Analysis and Control of Airport Runway Intrusion

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Abstract: In order to improve the accuracy of runway incursion predictions and identify the key factors influencing such incidents, this study employed a comprehensive approach. Firstly, an ARIMA model was established by analyzing runway incursion data from fiscal year 2019 to fiscal year 2023 in the United States. This time range allowed for a robust analysis of trends and patterns in runway incursions. Secondly, the least squares method was applied to conduct multiple regression analysis on the results and influencing factors of runway incursions specifically at the top 15 airports in China's civil transport network during the year 2011.The integration of these two methodologies resulted in the development of a reliable ARIMA prediction model, which effectively captured the complexities of runway incursions. Notably, the research findings highlighted those typical errors emerged as the primary contributing factor to these incidents. Such insights provide valuable directions and suggestions for targeted strengthening and training programs aimed at enhancing the competency of relevant practitioners within China's civil aviation safety departments. By adopting preventive measures based on this study's recommendations, it is expected that runway incursion accidents can be significantly reduced, ultimately bolstering the overall safety of China's civil aviation sector.

1 INTRODUCTION

Runway incursion is a problem that cannot be ignored in the field of aviation safety. In recent years, with the growth of global air traffic, the number of runway incursion incidents has been on the rise, posing a serious threat to flight safety.

In China, the aviation industry is rapidly developing, and runway incursion incidents occur from time to time. Runway incursion is not a newly emerged phenomenon, but it has become an important issue that has drawn abundant attention in recent decades. With the increase in air traffic volume and the workload of controllers, coupled with some human errors and equipment failures, the possibility of runway incursion has increased.

Several severe runway incursion incidents that have occurred internationally have not only caused significant economic losses, but also posed a serious threat to people's lives. According to Simple Flying, the US FAA confirmed 19 severe runway incursion incidents from January to October 2023, the highest number since 2016.

On January 2, 2023, an Airbus A350 passenger plane operated by Japan Airlines collided with a plane of the Japan Coast Guard at Tokyo Haneda Airport and caught fire, becoming the first ever total loss accident of an Airbus A350 passenger plane.379 passengers on the passenger plane narrowly escaped, 14 people were injured, and 5 people on the plane of the Japan Coast Guard died. According to the latest released call records by the Ministry of Land, Infrastructure, Transport and Tourism in Japan, the plane of the Japan Coast Guard entered the runway without permission, leading to a collision with the just landed JL516 passenger plane. It can be basically confirmed that this was an accident caused by runway incursion.

According to the ICAO in 2007, runway incursions occur when an aircraft, vehicle, or person is present on the runway incorrectly, posing a significant challenge to the safe operation of the airport surface, including the runway and taxiway system (Sabine et al. 2019). The Federal Aviation Administration (FAA) declares in the 2015 National Runway Safety Plan that the objective of runway safety is to improve safety by decreasing both the number and the severity of runway intrusions (Mathew et al. 2017, Seraphin 2019).

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The importance of preventing runway incursions is self-evident. For the aviation industry, every runway incursion could potentially become a disaster. Therefore, in-depth research on the causes, development process, and effective prevention of runway incursions has become an important topic in the field of aviation safety.

2 ANALYSE DATA

2.1 Analyzing the Influencing Factors of Runway Intrusion

Due to the relatively short time for runway incursion safety construction in China and the data being specific to airports, making it difficult to find from official websites, the analysis was conducted using runway incursion data published by the Federal Aviation Administration (FAA) website for fiscal years 2019-2023 (Cheng et al. 2019). The universal nature of the data makes the analysis results valuable in terms of runway incursion construction in China. The data in Table 1 is obtained from the statistics of runway incursions published on the official website of the Federal Aviation Administration (FAA).

Table 1: Runway intrusion data for fiscal years 2019-2023 published on the official website of the Federal Aviation Administration (FAA) of the United States

Years	OI	Other	PD	VPD	TOTAL
2019	324	16	1118	295	1753
2020	164	15	841	241	1261
2021	226	30	1033	285	1574
2022	309	26	1084	311	1730
2023	338	44	1070	380	1760

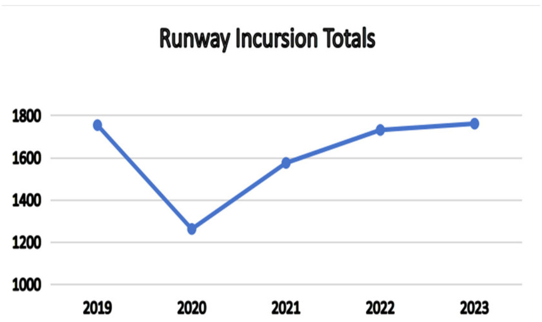

Figure 1: Line graph showing the number of runway incursions in the United States from fiscal year 2019 to fiscal year 2023 (Picture credit: Original).

