Hindawi
Mathematical Problems in Engineering
Volume 2019, Article ID 5710984, 12 pages
https://doi.org/10.1155/2019/5710984

Research Article

Analysis and Forecast of Global Civil Aviation Accidents for the Period 1942-2016

Yafei Li

Tianjin Key Laboratory for Air Traffic Operation Planning and Safety Technology, Civil Aviation University of China, Tianjin 300300, China

Correspondence should be addressed to Yafei Li; commissioner@126.com

Received 7 November 2018; Revised 18 January 2019; Accepted 3 February 2019; Published 18 February 2019

Academic Editor: Bernardo Spagnolo

With the increase of global civil aviation transportation, more and more researchers pay attention to the analysis of civil aviation accidents. Time series analysis can obtain the variation law in a large amount of data, and there is no research result of aviation accident time series yet. Based on the Mann-Kendall trend analysis and mutation analysis methods, this paper studied the change trend of accidents and casualties in different flight stages of civil aviation and built ARIMA (Autoregressive Integrated Moving Average model) time series analysis model to predict the number of civil aviation accidents and casualties by the long-term data in the world. (1) The number of civil aviation accidents fluctuates generally in the world; from 1942 to 2016, there were two fluctuation periods of civil aviation accidents. (2) The number of global civil aviation casualties from 1942 to 2016 showed a parabola trend of increasing first and then decreasing. The highest number of casualties appeared in 1972, which was 2373; on the different flight stages, the number of accidents was different. In the air route and approach phase, the number of accidents was the most, and the number of casualties was more than other flight phases, accounting for about 50% of the whole flight phase. (3) In addition to the land phase, the number of accidents showed a significant decrease in other flight phases; while the air route and total number of casualties decreased significantly, the number of casualties at other flight phases did not decrease significantly. There were no sudden changes in the number of global civil aviation accidents and approach casualties. (4) The sudden change point of the global civil aviation casualties was 2013, the sudden change point of the air route stage accidents was 1980, the sudden change point of approach stage accidents was 2012, and the sudden change point of air route stage casualties was 2006. According to the ARIMA (1,0,1) model, the numbers of global civil aviation accidents and casualties were predicted to 2025. Through time series research, we have explored the variation law in the historical data of long-term aviation accidents and predicted the possible changes of future aviation accidents, providing data reference for aviation safety research.

1. Introduction

With the development of economic globalization and economic, political, and cultural exchanges worldwide and the acceleration of turnover, the global civil aviation transportation industry continuously develops, and flight safety is increasingly taken seriously. Paying high attention to civil aviation accidents, the public easily lose confidence in civil aviation transportation, thus seriously restricting the development of civil aviation. Therefore, it is necessary to make in-depth research for improvement of the safety skill of airlines and reduction of the probability of aviation accidents. When managing civil aviation safety, officers should obtain accurate prediction data and forecast the future safety state, so as to timely take preventive measures against risks and losses before accidents [1–4]. Accurate and valid accident prediction can not only reduce economic losses and casualties but also boost the development of civil aviation safety management [5]. With the continuous improvement of the world's civil aviation technology and management level, a great deal of civil aviation safety data has been collected throughout the world, which boosts the development of research on civil aviation accident prediction to a certain extent and makes it an important part of the research on civil aviation safety.

Civil aviation accidents arise from many factors, including certain and unexpected factors. Certain factors involve aviators participant throughout the whole process of civil aviation, air traffic control, ground support, aviation maintenance, and mechanical fault; unexpected factors mainly involve severe weather (such as wind shear and clear air turbulence) and bird strike [3, 6]. Due to the involvement of the dynamic system of various information, it is impossible to give expression with a simple data model.

Scientifically understanding time series is based on an analysis of the trends and abrupt changes in time series [7]. This analysis may facilitate the understanding of the essence of time series and provide effective evaluation tools for related research. Having made many related studies [8–15], researchers have acquired the trends and abrupt changes in time series of different fields. As an important means to research the law of time series, time series forecast has been widely used in the fields of air pollution prediction [16–18], change and prediction of temperature and precipitation [19–22], economic development indicator analysis [23–25], and aircraft engine life prediction [26–28], yielding good prediction results. In 1976, GEP Box and GM Jenkins first proposed the famous Autoregressive Integrated Moving Average (ARIMA) Model to forecast time series [29]. This model takes the data series of forecasted objects formed with time as a random series and approximately describes it with mathematical models. Once this model is identified, it may forecast the future value of time series on a highly accurate basis according to its past and present values. In 1980, Huang Wenjie first used the seasonal ARIMA model to forecast the monthly temperature of Shanghai and obtained a good result [30].

In relation to the prediction on civil aviation accidents, domestic and overseas scholars have engaged in research. However, most were based on short-time (less than 10 years) series data to forecast the number of civil aviation incidents using the prediction algorithm, multiple regression, grey correlation, and neural network [2, 31–34], but no research has been made based on long-time (over 30 years) series data. Based on the law of change in data, time series prediction analysis may, to a certain extent, overcome the prediction difficulties resulting from the involvement of many factors in civil aviation accidents and confused data and ensure highly accurate prediction. Existing research mainly focuses on the practicability and accuracy of model, but less on the time series of civil aviation accidents and the characteristics of the accidents in different phases. Time series analysis can obtain the variation law in a large amount of data, and there is no research result of aviation accident time series yet.

This study drew on long-term sequence analysis methods in other fields. We chose trend analysis, mutation analysis, and ARIMA models and applied them to the field of aviation accident research. There is no innovation in the model method, but it provides new research fields and materials for time series analysis. Based on the data of civil aviation accidents worldwide, with the methods of Mann-Kendall trend analysis and abrupt change analysis, this research is made on the characteristics of change in the time series of civil aviation accidents worldwide. On this basis, this research builds an ARIMA model to forecast the number and fatalities of civil aviation accidents worldwide and makes a comparison between the forecast results in different phases, with a view to exploring the evolution and trend of civil aviation accidents worldwide and providing effective preventive measures against accidents and technical supports for China to analyze and predict aviation accidents.

2. Research Data and Source

The research is made in accordance with the statistical data of aviation accidents worldwide and the fatalities within 75 years from 1972 to 2016 at https://aviation-safety.net. Such data also involves the aviation accidents in all flight phases and the fatalities thereof from 1972 to 2016, which include take-off, initial climb, en-route, approach, and landing phases. This research will analyze the characteristics and change trend of aviation accidents in each flight phase and the fatalities thereof and forecast the aviation accidents worldwide in the coming 10 years and the fatalities thereof.

