Estimating Runway Friction Using Flight Data

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During the winter season, contamination of runway surfaces with snow, ice, or slush causes potential economic and safety threats for the aviation industry. The presence of these materials reduces the available tire-pavement friction needed for retardation and directional control. Therefore, pilots operating on contaminated runways need accurate and timely information on the actual runway surface conditions. Avinor, the company that operates most civil airports in Norway, have developed an integrated runway information system, called IRIS, currently used on 16 Norwegian airports. The system uses a scenario approach to identify slippery conditions. In order to validate the scenario model, it is necessary to estimate runway friction. The present paper outlines how this can be done using flight data from the Quick Access Recorder (QAR) of Boeing 737-600/700/800 NG airplanes. Data such as longitudinal acceleration, airspeed, ground speed, flap settings, engine speed, brake pressures are sampled at least each second during landings. The paper discusses some of the challenges with this. In particular, issues related to calibration of data are considered, and two different regression methods are compared.

Keywords: Runway Friction, Flight Data, Calibration, Error Detection, Data Filtration.

1. Introduction

Slippery runways represent a significant risk to aircrafts especially during the winter season. Accidents, such as the Southwest Airlines jet skidding off a runway at Chicago Midway Airport in December 2005, as well as the similar accident with the Delta Connection flight at the Cleveland Hopkins International Airport in Ohio in February 2007, show that this is indeed a serious problem. For more details about the Chicago Midway Airport accident see Rosenker et al. (2007).

In order to apply the appropriate braking action, the pilots need reliable information about the runway conditions. Unfortunately, the accuracy of runway reports can sometimes be unsatisfactory. Having reliable methods for identifying slippery runway conditions is very important. However, measuring the runway friction with a satisfactory precision is difficult. While many different measurement devices have been developed, it is hard to find equipment that produces stable and consistent results. Another problem is that in order to measure friction, the runway needs to be closed for traffic. Thus, such measurements cannot be carried out too frequently. As a result, the runway reports are not as useful as one could hope. In particular, heavy snowfalls, or sudden drops in temperature may result in rapidly changing conditions. See Giesman (2005) and Rosenker et al. (2007).

Avinor, the company that operates most civil airports in Norway, initiated the so-called SWOP-project, a research and development project with contributions from the three airlines SAS, Norwegian and Widerøe. The main goal was developing methodology for predicting runway conditions utilizing weather data in addition to runway reports. Throughout two winter seasons various kinds of weather data were collected, such as air and surface temperature, humidity, precipitation, visibility and wind. Using these data, a scenario based weather model for slippery conditions was developed. A complete report from this project is given in Aarrestad et al. (2007).

Based on the SWOP-project, Avinor developed an integrated runway information system, called IRIS, currently used on 16 Norwegian airports. See Søderholm et al. (2009). IRIS consists of three parts: a *weather* model, a *runway* model and a *development* model. The weather model uses a scenario approach to identify slippery conditions. A description of an early version of this model can be found in Huseby and Rabbe (2008), while revised versions are presented in Huseby and Rabbe (2012) and Huseby and Rabbe (2018). The runway model uses mainly runway report data and assesses runway conditions on a five-level scale ranging from *poor* to *good*. See Huseby et al. (2010) and Klein-Paste et al. (2012). The development model combines runway report data, precipitation and temperature data in order to issue warnings when the runway conditions are deteriorating.

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The IRIS models have been verified by comparing the results to runway friction estimates based on flight data. The estimates are calculated by applying an airplane brake performance model developed by Boeing. A detailed description of this model is beyond scope of this paper, but some further details can be found in Klein-Paste et al. (2012). Instead this paper focuses on how to prepare the input to the model, and on the results that can be obtained.

2. Calculating the friction coefficient

The flight data, collected over ten winter seasons, from season 2009/2010 until season 2018/2019 is provided by Scandinavian Airlines Service (SAS) and Norwegian Air Shuttle AS and is gathered from the Quick Access Recorder (QAR) of Boeing 737-600/700/800 NG airplanes. We have available flight landings from 16 Norwegian airports, but in this paper, we only use flight landings at Tromsø and Gardermoen (Norway's largest airport). These airports are chosen since they have gathered data for the longest time. Besides Tromsø and Gardermoen are very different with respect to weather conditions, number of flights and runway operations. The final data set, containing only landings at Tromsø and Gardermoen, consists of approximately 248 000 flight landings, where the distribution is shown in Table 1.

