

ECOLOGICAL BENEFIT EVALUATION AND DESIGN OPTIMIZATION OF URBAN ARCHITECTURAL COMPLEXES BASED ON FUZZY LOGIC

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Highlights:

- this study introduces the Fuzzy Logic-Based Ecological Design Optimization Framework (FLEDOF);
- the FLEDOF provides a comprehensive tool for urban planners and architects to make informed, sustainable decisions.

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Abstract. Assessing ecological advantages and refining urban architectural designs are essential for sustainable urban growth. A lot of study has been done on energy efficiency, resource conservation, and green materials, but there is still no complete framework for systematic ecological assessment and improvement. This paper presents the Fuzzy Logic-Based Ecological Design Optimization Framework (FLEDOF), which amalgamates environmental, economic, and social sustainability while tackling the uncertainties intrinsic to urban design. FLEDOF gathers information about energy use, carbon emissions, air quality, and the effects on ecosystems. It then uses fuzzy multi-criteria decision-making methods to rank and improve design options. The simulation findings show that energy efficiency has improved by 8–10% compared to traditional approaches, carbon emissions have gone down, and resources have been used more efficiently. The accuracy of data processing has even gone up to 98.5% under different building situations. The framework gives architects, urban planners, and policymakers useful information, such as ecological scores, performance measures, and implementation plans, so they may make smart choices. FLEDOF uses advanced fuzzy logic, iterative optimization, and multi-database integration to create a methodical, data-driven way to construct cities that will last. Its practical consequences support eco-friendly urban infrastructures and align with global sustainability goals, providing a strong basis for assessing and improving the ecological performance of urban architectural complexes.

Keywords: energy efficiency, sustainable urban growth, urban architectural complexes, carbon emission, multi-criteria decision-making, eco-friendly infrastructures, ecological benefits.

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1. Introduction

Rapid worldwide urbanization offers great opportunity for sustainable architecture design. Cities use 75% of natural resources and emit 70% of carbon (Das et al., 2024). By 2050, 68% of the world's population will live in cities (Ang et al., 2023), creating tremendous opportunities for sustainable architecture. This setting encourages innovative architectural design that promotes ecological preservation and urban growth. Complex urban architectural complexes effect energy, ecology, and society. Modern metropolises use 40% of global energy and 30% of greenhouse gasses (Mastrucci et al., 2023). This impact has raised awareness of sustainable architecture, especially in densely populated urban areas with strong environmental demands. Due to technology improvement and environmental awareness, LEED and BREEAM have become established assessment standards for sustainable architecture (Jones & Adewumi,

2024). These buildings have sustainable construction and operating standards that provide environmental measures for building performance. Urban ecological systems are too complicated and interdependent for multi-criteria analysis (Hafez et al., 2023). Traditional assessment methods frequently overlook the intricate interaction between environmental, economic, and social factors that support urban development (Parekh et al., 2024). This shortage is growing as cities face ecological concerns and pressure to adopt sustainable development plans. Urban sustainability offers several improvements. Energy optimization and carbon reduction are key areas where machine learning-based technologies are transforming building energy management (Uzair & Kazmi, 2023).

Renewable energy integration algorithms are becoming more sophisticated, enabling buildings to balance multiple energy sources in real time. Passive design optimization techniques are evolving, including advanced

computational modeling that can calculate factors like natural ventilation flow and daylight penetration (Joshua et al., 2024). Thermal envelope performance modeling has also advanced to account for dynamic environmental conditions, enabling more efficient building insulation and temperature control systems.

Better resource management is needed in a circular economy and resource management. Architectural and engineering firms can use recycled materials while retaining structural integrity because of the optimisation of computational material efficiency (Wang et al., 2023a). Life cycle assessment algorithms now analyze building components from the cradle to the grave, helping designers choose materials. Circular economy modeling technologies prepare designers early for building disassembly and material reuse. Climate resilience and adaptation offer 30% energy efficiency gains through climate-responsive design (Di Santo et al., 2023). Parametric climate adaptation modeling now includes future climatic scenarios, allowing buildings to be planned for present and anticipated conditions. Storms and climate change can now be accounted for in structural resilience simulation, keeping buildings safe and functional. Advances in computational fluid dynamics optimize passive systems for natural ventilation and thermal regulation (Ali-Fakulti & Alsayaydeh, 2024). Green infrastructure integration algorithms optimise vegetation and water management system location and selection to improve building performance and the environment. Energy optimization can increase climate resilience, while resource management can cut carbon emissions. The multiplier impact of this synergy is that improvements in one sector can help the entire urban sustainability system (Shaamala et al., 2024).

Urban energy systems, waste management, and greenhouse gas emissions depend on urban architectural complexes' energy consumption, resource efficiency, and ecological footprint (Dong et al., 2023). Climate change, resource shortages, and environmental deterioration have boosted demand for eco-friendly building designs. Existing methodologies rarely address the complexity of evaluating and optimizing urban architectural complexes' ecological advantages. Interdependencies between sustainability requirements and urban planning uncertainty cause these difficulties.

In order to highlight the originality of our work, we have provided a detailed explanation of how Fuzzy Logic Systems (FLS) and Fuzzy Multi-Criteria Decision-Making (Fuzzy-MCDM) techniques, such as Fuzzy-AHP and Fuzzy-TOPSIS, are uniquely combined in FLEDOF. This integration makes it possible to conduct an exhaustive and nuanced analysis of the various sustainable design possibilities that are available in urban architectural planning. This is a method that is not only novel but also immediately relevant.

Despite increased efforts to integrate sustainability into urban architectural design, present methods typically fail to handle the complex interaction between environmental, economic, and social issues under uncertainty. Traditional

optimization and decision-making frameworks use deterministic models, which may oversimplify real-world circumstances and ignore urban planning uncertainty. Recent research have focused on individual sustainability indicators, lacking a comprehensive framework that can prioritize many contradictory criteria. In frameworks that aid urban planners and architects' practical decision-making, complex fuzzy logic-based techniques are rarely used in ecological design optimization. This highlights a literature gap and the need for an integrated, uncertainty-resilient, multi-dimensional instrument to assist sustainable urban planning.

The present study offers the Fuzzy Logic-Based Ecological Design Optimization Framework (FLEDOF), which combines FLS and Fuzzy-MCDM (Sahoo & Choudhury, 2023) to address these issues. The methodology evaluates and prioritizes design possibilities methodically and comprehensively, balancing environmental protection, economic feasibility, and societal well-being (Lazarević et al., 2024). The FLEDOF gives urban planners and architects a practical and scientific instrument to make educated decisions that support global sustainability goals and create resilient, eco-friendly cities. The main objectives are:

- Use Fuzzy Logic System (FLS) to assess the ecological performance of urban architectural complexes, focusing on sustainability factors including energy consumption, carbon emissions, and ecosystem effect.
- Utilize Fuzzy-MCDM methodologies, such as Fuzzy-AHP and Fuzzy-TOPSIS, to prioritize sustainable design solutions and advise urban planners and architects.
- Develop the Fuzzy Logic-Based Ecological Design Optimization Framework (FLEDOF) to handle uncertainty in urban architectural planning by integrating environmental, economic, and social sustainability elements.

The FLEDOF system model, architecture, and performance evaluation are examined in this research to assess its efficacy. To better comprehend ecological benefit evaluation and design optimization in urban architectural complexes, it explores the study's difficulties, methodologies, and conclusions and its implications and future approaches.

Novelty and distinctive contributions of FLEDOF

FLEDOF is novel compared to existing fuzzy-based decision support systems (e.g., Fuzzy-AHP, Fuzzy-DSS) because it:

Integrates Fuzzy Logic Systems (FLS) with Fuzzy-MCDM techniques (Fuzzy-AHP and Fuzzy-TOPSIS) to comprehensively analyze and prioritize sustainable design alternatives. Balances environmental, economic, and social sustainability factors while handling uncertainties inherent in urban architectural planning. Enables adaptive and practical decision-making, providing urban planners and

architects with a reliable, scientifically grounded tool to optimize ecological performance.

Research gap

- Most current research concentrates on singular sustainability facets (e.g., energy efficiency, carbon mitigation, social/cultural repercussions) and seldom amalgamates environmental, economic, and social elements concurrently.
- Most current methods use deterministic or simplified models, which makes it hard for them to deal with uncertainties in urban planning and ecological performance.
- A lot of frameworks are theoretical or static, which means they don't have practical and flexible decision-support tools to help choose and improve sustainable design options.
- When looking at the effects on the environment and society, people frequently only look at one part of the system and don't think about how natural, social, and economic systems work together.
- Most fuzzy-based models are limited to specific regions, which makes them less useful in other urban settings.
- Advanced methodologies integrating fuzzy logic with machine learning or adaptive weighting are still inadequately investigated.

2. Related works

2.1 Fuzzy logic and decision support systems for energy sustainability and eco-friendly urban planning

Bressane et al. (2024) used a Decision Support Systems (DSS) framework that integrates NbS with fuzzy-based AI to maximize building energy sustainability. This method may improve project success, infrastructure, and the environment. Future research should examine adoption barriers and fuzzy-AI types. Integrating water management, waste reduction, and more advanced fuzzy logic models into the DSS framework, which improves Building Information Modeling (BIM), can improve it.

