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Research Article

A Hybrid Model for the Impact of COVID-19 Prevention Measures on the Sustainable Development of the Aviation System

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An airport is a complicated system that serves as a vital link in the aviation system. Airplanes are also a popular mode of transportation for daily travel and tourism. Now that COVID-19 is spreading over the world, many airlines are under severe financial strain. Therefore, long-term air traffic planning is critical, especially since the airport is a key region for COVID-19 to expand. To anticipate, simulate, and estimate the medical and health expenditures caused by the propagation of the epidemic under lax, mild, and strict social contact intervention, we utilize a hybrid model of the agent-based model and discrete event simulation. An agent-based model can capture individual behavior, and discrete event simulation can be used to explain the entire boarding process. Limiting the rate of wearing masks while traveling and upgrading airport facilities are the most effective strategies to manage the epidemic, given the convenience of travelers and the swift recovery of the national economy. Simulating passenger boarding will aid government agencies in improving airport equipment and facilities, facilitating passengers' reasonable travel plans, avoiding large-scale contact, preventing the spread of epidemic diseases, and promoting the long-term sustainability of densely populated public transportation systems such as airports.

1. Introduction

Since December 2019, a number of viral pneumonia outbreaks have occurred in Wuhan, Hubei Province [1]. On January 30, 2020, the World Health Organization announced that the outbreak of COVID-19 had become a public health emergency of international concern [2]. On March 11, 2020, the Director-General of the World Health Organization described the spread of COVID-19 as a pandemic, which is alarming in its spread and severity [3]. COVID-19 still shows no signs of slowing down after it claimed nearly half a million lives worldwide [4]. The outbreak of COVID-19 is also an unprecedented event in air transportation [5].

Airports are important places for the aggregation and dispersion of passenger flows due to the rapid spread of COVID-19, strong infectivity, latent concealment of infection, and large number of infected populations [5], and countries with large airports or road traffic are in the early hotspot of the COVID-19 epidemic [4]. High-density passenger flows are vulnerable to mutual infection during COVID-19. This poses a significant threat to the epidemic's effective control. COVID-19 transmission into counties in the United States with international airports is the first hotspot, and early public health containment strategies focusing on these places may help minimize disease transmission during future outbreaks of new respiratory viruses [6]. The airport has a large passenger flow and complex personnel, so epidemic prevention and control at the airport are very important. To prevent the spread of COVID-19, the U.S. Government has implemented two travel restrictions to protect travelers and transportation workers from the disease [7]. In addition, the European Union has also adopted a package of safety-related measures

to mitigate the impact of COVID-19 on various aspects of air service, airport slot allocation, and air cargo operations [8]. Due to the global COVID-19 pandemic, international air travel around the world has been largely banned, and airport traffic recovery has replaced airport congestion as the main challenge facing the world's major airports [9].

As the number of COVID-19 cases worldwide increases, the number of imported cases into China is also gradually increasing [10]. Some studies have pointed out that the infection rate and death rate are largely influenced by the preblockade period, followed by population density and airport traffic [4]. Both airports and governments should establish stringent countermeasures and actively take COVID-19-related actions during the pandemic phase, such as home quarantine and prohibiting infected or suspected patients from traveling [3].

Mianyang Airport is located in Mianyang City, Sichuan Province, and was completed in April 2001. Mianyang Airport is a new, modern airport located 10 kilometers from the city center with easy access. With a run-way length of 2,400 meters, an apron area of 111,000 square meters, and a terminal building construction area of 26,000 square meters, the airport is classified as civil 4D [11]. Mianyang Airport handled 4.1594 million passengers in 2019, up 5.6% from the previous year. Cargo throughput increased by 16.8% year over year to 8,800 tons, and flight numbers increased by 7.6% to 189,900. In China, it was placed 49th, 62nd, and 17th [12]. As of the summer season of 2019, there are 41 navigable cities such as Beijing, Shanghai, Guangzhou, Shenzhen, Haikou, and Kunming and 55 routes operated by 19 airlines such as Air China, China Southern Airlines, China Eastern Airlines, and Sichuan Airlines [11].

The air transportation business, which plays an important role in the global transportation system, is critical to the economic success and strategic growth of many countries. The emergence of COVID-19 could destroy the industry and fundamentally disrupt its operations, which is one of the unprecedented challenges facing the industry [13]. Currently, the negative consequences of a COVID-19 pandemic threaten people on an international scale [14]. This study discusses the spread of COVID-19 and the medical cost under different airport prevention and control measures. Taking Mianyang Airport as an example, we establish a hybrid model and use computer simulation to dynamically capture and simulate the spread of COVID-19 in airports, so as to calculate the relevant medical costs.

2. Literature Review

The spread of COVID-19 among people poses a high risk to countries with fragile health systems. Infectious diseases are transmitted from one person to another through close contact. Infectious diseases can spread quickly without effective control, resulting in massive human and economic losses. The SIR and SEIR models are often used to study the spread of COVID-19 [15]. Ribeiro et al. developed a susceptible-infection-recovery (SIR) model to explore the transmission of COVID-19 between cities and proposed measures to contain the spread of COVID-19 [16]. In addition to the traditional SIR and SEIR models, hybrid models have been used in the analysis of various COVID-19 outbreaks. Based on a hybrid model approach, Castillo Ossa et al. combined the system dynamics of differential equation SIR models with recurrent neural network-based extrapolation to simulate and predict the evolution of COVID-19 and to analyze the spread of COVID-19 under different scenarios of COVID-19 diffusion and spread [17]. Zhang and Liu proposed a hybrid intelligent model based on the spread of COVID-19, taking into account the impact of various control measures on the spread of the epidemic, such as government investment, media campaigns, and medical treatment; using genetic algorithms to optimize the transmission rate; proposing an improved SIQR (susceptible-infected-quarantined-recovered) model; and also a SIQR model embedded with long and short-term memory (LSTM) to further optimize other parameters of the system model and finally obtain the optimal prediction model and control measures [18].

The widespread use of system dynamics for epidemic analysis of COVID-19 has coincided with the growing popularity of the agent-based model. Silva et al. proposed an agent-based model (ABM) based on SEIR, which used agents to simulate the COVID-19 epidemic. Furthermore, the ABM model not only simulates the dynamic changes of the COVID-19 epidemic but also simulates the economy of the main society, which is helpful in estimating the economic impact of different intervention types [19]. Tatapudi et al. developed and used an agent-based model for COVID-19, which simulated the daily social mixed behavior of transmission between susceptible populations and infected people [20]. The prediction and analysis of confirmed and fatal COVID-19 cases has recently been a hot issue in epidemiology research. Guo and He developed an artificial neural network (ANN) based on COVID-19. By introducing root mean square error, correlation coefficient (R), and mean absolute error, the statistical indicators of the model were validated and evaluated, and the artificial neural network was used to predict the confirmed and death cases of COVID-19 [21].

At present, the aviation industry is severely impacted by COVID-19 and is facing one of the most serious crises in its history [22]. The air transport industry is responsible for the movement of millions of people and tons of cargo every day, and COVID-19 has dealt a serious blow to the aviation industry, with huge implications for the national and international economy and politics [23]. Airports are an important cause of the global spread of COVID-19 [12]. In view of the unprecedented challenges brought by the COVID-19 pandemic to the aviation industry [24], Guo et al. integrated aircraft take-off and landing, passenger throughput, and cargo throughput into the resilience indicator model to compare the resilience evaluation under different prevention and control strategies, so as to reflect the speed of airport recovery during COVID-19 [25]. Bao et al. built a global air transport network by analyzing flight data from over 3,765 different airports from the Official Aviation Guide, describing the impact of the removed airports and flights on the entire air transport network, and

found that these actions led to an increase in the average distance between airports and an increase in the number of long-haul routes [23]. Furthermore, Sun, Wandelt, and Zhang studied the impact of COVID-19 on global air transport from a complex systems perspective at different scales, including the world airport network, the links between different airports, and the international airport network for direct flights, on a country-by-country basis [5].

