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Optimization of COVID-19 prevention and control with low building energy consumption

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ABSTRACT

COVID-19 is a global threat. Non-pharmaceutical interventions were commonly adopted for COVID-19 prevention and control. However, during stable periods of the pandemic, energy would be inevitably wasted if all interventions were implemented. The study aims to reduce the building energy consumption when meet the demands of epidemic prevention and control under the stable period of COVID-19. Based on the improved Wells-Riley model considering dynamic quanta generation and pulmonary ventilation rate, we established the infection risk - equivalent fresh air volume - energy consumption model to analyze the infection risk and building energy consumption during different seasons and optimized the urban building energy consumption according to the spatio-temporal population distribution. Shopping centers and restaurants contributed the most in urban energy consumption, and if they are closed during the pandemic, the total infection risk would be reduced by 25%–40% and 15%–25% respectively and the urban energy consumption would be reduced by 30%–40% and 13%–20% respectively. If people wore masks in all public indoor environments (exclude restaurants and KTV), the infection risk could be reduced by 60%–70% and the energy consumption could be reduced by 20%–60%. Gyms pose the highest risk for COVID-19 transmission. If the energy consumption kept the same with the current value, after the optimization, infection risk in winter, summer and the transition season could be reduced by 65%, 53% and 60%, respectively. After the optimization, under the condition of $R_t < 1$, the energy consumption in winter, summer, and the transition season could be reduced by 72%, 64%, and 68% respectively.

1. Introduction

By the end of 2021, COVID-19 had infected more than 273 million people and killed 5.3 million people around the world [1]. More than 99% of SARS-CoV-2 infections occurred in indoor environments [2]. Long-range airborne transmission is one of the main routes for SARS-CoV-2 spread [3–5]. People use various non-pharmaceutical interventions (NPI) (e.g. indoor ventilation, air purifiers, ultraviolet, and masking) to reduce the infection risk of COVID-19, with increasing the fresh air exchange rate being the most popular intervention [6–9]. However, excessive ventilation inevitably wastes energy, particularly on hot or cold days. As of 2022, the global economy is expected to lose nearly $8.5 trillion [10]. In China, energy consumption of HVAC systems increased by 128% during the COVID-19 pandemic [11]. This highlights the need to urgently reduce energy consumption while simultaneously meeting the requirements of COVID-19 prevention during stable epidemic periods when only a few people are infected.

However, many indoor environments still implement the same high intensity interventions during the stable period as are necessary during the pandemic outbreak. Many organizations (WHO, ASHRAE) have proposed epidemic control measures for the stable period, but these proposals have a number of problems [11]. Firstly, people undertake different activities in different indoor environments [12]. Metabolic intensity and types of indoor environments have an impact on personal exposure and COVID-19 prevention strategies, but few control measures consider these influencing factors. Secondly, the viral RNA loads in the exhaled aerosols from an infected person changes over time, and this is not considered in many models [13]. Thirdly, in the traditional Wells-Riley model, virus inactivation and aerosol deposition are rarely considered. Finally, most studies focus on COVID-19 prevention and control for a single indoor environment, ignoring the correlation of various indoor environments, which makes it difficult to optimize

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building energy efficiency and infection risk control for different indoor environments [14].

Many models such as Computational Fluid Dynamics (CFD), Gaussian dispersion model, and Wells-Riley model were used for simulation on virus transmission via long-range airborne route. CFD model could accurately assess the virus exposure based on detailed parameters of indoor environment, such as the position of air vents and indoor objects, however, it would take a long time and is generally used in a single indoor environment [15]. Although with lower accuracy than CFD, Gaussian dispersion model could obtain real-time virus exposure according to the indoor wind speed and the movement of the infected and susceptible people [16,17]. However, it is almost impossible for simulation on large numbers of indoor environments because of long time consumption and detailed requirements on indoor parameters.

Wells-Riley model is often used to simulate the virus transmission via long-range airborne route [18]. The model provided the quantitative relationship between infection risk and fresh air volume with the constant virus generation rate. However, the traditional Wells-Riley model does not consider the time-variant attenuation of virus generation by the patient and the inhalation and exhalation rate under different metabolism (e.g. exercising, standing, sitting). It may lead to a great impact on the accuracy of the results. In this study, we developed an improved Wells-Riley model that considers dynamic virus generation and pulmonary ventilation rate for different human activities in various indoor environments. We considered 10 typical indoor environments, three seasons (summer, winter, and a transition season) and four population groups (workers, students, the elderly, and the immobile) for optimizing COVID-19 infection risk ($R_t < 1$) and energy consumption. The results of this study will help to intelligently balance controlling COVID-19 transmission and reducing energy consumption, which is very important for sustainable cities and society.

