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Research Article

Mechanism Analysis of the Impact of COVID-19 on the Whole Process of Aircraft Turnaround Operations

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Efficient aircraft turnaround operations at airports are vital to ensure overall air traffic network performance. After the outbreak of COVID-19, the traditional aircraft ground handling process has changed significantly due to new requirements put forward by the pandemic prevention and control policy. To better understand how COVID-19 has affected ground handling operations, a discrete-event simulation model of turnaround is established to analyze the change in the whole turnaround process before and after the pandemic. The critical path of turnaround operations was used to identify the significantly affected subprocesses to which airports should pay attention. For a case study on the two busiest airports in China, the aircraft turnaround time increased by about 18% after COVID-19. Cabin cleaning, catering, and passenger embarking were the main processes in causing this increase. By evaluating the impact mechanism of COVID-19 on turnaround operations, the study sheds light on strategic, tactical, and operational approaches for relevant authorities.

1. Introduction

As one of the three basic components of the aircraft operation process at an airport, turnaround has been considered to be crucial for flight on time performance [1] and the overall airport operation efficiency [2] in addition to arrival and departure. The turnaround process starts from landing until an aircraft reaching its parking stand. It includes multiple complicated ground handling activities to get the aircraft prepared for the next flight. If one turnaround activity is not completed on time, the accumulated delay of the subsequent activities can significantly influence the punctuality of departure flights [3]. It is thus important to investigate the distribution pattern of duration time for aircraft turnaround activities.

In the realm of aircraft turnaround operation, researchers have focused on how to depict the characteristics of turnaround activities. The techniques adopted were usually microscopic models built by means of discrete-event or agent-based simulation methods [4–8]. Based on the aforementioned simulation methodologies, several key processes such as refueling operations [9], boarding process [10–12], and cargo/baggage loading and unloading [13] were paid attention. In particular, Malandri et al. [13] investigated the duration time of cargo and baggage unloading and found that the probability density functions complied for discrete distributions such as Gauss, Log-normal, or Laplace for different time intervals. This means that the distribution pattern of duration time for a single turnaround activity should be specified differently when adopting simulation methodologies to represent turnaround processes.

Although some ground handling activities may be more important than others due to safety restrictions, it is the entire process that systematically decides the efficiency of the aircraft turnaround. Therefore, the measurement of the turnaround time that refers to the sum of all the activities has been attracted attentions. Under the new coordination and communication mechanism of "Collaborative Decision Making (CDM)" [14], the availability of data on the whole turnaround process helps to apply more advanced methods such as optimization [15, 16], neural network [17], Petri net

[18], and machine learning [19] to predict the turnaround time. The Critical Path Method (CPM), among the optimization methodologies has been applied to model the turnaround process [20, 21]. However, the existence of the operational uncertainties such as delays or the propagation of delays [3, 20, 22–26] has made the calculation of the turnaround time based on the CPM inaccurate. This paper aims to develop a combination method to accurately measure the entire turnaround time by integrating the simulation method and the CPM.

The outbreak of the Coronavirus pandemic 2020 has had an unprecedented effect on the global economy and industry operations, and civil aviation was among the "hardest hit" areas affected by COVID-19 [27, 28]. From an operational perspective, the worldwide COVID-19 pandemic has profound impacts on flight ground handling operations in terms of the changes on turnaround activities and operation time, as well as the duration and scope of the subsequent impacts [29]. The epidemic prevention and control policies have placed new requirements on flight turnaround processes through adding new activities, such as the disinfection of cabin for both passenger and cargo [30, 31]. Then the required passenger de-/boarding and new disinfection procedures may increase the entire turnaround time. However, it is unclear how the operation time of those new added turnaround activities are distributed and to what extent it changes the measurement of the entire turnaround time. Moreover, aircraft rotations may be significantly affected along the entire day of operations, especially in-between fights that have no or limited assigned schedule buffers. Scheduling aircraft turnarounds at airports requires the coordination of several organizations, including the airports, airlines, and ground service providers [32]. The aforementioned three major aspects will bring new challenges to the efficiency performance for these organizations [33]. To the best of our knowledge, little effort has been devoted to systematically model the impacts of COVID-19 on the aircraft turnaround process and the changes of the entire turnaround time.

This paper, therefore, aims to explore the duration time distribution patterns of aircraft turnaround activities and their evolutionary mechanisms under the background of COVID-19 at the level of critical paths and the whole process. A combined method based on the simulation method and the CPM is adopted to measure the aircraft turnaround time. The results are expected to provide theoretical references for agents to develop more flexible strategies in the event of major public health emergencies such as COVID-19, thus improving stability in in-flight operations.

The paper is structured as follows. Section 2 describes the aircraft turnaround operations in detail and presents post-pandemic adaptations of the process made by airlines and airports domestically and internationally. In Section 3, the research method is explained and the simulation model is described in detail. Section 4 presents a case study on the two busiest airports in China. Finally, Section 5 provides the conclusions and discusses future research directions on turnaround operations, as well as the limitations of this study.

2. Aircraft Turnaround Operations

2.1. Turnaround Process. Aircraft turnaround is a fundamental component of airport operations, and it includes all necessary activities for preparing an aircraft for the next flight. Several activities have to be performed from the moment the aircraft reaches its parking stand after landing. Because of regulations and physical restrictions, such as the limited amount of space around the aircraft, turnaround operation activities must be conducted in a precise chronological order: some of them have to be necessarily performed sequentially, while others can be carried out simultaneously. The efficiency of aircraft turnaround can be defined as the ability to execute the required operations within the available time, in order to enable a punctual flight departure.

Ground handling of aircraft turnaround is a service process with strict requirements, consisting of more than 10 interdependent subprocesses and involving more than 30 different personnel [34]. Flight ground handling process is usually divided into three categories according to different service objectives, which are for passengers, for checked baggage and cargo, and for aircraft. Among them, the specific activities include the placing and removing of the block, passenger embarkation and disembarkation, baggage and cargo loading and unloading, aircraft refueling, catering, and cabin cleaning as shown in Figure 1. Each operation in the flight ground handling service process in Figure 1 not only has a constraint on its own operation time, but the service sequence of each operation also has a constraint relationship, which is known as the time constraint and sequential constraints.

2.2. Turnaround Time. Turnaround time (TAT) is defined as the time on the ground between two flight legs of an aircraft, starting with in-block time (IBT) on the inbound segment and ending with off-block time (OBT) on the outbound segment [35]. The duration of certain ground handling operations and, consequently, of the entire turnaround may change depending on the aircraft type, the number of passengers, and quantity of cargo. Furthermore, TAT can be influenced by the efficiency of turnaround operations and the airport's operational conditions [36]. TAT calculated in this paper are based on the assumption that the time of each activity of the turnaround process is guaranteed to be seamless, which means that when the previous activity is completed, the next activity will begin immediately after it. So the turnaround time of flights calculated in this study is the minimum total turnaround time (MTTT) before and after the epidemic. The Civil Aviation Administration of China (CAAC) set regulations on minimum total turnaround time for various aircraft types at airports of different levels, which are shown in Table 1 [37].

2.3. Postpandemic Process Adaptations. With the ramp-up of fight operations following the pandemic shut down, many airlines have implemented increased hygienic precautions and redesigned their standard operating procedures for the turnaround to adhere to stricter official regulations regarding sanitary conditions at the airport and inside the

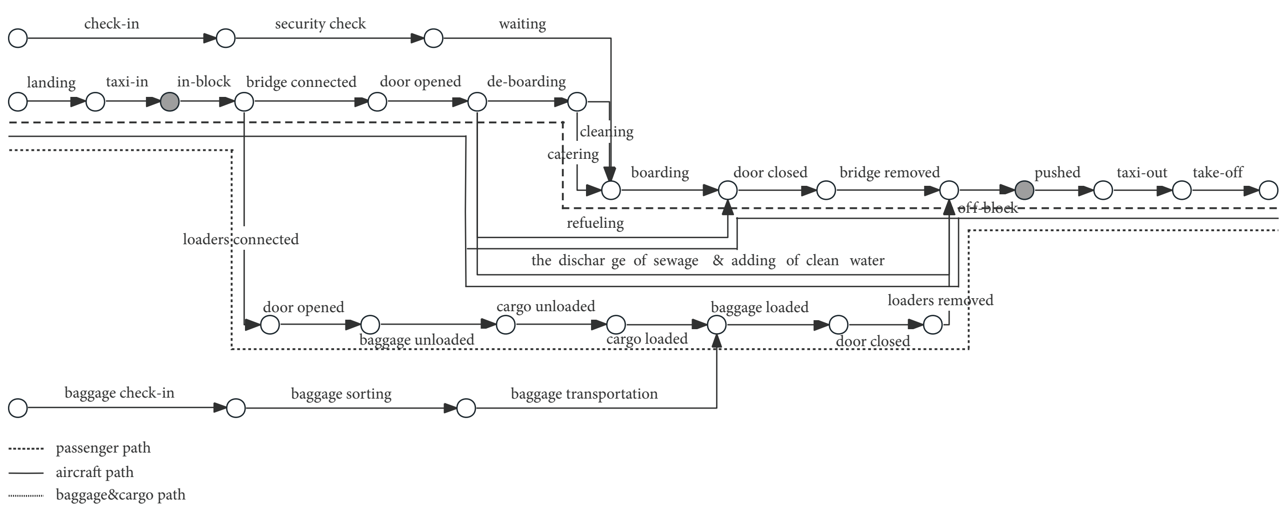


Figure 1: The flowchart of aircraft turnaround process.

cabin. For example, Emirates decided to reduce the seat load to respect distance requirements during the entire fight. Also, other airlines, such as Air France and American Airlines, decided to employ seat allocation restrictions so that passengers are evenly allocated in the aircraft cabin. Delta Airlines followed a similar approach and applied the back-to-front boarding strategy to reduce contacts in the cabin. Air Canada adapted arrival rates during boarding to guarantee enough physical distance between passenger groups. All airlines required their employees and passengers to wear masks for the entire journey, while many additionally provide hand sanitizers in lavatories and at cabin doors. Catering was simplified to a few packaged items and water bottles, reducing the number of trolleys which need to be loaded onto the aircraft during the turnaround [38].

