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Optimizing personnel allocation: An integer linear programming problem for enhanced workplace efficiency

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ABSTRACT

In large organizations, the allocation of personnel within office spaces presents significant challenges, particularly with the adoption of modern working methodologies such as smart working, co-working, and agile working. This paper addresses the optimization of workspace assignments to balance occupancy levels while ensuring cohesion within organizational units and compliance with individual work schedules. The proposed approach incorporates constraints to prevent overcrowding, maintain consistent desk assignments, and enforce separation between specific personnel groups. A multi-objective Integer Linear Programming formulation is developed and validated through a real case study. Results demonstrate that the methodology effectively reduces peak occupancy imbalances and strengthens team cohesion, providing human resources departments with a practical decision-support tool that requires minimal technical expertise. The solution features an intuitive web interface that facilitates efficient space management in dynamic working environments.

1. Introduction

In large organizations and corporations with extensive office space and numerous personnel, optimizing staff distribution within available workspaces poses significant challenges. The global shift towards hybrid work models, accelerated by the COVID-19 pandemic, has further complicated this task. Flexible schedules and fluctuating occupancy rates require dynamic solutions to ensure efficient space utilization while maintaining team cohesion and productivity. Contemporary approaches, such as smart working, co-working, and agile frameworks, reduce pressure on facilities by carefully planning human resources and scheduling on-site presence in advance. For example, structures can accommodate more workstations within the same spaces while still complying with regulations on distancing and the minimum required space per worker However, these new practices increase the complexity of assigning personnel to rooms, as management must consider absence days, minimize maximum room occupancy to prevent overcrowding, and preserve the unity of organizational units by avoiding unnecessary staff dispersion across different rooms.

A seemingly straightforward solution might involve dynamically rotating personnel among rooms, assigning them daily. However, studies have shown that this approach can negatively impact employee well-being and productivity. In fact, employees benefit from stable assignments, even to the same workstation within the same room, as they enhance their sense of belonging and reduce disruptions. In addition, dynamic assignments can increase the time it takes employees to settle in at the beginning of their workday, thereby reducing overall efficiency. The most conventional approach would be to assign all personnel from the same organizational unit to the same room. Although this may seem logical, it often leads to suboptimal space utilization and does not adequately address the complexities of modern workspace requirements (Bosch-Sijtsema et al., 2010; Ditchburn, 2014; Mercer, 1966; Shepheard, 2015).

In this article, our objective is to optimize the distribution of personnel in office environments to improve operational efficiency. We achieve this by developing an Integer Linear Programming (ILP) model that addresses the limitations of existing methods. The proposed model integrates modern working practices, individual attendance schedules, room capacity constraints, and organizational unit cohesion into a unified optimization framework. Taking into account the variability in employee attendance and the need for consistent and stable desk assignments, the approach provides a balanced solution that improves workspace efficiency while maintaining employee well-being and team collaboration.

Nevertheless, while the proposed framework accounts for flexible schedules and varying attendance patterns over a defined planning horizon (typically a working week), it does not continuously react to or adapt to minor real-time perturbations, such as sudden absenteeism or last-minute scheduling changes. The presented model emphasizes

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the balance between flexibility and stability, thereby providing robust solutions suitable for practical implementation without the need for constant revision of allocation decisions.

A critical aspect of developing an effective allocation strategy involves taking into account the inherent fluctuations in the presence of the employee. Personnel may take leave, maintain flexible hours, work remotely, or encounter unforeseen circumstances that prevent scheduled office attendance. Planning for full occupancy is thus impractical and can lead to inefficiencies or overcrowded workspaces. To address this, the model presented incorporates the maximum desired occupancy levels for each room, which serve as target occupancy rates below the physical capacity. This consideration accounts for attendance variations and helps prevent overcrowding, ensuring that the workspace remains comfortable and functional despite unexpected attendance fluctuations. By integrating these reduced occupancy levels into the optimization, this model aims to create a practical and resilient allocation strategy that aligns with actual usage patterns and enhances overall workplace efficiency. In addition, accommodating attendance variability enables the model to provide stable, consistent desk assignments, thus contributing to employee well-being and fostering effective team collaboration.

The remaining parts of the paper are organized as follows: Section 2 provides a review of the literature and outlines the main contribution, Section 3 describes the problem from a mathematical point of view and identifies the decision variables, the problem's constraints, and the objective function. Section 4 presents a case study from the real world, outlining the outputs we expect from the system. Section 5 introduces the publicly accessible tool that has been developed. Eventually, Section 6 draws the conclusions.

2. Literature review and paper contribution

In the literature, very few studies have explored the application of optimization methods to human resource management, and even fewer have specifically focused on the context of office space allocation.

Bosch-Sijtsema et al. (2010) provided a critical examination of dynamic staff allocations and investigated the impact of drop-in desks in a large technology firm. Even if such layouts encouraged interaction and a vibrant work atmosphere, they also hindered productivity through navigation challenges, distractions, and a diminished sense of team identity. Complementing this, Nithin and Suma (2017) presented a workspace management system for a software organization that incorporates activities such as layout configuration and hot desk. Although effective in managing workspaces, it primarily focused on technical tools rather than optimizing resource allocation.

Recent advances in multi-objective optimization and robust methodologies have significantly improved human resource management applications. These improvements particularly benefit personnel scheduling and allocation within healthcare systems. Shiri et al. (2021) proposed a robust multi-objective framework for home healthcare scheduling and routing under uncertainty, focusing on cost minimization, skill-level optimization, and qualitative criteria in facility selection. However, their methodology presented certain limitations. Specifically, it lacked explicit constraints that addressed employee cohesion, stable workspace assignments, and the prevention of overcrowding. These factors constitute critical elements in modern office-space allocation scenarios, significantly influencing both operational efficiency and employee satisfaction. Additionally, their approach does not consider generalized workspace dynamics common in hybrid working contexts and does not account for personnel attendance variability.

Expanding on these aspects, Hamid et al. (2020) recently proposed a multi-objective mathematical model for nurse scheduling that explicitly incorporates human factors, including personnel satisfaction, skill distribution, and compatibility in decision-making styles. This advancement provides valuable elements of interpersonal compatibility and satisfaction previously overlooked by Shiri et al. (2021), demonstrating a deeper integration of human factors into personnel scheduling problems.

Nevertheless, several methodological limitations remain evident in their approach. Firstly, their modeling framework is highly tailored to nurse rostering within healthcare, limiting its direct applicability to broader office environments or agile workplace management contexts. Secondly, their reliance primarily on metaheuristic techniques, while effective for large-scale NP-hard problems, lacks rigorous optimality guaranties, potentially yielding suboptimal solutions. In contrast, the approach presented here adopts an ILP-based methodology, solved via established commercial optimization solvers, and proposes a generalized formulation directly applicable to modern office working contexts.

Moreover, the work by Cakir et al. (2022) presented an ILP model for multi-mode resource-constrained discrete-time cost trade-off problems in the context of software engineering projects. Their framework effectively balances conflicting project requirements under limited resources, demonstrating the potential of computational optimization methods to manage complex resource allocation challenges. Nevertheless, a key methodological limitation of their approach lies in its complexity and computational effort, especially when handling large-scale instances typical of real-world environments. Furthermore, despite introducing constraint programming and metaheuristic solutions, their model was not designed to incorporate the fluctuations typical of modern workplace attendance patterns and the variability in personnel's daily schedules. These methodological gaps are addressed in this paper by developing an ILP-based optimization model tailored for dynamic workspace allocation.

Muñoz et al. (2024) recently proposed an ILP model aimed at optimizing staff scheduling and shelf-stocking activities for retailers, considering different alternatives to shelf-stocking schedules, including day, night and semi-night shifts. Their approach offers valuable insights into workforce management in grocery retail settings, explicitly addressing cost minimization while accounting for shelf capacity constraints, labor costs, and stock-out penalty costs. Despite the effectiveness of their model in devising optimal shift schedules for shelf-stockers, a significant methodological limitation arises: their framework focuses exclusively on minimizing economic costs associated with labor allocation and stock replenishment, without considering broader socio-organizational factors such as personnel cohesion, employee satisfaction, or stable spatial allocation. Additionally, as their research is specifically tailored to the retail industry, the proposed methodology lacks the necessary generalizability for broader office workspace management contexts, thereby necessitating the development of more comprehensive approaches that transcend sector-specific constraints while maintaining the rigor of multi-objective optimization frameworks.

