FUEL CONSUMPTION MONITORING OF TURBOPROP ENGINE

Jaroslav JURACKA[1] & Zuzana Hubnerova[2]

[1]Brno University of Technology, Institute of Aerospace Engineering
[2]Brno University of Technology, Institute of Mathematics

Abstract

The paper describes a statistical approach to the diagnosis and evaluation of the consumption changes of aircraft turboprop engine, which can be implemented on any turboprop engine. The authors chose the method of regression analysis using a polynomial function of two explanatory variables and applied the procedure on real flight data. Furthermore, the influence of the ambient temperature on the engine characteristics is discussed and analyzed. The results of the analyzes show a real benefit showing changes in engine consumption.

Keywords: Engine monitoring, Linear regression, Likelihood ratio test

1. Introduction

Currently, the impact of air transport on the environment is very carefully evaluated. In particular, the Green Deal [4] sets significant targets for carbon neutrality. As part of individual activities, different technical solutions are appearing in aviation, considering airplane propulsion with electric energy [4, 15] powered by batteries or the use of hydrogen or alternatives as the SAF. However, it is clear that the need of this existing solutions for high propulsion performance is limited. However, before the new approaches can be significantly introduced into common aviation practice, it is necessary to look for all possible solutions to reduce emissions. One of the possible solutions is also keeping of low engine consumption and higher efficiency thanks to high-quality engine adjustment and monitoring of its consumption. World manufacturers have implemented various systems for continuous recording of operational parameters of engines after installation in the aircraft with the aim of monitoring the condition of the engine. An example is the Canadian engine producer Prett & Whittney, which offers the operator continuous monitoring of the aircraft and its parameters within the GARMIN avionics system. These systems then enable various evaluation systems, e.g. [1]. However, the possibilities of these systems also enable the evaluation of operational efficiency and specific consumption [2]. This article therefore aims to evaluate the available parameters applicable to the monitoring of engine consumption and presents with a specific example and using sophisticated statistical methods.

2. State of Art

A turboprop engine can be seen as a machine that converts chemical energy into mechanical work. From this point of view, engine monitoring can be divided into two parts. Monitoring the thermodynamic process that takes place in the engine in an attempt to evaluate its effectiveness and efficiency and on the other hand monitoring the mechanical condition of the engine. The monitoring of the mechanical condition of the set is usually described by mechanical quantities, such as vibrations or engine power [5]. These are then part of separate analyzes with regard to high-frequency and low-frequency vibration anomalies depending on the excitation (speed of the generator turbine or propeller) and are not the subject of this article. The second monitoring contribution is focused on a thermodynamic process, where the engine is perceived as a device into which a mass of air enters at a given speed, which, after adding fuel and burning, releases energy, which is subsequently transformed into mechanical work on the shaft. There are different methods of identifying a possible

fault condition or changes in engine parameters and subsequent trend analysis. Recently, papers presented methods based on regression analysis [2], Artificial Neural Network with Data clustering with fuzzy logic approach [6] or mathematical models (digital twins) of the given engine [7]. The algorithms of artificial intelligence have been recently applied to diagnose an impeding failure and health monitoring. Papers [8, 9, 10, 11, 12, 13] provide a review of available methods. Most of them rely on the machine learning approaches.
When analyzing the trend of the parameter development, a current problem is the fact that the required deviation is usually smaller than the accuracy of the method, therefore statistical methods or fuzzy methods are often mentioned. Some modern approaches also use artificial intelligence.

3. Data processing

Due to digital data logging, there is sufficient data from individual engine operation for most engines today. When analyzing them, it often turns out that the missing information is the temperature and pressure at the engine inlet and behind the engine compressor which is significant for digital twin models. Despite these missing data, it turns out that it can be beneficial to analyse the available
Data from light aircraft engine PT6-42 measured during 1531 flights in the period of December 2011 till August 2022 were created a rich base for the presented analysis.
For the purposes of the analysis, firstly, the engine fuel consumption has been chosen as the reference characteristics with respect of main impact on environment. This dependence is based on the concept of maintaining the correct combustion ratio, i.e. the amount of air passing through the engine as expressed in revolutions (generator speed) and the amount of fuel is directly measured by the fuel flow. As part of the previous experience, regression analysis with a quadratic polynomial of the dependence of consumption on the speed of the gas generator was used [1].
Next, the dependence of torque moment on gas turbine speed was studied, because the torsion moment express of engine power with constant propeller speed. Generator speed express the amount of air going through engine. This relation should describe a engine quality and health development in time.
In the analysis, it is necessary to compare the engine parameters under the same conditions, which is very demanding in the conditions of the changing atmosphere (pressure, temperature, humidity, density). Therefore, the standard conversion relations into International Standard Atmosphere (IAS) conditions according to [3] are employed, which compensate for temperature or pressure. The following available characteristics for evaluation of engine thermodynamic work have been used:

- Ambient atmospheric pressure p_0 [Pa]
- Ambient atmospheric temperature T_0 [°C]
- Current fuel flow FF [GPH]
- Gass turbine speed NG [RPM, min^{-1}, %]
- Torque moment TQ [Nm, %]

Than the Fuel consumption (in kg h^{-1}), Gass turbine speed and Torque moment were standardized to IAS conditions as follows

$$\begin{aligned} FCS &= FF \cdot \rho_{fuel} \cdot \frac{p_{ISA_{0m}}}{p_0} \sqrt{\frac{273.15 + T_{ISA_{0m}}}{273.15 + T_0}} \\ NGS &= NG \cdot \sqrt{\frac{273.15 + T_{ISA_{0m}}}{273.15 + T_0}} \\ TQS &= TQ \cdot \frac{p_{ISA_{0m}}}{p_0} \end{aligned}$$

with fuel density $\rho_{fuel} = 0.797$kg m^{-3}, defined atmosphere pressure by ISA $T_{ISA_{0m}} = 15°C$ and defined atmosphere temperature by ISA $p_{ISA_{0m}} = 101325$Pa.

