Analysis of CO Concentration Monitoring Data in Apron Environment

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Abstract. The paper analysed CO concentration monitoring data in apron environment to explore the influence factors, and proposed the additive model for CO 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 multivariate linear regression. The additive calibration model by ARIMA and Multiple regressions for CO was reconstructed based on linear interpolation filling. The error analysis showed that the accuracy of CO was improved. The prediction effect was also improved by considering the interaction effect.

1. Introduction

The rapid development of air transport industry had brought about the continuous growth of air carbon emissions and the increasing impact on the environment. More and more attention had been paid to the aviation carbon emissions with the increasing global climate problem. According to the data released by the EPA of USA, the nitrogen oxide (NOx) and carbon monoxide (CO) produced by aero engines in USA accounted for 2% of the total NOx and CO produced by mobile pollution sources, and could reach 4% in the area near the airport, and the emissions of civil aero engines increase the fastest [1].

CO was the most widely distributed and numerous pollutants in the atmosphere. It was the product of incomplete combustion of carbonaceous materials. The main source of CO in the atmosphere was the exhaust of internal combustion engine, followed by the combustion of fossil fuel in boiler. CO was a colourless, tasteless, odourless toxic gas, which was difficult to dissolve in water. It was a very toxic pollutant to blood and nervous system. The difference between gas density and air density was very small under standard conditions, which was easy to be ignored and lead to poisoning.

The automatic monitoring system of urban air environment was mainly built in the streets and parks, focusing on the monitoring of particles in the air. With the coverage of outdoor air environment monitoring, the focus of air quality monitoring was gradually shifting, especially the public transport places will become the next focus of environmental concern since 2018[2]. As the place for flight take-off and landing, passenger turnover and ground work, the air quality of the airport had a significant impact on passengers, aviation enterprise staff and surrounding residents. Chinese Ministry of environmental protection issued the approval principle of environmental impact assessment documents for airport construction projects, and proposed to set up an automatic monitoring system of airport ambient air quality for airports with annual passenger throughput (short-term or long-term) of more than 10 million people in 2018[3]. With the advantages of flexiblity, real-time and economy, micro air monitors would be more and more widely used in apron, air terminal, passenger cabin and other places.
CO emitted by aviation had an increasing impact on the environment and climate. Aviation energy conservation and emission reduction is an important task for the government and every airline, and an important part of green civil aviation construction. There were two aspects in the study of the impact of aviation emissions on the environment, i.e. aircraft takeoff and landing stage and aircraft cruise stage. The aircraft emission area was concentrated and the emission density was high during the take-off and landing stage, accounting for about 25% of the whole flight process, which has a significant impact on the air quality near the ground [4]. The main factor affecting CO emission was the excess air coefficient of combustible mixture. In the process of take-off, the CO emission was very large when the aircraft was in full load operation and cold start. In the process of landing, the CO emission would increase when the oil supply control of deceleration transition condition was poor. In addition, the ground support equipment, tail gas of aircraft auxiliary power unit, vehicles entering and leaving the airport, boilers, oil depots, etc. will produce air emissions, which had a significant impact on the airport and its surrounding areas. There were many pollution sources in the airport, the operation mode was changeable, involving many variables, and the comprehensive calculation model was complex [5].

Experts and scholars had done a lot of research on aviation emissions. Developed countries began the relevant research as early as the 1950s. Domestic research had also been launched with the rapid development of Chinese air transport industry. The primary purpose of aviation emissions research was to obtain the estimation of aviation emission. The main research methods were modelling research and monitoring research. International Civil Aviation Organization (ICAO) had developed the emissions database of aircraft type, and the emissions estimation models could be established based on the emissions standards [6]. Monitoring method was the most commonly used research method. The most direct data was obtained through the monitors at the relevant locations.

We reviewed the CO concentration monitoring data in apron environment by micro air monitor and found that the monitoring data was mainly affected by internal and external factors. CO 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 addictive model based on linear interpolation filling. Part 4 was the error analysis. The relative errors were computed and analysed. Part 5 was the conclusion.

2. Exploratory Analysis

In this part, we remodeled CO concentration monitoring data of apron by micro air monitor combined 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.

\[ Y = A + B \]  

(1)

2.1. A based on ARIMA

A was the predicted value of CO 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.

\[
\text{AR (Auto-regressive)} : \quad \Delta x_t = \sum_{j=1}^{p} \varphi_j x_{t-j} \quad (2) \\
\text{MA (Moving-Average)} : \quad \Delta x_t = \mu_t + \sum_{j=1}^{q} \theta_j x_{t-j} \quad (3) \\
\text{ARMA} : \quad \Delta x_t = \mu_t + \sum_{j=1}^{p} \varphi_j x_{t-j} + \sum_{j=1}^{q} \theta_j x_{t-j} \quad (4)
\]
2.2. B based on multiple regression
Considering external meteorology factors, the difference between CO concentration monitoring data of apron by micro air monitor and the standard data by emission 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.

\[ B = \Delta = \beta_0 + \beta_1 \text{VAR1} + \beta_2 \text{VAR2} + \beta_3 \text{VAR3} + \beta_4 \text{VAR4} + \beta_5 \text{VAR5} + \beta_6 \text{VAR12} + \cdots \]  

\[ \text{VAR12} = \text{VAR1} \times \text{VAR2}, \text{namely the interactive effect between VAR1 and VAR2, and so on.} \]

3. Model based on linear interpolation filling
Since the time interval of the CO 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].