2. Methods

2.1. Infection risk-energy consumption model

2.1.1. Improved Wells-Riley model

The Wells-Riley model is usually used to evaluate virus transmission via long-range airborne routes.

$$P = \frac{C}{S} = 1 - \exp \left( \frac{lpq}{Q} \right)$$

Where $P$ is the probability of infection; $C$ is the number of people infected via long-range airborne transmission; $S$ is the initial number of susceptible people; $l$ is the number of the infected (assumed to be 1 in each indoor environment); $q$ is the quanta generation rate ($/h$); $p$ is the pulmonary ventilation rate (set to 0.4 $m^3/h$ resting state); $Q$ is the indoor fresh air ventilation rate ($m^3/h$).

Quanta was assumed to be a constant value in the traditional Wells-Riley model. However, measurement of exhaled aerosols of infected individuals has shown that the viral RNA load decreases gradually after the onset of symptoms. Therefore, the quanta generation rate should also decrease with time. The infectious period of COVID-19 is set to 10 days [19]. According to measured data of viral RNA loads, the quanta produced by the infected can be calculated as:

$$\delta(t) = 10^{-0.12t}$$

where, $t$ is the number of hours since the onset of the infectious period; $\delta(t)$ is the attenuation coefficient for quanta generation.

Metabolic intensity determines the inhalation and exhalation rates. Therefore, the quanta generation rate of the infected would be higher if the pulmonary ventilation rate is higher. The metabolic intensity coefficients in different indoor environments are $m$ (the multiple of pulmonary ventilation rate to resting state), set as follows: at home, $m$ is 1; in classrooms, offices, subways, and restaurants, $m$ is 1.25; in cinemas, shopping malls, railway stations/airports, and Karaoke Televsions (KTVs), $m$ is 1.5; in gyms, $m$ is 2 [20].

Time-variant virus generation rate during the infectious period of patients [19] and dynamic exposure velocity influenced by the human activities (e.g. exercising, standing) were considered into the improved Wells-Riley model, can be expressed as (Eq. (3)):

$$P = 1 - \exp \left( - \frac{l \cdot m^2 \cdot p \cdot \sum_{i=0}^{t} q_0 \cdot \delta(t)}{Q} \right)$$

where, $q_0$ indicates the initial quanta generation rate at the onset of symptoms, set to 48 $h^{-1}$ [18].

2.1.2. Energy consumption model

Energy consumption of air conditioning system is defined as the cooling and heating load of the central air conditioning system and split air conditioning used in residential buildings, excluding the energy consumption of water pumps, cooling towers and other related equipment. Air conditioning system is defined as the central air conditioning system in public buildings or split air conditioning used in residential buildings, excluding water pumps, cooling towers, and other related equipment. In order to find the balance between COVID-19 prevention ($R_t < 1$) and energy consumption, an energy consumption model based on human comfort was established. Based on the infection risk-energy consumption model, we developed an optimization strategy that considers both energy consumption and epidemic control for different population groups, in various indoor environments during the stable epidemic period.

2.1.2.1. Season, population group and indoor environment. The energy consumption to ensure indoor human comfort, changes with the seasons. For our purposes we considered three seasons: winter, summer and a transition season. In this study, winter (January, February, November and December), summer (June, July, August, and September), and transition season (March, April, May, and October) was divided based on the temperature distribution (Appendix K). In addition, due to different commuting patterns, the population was divided into four categories: student, worker, the elderly (aged between 61 and 80), and the immobile (aged under 3 and over 80) [21]. Previous studies showed that the daily movement of students, workers, the elderly, and the immobile is quite different [22]. By analyzing the spatio-temporal distribution of these four population groups, the strategy on COVID-19 prevention and control and urban energy consumption reduction simultaneously considering 10 types of indoor environments could be optimized. As of November 2020, there were 21.9 million people in Beijing (students 10.1%, workers 71.9%, the elderly 10.5%, and the immobile 7.5%) [22]. The 10 typical indoor environments we considered were: home, office, classroom, restaurant, subway, shopping center, railway station/airport, cinema, KTV, and gym.

2.1.2.2. Equivalent fresh air volume. We adopted the concept of equivalent fresh air volume, which refers to all methods that can remove indoor viruses (e.g. natural inactivation, deposition, human inhalation, and some NPIs) (Eq. (4) and (5)). We considered four NPIs including indoor ventilation, air purification, ultraviolet (UV-C), and mask wearing.

$$Q_{eq} = ACH_{eq} \times V$$

$$ACH_{eq} = ACH_e + ACH_{ap} + ACH_{uv} + ACH_d + ACH_{uv} + ACH_{eq}$$

where, $Q_{eq}$ is equivalent fresh air volume ($m^3/h$); $V$ is the volume of the indoor environment ($m^3$); $ACH_e$ is the equivalent air change rate (ACH) of the indoor environment; $ACH_{eq}$ is the actual $ACH$; $ACH_{ap}$ and $ACH_{uv}$
are the equivalent ACH by the air purifier and the UV-C, respectively; 
ACH_{e} and ACH_{i} are the equivalent ACH due to virus inactivation and 
aerosol deposition; ACH_{n} is the equivalent ACH due to inhalation by 
people. The calculations for all the equivalent ACHs mentioned above 
are shown in Appendix A.