4. Methodology

In the article, differently from [1], there is proposed a method of comparing engine conditions in subsequent flights in terms of measured pair dependencies between characteristics of interest during the climbing after take off. That was established as optimal flight phase of engine work with standard progress at nominal power, when the engine is under the heaviest load during the flight. This required automatic identification of the climbing sequence in a flight recorded.

4.1 Set of initial "in-control" flights

A sufficient set of initial flights was identified to establish initial characteristics set by engine producer. This was assumed as the correct characteristics. Unlike in [1], the selected in-control flights had to be made during the whole year to avoid ignoring potential dependencies on changing condition during the year. Considering the reference flights in a time period shorter than a year only resulted in a periodic behavior of the measure delta applied in [1].
Similarly to [1], a polynomial regression of standardised values FCS (as well as TQS) on NGS in the following form was considered.

$$\begin{aligned} FCS_{ref,i} &= \beta_0 + \beta_1 NGS_{ref,i} + \beta_2 NGS^2_{ref,i} + \beta_3 NGS^3_{ref,i} + e_{ref,i}, \\ FCS_{f,j} &= \beta_0 + \beta_1 NGS_{f,j} + \beta_2 NGS^2_{f,j} + \beta_3 NGS^3_{f,j} + \delta_0 + \delta_1 NGS_{f,j} + \delta_2 NGS^2_{f,j} + \delta_3 NGS^3_{f,j} + e_{f,j}, \end{aligned}$$

where ref stands for an index of a reference flight, i is an index of the measurement in flight ref $(i = 1, \ldots, n_{ref})$, f is the examined flight, $j = 1, \ldots, n_f$ and $\beta_0, \ldots, \beta_3, \delta_0, \ldots, \delta_3$ are unknown parameters with the classical assumption of normality, unbiasedness and homoscedasticity with independence of the random errors $e_{f,i}$ or $e_{ref,i}$. In such a parametrization a hypothesis on $\delta_0 = \ldots = \delta_3 = 0$, which can be tested by a classical F tests allows us to assess whether the regression dependence of FCS on NGS in examined flight differs from the same dependence in the reference flights.
That way, a homogeneous group of in-control initial flights with the same parameters of dependence of FCS on NGS (or of TQS on NGS) and use them as a reference flights for the following flights could be identified a in some sense. Note, that F test was conducted under very low significance level of 2e-09, which corresponds to 6σ normality quantile. Such a low significance level reflects the fact, that there is an enormous number of factors which influence the dependence and are ignored in this approach.

4.2 Adjustment of applied model

However, the assumptions of the regression were not fulfilled what led to the following improvements of the initial approach. The normality of the residuals was not fulfilled, that is why a minute averages of the measurements were modelled instead of the original measurements. The minute averages are denoted by $\overline{FCS}$, $\overline{TQS}$ and $\overline{NGS}$ hereinafter. However the number of measurements in a minute was not constant. The minutes with at least 12 measurements were considered in the analysis. Moreover, there was observed, that the variance of the residuals was not constant and depended on NGS. Therefore, a model where also variance depends on NGS and the number of measurements in a minute N_i had to be applied [14]. After these adjustments, the procedure of identifying a homogeneous group of flights and testing the following flights was conducted again. The value of F criterion with a periodic behaviour was observed again. This led to an idea, that flights under similar "seasonal" conditions should be considered separately. Therefore, the flights were separated into 9 categories T1,..., T9 differing in the atmospheric temperature $T0$ at 1500m above mean sea level (AMSL) (denoted $T1500$ hereinafter), e.g. T1 for temperatures between -30°C to 0°C, see Figure 1. The boundaries were set by appropriate quantiles of the observed values of $T1500$.

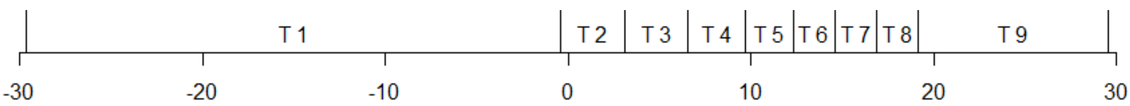

Figure 1 – Categories of flights based on quantiles of atmospheric temperature $T0$ at 1500m AMSL