For domestic operations in China, the Civil Aviation Administration of China (CAAC) issued technical guidelines on epidemic prevention and control for airlines and airports, setting out new requirements for airlines [30] and airports in terms of flight operations [31]. Differentiated management is implemented for international/regional flights, and differentiated prevention and control is carried out in the areas of crew personal protection, in-flight service, and aircraft environmental hygiene management. The risk classification for prevention and control is based on a combination of indicators such as the outbreak situation at the point of origin, flight distance, and seat availability.

In principle, domestic flights were not graded, and normalised prevention and control management measures should be implemented. If there's another localised outbreak in the place of origin of the flight, according to the different response levels of public health emergencies issued locally in the place of origin or relevant requirements, preventive and control measures need to be taken in accordance with the requirements of different epidemic prevention risk levels of flights.

3. Research Method

There are three stages in this study. Firstly, the duration distribution of each activity of turnaround process before and after the epidemic, functioning as the input of the simulation model, is identified through Pearson's chi-square goodness-of-fit test. After that, a simulation model for the whole process of flight ground operations is constructed using the AnyLogic simulation platform, including aircraft, passenger, and luggage operations. Lastly, the total flight turnaround time before and after the epidemic is calculated through simulation experiments. Critical paths of aircraft ground operations are determined based on the Critical Path Method (CPM).

3.1. Assumptions

(a) There is no time gap between any two connected turnaround activities. In other words, when one activity is completed, the next one can be started immediately. So the turnaround time calculated in this case is the minimum total turnaround time (MTTT).

(b) In this paper, only one single flight operation is considered in the simulation modeling and multiple flights are not included.

3.2. Duration Distribution Analysis of Turnaround Activities. CAAC has relevant regulations on the MTTT for each aircraft type. However, due to changes in the ground handling environment, there are fluctuations in the time of each turnaround activity for various aircraft types at the airport, often subject to a certain distribution, resulting in an overall turnaround time that is not a fixed value. Therefore, it is crucial to analyze the duration distribution of each activity to obtain the service time of the whole ground operations, namely, total turnaround time. This paper generates the probability distribution of each activity of flight ground operations by using the MATLAB platform. Due to the fact that the true distribution of samples is unknown, we used goodness-of-fit measures with curve fitting methods to empirically fit distributions of sample data.

Previous studies on time distributions of subprocesses have generally considered only one distribution [3] or a few distributions [39], ignoring the variability in the duration

Table 1: MTTT classification table for different models.

Number of seats	Common models	Airports with a passenger throughput of			
		30 million (inclusive) passengers or more (min)	20 million (inclusive) to 30 million (exclusive) passengers (min)	10 million (inclusive) to 20 million (exclusive) passengers (min)	Others (min)
≤60 seats	MA60, E145, AT72, CRJ2, etc.	45	40	30	30
61–150 seats	AJ27, CRJ7, CRJ9, MD82, A319, B733, B737, B73G, etc.	55	50	45	40
151–250 seats	C919, T204, A310, A320, A321, B738, B739, B788, etc.	65	60	50	45
251–500 seats	MD11, A333, A350, B748, B773, B789, etc.	75	70	70	65
>500 seats	A388, etc	120	110	110	110

Source: minimum turnaround time standard for different plane types at different airports established by CAAC.

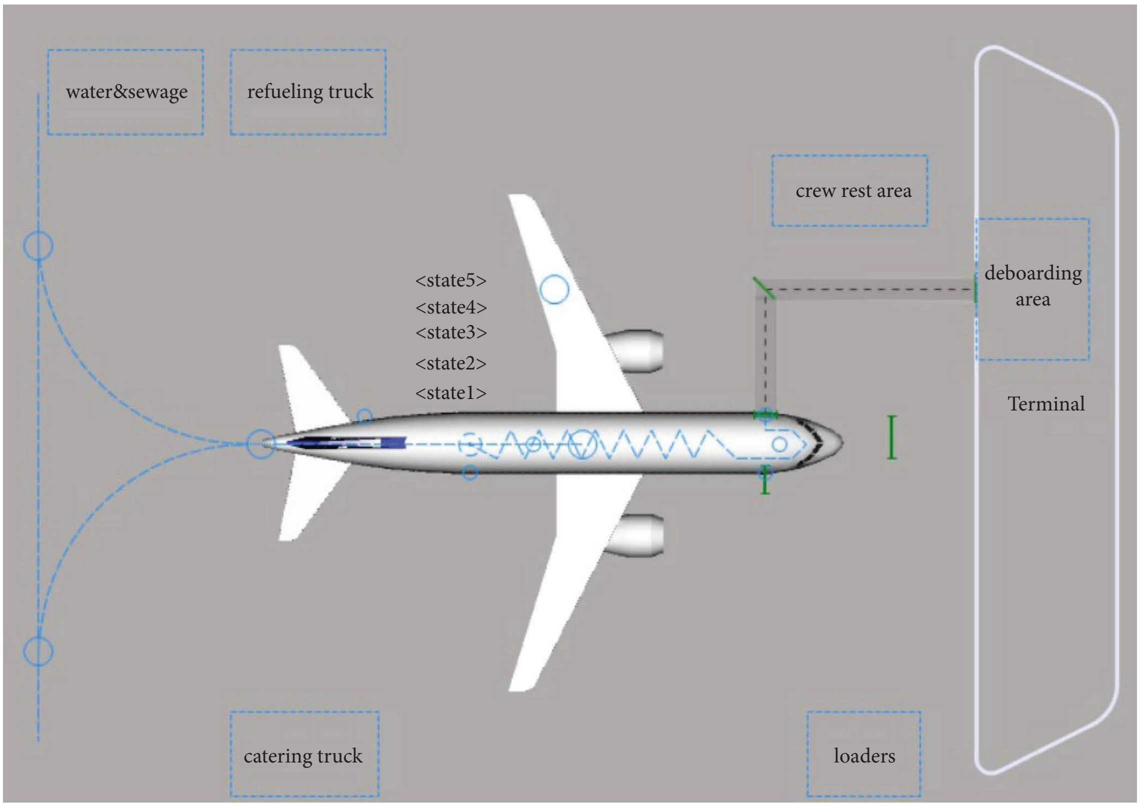


Figure 2: Aircraft turnaround simulation model in a two-dimensional view.

distribution of different activities. Hence, this paper takes several kinds of distributions into account, including Normal, Lognormal, Gamma, Logistic, Exponential, Weibull, and Rayleigh Distribution, being expressed in Appendix A.

For the duration of each turnaround activity, all candidates above are evaluated for best fit. This procedure was found efficient in [40].

3.3. Aircraft Turnaround Simulation Model. Given the complexity of the turnaround process and the stochasticity of time duration, simulation is considered to be an appropriate method for performance assessment [7]. The simulation model of aircraft turnaround process is implemented using the AnyLogic software. The simulation model for flight ground operations constructed in this study is based on the assumption that all activities of turnaround process are seamlessly integrated. Therefore, the calculated turnaround time is the minimum turnaround time. Once the model is built and validated and the distribution of each activity is simulated, the overall turnaround time and time for subprocesses are evaluated for scenarios before and after COVID-19.

The turnaround simulation model mainly employs Process Modeling Library to represent the activities of ground handling operations, which supports discrete-event modeling otherwise known as process-centric modeling. The "delay" component in the Process Modeling Library is widely adopted to denote the duration time of each activity. The detailed operation of each subprocess (i.e., how do the cleaners do the cleaning and disinfection in the cabin) is not considered in this simulation model.

The main entities in this simulation model are aircraft and airport terminal, which connects with the aircraft through an aerobridge (Figure 2). In this model, several areas are designated for the parking of various vehicles, including catering trucks, refueling trucks, and main deck loaders. When required, these vehicles depart from their parking place to perform operations on aircraft, and after finishing their tasks they return to the belonging places. The text in the upper left corner of the aircraft indicates the particular turnaround operation being carried out at the moment, which clearly presents the series and parallel relationship of turnaround activities.

