3	2	3	3
4	1	1.6	1.22	10	6.79	1	2	3	4	5	4	2
6	1	1.36	8.59	3.79	5.25	3	4	3	2	1	4	5
8	0.995	2	1.17	8.8	6.45	1	2	3	4	4	4	2
10	0.945	1.18	2.1	7.17	3.06	3	4	3	1	2	4	4
11	0.946	1.26	2.18	6.84	2.26	3	5	3	1	2	4	4
17	0.990	1.53	4.25	4.58	3.41	3	5	3	2	2	4	4
21	1	3.69	1	7.43	4.94	2	2	3	4	4	3	2
30	1	2.31	1.94	4.14	9.67	5	3	3	2	3	1	2
31	0.901	2.91	1.4	6.09	1	2	5	3	4	2	3	4
35	0.918	4.27	1.16	3.72	5.96	2	2	3	2	4	3	3
39	0.902	2.02	1.43	7.36	3.39	2	4	3	4	3	3	4

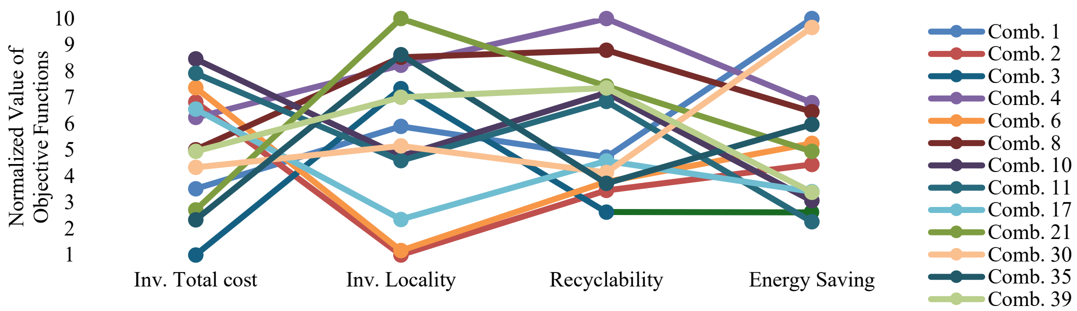

Figure 11: Parallel coordinates chart of the high-efficiency non-dominated solutions

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4.5. Results of Phase 5: Multi-Criteria Decision-Making

The high-efficiency solutions retained after the DEA filtering stage were evaluated using multi-criteria decision-making (MCDM) methods under stakeholder-driven preferences.

Pairwise comparison was conducted with an emphasis on cost minimization. The consistency ratio of the weighting matrix was 0.09, indicating acceptable consistency. The resulting weights were assigned as follows: cost (0.56), locality (0.26), recyclability (0.11), and energy saving (0.07).

Three MCDM methods with different decision logics were applied to identify the final solution.

- Using the Simple Additive Weighting (SAW) method, Alternative 3 achieved the highest ranking.
- The VIKOR method (with compromise parameter ν = 0.5) also identified Alternative 3 as the preferred solution.
- In contrast, the ELECTRE-I method (non-compensatory outranking approach) selected Alternative 21 as the best option.

A comparative analysis of the selected alternatives is presented in Figure 12. The divergence in results highlights the influence of decision logic (compensatory vs. non-compensatory) on the final selection and underscores the importance of stakeholder preference in the last phase of the framework.

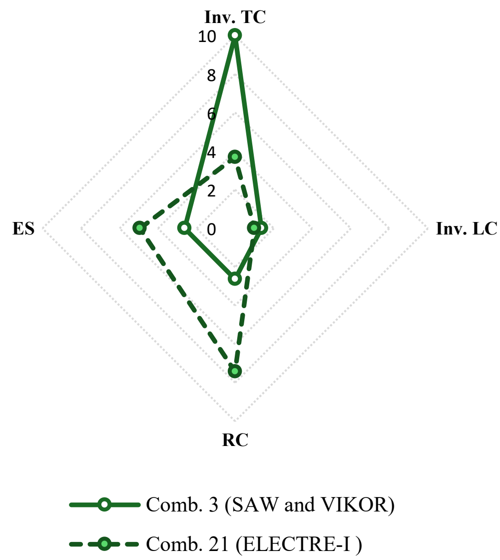

Figure 12: Comparative radar charts of the prominent solution obtained from different MCDM methods

4.6. Discussion

The results of the case study clearly highlight the effectiveness of structuring IFC-based BIM data within a graph database for supporting complex decision-making tasks in the construction domain. Unlike conventional workflows that rely on relational databases or ad-hoc API-based data extraction, the proposed approach leverages the inherent relational and

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hierarchical structure of IFC data by mapping it into a graph representation. This alignment between data structure and data model substantially improves the accessibility, consistency, and interpretability of the underlying information.