From Figure 1, it can be observed that the number of runway incursions decreased significantly from 2019 to 2020 and gradually increased to the level of 2019 from 2020 to fiscal year 2023. The decline in runway incursions in fiscal year 2020 can be attributed to the impact of the COVID-19 pandemic, which led to a 60.1% decline in air passenger traffic and a significant decrease in flight operations (Daniel et al. 2021). The aviation industry in the United States was heavily affected by the pandemic from fiscal year 2020 to fiscal year 2022, resulting in significant lay-offs of controllers. With the recovery of the aviation industry in 2023, there was an increase in civil aviation passenger traffic, leading to a significant increase in the workload of controllers and an increase in runway incursion accidents.

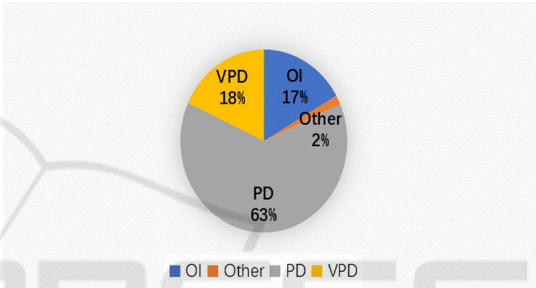

Figure 2: Pie chart depicting the types of runway incursion incidents in the United States from fiscal year 2019 to fiscal year 2023 (Picture credit: Original).

Based on Figure 1 and Figure 2, it can be concluded that pilot deviation (PD) is the primary cause of runway incursions in the United States from fiscal year 2019 to fiscal year 2023, accounting for 63% of the total. The human factor is a crucial element in ensuring the safety of air operations. The European Union Safety Agency report (Harris and Li, 2011) reveals that approximately a quarter of large commercial air transport accidents and serious incidents attribute to human factors (HF) or human performance (HP) issues (Paulina & Skorupski 2022). Therefore, it is crucial to enhance prevention and management measures related to pilot deviation. Runway incursions often occur due to human errors, particularly those made by pilots. By identifying pilot risk factors in runway incursion accidents, it is possible to significantly reduce the number of fatalities and financial losses caused by airlines, as well as the frequency of general airline runway incursion accidents and incidents (Yu-Hern & Wong 2019).

2.2 Establishment of ARIMA Model

The author selected data on the number of runway incursions for the first to third quarters of the fiscal years 2019 to 2023, as published by the FAA, to conduct time series analysis and establish an ARIMA model for runway incursions, as shown in table 2. The ARIMA model, an acronym for AutoRegressive Integrated Moving Average Model, was introduced in the early 1970s by Box and Jenkins (Ivan et al. 2023). It is a widely recognized time series prediction technique, also known as the Box-Jenkins model or the Box-Jenkins method (Gao & Yang 2008). Using the autocorrelation and partial autocorrelation analysis methods, the characteristics of the runway incursion time series model were analysed.

Table 2: Quarterly runway intrusion data for fiscal years 2019-2023 published on the official website of the Federal Aviation Administration (FAA) in the United States.

2019.1	2019.2	2019.3	2019.4
440	382	445	486
2020.1	2020.2	2020.3	2020.4
419	295	217	330
2021.1	2021.2	2021.3	2021.4
318	296	485	475
2022.1	2022.2	2022.3	2022.4
401	399	445	485
2023.1	2023.2	2023.3	2023.4
367	408	481	504

In this model, At the zeroth order of differencing, the significance p-value was 0.561, indicating non-significance. The null hypothesis cannot be rejected, suggesting that the sequence is not stationary. At the first order of differencing, the significance p-value was 0.000, indicating significance. The null hypothesis can be rejected, suggesting that the sequence is stationary. At the second order of differencing, the significance p-value was 0.067, indicating non-significance. The null hypothesis cannot be rejected, suggesting that the sequence is not stationary.