3. Research Methods

3.1. Mann-Kendall Trend Analysis. Mann-Kendall trend analysis is a nonparametric statistical method for rank correlation test on the rank of statistic series and time series; dependent variables may be nonnormally distributed, so it applies to analysis of the trend in statistical variables. Given that H_0 is the sample of the time series $A_1, A_2, \ldots, A_n$ as independent identically distributed random variables, then the statistic S is given by

$$S = \sum_{i=2}^{n} \sum_{j=1}^{n-1} \operatorname{sign}\left(X_i - X_j\right) \tag{1}$$

$$a_{ij} = \operatorname{sign}\left(X_i - X_j\right) = \operatorname{sign}\left(R_i - R_j\right) = \begin{cases} 1, & X_j < X_i \\ 0, & X_j = X_i \\ -1, & X_j > X_i \end{cases} \tag{2}$$

where R_i and R_j refer to the rank of X_i and X_j, respectively. When $n > 10$, S is normally distributed with the mean and variance as follows:

$$E(S) = 0 \tag{3}$$

$$\operatorname{var}(S) = \frac{n(n-1)(2n-5)}{18} \tag{4}$$

where E(S) refers to the mean and var(S) refers to the variance. The statistic Z is defined as follows:

$$Z = \begin{cases} \dfrac{S-1}{\sqrt{\operatorname{var}(S)}}, & S > 0, \\ 0, & S = 0, \\ \dfrac{S+1}{\sqrt{\operatorname{var}(S)}}, & S < 0 \end{cases} \tag{5}$$

The statistic Z is Mann-Kendall's rank correlation coefficient. Positive Z or negative Z, respectively, means that there is an upward or downward trend. The absolute value of Z reflects the significance level of trend. When the significance level is consistent with a 99%, 95%, or 90% confidence interval, Z is 2.32, 1.64, or 1.28, respectively [35].

3.2. Mann-Kendall Abrupt Change Analysis. In relation to time series x of n sample sizes, a rank series is built as follows:

$$S_k = \sum_{i=1}^{k} r_i \quad (k = 2, 3, \ldots n) \tag{6}$$

$$r_i = \begin{cases} 1 & x_i > x_j \\ 0 & x_i \le x_j \end{cases} \quad (\mathrm{j} = 1, 2, \ldots, \mathrm{i}) \tag{7}$$

$$r_i = \begin{cases} 1 & \text{When } x_i > x_j \\ 0 & \text{Otherwise,} \end{cases} \quad (\mathrm{j} = 1, 2, \ldots, \mathrm{i}) \tag{8}$$

The rank series S_k refers to the number of values when $x_i > x_j$. For the purpose of definition, the statistics UF_k and UB_k are assumed to be stochastically independent in a time series, and UF_k is calculated as follows:

$$UF_k = \frac{[S_k - E(S_k)]}{\sqrt{\mathrm{var}(S_k)}} \quad (k = 1, 2, \ldots, n) \tag{9}$$

$$\mathrm{E}(S_k) = \frac{\mathrm{n}(\mathrm{n}+1)}{4} \tag{10}$$

$$\mathrm{var}(S_k) = \frac{\mathrm{n}(\mathrm{n}-1)(2\mathrm{n}+5)}{72} \tag{11}$$

UF series, which follows the standard normal distribution, is a statistic series calculated according to the time series x in order; $\mathrm{E}(S_k)$ and $\mathrm{var}(S_k)$ respectively refer to the mean and variance of S_k. If the significance level is given, through check of the normal distribution table, when $|UF_i| > U_a$, the series has an obvious change in trend, and the above process is repeated according to the time series x in reverse order, and UB_k=$-UF_k$ [36].

3.3. Time Series Analysis. Time series analysis is an important statistical analysis and forecast method that describes the statistical characteristics of a variable and reveals the law of change in data according to the statistical relationship between data. A civil aviation accident is a random incident affected by many random factors in the civil aviation system and cannot be represented with a definite function. Statistically, there is a certain correlation between the civil aviation accidents of long-time series, so a time series model may be used to forecast civil aviation accidents. The Autoregressive Moving Average (ARMA) model consists of the autoregressive (AR) model and the moving average (MA) model. As a common time series forecast method [37], the model may be used to fit the time series data of civil aviation accidents for forecast. The ARMA stationary time series model is defined as follows:

$$\begin{aligned} x_t &= \varphi_0 + \varphi_1 x_{t-1} + \ldots + \varphi_p x_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} \\ &\quad - \ldots - \theta_q \varepsilon_{t-q} \\ \varphi_p &\ne 0, \\ \theta_q &\ne 0 \\ \varepsilon_t &\sim WN\left(0, \sigma^2\right) \\ \left(x_s \cdot \varepsilon_t\right) &= 0, \quad \forall_s < t \end{aligned} \tag{12}$$

where p and q refer to the order of autoregressive (AR) part and moving average (MA) part, respectively. When $\varphi_0 = 0$, through introduction of the delay operator B, the centralized ARMR(p, q) model is as follows:

$$\varphi(\mathrm{B}) x_t = \theta(B) \varepsilon_t \tag{13}$$

3.4. Forecast Accuracy Evaluation. This research evaluates the accuracy of the model using root-mean-square error (RMSE) and mean absolute error (MAE) as follows:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - \widehat{y}_i\right)^2} \tag{14}$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \widehat{y}_i\right| \tag{15}$$

where y_i refers to the actual value of sample i; $\widehat{y}_i$ refers to the predicted value of sample i; n refers to the number of samples.

Mann-Kendall trend analysis and abrupt analysis are nonparametric statistical test methods. It has the advantages that the sample does not follow a certain distribution, is not interfered by individual abnormal values, can objectively characterize the overall trend of the sample sequence, and is often used to analyze the trend and characteristics of long-term sequence samples. Common trend analysis methods also include linear functions, quadratic functions, and moving averages. The data analyzed in this manuscript is civil aviation accident data, and there are abnormal value interferences. Therefore, Mann-Kendall trend analysis and abrupt analysis methods are selected. If other trend analysis methods are used, the accuracy of the analysis results may be reduced.

The ARIMA time series analysis model is a model that converts a nonstationary time series into a stationary time series and then returns the dependent variable only to its lag value and the present and lag values of the random error term. The model is very simple, requiring only endogenous variables without the need for other exogenous variables. Other commonly used predictive models include linear regression models and neural network models, which require exogenous variables to make predictions. However, the aviation accidents predicted by this research have many exogenous variables, which are unstable and unpredictable. The ARIMA

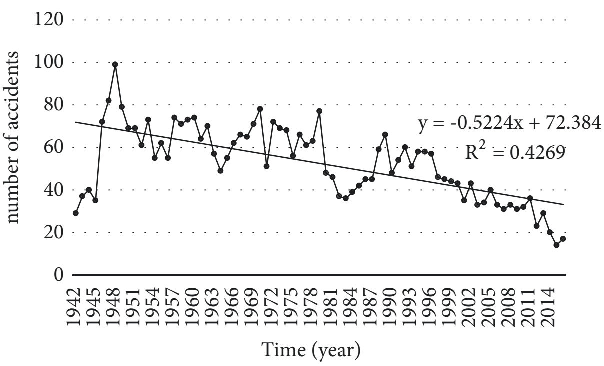

Figure 1: Trends of global civil aviation accidents over the years (y: number of accidents, x: year, R^2: coefficient of determination).

