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Multi-Objective Optimization for Flexible Building Space Usage

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***Abstract*—Globally, more than 30% of the world's energy consumption arises in buildings. Optimization of buildings is a key opportunity for reducing energy consumption and carbon emissions, improving operational efficiency and occupant well-being and comfort. While building generative design and control systems have received considerable research attention, optimizing space utilization, particularly for flexible spaces is an under-developed research area that is relevant to existing buildings. Flexible spaces, for example, rooms with movable walls, are increasingly common in modern building designs where space requirements are dynamic. In this paper, a novel space usage optimization framework is proposed, including a practical task formulation that enables room reallocation, combination and removal, a machine learning model for energy cost estimation (XGBoost) based on real sensor data and a multi-objective optimization component to minimize energy consumption and maximize room thermal comfort simultaneously (NSGA-II). Its effectiveness is tested and discussed through two representative problem scenarios. Our case studies show that we can reduce energy cost substantially by around 40% in comparison with the original space usage setting, while additionally improving thermal comfort for the occupants. This work shows great potential of using AI techniques for optimizing building space usage.**

***Index Terms*—Building Optimization, Building Space Management, Flexible Space Utilization, Energy Optimization, Multi-Objective Optimization, Machine Learning**

I. Introduction

Buildings contribute to more than 30% of the world's energy consumption, with 17% of carbon emissions attributed to heating and cooling in buildings [1], [2]. The challenge of improving building energy efficiency has become a research focus over the past few decades [3]. Identifying potential optimal solutions will be crucial to addressing this challenge. Specifically, flexible building space usage, where the space can be redivided by moveable walls to meet working needs, can enhance the energy efficiency of buildings by optimizing space utilization. As behaviours in the modern workforce and workload develops, requirements need to be mirrored in contemporary workspaces. Furthermore, since the COVID-19 pandemic, many workers have adopted a blend of online and offline work in the real world, directly resulting in a decrease in the efficiency of building space utilization [4]. This shift in work patterns also increases the importance of researching flexible building space usage.

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Optimizing building space usage needs to consider conflicting criteria, such as energy consumption vs. thermal comfort of indoor environment [5]. In general, as the indoor environment becomes more comfortable for occupants, energy consumption also increases. To estimate building energy consumption, there are two main types of approaches: physical modelling and data-driven approaches [2]. Physical modelling approaches simulate energy consumption based on the understanding of detailed building and environmental parameters and developing a complex physics-based mathematical formulation of the problem. Examples of software that adopt such modelling approaches are EnergyPlus and eQuest. However, this information is not always available. In contrast, data-driven prediction methods rely on data from installed sensors and employ machine learning (ML) algorithms to learn and predict energy consumption. They are easy to apply and have already been used in building energy management and occupancy analytics research [6] [7]. For the second criterion, thermal comfort is defined as "the condition of the mind in which satisfaction is expressed with the thermal environment" [8], [9]. It is derived from calculating the Predicted Mean Vote (PMV) [10] value associated with occupancy. In [11], the PMV can be used to predict comfort conditions in buildings with heating, ventilation, and air-conditioning (HVAC).

In building optimization, initially, research efforts were focused on building envelope design and control systems [5], [12], [13], while research focused on building space optimization still needs to be explored, particularly regarding flexible building space usage. In [14], the authors optimize the space layout planning and formulate it as a linear assignment minimization problem. While their work is related to optimizing building space, they focus solely on space allocation rather than space usage. In [15], the authors focus on space use efficiency in academic buildings. Space use efficiency is referred to as ensuring space availability for certain activities while decreasing the building costs and increasing the usage time. This is early work in this area by only allowing room removals, so the optimization strategy for space usage lacks flexibility.

This paper aims to offer the data-driven multi-objective optimization framework, which has the following benefits: 1) enabling flexible building space usage to improve building space efficiency; 2) having great applicability without requiring physical models of buildings; 3) allowing conflicting objectives in optimisation. The contributions of this work are listed as follows:

- We formulate the novel task of building space optimisation that enables flexible space usage. The formulation includes a mathematical model that considers two conflicting objectives (energy consumption and thermal comfort) and practical actions on room changes (room division, combination and removal) in collaboration with building domain experts.
- A ML algorithm, called eXtreme Gradient Boosting (XGBoost) [16], is used to learn the objective function of energy consumption, based on a dataset including a wide range of sensor data (i.e., indoor temperature data, indoor humidity data, occupancy data, energy data and outdoor environmental data).
- A multi-objective optimization algorithm, named Nondominated Sorting Genetic Algorithm II (NSGA-II) [17], is used to find the optimal solutions for a given floorplan with two types of rooms (i.e., office and meeting rooms).
- Through exploration of two case studies, we demonstrated the potential of the proposed method for reducing energy costs while improving occupants' thermal comfort.