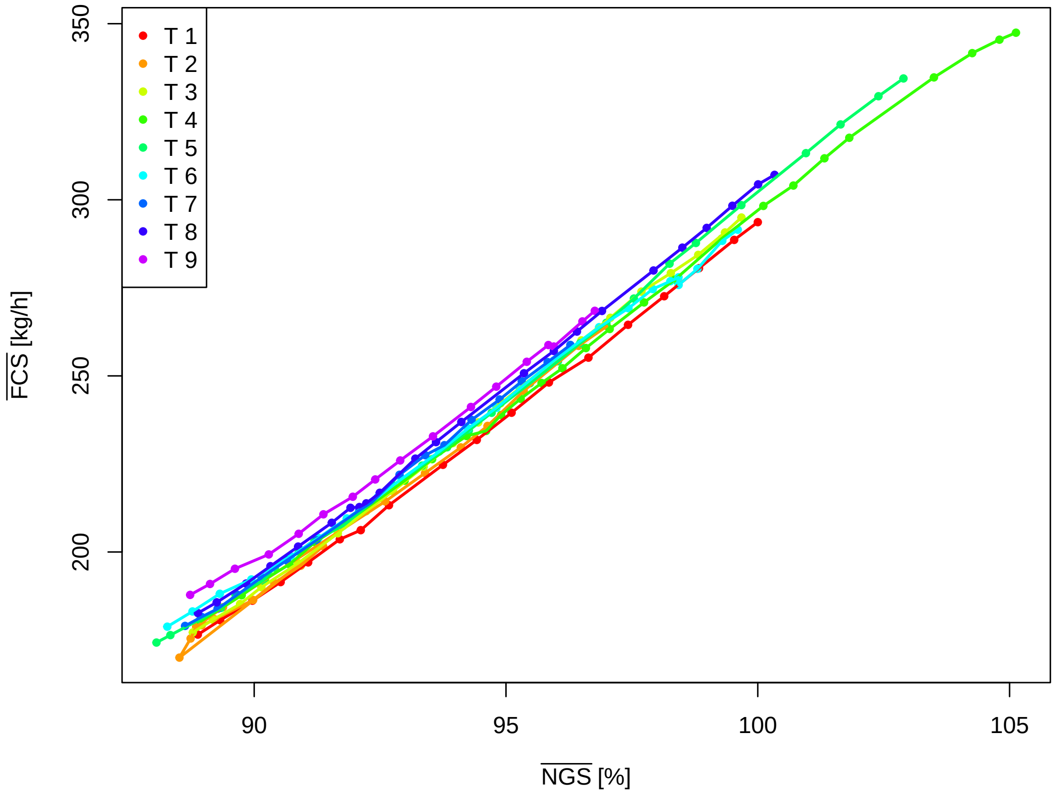

Figure 2 – Dependence of minute average $\overline{FCS}$ on minute average $\overline{NGS}$ in selected typical flights in categories defined by measured atmosphere temperature at 1500m AMSL defined in Figure 1

In each category, a typical flight with the biggest number of flights in the same category $T1500$ that were not found significantly different from the assessed flight was selected and its dependence of $\overline{FCS}$ on $\overline{NGS}$ can be seen in Figure 2.
This observation led to a conclusion, that a new model reflecting the temperature $T1500$ needs to be taken into account. That would also decrease the number of needed reference flights. In the end, 73 reference flights out of 1531 were taken with the following model

$$\begin{aligned} \mu(\overline{FCS}_{f,i}) &= \beta_0 + \beta_1\overline{NGS}_{f,i} + \beta_2\overline{NGS}^2_{f,i} + \beta_3\overline{NGS}^3_{f,i} + \beta_4 T1500_f + \beta_5 T1500^2_f + \\ &\quad + \beta_6\overline{NGS}_{f,i}T1500_f + \beta_7\overline{NGS}^2_{f,i}T1500_f + \beta_8\overline{NGS}^3_{f,i}T1500_f + \\ &\quad \delta_{f,0} + \delta_{f,1}\overline{NGS}_{f,i} + \delta_{f,2}\overline{NGS}^2_{f,i} + \delta_{f,3}\overline{NGS}^3_{f,i} \end{aligned} \tag{1}$$

$$\ln(\sigma(\overline{FCS}_{f,i})) = \alpha_0 + \gamma_1 N_{f,i} + \gamma_2\overline{NGS}_{f,i} + \gamma_3 T1500_f + \gamma_4\overline{NGS}_{f,i}T1500_f, \tag{2}$$

with indexes of minutes $i = 1,\dots,n_f$ in flights $f = 1,\dots,N_{ref}+1$, taking $\delta_{ref,0} = \dots = \delta_{ref,3} = 0$ for the reference flights. The model was selected as the most suitable by a stepwise algorithm. Thanks to the assuming of normality of the response variable $\overline{FCS}$ the unknown parameters can be estimated by the method of maximum likelihood. Moreover, the hypothesis that the dependence of $\overline{FCS}$ on $\overline{NGS}$ in the examined flight does not differ from the dependence in the reference flights can be based on the likelihood ratio test with the test criterion Deviance. Again, the significance level 2e-09 was considered to allow for various unknown (missed) sources of randomness.

4.3 Obtained results

Figure 3 plots the estimated surface for expected $\overline{FCS}$ depending on $T1500$ and $\overline{NGS}$. The influence of $T1500$ was tested significant at significance level 5%. As can be seen in the final equation (1), the value of $T1500$ does not just increase the estimate of $\overline{FCS}$ during the flight by a constant $\hat{\beta}_4 T1500_f +$

$\hat{\beta}_5 T1500_f^2$ but the interaction term $\beta_6 \overline{NGS}_{f,i} T1500_f + \beta_7 \overline{NGS}_{f,i} T1500_f + \beta_8 \overline{NGS}^3_{f,i} T1500_f$ is significant as well. Note, that parameter estimates enable to observe the effect of a unit change in $T1500$ on $\overline{FCS}$. Overall the unit increase in $T1500$ means an increase in $\overline{FCS}$ which depends on $\overline{NGS}$ as can be see in Figure 4. The highest increase in $\overline{FCS}$ caused by a unit increase in $T1500$ is at $\overline{NGS} = 100\%$ approximately.

