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MODELING OF LTO APPROACH TIME-IN-MODE VALUES IN MATLAB USING THE GENERALIZED EXTREME VALUE DISTRIBUTION

Bo Stloukal[a,*], Ivan Nagy[b]

[a] *Czech Technical University in Prague, Faculty of Transportation Sciences, Department of Air Transport, Horská 3, 128 03 Prague 2, Czech Republic*

[b] *Czech Technical University in Prague, Faculty of Transportation Sciences, Department of Applied Mathematics, Na Florenci 25, 110 00 Prague 1, Czech Republic*

[*] corresponding author: stloubo@fd.cvut.cz

Abstract. The landing and take-off (LTO) cycle, which is used to calculate emissions of aircraft below 3 000 feet, consists of four operating modes, each of which has a standardized time duration or time-in-mode (TIM). In this paper, we model TIM values of the Approach operating mode for two aircraft types (Boeing 737-800 and Airbus A320) arriving on Runway 24 at Prague Václav Havel Airport using the generalized extreme value (GEV) distribution. Predictions of the TIM values are made using the models, and the performance of each model is evaluated. The results show that for both aircraft types, the predicted TIM values lead to total emissions estimates deviating on average by 1 to 2 percent from estimates made using the real TIM values, showing good model performance. The presented approach is also shown to be beneficial in comparison with using the standard TIM value (240 s), highlighting the feasibility of further research in this area as one of the avenues of improving the LTO cycle methodology.

Keywords: Aircraft, emissions, approach, LTO cycle, time-in-mode, generalized extreme value distribution.

1. Introduction

The process of aircraft engine emissions certification is regulated by standards and recommended practices defined by the International Civil Aviation Organization (ICAO). Specifically, requirements concerning emissions below 3 000 feet above ground level (AGL) are outlined in the Annex 16 to the Convention on International Civil Aviation, Volume II [1]. These cover several emission species, including gaseous pollutants and non-volatile particulate matter, which have a direct impact on local air quality and hence the health of local populations [2, 3]. In order to assess the amount of these emissions, the reference emissions landing and take-off (LTO) cycle is defined within the Annex, for which four operating modes are given (Idle, Take-Off, Climb-Out and Approach). Each of these has a given thrust setting as well as time duration, or time-in-mode (TIM) value. As part of the certification process, data on specific fuel consumption and emission indices (i.e., mass of emissions per mass of fuel consumed) for each emission species are collected for each LTO operating mode [1]. While originally intended for engine emissions certification, since they are openly available in emission databanks, these data are also frequently used for the purpose of estimating the amount of emissions emitted by aircraft at and near airports. This includes the development of inventories of the individual emission species (for example in [4–8]).

The TIM value is a large source of uncertainty within the calculations of emissions of airport movements, especially for the LTO operating modes Idle and Climb-Out, where the default values as given by ICAO are often overestimating the actual values [9, 10]. This uncertainty can be explained by the presence of various factors influencing the TIM values. For example, one study analyzed the factors influencing taxi time of aircraft and hence the TIM for the operating mode Idle. According to its presented results, the factors ranged from weather-related factors such as wind or visibility to traffic-related factors including number of movements or runway occupancy time [11]. Attention has also been paid to the LTO operating modes Climb-Out and Approach, which are influenced, among other factors, by the definition of the so-called mixing height. The mixing height (or the mixing layer height) is a parameter which influences the dispersion of pollutants near the surface, including aircraft emissions. Pollutants emitted below it have a direct impact on local air quality and hence the health of the local population [12]. The ICAO standards assume a constant mixing height of 3 000 feet AGL. Since the mixing height clearly influences the TIM of the mentioned operating modes, some studies have considered its value variable rather than constant while determining the TIM values [13–16]. Other studies have included the evaluation of the TIM values without considering this factor [10, 17–20].