When aircraft arrives at its corresponding stand, turnaround can commence, and a series of activities, each of which can be described with j, are performed. The activities modelled are previously shown in Figure 1. Operations must be performed in the order shown in the graph, where arrows express conditions necessary to perform the successive ones. If there is no arrow connecting two activities, they are independent of one another, and therefore they can be performed simultaneously.

In terms of variable output, this model sets a time set to store various time indicators that need to be output. According to the simulation results, the duration of each subprocess t_{ij} can be calculated in the following equation:

$$t_{ij} = tf_{ij} - ts_{ij}, \tag{1}$$

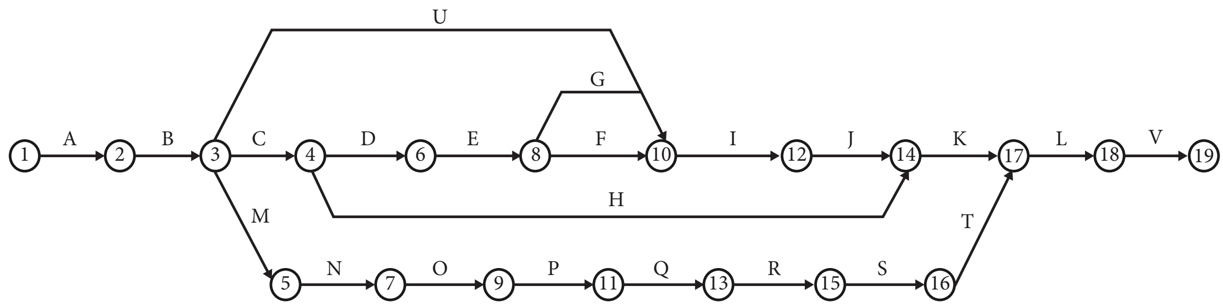


Figure 3: Activity-on-edge network diagram of aircraft ground handling.

where i represents the number of simulations, j represents the activity of turnaround operations, ts_{ij} indicates the start time of the activity j in the i th simulation, and tf_{ij} means the finish time of the activity.

Turnaround time of the i th simulation is computed as the difference between the corresponding "off-block time," which is denoted as tf_i, and "in-block time," indicated by ts_i:

$$\mathrm{TAT}_i = \sum_{j\in CP} t_{ij} = tf_i - ts_i. \quad (2)$$

It is assumed that ground resources, such as catering vehicles, fuel tank, loaders are always available, and no delay is caused by their absence.

The simulation model built above is capable of determining the total TAT for two mainstream types of aircraft. The categorization of aircraft types is defined in accordance with Annex 14 issued by ICAO. Aircrafts of type C are those with wingspans greater than 24 meters and less than 36 meters, including the B737 family, and the A320 family of mainstream models. While type E models are those with wingspans greater than 52 meters and less than 65 meters, such as B777, B787, and A350. This simulation model also supports the identification the critical path(s) of the turnaround process through simulation results.

3.4. Critical Path Method. After obtaining the turnaround time and the time data of subprocesses for each flight through simulation, the critical paths for the flight ground handling operations are solved. By analyzing the variation degree of time duration of the activities on critical path, the important activities that lead to the variation of the total turnaround time are analyzed to provide a theoretical reference for the airline to optimize its resource allocation. One of the most commonly used and closely related scheduling techniques in project management, CPM (critical path method), is considered for solving the critical path and scheduling aircraft ground handling operations.

The activity-on-edge (AOE) network is used to represent the ground handling operations for aircraft, where each activity is shown by an arc and the nodes depict the precedence relationships between the activities. Figure 3 illustrates the ground operations AOE network according to each activity and its immediate predecessors. These nodes represent A: taxi-in, B: in block, C: bridge connected, D: cabin-door opened, E: passenger de-boarding, F: cleaning and disinfection, G: catering, H: refueling, I: passenger boarding, J: cabin-door closed, K: bridge disconnected, L: off block, M: deck loaders connected, N: cargo-door opened, O: baggage unloaded, P: cargo unloaded, R: cargo loaded, S: baggage loaded, T: deck loaders disconnected, U: sewage discharged and water added, V: taxi-out.

Because activity "A" has no immediate predecessors, it is connected to the starting node in the network, namely node 1. Similarly, since activities "V" have no immediate successors, it should be the finishing node indicating the end of aircraft turnaround operations. Critical path is the path with those "critical activities" that have no slack time. Our research is based on the assumption that subprocesses are closely linked, so the estimated overall turnaround time equals the length of the longest path through the network [41], which can be called the critical path. The variation in the duration time of subprocesses on critical path is analyzed to identify the subprocesses that have a significant impact on the overall change in turnaround time, the results of which are described in detail in the Case study section below. Theoretically, an increase in a subprocess's duration time may lead to an/a increase, decrease or no change in the TAT of the identified critical path. On the one hand, it is possible that some subprocesses (e.g., cabin cleaning, catering, cargo unloading, etc.) are the "bottleneck" nodes on the critical path. The increase of their duration time has larger possibility to bring delays and further engender the extension of TAT. On the other hand, the decrease/no change in the TAT is mainly due to the characteristics of the flight *per se*. Unrestricted flights can depart earlier with no delay. If ground handling operations allow earlier completion to pursuit higher efficiency, the TAT can be decreased. The following case study section is designed to verify the hypothesis above.

4. Case Study

4.1. Research Data. Historical flight turnaround operation data were collected from the Airport-Collaborative Decision Making (A-CDM) system of the two busiest airports in China, namely Beijing Capital International Airport (PEK) and Shanghai Pudong International Airport (PVG), in order to compare the changes in-flight turnaround times and to analyze the impact of the pandemic prevention and control on flight ground operations. The A-CDM system of the airport aggregates operational data from various stakeholders, including the airport, airlines, air traffic control

(ATC), and ground handling service department, which is widely used in Europe and domestic large and busy airports [42]. On top of the data provided by this system, we also watched back the whole process of turnaround through the Airport Digital Video System (ADVS) with the authorization of the airport, manually recording other turnaround activities needed for the study.

The data we adopted included the actual turnaround data of PVG and PEK from 2017-2019 before the pandemic and PEK and PVG from April to July in 2021 after the pandemic. Table 2 shows the raw data example of each flight operation. Each flight record contained the start and end time of different turnaround activities shown in Figure 3, so the duration time of each activity could be directly calculated for each flight. By calculating and collating the collected raw data, the time parameters of each operational process of flight ground handling activities were obtained.

The current sample includes airlines based at both airports (e.g., CA, MU, FM, etc.) for a total of nearly 30 airlines, more than 50% of the number of airlines in 2021. This includes different types of domestic airlines. In terms of ownership type, the sample includes state-controlled airlines such as CA, CZ, MU, HU, etc., as well as private airlines such as 9C, HO, etc. In terms of airline business model, the sample contains full-service carriers such as CA, 3U, and MF, as well as low-cost carriers such as 9C, 8L, and PN. In summary, the flight sample of this study contains most of the typical domestic airlines.

The data cleaning process is conducted to mainly delete extreme duration time that does not comply with the operation criteria of a specific turnaround activity. For instance, we delete samples with de-boarding time less than 3 mins and boarding time less than 6 mins. For cleaning, catering, and refueling activities, samples with duration time less than 3 mins or larger than the turnaround time are excluded. In addition, as the data is mainly exported from the A-CDM system, samples with abnormally short duration time are manually adjusted into a standard format. For instance, in block times with 0 values are changed into 1 min to facilitate calculation.

4.2. Results and Discussion

4.2.1. Fitting Time Distributions of Individual Subprocesses. The cleaned data is statistically analyzed to determine the pattern of time distribution for each activity. The procedure of determining time distribution for each activity is illustrated by taking the prepandemic cargo unloading process as an example. Analysis of the duration of cargo unloading sample of type C showed that the unloading time is mainly concentrated between [5, 10] min. Further, it was found that the duration of this activity reflects a statistical behavior which is best fitted with a Weibull distribution. Figure 4 depicts the fit quality for cargo unloading process under 6 possible distributions.

Statistical indicators confirm that Weibull is the most appropriate distribution for this activity. Based on a dataset of $n = 929$ values, the real data is successfully (chi-square test positive) fitted with a Weibull distribution with the following

Table 2: The raw data example of each flight operation.

Attribute	Description	Example
Date	Date of flight (YYYYMMDD)	20210419
Gate	Assigned gate	565
Fleet	Fleet type	B737-800
Origin	Departure airport (IATA 3-digit code)	CTU
Destination	Arrival airport (IATA 3-digit code)	PEK
STD	Schedule time of departure	0930
STA	Schedule time of arrival	1055
STX	Start time of X activity	1110
ETX	End time of X activity	1125

Note. The "X" in STX and ETX is the activities of aircraft turnaround operations shown in Figure 1, such as cabin cleaning, catering, refueling, cargo loading, and so on.