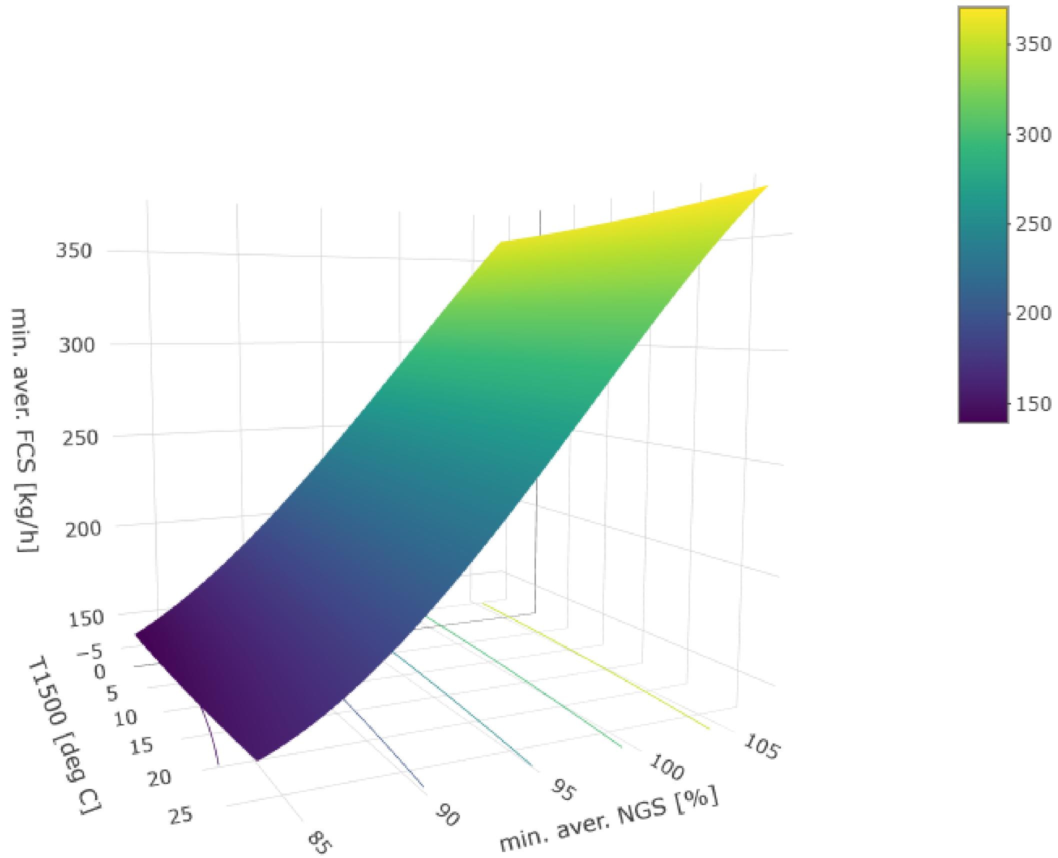

Figure 3 – Estimated expected minute average $\overline{FCS}$ (min. aver. FCS) depending on atmospheric temperature at 1500 m AMSL $T1500$ and minute average of NGS (min. aver. NGS)

Next, the following flights were tested against the in-control flights using the likelihood ratio test with criterion Deviance. Obtained Deviance was compared with the appropriate quantile corresponding to the significance level 2e-09 to allow for various unknown (missed) sources of randomness as earlier. See the obtained values for the dependence $\overline{FCS}$ on $T1500$ and $\overline{NGS}$ in Figure 5. In case a significant difference was identified, median of the residuals for the data of the flight of interest was calculated. In case, the median of the residuals was positive and negative, the point is displayed in red and in blue, respectively. Green vertical dashed lines identify the dates of engine inspection and maintenance. The vertical black solid line separates the set of initial flights from the following flights. The "in-control" flights are represented by the black points bellow the critical value for the criterion Deviance corresponding to the 2e-09 significance level. It can be clearly seen, that the criterion Deviance increased extremely in the later years and most of the outlying flight had positive median of the residuals. More precisely, there were only 4 flight with significantly different dependence of $\overline{FCS}$ on $T1500$ and $\overline{NGS}$ from the "in-control" set of flights. A deeper analysis revealed suspicious measurements of the ambient atmospheric temperature $T0$ during all four flights, which influences the analysed values of FCS and NGS.
To be able to interpret the differences in the models more closely, the medians in the residuals for the "in-control" flights, following flights until January 2019 and following flights after January 2019 are plotted in Figure 6. The shift can be clearly seen. Note, that residuals are differences between

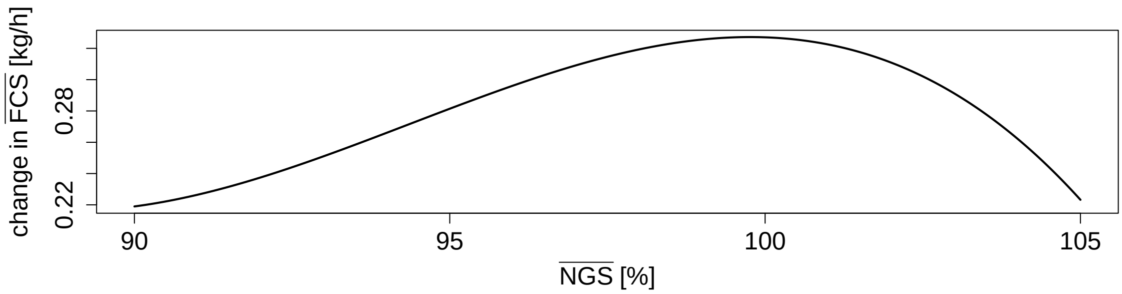

Figure 4 – Increase in predicted $\overline{FCS}$ caused by a unit change (1°C) in atmospheric temperature at 1500 m AMSL ($T1500$) as a function of $\overline{NGS}$

