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RESEARCH ARTICLE

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Energy-optimised dynamic occupancy scheduling for offices with desk sharing

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ABSTRACT

Desk-sharing concepts offer significant potential for improving space utilisation in modern office buildings, but their impact on HVAC energy consumption is often neglected in seat allocation planning. This study proposes an automatic scheduling tool for energy-aware seat allocation that determines occupancy plans in advance based on expected attendance patterns, without relying on real-time sensor data. The approach is formulated as a mixed-integer linear programme (MILP) that integrates employee attendance, thermal room dynamics, HVAC capacity limits, and organisational constraints such as departmental adjacency. The model is evaluated in a representative office scenario over a full working week using 100 randomly generated occupancy cases. The results show that the optimised schedules achieve an average HVAC energy cost reduction of 29.1 % compared to conventional fixed-seat assignments, with savings ranging from 16.0 % to 45.3 %. By directly incorporating HVAC energy optimisation into desk-sharing planning, this work extends existing scheduling approaches and provides a foundation for future integration of more detailed building energy models.

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Desk sharing; scheduling; mathematical modeling; optimization; MILP

1. Introduction

Flexible workplace concepts such as hot desking, desk sharing, hoteling, and activity-based working (ABW) have become increasingly important in modern office environments [1,2]. Driven by rising real estate costs, hybrid work models, and the need for more efficient space utilisation, organisations are moving away from permanent desk assignments towards more dynamic workplace structures. While these concepts improve spatial efficiency, they also create new operational challenges, particularly regarding building energy management.

Heating, ventilation, and air-conditioning (HVAC) systems account for a substantial share of office energy consumption, typically around 30–40% of the total building demand [3]. In conventional office settings, HVAC operation is often based on static assumptions regarding occupancy. In flexible office environments, however, occupancy patterns vary significantly across days and spaces, making static HVAC operation increasingly inefficient. This creates an opportunity to align workplace scheduling decisions with building energy performance.

Existing research has mainly focused on reactive energy optimisation strategies. A first stream of literature uses occupancy sensors and real-time monitoring to adapt HVAC operation dynamically to current room usage [4–6]. A second stream focuses on thermodynamic and simulation-based HVAC optimisation under given occupancy patterns [7–9]. Further studies investigate occupancy-related effects such as remote work scenarios or occupancy-dependent temperature setpoint optimisation [10,11]. Comprehensive reviews of these approaches are provided in [12].

Although these works demonstrate considerable energy-saving potential, they share a common assumption: occupancy is treated as an input to the optimisation process, either observed in real time or predefined.

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Thus, optimisation is performed in reaction to occupancy rather than through the planning of occupancy itself.

This paper addresses this gap by proposing a proactive optimisation framework for desk-sharing office environments. Instead of adjusting HVAC systems after occupancy patterns are known, the presented approach optimises seat allocation in advance based on planned employee attendance. Using information such as booking systems or calendar entries, the model determines energy-efficient room assignments while respecting operational constraints such as departmental grouping and seat capacity limitations.

To this end, a mixed-integer linear programming (MILP) model is developed that integrates employee attendance planning with a simplified thermal building model. The objective is to minimise HVAC-related energy costs while maintaining thermal comfort and operational feasibility. In contrast to existing reactive approaches, the proposed method directly embeds energy considerations into the workplace scheduling process itself.

The model is evaluated using a representative office case study over a one-week planning horizon. Numerical experiments demonstrate significant energy-saving potential compared to conventional fixed-seat allocations and highlight the computational tractability of the approach.

The remainder of this paper is structured as follows. Section 2 introduces the mathematical model. Section 3 presents the numerical experiments and results. Section 4 concludes the paper and discusses future research directions.

2. Mathematical modelling for optimising an office occupancy schedule

Optimising office occupancy scheduling with respect to energy consumption is a complex yet highly rewarding challenge, particularly in modern work environments characterised by flexible workspace concepts. Building on existing research in energy-aware office scheduling and occupancy-driven building control, this section introduces a novel mathematical modelling framework designed to minimise HVAC-related energy costs. The model employs a data-informed, constraint-respecting approach to assigning workers to office spaces and thereby supports the development of optimised occupancy schedules over a specified scheduling horizon.

2.1. Notation

Symbol	Description	Unit
I	Set of offices	-
K	Set of workers	-
J	Set of days	-
D	Set of departments	-
$i \in I$	Index of a specific office	-
$k \in K$	Index of a worker	-
$j \in J$	Index of a day	-
$d \in D$	Index of a department	-
$T(i, j)$	Indoor temperature of office i at start of day j	°C
$T^{\min}_{\text{occ}}$, $T^{\max}_{\text{occ}}$	Minimum/Maximum temperature of comfort range	°C
$T^{\min}_{\text{empty}}$, $T^{\max}_{\text{empty}}$	Minimum/Maximum temperature of unoccupied offices	°C
Δt	Discretization time interval	h
$C(i)$	Effective thermal capacitance of office i	$\text{kW}h K^{-1}$
$U(i)$	Heat-loss coefficient to outdoors for office i	$\text{kW}K^{-1}$
$T^{\text{out}}(j)$	Outdoor temperature on day j	°C
a	Heating per person	kW
$b_{\text{seats}}(i, j)$	Occupancy of office i on day j	-
Q^{heat}, Q^{cool}	Heating/cooling power supplied	kW
$h(i, l)$	Thermal coupling between offices i and l	$\text{kW}K^{-1}$
$z(i, j)$	Binary occupancy of office i on day j (1 = occupied)	-
$COP^{\text{heat/cool}}$	Coefficient of Performance	-
$c(j)$	Electricity price on day j	€ per kWh
$e(i, j)$	Energy cost of HVAC system of office i on day j	€
$w(i, k)$	Assignment of worker k to office i (binary)	-

Symbol	Description	Unit
$Z(i)$	Seating capacity of office i	-
$p(k, j)$	Daily presence of worker k on day j (binary)	-
$b(i, j)$	Fractional occupancy of office i on day j	-
$q(d, i, j)$	Auxiliary variable (binary), assignment of department d to office i on day j	-
$r(d, i, j)$	Auxiliary variable (binary), partial occupation of department d of office i on day j	-
l_{D}	Amount of allowed partially occupied offices by a department	-

2.2. Problem definition and notation

We consider an office complex consisting of a finite set of offices I, within which a set of workers K must be allocated for a given schedule period, typically defined as a workweek represented by the set of days J. Scheduling involves determining, for every worker, the single office they will use throughout the entire scheduling horizon (e.g. one week). This decision is guided by the expected daily presence of each worker, which serves as an input to the model.

