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Environmental and energy performance assessment of buildings using scenario modelling and fuzzy analytic network process

Shushan Hu[a,c], Cathal Hoare[c], Paul Raftery[b], James O'Donnell[c,]

[a]School of Computer Science and Information Engineering, Hubei University, Wuhan, China
[b]Center for the Built Environment (CBE), University of California, Berkeley 390 Wurster Hall 1839, Berkeley, CA 94720-1839, USA
[c]School of Mechanical and Materials Engineering and UCD Energy Institute, University College Dublin, Belfield, Dublin 4, Ireland

Abstract

A well-recognised gap exists between measured and predicted building energy performance. Some practical assessment approaches offer the potential to reduce this gap using multiple indicators that evaluate building performance. Such approaches rely on subjective analysis of indicators' relative weights but are typically limited to a fixed assessment structure. Scenario modelling is one method that enables flexible and multi-granular environmental and energy performance assessment by coupling building function with other pivotal aspects of building operation. However, this method weighs all performance criteria equally. The objective of this paper is to empower building managers with enhanced environmental and energy performance assessment by integrating scenario modelling with a Fuzzy Analytic Network Process. Scenario modelling decomposes environmental and energy performance assessment into a set of flexible mappings between performance indicators and multi-granular building objects while Fuzzy Analytic Network Process enables calculation of relative weights by encapsulating ambiguity in domain expertise and complex interactions among often conflicting criteria. A case study demonstrated the engineering value of this approach. The sports cen-

Email addresses: `shushan.hu@hubu.edu.cn` (Shushan Hu), `cathal.hoare@ucd.ie` (Cathal Hoare), `p.raftery@berkeley.edu` (Paul Raftery), `james.odonnell@ucd.ie` (James O'Donnell)

tre obtained an operational score of 56.9 out of 100, or level 4 of 6 (i.e. very good) in terms of operational performance classification using calculated relative weights and intermediate results for eight carefully-identified indicators. When compared to an equivalent assessment using equally weighted criteria, the proposed approach enables more informative and targeted evaluations. With these results, building managers can quickly identify inefficient areas of building operation and improve energy consumption while maintaining building function. The approach is applicable for a wide range of buildings.

Keywords: Building energy performance assessment, Multiple criteria decision making, Scenario modelling, Fuzzy analytic network process, Relative weight analysis

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1. Introduction

Improving the environmental and energy performance of buildings (defined as the indoor environmental conditions and the energy associated with operation) is a major societal challenge. Buildings are recognised as being the single largest contributor to global CO_2 emissions [1], accounting for 40% of EU energy consumption and 36% of the EU's CO_2 emissions [2]. Against this backdrop, buildings generally do not perform as designed and a recognised gap exists between measured and predicted environmental and energy performance of most buildings [3]. An essential contributing pathway to the gap lies in effective environmental and energy performance assessment [4].

Analysis methods applied to building energy performance assessment vary in complexity and approach [5]. Table 1 categorises existing methods into three types and comprehensively analyses the pros and cons of each type. Normative comparison methods include those from the Netherlands Normalisation Institute [6], ENERGY STAR [7], and the more advanced U.S. General Services Administration Building Performance Assessment Toolkit [8]. ASHRAE developed the Building Energy Quotient rating program that provides information on building energy performance with two separate evaluations [9]. These methods provide objective performance indicators that are communicable between different stakeholders [10].

Augenbroe advocates for an integrated use of multiple indicators to assess building environmental and energy performance [11]. Researchers also tried to perform relative weight analysis on multiple indicators for comprehensive

Nomenclature

AECOO Architecture, Engineering, Construction, Owner and Operator

AHP Analytic Hierarchy Process

AHU Air Handling Unit

ANP Analytic Network Process

API Application Programming Interface

BEP Building Energy Performance

BEPS Building Energy Performance Simulation

BMS Building Management System

BREEAM Building Research Establishment Environmental Assessment Method

CHP Combined Heat and Power

EPC Energy Performance Certificate

FANP Fuzzy Analytic Network Process

FCU Fan Coil Unit

FDD Fault Detection and Diagnosis

LEED Leadership in Energy and Environmental Design

MCDM Multiple Criteria Decision Making

TFN Triangular Fuzzy Number

TOPSIS Technique for Order Preference by Similarity to Ideal Solution

assessment results. For example, LEED uses 6 weighted indicators to identify practical and measurable green building design, construction, operations, and maintenance solutions [12]. BREEAM applies 9 weighted indicators to the strong focus in the UK on sustainability in building design, construction and use [13].

These assessment frameworks have engendered a shift in assessing building performance with multiple indicators but face the challenge of conducting an objective and accurate analysis on relative weights of indicators. The main cause is the qualitative nature of domain expertise and mutually influenced relationships between indicators.

Multiple Criteria Decision Making (MCDM) theory emerged as an opportunity for solving the issue with a calculable mathematical model. MCDM originated in the domain of operations research and could be more specifically used for evaluating multiple conflicting criteria with complex interrelationships. Some MCDM based methods have been developed to generate solutions for building performance problems, including Analytic Hierarchy Process (AHP) [15], Analytic Network Process (ANP)[16], and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS)[17].

Table 1: Overview of existing assessment methods that evaluate building environmental and energy performance by simultaneously applying multiple key performance indicators.

Method	**Pros**	**Cons**	**Ref.**
Normative comparison methods	Multiple criteria comprehensively assess building environmental and energy performance. These methods resulted in considerable energy conservation (over 20% of total energy costs and over 30% of heating and cooling costs) in a large number of studied buildings.	These methods can fail when they involve building-to-building comparison if all the compared buildings operate inefficiently. They also require experts with the appropriate knowledge and skills, resources and time.	[6] [7] [8]
Criteria weighted methods	These methods decompose building energy performance into multiple criteria and evaluate their relative weights in order to perform comprehensive assessment on building energy performance.	These methods obtain relative weights based on achieving a consensus through ranking judgements made by a panel of experts and fall short of calculating objective relative weight for single criterion.	[12] [13] [14]
MCDM based methods	These methods apply MCDM theory to quantify uncertainty of expertise and mutually influenced relationships between criteria. Objective results on relative weights enable more comprehensive building energy performance assessment.	The fixed structure of criteria in these methods limits the range of suitable buildings. The reason is each building has a unique data set and a potentially unique set of operating requirements.	[15] [16] [17]

However, the constant structure of these MCDM based approaches limits the range of suitable buildings. In particular, each building has a unique data set and a potentially unique set of operating requirements, which makes standardised approaches to energy performance assessment difficult to implement.

The objective of this paper is to propose a novel solution for building energy performance assessment by providing enhanced inferred information to building managers. Assessment results allow these managers to identify areas of inefficiency and optimise energy consumption while continuing to deliver building function (e.g. a comfortable office space). The approach applies to real-time or retrospective analyses of building environmental and energy performance through a comprehensive yet easy to use pathway for building managers. Compared with traditional solutions, the novel method reduces the need for burdensome reinterpretation and conversion from engineering experts during the relative weight calculation process.

The remainder of this paper is structured as follows: Section 2 presents a review on building energy performance based on multiple criteria and relative weights analysis of criteria with MCDM. Section 3 details the overarching framework that enables environmental and energy performance assessment using an overall score based on multiple weighted performance criteria with appropriate levels of technical detail. Section 4 demonstrates the effectiveness and engineering value of the approach by assessing environmental and energy performance of a sports centre in University College Dublin and objectively discusses the strengths, weaknesses and limitations of the proposed framework. Section 5 reflects on the broader application potential of the approach.