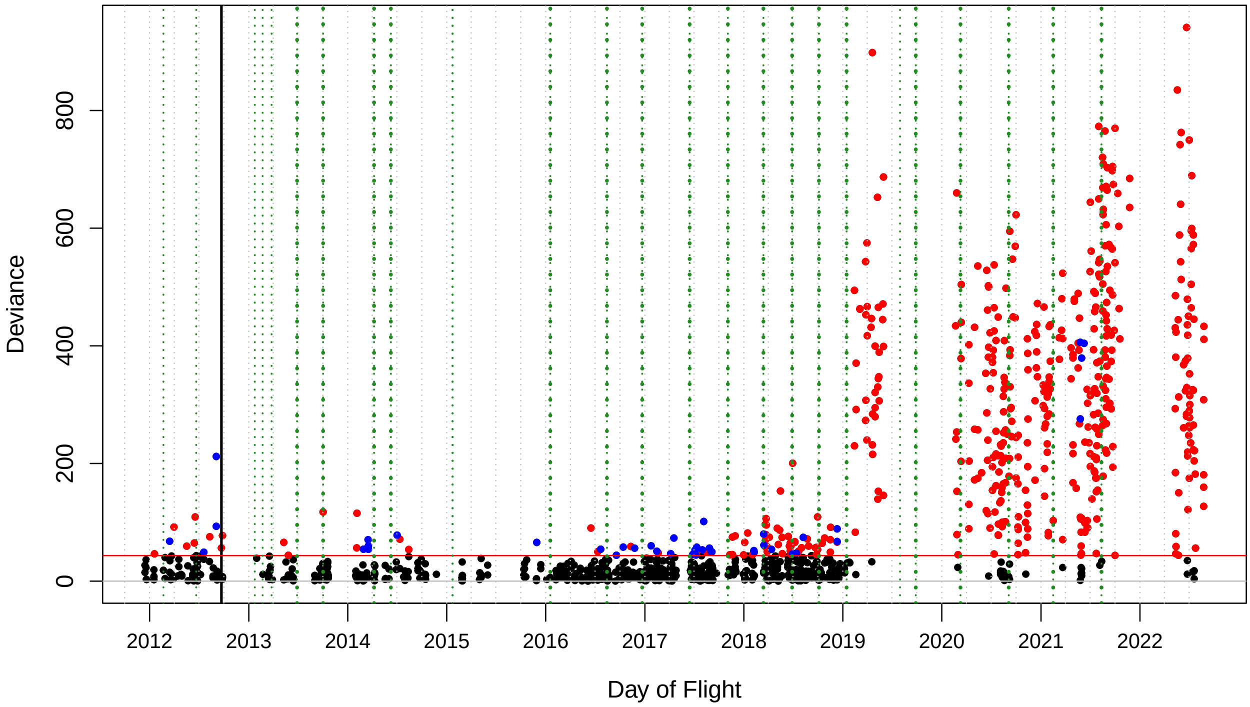

Figure 5 – Values of criterion Deviance D used to test the equality of the dependence between $\overline{FCS}$ and atmospheric temperature at 1500 m AMSL $T1500$ and minute average of NGS ($\overline{NGS}$) during the in-control flights to the flights of interest (on the displayed date).

measured minute average of $\overline{FCS}$ and it's prediction based on the model estimated from the "in-control" flights.
Also, the predictions of the dependence of minute average $\overline{FCS}$ on minute average $\overline{NGS}$ based on the "in-control" flights are compared to the real observation of the following flights after January 2019 with similar temperature $T1500$ at 1500m AMSL in Figure 7.
Presented methodology was able to identify these increases in the fuel consumption, however the reason for this is up to a discussion with the engineers in maintenance centre. There is necessary note, that for current engine the simple service record do not allow recognize a change reason. Also it should be noted, that the frequencies of the "take-off" airports countries, which could coincide with the quality of the fuel, did not change significantly. On the other hand, the increase could also for example be caused by a reset of the fuel consumption measurement device.
Similarly to the analysis of fuel consumption, a dependence of minute average standardized torque