More specifically, regarding workspace allocation, Chiera's paper (Chiera, 1994) on High-Performance Work Organization provides foundational principles that shape modern workspace management methodologies such as smart working and agile working. Despite its pioneering role in the literature, Chiera emphasizes the importance of a collaborative, integrated approach between management and workforce to ensure workplace efficiency and employee well-being. Nevertheless, due to its historical context, this contribution lacks more recent advances, such as quantitative optimization techniques, formal mathematical modeling frameworks, and computational optimization methodologies, necessary to address contemporary personnel allocation challenges systematically.

A further method in resource-optimization contexts is offered by event-driven control strategies applied to hybrid discrete-event systems, particularly those modeled as generalized batch Petri nets. Liu et al. (2023) introduced an ON/OFF event-driven control problem solved via linear programming (LP) formulations that drive hybrid Petri nets from blocking initial configurations to attractive steady-state regions. In a subsequent work (Liu et al., 2025), they refined this paradigm, presenting advanced event-driven controllers that maximize throughput and optimize temporal performance while maintaining batch coherence constraints and ensuring physical system stability. Both studies employed rigorous event-based LP optimization methods, conceptually similar to the ILP-based approach introduced in this work. Nonetheless, while their methodological foundations align with the optimization-oriented perspective proposed in this paper, significant limitations arise regarding human-centric office space management. Specifically, their frameworks inherently focus on physical-process modeling aspects prevalent in high-throughput manufacturing, neglecting central human factors and socio-organizational constraints ubiquitous in modern agile workplaces. Such considerations precisely motivate the ILP formulation proposed in the current paper.

The present work aligns with these studies by focusing on optimizing office space allocation through a collaborative, adaptive framework, specifically targeting human resources within contemporary working methodologies.

Xu et al. (2015) present the development of a multiple ontology workspace management system and its performance assessment. The system aims to facilitate the storage and manipulation of ontology models for knowledge-driven manufacturing execution systems. User authentication is introduced to maintain data privacy and integrity. Performance tests demonstrate that the system offers adequate performance for a large number of users. Although their work involves managing multiple ontology workspaces, it does not directly address optimizing office space utilization in the context of modern working methodologies.

In the realm of human resource allocation, Ma et al. (2022) propose a novel approach based on decision tree algorithms to allocate human resources across project groups dynamically. The authors establish a multi-objective optimization model to minimize project duration and total cost loss by dynamically allocating human resources, adhering to principles that maximize the capabilities of project management personnel, and prioritizing the needs of high-priority projects. While their methodology seeks to reduce project costs and duration, thereby improving overall benefits for construction enterprises, their perspective differs from that adopted in this paper, as they do not consider office space optimization.

Xiao (2020) introduces an enterprise human resources optimal allocation model using particle swarm optimization and big data fusion techniques. The method constructs a database model and uses OLAP tools to build a table model for optimal human resource allocation. While the proposed method achieves better information fusion and optimized allocation of enterprise human resources, it does not specifically address the challenges of optimizing office space utilization in consideration of modern working practices, such as smart working, co-working, and agile working.

In addition to traditional methods, recent advances have seen the rise of artificial intelligence in human resources. Gupta and Kumar (2024) provide a comprehensive overview of how Artificial Intelligence (AI) addresses various aspects, including recruitment, learning and development, employee experience, and data-driven decision-making. Moreover, the authors emphasize the role of AI in enhancing hiring processes and enabling data-driven decision-making. Nonetheless, they do not optimize office space allocation. Deng et al. (2021) propose a simulation and optimization framework to improve thermal comfort in buildings by jointly controlling room environmental conditions and assigning occupants to rooms based on their personalized comfort preferences. They utilize machine learning models to predict individual thermal comfort levels and formulate the problem as a joint optimization of occupant-room assignment and room condition control. While their work represents a cornerstone in applying optimization techniques to personnel placement, it focuses on thermal comfort rather than the broader challenges of space optimization in office environments. However, AI models often require large datasets for training, may lack transparency in their decision-making processes, and can be challenging to interpret and validate in practice.

A notable application of optimization in resource allocation is presented by Nguyen et al. (2022), who developed a solver for military training scheduling using Knuth's Dancing Links scheme. While distinct in context, their approaches share the same goal of efficient resource assignment under complex constraints, highlighting methodologies that could inspire innovations across various domains, including the optimization strategies examined in this work.

Contribution: Given the gaps in existing literature, the new contributions of this paper are as follows: (1) an ILP model is formulated for optimizing office space allocation, specifically addressing the unique challenges in human resources management; (2) the model incorporates real-world constraints, including room capacities, personnel schedules, and organizational policies, alongside individual preferences for realistic and applicable solutions; (3) the proposed system is validated through a detailed case study, highlighting its ability to satisfy imposed constraints while enhancing space utilization; (4) a practical tool integrated into a web interface enables human resources departments to optimize workspace allocation without requiring advanced technical expertise.

3. Problem formulation

In this section, we describe the problem under consideration and then define the decision variables and the constraints of the ILP.

3.1. Problem statement

In large organizations, staff distribution within office facilities presents significant challenges, particularly when implementing contemporary work arrangements including smart working, co-working, and agile methodologies. We consider a set of N individuals who must be allocated to S rooms for each working day of the week. Each room s is equipped with P_s workstations, and only one workstation can be assigned to each individual.

The allocation process considers several preferences and constraints:

(i) **Team Cohesion:** Individuals are divided into working groups or teams. It is preferable to assign members of the same team to the same room to foster collaboration, improve communication, and enhance overall productivity.
(ii) **Separation of Specific Individuals:** Certain pairs of employees cannot be assigned to the same room due to specific organizational requirements, which may include conflicts of interest, confidentiality concerns, or interpersonal issues.
(iii) **Flexible Work Schedules:** Employees have the option to select which days of the week they prefer to work from home. This results in variable office attendance that must be considered in the allocation to ensure rooms are neither overutilized nor underutilized on any given day.
(iv) **Consistent Workstation Assignments:** To enhance employee comfort and reduce disruptions, it is desirable for each individual to retain the same workstation on the days they are present in the office.
(v) **Maximum Desired Capacity:** To prevent overcrowding and comply with health and safety regulations, each room has a maximum desired occupancy level, which is a fraction of its total capacity.

The goal is to develop an allocation strategy that respects these preferences and constraints, resulting in the optimal assignment of personnel to rooms and workstations over the planning period (e.g., one week).

To address this problem, we formulate a multi-objective function aiming to:

Table 1
Summary of parameters and notation.

Symbol	Description
N	Total number of people.
$S_R = \{s \mid s = 1, \dots, S\}$	Set of rooms.
S	Total number of rooms.
P_s	Set of workstations in room s, with $s = 1, \dots, S$.
I	Set of pairs of people who should *not* be assigned to the same room on the same day. Each element in I is a pair (n, m) representing individuals who should be kept separate.
G_P	Set of preference groups (e.g., organizational units or teams). Each group $G \in G_P$ is a subset of individuals who are encouraged to be assigned to the same room to promote collaboration.
$d \in \{1, \dots, K\}$	$d = i$ for $i = 1, \dots, K$ denotes the ith day of the week.
K	Total number of days for which the assignment is being planned.
$a_{nd} \in \{0, 1\}$	$a_{nd} = 1$ if person n is scheduled to be in the office on day d.
D_n	Ordered set of the week days in which person n is expected to be in the office, $D_n = \{d \mid \text{person } n \text{is in the office on day } d\}$.
$D_n(j)$	jth element of D_n.
$max\_capacity$	Maximum desired room capacity (in the following $max\_capacity = 0.8$).
$BigM$	A big number used to linearize alternative constraints. $BigM$ is chosen to be sufficiently large to ensure that the constraints are always satisfied when necessary. In this model, $BigM$ is defined as: $BigM = 20 \times \max(N, \max_s P_s)$.

Table 2
Summary of decision variables and notation.