2. Multiple criteria based building performance assessment

Significant issues surround environmental and energy performance assessment of buildings and a number of studies have illustrated the multi-faceted nature of the environmental and energy performance gap [18]. De Wilde attributed components of the gap to three broad stages of the building lifecycle: the design, construction (including handover) and operation phases. The CarbonTrust have listed some common faults (e.g. orientation and construction materia) characterised as inadequate predictions at design time and poor communication of performance intent from the design team [19]. For the operational phase, Chen et al. [20] summarised that building occupancy

Table 2: Relative weights of environmental and energy sections in LEED

Criteria	**Weight(%)**
Indoor environmental quality	17%
Energy and atmosphere	38%
Location and transportation	15%
Sustainable sites	10%
Water efficiency	12%
Material and resource	8%

is of great importance for energy efficient control of buildings. Carlucci et. al [21] identified that thermal comfort of occupant is one of the main sources leading to uncertainty around building energy consumption. Xu et. al [22] stated that efficient control strategies on various lighting systems can play a key role in improving energy performance of open-plan offices. A key observation arising from these studies is that in-depth building environmental and energy performance analysis requires an integrated use of multiple criteria.

2.1. Performance assessment based on multiple criteria

Multiple domain evaluation on building environment and energy performance is important to understand the performance and optimise the operation of a building to ensure it is meeting the needs of the organisation/occupants. Following this principle, multiple criteria analysis is mandatory for use in the evaluation and some building rating systems have been developed as important tools in assessing environmental energy performance of a building [23]. For example, LEED provides a framework to create healthy, highly efficient and cost-saving green buildings with six main performance criteria (Table 2). The criteria of energy and atmoshpere is the most import factor and has a 38% relative weight. The indoor environmental quality takes the seond biggest weight ration. The framework is available for buildings through the whole life cycle, including D+C (Design and Construction), O+M (Operations and Maintenance) [24]. LEED O+M applies to performance of existing buildings [12].

BREEAM aims to construct an integrated framework that assesses environmental and energy performance of buildings through nine main performance criteria.[25]. The energy and indoor environment (i.e. health & well being) also works as the two most important factors, but two new criteria (i.e. land use & ecology, pollution) shows in the list and takes medium importance. This framework also contains standards for three building phases (i.e. New Construction, In-Use, and Refurbishment & Fit-out). BREEAM In-Use mitigate the operational impacts of existing assets on the environment across a large range of environmental issues (Table 3) [13].

In addition, Green Globes was developed by ECD Energy & Environment Canada Ltd. as a building environmental performance rating system with seven assessment topics [14]. The national Ministry of Construction of China promulgated an Evaluation Standard for Green Building (i.e. six main indicators) to improve the development of green buildings [26]. In Australia, the Green Star index uses eight criteria to assess building energy performance in hot climates where cooling systems and solar shading are of major importance [27]. The Green Mark rating tool has sought to influence design and operation of buildings in Singapore [28].

When viewed collectively, these approaches present opportunities to apply multiple criteria for building environmental and energy performance assessment but fall short of calculating objective relative weights for single criteria. These methods obtain weights based on achieving a consensus through ranking judgements made by a panel of experts. A notable gap emerges due to the ambiguous characteristics of expertise and complicated interrelationships between indicators with possible improvements in the objectiveness and precision of weighted results.

Table 3: Relative weights of environmental and energy sections in BREEAM

Criteria	**Weight(%)**
Management	12%
Health & well being	15%
Energy	19%
Transport	8%
Water	6%
Materials	12.5%
Waste	7.5%
Land use & ecology	10%
Pollution	10%

2.2. Relative weight analysis of criteria with MCDM

Multiple criteria decision making (MCDM) theory emerges as an opportunity to objectively calculate the relative weights of performance indicators in the building energy field [29]. MCDM introduces a mathematical perspective for problem structuring and criteria aggregation, in which a progressive learning process is built to enhance problem understanding for the decision makers and facilitates the analysis of mutex relationships among conflicting criteria. A well developed MCDM solution called TOPSIS conducts decision making with complex monotonic evaluating criteria that can be increasing and decreasing where the fundamental principle chooses alternatives approximating the ideal solution [17]. Lee and Lin presented a new approach that integrates TOPSIS into building energy performance appraisal domain [30]. Wang et. al. developed a new TOPSIS method by considering the trade-off between Multiple Linear Regression and Principal Component Analysis [31].

Other two solutions for MCDM problems are AHP and ANP. AHP decomposes a problem into a hierarchy structure consisting of easily comprehended sub-problems [32]. Yagmur et al. [15] used the AHP model, containing five criteria and four sub-criteria, to determine priority analysis in relation to localisation of equipment for a thermal power plant. AHP assumes the decision criteria are considered to be independent of one another which violates with many real-world cases. ANP organises a problem with a network structure and consider dependencies among sub-problems by quantitatively calculating the level of dependencies and feedback among them [33]. Atmaca et al. [34] used ANP to determine the suitability of power plants in Turkey. A multiple criteria evaluations of six different energy plants were performed with respect to some major criteria.

Conventional ANP methods are ineffective in dealing with inherent fuzziness and uncertainty of judgement during a pairwise comparison process. In order to address this issue, researchers developed FANP that integrates fuzzy set theory and ANP to perform an objective and precise analysis on criteria within decision making problems. To this extent, fuzzy set theory provides the capability to quantify fuzziness and uncertainty. Some FANP based approaches have been developed for multiple criteria problems in the Architecture, Engineering, Construction, Owner and Operator (AECOO) domain. For example, Kabak et al. developed a system that leverages FANP and seven key indicators to assess the energy performance of buildings in Turkey [16]. The authors used the logarithmic least squares method to calculate relative weights for performance indicators. Buyukozkan et al. identified the most suitable renewable energy resource alternative by taking complex decision criteria and subjective and qualitative judgements [35]. The FANP model in this case contained five alternatives (Wind, Solar, Biogas, Hydro, and Geothermal) and twenty criteria grouped into five aspects. Sadeghi et al. used FANP to assess the mix of energy sources for producing electricity from the perspective of sustainable development [36]. The approach handles multiple qualitative and quantitative criteria with conflicting objectives when evaluating competing energy options for electricity production.

However, these MCDM based solutions organise multiple indicators in a fixed assessment structure which results in some prerequisites narrowing the fitting-range. Buildings operate for diverse functional requirements, for example laboratories and offices) and BMS can collect unique performance data for each building. Therefore, meaningful and insight energy performance assessment requires a flexible and generic mapping between building objects and multiple indicators.

3. Integrating scenario modelling and FANP

The objective of this paper is the integrating scenario modelling with FANP to comprehensively assess building environmental and energy performance (Figure 1) based on previous research [37, 38, 39, 40]. The approach leverages scenario modelling to decompose the assessment problem into a flexible and multi-granular structure. FANP is able to calculate relative weights of multiple criteria through quantising the complicated interactions among those criteria. The end product is an overall energy performance assessment score that can be calculated using these relative weights and intermediate results of each criterion.

Scenario modelling is one structured assessment technique that encapsulates all aspects of environmental and energy management in buildings. The method [41] proposes that building energy performance assessment requires five categories (i.e. called performance aspects) and defined as: building function, thermal loads, systems performance, energy consumption, and legislation. The technique posits that these performance aspects are appropriate for the stakeholder in charge of commercial building energy management (i.e. the building manager). The building manager implements the organisation's strategy for an individual building and ensures that the built environment will perform the functions for which the building was designed and constructed.

