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Managing Energy Consumption and COVID-19 Infection Risk in Buildings Using Optimal Occupant Distribution

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Abstract

Occupant density is a critical factor influencing both energy consumption and the spread of virus infections in indoor educational environments. There is a growing need to design safe and efficient classrooms, laboratories, and lecture halls. This study presents an optimal distribution pattern of students that reduces the risk of COVID-19 infection while lowering energy consumption associated with heating, ventilation, and air conditioning (HVAC) systems. A case study of Level 1 of the M5 building at Jordan University of Science and Technology (JUST) was conducted, where the energy consumption was simulated using DesignBuilder and infection risk was modeled in MATLAB. The optimization problem was solved using a Multi-Objective Genetic Algorithm (MOGA) with data collected from four and five consecutive summer days. The study presents two optimal student distribution scenarios that reduce both infection risk and energy use. Results show that infection risk can be reduced by at least 12.7% and energy consumption by 5.7%. Furthermore, the study proposes new in-person and hybrid education models that shorten both working hours and class durations.

Keywords: Occupant density, HVAC energy consumption, COVID-19 infection risk, Building energy optimization, Multi-objective genetic algorithm (MOGA), Indoor air quality (IAQ), DesignBuilder simulation.

1. Introduction

The world is currently facing global warming driven by greenhouse gas emissions from fossil fuels, where buildings are responsible for 25% of CO_2 emissions and one-third of global energy use, making them a significant contributor to climate change [1]. The world is increasingly moving toward employing NetZero buildings to reduce CO_2 emissions and improve building energy efficiency. This goal depends not only on advanced technologies but also on human behavior. Occupant density affects a building's internal temperature, which in turn influences the energy consumption of the HVAC system. Although various factors impact HVAC performance, occupancy time plays a particularly important role in building energy management [2], [3]. Therefore, an optimal timetable for the occupants could significantly reduce overall energy consumption.

Additional heat is added to the internal loads due to the heat produced by occupants' activities, which leads to an increase in the energy consumption of the cooling system. Changes in atmospheric conditions are also closely related to energy consumption in buildings. Therefore, HVAC energy consumption fluctuates with varying weather conditions throughout the day. During hot weather, occupancy is reduced to accommodate the increased HVAC energy demand. By following this strategy, energy management in the building can be improved, reducing both energy consumption and the required capacity of renewable energy technologies. This results in greater preservation of the environment in the future when renewable energy system components are recycled or disposed of. This study aims to minimize both HVAC energy consumption and COVID-19 infection risk by determining the optimal student distribution pattern on Level 1 of the M5 building at JUST.

The multi-objective genetic algorithm (MOGA) is used in this study to reach the optimum occupant distribution. Several parameters influence both HVAC energy consumption and COVID-19 infection in the building, including air exchange rate, occupant behavior, occupant distribution, occupant activities, working hours, exposure duration, the effect of face masks, and others [4], [5]. Among these factors, the most prominent in terms of their impact on both HVAC energy consumption and the number of infected people are the number of working days, working hours, and class duration. The optimum attendance time of the occupants inside the building, and thus the optimum occupant distribution, can be determined by testing different distribution patterns of people in the building that correspond to the internal loads (energy consumption) and the climate conditions. Both energy consumption and the number of infected individuals must be considered simultaneously [5].

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The behavior of building occupants has been examined in terms of four factors: energy consumption, thermal comfort, indoor air quality (IAQ), and visual comfort, with the goal of improving indoor environmental quality and reducing energy use. It was observed that occupant behavior has the greatest influence on total energy consumption [6]. Further studies have focused on optimal building design by examining thermal comfort, thermal energy consumption, and life-cycle economic–environmental values. The proposed models can be applied in buildings to achieve better energy savings [7]. In addition, an occupant-centric method has been used to identify the best design for windows and shading [8].

Improving building energy efficiency has a significant impact on the sustainability of the urban environment. Therefore, energy consumption in various sectors in Jordan has been studied, and the findings concluded several factors that affect energy efficiency in buildings, such as building size and characteristics (e.g., building design) [9].

In early 2020, the world faced a crisis caused by the COVID-19 pandemic. While the search for medicine and vaccines was considered a task for the medical field, risk assessment became the responsibility of engineers. An infection risk model was developed to estimate the number of people infected by asymptomatic severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2). To implement the model, the quanta emission rate of the virus was determined using a reproductive number–based fitting approach [10]. The Wells-Riley model was also used to study occupant infections with COVID-19 [11]. Another study considered both the infection risk of COVID-19 and the energy consumption of the HVAC system to propose an optimal occupant distribution in the building during the day. This study, applied in Tehran, concluded that the number of infected people could be reduced by up to 56% and energy consumption by 32% [5].

Lockdowns for the education sector have drawbacks, especially for practical university majors, so in-person learning is required. Jordan University of Science and Technology houses many buildings with different configurations and purposes. One building is selected as a case study to develop an optimal occupant distribution pattern. The proposed model will manage an occupancy schedule that distributes the occupants over the day, confirming a lower infection risk and energy consumption of the HVAC system (which is one of the main causes of energy consumption in buildings), using the Multi-Objective Genetic Algorithm (MOGA) to solve the problem and provide the optimum solutions after the step of linking the outputs of the virus infection risk in MATLAB and the energy consumption per hour in DesignBuilder [12]. The simulation work was executed for 4 and 5 consequent days in summer for a case study at Jordan University of Science and Technology, relying on three parameters: number of working days, class duration, and working hours.Therefore, this research aims to reduce the energy consumption of HVAC system and Minimize the COVID-19 infection risk.

While previous studies have examined either HVAC energy optimization or infection risk separately, there is limited research that integrates both factors to determine optimal occupancy strategies in educational buildings during pandemics. This study addresses this gap by proposing a combined simulation and optimization framework that balances energy efficiency with health safety.