Based on the above analysis and using the AIC information criterion to find the optimal parameters, the author concluded that the ARIMA (1,0,0) model is appropriate, as shown in table 3.

Table 3: ADF Inspection Form.

ADF Inspection Form							
variable	Differential order	t	P	AIC	critical value		
					1%	5%	10%
TOTAL	0	-1.445	0.561	123.171	-3.889	-3.054	-2.667
	1	-4.703	0.000***	122.725	-4.069	-3.127	-2.702
	2	-2.74	0.067*	120.683	-4.138	-3.155	-2.714

2.3 Model Evaluation and Testing

According to the AIC information criterion, the Q-statistic results suggest that Q6 is not significant at the 0.05 level. Therefore, author cannot reject the hypothesis that the model's residuals constitute a white noise sequence. Furthermore, the goodness of fit R^2 value is 0.243, indicating that the model satisfies the basic requirements, as shown in table 4.

Table 4: ARIMA model (1,0,0) validation table.

Term	Symbol	Value
	Df Residuals	18
Number of samples	N	20
Q statistic	Q6(P value)	0.509(0.475)
	Q12(P value)	7.606(0.268)
	Q18(P value)	13.536(0.331)
Information Criterion	AIC	231.234
	BIC	234.221
Goodness of fit	R^2	0.243

The model equation is as follows: $y(t) = 206.872 + 0.495 * y(t-1)$

Through graphical analysis, it can be observed that the trend of the actual values is similar to that of the model's fitted values, as shown figure 3. Thus, the model can be used for prediction and is considered accurate.

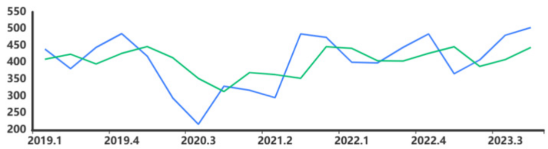

Figure 3: Runway incursion ARIMA model Least Squares Method Safety Original data values of time series model (blue) and fitted values of the model (green) (Picture credit: Original).

This model can be employed to forecast future runway incursion frequencies, providing valuable insights for prevention, monitoring, and management.

2.4 Establishment of Multiple Linear Regression Model

Fifteen airports with the highest number of aircraft takeoffs and landings in China in 2011 were selected as the research objects. Relevant data on runway incursions in these fifteen airports over the past five years were collected, as shown table 5.

The author aims to determine whether typical threats or typical errors are more important factors contributing to runway incursions. Therefore, a multiple linear regression model was developed to investigate the relationship between the independent variables (typical threat occurrences and typical error occurrences) and the dependent variable (runway incursion occurrences).

Table 5: 15 Runway intrusion data from Chinese airports.

AIRPORT CODE	typical threats **Quantity/ Starting**	typical errors **Quantity/ Starting**	runway incursions **number of times**
1	418	109	22
2	511	132	28
3	475	121	25
4	561	117	30
5	359	102	19
6	431	93	20
7	354	95	18
8	399	103	24
9	418	110	23
10	409	95	21
11	565	97	27
12	251	69	11
13	315	83	22
14	387	91	19
15	477	87	25

$$\min Q=\sum_{i=1}^{n}\left(y_i-\widehat{b_0}-\widehat{b_1}x_{1i}-\widehat{b_2}x_{2i}\right)^2$$

$$\text{Make}\frac{\partial Q}{\partial \widehat{b_0}}=\frac{\partial Q}{\partial \widehat{b_1}}=\frac{\partial Q}{\partial \widehat{b_2}}=0,\ \text{ to obtain}$$