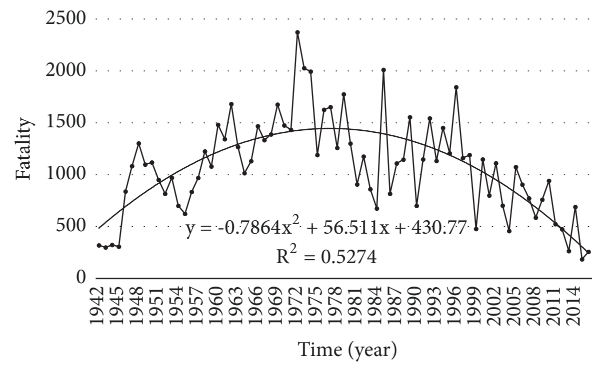

Figure 2: Trends of global civil aviation casualties over the years.

time series analysis model can solve this problem, which predict from the characteristics of the data itself. So, the ARIMA model meets the research needs.

The root-mean-square error and the mean absolute error are methods commonly used to evaluate the accuracy of the model. Other evaluation methods include standard deviation and mean squared error. The root-mean-square error is used to measure the deviation between the observed value and the true value. The mean absolute error is the average of the absolute error, which can better reflect the actual situation of the predicted value error. The standard deviation is used to measure the degree of dispersion of a set of data. The root-mean-square error is used to evaluate the degree of change of the data. The smaller the value, the better the accuracy of the prediction model describing the experimental data. Its evaluation effect is similar to root-mean-square error. The main purpose of this study is to analyze the deviation between the predicted data and the real data, so we choose the RMSE and MAE models that are more suitable for the requirements.

4. Research Result and Analysis

4.1. Analysis of the Change Trend of Key Indicators of Civil Aviation Accidents

4.1.1. Analysis of the Change Trend of Civil Aviation Accidents Worldwide. This research analyzes the trend of change in the number and fatalities of civil aviation accidents worldwide using Excel. As shown in Figure 1, the number of civil aviation accidents worldwide reduces in a fluctuant way on the whole. From 1942 to 1948, the number significantly increased by 10 per year from 29 to 99, showing that accidents rapidly increased with the continuous development of civil aviation; from 1948 to 1983, the number reduced in a fluctuant way by 1.5 per year and reached the maximum of 78 in 1970 and then reduced to the minimum of 36 in 1983; from 1983 to 1989, the number increased by 4 per year from 36 to 66; after 1989, the number rapidly reduced by 1.8 on an annual basis, and until 2016, there were only 17 accidents equal to 17% of the number in 1948, showing that the number of civil aviation accidents was greatly reduced.

According to Figure 1, there were two periods of change in the number of civil aviation accidents worldwide. The first period was 42 years from 1942 to 1983, during which the number rapidly grew within the first 7 years (1942-1948) and then reduced in a fluctuant way within the 35 years thereafter (1948-1983). Likewise, during the period from 1983 to 2016, the number rapidly grew within the first 7 years (1983-1989) and then reduced in a fluctuant way within the 27 years thereafter (1989-2016). However, the change in the second period was less than that in the first period, as the number increased by 70 in the first period (1942-1948) and by 30 in the second period (1983-1989) and reduced by 63 in the first period (1948-1983) and by 52 in the second period.

According to the periods of occurrence, potential civil aviation accidents accumulated to release and reaccumulated to release again. After several years of low-frequency accidents, civil aviation accidents outbroke together within several years, such as 1942-1948 and 1983-1989, during which the number of accidents rapidly increased. However, after the outbreak, accidents decreased in a fluctuant way within a certain period during which the number was kept relatively stable. On the whole, the periodic change in the number of civil aviation accidents gradually reduced, and within the two periods, the increment of accidents reduced from 10 to 4 per year, and the decrement increased from 1.5 to 1.8 per year. This shows that the increase of accidents slowed down and the decrease accelerated in the second period. Increased aircraft performance and personnel quality are the main reasons for the reduction of civil aircraft accidents. On the one hand, due to the continuous advancement of aviation technology, the performance and reliability of civil aviation aircraft are gradually improved, and the probability of aircraft accidents occurring continuously decreases. On the other hand, the quality of aviation practitioners continues to improve. The trainings of pilots, air traffic control, maintenance, and crew members have been continuously strengthened, safety awareness has been significantly improved, and the ability to handle emergency emergencies has been continuously enhanced. These trainings reduce the human factors of aviation and aviation accidents.

4.1.2. Analysis of the Change Trend of Fatalities of Civil Aviation Accidents Worldwide. As shown in Figure 2, there

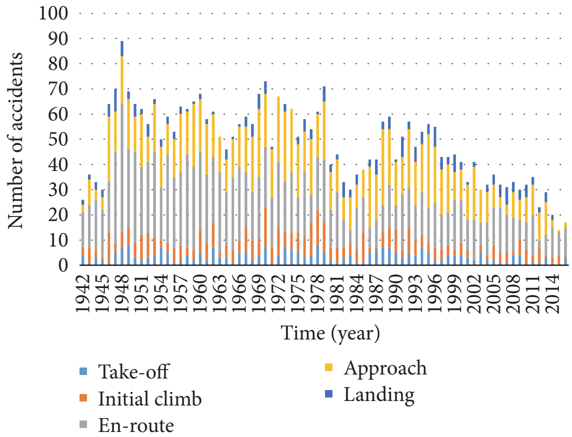

Figure 3: The number of civil aviation accidents in different flight stages.

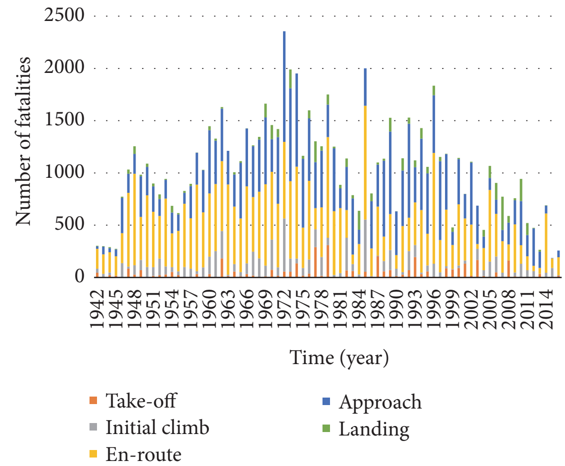

Figure 4: The number of civil aviation casualties in different flight stages.

are significant differences between the trends of change in the fatalities and the number of civil aviation accidents worldwide. From 1942 to 2016, the fatalities first increased and then reduced, showing a parabolic trend. From 1942 to 1972, the fatalities grew in a fluctuant manner by around 68 persons per year. Different from the year when the number of accidents was maximum, 1972 was the year when the fatalities reached the maximum. The maximum number of aviation accidents and casualties is not in the same year. This is due to the fact that early civil transport aircrafts were mainly small and the reliability was relatively poor. There are a large number of aviation accidents, but each aircraft carries fewer passengers. Therefore, in the year with the highest number of aviation accidents (1948), the number of casualties did not reach the maximum. With the Boeing 737 in service in 1968, the number of large passenger aircraft has increased in civil aviation transportation, the reliability of aircraft has increased gradually, and the number of aviation accidents has decreased. However, as the number of passengers carried by each aircraft has increased significantly, the number of casualties per aviation accident has increased. Therefore, in the absence of significant improvements in aircraft reliability, the year of 1972 was the largest number of casualties in aviation accidents

After 1972, the fatalities reduced by 47 persons per year from 2373 to 258 and reached the minimum of 186 persons in 2015 among those within the recent 75 years. During the two periods of 1964-1980 and 1991-1998, the fatalities reached the maximum and over 1000 persons every year. The high fatalities within the two periods were also the main cause of a parabolic trend of change in the fatalities of civil aviation accidents worldwide. Different from the frequency of civil aviation accidents, the fatalities had no periodic changes.