Each office $i \in I$ is equipped with an HVAC system to maintain the room temperature within a defined comfortable range. In addition to the outdoor temperature and the temperatures of adjacent rooms, the occupancy of the room also plays a crucial role. Every person present in the office increases the room temperature, thereby creating a clear temperature-dependence on the room's occupancy. Empirical studies for example from [13] and [14] examine the relationship between occupancy rates and HVAC energy use and highlight that significant energy savings become achievable when HVAC control strategies respond dynamically to occupancy levels. Incorporating this insight into the optimisation model enables the system to account for occupancy-dependent variations in energy consumption.

2.3. Temperature control via HVAC

In this paper, the HVAC system is treated as the primary energy consumer for indoor temperature control. For the thermal model, let $b_{\mathrm{seats}}(i, j)$ denote the number of employees assigned to office i on day j, and let $Z(i)$ denote the seating capacity of office i. A central element of the model is the incorporation of different comfort requirements depending on office usage. Occupied offices are required to satisfy stricter thermal comfort limits, while unoccupied offices may operate in a wider setback temperature range. To distinguish between these two operating modes, a binary occupancy indicator $z(i, j) \in \{0, 1\}$ is introduced, where $z(i, j) = 1$ if office i is occupied on day j, and $z(i, j) = 0$ otherwise. The occupancy indicator is linked to the seat allocation variable through the following linear constraints:

$$b_{\mathrm{seats}}(i, j) \leq Z(i) \cdot z(i, j) \qquad \forall \quad i, j \in I, J \tag{1}$$

$$b_{\mathrm{seats}}(i, j) \geq z(i, j) \qquad \forall \quad i, j \in I, J \tag{2}$$

These constraints ensure that $z(i, j) = 1$ whenever at least one employee is assigned to office i on day j.
Based on this occupancy indicator, the admissible temperature bounds are formulated as:

$$T(i, j) \geq T^{\min}_{\mathrm{occ}} \cdot z(i, j) + T^{\min}_{\mathrm{empty}} \cdot (1 - z(i, j)) \qquad \forall \quad i, j \in I, J \tag{3}$$

$$T(i, j) \leq T^{\max}_{\mathrm{occ}} \cdot z(i, j) + T^{\max}_{\mathrm{empty}} \cdot (1 - z(i, j)) \qquad \forall \quad i, j \in I, J \tag{4}$$

Thus, occupied offices must remain within the comfort interval $[T^{\min}_{\mathrm{occ}}, T^{\max}_{\mathrm{occ}}]$, whereas vacant offices may operate within the wider interval $[T^{\min}_{\mathrm{empty}}, T^{\max}_{\mathrm{empty}}]$.

The thermal dynamics of the rooms are described by a linear resistance-capacitance (RC) model, which is a classical thermodynamic room model [15]. The temperature evolution follows from an energy balance that accounts for heat losses to the surroundings, internal heat gains, and the heating/cooling power supplied by the HVAC system. For each room, the following relation holds:

$$T(i,j+1) = T(i,j) + \frac{\Delta t}{C(i)} \cdot \Big[U(i) \cdot \big(T^{\text{out}}(j) - T(i,j)\big) + \alpha \cdot b_{\text{seats}}(i,j) + Q^{\text{heat}}(i,j) - Q^{\text{cool}}(i,j) + \sum_{l \in I} h(i,l)(T(l,j) - T(i,j))\Big] \qquad \forall\ i \in I,\ \ j \in J \tag{5}$$

Here, $C(i)$ denotes the effective thermal capacitance of office i, $U(i)$ the heat-loss coefficient to the outdoor environment, $T^{\text{out}}(j)$ the outdoor temperature, and $h(i,l)$ the thermal coupling between neighbouring rooms. The internal heat load is modelled as proportional to the occupancy of office i on day j via the factor α [14]. The heating and cooling powers $Q^{\text{heat}}(i,j)$ and $Q^{\text{cool}}(i,j)$ are bounded by technical limits:

$$0 \le Q^{\text{heat}}(i,j) \le Q^{max}_{heat} \qquad \forall\ \ i,j \in I,J \tag{6}$$

$$0 \le Q^{\text{cool}}(i,j) \le Q^{max}_{cool} \qquad \forall\ \ i,j \in I,J \tag{7}$$

The variable $T(i,j)$ represents the indoor air temperature of office i at the beginning of day j, whereas $T(i,j+1)$ denotes the temperature at the beginning of the following day. The initial indoor temperature is fixed as:

$$T(i,1) = T^{init}(i) \qquad \forall\, i \in I \tag{8}$$

The initial thermal state $T(i,1)$ represents the room temperature at the beginning of the first working day of the planning horizon. Since no optimisation is performed for the preceding day, this value corresponds to the thermal state carried over from the previous day. For a weekly planning horizon starting on Monday, this can be interpreted as the terminal thermal state of the preceding Sunday, which serves as the boundary condition of the dynamic model. To ensure physical consistency, the initial condition must satisfy the admissible setback temperature range:

$$T^{\min}_{\text{empty}} \le T^{init}(i) \le T^{\max}_{\text{empty}} \qquad \forall\, i \in I\,. \tag{9}$$

In this work, a full day is represented by a single time step. Accordingly, the discretization interval is chosen as $\Delta t = 24$ hours. The model operates on a daily time resolution, reflecting the practical observation that seat allocation decisions are typically made on a per-day basis and remain fixed throughout the working day. While finer temporal resolutions (e.g. hourly) would allow for a more detailed representation of occupancy patterns and HVAC dynamics, such decisions are more appropriately addressed at a lower operational level. This motivates a hierarchical modelling approach, in which the proposed optimisation determines a daily seat allocation, while more detailed time-resolved control strategies (e.g. for heating and cooling) can be applied subsequently. In this way, the structural optimisation of occupancy planning is clearly separated from the dynamic control of building systems. The units and typical value ranges of the parameters used can be found in Table 1 [16].