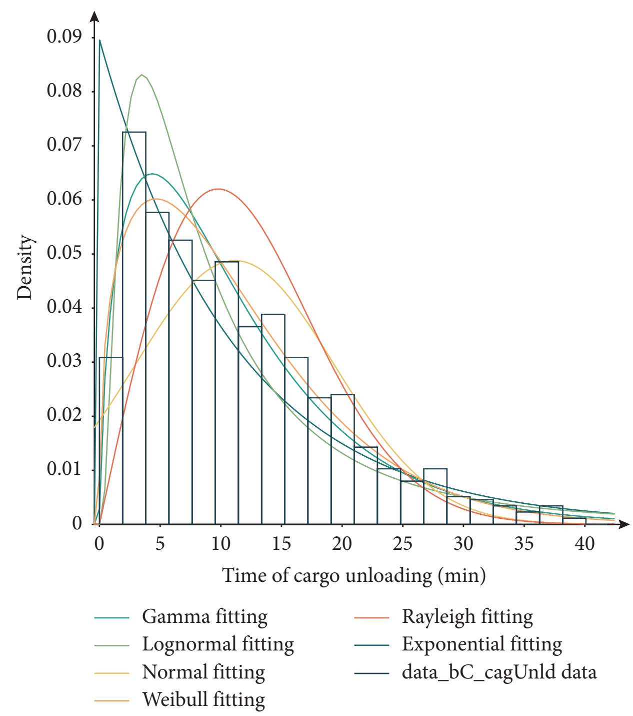


Figure 4: Prepandemic cargo unloading time distribution fitted with candidate distributions.

parameter: $\alpha = 1.34$, $\beta = 12.35$, min = 1. The corresponding chi-square value of $\chi^2 = 10.13$ is smaller than the required value χ^2 (95%, 18) = 28.87. This goodness of fit could be implemented for all the remaining ground handling activities, including type C and type E, which can be seen in Tables 3 and 4.

4.2.2. Changes in the Overall Turnaround Time. Based on the simulation model of the whole process of flight ground operations established in Section 3.2, the minimum turnaround time of domestic passenger flights under the influence of pandemic measures was simulated, and the results obtained are shown in Figures 5 and 6.

The minimum turnaround time for flights of type C before the pandemic is mainly distributed around 60 min, but the mean value after the pandemic is around 70 min. For flights of type E, the turnaround time before the pandemic is

Table 3: Statistical distribution for subprocesses before the pandemic.

Activity	Type C	Type E
De-boarding	Lognormal (1.70, 0.27, 3)	Lognormal (1.62, 0.27, 3)
Cleaning	Logistic (3.12, 14.39)	Logistic (3.61, 17.61)
Catering	Lognormal (2.55, 0.43, 3)	Normal (5.69, 18.73)
Boarding	Lognormal (2.65, 0.39, 4)	Lognormal (2.93, 0.15, 6)
Refueling	Weibull (3.25, 13.88, 3)	Lognormal (2.41, 0.44, 5)
Baggage unloading	Lognormal (1.73, 0.51, 1)	Gamma (4.06, 1.27, 2)
Cargo unloading	Weibull (1.34, 12.35, 1)	Lognormal (2.13, 0.82, 3)
Cargo loading	Weibull (1.44, 13.23, 1)	Normal (10.44, 10.69)
Baggage loading	Lognormal (1.79, 0.57, 1)	Lognormal (1.62, 0.70, 2)
Sewage-water	Weibull (2.26, 3.40, 1)	Weibull (2.26, 3.40, 1)

Table 4: Statistical distribution for subprocesses after the pandemic.

Activity	Type C	Type E
De-boarding	Logistic (0.50, 2.70)	Lognormal (0.64, 0.40, 1)
Cleaning	Lognormal (2.80, 0.58, 4)	Logistic (6.46, 21.62)
Catering	Lognormal (2.69, 0.54, 3)	Lognormal (3.15, 0.43, 8)
Boarding	Lognormal (1.98, 0.37, 3)	Lognormal (1.59, 0.34, 2)
Refueling	Lognormal (2.59, 0.41, 3)	Logistic (3.49, 16.17)
Baggage unloading	Lognormal (1.63, 0.64, 1)	Gamma (1.58, 4.25, 1)
Cargo unloading	Weibull (1.21, 11.59, 1)	Exponential (0.08, 1)
Cargo loading	Weibull (1.34, 10.82, 1)	Weibull (1.36, 10.55, 1)
Baggage loading	Lognormal (1.64, 0.64, 1)	Exponential (0.16, 1)
Sewage-water	Lognormal (1.74, 0.61, 2)	Lognormal (1.96, 0.68, 2)

around 65 min, while the turnaround time increases to around 80 min after the pandemic. The minimum turnaround time has increased compared to the prepandemic period for both types of aircraft.

As shown in Table 5, the average turnaround time after the pandemic for flight of type C is about 73.8 mins, an increase of 17.7% compared with that before the epidemic (62.7 mins). The standard deviation of the postepidemic turnaround time was larger, indicating the distribution of turnaround time was more discrete.

The dispersion of the minimum turnaround time distribution for type E models is higher than before as can be seen in Figure 6(b), which is also verified in the data in Table 5. The minimum value of the minimum turnaround time for type E aircraft after COVID-19 is 56 min, which is similar to that before the epidemic, but the maximum value reaches to 114 min, with an extreme difference of 58 min. The higher dispersion of the distribution also leads to an increase in the variability and uncertainty of the resource occupation time for aircraft of type E, which poses a challenge to the work of the airport's staff of stand allocation and gate allocation.

4.2.3. Changes in Critical Paths of Turnaround Operations. Given that the durations of subprocesses are stochastically distributed and depend on different trigger parameters [39], the critical path can be different for individual turnarounds [43]. The critical path method (CPM) was used to identify the critical path of ground handling operations of each flight before and after the pandemic based on simulation data from turnaround operations. The critical paths of turnaround operations for the flights of type C are the following three cases, which are visualized in Figure 7:

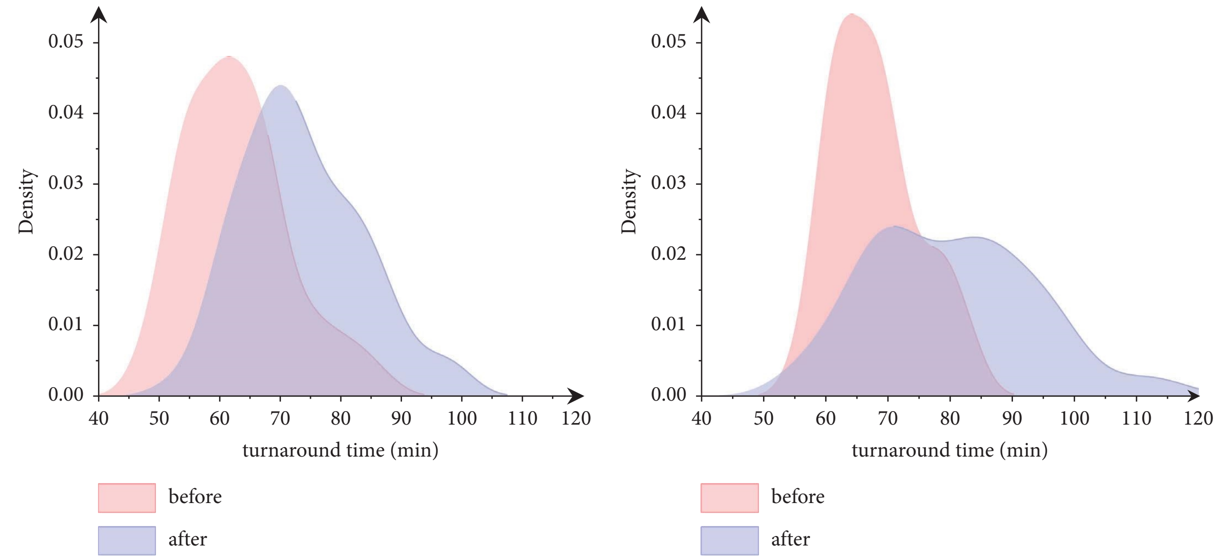
(1) In block-jet bridge connected-cabin door opening-de-boarding-cabin cleaning-boarding-door closing-jet bridge disconnected-off block.

(2) In block-jet bridge connected-cabin door opening-de-boarding-catering-boarding-door closing-jet bridge disconnected-off block.

(3) In block-loaders connected-cargo door opening-baggage unloading-cargo unloading-cargo loading-baggage loading-cargo door closing-loaders disconn ected-off block.