Symbol	Description
$u_{nsd} \in \{0, 1\}$	$u_{nsd} = 1$ if person n is in room s during day d; 0 otherwise. This variable indicates the room occupancy of person n without specifying the exact workstation.
$v_{nspd} \in \{0, 1\}$	$v_{nspd} = 1$ if person n is assigned to workstation $p \in P_s$ in room s during day d (where d represents a specific day); 0 otherwise. It determines the specific workstation assignment.
$switch \in \{0, 1\}$	Used to select between constraints. $switch = 1$ activates the maximum desired capacity constraint, while $switch = 0$ activates the absolute maximum capacity constraint.
$z \geq 0$	An auxiliary variable representing the maximum percentage of occupancy in any room during the week, used in the minmax function.
$y_{nmsd} \in \{0, 1\}$	$y_{nmsd} = 1$ if both person n and m (where $m < n$) are assigned to room s on day d; 0 otherwise. This variable tracks the co-location of personnel.

1. **Minimize Maximum Room Occupancy:** Reduce the highest occupancy percentage among all rooms on various days to prevent overcrowding and ensure balanced space utilization.
2. **Maximize Team Cohesion:** Assign members of the same team to the same rooms whenever possible to foster collaboration and enhance group dynamics.

3.2. Parameters

For definitions of the parameters and notation used throughout this paper, refer to Table 1.

3.3. Decision variables

For specifications of the decision variables, please refer to Table 2.

3.4. Constraints

Alternative constraints: maximum desired capacity

The first two constraints use the $switch$ binary variable that enables the model to select between the maximum desired capacity and the absolute maximum capacity constraints. The use of $BigM$ allows for the deactivation of one constraint when the other is in effect. The binary nature of $switch$ ensures that only one constraint is active at any given time, allowing the model to adapt based on specific solution needs.

Consider, for instance, the scenario in which the human resources department sets a very restrictive target for room occupancy, for example, $max\_capacity = 0.2$. In practice, this would mean that in a room with 10 available workstations $P_s = 10$, at most 2 people can be assigned to the room daily. For most real-world organizations, this constraint would be overly restrictive, potentially making the problem infeasible. Consequently, the optimization procedure would not be able to return any valid assignment, which would significantly impact the usability and practical relevance of the entire system. The introduction of the $switch$ binary variable and the $BigM$ parameter allows the proposed model to effectively handle such infeasible scenarios by dynamically activating a fallback constraint, namely the *absolute maximum capacity of a room*. In doing so, the model dynamically adapts to overly restrictive user choices, ensuring that a feasible and practical solution is always provided.

Alternative constraint 1 - maximum desired capacity of a room

To prevent overcrowding, the total number of personnel assigned to room s on day d must not exceed the maximum desired capacity, defined as a fraction max_capacity of the total number of available workstations P_s. This condition is expressed by:

$$\sum_{n=1}^{N} u_{nsd} \leq \text{max\_capacity} \times P_s + \text{BigM}(1 - switch) \quad \forall s \in S_R, \text{ and } d = 1, \dots, K \tag{1}$$

Alternative constraint 2 - absolute maximum capacity of a room

As an alternative to the maximum-capacity constraint, we impose an absolute constraint that ensures the number of people in a room never exceeds the total number of workstations available there.

$$\sum_{n=1}^{N} u_{nsd} \leq P_s + BigM(switch) \quad \forall s \in S_R, \text{ and } d = 1, \dots, K. \tag{2}$$

This constraint serves as a fallback if problems arise with the previous constraint or if no feasible solutions can be found under the maximum desired capacity constraint.

Constraint on the uniqueness of the room for each person for each day

To prevent overlaps and conflicts in room assignments, each person n must be assigned to at most one room on any day d when they are scheduled to be in the office.

$$\sum_{s=1}^{S} u_{nsd} \leq a_{nd} \quad \text{for } n = 1, \dots, N;\ d = 1, \dots, K. \tag{3}$$

If $a_{nd} = 1$, meaning person n is scheduled to be in the office on day d, then the left-hand side ensures that they are assigned to at most one room on that day. If $a_{nd} = 0$, indicating they are not scheduled to be in the office.

Constraint on the uniqueness of the workstation for each person per day

Each workstation p in room s on day d is assigned to at most one individual n:

$$\sum_{n=1}^{N} v_{nspd} \leq 1 \quad \forall s \in S_R, p \in P_s, d = 1, \dots, K \tag{4}$$

Constraint on the specific assignment of a desk within the room

For each person n, on each day d, and in each room s, the sum of the workstation assignment variables v_{nspd} over all desks p in room s must equal the room assignment variable u_{nsd}:

$$\sum_{p=1}^{P_s} v_{nspd} = u_{nsd} \quad \forall s \in S_R, p \in P_s, \ d = 1, \dots, K. \tag{5}$$

If $u_{nsd} = 1$, then person n is assigned to room s on day d and the sum $\sum_{p=1}^{P_s} v_{nspd}$ must equal 1. This means that person n is assigned to exactly one specific desk p within that room s on day d.

Constraint on the consistency of the specific desk

To maintain consistency in desk assignments and enhance personnel's work experience, each person n should retain the same desk p in room s on all days they are scheduled to be in the office. This consistency reduces logistical complexities and contributes to a more efficient and comfortable working environment (Bosch-Sijtsema et al., 2010; Ditchburn, 2014; Mercer, 1966; Shepheard, 2015). The imposed constraint is the following:

$$v_{nspD_n(j)} = v_{nspD_n(j+1)} \quad \forall s \in S_R, p \in P_s, \ d = 1, \dots, K \text{ and } j = 1, \dots, \mathrm{Card}(D_n) - 1 \tag{6}$$

Constraint on the assignment of the person present to a desk

To ensure that each person n is assigned to exactly one desk on each day $d \in D$ when they are scheduled to be present in the office, the following condition must be satisfied:

$$\sum_{s=1}^{S} \sum_{p=1}^{P_s} v_{nspd} = a_{nd} \quad \text{for } n = 1, \dots, N; \ d = 1, \dots, K. \tag{7}$$

Constraints on the preference of units in rooms

To promote organizational cohesion and enhance collaboration among personnel, the model aims to assign individuals from the same preference group to the same room whenever feasible.

For each group $G \in G_P$, and for all pairs of personnel $n, m \in G$ with $n < m$, the following constraints link the auxiliary variable y_{nmsd} to the room assignments:

$$\begin{cases} y_{nmsd} \le u_{nsd} & \forall n, m \in G, s \in S_R, d = 1, \dots, K \\ y_{nmsd} \le u_{msd} & \forall n, m \in G, s \in S_R, d = 1, \dots, K \\ y_{nmsd} \ge u_{nsd} + u_{msd} - 1 & \forall n, m \in G, s \in S_R, d = 1, \dots, K \end{cases} \tag{8}$$

This set of constraints ensures that y_{nmsd} equals 1 if both n and m are assigned to room s on day d. The condition $n < m$ ensures that each pair is considered only once, avoiding redundant calculations.

Constraint on the separation of specific people

A separation constraint is introduced to ensure that certain people, identified by the set I, are not assigned to the same room on a given day. The following constraints prevent any pair of people (n, m) belonging to the set I from being assigned to the same room s on the same day d:

$$u_{nsd} + u_{msd} \le 1 \quad \forall (n, m) \in I, \forall s \in S_R, d = 1, \dots, K. \tag{9}$$

3.5. Objective function

To achieve the outlined objectives outlined in Section 3.1, we formulate a multi-objective function combining occupancy minimization with team cohesion. Since the optimization problem is formulated as a *minimization*, we incorporate the team cohesion objective by minimizing the negative of the team cohesion term.

Our initial multi-objective function can be expressed as:

$$\min \left[\lambda \cdot \max_{s,d} \left(\frac{\sum_{n=1}^{N} u_{nsd}}{P_s} \right) - (1 - \lambda) \cdot \left(\frac{1}{N^2 SK} \sum_{n,m,s,d} y_{nmsd} \right) \right]. \tag{10}$$

Note that:

- $\lambda \in [0, 1]$ is a weighting factor balancing the emphasis on minimizing occupancy and maximizing team cohesion.
- $\max_{s,d} \left(\frac{\sum_{n=1}^{N} u_{nsd}}{P_s} \right)$ represents the maximum room occupancy ratio.
- $\sum_{n,m,s,d} y_{nmsd}$ measures the total team cohesion.