Table 1. Number of landings and friction limited landings at Gardermoen airport and Tromsø airport.

Property	Gardermoen	Tromsø
Number of landings	228 700	19 278
Friction limited landings	8 342	5 762
% friction limited landings	3.6%	29.9%

The airplane braking coefficient, μ_B, is calculated using the performance model developed by Boeing. This model uses the aircrafts' airspeed, longitudinal acceleration, gross weight, engine force, flap positions and deployment of thrust to calculate μ_B. The braking coefficient is used to represent the contribution of the wheel brakes to stopping the airplane, and is defined as the ratio of the stopping force contribution of the wheel brakes to the average airplane weight on wheels.

An important problem when analyzing flight data is deciding whether a landing is *friction limited* or not. Unless the pilot challenges the runway friction during the landing, the maximum friction available will not be utilized. In this case, μ_B reflect the amount of tire-pavement friction that was used. When wheel brakes are applied fully or to a high degree on slippery runways, the maximum attainable friction from the runway is used during the stop. In this case, the airplanes deceleration is limited by the friction available from the runway, and the obtained μ_B will reflect the amount of tire-pavement friction that is available. Such a landing is referred to as *friction limited*, and since the braking coefficient reflects the available tire-pavement friction, we refer to it as the *friction coefficient*.

To figure out if the brakes are applied fully during a landing, we check whether the brake pressure "requested" by the pilot exceeds the brake pressure corresponding to the measured deceleration. Whenever this occurs, the anti-skid system is activated, and all the available friction is used, i.e., the landing is friction limited.

As it is not possible to obtain a precise estimate of μ_B when a landing is not friction limited, only friction limited landings can be used for this purpose, i.e., 3.6% and 29.9% of the landings at respectively Gardermoen and Tromsø (Table 1).

3. Calibration of acceleration measurements

In order to estimate the friction coefficient from the flight data, the acceleration of the landing aircraft is an important factor. Unfortunately, the measurement of the accelerations $a(t)$ is known to be biased. Thus, the true acceleration $\alpha(t)$ can be expressed with the following model:

$$\alpha(t) = a(t) + \epsilon. \tag{1}$$

The bias term ϵ is typically time-dependent, but since we consider a relative short time interval during a landing, the bias is assumed to be constant. To estimate the bias for each landing, velocities and positions are needed. However, GPS coordinates are sampled at different points of time than the other aircraft data. This may lead to time series of positions that are non-physical, as seen in Figure 1. This is sometimes the case for the measured ground speed as well. These effects must be taken into account when velocities and positions are used together with other data. Accelerometer data is sampled with a higher sampling rate and is therefore a more reliable source than the GPS coordinates. As numerical integration is a well-behaved process in the sense integrals smoothen the result, this is a feasible method to obtain velocities and positions from the accelerometer data. In the next subsection we will show how the bias, ϵ, as well as the initial speed, v_0, can be estimated by combining accelerometer data and positions.

3.1. *Computation of the calibrated acceleration*

Given the initial speed $v_0 = v(t_0)$ the velocity $v(t)$ is given by integration of the acceleration:

$$\begin{aligned} v(s) &= v(t_0) + \int_{t_0}^{s} \alpha(r)dr \\ &= v(t_0) + \int_{t_0}^{s} a(r)dr + \epsilon(s - t_0) \end{aligned} \quad (2)$$

Similarly the position $x(t)$ is given by:

$$\begin{aligned} x(t) &= x(t_0) + \int_{t_0}^{t} v(s)ds \\ &= x(t_0) + v(t_0)[t - t_0] + \\ &\quad \int_{t_0}^{t}[\int_{t_0}^{s} a(r)dr]ds + \epsilon(t - t_0)^2/2. \end{aligned} \quad (3)$$

The numerical integrations in Eq. (2) and Eq. (3) can be approximated by using the trapezoidal rule with timestep equal to the sampling interval.