4.1.3. Analysis of the Change Trend of Civil Aviation Accidents in Different Flight Phases. In different flight phases, the number of civil aviation accidents was different. According to Figure 3, in 1942-2016, the number of accidents was maximum in the en-route and approach phases. In 1942-1967, the number in the en-route phase was higher than in the approach phase, and after 1967, the number was maximum alternately in the en-route and approach phases; the number was minimum in the take-off and landing phases, and prior to 1980, the number in the climb phase was mostly higher than in the take-off and landing phases, but after 1980, the number was similar in the three phases and reached the maximum alternately.

According to the law of time change in each flight phase, from 1942 to 2016, the number of civil aviation accidents had a fluctuant change and was not greatly reduced in the take-off and landing phases but first increased and then decreased in the climb and approach phases and reduced in a fluctuant manner in the en-route phase; the number reduced in a fluctuant manner in the climb phase after 1978, and in the approach phase after 1984.

In other words, since the statistical data of the number of civil aviation accidents worldwide was available, although the civil aviation technology continuously developed, the number of accidents in the take-off and landing phases was not greatly reduced but randomly changed in a fluctuant manner. This shows that accidents in the two phases arose from many factors (such as wind shear and icing) and could not decrease with the development of technology. However, with the development of the technologies of aircraft manufacturing, navigation and automatic driving and the aerodynamic performance of aircraft, the performance and flight capacity of civil aircraft greatly improved, and in the climb and approach phases, especially in the en-route phase, aircrafts were subject to less disturbance of other factors, thus making the number of accidents annually reduce up to a quite low level.

4.1.4. Analysis of the Change Trend of Fatalities in Different Flight Phases. As shown in Figure 4, the fatalities were greatly different in different flight phases. In the en-route and approach phases, the fatalities were high and over a half of the total in all flight phases. Before 1972, the fatalities in the en-route phase were higher than that in the approach phase but approximated the latter thereafter. This research

Table 1: The significant test results of change trend of global civil aviation accidents key indicators.

No.	Indicator	Kendall's tau	Significance level	Trend
1	Number of accidents	-0.523	0.05	Significantly decrease
2	Number of accidents in the take-off phase	-0.151	0.1	Significantly decrease
3	Number of accidents in the climb phase	-0.222	0.05	Significantly decrease
4	Number of accidents in the en-route phase	-0.540	0.05	Significantly decrease
5	Number of accidents in the approach phase	-0.188	0.05	Significantly decrease
6	Number of accidents in the landing phase	0.04	0.633	Not significant
7	Fatalities	-0.123	0.1	Significantly decrease
8	Fatalities in the take-off phase	0.012	0.887	Not significant
9	Fatalities in the climb phase	-0.106	0.182	Not significant
10	Fatalities in the en-route phase	-0.226	0.05	Significantly decrease
11	Fatalities in the approach phase	0.048	0.546	Not significant
12	Fatalities in the landing phase	0.114	0.151	Not significant

only analyzed the change trend in time series of the fatalities in the en-route and approach phases. According to Figure 4, in 1942-2016, the fatalities slightly reduced in a fluctuant way in the en-route phase. In 2016, the fatalities were only 19 persons less than that in 1942 in the en-route phase. 1985 and 1996 were the years when the fatalities reached the maximum of over 1000 persons in the en-route phase. Through comparison, the fatalities were not greatly reduced with the continuous decrease of civil aviation accidents in the en-route phase. This might be associated with the increasing size of airliners. Since the fatalities of each civil aviation accident increased with an airliner's passenger capacity, and it was difficult to give a rescue in the en-route phase, the fatalities had not greatly reduced in the phase since 1942.

In the approach phase, the fatalities first increased and then decreased and reached the maximum in 1972 and annually reduced thereafter. Until 2016, there were only 65 fatalities. This was substantially consistent with the trend of change in the number of accidents in the approach phase.

4.1.5. Mann-Kendall Trend Analysis of Key Indicators of Civil Aviation Accidents. With the method of Mann-Kendall trend analysis, we obtain the trend of change in the key indicators of civil aviation accidents listed in Table 1. The Kendall's tau of the number and fatalities of civil aviation accidents worldwide was -0.523 and -0.123, respectively, and passed the significance test, for which the confidence interval was 95% and 90%, respectively. The result shows that the statistic was less than 0, and the number and fatalities of accidents significantly reduced, at the level of 0.05 and 0.1, respectively.

In relation to the number of accidents in different flight phases, the confidence interval was 90% for Kendall's tau in the take-off phase and 95% for Kendall's tau in the climb, en-route, and approach phases, but the trend was not significant in the landing phase. Except in the landing phase, all the statistics were less than 0, showing that the number of the accidents in the flight phases significantly reduced; as to the fatalities, only the Kendall's tau in the en-route phase passed the significance test, for which the confidence interval was 95%, and the statistic was less than 0, showing that the fatalities significantly reduced in the phase, but insignificantly in other flight phases.

4.2. Mann-Kendall Abrupt Change Analysis of Key Indicators of Civil Aviation Accidents. According to the Mann-Kendall abrupt change analysis, Mann-Kendall test is made on the data of civil aviation accidents worldwide, and curves UF and UB (equation (9)) may be drawn in relation to the key indicators of civil aviation accidents. When a critical value is exceeded, the upward or downward trend is significant. The scope beyond the critical line is defined as the time region of abrupt change. When UF intersects with UB at a point within the critical region, then an abrupt change starts at the time corresponding to the point.

Figure 5 gives the curve UF-UB concerning the number of civil aviation accidents. According to curve UF, the number increased in a fluctuant way before 1950 and slowly reduced thereafter and started to rapidly reduce after 1980 and was less than the critical value in 1990 when an downward trend was significant. In 2003, UF intersects UB at a point beyond the critical region, which may not reflect that 2003 was the year when an abrupt change started. This shows that there was no abrupt change of the number of accidents.

Curve UF-UB concerning the fatalities is shown in Figure 5. According to curve UF, the fatalities increased in a fluctuant manner before 1978 and exceeded the critical value in 1961, from when an upward trend was significant; the fatalities reduced after 1978 and were less than the critical value in 2000, from when a downward trend was significant. UF intersects UB at a point within the critical region in 2013 when an abrupt change occurred.

