Engine Load Prediction during Take-Off for the V2500 Engine

Robert Meissner[1], Patrick Reichel[2], Peter Schlick[3], Christian Keller[4], and Kai Wicke[5]

[1,5] *German Aerospace Center (DLR), Hamburg, 21129, Germany*
robert.meissner@dlr.de
kai.wicke@dlr.de

[2] *Technische Universität Braunschweig, Braunschweig, 38106, Germany*
p.reichel@tu-braunschweig.de

[3] *MTU Aero Engines AG, München, 80995, Germany*
peter.schlick@mtu.de

[4] *MTU Maintenance Hannover GmbH, Hannover, 30855, Germany*
christian.keller@mtu.de

Abstract

The aviation industry faces an ever increasing pressure to reduce its cost in order to gain competitive advantages. Since aircraft maintenance contributes strongly with about 17% to the overall direct operating cost (DOC), maintenance providers are required to continuously reduce their cost share as well. As a result, a lot of effort is put into the exploitation of the potential of emerging digitalization technologies to predict upcoming system faults and, therefore, reduce the projected maintenance impact. The detection of early stage faults and prediction of remaining useful lifetimes (RUL) for various systems, including aircraft engines as high-value assets, has been a focal point for many research activities already. A key aspect – necessary for an accurate prediction of future behavior – is the correct mapping of ambient conditions that have led to the respective system condition. Therefore, it is necessary to combine data information throughout an aircraft's life from different stakeholders to gain valuable insights. However, as the aviation industry is strongly segregated with many parties involved, trying to gain their own competitive advantage, the required information about the operating condition is often not available to independent maintenance providers. Thus, modeling engine degradation often needs to rely on estimated nominal conditions, limiting the ability to precisely predict engine faults. With this paper, we will develop a model that allows users to estimate the experienced engine load during take-off by only using publicly available information, i.e. airport weather information reports and public flight data. The calculated engine load factors are computed in terms of an engine pressure ratio (EPR) derate. The results are benchmarked with the actual engine derate, obtained for different operators and various ambient conditions, to enable an identification of challenges for the load prediction and areas of improvement. The developed model will help to adjust engine failure projections according to the experienced ambient conditions and, therefore, supports the development of better engine degradation models.

1. Introduction

The aviation industry is a highly competitive environment and constantly seeking for advantages towards a more cost-efficient operation in order to gain or keep market shares. Therefore, all stakeholders in airline operations are required to minimize their cost share constantly. According to Hölzel (2019), aircraft maintenance contributes strongly to the overall operational cost with an estimated share of about 17% of the direct operating cost (DOC) or about 10% of the total operating cost (TOC), respectively. Thus, cost savings in aircraft maintenance promise a significant impact on the resulting overall aircraft operation cost. As a result, a lot of effort is put into the exploitation of the potential of emerging digitalization technologies to predict upcoming system faults and, therefore, reduce costly maintenance downtime and operational irregularities, e.g. flight delays or cancellations.

The detection of early stage faults and prediction of remaining useful lifetimes (RUL) for various systems has been a focal point for many research activities already. Since the aircraft engines represent high-value assets with a comparably high maintenance share of about 35-40% according to Ackert

(2011), the development of engine health management (EHM) technologies has been a significant effort in research through the years. To get an overview of approaches that have been developed for an engine condition monitoring, we present selected work for an engine state detection and degradation modeling. In general, it needs to be noted that the vast majority of previous work requires extensive sensor values to be available and accessible for the state detection.

Chatterjee and Litt (2003) have developed a model to compensate age- and degradation-related performance deficiencies for an autonomous propulsion control. Their presented approach is based on various efficiency parameters found in literature and includes different key engine components, such as the low pressure compressor (LPC), the high pressure compressor (HPC), the low pressure turbine (LPT), and the high pressure turbine (HPT). In order to adjust their model for a continuous compensation of observed performance loss, i.e. thrust loss, they use derived health conditions corresponding to engines with 3,000 and 6,000 operating hours, respectively.

Kurosaki et al. (2004) utilize sensor output data from the engine control unit (ECU) to develop their model for engine deterioration. By using only sensors that are already installed on the aircraft, they avoid the need for costly retrofits. Additionally, their approach does not require previous experience with the engine type and, therefore, can be applied to newly developed engine models.

Rausch, Goebel, Eklund, and Brunell (2005) have developed a model to rapidly detect performance anomalies, e.g. due to engine deterioration, based on sensor output during flight and adjust engine control inputs accordingly. The sensor data used for this study are taken from a physics-based aircraft engine model and can incorporate differences in production and performance to represent different engines. Based on the in-service deterioration, the parameter values will be changed from their nominal new condition with respect to the severity of the fault and do also incorporate sensor inaccuracies. However, the presented approach has been developed to avoid immediate undesired behavior of the engine system and is not considering an overall engine health management strategy, e.g. load reduction to extend the engine's lifetime.

Besides these approaches of degradation detection and, subsequently, RUL prediction, Hanumanthan (2009) has developed a method to estimate the operating severity - based on the ambient conditions (e.g. outside air temperature [OAT] and airport elevation) and thrust derate. Additionally, he developed an approach to predict the resulting Shop Visit Rate (SVR), i.e. the number of removals per 1,000 hrs. of engine operation, for scheduled maintenance - based on performance deterioration in terms of exhaust gas temperature (EGT). Hanumanthan states the importance of the ambient conditions for the severity and SVR estimation. In his study, however, he uses these ambient factors as input for the model and has examined them exclusively parametrically. Thus, the correct forecast of the operating conditions will be vital for a precise prediction.

Albeit all of the presented models provide valuable approaches to measure and detect engine deterioration and upcoming faults, they often neglect the ambient conditions leading to the deterioration or consider them as prerequisite for their simulations. As Zaita, Buley, and Karlsons (1998), Goebel, Qiu, Eklund, and Yan (2007), Saxena, Goebel, Simon, and Eklund (2008), and Lim, Levine, Ngo, Kirby, and Mavris (2018) point out, a key aspect – necessary for an accurate prediction of future behavior – is the correct mapping of ambient conditions that have led to the respective system condition. Therefore, it is necessary to combine data information throughout an aircraft's life from different stakeholders with the sensor data - describing the system condition itself to gain further insights. Additionally, sensor data might not be available in the extent necessary to rely on the developed models to predict engine deterioration. Among others, these limitations stem from the following reasons:

Market segregation. As the aviation industry is strongly segregated with many stakeholders involved trying to gain their own competitive advantage (e.g. operator, maintenance provider, and manufacturer), the required information about the operating condition and system performance, i.e. sensor data, is often not available to 3rd parties ((Robertson & Perera, 2002), (Roy, Stark, Tracht, Takata, & Mori, 2016), (Groenenboom, 2019)). Thus, modeling engine degradation often needs to rely on estimated nominal conditions, limiting the ability to precisely detect engine faults and predict upcoming failures.

