DigiGuide: A DT-based Occupant Guiding System for Optimizing Comfort and Energy Consumption

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***Abstract*—Balancing occupant comfort while minimizing energy consumption is not trivial. Traditional methods rely on environmental control guided by occupant feedback but often fall short in addressing individual preferences effectively. This paper presents DigiGuide, an innovative system that leverages Digital Twin (DT) methodologies combined with multi-objective optimization algorithms to guide occupants to spaces that best meet their multi-variant comfort needs. DigiGuide forecasts future indoor environmental conditions and occupant states in real-time by relying on the DT of the physical environment. It then leverages a genetic algorithm to simultaneously optimize occupant movement guidance to balance comfort needs with energy efficiency. DigiGuide is validated using two realistic large-scale scenarios: a co-working open space and an airport in Paris, France. Results demonstrate that DigiGuide achieves an average of 18.2% lower discomfort with 8.6% lower energy consumption compared to baseline approaches.**

***Index Terms*—Digital Twin, Energy Efficiency, Occupant Comfort, Multi-objective Optimization**

I. Introduction

Buildings are among the largest contributors to global energy consumption [1], in part, due to the need for indoor comfort to support occupants' productivity and well-being [2]. Nevertheless, building occupants remain dissatisfied with indoor environments due to thermal conditions and noise levels [3]. Balancing energy savings with diverse, subjective occupant comfort needs (e.g., one person may prefer warmth and quiet while another desires a cooler, more social environment) is inherently challenging [4].

Traditional approaches adjust indoor environments based on occupant discomfort [5]. IoT devices are widely used to estimate comfort by analyzing occupants' activities, feedback, and body temperature [6]–[8]. However, accommodating diverse comfort preferences is challenging, as no single setting satisfies everyone. Additionally, indoor comfort is shaped by multiple interconnected factors. For example, adjusting temperature settings can unintentionally affect noise levels and perceived crowdedness, as occupants tend to gather in cooler areas during warmer months. Moreover, factors like noise and crowdedness cannot be directly regulated based on occupant feedback as easily as temperature.

Alternative approaches involve *occupant guiding systems*, which direct individuals to locations—such as specific rooms or workspaces—that better suit their comfort needs [9]. Previous research has explored how directing individuals based on their environmental preferences can enhance both comfort and energy efficiency [10], [11]. However, most work focuses solely on thermal comfort, overlooking the dynamic and multifaceted nature of occupant comfort. Also, they do not account for the dynamic environment and its impact. For instance, guiding occupants to one location may affect the indoor environment and comfort levels (e.g., noise/crowdedness levels) of other people. To address this, Digital Twin (DT) solutions (digital replicas of physical buildings and its occupants) have been leveraged to model the dynamic nature [12], [13]. However, to the best of our knowledge, no existing occupant guiding system addresses the complex Multi-Objective Optimization (MOO) problem of balancing dynamic, multi-factored occupant needs with energy consumption.

This article presents DigiGuide, a novel occupant guiding system that leverages DT methodologies and MOO techniques. In particular, DTs are used to continuously model building environments and occupant comfort, allowing DigiGuide to forecast the states of the building and occupants. This enables both occupant guidance and environmental control guidance generation while performing self-evaluation and adaptation. DigiGuide proactively (prior to discomfort detection) guides occupants to proper locations by balancing multi-variant comfort needs of occupants such as thermal comfort, acoustic comfort and crowdedness together with energy consumption. The key contributions of this paper are:

- A cross-building solution to jointly optimize multi-variant comfort and energy consumption. DigiGuide allows building administrators to prioritize energy savings or different occupant comfort needs (§III).
- A formal building and occupant model used to postulate the multi-objective optimization problem (§IV).
- A DT-based approach to accurately estimate and predict occupants' comfort in dynamic indoor environments, enabling proactive adaptation to occupants' comfort (§V).

We validate DigiGuide in two large-scale scenarios, a co-working open space building and an airport, by defining DTs based on real buildings and realistic inhabitant behavior. Our experiments demonstrate that DigiGuide outperforms baselines in terms of comfort and energy savings, achieving a better balance across multiple objectives.

II. Related Work

Recent advancements in Smart Computing and IoT have spurred considerable research aimed at enhancing energy efficiency and occupant comfort in buildings [14]–[16]. Many existing works seek to regulate the indoor environment using periodic comfort surveys or sensor-based assessments [17]. Individual comfort is aggregated to regulate environmental parameters such as indoor temperature setpoint [5], [18]. However, when occupants have different preferences, whichever preference is met will make another part of the occupants uncomfortable.

To address this, recent research has explored comfort satisfaction by moving people to spaces that match their preferences. For example, Xia et al. [19] propose a system that moves people inside the building to compensate for environmental control to optimize energy and comfort, but their method does not model how the presence of guided occupants affects the comfort of others in the destination space. Berelson et al. [20] match individuals to specific desks based on environmental sensing on temperature, lighting, and noise levels and prior comfort feedback. Similarly, Sood et al. [9] implemented an occupant guiding application in a real building to allocate spaces based on occupant preferences. While these approaches personalize allocation, they assume a relatively stable indoor environment and do not consider the interdependencies between comfort factors or their dynamics. For example, a space may initially align with an occupant's comfort preferences, but by the time the person arrives, dynamic factors such as increased occupancy or shifting sunlight may change the conditions and lead to discomfort for all occupants.