2. Methods and Methodology

This work was carried out using DesignBuilder software to examine the energy consumption of HVAC systems in Level 1 of the M5 building at JUST. The infection risk of COVID-19 was calculated by implementing equations related to virus transmission in MATLAB. The results of infection risk and energy consumption were then entered into the multi-objective genetic algorithm (MOGA) to provide optimal solutions. The required parameters were collected from the concerned authorities at the university, including the Engineering Project Management Department, the Admissions and Registration Office, and the Academic Development Center.

2.1. Energy Consumption

A crowded building results in increased internal heat gains, which raise the cooling loads and energy consumption of the HVAC system. Humans generate heat through metabolic processes that increase the zone air temperature; this is considered sensible heat energy.

The amount of cooling or heating energy ($Q_{\text{ooling, heating}}$)provided to the zone by the HVAC system is shown in Eq. (1).

$$Q_{\text{cooling, heating}} = m_{SA}(h_{\text{out}} - h_{\text{zone}}) \quad (1)$$

where m_{SA}: is the mass flow rate of air supplied from the HVAC system to the zone, and h_{out}/ h_{zone}: represent the enthalpy of the supply air and the zone air, respectively.

Changes in outdoor temperature affect the operation of the HVAC system, leading to variations in indoor conditions. These fluctuations influence peak load and energy pricing, which can be mitigated by optimizing occupant distribution. If this factor is considered in building energy management, the peak load can be reduced, and therefore energy costs will decrease [13]. This is achieved by determining the optimum distribution of the building's occupants.

2.2. Mathematical Model of COVID-19 to Compute the Infection Risk

To compute the infection risk of COVID-19, the number of virus particles present in a space must first be estimated. For this purpose, the Gammaitoni model provides a quanta level that varies with time [5], [14]. This model is suitable for supermarkets, airplanes, cars, and other confined spaces [5], [15], [16], [17]. Its differential equations were solved using initial conditions to calculate the quanta concentration over time. In this case, the infection risk was computed to estimate the number of new infections in the building, under the following assumptions:

1. The change in susceptibility is ignored.
2. The rate of virus quanta generation is constant.
3. The model time scale is longer than the latent period of the disease, and the number of infected occupants in the classroom is constant.
4. Respiratory droplets are assumed to be distributed instantaneously and uniformly throughout the building.

5. Respiratory droplets are removed by fresh air ventilation at a constant rate.

The assumptions contribute to forming the equations [2 to 5] as the Gammaitoni model is solved to derive Eq. 2.

Based on these simplifications of assumptions, Eq. (2) was formed. It provides the number of infectious airborne particles, expressed as the quanta concentration at time ttt within the space (n(t)). The IVRR is then calculated usingEq. (3) [5].

$$\mathrm{n(t)} = \frac{\mathrm{ERq.I}}{\mathrm{IVRR.V}} + \left(n_0 + \frac{\mathrm{ERq.I}}{\mathrm{IVRR.V}}\right) . \frac{\mathrm{e}^{-\mathrm{IVRR.t}}}{\mathrm{V}} \quad (2)$$

where ERq: represents the virus particles spread in the air due to inhalation and exhalation, based on the virus characteristics; I: number of infected people in the building, IVRR: elimination rate of the virus, V: building volume (m^3), n_0: initial concentration of the virus particles, t: exposure time of the affected persons (hr).

$$\mathrm{IVRR} = \mathrm{AER} + \mathrm{C_{settling}} + \mathrm{C_{inactivation}} \quad (3)$$

where AER: air exchange rate (hr^{-1}), $C_{settling}$: virus settlement coefficient (hr^{-1}), $C_{inactivation}$: virus inactivation rate (hr^{-1}).

After determining the virus characteristics and building parameters, the concentration of virus particles can be calculated. Using Eq. (4), the infection risk (R) can then be computed for non-infected individuals. In addition, Eq. (5) is used to calculate the new number of infected people with coronavirus (In) [5].

$$\mathrm{R} = \left(1 - \mathrm{e}^{-\mathrm{IR}\int_0^{\mathrm{T}} \mathrm{n(t)dt}}\right) \quad (4)$$

where IR: inhalation rate of people (m^3/hr), T: exposure time of occupants (hr).

$$\mathrm{In} = \mathrm{SxR} \quad (5)$$

S: the occupants’ number in the building.

To calculate the risk of infection, the hourly concentration of virus quanta must first be determined. The values of the required variables are listed in **Table 1**, and each is substituted into the corresponding equations (Eqs. (2)–(5)) [5].

The proportion of infected people with coronavirus was 0.38% until 3 August 2020 [5], [19], [20]. This proportion is used in the present study to compute the number of infected occupants in the M5 building, represented by (I) in Eq. (2). By 21 July 2021, the number of COVID-19 cases in Jordan had reached 762,706 out of a population of 10.2 million, corresponding to an infection proportion of 7.4%.

2.3. Optimization Process

The importance of genetic algorithms (GAs) lies in their ability to solve multi-objective problems. They can find solutions across discontinuous and complex solution spaces, including those beyond the Pareto front. The crossover operator exploits the outer region of the Pareto front to identify non-dominated solutions. In addition, GAs provide solutions without the need for scaling, prioritization, or weighting, which makes them a suitable approach for multi-objective problems.

The optimization problem in this study was solved using a multi-objective genetic algorithm (MOGA), selected for its ability to handle conflicting objectives by minimizing both energy consumption and infection risk. In this work, MOGA was tailored by defining the student distribution pattern as the decision variables and by assigning two objective functions: total HVAC energy demand and probability of infection. Constraints were applied based on classroom capacity and safety thresholds (e.g., minimum interpersonal distance and maximum occupancy per room), making the algorithm well-suited to simulate realistic scenarios in educational settings. The research methodology is illustrated in Figures 3.1 and 3.2, which summarize the process steps in a block diagram. The process began with data collection about the building and ended with optimization using MOGA, where the number of people represented the decision variables for each hour, expressed as discrete values ranging from a minimum of 40 to a maximum of 274.

