Since January 2020 Elsevier has created a COVID-19 resource centre with free information in English and Mandarin on the novel coronavirus COVID-19. The COVID-19 resource centre is hosted on Elsevier Connect, the company's public news and information website.

Elsevier hereby grants permission to make all its COVID-19-related research that is available on the COVID-19 resource centre - including this research content - immediately available in PubMed Central and other publicly funded repositories, such as the WHO COVID database with rights for unrestricted research re-use and analyses in any form or by any means with acknowledgement of the original source. These permissions are granted for free by Elsevier for as long as the COVID-19 resource centre remains active.
Optimization of energy efficiency and COVID-19 pandemic control in different indoor environments

Yong Guo a, b, Nan Zhang c,*, Tingrui Hu c, Zhenyu Wang d, Yinping Zhang a, b

a Department of Building Science, Tsinghua University, Beijing, China
b Beijing Key Laboratory of Indoor Air Quality Evaluation and Control, Beijing, China
c Beijing Key Laboratory of Green Built Environment and Energy Efficient Technology, Beijing University of Technology, Beijing, China
d College of Economics and Management, Beijing University of Technology, Beijing, China

ABSTRACT

The COVID-19 pandemic has led to considerable morbidity and mortality, and consumed enormous resources (e.g. energy) to control and prevent the disease. It is crucial to balance infection risk and energy consumption when reducing the spread of infection. In this study, a quantitative human, behavior-based, infection risk-energy consumption model for different indoor environments was developed. An optimal balance point for each indoor environment can be obtained using the anti-problem method. For this study we selected Wangjing Block, one of the most densely populated places in Beijing, as an example. Under the current ventilation standard (30 m³/h/person), prevention and control of the COVID-19 pandemic would be insufficient because the basic reproduction number \( R_0 \) for students, workers and elders are greater than 1. The optimal required fresh air ventilation rates in most indoor environments are near or below 60 m³/h/person, after considering the combined effects of multiple mitigation measures. In residences, sports buildings and restaurants, the demand for fresh air ventilation rate is relatively high. After our global optimization of infection risk control \( R_0/C_20 \), energy consumption can be reduced by 13.7% and 45.1% on weekdays and weekends, respectively, in contrast to a strategy of strict control \( R_0 = 1 \) for each indoor environment.

© 2022 Elsevier B.V. All rights reserved.

1. Introduction

The pandemic of the emerging respiratory infection, Coronavirus Disease 2019 (COVID-19), has been a great challenge for healthy cities and societies [1]. The global economic loss caused by COVID-19 is estimated to be between $5.8 and $8.8 trillion [2]. More than 99% of COVID-19 infections occurred in indoor environments [3], with the airborne route considered to be the main route for SARS-CoV-2 transmission [4–6].

Non-pharmaceutical interventions (e.g. ventilation, air disinfection by filtration or UV light, mask wearing) are necessary for COVID-19 prevention and control since the airborne route dominates transmission [7–10]. To minimize infection risk, many indoor environments maximized ventilation, installed air disinfection equipment, and made wearing masks mandatory, which inevitably resulted in greatly increased resource consumption [11–13]. The increased energy used by building residents resulted in high energy bills and also a scarcity in the energy supply [14–16]. A case study undertaken in China found that during the pandemic, the energy consumption of HVAC systems increased by 128% [17]. Since buildings consume over one-third of energy globally, with 40–50% of it being expended on HVAC systems [18], the goal of making buildings energy efficient is of great significance for achieving the global carbon–neutral target [19–20].

Human behavior and environmental features vary greatly in different indoor environments, and so directly affect the particular epidemic prevention strategies used [21]. Although many organizations (e.g. ASHRAE, WHO) and researchers have proposed building and system-related control mechanisms to mitigate infection risk during the COVID-19 pandemic, several shortcomings remain. First, the differences in virus inhalation and exhalation caused by people’s physical activity in indoor environments were rarely considered. Second, the time-varying characteristics of viral load in COVID-19 patients can influence the infection risk significantly, but this was mostly ignored. Third, qualitative recommendations fail to specify the degree to which disinfection measures are needed to achieve an acceptable level of risk in a particular space [22]. Fourth, an acceptable value for the probability of infection (PI) used as an index of a safe environment, is still unclear [7]. Fifth,
the Wells-Riley model was modified and employed extensively to quantitatively calculate PI, while its time-independent assumption remained unnoticed. It is therefore not always in line with the actual situation, especially when the exposure period is relatively long [23]. Finally, current studies considered a single indoor environment rather than multiple indoor environments to maximize their efficiency, and this introduced large errors [24].