Mrówczyńska et al. (2021) provided energy planning for high-building-intensity communities that must cut energy use and use renewable energy for sustainable urban growth. Six metropolitan districts were assessed for energy scenario feasibility using the Energy Potential Index (EPI). According to the study, development intensity is the most crucial aspect of city energy policy scenarios. With an EPI of 57.14%, Quarter 10 will most likely benefit from the scenario I energy strategy. Quarter 17 is best for renewable energy situations.

Ding et al. (2021) indicated that the number of environmentally friendly buildings in China has grown substantially from 2006 to 2018, with more than 13,000 structures having achieved certification by that year. High-quality, eco-friendly, and sustainable structures improve social impacts and quality of life. 1,018 structures received two-star

design certification in 2019, including 149 for operation. AHP-based fuzzy evaluation can lead to large-scale development in Zhejiang Province by implementing city-level green building formulation indicators. Other provinces and cities other than Zhejiang have no practical cases for special planning formulation. The Delphi approach is needed to apply the study team's recommendation to divide the criterion layer into objective technical, social, and policy effect indicators.

2.2. Social, cultural, and environmental dimensions in sustainable urban design: a fuzzy logic approach

Naghibi Iravaniet et al. (2024) addressed people's emotions and psyche to develop sustainable design and avoid spiritual, cultural, and social losses. The research uses phenomenology to evaluate building designs from end users' perspectives, ensuring excellence. Data is collected quantitatively utilizing surveys and Riashi's equations in Expert Choice software. MATLAB 2018 uses fuzzy logic. Fuzzy weight differences between buildings cannot be ranked. Researchers offer Arak City building designs based on indicators and evaluations after evaluating data. In Arak, house design and fuzzy logic are studied.

Zhao et al. (2023) presented the construction sector is embracing green buildings because they help meet carbon peak and carbon neutral goals. China frequently only benefits economically or environmentally from their overall benefits. This study seeks to create a social and cultural appraisal of green buildings' benefits. Environmental, social, economic, and cultural advantages are the major markers of benefit improvement. Green buildings produce less pollution and conserve energy, water, and materials. Reduce building loss and increase their lives, benefiting the environment. Green buildings should inspire businesses to adopt environmental and social responsibility. Prioritize technological research, management, and people-centeredness to develop green buildings.

Česić et al. (2024) provided that Urban Heat Islands (UHIs) increase as manmade surfaces replace natural land. This work reviews literature and bibliometric data to discover fuzzy theory-based decision support systems and multi-criteria decision-making trends for UHI management. Scopus was used to collect data. The study uses Multi-Critical Analysis (MCA) and decision support systems in UHI management, focusing on fuzzy theory. The study's shortcomings include depicting static literature and employing Scopus records. Future research could focus on developing fuzzy DSS models based on artificial intelligence and machine learning.

2.3 Ecological and social impact evaluation in urban green spaces and low-carbon development

Wang et al. (2024) investigated the shoreline plantscapes of 32 traditional hamlets in Western Hunan, China, with the goals of fostering ecological culture, raising environmen-

tal standards, and promoting sustainable management of ecological resources. The Scenic Beauty Estimation method examines fifteen landscape elements vital to beautifying these local waterfronts. Aesthetic assessments and beauty quality ratings were shown to be significantly correlated in the study, which emphasizes the significance of seasonal fluctuation, scale affinity, and hierarchical structure. The evaluation model gives a theoretical foundation for building and evaluating these landscapes.

Ji et al. (2023) stated that Urban Green Spaces (UGSs) sequester carbon and balance nature, community, and economy. The entropy approach and coupling harmony degree model are used to assess UGSs' ecological advantages in Nanjing City, China. Between 2011 and 2020, UGS's ecological benefits gradually increased, with subsystem coupling harmonic degrees changing. UGS ecological benefits could be improved by coupling harmonic degrees. Social and economic UGS subsystems scored higher in Nanjing City than natural environment subsystems, indicating natural environment limits on UGS creation. According to studies, the sustainability of UGS development requires combined optimization of the natural environment and social economy.

Alghassab (2024) demonstrated that Saudi Arabia uses a fuzzy-based smart energy management system to

minimize oil use and boost energy efficiency. The system adjusts energy-consuming devices based on user preferences, occupancy patterns, and real-time energy pricing. The method has reduced peak demand and improved energy efficiency in Saudi residential developments. But, data privacy, security, infrastructure integration, user acceptance, scalability, and cost-effectiveness must be addressed. Saudi Arabia can achieve its sustainability goals and create a greener, more resilient energy industry by encouraging stakeholder collaboration on these innovative technologies.

Hsueh et al. (2022) established a low-carbon, eco-friendly country development model. The Delphi approach, AHP, and fuzzy logic theory underpin the model. Green building materials, photovoltaic power generation, energy-saving equipment, green roofs, planting/vegetation, rainwater collection/water recycling, subsidies, resident participation, and appropriate norms are considered in the model. Green facilities are most important, followed by community participation and ecological facilities. The model is tested with Guangzhou's Conghua District homes. The model shows that low-carbon, eco-friendly growth requires government backing, public awareness, and participation. Table 1 shows the comparative analysis of recent research on AI-based air quality prediction.

Table 1. Comparative analysis of recent research on AI-based air quality prediction

Authors	Objective	Methods	Findings	Advantages	Disadvantages	Research gap
Calo et al. (2024)	Predict spatial air quality in urban environments	Message Passing Graph Neural Networks	Accurate spatial predictions across cities	Captures spatial dependencies effectively	Focused only on spatial aspect, less temporal modeling	Lack of real-time adaptive forecasting
Wu et al. (2021)	Spatiotemporal air quality forecasting	Inductive GNN with Kriging	Improved AQI interpolation and forecasting accuracy	Inductive learning allows unseen node prediction	High training complexity	Needs scalability across cities with sparse data
Zeinal-nezhad et al. (2020)	Hybrid prediction model for pollution levels	Regression + ANFIS (Neuro-Fuzzy)	ANFIS improved accuracy over baseline regression	Handles nonlinearity and expert-based tuning	Sensitive to input feature quality	Limited real-time applicability and interpretability
Xayasouk et al. (2020)	AQI prediction using deep learning	LSTM + Deep Autoencoder	High performance on PM2.5 and PM10 forecasting	Captures temporal patterns and reduces dimensionality	Requires large training data, risk of overfitting	No integration of exogenous environmental signals
Bekkar et al. (2021)	Smart city air pollution modeling	CNN + LSTM hybrid model	Accurate PM2.5 prediction in urban centers	Deep hybrid improves temporal-spatial capture	High computational burden	Lacks explainability for stakeholders
Mao et al. (2021)	Multi-pollutant prediction model	Hybrid Deep Learning (CNN-LSTM-GRU)	Simultaneous prediction of multiple pollutants	Robust modeling of spatio-temporal dynamics	Complex structure hinders deployment	Needs real-world validation in heterogeneous regions
Li et al. (2016)	AQI forecasting using deep architecture	Stacked Autoencoders + DNN	Captures nonlinear feature interactions	Performs well under variable pollutant conditions	Difficult to interpret results	Does not explicitly handle uncertainty
Saez and Barceló (2022)	Spatiotemporal pollution prediction in Spain	Bayesian Hierarchical Model	High accuracy in temporal-spatial PM2.5 prediction	Probabilistic framework accounts for uncertainty	Computationally expensive	Not easily extensible to real-time prediction

End of Table 1

Authors	Objective	Methods	Findings	Advantages	Disadvantages	Research gap
Zhang et al. (2022)	Improve PM2.5 prediction in China	Temporal Difference Graph Transformer	Outperformed traditional GCNs and LSTMs	Combines spatial, temporal, and transformer advantages	Requires large training graph	Limited to PM2.5 only, lacks multi-pollutant extension
Lu and Li (2020)	Urban sensor forecasting	Attention-Adjusted Graph Spatio-Temporal Networks	Short-term value forecasting with high precision	Attention mechanism improves focus on key nodes	Complex graph construction	Not generalized across different pollutants
Ouyang et al. (2021)	Dynamic air quality prediction	Spatial-Temporal Graph CNN	Captures real-time fluctuation in AQI	Dynamic GCN improves modeling of transitions	Training instability under noisy data	Evaluation limited to short time windows
Wang et al. (2023b)	Monitor industrial AQI via graphs	STGNN on control systems	Effective at identifying pollutant variation patterns	Integrates control signals with environmental metrics	Limited external generalization	Not focused on public-level AQI forecasting
Han et al. (2023)	Semi-supervised AQI forecasting	Self-supervised Hierarchical GNN	Reduced label dependency, improved generalization	Less reliance on labeled data	Complex multi-level design	Needs better interpretability for decisions
Zhang et al. (2017)	Forecast AQI in Beijing	Deep Learning with Multiple Input Sources	DeepAir model performs well on PM2.5 and AQI	Fuses spatial-temporal and external factors	Lacks uncertainty quantification	Does not explicitly handle uncertainty

3. Proposed Fuzzy Logic-Based Ecological Design Optimization Framework (FLEDOF)

FLEDOF evaluates and optimises urban architectural complexes for ecological benefits. The framework has a multi-source input database system, intelligent data preparation module, fuzzy logic inference engine, and multi-criteria decision-making optimization procedure. Building Database (BDB) contains structural and architectural parameters, Environmental Database (EDB) ecological elements, and Performance Database (PDB) efficiency measurements. A preprocessing module normalizes and standardizes files for fuzzy logic processing from these databases. The basic fuzzy logic system uses a knowledge base to manage ecological assessment uncertainties, while the decision-making layer ranks design choices using Fuzzy-AHP and Fuzzy-TOPSIS. Iterative performance checks and solution refinement produce design solutions, performance metrics, and implementation plans during optimization. The systematic approach to urban architectural design balances environmental impact, economic feasibility, and social sustainability.