In addition, our study also considered the impact of mask wearing on 
reducing exposure. Wearing masks can reduce both virus generation and 
and exposure. Surgical masks, which are commonly used, reduce viral copy 
numbers in the fine fraction 2.8-fold (95% CI 1.5–5.2) and in the coarse 
fracion 25-fold (95% CI 3.5–180) [7].

Using the above formulas, we can calculate the equivalent fresh air 
ventilation according to the specific epidemic prevention measures 
being taken in the indoor environment.

In the case where the prevention measure was mask wearing, the 10 
indoor environments were divided into three categories: no-mask indoor 
environments (home, restaurant, KTV, and gym), familiar indoor envi-
rions (office, classroom), and strange indoor environments (subway, 
shopping center, railway station/airport, cinema). Then in the 
simulation, we considered 3 conditions for mask wearing: (1) only worn 
in strange indoor environments; (2) only worn in both familiar and 
and strange indoor environments; (3) worn nowhere. More detailed infor-
mation on mask wearing can be found in Appendix B.

2.1.2.3. Energy consumption. The quantitative relationship between 
equivalent fresh air volume and building energy consumption is shown in Eq. (6):

\[
e = e_{\text{e}} + e_{\text{fan}} + e_{\text{AP}} + e_{w} \tag{6}
\]

where \( e \) (kW) is the building energy consumption for epidemic 
prevention and control; \( e_{\text{e}} \) (kW) is the building energy consumption to 
maintain the indoor temperature for human comfort considering 
ventilation from the outdoor fresh air; \( e_{\text{fan}} \) (kW) is the energy con-
sumption of fans bringing outdoor fresh air indoors; \( e_{\text{AP}} \) (kW) is the 
energy consumption of air purifiers; \( e_{w} \) (kW) is the energy consumption of 
UV-C.

When providing outdoor fresh air, it is necessary to balance the 
heating or cooling load required to maintain the indoor air temperature.
The quantitative relationship between the actual fresh air volume and 
energy consumption in the indoor environment is shown in Eq. (7) [23].

\[
e_{a} = \frac{Q_{a} \Delta h \cdot t}{COP} \tag{7}
\]

where \( t \) is the time of ventilation; \( Q_{a} \) is the actual air volume (m³/h); \( \Delta h \) is 
the air density (1.293 kg/m³); \( \Delta h \) is the enthalpy difference between 
indoors and outdoors (kJ/kg); the coefficient of performance (COP) is 
the air conditioning energy efficiency coefficient, which is set to be 3.5 
in winter and the transition season, and 3 in summer [24], when 
calculating the actual fresh air volume to maintain indoor temperature 
and relative humidity, \( \Delta h \) changes according to season (Appendix C).

Energy consumption of the fan \( (e_{\text{fan}}) \) can be obtained from Eq. (8). To 
simplify the calculation, we assumed a specific fan-power of 1 kW m⁻³.s for 
ventilation systems without heat-recovery [25,26].

\[
e_{\text{fan}} = \int_{0}^{t} SFP \cdot Q \cdot dt = SFP \cdot Q \int_{0}^{t} dt = Qt \tag{8}
\]

Energy consumption of UV-C is 40 W/h for every 40 m² and for air 
purification is 45 W/h for an air volume of 350 m³ [27]. The detailed 
selection of UV-C and air purifier can be found in Appendix D.

2.2. The optimized sequence of interventions

When finding the minimum energy consumption to meet the re-
requirements of epidemic prevention, epidemic prevention takes prece-
dence over human comfort. Finally, we determined the sequence of 
terventions to be as follows (Fig. 1).

A national standard for fresh air volume (SV) in each indoor envi-
ronment was the first requirement (detailed values are given in 
Table S2). After that, providing comfortable fresh air (CV), using air 
filters (AP), and opening UV-C (UV) were selected for COVID-19 
prevention. The order in which these above-mentioned interventions 
should be performed depends on the energy consumption for the specific 
condition. Detailed settings for air filters and UV-C can be found in 
Appendix D. If COVID-19 cannot be controlled \( (R_{t} > 1) \) even after all the 
above interventions have been implemented, extra air purifiers (EAP) 
would be used (the number of extra air purifiers is set according to 
Appendix D). Finally, triple comfortable fresh air volume (TV) was used 
to minimize the infection risk of SARS-CoV-2.