To linearize the objective function and remove the max operator, we introduce an auxiliary variable z and the following constraint:

$$z \ge \frac{\sum_{n=1}^{N} u_{nsd}}{P_s}, \quad \forall s \in S_R, d = 1, \dots, K. \tag{11}$$

Thanks to (11), z is greater than or equal to the occupancy ratio of any room s on any day d.

With the introduction of z, we can reformulate the multi-objective function in a linearized form:

$$\min \left[\lambda z - (1 - \lambda) \cdot \left(\frac{1}{N^2 SK} \sum_{n,m,s,d} y_{nmsd} \right) \right]. \tag{12}$$

The first term targets the minimization of the maximum room occupancy ratio by varying the auxiliary variable z. This clearly aligns with the objective of reducing crowding across the available office spaces.

The second term is used to maximize the team cohesion. By dividing the team cohesion term by $N^2 SK$, we ensure that this component's value ranges between 0 and 1, thereby aligning it with the range of z.

3.6. ILP formulation

In this subsection, we report the mathematical formulation of the proposed optimization problem:

$$\text{Minimize} \quad \lambda z - (1 - \lambda) \frac{1}{N^2 SK} \sum_{n,m,s,d} y_{nmsd}$$

subject to:

$$\sum_{n=1}^{N} u_{nsd} \le \text{max\_capacity} \times P_s + \text{BigM}(1 - switch) \quad \forall s \in S_R, \text{ and } d = 1, \dots, K$$

$$\sum_{n=1}^{N} u_{nsd} \le P_s + BigM(switch) \forall s \in S_R, \text{ and } d = 1, \dots, K$$

$$\sum_{s=1}^{S} u_{nsd} \le a_{nd} \quad \text{for } n = 1, \dots, N; \ d = 1, \dots, K$$

$$\sum_{n=1}^{N} v_{nspd} \le 1 \quad \forall s \in S_R, p \in P_s, d = 1, \dots, K$$

$$\sum_{p=1}^{P_s} v_{nspd} = u_{nsd} \quad \forall s \in S_R, p \in P_s,\ d = 1, \dots, K$$

$$v_{nspD_n(j)} = v_{nspD_n(j+1)} \quad \forall s \in S_R, p \in P_s,\ d = 1, \dots, K \\ \text{and } j = 1, \dots, \mathrm{Card}(D_n) - 1$$

$$\sum_{s=1}^{S} \sum_{p=1}^{P_s} v_{nspd} = a_{nd} \\ \text{for } n = 1, \dots, N;\ d = 1, \dots, K$$

$$\begin{cases} y_{nmsd} \leq u_{nsd} & \forall n, m \in G, s \in S_R, d = 1, \dots, K \\ y_{nmsd} \leq u_{msd} & \forall n, m \in G, s \in S_R, d = 1, \dots, K \\ y_{nmsd} \geq u_{nsd} + u_{msd} - 1 & \forall n, m \in G, s \in S_R, d = 1, \dots, K \end{cases}$$

$$u_{nsd} + u_{msd} \leq 1 \quad \forall (n, m) \in I, \forall s \in S_R, d = 1, \dots, K$$

$$z \geq \frac{\sum_{n=1}^{N} u_{nsd}}{P_s}, \quad \forall s \in S_R, d = 1, \dots, K \tag{13}$$

4. Case study

This section presents the application of the described ILP problem to a real-world scenario. The case study examined staff distribution within a General Directorate of the *Ministry of the Republic of Italy*.

It is worth noting that the maximum desired room occupancy threshold of 0.8 was determined based on an internal preliminary analysis conducted by the personnel management department of the administration under consideration in this study. This analysis identified significant underutilization of existing office space, indicating an optimal occupancy threshold of 80%. Indeed, a higher theoretical occupancy would likely yield limited practical benefits due to typical underutilization caused by unpredictable absences (e.g., sick leave, training, and organizational mobility). Thus, setting the occupancy threshold at 0.8 results in realistic yet notably improved outcomes, effectively enhancing workspace quality without compromising practical feasibility.

To facilitate the validation of the optimization tool's functionality, we selected a structure with rooms specifically sized to accommodate entire organizational units. This design choice allows us to effectively monitor and assess how well the optimization model adheres to the constraints and objectives defined in the earlier sections.

Employees were instructed to choose up to 2 days of smart working or a similar arrangement, while also considering the possibility of full office presence. The choice was based on the current institutional policy and the specific needs of each employee, with the sole request to keep this day "stable" during the experimentation period. As discussed in Section 1, the capacity indicated here will only be the maximum possible, with other factors intervening within human resources, which inevitably lead to this value decreasing. In order to verify the functioning of the optimization system, and without prejudice to the principle whereby each employee is permanently assigned to a workstation as indicated by the constraint (6), the employees were distributed in the rooms starting from the assumption that the workstations were available to everyone, given the organization of the institution. The intent, therefore, is to reduce pressure on the structure by reducing overcrowding in the rooms, rather than accommodating a greater number of employees on a limited number of workstations. By doing so, the case study is sized to ensure sufficient workstations are available for all people in the organization.

The proposed case study includes twenty-five people ($N = 25$) divided into four distinct organizational units, which correspond to the preference groups G_P. There are five rooms ($S = 5$) offering a total of forty workstations ($P_1 = 8,\ P_2 = 7,\ P_3 = 10,\ P_4 = 8,\ P_5 = 7$).

The personnel are grouped into the following preference groups:

- **Group A** ($G_A = \{1, 2, 3, 4, 23\}$).
- **Group B** ($G_B = \{5, 6, 7, 8, 9, 10, 11, 12, 24\}$).
- **Group C** ($G_C = \{13, 14, 15, 16, 17, 25\}$).
- **Group D** ($G_D = \{18, 19, 20, 21, 22\}$).

These groups represent the organizational units within the General Directorate and are used in the model to promote team cohesion by assigning members of the same group to the same rooms whenever possible. Furthermore, the model reflects the strategic decision to distribute the last three newly hired personnel units across the first three offices.

As indicated in Section 3 and in Constraint (9), certain pairs of individuals must *not* be assigned to the same room in accordance with specific organizational requirements. In the case study, we have restricted the set of such pairs to $I = \{(1, 18)\}$.

Each individual specified their preferred days for working remotely, resulting in variable weekly attendance, represented in Table 3.

Table 3
Schedule of alternative frameworks to in-person work.

Personnel	Mon	Tue	Wed	Thu	Fri
Alessandro				X	
Alessia			X		
Alice				X	
Andrea				X	
Anna					X
Aurora		X			
Chiara				X	
Davide					X
Emma					X
Francesco	X				
Gabriele	X				
Giorgia					X
Giulia			X		
Greta			X		
Lorenzo		X			
Luca				X	
Marco		X			
Martina				X	
Matteo			X		
Riccardo	X				
Simone				X	
Sofia			X		
Grazia			X		
Graziella		X	X		
Gabriella	X			X	

4.1. The optimization results

The model was implemented using the Python API of IBM ILOG CPLEX Optimization Studio®, specifically the latest version available at the time of writing (22.1.1). We executed the code on a server equipped with an AMD Ryzen 9 7950X3D processor (16 cores and 32 threads), 1.9TB of disk space, and 128 GB of RAM. The choice of a high-performance machine was motivated by the need to run the script multiple times with different λ values to obtain the results presented in Table 4. We utilized Python libraries such as *openpyxl*, *numpy*, *pandas*, *seaborn*, and *matplotlib* for data handling and visualization.

The solutions were obtained considering different values of λ, and to analyze the results with the greatest possible level of detail, logs were also inserted into this script to automatically extrapolate significant data and merge them into a CSV file whose results are reported in Table 4. This table presents the optimization results and technical data, including the decision variables evaluated during the optimization process.

Table 4
Lambda iterations.