This paper considers virus inhalation and exhalation for different metabolisms and provides a balance point taking into consideration both infection risk and energy consumption based on human activity in 12 typical indoor environments. An improved infection risk-energy consumption model was developed based on an improved Wells-Riley model. Optimal interventions for typical indoor environments, taking human behavior into account, were determined by the anti-problem method. The results are useful for controlling infection risk, and also for reducing energy consumption due to the pandemic, which is critical for sustainable cities and society during the pandemic.

2. Methods

2.1. Improved infection risk estimation model based on airborne transmission

The Wells-Riley model (Eq. (1)) is frequently used to assess infection risk via airborne transmission in enclosed environments.

\[ P = \frac{C}{S} = 1 - \exp \left( -\frac{lt}{Q} \right) \]  

(1)

where \( P \) is the probability of infection; \( C \) is the number of infection cases due to exposure to airborne virus particles; \( S \) is the initial number of susceptible cases, \( I \) is the number of source infectors, \( q \) is the quanta generation rate (quanta/h), \( p \) is the pulmonary ventilation rate for a person (m\(^3\)/h), \( t \) is the exposure time (h), and \( Q \) is the room ventilation rate with fresh air (m\(^3\)/h).

Besides the steady-state and well-mixed assumptions, the Wells-Riley model also implicitly assumes that accumulation of quanta is a time-independent process where each quantum has a fixed probability (63.2%) of initiating infection [25]. In this assumption, the probability of infection is only related to the total amount of inhaled pathogens, but not related to the duration of exposure. However, temporally clustered pathogens have a better chance of overwhelming the immune system than pathogen exposure that occurs at lower levels for longer periods of time [23]. Hence, this time-independent assumption is not always in line with actual situations and may lead to errors, especially when the exposure period is relatively long.

To overcome this limitation of the Wells-Riley model, we introduced the parameter \( \gamma \) to represent the decay rate of the pathogens accumulated in a susceptible person’s respiratory tract, according to previous treatment methods of the dose–response model [23]:

\[ \frac{dm_t}{dt} = -\gamma m_t \]  

(2)

\[ m_0 = \frac{I_q p Q}{Q} \]  

(3)

where \( t \) represents the time from exposure, \( m(t) \) represents the total pathogen within the host at a given time. In particular, \( m_0 \) represents the initial amount of pathogen that is accumulated in a susceptible person’s respiratory tract.

It was found that the viral load on a COVID-19 infected person’s throat swab gradually decreased after symptom onset [26]. Therefore, the quanta generation rate \( q \), which is assumed to be proportional to the viral load, also decreased with time [21, 27]. We thus obtained the fitting mathematical expression for a COVID-19 infected person’s time-varying quanta generation rate according to the temporal patterns of the viral shedding curve described in previous research [26]. This can be found in Appendix A, as well as the transformational relation between the Ct value and virus load [28].

\[ q_t = \frac{q_0}{2^{\gamma t}} \]  

(4)

where \( q_0 \) represents the initial quanta generation rate at symptom onset, and \( t \) is the time (h) since symptom onset.

As we know, inhalation and exhalation rates depend on human activity. Hence, a change in an infected person’s quanta generation rate (\( q_t \)) and a susceptible person’s pulmonary ventilation rate (\( p \)) can have a multiplying effect on the infection risk (Appendix A).

Combining Eq. (1) with Eqs. (3) and (4), we can obtain the total virus exposure (\( m_f \)) and the modified Wells-Riley model:

\[ m_f = \int_0^T m_0 dt = \frac{I_q p Q}{Q} \int_0^T e^{-\gamma(T-t)} \int_0^T e^{-\gamma t} dt \]  

(5)

\[ P_m = \frac{C}{S} = 1 - e^{-m_f} = 1 - e^{-\gamma t} \]  

(6)

where \( T \) represents the total exposure time.

Infection risk can be accurately assessed using our modified Wells-Riley model, which now considers time-varying infectivity, virus inhalation and exhalation resulting from human activity, and vulnerability related to the length of total exposure.

2.2. Infection risk-energy consumption model

To determine the optimal point at which COVID-19 prevention and energy consumption is balanced, the quantitative relationship between them needs to be confirmed. We therefore established an infection risk-energy consumption model that considers human behavior in different indoor environments. Under the acceptable infection risk (\( R_0 < 1 \)), we investigated the optimal interventions to obtain the lowest equivalent fresh air ventilation rate (Section 2.2.3) and energy consumption (Section 2.2.4) for each indoor environment on the basis of the improved Wells-Riley model.