Signal transmission limitation. The increasing amount of on-board data generated can only be exploited when it can be transferred to a suitable ground-station for further processing in a cost efficient and reasonably timed manner. Especially for older aircraft types, which do not provide an on-board infrastructure that has been designed to process and transmit large quantities of data, models are often limited to rely on snapshots rather than continuous measurements. (Aircraft Commerce, 2019)

With this paper, we will develop a model that allows users to estimate the experienced engine load during take-off by only using publicly available information, e.g. airport weather reports and public flight data, to compensate for the previously mentioned limitations. The calculated load factors are computed in terms of an engine pressure ratio (EPR) derate. Unlike the engine's EGT, this ratio is solely dependent on the required thrust and does not change for different ambient conditions (e.g. OAT) or engine degradation levels. Additionally, it does not require further knowledge about the engine in order to convert the EPR information into its generated thrust equivalent to subsequently calculate the corresponding thrust derate. Thus, we can limit the model's complexity. The computed derate will help to adjust engine failure projections according to the experienced ambient conditions. Subsequently, the developed model will support the improvement of engine degradation models.

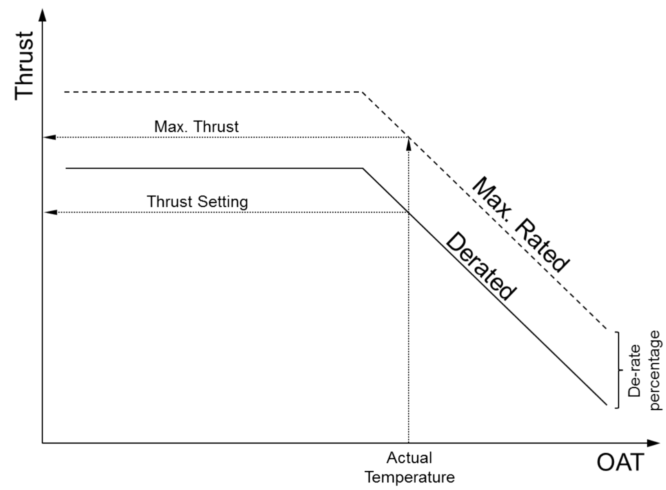
To present our methodological approach and the derived framework, we have structured this paper as followed: In section 2, we will present the state-of-the-art approach for engine derating and explain why an engine derate is favorable over a full power take-off. The developed method will be explained in section 3, including the underlying assumptions and approaches to estimate values that are not publicly available. We will compare the calculated results from our model with true engine load values obtained for different operators and various ambient conditions in section 4. Due to data availability and market share, we will focus in this paper on the prediction and validation of engine load values for the V2500-A5 engines, used for the A320 family, among others. However, the method shall be adoptable for other engine models and aircraft types as well.

2. ENGINE THRUST REDUCTION

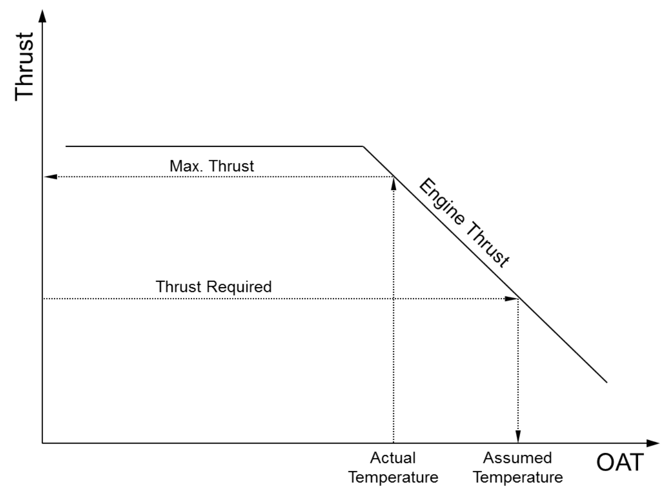
Engine loads, besides other factors like flight length and cycles per year, significantly influence the times between engine refurbishments and the associated refurbishment costs (James & O'Dell, 2005). As Ting (2002) points out, maintenance cost increase exponentially with an increasing EGT. Therefore, operators thrive to reduce the engine load during take-off and initial climb as much as possible under the given ambient conditions in order to reduce engine related maintenance cost and extend the engine on-wing time ((Donaldson, Fischer, Gough, & Rysz, 2007), (Thomas, 2011)). As an upper derating limit however, the engine thrust shall not be reduced below 75% of its nominal, full-rated thrust, according to the applicable regulatory specifications (European Aviation Safety Agency, 2007). Due to the exponential nature of engine degradation, the effect of on-wing time extension has the highest impact for small derates, since the marginal effect decreases for higher thrust reductions. (Ting, 2002)

To determine if a derate is possible and to what extent an engine can be derated, operators will need to take the following factors into account ((Federal Aviation Administration, 1993), (Ting, 2002)):

- Runway (length, slope, and obstacles),
- Runway surface condition,
- Airport elevation and pressure,
- Actual take-off weight (TOW),
- Ambient weather conditions (e.g. wind strength, runway condition),
- Flap/Slat settings, and
- Engine bleed configuration.



(a) Derate method



(b) Assumed Temperature method

Figure 1. Reduced engine thrust methods (Ting, 2002)

There are three main methods for derating aircraft engines that are currently used ((Federal Aviation Administration, 1993), (Ting, 2002)):

Fixed derate method. This method will use a predefined derate value to lower the engine's thrust rating as a percentage of the nominal thrust setting by the manufacturer. This pre-set engine thrust derate cannot be changed by the operator (Ting, 2002). Since no variations according to ambient operating conditions are allowed and possible, we will not focus on this approach within this paper.

Variable derate method. This method will use a derate value from a range of allowable ratings to lower the engine's thrust rating as a percentage of the nominal thrust setting. Thus, the engine will artificially be adjusted in its performance and as a result be virtually equivalent to a smaller engine (Yin & Li, 2016). The level of engine thrust derate can be changed by the operator to adapt for varying ambient conditions, as seen in figure 1a. This method is allowed to be used even if the runway is contaminated. However, an initially selected derate level shall not be overwritten during a commenced take-off run by advancing the thrust lever angle (TLA) beyond the initially calculated thrust setting, except for emergency situations (Daidzic, 2012). Otherwise, the aircraft may experience a loss in directional control and veer off the runway, since the minimum control speed (v_{mcg}) has been determined using the reduced thrust. (Ting, 2002)

Assumed Temperature (T_{Flex}). This method will simulate the OAT to be higher than the actual OAT to limit the engines performance (Ting, 2002). This approach takes advantage of physical limitations for the different components of an engine. Especially for higher OATs, the engine needs to gradually reduce its thrust to limit the turbine inlet temperature (TIT). Thus, by simulating operation at a higher OAT, the engine will automatically reduce its thrust accordingly, as can be seen in figure 1b. The selected temperature setting and resulting thrust can be overwritten by the flight crew without the danger of a loss in control over the aircraft. However, the assumed temperature derate is strictly limited when the runway is contaminated. (Ting, 2002)