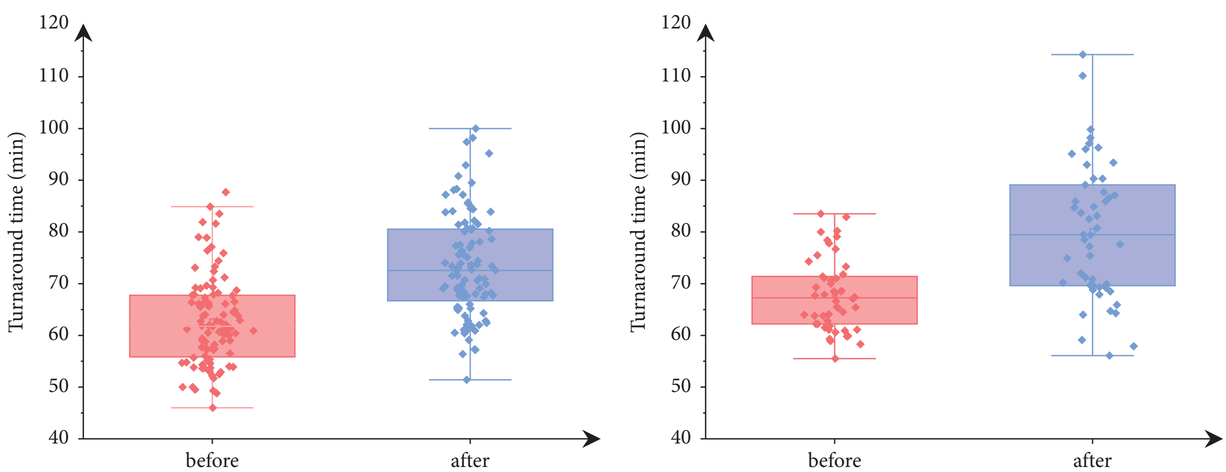
The distribution of three types of critical path for aircraft of type C before and after COVID-19 is shown in Figure 8. Three critical paths are composed of two cabin paths, denoted as path 1 and path 2, and one cargo path, denoted as path 3. From Figure 8, it can be seen that the critical paths for ground handling operations before and after the pandemic did not change, but the structure did. What's more, critical path of more than 75% of the turnaround flights comes from cabin operations, and only 14% of the flights depend on cargo processes to determine the overall turnaround time after the epidemic. Therefore, optimizing the resource allocation of cabin operations and improving the efficiency of the flight cabin process can effectively shorten the flight turnaround time, thus reducing flight delays and improving airport operation efficiency.

4.2.4. Changes in the Distribution of Service Time for Individual Turnaround Activities. For critical path 1, i.e., in block-jet bridge connected-cabin door opening-passenger disembarkation-cabin cleaning-passenger embarkation-cabin door closing-jet bridge removing-off block, the



(a) (b)

FIGURE 5: Distribution of minimum turnaround time before and after the pandemic. (a) Distribution of MTTT of type C before and after COVID-19. (b) Distribution of MTTT of type E before and after COVID-19.



(a) (b)

FIGURE 6: Box plot of minimum turnaround time before and after the pandemic. (a) Boxplot of MTTT of type C before and after COVID-19. (b) Boxplot of MTTT of type E before and after COVID-19.

TABLE 5: Statistical indexes of minimum turnaround time.

Indexes (min)	Type C				Type E			
	Avg	Std dev	Max	Min	Avg	Std dev	Max	Min
Before	62.7	8.71	87.7	46	67.8	6.94	83.5	55.5
After	73.8	10.72	110.5	51.4	80.2	13.22	114.3	56.1

percentage of this path reaches 48% after the epidemic, which is more than twice of that before. Figure 9 shows the changes of total turnaround time and duration of each subprocess on this critical route. We can see that the total turnaround time increases on this critical path, where the change in passenger disembarkation time is smaller. The increase in the overall turnaround time is mainly caused by cabin cleaning and passenger embarkation.

The statistics presented in Table 6 further indicate that the total average turnaround time for flights with critical path 1 increased by 25% after the epidemic, with a greater change than the overall average turnaround time (17.7%).

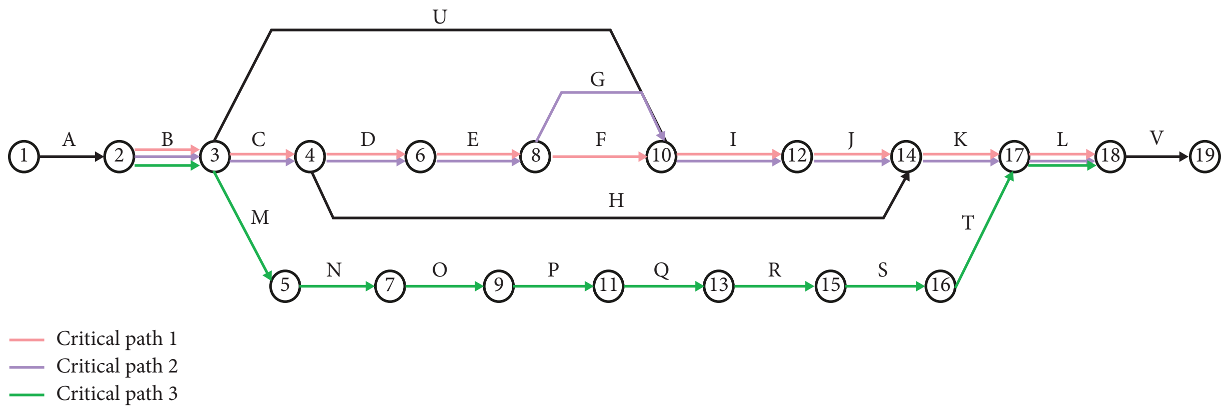


Figure 7: Three critical paths of turnaround operations.

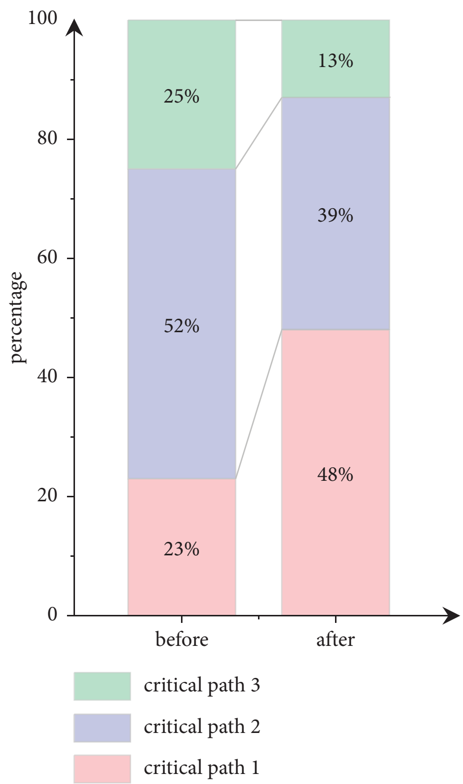


Figure 8: Percentage of critical paths for turnaround flights before and after COVID-19.

On this path, the average time of passenger disembarkation decreased slightly from 8.2 min to 6.7 min. However, the cabin cleaning time increased significantly by 81.5%, while the average time of passenger embarkation increased by 25% with a more discrete distribution. Changes in the duration time of these two activities were the main reasons for the increase in the total turnaround time on this path.

The airline industry as a whole has been operating poorly in the wake of the outbreak. The various prevention and control policies introduced by the government and the reduced willingness of passengers to travel have led to a continuous decline in the passenger load factor of most airlines. Although the epidemic situation in 2021 has eased, the decrease in the number of passengers still makes a corresponding decrease in disembarkation time.

According to on-site observations of the flight ground operation process, cleaning personnel on domestic passenger flights were required to wear protective clothing when entering the cabin for cleaning operations after the epidemic. Compared with the free and convenient operation before, wearing protective clothing made the cleaning staff work less freely and more difficult, slowing down the operation speed and thus increasing the operation time. In addition, after the basic cleaning work is completed, the cleaning personnel were required to use disinfectant to deeply clean the cabin in all directions without dead ends. The implementation of deep cleaning reduces the risk of flight infection while also increasing the workload of the cleaning staff, leading to the increase of the cleaning time.

In the wake of the epidemic, airports are requiring passengers to strictly implement a “one-meter line” policy and promoting “noncontact” services to reduce the density of people and avoid the contact between people. This approach reduces the potential risk of transmission by increasing social distance but increases overall boarding time at the same time. Under the regular prevention and control mechanism, airports require passengers on outbound flights to present a health code and trip code upon boarding, and some airports require a negative nucleic acid test report within 48 hours before boarding. The check of two codes and the nucleic acid report have increased the average boarding time per passenger in China, and with little change in the number of passengers, the overall boarding time has increased accordingly.

Critical path 2, i.e., in block-jet bridge connected-cabin door opening-de-boarding-catering-boarding-door closing-jet bridge disconnected-off block also occupies a large proportion before and after COVID-19. Figure 10 shows the changes of the total turnaround time and the time of each subprocess on this path before and after the epidemic. From this figure, it can be seen that the total turnaround time of this path increased. Individually, the time of passenger disembarkation decreased slightly, but the catering and passenger embarkation time increased.

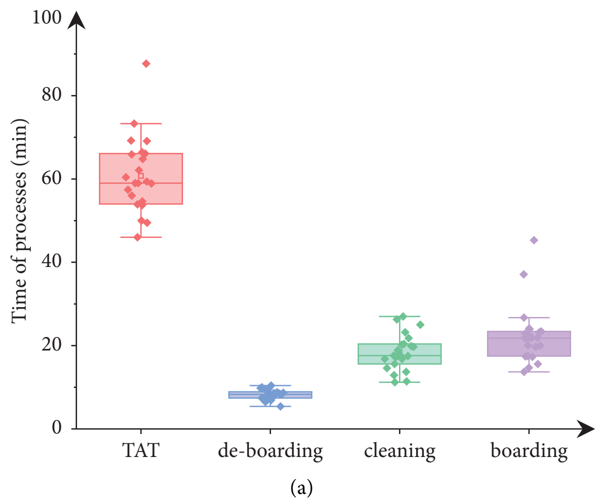


Figure 9: Comparison of the duration time of subprocesses on critical path 1 before and after COVID-19. (a) Boxplot of time of subprocesses before COVID-19. (b) Boxplot of time of subprocesses after COVID-19.