Building data, environmental characteristics, and performance indicators are integrated into a fuzzy logic-based inference and decision-making framework in the described architecture to assist sustainable building design. The system starts with three databases: the Building Database (BDB), which stores static data like structure type, dimensions, and location; the Environmental Database (EDB), which records dynamic data like temperature, humidity, and solar radiation; and the Performance Database (PDB), which logs critical operational data like energy usage,

emissions, and costs over time. These databases are vital for understanding the built environment and its external influences. The ambiguity of building performance evaluation is handled by fuzzy logic. Fuzzifiers convert precise input values into fuzzy linguistic variables that a rule-based inference engine and fuzzy knowledge base process. Defuzzifiers turn results into actionable outputs. This fuzzy logic component lets the system model human reasoning and handle imprecise inputs.

Fuzzy-AHP and Fuzzy-TOPSIS multi-criteria decision-making procedures improve the framework in the decision-making module. These tools structure design alternative evaluation and ranking based on various, often contradictory criteria. Optimal performance is achieved by testing and improving solutions in the design refinement loop. Finally, the system produces cost analysis, energy efficiency reports, and detailed design designs. The architecture provides a solid basis for smart construction decision support in adaptive, data-driven building designs that meet energy efficiency and sustainability goals.

As seen in Figure 1, the FLEDOF is a methodical approach to sustainable urban development that utilizes a data-driven methodology to concentrate on the ecological benefits of urban growth. The Building Database (BDB), the Environmental Database (EDB), and the Performance Database (PDB) are the three primary components that make up this overall system. Information pertaining to the environment and performance is stored in the EDB, whereas architecture is stored in the BDB. In addition to standardizing measurement scales, the preprocessing program is responsible for correcting missing data. The evaluation process makes use of fuzzy logic, which depicts the

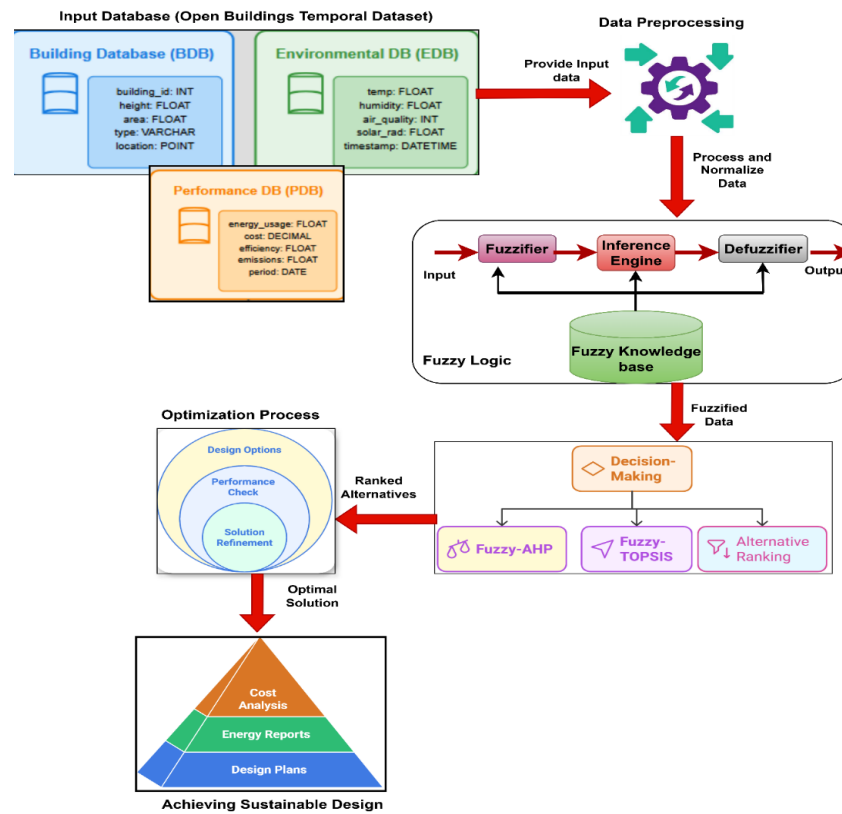


Figure 1. Proposed fuzzy logic-based ecological design optimization framework

interactions between ecological parameter interactions and criteria established by experts. A rule basis is applied by the inference engine after the input values have been processed into fuzzy sets. Using defuzzification, ambiguous outputs are transformed into actionable data, which allows for ecologically sound analysis of design possibilities.

The decision-making layer hierarchically weights ecological criteria using Fuzzy-AHP and Fuzzy-TOPSIS. Iterative optimisation improves design ideas to meet or exceed sustainability goals while remaining practical. The FLEDOF method for sustainable urban development produces Design Solutions with optimal architectural configurations and material selections, Performance Metrics with environmental impact, energy efficiency, and sustainability scores, and Implementation Plans with practical instructions for implementing selected designs. Hierarchical (01–03) outputs enable systematic implementation. FLEDOF uses uncertainty handling, multi-criteria decision-making, and systematic optimization to overcome architectural design restrictions.

3.1. Input databases

3.1.1 Building Database (BDB)

The Building Database (BDB) helps the FLEDOF assess ecological benefits and optimize urban architecture. BDB calculates energy, emissions, and environmental impacts using volume and age. Data includes building_id, height, area, kind, location, and construction_year. Height and area are crucial for structural volume and energy perfor-

mance, whereas Building_id is unique for each building. Type characterizes the building, while location coordinates environmental impact and resource availability. Age and sustainability improvements depend on the building's construction year. The structure Volume (V) is essential for evaluating energy needs, solar exposure, and material usage, as it indicates the whole structural space of a structure Eq. (1):

$$V = \text{height} \times \text{area}. \quad (1)$$

The Building Age (A), calculated using FLEDOF criteria, influences retrofitting feasibility, energy efficiency, and environmental compliance by dividing the current year by the construction year, as shown in Eq. (2):

$$A = \text{current year} - \text{construction year}. \quad (2)$$

Algorithm 1: Calculate Building Features

```

function calc_building_features (b_list) do
  Input: b_list (list of building records)
  Output: list of (id, vol, age)
  year = get_current_year ()
  res = []
  for b in b_list do
    vol = b.h * b.a
    age = year - b.c_year
    res.append ((b.id, vol, age))
return res

```

Algorithm 1 calculates each building's volume and age to assess energy use and environmental impact. The Environmental Database computes solar potential and ecosystem scores using simple weighted factors like sunlight, temperature, and air quality. The Fuzzy Logic System translates energy, carbon, and air quality measurements into an ecological performance score using easy-to-understand rules. Fuzzy-AHP prioritizes sustainability criteria, while Fuzzy-TOPSIS ranks design alternatives to identify the most environmentally friendly options. The optimization loop then iteratively improves these designs to provide clear, actionable recommendations for architects and planners.

3.1.2. Environmental Database (EDB) calculation algorithm

The method uses building areas to determine solar energy potential and ecosystem index for all environmental database information. The weighted environmental considerations make it suited for ecological performance assessment. The solar potential (*solar_pot*) is calculated by dividing the sunlight rate (*sr*) by the building's area (*area*), where *sr* is the sunlight rate and *area* is the building's area, as shown in Eq. (3):

$$solar_pot_i = sr_i \times area_i \quad (3)$$

In Eq. (3), sr_i is the sunlight rate for location i and $area_i$ is the area of the building at location i . Equal weights are given to environmental parameters like temperature, humidity, quality, and sunlight in the Ecosystem Index (*eco_idx*). To compute the index for a location, use the Eq. (4) as follows:

$$eco_idx_i = (w_t \times t_i) + (w_h \times h_i) + (w_q \times q_i) + (w_s \times s_i) \quad (4)$$

In Eq. (4), t_i, h_i, q_i, s_i are the temperature, humidity, quality, and sunlight values for location i , $w_t = w_h = w_q = w_s = 0.25$ are the weights for the environmental factors.

Algorithm 2: Calculate_Enviornmental_Indices

function calc_env_metrics (e_list, b_areas) **do**

Input: e_list (list of env records), b_areas (dict {loc: area})

Output: list of (loc, solar_pot, eco_idx)

res = []

w = { "t": 0.25, "h": 0.25, "q": 0.25, "s": 0.25 }

for e in e_list **do**

if e.loc in b_areas **then**

area = b_areas [e.loc]

solar_pot_i = sr_i × area_i Eq. (3)

eco_idx_i = (w_t × t_i) + (w_h × h_i) + (w_q × q_i) + (w_s × s_i) Eq. (4)

res.append((e.loc, solar_pot, eco_idx))

return res

In Algorithm 2, the Environmental Database (EDB) Calculation Algorithm produces solar energy potential and ecosystem index for building-area-based environmental information. Ecological performance is assessed using weighted environmental parameters. The method starts with an empty list "res" and a weight dictionary "w" with equal weights for temperature, humidity, quality, and sunlight. The program checks each entry in "e_list" for a place in the "b_areas" dictionary. If found, the area is fetched from "b_areas". Sunlight rate and building area determine solar potential. Environmental parameters are weighted to calculate the ecosystem index.