Lambda	Av. Occ.	Same team allocation	Execution time [H]	Ticks	Decision variables
1.0	0.48	13	0.41	416	197
0.9	0.49	21	0.27	459	2245
0.8	0.49	21	0.26	457	2251
0.7	0.49	21	0.28	495	2336
0.6	0.49	21	1.31	2631	2297
0.5	0.49	21	4.21	6778	2262
0.4	0.49	21	6.55	10 338	2251
0.3	0.49	21	7.21	11 127	2692
0.2	0.49	21	15.56	20 435	2445
0.1	0.49	21	22.10	29 018	2255
0.0	0.50	25	0.59	1374	2367

Upon reviewing the experimental data, it becomes evident that the system identifies three main scenarios, each reflecting a unique balance between average room occupancy and team cohesion. These solutions demonstrate the model's effectiveness in balancing the inherent trade-offs involved in personnel allocation.

In the first scenario, the system prioritizes maximizing occupancy, potentially at the expense of team cohesion ($\lambda = 1$). This solution focuses on minimizing space utilization and ensuring rooms are filled to their optimal capacity, with less emphasis on grouping individuals by team.

The second scenario, which is obtained using lambda values ranging from 0.1 to 0.9, offers a more balanced compromise. Here, the model optimizes both occupancy and team cohesion to an intermediate level, achieving a practical balance between spatial efficiency and organizational unity. This point embodies a harmonious trade-off where neither objective is strongly favored over the other.

Finally, the third scenario suggests a configuration that prioritizes team cohesion ($\lambda = 0$). In this scenario, the model prioritizes maximizing team member groupings, even if it results in lower occupancy rates. This highlights a focus on social optimization, enhancing team interaction and collaboration within shared spaces.

This interpretation is further supported by the trends observed in Fig. 1, where the relationship between organizational units and room allocation varies as a function of λ. The graph shows that as λ decreases from 1.0 to 0.0, the allocation strategy shifts in response to the multi-objective function employed. Specifically, when $\lambda = 1.0$, the model prioritizes minimizing the maximum room occupancy percentage. This leads to a configuration in which a single team uses more rooms, with more teams co-located in the same spaces, thereby maximizing space efficiency while maintaining acceptable occupancy levels.

Conversely, as λ decreases, the second term of the objective function (which favors the co-location of personnel of the same team) gains more influence. This results in a shift towards a configuration that prioritizes social optimization and team cohesion over strict occupancy efficiency. The model thus begins to agglomerate teams in the same rooms, even if this means utilizing space less efficiently and saturating occupied rooms.

This phenomenon is most evident when $\lambda = 0$, at which point the first objective of the multi-objective function is effectively nullified, leaving only the summation of y_{nmsd} over all indices n, m, s, and d to guide the optimization process. Under this extreme configuration, the model prioritizes the co-location of organizational units to the greatest extent, resulting in a scenario where all teams are allocated to a single room. This completely disregards room occupancy efficiency, as the model focuses exclusively on maximizing the team allocation preferences.

In this particular case, where the organizational units outnumber the available rooms (please note that the problem was structured with four units as opposed to five rooms), one room is left entirely vacant. A more comprehensive view of the results is depicted in Appendix A, Fig. A.5. The results shown highlight how the teams are distributed across the room for different values of λ. If $\lambda = 0$ people pertaining to the same team are assigned to only one room. On the contrary, if $\lambda = 1$ people of the same team are distributed in different rooms by maximizing the occupancy of the rooms. Intermediate solutions are obtained for $0 < \lambda < 1$, emphasizing the trade-off between optimizing for team cohesion and space efficiency.

For a deeper analysis of the results, Fig. 2 simultaneously illustrates the average room occupancy and the total number of personnel allocated to the same rooms as their team colleagues across different values of λ. A superficial inspection of this graph might lead to identifying the configuration corresponding to $\lambda = 0$ as seemingly ideal. Indeed, this setting exhibits simultaneously the highest team cohesion (i.e., the maximum number of people allocated with colleagues from their teams) and the lowest corresponding average room occupancy.

Nonetheless, this conclusion is misleading when investigated more thoroughly. Fig. 3 clearly highlights a significant drawback associated explicitly with the $\lambda = 0$ scenario, which remains unnoticed when observing only the aggregated metrics. Specifically, by closely examining the heatmap, it becomes clear that when $\lambda = 0$, one room (Room_02) remains completely unused for the entire scheduling period. Such a scenario is inherently inefficient from the perspective of facility resource allocation.

Conversely, intermediate scenarios clearly emerge as the most effective solutions overall. Although Fig. 2 does not show significant differences in numerical performance between these solutions and other intermediate ones ($\lambda \in [0.1, 0.9]$), especially with regard to the analysis of same-team allocation, the detailed occupancy analysis presented in Fig. 3 reveals additional advantages. In particular, carefully inspecting the heatmap for $\lambda = 0.5$ and $\lambda = 0.6$, these solutions appear superior as they explicitly relieve occupancy on Wednesday and even more so on Thursday in Room_04, which is overall among the most crowded rooms. This detailed insight underscores the value of the multi-objective optimization model and the critical role of graphical visualizations in guiding informed decisions toward the optimal allocation scenario.

The obtained results confirm the model's correctness, demonstrating its ability to navigate between competing objectives depending on the chosen λ value.

To further validate the proposed ILP model and underline its advantages, we briefly analyze two alternative simplified heuristic approaches. A first candidate is the *First-Fit Decreasing* heuristic (Yue & Zhang, 1995), commonly applied in bin packing problems, where individuals are ordered by decreasing weekly attendance frequency and sequentially allocated into the minimum number of rooms, saturating each room before opening a new one. Although straightforward, this approach tends to saturate rooms, which conflicts with our goal of minimizing maximum occupancy to ensure workplace flexibility. A second heuristic might evenly distribute employees across available rooms, regardless of their individual attendance schedules, thereby ignoring each worker's weekly attendance variability. Such heuristic inevitably results in a suboptimal weekly occupancy distribution. Conversely, our proposed ILP explicitly considers individuals' attendance variability and optimizes weekly space usage accordingly. Moreover, thanks to its multi-objective formulation based on the parameter λ, the ILP framework offers multiple solutions that balance occupancy and team cohesion, thereby providing decision-makers with enhanced flexibility tailored to their managerial requirements.

However, based on the results discussed in this section, an organization with limited computational resources may focus exclusively on exploring solutions for $\lambda \in \{0, 0.6, 1\}$. Notably, the solution for $\lambda = 0.6$ is highly similar to that for $\lambda = 0.5$, but with a reduced computational time, according to Table 4.