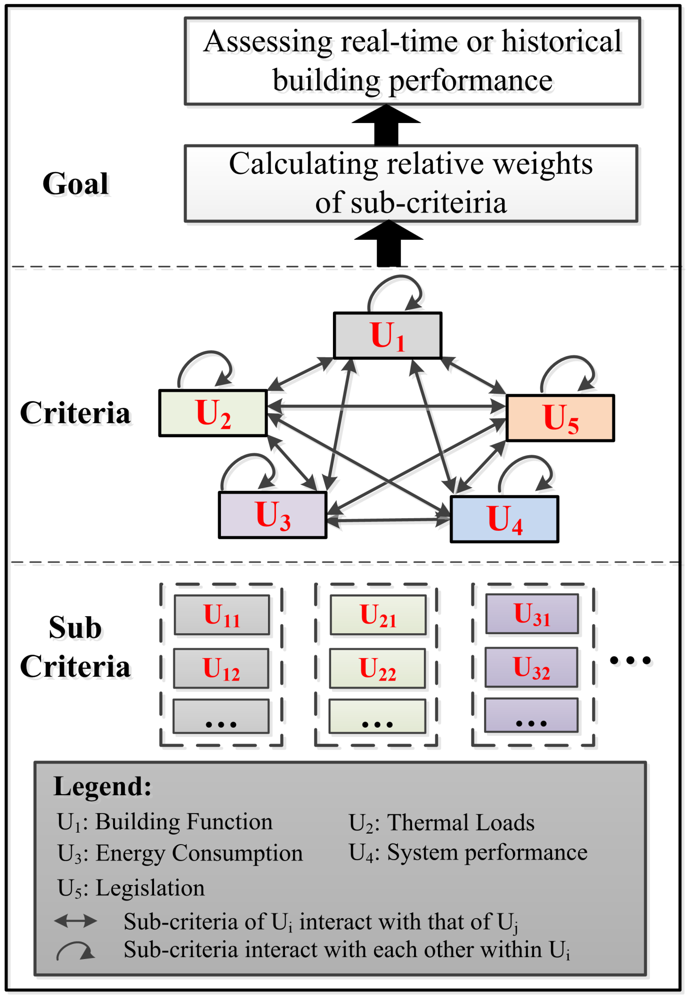

Figure 1: The combination of scenario modelling and FANP to enable an overall score for building environmental and energy performance.

Performance objectives represent a qualitative performance description validated by indicators (i.e. called performance metrics). Scenario Modelling applies a conceptual and hierarchical structure to organise interrelationships among performance aspects, building objects, and performance objectives. Figure 2(A) illustrates the explicit class structure for a scenario model and Figure 2(B) shows an example of thermal comfort evaluation and associated energy consumption.

FANP provides an unique opportunity for decision support systems by

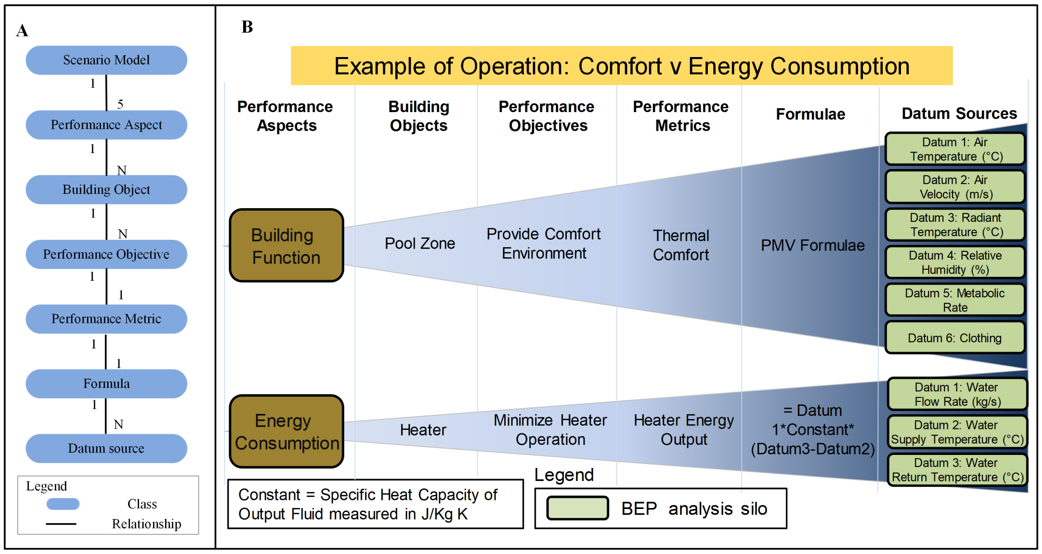

Figure 2: A) Class diagram representation of scenario modelling that enables flexible energy performance assessment and B) a scenario model example evaluating thermal comfort against associated energy consumption.

integrating fuzzy set theory and the ANP method [42]. Zadeh et al. [43] introduced Fuzzy set theory as a mechanism to overcome the problem of ambiguous data input to mathematical logic and language. This theory emphasise the fuzziness of the factors applied when conducting comprehensive evaluation. ANP defines a well mathematical model to account for the complex inter-relationships among criteria and objectively calculate their relative weights. Finally, FANP provides an accurate and objective solution for multiple criteria problems with a range of advantages that include [44]: 1) Quantising the uncertainty of imprecision and vagueness of natural language; 2) Dealing with complex correlations among decision levels and attributes; 3) Reflecting vague data effectively.

The key concept of this approach comprises four main steps (Figure 3):

1. Modelling environmental and energy performance assessment into mappings between multi-granular building objects and multiple criteria (Section 3.1);
2. Forming pairwise comparisons of criteria with fuzzy set theory (Section 3.2);
3. Calculating relative weights of criteria through the ANP method (Section 3.3) and

4. Scoring overall building energy performance based on the calculated relative weights (Section 3.4).

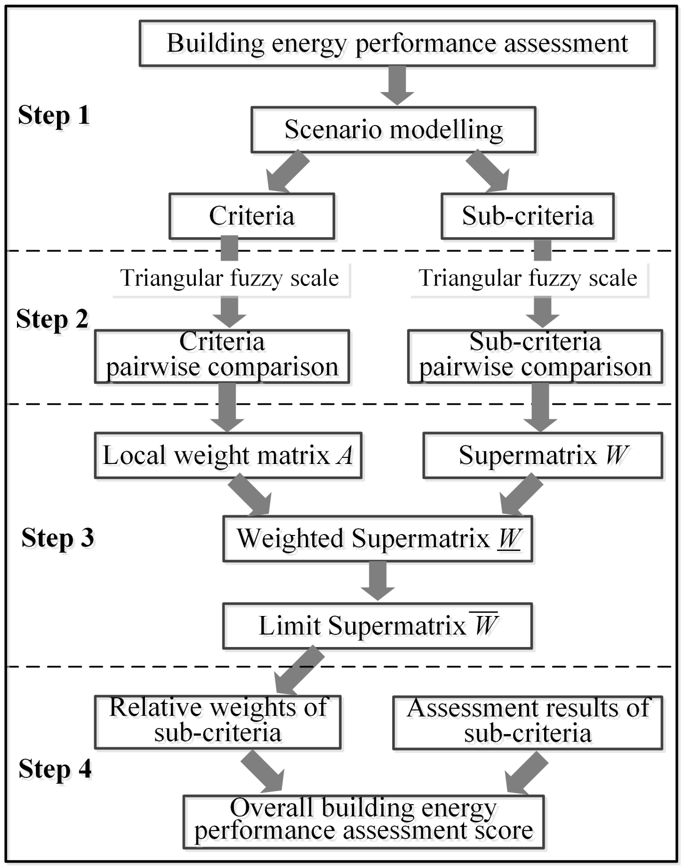

Figure 3: A four step workflow that evaluates building environmental and energy performance by integrating scenario modelling and FANP to obtain relative weights for sub-criteria.

3.1. Step 1: Modelling building energy performance assessment

Within the context of a given building, the approach regards performance aspects as criteria in a proposed ANP model (Figure 1). The maximum number of criteria is five (i.e. $U = \{U_1, U_2, U_3, U_4, U_5\}$) that consistently aligns with the five performance aspects defined by scenario modelling, namely building function, thermal load, energy consumption, system performance, and legislation. Each criterion (i.e. U_i $[i = 1, 2, \ldots, 5]$) comprises a number of sub-criteria which are called performance objectives in scenario models (i.e. $U_i = \{U_{i1}, U_{i2}, \dots, U_{ij}\}[j = 1, 2, 3, \dots, n]$). In addition, an ANP model still contains correlations among criteria and sub-criteria that play a key role in calculating relative weights of sub-criteria [45]. The approach categories these correlations into two types (Figure 1):

1. Sub-criteria of criterion U_i interact with sub-criteria belonging to criterion U_k
2. Sub-criteria interact with each other within the same criterion U_i.