The paper is organized as follows: Section II details the literature review. Section III presents the problem formulation related to flexible building space usage and the mathematical formulas for multi-objective optimization. Section IV describes the whole framework of flexible building space usage optimization. Section V offers two case studies along with experimental results obtained through the application of this algorithm. Finally, Section VI concludes the paper.

II. Literature Review

In this section, we first review the optimization research in the smart building field from three aspects: problem formulation, objective functions, and optimization methods. The new challenges introduced by flexible building space usage optimization compared to traditional space optimization are pointed out. We also briefly introduce the NSGA-II for multi-objective optimisation [17]. Then, we review the mainstream ML methods used to predict energy consumption and justify the choice of using XGBoost in this research.

A. Optimization Methods in Smart Buildings

With regard to energy consumption and thermal comfort in building optimization, there are three main research areas: building architectural design, building control systems, and building space efficiency. In [5], [12], the authors focus on building architectural design, such as building orientation, window–wall ratio, wall heat transfer coefficient, and more. They consider at least two objectives: energy consumption and thermal comfort. NSGA-II is applied to identify sets of optimal solutions. In [13], the authors focus on the HVAC control system to balance indoor air quality, thermal comfort and energy consumption. The authors utilize a hybrid model incorporating the extreme learning machine [18] and the grey wolf optimizer [19] to predict and optimize indoor environments without increasing energy consumption. For the last aspect, there has been relatively limited previous research in optimizing building space usage, especially flexible building space usage. In [14], the authors focus on the space layout problem, a classical layout problem [20] to address the assignment of activities to building spaces. They formulate the multi-objective optimization problem as a linear assignment minimization problem, considering three metrics: energy consumption, occupant flow pattern, and occupant dissatisfaction. While they concentrate on optimizing building space, their work centres more on reallocating the original rooms within a given space rather than optimizing building space usage. In [15], the authors focus on space use efficiency in academic buildings. Four indicators are developed for space use measurement, including proportion of usage status, probability of concurrent usage, planned occupancy rate and maximum possible occupancy rate. Based on the results of the four indicators, the potential optimization operation involves closing a small lecture hall, resulting in a 6% reduction in the combined energy usage of all eight investigated lecture halls. Although their work can identify rooms that are not needed, their identified solutions are not optimal in the sense that rooms are often used below capacity. Different from the aforementioned work, our framework includes a flexible building space optimization strategy to reallocate room areas and types, and adjust the number of rooms. The method we provide aims to optimize energy consumption and thermal comfort simultaneously, considering a flexible optimization strategy.

This paper adopted the well-known NSGA-II to solve the multi-objective optimization problem. NSGA-II is a classic multi-objective evolutionary algorithm. By employing the Pareto nondominated sorting and crowding distance to distinguish between solutions, NSGA-II can provide a set of high-quality trade-off solutions. This makes it well suited to navigating the large number of possible solutions in flexible building space optimization, where an exhaustive evaluation would be computationally demanding. One reason we choose NSGA-II is that the algorithm can maintain the diversity of solutions in bi-objective cases (due to the nature of the used crowding distance [21]), as our optimization problem falls into. In addition, NSGA-II has been frequently used in building optimization [5], [12].

B. Machine Learning Techniques to Predict Energy Consumption

To predict the energy consumption of smart buildings, various regression ML techniques have been adopted, including random forest (RF), support vector regression (SVR), artificial neural networks (ANNs), and eXtreme Gradient Boosting (XGBoost) [1], [22], [23]. Given building sensor information as inputs, including indoor environmental data, occupancy, HVAC control, outdoor environmental data and building structural parameters, the estimated energy consumption is the output of the learning task. This estimation can be used in energy usage optimization as a key objective function. We need an accurate and reliable estimation to guarantee an optimal building control strategy.

Our paper adopts the XGBoost algorithm to train the regression model. XGBoost is a scalable end-to-end tree boosting system recognized for its efficiency and flexibility. It is based on the gradient-boosting decision tree, which builds an ensemble of weak learners with the new weak learner to fit the predicted residual. The final predicted result is obtained by summing the scores in the corresponding leaves [16], [24].