2.2.1. Population groups and typical indoor environments

For this study, we divided the population into 3 categories: students, workers and older people. All indoor environments were divided into 12 categories: residence A (during non-working hours), residence B (during working hours), indoor workplace, school, sports building, public transport, subway station, restaurant, supermarket, shopping center, wholesale market (e.g. Xinfadi market), which lead to a serious outbreak in Beijing [29], and other indoor environments (e.g. pets markets and home appliance stores). Both weekdays and weekends are considered in the study because people’s daily movement differs considerably between these two times. The detailed distribution of \( R_0 \) for weekdays and weekends are listed in Tables 1 and 2.

2.2.2. \( R_0 \) value in each indoor environment

In general, an epidemic would eventually disappear if \( R_0 \) (the basic reproductive number) is less than 1, and control measures which can reduce the reproductive number to less than 1 are regarded as effective [30]. Since an infected person would likely infect others in several different places during their infectious period, it is hard to calculate the best \( R_0 \) for each indoor environment to ensure that the final \( R_0 \) is smaller than 1. To address this problem, we have two different approaches:

- The first approach which we have called the local method, focuses on a single indoor environment. Considering the worst situation, we assume that an infected person remains in a specific...
specific value of less than or equal to 1 (Appendix C). According to this approach, the reproduction number for each of the 12 indoor environments from Residence A to Others) in different indoor environments for students, workers, and elders for weekdays and weekends.

| Indoor environment | Student | Worker | Elder | Student | Worker | Elder |
|--------------------|---------|--------|-------|---------|--------|-------|
| Residence A*      | R_{01}  | R_{01}  | R_{01} | R_{01}  | R_{01}  | R_{01} |
| Residence B*      | –       | –      | –      | –       | –      | –     |
| Workplace          | –       | R_{03} | –      | –       | –      | –     |
| School             | R_{04}  | –      | –      | –       | –      | –     |
| Sport building     | –       | R_{05} | –      | –       | –      | –     |
| Public transport   | R_{06}  | R_{06} | –      | R_{06}  | R_{06} | –     |
| Subway station     | R_{07}  | R_{07} | –      | R_{07}  | R_{07} | –     |
| Restaurant         | –       | R_{08} | –      | R_{08}  | R_{08} | –     |
| Supermarket        | –       | –      | –      | –       | –      | –     |
| Shopping center    | –       | –      | –      | R_{10}  | –      | –     |
| Wholesale market   | –       | –      | –      | R_{11}  | –      | –     |
| Others             | –       | –      | –      | R_{12}  | –      | –     |

* Residence A: residence during non-working hours.
* Residence B: residence during working hours.

The total equivalent fresh air ventilation rate ($Q_{total}$) can be calculated according to Eqs. (9-10), the detailed derivation can be found in Appendix F:

$$Q_{i} = \frac{q_{0i}P_{i}}{\ln(1 - \frac{w_{i}}{\rho_{i}})} \int_{0}^{t_{i}} e^{-\frac{\Delta h}{C_{0}P_{i}}} \frac{\Delta h}{C_{0}P_{i}} \, dt$$

(8)

The second approach is a global method. We defined the corresponding epidemic prevention and energy consumption requirements can be determined. The derivation and proof can be found in Appendix B.

The second approach is a global method. We defined the corresponding epidemic prevention and energy consumption requirements can be determined. The derivation and proof can be found in Appendix B.

The second approach is a global method. We defined the corresponding epidemic prevention and energy consumption requirements can be determined. The derivation and proof can be found in Appendix B.

### 2.2.4. Energy consumption

The ultimate goal is to find the optimal point at which COVID-19 prevention ($R_{0} \leq 1$) is balanced against energy consumption. The quantitative relationship between actual fresh air ventilation rates ($Q_{i}$) and energy consumption in buildings should be confirmed first. As we know, when providing additional ventilation, an increase in fan power, and increased energy consumption for heating or cooling (Eq. (11)) to maintain indoor air temperature is needed. The detailed parameters of Eq. (11) are described in Table 3.

$$E_{AC-load} = \int_{0}^{t} \rho_{a}Q \left( \frac{\Delta h}{COP_{r}} - \frac{\Delta h}{COP_{r}} \right) dt$$

(11)

Notably, enthalpy ($h$) can be calculated using Eq. (12), wherein $w$ is the moisture of the air.

$$h = 1.005 \, \text{tem} + w(2500 + 1.84 \, \text{tem})$$

(12)