Many elements of people's economic and social activities have changed as a result of COVID-19 [26]. In order to measure the impact on passenger flow, Dabachine et al. established a simulation model at Casablanca Mohammed V International Airport [14]. Di Mascio, Moretti, and Piacitelli investigated whether the available space for queuing and waiting is large enough to accommodate new social distancing rules for passengers in response to COVID-19 emergencies [27]. Due to the complexity and randomness of passenger flow dynamics and the difficulty of predicting passenger response behavior, Milne et al. used random simulation and agent-based models to evaluate the results of changing the number of boarding groups under the epidemic. It is concluded that if the minimum social distance on the aisle is increased from 1 m to 2 m, the boarding time will be increased. But the health risks of passengers walking along the aisle and those who have sat before will be reduced [28]. Delcea et al. established the ideal configuration to give reduced boarding time while addressing passenger health hazards by combining these with the advantages afforded by grey clustering and an agent-based model [22]. There are no hybrid models that can accurately predict and quantify the interrelationship between the number of COVID-19 infections, policy interventions, and passenger behavior at airports.

In light of the decline in COVID-19 infection rates in early summer 2021, many European governments have cancelled nonpharmaceutical interventions (NPIS) aimed at pandemic control. In practice, NPIS that rarely affect personal freedom, such as public space disinfection, as well as highly restrictive NPIS, such as limits on walking outside and wearing masks, have been discovered. All NPIS, once removed, can lead to a rise in infection rates as well as a variety of negative consequences [29]. Furthermore, Guo et al. discovered that COVID-19 had an unprecedented impact on air pollution in the Beijing-Tianjin-Tangshan region, and since COVID-19 led to urban lockdown and also affected the transportation industry and manufacturing, pollution emissions were naturally reduced. As a result, reducing social and economic activities not only had a positive effect on epidemic prevention and control but also had a positive effect on epidemic prevention and control. Reducing social and economic activities not only helps to prevent and control epidemics but also helps to improve air quality [30].

3. Materials and Methods

3.1. Data. Due to the impact of the COVID-19 epidemic, transportation hubs across the country strictly control the flow and circulation of passengers, making it difficult to collect data. Therefore, the data for this study were obtained from field research and literature. Before building the model, we traveled to Mianyang Airport for field investigation, assessed the size of the airport (the measurement tool is SNDWAY SW-900A), purchased a ticket and entered the airport waiting hall, and gained a better understanding of the entire process of travelers entering the airport. The passenger throughput of Mianyang Airport was 4,159,370 in 2019 and 2,890,912 in 2020, 30.5% less than in the same period last year. Parameters and data sources in the model are given in Table 1.

We predict the airport situation from 12 : 00 to 20 : 00 on Wednesday. The number and type of aircraft are given in Table 2. The simulation lasts eight hours.

3.2. Methods. Following Zohdi [39], we built an interaction model based on the agent-based model and discrete event simulation. We can regard agents as individuals, and each agent enters the airport according to the process of discrete event simulation.

3.2.1. Agent-Based Model (ABM). (1) Agent-to-agent interaction and rules: when two agents are considered close to each other, "contagion" will occur. In the agent-based model, it is assumed that there are two states of agents, namely, susceptible (S) and another one is asymptomatic infection (A). If S and A make contact within a limited radius, they will receive a message that "infection" is likely to occur, and there will be no secondary infection at the airport. A detailed code is shown in Figure 1.

The contact process and action track of passengers after entering the airport are shown in Figure 2.

3.2.2. Discrete Event Simulation (DES). Discrete event simulation (DES) can describe the limited process of resources through the structured workflow related to the queuing process, queuing network, and waiting time, focusing on resource utilization [40]. This article evaluates the impact of the passenger entry procedure and the number of service windows on the number of infections and medical expenses. It uses discrete event simulation to simulate the entire process of passenger entry and boarding. The service mode of the whole process of passenger boarding follows the requirements of queuing theory. The input process, the queuing rules, and the service organization are the three essential components of the queuing system. The input process refers to the process by which passengers enter the queuing system according to a certain rule. Queuing rules are the rules for passengers to queue up after entering the service system. We adopt FCFS, that is, first come, first served. Service organization refers to the number of service desks and service rules in the queuing system. The number of service desks refers to the number of ticket gates and security checkpoints, and the service rules refer to the service time of each ticket gate and security checkpoint.

Table 1: Model parameters in the hybrid model.

Model parameters	Value	Data sources	Unit
Infectivity with asymptomatic infection	0.0411	[31, 32]	dnml
Contact rate	2	Field research and [33]	Person/minute
Passenger flow	Triangular (5, 10, 25)	Field research and website*	Person/minute
Code and temperature test time	Triangular (12, 15, 17)	Field research	Seconds
Check-in time	Triangular (5, 10, 15)	Field research	Seconds
Meal time	Triangular (15, 20, 25)	Field research and assumption	Minutes
Shopping time	Triangular (3, 5, 7)	Field research and assumption	Minutes
Bathroom time	Triangular (1, 3, 5)	Field research	Minutes
Hall waiting time	Triangular (10, 20, 30)	Field research and assumption	Minutes
Security time	Triangular (1, 2, 3)	Field research	Minutes
Waiting hall delay time	Triangular (35, 45, 55)	Field research	Minutes
Boarding time	Triangular (1, 2, 3)	Field research	Minutes
Passenger walking speed	1–1.5	Field research and [34]	m/s
Number of ticket barriers	13	Field research	
Number of security checkpoints	4	Field research	

*https://www.caac.gov.cn/XXGK/XXGK/TJSJ/202104/t20210409_207119.html.

Table 2: The number and type of aircrafts.

Plane models	Loading capacity	The number of planes	Sources
B738	164	17	[35, 36]
B737	164	2	[35, 36]
A320	150	4	[35, 37]
A319	124	3	[35, 38]

```
Action

for (Passenger p:passengers)
{
    for (Passenger n:passengers)
    {
        if (!p.equals(n))
        {
            double distance = p.distanceTo(n);
            if (distance <= this.numberOfUnitFor1meter * this.radiusOfTransmissionBoundaryInMeter)
                {
                    p.connectTo(n);
                }
        }
    }
}
```

Figure 1: The interaction process between ABM and DES in AnyLogic, as well as the contact mode and limited range code of each passenger in ABM and DES.

$$\rho = \frac{\lambda}{\mu},$$
$$L_q = \frac{\rho}{(1-\rho)} - \frac{(N+1)\times\rho^{N+1}}{1-\rho^{N+1}}, \tag{1}$$

where L_q is the average number of passengers in the whole airport system, ρ is the service intensity, λ is the average number of passengers arriving per unit time, i.e., the average arrival rate, μ is the average number of passengers completing security check or ticket check per unit time, i.e., the average service rate, and N indicates the capacity limit of the service system.

$$L_s = L_q - (1 - P_0),$$
$$\lambda_e = \mu \times (1 - P_0), \tag{2}$$

where L_s is the average queue number, λ_e is the effective arrival rate, and $P_n(t)$ is the probability that there are exactly n passengers in the airport system at time t. In particular, P_0 is the probability that the service station is idle, which can also be understood as the probability that passengers will be served upon arrival.

Based on discrete event simulation, it has become a popular and effective decision-making tool for optimizing the entire passenger entrance process in order to reduce the number of travelers infected in airports. Figure 3 shows the discrete event simulation framework, which depicts the entire process of travelers entering the airport. Passengers enter the airport hall through the entrance line and security check. Visitors must check in at the check-in window upon entering the hall. Then, some of them wait in the hallway, while others walk to restaurants, stores, and restrooms, among other places. Finally, the passengers waited at the boarding gate. The dimension drawing of Mianyang Airport is shown in Figure 4.

3.2.3. Hybrid Model. We can estimate the average passenger flow at Mianyang Airport per minute based on our field research. In the agent-based model (ABM), asymptomatic infection and susceptible represent passengers who enter two different states in a discrete event simulation (DES), whereas they randomly enter DES and continue to infect in DES. ABM describes the spread of the COVID-19 among passengers, and DES records the entire process of passengers entering and passing through Mianyang Airport. The number of ticket gates and security checks in DES will affect the spread of the COVID-19 epidemic in ABM, as would the social distance between passengers. We connect DES with the 2D map of Mianyang Airport. DES can also simulate the distribution of passengers in the airport. The interaction process of the hybrid model based on ABM and DES is shown in Figure 5. The ABM and DES models interact with each other and describe the complex information of Mianyang Airport, such as the risk of COVID-19 epidemic transmission and the layout of airport prevention and control facilities, thus forming a hybrid model of ABM and DES that cannot be described by the traditional single model.