2.3. Urban energy consumption

To calculate urban energy consumptions, we obtained the opening 
and closing times of the 10 typical indoor environments (Table S4).

\[
E = \sum_{i=1}^{10} N(ie) \cdot t(ie) \cdot e_{\text{h}}(ie) \tag{9}
\]

where \( E \) is the daily energy consumption in Beijing (kW); \( N(ie) \) is the total 
number of each type of indoor environment \( (ie) \) in Beijing; \( t(ie) \) is the 
time spent (hours) by people in a specific indoor environment per day; 
\( e_{\text{h}}(ie) \) is the hourly energy consumption for a specific indoor environ-
ment (kW h⁻¹).

2.3.1. Single scenario optimization

The effective reproduce number \( R_{t} \) is defined as the expected 
number of secondary cases (second-generation patients) infected by one 
infected person (first-generation patients) [18]. If \( R_{t} < 1 \), the disease 
would eventually die out.

If we can ensure that \( R_{t} \) in each indoor environment is less than 1, the 
final \( R_{t} \) will be less than 1 no matter how people spent their time in the 
different indoor environments [28]. If \( R_{t} < 1 \) could be satisfied when the 
infected person stays in the same indoor environment during their entire 
infected period, \( R_{t} < 1 \) in all indoor environments could be achieved. 
The above epidemic prevention strategy is called local optimization. 
According to the sequence of NPIs we proposed (Fig. 1), the relationship 
between equivalent fresh air volume and energy consumption was ob-
tained. Based on the relationship between \( R_{t} \) and the probability of 
infection (Appendix F), the relationship between \( R_{t} \) and equivalent fresh 
air volume was calculated based on the improved Wells-Riley model. 
Finally, the relationship between energy consumption of each indoor 
environment, and \( R_{t} \) was obtained. In general, the relationship between 
\( R_{t} \), equivalent fresh air volume, probability of infection, and energy

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**Fig. 1.** The sequence of interventions considering energy consumption, COVID-19 prevention, and human comfort.
consumption was quantitatively obtained.

2.3.2. Multi scenarios optimization

In actuality, infected people do not usually stay in the same indoor environment for the whole infectious period. Since energy would be wasted if we assumed $R_t < 1$ held in all types of indoor environments, we need to find the best epidemic prevention strategy according to the length of time people spend in the different indoor environments per day. Based on 300 questionnaires (Appendix G) and a previous study [29], the time spent by the four population groups (worker, student, the elderly, and the immobile) in each indoor environment during the stable pandemic period is shown in Table 1.

According to the distribution of time spent indoors by the four groups of people in different indoor environments, a strategy to optimize energy consumption and infection risk control can be developed. We call this strategy population-based optimization. Considering that each population group has its own optimal strategy, in order to meet the demands for

| Indoor environment | Worker | Student | Elderly | The immobile |
|--------------------|--------|---------|---------|--------------|
| Home               | 12 h   | 12 h    | 17.5 h  | 24 h         |
| Office             | 8 h    | –       | –       | –            |
| Classroom          | –      | 8 h     | –       | –            |
| Restaurant         | 1 h    | 1 h     | 1 h     | –            |
| Subway             | 1.1 h  | 0.9 h   | 0.7 h   | –            |
| Shopping center    | 0.6 h  | 0.4 h   | 1 h     | –            |
| Railway station/airport | 0.04 h | 0.04 h | 0.04 h | –            |
| Cinema             | 0.04 h | 0.04 h  | 0.04 h  | –            |
| KTV                | 0.04 h | 0.04 h  | 0.04 h  | –            |
| Gym\(^a\)          | 0.21 h | 0.21 h  | –       | –            |

\(^a\) Because the proportion of fit elderly is low, we ignored the time the elderly spent in a gym.

Fig. 2. The relationship between energy cost and effective reproduction number ($R_t$) (a) with mask; (b) without mask. (the shaded part shows the $R_t$ that cannot be achieved in the indoor environment when all interventions were strictly implemented).
COVID-19 control, we adopt the most stringent strategy for each indoor environment for each population group, and this is called the global general optimization. However, with the global general optimization, if all indoor environments meet the most stringent epidemic prevention requirements, it will mean excessive measures for epidemic prevention in the other three population groups, which in turn means an unnecessary waste of energy. Therefore, we considered the distribution of the four population groups in Beijing (10.1% for students, 71.9% for workers, 10.5% for the elderly and 7.5% for the immobile), and obtained the more refined global optimization. We can then calculate the daily energy consumption in Beijing to meet the requirements of epidemic prevention.

When calculating the epidemic spread, we assume that the $R_t$ distribution in each indoor environment ranged from 0 to 5 with a resolution of 0.01. Taking energy consumption as the optimization objective, the optimal distribution of $R_t$ in different indoor environments were obtained. The minimum $R_t$ would be achieved when all interventions shown in Fig. 1 were implemented.