In this study, based on comfort preferences, the indoor temperature was set to be between 18°C to 26°C and the relative humidity was maintained in the 40–60% range according to IAQ and HVAC related standards (e.g. GB/T 18883–2002, GB50736-2012) [32]. In addition, we used a typical year’s outdoor temperature and moisture data for Beijing, exported from DeST (https://www.dest.net.cn). Since outdoor temperature and moisture differs between day and night, we calculated the average outdoor temperature and moisture for day and night in 12 months respectively (Appendix D).
Electricity consumption of a fan $W_{\text{fan}}$ (W) is conventionally expressed as Eq. (13):

$$W_{\text{fan}} = c_1 f_\text{AHU} + c_2 \left(\frac{f_\text{AHU}}{f_\text{max}}\right)^2 + c_3 \left(\frac{f_\text{AHU}}{f_\text{max}}\right)^3$$  \hspace{1cm} (13)

To simplify, we assumed a specific fan-power of 1 kW·m$^{-3}$·s for ventilation systems without heat-recovery [33–34], then the corresponding energy consumption can be determined by multiplying the amount of time that the ventilation was turned on and the corresponding ventilation rate (Eq. (14)).

$$E_{\text{fan}} = \int_0^T SFP \cdot Q_\text{s} \, dt$$  \hspace{1cm} (14)

Therefore, the quantitative relationship between fresh air ventilation rates and energy consumption ($E_{\text{c}}$) in buildings can be established (Eq. (15)).

$$E_{\text{c}} = E_{\text{AC-load}} + E_{\text{fan}} = \int_0^T \rho_a Q_\text{s} \left(\frac{\Delta h^\text{h}}{\text{COP}_\text{h}} - \frac{\Delta h^\text{c}}{\text{COP}_\text{c}}\right) + SPF \cdot Q_\text{s} \, dt$$  \hspace{1cm} (15)

Subsequently, the total energy consumption in the investigated region can be determined by Eq. (17) and the infection risk-energy consumption model can be established.

$$E_{\text{total}} = \sum_i \xi_i E_{\text{c},i}$$  \hspace{1cm} (16)

where $\xi_i$ is the weighting coefficient of place $i$; $N_i$ is the number of indoor environments similar to place $i$ within the space studied; $n_i$ is the average number of people in place $i$.  

### Table 3 Parameters of different HVAC mitigation strategies.

| Parameter | Description                  | Unit    | Value | Source                  |
|-----------|------------------------------|---------|-------|-------------------------|
| $Q_\text{s}$ | Ventilation rate of fresh air | m$^3$/h | –     | –                       |
| $Q_{\text{AC}}$ | Air cleaner ventilation rate | m$^3$/h | –     | –                       |
| $\eta_1$ | Mask efficiency for susceptible | –      | 0.4   | Leung et al. [37]        |
| $\eta_2$ | Mask efficiency for infector | –      | 0.9   | Leung et al. [37]        |
| $\eta_{\text{AC}}$ | Air cleaner efficiency | –      | 0.8   | Shen et al. [19]         |
| $q_{\text{ac}}$ | Fresh air volume per unit area for air cleaner | m$^3$/h/m$^2$ | 12    | US EPA [35]              |
| $A$ | Per capita living space | m$^2$/person | –     | GB 50016–2014 [36]       |
| $\eta_{\text{R}}$ | Disinfection efficiency of return air | –      | 0.9   | Shen et al. [19]         |
| $\alpha$ | Fresh air ratio | –      | 0.8   | Shen et al. [19]         |
2.3. The concept and application of the anti-problem method

The objective of an anti-problem method (or back-modeling method) is to find the most suitable model parameters to obtain the predetermined results. In the global solution approach, the value of $R_0$ is not fixed, and the values of total energy consumption and equivalent fresh air ventilation rate can be a function of $R_0$. We can determine the ideal distribution of $R_0$ values to minimize the total energy consumption or the total equivalent fresh air ventilation rate. In the global solution approach, there are two different optimization goals, minimized total equivalent ventilation rate (mode 2–1) and minimized total energy consumption (mode 2–2), in contrast to the local optimal solution (mode 1).

Employing the anti-problem method, our optimization results are the ideal value of $R_0$ and corresponding constraint conditions should then be established (Appendix C), so as to control the outbreak and calculate the epidemic requirements. Finally, the ideal equivalent fresh air ventilation rate for 12 typical indoor environments can be determined. The detailed diagram of this calculation is shown in Fig. 1.

2.4. Equivalent and actual fresh air ventilation rate

The equivalent fresh air ventilation rate was analyzed on the basis of calculated epidemic prevention requirements. On the other hand, the equivalent fresh air ventilation was deduced by non-pharmaceutical interventions (Eq. (18)), whose detailed derivation can be found in Appendix E.

$$Q_i = \frac{Q_{i,c} + \eta_{a}Q_{i,c} + \eta_{b}(1-\eta_{a})Q_{i,s}}{(1-\eta_{1})(1-\eta_{2})}$$  \hspace{1cm} (18)

All parameters are explained in Table 4. The ventilation rate of the air cleaner, $Q_{i,c}$, is the product of per capita living space ($A$, m²/person) and fresh air volume per unit area ($q_{ac}$, m³/h/m²). Their specific values can be determined according to the U.S. EPA’s guide [35] and GB 50016–2014 [36].