The daily energy cost of an HVAC system is derived from the electrical energy demand for heating and cooling, taking into account the respective performance coefficients COP^{heat} and COP^{cool} (Coefficient of Performance) as well as the time-dependent electricity price $c(j)$:

Table 1. Units and typical value ranges of the parameters used for energy balance in Equation (5). [16]

Parameter	Unit	Value Range
Thermal capacitance C	$\text{kWh}K^{-1}$	50–150
Heat-loss coefficient U	$\text{kW}K^{-1}$	0.2–0.5
Coupling between neighbouring rooms h	$\text{kW}K^{-1}$	0.02–0.05
Heating per person α	kW	~ 0.1
Heating power Q^{heat}	kW	0–10
Cooling power Q^{cool}	kW	0–15
Coefficient of Performance COP		3–5

$$e(i,j) = c(j) \cdot \Delta t \cdot \left(\frac{Q^{\text{heat}}(i,j)}{COP^{\text{heat}}} + \frac{Q^{\text{cool}}(i,j)}{COP^{\text{cool}}} \right) \qquad \forall \quad i,j \in I,J \tag{10}$$

Within the scope of the considered use case, a constant COP is assumed for the HVAC system and, for simplicity, treated as identical for heating and cooling. More detailed HVAC models may incorporate different COP values for heating and cooling as well as operating-condition-dependent variations.

Although the framework relies on this simplified structure, more detailed models, possibly including dynamic thermal behaviour, weather-dependent loads, or integration with MPC-based building climate control [17], could be incorporated without altering the overall formulation.

2.4. Allocation constraints and occupancy variables

To ensure practicality and maintain consistency in the working environment, each worker $k \in K$ must be assigned to exactly one office $i \in I$ for the entire scheduling period. While the optimisation jointly considers the daily attendance patterns over the full planning horizon, switching between offices during the week is not permitted. This requirement is expressed through the binary decision variable $w(i,k)$, which equals 1 if worker k is allocated to office i, and 0 otherwise. Enforcing a single allocation per worker is achieved through:

$$\sum_{i \in I} w(i,k) = 1 \qquad \forall \quad k \in K\,. \tag{11}$$

For each day $j \in J$, the scheduled daily presence $p(k,j)$ of each worker is known, serving as an input parameter to the model:

$$p(k,j) = \begin{cases} 1 & \text{if worker } k \text{ is present on day } j \\ 0 & \text{otherwise} \end{cases} \tag{12}$$

Whether a seat is occupied on any specific day depends on both the office assignment and the worker's presence. The total number of occupied seats in office i on day j is then determined by:

$$b_{\text{seats}}(i,j) = \sum_{k \in K} w(i,k) \cdot p(k,j) \qquad \forall \quad i,j \in I,J\,. \tag{13}$$

Normalising by the office capacity yields the fractional occupancy:

$$b(i,j) = \frac{b_{\text{seats}}(i,j)}{Z(i)} \qquad \forall \quad i,j \in I,J\,. \tag{14}$$

Office capacities impose an additional structural constraint. Since workers are assigned to one office for the entire planning horizon, the available seating capacity $Z(i)$ of each office must be sufficient for all workers assigned to that office on each day j of the planning horizon J. This is expressed as:

$$b_{\text{seats}}(i,j) \leq Z(i) \qquad \forall \quad i,j \in I,J\,. \tag{15}$$

Hence, the daily energy consumption $e(i,j)$ for each office is calculated from Equation 10. The aggregate optimisation objective is the minimisation of total HVAC energy cost across all offices and days:

$$min \sum_{j \in J} \sum_{i \in I} e(i,j)\,. \tag{16}$$

The set of decision variables to be optimised comprises the heating and cooling powers $Q^{\text{heat}}(i,j)$ and $Q^{\text{cool}}(i,j)$, together with $w(i,k)$, which defines the assignment of workers k to office i.

2.5. Team and department-oriented constraints

Workplace collaboration and team integrity are critical in many companies. To reflect these organisational needs, the model supports advanced constraints based on departmental structure. Let D be the set of departments, with $K_d \subseteq K$ representing the workers in department $d \in D$. To minimise dispersion and support team-based work, it may be required that members of a department are co-located in the same office, either

for each individual day j or across the total scheduling horizon $|J|$. This concept assumes that there are enough seats in individual offices for the department sizes under consideration. If this is not given, it will be necessary to divide the departments among several offices; this is discussed in Section 2.6.

To represent whether a department occupies a given office on a specific day, the auxiliary binary variable $q(d, i, j)$ is introduced. It takes the value 1 if at least one member of department d is seated in office i on day j, and 0 otherwise. The following constraints ensure correct behaviour of this variable:

$$q(d,i,j) \leq \sum_{k \in K_d} w(i,k) \cdot p(k,j) \qquad \forall \quad d,i,j \in D,I,J, \tag{17}$$

$$Z(i) \cdot q(d,i,j) \geq \sum_{k \in K_d} w(i,k) \cdot p(k,j) \qquad \forall \quad d,i,j \in D,I,J\,. \tag{18}$$

These jointly ensure that $q(d, i, j)$ becomes 1 as soon as a department has any presence in office i.

To preserve cohesion within departments, it may be required that each department occupies at most one office per day:

$$\sum_{i \in I} q(d,i,j) \leq 1 \qquad \forall \quad d,j \in D,J\,. \tag{19}$$

Alternatively, this requirement can be enforced across the entire scheduling period:

$$\sum_{i \in I} \max_{j \in J}(q(d,i,j)) \leq 1 \qquad \forall \quad d \in D\,. \tag{20}$$

2.6. Extended department partitioning for small offices

In practice, spatial limitations may preclude co-location of all department members; small offices may necessitate a department's division across multiple rooms. The model supports this situation by introducing a parameter I_{D}, which determines how many partially occupied offices a department d may use. To detect partial occupation, the auxiliary variable $r(d, i, j)$ is introduced:

$$Z(i) \cdot r(d,i,j) \geq Z(i) \cdot q(d,i,j) - \sum_{k \in K_d} w(i,k) \cdot p(k,j) \qquad \forall \quad d,i,j \in D,I,J\,. \tag{21}$$

Daily and weekly limits on partial office usage are set through:

$$\sum_{i \in I} r(d,i,j) \leq I_{\mathrm{D}} \qquad \forall \quad d,j \in D,J, \tag{22}$$

$$\sum_{i \in I} \max_{j \in J}(r(d,i,j)) \leq I_{\mathrm{D}} \qquad \forall \quad d \in D\,. \tag{23}$$

Equation 21 ensures that $r(d, i, j)$ takes the value 1 as soon as the capacity $Z(i)$ of office i occupied by department d ($q(d, i, j) = 1$) is greater than the number of places actually occupied by department d in office $ir(d, i, j)$ can therefore only take the value 0 if the office i is either not occupied at all or is completely occupied by the department d. Equations 22 and 23 thus ensure that no more than I_{D} offices are only partially occupied by any department. The standard case is considered to be $I_{\mathrm{D}} = 1$ in order to keep the distribution of workers as small as possible. Like the occupancy schedule $w(i, k)$, the auxiliary variables are also determined later by the optimiser implicitly.