3.2. Step 2: Forming pairwise comparison matrices of criteria

This step forms pairwise comparison matrices for criteria and sub-criteria of ANP models. The pairwise comparison quantifies the relative level of importance between two criteria or sub-criteria. Engineering experts or experienced mechanical engineers assist calculation of relative weights of multiple criteria, and significantly contribute to completing pair-wise comparisons of criteria. Compared with traditional solutions, this research designs an easy to use method to reduce efforts needed from engineering experts.

This method only requires that experts estimate how much a criterion/sub-criterion affect another criterion/sub-criterion (e.g. $E(U_i \rightarrow U_j)$). Five effect-levels are designed for experts (shown in Table 3). Two of these levels have an absolute boundary: E_1 indicates that U_i has no effect on U_j (e.g. occupancy status → outside temperature) and E_5 hints 100% effect that is led by self-affecting (i.e. $E(U_i \rightarrow U_i)$). It is worth noting that $E(U_i \rightarrow U_j)$ and $E(U_i \leftarrow U_j)$ are independent and experts should finish both of them.

Table 4: Linguistic scale for effect estimation between criteria

Linguistic scale	**Level**
No effect	E_1
Small effect	E_2
Moderate effect	E_3
Big effect	E_4
Self effect	E_5

Experts use fuzzy set theory to construct pairwise comparison matrices. The theory aims to solve the uncertainty that arises from subjectivity and vagueness of expertise in decision making problems. A fuzzy set is a class of objects with a continuum of membership grades. Such a set is characterised by a membership (characteristic) function, which assigns a grade of membership ranging between zero and one to each object [46]. Fuzzy numbers expand the idea of the confidence interval and are defined over a fuzzy set of real numbers.

Triangular fuzzy number (TFN) $\widetilde{M}$ [47] serves as a popular function based on fuzzy set theory (Figure 4). A TFN is denoted simply as (l, m, u). The parameters l, m and u respectively denote the smallest possible value, the most promising value, and the largest possible value that describe a fuzzy event. Each TFN has linear representations on its left and right side according to the membership function in Eq. (1). A tilde '$\sim$' above a symbol indicates if the symbol represents a fuzzy set.

$$\mu_{\widetilde{M}}(x) = \begin{cases} 0 & x < l \\ (x-l)/(m-l) & l \leq x \leq m \\ (u-x)/(u-m) & m \leq x \leq u \\ 0 & x > u \end{cases} \tag{1}$$

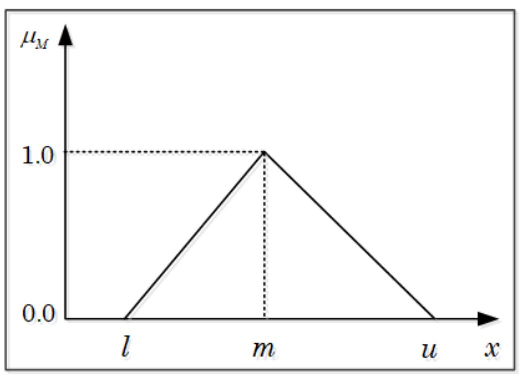

Figure 4: A triangular fuzzy number $\widetilde{M}$
representing the smallest possible value (l), the most promising value (m), and the largest possible value (u).

TFN normally uses three levels of fuzzy scale (i.e. 5, 7, and 9) to solve MCDM problems [48]. More levels indicate more ambiguous boundaries between adjacent scales. In order to reduce workload and intervention from engineering experts, this research applies the smallest level of fuzzy scale (i.e. 5) for building energy performance assessment. The full numerical scale is from 1 to 9 and is divided into five segments (i.e. 1, 3, 5, 7, and 9). The use of these crisp numbers might be criticised due to their inability to adequately handle the uncertainty and imprecision associated with expertise. The triangular fuzzy number theory extends these numbers into triangular fuzzy scales (the second column in Table 5). The distance between l and m (as well as between m and u) is set as 1/2 by taking impreciseness of expertise and boundaries of scales into consideration. The third column is the reciprocal value of the second column in Table 5. The fuzzy scale is adjustable according to specific requirements that may arise in the future.

Table 5: Linguistic scale for relative weight in the fuzzy set theory

Linguistic scale for importance	**Triangular fuzzy scale**	**Triangular fuzzy reciprocal scale**	**Table 3 transformation**
Equally important	(1/2,1,3/2)	(2/3,1,2)	E_1 vs E_1
Weakly more important	(5/2,3,7/2)	(2/7,1/3,2/5)	E_2 vs E_1
Strongly more Important	(9/2,5,11/2)	(2/11,1/5,2/9)	E_3 vs E_1
Very strongly important	(13/2,7,15/2)	(2/15,1/7,2/13)	E_4 vs E_1
Absolutely important	(17/2,9,19/2)	(2/19,1/9,2/17)	E_5 vs E_1

In order to form pairwise comparison matrices, this study defines a rule (4th column in Table 5) to transform effect estimation results in Table 4 to triangular fuzzy scales in Table 5. For example, Table 6 illustrates a pairwise comparison matrix that regards criterion U_1 as the reference. Cell (3,2) (i.e. (l_{21}, m_{21}, u_{21})) represents a pairwise comparison between $E(U_2 \to U_1)$ and $E(U_1 \to U_1)$. Assuming $E(U_2 \to U_1) = E_1$, it can be inferred that $(l_{21}, m_{21}, u_{21}) = (17/2, 9, 19/2)$, since $E(U_1 \to U_1)$ has an absolute value (i.e. E_5).

Table 6: An pairwise comparison example about criteria under criterion U_1.

U_1	U_1	U_2	$\dots$	U_n
U_1	(l_{11}, m_{11}, u_{11})	(l_{12}, m_{12}, u_{12})	$\dots$	(l_{1n}, m_{1n}, u_{1n})
U_2	(l_{21}, m_{21}, u_{21})	(l_{22}, m_{22}, u_{22})	$\dots$	(l_{2n}, m_{2n}, u_{2n})
$\dots$	$\dots$	$\dots$	$\ddots$	$\dots$
U_n	(l_{n1}, m_{n1}, u_{n1})	(l_{n2}, m_{n2}, u_{n2})	$\dots$	(l_{nn}, m_{nn}, u_{nn})

3.3. Step 3: Calculating relative weights of criteria

In this step, this study uses an algorithm called fuzzy preference programming to calculate the relative weights of criteria and sub-criteria in ANP models. The algorithm designed by Mikhailov [49] provides an accurate and effective pathway to derive crisp weights from fuzzy comparison matrices. The method can acquire the consistency ratios of fuzzy pairwise comparison matrices without additional study [48]. In doing so, this step firstly calculates a crisp priority vector $w = (w_1, w_2, \ldots \ldots, w_n)^T$ using TFN values in each pairwise comparison matrix. For each crisp priority vector, the priority ratios w_i/w_j satisfy the double-side inequality shown in Eq. (2), where the symbol $\widetilde{\leq}$ denotes the statement 'fuzzy less or equal to'.

$$l_{ij} \widetilde{\leq} \frac{w_i}{w_j} \widetilde{\leq} u_{ij} \tag{2}$$

Each crisp priority vector w satisfies the inequality in Eq. (2) with some degree, which can be measured by a linear function (Eq. (3)) obtained by replacing the variable x in Eq. (1) with w_i/w_j. The function is linearly increasing over the interval $(-\infty,\ m_{ij})$ and is linearly decreasing over the interval $(m_{ij},\ \infty)$. It coincides with the triangular fuzzy scale $(l_{ij},\ m_{ij},\ u_{ij})$

$$\mu_{ij}(\frac{w_i}{w_j}) = \begin{cases} \frac{(w_i/w_j)-l_{ij}}{m_{ij}-l_{ij}} & \frac{w_i}{w_j} \leq m_{ij} \\ \frac{u_{ij}-(w_i/w_j)}{u_{ij}-m_{ij}} & \frac{w_i}{w_j} \geq m_{ij} \end{cases} \tag{3}$$