Another strand of work explores how grouping people with similar preferences can improve comfort and energy outcomes. Nagarathinam et al. [10] shows that a room facing the sun can operate at a higher setpoint with reduced energy cost, thereby potentially enhancing both energy efficiency and comfort by guiding occupants who prefer warmth to sun-faced rooms and vice versa. Ding et al. [11] evaluate the impact of guiding people on energy efficiency and thermal comfort by clustering all the occupants based on the number of available rooms and matching them to each room. Additionally, [21] guides people to comfortable spaces considering occupant diversity by differentiating long-term and short-term occupants. Despite these advancements, these approaches focus solely on thermal comfort and its associated energy consumption, often assuming static and predefined occupant arrivals and preferences, which limits their applicability in dynamic real-world building environments with fluctuating occupancy and evolving comfort needs.

To the best of our knowledge, DigiGuide is the first system to integrate Digital Twin-based forecasting with multi-objective optimization to simultaneously guide occupant movement and recommend environmental adjustments across multiple comfort dimensions while minimizing energy consumption.

III. The DigiGuide Approach

A. *DigiGuide Overview*

DigiGuide postulates the problem of guiding people to appropriate locations and modifying environmental conditions based on comfort and energy requirements as an MOO problem. Then, it leverages a genetic algorithm (GA) to solve it. This way, DigiGuide generates three types of guidance: (1) guiding occupants to suitable locations based on their comfort needs, (2) re-guiding occupants to other locations in response to changes in the environmental conditions to enhance overall occupant comfort, and (3) providing environmental control recommendations to building administrators, such as temperature adjustments. To this end, DigiGuide uses three main components (see Figure 1):

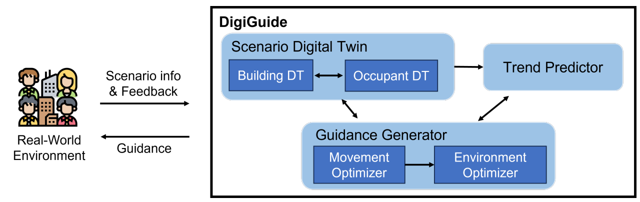

Fig. 1: Overview of the DigiGuide System.

Scenario Digital Twin captures real-world building structure, dynamic environmental conditions, and occupant behavior. It continuously observes and records the indoor environment (e.g., temperature, noise, crowdedness), occupant interactions (e.g., locations, comfort levels, environmental impact), and energy consumption. By analyzing current conditions alongside historical data, it provides predictive insights for future condition estimation. For instance, while indoor noise levels generally correlate with the number of occupants, the exact relationship varies across rooms due to differences in room size and usage. By periodically analyzing historical records, this component identifies these relationships for each room. This analysis is stored in Scenario DT so that the Trend Predictor component can leverage it for rapid predictions. Built on Co-zyBench [5], the Scenario DT supports high-fidelity thermal modeling of the building and occupants, including heat gain/loss, energy consumption of Heating Ventilation and Air Conditioning (HVAC) systems, as well as occupant movement and thermal comfort. However, to provide a comprehensive comfort assessment, DigiGuide extends its capabilities beyond thermal modeling by incorporating additional environmental factors such as crowdedness and acoustic environment (see Section III-B).

Trend Predictor forecasts indoor environmental conditions, occupant comfort levels, and energy consumption utilizing insights from Scenario DT. It anticipates the consequences of implementing the generated guidance. Specifically, occupant comfort levels are estimated based on the predicted future indoor conditions and individual comfort needs. For example, to predict the noise level change in the room if guiding occupants there, it is based on the insights from Scenario DT about how much noise an occupant would generate and the resulting overall noise level. Then it estimates the acoustic comfort of the guided people and all occupants already in the room based on the predicted noise level. Energy consumption is also predicted by leveraging historical records. For example, a linear regression model is utilized to analyze the relationship between HVAC energy usage and temperature differences between outdoor temperature and indoor setpoint [22].

Guidance Generator comprises an optimizer for movement guidance and environmental control guidance. The Movement Optimizer assists both occupants seeking a new room, as well as those already inside but experiencing discomfort and wanting to change to another room. It determines optimal locations by balancing multiple objectives and constraints, including multiple comfort needs, energy efficiency, and spatial limitations. Using a genetic algorithm, it seeks the optimal solution for the MOO problem. The optimizer employs *what-if-analyses* with the Scenario DT and Trend Predictor to assess the generated guidance and update it accordingly. Given the dynamic nature of buildings and occupant needs, comfort levels may change over time. For instance, mood fluctuations can influence thermal preferences. Regularly adjusting indoor conditions is essential for maintaining comfort while reducing occupant movement. The Environment Optimizer identifies optimal environmental conditions and generates environmental adjustments to optimize overall occupant comfort for each space.

B. DigiGuide Comfort Definitions and Implementation

Before deployment, DigiGuide undergoes an initialization phase with DT modeling and configurations. The Building DT is configured with static building information, including spatial layout, climate type, and energy-related device capabilities such as HVAC capacity and energy efficiency. The Occupant DT is modeled with occupant comfort needs and comfort levels. To ensure DigiGuide generalizes its guidance generation to accommodate diverse building and occupant scenarios, comfort objectives can be configured by modeling: (1) current environmental conditions, and (2) occupant comfort and its needs. We present the modeling of several key comfort objectives, including thermal comfort, acoustic comfort and crowdedness, to illustrate how they are configured.