As of this paper, we will focus on the approach of the assumed temperature method to calculate the reduced engine thrust, since this method is the predominant approach for the Airbus A320 family. To determine the assumed temperature to be inserted into the flight management computer (FMC), the flight crew has to calculate the required engine thrust settings based on the ambient parameters that have been mentioned previously. If these ambient conditions are particularly favorable, e.g. cold temperatures, low take-off weight, low airport elevation, or high available runway length, an engine derate may be an option to reduce the engine load. With the help of a take-off chart, as shown in table 1 for a randomly selected airport, the flight crew can determine the maximum permissible OAT for the actual TOW of the flight, i.e. the weight values provided here. The values of this table already incorporate factors like runway length, airport elevation and flap-/slat-settings. For an example on how to read this table, we will assume the following scenario: An aircraft is commencing its flight from the chosen airport represented in table 1 with headwind of 10 kt. and an actual OAT of 14° Celsius. Thus, the maximum allowable take-off weight (MATOW) for this flight equals 74.9 tons. However, since the aircraft has an (assumed) actual TOW for the respective flight of just 71 tons, the aircraft could still safely take-off from the respective airport under the given ambient conditions at an OAT of 58° Celsius. Therefore, the flight crew would insert the assumed OAT of 58° Celsius into the FMC. If the value for temperature, wind condition, or any other parameter is in between the given finite steps in table 1, the values will need to be interpolated accordingly. For example, if the head wind for this flight had been 15 kt., the resulting MATOW would have been 75.25 tons instead. The provided information about the (assumed) OAT will be processed by the ECU and will result in corresponding EPR's as regulatory value for an engine performance management and the respective engine thrust, accordingly. The EPR values are different for each:

Table 1. Extract from an exemplary take-off chart for the A320 (Airbus, 2002)

OAT (C)	**Conf. 2**				
	Tailwind (-10 kt)	Tailwind (-5 kt)	Wind (0 kt)	Headwind (10 kt)	Headwind (20 kt)
-6	72.0 t	73.4 t	74.8 t	75.6 t	76.3 t
4	71.6 t	73.0 t	74.4 t	75.2 t	75.9 t
14	71.2 t	72.5 t	74.0 t	74.9 t	75.6 t
24	71.0 t	72.1 t	73.6 t	74.5 t	75.2 t
34	70.8 t	71.7 t	73.1 t	74.1 t	74.9 t
44	70.5 t	71.7 t	72.7 t	73.7 t	74.5 t
54	70.4 t	71.5 t	72.0 t	72.1 t	72.0 t
56	69.5 t	70.6 t	71.3 t	71.4 t	71.3 t
58	68.3 t	69.4 t	70.4 t	71.4 t	71.6 t
60	67.2 t	68.2 t	69.3 t	70.2 t	71.0 t

- engine type,
- engine bleed setting,
- OAT,
- pressure altitude, and
- Mach number.

These values are provided in tabular form and can be determined through interpolation. Once the corresponding EPR has been obtained, we can calculate the engine load factor with eq. 1 in terms of EPR.

$$\mathrm{LF} = \frac{\mathrm{EPR}_{\mathrm{max}} - \mathrm{EPR}_{\mathrm{flex}}}{\mathrm{EPR}_{\mathrm{max}} - 1} \tag{1}$$

$\mathrm{EPR}_{\mathrm{flex}}$ symbolizes the EPR from the derated engine and $\mathrm{EPR}_{\mathrm{max}}$ serves as the maximum available EPR under the given ambient conditions. For this paper, we will use the relationship in eq. 1 as an indicator of experienced engine stress during take-off. It has to be noted, though, that additional parameters could be used for estimating the engine load, e.g. the engine thrust derate or the EGT ratio, requiring additional information about the relationship of EPR and thrust or EGT, respectively.

3. DATA ACQUISITION AND BASIC ASSUMPTIONS

Based on the approach to determine the possible engine load reduction presented in the previous section, we have developed a framework that allows users to estimate engine loads for singular flights, as depicted in figure 2. The framework

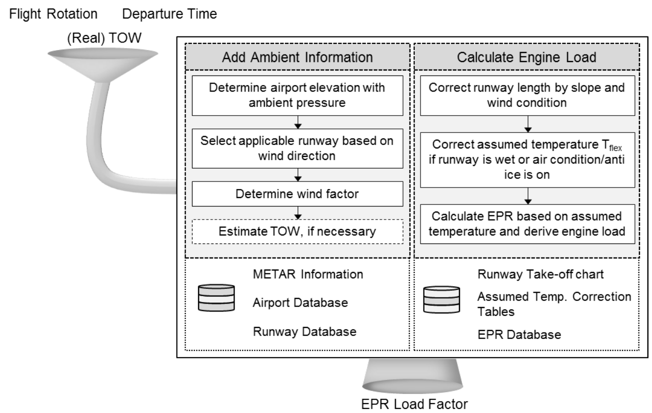


Figure 2. Schematic overview of developed engine load estimation framework

consists of two separate units to add ambient information and calculate the resulting expected engine load.

At the beginning, based on the flight rotation, i.e. the departure airport, and the departure time provided by the user, the framework will retrieve the corresponding airport, runway(s), and weather information (Meteorological Aerodrome Report [METAR])[1]. An example of such a METAR report is shown in table 2. These METAR reports will be issued at predetermined times and represent the current weather condition at the time of recording at the respective station (Deutscher Wetterdienst, 2019). Due to the snapshot characteristic, it is possible that the examined departure occurred in between two consecutive weather reports. In this case, we have interpolated the values, i.e. temperature, wind direction, and wind strength, with respect to the time of departure.

As the next step, the TOW information for the respective flight has to be retrieved. If not known and since there are no publicly available databases for these information on a singular flight level, the framework will estimate the value based on the great circle distance (GCD) between origin and destination airport with the help of a simple regression. The regression formulae have been developed with historical operational data for different operator regions (see eqs. (2) - (5)) that have been provided by MTU (ref. section 4.1).

Once all information about the ambient condition has been gathered, the true available runway length will be corrected by the effects of runway slopes, head- or tailwinds, and the runway condition, as described in the flight crew operating manual (FCOM) (Airbus, 2002). As a general rule, the actual available runway length will be artificially shortened for uphill slopes and tailwinds and will be extended for downhill takeoffs and headwinds. With these input values, we are able to calculate the assumed temperature to be selected by the

[1]The relevant airport and runway information for this study can be downloaded at `https://ourairports.com/data/`.

Table 2. Exemplary METAR report for the airport of Hamburg[2]

EDDH	**161720Z**	**31011KT**	**9999**
Station	*Date & Time*	*Wind direction & wind speed*	*Visibility*
FEW033	**12/04**	**Q1016**	**NOSIG**
Sky condition	*Temperature & dew point [in °C]*	*Pressure [in hPa]*	*Weather phenomena*

flight crew with the help of performance tables as shown in tab. 1. Subsequently, the calculated assumed temperature can be used to estimate the corresponding $\mathrm{EPR}_{\mathrm{flex}}$ and $\mathrm{EPR}_{\mathrm{max}}$, using engine-related performance tables from the existing Performance Engineers' Programs (PEP) software framework (Airbus, n.d.).