Two main assumptions construct the basis for solving the prioritisation problem. The first assumption requires the existence of a non-empty fuzzy feasible area P (Eq. (4)) on the $(n-1)$ dimensional simplex Q^{n-1} (Eq. (5)). If the fuzzy judgements are inconsistent, $u_p(w)$ could take negative values for all normalised priority vectors $w \in Q_{n-1}$.

$$u_p(w) = \min_{ij}\{u_{ij}(w) | i = 1, 2, \ldots n-1; j = 2, 3, \ldots n; j > i\} \tag{4}$$

$$Q^{n-1} = \{(w_1, w_2, \ldots w_n) | w_i > 0, \sum_{i=1}^{n} w_i \ = 1\} \tag{5}$$

The second assumption specifies a selection rule, which determines a priority vector having the highest degree in the aggregated function (Eq. (4)). $u_p(w)$ is a convex set and there is always a priority vector $w^* \in Q_{n-1}$ (Eq. (6)) that has a maximum degree. The maximum prioritisation problem is transformed into a bilinear one (Eq. (7)) by integrating Eq. (3) and Eq. (6). The variable λ measures the degree of membership of a crisp priority vector. The optimal solution to the linear problem is a vector (w^*, λ^*). w^* represents the weight vector that has a maximum degree of membership in the fuzzy feasible area, whereas the second component gives the value of that maximum degree. The optimal value λ^* (i.e. maximum: 1) indicates that all solution ratios satisfy the fuzzy judgement completely, which means that the initial set of fuzzy judgements is consistent.

$$\lambda^* = u_p(w^*) = \max_{w \in Q^{n-1}} \min_{ij} \{u_{ij}(w)\} \tag{6}$$

$$\begin{aligned}
&Max\ \lambda \\
&(m_{ij} - l_{ij})\lambda w_j \ - \ w_i \ + \ l_{ij} w_j \ \leq \ 0, \\
&(u_{ij} - m_{ij})\lambda w_j \ + \ w_i \ - u_{ij} w_j \ \leq \ 0, \\
&i = 1, 2, \ldots, n-1; \ j = 2, 3, \ldots, n; \ j > i \\
&\sum_{k=1}^{n} w_k \ = 1 \\
&w_k > 0, \ k = 1, 2, \ldots, n.
\end{aligned} \tag{7}$$

This step can calculate a set of crisp priority vectors (i.e. $w^1, w^2, ..., w^n$) using multiple pairwise comparison matrices. The parameter n is the number of criteria. Vector w^i is the crisp priority vector calculated with the pairwise comparison matrix regarding criterion U_i as the reference. These vectors comprise a local weight matrix A (Eq. (8)), in which the vector $w^1 = (a_{11}, a_{21}, \ldots, a_{n1})^T$ is computed using the matrix in Table 6.

$$\begin{aligned}
A &= (w^1, w^2, ..., w^n) \\
&= \begin{bmatrix} a_{11} & a_{12} & \ldots & a_{1n} \\ a_{21} & a_{22} & \ldots & a_{2n} \\ \ldots & \ldots & \ddots & \ldots \\ a_{n1} & a_{n2} & \ldots & a_{nn} \end{bmatrix}
\end{aligned} \tag{8}$$

The approach performs the same calculation process upon all pairwise comparison matrices of sub-criteria. A number of local-weight matrices are available to construct a supermatrix W (Eq. (9)), in which n is the number of criteria. Similar to the matrix A in Eq. (8), $W_{ij} (i \leq n, j \leq n)$ is a local weight matrix computed with pairwise comparison matrices of sub-criteria.

$$W = \begin{bmatrix} W_{11} & W_{12} & \dots & W_{1n} \\ W_{21} & W_{22} & \dots & W_{2n} \\ \dots & \dots & \ddots & \dots \\ W_{n1} & W_{n2} & \dots & W_{nn} \end{bmatrix} \tag{9}$$

Eq. (10) presents the calculation of a weighted supermatrix, which is the dot product of the matrix A and the supermatrix W.

$$\begin{aligned} \underline{W} &= A * W \\ &= \begin{bmatrix} a_{11}W_{11} & a_{12}W_{12} & \dots & a_{1n}W_{1n} \\ a_{21}W_{21} & a_{22}W_{22} & \dots & a_{2n}W_{2n} \\ \dots & \dots & \ddots & \dots \\ a_{n1}W_{n1} & a_{n2}W_{n2} & \dots & a_{nn}W_{nn} \end{bmatrix} \end{aligned} \tag{10}$$

Eq. (11) shows the calculation of a limit supermatrix based on the weighted supermatrix (i.e. $\underline{W}$). m is the number of sub-criteria. Vectors in the limited supermatrix have the same value (i.e. $C_1 = C_2 = \cdots = C_n$).

$$\begin{aligned} \overline{W} &= \lim_{k\to\infty}(\underline{W}^k) \\ &= (C_1, C_2, \cdots, C_m) \\ C_i &= (c_1, c_2, \dots, c_m)^T \\ &(1 \leq i \leq m) \end{aligned} \tag{11}$$

3.4. Step 4: Scoring the overall building energy performance

This final step selects the first vector (i.e. $C_1 = (c_1, c_2, \cdots, c_m)$) of the limit supermatrix $\overline{W}$ to be the relative weights of sub-criteria, which will be used to score the overall building energy performance. After obtaining assessment results for each sub-criterion, the approach calculates overall assessment result using Eq. (12), where the parameter c_i indicates the relative weight of the *ith* sub-criterion and the parameter r_i is assessment result of the *ith* sub-criterion.

$$R = \sum_{i=1}^{n} c_i * r_i \tag{12}$$

The scale used for communication of overall building energy performance ranges from 0-100 and directly aligns with the BREEAM levels of performance classification (Table 7). The concept of a scale ranging from 0-100 is widely prevalent in society and is also adopted in certain member states of the EU for energy performance certification (EPC) of buildings.

Table 7: Performance classification and scores of BREEAM

Linguistic label	Score
Unclassified	< 30
Pass	≥ 30
Good	≥ 45
Very good	≥ 55
Excellent	≥ 70
Outstanding	≥ 85

4. Demonstration

In order to demonstrate the engineering value of integrating scenario modelling and FANP in the field of building energy performance assessment, this research performed a case study of building energy performance assessment upon the sports centre building in University College Dublin (UCD), Ireland. The building extends over 11,000 m^2 and spreads over a three-storey complex linking the existing sports and student centres. It contains facilities for student health, debating, drama, societies, media and leisure amenities in addition to a 50 m x 25 m swimming pool with related ancillary areas. The heating and cooling load of the building is covered by two CHP units, two boilers, a district heating installation and an air cooled chiller. The delivery equipment consists of 8 AHUs, FCUs, underfloor heating and baseboard heaters. In addition, this research developed an ANP as a Java Application Programming Interface (API) using the MATLAB software. A integrated software tool is coded within Eclipse to calculate relative weights using the ANP API and pairwise comparison matrices stored as a CSV file.

4.1. A scenario model for energy performance assessment

This case study defined a scenario model to reflect some key concerns in the area of thermal comfort and energy consumption of the building (Figure 5). The scenario model examines three separate performance aspects (i.e. Building Function, Energy Consumption, and Thermal Load) for important building objects including key zones and HVAC systems. The Building Function aspect contains three performance objectives that describe the thermal comfort status in the building. Two objectives detail the air temperature and relative humidity of the pool hall zone. The third objective details temperature conditions in the whole building. The three objectives are measured by three functional metrics which return the temperature and relative humidity values for the time period in question.