Table 6: Statistical indexes of the duration time of subprocesses on critical path 1 before and after COVID-19.

Indexes (min)	Before				After			
	Avg	Std dev	Max	Min	Avg	Std dev	Max	Min
Turnaround time	60.7	1.89	87.7	46	75.9	10.92	100	51.4
De-boarding	8.2	1.22	10.4	5.4	6.7	1.40	9.8	2.9
Cabin cleaning	18.4	4.32	27	11.2	33.4	11.52	58.3	19.2
Boarding	22.3	6.88	45.3	13.7	27.9	12.09	73.9	11

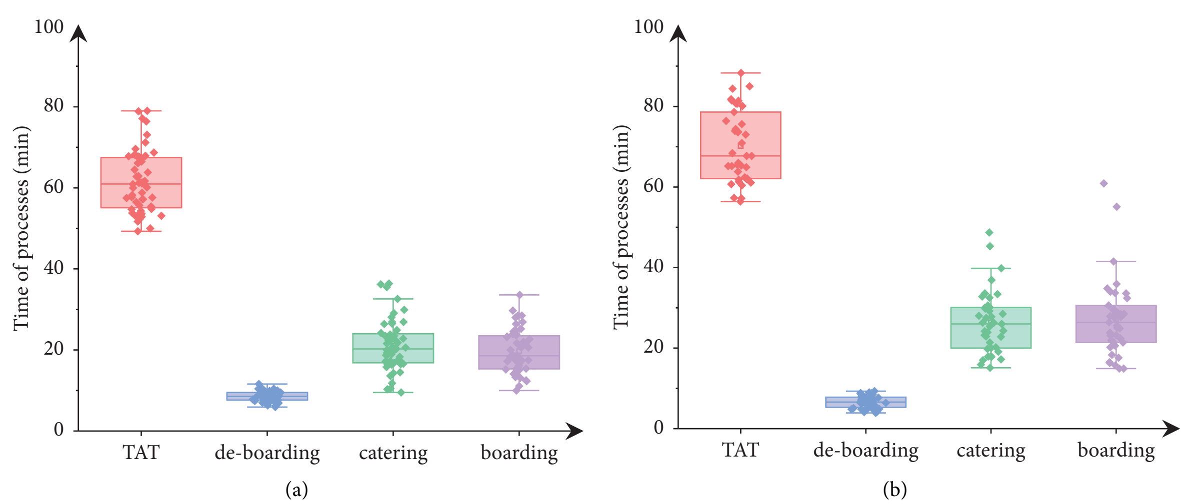


Figure 10: Comparison of the duration time of subprocesses on critical path 2 before and after COVID-19. (a) Boxplot of time of subprocesses before COVID-19. (b) Boxplot of time of subprocesses after COVID-19.

The statistics in Table 7 demonstrate that the total average turnaround time of flights with critical path 2 increased by 14% after the epidemic, the change of which was smaller than the overall average turnaround time (17.7%). On this path, the average passenger disembarkation time decreased from 8.6 min to 6.7 min, with a 22% decrease. However, both catering and passenger boarding times increased, by 25.7% and 38.1% respectively, which was the main reason for the increase in total turnaround time of critical path 2 after COVID-19.

With the domestic epidemic situation gradually turning for the better, domestic airlines have started to resume the supply of hot food aboard. Under the premise of further strengthening the control of food safety and hygiene and improving the quality of in-flight services, major airlines are scrambling to introduce special dishes to meet the diversified

Table 7: Statistical indexes of the duration time of subprocesses on critical path 2 before and after COVID-19.

Indexes (min)	Before				After			
	Avg	Std dev	Max	Min	Avg	Std dev	Max	Min
Turnaround time	61.5	7.61	79	49.3	70.2	8.87	88.3	56.4
De-boarding	8.6	1.24	11.6	5.9	6.7	1.53	9.3	3.9
Catering	21.0	6.27	36.4	9.5	26.4	7.74	48.7	15.1
Boarding	19.7	5.29	33.6	10	27.2	9.66	60.9	14.9

needs of passengers. To accelerate the construction of Bureau's new safety capacity, airlines are focusing on studying the refinement of in-flight meal provision management and providing customized services for passengers. In addition, the catering activity is subject to strict compliance with epidemic prevention requirements, such as the disinfection of catering staff before and after meal preparation. The richness of meals and the complexity of the activity increase the meal preparation time, thus affecting the total flight turnaround time.

Critical path 3 is the cargo process line, i.e., in block-loaders connected-cargo door opening-baggage unloading-cargo unloading-cargo loading-baggage loading-cargo door closing-loaders disconnected-off block. Figure 11 shows that changes in time of baggage loading and unloading and cargo loading are small and the increase of total turnaround time is mainly caused by the cargo unloading activity.

As can be seen in Table 8, the MTTT for flights with critical path 3 increased by 11.5%. Except for the unloading activity, there was no significant change in the average time of baggage loading and unloading and cargo loading activities. In terms of the discrete degree of time distribution, the time distribution of the cargo unloading after the pandemic was more discrete. According to the calculation results, this activity is the main reason for the increase of the total time of path 3 after the pandemic.

To reduce the risk of virus transmission, ground handling agents were required to wear protective clothing for loading and unloading after COVID-19, making the operation more difficult. At the same time, the number of passengers checking in baggage decreased due to the decreased load factor. The offsetting effect of these two factors resulted in a small change in average baggage handling time. With global passenger traffic hit hard by the epidemic, air cargo demand increased rather than decreased. Airlines got the chance to make full use of the belly of the passenger aircraft to compensate for the lower passenger demand, creating new opportunities for the air cargo market. As a result, the average unloading time for cargo increased significantly. With no significant change in baggage loading and unloading and cargo loading times, the total turnaround time on this route increased consequently.

The increase in time for these key turnaround activities (e.g., cleaning, catering, cargo loading and unloading, etc.) also led to an increase in overall turnaround time, which is consistent with the findings in Section 4.2.2. The increase in-flight turnaround time alters the airport slot occupancy time and has a significant impact on slot turnaround efficiency. It also affects the airport's peak hour ground service capacity. The in-depth analysis of each turnaround process is the basis for the refined management and prediction. Comparative analysis of the duration time of these important turnaround activities before and after COVID-19 helps airports and airlines to accurately judge and analyze the causes of flight departure delays. For airlines, the increase in the minimum turnaround time of flights needs to be taken into account when preparing flight schedules to avoid flight delays as well as delay propagation caused by short scheduled turnaround time, in order to maintain the stability and robustness of the airline network.

4.3. Insights for Future Aircraft Turnaround Operations and Procedures. In the document issued by the civil aviation regulator in China in 2019, the minimum turnaround time for aircraft of type C at airports with a passenger throughput of 30 million passengers or more is 65 min and 75 min for type E before the pandemic. After the epidemic, the ground handling situation has changed dramatically, and the minimum turnaround time for all types of aircraft at large and busy airports must be adjusted accordingly. According to the analysis of the simulation results in Section 4, the average minimum turnaround time after COVID-19 was 73.8 min for aircraft of type C and 80.2 min for type E. This result provides a reliable theoretical basis for the regulator to update the minimum turnaround time standard for ground operations. It is recommended that the minimum turnaround time for aircraft of type C should be adjusted to 75 min and 80 min for aircraft of type E at airports with a passenger throughput of over 30 million passengers. This allows CAAC to adjust the minimum turnaround time standard when major public health emergencies such as COVID-19 occur, so as to make full use of resources such as stand and improve the punctuality of flight departure.

The turnaround time of flights at airports is subject to a high degree of uncertainty and can be influenced by a variety of factors including the type of aircraft, flight density, number of passengers, and so on. Aircraft space and gate resources are important resources for airports. The uncertainty of turnaround time will lead to the variation of aircraft occupancy time for gates and stands. Airports should strengthen their advance forecasting of turnaround time of flights with different characteristics. In addition to keeping in mind the minimum turnaround time of type E aircraft set by CAAC, gate and stand allocation personnel should also consider the forecasted turnaround times of flights with different attributes to effectively allocate gate and stand resources. On this basis, the airport slot allocation also needs to pay attention to the connection time between flights assigned to the same stand. Otherwise, it may lead to