In this paper, we focus on the Approach operating mode of the LTO cycle, specifically on the modeling and predicting of its TIM values for two aircraft types. For this purpose, data on real TIM values calculated from two weeks' worth of Automatic Dependent Surveillance–Broadcast (ADS-B) data from Prague Václav Havel Airport were utilized. Using MATLAB, random samples of the data were repeatedly fitted with the generalized extreme value distribution, eventually leading to the estimation of the probability density functions (PDF) of its parameters. From these, point estimates of the distribution parameters were made, and the resulting model was then used to generate TIM values. The predicted TIM values were then compared with the real data and the performance of the model was evaluated using defined metrics. The presented results show a good performance of the model, demonstrating the feasibility of this approach with practical implications for the development of airport emission inventories. To the best of our knowledge, this is the first paper which focuses on the modeling of the TIM values of the Approach operating mode, or any LTO cycle operating mode in general, using the generalized extreme value distribution.

2. Materials and methods

2.1. Data used

In this paper, a dataset resulting from one of the authors' previous work [21] was used. This dataset originally included the TIM values of each operating mode of the LTO cycle of individual aircraft movements at Prague Václav Havel Airport over a two-week period (17th–30th June 2023). These values had been estimated using ADS-B surveillance data covering the airport and surrounding area that were provided by the Air Navigation Services of the Czech Republic. As this paper focuses on the Approach LTO operating mode, only data for arrivals landing on Runway 24 were used. More specifically, data for two aircraft types were used, namely the Boeing 737-800 (ICAO code B738; $n = 670$) and the Airbus A320 (ICAO code A320; $n = 366$); these two were the most commonly represented aircraft types within the data.

2.2. TIM estimation

The TIM values from the dataset mentioned in 2.1, used in this paper, were originally estimated from the real aircraft ADS-B data using the procedure, which is described in this subsection for the sake of completeness.

Let $\mathcal{M}_{i,j}$ be an ADS-B message broadcast by aircraft movement j; where $i \in 1, ..., n_{msg}$ and n_{msg} is the number of messages. Then, let $h_{i,j}$ be the geometric height and $bvr_{i,j}$ be the barometric vertical rate broadcast by the aircraft at time $t_{i,j}$ within message $\mathcal{M}_{i,j}$, and let $h_{GND,j}$ be the geometric height broadcast by the aircraft while on the ground.

As the Approach LTO operating mode begins by descending below the mixing height, which was assumed to be 3 000 feet above ground level (AGL) according to ICAO, the first message satisfying the condition $h_{i,j} < (h_{GND,j} + 3000)$ ft while $i > 1$ was found. The time of descent below the mixing height, $t_{MH,j}$, was then assumed to be between $t_{i-1,j}$ and $t_{i,j}$; its exact value was found using linear interpolation by considering $h_{i-1,j}$ and $h_{i,j}$.

The end of the operating mode was then given as the time of flare ($t_{FL,j}$), which is the moment when engine thrust is reduced to idle seconds before the aircraft touches down on the runway. Since the aircraft nearly levels out briefly during the flare, the first message was found for which the condition $|bvr_{i,j}| < 200\,\mathrm{ft\,min^{-1}}$ while $(h_{i,j} - h_{GND,j}) \leq 50\,\mathrm{ft}$ (in order to prevent a false detection of flare earlier during the approach) was satisfied. Then, the time $t_{FL,j}$ was given as the mean of $t_{i-1,j}$ and $t_{i,j}$ (here, the mean was used since multiple parameters were involved rather than the single one in the case of $t_{MH,j}$, where interpolation could be done).

Having found both times, the TIM value of LTO operating mode Approach for aircraft movement j was then computed as $TIM_j = t_{FL,j} - t_{MH,j}$.

2.3. Estimation of model parameters

The aim of this paper was to model the TIM values of the Approach LTO operating mode, which was done separately for the two chosen aircraft types. During initial analysis of the data, it was deemed that the generalized extreme value (GEV) distribution was the best option for constructing the models in both cases. This was based on visual analysis of the shape of the histogram and PDF fitted to the real TIM values, as well as the standard errors of the distribution parameters according to the Distribution Fitter in MATLAB. Therefore, further work in this paper focused solely on this distribution, with the procedure being identical for both aircraft types.