Thermal conditions are represented by indoor temperature, which is dynamically adjusted by HVAC systems. *Noise level* is measured using the sound pressure level (SPL) in decibels (dB). The total SPL in a room is derived by aggregating noise from multiple sources [23], including static background noise (e.g., indoor equipment and external noise) and occupant-generated sounds. This is computed using:

$$L_\Sigma = 10\log_{10}\left(10^{\frac{L_1}{10\,\mathrm{dB}}} + 10^{\frac{L_2}{10\,\mathrm{dB}}} + \cdots + 10^{\frac{L_n}{10\,\mathrm{dB}}}\right)\ \mathrm{dB}. \quad (1)$$

where L_Σ is the total SPL and $L_1, L_2, \ldots, L_n$ are sound levels from different sources. *Crowdedness* is modeled based on room area, room type, and occupant number. The room's capacity is first estimated based on the room size and predefined required area per occupant: $capacity = room\ size/area\ per\ occupant$. For example, each occupant may require 5m^2 in office rooms while 2m^2 in meeting rooms. Using this estimate, crowdedness is then defined as: $crowdedness = occupant\ number/capacity$.

We classify occupant comfort needs into three types: (1) *preferences*, such as thermal preferences, where deviations cause discomfort; (2) *tolerances*, such as noise and crowdedness, where discomfort occurs only beyond a threshold; and (3) *general expectations*, such as walking distance, which do not involve a strict comfort threshold but should be minimized (or maximized) to improve overall satisfaction. We categorize each need into several levels so that occupants can provide preferred levels rather than exact numbers. Thermal preferences are divided into three categories: preference for warmer, neutral, or cooler. Noise and crowdedness tolerance are each classified into four levels to reflect varying occupant sensitivities.

We map the actual comfort level of an individual located in a certain space based on their comfort needs and environmental conditions. Occupant thermal comfort level is evaluated using the Thermal Sensation Vote (TSV) 7-point scale [24], which quantifies thermal sensation from -3 (cold) to +3 (hot). We create the vote sheet as shown in Table I using previous surveys related to thermal comfort [25], [26]. For example, at 23 degrees, people who prefer warmer feel slightly cold (-1), while people who prefer neutral and cooler feel comfortable (0). For acoustic and crowdedness comfort, we evaluate the extent to which the space's noise and occupancy levels exceed an individual's tolerance. Therefore, discomfort is recorded only when these levels surpass the individual's preferred threshold. Finally, walking distance is modeled as the meters an occupant averagely needs to move to the destination.

The DigiGuide system implementation is available as open-source at https://github.com/satrai-lab/DigiGuide[1]

TABLE I: Temperature preference matrix.

	19°C	20°C	21°C	22°C	23°C	24°C	25°C	26°C	27°C	28°C	29°C
Warm Preferred	-3	-2	-2	-1	-1	0	0	0	1	1	2
Neutral	-2	-1	-1	0	0	0	0	1	1	2	2
Cold Preferred	-1	-1	0	0	0	1	1	2	2	3	3

IV. System Model and Problem Definition

We formally define the model for the building and its occupants in DigiGuide. Then, we present the formulation of the selection of the best occupant guidance plan for appropriate places and environmental settings as an MOO problem.

A. Building and Occupant Models

As shown in Figure 2, we model the building as a tuple $\mathcal{B} = (\mathcal{S}, \mathcal{P}, \mathcal{C}, \mathcal{U}, \mathcal{X}, \mathcal{E})$, where $\mathcal{S}$ is the set of spaces within the building (including rooms and other indoor spaces and external areas). A space $s = (s_{id}, s_{type}, \mathcal{P}_s, \mathcal{C}_s)$ where s_{type} defines the space type (e.g., office room, meeting room) and $\mathcal{P}_s, \mathcal{C}_s$ are subsets of $\mathcal{P}$ and $\mathcal{C}$. $\mathcal{P}$ is the set of Points of Interest (POI), which are physical locations relevant to environment

[1]DigiGuide implementation details is available in the GitHub repository.

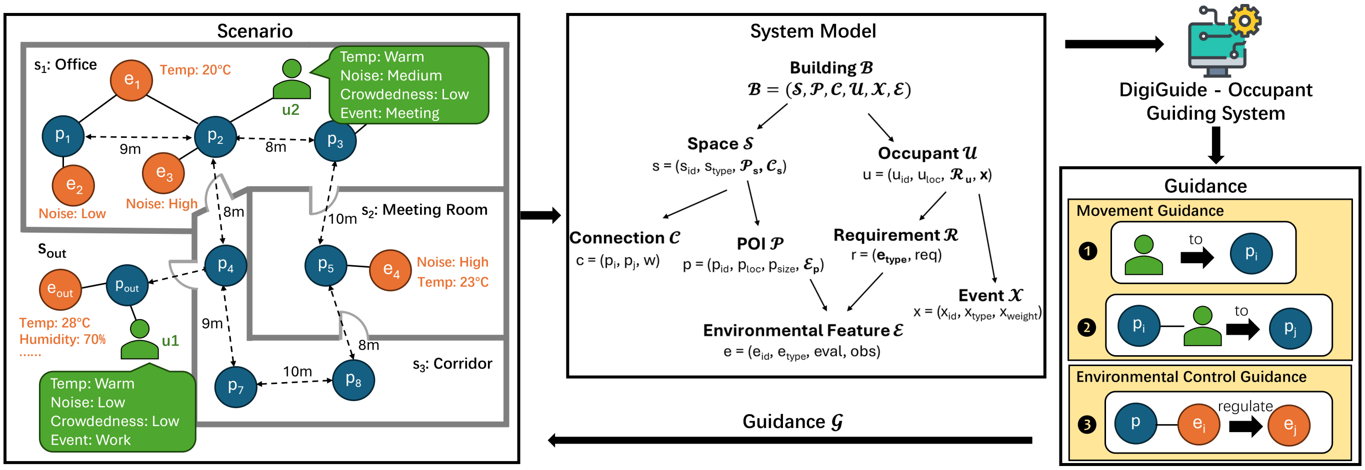

Fig. 2: Illustration of the DigiGuide System Model.