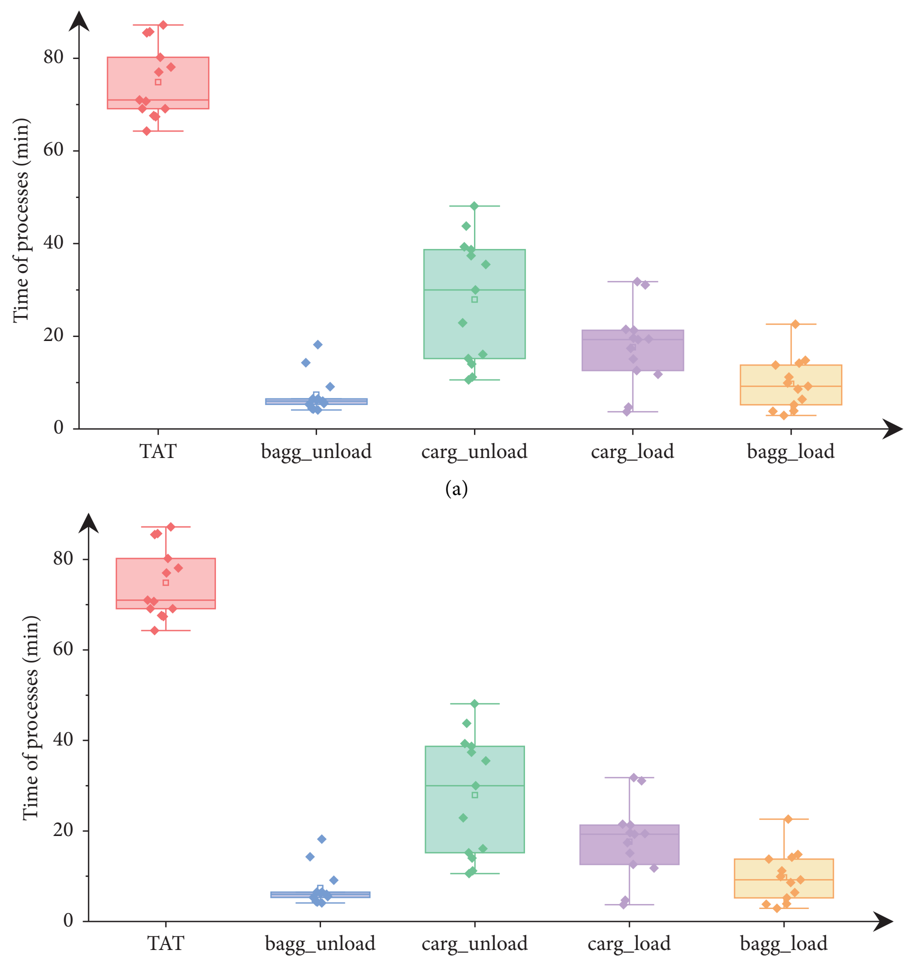


FIGURE 11: Comparison of the duration time of subprocesses on critical path 3 before and after COVID-19. (a) Boxplot of time of subprocesses before COVID-19. (b) Boxplot of time of subprocesses after COVID-19.

TABLE 8: Statistical indexes of the duration time of subprocesses on critical path 3 before and after COVID-19.

Indexes (min)	Before				After			
	Avg	Std dev	Max	Min	Avg	Std dev	Max	Min
Turnaround time	67.1	9.35	48.8	84.9	74.8	7.88	87.2	64.3
Baggage unloading	6.9	2.95	14.3	3.4	7.4	4.21	18.2	4.1
Cargo unloading	18.7	8.40	37.3	4.4	27.9	13.41	48.1	10.6
Cargo loading	18.8	11.09	42.1	1.6	17.6	8.40	31.8	3.7
Baggage loading	10.5	8.74	43.6	4.3	9.7	5.62	22.6	2.9

frequent adjustments of parking stands and gates, which will affect passengers' flight experience and service quality. After giving due consideration to these, the efficient use of stand and gate resources can be achieved while no conflicts would arise.

It can be seen from the above analysis that of all the activities on the critical paths, the one with the largest increase in duration is the cabin cleaning activity. The duration of cleaning increased by 81.5% compared to the preepidemic period, which is the main reason for the increase in turnaround time on this path. Airlines are making improvements and optimizations to the cleaning activity to improve the efficiency of the whole turnaround process. As already mentioned, some airlines (e.g., Ryanair) have totally omitted the cleaning activity or use cabin crew members instead of dedicated personnel to perform it in order to reduce required ground times [29]. To optimize the overall turnaround time, airlines and ground handling service providers need to accelerate the optimization of the cabin cleaning activity and the investment of resources in this activity. The ground handling service department could conduct trials and evaluations on the cleaning sequence of different areas of the cabin (such as galley, lavatory, seats, aisles, and cockpit), the allocation of cleaning personnel in different areas, and the sequential arrangement of cleaning and disinfection. In this way, the optimal cleaning method for airlines with different characteristics can be determined to shorten the time of cleaning, improve the efficiency of flight ground handling operations, and ultimately enhance the rate of airport departure punctuality.

5. Conclusion

In this paper, impacts generated by the prevention and control of COVID-19 on aircraft turnaround operations at airports have been investigated. The methodology proposed in this paper for the impact assessment entails two phases. In the first one, the distribution pattern of service time of each activity of flight ground operations before and after the pandemic was explored. A simulation model of the whole process of flight turnaround was established to calculate the minimum turnaround time of flights with stochastic service times of turnaround activities. In the second phase, impacts are evaluated by analyzing the change in the simulated turnaround time and in the critical path of ground handling operations. Three critical paths are respectively analyzed to explore the variation in total turnaround time and duration time of subprocess time on each route.

Results show that the overall minimum turnaround time for flights of type C increased by 17.7% and that of type E increased by 18.3% compared to the preoutbreak period. For cabin process lines, cleaning, catering, and boarding activities were the main reasons for the increase in turnaround time. For the cargo process lines, the increase in cargo demand instead of decrease caused a corresponding increase in the time duration of cargo and mail handling, which also presents a business opportunity for struggling carriers in China.

This work represents a preliminary framework to be used by decision makers to evaluate appropriate strategies in order to ensure the stability and reliability of airport turnaround operations. Airports are supposed to focus on the important activities that change significantly during the outbreak of COVID-19. In the implementation of measures optimizing the allocation of turnaround resources, the turnaround time of the ground handling process can be shortened, thus enhancing the overall operational efficiency of turnaround services.

This study has its limitations. A major one is that only single flight is considered in the analysis, and additional issues may arise with including this aspect into the model. In other words, all ground handling resources are assumed available without shortage. Another drawback is that this paper does not consider the change of current work status of personnel after the liberalization of the epidemic. Assessment of change in individual capacity of turnaround personnel after infection is the next research direction. Furthermore, we may extend the results of this research to identify potential critical path in future operations when certain activities of turnaround process are constrained in order to better allocate the resources, thus shortening the turnaround time.

Appendix

A. Principles of the Chi-square Goodness-of-fit Test and Formulas for Each Distribution Involved in the Test

The Pearson chi-square goodness-of-fit test is a nonparametric test. It is an important part of the goodness-of-fit test as it uses the sample data to make inferences about the shape of the overall distribution, thus determining whether the sample distribution matches a known theoretical distribution. In this paper, the Pearson chi-square test is chosen to test various distributions. The formula for calculating Pearson's chi-square test statistic is as follows:

$$\chi^2 = \frac{\sum_{i=1}^{k} \left(f_i - np_i\right)^2}{np_i}, \tag{A.1}$$

where f_i is the actual frequency of the i th interval, np_i is the theoretical frequency falling into the i th interval, and k is the number of sample groupings. If the value of the test statistic is greater than the critical value, it means that the difference between the actual frequency and theoretical frequency is large, indicating the fitted result is more different from the actual one. Conversely, it indicates the fitting result is more satisfactory.

Several kinds of distributions, including Normal, Lognormal, Gamma, Logistic, Exponential, Weibull, and Rayleigh Distribution, are expressed with the following probability density functions in the following equations:

$$f(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\left((x-\mu)^2/2\sigma^2\right)}, \tag{A.2}$$

$$f(x,\mu,\sigma) = \frac{1}{(x - \min)\sqrt{2\pi\sigma^2}} e^{-\left([\ln(x-\min)-\mu]^2/2\sigma^2\right)}, \tag{A.3}$$

$$f(x,\alpha,\beta) = \frac{(x - \min)^{\alpha-1}}{\beta^{\alpha}\Gamma(\alpha)} e^{-((x-\min)/\beta)}, \tag{A.4}$$

$$f(x,\alpha,\beta) = \frac{e^{-((x-\alpha)/\beta)}}{\beta\left(1 + e^{-((x-\alpha)/\beta)}\right)^2}, \tag{A.5}$$

$$f(x;\lambda) = \begin{cases} \lambda e^{-\lambda x}, & x \geq 0, \\ 0, & x < 0, \end{cases} \tag{A.6}$$

$$f(x,\alpha,\beta) = \frac{\alpha}{\beta}\left(\frac{x - \min}{\beta}\right)^{\alpha-1} e^{-((x-\min)/\beta)^{\alpha}}, \tag{A.7}$$

$$f(x) = \frac{x - \min}{\sigma^2} \exp\left(-\frac{(x - \min)^2}{2\sigma^2}\right). \tag{A.8}$$

Data Availability

The data that support the findings of this study are available from the corresponding author on request. The data are not publicly available due to their containing information that could compromise the privacy of research participants.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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References

[1] C. L. Wu and R. E. Caves, "Flight schedule punctuality control and management: a stochastic approach," *Transportation Planning and Technology*, vol. 26, no. 4, pp. 313–330, 2003.

[2] S. Szabo, M. Pilát, S. Makó, P. Korba, M. Čičváková, and Ľ Kmec, "Increasing the efficiency of aircraft ground handling—a case study," *Aerospace*, vol. 9, no. 1, p. 2, 2021.

