Research on O₃ Concentration Monitoring Data in Aircraft Cabin

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Abstract. The paper explored the hourly and daily characteristics of O₃ concentration monitoring data in aircraft cabin by micro air monitor, and proposed the additive model for O₃ considering the influence of internal and external factors. Linear interpolation filling the missing values could effectively solve the problem of data missing and improved the effect of the additive model of ARIMA and multiple regressions. The additive calibration model by ARIMA and Multiple regressions for O₃ was reconstructed based on linear interpolation filling. The error analysis showed that the accuracy of O₃ was improved. The prediction effect was also improved by considering the interaction effect.

1. Introduction
Aircraft is exposed to the high concentration ozone (O₃) environment in the stratosphere when aircraft is flying at high altitude. The cruising altitude of the aircraft is about 5490-12500 M, and O₃ concentration in the air is relatively high, about 1071-1714 ug / m³ at the altitude over 10000 m [1]. Moreover, the intensity of cosmic rays is also increasing with the increase of altitude and latitude. O₃ is formed by photochemical reactions in the atmosphere under the condition of UV and precursor pollutants such as nitrogen oxides (NOx) and volatile organic compounds (VOCs) [2]. The air containing O₃ enters the aircraft cabin through the air conditioning system, and some O₃ would be decomposed and automatically be reduced to oxygen (O₂) by the high temperature. Some O₃ still could enter the aircraft cabin directly, and only a part of O₃ could be removed by the ventilation system of the aircraft. Due to the small space and dense personnel in aircraft cabin, once toxic and harmful gases appear, the concentration may rise rapidly [3].

O₃ has strong oxidizing and irritant properties. Its water solubility is small and it is easy to enter the deep part of respiratory tract. It has adverse effects on the respiratory system and cardiovascular system of aircrew and passengers, especially long working aircrew, infants and adults with cardiopulmonary disease [4]. O₃ could also react with aircraft cabin interior materials to produce more complex and harmful oxides, resulting in secondary pollution. It not only seriously affects the air quality in the aircraft cabin, but also causes more harm to human and cabin materials [5]. The problem of O₃ pollution and its concentration control is important in aircraft cabin environmental control research.

According to the special aircraft cabin environment and the airworthiness requirements of civil aviation, the aircraft cabin environment must be measured and evaluated in the aircraft type test. O₃ concentration is related to altitude, longitude and latitude, season and weather conditions. The monitoring methods and instruments of O₃ concentration are limited due to the particularity of the aircraft [6].
We reviewed the O$_3$ concentration monitoring data in aircraft cabin environment by micro air monitor and found that the monitoring data was mainly affected by internal and external factors. O$_3$ concentration monitoring data conformed to time series and ARIMA model could be used to describe the trend before and after its own data. It was affected by meteorology factors, namely wind, pressure, precipitation, temperature, and humidity, and multiple linear regressions could be used to describe the influence of the meteorology factors. It showed an additive relationship so that an additive calibration model was established.

The paper was structured as follows. Part 2 was the exploratory analysis for the additive model based on ARIMA and multiple linear regressions. Part 3 was the model was the additive model based on linear interpolation filling. Part 4 was the error analysis. The relative errors were calculated and compared. Part 5 was the conclusion.

2. Exploratory Analysis
We explored the hourly and daily characteristics of O$_3$ concentration monitoring data in aircraft cabin by micro air monitor.

O$_3$ concentration was significantly higher in winter and spring than that in summer and autumn, whether the average concentration or the concentration in a certain period of a day (P<0.001). The highest O$_3$ concentration was in December. The lowest O$_3$ concentration was in August. The change within one day was unimodal, which was closely related to the atmospheric photochemical reaction process and changed with the change of solar radiation intensity. From 0:00 a.m. to 6:00 a.m., hourly O$_3$ concentration gradually decreased, but the change was not significant. The lowest concentration of O$_3$ was at 6:00 a.m. Since then, due to the enhancement of photochemical reaction, the concentration of O$_3$ gradually increased. It rose to 13:00-15:00 and reached the highest value in the day, then decreased gradually with the weakening of photochemical reaction, and the change became stable at 21:00 (Fig.1).