2.7. Exclusion constraints and sharing rules

The model can also impose specific interaction rules between departments. For instance, to prevent two departments from ever sharing the same office:

$$q(d_m,i,j) + q(d_n,i,j) \leq 1 \qquad \forall \quad i,j \in I,J\,. \tag{24}$$

Similarly, exclusive occupancy of an office by a single department can be enforced by:

$$q(d_m,i,j) + \sum_{\{d \in D | d \neq d_m\}} q(d,i,j) \leq 1 \qquad \forall \quad i,j \in I,J\,. \tag{25}$$

2.8. Mixed-integer linear programming and applicability to the occupancy optimisation model

The mathematical formulation developed in the preceding sections results in a mixed-integer linear programme (MILP), a class of optimisation problems that is particularly well suited for decision-making tasks involving discrete assignments subject to linear relationships. MILP models are widely applied in operational scheduling contexts—such as workforce scheduling, facility layout, or building energy management—because they allow complex combinatorial structures to be represented with high modelling accuracy while enabling globally optimal solutions to be computed using modern solver technology [18,19].

In the present context, the heating and cooling powers $Q^{\text{heat}}(i, j)$ and $Q^{\text{cool}}(i, j)$ and the binary assignment variables $w(i, k)$, together with the auxiliary variables for departmental occupancy, introduce discrete structure reflecting real-world office scheduling decisions: a worker either occupies a given office or not, and a department either appears in a specific room on a particular day or does not. Simultaneously, all constraints describing heat balance, office capacities, daily occupancy levels, and energy consumption are linear, which guarantees that the overall model fits within the MILP framework without requiring nonlinear reformulation or approximation. This linearity ensures full solver compatibility and maintains the interpretability of the resulting allocations.

From a computational perspective, MILP proves particularly advantageous because modern solvers such as Gurobi [20] employ sophisticated techniques—including branch-and-bound, cutting planes, presolve routines, and symmetry detection—that efficiently exploit the structural sparsity of the model. The occupancy scheduling problem naturally exhibits such sparsity: most workers can only occupy a small subset of offices due to capacity or team constraints, and departmental interactions are limited to a few binary decisions per day. As a result, even though the problem contains several hundred or thousand binary variables depending on the office size and scheduling horizon, it remains tractable for realistic office environments. The optimisation problems were solved using the Gurobi Optimiser. All optimisation scenarios were solved using MATLAB R2022b and Gurobi 9.5.1 on a standard desktop PC equipped with an Intel Core i7 processor (2.2 GHz) and 32 GB RAM. A relative optimality gap of 0.01 % was used for all optimisation runs. The computational effort depends on the size and complexity of the considered problem instances. The computational results and scalability of the proposed model are evaluated in the numerical experiments presented in Section 3.4.

Moreover, the MILP formulation supports flexibility and extensibility. Additional rules, such as comfort limits, time-dependent occupancy constraints, or links to HVAC operating schedules, can be incorporated by adding linear constraints or new auxiliary variables. This modularity ensures that the model can evolve with organisational needs, making MILP a particularly suitable optimisation paradigm for energy-aware and structurally constrained office occupancy scheduling.

With respect to scalability, it should be noted that the computational effort of the proposed MILP formulation increases with problem size due to the growing number of binary variables and constraints. While larger instances can still be solved using state-of-the-art solvers, solution times increase accordingly. In practical applications, however, large office environments are typically structured into spatially and organisationally coherent units (e.g. floors, or buildings), which naturally limits problem size. This allows the overall problem to be decomposed into smaller subproblems that can be solved efficiently without significant loss of optimality.

2.9. Summary

By integrating occupancy-sensitive energy modelling with organisational and team-based constraints, the proposed framework provides a comprehensive mixed-integer programming formulation for generating energy-efficient seating plans. The explicit definition of all variables, parameters, and relationships ensures transparency and facilitates adaptation to diverse office layouts, departmental structures, and scheduling requirements.

3. Results

This section presents the results of applying the proposed mathematical model to various scenarios of office occupancy scheduling, focusing on the optimisation of energy consumption by the HVAC system. The

evaluation follows a structured approach: First, the model is validated with simple examples to illustrate the basic functionality and handling of department-based constraints. Subsequently, a realistic use case with a larger office scenario demonstrates the practical applicability and impact of the optimisation approach.

The parameters for the thermal balance were randomly drawn from the ranges listed in Table 1 using a uniform distribution for each of the 100 generated occupancy scenarios. The admissible temperatures for occupied offices were set to $T^{\min}_{\text{occ}} = 21°\text{C}$ and $T^{\max}_{\text{occ}} = 24°\text{C}$, whereas for unoccupied offices the wider setback limits $T^{\min}_{\text{empty}} = 16°\text{C}$ and $T^{\max}_{\text{empty}} = 28°\text{C}$ were used. The coefficient of performance was fixed at $COP = 3.5$ for both heating and cooling throughout all scenarios. The heating and cooling powers were bounded by

$$0 \leq Q^{\text{heat}}(i,j) \leq 10 \ \text{kW} \qquad \forall \ \ i,j \in I,J \tag{26}$$

and

$$0 \leq Q^{\text{cool}}(i,j) \leq 15 \ \text{kW} \qquad \forall \ \ i,j \in I,J\,. \tag{27}$$

The internal heat gain per occupant was assumed constant with $\alpha = 0.1\text{kW}$. Additionally, a fixed electricity price of $c = 0.25$ € per kWh was assumed for the one-week simulation period. A constant electricity price is assumed throughout the planning horizon to isolate the effect of seat allocation on energy consumption. This modelling choice enables a clear assessment of the energy-saving potential resulting from occupancy planning alone, independent of external price fluctuations. The framework also allows for the direct inclusion of time-dependent electricity prices. The outdoor temperature for each day was generated randomly for each scenario within realistic seasonal bounds. To ensure meaningful HVAC operation, the temperature on each day was selected such that it remained entirely either above or below the occupied comfort interval, thereby inducing either heating or cooling demand. Initial room temperatures $T^{init}(i)$ were sampled uniformly within the admissible temperature bounds at the beginning of the scheduling horizon. This initialisation avoids distortions caused by extreme initial conditions and ensures that the resulting energy demand reflects the interaction between occupancy, thermal dynamics, and HVAC control over the full planning horizon. A statistical summary of the sampled thermal parameters across all scenarios is provided in Table 2, illustrating the variability of the generated test instances.