For the sake of simplifying the modeling complexity, we have made the following assumptions for the framework's development:

- A_1 The aircraft will always be assigned to the runway with the strongest headwind.
- A_2 Operational restrictions for take-off directions[3] will be neglected.
- A_3 If the airport has had rain at the last recorded weather status (within a maximum permissible time frame of 3 hours), the runway is assumed to be wet.
- A_4 Both, engine anti-ice and wing anti-ice, will be activated whenever the temperature is below 10° Celsius and the weather reports indicates high humidity.
- A_5 The take-off will be conducted with a slat-/flap-setting of configuration 2.

4. MODEL VALIDATION

The aspect of model validation will be threefold. First, we will develop a model for the prediction of the TOW. This step is required since the permissible assumed temperature is heavily dependent on the TOW and there is no public database for it available. With the TOW and other ambient conditions as input, we will then validate the calculated, corresponding assumed temperature T_{flex}. Finally, we will verify the estimated engine derate (based on the calculated T_{flex}) and compare the resulting engine load with real operational data to benchmark the developed model.

[2]This weather report and historical weather reports for all major commercial airports can be retrieved from `https://mesonet.agron.iastate.edu/request/download.phtml`.

[3]For example, at Frankfurt airport's runway 18, aircraft are only allowed to take off in southern direction. However since there is no available database, our simulation would not restrict take offs in the northern direction if the prevailing wind at the time of departure is from this direction.

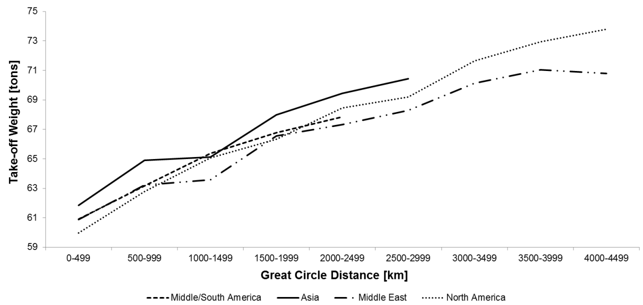


Figure 3. TOW distribution for different operator regions and great circle distances

4.1. Estimation of take-off weight

As a first step, we have to verify our estimation method for the TOW as input for the engine load calculation method. The basic idea here is to use a regression model to estimate the relationship between the flight's GCD and the resulting TOW. Historical flight operating data serves as basis for the calculation. Brooks, Clark, Melikov, Miers, and Mestre (2016) have conducted a similar study to identify a possibility for TOW estimation based on the GCD. However, for their study they have used the TOW average for flight connections between a given set of airports. Therefore, differences in operational procedures for various airlines, possibly resulting in different TOW's for the same connection, would be neglected. Additionally, they have focused their study solely on connections from or to the U.S. market. As can be seen in figure 3 however, the distribution of TOWs can significantly differ from one region of operation to another. Subsequently, we have separated the TOW regression estimation based on the primary geographical region of operation, i.e. Asia, Middle East (ME), Middle/South America (MSA), and North America (NA), utilizing representative airline operators for each region:

$$\mathrm{TOW}_{\mathrm{Asia}} = -4.4 \cdot 10^{-7} \cdot \mathrm{GCD}^2 - 0.0047 \cdot \mathrm{GCD} + 60.595 \quad (2)$$

with an R^2 of 0.386,

$$\mathrm{TOW}_{\mathrm{ME}} = -3.9 \cdot 10^{-7} \cdot \mathrm{GCD}^2 + 0.0045 \cdot \mathrm{GCD} + 59.462 \quad (3)$$

with an R^2 = 0.344,

$$\mathrm{TOW}_{\mathrm{MSA}} = -1.56 \cdot 10^{-7} \cdot \mathrm{GCD}^2 + 0.0078 \cdot \mathrm{GCD} + 58.117 \quad (4)$$

with an R^2 of 0.32, and

$$\mathrm{TOW}_{\mathrm{NA}} = -2.995 \cdot 10^{-7} \cdot \mathrm{GCD}^2 + 0.0048 \cdot \mathrm{GCD} + 58.926 \quad (5)$$

with an R^2 of 0.576.

For these TOW estimation regression equations, the following assumptions have been made:

1. The GCD between origin and destination airport must be greater than 100 km to exclude maintenance check flights with little representation of real airline operations.
2. The TOW must be within the specification limits of an A320, i.e. greater than the operating empty weight (OEW) of 41.3 tons and less than the MATOW of 78 tons (Airbus, 2011).

As can be seen by the comparably small regression coefficients, there might be additional factors beyond the GCD influencing an aircraft's TOW. Among others, reasons for that can be:

- Different passenger load factors (e.g. due to seasonal changes),
- Inbound flight to an airline's hub vs. an outbound flight to a remote airport, or
- Different fuel strategies for destinations in an airline's network.

An indicator for these secondary factors can be observed when analyzing the TOW spread, i.e. the difference between the minimum and the maximum recorded TOW, over the whole span of GCDs for the different operating regions, as shown in figures 7 - 10 in the appendix. It can be seen there that the actual TOW can differ significantly for comparably similar GCDs, i.e. for the same route distances flown, different passenger, cargo and/or fuel loads will be carried.

Using these regression estimates, we calculated the expected TOW for each flight leg and compared it to the existing historical flight data provided by MTU. The result can be seen in figure 4. In general, a comparison of the predicted TOW with actual recorded TOW shows a good alignment of the estimated TOW median with the median of the TOW for historical flight events (ref. table 3). The differences between these medians are less than 2% for all regression models and operator regions. However, the regression seems to systematically underestimate

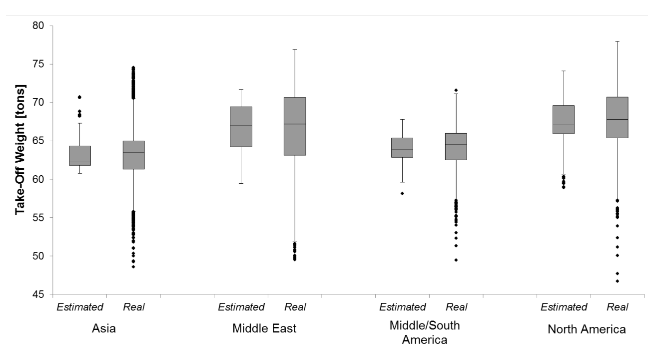


Figure 4. Estimated vs. real TOW distribution for different operator regions

Table 3. Comparison of the average and median for historical and estimated TOWs

Region	Source	TOW		
		Mean	Median	Diff.[a]
Asia	Real	63.20 t	63.46 t	-1,88%
	Est.	63.30 t	62.27 t	
Middle East	Real	66.69 t	67.20 t	-0,34%
	Est.	66.73 t	66.97 t	
North America	Real	67.70 t	67.81 t	-1,09%
	Est.	67.69 t	67.07 t	
Middle/South America	Real	64.02 t	64.52 t	-1,04%
	Est.	64.01 t	63.85 t	

[a] Relative difference of the median for estimated TOW's compared to the median of historical TOWs.