In order to calculate the velocity and position from Eq. (2) and Eq. (3), we need to find an estimate for v_0 and ϵ. The QAR of the aircrafts measures the ground speed, from which the initial velocity could be gathered from. As these measurements sometimes give curves that are not smooth, they are not considered to be a very reliable source for the initial velocity. The very first measurements of the ground speed, which would be the initial velocity, are in addition extra unreliable, as it might takes a few seconds before the wheels spin properly after touchdown.

Due to these issues, it may be better to estimate both the bias term and the initial speed from the measured accelerations and GPS positions. These measurements are combined in a linear regression. The time points where we have recorded position values, are denoted by $t_1, ..., t_n$. Thus, we improve the precision by using all position values. We introduce the following notation for describing differences in time and positions:

$$\begin{aligned} s_i &= t_i - t_0, \quad i = 1, ..., n, \\ y_i &= x(t_i) - x(t_0), \quad i = 1, ..., n \\ z_i &= \int_{t_0}^{t_i}[\int_{t_0}^{s} a(r)dr]ds, \quad i = 1, ..., n. \end{aligned}$$

The relation between velocities, accelerations and positions from Eq. (3) can then be expressed as:

$$y_i - z_i = v_0 s_i + \epsilon s_i^2/2, \quad i = 1, ..., n. \quad (4)$$

By introducing the following matrix:

$$S = \begin{bmatrix} s_1 & s_1^2/2 \\ s_2 & s_2^2/2 \\ \vdots & \vdots \\ s_n & s_n^2/2 \end{bmatrix}$$

we can rewrite Eq. (4) as the following regression model:

$$(\boldsymbol{y} - \boldsymbol{z}) = S \begin{bmatrix} v_0 \\ \epsilon \end{bmatrix}, \quad (5)$$

where $\boldsymbol{y} = (y_1, ..., y_n)^T$ and $\boldsymbol{z} = (z_1, ..., z_n)^T$. The least-squares estimates for the unknown quantities v_0 and ϵ are given by:

$$\begin{bmatrix} \hat{v_0} \\ \hat{\epsilon} \end{bmatrix} = (S^T S)^{-1} S^T (\boldsymbol{y} - \boldsymbol{z}). \quad (6)$$

which gives us the parameters needed to calculate a calibrated acceleration. When using the calibrated acceleration $\alpha(t)$ to estimate the friction coefficient instead of the uncalibrated one $a(t)$, we refer to it as the calibrated friction coefficient.

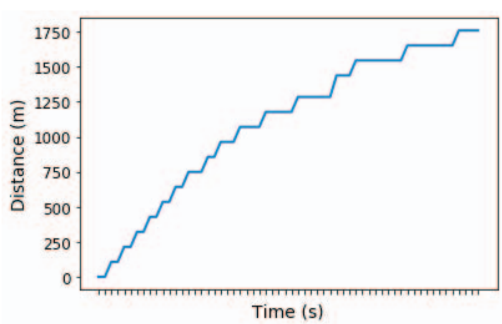

Fig. 1. A typical example of a time series of distances from the point where the aircraft touches the ground. The distances are calculated from the GPS positions recorded, and the asynchronous sampling between the GPS and the QAR makes inconsistent time series of positions.

3.2. *The effect of calibration on the friction coefficient*

To investigate the effect of calibration on the friction coefficient, the friction coefficients of both calibrated measurements μ_{cal} and the uncalibrated, raw measurements μ_{raw} are compared. A scatter plot between the two coefficients are given in Figure 2, showing a Pearson correlation of 0.87.

