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THRUST ESTIMATION FOR DEPARTING JET AIRCRAFT USING POSITION DATA BASED ON A MACHINE LEARNING APPROACH

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ABSTRACT

Aircraft noise simulations need to be highly accurate, for which they require either thrust or the closely related rotational speed of the engine's low-pressure compressor, N1, as input parameter. However, often only position data are available, and N1 or thrust has to be estimated. Current parameter estimation models are only available for few aircraft types and often need additional, non-readily available information. In this contribution, a machine learning approach using the random forest algorithm to estimate N1 of narrow and wide body aircraft during departure is presented. To train the models, flight data recorder (FDR) data were used. The datasets were divided in training and validation data to identify the best combination of features and avoid overfitting. The resulting N1 estimation models only require readily available position and ground temperature data. The performance of the models is evaluated by comparing the noise calculation levels obtained using estimated N1 values to those obtained using N1 values from FDR data.

Keywords: *engine thrust, jet aircraft, aircraft noise, N1 estimation, random forest*

1. INTRODUCTION

Aircraft noise has negative impact on health [1] and must be monitored by noise measurements and/or calculations. The results of aircraft noise calculations usually have a large-scale impact, e.g., for land-use planning. Therefore, aircraft noise models need to be highly accurate and should represent the actual air operations (fleet mix, routes, etc.) as good as possible. sonAIR [2], a next generation aircraft noise calculation model, improves the accuracy by using real trajectories and corresponding flight variables. It further separates engine and airframe noise and also noise emission and propagation [3]. For the aircraft specific engine noise models, a crucial parameter is N1 (also indicated as %N1), the rotational speed of the jet engine's low-pressure shaft, which is highly correlated with the engine noise emission. Other aircraft noise models, such as the widely used AEDT [4], require thrust levels instead of N1. N1 is a flight parameter that, in contrast to thrust, is logged within the flight data recorder (FDR) and thus more readily available. In some cases, FDR data are accessible for noise calculations, and calculations with sonAIR can be conducted with logged N1 values. However, often only position data (radar or ADS-B) are available, and N1 has to be estimated using dedicated estimation approaches.

Since most aircraft noise models use either thrust or N1 as calculation parameter, different methods to estimate these parameters exist. Common approaches as described in Doc 29 [5] and Doc 9911 [6] or as used in the BADA model [7] depend on engine coefficients, which are specific for certain flight conditions and sections (e.g., max take-off thrust, max climb thrust, etc.). Other operational changes like reduced take-off thrust or reduced climb thrust require either take-off weight information or fixed reduction percentage values. A major drawback is that these methods are based on kinematic approaches, which require additional specifications such as lift coefficients at certain aircraft configurations. Furthermore, engine specific information is required, which can differ significantly for individual types and is not necessarily available for the considered aircraft.

So far, no estimation model that uses only basic input data and is capable of handling rather complex thrust or N1

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curves exists. The approach described in [8] estimates N1 based on position data only, but has to make assumptions about fixed thrust reduction altitudes, configuration settings and derated thrust levels. Further, the transition to the climb section is also linked to a fixed altitude and aircraft configuration, which are in reality often highly variable. This paper presents the development of an N1 estimation model based on a machine learning approach that addresses the limitations of previous models. Since airframe noise clearly dominates over engine noise during approaches [9], the N1 estimation is applied for departures only.

2. METHODS

2.1 Data preparation and model building

The machine learning method used to estimate N1 is the random forest algorithm. It is well suited due to its low bias and reduced variance, which decreases its sensitivity to noise in training data that often occurs. To have a robust approach that performs also well on newly modeled aircraft types, the same model features and hyperparameters [10] are used for all aircraft types. The training datasets are FDR data provided by Swiss International Airlines from airports around the world. They cover noise abatement departure procedures NADP 1 and NADP 2, with a data resolution of two seconds. Besides N1 values, FDR data comprise position and weather data. The aircraft types included in this dataset are types that often operate at Zurich airport (ZRH) and other European airports. Table 1 lists the aircraft types (ICAO designation) and the number of departures included in the training dataset.

Table 1. List of aircraft types and the number of departures included in each training dataset.