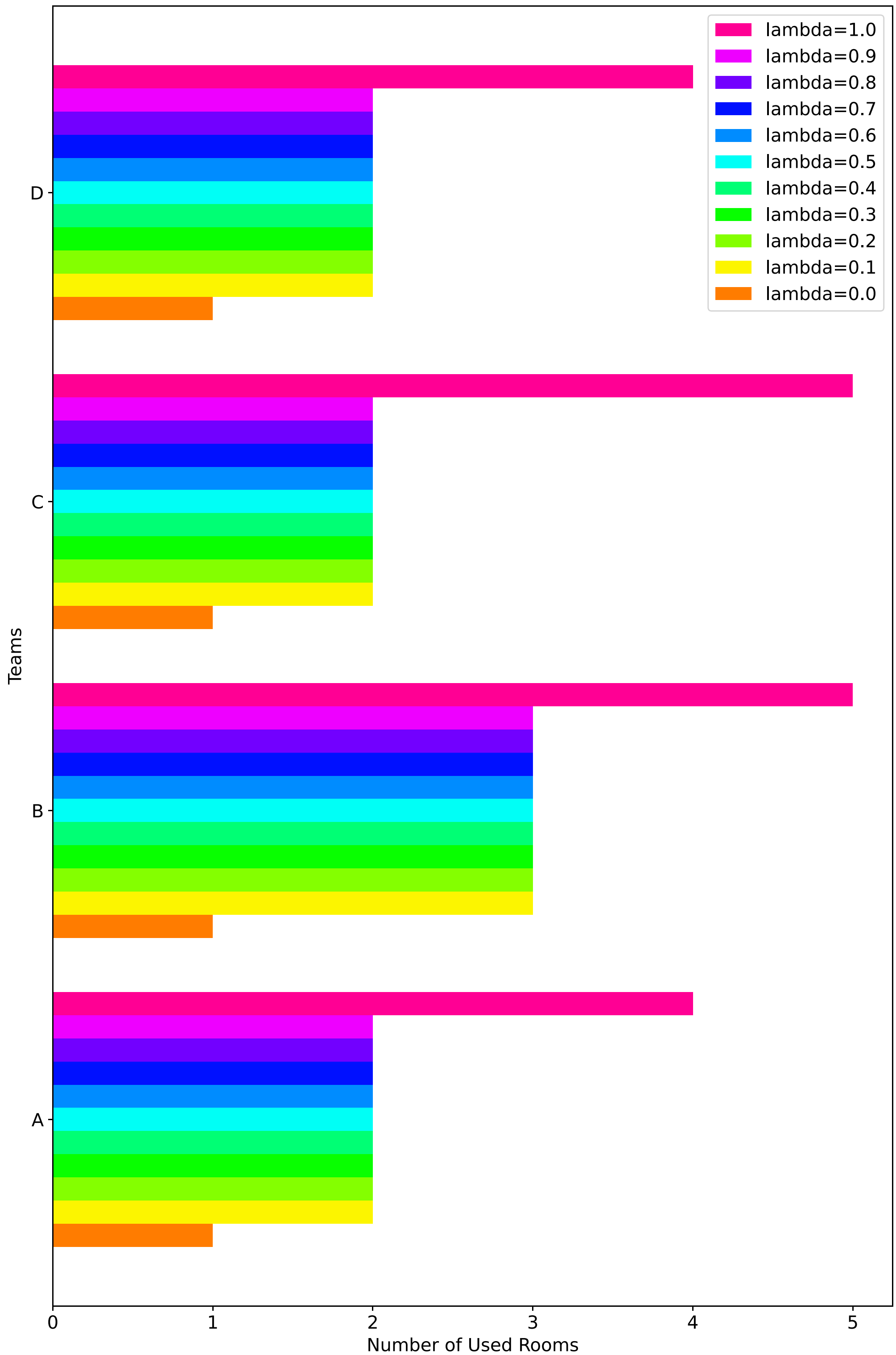

Fig. 1. Relationship between team distribution and the number of used rooms for $\lambda \in [0.0, 1.0]$.

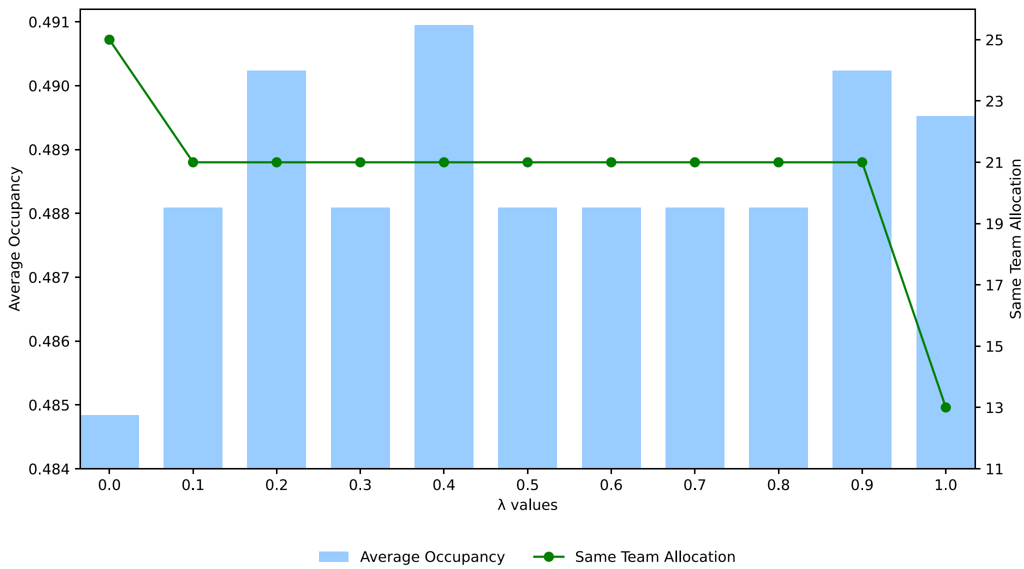

Fig. 2. Average occupancy and same team allocation as functions of lambda.

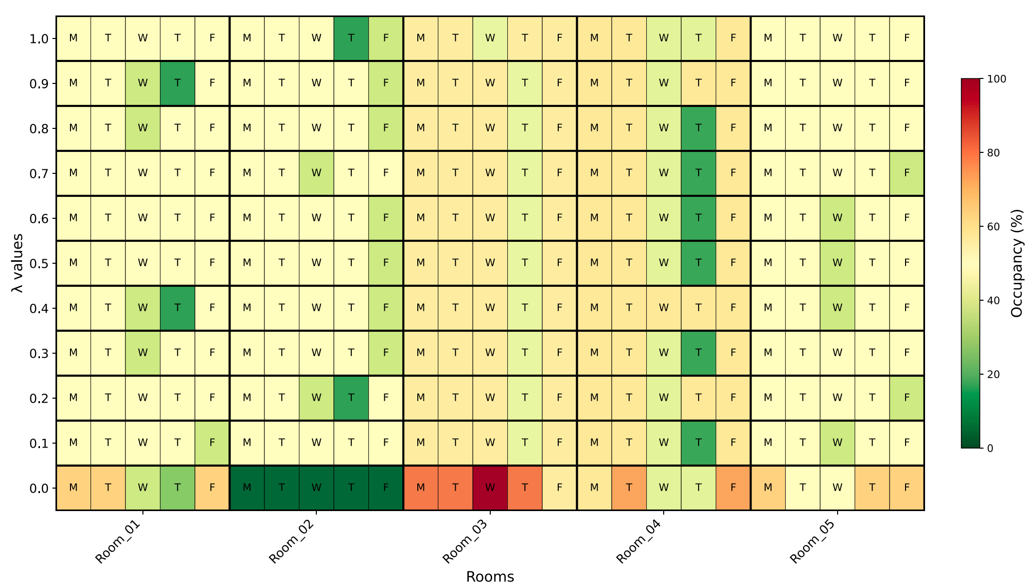

Fig. 3. Heatmap representing daily occupancy of rooms for different lambda values.

5. Front-end

The final objective of the work is to provide an optimization tool for the offices responsible for personnel management. To achieve this, the structures must be equipped with a simple tool for loading data and reading outputs. Considering the project's institutional target, we ensured that the web interface can read data from a spreadsheet, with a supplied template ready for compilation from the same interface, as shown in Fig. 4. The tool discussed in this study is currently available at the following web address: https://rgsgo.it/roomsoptimization.

The back-end receives the file, extracts the data, and processes it directly. Subsequently, the Python code extracts the data from the solver and organizes it into a JSON file. This makes it easy to present the data on the front end and reorganize it into a new spreadsheet. Therefore, the human resources office can upload the staff list and their schedules to a spreadsheet, as well as the list of rooms and their corresponding positions to a second spreadsheet, which is then uploaded to the web platform. The back-end solver performs the optimization and returns a new spreadsheet ready for download containing the assignments. Furthermore, the web interface provides graphs showing the optimization results.

The developed web-based tool is characterized by strong computational efficiency, as the presented ILP formulation provides quick optimization, with typical runtimes in the order of seconds or minutes for realistic-size problems. Directly uploading Excel spreadsheets enhances ease of use, allowing the personnel management office to quickly adopt the tool without extensive technical setup or specific informatics competencies.