Moreover, the value of the actual fresh air ventilation rate can be calculated using Eq. (18), while considering the combined effects of multiple mitigation strategies. In our actual calculation, the combined effect of wearing a mask and supplying fresh air was considered in indoor environments where wearing masks is appropriate. For indoor environments where wearing masks is not suitable, the combined effect of supplying fresh air, using air cleaners and so on, were considered.

We can also calculate the maximum equivalent fresh air ventilation rate according to the specific facilities and design of an indoor environment, and compare it to the previously calculated equivalent fresh air ventilation rate to judge whether it is reasonable.

Table 4
The minimal equivalent fresh air ventilation rates ($Q_i$) and people’s pulmonary rates ($p_i$) for different indoor environments without any control methods.

| Indoor environments | $p_i$ (m²/h) | $Q_i$ (m³/h/person) |
|---------------------|--------------|---------------------|
| Residence           | 0.4          | 275                 |
| Workplace           | 0.5          | 672                 |
| School              | 0.5          | 602                 |
| Sport building      | 2            | 10,833              |
| Public transport    | 0.5          | 672                 |
| Subway station      | 0.5          | 695                 |
| Restaurant          | 0.5          | 687                 |
| Market              | 0.6          | 997                 |
| Shopping center     | 0.6          | 1,001               |
| Composite market    | 0.6          | 989                 |
| Other               | 0.6          | 989                 |

2.5. Case study

For this study we selected Wangjing Block, one of the most densely populated places in Beijing, which covers an area of 28.27 square kilometers and has a population of 1,551,550 (https://www.data-dance.com/).

Detailed data of this area (e.g. type and number of buildings, age distribution) was obtained from the CITY MAPPING platform (https://www.data-dance.com/). Based on this, the weighting coefficient for each indoor environment was calculated (Appendix F).

3. Results

3.1. Local optimal solution

First, we focused on the single indoor environment. Considering the worst situation, we assumed that the COVID-19 patient remained in the same indoor environment for the entire infectious period. To ensure this patient would not be the cause of an epidemic outbreak, $R_0$ for each environment could not be more than 1.

People’s pulmonary rates ($p_i$) for the different indoor environments were calculated according to the Exposure Factors Handbook of Chinese Population released by Ministry of Environmental Protection of China. The corresponding equivalent ventilation rate for each indoor environment can then be determined by employing our modified model, as shown in Table 5.

In this way, the optimal epidemic interventions for each indoor environment, that we have called the local optimal solution, can be determined.

3.2. Global optimal solution - minimizing the total equivalent ventilation rate

In an actual situation, one COVID-19 patient may spend time in multiple indoor environments during their infectious period. It is important to calculate a comprehensive $R_0$ by conducting interventions (globally optimal).

As the optimization target of minimizing the total equivalent ventilation rate, we obtained the ideal $R_0$ distribution and the minimal equivalent fresh air ventilation rates for different indoor environments on both weekdays and weekends (Table 6). There are several differences between the results for weekends and weekdays. For the calculated minimal equivalent fresh air ventilation rates on weekends, compared with the results for weekdays, a decrease was observed in Residence A (-34%), Residence B (-44%), Sports building (-3%), Public transport (-34%), Subway station (-31%), Restaurant (-32%), and Supermarket (-32%) while an increase was observed in Shopping center (170%), Wholesale market (170%) and Other (170%).

3.3. Global optimal solution - Minimizing the total energy consumption

To minimize total energy consumption, we obtained the ideal $R_0$ distribution and the critical equivalent fresh air ventilation rates for the different indoor environments on both weekdays and weekends (Table 7).

The results for the two different optimization targets are quite different. On weekdays, the minimal equivalent fresh air ventilation rates for Residence A (34%) and School (76%) increased while that for Sports building (-25%), Restaurant (-67%) and Supermarket (-50%) declined. On weekends, the minimal equivalent fresh air ventilation rates for Residence A (70%) and Public transport (52%) increased while that for Residence B (-35%), Sports building (-
38%), Restaurant (-63%), Shopping center (-25%) and Wholesale market (-26%) decreased.

3.4. Analysis of actual fresh air ventilation rate

Based on the calculation above, we obtained the equivalent fresh air ventilation rate for each indoor environment. However, this is not enough is provide guidance for epidemic prevention. At a minimus, the actual fresh air ventilation rate is needed.