### 3. Results

#### 3.1. Local optimal solution for each indoor environment

**3.1.1. Per capita energy consumption**

Energy consumption increases with the increase of per capita equivalent fresh air volume (Fig. 2 and Appendix H). As heat production by the human body increases the cooling load in summer and reduces the heating load in both winter and transition seasons, energy consumption is the highest in summer when the per capita equivalent air volume is low. However, because the enthalpy difference in winter is greater than that in summer and transition seasons, with the increase in per capita equivalent fresh air volume, the energy consumption in winter becomes gradually greater than that in summer and transition seasons. When no mask wearing, in order to control COVID-19 transmission ($R_t < 1$), the per capita energy consumption of subways is the highest (1.3 kW/h/p in winter, 0.6 kW/h/p in summer, and 0.5 kW/h/p in the transition season); and of homes is the lowest (0.02 kW/h/p in winter, 0.015 kW/h/p in summer and 0.01 kW/h/p in the transition season) (Fig. 2). Classrooms, railway stations/airports, cinemas, KTVs and gyms cannot meet epidemic prevention requirements, even if all the above interventions are taken, for example, $R_t$ in gyms is greater than 5.

When masks are worn, the per capita energy consumption of subways is still the highest (0.1 kW/h/p in winter, 0.2 kW/h/p in summer and 0.05 kW/h/p in the transition season); while per capita energy consumption of offices is the lowest (0.01 kW/h/p in winter, 0.04 kW/h/p in summer and 0.005 kW/h/p in the transition season). The lowest $R_t$ in homes, offices, classrooms, restaurants, subways, shopping center, railway stations/airports, cinemas and KTVs when all interventions were strictly implemented without (with) masks are 0.04, 0.52 (0.07), 1.1 (0.15), 0.89, 0.9 (0.12), 0.66 (0.09), 1.34 (0.18), 1.39 (0.18), 1.56 respectively. The corresponding $R_t = 1$ epidemic prevention strategy for each indoor environment is shown in Table 2.

#### 3.1.2. Energy consumption of NPIs

The relative importance of NPIs changes with the epidemic prevention level (Fig. 3). When the epidemic prevention is weak ($R_t$ would be high), UV-C and air purifiers have important roles in epidemic prevention and control for energy efficiency, but when the epidemic prevention requirements are high, ventilation contributes more.

The energy consumption due to ventilation accounted on average, for more than 80% of the total energy consumed (Fig. 4). In subways and shopping centers, the energy consumption due to ventilation was more than 95%.

When people wear masks to achieve a minimum $R_t$ in offices, classrooms, subways, shopping centers, railway stations/airports and cinemas, the energy consumption is reduced by 80%–98%, 67%–98%, 77%–97%, 77%–98%, 63%–98% and 57%–98% respectively (Appendix D).+ 

### 3.2. Global optimization for all population groups and indoor environments

#### 3.2.1. Four population groups

Fig. 5 shows the energy consumption for population group-based optimization and global optimization. Daily urban building energy consumption for the population group-based optimization will produce a great waste of energy. Energy consumption under global optimization could be reduced by about 20% compared with the energy consumption for the population group-based optimization, and it could also meet the requirements of COVID-19 prevention and control. Homes and shopping centers consumed the most energy, accounting for 37% and 31% in winter, 29% and 39% in summer, and 39% and 21% in the transition season, respectively. Cinemas and KTVs consumed the least energy, accounting for 1–2% in all seasons. If masks are strictly worn in offices, classrooms, subways, shopping centers, railway stations/airports and
cinemas, energy consumption could be reduced by 19%, 60%, and 59% in summer, winter, and transition seasons, respectively.

3.2.2. Energy consumption during different indoor environment shutdowns

To control the spread of an epidemic as soon as possible, some public indoor environments could be closed, which will also affect urban energy consumption. Summer is the season when COVID-19 prevention and control measures result in the highest energy consumption, followed by winter and then the transition season (Fig. 6). When railway stations/airports, cinemas and KTVs are closed, even though there is no energy consumption by these buildings at that time, the total urban energy consumption increases by 1%–5% because people then spend more time in their homes. If indoor environments that have high energy consumption are closed (e.g. shopping centers and restaurants), urban energy consumption would be significantly reduced, a reduction of 31.5–40.2% when shopping centers are closed, and 12.6–20.5% when restaurants are closed. This means that closing public indoor environments can reduce the infection risk, but may not reduce total urban energy consumption.

3.2.3. $R_t$ distribution under different mask wearing conditions based on the global optimization

Based on the global optimization, if people do not wear masks in all public indoor environments, the COVID-19 prevention strategy of restaurants, shopping centers and KTVs would be weakest ($R_t$ is the highest) in summer and winter, and of homes and offices should be the strongest (Fig. 7a). The COVID-19 prevention strategy in the transition season is quite different from those used in winter and summer. COVID-19 prevention strategies in restaurants and KTVs during the transition season are stricter than those in winter and summer. The energy consumption of indoor environments in summer is different from that in winter and the transition season (Fig. 7b). Without considering human heat production, in winter and transition seasons, the difference of per capita energy consumption in each indoor environment is greater than that in summer. Based on the global optimization, the interventions in the indoor environment could be partially reduced, and the energy consumption in

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**Fig. 3.** The relationship between equivalent fresh air volume and effective reproduction number ($R_t$) in 10 typical indoor environments.