Simplifying the system of equations mentioned above:

$$\begin{cases}\dfrac{\partial Q}{\partial b_0^*}=-2\displaystyle\sum_{i=1}^{n}(y_i-b_0-b_1x_{1i}-b_2x_{2i})\\ \dfrac{\partial Q}{\partial b_1}=-2\displaystyle\sum_{i=1}^{n}(y_i-b_0-b_1x_{1i}-b_2x_{2i})\,x_{1i}\\ \dfrac{\partial Q}{\partial b_2}=-2\displaystyle\sum_{i=1}^{n}(y_i-b_0-b_1x_{1i}-b_2x_{2i})\,x_{2i}\end{cases}$$

$$\begin{cases}n\widehat{b_0}+\displaystyle\sum_{i=1}^{n}x_1\,\widehat{b_1}+\sum_{i=1}^{n}x_2\,\widehat{b_2}=\sum_{i=1}^{n}y_i\\ \displaystyle\sum_{i=1}^{n}x_{1i}\,\widehat{b_0}+\sum_{i=1}^{n}x_{1i}^2\,\widehat{b_1}+\sum_{i=1}^{n}x_{1i}\,x_{2i}\widehat{b_2}=\sum_{i=1}^{n}x_{1i}\,y_i\\ \displaystyle\sum_{i=1}^{n}x_{2i}\,\widehat{b_0}+\sum_{i=1}^{n}x_{1i}\,x_{2i}\widehat{b_1}+\sum_{i=1}^{n}x_{2i}^2\,\widehat{\beta_2}=\sum_{i=1}^{n}x_{2i}y_i\end{cases}$$

Solving the first equation yields:

$$\widehat{b_0}=\bar{y}-\widehat{b_1}\bar{x}_1-\widehat{b_2}\bar{x}_2$$

In the above equation system：

$$\bar{y}=\frac{1}{n}\sum_{i=1}^{n}y_i\,;\quad \bar{x}_1=\frac{1}{n}\sum_{i=1}^{n}x_{1i}\,;\quad \bar{x}_2=\frac{1}{n}\sum_{i=1}^{n}x_{2i}$$

Substituting b_0 into the second and third equations gives:

$$\begin{cases}l_{11}\widehat{b_1}+l_{11}\widehat{b_2}=l_{10}\\ l_{21}\widehat{b_1}+l_{22}\widehat{b_2}=l_{20}\end{cases}$$

Wherein：

$$l_{kj}=\sum_{i=1}^{n}(x_{ki}-\bar{x}_k)\left(x_{ji}-\bar{x}_j\right)\quad k,\ j=1,\ 2$$

$$l_{k0}=\sum_{i=1}^{n}(x_{ki}-\bar{x}_k)\left(y_i-\bar{y}\right)\quad k=1,\ 2$$

Thus, b0, b1, and b2can be solved as follows:

(1) By solving the above equation, it can be concluded that the parameters of the binary linear regression model in the case are:b1=0.040121 , b2=0.068627 , b0=-1.5452Therefore, the two-variable linear regression model for the case is

represented as:y = 0.040121x1 + 0.068627x2 - 1.5452.

(2) From Table 6, the calculated F-statistic value is 29.71081. Considering a significance level of α = 0.05, using the FINV function in Excel, author find that F0.95（2，13） = 3.885294. Since F > F0.95（2，13）, the model's confidence level is 95%.

(3) As shown in Table 6, the coefficient of determination (R^2) for the two-variable linear regression equation is 0.8319836. This indicates that the model performs well and satisfies the requirements for handling collinearity among variables.

(4) Additionally, all the VIF values for the two independent variables are below 10, indicating that there is no issue of multicollinearity in the model. Thus, the model is well-constructed.

Table 6: Linear regression equation parameters.

Regression Statistics	
Multiple R	0.912131
R Square	0.831984
Adjusted R Square	0.803981
error	2.073037
Observations	15

By establishing a multiple linear regression model, author can determine the relationship between typical errors and typical threats with runway incursions. From the model in this case, it is evident that the regression coefficient for typical errors is greater than that for typical threats. This implies those typical errors have a stronger influence on runway incursions. Therefore, effective monitoring and reduction of runway incursions should focus on controlling and mitigating typical errors.

3 CONCLUSION

Based on the relationship between the number of runway incursions in the United States and time series, an ARIMA prediction model has been established. Using least squares method, multiple regression analysis was performed on the results and influencing factors based on the runway incursion data of the top 15 airports in China's civil transport airports in 2011.The research conclusions are as follows:

(1) Using the obtained ARIMA time prediction model to predict runway incursion events can obtain relatively reliable results.

(2) Using least squares method to perform multiple regression analysis on the results and influencing factors can show that typical errors are the main influencing factors of runway incursions.

(3) Through the above two methods, some references can be provided for runway safety issues in China's civil aviation industry.

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