This research only considers the flight phases in which there were many accidents and fatalities, namely, the en-route and approach phases. There are phase characteristics of aviation accidents. According to the previous analysis, the route and approach phase are the most frequent stages of aviation accidents. In the analysis of abrupt change in aviation accidents, we chose these two stages mainly for two reasons. First of all, these two stages are more important. It is of practical significance to analyze the abrupt characteristics of aviation accidents for aviation accident research. Secondly,

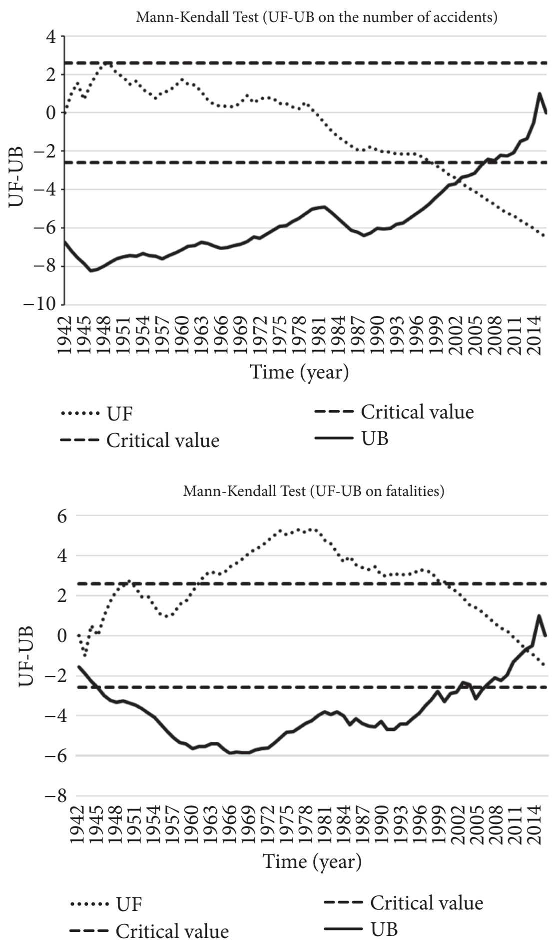

Figure 5: Mann-Kendall test of global civil aviation accident and casualties.

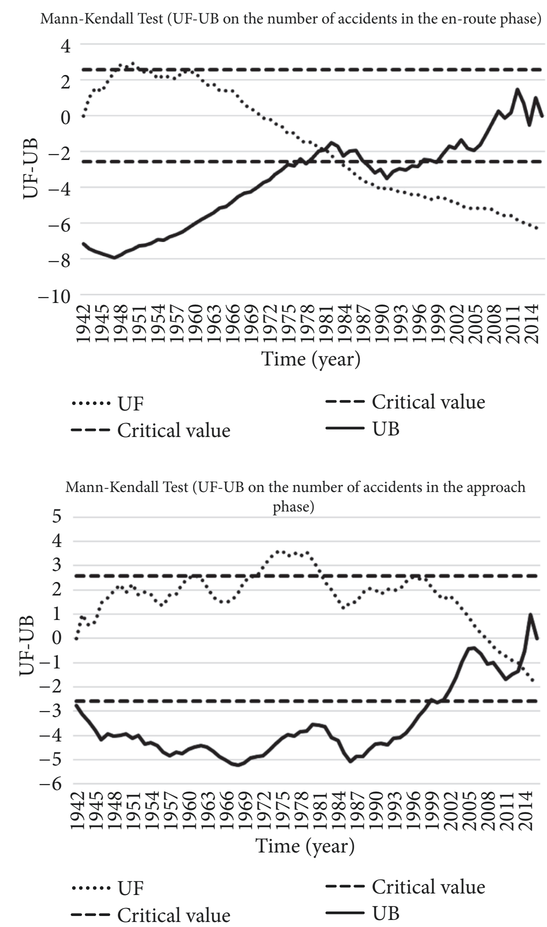

Figure 6: Mann-Kendall test of the number of global civil aviation accidents at different stages.

the amount of aviation accident data in these two stages is large, which is convenient for the analysis of the abrupt change characteristics. Therefore, due to the limitation of the length of the article, we have not analyzed the abrupt characteristics of aviation accidents in other stages.

Figure 6 gives a curve concerning Mann-Kendall test on the number of civil aviation accidents. In the en-route phase, series curve UF rose in a fluctuant manner before 1950 and thereafter significantly declined. In 1980, UF intersects UB at a point within the critical region and was lower than the lower limit of the critical value in 1984, from when a downward trend was significant. 1980 was the year when an abrupt change started.

In the approach phase, series curve UF slowly rose before 1978 and exceeded the critical value in 1970, declined in a fluctuant way from 1978 to 1995, and rapidly declined after 1995. UF intersects UB at a point within the critical region in 2012 when an abrupt change occurred.

The Mann-Kendall test on the fatalities is shown in Figure 7. In the en-route phase, curve UF rose in a fluctuant way from 1942 to 1975, exceeded the critical value in 1965, and declined in a fluctuant way after 1975. UF intersects UB at a point in 2006 within the critical region, from when a downward trend was significant. An abrupt change occurred in 2006.

In the approach phase, curve UF exceeded the upper limit of the critical value in around 1960, from when the fatalities increased significantly; it moved downward and was lower than the upper limit of the critical value in around 2006, from when the fatalities decreased significantly. There was no obvious abrupt change in the fatalities in the approach phase.

4.3. Time Series Forecast on Key Indicators of Civil Aviation Accidents. As a time series analysis method, an ARIMA model requires a stationary time series. Nonstationary time is preprocessed to be stationary. First, take the natural logarithm of a time series to eliminate its heteroscedasticity; second, transform the time series into a stationary series with the first-order difference method. Through observation of the autocorrelation function (ACF) and the partial autocorrelation function (PACF) in Figure 8, this research makes a comparison between the parameters of the ARIMA models of high likelihood (Table 2). ACF and PACF are commonly used analytical methods for ARIMA models. The ARIMA parameter values p, d, and q can be determined by ACF and PACF maps. ACF and PACF are important methods for

Table 2: Comparison of parameters of different ARIMA models in global civil aviation accidents.

Model	AIC	C	R	Whether residual error sequence is white noise
ARIMA (1,0,1)	348.64	67%	0.82	No
ARIMA (1,1,1)	322.84	33%	0.56	No
ARIMA (1,0,1) Natural logarithm transformation	-246.79	74.15%	0.86	Yes
ARIMA (1,1,1) Natural logarithm transformation	-244.426	6.75%	0.26	Yes

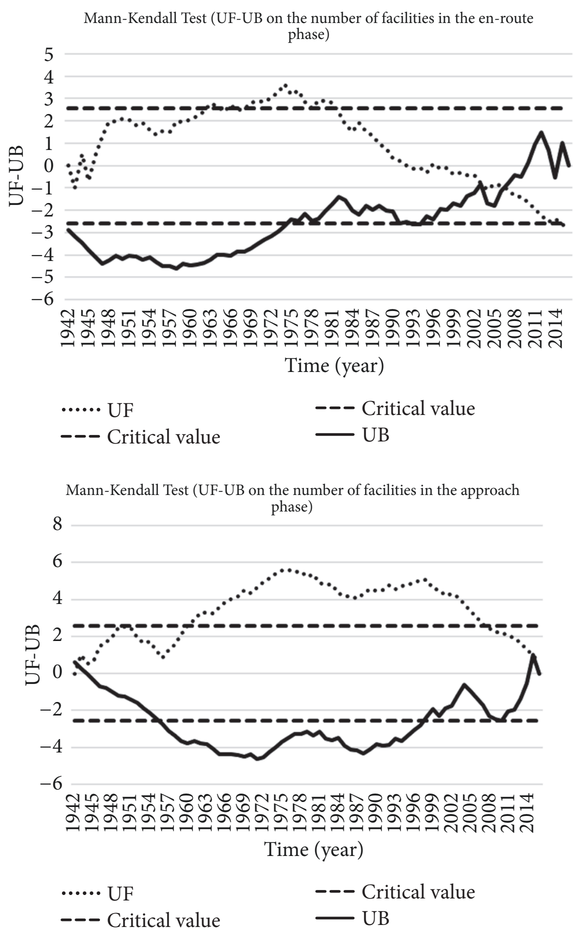

Figure 7: Mann-Kendall test of the number of global civil aviation casualties at different stages.