Aircraft type	#Departures
A319	190
A320	194
A321	197
A333	189
A343	170

From an operational perspective regarding the estimation of N1, NADPs can be separated into three sections. The first section is from take-off to thrust reduction height, the second the transition from thrust reduction to climb thrust, or usually continuous climb [11], and the third the continuous climb phase. Accordingly, these sections are called initial climb (IC), initial climb to continuous climb (ICCC) and continuous climb (CC). Figure 1 exemplarily shows typical N1 curves over height and the separation into the three sections. Random engine spool downs that clearly deviate from the typical N1 curves were not considered for model training, since they introduce unnecessary bias for situations that are hard to accurately predict, happen only rarely or at greater altitude and are thus also not important for the resulting noise exposure on ground.

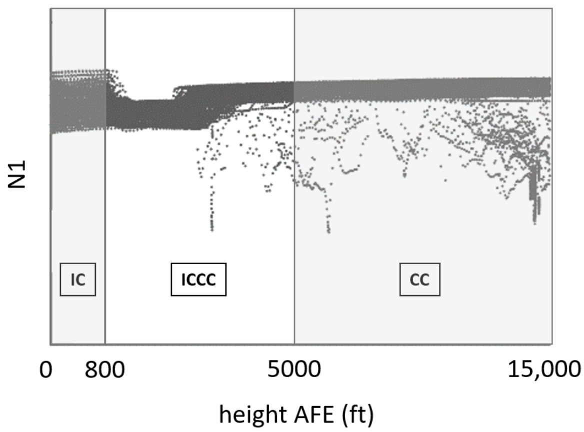

Figure 1. Exemplary N1 curves over height (A319) and the separation into three sections IC, ICCC and CC. Spool downs that deviate from the typical N1 curve are not considered for model training.

For each of the three sections, N1 correlates with different flight parameters. Hence, for each section, a random forest model with a unique set of features was built. Table 2 lists the features chosen for each flight section. The "ground roll distance" is defined as the distance from break release point to take-off (35 ft over runway height [12]). "Delta temperature ISA" is the temperature difference at a given altitude relative to ground temperature by the method defined for the International Standard Atmosphere (ISA) [13].

The feature selection and hyperparameter settings are

Table 2. List of aircraft types and the number of departures included in each training dataset.

Departure section (altitude range)	Model features
IC (0–1500 ft)	Groundspeed Flight altitude (relative) Ground roll distance Take-off speed
ICCC (1500–5000 ft)	Flight altitude (relative) Ground temperature Take-off speed Thrust reduction height (NADP)
CC (>5000 ft)	Groundspeed Ground temperature Delta temperature ISA

based on preliminary evaluations, where a set of model was generated and cross-validated with a data holdout of 25%. A variety of criteria were assessed to select the model parameters, such as overall estimation errors and its pattern, the consistency over multiple cross-validation runs but also over different aircraft types, and the availability of the model features. Further, the robustness regarding data resolution and data noise were considered.

2.2 Model validation with noise calculations

The model performance was validated with noise calculations at virtual microphone positions using real flight trajectories at ZRH (395 flights). The trajectories include two runways (16 and 28) with different lengths and a general thrust reduction height at 1500 ft above field elevation (AFE). The noise calculations were conducted with sonAIR [2]. The flight tracks of all simulated trajectories and virtual microphone positions are shown in Figure 2. Within these departure trajectories, IC and ICCC sections are covered. The CC section models cannot be validated with these simulations; however, it is assumed that the random forest models perform similar or better in this section due to the simpler N1 curves (despite random spool downs). Further, at greater altitudes than where the simulated trajectories end, noise exposure levels on ground decrease below legal Swiss noise exposure limits [14]. The validation includes all aircraft types listed in Table 1. For each departure, the N1 values were estimated with the random forest models generated within this paper and used to calculate the noise exposure of each single flight.