III. Problem Formulation for Flexible Building Space Optimization

In this section, we define the flexible building space usage problem. On one building floor, we assume that rooms (such as offices and meeting rooms) constitute an entire space, and the walls between the rooms are movable. We aim to tackle the challenge of reallocating and flexibly utilizing the building space, specifically the problem of redividing the overall space into different independent rooms. Based on the assumptions, we then translate the problem into a multi-objective optimization model. We aim to find a set of optimal room division solutions under certain constraints, considering the energy cost and thermal comfort simultaneously.

A. Assumptions, Decision Variables and Output

1) Assumptions: We first outline the assumptions regarding time availability in both offices and meeting rooms. The available office time is assumed to be suitable for all occupants without considering any conflicting office usage hours. As for the meeting rooms, we are presently not factoring in the consequences of reducing the number of meeting rooms on the schedule, including potential conflicts or meeting cancellations due to the reduced availability of meeting rooms. As a surrogate for the simulation of the meeting schedule, we assume each meeting room is available for 8 hours and use the number of meetings and the number of participants in each meeting to calculate the meeting room utilization rate and establish the necessary constraints. The total sum of room areas and the overall number of occupants remains constant.

2) Decision Variables: A solution for the flexible space is given by X which is an array of rooms where each row represents a different room and each column contains room information as in Table I.

3) Output: The output of f_{cost} is the estimated energy cost for the entire space, given as an area-independent unit-less value. The thermal comfort for all occupants is given by f_{tc}, which uses the sum of absolute PMV values (See Fig.1) to measure the total deviation from comfortable conditions.

B. Mathematical Model

The mathematical model of two-objective optimization for flexible building space usage is defined as:

$$\text{Minimize} \quad f_{\text{cost}} = \sum_{i=1}^{n} (w_i \cdot \text{Model}_{\text{ML}}(X_{i,rt}, X_{i,rh}, \ldots X_{i,occ}, d_{oe})) \quad (1)$$

$$\text{Minimize} \quad f_{\text{tc}} = \sum_{i=1}^{n} (|\text{PMV}(X_{i,rt}, X_{i,rh})| \cdot X_{i,occ}) \quad (2)$$

$$\begin{aligned} \text{Subject to} \quad & X_{i,occ} \leq mc_i, \quad i = 1, \ldots, n \\ & n_{occc} = \sum_{i=1}^{n} X_{i,occ} \\ & \sum_{i=1}^{n_{mr}} \sum_{j=1}^{n_m} ut_{ij} \leq \sum_{i=1}^{n_{mr}} at_i \end{aligned} \quad (3)$$

- f_{cost} and f_{tc} are the objective functions of cost and thermal comfort respectively.
- X describes the division of the entire space into separate rooms and for each, contains information about the availability, room type, room status, area, maximum capacity, temperature, humidity and number of occupants.
- n is the number of rooms, which is equal to the number of rows in X, and the i-th room is represented by i.
- $w_i = \frac{X_{i,\text{area}}}{\sum_{i=1}^{n} X_{i,\text{area}}}$, the weighting for each room is used with a machine learning model for estimating the room cost, denoted as Model_{ML}, which takes inputs of $X_{i,rt}$, $X_{i,rh}$, $X_{i,occ}$ and d_{oe}. Weighting allows the area-independent energy cost prediction to be scaled to the total area.
- $X_{i,\text{area}}$ represents the room area in the i-th room.
- $X_{i,rt}$ represents the room temperature in the i-th room.
- $X_{i,rh}$ represents the room humidity in the i-th room.
- $X_{i,occ}$ is the number of occupants in the i-th room.
- d_{oe} represents the outdoor environmental data, for example, outdoor temperature and humidity which impacts the cost of occupied rooms.
- PMV is an index used to predict the mean value of votes of a group of occupants on a seven-point thermal sensation scale shown in Fig. 1 [25], [26].
- In the constraints, mc_i is the maximum capacity of room i, n_{occ} is the number of total occupants, n_m and n_{mr} are the number of meetings and meeting rooms, respectively, ut is the usage time and at is the available time for a meeting room, for example, ut_{ij} represents the usage time of the j-th meeting in the i-th room.

An array Z is defined following the encoding in Table I, which contains the fixed initial temperature and humidity information as 'zones' and is required to calculate the objective values for solutions.