In this paper, we use relative difference when comparing two numbers (a and b), defined by:

$$\text{Diff}_{\text{rel}}(a, b) = \frac{a - b}{|a + b|/2} \quad (7)$$

unless otherwise is stated. A summary and the relative difference of the two coefficients are listed in Table 2. The calibrated friction coefficient has a lower mean value, being 5.2% lower than the uncalibrated friction coefficient. Consequently, this increases the number of landings being classified as friction limited, such that the calibrated frictions lead to 4.5% more friction limited landings then the uncalibrated ones. In addition, the calibrated frictions are more scattered, with a standard deviation 14.2% higher than the uncalibrated. The distributions of both friction coefficients are shown in Figure 3, and it can be seen how the calibrated friction coefficients tends to be a bit lower and more scattered than the uncalibrated coefficients.

Table 2. Summary for the calibrated and uncalibrated friction coefficient. *FricLim landings* refers the percentage of landings that are classified as friction limited.

Property	μ_{cal}	μ_{raw}	Diff_{rel}
Mean	0.121	0.127	-5.2%
Standard deviation	0.045	0.039	14.2%
FricLim landings	5.63%	5.38%	4.5%

The reasons why the calibrated friction coefficient tends to be lower can be revealed by getting a closer look at the relationships between the estimated initial speed v_0, the bias term ϵ and the difference between the calibrated and uncalibrated friction coefficients, which is denoted by μ_{diff} where $\mu_{\text{diff}} = \mu_{\text{cal}} - \mu_{\text{raw}}$. Figure 4 shows a scatter plot between ϵ and μ_{diff}. Here we can see a strong linear relationship, with a Pearson correlation of $\rho = -0.97$. We see that when the bias term is positive, the calibrated friction is lower than the uncalibrated, and when the bias term is negative, the calibrated friction is higher than the uncalibrated. Around $e_p = 0$, μ_{diff} is also approximately zero, revealing that the bias term e_p is the main factor that distinguishes the calibrated value from the uncalibrated.

Going back to Eq. (1), we can see the reason behind the behavior of the calibrated friction. As the acceleration is a *retardation*, both $\alpha(t)$ and $a(t)$ are negative numbers. With a positive bias term, the calibrated value is closer to zero, which means that the retardation is reduced. A smaller retardation would in general mean less available friction, which again comes from a smaller friction coefficient between the tire and pavement. Thus, a positive bias term makes the calibrated friction coefficient smaller than the uncalibrated one, and the other way around for negative bias terms. As the bias terms has a positive mean value (+0.06 m/s), the calibrated friction coefficients are at average lower than the uncalibrated ones.

The initial speed v_0 has a smaller impact on the difference, as this is only a supporting variable estimated to calculate the bias term, and it is not directly used in calculating the friction coefficient. We still see a small tendency that the calibrated friction gets larger than the uncalibrated one when the initial speed increases, with a Pearson correlation between v_0 and μ_{diff} of $\rho = 0.42$.

We verify that the estimation of the initial speed

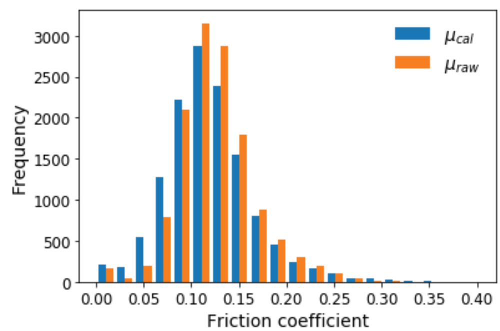

Fig. 3. Distributions of calibrated and uncalibrated friction coefficients.

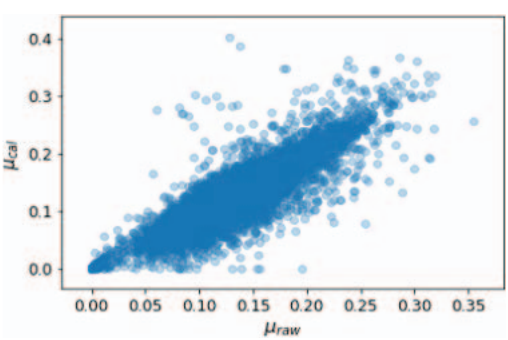

Fig. 2. Scatter plot between the calibrated and uncalibrated friction coefficients.