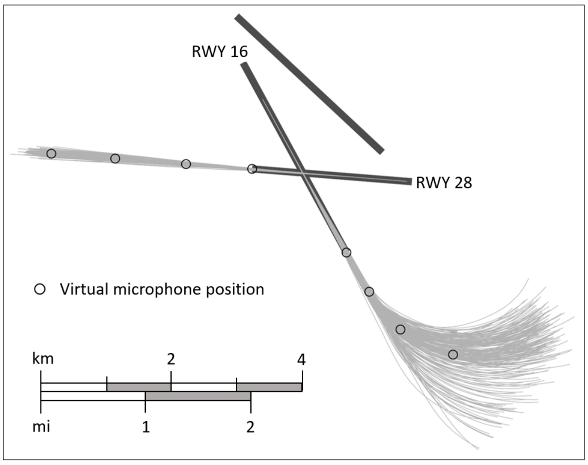

Figure 2. Runways at ZRH and tracks of all simulated departure flights to validate the N1 estimation models with noise exposure calculations. The circles indicate virtual microphone positions, where noise exposure levels are calculated for each flight.

To determine the model performance and its accuracy regarding noise calculations, the sonAIR calculations based on estimated N1 values were compared to those using real N1 values from FDR. The results of the validation are presented in the following Section 3.

3. RESULTS

Figure 3 shows the overall difference between estimated N1 values and those from FDR data (estimated minus FDR). The black line indicates the mean and the shaded area the standard deviation of the N1 value differences. For the IC section, the maximum mean difference is well below 1 %N1 and the standard deviation is very constant at around ±2 %N1. The thrust reduction height at 1500 ft AFE is clearly visible, where N1 values are generally slightly underestimated and the standard deviation increased. After thrust reduction at around 2000 ft AFE, the mean and standard deviation strongly decrease.

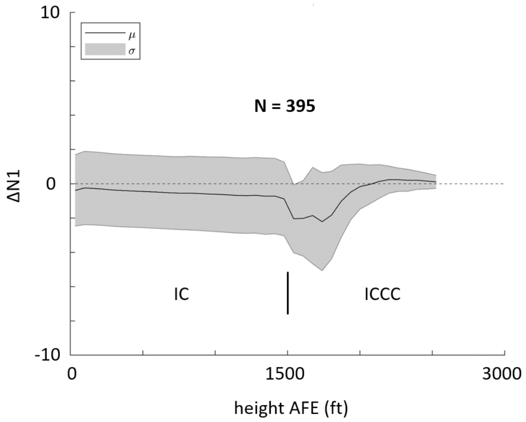

Figure 3. Mean difference (μ) and standard deviation (σ) of estimated N1 values and values from FDR data for all simulated flights (N = 395). The thrust reduction height at 1500 ft AFE is clearly visible.

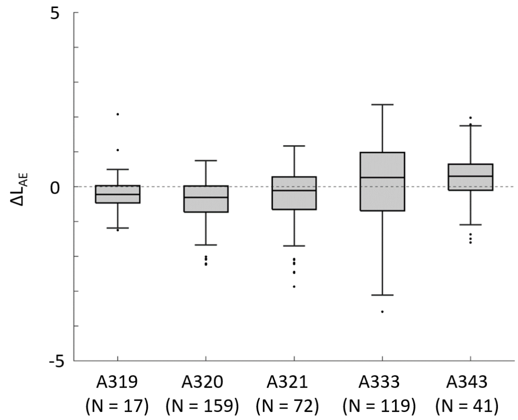

Figure 4. Box-and-whisker plots of noise exposure differences ΔL_{AE} (estimated N1 minus N1 from FDR data) from noise calculations with sonAIR at virtual microphone positions.

Figure 4 shows the differences between noise exposure calculations of estimated N1 values and those from FDR data over all virtual microphone positions, separately for each aircraft type. For all aircraft types, the median deviation (black line in box plot) is below 0.5 dB. Hence, no overall systematic offsets occur. The narrow body aircraft types (A319, A320 and A321) show a similar scatter, and the boxes and whiskers are symmetric. The wide body aircraft types (A343 and especially A333) generally show a somewhat larger scatter.