3.1. Simple examples for model verification

To verify the correctness and robustness of the mathematical model, we first apply optimisation to simplified scenarios. This not only confirms the logic behind the constraints especially those related to department allocation and fragmentation but also establishes confidence in the model's practical feasibility.

The process begins by testing the department assignment constraints. Equations 17 and 18 define when a department is present in a particular office on a given day and serve as the basis for the auxiliary variable $q(d,i,j)$. Two main concepts are considered: (1) assigning each department to a single office per day (Equation 19), and (2) limiting the office assignments over the entire week (Equation 20).

For illustrative purposes, consider a model office with two departments, each consisting of five workers. The office space comprises two rooms: Office 1 provides five seats, while Office 2 offers three seats. Table 3

Table 2. Statistical summary of the sampled thermal and environmental parameters used in the numerical experiments across the 100 generated occupancy scenarios. For each parameter, the mean, standard deviation (Std), minimum, and maximum are reported.

Parameter	Mean	Std	Min	Max
C in kW hK^{-1}	100.4	14.3	75	125
U in kW K^{-1}	0.35	0.15	0.2	0.5
h in kW K^{-1}	0.035	0.0075	0.02	0.05
T^{out} in °C	22	6.54	11	32
T^{init} in °C	22.5	3.15	18	27

documents the presence pattern of the workers over the five-day working week. Each worker's schedule is marked, showing variability in daily attendance among both departments.

Applying the optimisation model under the daily constraint (Equation 19), and separately under the weekly constraint (Equation 20), yields the occupancy schedules illustrated in Figures 1 and 2, respectively. The graphical representation clearly assigns workers to offices, colour-coded per day of the week.

Under the weekly constraint, the solution assigns each department its designated office for the entire week, ensuring exclusive occupancy by department members. However, under the daily constraint, the solution leverages the flexibility of variable attendance: On days when workers from both departments are present, offices can be shared more efficiently, provided seating capacity is respected. This strategy results in a more dynamic use of office space.

The model's extension for incomplete room occupation, as formulated in Equations 21 to 23, does not affect the solution in this particular basic example. To demonstrate its utility, a further test is conducted by adding one worker who is present every day for the week in Department 1. This creates a situation in which exclusive assignment is no longer feasible, and the occupancy schedule must be adapted for both daily and weekly constraints. Figure 3 displays the resulting optimised schedule, illustrating the logical allocation strategy to achieve minimum energy cost within the available office space, and confirming the effectiveness of the model in handling edge cases and constraint extensions.

Table 3. Worker presence for a five-day work week for the model verification example. (x = worker present, Department 1 - Worker ID 1-5, Department 2 - Worker ID 6-10).

Worker ID	Monday	Tuesday	Wednesday	Thursday	Friday
1	x		x		x
2	x		x		x
3	x		x		x
4	x	x	x	x	x
5	x	x	x	x	x
6		x		x	
7		x		x	
8		x		x	
9	x		x		x
10	x		x		x

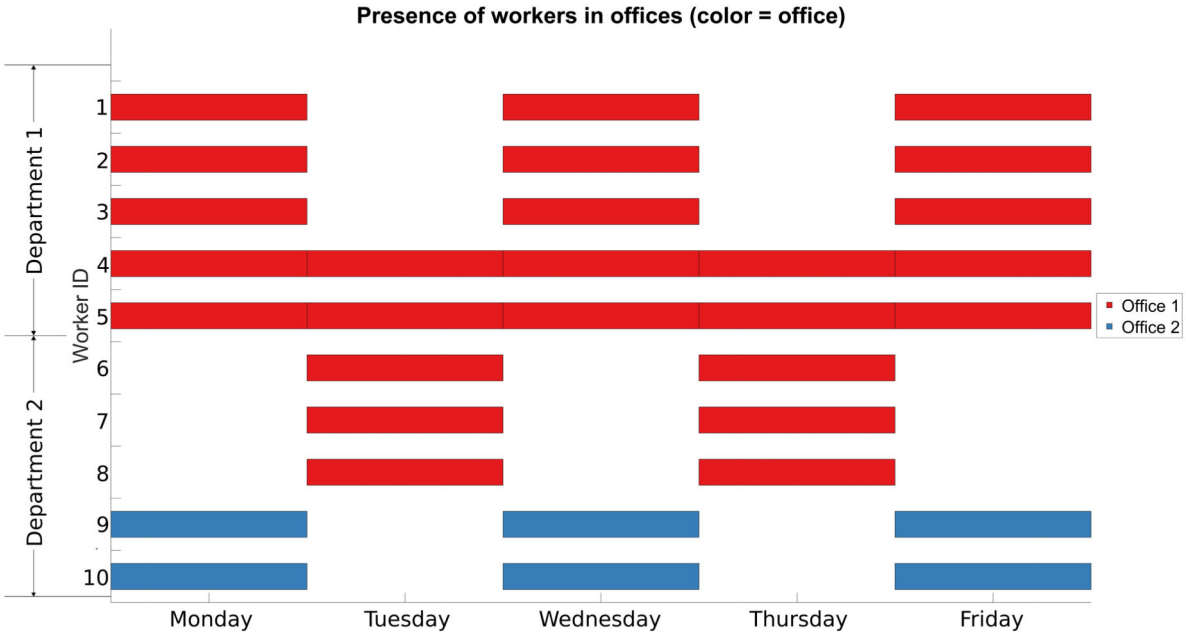


Figure 1. Result of optimisation according to Equation 19 for daily observation with worker presence according to Table 3. Workers are listed vertically, and working days are listed horizontally, colour-coded to indicate the office assigned to each worker on the respective day.

