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Prediction of Aero-Engine Exhaust Gas Temperature Based on Autoregressive Integrated Moving Average Model

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Abstract. Forecasting the performance of aero-engine is a crucial problem that facilitates the avoiding unnecessary delays of aircraft. By applying the Autoregressive Integrated Moving Average Model to aero-engine gas path system, we find that the ARIMA method is suitable for forecast Exhaust Gas Temperature fluctuation series. Further, we find the trend of predicted values and original values are similar and the error between them is small.

Introduction

Modern commercial aircraft require advanced prognostic and diagnostic schemes to determine engine performance in an effort to reduce operational and maintenance costs as well as limit aircrafts' downtime [1, 2]. For this purpose, Condition Based Maintenance (CBM), which decisions on operation and maintenance are based on the actual conditions reflected in sensor readings for aircraft are increasingly practiced by commercial airliners. Compared to traditional time based maintenance where maintenance schedules follow in regular intervals, CBM allows for the streamlining of maintenance procedures and potentially avoids unnecessary delays [3-5]. However, for the intention of streamlining maintenance procedures and avoiding unnecessary delays, the engine performance and health are need to estimate before upcoming flights.

This paper is focused on prediction of engine performance by applying Autoregressive Integrated Moving Average Model (ARIMA). The Autoregressive Integrated Moving Average Model offer the main advantage, ability to implicitly detect non-stationary in time series, catering for the complex non-stationary of aero-engine performance parameters.

The structure of the paper is as follows. In section 2, we focus on Autoregressive Integrated Moving Average Model enabling us to forecast the parameter characteristic of aero-engine. In section 3, we discuss the prediction of aero-engine Exhaust Gas Temperature time series. The conclusion of the paper is drawn in Section 4.

Methodology and Algorithm

ARIMA methodology.

ARIMA (p, d, q) methodology also allows models to be built that incorporate both autoregressive and moving average parameters together, where p represents the order of the autoregressive components, d is the number of differencing operators, and q means the highest order of the moving average term.

The choice of (p,d,q).

Here, we apply the ARIMA methodology to analyze the data of aircraft parameters collected at PW4000 aero-engine. Fig 1 show the Exhaust Gas Temperature (EGT) time series. By calculating the auto-correlative function and par-correlative function of the EGT series, we find that the EGT series is non-stationary and should be re-expressed such that they become stationary with respect to the variance and the mean. After first order difference of the original time series, the stationeriness is appeared (see Fig 2). And then, we employ the Minimum information criterion (AIC) to determine ARIMA(3,1,2).

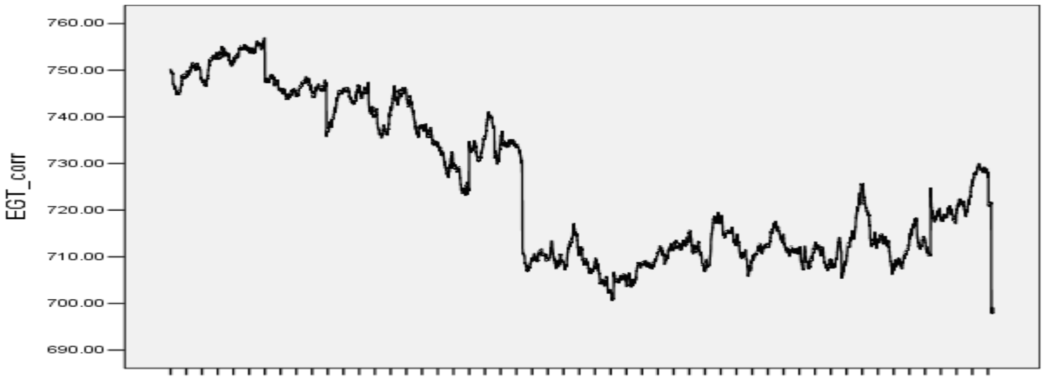

Fig. 1 the Exhaust Gas Temperature time series

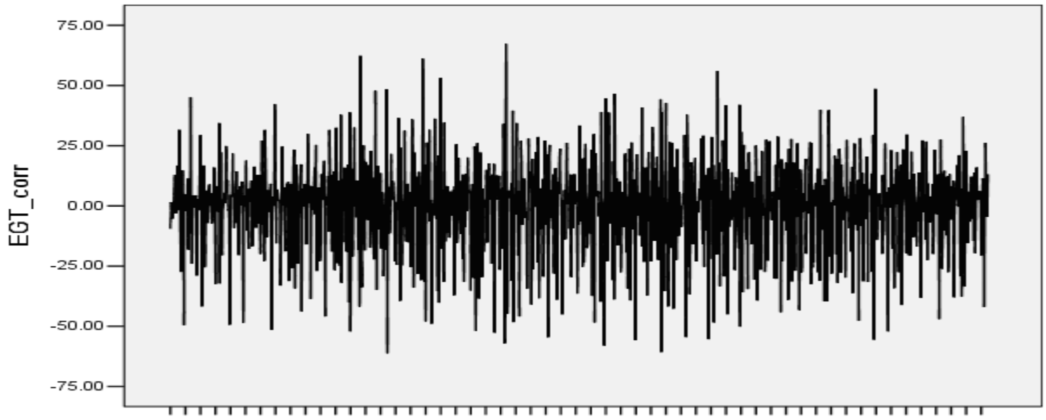

Fig. 2 the first order difference of Exhaust Gas Temperature time series

ARIMA(3,1,2) Analysis.