4. DISCUSSION

For three narrow body and two wide body aircraft types, an N1 estimation model based on the random forest algorithm was built. The method is applied to departures, which were divided into three procedural sections (c.f. Figure 1) in which N1 correlates with different flight parameters. The model features for each section were selected accordingly.
For the IC section, only time and position data are required. This section has the highest impact in terms of noise exposure on ground, due to the low flight altitude. If no NADP thrust reduction is applied, the IC can be extended up to CC altitude. Otherwise, thrust reduction for the ICCC section has to be estimated, which depends on the departure airport/NADP (thrust reduction height is fixed) and the aircraft type. Regarding N1 estimation, this section is the most complex one, as thrust levels are strongly variable; however, it was shown that the random forest models also perform well in this section, with slightly increased deviations.
For individual aircraft types, depending on the complexity of N1 setting sequences during departure, the model performances differ accordingly. However, validations with noise calculations showed that the average N1 estimation is very accurate. This implies that the random forest approach developed here is well suited for aircraft noise calculations.
Compared to other N1 estimation models, no engine or aircraft specific parameters are required. The method is therefore more readily applicable, similarly for all jet engine aircraft types. Further, no assumptions about operational changes at fixed altitudes have to be made. Thrust reductions for NADP and derated climb thrust settings are implicitly contained within the model structure, which makes the N1 estimation method independent of the departure airport.

5. CONCLUSION

This paper presents the model building for estimating N1 of departing aircraft based on a machine learning approach using the random forest algorithm. It is similarly applicable for narrow as well as wide body aircraft types, using a minimum and readily available set of input pa-

rameters. The resulting models are trained with FDR data from departures at airports around the world.
The models' accuracy was tested by comparing noise calculations for departure trajectories obtained from FDR data, which included recorded N1 values, with estimated N1 values at virtual measurement stations. Overall, good results were obtained, with median level differences below 0.5 dB for the studied aircraft types.

6. ACKNOWLEDGMENTS

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7. REFERENCES

[1] WHO, "Environmental noise guidelines for the european region," report, 2018.

[2] J. M. Wunderli, C. Zellmann, M. Köpfli, M. Habermacher, O. Schwab, F. Schlatter, and B. Schäffer, "sonair - a gis-integrated spectral aircraft noise simulation tool for single flight prediction and noise mapping," *Acta Acustica United with Acustica*, vol. 104, no. 3, pp. 440–451, 2018.

[3] C. Zellmann, B. Schäffer, J. M. Wunderli, U. Isermann, and C. O. Paschereit, "Aircraft noise emission model accounting for aircraft flight parameters," *Journal of Aircraft*, vol. 55, no. 2, pp. 682–695, 2017.

[4] U. D. of Transportation Volpe National Transportation Systems Center, "Aviation environmental design tool (aedt) technical manual, version 3d," report, 2021.

[5] ECAC, *ECAC.CEAC Doc 29: Report on Standard Method of Computing Noise Contours around Civil Airports, Volume 2: Technical Guide. 4th ed.* Neuilly-sur-Seine, France: European Civil Aviation Conference (ECAC), 2016.

[6] ICAO, *Recommended Method for Computing Noise Contours Around Airports. Doc 9911. 1st ed.* Montréal, Canada: International Civil Aviation Organization (ICAO), 2008. NR.

[7] D. Poles, "Base of aircraft data (bada) aircraft performance modelling report," report, Eurocontrol, 2009.

[8] O. Schwab and C. Zellmann, "Estimation of flight-phase-specific jet aircraft parameters for noise simulations," *Journal of Aircraft*, vol. 57, no. 6, 2020.

[9] U. Römer, L. Bertsch, S. B. Mulani, and B. Schäffer, "Uncertainty quantification for aircraft noise emission simulation: methods and limitations," *AIAA Journal*, vol. 60, no. 5, pp. 3020–3034, 2022.

[10] P. Probst, M. N. Wright, and A.-L. Boulesteix, "Hyperparameters and tuning strategies for random forest," *WIREs Data Mining and Knowledge Discovery*, vol. 9, no. 3, p. e1301, 2019. https://doi.org/10.1002/widm.1301.

[11] Eurocontrol, "European cco / cdo action plan," report, 2020.

[12] J. D. J. Anderson, *aircraft performance and design*. New Delhi: Tata McGraw Hill Education Private Limited, fifth reprint 2012 ed., 1999.

[13] ISO (International Organization for Standardization), "ISO 2533:1975 Standard Atmosphere," 1975.

[14] LSV, "Lärmschutz-Verordnung (LSV) vom 15. Dezember 1986 (Stand am Stand am 1. Juli 2021)," report, 1986. NR.