For the Energy Consumption aspect, the first objective uses a functional metric to sum the energy consumption of two boilers that serve the heating needs of the swimming pool and the building. Two additional objectives evaluate energy consumption of AHUs and pumps in the building. The intention of the three objectives is to examine the energy efficiency of HVAC components. The last aspect focuses on the thermal load of key objects within the whole building. This aspect is significantly affected by the building function aspect or desired indoor environmental conditions. Within this aspect, the scenario model uses one performance objective to minimise the thermal load of the pool hall zone and another objective targets at the thermal load of the whole building. The parameter Tb-h in these two objectives indicates the base temperature used for calculation of degree day at a given location.

The three performance aspects include a total of eight performance objectives (see Figure 5) and constitute an integrated scenario model for building energy performance assessment. Evaluation of the scenario model provides a clear picture of the thermal conditions in the space and how these conditions relate to energy consumption of HVAC components and thermal load of spaces. In doing so, the study transforms the scenario model into a ANP model by considering performance aspects as criteria and performance objectives as sub-criteria (in Table 8).

4.2. Relative weights calculation

In order to perform pair-wise comparison, engineering experts are responsible for estimating the effects between criteria (i.e. performance aspects) and sub-criteria (i.e. performance objectives) using the scales defined in Table 4. Table 9 reports the estimation results on performance aspects. Besides these diagonal cells, the values of other cells suggest that strong correlations exist among the three performance aspects. Most notably the values of cell (2,3) and (3,2) indicate that U_1 and U_2 produce different levels of effect on each other.

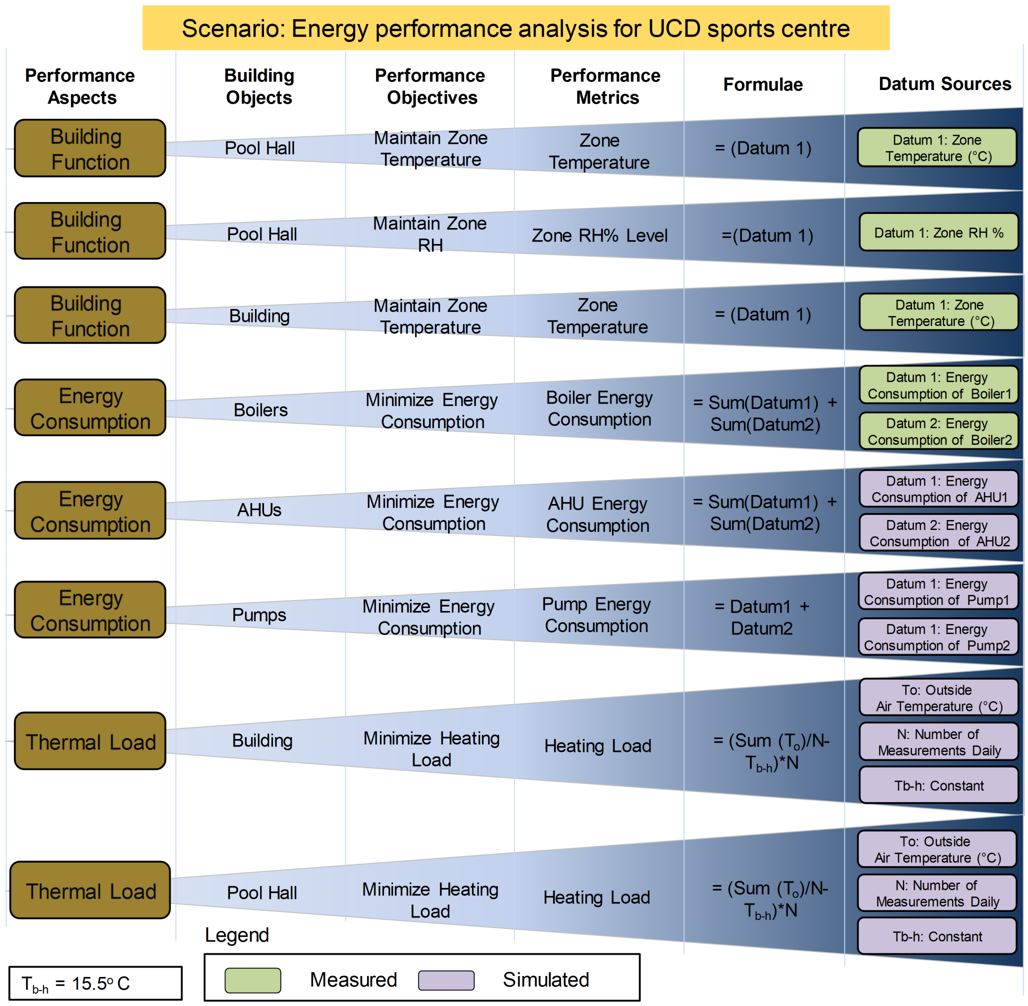

Figure 5: A scenario model assessing environmental and energy performance of the UCD sports centre.

Table 10 presents estimation results on performance objectives. Experts fill many low-effect levels that indicate weak interactions among performance objectives (Table 10). For example, both cell (3,4) and (4,3) fill the value of E_1. The cause is that the relative humidity of Pool Hall (i.e. U_{12}) and the temperature of the whole building (i.e. U_{13}) have little effect on each other. This study forms pairwise comparison matrices based on these effect estimation results. For example, Table 11 shows the pairwise comparison

Table 8: The ANP model transformed from the scenario model.

Criteria	Sub-Criteria
U_1:Building Function	U_{11}:Maintain zone temperature, Pool Hall. U_{12}:Maintain zone RH, Pool Hall. U_{13}:Maintain zone temperature, Gym.
U_2:Energy Consumption	U_{21}:Minimise energy consumption, Boilers. U_{22}:Minimise energy consumption, AHUs. U_{23}:Minimise energy consumption, Pumps.
U_3:Thermal Load	U_{31}:Minimise heating load, Building. U_{32}:Minimise heating load, Pool zone.

Table 9: Effect estimation between performance aspects as defined in the scenario model for the UCD Sports Centre.

	U_1	U_2	U_3
U_1	E_5	E_4	E_3
U_2	E_2	E_5	E_2
U_3	E_2	E_4	E_5

matrix for U_{11}, U_{12}, U_{13}, which regards U_{11} as reference sub-criteria.

Table 10: Effect estimation between performance objectives as defined in the scenario model for the UCD Sports Centre.

	U_{11}	U_{12}	U_{13}	U_{21}	U_{22}	U_{23}	U_{31}	U_{32}
U_{11}	E_5	E_3	E_2	E_4	E_4	E_3	E_3	E_4
U_{12}	E_3	E_5	E_1	E_2	E_3	E_1	E_2	E_2
U_{13}	E_2	E_1	E_5	E_3	E_3	E_2	E_2	E_2
U_{21}	E_1	E_1	E_1	E_5	E_1	E_1	E_1	E_1
U_{22}	E_1	E_1	E_1	E_1	E_5	E_2	E_1	E_1
U_{23}	E_1	E_1	E_1	E_1	E_1	E_5	E_1	E_1
U_{31}	E_1	E_1	E_1	E_4	E_4	E_2	E_5	E_2
U_{32}	E_1	E_1	E_1	E_2	E_2	E_2	E_2	E_5

This demonstration uses pairwise comparison matrices to calculate 24 local weight vectors. These vectors can comprise a weighted supermatrix (i.e. $\underline{W}$, see Eq. 13). The limited supermatrix (i.e. $\overline{W}$) calculation reaches

Table 11: A pairwise comparison matrix of sub-criteria in the scenario model for the UCD Sports Centre

U_{11}	U_{11}	U_{12}	U_{13}
U_{11}	$(1, 1, 1)$	$(9/2, 5, 11/2)$	$(13/2, 7, 15/2)$
U_{12}	$(2/11, 1/5, 2/9)$	$(1, 1, 1)$	$(5/2, 3, 7/2)$
U_{13}	$(2/15, 1/7, 2/13)$	$(2/7, 1/3, 2/5)$	$(1, 1, 1)$

the convergence point when the power of the weighted supermatrix is bigger than the 88^{th} power (shown in Eq. 14). All column vectors in the supermatrix have the same value and the first vector of the supermatrix is selected as the relative weights of sub-criteria.