The primary data source for this study is the online platform (<https://www.aqistudy.cn>), which provides comprehensive AQI data for various urban locations. Physical sensors were deployed solely for validating the accuracy of this online data. Consequently, detailed hardware specifications and communication protocols have been omitted for brevity, focusing instead on the core contribution – the Random Forest model for AQI prediction using validated data. This restructuring clarifies the relative importance of the model and avoids confusion about secondary hardware details.

3.1.3. Performance Database (PDB)

The Performance Database (PDB) tracks and analyzes building performance. The inputs are Building_id, timestamp, energy_usage, emissions, efficiency, and cost. A formula compares the building's energy usage to a baseline to calculate outputs. Energy efficiency score and carbon emissions per unit area measure the building's efficiency and carbon footprint. A higher score indicates higher emissions per building area, promoting sustainability. PDBs can be processed with pseudocode like this.

$$E_{eff} = \frac{energy_usage}{baseline_energy} \quad (5)$$

In Eq. (5), Energy efficiency is calculated by comparing building energy usage to a baseline. A benchmark or historical value could be the baseline energy. A value of $E_{eff} > 1$ indicates inefficiency, as the building uses more energy than the baseline. If $E_{eff} < 1$, the building performs more efficiently.

$$C_{area} = \frac{emissions}{area} \quad (6)$$

In Eq. (6), Carbon Emissions Per Unit Area (C_{area}) is a metric evaluating a building's carbon footprint per square meter, with higher values indicating higher emissions, aiming for sustainability.

3.2. Data preprocessing

Data preprocessing in FLEDOF is essential for ensuring data quality, consistency, and dependability before implementing Fuzzy-Multi Criteria Decision-Making (Fuzzy-MCDM) (FLS) and Fuzzy-MCDM methods like Fuzzy-AHP

and Fuzzy-TOPSIS. Ecological benefit evaluation data preparation is explained below:

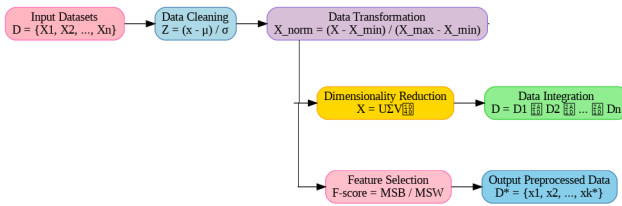


Figure 2. Data preprocessing

In Figure 2, TheFLEDOF collects building, environmental, and performance data using the Google Open Buildings Temporal Dataset (Google Research, n.d.). Building metadata missing values, environmental data non-uniform timestamps, and performance metrics outliers are addressed. Data cleaning includes missing data, outlier detection, and noise removal. Data transformation prepares data for fuzzy logic and MCDM. Normalization, feature engineering, categorical data encoding, and time stamp alignment are used. Standard keys like building_id and timestamp integrate data from several databases. Using PCA, data is simplified without losing vital information. Feature selection selects fuzzy logic systems and decision-making-relevant features. Before FLEDOF, data is validated for accuracy and reliability. Cross-validation, statistical testing, and normalcy tests are steps.

Data cleansing removes inconsistencies and missing or incorrect data. Imputation, domain-specific estimations, and missing data removal are used. Z-score or IQR algorithms detect and remove outliers, while low-pass filtering removes environmental time series data noise.

$$z = \frac{x - \mu}{\sigma} \quad (7)$$

In Eq. (7), The Z-score method detects and removes outliers by comparing the mean value of a data point to its standard deviation. The normalization process, which is the next stage, is ensuring that all variables are on a comparable scale by applying Eq. (8).

$$X_{norm} = \frac{(X - X_{min})}{(X_{max} - X_{min})} \quad (8)$$

In Eq. (8), X is the original value, and X_{max} , X_{min} are the minimum and maximum values of the attribute. Data transformation comprises normalization to scale attributes, feature engineering to calculate energy and carbon intensity, and categorical data encoding. Timeline alignment and integration integrate datasets using building_id and timestamps. Principal component analysis reduces data dimensions, whereas feature selection finds important features through correlation analysis and information gain. Cross-validation and statistical testing ensure ecological benefit evaluation and decision-making accuracy. Principal Component Analysis (PCA) is applied to reduce the dimensionality of the dataset while retaining the most relevant

information. In this study, principal components that collectively retain 95% of the total variance were selected, and only components with significant eigenvalues were retained. The selected components were further analyzed to ensure ecological interpretability, preserving key sustainability variables such as energy usage, carbon emissions, building area, and environmental factors, so that dimensionality reduction does not compromise the assessment of ecological performance.

Energy Intensity:

$$Energy\ Intensity\ (EI) = \frac{Energy\ Usage}{Area} \quad (9)$$

Carbon Intensity:

$$Carbon\ Intensity\ (CI) = \frac{Emissions}{Area} \quad (10)$$

In Eqs. (9)–(10), *Carbon Intensity* (Emissions per m²) and *Energy Intensity* (Energy Usage per m²) are qualities that are derived for efficient analysis.

Table 2. Sample preprocessed dataset

Build- ing ID	Height (m)	Area (m ²)	Energy usage (kWh)	Emissions (kg CO ₂)	Effi- ciency (%)	Air quality index
1	25	2000	1500	200	75	50
2	30	3500	1800	300	70	45
3	40	5000	2500	400	65	55
4	20	1500	1300	150	80	48
5	35	4000	2100	320	68	50
6	28	2800	1700	250	72	52
7	50	6000	3000	500	60	60
8	18	1200	1000	100	85	43
9	32	3600	1900	280	70	47
10	45	5200	2600	420	64	53
11	22	1800	1400	160	78	46
12	48	5800	2900	480	62	59
13	25	2500	2000	230	74	49

The preprocessed data Table 2 for structured analysis comprises building ID, height, area, energy usage, emissions, efficiency, and air quality index. These criteria assess energy efficiency, carbon emissions, and environmental effects for sustainable architectural design optimization and ecological benefit assessments.

3.3. Fuzzy Logic System (FLS) for ecological benefit evaluation

Sustainable urban development requires assessing ecological benefits and maximizing urban architectural complex design. While research has advanced in energy efficiency, resource conservation, and green materials, a complete and systematic technique to measure and improve ecological performance in urban architectural planning is needed. This study offers the Fuzzy Logic-Based Ecologi-

cal Design Optimization Framework (FLEDOF), a modular, holistic method that blends environmental, economic, and social sustainability to fill this gap. Advanced fuzzy multi-criteria decision-making approaches are used in FLEDOF to manage complicated urban planning uncertainty. Energy consumption, carbon emissions, and ecological effect data are collected and analysed to prioritize sustainable design choices. Compared to standard methods, FLEDOF increase energy efficiency and decrease emissions, according to simulations. It helps architects and urban planners make sustainable decisions. FLEDOF's capabilities also support eco-friendly urban infrastructure policy goals, contributing to global sustainability goals. This research provides a solid platform for ecological evaluation and sustainable improvement of urban architectural projects by merging fuzzy logic with architectural performance measures.

The FLS analyzes normalized dataset data using fuzzy rules to give actionable insights regarding the ecological performance of urban architectural complexes. It consists of a defuzzifier, an Inference Engine, and a fuzzyfier. The Fuzzy Logic System (FLS) evaluates the ecological performance of urban architectural complexes. With the help of fuzzy rules, we may extract useful information from normalized datasets. The fuzzy inference system to include specifics about the fuzzy rule base, such as the amount of rules and their selection based on expert input and observable patterns. We also explained how to build membership functions for each input variable, which are mostly triangular and trapezoidal.

The Fuzzy Logic Block implements a rule-based reasoning mechanism that maps crisp numerical inputs into fuzzy sets, evaluates them according to expert-defined or learned fuzzy rules, and produces defuzzified outputs representing actionable decisions or control signals. The process involves four main stages: fuzzification (converting inputs into fuzzy values using membership functions), rule evaluation (applying fuzzy inference rules), aggregation (combining rule outputs), and defuzzification (transforming fuzzy outputs into crisp values). This framework allows the system to handle uncertainty and approximate reasoning, making it suitable for complex, nonlinear, or imprecise environments.

Algorithm 3: Fuzzy Logic Block

```

Inputs:
    crisp_inputs: A set of numerical input variables
for fuzzy inference
Outputs:
    fuzzy_outputs: Defuzzified output(s) representing
system decision or control action
fuzzified_inputs = ApplyMembershipFunctions(crisp_
inputs)
rule_results = EvaluateFuzzyRules (fuzzified_inputs)
aggregated_result = AggregateRuleOutputs (rule_
results)
fuzzy_outputs = Defuzzify (aggregated_result)
Return fuzzy_outputs

```

In Algorithm 3 Fuzzy Logic Block converts crisp numerical inputs into fuzzy sets using membership functions. It evaluates these inputs with fuzzy rules, aggregates the results, and defuzzifies them into crisp outputs. The outputs provide actionable decisions or control signals, enabling reasoning under uncertainty.