Information about the M5 building and its HVAC system was collected from the Engineering Project Management Department. Data about lectures was obtained from the Admissions and Registration Office and the Academic Development Center at Jordan University of Science and Technology. **Figure 1** presents a summary of the data collected from these university authorities. The process began with inserting the collected data into DesignBuilder, while part of it was also used to solve the infection risk equation in MATLAB, as shown in **Figure 2**.

Table 1.The values of the desired variables in Eq. 2 to Eq. 5 to solve the infection risk.

Equation’s variables	The values
Proportion of infected people with COVID-19	0.38%
ERq	142 (quanta/hr) [16]
Height of the virus generating source	1.5 m (estimated)
Settling velocity	0.0001 m/s [18]
Virus settling rate	0.24 (hr^{-1})
Virus half-life coefficient	0.63 (hr^{-1}) [15], [16]
n_0 at the beginning	0
IR (inhalation rate of infected people)	0.96 hr^{-1}[16]
Exposure time (T) (it is the class duration)	1 hr

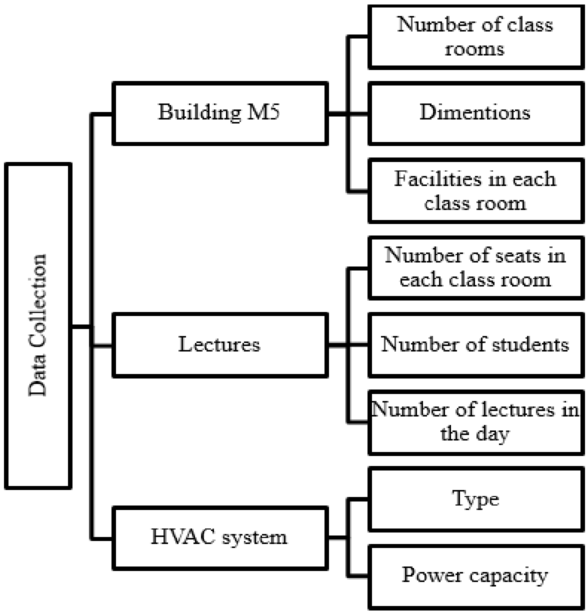


Figure 1. Block diagram of data collection for the M5 building.

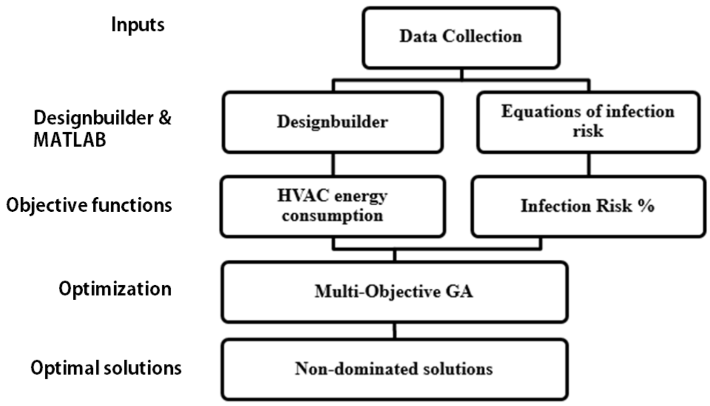


Figure 2. Block diagram of the optimization process.

The outputs of HVAC energy consumption and the number of infected people were optimized using MOGA in MATLAB. Non-dominated solutions were processed by crossover and mutation operators and presented on the Pareto front curve, which represents the optimal trade-off solutions for energy consumption and infection risk. Eqs. (6) and (7) are the constitutive optimization equations [5].

$$\text{Min } In_t = \sum_{d=t}^{4}\sum_{t=8}^{14}(In\ (t,x)) \quad (6)$$

$$\text{Min } E = \sum_{d=t}^{4}\sum_{t=8}^{14} E_c\ (t,x(t)) \quad (7)$$

Equation (6) represents the total number of infected occupants, which must be minimized to achieve the first objective function. To obtain the second objective, Eq. (7) expresses EEE as a minimization statement of HVAC energy consumption, specifically cooling energy (Ec). The summation is performed at each time step ttt for a given number of occupants (x) during the working hours (8:00 to 14:00) over four consecutive days, and then repeated for five working days [5].

$$\sum_{t=8}^{14} x(t) = 1314 \quad (8)$$

$$40 \leq x(t) \leq 274 \quad (9)$$

Equations (8) and (9) are considered the constraints of the optimization problem, as they define its limitations. Eq. (8) represents the aggregated number of occupants in the building during working hours (8:00 to 14:00), while Eq. (9) specifies the minimum and maximum allowable number of occupants for a given hour [5].

2.4. Building Characteristics

The building characteristics include its dimensions, wall divisions, thermal properties, and thickness. This study was applied to Level 1 of the M5 building at Jordan University of Science and Technology in Irbid, Jordan. The total area of this level is 656.65 m², with a length of 45.6 m, a width of 14.4 m, a wall height of 3 m, and two exit doors. Level 1 of the M5 building was divided into five classrooms. **Figure 3** shows the floor plan of this level, where the lectures are held. The plan clearly indicates five zones, each representing a classroom. In addition, a 3D model of this level was constructed in DesignBuilder.

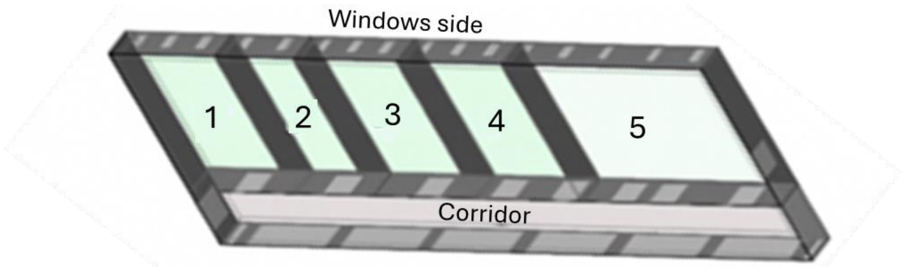


Figure 3. Layout of classrooms on the first level of the M5 building.