From a usability standpoint, the only relevant challenge encountered was related to input data preparation. Indeed, users manually

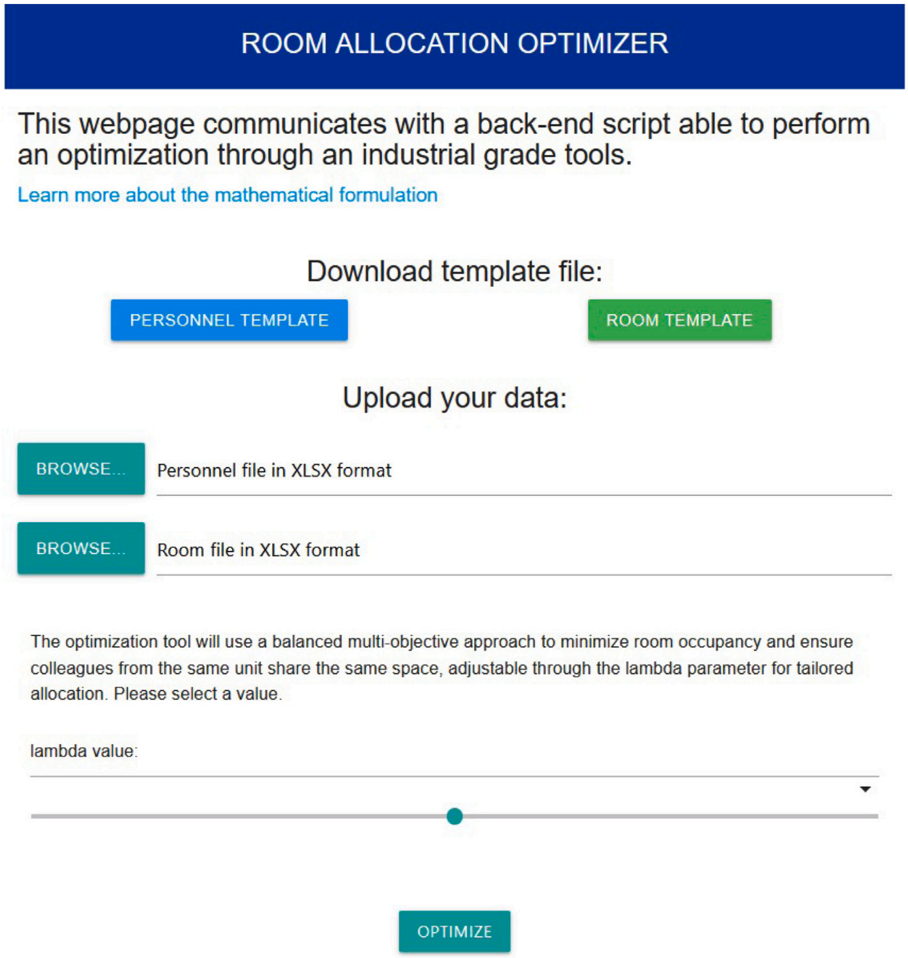

Fig. 4. Front-End webpage.

compile Excel sheets containing employee schedules and room information, where the complexity of preparation scales with organization size. Hence, for larger scenarios, the greatest barrier to usability resides in data compilation and formatting. Nevertheless, initial tests with end-users reported a positive user experience due to the intuitive and straightforward interface.

Potential improvements can focus on enhancing scalability and practicality by integrating this prototype into existing management software through dedicated Application Programming Interfaces (APIs). In such scenarios, employee schedules and room assignments can be automatically retrieved, significantly reducing the data preparation burden and improving overall user experience in larger-scale organizational contexts.

Given the ultimate goal of this work, the outputs that are useful to a human resources coordination office are listed in the following.

- **Distribution of people**: This output shows where each person sits in each room and on each day. In other words, the layout generated here shows for each person n in which room s they are located during day d, according to the variable u_{nsd}.
- **Room layout**: Based on the previous output, the system can generate a basic room layout indicating the workstation and room to which employees are assigned.
- **List of employee assignments**: A list containing all employees as well as the room and workstation to which they are assigned.
- **Percentage of occupancy per room and day**: For each room s and each day d, it is known how full every room actually is.

At the end of the optimization, it is possible to obtain both the graphs and files representing the optimal solution found by the implemented tool.

6. Conclusions

This paper aimed to design an effective tool for optimizing staff distribution in the available rooms of companies or public buildings. To this aim, a multi-objective ILP problem is formulated to account for competing priorities, ensuring that the final solution achieves spatial efficiency while aligning with the organization's social and operational requirements.

When applying the solution in a real-world scenario, the importance of organizational units is underlined. Although we have provided the option to prioritize grouping personnel within the same team, organizational units may still emerge fragmented from a reorganization process that strongly emphasizes reducing average occupancy rather than aggregating personnel from the same units. Our approach provided management offices with a tool designed to optimize space allocation, ensure proper personnel management, and identify potential critical issues that warrant evaluation during the implementation phase.

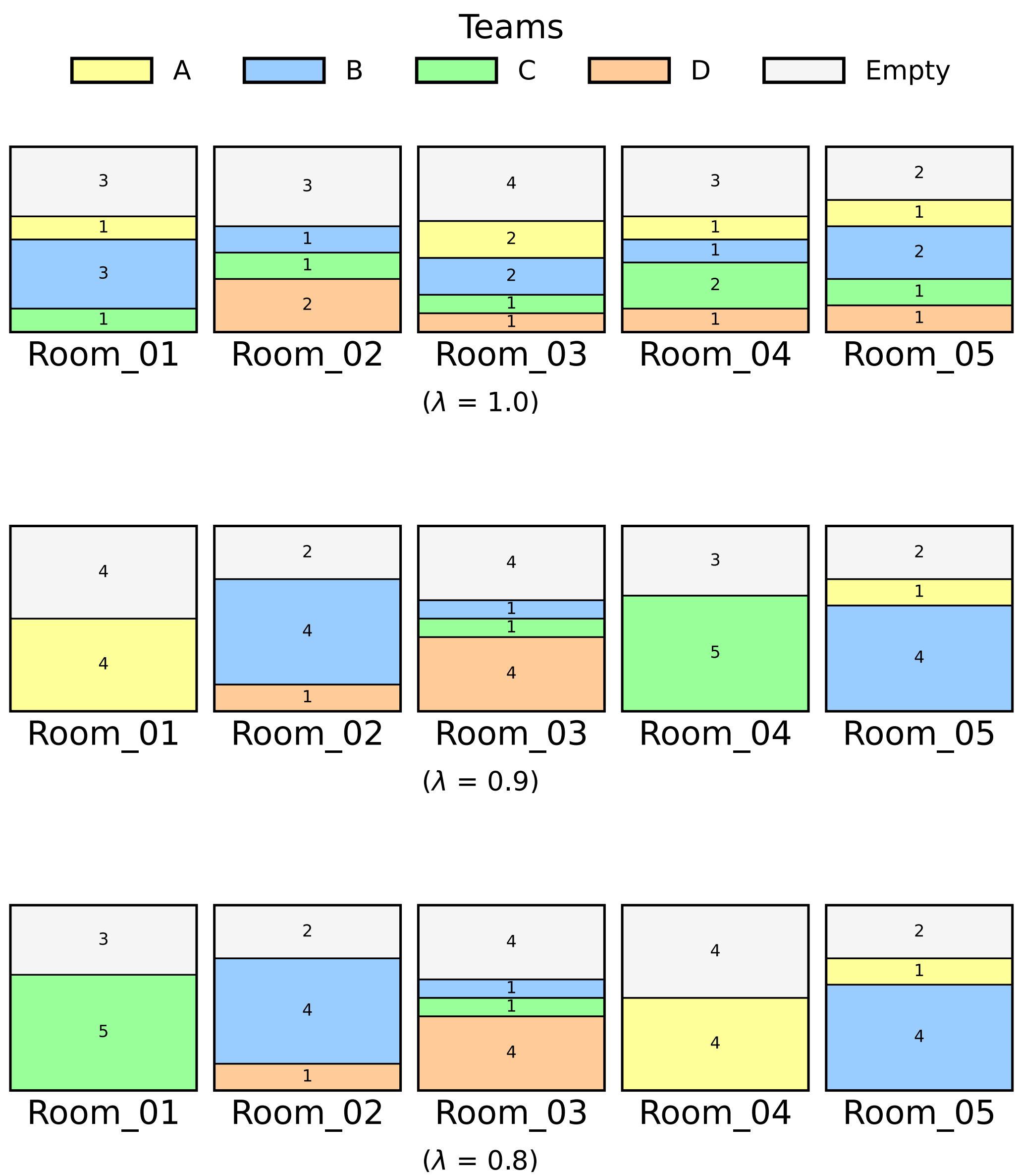

Fig. A.5. Room Assignments Graph for $\lambda \in [0.0, 1.0]$.