We built a hybrid agent-based model and discrete event simulation model in the commercial software AnyLogic 8 Professional 8.7.4 (https://www.anylogic.com).

Step 1: create an agent-based model by adding agents (passengers).
(a) Susceptible
(b) Asymptomatic infection
(c) Infection rules: "Agent-to-agent interaction and rules"
Step 2: create discrete event simulation based on the Mianyang Airport entrance process.
Step 3: configure the passenger flow and add agents (passengers) to the DES.
Step 4: for each agent, an agent is in the infection radius, according to "Agent-to-agent interaction and rules" to infection; otherwise, keep the state susceptible.
Step 5: determine the asymptomatic infection at Mianyang Airport.
Step 6: repeat steps 3–5 until the simulation timer runs out.

Algorithm 1: Specific implementation process of agent-based model.

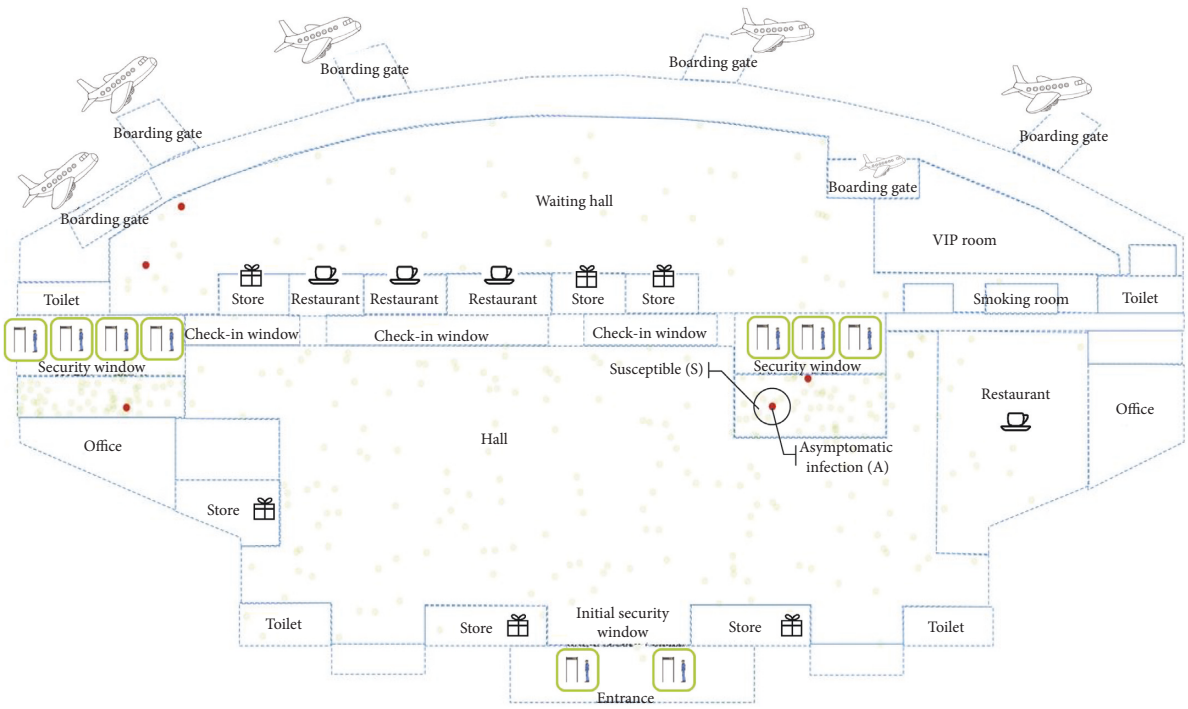

Figure 2: Action track and specific location of each passenger after entering the airport in an agent-based model. The red dots represent infected passengers, and the other dots represent susceptible passengers.

4. Results and Discussion

The global aviation industry is currently facing one of the biggest sustainability challenges due to the COVID-19 pandemic [41]. Destination-based features, particularly health and safety measures at airports, are likely to have a considerable impact on travel decisions during the COVID-19 pandemic [42]. As a result, the topic of how to construct a safe airport to avoid the spread of the virus is critical. Measures, particularly those connected to social distancing, would alter the structure of passenger traffic handling at airports, according to the WHO [41].

As the COVID-19 pandemic continues to spread over the world, many regions faced with an extraordinary need to find new measures to contain future outbreaks [43]. A particularly important example is a mass gathering event. Mass gatherings have been proven to have the potential to become superspreading occurrences [43]. Therefore, we analyze the effectiveness of control measures in Mianyang Airport in containing the spread of COVID-19. The following are the assumptions and baseline.

4.1. Baseline and Assumption

Assumption 1. COVID-19 is assumed to spread within a 1-meter radius of an infected person.

Assumption 2. The airport is empty at the beginning.

Assumption 3. Assume that none of the passengers wearing masks has an infectivity of 0.0411, that 55% of the passengers wearing masks has an infectivity of 0.0411×0.45, and that

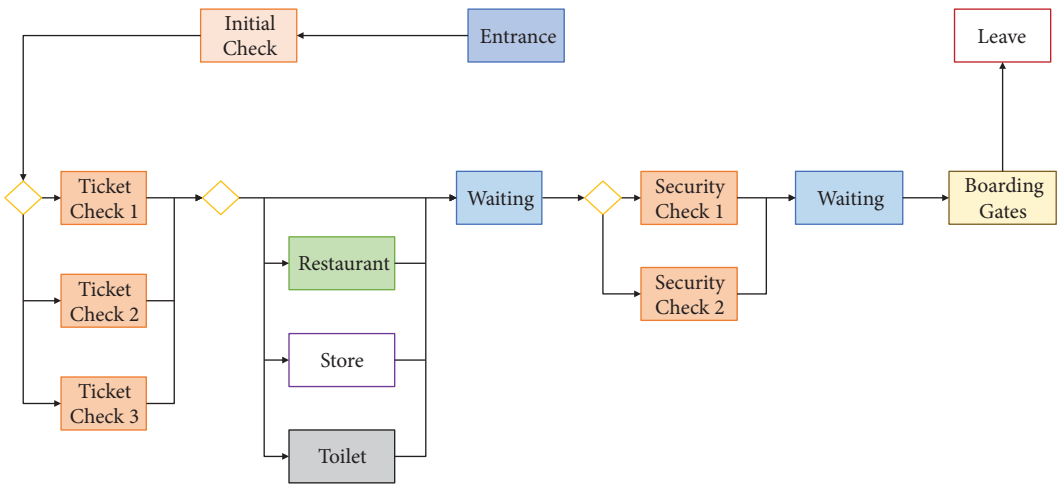

Figure 3: Specific procedures for each passenger to enter the airport and possible places to pass, such as restaurants, stores, and toilets.