Using triangular or trapezoidal membership functions, the Fuzzifier turns crisp input variables into fuzzy sets. Pre-defined fuzzy rules capture input-output interactions, including E_u : Energy usage (kWh/m²), C_e : Carbon emissions (kg/m²), A_i : Air quality index (normalized value) and R_e : Resource efficiency (%) in the Inference Engine. Membership functions map input data to fuzzy sets:

$$\mu(x) = \begin{cases} 0, & x \leq a \\ \frac{x-a}{b-a}, & a < x \leq b \\ 1, & b < x \leq c \\ \frac{c-x}{c-b}, & b < x \leq c \\ 0, & x \geq c \end{cases} \quad (11)$$

In Eq. (11), $\mu(x)$ is the membership value for input x , and a , b , and c are the parameters defining the triangular membership function for each input. The inference engine assesses ecological performance according to previously established fuzzy rules. These regulations capture inputs (such as energy consumption, emissions, and air quality) and outputs (such as ecological score).

$$\mu_{rule} = \min(\mu(E_u), \mu(C_e), \mu(A_i)) \quad (12)$$

In Eq. (12), $\min$ is the AND operator for combining membership values. μ_{rule} : Aggregated membership value for the rule. The Defuzzifier uses the Centroid of Area (COA) to smooth up fuzzy outputs.

$$z^* = \frac{\int z \cdot \mu(z) dz}{\int \mu(z) dz} \quad (13)$$

Eq. (13) defines the ecological score output variable z , where $\mu(z)$ is the aggregated membership function and z^* is the defuzzified crisp ecological score. The Fuzzy Linear System (FLS) evaluates environmental performance based on Energy Intensity (EI), Carbon Intensity (CI), and Ecological Performance Score (EPS). Crisp ecological scores are categorized into high, medium, and low fuzzy sets.

The fuzzy rule base consists of 3 rules, developed using a combination of expert knowledge and systematic fuzzy-MCDM methodology to ensure comprehensive coverage of all relevant scenarios. Representative rules include:

- Rule 1: If EI is low AND CI is low, EPS is high;
- Rule 2: If EI is high AND CI is medium, EPS is medium;
- Rule 3: If CI is high OR AI is low, EPS is low.

Integration with Fuzzy-MCDM weights the sustainability factors and ranks design alternatives based on ecological performance. Table 3 summarizes the input parameters, descriptions, units, ranges, and weights used in the proposed FLS dataset. These updates follow the FLEDOF

paradigm to analyze and optimize urban architecture complexes while accounting for uncertainties in environmental performance.

Table 3. Dataset mapping to fuzzy logic system

Input parameter	Description	Unit	Range
Energy usage	Total energy consumed per building area	kWh/m ²	0–500
Carbon emissions	Total emissions per building area	kg/m ²	0–100
Air quality index	Air quality normalized value	Index	0–100
Resource efficiency	Efficiency of material/resource use	Percentage (%)	50–100

In Table 3, the dataset maps major sustainability indicators to the Fuzzy Logic System to assess the ecological performance of urban architecture complexes. Energy usage, carbon emissions, air quality index, and resource efficiency are input factors. Each parameter has a clear description, units, and range for accurate evaluation. This mapping helps the Fuzzy Logic System handle different sustainability metrics for accurate ecological benefit assessments for design optimization.

3.4. Fuzzy Multi-Criteria Decision-Making (Fuzzy-MCDM)

To evaluate and prioritize design alternatives, the FLEDOF uses Fuzzy Multi-Criteria Decision-Making (fuzzy-MCDM) techniques in its Decision-Making block. The methods used include fuzzy-AHP and fuzzy-TOPSIS, which stand for Fuzzy Analytical Hierarchy Process and Fuzzy Technique for Order Preference by Similarity to Ideal Solution, respectively. To make educated decisions on the best urban architectural designs, this block ensures that uncertainties in sustainability and ecological indicators are included, as shown in Figure 3.

Data that has been fuzzified, including Environmental Utility, Cost Efficiency, Air Quality Index, and Renewable Energy, are input into Figure 3. For the purpose of evaluating criteria and producing a fuzzy decision matrix to reflect the available choices, the fuzzy analytical hierarchy process

(Fuzzy-AHP) should be utilized. The Fuzzy Positive Ideal Solution (FPIS) and the Fuzzy Negative Ideal Solution (FNIS) are the measurements that serve as comparison standards. Use the optimum solution distances and the Closeness Coefficients (CC) to calculate the parameters. CC rankings are based on the idea that higher values imply superior choices.

The Decision-Making Layer integrates quantitative metrics and fuzzy logic outputs to generate actionable strategies or control signals. It applies decision rules, optimization criteria, and constraints to prioritize actions based on multiple objectives, such as energy efficiency, sustainability, or safety. By systematically combining all processed information, this layer enables robust, data-driven decision-making even in complex or uncertain environments.

Algorithm 4: Decision Making Layer

```

Inputs:
  processed_metrics: Quantitative metrics from
  building analysis or sensors
Outputs:
  decisions: System-level control actions or recommendations
  combined_inputs = CombineMetricsAndFuzzy
  (processed_metrics, fuzzy_outputs)
  decisions = ApplyDecisionRules (combined_inputs)
  optimized_decisions = EnforceConstraints (decisions)
Return optimized_decisions

```

Algorithm 4 provides Decision-Making Layer integrates building metrics and fuzzy logic outputs to generate system decisions. It applies rules, optimizations, and constraints to prioritize and refine actions. The output provides actionable recommendations for control, energy management, or sustainability optimization.

3.4.1. Fuzzy-AHP for criteria weighting

The Fuzzy-AHP Process ranks sustainability criteria by significance to overcome ambiguity and subjectivity in decision-making. The approach uses Triangular Fuzzy Numbers (TFNs) to describe subjective assessments in a range format, accommodating ambiguity in human judgment. A fuzzy pairwise comparison matrix, normalization, and weight calculation ensure judgment consistency. Fuzzy-AHP incorporates uncertainty, determines accurate weights, and improves decision-making by quantifying the criteria's relative relevance. Fuzzy-TOPSIS ranks and selects alternatives using Fuzzy-AHP weights to ensure the most sustainable and optimal design solutions meet the specified framework's objective.

$$\tilde{A} = \begin{bmatrix} 1 & \tilde{a}_{12} & \tilde{a}_{13} \\ \frac{1}{\tilde{a}_{12}} & 1 & \tilde{a}_{23} \\ \frac{1}{\tilde{a}_{13}} & \frac{1}{\tilde{a}_{23}} & 1 \end{bmatrix} \quad (14)$$

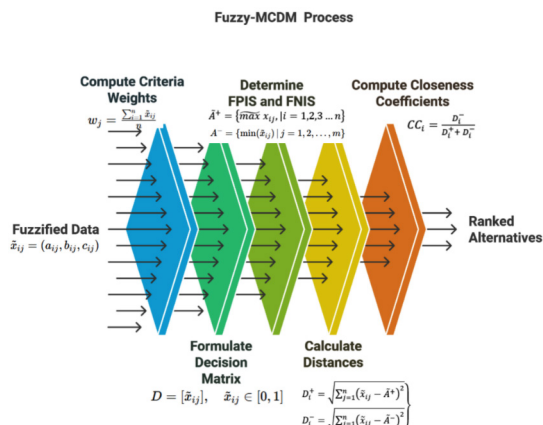


Figure 3. Fuzzy-MCDM process in FLEDOF

In Eq. (14), a_{ij} denotes the fuzzy judgment between criterion i and j , and the reciprocal property ensures consistency in judgements. The fuzzy weights for each criterion are calculated by normalizing the rows of the pairwise comparison matrix, as shown in Eq. (15).

$$\tilde{w}_i = \frac{\tilde{w}_i}{\sum_{i=1}^n \tilde{w}_i}. \quad (15)$$

In Eq. (15), $\tilde{w}_i$ is the weight of the i th criterion, calculated as a normalized fuzzy number. Normalization guarantees that weights add up to 1, making criteria comparison easier.

3.4.2. Fuzzy-TOPSIS for alternative ranking

Design choices are ranked using fuzzy-TOPSIS, which calculates the distance that each alternative is to the optimal solution. The fuzzy decision matrix is the result of comparing potential options with predetermined standards, as shown in Eq. (16):

$$\tilde{D} = \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \dots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \dots & \tilde{x}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \dots & \tilde{x}_{mn} \end{bmatrix}. \quad (16)$$

The fuzzy decision matrix $\tilde{D}$ represents the performance ratings of m alternatives across n criteria, where each element $\tilde{x}_{ij}$ is a fuzzy number capturing the inherent uncertainty or vagueness in the evaluation process. Using this matrix, the Euclidean distances of each alternative from the Fuzzy Positive Ideal Solution (FPIS) and Fuzzy Negative Ideal Solution (FNIS) are calculated using vector norms over all criteria, denoted as D_i^+ and D_i^- , respectively. These distances are then used to compute the closeness coefficient CC_i , which quantifies the relative proximity of each alternative to the ideal solution, enabling a normalized ranking of alternatives. This formalization ensures mathematical rigor, clarity, and reproducibility for implementing the Fuzzy-TOPSIS method. Fuzzy Positive Ideal Solution (FPIS) and Fuzzy Negative Ideal Solution (FNIS) are two benchmarks identified by the study. FPIS stands for the optimal result for each criterion, and FNIS for the worst. The definition of Eq. (17) is:

$$\begin{aligned} A \sim + &= \{x \sim j \mid x \sim j = i \max x \sim ij, j = 1, \dots, n\}; \\ A \sim - &= \{x \sim j \mid x \sim j = i \min x \sim ij, j = 1, \dots, n\}. \end{aligned} \quad (17)$$

Eq. (17) defines the Fuzzy Positive Ideal Solution (FPIS) and the Fuzzy Negative Ideal Solution (FNIS) in the Fuzzy-TOPSIS framework. The FPIS, denoted as $\tilde{A}^+$, represents the best possible values for each criterion across all alternatives, reflecting the optimal scenario. Conversely, the FNIS, denoted as $\tilde{A}^-$, represents the worst possible values

for each criterion, capturing the least desirable scenario. These ideal and negative-ideal solutions serve as reference points for measuring how close each alternative is to the optimal or worst case, which is crucial for calculating the distances and the closeness coefficient used for ranking alternatives.