**Fig. 4.** Relationship between energy consumption and effective reproduction number ($R_t$).
winter and transition season is low because of human heat production.

3.2.4. Energy optimization level

Table 3 lists the energy consumption and target $R_t$ in the different indoor environments for the different optimization methods. When compared to the local pure-ventilation strategy (Strategy 2), local optimization saves energy by 30%–60%; population group-based optimization saves energy by 70%–90%; global optimization without masks (Strategy 5) saves energy by 75%–95%. Compared to Strategy 5, Global optimization with masks saves energy by 20%–60%. Of all the indoor environments, with global optimization, the most energy was saved for shopping centers, and the least for homes.

4. Discussion

In this work, we developed an improved Wells-Riley model that considers dynamic quanta generation and variable pulmonary ventilation rates, in different indoor environments as a result of the intensity of human activity. We then established an infection risk-energy consumption model. We considered four common NPIs, and using these models were able to propose the COVID-19 prevention strategy that will achieve the lowest daily urban building energy consumption, for three seasons and 10 indoor environments.

The traditional Wells-Riley model is used to calculate infection risk of virus transmission via long-range airborne route [30]. The model provided the quantitative relationship between infection risk and fresh air ventilation considering the constant personal virus generation rate and inhalation. However, in the traditional Wells-Riley model, virus generation (quanta) was considered as a constant value during the whole infectious period [31]. Moreover, the personal inhalation and exhalation was also a constant, which does not take the impact of the change of inhalation and exhalation by metabolic intensity of human body due to different activities (e.g. exercising, standing) into account [32,33]. However, the time-variant attenuation rate of virus generation rate (quanta) gradually decreased during the infectious period and the personal inhalation and exhalation rate would be determined by human activities.

In the COVID-19 pandemic, in order to quickly control the spread of the epidemic, some extreme methods (maximal ventilation) may be used to achieve the purpose without considering the energy conservation. It would inevitably cause a lot of energy waste if the same strategy was used in stable period of the pandemic [34]. In China, the objective of “dynamic clearing” appeals providing moderate interventions on COVID-19 during the stable period of the pandemic ($R_t < 1$) [35]. Chinese President Xi put forward the goal of carbon peak and carbon neutral [36]. Therefore, it is important to carry out epidemic prevention and control under low building energy consumption during the stable period of the pandemic.

Because COVID-19 is known to spread via long-range airborne transmission, NPIs such as ventilation, air purification, ultraviolet, and mask wearing were adopted to reduce infection risk [37–40]. Natural ventilation is one of the most effective interventions for COVID-19 prevention and control for all indoor environments, however, high natural ventilation rates can lead to human discomfort, and waste building energy. Air purification is one of the most energy-saving interventions, and can ensure air circulation in the local zone, however, it may increase noise pollution. UV-C, which consumes little energy, is good for COVID-19 prevention and control without noise pollution, however, it is harmful to the human body, and must be used strictly according to safe standards [41]. Mask wearing is a convenient, economical, and effective intervention. Many agencies (e.g. WHO, ASHRAE) and researchers have stressed the importance of wearing masks during the COVID-19 pandemic [42]. We found that mask wearing is not only an effective intervention for COVID-19 prevention, but also the most effective way to prevent the additional energy consumption of other NPIs. However, wearing a mask indoors can make the wearer feel uncomfortable. Therefore, in this paper we analyze these four NPIs to provide additional information on which strategies to balance disease prevention and energy use will be acceptable. This will prove useful in cases where people cannot wear masks for a long time, such as in restaurants, KTVs, and gyms, or even in environments where it is just uncomfortable for people to wear masks for a long time.

Most contemporary studies focus on interventions for COVID-19 prevention in a single indoor environment [14]. In some offices, air purification and an ultraviolet system were used simultaneously, and ventilation was increased by 50% to prevent COVID-19 spread [11]. In subways, ventilation was increased to the maximum to reduce the infection risk caused by high population density. In classrooms, during the pandemic, schools carried out online teaching to shield students from infection, and advocated paying attention to hand hygiene, disinfecting hands and increasing ventilation [43]. However, none of these studies looked at different indoor environments based on real data of people’s activities, and how long they stay, in different indoor environments. Although the obtained interventions could achieve the requirements for COVID-19 prevention ($R_t < 1$), some would lead to energy waste [44]. Considering how people really behave indoors (e.g.
the distribution of time spent indoors, their activities), we found that shopping centers and restaurants were the environments that had high infection risk, and so should receive more attention. The serious COVID-19 outbreak in Xinfadi shopping center [45] in Beijing and another in a restaurant in Guangzhou, underline the high risk of these indoor environments [46]. Many countries realized this fact and closed restaurants [47] and shopping centers [48] during the pandemic. Using our analysis, restaurants and shopping centers could be kept open if appropriate interventions were implemented based on the global optimization method. However, when it is necessary to control COVID-19 transmission rapidly, closing restaurants and shopping centers during the outbreak is recommended. In addition, since shopping centers have extremely high energy consumption, a lot of energy could be saved by closing them while $R_t$ is high.