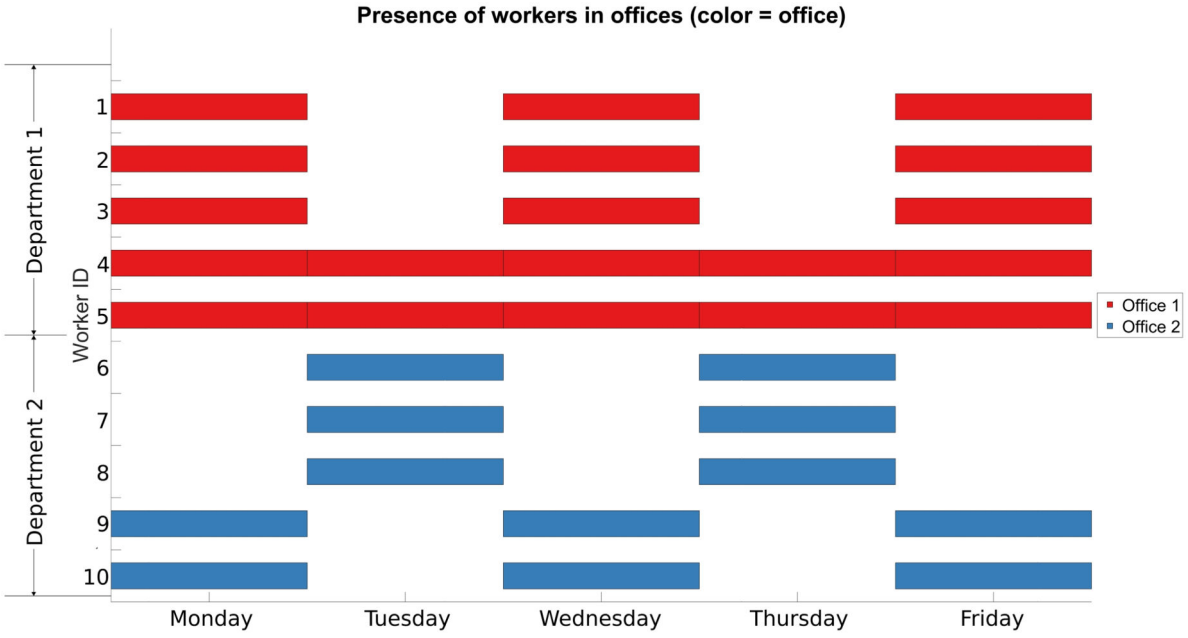


Figure 2. Result of optimisation according to Equation 20 for consideration of the entire week with worker presence according to Table 3. Workers are listed vertically and working days are listed horizontally, colour-coded to indicate the office assigned to each worker for the weekly planning horizon.

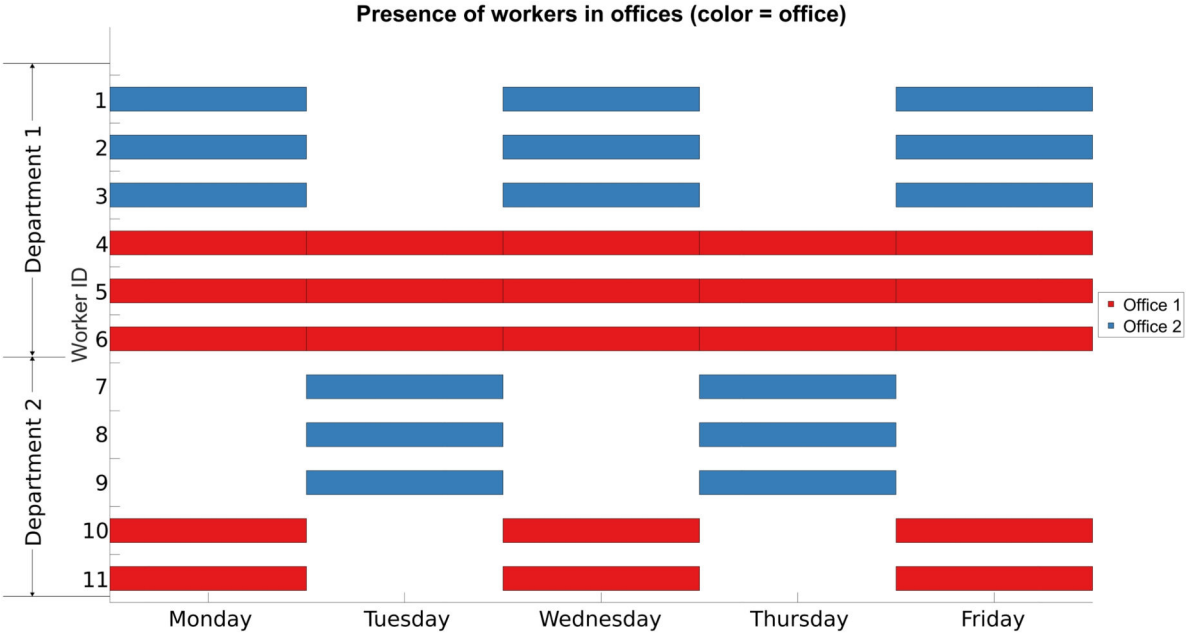


Figure 3. Result of optimisation according to Equation 22 and 23. Workers are listed vertically, and working days are listed horizontally, colour-coded to indicate the office assigned to each worker for the weekly planning horizon.

In summary, these simple model office examples demonstrate the mathematical model's capability to optimise occupancy under a range of allocation concepts, under the daily department allocation formulation and lower energy use when attendance is variable.

3.2. Use case model office

Having validated the model's fundamental operations, attention now turns to a more complex and practically motivated use case that reflects typical conditions found in real-world office environments. The

parameterisation of this scenario follows commonly applied scheduling guidelines and standard workplace specifications, such as those defined in DIN EN ISO 9241. This ensures that the modelled conditions not only remain realistic but also correspond to spatial and organisational structures found in many contemporary office settings.

The exemplary company considered here employs a total of 58 workers, who are distributed across six departments of varying sizes. Departments 1–3 each consist of 10 employees, Department 4 comprises 15 employees, Department 5 includes 8, and Department 6 accounts for the remaining 5 employees. In addition to differences in size, departments also exhibit distinct attendance requirements. Their respective weekly office presence obligations are set to 3, 3, 2, 4, 2, and 3 days. These attendance days are assigned individually for each employee through a random draw, leading to diverse and non-uniform weekly occupancy profiles across the entire workforce. In a real operational context, this information would typically be derived from digital calendar systems or room-booking applications maintained directly by employees, or from centralised scheduling tools used by team leads or facility management. In practical applications, updated attendance information can be incorporated before the beginning of a planning horizon by re-solving the optimisation problem based on revised weekly attendance forecasts. This allows the proposed framework to adapt dynamically to changes such as short-term absences or schedule modifications.

The available office space consists of seven group offices differing in size and seating capacity. The respective room capacities are 10, 5, 5, 15, 14, 10, and 6 workplaces. As described above, the temperature evolution of an office follows the thermal balance given in Equation (5), and the corresponding parameters are randomly drawn from the ranges listed in Table 1 for each office.