The GEV distribution was originally proposed in the 1950s [22]; it combines together three extreme value distributions, namely the Gumbel, Weibull and Fréchet distributions [23]. The PDF of the GEV distribution of variable x (in this case the TIM value), whose formula is shown in Equation (1), is a function of three parameters – the shape parameter k, scale parameter σ and location parameter μ. Based on the value of k, the function corresponds to one of the aforementioned distributions [24].

$$f(x|k,\mu,\sigma) = \sigma^{-1} \cdot \exp\left\{-\left(1 + k \cdot \frac{(x-\mu)}{\sigma}\right)^{-\frac{1}{k}}\right\} \cdot \left(1 + k \cdot \frac{(x-\mu)}{\sigma}\right)^{-\frac{k+1}{k}} \quad (1)$$

The first step in order to estimate the model parameters $\hat{\theta} = \{\hat{k}, \hat{\sigma}, \hat{\mu}\}$ was to estimate the PDF for each of the three model parameters, which was done as follows. For a total of 100 000 iterations, a random sample of $n/2$ real TIM values (i.e., 50 % of the data) was first selected. Then, the GEV distribution was fitted to the data; its parameters were estimated using the `gevfit` function in MATLAB. The parameters were then saved for further use; at the end, there was a $3 \times 100\,000$ matrix containing the parameters in its respective rows. The PDF for each parameter (i.e., for each row of the matrix) were then estimated using kernel smoothing (MATLAB: `ksdensity`).

From each constructed PDF, a point estimate of the given parameter used for the subsequent model was made, which corresponded to the peak of the function (i.e., the most likely value of the parameter was used). The resulting point estimates $\hat{\theta}$ were then used further as model parameters.

2.4. Evaluation of estimated model

Once the model parameters had been estimated for both aircraft types, it was possible to make predictions of the TIM values ($\hat{\tau}$) using the derived models. This was once again done over 100 000 iterations. In each iteration, n TIM values were generated using the `gevrnd` function to match the number of real TIM values. The TIM predictions were then evaluated for both aircraft types individually as follows.

First, it was assessed whether the predictions $\{\hat{\tau}_j\}_{j=1}^n$ and the real values $\{\tau_j\}_{j=1}^n$ came from the same distribution. This was done using the `ranksum` (Mann-Whitney U-test) function in MATLAB at the default significance level ($\alpha = 0.05$). For each iteration, the p-value was saved. Afterwards, the proportion of p-values less than α within all p-values was evaluated; this ratio π_p was therefore given as the probability that, upon a simulation run, the distribution of the predicted TIM values would be different than that of the actual TIM values:

$$\pi_p = \frac{n_{(p<0.05)}}{100\,000}, \tag{2}$$

where $n_{(p<0.05)}$ was the number of p-values less than 0.05.

Next, the so-called time sum percentage error (TSPE) was introduced and evaluated for each iteration. The TSPE estimated the percentage difference in the resulting total amount of emissions of the aircraft type during the Approach operating mode calculated using the predicted TIM values compared to the emissions where real TIM values were used for the calculations. The TSPE was given as follows:

$$TSPE = 100 \cdot \frac{|\Sigma_{j=1}^n \tau_j - \Sigma_{j=1}^n \hat{\tau}_j|}{\Sigma_{j=1}^n \tau_j}, \tag{3}$$

where $\Sigma_{j=1}^n \tau_j$ and $\Sigma_{j=1}^n \hat{\tau}_j$ were the sums of all real and predicted TIM values respectively. The mean and median TSPE values were then determined, as well as the interquartile range (IQR).

Finally, in every iteration, both of the aforementioned sums were evaluated relative to the sum $\Sigma_{j=1}^n 240 = 240n$, which was the total time sum when the standard TIM value as defined by ICAO (240 s) was used for all aircraft movements. For this purpose, the relative sum closeness (RSC) metric was introduced, which was defined as follows:

$$RSC = \frac{|\Sigma_{j=1}^n \tau_j - \Sigma_{j=1}^n \hat{\tau}_j|}{|\Sigma_{j=1}^n \tau_j - 240n|}, \tag{4}$$

with its purpose being to compare the resulting total emissions calculated using the predicted TIM values and the standardized value. For RSC $\in \langle 0, 1)$, using the predicted TIM values was better than using the standardized TIM value in terms of resulting accuracy of total calculated emissions, and vice versa for RSC $\in (1, +\infty)$. Alternatively, the inverse value of RSC shows how many times more accurate the resulting emissions estimates were after using the predicted TIM values instead of the standard value.