monitoring and regulation or occupant movement. One room may contain multiple POIs to capture environmental variations in different areas. Or a corridor can be segmented into POIs to model realistic movement trajectories, where each room entrance and corridor turn is defined as a POI, ensuring occupants move following feasible paths. In addition, we assume that $\mathcal{S}$ always contains a special space s_out which represents anything outside of the building. This has one POI p_out. A POI is defined as $p = (p_{id}, p_{loc}, p_{size}, \mathcal{E}_p)$, where p_{loc} specifies its spatial coordinates and p_{size} represents the total area; $\mathcal{E}_p \subseteq \mathcal{E}$ represents the set of environmental factors (e.g., temperature, noise) measured or controlled at p. Each $c \in \mathcal{C}$ denotes the spatial connections between POIS, modeled as a tuple $c = (p_i, p_j, w)$, where w represents the distance between point p_i and p_j.

$\mathcal{U}$ is the set of occupants inside the building or those who are planning on being in the building. Each occupant is modeled as $u = (u_{id}, u_{loc}, \mathcal{R}_u, x)$, where u_{loc} is the current location that is associated with the closest POI and $\mathcal{R}_u = \{(e_{type}, req)\}$ is the set of comfort needs. For each environmental factor e_{type}, req specifies the desired level. Moreover, x defines the event that the occupant attends.

$\mathcal{X}$ is the set of events occurring in the building. An event represents a specific occurrence (e.g., individual work and meetings) that occupants attend. Each event is defined as $x = (x_{id}, x_{type}, x_{weight})$, where x_{type} denotes the event type, x_{weight} specifies priority of occupant comfort needs for each event. For example, attending meetings may weaken the need for room crowdedness.

$\mathcal{E}$ is the set of observed environmental factors, e.g., indoor temperature and noise level. An environmental factor is defined as $e = (e_{id}, e_{type}, eval, obs)$, where $eval$ provides a function for evaluating the occupant comfort levels that correspond to this factor type e_{type} and current observation obs.

Moreover, time is divided into a series of time periods $\mathcal{T} = \{1, 2, \ldots, T\}$. The location for each occupant over time is modeled by the binary decision variable $l_{i,p,t} \in \{0, 1\}$ which equals 1 if occupant u_i at time t is in POI p and 0 otherwise. Each occupant must be at exactly one POI (inside our outside the building) at each time slot:

$$\sum_{p \in \mathcal{P}} l_{i,p,t} = 1, \quad \forall i \in \mathcal{U}, \forall t \in \mathcal{T}. \tag{2}$$

Each occupant's discomfort is quantified based on their comfort needs $\mathcal{R}$ for each environmental factor. Specifically, the discomfort experienced by occupant u at POI p and time t for feature e is defined as:

$$d_{u,e}(p, t) = e.eval(p, req, t). \tag{3}$$

B. Multi-objective Optimization Problem

DigiGuide generates a set of guidance $\mathcal{G}$ that comprises three categories:

– $G_m = \{(t, u_i, p_{src}, p_{dst})\}$ is the movement guidance. Here, p_{src} and p_{dst} are the current and destination POIs. The guidance must satisfy: (i) p_{dst} is appropriate for the occupant's event type; (ii) for occupants with the same event, the guidance is consistent; (iii) $p_{src} \neq p_{dst}$.

– $G_r = \{(t, u_i, p_{src}, p_{dst})\}$ is movement re-guidance for occupants experiencing discomfort. In this case, if occupant u_i feels uncomfortable at p_{src} (i.e., $d_{i,e}(p_{src}, t) > 0, \forall e \in \mathcal{E}$), then the destination must satisfy

$$d_{i,e}(p_{dst}, t') < d_{i,e}(p_{src}, t'), \tag{4}$$

where t' is the time slot when u_i will arrive at p_{dst}. Additionally, $p_{src} \neq p_{dst}$ and p_{dst} must be of the room type that u_i is requesting.

– $G_e = \{(t, p_{src}, \text{setpoint})\}$ is environment control guidance for regulating the environment. This guidance recommends that a factor $e_i \in \mathcal{E}$ be set to a specific setpoint and it must ensure that the adjustment leads to reduced discomfort for the controllable feature, i.e.,

$$\sum_{u' \in \mathcal{U}'} d_{u,e}(p'_{src}, t) < \sum_{u \in \mathcal{U}} d_{u,e}(p_{src}, t), \tag{5}$$

where p'_{src} is the POIs that are influenced by device d_i with the environment state after adjustment and $\mathcal{U}'$ represents the occupants that will be in the POIs when the adjustment works.