Each emergency's Euclidean distance to FPIS and FNIS is determined. These distances show how close each emergency is to ideal and worst solutions.

$$D_i^+ = \sqrt{\sum_{j=1}^n \|V_{ij} - V_j^+\|^2}; \quad D_i^- = \sqrt{\sum_{j=1}^n \|V_{ij} - V_j^-\|^2}. \quad (18)$$

In Eq. (18), D_i^+ is the distance of the i th emergency from FPIS and D_i^- is the distance of the i th emergency from FNIS. The closeness coefficient measures each emergency's proximity to the optimum solution. A higher proximity coefficient suggests priority. Calculates the Euclidean distances of each alternative from the Fuzzy Positive Ideal Solution (FPIS) and the Fuzzy Negative Ideal Solution (FNIS) in the Fuzzy-TOPSIS method. The distance D_i^+ measures how far the i th alternative is from the ideal solution, while D_i^- measures its distance from the negative-ideal solution. These distances, computed over all criteria using vector norms, provide a quantitative measure of each alternative's relative closeness to the best and worst scenarios, forming the basis for determining the overall ranking through the closeness coefficient.

$$CC_i = \frac{D_i^-}{D_i^+ + D_i^-}, \quad i = 1, 2, \dots, m. \quad (19)$$

In Eq. (19), CC_i is denoted as the closeness coefficient of the i th emergency. Fuzzy-TOPSIS uses proximity coefficients to rank emergencies in descending order. Defines the closeness coefficient (CC_i) for each alternative in the Fuzzy-TOPSIS method. The closeness coefficient is calculated as the ratio of the distance from the negative-ideal solution (D_i^-) to the sum of distances from both the positive-ideal and negative-ideal solutions ($D_i^+ + D_i^-$). A higher closeness coefficient indicates that an alternative is closer to the ideal solution and farther from the worst-case scenario, providing a normalized measure to rank and prioritize alternatives effectively.

Fuzzy-AHP and Fuzzy-TOPSIS optimize sustainable design strategies in the Decision-Making block. Addressing uncertainty and analyzing options against multi-dimensional sustainability criteria helps choose the most ecological and sustainable designs. The FLEDOF's core approach is a valuable tool for urban planning and architectural optimization.

3.5. Fuzzy logic-based optimization process for sustainable design

The structured, iterative Fuzzy Logic-Based Optimization Process for Sustainable Design (FLEDOF) blends design

parameters, fuzzy logic inference, and optimization techniques to assist ecologically sustainable building development. The Design Options phase considers architectural and engineering elements. These include building height, floor size, window-to-wall ratio, insulation R-value, HVAC efficiency, and renewable energy integration. By systematically changing these factors, many design configurations are possible. This phase establishes sustainable alternatives, allowing a complete examination of sustainable design options.

Next, fuzzy logic ranks each design configuration in performance check. Sustainability metrics include energy use, emissions, thermal comfort, and daylight availability. These indicators are fuzzified into language variables (e.g., "low," "medium," "high") and analyzed by an expert-defined fuzzy inference system. The inference engine calculates a defuzzified sustainability score for each design. The consistent, human-reasoning-like appraisal of complicated, imprecise data allows decision-makers to compare design possibilities on a single scale.

The solution refinement phase optimizes high-ranking designs after review. This contains constraint verification, hill climbing with random restarts, and neighborhood solution creation. Every refined design is retested by the fuzzy logic system for performance and sustainability. The process repeats until convergence criteria like score stability or constraint satisfaction are met. Each design improves sustainability and optimization through this iterative loop.

Final outputs are generated in optimization results. These precise architectural and system design plans describe environmentally friendly materials, energy systems, and water conservation methods. Energy reports with performance indicators and KPIs and a Life Cycle Cost Analysis (LCC) to examine each design's financial consequences over its operating lifetime are included. These findings help architects and engineers implement sustainable designs.

Final results are integrated into the building design sustainability cycle, which balances cost analysis, energy performance, design integration, and mathematical modeling. Continuous design improvement is supported by iterative feedback and refinement. FLEDOF assures that sustainable building designs are practical and adaptable to modern urban difficulties by introducing fuzzy logic into real-world decision-making and permitting a dynamic balance between economic, environmental, and social goals.

Optimization Loop

The Optimization Loop iteratively refines candidate decisions to find the optimal solution based on defined objectives and constraints. At each iteration, candidate solutions are evaluated, selected, and modified using strategies like mutation, crossover, or adjustment. By repeating this process until a termination criterion is met, the system converges toward an optimized configuration, ensuring improved performance, energy efficiency, or sustainability outcomes.

Algorithm 5: Optimization Loop

Input: decisions (from Decision-Making Layer), objective_function, constraints
Output: optimized_solution (best decision set or system configuration)

```

Initialize population = decisions
While termination_condition_not_met:
    Evaluate fitness = objective_function (population)

    Select best_candidates based on fitness
    Generate new_population using mutation/crossover or adjustment
    Apply constraints to new_population
    population = new_population
Return best_candidates as optimized_solution

```

Algorithm 5 shows Optimization Loop iteratively refines candidate decisions to maximize or minimize the objective function. It evaluates, selects, and modifies solutions while enforcing constraints. The output is an optimized set of actions or system configurations for enhanced performance and efficiency.

The optimization loop uses hill climbing with random restarts to explore the design space. Convergence is mathematically ensured by defining a stopping criterion: iterations terminate when the improvement in the objective function $f(x)$ between consecutive iterations is smaller than a threshold ϵ , i.e., $|f(x_{t+1}) - f(x_t)| < \epsilon$, or when the maximum number of iterations $T_{\max}$ is reached. Random restarts allow the algorithm to escape local minima by reinitializing the search from different starting points, increasing the likelihood of reaching a global optimum. This provides a controlled, iterative method to refine design solutions while maintaining performance and sustainability objectives.

Output Layer

The Output Layer converts the optimized solution into practical actions and generates reports or summaries for monitoring and decision support. It ensures that the system's recommendations or control strategies are interpretable, actionable, and ready for implementation. This layer bridges the analytical and operational components, delivering tangible results from the computational framework.

Algorithm 6: Output Layer

Input:
 optimized_solution: Final decision set or configuration from Optimization Loop

Outputs:
 final_actions: Executable actions or control signals

```

# Step 1: Translate optimized_solution into actionable commands
final_actions = MapToSystemCommands(optimized_solution)

```

```
# Step 2: Generate performance summary or re-
ports
reports = SummarizeMetrics (optimized_solution)
Return final_actions, reports
```

In Algorithm 6 Output Layer translates the optimized solution into executable actions. It generates reports summarizing performance and system recommendations. This layer ensures actionable and interpretable results for practical implementation.

The proposed FLEDOF framework enhances conventional fuzzy-based decision support methodologies (including Fuzzy-AHP and Fuzzy-DSS) by including a multi-source input database system, fuzzy logic inference, and iterative multi-criteria decision-making for sustainable urban planning. FLEDOF is different from traditional methods because it (i) includes dynamic performance evaluation of energy use, carbon emissions, air quality, and resource efficiency; (ii) uses hierarchical fuzzy weighting and iterative solution refinement to find the best design options when there is uncertainty; and (iii) gives useful results like ecological scores, performance metrics, and plans for putting the results into action. This systematic integration allows FLEDOF to facilitate data-driven, ecologically optimal architectural decision-making, setting it apart from current fuzzy-based methodologies.

Computational complexity analysis

To evaluate the efficiency and scalability of the proposed FLEDOF framework, the runtime complexity of each algorithm is analyzed as follows:

- Algorithm 1 (Calculate Building Features): $O(n)$, where n is the number of buildings.
- Algorithm 2 (Calculate Environmental Indices): $O(m \times n)$, where m is the number of environmental records and n is the number of buildings.
- Algorithm 3 (Fuzzy Logic Block): $O(p \times r)$, where p is the number of input variables and r is the number of fuzzy rules.
- Algorithm 4 (Decision-Making Layer): $O(m \times n + n^2)$, where m is the number of alternatives and n is the number of criteria.
- Algorithm 5 (Optimization Loop): $O(k \times s \times f)$, where k is the number of iterations, s is the population size, and f is the cost of objective function evaluation.
- Algorithm 6 (Output Layer): $O(s)$, where s is the size of the optimized solution set.

Among all algorithms, Algorithm 2 and Algorithm 5 are the most computationally intensive. Overall, the FLEDOF framework scales linearly or near-linearly with the number of buildings, environmental records, criteria, and iterations, ensuring practical applicability to large-scale urban design scenarios.