TABLE I
ROOM ENCODING AND TEMPERATURE AND HUMIDITY ZONES

Room Encoding				
Availability	0 (permanently closed)	1 (temporarily closed)	2 (used)	
Type	0 (office)	1 (meeting room)		
Status	0 (not used)	1 (used individually)	2 (combined rooms)	3 (divided rooms)
Area ($\mathbf{m^2}$)	$X_{i,\text{area}}$ (room area)			
Maximum capacity	mc_i (maximum capacity)			
Temperature (°C)	$X_{i,rt}$ (room temperature)			
Humidity (%)	$X_{i,rh}$ (room relative humidity)			
Occupants	$X_{i,occ}$ (number of occupants)			
Temperature and Humidity Zones				
Area ($\mathbf{m^2}$)	$Z_{j,\text{area}}$ (zone area)			
Temperature (°C)	$Z_{j,zt}$ (zone temperature)			
Humidity (%)	$Z_{j,zh}$ (zone humidity)			

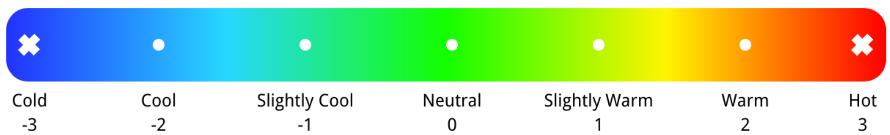

Fig. 1. PMV index for individual occupant thermal comfort [26]

IV. FLEXIBLE BUILDING SPACE USAGE OPTIMIZATION

In this section, we present the framework of flexible building space usage optimization. In room encoding and updating rules, we explain how to initialize room settings and adjust the room usage. In the subsequent subsections, we introduce the public dataset used to train the model, the ML algorithm to predict the energy cost and the adapted NSGA-II used to find optimal solutions. The code can be accessed by GitHub using this link: https://github.com/soda-bread/CAI-2024_Flexible-Building-Space-Usage-Opt/tree/master.

A. Room Encoding

Table I explains the room encoding that forms the potential solutions. Eight parameters are designed to characterize fundamental room features, encompassing availability, type, status, area, maximum capacity, temperature, humidity, and occupants. All input values are numerical. Room type and usage status are encoded with integers, while the remaining variables are represented by their corresponding numerical values.

B. Updating Rules

For operations involving the update of the room encoding list, we consider three distinct optimization strategies to modify room occupancy usage. These strategies include combining rooms, dividing a room into two smaller rooms, and removing a room. Detailed update rules are shown below.

The flow chart of these operations is shown in Fig. 2. For each solution in a generation, the algorithm uniformly at random selects one of the three update rules (i.e., combining, dividing, removing) and applies the corresponding modification to a room. Then, it invokes the check function to verify whether all updated rooms meet the constraints, i.e., the number of occupants with maximum capacity and the designated usage time for meeting rooms. Finally, the algorithm updates the temperature and humidity values of each room based on the initially provided temperature and humidity zones.

1) Combining Rules: First, check if the number of rooms is greater than 1. Then, randomly select two rooms with adjacent room numbers, i.e., only adjacent rooms are allowed to combine. Verify that the room types are the same. Create the new room and update the maximum capacity, area, and number of occupants.

2) Dividing Rules: First, randomly select a room number to designate as the room to be divided. Next, generate two new rooms and update the maximum capacity, area, and number of occupants. The division of the original room is carried out as evenly as possible, with the area, maximum capacity and occupancy of the new rooms being half of those of the original room. In cases where the number of occupants in the original room is odd, a random selection is made to assign the last remaining occupant to one of the two divided rooms. The same applies to the maximum capacity.

3) Removing Rules: Initially, randomly select a room number for removal. Subsequently, remove the room by updating the "Status" from 1 to 0 and the "Availability" from 2 to 1 (See Table I). The room is temporarily closed and unavailable for use and therefore does not contribute to cost and has a zero thermal comfort, but the physical space allocated to the room is preserved. It means that when computing the total area of all rooms, the area of the removed rooms will still be included in the calculation, maintaining the overall total area unchanged.

4) Checking Rules: To satisfy the constraints outlined in Equation 3 above, we have defined two functions for validating generated rooms. The first function checks whether the number of occupants is less than or equal to the maximum capacity in