Together, these decisions define the complete guidance set: $\mathcal{G} = \{G_m, G_r, G_e\}$. We define the overall discomfort led by the guidance $\mathcal{G}$ of all occupants on the environment factor e as:

$$f_e(\mathcal{G}) = \sum_{t \in \mathcal{T}} \sum_{u_i \in U} \sum_{p \in \mathcal{P}} d_i(p', t') \times l_{i,p,t'}, \tag{6}$$

where t' is the estimated time when the occupants arrive at the guided POIs or the time the environmental control is conducted, while p' refers to the POI with the estimated future environmental conditions.

The generated $\mathcal{G}$ should minimize the overall discomfort of all environmental factors and energy consumption:

$$\min_{\mathcal{G}} \big(f_1(\mathcal{G}), f_2(\mathcal{G}), ..., f_{|\mathcal{E}|}(\mathcal{G}), energy\big) \tag{7}$$

V. Multi-objective Guidance Generation

A fundamental challenge in MOO for occupant guidance lies in its inherent computational complexity. The number of feasible movement guidance solutions grows exponentially. Consider a large office building where office rooms are segmented into $|\mathcal{P}|$ of POIs in total. Guiding $|\mathcal{U}|$ occupants to these POIs has $|\mathcal{U}|^{|\mathcal{P}|}$ solutions. Exhaustively searching to find the optimal guidance is computationally costly and hence infeasible since a person looking for a room might not be willing to wait minutes to obtain an answer. Additionally, occupant movement affects indoor environmental conditions and, consequently, the overall discomfort of all occupants $f(\mathcal{G})$. Therefore, evaluating guidance solutions requires comprehensive evaluations that estimate how guidance influences the future comfort of all occupants and energy consumption, rather than focusing solely on individual satisfaction.

To address this, DigiGuide employs DTs and a heuristic genetic algorithm based on NSGA-III (Non-dominated Sorting Genetic Algorithm III) [27], a well-established method for solving MOO problems. This algorithm iteratively evolves a population of candidate solutions through selection, crossover, and mutation, where solutions are preferred for the next generation if there are no other solutions that are better in all objectives. DigiGuide first generates G_m to guide newly arriving people and occupants who are comfortable but need to change location, for example, an occupant in their solo work room seeking a meeting room for a meeting. Next, the Trend Predictor, in conjunction with the Scenario DT, evaluates all occupants' potential future comfort levels if G_m is to be implemented. The comfort is predicted considering their individual comfort needs and the environmental changes, that occur naturally (e.g., temperature might get warmer in the middle of the day) or are caused by G_m (e.g., the noise and crowdedness levels of a room may change due to increased occupancy). If any occupants are experiencing (or predicted to experience) discomfort, G_r is generated to re-guide them to more comfortable locations. Finally, DigiGuide generates optimal environment control guidance G_e for each location based on occupant comfort needs.

Computing movement guidance and re-guidance plans. Algorithm 1 shows how DigiGuide uses NSGA-III to generate movement guidance. Given a set of occupants that need to be guided $\mathcal{U}$, the Building DT $\mathcal{B}$, environmental factors $\mathcal{E}$, and events $\mathcal{X}$, the algorithm first groups occupants by event to account for different comfort needs and destination requirements (Lines 1-4). For instance, multiple occupants attending a meeting share a single meeting room with lower priority on crowdedness levels.

Algorithm 1 Movement Guidance/Re-guidance Generation

Input: Occupants to guide $\mathcal{U}$, Building DT $\mathcal{B}$, Environmental factor $\mathcal{E}$, Events $\mathcal{X}$, Generation number gen, Population size pop

Output: Optimized movement guidance or re-guidance G

```
1:  for u ∈ 𝒰 do
2:      x ← FindEvent(u, 𝒳)
3:      Attend[x] ← Attend[x] ∪ u
4:  end for
5:  for x ∈ Attend do
6:      S_0 ← RandomSolutions(x.solution_len, pop)
7:      for s ∈ S_0 do
8:          𝒫_s ← TrendPredict(s)
9:          f_comfort(s) ← EvalComfort(ℰ, 𝒫_s, 𝒰'[x])
10:         f_energy(s) ← EnergyCost(ℬ, s)
11:     end for
12:     for gen do
13:         S' ← GenerateOffspring(S_0)
14:         for s ∈ S' do
15:             𝒫_s ← TrendPredictor(s)
16:             f_comfort(s) ← EvalComfort(ℰ, 𝒫_s, 𝒰'[x])
17:             f_energy(s) ← EnergyCost(ℬ, s)
18:         end for
19:         F ← NonDominatedSort(S')
20:         S_0 ← SelectNextGen(F, pop)
21:     end for
22:     s* ← arg min_{s∈S_0} Σ_{e∈ℰ} x.w_e * f_e(s)
23:     G ← G ∪ {s*}
24: end for
25: return G
```

For each event x, a diverse population of pop movement guidance—each representing a candidate guidance—is randomly generated. Each guidance specifies $solution\_len$ POIs as destinations (Line 6). These candidates are evaluated based on predicted environmental conditions (Line 8), occupant comfort (Line 9), and energy cost (Line 10). After, the optimization process iteratively refines the generated guidance using NSGA-III over gen generations.

In each iteration, the algorithm applies crossover and mutation (Line 13) to introduce variation into the new populations based on the previous evaluation steps (Lines 16-17) to assess the effectiveness of each guidance. Since MOO involves conflicting objectives and no single solution can simultaneously optimize all objectives, the algorithm approximates the Pareto front (Line 19), which is a set of guidance where improving one objective can inevitably affect another. The selection process (Line 20) retains the best solutions for the next iteration.