For RSC, the same statistical measures as for TSPE were computed, plus the coefficient β_{RSC}, which was given as the number of RSC values that were less than 1 divided by the total number of RSC values (i.e., 100 000). This coefficient therefore gave the probability that, upon a simulation run, using the predicted TIM values would bring more accurate results regarding the total calculated sum of emissions than when using the standard TIM value.

3. Results

Figure 1 shows the PDF for the GEV distribution parameters k, σ and μ that were estimated using kernel smoothing for both aircraft types.

Based on the functions, the point estimates of the GEV distribution (model) parameters $\hat{k}, \hat{\sigma}, \hat{\mu}$ were determined; these are presented in Table 1. As has already been mentioned, the probability densities were maximal for these values.

Parameter	**Boeing 737-800**	**Airbus A320**
$\hat{k}$	0.093	0.393
$\hat{\sigma}$	19.153	32.537
$\hat{\mu}$	202.409	228.721

Table 1. Estimated GEV distribution parameters for the Boeing 737-800 and Airbus A320 models.

Upon estimating the model parameters for both aircraft types, predicted TIM values were computed over 100 000 iterations and compared with the real values as described earlier. The resulting distributions of the p-values for both aircraft types are plotted in the histograms in Figure 2, where the relative frequencies are shown instead of the absolute frequencies for practical reasons. It should be noted that the width of each bin is 0.05, therefore only the leftmost bin corresponds to the rejection region (where $p < 0.05$) – this bin is highlighted in red in both histograms. The value of the ratio π_p defined in Equation (2) was therefore

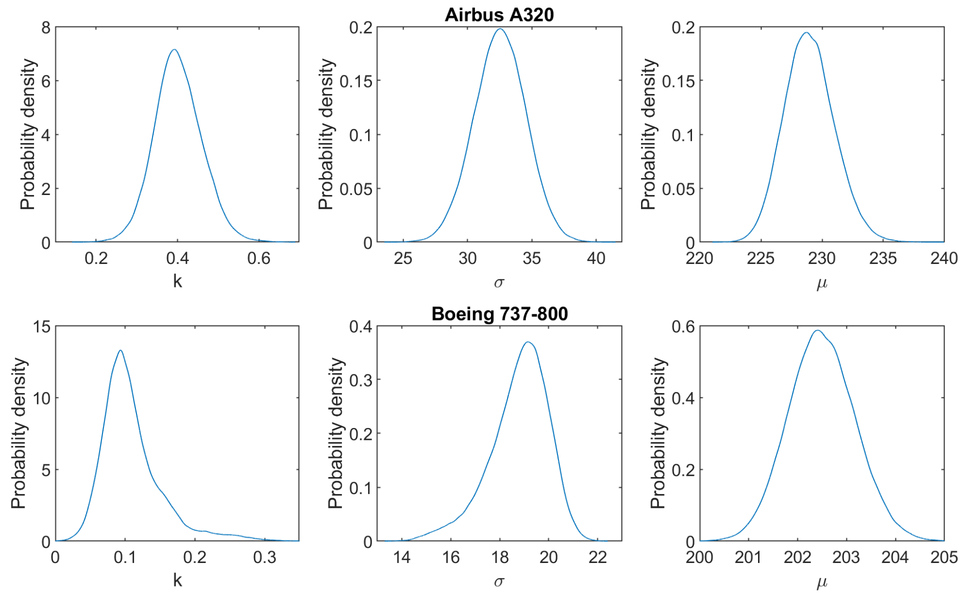

FIGURE 1. PDF estimates of GEV distribution parameters k, σ, μ for the Airbus A320 and Boeing 737-800.

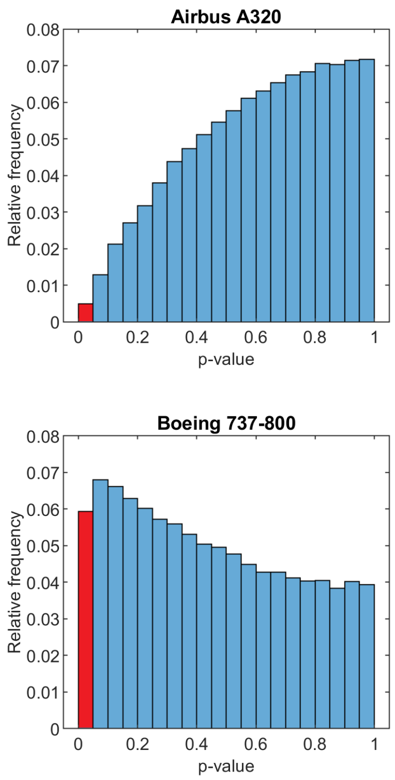

FIGURE 2. Histograms of ranksum test p-values after 100 000 simulation runs of the models, including the rejection regions (highlighted red).