3.3. Comparison scenario

To evaluate the benefits of the proposed energy-optimised desk-sharing procedure, a reference scenario with fixed seat assignments is considered. This serves to contextualise the performance of the optimisation model and to quantify potential improvements in energy efficiency.

The comparison scenario represents a traditional, industry-standard approach in which individual departments are assigned fixed office spaces. In this conventional allocation, rooms are selected manually according to a size-matching heuristic, such that department sizes are assigned to offices with similar seating capacities while minimising fragmentation across multiple rooms whenever possible. This allocation reflects a practically reasonable and near-capacity-efficient permanent seating arrangement based on organisational structure alone. For the use-case model, this results in six of the seven offices being permanently assigned to employees. However, this static form of allocation does not explicitly account for the detailed weekly attendance structure nor for the energy characteristics of the rooms. In particular, while the permanent assignment is chosen to be structurally efficient with respect to department sizes and office capacities, it cannot adapt to variations in daily presence. As a result, although workplace availability is guaranteed, the overall energy demand may be higher than necessary.

The fixed seat allocation in the comparison scenario can be directly substituted into the energy balance expression of Equation (5) for $b_{\text{seats}}(i, j)$. Consequently, the decision variables of the MILP problem reduce to the heating and cooling powers $Q^{\text{heat}}(i, j)$ and $Q^{\text{cool}}(i, j)$. Assuming identical parameters in the thermal balance, the conventional department-based allocation serves as a reference point for quantifying the potential energy savings enabled by the optimised desk-sharing solution developed in this work.

3.4. Optimisation of the occupancy schedule for the model office

The formulated MILP model is applied to generate energy-optimised seat allocations for the model office described in the previous section. For all departments, the daily occupancy logic is used, ensuring that each department may have at most one office that is not fully occupied on any given day ($I_{\text{D}} = 1$). This reflects realistic departmental structures, where the presence of multiple incompletely filled rooms would be operationally undesirable. As outlined above, the required weekly attendance days for each employee are assigned randomly. To evaluate model robustness and average behaviour, 100 such attendance configurations are generated, representing different possible weekly occupancy patterns of the workforce.

The optimisation is carried out using the Gurobi Optimiser [20] (version 9.5.1), integrated into Matlab R2022b, with a relative optimality gap of 0.01 %. For each sampled occupancy configuration, the model jointly optimises worker allocations over all days of the working week, while enforcing a consistent office assignment for each worker across the entire planning horizon. Figure 4 illustrates a representative example of such an optimised weekly schedule. The figure displays the assignment of all workers across the five working days, with colour coding indicating the respective office used.

Compared to the fixed seat allocation, in which six offices are used continuously, it is immediately apparent that the optimised weekly seat assignment allows for a reduction in the total number of offices utilised over the week (in the example shown in Figure 4, only four offices are utilised). As a result, less energy is required for heating or cooling to maintain the desired temperature ranges, leading to a noticeable reduction in energy consumption through the constrained energy-optimised allocation.

Across the 100 randomly generated occupancy scenarios, the constrained energy-optimised allocation (respecting departmental grouping and weekly consistency of seat assignments) achieved a mean reduction in HVAC energy cost of 29.1% compared with the conventional fixed seat allocation. The observed savings ranged from 16.0% to 45.3%. Figure 5 illustrates the distribution of relative energy savings across all scenarios, demonstrating that the proposed optimisation consistently yields substantial reductions under varying occupancy patterns.

To complement the computational results of the considered use-case, additional scalability experiments were conducted by varying the number of workers and offices. For each problem size, 100 randomly generated occupancy scenarios were solved using the same thermal model and optimisation settings. Table 4 summarises the resulting problem dimensions and solver times. The results show that the model size increases with the number of workers and offices, leading to higher computational effort. While the small and medium-sized instances remain computationally efficient, the largest tested scenario exhibits a noticeable increase in runtime, with an average solver time of 57.2s and a maximum of 161.2s. All experiments were solved using a relative optimality gap of 0.01 %, ensuring high-quality solutions while maintaining computational tractability. Overall, the scalability analysis indicates that the proposed MILP formulation remains suitable for realistic office planning applications and repeated scenario-based evaluations.

The potential savings are in line with estimates reported in the literature, which are based on approaches utilising real-time sensor data [6]. It should be emphasised that the reported savings are derived from a simplified HVAC cost model. A more nuanced representation including dynamic set-points,

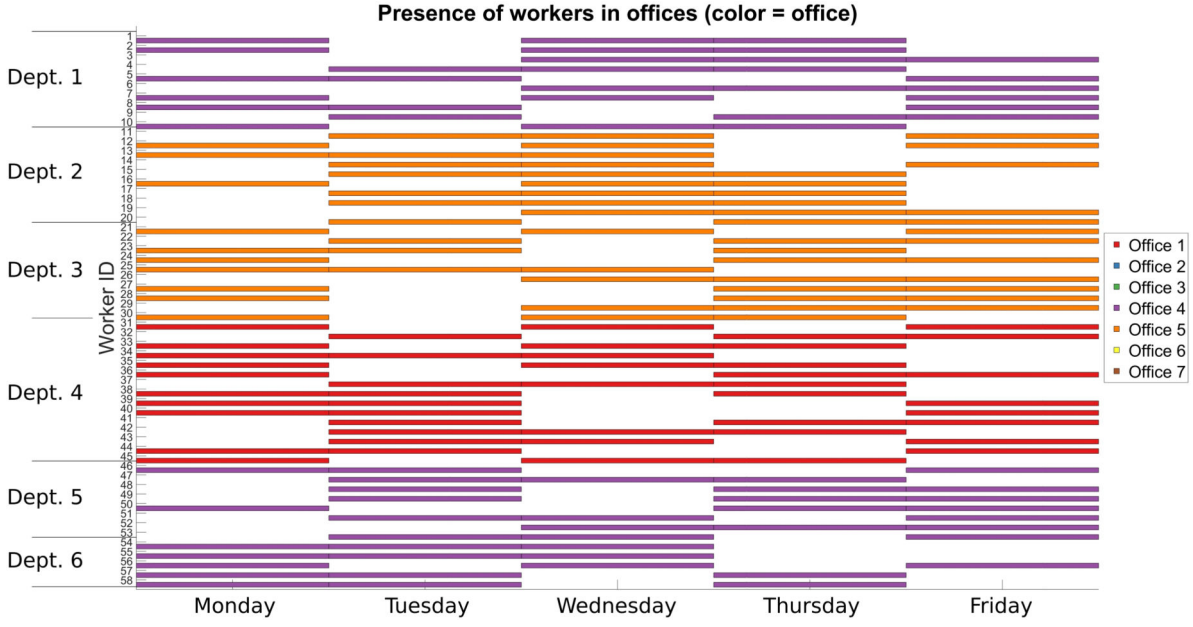


Figure 4. Result of optimisation for an example of occupancy requirements for the model office. Workers are listed vertically, and working days are listed horizontally, colour-coded to indicate the office assigned to each worker for the weekly planning horizon.