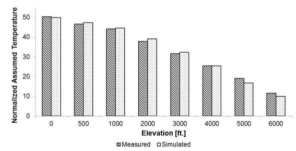
the TOW as the median difference is negative. Comparing the boxplot whiskers in fig. 4, it becomes apparent that the TOW estimation will narrow the TOW spread as both the maximum and the minimum TOW do not contain the extreme values of the historical data. Based on the alignment of the median as well as the boxplots of the TOW estimates with the historical data, we would expect the imposed error by estimating the TOW to be lowest for the operating region of the Middle East. It has to be noted though, that the plots in fig. 4 neglect differences in the GCD flown and can therefore only be taken as an indicator for the quality of the TOW estimation through the proposed regression. In order to improve the capability to precisely estimate the TOW of a flight, especially with respect to the low coefficients of determination R^2, additional parameters should be incorporated in future studies. These can be, among others:

- seasonal differences in aircraft load factors,
- price differences for refueling at the home base and the destination, encouraging operators to make use of different fuel strategies, and
- the distinction between inbound flights to the operator's hub and outbound flights to remote destinations, possibly resulting in different passenger load factors.

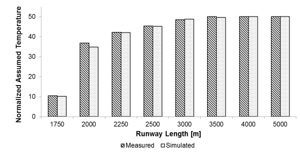
We will examine the effect of the uncertainty in estimating the TOW on the aircraft engine load prediction in the following subsections. Subsequently, the improvements due to an improved TOW estimation can be determined.

4.2. Assumed temperature validation

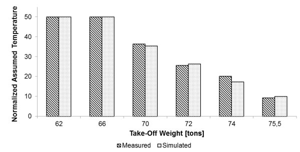
After we have validated our estimation model for the anticipated TOW for flights in different regions, we need to verify the correctness of the assumed temperature T_{flex} simulation. For the validation, we have used the Tool FLYSMART from Airbus (European Aviation Safety Agency, 2013). Used for flight operations, this tool performs the certified calculation of



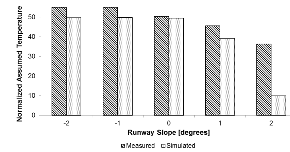
(a) Normalized assumed temperature vs. airport elevation[4]



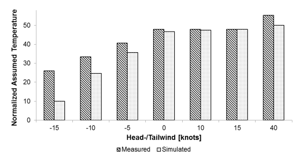
(b) Normalized assumed temperature vs. runway length[5]



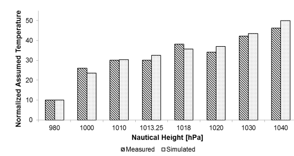
(c) Normalized assumed temperature vs. TOW[6]



(d) Normalized assumed temperature vs. runway slope[7]



(e) Normalized assumed temperature vs. head/tail wind[8]



(f) Normalized assumed temperature vs. QNH[9]

Figure 5. Validation of assumed temperature calculation

the permissible value and is therefore used as our benchmark (Airbus, 2017).

As can be seen in figures 5a to 5f, we varied various input parameters, e.g. the airport's elevation, the runway length and slope, the TOW or the nautical height (QNH), and calculated the resulting assumed temperature - both with FLYSMART and our developed simulation tool. In order to comply with the proprietary nature of the underlying data, we have normalized these values to be within a band of 10 to 50 degree Celsius.

In general, the simulated T_{flex} shows a good match with the true values, calculated by FLYSMART. The only exception hereby is for high uphill runway slopes (ref. fig. 5d) and strong tailwinds during take-off (ref. fig. 5e), where the true assumed temperature will be underestimated, leading to an overestimated engine load. However, normal operation at these conditions is very unlikely, since most runways for applicable commercial airports have slopes of fractions of 1° down- or uphill, respectively. Similarly, a tailwind of 15 knots dur-

[4] TOW: 70 tons. QNH: 1013.25 hPa. Runway length: 3000 m. Runway Slope: 0°. Wind strength: 0 kt.
[5] TOW: 70 tons. QNH: 1013.25 hPa. Elevation: 0 ft. Runway Slope: 0°. Wind strength: 0 kt.
[6] QNH: 1013.25 hPa. Elevation: 0 ft. Runway length: 3000 m. Runway Slope: 0°. Wind strength: 0 kt.
[7] TOW: 70 tons. QNH: 1013.25 hPa. Elevation: 0 ft. Runway length: 3000 m. Wind strength: 0 kt.
[8] TOW: 70 tons. QNH: 1013.25 hPa. Elevation: 0 ft. Runway length: 3000 m. Runway Slope: 0°.
[9] TOW: 70 tons. Elevation: 0 ft. Runway length: 3000 m. Runway Slope: 0°. Wind strength: 0 kt.

ing take-off represents an upper limit of allowable operation. As the vast majority of departure procedures occur against the predominant wind direction, the deviation for strong tailwinds seems to be negligible (Federal Aviation Administration, 1993).

Besides the comparison of our simulation with the true operational values, we can further identify to what extent the inputs influence the resulting assumed temperature. As fig. 5a shows, the airport's elevation, i.e. the resulting air density, plays a major role in determining the correct assumed temperature, since the change of the calculated T_{flex} is rather high and steadily increasing over airport elevations. Subsequently, the resulting engine load will strongly depend on this input and as a general rule it can be said: The maximum possible derate decreases with increasing altitude. Although fig. 5b suggests a big impact of the runway length on the assumed temperature, especially for short runways below 2,500 meters available runway length, it has to be noted that the typical required runway length for narrow-body short- and medium haul aircraft is around 3,000 meters[10] (Federal Aviation Administration, 2005). Therefore, for realistic regions of available take-off length, the assumed temperature hardly changes for longer or slightly shorter runways. The effect for the runway slope and head- or tailwind behaves similarly and has been discussed previously. A much more significant influence on the resulting T_{flex} can be observed for the aircraft's TOW (ref. fig. 5c) and the ambient QNH (ref. fig. 5f). Especially for high TOWs, low QNHs, and low airport elevations, the maximum possible engine derate can vary significantly.

While factors like airport elevation as well as runway length and slope are not subject to frequent changes and can be easily retrieved from a database, ambient conditions, such as wind strength and direction as well as the QNH, are not as straightforward to utilize. For historical flight data, this information has been observed and can be retrieved in form of METAR weather reports. If we want to predict future behavior, however, these values are subject to frequent changes and comparably high uncertainties. An even bigger challenge poses the actual TOW, since neither for historical nor for future flights, public data are available. Therefore, the prediction has to be based on other explaining factors, e.g. time of departure or airport characteristics, and modeled using historical data.