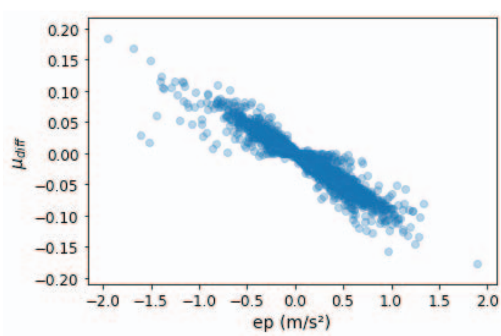

Fig. 4. Scatter plot of the bias term against the difference between the calibrated friction coefficients and the uncalibrated.

from the data seems reasonable by comparing the difference between the measured initial velocity from ground speed v_0^g and the initial velocity estimated from the regression v_0. A summary of the differences is shown in Table 3, and a scatter plot between the two initial velocities is given in Figure 5. We see that the estimated v_0 is at average 4.9 m/s lower than the measured one, a relative difference of 7.5%.

Table 3. Summary of differences between v_0 estimated using linear regression and the measured v_0^g.

Property	Value
Mean v_0	62.6 m/s
Mean v_0^g	67.5 m/s
Difference in mean	-4.9 m/s
Relative difference in mean	-7.5%
Correlation	0.66
Mean absolute difference	5.7 m/s

3.3. *Comparison with the SNOWTAM Reports*

The friction coefficient is converted to Braking Action (BA), which is the international format for braking action declarations for SNOWTAM Reports, given by the International Civil Aviation Organization (ICAO). This is an integer in the range from 0 to 5, which the airport inspectors use to report the runway surface conditions. The relationship between the friction coefficients and the braking action is given in Table 4. This paper uses the same thresholds as Klein-Paste et al. (2012), which is based on aircrafts' landing distances as a function of braking action.

As the estimated friction coefficient will be used to evaluate and report the quality of the

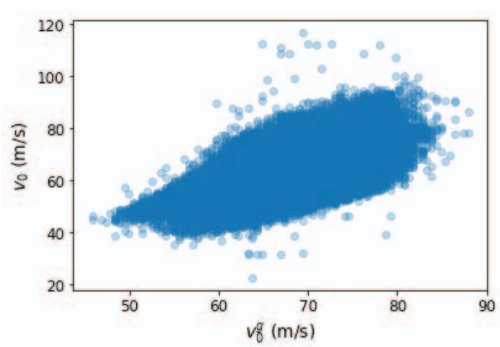

Fig. 5. Scatter plot of the estimated initial velocity v_0 against the measured initial ground speed v_0^g.

Table 4. Intervals for converting friction coefficients to the categorized braking actions.

Braking Action	Description	Friction Coefficient μ_B
0	NIL	[0.000, 0.050]
1	Poor	(0.050, 0.075]
2	Poor-medium	(0.075, 0.100]
3	Medium	(0.100, 0.150]
4	Medium-good	(0.150, 0.200]
5	Good	(0.200, ·]

SNOWTAM reports, it is important that the estimate is as accurate as possible. Therefore, we want to investigate the effect of the calibration with comparison with the SNOWTAM reports.

As SNOWTAM reports describe the runway braking action (BA) on a five-level scale, it is of interest to know how often the calibration makes the estimated runway braking action move from one level to another, as this will have a large effect on the comparison with the SNOWTAM reports. From the column *Cal - raw* in Table 5 it can be seen that two thirds of the time, the calibrated and uncalibrated BA are the same. This means that one third of the time, the changes made when calibrating the friction coefficients are large enough for the BA to change one or more levels. Table 6 shows the mean value and standard deviations of calibrated and uncalibrated BA, which gives a relative difference in mean of -6.8%.

Table 5. Percentage of BA which is equal or different between calibrated, uncalibrated and SNOWTAM BA (respectively *Cal*, *Raw* and *Snow*). The difference of +3, +4 and +5 are excluded, as they were all approximately zero.