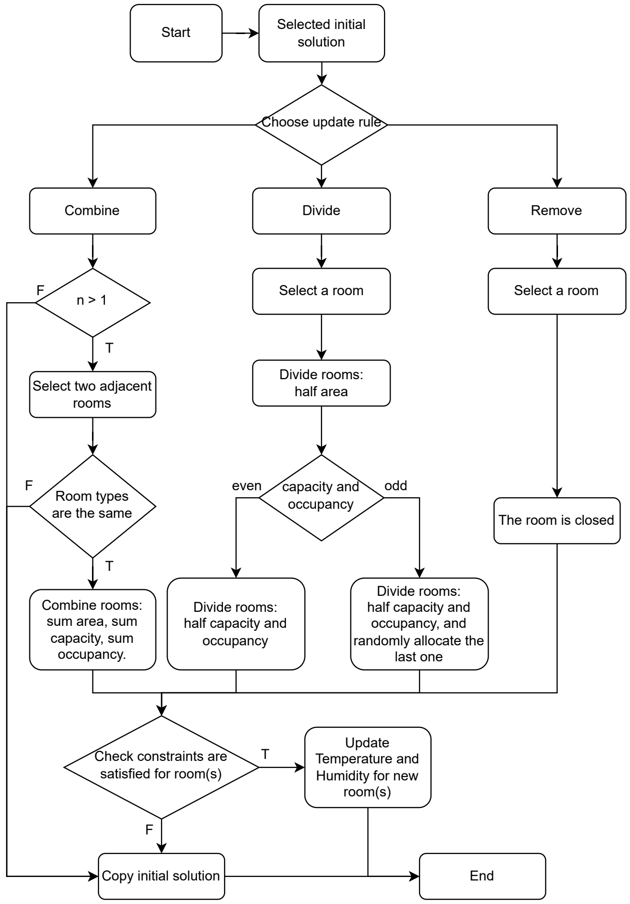

Fig. 2. Flow chart of room updating rules

each room. The second function verifies that the usage time is less than or equal to the available time of meeting rooms. If the newly generated solution meets all constraints, it will be recorded; otherwise, the original solution will be retained.

5) Updating Temperature and Humidity Rules: The temperature and humidity values of the rooms are updated based on the initial temperature and humidity in Z. The process of calculating these values can be expressed as follows:

$$X_{i,rt} = \sum_{j=1}^{|Z|} \frac{X_{i,area} \cap Z_{j,area}}{X_{i,area}} \cdot Z_{j,zt} \quad \text{for} \quad i = 1, \ldots, n$$
$$X_{i,rh} = \sum_{j=1}^{|Z|} \frac{X_{i,area} \cap Z_{j,area}}{X_{i,area}} \cdot Z_{j,zh} \quad \text{for} \quad i = 1, \ldots, n \tag{4}$$

where $X_{i,rt}$ and $X_{i,rh}$ are the updated room temperature and humidity, we use the notation $X_{i,area} \cap Z_{j,area}$ here to mean the overlapping area of the room i with the zone j. Presently, we consider the temperature and humidity to be static (not evolving with time to allow equilibration) while solving the optimization problem; the inclusion of heating devices and vent locations is a future direction.

C. Building Operation Dataset Description

The dataset utilized to train the ML algorithm is sourced from a room-level and building operation dataset [6] and was collected by sensors from five rooms including two lecture rooms, two offices and one library. This dataset contains indoor environmental data, energy data, HVAC operations data, outdoor weather data, Wi-Fi and occupancy data. In our work, we utilize the indoor environmental data, the energy data, the occupancy data, and the outdoor weather data to build a regression model for energy cost estimation. We only use the data from four rooms, comprising two offices and two lecture rooms, and assume to treat the lecture rooms as meeting rooms. Because the occupancy duration in lecture rooms is similar to that in meeting rooms.

D. Machine Learning Algorithms to Predict the Energy Cost

To estimate the energy cost, we adopt the XGBoost algorithm [16] to train a regression model based on the dataset described above. The model learns the mapping from the input including indoor environmental data, occupancy data and outdoor weather data to the output including all indoor energy consumption data. We utilize Optuna [27] to discover optimal hyper-parameters, train the model, and leverage the well-trained model to predict the energy cost when provided with a set of input data. Detailed training process can be seen in the Section V.

E. Optimization Using NSGA-II

To find high-quality solutions and establish a baseline for the multi-objective optimization problem formulated above, we employ the well-known NSGA-II. In our approach, for generating new solutions (i.e., new rooms), we replace the mutation operators of NSGA-II with the updating rules as in Fig. 2. This is necessary due to the novel solution encoding introduced for this problem, which also prevents the straightforward application of crossover operators.

V. Results

We first perform hyper-parameters tuning of XGBoost using Optuna. After 500 trials, the best hyper-parameter values (from their testing ranges) for the XGBoost regression model of offices are as follows: the maximum depth is 8 (3, 20), the number of estimators is 607 (100, 2000), and the learning rate is 0.138 (0.01, 0.3). For the model of meeting rooms, the best hyper-parameters from the same ranges are as follows: the maximum depth is 8, the number of estimators is 1396, and the learning rate is 0.115. Next, we train the XGBoost regression model for both meeting rooms and offices with their respective best hyper-parameters. Our evaluation metric is the Mean Squared Error (MSE). We conduct a thorough comparison of three regression algorithms (which are linear regression, neural network and XGBoost). XGBoost gives the lowest MSE of 0.135 and 0.264 for both the office and meeting room models.