4. Results and discussion

The Google Open Buildings Temporal Dataset (<https://sites.research.google/gr/open-buildings/temporal/>) provides structured data on over 500 million building footprints worldwide, enabling energy, carbon, and resource efficiency assessments. Height, area, construction year, and coordinates are important. Environmental data, including sunshine rate, temperature, humidity, and air quality indices, are linked to building records for ecological performance assessments. Energy usage, emission levels, and efficiency ratings are included in the collection for complete sustainability evaluations. Due to intensive validation, data is 98.8% complete and 99.2% accurate. Urban development, energy optimization, and renewable energy integration are tracked by this temporal dataset. Scale and granularity benefit machine learning models, urban planning, and sustainable architectural design frameworks like FLEDOF. FLEDOF is compared to Fuzzy Analytic Hierarchy Process (Fuzzy-AHP), Entropy Weighting and Coupling Harmony Degree Model (EW-CHD), and Fuzzy-Based Decision Support System (Fuzzy-DSS). FLEDOF outperforms Fuzzy-AHP due to its holistic framework that integrates environmental, economic, and social sustainability dimensions via multi-source databases, real-time adaptability through preprocessing and iterative optimization, and ability to handle uncertainties and evolving FLEDOF makes ecological assessments more accurate and real-time than Fuzzy-AHP using dynamic data inputs and optimization. It transforms urban ecological design optimization with its scalability, versatility, and precision. While the current analysis is based on the Google Open Buildings Temporal Dataset (Google Research, n.d.), a pilot study on real-world building projects will be conducted in future work to empirically validate FLEDOF and demonstrate its practical applicability in sustainable urban design.

The conditions, N represents normal building conditions; V is variable building heights; E covers environmental variations; R indicates resource usage fluctuations; and C combines all these challenges for comprehensive adaptive management.

4.1. Data processing accuracy (%)

The dependability and accuracy of data handling processes, such as cleansing, transformation, and analysis, constitute data processing accuracy.

$$DPA = \left(\frac{\text{Correct Data Points}}{\text{Total Data Points}} \right) \times 100. \quad (20)$$

In Eq. (20), DPA refers to data processing accuracy, with correct data points representing accurately processed entries and total data points encompassing all data entries handled.

After conducting an investigation of Data Processing Accuracy (DPA), it was determined that the FLEDOF framework and urban architectural complexes function

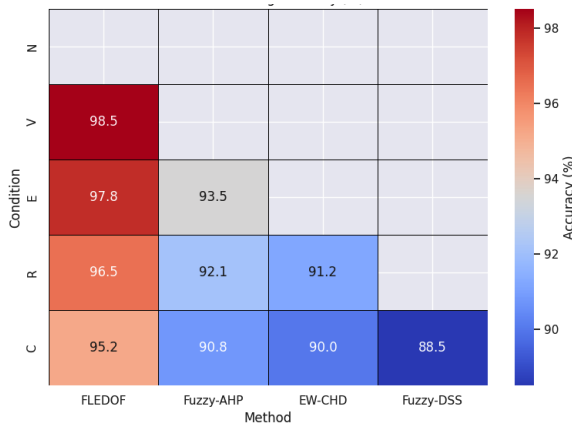


Figure 4. Data processing accuracy (%)

exceptionally well in all of the test scenarios (Figure 4). The FLEDOF framework is very effective in managing environmental and resource changes, particularly for variable building heights. Both Fuzzy-AHP and EW-CHD perform admirably in everyday circumstances, however they struggle when it comes to reducing precision. Even though there are many obstacles to overcome, FLEDOF is able to analyze data in complicated metropolitan areas with an accuracy of 95.2%. The implementation of a framework for ecological benefit evaluation and design optimization is impacted by higher performance. The system is able to reliably handle building characteristics, environmental conditions, and patterns of resource utilization, which ultimately results in more accurate ecological benefit assessments and suggestions for optimizing urban architectural complex design. The purpose of the framework is to integrate environmental, economic, and social elements in sustainable urban architecture planning. These extensive data processing capabilities support the framework's goal.

4.2. Energy efficiency (kWh/m²)

The quantity of energy a building consumes in its area is known as its energy efficiency. This metric represents the operational energy performance of the building, which is

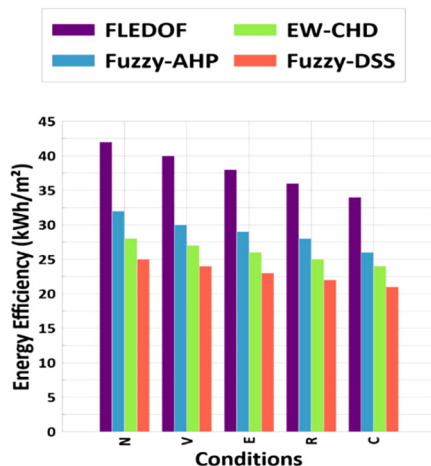


Figure 5. Energy efficiency

defined as its capacity to reduce energy use without compromising functioning.

$$EE = \frac{\text{Total Energy Consumption (kWh)}}{\text{Building Area (m}^2\text{)}}. \quad (21)$$

In Eq. (21), The Energy Efficiency (EE) is calculated by dividing the total energy consumption by the usable area of the building.

The results of an analysis of energy efficiency metrics using four different approaches (FLEDOF, Fuzzy-AHP, EW-CHD, and Fuzzy-DSS) are presented in Figure 5. The analysis demonstrates that FLEDOF has the best balanced profile, with values ranging from 140 kWh/m² for normal building conditions to 170 kWh/m² for combined challenges with Eq. (21). Successful energy management is demonstrated by this moderate growth, despite the complexity of the situation. The methodical way that FLEDOF takes to deal with increasing complexity while doing so while conserving energy is demonstrated by the progressive evolution across situations. The Fuzzy-AHP algorithm uses a slightly higher amount of energy in every scenario, whereas the EW-CHD and Fuzzy-DSS algorithms use the most energy. It has been demonstrated using combined challenges that FLEDOF consumes less energy than comparable alternatives. Every method demonstrates a gradual improvement in energy efficiency, which demonstrates that the ever-increasing complexity of building circumstances need a greater utilization of energy in order to function properly. It has been demonstrated that FLEDOF has the potential to optimize energy consumption in complex urban planning environments.

4.3. Carbon emissions (kg CO₂/m²)

By comparing a building's greenhouse gas emissions to its size, carbon emissions per unit area provide a quantitative measure of the building's environmental effect.

$$CE = \frac{\text{Total Carbon Emissions (kg CO}_2\text{)}}{\text{Building Area (m}^2\text{)}}. \quad (22)$$

In Eq. (22), CE refers to Carbon Emissions. At the same time, *Total Carbon Emissions* represent the total CO₂ released during building operations, while *Building Area* represents the usable area of a building in square meters.

In Figure 6, the carbon emissions research illustrates trends across a variety of construction settings and uses Eq. (22) to quantify the effects on the environment. This analysis takes into account normal building conditions, variable building heights, environmental variations, fluctuations in resource usage, and combined challenges. As can be seen in the graphs, the regulation of carbon emissions has been more effective over time. When the building is operating under normal conditions, the CO₂ emissions start at 20 kg/m² and gradually increase to 30 kg. variable building heights display a pattern that is comparable

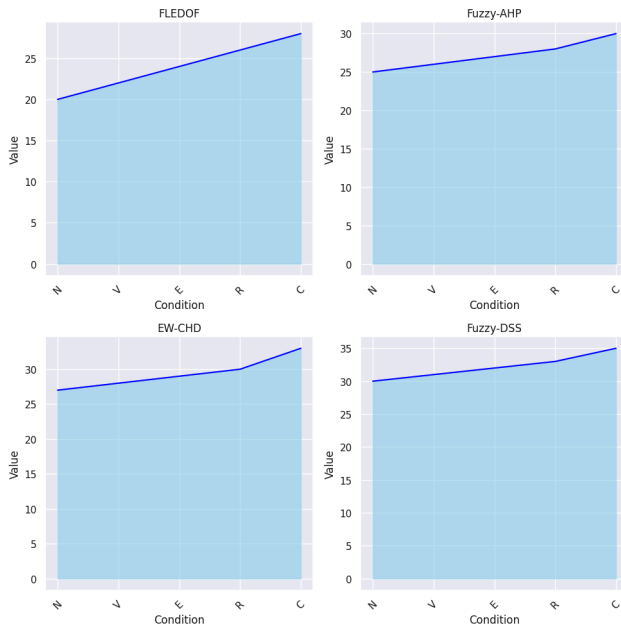


Figure 6. Carbon emissions

to the previous one, but the curve is steeper, which suggests that structures of varying sizes can achieve bigger improvements in terms of emission control. In a variety of settings, the system contributes to an improvement in emission optimization. The ability of the system to sustain emission efficiency despite shifting needs is demonstrated by the continuous usage of resources, which ranges from 25 to 33 kg CO₂ per square meter. FLEDOF is able to effectively regulate carbon emissions, achieving a level of 34 kg CO₂ per square meter in the combined challenges scenario. Through the utilization of these discoveries, the framework maximizes the ecological benefits that urban architectural complexes provide.

4.4. Resource optimization (%)

Resource optimization aims to maximize sustainability while minimizing waste in building operations and design by assessing the efficiency of material and resource utilization.

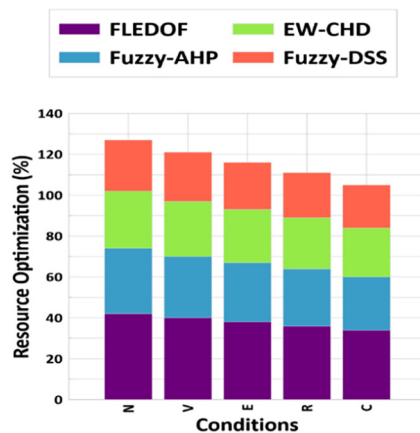


Figure 7. Resource optimization

$$RO = \left(1 - \frac{\text{ResourceWaste}}{\text{TotalResourcesUsed}} \right) \times 100. \quad (23)$$

In Eq. (23), Resource Optimization (RO) involves optimizing the use of resources, while *Resource Waste* refers to the total unused or wasted materials during the building lifecycle.