After multiple generations, the final Pareto front is obtained with a set of optimal guidance. Among the final Pareto front solutions, we select the guidance that minimizes a weighted sum of normalized objective values (Line 22), where each comfort objective is weighted equally. This ensures a balanced solution without favoring one comfort type over others or over energy consumption. The weights can be adjusted by administrators based on preference priorities.

Computing environmental control guidance plans. While NSGA-III optimizes movement guidance G_m and G_r, dynamic occupant comfort needs and environment changes introduce further uncertainty. For example, in summer, an individual arriving from the hot outdoors may initially prefer a cooler room but later favor a warmer setting. To address this, DigiGuide integrates the Environment Optimizer to dynamically adjust the indoor environment. Based on that, aggregating occupant comfort needs can effectively regulate the environment for occupant comfort [18], [28], the optimizer continuously collects occupant feedback or analyzes their sensations on factors such as temperature. This feedback and analysis are then processed to regulate the environment settings dynamically, such as modifying HVAC settings.

Instead of relying solely on movement-based guidance, localized environmental adjustments allow occupants to remain comfortable in their assigned locations, minimizing unnecessary movement and improving energy efficiency.

VI. Experimental Evaluation

In the following, we evaluate DigiGuide in two large-scale, realistic scenarios: (1) A co-working open space where occupants take part in diverse activities (individual work and meetings); (2) An airport where travelers need to wait until their flights depart. We analyze the impact of DigiGuide on balancing multiple occupant comfort factors including thermal, acoustic, crowdedness, and walking distance. With respect to energy consumption, we focus the analysis on the impact of DigiGuide on HVAC use, which represents the largest energy consumer in buildings [29]. Each experiment, which simulates three complete months during the summer in Paris climate conditions, is executed five times and the results are averaged. The experiments are conducted on a Linux server with an Intel Xeon Silver 4410Y (24 cores, 3.9 GHz) and 128 GB RAM, running Ubuntu 22.04.

A. Evaluation Scenarios

For both scenarios, we define DTs with their diverse characteristic and occupant profiles/activities, as well as, indoor environmental conditions such as static sound levels per each POI sampled from a normal distribution $N(40, 10)$dB and indoor temperature simulated using EnergyPlus, a widely adopted open-source tool [30]. We also simulate occupant comfort needs including thermal/noise preferences, crowdedness tolerance (see Section III-B), and assign them to occupants randomly following a normal distribution. Finally, occupants dynamically influence the indoor environment by: (i) emitting heat at an average equipment load of 200W with a fraction radiant of 0.3 [31], indicating the proportion of total emitted heat; and (ii) creating noise contributions following a normal distribution $N(53, 4)$dB (based on [32]).

Scenario 1: Co-working Open Space. We developed a DT model of the Drahi-X Innovation Center building at École Polytechnique in France (Figure 3a), which consists of offices in various sizes: 12 large (25–60 m^2), 106 medium (10–25 m^2), and 9 small (8–10 m^2), along with 8 meeting rooms (60–200 m^2). The space required per occupant varies by room type: 10 m^2 in small/medium offices, 8 m^2 in large offices, and 2 m^2 in meeting rooms. As a result, small offices accommodate 2–4 occupants, medium offices 5–10, large offices more than 10, and meeting rooms 30–100. To model realistic occupant movement, large offices and corridors are divided into multiple POIs placed near entrances.

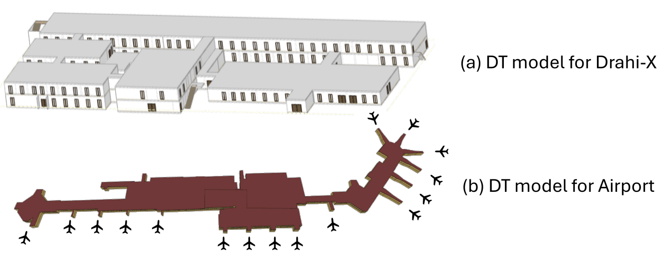

Fig. 3: Building DTs for evaluation.

Each day, 160 occupants follow work and meeting schedules based on their profiles (10% are managers, 30% employees from one department, and the remaining 60% from another). Their working hours span from 7 AM to 10 PM, with an average of 10 hours. Meetings occur daily for employee groups, with some meeting every afternoon and others meeting with managers twice a week. During individual work, all comfort factors are equally weighted, whereas in meetings, we make noise and crowdedness tolerance less important. Additionally, for individual work, all occupants contribute to noise levels, while in meetings, we assume that only one person speaks at a time.

Scenario 2: Airport. We model Terminal 4 of Orly Airport in France, one of the largest terminals of France's major airports, focusing on key areas: three floors, 16 boarding gates, 40 waiting areas (40–130 m^2) on the second floor, and three VIP lounges on the third floor. Figure 3b illustrates the Building DT, constructed using Google Maps and official floor plans [33], [34]. Passengers require at least 1.5 m^2 in waiting areas, while VIP lounges provide quieter environments with a minimum of 3 m^2 per person. Corridors are segmented into POIs near boarding gates, waiting areas, lounges, lifts, and stairways to model realistic movement trajectories.