4.3. Engine load verification

As has been stated in chapter 2, as of this paper, we will estimate the engine load with the help of the EPR derate percentage according to eq. 1. There are also other forms of engine load calculation possible, e.g. considering the resulting thrust or EGT ratio. However, thrust is linearly proportional to EPR in a good first-order approximation. Thus, there would not be any benefit over the approach of an EPR related load estimation. Considering the EGT ratio would incorporate the state of engine degradation. However, additional ambient factors, e.g. percentage of air pollution, are required to correctly map the influence of degrading core components with the resulting EGT, increasing the complexity of the model. Additionally, proprietary information about the engine's EPR/EGT relationship needs to be known in order to use the EGT as an indicator of engine load. Therefore, neither of the latter approaches are suitable for this study.

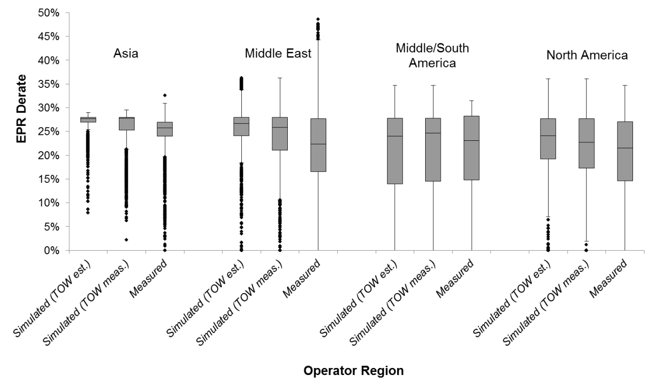


Figure 6. Simulated vs. real EPR distribution for different operator regions and TOW input

In figure 6, the distribution of EPR values for different operator regions can be seen. We have subdivided the plots in values that have been measured historically during engine operation, values that have been simulated using the true TOW as input, and values that have been simulated with the TOW estimation according to section 4.1 as input. Negative values for derates have been filtered as they indicate measurement inaccuracies during the snapshot record.

In general, it can be noted that the shown uncertainties are mainly stemming from the following reasons.

Uncertainty of chosen assumed temperature. The model we have validated in the previous section only provides information of the maximum permissible assumed temperature T_{flex} to be selected. The true value, chosen by the flight crew for the respective flight, however, is unknown and subject to the personal preference and experience of the flight crew.

Snapshot characteristic of recorded data. The historical engine performance data underlying for this paper represents only a snapshot within the normal engine operation. This snapshot will be triggered at the moment the highest EGT has been recorded for a definite time period. Thus, the recordings are dependent on the current altitude and air speed during the snapshot. An analysis revealed that the vast majority of these snapshots have been recorded at a speed of Mach 0.25 and an altitude of 1,000 ft. above ground. To limit the complexity of the simulation, we have taken this ambient condition as ref-

[10]The calculation has been conducted for the B737-900, taking-off at its designed MATOW from an elevation of 1,000 ft. with no wind or runway slope. The OAT has been assumed to be about 29°C.

erence to adjust our model, neglecting differences of altitude and speed between the various snapshots.

Transient engine condition. Since the mentioned snapshots will be triggered by the maximum recorded EGT, the snapshot may not necessarily represent the parameter settings during take-off, but may have shifted to a climb setting already. Therefore, the EPR will have been adjusted accordingly, misleading to an incorrect engine load calculation. We have filtered engine transient behavior by consideration of measurements with a corresponding TLA between 30° and 40°. For the A320, TLAs above 40° indicate a manual full power take-off, whereas values below 30° represent climb thrust settings.

Since the EPR derate values shown here have been calculated under the ambient condition of an airspeed of Mach 0.25 and at an height of 1,000 ft. above ground, they are higher than they would be at standstill condition on ground. As can be seen from fig. 6 and tab. 4, the simulated engine loads for the operating regions of *North America* and *Middle/South America* match the real, recorded values during operation rather well with the measured TOW as input. The relative error for both these operating regions is less than 2 percentage points when comparing the median EPR derate. For the operating region of *North America*, the median EPR derate even improves by using the TOW estimates rather than the historically recorded values. Comparing the medians of EPR derate for operators of the *Middle East* region shows a comparably large discrepancy of up to 4.3 percentage points. This difference indicates that either the input factors, predominantly the estimated TOW as all other values can be accurately[11] retrieved from databases, have falsely been determined or the take-off procedure differs for operators from this region.

By comparing the median of the EPR derate with the respective mean (ref. table 4), a disadvantage that arises with using derate simulation forecasts is an increase of the distribution's skewness, i.e. the engine load factor forecasts will not be symmetrically distributed, but be tilted towards higher derate values. The skewness of the distribution has its peak for engine load prediction within the operating region of *Asia*, where the upper quartile and the median are almost equal, i.e. projected derate values are mainly centered around the upper end of the respective box plot. For all examined regions except *Middle/South America*, the spreads of the derate boxplots are reduced and moved towards higher values. For the operator region in the *Middle East*, the overall spread for the real derate values is significantly higher than for all other regions. Therefore, it has to be examined whether the TLA filter criterion has been appropriately selected here to exclude transient engine settings.

[11] For some regions, METAR reports will be issued at larger time intervals of up to 3 hours. Thus, changes in QNH and OAT in between the snapshots may significantly influence the precision of the T_{flex} calculation.

Table 4. Comparison of the average and median for historical and simulated EPR derates for different TOW inputs

Region	Source	TOW	EPR derate		
			Mean	Median	Diff.[a]
Asia	Sim.	Est.	26.3 %	27.7%	2.0
		Meas.	25.5 %	27.8%	2.1
	Meas.	Meas.	24.4 %	25.7%	-
Middle East	Sim.	Est.	26.2%	26.7%	4.3
		Meas.	24.4%	25.9%	3.5
	Meas.	Meas.	22.0%	22.4%	-
North America	Sim.	Est.	22.1%	24.1%	2.6
		Meas.	21.3%	22.7%	1.2
	Meas.	Meas.	20.1%	21.5%	-
Middle/South America	Sim.	Est.	19.9%	24.0%	0.9
		Meas.	20.3%	24.6%	1.5
	Meas.	Meas.	21.2%	23.1%	-

[a] Given in percentage points of the difference between the simulated EPR derate median to the measured median.

As it has been stated in section 4.1 and can be seen in tab. 3, the regression model tends to underestimate the true TOW. Taking this smaller TOW as input subsequently leads to an overestimated EPR derate simulation, as can be seen in tab. 4 when comparing the simulated derate medians for the estimated and real TOW inputs. Once the TOW estimation will be adjusted, we expect the derate values to change accordingly. Since the EPR value decreases with increasing speed, it has to be noted though that the real derate values will lower once they are adjusted to standstill conditions.