The maximum number of students per hour in the M5 building is 274, based on six classrooms operating during summer 2018. The total number of occupants throughout the day is 1,314. The working hours extend from 8:00 a.m. to 5:00 p.m., during which different occupant distributions (chromosomes) are assigned within the period. The Air Exchange Rate (AER) of the HVAC system was found to be 3 hr^{-1} in accordance with ANSI/ASHRAE standards [5].

The layers of the construction walls were assumed to follow typical building practices in Jordan, due to the lack of detailed construction information and resources for JUST [21]. These layers were defined in the DesignBuilder construction tab with their corresponding thicknesses and material properties, where the simulation was conducted. The thermal resistance for horizontal heat flux through uniform layers was calculated using Equation (10) [22].

$$\mathrm{R}\left(\frac{\mathrm{m^2.K}}{\mathrm{W}}\right) = \frac{\mathrm{d}}{\lambda} \tag{10}$$

where R represents the thermal resistance of the wall layer, d is the layer thickness, and λ is the thermal conductivity.

Based on Eq. (10), the thermal resistance for each construction layer was calculated and is presented in **Table 2**. The table includes R-values for the configurations of the building elements, including the walls, roof, and ground floor.

Table 2.Thermal resistance values of construction elements (walls, roof, and ground floor).

Elements	Configuration	R (m^2.k/w)
External wall	Solid concrete block	0.114
	Air gap	1.923
	Hollow concrete	0.1
	Cement plaster	0.0125
Internal wall	Cement plaster	0.025
	Concrete block	0.267
	Cement plaster	0.025
Ground floor	Concrete slab	0.01
	Mortar	0.0083
	Terrazzo	0.08
Roof	Concrete tiles for roofing	0.044
	Screed	0.067
	Reinforced concrete	0.167
	Plaster	0.0108

3. Results and Discussion

This section presents the results obtained from the simulation and optimization framework described earlier, followed by a discussion of their implications. The analysis focuses on two main objectives: reducing infection risk during the COVID-19 pandemic and minimizing HVAC energy consumption in educational buildings. By applying different occupant distribution strategies in the M5 building, the outcomes demonstrate how balancing these objectives can improve both health safety and energy efficiency.

3.1. The Effect of Occupant's Distribution on the Infection Risk of Coronavirus

The renewable energy sector has gained significant attention in Jordan, with rising rates of electricity generation from clean sources and the adoption of related technologies [23–24]. Improving building efficiency reduces the required size of renewable energy systems and, at the same time, helps mitigate the transmission risk of airborne diseases through effective ventilation while lowering HVAC energy consumption [25]. Maintaining indoor air quality, balancing energy use, and ensuring occupant thermal comfort remain significant challenges [26].

In this study, we examined the effect of occupant distribution on energy management in the M5 building. The first model represents the actual student distribution during summer 2018, based on occupancy data for four working days. The second and third models present the optimal occupant distributions for four and five working days, covering the periods of 21–24 July and 25 July, respectively.

The infection risk of COVID-19 depends on both occupant density and exposure time, as described by Eq. (3). **Figure 4** illustrates how infection risk varies with student count and exposure duration. For example, 274 students present for 20 minutes may produce the same infection probability as 70 students present for 60 minutes. Higher student density increases the likelihood of airborne transmission due to shared air and limited ventilation, while longer exposure leads to greater cumulative inhalation of virus-laden aerosols. Together, these factors explain the upward trend in infection risk as both exposure time and student number increase.

In summer 2018, data collected from the Admissions and Registration Unit showed that 274 students attended each of the first four lectures. Attendance then dropped to 178 students in the fifth lecture, held between 14:30 and 16:00, and decreased further to 40 students in the final lecture between 16:00 and 17:30.

In this study, the first model of occupant distribution is shown in Figure 5, representing actual conditions in Level 1 of the M5 building at Jordan University of Science and Technology. The total energy consumption was 765 kWh for four working days and 964 kWh for five working days. The corresponding infection risks were 0.42%, 0.30%, and 0.073% for different occupant densities. These results confirm the findings of Figure 4, which showed that infection risk increases with higher population density. In this case, the number of working hours was nine, with a class duration of 1.5 hours.

3.2. Investigated Parameters

In this section, three parameters were investigated: class duration, working hours, and the number of working days. The following assumptions were applied in the simulations:

- The total number of occupants was 1,266 for five working days.
- The total number of occupants was 1,314 for four working days, based on data from the Admissions and Registration Unit at JUST.

Class duration was examined first to evaluate its impact on both COVID-19 infection risk and HVAC energy consumption. **Figure 6** illustrates how longer lesson times increase both energy consumption and the number of infections over a nine-hour working day, with totals calculated across all simulated days.

The number of working days was also considered when testing the first parameter, class duration. **Figure 6(a)** and **Figure 6(b)** show the simulations for four and five working days, respectively. Reducing lecture time from 90 minutes to 60 minutes lowered the COVID-19 infection risk by 28% for four working days and by 12.7% for five working days. At the same time, HVAC energy consumption decreased by 19.6% and 5.7% for four and five working days, respectively.