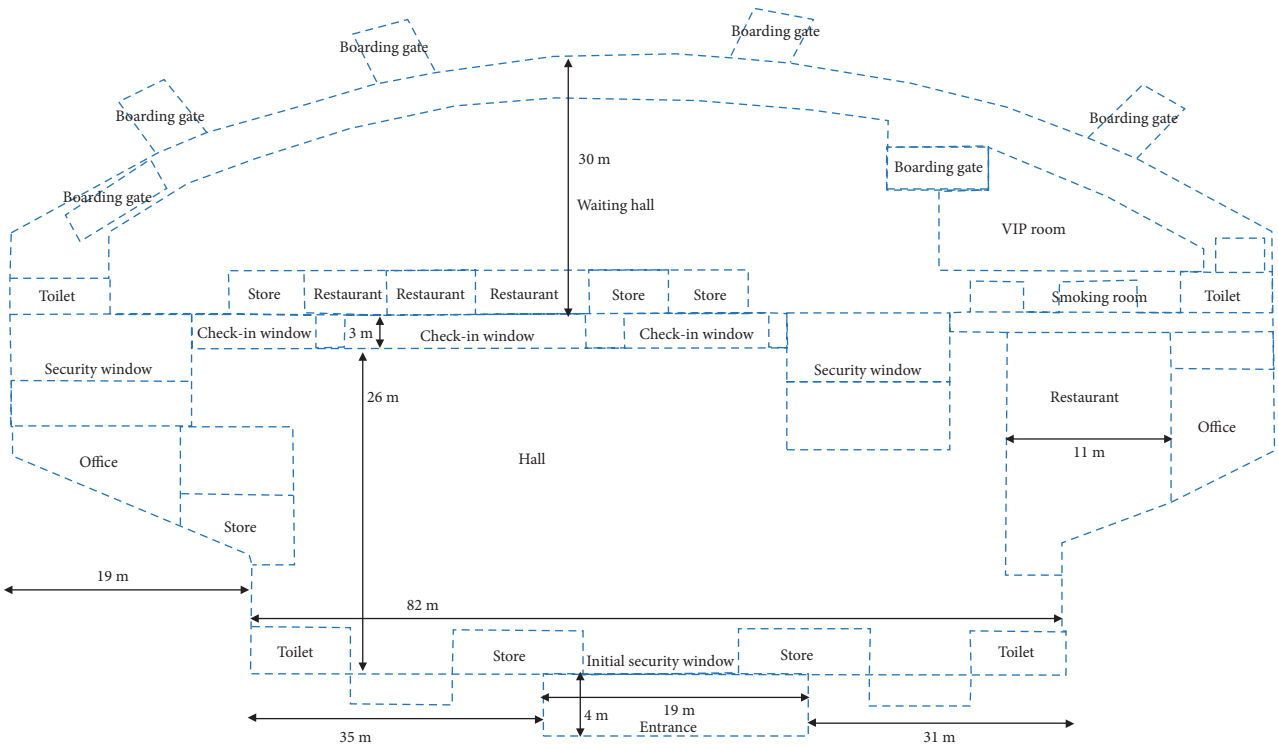

Figure 4: Detailed dimensional drawing of the airport in discrete event simulation, including the waiting hall, ticket gate, security gate, and other facilities.

90% of the passengers wearing masks has an infectivity of 0.0411×0.10.

Assumption 4. Assume that the time of asymptomatic infected persons entering the airport is a triangular distribution, that is, an asymptomatic infected person randomly enters the airport within a triangular (5, 10, 15) minutes.

Assumption 5. Based on field research and interviews with passengers, we assume that 60% of passengers will randomly enter restaurants, shops, and bathrooms. Passengers' stay time in restaurants, shops, and sanitation is triangular distribution, and specific time is given in Table 1.

Assumption 6. The baseline scenario is prevention and control measures based on the normal operation of Mianyang Airport and normal passenger flow.

Assumption 7. According to the COVID-19 Prevention and Control Plan (version 8), assume that each row of the plane contains seven passengers and that the close contacts of

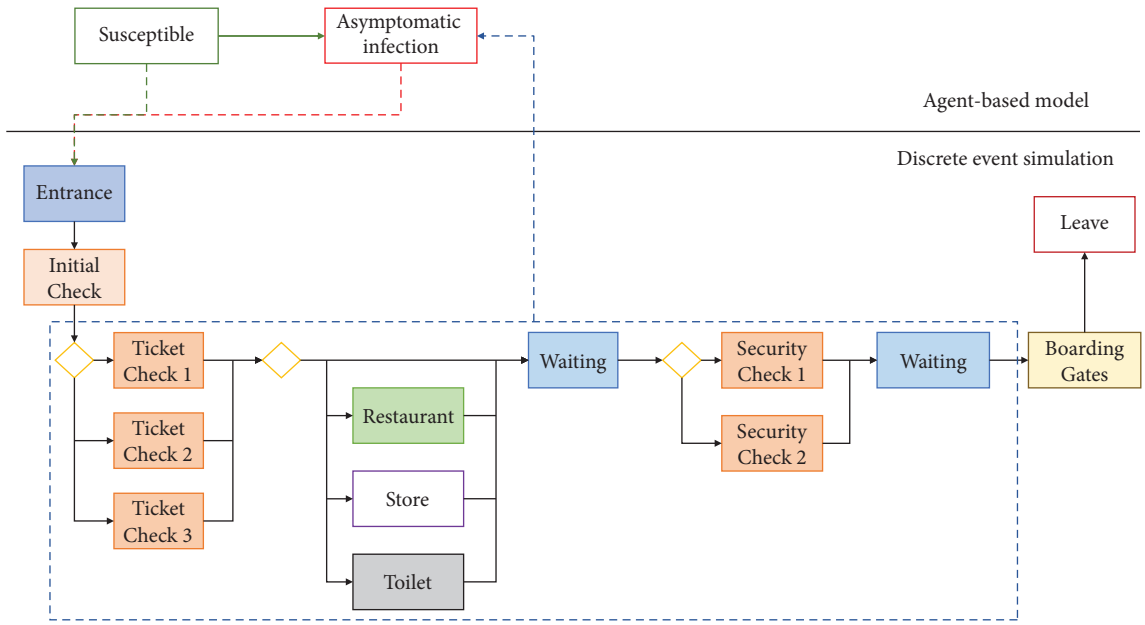

Figure 5: The specific process and interaction process of the hybrid model based on ABM and DES. The dotted line represents the interaction process of the hybrid model based on ABM and DES. The solid line represents the specific process of entering ABM and DES.

Table 3: Cost of close contacts and confirmed cases.

Cost component	Chinese yuan (RMB¥)	United States dollars (US$)	Source
Close contact diagnosed as COVID-19 negative	584.08	84.53	[39]
Suspected case diagnosed as COVID-19 negative	973.70	140.91	[39]
Confirmed case, nonsevere	6488.90	939.06	[39]

Table 4: Number of infected and passenger flow with none of passenger wearing masks.

Scenarios	Airport facilities	Social distance (contact rate, CR)	1 asymptomatic infections (A1)	5 asymptomatic infections (A5)	10 asymptomatic infections (A10)
Normal passenger flow (1)	Current setting (A)	CR = 20 (a)	2/4742*	11/4811	20/4863
		CR = 20 ∗ 0.8 (b)	2/4810	11/4956	19/4917
		CR = 20 ∗ 0.6 (c)	1/4988	8/4962	17/4816
	Waiting hall capacity reduced by 20% (B)	CR = 20 (a)	1/4828	6/4775	13/4880
		CR = 20 ∗ 0.8 (b)	1/4816	6/4893	13/4993
		CR = 20 ∗ 0.6 (c)	1/4773	6/4948	12/4876
	Add 4 ticket gates and security gates (C)	CR = 20 (a)	2/4896	7/4896	13/4882
		CR = 20 ∗ 0.8 (b)	1/4942	6/4918	13/4815
		CR = 20 ∗ 0.6 (c)	1/4831	6/4896	13/4876
80% passenger flow (2)	Current setting (A)	CR = 20 (a)	2/3953	7/3786	17/3939
		CR = 20 ∗ 0.8 (b)	1/3975	6/3885	16/3847
		CR = 20 ∗ 0.6 (c)	1/3936	6/3872	14/3815
	Waiting hall capacity reduced by 20% (B)	CR = 20 (a)	1/3767	6/3878	12/3778
		CR = 20 ∗ 0.8 (b)	1/3868	6/3929	12/3888
		CR = 20 ∗ 0.6 (c)	1/3928	6/3884	12/3816
	Add 4 ticket gates and security gates (C)	CR = 20 (a)	1/3899	6/3801	12/3783
		CR = 20 ∗ 0.8 (b)	1/3869	5/3867	11/3895
		CR = 20 ∗ 0.6 (c)	1/3812	5/3896	11/3897

*Infectious/passenger flow.

asymptomatic patients are all passengers in the same row, three rows in front, and three rows in front of the case.

Assumption 8. Assumed that 20% of asymptomatic patients are suspected cases diagnosed as COVID-19 negative, and 80% of them are in close contact diagnosed as COVID-19 negative.

First of all, we used the data obtained from the field survey as the baseline of the model to obtain the total passenger flow of Mianyang Airport and the number of

Table 5: Number of infections and passenger flow with 55% of passengers wearing masks.