5. CONCLUSION AND OUTLOOK

With this paper, we have presented an approach to estimate the engine load using publicly available information as input factors. For the developed model, we have utilized public weather reports and airport information to determine the applicable ambient conditions. These conditions have been used as input parameters to calculate the resulting maximum permissible assumed temperature T_{flex} and subsequently the corresponding EPR values with the help of available information for the V2500 engine through existing FCOMs and the PEP software tool. Since no public database about TOWs exist, we have developed a regression model to estimate the TOW based on the GCD between origin and destination airport as well as the geographical region of operation. The results have been compared to real, historical operational data provided by MTU. On average, the comparison shows a good alignment of the obtained simulation results with the real measurement data, although the regression model is slightly underestimating the real TOW.

To limit the complexity of the EPR derate simulation, we have made the following assumption:

Operational procedures. Specific runway take-off direction restrictions have been neglected.

Engine degradation. As of this paper, we have not considered any performance changes induced by a deteriorating system.

Take-off configuration. The flap/slat setting has been assumed to be in configuration 2, slightly influencing the range of possible derates.

TOW regression. The TOW as important input factor for the assumed temperature $\mathrm{T_{flex}}$ and subsequent derate calculation has only been estimated based on a regression over the GCD.

Analyzing the results from our simulation, the EPR derate values show a good agreement of the simulated with the historically recorded ones. Comparing the medians, we can limit the relative error between our simulation and historical data records to less than 2 percentage points. Only for the operating region of the *Middle East*, this error increases to more than 4 percentage points. Considering the alignment of these medians, our simulation allows derate considerations on a fleet level, but not necessarily on a individual engine-serial level as it would additionally require the distributions to match. However, an analysis of the distribution boxplots revealed that the simulation tends to overestimate the EPR derate for all operator regions except *Middle/South America*.

In order to improve the obtained results, the TOW prediction should not be based on a simple regression with one input parameter, but include additional parameters such as the real distance flown, airport characteristics (hub or remote destination) or the payload. This will increase the accuracy of the TOW prediction and, consequently, improve the resulting EPR derate model. Additionally, the development of a database to model operational restrictions (e.g. take-off direction) may further enhance the derate calculation, since the wind direction and strength influences the $\mathrm{T_{flex}}$ calculation. Finally, in order to derive maintenance decisions, the resulting engine degradation from specific engine load factors should also be the focus of further research.

ACKNOWLEDGMENT

The authors would like to thank MTU Aero Engines AG and MTU Maintenance Hannover GmbH for providing the underlying data and the constant knowledge exchange for fruitful discussions.

ABBREVIATION

T_{flex}	assumed temperature
DOC	direct operating cost
ECU	engine control unit
EHM	engine health management
EPR	engine pressure ratio
EGT	exhaust gas temperature
FMC	flight management computer
GCD	great circle distance
HPC	high pressure compressor
HPT	high pressure turbine
LPC	low pressure compressor
LPT	low pressure turbine
$MATOW$	maximum allowable take-off weight
$METAR$	meteorological aerodrome report
QNH	nautical height
OEW	operating empty weight
OAT	outside air temperature
PEP	performance engineers' programs
RUL	remaining useful life
TOW	take-off weight
TLA	thrust lever angle
TOC	total operating cost
TIT	turbine inlet temperature

REFERENCES

Ackert, S. (2011). Engine maintenance concepts for financiers: Elements of turbofan shop maintenance costs. *Aircraft Monitor*. Retrieved 19.02.2020, from `http://www.aircraftmonitor.com/uploads/1/5/9/9/15993320/engine_mx_concepts_for_financiers___v2.pdf`

Airbus. (n.d.). *Performance engineers' programs.* Author. Retrieved 21.04.2020, from `http://122.166.54.52/AIPEP/start.htm`

Airbus. (2002). *A318/a319/a320/a321: Flight crew operating manual (rev. 21).*

Airbus. (2011). *A320 airplane characteristics for airport planning*. Blagnac. Retrieved 2012-01-16, from `https://www.airbus.com/support/maintenance-engineering/technical-data/aircraft-characteristics/`

Airbus. (2017). *Afi flight operations safety awareness seminar (fosas): Efb, flysmart and eqrh.* Nairobi. Retrieved from `https://www.icao.int/ESAF/Documents/meetings/2017/AFI%20FOSAS%202017/Day%203%20Docs/Day_3_2_EFB.pdf`

Aircraft Commerce. (2019). Airline results of using big data & predictives. *Aircraft Commerce*(125), 36–42.

Brooks, J., Clark, J.-P., Melikov, K., Miers, J., & Mestre, V. (2016). Airline flight data examination to improve flight performance modeling. *FAA Center of Excellence for Alternate Jet Fuels & Environment Annual Technical Report*, 485–551. Retrieved 28.02.2020, from https://ascent.aero/documents/2017/11/2016-ascent-annual-report.pdf/

Chatterjee, S., & Litt, J. (2003). Online model parameter estimation of jet engine degradation for autonomous propulsion control. *AIAA Guidance 2003*. doi: 10.2514/6.2003-5425

Daidzic, N. (2012). Jet engines thrust ratings. *Professional Pilot*, 108–112. Retrieved 24.04.2020, from https://www.researchgate.net/profile/Nihad_E_Daidzic/publication/316515941_Jet_engine_thrust_ratings/links/5901def70f7e9bcf65489a6a/Jet-engine-thrust-ratings.pdf

Deutscher Wetterdienst. (2019). *Metar / speci / trend / taf: Wettermeldungen und -vorhersagen für die luftfahrt* (2nd ed.). Offenbach. Retrieved from https://www.dwd.de/SharedDocs/broschueren/DE/luftfahrt/metar_taf.pdf?__blob=publicationFile&v=1

Donaldson, R., Fischer, D., Gough, J., & Rysz, M. (2007). Economic impact of derated climb on large commercial engines. *2007 Performance and Flight Operations Engineering Conference*, 1–14.