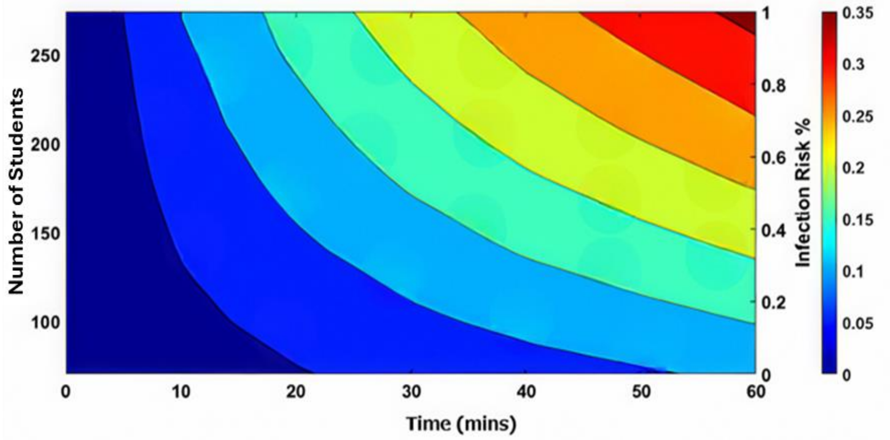


Figure 4. Infection risk with respect to number of students and exposure time [5].

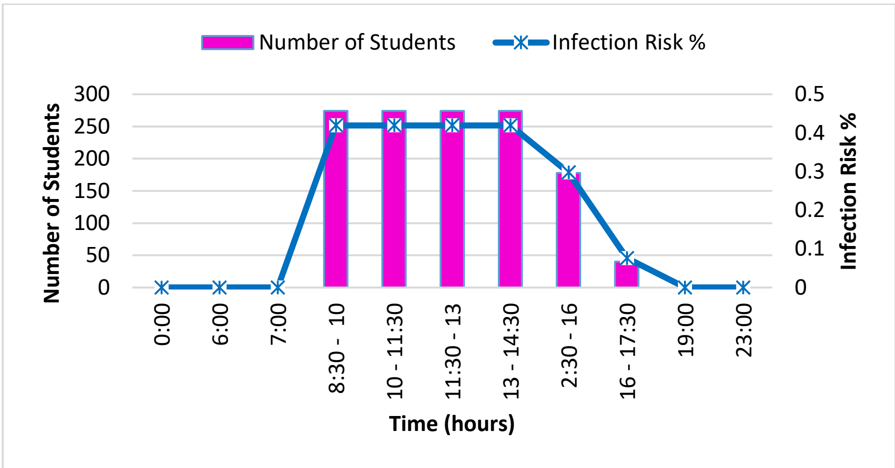
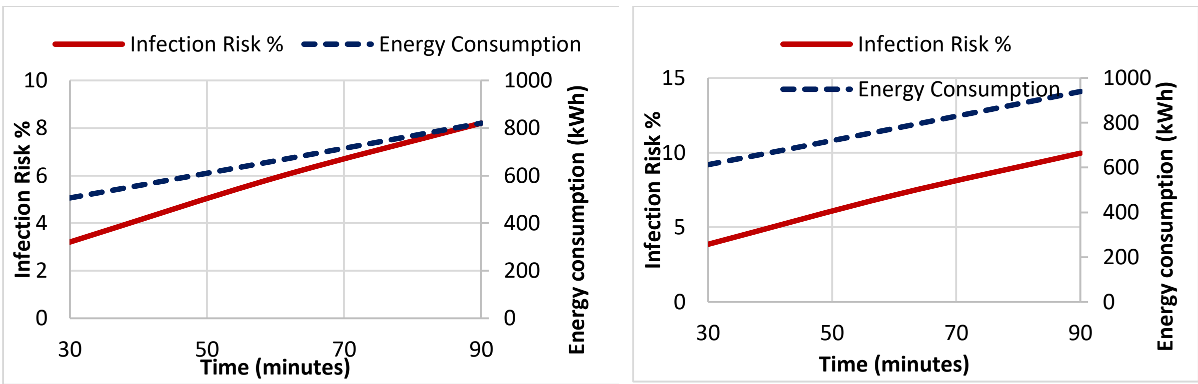


Figure 5. Actual student distribution in the M5 building during summer.



(a) **(b)**

Figure 6. Effect of class duration on infection risk and HVAC energy consumption: (a) Simulation over four working days; (b) Simulation over five working days.

Expanding the number of working days and hours increases the operating time of the HVAC system, which in turn raises energy consumption. However, the number of infections decreases because occupant density is reduced when working days and hours are extended. **Figure 7** illustrates the relationship between infection cases and HVAC energy consumption as working hours increase. This relationship reflects a classic trade-off, where minimizing infection risk through lower occupant density and longer exposure times comes at the cost of higher energy use.

Figures 6 and **7** together illustrate the Pareto front between infection risk and energy consumption. The curve shows that beyond a certain point, further reductions in infection risk lead to disproportionately higher energy use. The inflection point, or "knee point," identifies the optimal balance between maintaining acceptable health safety and limiting energy consumption. This point served as the basis for selecting the recommended class durations and scheduling strategies in the study, where occupant density was reduced while working hours were increased.

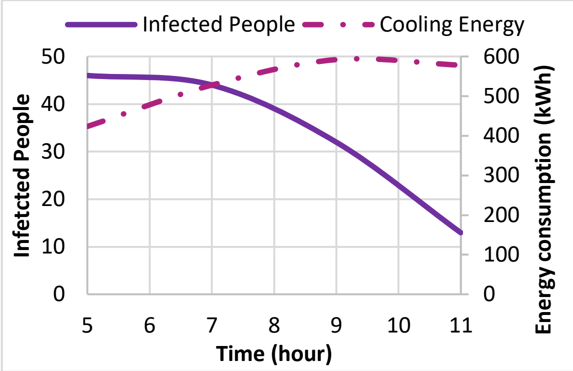
Figure 7(a) shows the results for four working days: the number of infections decreased from 46 at 5 working hours to 13 at 11 working hours, while energy consumption increased from 424 kWh to 578 kWh. In **Figure 7(b)**, which represents five working days, the number of infections was 41 after 5 hours, with energy consumption at 461 kWh. By 11 working hours, infections declined to 5, but energy consumption rose to 643 kWh.