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

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 CO concentration data showed that it was basically stable. So, the difference order was set as d=0. By comparing the BIC values, we got the minimum BIC (3, 1) =-3.64191 of ARIMA model when p=3 and q=1. So, ARIMA (0, 3, 1) was finally used to predict CO concentration. The parameters of ARIMA model based on Maximum Likelihood Estimation were showed in Table1.
### Table 1: Maximum Likelihood Estimation for CO

| 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    |

### Table 2: Parameter Estimate by Multiple Linear Regression for CO

| Variable | Estimate | SD     | SS        | F         | P     |
|----------|----------|--------|-----------|-----------|-------|
| Intercept| 36.84781 | 1.90499| 69.86278  | 374.14    | <0.0001|
| VAR1     | -0.10547 | 0.01392| 10.71345  | 57.38     | <0.0001|
| VAR2     | -0.03504 | 0.00183| 68.20465  | 365.26    | <0.0001|
| VAR3     | 0.00034993| 0.0008126| 3.46260  | 18.54     | <0.0001|
| VAR4     | -0.04129 | 0.00211| 71.77304  | 384.38    | <0.0001|
| VAR5     | -0.00188 | 0.00044455| 3.32771  | 17.82     | <0.0001|

### Table 3: ANOVA for Multiple Linear Regression

| Variation | df | SS        | MS        | F         | P     |
|-----------|----|-----------|-----------|-----------|-------|
| Model     | 5  | 177.17965 | 35.43593  | 222.84    | <0.0001|
| Errors    | 4128 | 656.43371 | 0.15902   |           |       |
| Total     | 4133 | 833.61336 |           |           |       |

### Table 4: Parameter Estimate by Interactive Regression for CO

| Variable | Estimate | SD     | SS        | F         | P     |
|----------|----------|--------|-----------|-----------|-------|
| Intercept| 81.4667  | 6.15078| 27.58721  | 175.43    | <0.0001|
| VAR2     | -0.07951 | 0.00598| 27.83687  | 177.02    | <0.0001|
| VAR3     | 0.18207  | 0.02242| 10.37481  | 65.97     | <0.0001|
| VAR4     | -2.27564 | 0.09023| 100.03620 | 636.14    | <0.0001|
| VAR5     | -0.66151 | 0.07173| 13.37568  | 85.06     | <0.0001|
| VAR12    | -0.00012571| 0.00002116| 5.5507  | 35.29     | <0.0001|
| VAR14    | 0.00243  | 0.00156| 0.38073   | 2.42      | 0.1198 |
| VAR23    | -0.00017083| 0.00002151| 9.91729  | 63.06     | <0.0001|
| VAR24    | 0.00221  | 0.00008883| 97.62770 | 620.82    | <0.0001|
| VAR25    | 0.00065255| 0.00006984| 13.72721 | 87.29     | <0.0001|
| VAR34    | -0.00024815| 0.00002619| 14.11420 | 89.75     | <0.0001|
VAR35   -0.00006598    0.00000503  27.02121  171.83 <0.0001
VAR45    0.00026396    0.00006498  2.5945  16.50 <0.0001

Table 5 ANOVA for Interactive Regression

| Variation | df  | SS      | MS      | F     | P       |
|-----------|-----|---------|---------|-------|---------|
| Model     | 12  | 252.3343 | 21.0279 | 133.72 | <0.0001 |
| Errors    | 4121 | 648.0510 | 0.1573  |       |         |
| Total     | 4133 | 900.3854 |        |       |         |

Fig. 2 Forecast of CO Based on ARIMA

4. Discussions
In this part, we mainly focused on the prediction validity of the model. After removing the samples for the modeling, 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.

\[
\text{Average relative error} = \frac{|PV - SV|}{SV \times \pi}
\]
We got the predictive values by the additive calibration models based on linear interpolation filling. We also compared the monitoring data of ARIMA and monitoring data. The results were showed in Table 6.

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.

| CO     | Y = A + B         | ARIMA | Monitoring Data |
|--------|-------------------|-------|-----------------|
|        | Linear  | Interactive | 0.5245 | 0.5220 |
|        | 0.4511 | 0.3035       |       |        |

**5. Conclusion**

The paper proposed the additive model for CO concentration monitoring data considering the influence of internal and external factors. At the same time, the lack of monitoring data would be 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 CO concentration was better. The prediction effect was improved by considering the interaction effect.

The paper could effectively improve the monitoring accuracy of CO concentration in apron environment. The impact of apron ground equipment would be incorporated into the model to improve the monitoring accuracy next. The research could provide data reference for energy conservation and emission reduction of aviation enterprises.

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