European Aviation Safety Agency. (2007). *Certification specification for large aeroplanes (amendment 3): Cs-25.* Retrieved 24.02.2020, from https://www.easa.europa.eu/sites/default/files/dfu/CS-25_Amdt%203_19.09.07_Consolidated%20version.pdf

European Aviation Safety Agency. (2013). Electronic flight bag (efb) evaluation report: Flysmart with airbus for ipad. Retrieved 19.03.2020, from https://www.easa.europa.eu/sites/default/files/dfu/certification-experts-docs-oeb-reports-airbus-Fly-Smart-with-Airbus-for-iPad---EFB-Software---Final-signed.pdf

Federal Aviation Administration. (1993). *Pilot guide to takeoff safety*. Retrieved 21.02.2020, from https://www.faa.gov/other_visit/aviation_industry/airline_operators/training/media/takeoff_safety.pdf

Federal Aviation Administration. (2005). *Advisory circular: Runway length requirements for airport design: Ac 150/5325-4b.* Retrieved 19.03.2020, from https://www.faa.gov/documentLibrary/media/Advisory_Circular/AC_150_5325-4B.pdf

Goebel, K., Qiu, H., Eklund, N., & Yan, W. (2007). Modeling propagation of gas path damage. *2007 IEEE Aerospace Conference*, 1–8. doi: 10.1109/AERO.2007.352835

Groenenboom, J. (2019). *The changing mro landscape.* Athens, Greece. Retrieved from https://www.iata.org/contentassets/81005748740046de878439e6c54f2355/d1-1100-1130-the-changing-mro-landscape_icf.pdf

Hanumanthan, H. (2009). *Severity estimation and shop visit prediction of civil aircraft engines* (Ph.D. Thesis, Cranfield University, Cranfield). Retrieved 06.03.2020, from https://dspace.lib.cranfield.ac.uk/handle/1826/7634

Hölzel, N. (2019). *Ein bewertungsansatz zur analyse von zustandsmanagementsystemen in verkehrsflugzeugen unter berücksichtigung neuer instandhaltungskonzepte* (Ph.D. Thesis, TU Hamburg, Hamburg). doi: 10.15480/882.2543

James, W., & O'Dell, P. (2005). Derated climb performance in large civil aircraft. *2005 Performance and Flight Operations Engineering Conference*, 1–14.

Kurosaki, M., Morioka, T., Ebina, K., Maruyama, M., Yasuda, T., & Endoh, M. (2004). Fault detection and identification in an im270 gas turbine using measurements for engine control. *Journal of Engineering for Gas Turbines and Power*, *126*(4), 726–732. doi: 10.1115/1.1787515

Lim, D., LeVine, M. J., Ngo, V., Kirby, M., & Mavris, D. N. (2018). Improved aircraft departure modeling for environmental impact assessment. *2018 Aviation Technology, Integration, and Operations Conference*. doi: 10.2514/6.2018-3503

Rausch, R. T., Goebel, K. F., Eklund, N. H., & Brunell, B. J. (2005). Integrated in-flight fault detection and accommodation: A model-based study. *2005 Turbo Expo*, 561–569. doi: 10.1115/GT2005-68300

Robertson, N., & Perera, T. (2002). Automated data collection for simulation? *Simulation Practice and Theory*, *9*, 349–364.

Roy, R., Stark, R., Tracht, K., Takata, S., & Mori, M. (2016). Continuous maintenance and the future – foundations and technological challenges. *CIRP Annals*, *65*(2), 667–688. doi: 10.1016/j.cirp.2016.06.006

Saxena, A., Goebel, K., Simon, D., & Eklund, N. (2008). Damage propagation modeling for aircraft engine run-to-failure simulation. *2008 International Conference on Prognostics and Health Management (PHM)*, 1–9. doi: 10.1109/PHM.2008.4711414

Thomas, G. (2011). Engine maintenance from an oem perspective. *The Engine Yearbook 2011*, 48–53. Retrieved 05.03.2020, from `https://issuu.com/ubmaviationpublications/docs/eyb_2011_ipad/125`

Ting, D. (2002). *Reduced thrust: Performance engineer operations flight operations engineering.* Retrieved from `http://www.smartcockpit.com/docs/Reduced_Thrust_Operations.pdf`

Yin, H., & Li, Y. (2016). Reduced thrust take-off control law design for large commercial aircraft. In *Proceedings of the6th international conference on mechatronics, materials, biotechnology and environment (icmmbe 2016).* Paris, France: Atlantis Press. Retrieved from `https://www.researchgate.net/profile/Nihad_E_Daidzic/publication/316515941_Jet_engine_thrust_ratings/links/5901def70f7e9bcf65489a6a/Jet-engine-thrust-ratings.pdf` doi: 10.2991/icmmbe-16.2016.76

Zaita, A. V., Buley, G., & Karlsons, G. (1998). Performance deterioration modeling in aircraft gas turbine engines. *Journal of Engineering for Gas Turbines and Power*, *120*(2), 344–349. doi: 10.1115/1.2818128

APPENDIX

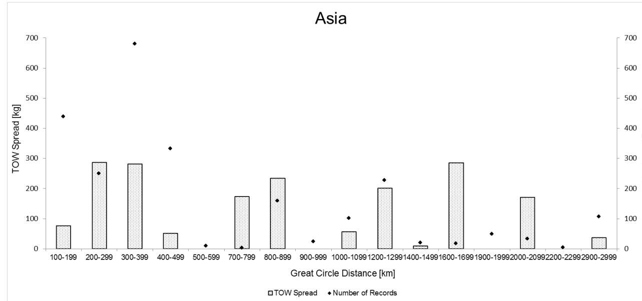


Figure 7. Spread of the TOW for different GCDs for the operating region of Asia

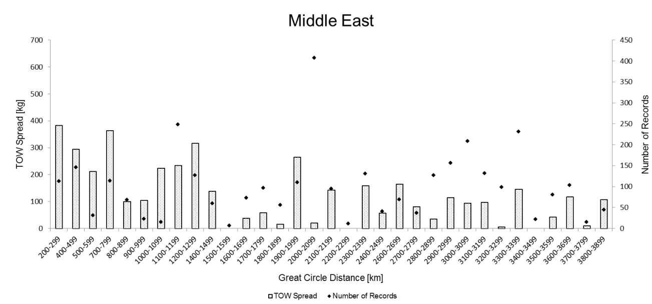


Figure 8. Spread of the TOW for different GCDs for the operating region of the Middle East

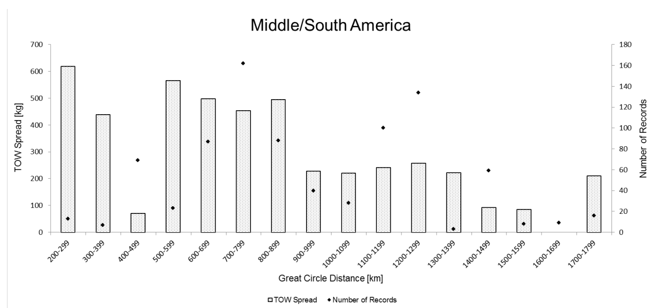


Figure 9. Spread of the TOW for different GCDs for the operating region of Middle/South America

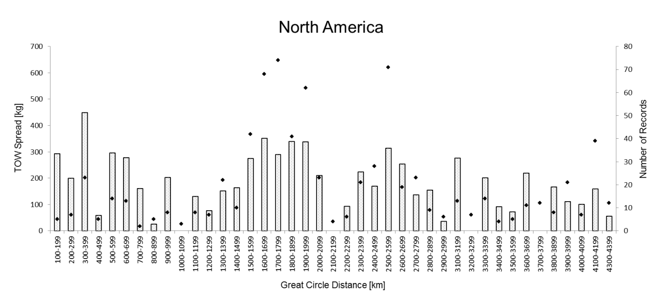


Figure 10. Spread of the TOW for different GCDs for the operating region of North America