Correlation analysis showed that O$_3$ concentration was negatively correlated with wind and precipitation, positively correlated with pressure, temperature and humidity (Table 1).

| Statistics | Wind   | Pressure | Precipitation | Temperature | Humidity |
|------------|--------|----------|---------------|-------------|----------|
| r          | -0.4901| 0.2533   | -0.5428       | 0.4800      | 0.3277   |
| p          | <0.0001| <0.0001  | <0.0001       | <0.0001     | <0.0001  |

We remodeled O$_3$ concentration monitoring data with meteorological factors. We divided the variation of the dependent variable (Y) into two parts. Its internal factor (A) and the external factor (B). The internal factor was caused by its autocorrelation. The external factor was caused by meteorological factors. The two parts were additive.

\[
Y = A + B
\]

2.1. A based on ARIMA
A was the predicted value of O$_3$ concentration monitoring data of apron by micro air monitor based on ARIMA. ARIMA model was a famous time series model proposed by Box and Jenkins. It mainly
included the following three forms [7]. Maximum likelihood estimation method was used for parameter estimation.

AR (Auto-regressive) :  
\[ \Delta x_t = \sum_{j=1}^{p} \varphi_j x_{t-j} \]  
(2)

MA (Moving-Average) :  
\[ \Delta x_t = \mu_t + \sum_{j=1}^{q} \theta_j x_{t-j} \]  
(3)

ARMA :  
\[ \Delta x_t = \mu_t + \sum_{j=1}^{p} \varphi_j x_{t-j} + \sum_{j=1}^{q} \varphi_j x_{t-j} \]  
(4)

2.2. B based on multiple regression

Considering external meteorology factors, the difference between O\(_3\) concentration monitoring data in aircraft cabin by micro air monitor and the standard data by estimation model of ICAO was the dependent variable, and meteorology factors were the independent variables (VAR1~VAR5, i.e., wind, pressure, precipitation, temperature, humidity). B was based on multiple regressions based on the least square method for parameter estimation [8].

We considered the simple linear regression and interactive regression model.

\[ B = \Delta = \beta_0 + \beta_1 VAR1 + \beta_2 VAR2 + \beta_3 VAR3 + \beta_4 VAR4 + \beta_5 VAR5 + \beta_6 VAR12 + \cdots \]  
(5)

VAR12=VAR1*VAR2, namely the interactive effect between VAR1 and VAR2, and so on.

3. Model based on linear interpolation filling

Since the time interval of the O\(_3\) concentration monitoring data was inconsistent and the lowest common multiple was huge, it was considered that it may lead to higher bias of the model if the huge time interval was ignored. In order to prevent this kind of situation, we adopt linear interpolation to fill the missing [9].

\[ y = \frac{y_2-y_1}{t_2-t_1} (t-t_1) + y_1 \]  
(6)

Where, \( y \) and \( t \) referred to the variable value and time to be filled, respectively. \( y_2 \) and \( t_2 \) referred to the observation value and time of monkey at a recorded time point. \( y_1 \) and \( t_1 \) referred to the observation value and time of the previous recorded time point.

The ACF and the PACF of O\(_3\) concentration data showed that it was basically stable. So, the difference order was set as \( d=1 \). By comparing the BIC values, we got the minimum BIC (0, 2) =5.025046 of ARIMA model when \( p=0 \) and \( q=2 \). So, ARIMA (0, 2, 0) was finally used to predict O\(_3\) concentration.
| Parameter | Estimate | SD  | t   | P     | Lags |
|-----------|----------|-----|-----|-------|------|
| MA1,1     | 0.97915  | 0.0049618 | 197.34 | <0.0001 | 1    |
| AR1,1     | 1.40198  | 0.02398  | 58.47 | <0.0001 | 1    |
| AR1,2     | -0.46695 | 0.03971  | -11.76| <0.0001 | 2    |
| AR1,3     | 0.06496  | 0.02459  | 2.64  | 0.0083  | 3    |