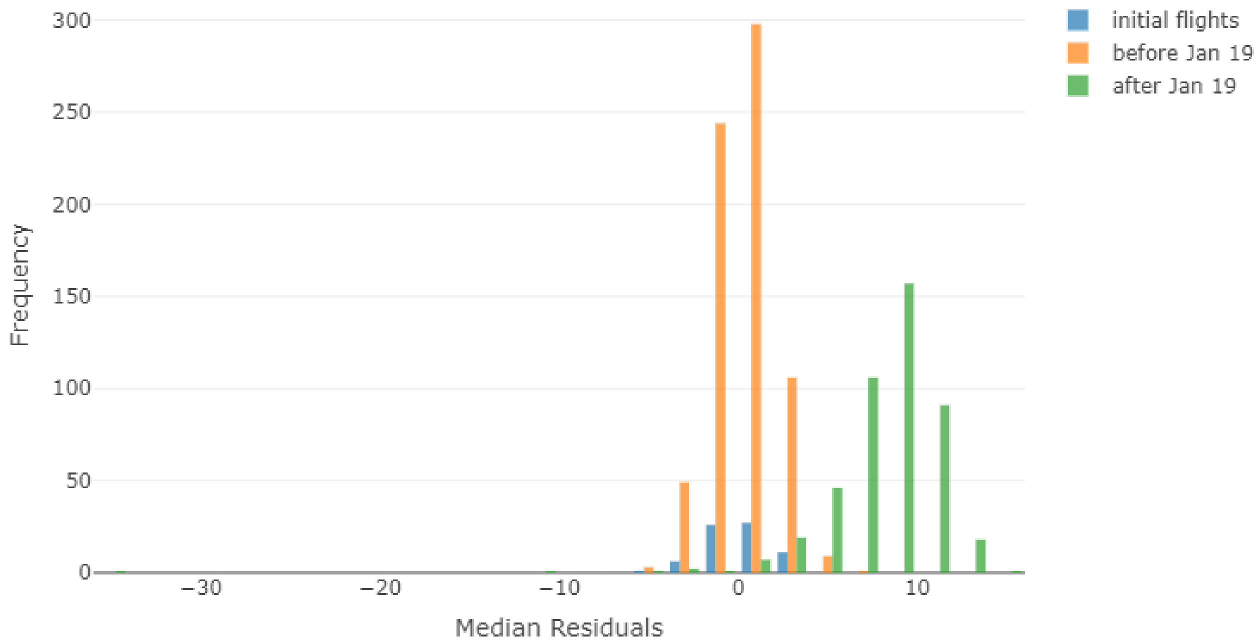

Figure 6 – Histograms of medians of residuals in models of $\overline{FCS}$ for each flight

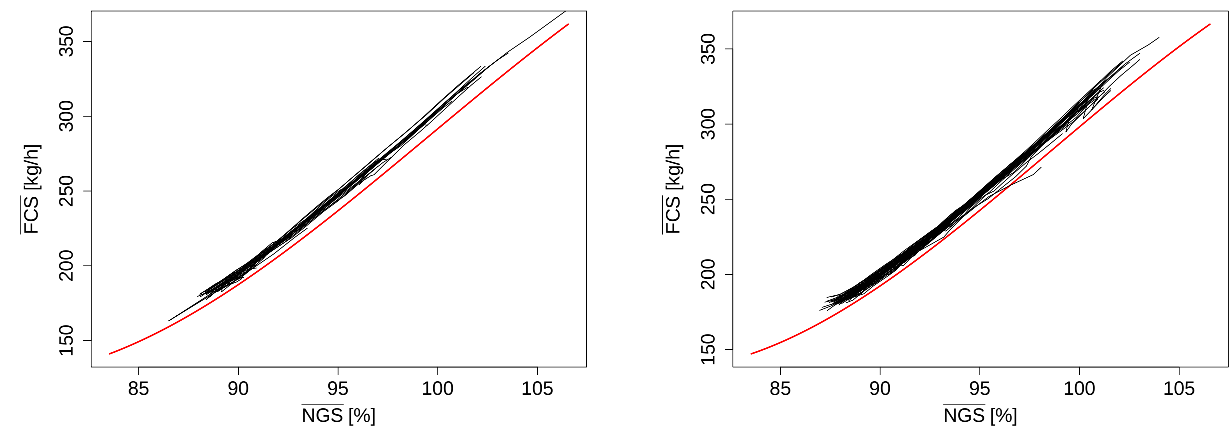

Figure 7 – Comparison of predictions for 1.35°C and 15.75°C at 1500m AMSL and measured data during flights after January 2019 with Deviance significant at 2e-09 level with the atmospheric temperature in the temperature category T2 with range (-0.4°C,3.1°C) and temperature category T7 with range (14.6°C,16.9°C) at 1500m AMSL in the left and right graph, respectively.