equal to the "height" of the leftmost bin. The values were $\pi_{p,A320} = 0.005$ and $\pi_{p,B738} = 0.059$; in other words, the distributions of the real and predicted TIM values were different in roughly 0.5 % and 5.9 % of simulation runs for the Airbus A320 and Boeing 737-800 respectively (i.e., the null hypothesis of the `ranksum` test was rejected in those cases).

Figure 3 shows the distributions of the computed TSPE values, illustrated for both aircraft types by means of a histogram accompanied by a boxplot. Analogically, Figure 4 shows the distributions of the computed RSC values for both aircraft types. The evaluated statistical measures for both metrics as listed in 2.4 are given in Table 2.

Statistical measure	Boeing 737-800 TSPE	Boeing 737-800 RSC	Airbus A320 TSPE	Airbus A320 RSC
Mean	0.446	0.039	1.686	0.163
Median	0.382	0.034	1.344	0.132
IQR	0.463	0.040	1.688	0.165
β_{RSC}	–	1.000	–	0.999

TABLE 2. Evaluated statistical measures for TSPE and RSC for the Boeing 737-800 and Airbus A320 models.

Finally, Figure 5 shows example results of predicting the TIM values using the model parameters $\hat{\theta}$ for both aircraft types. In the figure, the real and predicted TIM values are shown together in the form of overlapping histograms. In both presented cases, the p-value of the `ranksum` test was 1.

4. DISCUSSION

As was already mentioned in the previous section, the first step in constructing the model used for subsequent prediction of the TIM values was to estimate the PDF of each GEV distribution parameter. In order to investigate the behavior of the parameters and thus their distributions (i.e., probability densities) in order to make good point estimates of the parameters $\hat{\theta}$ later on, a different sample of the data was selected every iteration. Given the results presented

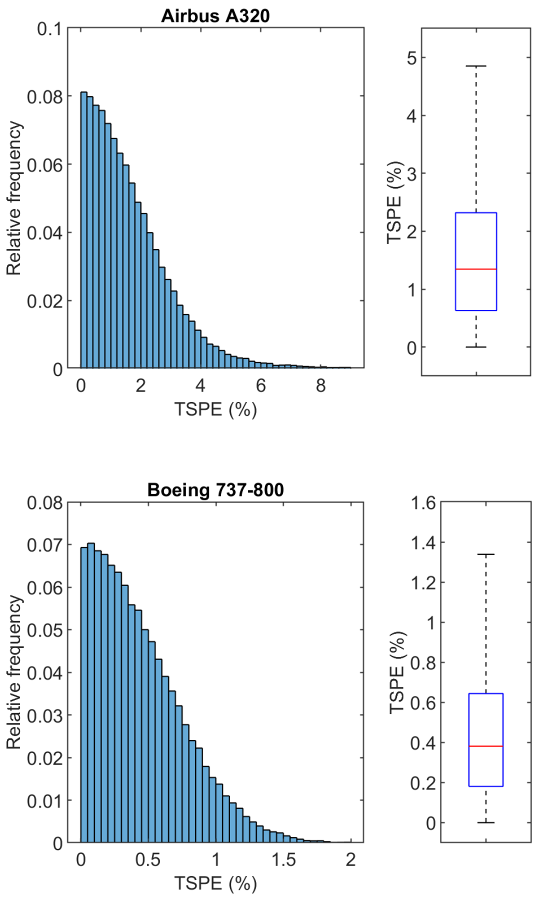

FIGURE 3. Histograms and boxplots of TSPE values after 100 000 simulation runs of the models.