[3] C. Malandri, L. Mantecchini, and V. Reis, "Aircraft turnaround and industrial actions: how ground handlers' strikes affect airport airside operational efficiency," *Journal of Air Transport Management*, vol. 78, pp. 23–32, 2019.

[4] C. L. Wu and R. E. Caves, "Modelling and simulation of aircraft turnaround operations at airports," *Transportation Planning and Technology*, vol. 27, no. 1, pp. 25–46, 2004.

[5] M. M. Mota, P. Scala, M. Schultz, D. Lubig, M. Luo, and E. J. Perez, "The rise of the smart passenger i: analysis of impact on departing passenger flow in airports," in *SESAR Innovation Days 2021*, New York, NY, USA, December 2021.

[6] A. Norin, T. A. Granberg, D. Yuan, and P. Värbrand, "Airport logistics–A case study of the turn-around process," *Journal of Air Transport Management*, vol. 20, pp. 31–34, 2012.

[7] M. M. Mota, G. Boosten, N. De Bock, E. Jimenez, and J. P. de Sousa, "Simulation-based turnaround evaluation for lelystad airport," *Journal of Air Transport Management*, vol. 64, pp. 21–32, 2017.

[8] W. H. Ip, V. Cho, N. Chung, and G. Ho, "A multi agent based model for airport service planning," *International Journal of Engineering Business Management*, vol. 2, p. 7, 2010.

[9] T. E. Kannon, S. G. Nurre, B. J. Lunday, and R. R. Hill, "The aircraft routing problem with refueling," *Optimization Letters*, vol. 9, no. 8, pp. 1609–1624, 2015.

[10] L. Luo, S. Hong, S. Shang, X. Zhou, J. Yang, and Y. Pan, "Intelligent boarding modelling and evaluation: a simulation-based approach," *Journal of Advanced Transportation*, vol. 2021, Article ID 9973336, 12 pages, 2021.

[11] R. J. Milne, C. Delcea, L. A. Cotfas, and M. Salari, "New methods for two-door airplane boarding using apron buses," *Journal of Air Transport Management*, vol. 80, Article ID 101705, 2019.

[12] R. J. Milne, L. A. Cotfas, C. Delcea, L. Crăciun, and A. G. Molănescu, "Adapting the reverse pyramid airplane boarding method for social distancing in times of COVID-19," *PLoS One*, vol. 15, no. 11, Article ID e0242131, 2020.

[13] C. Malandri, M. Briccoli, L. Mantecchini, and F. Paganelli, "A discrete event simulation model for inbound baggage handling," *Transportation Research Procedia*, vol. 35, pp. 295–304, 2018.

[14] S. Okwir, P. Ulfvengren, J. Angelis, F. Ruiz, and Y. M. Núñez Guerrero, "Managing turnaround performance through collaborative decision making," *Journal of Air Transport Management*, vol. 58, pp. 183–196, 2017.

[15] D. Guimarans and S. Padron, "A stochastic approach for planning airport ground support resources," *International Transactions in Operational Research*, vol. 29, no. 6, pp. 3316–3345, 2022.

[16] L. Glomb, F. Liers, and F. Rösel, "Optimizing integrated aircraft assignment and turnaround handling," *European Journal of Operational Research*, vol. 310, no. 3, pp. 1051–1071, 2023.

[17] Y. Gao, Z. Huyan, and F. Ju, "A prediction method based on neural network for flight turnaround time at airport," in *2015 8th International Symposium on Computational Intelligence and Design (ISCID)*, IEEE, Hangzhou, China, December 2015.

[18] Q. Luo, Y. Chen, L. Chen et al., "Research on situation awareness of airport operation based on Petri nets," *IEEE Access*, vol. 7, pp. 25438–25451, 2019.

[19] S. Yıldız, O. Aydemir, A. Memiş, and S. Varlı, "A turnaround control system to automatically detect and monitor the time stamps of ground service actions in airports: a deep learning and computer vision based approach," *Engineering Applications of Artificial Intelligence*, vol. 114, Article ID 105032, 2022.

[20] M. Schultz, T. Kunze, B. Oreschko, and H. Fricke, "Microscopic process modelling for efficient aircraft turnaround management," in *Air Transport and Operations*, The Netherlands, July 2013.

[21] A. Aziz, M. N. Brohi, T. R. Soomro, T. M. Ghazal, H. M. Alzoubi, and M. Alshurideh, "Aircraft turnaround manager (atm): a solution to airport operations," *The Effect of Information Technology on Business and Marketing Intelligence Systems*, pp. 679–702, Springer International Publishing, Berlin, Germany, 2023.

[22] Y. Cao, C. Zhu, Y. Wang, and Q. Li, "A method of reducing flight delay by exploring internal mechanism of flight delays," *Journal of Advanced Transportation*, vol. 2019, Article ID 7069380, 8 pages, 2019.

[23] C. L. Wu and R. E. Caves, "Modelling of aircraft rotation in a multiple airport environment," *Transportation Research Part E: Logistics and Transportation Review*, vol. 38, no. 3-4, pp. 265–277, 2002.

[24] C. L. Wu and K. Law, "Modelling the delay propagation effects of multiple resource connections in an airline network using a Bayesian network model," *Transportation Research Part E: Logistics and Transportation Review*, vol. 122, pp. 62–77, 2019.

[25] J. T. Wong and S. C. Tsai, "A survival model for flight delay propagation," *Journal of Air Transport Management*, vol. 23, pp. 5–11, 2012.

[26] C. L. Wu, "Monitoring aircraft turnaround operations–framework development, application and implications for airline operations," *Transportation Planning and Technology*, vol. 31, no. 2, pp. 215–228, 2008.

[27] X. Sun, S. Wandelt, C. Zheng, and A. Zhang, "COVID-19 pandemic and air transportation: successfully navigating the paper hurricane," *Journal of Air Transport Management*, vol. 94, Article ID 102062, 2021.

[28] D. Xue, Z. Liu, B. Wang, and J. Yang, "Impacts of COVID-19 on aircraft usage and fuel consumption: a case study on four Chinese international airports," *Journal of Air Transport Management*, vol. 95, Article ID 102106, 2021.

[29] M. Schultz, J. Evler, E. Asadi, H. Preis, H. Fricke, and C. L. Wu, "Future aircraft turnaround operations considering post-pandemic requirements," *Journal of Air Transport Management*, vol. 89, Article ID 101886, 2020.

[30] CAAC, *Epidemic Prevention and Control Technical Guide of Transportation Airlines*, Civil Aviation Administration of China, Beijing, China, 7th edition, 2021.

[31] CAAC, *Epidemic Prevention and Control Technical Guide of Transportation Airports*, Civil Aviation Administration of China, Beijing, China, 8th edition, 2021.

[32] Y. S. Gök, S. Padrón, M. Tomasella, D. Guimarans, and C. Ozturk, "Constraint-based robust planning and scheduling of airport apron operations through simheuristics," *Annals of Operations Research*, vol. 320, no. 2, pp. 795–830, 2023.

[33] S. Helm, S. Loth, and M. Schultz, "Advancing total airport management—an introduction of performance based management in the airport context," in *Proceedings of the 19th ATRS World Conference*, Singapore, January 2015.

[34] IATA, *IATA Ground Operations Manual*, International Air Transport Association, Montreal, Canada, 2018.

[35] IATA, *Airport Handling Manual (AHM)*, International Air Transport Association, Montreal, Canada, 29th edition, 2008.

[36] B. Oreschko, T. Kunze, M. Schultz, H. Fricke, V. Kumar, and L. Sherry, "Turnaround prediction with stochastic process times and airport specific delay pattern," in *International Conference on Research in Airport Transportation (ICRAT)*, Berkeley, CA, USA, June 2012.

[37] CAAC, *Notice on the Release of the New Version of the Standards of Flight Segment Turnaround Time and the Standards of Minimum Turnaround Time for Aircraft Types*, Civil Aviation Administration of China, Beijing, China, 2019.

[38] J. Puckett, "How airlines are changing their in-flight rules for Coronavirus," 2024, https://www.cntraveler.com/.

[39] H. Fricke and M. Schultz, "Delays impacts onto turnaround performance optimal time buffering for minimizing delay propagation," in *USA/Europe Air Traffic Management Research and Development Seminar (ATM2009)*, New York, NY, USA, June 2009.

[40] H. Fricke and M. Schultz, "Improving aircraft turn around reliability," in *Third International Conference on Research in Air Transportation*, New York, NY, USA, June 2008.

[41] K. Sheibani, "Scheduling aircraft ground handling operations under uncertainty using critical path analysis and Monte Carlo simulation: survey and research directions," *International Journal of Business Strategy and Automation (IJBSA)*, vol. 1, no. 1, pp. 37–45, 2020.

[42] J. Rott, F. König, H. Häfke et al., "Process Mining for resilient airport operations: a case study of Munich Airport's turnaround process," *Journal of Air Transport Management*, vol. 112, Article ID 102451, 2023.

[43] J. Evler, E. Asadi, H. Preis, and H. Fricke, "Stochastic control of turnarounds at HUB-airports," in *Proceedings of the Eighth SESAR Innovation Days*, pp. 3–7, Salzburg, Austria, December 2018.