3.3. Optimal Student's Distribution

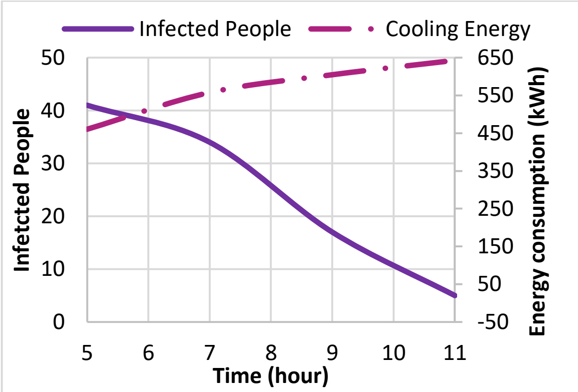
Based on the analysis of working hours, class duration, and the number of working days, two models of student distribution are proposed. The first model is a hybrid model with four working days and reduced working hours of seven per day. As shown in Figure 6(a), class duration is shortened to 60 or 45 minutes, with the remaining material delivered through online learning. The second model is an in-person model with five working days and reduced working hours of six per day. As illustrated in Figure 7(b), class duration is also shortened to 60 or 45 minutes. However, this model results in fewer students overall, with the total number reduced from 1,314 to 1,266, a difference of 48 students.

For the first proposed model of optimal student distribution, the Pareto front was generated from the optimal set of solutions for the two objectives: minimizing new infections and minimizing energy consumption, over four summer working days. These solutions were obtained using the multi objective genetic algorithm (MOGA) in MATLAB.

Figure 8 presents the Pareto front that illustrates the trade-off between infection cases and total HVAC energy consumption over four consecutive summer days. The minimum observed infection count is about 36, while the lowest energy use is 484.8 kWh. The knee point, which represents the most balanced compromise between reducing infections and limiting energy use, occurs at approximately (36, 485.6 kWh). This point was chosen as the optimal solution, as it provides notable infection reduction without a disproportionate rise in energy consumption.



(a)



(b)

Figure 7. Effect of working hours on infection risk and HVAC energy consumption: (a) Four consecutive working days; (b) Five consecutive working days.

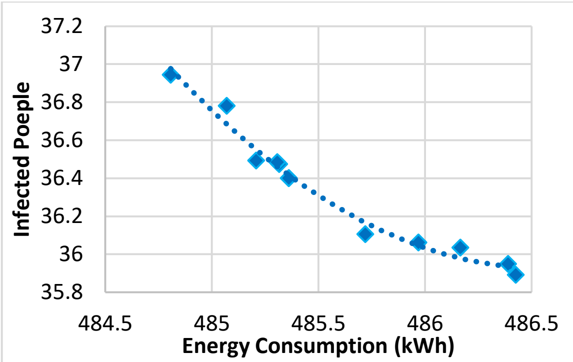
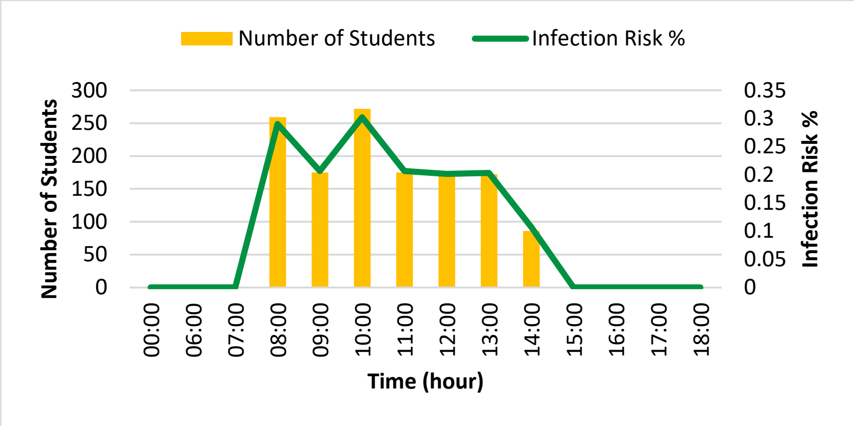


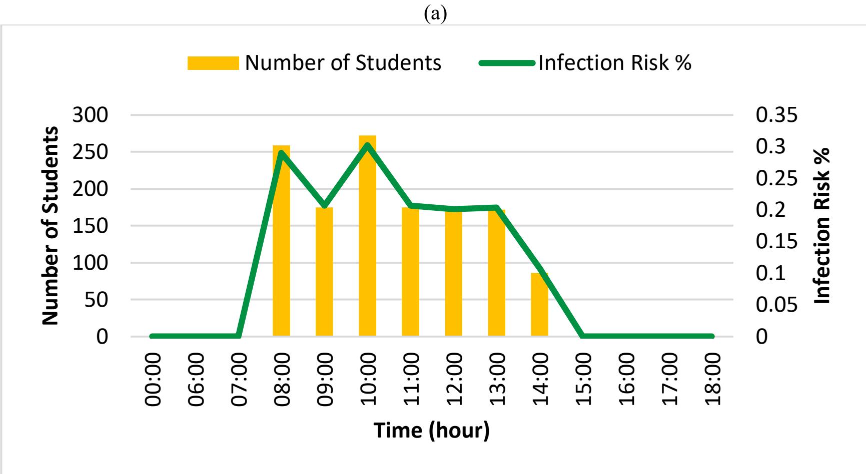
Figure 8. Pareto front for optimal occupant distribution over four consecutive summer days.

In this model, the decision variables represent the hourly distribution of students throughout the day. **Figure 9** illustrates three distribution patterns for a total of 1,314 students across seven classes and seven working hours per day, from July 21 to 24. Based on the configuration associated with **minimal infection risk**, shown in **Figure 9(a)**, the average infection probability is approximately 0.217%.

In contrast, **Figure 9(b)** illustrates the distribution pattern that achieves the lowest energy consumption (748.7 kWh), but with a higher infection risk. **Figure 9(c)** shows the occupant distribution pattern corresponding to the knee point, which combines the optimal solution for minimizing both the number of infections and energy consumption.