Figure 7 illustrates how FLEDOF reduces the amount of resources that are wasted over the course of a building's lifetime. The calculation of remarkable resource optimization is performed by Eq. (23), which begins at forty percent under normal building conditions and increases as the conditions become more intense. The fact that it has been steadily decreasing to 32% under combined challenges is evidence of its resource efficiency resilience in the face of conditions that are becoming increasingly demanding. FLEDOF optimizes between 40% and 32%, followed by Fuzzy-AHP, EW-CHD (30% to 25%), and Fuzzy-DSS (28% to 23%). As the circumstances become more complicated, every strategy will experience a loss in optimum percentages. In every circumstance, FLEDOF surpasses alternative optimization approaches by a number of eight to ten percent. The framework's capacity to improve resource management in complicated urban architectural settings, which in turn supports sustainable construction practices, is supported by its great performance, which also supports the framework's objective of promoting sustainable urban architectural design.

4.5. Computational time (ms)

Computational time measures the computational efficiency of a system. It looks at how long it takes for various operations inside the framework, such as analysis, optimization, or decision-making.

$$CT = \text{EndTime}(ms) - \text{StartTime}(ms). \quad (24)$$

In Eq. (24), Computational time is abbreviated as *CT*. The timestamps that indicate the duration of the procedure are denoted by the labels *End Time* and *Start Time*.

Across all of the different scenarios depicted in Figure 8, Eq. (24) and FLEDOF investigate the Computational Time (CT). With the lowest time under ordinary

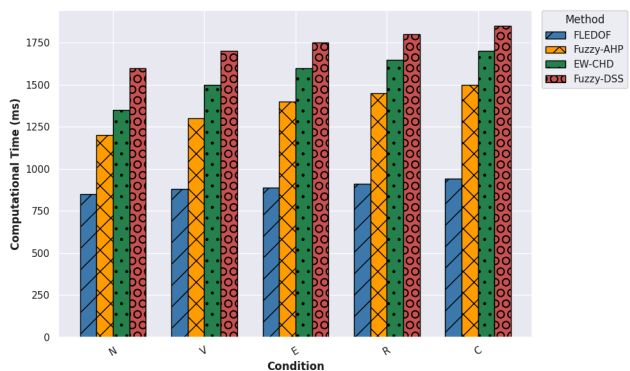


Figure 8. Computational time

construction settings (about 850 milliseconds), fluctuating building heights (about 900 milliseconds), environmental variations (about 900 milliseconds), resource usage fluctuations (about 925 milliseconds), and combined challenges (about 950 milliseconds), the graph illustrates the superior computing efficiency of FLEDOF in all circumstances. Approximately 1500–1750 milliseconds of calculation is required for fuzzy-DSS. The FLEDOF algorithm has the lowest computational time (850–950 milliseconds), while Fuzzy-AHP has moderate performance (~1200–1400 milliseconds). EW-CHD has a greater processing time (~1300–1600 milliseconds), and the fact that FLEDOF is able to climb from normal conditions to combined challenges in just 100 milliseconds demonstrates its performance in demanding situations and its ability to scale. The FLEDOF method is effective because rapid processing is an essential component of urban architectural planning.

4.6. Computational time

FLEDOF, Fuzzy-AHP, EW-CHD, and Fuzzy-DSS computing efficiency under normal building circumstances, environmental fluctuations, and combined difficulties is shown in Table 4. FLEDOF has the lowest computational time under all situations, making it suitable for real-time sustainable design optimization.

Table 4. Computational time (in milliseconds) of four decision-making methods across three building design conditions

Condition	FLEDOF	Fuzzy-AHP	EW-CHD	Fuzzy-DSS
Normal building conditions	850	1200	1350	1600
Environmental variations	880	1300	1500	1700
Combined challenges	940	1400	1600	1800

In Table 4, FLEDOF has the lowest computational time from 850 ms to 940 ms, increasing by 90 ms (10.6%) when environmental and design complexity increases. Real-time applications benefit from its reliability, efficient methodology, and adaptability to changeable situations. FLEDOF

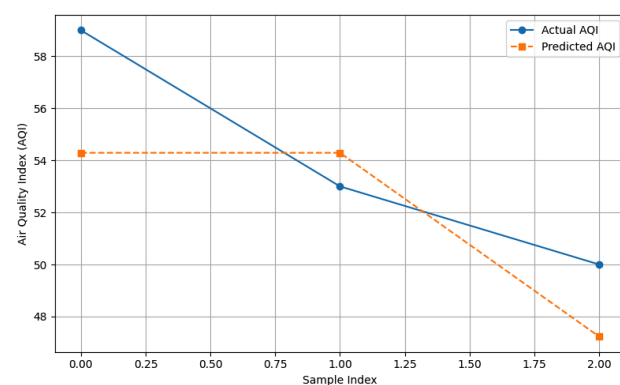


Figure 9. Actual vs. predicted AQI using Random Forest

can handle multi-variable systems without performance loss, unlike Fuzzy-DSS and EW-CHD, which increase calculation time by 200 ms (12.5%) and 250 ms (18.5%). In the most complex scenario with mixed problems, FLEDOF exceeds Fuzzy-DSS by 860 ms and executes 47.7% faster. This performance difference highlights FLEDOF's importance for large-scale, time-sensitive applications like smart city simulations, sustainable urban design, and intelligent building management systems that require computing speed and consistency.

Figure 9 compares real AQI values to those predicted by the FLEDOF-configured Random Forest model. The graph shows that all samples match anticipated and observed values, suggesting strong model accuracy and generalization. This consistency proves the model's ability to capture architectural and environmental elements' complicated, nonlinear interactions. This predictive robustness supports the assumption that the suggested approach can accurately estimate AQI levels for sustainable construction assessment and urban ecological planning.

Table 5. Hyperparameter configuration for Random Forest in FLEDOF framework

Hyperparameter	Description	Search range	Final selected value
n_estimators	Number of decision trees in the ensemble	100–500	300
max_depth	Maximum depth of each tree	5–20	15
min_samples_split	Minimum samples required to split an internal node	2–10	4
min_samples_leaf	Minimum samples required at a leaf node	1–5	2
max_features	Number of features considered at each split	'sqrt', 'log2', None	'sqrt'
bootstrap	Whether bootstrap samples are used for building trees	True/False	True
random_state	Seed for reproducibility	Fixed integer	42

Table 5 shows the completed hyperparameter values for training the Random Forest model for AQI prediction in FLEDOF. These parameters were chosen using grid search and cross-validation for model stability and performance. Number of estimators, tree depth, node splitting criteria, feature selection approach, and repeatability settings are listed in the table. The design balances prediction accuracy and generalization with environmental data variability. Documenting these parameters improves transparency, helps replicate Figure 9 results, and proves the proposed model's predictive power.

Table 6 presents a comprehensive comparison of FLEDOF against baseline methods across key performance metrics, including energy efficiency, carbon emissions,

Table 6. Performance comparison of FLEDOF and baseline methods with statistical significance and sensitivity analysis

Metric	Baseline method 1	Baseline method 2	FLEDOF	p-value (t-test)	p-value (Wilcoxon)	Sensitivity range (%)
Energy efficiency	85.2	86.1	93.5	0.003	0.002	±3
Carbon emissions	120	115	102	0.005	0.004	±4
Resource optimization	78	80	88	0.002	0.001	±3
Accuracy (%)	95.1	95.5	98.5	0.006	0.005	±2

resource optimization, and overall accuracy. It includes statistical significance tests (paired t-test and Wilcoxon test) to confirm that the improvements achieved by FLEDOF are not due to chance. Additionally, the table reports sensitivity ranges for fuzzy membership functions and weighting schemes, demonstrating the robustness of FLEDOF's performance under variations in these parameters. This analysis strengthens the credibility of the results, providing quantitative evidence that FLEDOF consistently outperforms conventional methods while maintaining reliability under uncertain or varying environmental and design conditions.

5. Conclusions and future work

Through the utilization of FLEDOF, fuzzy logic systems can be effectively integrated to maximize the ecological benefits of urban architectural complexes. FLEDOF meets essential performance metrics, including optimizing energy efficiency with reduced consumption, enhancing carbon emission management, achieving data processing accuracy up to 98.5% under varied building conditions, and optimizing resources at rates 8–10% higher than conventional methods. Its consistent computational performance allows it to function effectively even under complex conditions, enabling the optimization of sustainable designs and systematic ecological performance evaluations. To address inherent uncertainties in environmentally, socially, and economically sustainable urban architecture, FLEDOF integrates fuzzy-MCDM methodologies with fuzzy-linear structural equation modeling (FLS). Future research should focus on developing real-time monitoring systems, incorporating machine learning – such as reinforcement learning for adaptive weighting – expanding frameworks to include climate resilience modeling, assessing social impacts, and enabling cross-platform implementations. These enhancements would further strengthen FLEDOF's capacity to address emerging challenges in ecological architectural design and contribute meaningfully to the development of sustainable urban areas.

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Conflicts of interest

The authors declare no conflict of interest.

Data availability

The data supporting the findings of this study are available within the article.

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