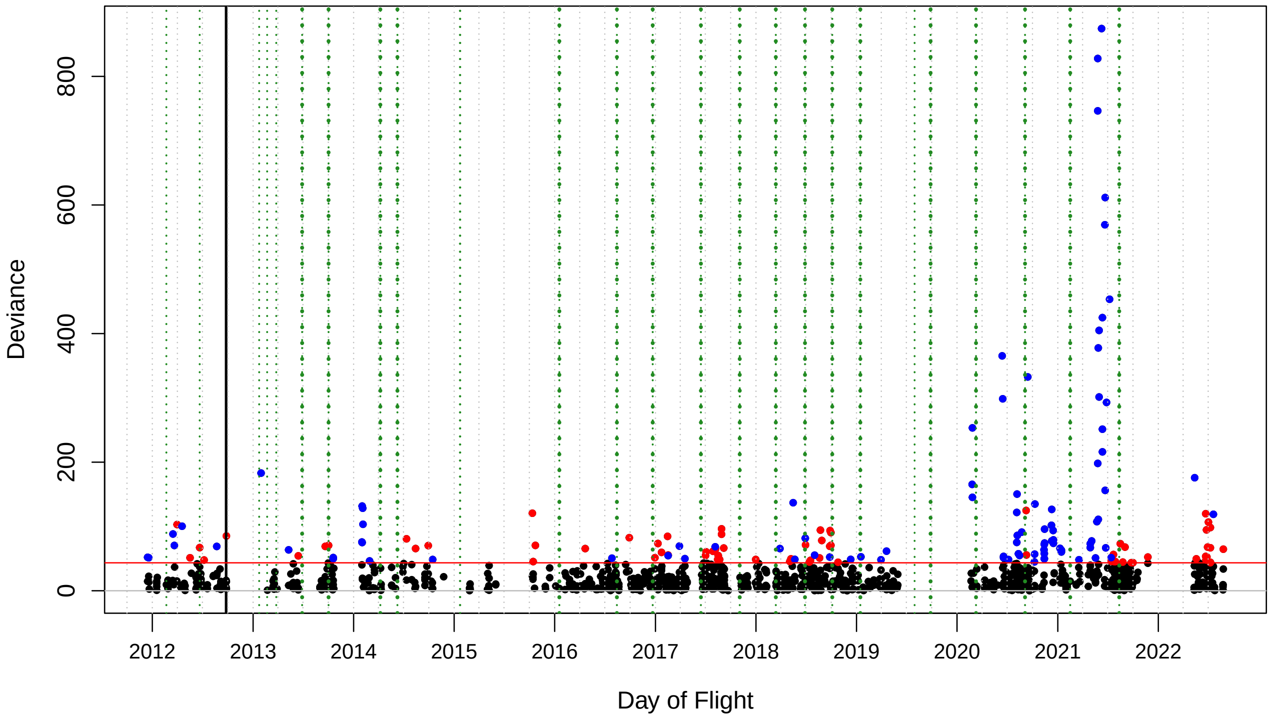

Figure 8 – Values of criterion Deviance D used to test the equality of the dependence between $\overline{TQS}$ and atmospheric temperature at 1500 m AMSL $T1500$ and minute average of NGS ($\overline{NGS}$) during the in-control flights to the flights of interest (on the displayed date).

moment $\overline{TQS}$ on $T1500$ and $\overline{NGS}$ was explored. In this case the following model was chosen

$$\begin{aligned} \mu(\overline{TQS}_{f,i}) &= \beta_0 + \beta_1\overline{NGS}_{f,i} + \beta_2\overline{NGS}^2_{f,i} + \beta_3\overline{NGS}^3_{f,i} + \beta_4 T1500_f + \beta_5 T1500^2_f + \\ &\quad + \beta_6\overline{NGS}_{f,i}T1500_f + \beta_7\overline{NGS}^2_{f,i}T1500_f + \beta_8\overline{NGS}^3_{f,i}T1500_f + \\ &\quad \delta_{f,0} + \delta_{f,1}\overline{NGS}_{f,i} + \delta_{f,2}\overline{NGS}^2_{f,i} + \delta_{f,3}\overline{NGS}^3_{f,i} \qquad (3) \\ \ln(\sigma(\overline{TQS}_{f,i})) &= \alpha_0 + \gamma_1 N_{f,i} + \gamma_2\overline{NGS}_{f,i} + \gamma_3 T1500_f + \gamma_4\overline{NGS}_{f,i}T1500_f, \qquad (4) \end{aligned}$$

with indexes of minutes $i = 1,\ldots,n_f$ in flights $f = 1,\ldots,N_{ref}+1$, taking $\delta_{ref,0} = \ldots = \delta_{ref,3} = 0$ for the reference flights. The final comparison of the models in "in-control" flights and following flights by the criterion Deviance is presented in the Figure 8. Here, it is observed, that the median of the residuals of the outlying flights were mostly negative after January 2020 which could be explained by lower engine power. Also, it should be noted, that the flight with Deviance greater than 500 were those with fault ambient temperature measurements identified by the analysis of the dependence of $\overline{FCS}$ on $\overline{NGS}$. The histograms of the medians for all flights are given in Figure 9. The flights with the smallest medians of residuals are those with fault ambient atmospheric temperature measurements and the greatest Deviance.

5. Discussion

The changes in pair dependence of characteristics of light aircraft engine and the surrounding atmosphere during the climbing of measured flights were assessed in presented paper. The influence of the ambient atmospheric temperature at 1500 m AMSL was taken into account as it was found significant (at 5% significance level). Pairs of standardized fuel consumption FCS with standardized gas turbine speed NGS and standardized torque moment TQS with standardized gas turbine speed NGS were considered. It is clear from the complexity of the variable conditions during the flights not reflected in the pair analysis is rather naive approach. It should be noted that some of the potentially important factors, such as the payload mass, fuel quality, humidity, air density, etc, were not available. Yet, when allowing for various missed sources of variability (by taking 2e-09 significance level for the likelihood ratio test) some conclusions could still have been derived.