We separately analyzed two specific cases aiming at minimizing the total equivalent fresh ventilation rate (mode 2–1) and total energy consumption (mode 2–2).

Surgical mask wearing is one of the most effective measures for COVID-19 prevention and control [38]. All 12 indoor environments were classified into two categories, based on whether they were acceptable or appropriate for mask wearing. The amount of fresh air (Qs) in the indoor environments where it is appropriate for mask wearing, after considering the mask wearing are listed in Table 8.

The required fresh air ventilation rates for workplaces and public transport on weekdays and supermarkets, shopping centers and wholesale markets on weekends, are nearly 50 m³/h/person, which is higher than other environments, and the current standard of 30 m³/h/person in many indoor environments proposed by China Construction Research Institute.
In mode 2–2, the calculated results are similar to those of mode 1 (local optimization), with only schools and supermarkets showing a difference on weekdays, and public transport, shopping centers and wholesale markets showing a difference on weekends. Most of the required fresh air ventilation rates are near or below 30 m³/h/person, which is not difficult to achieve.

For residences, sport buildings and restaurants, where wearing masks is inconvenient or unacceptable, we obtained their final required fresh air ventilation rate after considering the effect of multiple mitigation strategies other than wearing masks (Table 9).

Indoor environments where it is not suitable for mask wearing, need a relatively high fresh air ventilation rate, especially for sport buildings. Therefore, it is important for sports buildings to limit their opening hours and improve epidemic prevention measures, such as regularly carrying out air elimination. Masks that are both efficient and suitable for physical exercise should receive considerable additional research and development in the future.

### 3.5. Analysis of infection and energy consumption

#### 3.5.1. \( R_0 \) distribution before equivalent ventilation rate optimization

As shown in Fig. 2, we calculated the \( R_0 \) value for 3 different groups at a ventilation rate of 30 m³/h/person. On weekdays, the \( R_0 \) for students, workers and older people are far greater than 1. The \( R_0 \) contribution of students and older people are mainly from residences. The \( R_0 \) for workers is about 5–7 times that of students and older people because they spend more time in sports buildings. The \( R_0 \) in sports building is 3–4 times higher than the total \( R_0 \) in other indoor environments. It is obvious that sports building can be very dangerous during a pandemic, and can be regarded as the key location for possible infection transmission and even potential ‘superspreading’ events. It is necessary to limit the number of people and their length of stay for sport buildings with regular ventilation, or even close them down if necessary.

Compared with weekdays, the \( R_0 \) for students, workers, and older people increased by 900%, 6%, and 11% on weekends, respectively. For students and workers, sports buildings and restaurants are the most dangerous indoor environments, while for older people, residences are a high-risk area.

#### 3.5.2. Energy consumption under 3 modes

Energy consumption presents a bimodal distribution, in winter and summer, energy consumption is relatively high, which is mainly due to the increase in heating or cooling load caused by large temperature differences between indoor and outdoor air (Fig. 3). In addition, during the winter and summer months, the energy consumption of the 3 modes were significantly different than in the other months.

Mode 1 (local optimization) has the highest energy consumption, and mode 2–2 (global optimization, minimized total energy consumption) has the lowest. Compared with the locally optimal solution (mode 1) on weekdays, the energy consumption for the global optimal solution (mode 2–1 and mode 2–2) was reduced by 9.4% and 13.7% respectively. At weekends, the differences between these modes became more apparent, and the corresponding energy consumption is reduced by 32.8% and 45.1% respectively.

### 4. Discussion

In this study, we developed a new approach to determine optimized COVID-19 prevention strategies for typical indoor environments that considers both infection risk and energy consumption. During the COVID-19 pandemic, many health organizations (e.g. US CDC) advised commercial and public sectors to maximize the outdoor air circulation and ventilation rates [13,39]. However, it is still not clear whether the maximum ventilation rate using fresh air is excessive or insufficient to meet the needs of pandemic prevention in different indoor environments. This uncertainty may lead to the increased potential for an infection outbreak or to significant energy consumption. It is very important to understand the balance between infection spread and energy conservation in different types of indoor environments.

The association between ventilation in buildings and infectious disease transmission has been confirmed, however the authors failed to quantify the minimum ventilation requirements in buildings to avoid the infectious disease outbreak via the airborne route, because they had insufficient data [11]. Another important reason is that previous studies have mainly focused on the probability of infection (PI), but it is difficult to determine the critical safe value of PI because these studies were confined to individual or single indoor environments. From a public health perspective, pandemic prevention should be shifted to reduce infection risk to the level that will stop epidemic growth in a certain region that has multiple indoor environments [22]. The basic reproduction number, \( R_0 \), is used as a parameter with a definite critical value (\( R_0 \leq 1 \)) to calculate the minimum ventilation requirements [30].