Scenarios	Airport facilities	Social distance (contact rate, CR)	1 asymptomatic infections (A1)	5 asymptomatic infections (A5)	10 asymptomatic infections (A10)
Normal passenger flow (1)	Current setting (A)	CR = 20 (a)	2/4848*	9/4808	18/4827
		CR = 20 ∗ 0.8 (b)	2/4796	8/4830	14/4822
		CR = 20 ∗ 0.6 (c)	1/4813	7/4891	13/4806
	Waiting hall capacity reduced by 20% (B)	CR = 20 (a)	2/4876	6/4769	13/4748
		CR = 20 ∗ 0.8 (b)	1/4798	6/4744	13/4741
		CR = 20 ∗ 0.6 (c)	1/4877	6/4898	13/4730
	Add 4 ticket gates and security gates (C)	CR = 20 (a)	1/4845	7/4762	12/4795
		CR = 20 ∗ 0.8 (b)	1/4875	6/4906	12/4897
		CR = 20 ∗ 0.6 (c)	1/4838	6/4914	12/4797
80% passenger flow (2)	Current setting (A)	CR = 20 (a)	2/3846	6/3850	14/3890
		CR = 20 ∗ 0.8 (b)	2/3814	6/3725	13/3792
		CR = 20 ∗ 0.6 (c)	1/3862	6/3723	13/3875
	Waiting hall capacity reduced by 20% (B)	CR = 20 (a)	1/3731	6/3805	12/3734
		CR = 20 ∗ 0.8 (b)	1/3792	6/3910	11/3926
		CR = 20 ∗ 0.6 (c)	1/3772	6/3715	11/3747
	Add 4 ticket gates and security gates (C)	CR = 20 (a)	1/3799	6/3913	12/3884
		CR = 20 ∗ 0.8 (b)	1/3763	5/3887	11/3835
		CR = 20 ∗ 0.6 (c)	1/3834	5/3918	11/3913

*Infectious/passenger flow.

Table 6: Number of infections and passenger flow with 90% of passengers wearing masks.

Scenarios	Airport facilities	Social distance (contact rate, CR)	1 asymptomatic infections (A1)	5 asymptomatic infections (A5)	10 asymptomatic infections (A10)
Normal passenger flow (1)	Current setting (A)	CR = 20 (a)	1/4821*	6/4893	12/4817
		CR = 20 ∗ 0.8 (b)	1/4823	6/4800	12/4779
		CR = 20 ∗ 0.6 (c)	1/4802	6/4895	11/4912
	Waiting hall capacity reduced by 20% (B)	CR = 20 (a)	1/4806	6/4832	12/4870
		CR = 20 ∗ 0.8 (b)	1/4751	6/4775	12/4864
		CR = 20 ∗ 0.6 (c)	1/4844	6/4845	11/4849
	Add 4 ticket gates and security gates (C)	CR = 20 (a)	1/4774	5/4804	11/4764
		CR = 20 ∗ 0.8 (b)	1/4837	5/4846	11/4892
		CR = 20 ∗ 0.6 (c)	1/4756	5/4878	10/4732
80% passenger flow (2)	Current setting (A)	CR = 20 (a)	1/3908	6/3826	12/3925
		CR = 20 ∗ 0.8 (b)	1/3874	6/3821	11/3919
		CR = 20 ∗ 0.6 (c)	1/3821	5/3838	11/3880
	Waiting hall capacity reduced by 20% (B)	CR = 20 (a)	1/3813	6/3899	12/3875
		CR = 20 ∗ 0.8 (b)	1/3782	5/3747	11/3780
		CR = 20 ∗ 0.6 (c)	1/3876	5/3827	11/3780
	Add 4 ticket gates and security gates (C)	CR = 20 (a)	1/3894	5/3857	10/3726
		CR = 20 ∗ 0.8 (b)	1/3865	5/3893	10/3793
		CR = 20 ∗ 0.6 (c)	1/3712	5/3845	10/3932

*Infectious/passenger flow.

people infected by the epidemic in the airport under different circumstances, and then, we calculated the medical cost of infected patients and close contacts according to the report of Jin et al. [44], as given in Table 3.

4.2. Analysis of Infections. Due to the randomness of the model, each scenario is run 10 times, and the model results are the average of the results of those 10 times. The results obtained are given in Tables 4–6. It can be seen from Table 4 that if the airport maintains the current setting, the number of infections in this case is higher than that in other cases, whether changing the passenger flow or wearing masks. Under the condition of normal passenger flow, when none of the passengers wear masks, the number of infected persons with reduced waiting hall capacity (1-B) is less than the number of infected persons with increased ticket gates and security gates (1-C). However, in Tables 5 and 6, when 55% and 90% of passengers wear masks, the number of infections with increased ticket gates and security gates (1-C) is less than the number of infections with reduced waiting hall capacity (1-B). In the case of an 80% passenger

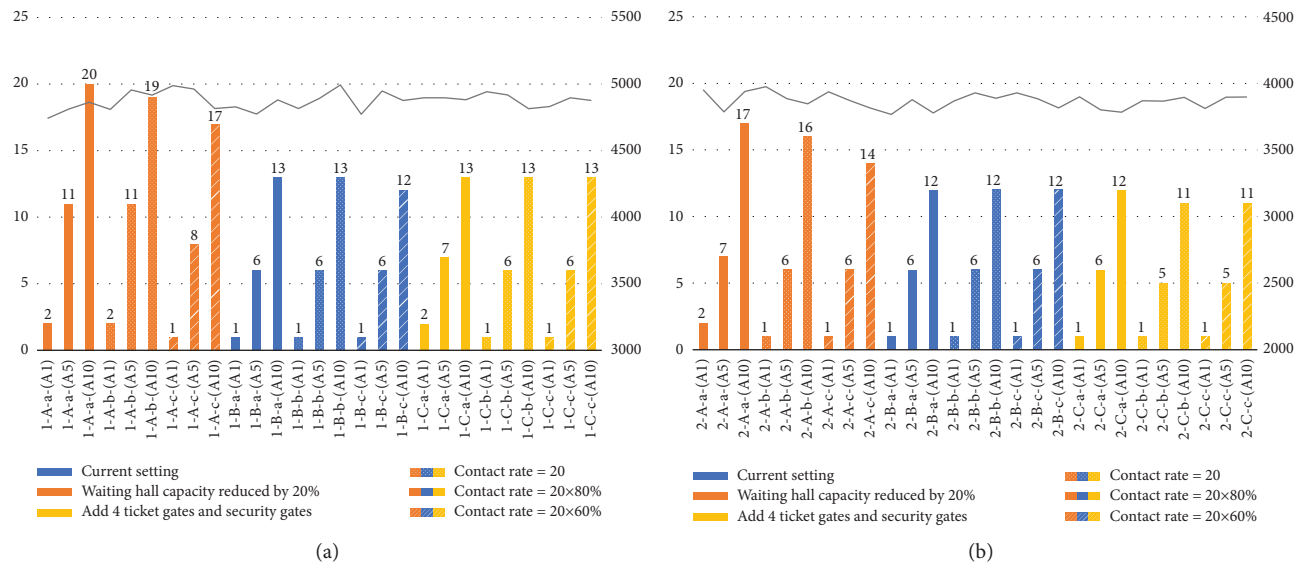

Figure 6: The number of infections when none of the passenger is wearing masks. Blue, orange, and yellow represent different airport facilities, respectively. The solid, hollow, and slash of the histogram represent different social distances, respectively. The black solid line is the trend line of passenger flow.