| Variable | Estimate  | SD   | SS   | F     | P     |
|----------|-----------|------|------|-------|-------|
| Intercept| 857.74882 | 157.84276 | 37857 | 29.53 | <0.0001 |
| VAR1     | 19.23579  | 1.15370 | 356372| 277.99| <0.0001 |
| VAR2     | -0.83056  | 0.15191 | 38322 | 29.89 | <0.0001 |
| VAR3     | -0.12233  | 0.00673 | 423155| 330.09| <0.0001 |
| VAR4     | 0.87709   | 0.17449 | 32391 | 25.27 | <0.0001 |
| VAR5     | -0.46702  | 0.03683 | 206080| 160.76| <0.0001 |

| Variation | df | SS    | MS   | F     | P    |
|-----------|----|-------|------|-------|------|
| Model     | 5  | 357933 | 71587| 437.96| <0.0001|
| Errors    | 3409 | 557216 | 163.45450 |
| Total     | 3414 | 91550 |

| Variable | Estimate  | SD   | SS   | F     | P     |
|----------|-----------|------|------|-------|-------|
| Intercept| -3364.52873 | 469.59363 | 60457 | 51.33 | <0.0001 |
| VAR1     | 23.07358  | 5.16527 | 23501 | 19.95 | <0.0001 |
| VAR2     | 3.23053   | 0.45647 | 58989 | 50.09 | <0.0001 |
| VAR4     | 62.83001  | 7.54856 | 81592 | 69.28 | <0.0001 |
| VAR5     | 55.59120  | 6.16994 | 95608 | 81.18 | <0.0001 |
| VAR13    | -0.05266  | 0.01174 | 23685 | 20.11 | <0.0001 |
| VAR14    | -0.42118  | 0.15527 | 8665.99660 | 7.36 | 0.0067 |
| VAR15    | 0.09954   | 0.05449 | 3930.93181 | 3.34 | 0.0678 |
| VAR24    | -0.05646  | 0.00745 | 67592 | 57.39 | <0.0001 |
| VAR25    | -0.05385  | 0.00600 | 94786 | 80.48 | <0.0001 |
| Variation | df | SS    | MS   | F      | P    |
|-----------|----|-------|------|--------|------|
| Model     | 12 | 3456425 | 288035 | 244.57 | <0.0001 |
| Errors    | 4121 | 4853387 | 1177.72081 |       |       |
| Total     | 4133 | 8309813 |       |        |       |

**Table 6 ANOVA for Interactive Regression**

4. Discussions
In this part, we mainly focused on the prediction validity of the model. After removing the samples for the modelling, the remaining samples were used to test the prediction precision. We compared the predictive values (PV) and the standard values (SV), and calculated the average relative error to evaluate the calibration effects.

\[
\text{Average relative error} = \frac{|PV - SV|}{SV \times n}
\]  

We got the predictive values by the additive calibration models based on linear interpolation filling. We also compared the monitoring data on ARIMA and monitoring data. The results were showed in Table 4.1.

The prediction effect of the additive calibration models was higher than that of ARIMA and monitoring data. The prediction effect was improved by considering the interaction effect.
| O3 | Y = A + B | ARIMA | Monitoring Data |
|----|----------|------|----------------|
|    | Linear   | Interactive |              |
|    | 0.4102   | 0.3399     | 0.6879        | 0.6853        |

5. Conclusion
The paper proposed the additive model for O3 concentration monitoring data considering the influence of internal and external factors. At the same time, the lack of monitoring data would lead to the poor fitting effect of the model. The paper proposed linear interpolation to fill the missing data, reconstruct the model, and calculated the average relative errors.

The prediction effect of additive calibration model based linear interpolation filling for O3 concentration was better. The prediction effect was improved by considering the interaction effect. O3 concentration is related to altitude, longitude and latitude, season and weather conditions. It is also related to aircraft type, number of people in aircraft cabin, airborne equipment, etc. We would study O3 concentration monitoring data in aircraft cabin of different dimensions, routes and types by micro air monitor next. The study was useful to the monitoring and control of air quality in aircraft cabin environment. Accurate monitoring data could provide reference for the further study of the efficiency of aviation O3 converter.

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