In the case studies presented, our initial room settings are derived from the room encoding. To predict the energy cost

TABLE II
ROOM SETTINGS AND TEMPERATURE AND HUMIDITY ZONES IN CASE STUDY 1

Room Encoding						
Room number	1	2	3	4	5	6
Availability	2	2	2	2	2	2
Type	0	0	0	0	0	1
Status	1	1	1	1	1	1
Area ($\mathbf{m^2}$)	32	32	32	32	32	32
Maximum capacity	6	6	6	6	6	8
Temperature (°C)	22.5	23	23.5	23.2	22.9	22.2
Humidity (%)	85	82	80	83	86	89
Occupants	2	3	4	5	6	0
Temperature and Humidity Zones						
Area number	1	2	3	4	5	6
Area ($\mathbf{m^2}$)	32	32	32	32	32	32
Temperature (°C)	22.5	23	23.5	23.2	22.9	22.2
Humidity (%)	85	82	80	83	86	89

using XGBoost, we input the outdoor temperature as 25°C and outdoor humidity as 85%. For calculating the PMV result, we also set the airspeed to 0.1 m/s, the metabolic rate to 1 met, and the clothing level to 0.5 clo. For NSGA-II, the population size is set to 50 for both case studies, with a maximum of 50 generations for case study 1 and 80 generations for case study 2. The initial population is generated by applying the update rules randomly to 50 copies of the initial space layout. These update rules are the source of variation introduction in subsequent generations. The Empirical Attainment Functions (EAF) [28] for each case study are calculated from 40 repetitions and are included in the Supplementary Material.

A. Case Study 1

In case study 1, we consider a simple scenario: there are 6 rooms arranged in a row with a total area of 192 m^2, as shown in Fig. 3. The number of occupants is 20. Each room initially has an identical area (i.e., 32 m^2) and is arranged adjacent to each other, with a minimum requirement of 5 m^2 per room. Table II shows the initial room settings with the temperature and humidity zones. The constraints for meetings and meeting rooms are as follows: each meeting room has an available time of 8 hours; each meeting has a usage time of 1 hour; there are 6 meetings, and the maximum occupancy for each meeting room is 2.

We present the results from an example run for both initial and obtained solutions in Table III, implementing around 40% energy cost reduction with around 5% thermal comfort improvement. The objective optimization results are f_{cost} and f_{tc}, while f_{tc}/n_{occ} gives the per-occupant thermal comfort (see Fig. 1). After optimization using NSGA-II, the result is shown in Fig. 4. Unique solutions can share the same objective function values, (e.g. from similar closed spaces) resulting in a sparse non-dominated set. For example, Fig. 4 contains 50 non-dominated solutions with a variety of space utilization layouts. We select three points in this figure to illustrate the outcomes. Solution A represents the highest thermal comfort with the lowest total cost amongst the obtained solutions, while solution C represents the lowest thermal comfort with the highest total cost. Solution B represents a trade-off between the two objectives. Fig. 3 shows the initial room usage and obtained solutions after optimization.

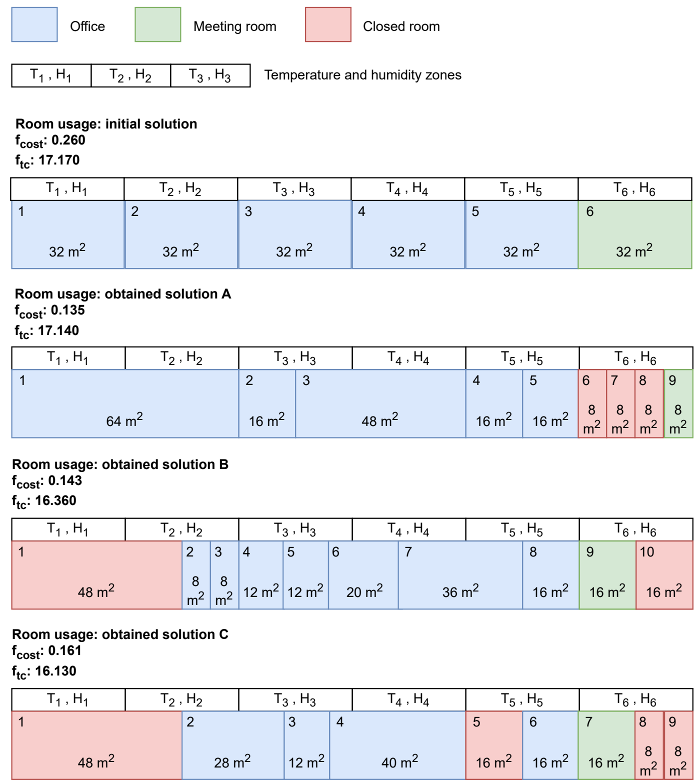

Fig. 3. Case study 1: Initial solution of room usage and example optimized solutions of room usage.