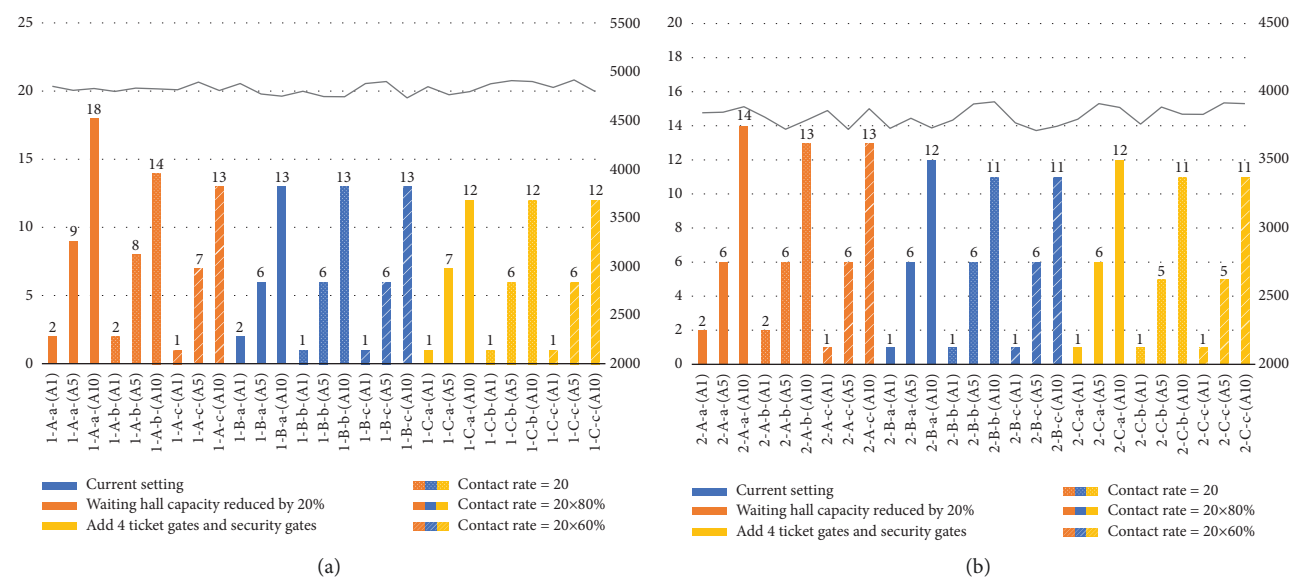

Figure 7: The number of infections when 55% of passengers are wearing masks. Blue, orange, and yellow represent different airport facilities, respectively. The solid, hollow, and slash of the histogram represent different social distances, respectively. The black solid line is the trend line of passenger flow.

flow, the number of infected people with increased ticket gates and security gates (2-C) is less than the number of people with reduced waiting hall capacity (2-B). If the passenger flow is controlled, the number of infected persons in the current setting (2-A) is also higher than the number of infected persons in the reduced waiting hall capacity (1-B) and increased ticket gates and security gates (1-C) in the case of uncontrolled passenger flow. Therefore, appropriate improvement of the existing layout can effectively reduce the number of infections and control the spread of the epidemic.

If the airport maintains the current setting, the greater the social distance, that is, the smaller the contact rate, the fewer people will be infected. However, in the case of reducing waiting hall capacity, the total capacity of the airport waiting hall can be controlled, the crowd aggregation can be reduced, the contact rate can be indirectly controlled, and the number of infected people is small. Therefore, the direct impact of controlling social distance is small. With the increase of ticket gates and security gates, the mobility of the crowd is increased, so that passengers can quickly pass through the ticket gates and security checkpoints, reducing the aggregation behavior of passengers queuing

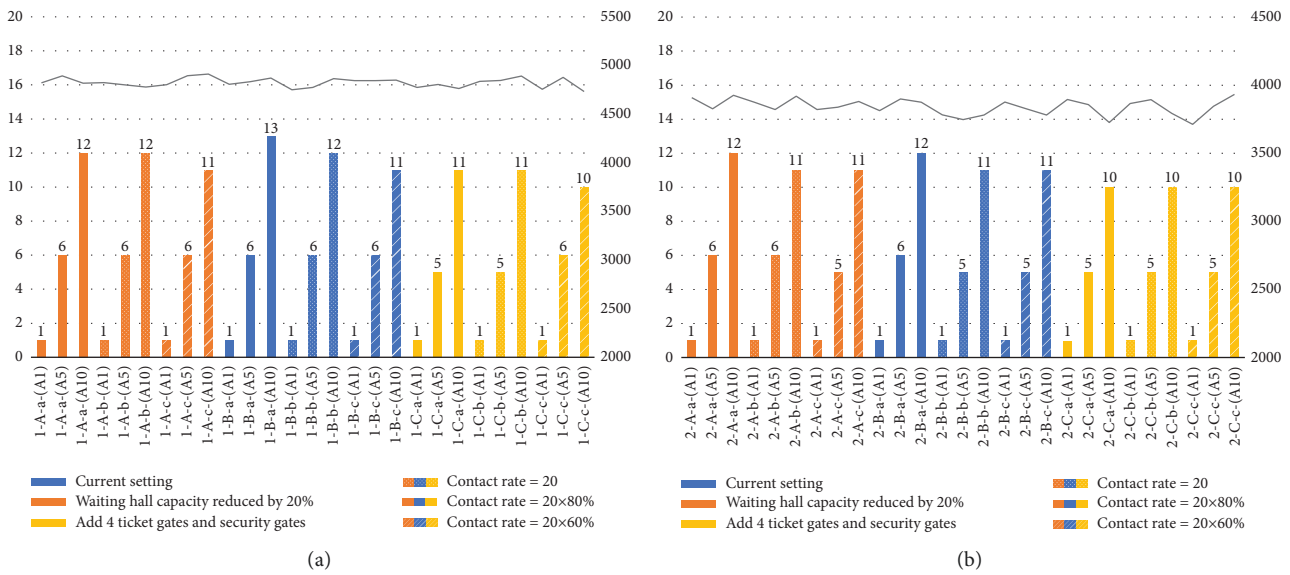

Figure 8: The number of infections when 90% of passengers are wearing masks. Blue, orange, and yellow represent different airport facilities, respectively. The solid, hollow, and slash of the histogram represent different social distances, respectively. The black solid line is the trend line of passenger flow.

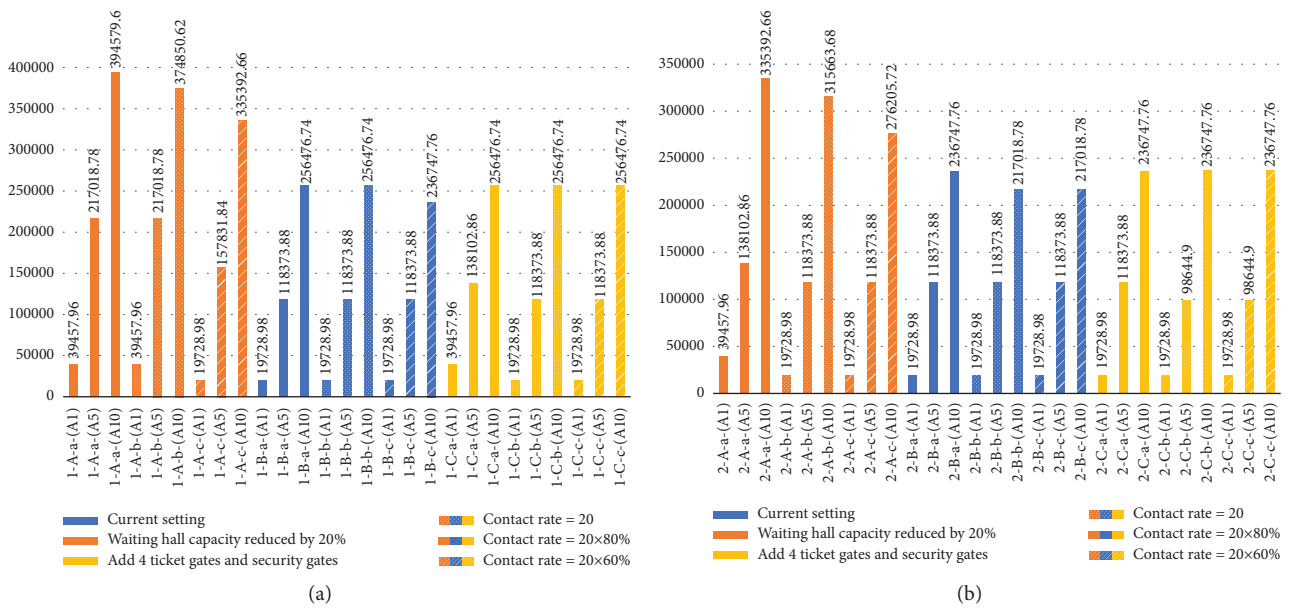

Figure 9: Medical costs when none of the passenger is wearing masks. Blue, orange, and yellow represent different airport facilities, respectively. The solid, hollow, and slash of the histogram represent different social distances, respectively.

for ticket inspection and security inspection. This indirectly controls the contact rate, and the number of infected people is very small. So, controlling social distance has little direct impact. Controlling social distance is useful in the current setting, but in the other two cases, controlling social distance has little effect.