People are generally very active in gyms, and this increased activity generates more virus by the infected and therefore the susceptible are
subjected to greater exposure [49]. We found that no matter what intervention was implemented in a gym, it is impossible to achieve the required COVID-19 prevention. Therefore, some gyms should be closed during the outbreak, and many countries did indeed close gyms to reduce the infection risk [50]. We believe that gyms can be opened during a stable period of the epidemic, but when there is a confirmed case, some gyms should be closed with the highest priority. KTV is also a high-infection risk indoor environment because of higher virus generation and inhalation. The virus production rate of people singing is 8.38 times higher than for breathing [32]. In a choir in Washington, USA, 53 out of 61 participants were infected from a single case [33].

Homes are also a critical environment for COVID-19 transmission. 70% of all COVID-19 patients were infected in a home [51]. People spent 12 h at home per day before the pandemic, and this increased to 15 h during the epidemic [29]. We found that the average energy consumption for homes during the pandemic, accounted for about 40% of the total urban building energy consumption.

Workers and students usually account for the majority of a city’s population. They frequently have complicated daily commutes. Schools and offices also connect people from different zones in a city. Because schools and offices are familiar places, few people kept wearing masks, so many countries called for classes to be suspended and offices to be closed [52,53]. Since people will use more energy at home, energy consumption would increase by 5%-8% if all classes and offices were closed.

Although only few people were in the railway stations and airport, they play a very important role in COVID-19 transmission because people from different cities and countries come into contact there. If there is an infected person in a railway station or airport, their transmission chain may affect others many thousands of kilometers away [54]. Even though these places meet the requirements for COVID-19 prevention based on our global optimization, it is suggested that very strict interventions should be implemented to prevent SARS-CoV-2 transmission between cities, provinces, and countries. To strengthen national and even global epidemic prevention and control, the $R_t$ of railway stations and airports should be kept to the minimum value of 0.18 by mandating that all people wear masks, and implementing all NPIs shown in Fig. 1 simultaneously. Compared to local optimization, the energy consumption will increase by 85%-90%, but considering the limited number of railway stations and airports in a city, it will have little impact on overall urban energy consumption.

In this work we found that under epidemic prevention and control measures, the energy consumption in summer was greater than in winter or the transition season. After balancing the heat generated by human bodies indoors, the indoor and outdoor enthalpy difference in winter is greater than that in summer. With the enhancement of epidemic prevention levels, energy consumption in winter becomes gradually greater than that in summer. With respect to the optimization of COVID-19 prevention and control, some indoor environments do not need to implement strict interventions, therefore, when a low level of epidemic prevention and control is warranted, energy consumption in summer would be greater than in winter. After global optimization, Beijing saved more than 96 million kwh of electricity per day (9 million USD, 57 million CNY).

Our research has the following limitations. First, long-range airborne transmission of virus particles was considered to be the main route of COVID-19 spread. Second, we used a typical design for each type of indoor environment without considering their diversity. Finally, the obtained results are based on real data from Beijing. For the results to be applied to other cities and countries, the local data of these places should...
Table 3
Hourly energy consumption (kW/h) of each indoor environment under different optimization strategies. (Corresponding epidemic prevention standards in Appendix L.)