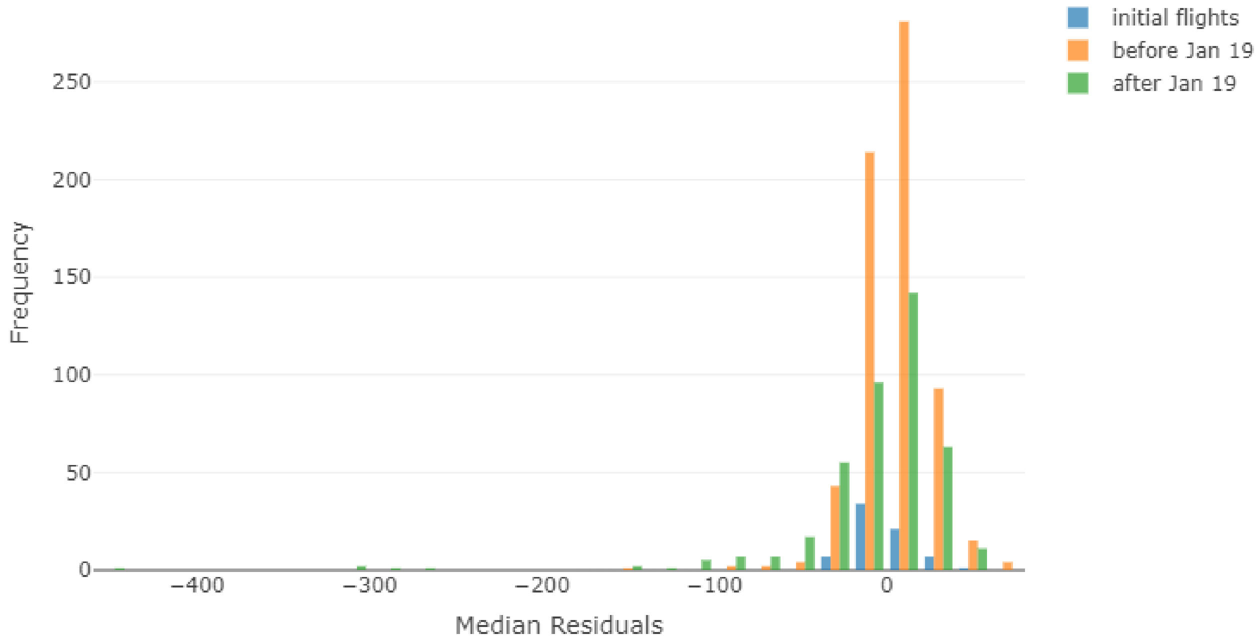

Figure 9 – Histograms of medians of residuals in models of $\overline{TQS}$ for each flight

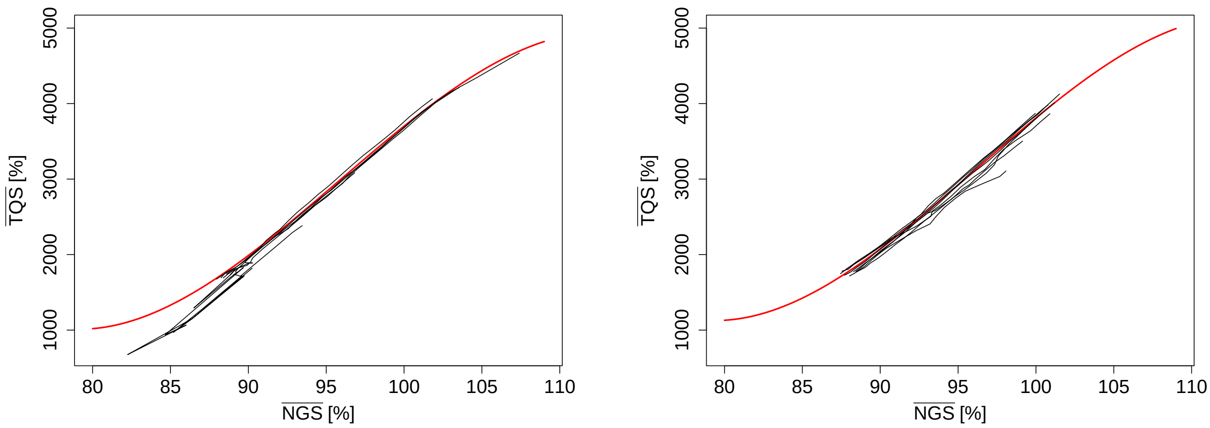

Figure 10 – Comparison of predictions for 1.35°C and 15.75°C at 1500m AMSL and measured data during flights after January 2019 with Deviance significant at 2e-09 level with the atmospheric temperature in the temperature category T2 with range (-0.4°C,3.1°C) and temperature category T7 with range (14.6°C,16.9°C) at 1500m AMSL in the left and right graph, respectively.

Identified changes in the dependence of standardized fuel consumption FCS with standardized gas turbine speed NGS were identified. In some cases, when the dependence during a following flight was significantly different than during the "in-control" flights and the median of residuals were unexpectedly small, the fault atmospheric measurements were revealed.
Some outlying flights were also uncovered during the analysis of the dependence of standardized torque moment TQS with standardized gas turbine speed NGS, but still in much lower number than in the case of $FCS \sim NGS$ model. The outlying flights after January 2020 had negative medians of the residuals, meaning that the minute average standardized torque moment tended to be lower than predicted from the "in-control" flights.
More complex models of FCS possibly incorporating measurements of more engine characteristics will be the topic of the future research. Note, that classical linear regression is not suitable in this case, because of strong multicolinearity of the variables during the climbing. Such a model would bring a deeper insight into the changes in the dependencies between the measured variables.
It is also possible to discuss fuel savings and CO2 emissions reducing. Assuming an increase of current aircraft fuel consumption of 10 kg/h and an average climb time of 30 minutes, 5 kg of fuel will be saved on each flight (which represents a 5% saving at 200 kg/h) by correct adjustment of the investigated engine. In a similar way, the fuel savings during level flight can be estimated as approximately 10 kg. Summary it represents 15 kg of fuel for 3 hours of typical flight on average. With an engine life cycle of 3,600 flight hours before overhaul, it represents 18 tons of extra fuel burned, which represents approx. 54 tons of CO2.
Presented approach was applied on data measured in another aircraft engine as well. Unlike in the discussed case, the analysis did not reveal frequent significant anomalies during the following flights.

6. Conclusion

The article presents the application of mathematical statistical methods to technical data collected from the operation of an aircraft turboprop engine. It is obvious that an increase in fuel consumption was evident on the engine in question, which can be clearly identified and therefore the condition of the engine can also be analyzed and the increase in fuel consumption can be eliminated by servicing. It is also clear that the mentioned method can, during continuous monitoring, help to eliminate similar changes in consumption and thus allow to maintain optimal fuel consumption of the engine, thereby saving the costs of operating the aircraft and improving environmental protection.

7. Contact Author Email Address

The authors' contact emails are: juracka@vutbr.cz, hubnerova@fme.vutbr.cz

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9. Copyright Statement

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