In order to test the advantages and disadvantages of the model, we test the residual sequence of the model. If the residual sequence is white noise, the model is appropriate for forecasting. By computing the P-value of the residual sequence, we obtain the p=0.9999>0.05 which indicate the residual sequence is white noise (see Fig 3).

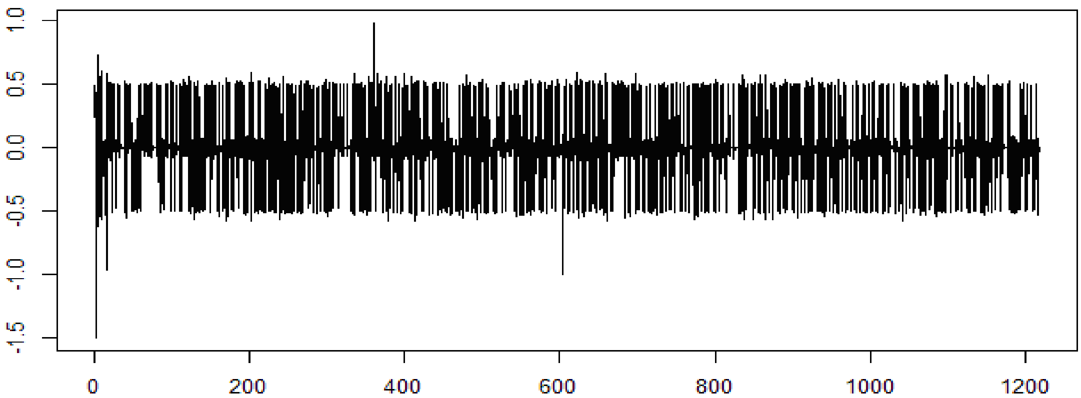

Fig. 3 the residual sequence of Exhaust Gas Temperature time series

The residual sequence of Exhaust Gas Temperature time series

For ARMA model, the maximum value and the minimum value of the prediction can be obtained by Eq.1 according to the desired confidence level.

$$U_U = \hat{W}_K(L) + T \bullet V(L) \bullet S_e$$
$$U_L = \hat{W}_K(L) - T \bullet V(L) \bullet S_e \qquad (1)$$

where S_e is the standard deviation of forecast error.

$$S_e^2 = \sum_{t=1}^{k} \hat{e}_t^2 / k - p - q_0 V(L) \qquad (2)$$

$$\begin{aligned} \varphi_1 &= \phi_1 - \theta_1 \\ \varphi_2 &= \phi_1\varphi_1 + \phi_2 - \theta_2 \\ &\ldots \\ \varphi_j &= \phi_1\varphi_{j-1} + \phi_2\varphi_{j-2} + \ldots + \phi_p\varphi_{j-p} - \theta_j \end{aligned} \qquad (3)$$

Here, we perform a hypothesis test using 95% confidence level, and obtain a p-value less than 0.05. Therefore, ARIMA (3,1,2) is suitable for forecast of EGT series. It can be seen from Fig. 4 that the trend of predicted values and original values are similar and the error between them is small.

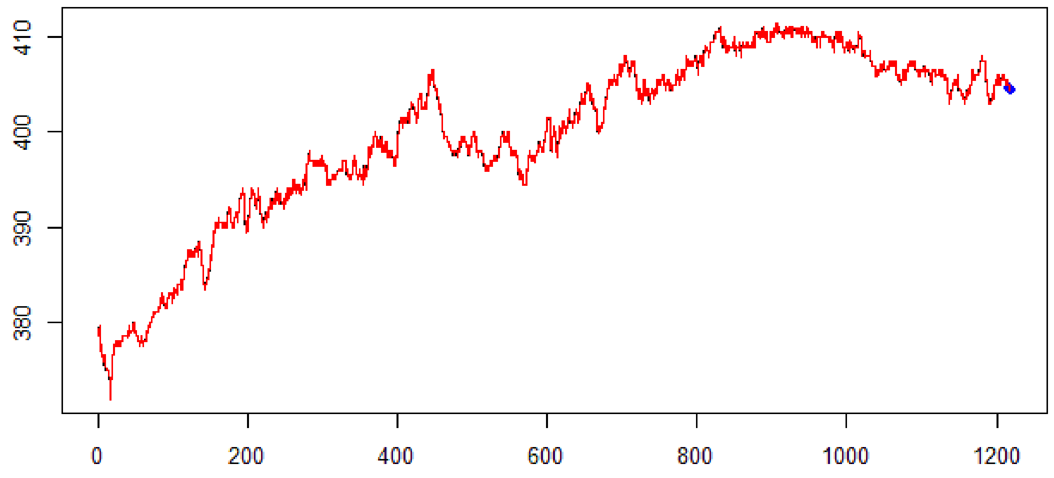

Fig. 4 the predictive values of Exhaust Gas Temperature time series

Conclusions

This paper introduced the Autoregressive Integrated Moving Average Model and applied it to aero-engine EGT time series. By employing the Minimum information criterion, we determine ARIMA(3,1,2) model in this paper. And then, , we perform a hypothesis test using 95% confidence level, and obtain a p-value less than 0.05, which indicate the ARIMA method is suitable for forecast Exhaust Gas Temperature fluctuation series. Further, we calculate the error between the predicted values and original values and find the error is small.

Acknowledgments

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