As can be seen from Figures 6–8, when the initial number of infections was small (A1 and A5), there was no significant difference in the number of infected people between 1-B, 1-C, 2-B, and 2-C. In the current setting, the number of infected people is the largest, and in other cases, the number of infected people is very small. When the social distance between passengers is small, that is, when the contact rate is high, the number of infected people is greater, and when the contact rate is low, the number of infected people is less. The number of infections changes significantly only when the initial number of infections is high (A10).

4.3. Medical Cost Analysis. The COVID-19 global pandemic has hit the airline industry hard since late 2019, with many industries affected by government restrictions. For example, travel restrictions have caused significant losses to

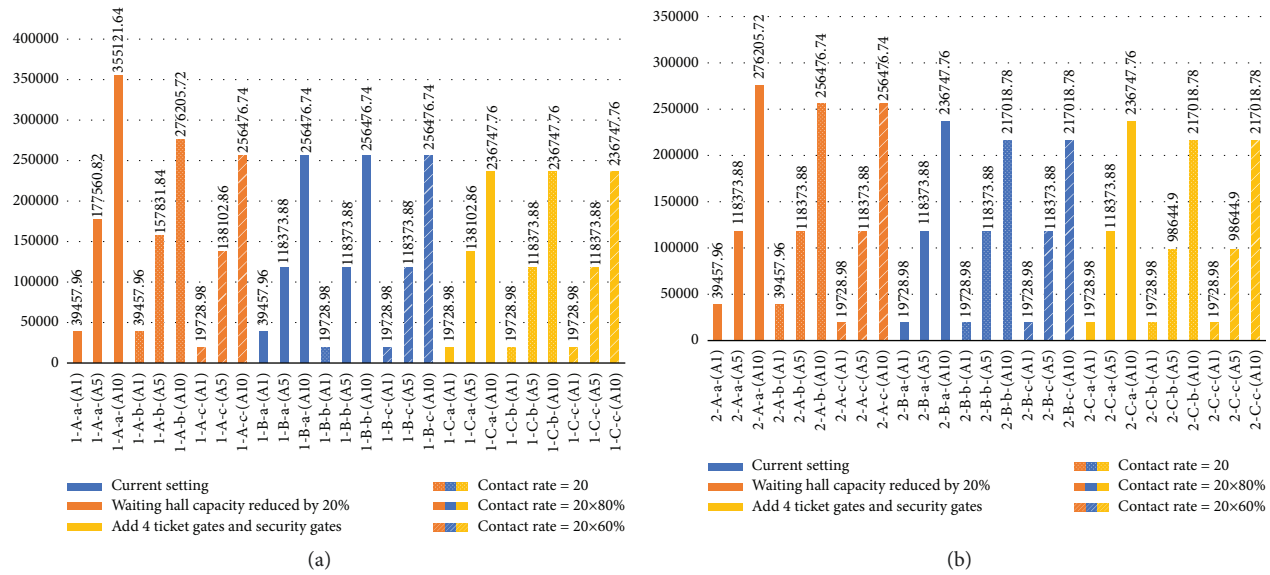

Figure 10: Medical costs when 55% of passengers are wearing masks. Blue, orange, and yellow represent different airport facilities, respectively. The solid, hollow, and slash of the histogram represent different social distances, respectively.

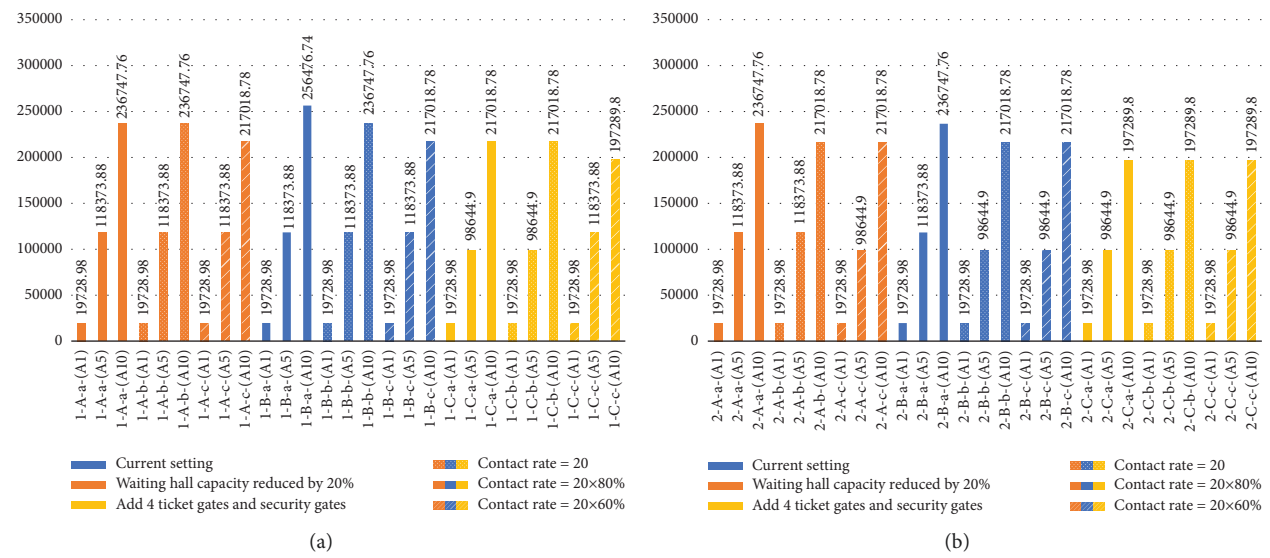

Figure 11: Medical costs when 90% of passengers are wearing masks. Blue, orange, and yellow represent different airport facilities, respectively. The solid, hollow, and slash of the histogram represent different social distances, respectively.

organizations within the aviation sector [45]. This has had an immediate impact on airport traffic and revenue [25]. In addition, the cost of medical care for COVID-19 patients is also putting enormous pressure on the government. According to the National Health Commission of China's COVID-19 Prevention and Control Plan (version 8), those who had close contact with asymptomatic patients, such as living together, working in the same closed environment, dining, and entertainment, but did not take effective measures before the asymptomatic patients were quarantined for the first time and shall be transferred to a centralized isolation place for medical observation within 12 hours. Based on the report by Jin et al. [44], the assumption is 7/8 calculation of medical costs for infected patients and close contacts. Medical costs composed of the costs of infected patients and close contacts, as given in Table 7. We calculated the number of close contacts and medical costs under various circumstances.

After the estimation and calculation of medical costs, it can be seen from Figures 9–11 that under normal passenger flow, when none of the passengers is wearing masks, the current setting will lead to the largest number of infections and higher medical costs. The medical cost was calculated according to the COVID-19 Prevention and Control Plan (Version 8) and the report of Jin et al. [44], and the maximum cost was nearly 400,000 RMB (62,640 dollars). With

Table 7: The number of infections, close contacts, and medical costs.