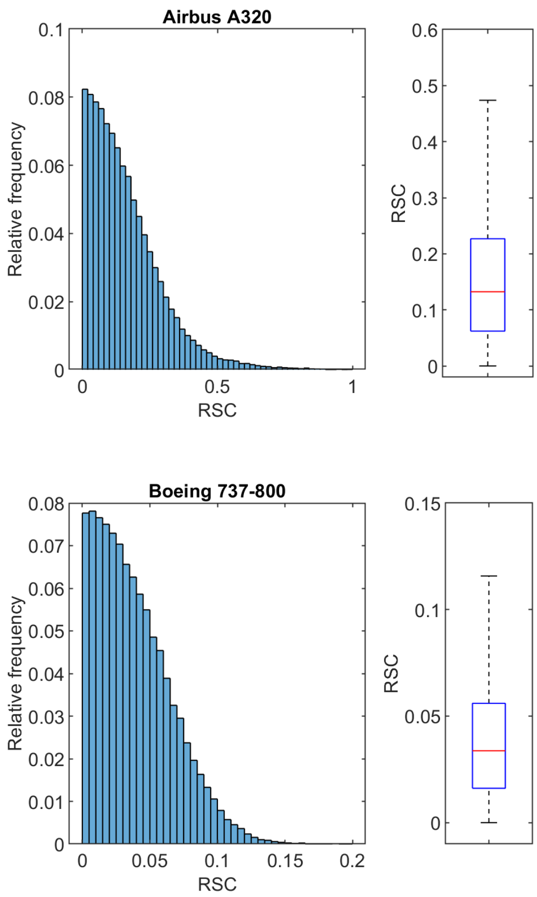

FIGURE 4. Histograms and boxplots of RSC values after 100 000 simulation runs of the models.

in Figure 1, the chosen number of iterations (100 000) may be considered sufficient in this regard.

The next step was therefore making point estimates of the model parameters $\hat{\theta}$ to use in the subsequent predicting of TIM values. Clearly, as the PDF in Figure 1 show, the estimates of the parameters constructed through the iterations were random variables. This was not considered in the model, where only the point estimates $\hat{\theta}$ were used. Therefore, the selection of the constant parameters was such to minimize the effect of this simplification. This was done by selecting the parameter values so that they corresponded to the maximums of the PDF. As will be shown in the following paragraphs, this simplification may be considered acceptable in terms of model performance.

Once the parameters $\hat{\theta}$ had been estimated for both aircraft types, the TIM values could be predicted using the constructed models. In order to evaluate the performance of the model, this was repeated 100 000 times. This number of simulation runs can be considered satisfactory given the clear results that were obtained. To allow for easier evaluation of the results, the number of generated TIM value predictions was equal to the number of the real values. Every simulation run, the two samples (predictions and real values) were compared using the `ranksum` test, whereby it was evaluated whether the samples came from the same distribution. Clearly, this would be the case with an appropriate model. The rate of null hypothesis rejection was described using the π_p ratio; its resulting values for both aircraft types may be considered indicative of a well-performing model in terms of how its parameters were set. Moreover, these results also indicate that the choice of the GEV distribution for the model was correct. Indeed, this can be seen in Figure 5, where the histograms of the real and predicted TIM values overlap to a relatively large extent.

Besides the `ranksum` test, the predictions were also evaluated using the two metrics defined in 2.4, namely the TSPE and RSC. The purpose of the TSPE was to evaluate the error in total calculated emissions after using the predicted TIM values instead of the real ones. Although the real values themselves were estimates from ADS-B data, they can be considered sufficiently close to the actual values and therefore act as a benchmark for the evaluation of the predictions. As the histograms and boxplots in Figure 3 show, the TSPE was generally low, with its values never exceeding 10 % for both aircraft types and with the median and mean values being only around 1–2 % according to Table 2. This percentage is in relation to the total sum of calculated emissions using the real