From a data management perspective, traditional approaches often require extensive API development and repeated parsing procedures to retrieve project-specific information from BIM models. These processes are typically time-consuming, error-prone, and difficult to generalise across different applications. In contrast, the graph-based representation enables direct and flexible querying of interconnected entities through a unified data layer. This facilitates implementation, improves reproducibility, and allows rapid retrieval of parameters required for optimisation and evaluation.

The use of IFC as a standardised and semantically rich data source further enhances the robustness of the framework. By preserving both object attributes and relationships during the transformation process, the proposed approach maintains the integrity of the original BIM model while enabling efficient analytical operations. This leads to more reliable input data for the optimisation and evaluation stages, ultimately improving the accuracy and credibility of the obtained results.

An additional advantage of the proposed framework is its independence from BIM authoring tools during the analytical stages. Once the IFC model is exported, the entire process—including data structuring, optimisation, efficiency evaluation, and decision-making—can be executed without further reliance on design software. This decoupling enhances workflow flexibility, reduces dependency on proprietary tools, and improves the portability of the framework across different projects and platforms.

In the optimisation phase, the availability of structured and queryable data from the graph database ensures consistent evaluation of candidate solutions. Compared to traditional approaches—where data extraction is often fragmented and dependent on manual intervention—the proposed framework provides a systematic and integrated workflow, reducing inconsistencies and improving the reliability of data management.

Furthermore, the integration of DEA and MCDM methods within this data-driven structure demonstrates the flexibility of the framework in supporting multiple decision paradigms. The variation observed in final selections across different MCDM methods (SAW, VIKOR, and ELECTRE-I) confirms that the framework can accommodate diverse stakeholder preferences rather than enforcing a single decision logic.

In contrast to most existing studies, which typically address BIM data processing, optimisation, and decision-making as separate and loosely connected stages, the proposed framework provides a fully integrated end-to-end pipeline that covers the entire decision-making process—from data extraction and structuring to optimisation, efficiency evaluation, and final selection. This integration reduces fragmentation across analytical stages and ensures consistency throughout the workflow, which has not been comprehensively achieved in prior research.

Importantly, the proposed framework is not limited to the specific case of building component selection. Its modular and data-centric architecture allows it to be extended to a wide range of decision-making problems in the construction domain, including design optimisation, resource allocation, safety assessment, and lifecycle analysis. The modular architecture suggests potential applicability to a broader range of construction decision-making problems.

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5. CONCLUSION

This study developed a comprehensive, integrated decision-support framework that transforms raw IFC-based BIM data into actionable decisions for the optimal selection of sustainable building components. The proposed five-phase pipeline—comprising data preparation, graph database construction using Neo4j, multi-objective optimisation, DEA-based efficiency evaluation, and MCDM—establishes a seamless end-to-end workflow that overcomes the fragmentation commonly observed in existing BIM-enabled approaches.

The framework was successfully implemented and validated through a realistic 33-storey residential building case study. The graph-based representation of IFC data enabled efficient parameter retrieval during optimisation, while the subsequent application of MOPSO generated a Pareto front of 40 non-dominated solutions. DEA filtering further reduced the solution space to high-efficiency alternatives, and the final MCDM stage produced a clear, stakeholder-aligned recommendation. The results demonstrated the framework's ability to systematically balance conflicting sustainability objectives while maintaining computational efficiency and decision transparency.

The main contributions of this work are twofold. First, it operationalises the transformation of complex, hierarchical IFC data into a scalable and queryable graph database that directly supports advanced analytical modules. Second, it demonstrates the value of combining multi-objective optimisation, DEA-based efficiency filtering, and MCDM within a single hierarchical pipeline, thereby enhancing both the robustness and practicality of data-driven decision-making in the AEC domain. Future research should focus on quantitative benchmarking against alternative data management approaches to provide a deeper understanding of the benefits and limitations of graph-based BIM representations. Real-time integration with live construction data and the development of a user-friendly interface are also promising directions for facilitating wider industry adoption.

Overall, the proposed framework represents a significant step towards more intelligent, data-centric, and sustainability-oriented decision-making in the construction industry and provides a solid foundation for the next generation of BIM-based optimisation and decision-support systems.

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