Scenarios	None of passenger wearing masks (infectivity = 0.0411)			55% of passengers wearing masks (infectivity = 0.0411 × 0.45)			90% of passengers wearing masks (infectivity = 0.0411 × 0.10)		
	Infectious	Close contact	Medical cost	Infectious	Close contact	Medical cost	Infectious	Close contact	Medical cost
1-A-a-(A1)	2	40	39457.96	2	40	39457.96	1	20	19728.98
1-A-a-(A5)	11	220	217018.78	9	180	177560.82	6	120	118373.88
1-A-a-(A10)	20	400	394579.6	18	360	355121.64	12	240	236747.76
1-A-b-(A1)	2	40	39457.96	2	40	39457.96	1	20	19728.98
1-A-b-(A5)	11A	220	217018.78	8	160	157831.84	6	120	118373.88
1-A-b-(A10)	19	380	374850.62	14	280	276205.72	12	240	236747.76
1-A-c-(A1)	1	20	19728.98	1	20	19728.98	1	20	19728.98
1-A-c-(A5)	8	160	157831.84	7	140	138102.86	6	120	118373.88
1-A-c-(A10)	17	340	335392.66	13	260	256476.74	11	220	217018.78
1-B-a-(A1)	1	20	19728.98	2	40	39457.96	1	20	19728.98
1-B-a-(A5)	6	120	118373.88	6	120	118373.88	6	120	118373.88
1-B-a-(A10)	13	260	256476.74	13	260	256476.74	13	260	256476.74
1-B-b-(A1)	1	20	19728.98	1	20	19728.98	1	20	19728.98
1-B-b-(A5)	6	120	118373.88	6	120	118373.88	6	120	118373.88
1-B-b-(A10)	13	260	256476.74	13	260	256476.74	12	240	236747.76
1-B-c-(A1)	1	20	19728.98	1	20	19728.98	1	20	19728.98
1-B-c-(A5)	6	120	118373.88	6	120	118373.88	6	120	118373.88
1-B-c-(A10)	12	240	236747.76	13	260	256476.74	11	220	217018.78
1-C-a-(A1)	2	40	39457.96	1	20	19728.98	1	20	19728.98
1-C-a-(A5)	7	140	138102.86	7	140	138102.86	5	100	98644.9
1-C-a-(A10)	13	260	256476.74	12	240	236747.76	11	220	217018.78
1-C-b-(A1)	1	20	19728.98	1	20	19728.98	1	20	19728.98
1-C-b-(A5)	6	120	118373.88	6	120	118373.88	5	100	98644.9
1-C-b-(A10)	13	260	256476.74	12	240	236747.76	11	220	217018.78
1-C-c-(A1)	1	20	19728.98	1	20	19728.98	1	20	19728.98
1-C-c-(A5)	6	120	118373.88	6	120	118373.88	6	120	118373.88
1-C-c-(A10)	13	260	256476.74	12	240	236747.76	10	200	197289.8
2-A-a-(A1)	2	40	39457.96	2	40	39457.96	1	20	19728.98
2-A-a-(A5)	7	140	138102.86	6	120	118373.88	6	120	118373.88
2-A-a-(A10)	17	340	335392.66	14	280	276205.72	12	240	236747.76
2-A-b-(A1)	1	20	19728.98	2	40	39457.96	1	20	19728.98
2-A-b-(A5)	6	120	118373.88	6	120	118373.88	6	120	118373.88
2-A-b-(A10)	16	320	315663.68	13	260	256476.74	11	220	217018.78
2-A-c-(A1)	1	20	19728.98	1	20	19728.98	1	20	19728.98
2-A-c-(A5)	6	120	118373.88	6	120	118373.88	5	100	98644.9
2-A-c-(A10)	14	280	276205.72	13	260	256476.74	11	220	217018.78
2-B-a-(A1)	1	20	19728.98	1	20	19728.98	1	20	19728.98
2-B-a-(A5)	6	120	118373.88	6	120	118373.88	6	120	118373.88
2-B-a-(A10)	12	240	236747.76	12	240	236747.76	12	240	236747.76
2-B-b-(A1)	1	20	19728.98	1	20	19728.98	1	20	19728.98
2-C-a-(A1)	6	120	118373.88	6	120	118373.88	5	100	98644.9
2-C-a-(A5)	11	220	217018.78	11	220	217018.78	11	220	217018.78
2-C-a-(A10)	1	20	19728.98	1	20	19728.98	1	20	19728.98
2-C-b-(A1)	6	120	118373.88	6	120	118373.88	5	100	98644.9
2-C-b-(A5)	11	220	217018.78	11	220	217018.78	11	220	217018.78
2-C-b-(A10)	1	20	19728.98	1	20	19728.98	1	20	19728.98
2-C-c-(A1)	6	120	118373.88	6	120	118373.88	5	100	98644.9
2-C-c-(A5)	12	240	236747.76	12	240	236747.76	10	200	197289.8
2-C-c-(A10)	1	20	19728.98	1	20	19728.98	1	20	19728.98

the same passenger flow, we can reduce the medical cost to 200,000 RMB (31,320 dollars) by reasonably setting up airport facilities, controlling crowd contact, and increasing the rate of wearing masks. Therefore, reasonable improvement of the current setting and reduction of the total capacity threshold of airports can reduce the number of infections and medical costs. As can be seen from Figures 9–11, in the case of the same passenger flow (A/C/E and B/D/F), the lowest medical cost without masks is basically consistent with that in the case of 90% masks. Because the number of infections is lower when there is low passenger flow (A/B, C/D, and E/F), the medical cost is lower as

well. In particular, no matter what kind of passenger flows, the medical cost is basically the same in the case of 90% mask wearing, which is lower than the case of no mask wearing and 55% mask wearing.

As Guo et al.'s study shows, the aviation system network will soon deteriorate after the outbreak of COVID-19, and the recovery level of the aviation industry depends on what prevention and control measures are taken [25]. To sum up, it is an effective measure to control the epidemic for the government to intensify efforts to limit passenger flows. However, in consideration of people's production and lives as well as national economic development, it is not the best way to blindly control passenger flows. In the case of normal passenger flow, the best plan to control the epidemic is the combination of adding 4 ticket gates and security gates. Since 90% of passengers wear masks, we can strictly control the contact rate, which can effectively reduce the number of COVID-19 infections. In the case of an 80% passenger flow, regardless of the contact rate, the best solution to control the epidemic is a combination of adding 4 ticket gates and security gates and having 90% of the passengers wear masks. A mask is an important personal protective equipment item that can prevent infectious respiratory tract infections [46]. Therefore, increasing the rate of wearing masks during restricted travel and improving airport facilities are more effective ways to control the epidemic and make it easier for passengers to travel normally.

5. Conclusions

The goal of this research is to create a hybrid model that combines an agent-based model and discrete event simulation to predict the impact of factors such as passenger entry procedures, number of service windows, and the rate of wearing masks on epidemic transmission and healthcare costs under lax, mild, and strict policy interventions. Individual behavior is captured by an agent-based model, and the entire boarding process is described by a discrete-event simulation. Limiting the rate of wearing masks during travel and upgrading airport facilities are the most effective strategies to contain the outbreak, given the convenience of travelers and the rapid recovery of the national economy. Both measures help to improve the long-term viability of aviation transportation. Limiting the rate of wearing masks during travel can lower infection and exposure rates directly, while upgrading airport layouts can help restrict the spread of the pandemic by managing crowd density and effectively reducing the number of infections. As a result, decision-makers should take ongoing and stringent control measures to prevent the epidemic from spreading further [21].

System dynamics models, agent-based models, and artificial neural networks have all been utilized in previous studies to assess and predict the spread of COVID-19 in the airline industry. In addition, the hybrid model of agent-based modeling and discrete-event simulation used in this study can simulate the passenger boarding process, which can aid government agencies in improving airport equipment and facilities, facilitating passengers' travel plans rationally, avoiding mass exposure, preventing the spread of epidemics, and promoting the long-term development of densely populated public transportation systems like airports.

The European aviation network system takes longer time to recover from than China's [25]. Future research could use hybrid simulation models to assess the network of airport prevention and control systems in European countries, allowing governments to swiftly develop realistic airport prevention and control options. This would not only slow the spread of the virus and make it easier for passengers to travel, but it would also help to ensure the long-term viability of the air transportation system and the restoration of aviation industry market operations.

Data Availability

The data for this study are publicly available and come from field research. Another part of the data can be found at (https://www.mianyangairport.com/index.php/Info), (https://en.wikipedia.org/wiki/Boeing_737), (https://en.wikipedia.org/wiki/Boeing_737_Next_Generation), (https://fr.wikipedia.org/wiki/Airbus_A320) (https://en.wikipedia.org/wiki/Airbus_A319), and (https://en.wikipedia.org/wiki/Airbus_A320_family).

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Authors' Contributions

Hongli Zhu conceptualized and validated the study, developed software, and performed formal analysis. Hongli Zhu and Yang Qin developed methodology, involved in data curation, wrote the original draft of the manuscript. Yang Qin and Qiao Zhao reviewed and edited the article and supervised the study. All authors have read and agreed to the published version of the manuscript.

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Supplementary Materials

The source code is provided in the Supplemental Materials, and scholars can open the source code and the original model by downloading the AnyLogic software to facilitate better use of this research on this basis and conduct further research. (*Supplementary Materials*)

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