Although the proposed approach was designed primarily for stable, mid-term planning rather than real-time adjustments, future research might explore ways to enhance model adaptability to unexpected disruptions, such as sudden absenteeism or evolving regulations. Additionally, extending our ILP framework to non-human contexts (e.g., dynamically allocating machinery, equipment, or sensors) is another promising research direction, especially when integrating *machine learning* algorithms to improve model efficiency and scalability further.

CRediT authorship contribution statement

Giuseppe Olivieri: Writing – original draft. **Agostino Marcello Mangini:** Validation, Supervision. **Maria Pia Fanti:** Writing – review & editing, Validation, Supervision.

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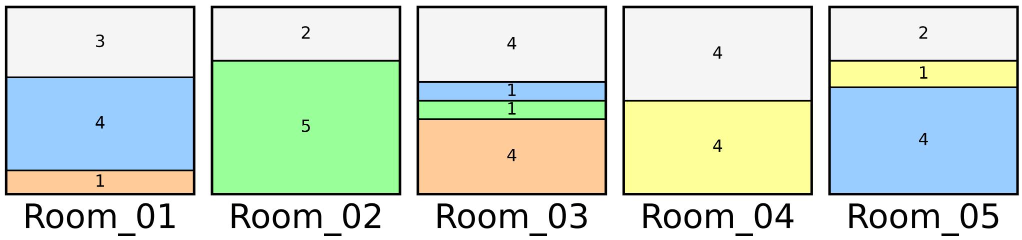
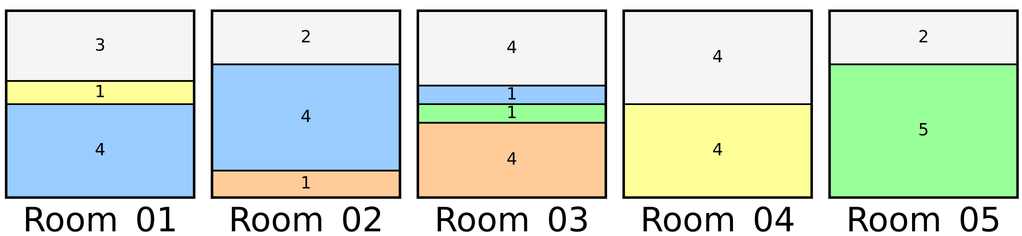
Appendix A. Room assignments graph

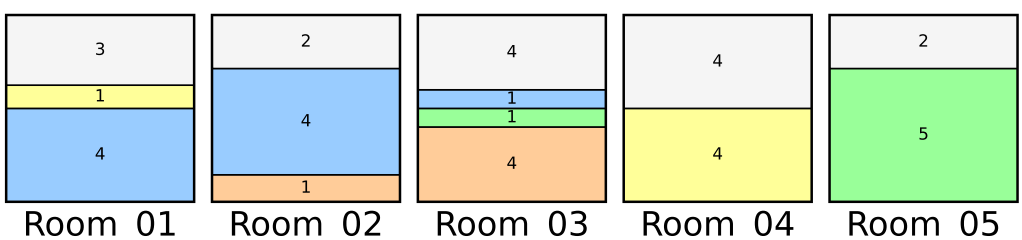
In this appendix, we present additional schematic visualizations (Fig. A.5) of personnel allocation across rooms as a function of the values of λ, which modify the impact of the occupancy ratio and the



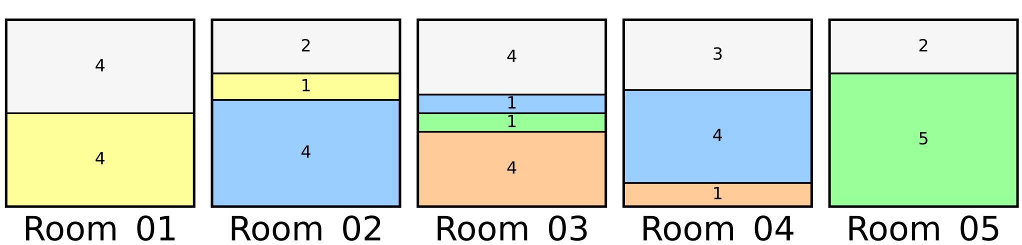
(λ = 0.7)



(λ = 0.6)



(λ = 0.5)



(λ = 0.4)

Fig. A.5. (*continued*).

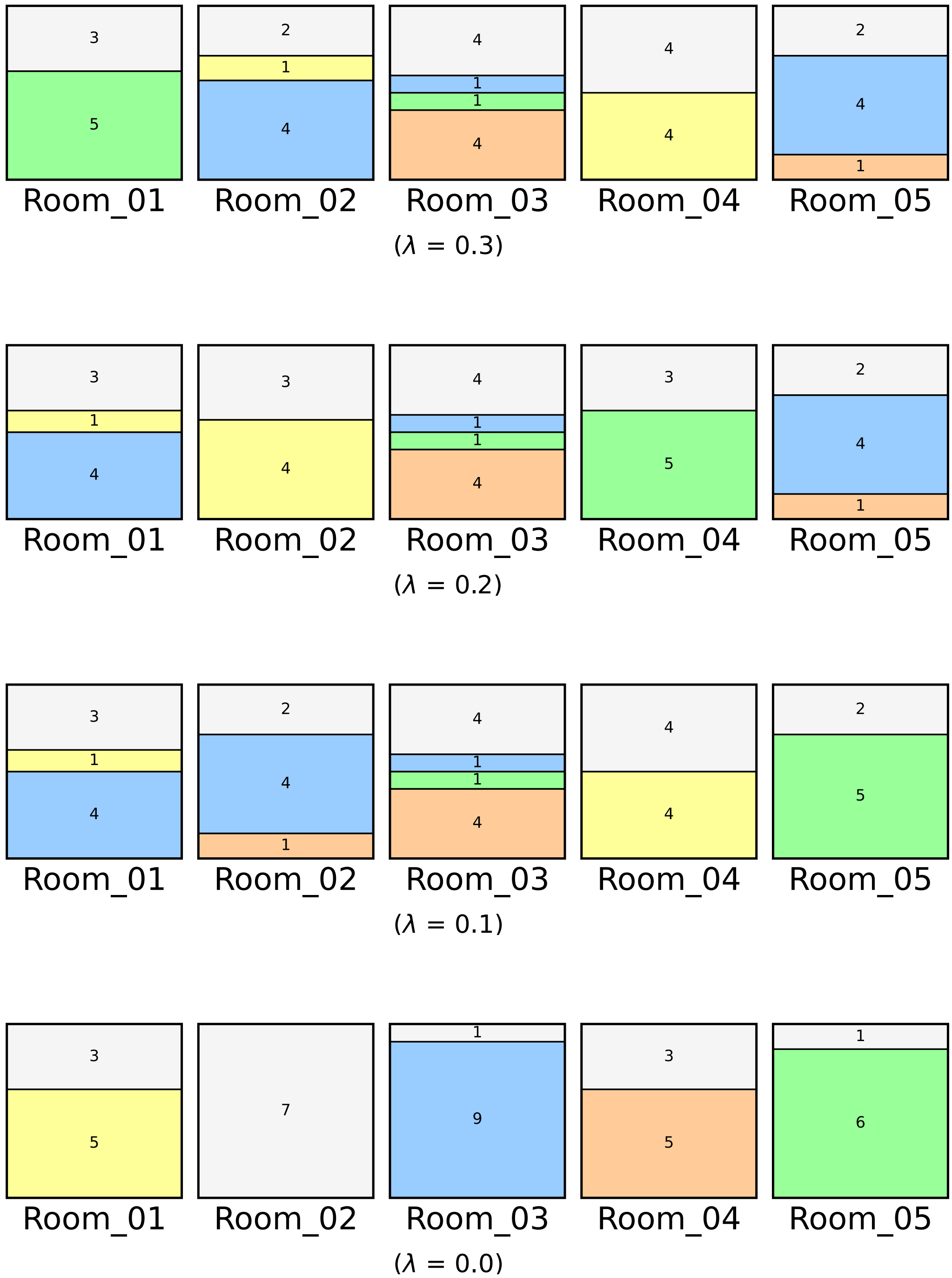


Fig. A.5. (*continued*).

team presence in the rooms. In each room, a different color is assigned to each team.

Data availability

No data was used for the research described in the article.

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