$$\underline{W} = \begin{bmatrix} 0.565656 & 0.160754 & 0.104442 & 0.124926 & 0.119999 & 0.124926 & 0.107462 & 0.127931 \\ 0.141414 & 0.565172 & 0.059323 & 0.022152 & 0.039999 & 0.022152 & 0.035821 & 0.025586 \\ 0.070707 & 0.051852 & 0.614013 & 0.052922 & 0.039999 & 0.052922 & 0.035821 & 0.025586 \\ 0.037037 & 0.037037 & 0.037037 & 0.490909 & 0.054545 & 0.044252 & 0.030082 & 0.030082 \\ 0.037037 & 0.037037 & 0.037037 & 0.054545 & 0.490909 & 0.083064 & 0.030082 & 0.030082 \\ 0.037037 & 0.037037 & 0.037037 & 0.054545 & 0.054545 & 0.472684 & 0.030082 & 0.030082 \\ 0.055556 & 0.055556 & 0.055556 & 0.166667 & 0.166667 & 0.099999 & 0.639318 & 0.091331 \\ 0.055556 & 0.055556 & 0.055556 & 0.033333 & 0.033333 & 0.099999 & 0.091331 & 0.639318 \end{bmatrix} \tag{13}$$

$$\overline{W} = \begin{bmatrix} 0.2216 & 0.2216 & \dots \\ 0.1249 & 0.1249 & \dots \\ 0.1104 & 0.1104 & \dots \\ 0.0666 & 0.0666 & \dots \\ 0.0712 & 0.0712 & \dots \\ 0.0657 & 0.0657 & \dots \\ 0.1901 & 0.1901 & \dots \\ 0.1495 & 0.1495 & \dots \end{bmatrix} \tag{14}$$

4.3. Results

This demonstration collected two types of data sources to evaluate performance metrics defined within the scenario model (see Figure 5). One source is measured data from the building as extracted using the Cylon system and at a resolution of 5 minutes. The source provides sufficient time-series data for four of the previously listed performance objectives. Another source is energy simulation results from a calibrated EnergyPlus model due to the absence of required sensors. The source provides energy data for the four remaining performance objectives

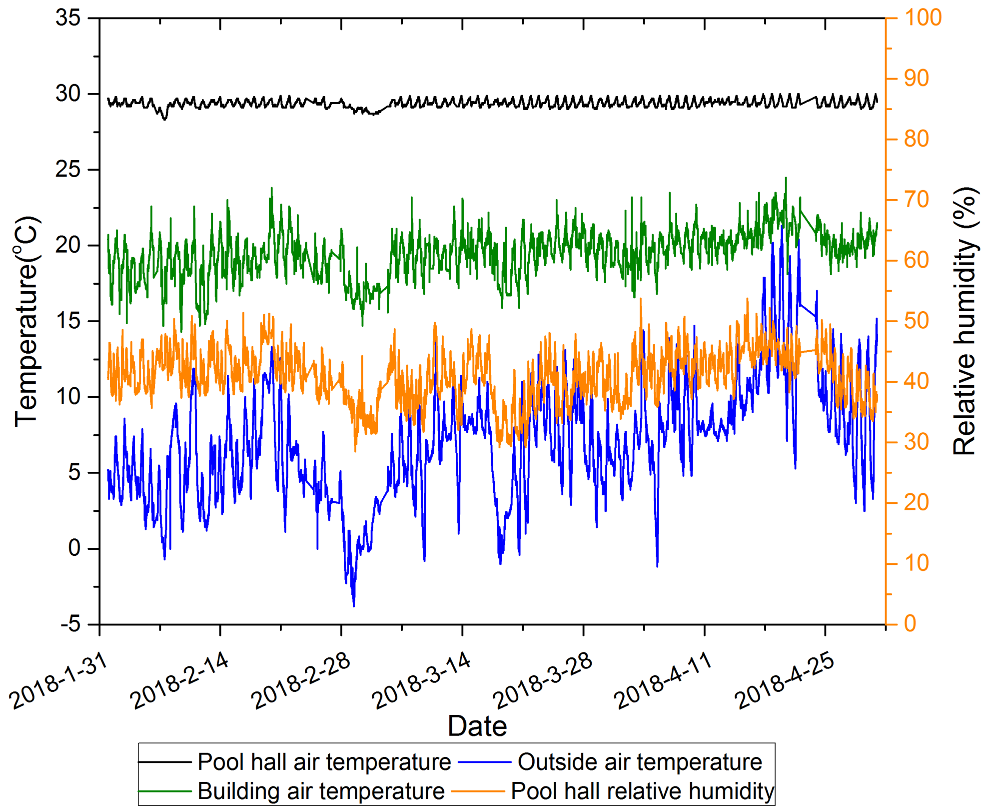

Figure 6: Assessment results of zone air temperature and relative humidity.

A clear picture emerges of the thermal comfort conditions in the building through the evaluation of a scenario model for an arbitrary 3-month period (i.e. Figure 6). The period is set from February to April 2018 when the outside temperature varied notably as the region transitioned from Winter to Spring. A closer look at the first two objectives related to the pool hall indicates that the zone conditions adhere to the specified functional intent. The temperature of the zone remains at 30 ^{o}C while relative humidity bounds of 35–50%.

The case study collected measured dry-bulb temperature values for specific important zones within the building (e.g. the changing room, gym, gym studio and pharmacy) as inputs for the temperature performance-objective of the whole building. The indoor temperature of the building indicates the mean temperature of each respective zone (e.g. values between 18-22 ^oC). According to thermal comfort status defined in ASHRAE 55-2010 [50], the indoor temperature of the building could be labelled as 'comfortable' as the temperature is above the lower bound of the acceptable range for adaptive thermal comfort. Using the adaptive thermal comfort approach [51], people tend to expect and accept lower temperatures in the winter or cold climates. The indoor temperature can be generally labelled as 'neutral' by taking the outside temperature (i.e. between 0-12 ^oC) into consideration

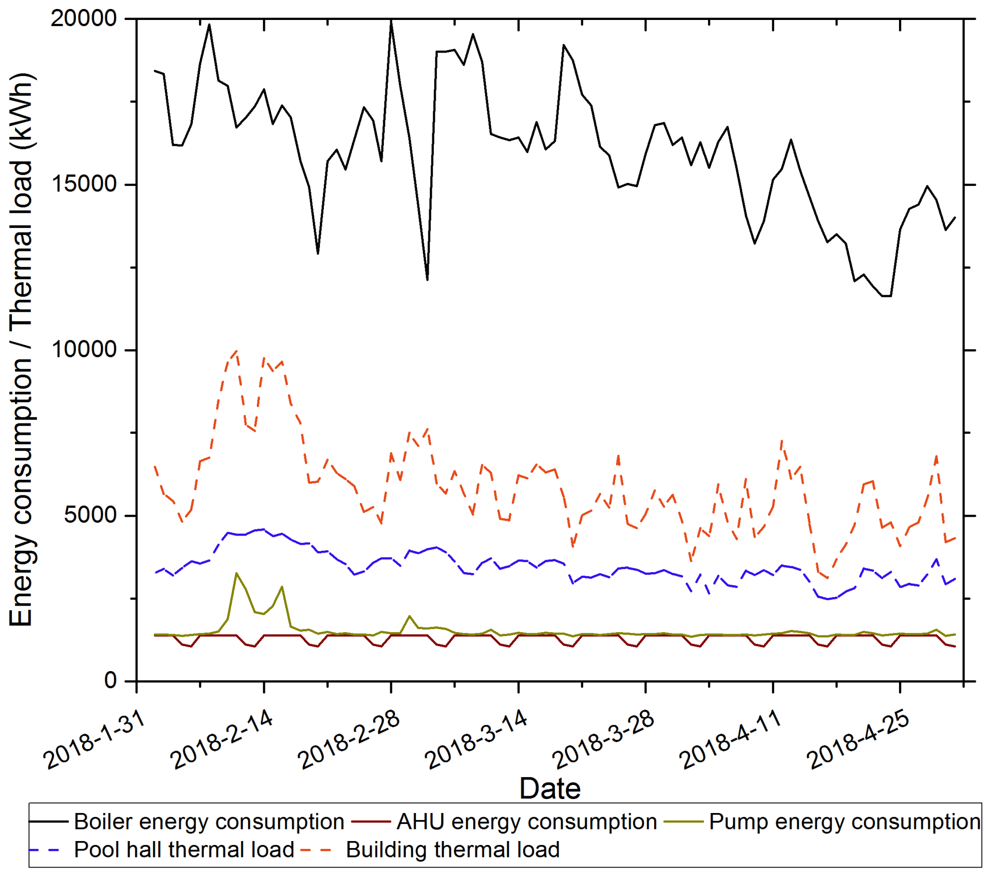

Figure 7: Assessment results of energy consumption for HAVC devices and important thermal loads.