Although it is necessary and feasible to determine the fresh air requirements for indoor environment as analyzed above, this task is complex because of the extreme complexity and uncertainty arising from multiple influencing factors and their complicated impact on the transmission dynamics of COVID-19 [40].

From an infected individual’s perspective, the viral load in their exhaled aerosols can gradually decrease after symptom onset [26,41], however previous studies usually use a standard fixed value to represent this parameter, ignoring the fact that a varying viral load can significantly affect the spread of the disease [42].

From an indoor environment perspective, inhalation and exhalation rates varied depending on the indoor environment [43–44]. In addition, different types of building have opening hours and allowable number of people, which should be important considerations in the design of specific pandemic interventions [40,45]. Different buildings’ pandemic prevention ability can be distinct due to the aging of building equipment and the original design of the buildings’ systems [46]. Therefore, it is necessary to take the realization methods into consideration to ensure the determined pre-
Fig. 2. The value of $R_0$ when the fresh air ventilation rate is 30 m³/h/person on (a) weekdays and (b) weekends.
viation requirements are feasible and realizable. For this purpose, we can take the maximum fresh air ventilation rate that can be achieved as one of the constraint conditions for specific indoor environments, while in our current research, as the corresponding data limited, so this part was not elaborated. Since an infectious person may visit several places during their infectious period [47], we assigned typical indoor environments to 12 categories to find their globally optimal solution for fresh air ventilation rates. As far as we can determine, the majority of relevant studies are case studies confined to one, or one type, of indoor environment, with only a few studies advancing their investigation to more than one indoor environment [13,44,48–50].

From a social perspective, population characteristics (e.g. people's movements and activities, the age structure of the population), the built environment and spatiotemporal features of city infrastructure need to be simultaneously considered when deploying non-pharmaceutical interventions [51]. The path of a pandemic differs across regions and stages of the pandemic [52–53], and interventions should be adjusted accordingly. For example, in China, low-risk, medium-risk and high-risk regions represent the country's different epidemic states. Even in the same city, there may be several areas with different levels of risk, where the open requirements of indoor environments and people's activities are distinct [54]. Since the priority for medium and high-risk areas is to suppress any outbreak quickly, and to minimize the number of people infected as far as possible, the goal is not confined to restricting $R_0$ to be 1, but to get $R_0$ as low as possible, while paying less attention to energy consumption. But in low-risk areas, the priority shifts to avoiding the resurgence and spread of the epidemic, which is a regular task, and so balancing epidemic prevention and energy consumption should be investigated in these cases. Previous studies have not paid enough attention to this [21,55]. In our research, we considered the characteristics of region, stage of the epidemic, and human behavior simultaneously, and strategies to control infection and energy consumption could then be developed according to the actual situation.

In this research, we investigated the critical epidemic prevention requirements from local (mode 1) and global (mode 2–1 & 2–2) perspectives. Interventions for single indoor environments (mode 1) are not suitable for most environments. However, for places that are relatively isolated from the outside world, or places that people visit relatively infrequently (e.g. hospitals, prisons), we can just treat them as separate individuals, set their critical $R_0$ to be 1 and use Eq. (8) to determine their equivalent fresh air ventilation rate. On the other hand, for mode 1, the local optimization is not dependent on detailed information of people's behavior and the indoor environment, hence it is easier to implement than mode 2–1 and 2–2. If detailed data is lacking, the employment of mode 1 to determine the local optimal solution is a good choice. The calculated results for mode 1 can be regarded as a comparative reference for the other modes, so as to analyze the energy-saving potential of globally optimal solutions. When comparing mode 2–1 and 2–2, although the determined epidemic prevention requirements of mode 2–2 are the most efficient, the difference in energy consumption between the two modes is not obvious for weekdays (within 5%), especially in spring and autumn. In addition, mode 2–2 is based on information including comfort preferences and weather conditions, hence the calculation process for mode 2–2 is more complicated. We therefore suggest that the corresponding calculation mode be selected according to specific needs and the actual situation.

Our research has several limitations. First, our model was developed with the assumption that airborne transmission dominates infection spread. Second, the data for initial quanta generation rate ($q_0$) changed according to many factors such as environmental parameters, and a constant $q_0$ would introduce some errors. Third, since some statistical data concerning people and indoor environments of the investigated city are lacking, we used estimated values instead, and this may also introduce error. Finally, we regard the relationship between ventilation of different buildings and their energy consumption as consistent, while actually it is a complex matter dependent on the diversity of climates, building types, building characteristics and ventilation systems [46].