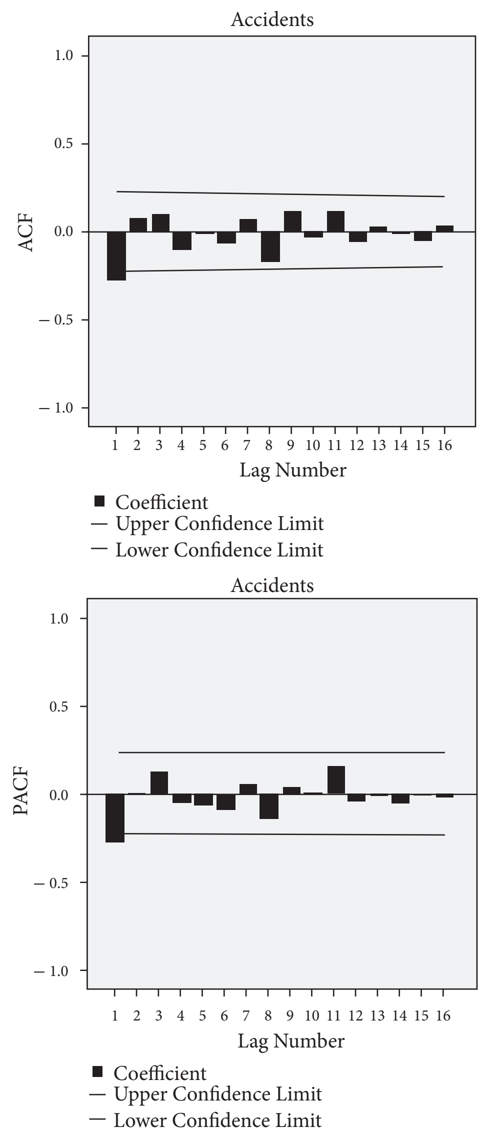

Figure 8: The correlation chart and partial correlation graph after global civil aviation accident time series difference.

determining the order of time series, which are used to analyze the truncation and smearing of time series. Truncation refers to the fact that the time series autocorrelation function (ACF) or partial autocorrelation function (PACF) is 0 after a certain order; smearing is a property in which ACF or PACF is not zero after a certain order. In the research of time series analysis, the two figures are commonly used to determine the parameters of ARIMA.

The models are selected based on AIC (Akaike info criterion), C (goodness of fit), and R (coefficient of correlation) and the fact whether the residual error sequence is white noise. AIC is a measure of the goodness of statistical model fit. It is based on the concept of entropy and can weigh the complexity of the estimated model and the goodness of the model fitting data. AIC, C, and R are common statistical model fitting criteria. In many researches, these three parameters are used to determine the simulation accuracy of the model.

Table 3: The actual value and forecast value of global civil aviation accidents.

Year	Actual value	Forecasted value	Relative error
2012	23	35.48	0.542
2013	29	25.87	-0.107
2014	20	28.82	0.441
2015	14	22.32	0.594
2016	17	16.23	-0.045
2017		17.57	
2018		18.29	
2019		19.01	
2020		19.73	
2021		20.43	
2022		21.18	
2023		22.48	
2024		23.14	
2025		23.79	

The smaller AIC is and the larger C and R are, the higher the accuracy of an ARIMA model becomes, and the residual error sequence should be white noise. Through comparison between the parameters in Table 1, ARIMA (1,0,1) is considered optimum through natural logarithm transformation, in which case AIC=-246.79, C=74.15%, and R=0.86, and the residual error sequence is white noise. This shows that there is no useful information in the residual error sequence, and the goodness of fit is high. Accordingly, the model may be used to forecast the time series of the number of civil aviation accidents worldwide.

The ARIMA (1,0,1) model is used to fit the number of civil aviation accidents in 1942-2016. The observed and fitted values are given in Figure 9. As the root-mean-square error (RMSE) and the mean absolute error (MAE) of the model are 9.9 and 7.4, respectively, the requirement of low error is met. To improve the forecast accuracy, with the rolling forecast method, this research forecasts the number of the civil aviation accidents in 2017-2020 using the model built in accordance with the data of 1942-2016 and then adds the forecasted values into the original time series to build a model with a new series for forecasting the number of civil aviation accidents in 2021-2025. Forecast results are listed in Table 3.

Likewise, the ARIMA model is used to forecast the fatalities of civil aviation accidents worldwide, which will not be discussed here due to limited space. ARIMA (1,0,1) is finally selected as the optimum model through natural logarithm transformation, in which case AIC=-146.57, C=50.92%, R=0.71, and the residual error sequence is white noise. Forecast results are listed in Table 4.

There is a large relative error between the forecasted values and the actual values of the number and fatalities of civil aviation accidents worldwide in 2012-2016, especially the fatalities in 2013 and 2015. From the perspective of the whole time series, the time series model selected is highly accurate; that is, the overall residual error is minimum. In this study, the ARIMA model is used to predict the time series of aviation accidents. Due to the instability of the time series, the overall simulation accuracy can only be guaranteed. However, for a certain year, there may be problems with poor prediction accuracy. In other prediction models exists the same question.

With the improvement of the technology in the aviation industry, especially in terms of the automatic level of aircraft and air traffic control, there will be a great decrease in the number of civil aviation accidents arising from mechanical breakdown and automation failure. However, human factors (misoperation of aviators and controllers) and emergencies (extreme weather) will become the main causes of civil aviation accidents in the future. Related studies show that since 1980s the rate of civil aviation accidents worldwide had been kept at a low level (http://news.carnoc.com/list/316/316196.html) and slowly reduced. This is similar to the conclusion of this research.

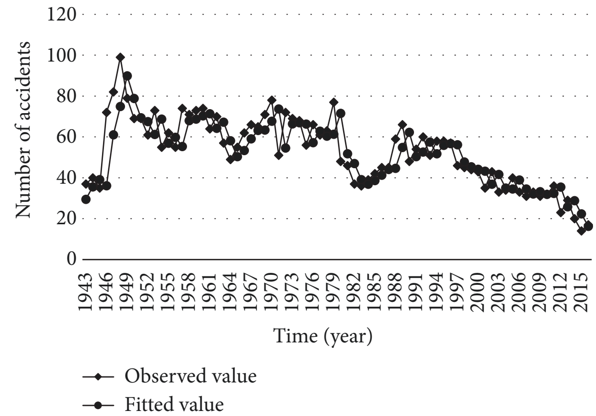

Figure 9: The actual value and fitting value of global civil aviation accidents.