TABLE III
COST AND THERMAL COMFORT IN CASE STUDY 1

	Initial solution	Solution A	Solution B	Solution C
f_{cost}	0.260	0.135	0.143	0.161
f_{tc}	17.170	17.140	16.360	16.130
f_{tc}/n_{occ}	0.859	0.857	0.818	0.807

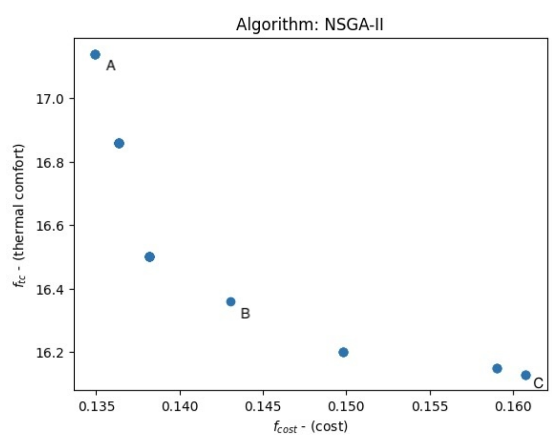

Fig. 4. Case study 1: Example NSGA-II result

Since the temperature and humidity zones (T_1, H_1 and T_6, H_6) have the least comfortable conditions according to the PMV calculation, closing rooms in these zones will greatly improve the thermal comfort. This is illustrated in solution C in both Figures 4 and 3. Similarly, solution A in these figures indicates that a combination of mixed office sizes, smaller meeting rooms and closed spaces can provide large reductions in energy costs.

TABLE IV
ROOM SETTINGS AND TEMPERATURE AND HUMIDITY ZONES IN CASE STUDY 2

Room Encoding											
Room number	1	2	3	4	5	6	7	8	9	10	11
Availability	2	2	2	2	2	2	2	2	2	2	2
Type	0	0	0	1	1	1	0	0	0	0	0
Status	1	1	1	1	1	1	1	1	1	1	1
Area ($\mathbf{m^2}$)	30	40	40	40	20	20	20	20	20	20	30
Maximum capacity	8	10	10	12	6	6	4	4	4	4	6
Temperature (°C)	22.7	23.4	23.0	23.0	22.6	23.0	23.3	23.5	23.5	23.1	22.9
Humidity (%)	87	84	82	85	88	85	84	82	82	83	85
Occupants	3	4	5	0	0	0	2	2	3	3	4
Temperature and Humidity Zones											
Area number	1	2	3	4	5						
Area ($\mathbf{m^2}$)	20	30	50	30	20						
Temperature (°C)	22.6	23.0	23.5	23.1	22.8						
Humidity (%)	88	85	82	83	86						