(a)



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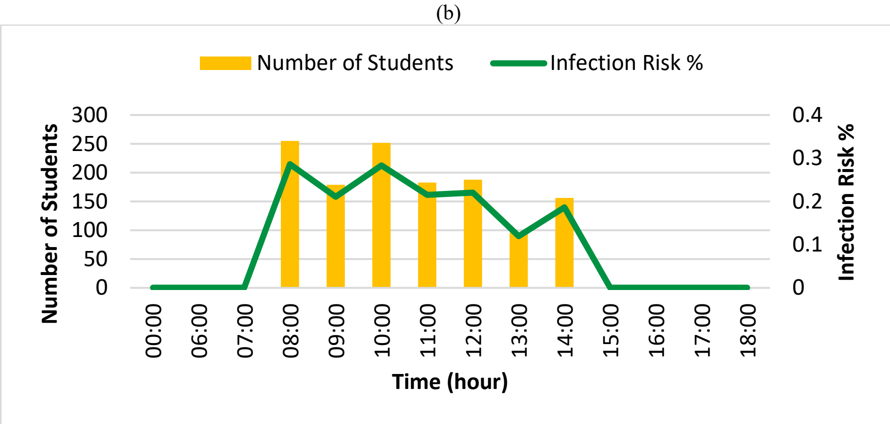


(c)

Figure 9. Occupant distribution for 4 days in summer: (a) Minimum infections; (b) Minimum energy consumption; (c) Optimal distribution at the Pareto front knee point.

The second suggested model of optimal student distribution was developed for 5 working days. The Pareto front shows the optimal solutions for the student distribution model over the summer period from July 21 to 25 (**Figure 10**). The minimum number of infections is approximately 41, while the lowest energy consumption is about 535.2 kWh. The knee point, representing the most balanced solution, occurs at (42 infections, 537 kWh).

Based on the Pareto front results, three student distribution patterns were developed (Figure 11). The total number of students is 1,266 per day, with five working days from July 21 to 25, six working hours per day, and a class duration of one hour. Figure 11(a) represents the distribution pattern that ensures minimal infection, with an average infection risk of 0.2409%. Figure 11(b) shows the student distribution pattern that achieves minimum energy consumption (535.2 kWh). Figure 11(c) illustrates the occupant distribution pattern at the knee point (42 infections, 537 kWh), which combines the optimal solutions for both minimal infection and minimal energy consumption.

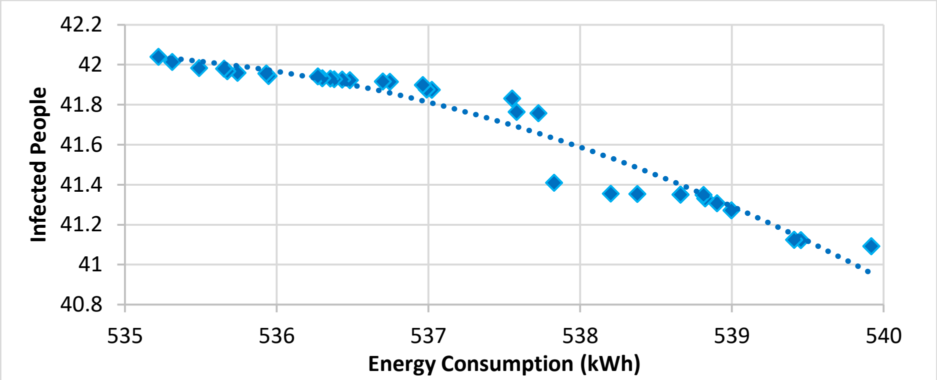
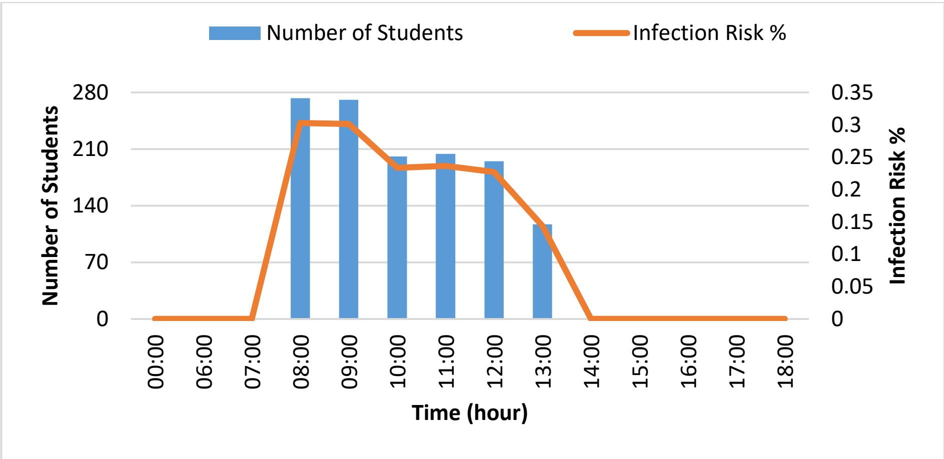
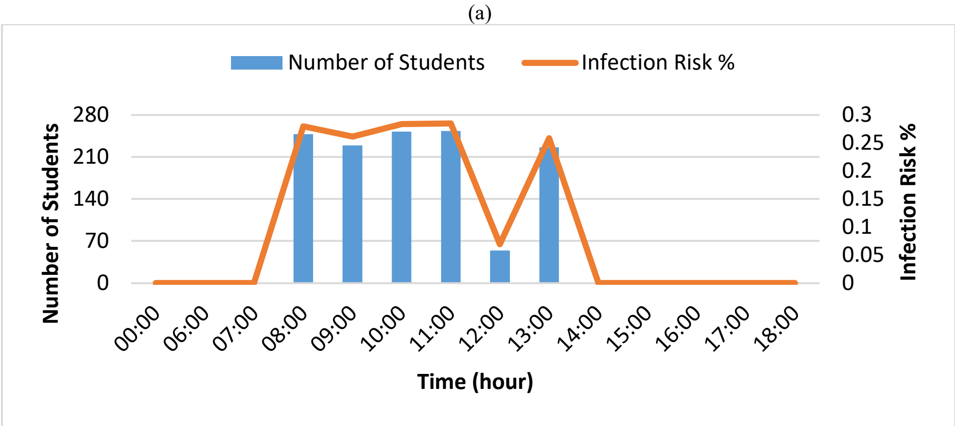