Flight schedules and passenger volumes are derived from Orly Airport's daily reports [35]: 100 daily flights (100–200 passengers/flight) totaling up to 20K passengers per day. Flights are evenly distributed between 7 AM and 11 PM, with passengers arriving 30–60 minutes before departure. To reflect real-world behavior, 10% of passengers are designated VIPs who can access both lounges and waiting areas. Additionally, 30% of passengers per flight are randomly assigned to groups of 2–5, representing families/friends who prefer to stay together. Walking distance is measured from a guided waiting area or lounge to the gate, reflecting real-world preferences where passengers choose seating near their departure gates.

While our current implementation uses simulated data, DigiGuide assumes access to commonly available sensing infrastructures such as WiFi-based localization, ambient sound monitoring, and temperature sensors. Prior work has demonstrated the feasibility of collecting such environmental and occupant data in smart spaces using semantic IoT frameworks [36], WiFi connectivity traces [37], and crowd-sourced privacy-aware sensing [38].

B. Baselines and Optimization Comparison

Most works in the literature either regulate the environment based on occupant feedback (limited to controllable factors like temperature) or allocate people to spaces focusing solely on thermal comfort (see Section II). Unfortunately, we were unable to find code or enough implementation details to implement the few works that consider a broader notion of comfort. Thus, we evaluate DigiGuide on two key aspects.

First, we define a baseline (*BL*) that reflects typical building operations to assess the improvement of DigiGuide upon current real-world building management strategies. In the baseline, occupants move based on their personal goals (e.g., find an empty workspace) and the indoor environment is controlled according to occupant comfort feedback (e.g., by controlling a thermostat or expressing their comfort using an app). The baseline simulated realistic occupant movement using the SmartSPEC trajectory simulator [39]. The baseline then implements two traditional environmental control strategies [5]: (1) *BL-Maj*: adjusts environmental conditions (e.g., temperature) based on the majority preference of occupants currently in a room. This approach maximizes the overall comfort level of all the occupants. (2) *BL-Drift*: first aggregates individual preferences to generate an initial control action (e.g., temperature setpoint). It then gradually adjusts this action toward a more energy-efficient direction, such as increasing the temperature setpoint in summer, while aiming to remain within acceptable comfort bounds.

Second, we examine the effectiveness of the GA-based MOO approach compared to the Weighted-Sum (*WS*) method, a widely used MOO approach [40]. The *WS* method reduces multiple objectives into a single function by minimizing a weighted sum of the performance of all objectives. In the experiments, we assign equal weights to each objective and compare DigiGuide with GA, *GA-Maj* and *GA-Drift* (depending on the specific environmental control strategy implemented), with DigiGuide with WS, *WS-Maj* and *WS-Drift*.

C. Hyperparameter selection

We investigate the impact of hyperparameter selection, specifically the choice of population sizes and generation numbers for the NSGA-III algorithm, in terms of energy consumption, comfort, and computational efficiency (execution time). The timely generation of guidance is vital, as occupants expect immediate recommendations without excessive delays. We show in Figure 4 the results for different population sizes (15, 35, and 70) and generation numbers (20, 50, and 100) on the algorithm's performance based on Scenario 1 (the results for Scenario 2 show a similar trend). Energy consumption and comfort values are standardized using negated Z-scores

$$Z' = -Z = -\frac{x - \mu}{\sigma} \tag{8}$$

where μ represents the average value of energy consumption or comfort results and σ denotes the standard deviation. Hence, positive values indicate a better performance than the average.

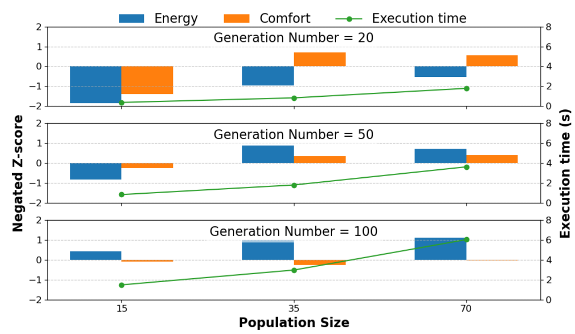

Fig. 4: NSGA-III performance by different hyperparameters.

Although larger population sizes may enhance guidance performance, as NSGA-III can evaluate and rank more candidate guidance, they also impose a higher computational cost. We observe that when it has more than 50 generations and 35 populations, although some optimization is still achieved, the gains are not substantial enough to justify the additional computational burden. Therefore, considering both performance and computational efficiency, we select a generation number of 50 and a population size of 35 as the optimal configuration for the NSGA-III algorithm in DigiGuide, which on average takes 1.8 seconds to generate guidance per person.

D. Performance in Evaluated Scenarios

Table II and Table III present the evaluation results for Scenarios 1 and 2, respectively, including energy consumption and various comfort metrics: thermal, acoustic, crowdedness, and walking distance. Lower values across all metrics indicate better performance.