Table 4: The actual value and forecast value of global civil aviation casualties.

Year	Actual value	Forecasted value	Relative error
2012	475	699	0.47
2013	265	609	1.29
2014	691	442	-0.36
2015	186	583	2.13
2016	258	370	0.43
2017		348	
2018		386	
2019		424	
2020		461	
2021		497	
2022		532	
2023		566	
2024		597	
2025		627	

5. Conclusion and Discussion

In combination with the data concerning the number and fatalities of civil aviation accidents worldwide, based on the Mann-Kendall trend analysis and abrupt analysis as well as the ARIMA model for time series forecast, this research analyzes the change trend and the node of abrupt change in relation to the number and the fatalities of accidents in different flight phases and forecasts the number and the fatalities by the end of 2025, drawing the following conclusions.

(1) On the whole, the number of civil aviation accidents worldwide reduced in a fluctuant way. In 1942-2016, there were two periods of change in the number of accidents. The number increased by 70 in the first period (1942 -1948) and by 30 in the second period (1983-1989) and reduced by 63 in the first period (1948-1983) and by 52 in the second period; during the two periods, the increment of the accidents reduced from 10 to 4 per year, and the decrement increased from 1.5 to 1.8 per year. There was a significant difference between the trends of change in the number and the fatalities of civil accidents worldwide. The fatalities first increased and then reduced, showing a parabolic trend, and 1972 was the year when the fatalities reached the maximum.

(2) In different flight phases, the number of aviation accidents was different, which was maximum in the en-route and approach phases and minimum in the take-off and landing phases; there was a large difference between different flight phases in the fatalities, especially in the en-route and approach phases; the fatalities were high and over a half of the total in all flight phases and changed in a similar manner.

(3) According to the result of Mann-Kendall trend analysis, the number of accidents in all flight phases other than the landing phase significantly reduced, but the fatalities significantly reduced only in the en-route phase, and the downward trend in fatalities was not significant in other phases. According to the result of Mann-Kendall abrupt change analysis, there was no abrupt change in the number and fatalities of accidents in the approach phase. 2013, 1980, 2012, and 2006 were the years when there was an abrupt change in the fatalities, the number of accidents in the en-route phase, the number of accidents in the approach phase, and the fatalities in the en-route phase, respectively.

(4) Through observation of the ACF and PACF of stationary series and analysis of the model accuracy, the ARIMA (1,0,1) model is selected to forecast the time series of the number and fatalities of civil aviation accidents worldwide, obtaining the forecasted values of the two by the end of 2025.

Forecasts of the number and fatalities of civil aviation accidents may be used as a reference for civil aviation safety management. With the extension of forecast period, the forecast error will gradually increase, and the accuracy will reduce. Thanks to the ARIMA model, the forecasts of the number and fatalities of accidents are highly accurate. Despite a large relative error of forecast from 2011 to 2025, ARIMA (1,0,1), whose residual error is minimum, is considered optimum from the perspective of overall time series. This research also forecasts the data concerning civil aviation accidents using the grey system forecast model GM(1,1), but the forecast results are poorly accurate, which are uncovered herein due to limited space.

Aviation accident analysis is an important part of aviation safety research. We used long-term sequence aviation accident statistics to analyze the characteristics of historical aviation accidents and predict the future direction of aviation accidents. The research methods we mainly use included statistical analysis and time series prediction, and some valuable conclusions have been made. The occurrence of aviation accidents is a complicated process, which may happen because of various reasons, including aircraft stability, climatic conditions, and human factors of the crew. Because the cause of aviation accidents is extremely complicated and it is impossible to construct a model to predict, we analyze the time variation of the aviation accident itself and use the time series analysis method to predict the number of future aviation accidents and the number of casualties. From the perspective of long-term sequence, the occurrence of aviation accidents has certain time regularity, which may be the result of a combination of various factors. But how to lead to the final occurrence of aviation accidents, the current research has no positive conclusions; we explored the time regularity of aviation accidents. In the future, we can explore the mechanism of aviation accidents and try to construct an accident mechanism model to simulate and analyze the process of aviation accidents.

To improve the accuracy of time series forecast in the future, other dependent variables like GDP (Gross Domestic Product), population, number of airports, and investment may be considered, and multiple independent variable forecast models may be used to conduct time series forecast. Through the analysis of historical aviation accident time series data, the characteristics of aviation accident data were obtained, and the possible trend of future global aviation accidents was predicted by ARIMA model. In the research, we only considered the variation characteristics of the aviation accident time series itself and did not consider other influencing factors and the changes of these influencing factors over time. Therefore, in future research work, the mechanism and process of aviation accidents should be analyzed in combination with the possible influencing factors of the aviation accidents, and intelligent models should be constructed to further improve the accuracy of prediction. In addition, from the aspect of data acquisition, aviation accidents are related to flight schedules. The more the flights, the higher the frequency of aviation accidents. Therefore, the flight schedule data corresponding to aviation accidents is also an important content of research. It has not yet been involved in the research. Flight schedule data should be collected as a supplement to improve the model precision in the future.

Data Availability

The aviation accidents data used to support the findings of this study may be released upon application to the Aviation Safety Network, who can be contacted at (https://aviation-safety.net).

Conflicts of Interest

The author declares that there are no conflicts of interest regarding the publication of this paper.

Acknowledgments

This study was supported by the National Natural Science Foundation of Tianjin (17JCQNJC08600) and National Natural Science Foundation of China (41501430, 61603396).

References

[1] G. D. Edkins, "The INDICATE safety program: evaluation of a method to proactively improve airline safety performance," *Safety Science*, vol. 30, no. 3, pp. 275–295, 1998.

[2] Y. G. Wang and X. M. Lu, "Grey relation analysis and grey model for civil aviation accidents forecasting," *Journal of Safety and Environment*, vol. 6, no. 6, pp. 127–130, 2006.

[3] Q. Cui and Y. Li, "The change trend and influencing factors of civil aviation safety efficiency: the case of Chinese airline companies," *Safety Science*, vol. 75, pp. 56–63, 2015.

[4] R. Greenberg, S. C. Cook, and D. Harris, "A civil aviation safety assessment model using a Bayesian belief network (BBN)," *The Aeronautical Journal*, vol. 109, no. 1101, pp. 557–568, 2016.

[5] G. Tamasi and M. Demichela, "Risk assessment techniques for civil aviation security," *Reliability Engineering & System Safety*, vol. 96, no. 8, pp. 892–899, 2011.

[6] J. Y. Ye, "Risk assessment of human factors in aviation safety using hazard regression model," *Environmental Earth Sciences*, vol. 65, no. 7, pp. 2063–2077, 2012.

[7] J. Verbesselt, R. Hyndman, A. Zeileis, and D. Culvenor, "Phenological change detection while accounting for abrupt and gradual trends in satellite image time series," *Remote Sensing of Environment*, vol. 114, no. 12, pp. 2970–2980, 2010.

[8] O. N. Bjørnstad and B. T. Grenfell, "Noisy clockwork: time series analysis of population fluctuations in animals," *Science*, vol. 293, no. 5530, pp. 638–643, 2001.