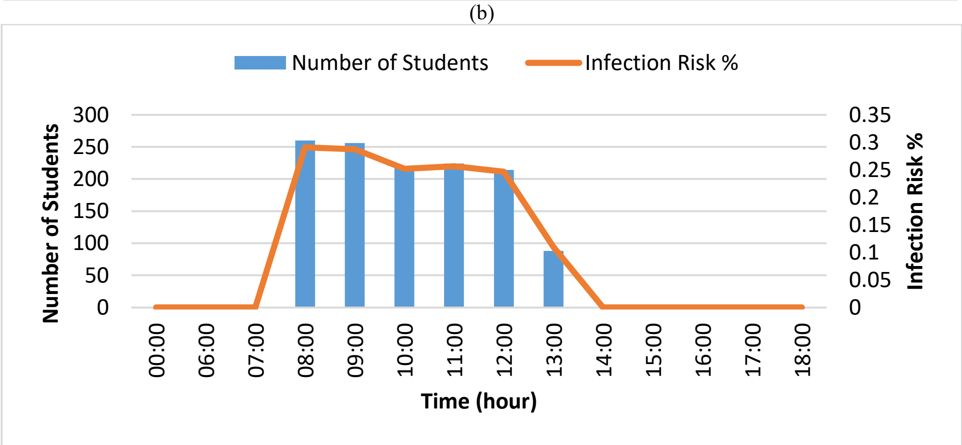
Figure 10. Pareto front for optimal occupant distribution over five consecutive summer days.



(a)



(b)



(c)

Figure 11. Occupant distribution for 5 days in summer: (a) Minimum infections; (b) Minimum energy consumption; (c) Optimal distribution at the Pareto front knee point.

By comparing student distribution over four and five working days according to **Figures 8, 9, 10, and 11** (the first and second optimal distribution models), it is observed that energy consumption is lower in the four-day schedule but infection risk is slightly higher compared to five days.

Specifically, energy consumption is 485.6 kWh over four days versus 537 kWh over five days. These values correspond to the common Pareto front point that balances minimal infections with minimal energy consumption. Since energy is directly proportional to time at constant power, consumption is higher across five days than four. As for infection risk, it is 1.5% per day for four working days and 1.4% per day for five working days. Thus, while extending the schedule slightly lowers daily infection risk, the total number of infected individuals over five days is greater than over four days.

3.4. Environmental Impact

Carbon dioxide emissions are a major contributor to global warming, and their levels have been rising in recent years. To examine how the proposed student distribution models could positively impact the environment, the occupant distribution patterns at the university were simulated using DesignBuilder software to estimate the potential reduction in CO_2 emissions.

Figure 12 illustrates the reduction in carbon dioxide emissions achieved through the proposed optimal student distribution models. Under the current distribution, emissions are 756.6 kg and 893.4 kg of CO_2 for four and five working days, respectively. In contrast, the optimal distribution reduces emissions to 542.2 kg and 569.8 kg, representing decreases of 28% and 25% compared with the baseline distribution.

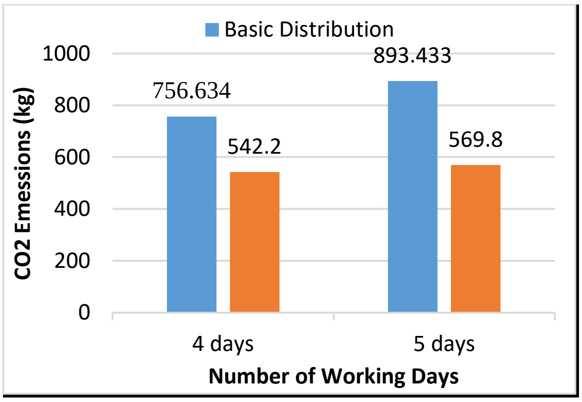


Figure 12. CO_2 emissions for baseline and optimal student distribution models.

4. Conclusion

This study proposed an optimal student distribution pattern for the M5 building at Jordan University of Science and Technology, aiming to reduce both COVID-19 infections and HVAC energy consumption. The analysis examined class duration, working hours, and the number of working days, and found significant relationships between these parameters and the outcomes.

The results can be summarized as follows: First, extending working hours increases HVAC energy consumption but can reduce infection risk if occupant density is spread out over time. Second, shorter class durations lower both energy use and infection risk. Third, increasing the number of working days while reducing occupant density decreases infection risk, but may lead to higher energy use.

Two distribution patterns were proposed. The first is a hybrid model with 7 working hours, 45- or 60-minute class durations, 4 working days, and 6 classes per day, with the remaining material delivered online. The second is an in-person model with 6 working hours, 45- or 60-minute class durations, 5 working days, and 6 classes per day. These patterns reduce HVAC energy consumption and infection risk by 12.7% and 5.7%, respectively.

This framework can be applied beyond universities to other public buildings, and may also be relevant for managing risks from airborne respiratory viruses beyond COVID-19. Governments could consider adopting regulations that account for working days, working hours, and class durations to improve health safety and energy efficiency.

Future Work

For future, the following parts are suggested for the researcher:

- Finding the optimal student's distribution pattern in winter.
- Including the energy consumption of lights, equipment, thermal comfort, in addition to HVAC system.
- Investigating the economic benefits of the optimum student's distribution

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