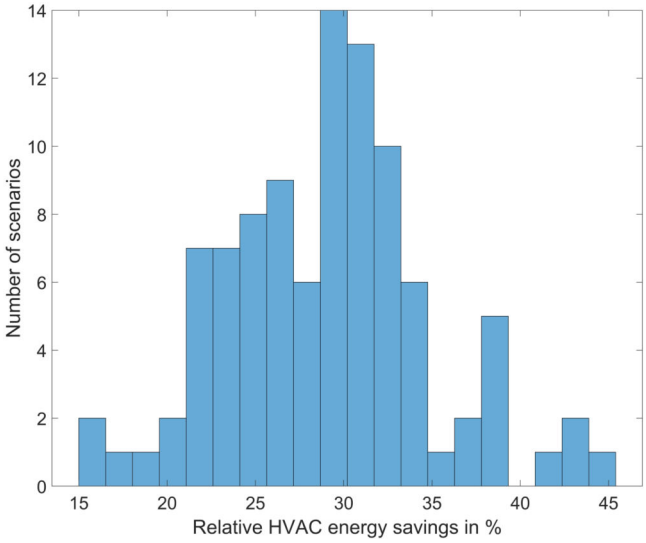


Figure 5. Histogram of the HVAC energy cost reductions obtained across the 100 randomly generated occupancy scenarios compared with the conventional fixed-seat allocation, illustrating the variability and robustness of the achieved savings.

Table 4. Scalability analysis of the proposed MILP formulation for different problem sizes. For each scenario, 100 randomly generated occupancy instances were solved. The table reports the number of constraints, decision variables, and the minimum, mean, and maximum solver time (ST). A relative optimality gap of 0.01 % was used in all experiments.

Scenario	Number constraints	Number variables	Min. ST	Mean ST	Max. ST
50 workers, 6 offices	4412	2322	3.5*s*	6.6*s*	22.4*s*
58 workers, 7 offices	5700	3045	2.5*s*	7.2*s*	28*s*
66 workers, 8 offices	7150	3864	4.8*s*	57.2*s*	161.2*s*

occupancy-driven ventilation control, or seasonal variability would likely amplify the achievable savings, particularly for larger offices or buildings with significant thermal inertia. Nevertheless, the results obtained here already underline the effectiveness and operational relevance of the proposed model. They demonstrate that the approach offers a flexible and computationally efficient tool capable of generating tangible energy reductions in realistic office scheduling scenarios.

4. Conclusion

This paper proposes a novel mathematical framework for energy-optimal occupancy scheduling and demonstrates that it is capable of generating energy-optimised workplace allocation schedules for a desk-sharing environment equipped with HVAC systems. The approach provides optimised occupancy schedules with an energy-saving potential of about 30% for a predefined scheduling horizon, in this case, a typical working week, while taking into account departmental structures, attendance requirements, and room-specific energy characteristics. By systematically balancing these constraints, the model enables coordinated, energy-efficient use of office spaces, thereby contributing directly to the reduction of HVAC-related energy consumption in multi-office complexes. In the computational experiments, consistent solution structures were observed across different occupancy scenarios, indicating stable model behaviour with respect to input variations.

In real-world deployments, the model can be integrated into existing digital building management workflows, particularly those associated with desk-sharing platforms and room-booking systems. Since the required input data (expected presence patterns, office capacities, and energy characteristics) are typically available within facility-management infrastructures, the implementation effort is comparatively low.

The presented concept thus establishes a structured foundation for energy-aware occupancy scheduling in desk-sharing settings. Beyond its immediate application, the methodology serves as a starting point for more advanced strategies in building energy optimisation. A particularly relevant extension involves integrating the weekly occupancy schedule generated by the MILP model into a model predictive control (MPC) framework for building climate control, as discussed in Langner et al. [17]. In such a setup, the occupancy

schedule would act as a forecast input that allows MPC algorithms to determine cost-optimal pre-heating or pre-cooling phases for each office room, especially under conditions of fluctuating or time-varying electricity prices. MPC approaches rely on detailed, dynamic thermal building models that incorporate additional influencing factors such as weather forecasts, solar gains, thermal inertia, and ventilation behaviour. Including such high-resolution thermal models in future versions of the occupancy optimisation framework would likely improve the fidelity and impact of the resulting energy-optimised seating plans.

Moreover, it is reasonable to assume that a coupled, iterative application of the two approaches—occupancy scheduling and MPC-based climate control—could yield even more pronounced energy savings. In such a combined scheme, the occupancy scheduling model could use feedback from MPC simulations to further refine its allocation decisions, while MPC controllers would, in turn, benefit from updated occupancy forecasts tailored to current or predicted climatic or energy market conditions. Exploring such joint or co-optimisation strategies therefore represents a promising direction for future research.

Beyond energy considerations, the presented concept also provides a basis for investigating additional comfort and usability criteria within shared-desk office environments. Future extensions may incorporate parameters such as thermal comfort indices, air quality requirements, noise constraints, ergonomic considerations, or user preferences regarding seating continuity or room switching frequency. Integrating such aspects would broaden the applicability of the model and allow for a more holistic assessment of occupant well-being alongside energy efficiency.

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MV, DB, and JM contributed to the conception, design, analysis, and interpretation of the data. MV draughted the manuscript. DB and JM critically revised the manuscript for important intellectual content and gave final approval of the version to be published. All authors have read and approved the final manuscript and agree to be accountable for all aspects of the work.

Author contributions

CRediT: **Markus Vogelbacher:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing; **Dennis Becker:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Resources, Software, Validation, Writing – review & editing; **Jörg Matthes:** Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Supervision, Validation, Writing – review & editing.

Disclosure statement

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Data availability statement

The data that support the findings of this study are available from the corresponding author, MV, upon reasonable request.

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