| Season            | Indoor environment | Strategy 1  | Strategy 2  | Strategy 3  | Strategy 4  | Strategy 5  | Strategy 6  |
|-------------------|--------------------|-------------|-------------|-------------|-------------|-------------|-------------|
| Winter            | Home               | 17.00       | 0.84        | 0.29        | 0.35        | 0.35        | 0.30        |
|                   | Office             | 25.55       | 20.45       | 7.58        | 6.83        | 7.62        | 0.57        |
|                   | Classroom          | 29.42       | 46.86       | 29.42       | 29.42       | 10.48       | 0.49        |
|                   | Restaurant         | 60.16       | 104.62      | 48.83       | 7.48        | 2.18        | 2.18        |
|                   | Subway             | 99.52       | 94.32       | 87.90       | 99.52       | 52.96       | 3.20        |
|                   | Shopping center    | 2904.79     | 307.63      | 1484.97     | 142.83      | 142.83      | 9.58        |
|                   | Railway station/airport | 274.86     | 560.57      | 274.86      | 115.25      | 64.82       | 5.43        |
|                   | Cinema             | 92.55       | 214.37      | 92.55       | 19.33       | 18.42       | 1.34        |
|                   | KTV                | 13.74       | 18.17       | 13.74       | 0.91        | 0.43        | 0.43        |
| Summer            | Home               | 7.26        | 0.61        | 0.41        | 0.47        | 0.47        | 0.42        |
|                   | Office             | 12.65       | 10.45       | 5.51        | 5.19        | 5.54        | 2.68        |
|                   | Classroom          | 17.64       | 24.43       | 17.64       | 17.64       | 10.46       | 7.13        |
|                   | Restaurant         | 36.00       | 53.18       | 31.50       | 14.80       | 12.79       | 12.79       |
|                   | Subway             | 49.83       | 47.61       | 45.22       | 49.83       | 33.44       | 11.56       |
|                   | Shopping center    | 1427.93     | 1488.40     | 864.98      | 306.76      | 306.76      | 234.08      |
|                   | Railway station/airport | 178.43     | 290.34      | 178.43      | 113.81      | 95.15       | 60.21       |
|                   | Cinema             | 65.24       | 113.07      | 65.24       | 35.86       | 35.84       | 23.62       |
|                   | KTV                | 8.22        | 9.93        | 8.22        | 3.08        | 2.95        | 2.95        |
| Transition season | Home               | 9.01        | 0.34        | 0.07        | 0.13        | 0.13        | 0.06        |
|                   | Office             | 12.76       | 9.94        | 3.32        | 2.51        | 2.68        | 0.46        |
|                   | Classroom          | 13.55       | 22.60       | 13.55       | 13.55       | 2.90        | 0.83        |
|                   | Restaurant         | 27.95       | 50.93       | 22.00       | 1.89        | 1.89        | 1.71        |
|                   | Subway             | 48.88       | 46.03       | 42.78       | 48.88       | 19.51       | 1.44        |
|                   | Shopping center    | 1485.93     | 1524.07     | 740.74      | 33.29       | 33.19       | 8.34        |
|                   | Railway station/airport | 136.16     | 271.05      | 136.16      | 50.62       | 24.09       | 6.87        |
|                   | Cinema             | 39.35       | 102.96      | 39.35       | 4.54        | 4.51        | 1.02        |
|                   | KTV                | 6.40        | 8.61        | 6.40        | 0.42        | 0.42        | 0.38        |

a Strict situation: all interventions (SV + AP + UV + CV + EAP + TV) were implemented.

b Local pure-ventilation strategy: ventilating with pure fresh air (no more than 3 times of comfortable air volume) to minimize R<sub>t</sub> (no less than 1).

c Local optimization: interventions were implemented based on the requirements to minimize R<sub>t</sub> (no less than 1). It is assumed that the infected person stays in the same indoor environment during the entire infectious period.

d Population group-based optimization: interventions were implemented based on the requirements to minimize R<sub>t</sub> (no less than 1). The distribution of time spent indoors by the four population groups was considered.

e Global optimization without masks.

f Global optimization with masks (mask wearing in offices, classrooms, subways, shopping centers, cinemas, railway stations/airports).

be used.

In the future research, more virus transmission routes such as short-range airborne, large droplets, and fomite route should be considered simultaneously to improve the infection risk-energy consumption model. Moreover, some experiments should be designed and implemented to verify the accuracy and reliability of the model. In this way, the obtained results would be much more useful for COVID-19 prevention and control during the period of “dynamic clearing”.

5. Conclusions

This paper established an infection risk-energy consumption model to simultaneously achieve the target of COVID-19 prevention and control (R<sub>t</sub> < 1) and save urban building energy. If the global optimization method is used instead of ventilating the indoor environment with 3 times of the human comfortable fresh air volume, the energy savings in winter, summer, and the transition season would be 96%, 92% and 94% respectively. Comparing the global optimization with the optimization for a single indoor environment, the energy savings in winter, summer, and the transition season would be 72%, 64%, and 68% respectively. This study provides detailed and reliable strategies for saving energy while also achieving adequate COVID-19 prevention and control. The study caters to the carbon neutral and carbon peak provided by Chinese President Xi, and helps to curb the spread of COVID-19 while still maintaining sustainable development of cities and societies.

CRediT authorship contribution statement

Tingrui Hu: Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation. Ying Ji: Writing – review & editing, Supervision, Methodology. Fan Fei: Visualization. Min Zhu: Writing – review & editing. Supervision. Tianyi Jin: Writing – review & editing. Supervision. Peng Xue: Writing – review & editing. Nan Zhang: Writing – review & editing. Writing – original draft, Supervision, Funding acquisition, Conceptualization.

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.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.buildenv.2022.109233.

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