Another performance analysis perspective evaluates the remaining performance objectives for energy consumption and thermal load of the building respectively (Figure 7). Due to the cold weather during part of the time-period in question, the two boilers consumed significant quantities of energy (15000-20000 kWh per day) in order to satisfy the heating demand. AHUs and pumps consume far less and are relatively consistent consumers of energy (i.e. around 1300 kWh per day). Regarding the thermal load, the pool hall is a substantial indoor space with very specific temperature requirements of 30 ^oC and accounts for the majority of the heating load. This study calculated thermal load of the building by summing thermal load for all zones in the building per measurement time-step. Since the building contains many other zones with diverse HVAC schedule, the thermal load of the building shows larger fluctuations compared to the pool hall on its own.

The case study applies the BREEAM-based performance classification scale (Section 3.4) to assist experts to evaluate performance objectives based on results shown in Figure 6 and Figure 7. The mean value of each performance label (e.g. unclassified and pass) indicates a reasonable number to calculate the final score of the scenario model. For example, the value of the label 'Good' can be calculated as $(45 + 55)/2 = 50$. Eq. (12) defines a membership function to compute the final score for energy performance assessment with sub-scores (Table 12).

Table 12: Performance classification of performance objectives as defined in the scenario model for the UCD Sports Centre.

Sub-criteria	Label	Weight
U_{11}	Excellent	0.2216
U_{12}	Excellent	0.1249
U_{13}	Very good	0.1104
U_{21}	Pass	0.0666
U_{22}	Good	0.0712
U_{23}	Good	0.0657
U_{31}	Pass	0.1901
U_{32}	Good	0.1495
Total score	56.9	
Total label	Very good	

The demonstration uses two types of relative weights to compute the final score in order to validate the effectiveness of the approach. The first type is the relative weights calculated by the approach (Table 12). The score of the scenario model is 56.9 which can be identified as 'Very good' according to the scale. The other type of relative weights assumes all sub-criteria defined in the scenario model are of equal importance. The model defined in this paper uses eight sub-criteria to assess environmental and energy performance of the building. Their relative weights can be calculated through dividing 1 by the sub-criteria number (i.e. 8). The weight vector is $(0.125, 0.125, 0.125, 0.125, 0.125, 0.125, 0.125, 0.125)^T$. This differs from the first result and the final score changes to 54.3 using these equal weights and operation is subsequently categorised as 'Good'.

4.4. Discussion

Several findings arise from the case study. First, the approach enables objective and precise relative weights for obtaining in-depth building environmental and energy performance assessment. Two types of relative weightings in the case study lead to two different assessment results (Table 12). The result based on the former look more comprehensive and better than the latter as the building has better intermediate results on important sub-criteria. For example, sub-criteria under criteria U_1 take the largest relative weight (i.e. 0.45) and obtain better performance scores compared to sub-criteria under other two criteria (i.e. U_2, U_3). In particular, the sub-criterion U_{11} has the biggest relative weight as the comfort indoor temperature is of paramount importance for a swimming pool. The sub-criterion reaches the 'Excellent' performance level as a result of the constant indoor temperature in the zone.

A second finding is that the approach can offer enhanced assessment results when analysing buildings' environmental and energy performance. Using the approach, building managers can assess historical and real-time environmental and energy performance and present the results through an intuitive real-time dashboard. The results contain two types of information: 1) is an overall performance score, with which building managers can generally judge if a building performs efficiently or not during operation and 2) contains relative weights and intermediate results for all sub-criteria. This combined information set can facilitate deeper analysis to support operations by building managers.

Furthermore, there are a number of limitations to this approach. Although scenario modelling provides a flexible and multi-granular assessment solution for a wide range of building typologies, building managers may need to perform small adjustments on the criteria selection when applying the approach to new buildings with different data streams and functional requirements. Engineering experts are responsible for finishing the pair-wise comparisons of criteria. The adoption of new performance criteria will bring additional comparison workload for these experts. The relative weights could vary due to subjective interpretation of performance indicators within some scenario models but could be tuned over time.

Finally, a number of prerequisites also arise from this approach. The evaluation of performance indicators (i.e. sub-criteria) requires datum streams from cross-domain data silos, which include measured records from sensors deployed in buildings and energy simulation results from an appropriately calibrated Building Energy Performance Simulation (BEPS) model. For many buildings only subsets of performance metrics will be calculable due to the absence of sensing data or simulation results. Installation of additional sensors may also be required in older buildings to obtain specific information related to environmental and energy performance (e.g. occupant behaviour). Calibration of a BEPS model requires burdensome interpretation and manipulation from engineering experts on building geometry transforming, construction material mapping, HVAC system deployment, and occupant behaviour modelling.

5. Conclusions

The well-recognised gap between measured and predicted building environmental and energy performance can be categorised as a multifaceted problem. In order to better analyse causes of the gap, multiple indicators play a key role in comprehensively evaluating energy performance of a given building. Some practical frameworks leverage multiple indicators to assess building environmental and energy performance. Significant technical challenges exist around the relative weight analysis to handle the fuzziness of expertise and complicated interactions between indicators. The constant assessment structure falls short in satisfying the unique data-set and function requirements of buildings.

This paper proposed and demonstrated a novel method for building environmental and energy performance assessment by integrating scenario modelling and Fuzzy Analytic Network Process. Scenario modelling decompose energy performance assessment into a set of mappings between multiple criteria and multi-granular building objects. Fuzzy Analytic Network Process serves as the main theoretical basis for the formation of pairwise comparison matrices using expertise and calculation of relative weights by quantising interrelationships among criteria with a mathematical model. A case study demonstrated the approach based on measured and simulated building energy data collected at University College Dublin's sports centre.

With this method, managers of commercial buildings or organisations that decompose functional intent and energy consumption in a hierarchical context-based manner can conduct in-depth and comprehensive building performance assessment through an easily navigable and holistic pathway. These results can assist identification of areas of inefficient operations while still maintaining building functions. Then these managers have reliable information when formulating energy efficient action plans with other stakeholders within an organisation. Better informed energy-related decisions can be made by upper management to improve building environmental and energy performance. Compared with traditional solutions, this novel method reduces the need for burdensome reinterpretation and conversion from engineering experts during the relative weight calculation process.

Another finding is that the approach provides a flexible and modular solution that is applicable for a wide range of buildings. The scenario modelling method provides a multi-granular mapping structure for building environmental and energy performance assessment. The structure significantly improves flexibility of mappings between performance indicators and building objects and allows the description of the approach for buildings in different climate zones and geographical locations. Engineering experts can setup a library of key performance indicators and form pairwise comparison on these indicators with triangular fuzzy scales. The library enables dynamic calculation of relative weights when different criteria are used to assess environmental and energy performance of new buildings. The library also can be shared with other engineers in turn and is updatable when new indicators are designed for building energy performance.

Future work will focus on integrating this approach with Fault Detection and Diagnosis algorithms [52]. The approach could also be used to analyse occupant behaviour [53] in buildings.

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