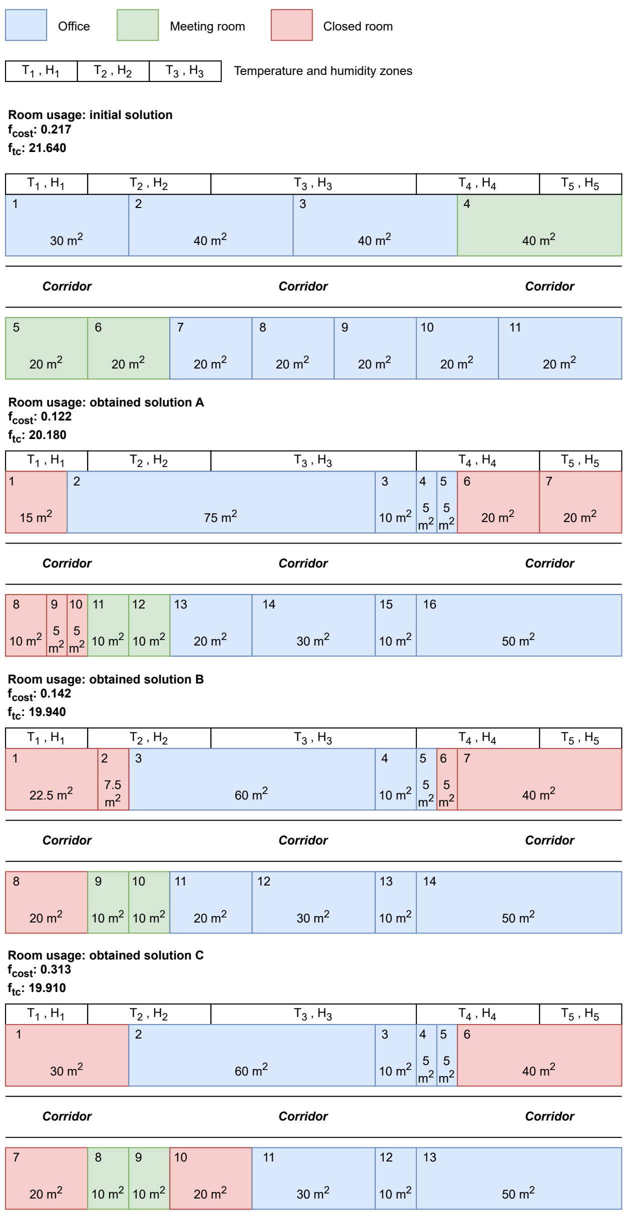

Fig. 5. Case study 2: Initial solution of room usage and example optimized solutions of room usage.

TABLE V
COST AND THERMAL COMFORT IN CASE STUDY 2

	Initial solution	Solution A	Solution B	Solution C
f_{cost}	0.217	0.122	0.142	0.313
f_{tc}	21.640	20.180	19.940	19.910
f_{tc}/n_{occ}	0.832	0.776	0.767	0.766

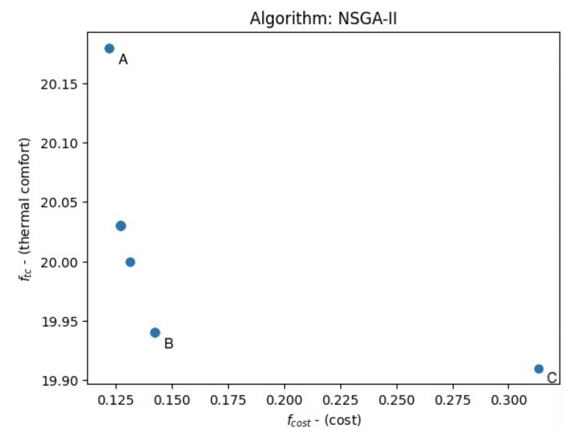

Fig. 6. Case study 2: Example NSGA-II result

B. Case Study 2

We consider a more complex and practical scenario in case study 2. There are 11 rooms arranged in two rows with a corridor in between, covering a total area of $300\,\mathrm{m}^2$ with 26 occupants. On the upper side, there are 4 larger rooms (room number: 1–4) which consist of 3 offices and 1 meeting room. On the lower side, there are 7 smaller rooms (room number: 5–11) comprising 5 offices and 2 meeting rooms. The rooms on the upper and lower sides are of different sizes, also maintaining a minimum requirement of $5\,\mathrm{m}^2$ per room. Table IV displays the initial room settings along with the temperature and humidity zones. The constraints for meetings and meeting rooms are as follows: available time for each meeting room is 8 hours; usage time for each meeting is 1 hour; there are 10 meetings, and the maximum occupancy for each meeting room is 3.

We present the results from an example run for both initial and obtained solutions in Table V with around 7% thermal comfort improvement. The obtained solutions are shown in Fig. 6. We choose three points in this figure to illustrate the different outcomes. Fig. 5 displays the initial room usage along with the obtained solutions.

The obtained solutions appear visually similar and improve the thermal comfort compared to the initial value. However, the differences in cost objective values are large. Thermal comfort improvements may largely be driven by reallocation of people to more comfortable spaces and the closing of rooms. These solutions show that the distribution of occupants across used spaces has a considerable impact on the cost and thermal comfort of the entire space. Therefore, further work can also consider the optimal allocation of people to flexible spaces.

VI. Conclusion

In this paper, we propose a data-driven optimisation framework for flexible building space usage that optimizes both energy cost and thermal comfort functions simultaneously. XGBoost was used to learn the cost objective function with the real data from a public building operations dataset and PMV was used to calculate occupants' thermal comfort. NSGA-II was used to find a set of optimal solutions for the proposed multi-objective modelling. In the two case studies, we have demonstrated that our approach finds the optimal space settings that reduce energy cost and improve thermal comfort. In the near future, we will consider how to predict energy cost over time and how to perform optimization in dynamic environments. Additionally, we will consider case studies with more complex floor plans to better align with real-world scenarios.

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