[9] L.-I. Cioca and L. Ivascu, "Risk indicators and road accident analysis for the period 2012-2016," *Sustainability*, vol. 9, no. 9, pp. 1530–1545, 2017.

[10] P. Taherei Ghazvinei, H. Hassanpour Darvishi, A. Mosavi et al., "Sugarcane growth prediction based on meteorological parameters using extreme learning machine and artificial neural network," *Engineering Applications of Computational Fluid Mechanics*, vol. 12, no. 1, pp. 738–749, 2018.

[11] R. Taormina, K.-W. Chau, and B. Sivakumar, "Neural network river forecasting through baseflow separation and binary-coded swarm optimization," *Journal of Hydrology*, vol. 529, pp. 1788–1797, 2015.

[12] M. Roozbeh, M. Babak, S. Shahaboddin, and C. Kwok-wing, "Coupling a firefly algorithm with support vector regression to predict evaporation in northern Iran," *Engineering Applications of Computational Fluid Mechanics*, vol. 12, no. 1, pp. 584–597, 2018.

[13] C. L. Wu and K. W. Chau, "Rainfall-runoff modeling using artificial neural network coupled with singular spectrum analysis," *Journal of Hydrology*, vol. 399, no. 3-4, pp. 394–409, 2011.

[14] N. Bahman, F. A. Sina, S. Shahaboddin et al., "Application of ANNs, ANFIS and RSM to estimating and optimizing the parameters that affect the yield and cost of biodiesel production," *Engineering Applications of Computational Fluid Mechanics*, vol. 12, no. 1, pp. 611–624, 2018.

[15] K. W. Chau, "Use of meta-heuristic techniques in rainfall-runoff modelling," *Water*, vol. 9, no. 3, p. 186, 2017.

[16] N. Gouveia and T. Fletcher, "Time series analysis of air pollution and mortality: effects by cause, age and socioeconomic status," *Journal of Epidemiology and Community Health*, vol. 54, no. 10, pp. 750–755, 2000.

[17] Y. L. Chen and Z. J. Zhao, "A multi-step-ahead prediction of ozone concentration using wavelet transform and traditional time series model," *Acta Scientiae Circumstantiate*, vol. 33, no. 2, pp. 339–345, 2013.

[18] A. Russo and A. O. Soares, "Hybrid model for urban air pollution forecasting: a stochastic spatio-temporal approach," *Mathematical Geosciences*, vol. 46, no. 1, pp. 75–93, 2014.

[19] A. Reiter, R. Weidinger, and W. Mauser, "Recent climate change at the upper danube-a temporal and spatial analysis of temperature and precipitation time series," *Climatic Change*, vol. 111, no. 3, pp. 665–696, 2012.

[20] T. A. Buishand and J. J. Beersma, "Jackknife tests for differences in autocorrelation between climate time series," *Journal of Climate*, vol. 6, no. 6, pp. 2490–2500, 2009.

[21] C. L. Wu, K. W. Chau, and C. Fan, "Prediction of rainfall time series using modular artificial neural networks coupled with data-preprocessing techniques," *Journal of Hydrology*, vol. 389, no. 1-2, pp. 146–167, 2010.

[22] A. W. Jayawardena and F. Lai, "Analysis and prediction of chaos in rainfall and stream flow time series," *Journal of Hydrology*, vol. 153, no. 1–4, pp. 23–52, 1994.

[23] R. Luginbuhl and A. De Vos, "Bayesian analysis of an unobserved-component time series model of GDP with markov-switching and time-varying growths," *Journal of Business and Economic Statistics*, vol. 17, no. 4, pp. 456–465, 1999.

[24] H. D. Long and G. L. Yan, "Research on GDP time series forecasting based on integrating SARIMA, GM(1,1) and BP neural networks," *Journal of Applied Statistics and Management*, vol. 32, no. 5, pp. 814–822, 2013.

[25] R. Luginbuhl and A. de Vos, "Seasonality and Markov switching in an unobserved component time series model," *Empirical Economics*, vol. 28, no. 2, pp. 365–386, 2003.

[26] Q. Huang, H. X. Su, J. Wang, and W. X. Huang, "A prediction method for aero-engine health management based on nonlinear time series analysis," in *Proceedings of the IEEE International Conference on Prognostics and Health Management*, pp. 1–8, IEEE, San Francisco, CA, USA, Apirl 2016.

[27] X. J. Ma, S. H. Ren, H. F. Zuo, and Z. H. Wen, "Prediction method of aero-engine life on wing based on LS-SVM algorithm and performance reliability," *Journal of Traffic and Transportation Engineering*, no. 3, pp. 92–100, 2015.

[28] H. L. Cao, Z. M. Wu, C. G. Qu, and L. P. Kang, "Life on wing prediction of aero engine based on CBM strategy," *China Mechanical Engineering*, vol. 26, no. 13, pp. 1725–1760, 2015.

[29] G. E. P. Box and G. M. Jenkins, "Time series analysis, forecasting and control, holden-day," *Journal of the Royal Statistical Society*, vol. 134, no. 3, pp. 20–30, 1976.

[30] W. J. Huang, H. X. Cao, L. Gu, and J. T. Xiang, "Application of ARIMA seasonal model of time series to long range forecast," *Science Bulletin*, vol. 25, no. 22, pp. 1030–1032, 1980.

[31] A. Samant, "Enhancing neural network traffic incident-detection algorithms using wavelets," *Computer-Aided Civil and Infrastructure Engineering*, vol. 16, no. 4, pp. 239–245, 2010.

[32] J. Hinkelbein, M. Schwalbe, C. Neuhaus, W. A. Wetsch, and H. V. Genzwürker, “Incidents, accidents and fatalities in 40 years of German helicopter emergency medical system operations,” *European Journal of Anaesthesiology*, vol. 28, no. 11, pp. 766–773, 2011.

[33] R. R. Fullwood, R. E. Hall, G. Martinez-Guridi, S. Uryasev, and S. G. Sampath, “Relating aviation service difficulty reports to accident data for safety trend prediction,” *Reliability Engineering & System Safety*, vol. 60, no. 1, pp. 83–87, 1998.

[34] W. R. Knecht, “The “killing zone” revisited: serial nonlinearities predict general aviation accident rates from pilot total flight hours,” *Accident Analysis & Prevention*, vol. 60, no. 60C, pp. 50–56, 2013.

[35] L. N. Zhao, S. B. Song, B. Hao, and Y. Y. Hou, “Identification of annual runoff series trend,” *Journal of Northwest A & F University*, vol. 38, no. 3, pp. 194–198, 2010.

[36] Z. Li, F.-L. Zheng, W.-Z. Liu, and D. C. Flanagan, “Spatial distribution and temporal trends of extreme temperature and precipitation events on the loess plateau of China during 1961–2007,” *Quaternary International*, vol. 226, no. 1, pp. 92–100, 2010.

[37] L. Y. Fu, S. Z. Tang, Y. G. Liu et al., “Developing, testing and application of rodent population dynamics and capture models based on an adjusted Leslie matrix-based population approach,” *International Journal of Biomathematics*, vol. 7, no. 3, pp. 88–285, 2014.