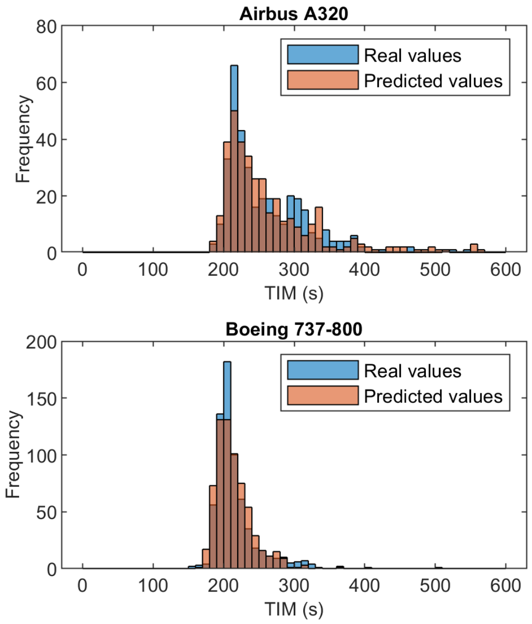

Figure 5. Example histograms of real and predicted TIM values for the Airbus A320 and Boeing 737-800.

TIM values. Therefore, using the predicted TIM values would, on average, yield emission estimates off by 1–2 % compared to using the real values. These results are in support of the constructed models as they show good performance regarding the predictions of aircraft emissions, since the calculated aircraft emissions are directly linked to the TIM values.

Benefits of using the model are also suggested by results regarding the RSC metric, which compared the predicted TIM values with the standard constant value of 240 seconds. More specifically, the differences in the sums of all TIM values were compared, which are directly linked to the resulting calculated emissions. As can be seen in Figure 4, the RSC values in the absolute majority of cases remained below 1, which is also confirmed by the values of the β_{RSC} ratio (showing the proportion of such cases) given in Table 2, as well as by the medians and means for both aircraft types (especially for the Boeing 737-800). These results clearly show that for the Approach operating mode of the LTO cycle and the analyzed aircraft types, the predicted TIM values are a better alternative to the standard TIM values, which is an expected result given the large rate of simplification associated with the original definition of the LTO cycle.

While the presented results show promising potential for future research in this area, there are certain limitations which need to be addressed. Firstly, without further validation, the presented results are only valid for the time period covered by the real data. In order to reliably assess the performance of the model over a longer time period, it would be desirable to also include another dataset from a later time period (e.g., several months later), on which the model would be tested. The results are also only valid for arrivals on Runway 24 at the airport; in the future, other runways should be assessed as well. Similarly, only two aircraft types were covered in this paper, therefore no conclusions can be made for other aircraft types. Since the model parameters were different for each aircraft type (as shown in Table 1), model construction is clearly necessary for every aircraft type individually. In this paper, factors that may influence the TIM values of the Approach LTO operating mode, such as arrival procedures or aircraft go-around rate, were not considered. Clearly, their changes may have an effect on the resulting TIM values, rendering the current model obsolete. Future work should therefore focus on investigating these factors and incorporating them into the model. Special attention should be paid to the topic of mixing height, which directly influences not only the TIM values, but the scope of emissions to consider in general. While the results show that modeling of TIM values is possible for the Approach LTO operating mode, further research is needed in order to be able to make the same conclusion for the other operating modes.

Nevertheless, despite the limitations mentioned above, the results presented in this paper show good model performance and may therefore be considered as an initial proof-of-concept regarding the use of modeling in order to estimate TIM values of the LTO cycle. Further in-depth research in this area may therefore provide practical outcomes, leading to improvements in the accuracy of calculations of airport aircraft movements' emissions without the need for extensive data covering every movement.

5. Conclusion

In this paper, we constructed models of the TIM values of the Approach LTO operating mode for the Boeing 737-800 and Airbus A320 aircraft at Prague Václav Havel Airport using the GEV distribution. The parameters of the model were given as point estimates made from the PDF of the individual GEV parameters. These were computed using kernel smoothing after repeatedly fitting the GEV distribution to random samples corresponding to 50 % of the original values. The models were then used to repeatedly generate predictions of TIM values for both aircraft types. Results of these repeated simulation runs showed a good model performance, with the resulting error in total sum of TIM values, relevant for emission inventory development, only being around 1–2 % on average. Furthermore, clear benefits of using this approach compared to the use of the standard TIM value for this operating mode are demonstrated, highlighting the feasibility of further research in this area. Such future research should include other operating modes of the LTO cycle while placing more emphasis on further model performance validation using more real data from different time periods. In order to allow for practical use in creating more accurate airport emission inventories, more aircraft types should also be included in the scope of research.

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