We hope our proposed model can be used as a tool to guide design and operation of building systems to improve health and sustainability. In the future, we will seek to work with relevant agencies to obtain more detailed data to improve the reliability of the results. Moreover, the focus of the indoor environment may shift from pathogens to the average CO$_2$ concentration and PM concentrations.
5. Conclusion

This work developed an infection risk - energy consumption model to find the optimal balance point between infection risk and energy conservation. Following our optimization, $R_0$ can be reduced to 1 to curb the pandemic, and energy consumption can be reduced by 13.7% and 45.1% on weekdays and weekends, respectively, compared to the strict condition ($R_0 = 1$) for each indoor environment throughout the whole pandemic period. In this way, we can quantify non-pharmaceutical intervention requirements and develop appropriate energy-efficient strategies for various indoor environments, contributing to curtailing the spread of COVID-19 and maintaining sustainable development."

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This study is financially supported by the National Natural Science Foundation of China (Grant No. 51976160 & 52108067).

Appendix. Supplementary information

Supplementary information to this article can be found online at https://doi.org/10.1016/j.enbuild.2021.11954.

References
A. Mizukoshi, C. Nakama, J. Okumura, K. Azuma, Assessing the risk of COVID-19 from multiple pathways of exposure to SARS-CoV-2: Modeling in healthcare settings and effectiveness of nonpharmaceutical interventions, Environ. Int. 147 (2021).

G. Buonanno, L. Stabile, L. Morawska, Estimation of airborne viral emission: Quanta emission rate of SARS-CoV-2 for infection risk assessment, Environ. Int. 141 (2020) 105794.

P. Kapalo, L. Vojtasko, D. Vasilisin, F. Domnit, C. Bacotiu, R. Kandrac, M. Batorova, Investigation of the influence of the level of physical activity on the air exchange requirements for a gym, Build. Environ. 204 (2021) 108123, https://doi.org/10.1016/j.buildenv.2021.108123.

J. Wang, J. Huang, Z. Feng, S.J. Cao, F. Haghighat, Occupant-density-detection based energy efficient ventilation system: Prevention of infection transmission, Energy Build. 240 (2021) 110883.

A. Piccinini, M. Hajdukiewicz, M.M. Keane, A novel reduced order model technology framework to support the estimation of the energy savings in building retrofits, Energy Build. 244 (2021) 110886, https://doi.org/10.1016/j.enbuild.2021.110886.

N. Zhang, W. Jia, H. Lei, P. Wang, P. Zhao, Y. Guo, C.H. Dung, Z. Bu, P. Xue, J. Xie, Y. Zhang, R. Cheng, Y. Li, Effects of Human Behavior Changes During the Coronavirus Disease 2019 (COVID-19) Pandemic on Influenza Spread in Hong Kong, Clin. Infect. Dis. 73 (5) (2021) e1142–e1150.

A. Zivelonghi, M. Lai, Mitigating aerosol infection risk in school buildings: the role of natural ventilation, volume, occupancy and CO2 monitoring, Build. Environ. 204 (2021).

L. Robert, R. Guichard, J. Klingler, V. Cochet, C. Mandin, Indoor air quality in shopping and storage areas, Indoor Air 31 (4) (2021) 1238–1251.

S. Freund, G. Schmitz, Implementation of model predictive control in a large-sized, low-energy office building, Build. Environ. 197 (2021) 107830, https://doi.org/10.1016/j.buildenv.2021.107830.

X.D. Andrianou, A. Pronk, K.S. Galea, R. Stierum, M. Loh, F. Riccardo, P. Pezzotti, K.C. Makris, Exposome-based public health interventions for infectious diseases in urban settings, Environ. Int. 146 (2021) 106246.

D. Azzolina, G. Lorenzoni, L. Silvestri, I. Prosepe, P. Berchiella, D. Gregori, Regional Differences in Mortality Rates During the COVID-19 Epidemic in Italy, Disaster Med, Public Health Prep, (2020) 1–7.

J.S. Jia, X. Lu, X. Yuan, G. Xu, J. Jia, N.A. Christakis, Population flow drives spatio-temporal distribution of COVID-19 in China, Nature 582 (7812) (2020) 389–394.

P. Zhu, X. Tan, Is compulsory home quarantine less effective than centralized quarantine in controlling the COVID-19 outbreak?, Evidence from Hong Kong, Sustain Cities Soc 74 (2021) 103222.

M. Awada, B. Becerik-Gerber, S. Hoque, Z. O’Neill, G. Pedrielli, J. Wen, T. Wu, Ten questions concerning occupant health in buildings during normal operations and extreme events including the COVID-19 pandemic, Build. Environ. 188 (2021) 107480, https://doi.org/10.1016/j.buildenv.2020.107480.