The results across both scenarios show that DigiGuide, particularly with *GA*, generally outperforms *BL*, in some situations significantly. While it falls short in crowdedness (co-working space) and noise comfort (airport), it achieves

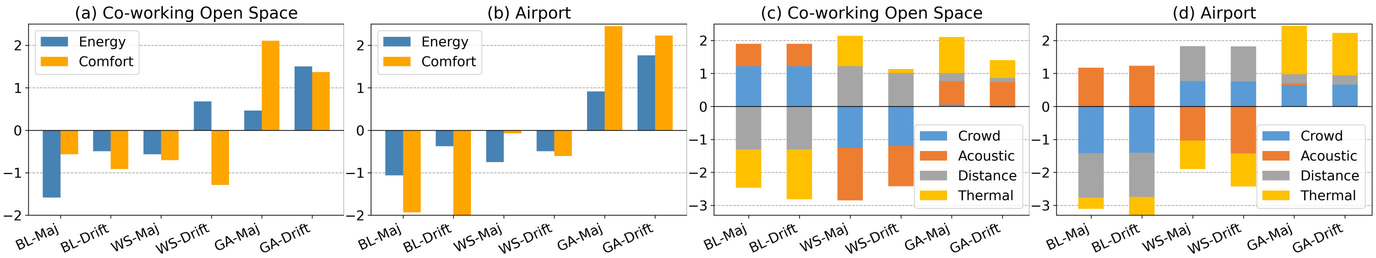

Fig. 5: Comparison of energy-comfort trade-offs and comfort metrics in both scenarios.

TABLE II: Co-working open space scenario performance.

	BL-Maj	BL-Drift	WS-Maj	WS-Drift	GA-Maj	GA-Drift
Energy (kwh)	1852.81	1807.83	1810.77	1759.52	1768.39	**1725.66**
Crowd (lvl)	**0.55**	**0.55**	1.34	1.32	0.92	0.95
Acoustic (lvl)	0.13	0.13	1.17	1.00	0.11	**0.10**
Thermal (TSV)	1.37	1.48	0.74	0.99	**0.69**	0.86
Distance (m)	60.12	60.12	**25.34**	28.16	38.75	40.41

TABLE III: Airport scenario performance.

	BL-Maj	BL-Drift	WS-Maj	WS-Drift	GA-Maj	GA-Drift
Energy (kwh)	125.25	122.21	122.41	121.91	116.64	**108.64**
Crowd (lvl)	0.43	0.43	**0.08**	0.09	0.10	0.10
Noise (lvl)	**0.80**	**0.80**	1.09	1.14	0.95	0.95
Thermal (TSV)	0.29	0.31	0.32	0.33	**0.18**	0.19
Distance (m)	466.78	466.78	**273.54**	273.79	336.55	336.55

an average of 18.2% lower discomfort and 8.6% lower energy consumption than *BL*, and 11.7% lower discomfort with 5.7% less energy compared to *WS*. We also observe that *Drift* reduces energy consumption by 2-4% compared to *Maj* but leads to a decline in thermal comfort, particularly for *WS* in co-working open space where it increases by 25%. In *GA* and *WS*, *Drift* slightly worsens not only thermal comfort but also crowdedness and walking distance. This highlights the effectiveness of DigiGuide (either with *GA* or *WS*) in achieving a balance across all comfort factors, preventing the degradation of one single factor.

To provide a more intuitive understanding of these results, Figure 5a and 5b illustrate the balance between energy consumption and overall comfort for each scenario. Since each comfort metric has a different scale, the energy and comfort value is computed as negated Z-score and the comfort value shown in the figure is the summary of the scores across all comfort objectives. Note that deviations from the average that are positive show better performance. We can observe that DigiGuide, both using the *GA* and *WS*-based approaches, achieves the best energy efficiency and overall comfort by having the largest score for both.

Figures 5c and 5d present the negated Z-score results for each comfort objective. Notably, all *GA* values are positive. Although *GA* does not outperform others in every objective, it consistently achieves above-average performance across all of them. This observation can demonstrate its ability to balance multiple objectives without over-prioritizing or neglecting any single factor. On the other hand, performance varies between the two scenarios. In the co-working open space, *GA* excels in acoustic comfort, whereas in the airport, it significantly improves crowdedness comfort. This discrepancy arises due to the differences in space utilization and human behavior. For instance, airports have sparsely occupied waiting areas near unused gates. Guiding passengers there can reduce crowdedness discomfort. Conversely, co-working spaces remain consistently occupied, making quiet and unoccupied locations within short walking distance harder to find. This emphasizes the significant differences between scenarios and it is necessary to have a generic system that can achieve a balance between conflicting objectives across different scenarios.

VII. Conclusions and Future Work

This paper introduces DigiGuide, an innovative occupant guiding system. By integrating DT methodologies and the genetic algorithm, it generates occupant movement and environmental control guidance. Experiments conducted in two large-scale scenarios demonstrate the applicability of DigiGuide and the significant improvement compared to baseline approaches. By leveraging DT modeling, DigiGuide's modular design enables adaptation to various building and occupant scenarios. Our evaluation also reveals that deploying DigiGuide in different settings requires customizing comfort need factors with corresponding evaluation methods, and accurate building and occupant behavior DT modeling. It provides DigiGuide with the flexibility to accommodate multiple scenarios, while it also increases customization complexity.

While these results are promising, several directions for future work remain. First, our current experiments have focused exclusively on environmental control for temperature. We plan to extend the evaluation to incorporate additional systems (such as lighting control) to evaluate our approach more comprehensively. Second, our solution currently assumes uniform priority among occupants' comfort needs within the same event. Future research will integrate personality traits to account for the diversity in comfort priorities. By addressing these areas, future work will further enhance the adaptability and robustness of DigiGuide.

Acknowledgment

This work is partially supported by the Horizon Europe project PANDORA under grant agreement number 101135775 and the China Scholarship Council (CSC 202208070121).

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