Difference	Cal - raw	Snow - cal	Snow - raw
+2	0%	2%	3%
+1	8%	9%	10%
0	67%	34%	41%
-1	21%	29%	30%
-2	3%	17%	13%
-3	1%	6%	3%
-4	0%	3%	0%
-5	0%	1%	0%

When comparing the calibrated and uncalibrated BA with the SNOWTAM reports, we use the mean absolute error between the calculated BA and the SNOWTAM BA, which is shown in the last row of Table 6. The mean error in SNOWTAM BA is 0.83 levels relative to the uncalibrated BA, and the mean error is 1.07 levels relative to

Table 6. Summary for the calibrated and uncalibrated friction coefficient converted to BA.

Property	Calibrated	Uncalibrated	Diff_{rel}
Mean	2.78	2.98	-6.8%
Standard deviation	1.07	0.89	20.6%
Mean absolute error	1.07	0.83	26.0%

Table 7. Summary for the calibrated friction coefficient using the estimated v_0 vs the measured v_0^g.

Property	μ_{v_0}	$\mu_{v_0^g}$	Diff_{rel}
Mean	0.121	0.143	-16.8%
Standard deviation	0.0445	0.0445	0.02%
FricLim landings	5.63%	5.06%	10.7%

the calibrated BA. We see that using the calibrated BA will increase the error of the SNOWTAM reports given under difficult runway conditions by 26%. This means that they will be considered as less accurate than they would if the uncalibrated BA was considered the true braking action. This is a relatively large difference and will have a significant impact on the evaluation of the accuracy of the SNOWTAM reports. The specific distributions of the error between the SNOWTAM reports and the calibrated and uncalibrated BAs are shown in column two and three in Table 5.

3.4. *Calibration using the measured initial speed*

We consider another method for calibrating the acceleration, namely using the measured initial velocity and only estimating the bias term ϵ, even though the measurements seem unreliable. When the initial speed does not need to be estimated together with the bias term, the regression formula changes as described below.

If we denote the two columns in the matrix (6) by respectively:

$$\boldsymbol{s_1} = (s_1, ..., s_n)^T$$
$$\boldsymbol{s_2} = (s_1^2/2, ..., s_n^2/2)^T$$

we can rewrite Eq. (4) as the following regression model:

$$\hat{\epsilon} = (\boldsymbol{s_2}^T \boldsymbol{s_2})^{-1} \boldsymbol{s_2}^T (\boldsymbol{y} - \boldsymbol{z} - v_0^g \boldsymbol{s_1}) \quad (8)$$

which uses the measured initial ground speed v_0^g. A comparison of the results of the two calibration methods is shown in Table 7. We see that using the measured initial speed had quite a large effect on the friction coefficient, having a higher mean value of 17% and consequently 11% less friction limited landings. $\mu_{v_0^g}$ also has a mean value larger than μ_{raw} given in Table 2, which means that the two calibration methods have quite different effects on the friction coefficient, since μ_{v_0} has a mean value lower than μ_{raw}. This relatively large difference comes from the difference in the initial velocity (4.9 m/s) shown in Table 3.

Until now, μ_{v_0} has been considered the most appropriate friction coefficient based on experience with the measurements, and it is used in the warnings systems of IRIS. As there is no measured ground truth to compare the friction coefficients with, it is not a simple task to show which method gives the most accurate values. This will be subject to further exploration, which will include comparisons with weather data.

4. Stability of brake pressure

The measurements of brake pressure have a high influence on several aspects of the calculations. It has a main contribution on deciding whether a landing is friction limited or not, but it also has an important contribution to calculating the friction coefficient during the landing. We have therefore done an exploration of the stability of the brake pressure, and whether all measurements along the time series of the landings are reliable, or if some parts of the landing should be filtrated out. Especially, we have investigated the different parts of the landing according to the use of thrust reversal, a diversion of the aircraft's engine thrust such that it contributes to the deceleration during landing. It is of interest to verify that the brake pressure is usable during the phase when the thrust reversal is deployed, meaning confirming that the pilots apply the brakes to a high degree also when the thrust reversal system is in use. There has been some uncertainty to how the measurements of the brake pressure are affected by the use of thrust reversal systems, and especially if the measurements are unstable in the period where the thrust reversal is turned on/off, also called the transit phase. Therefore, we have done a specific exploration of the stability of the measurements during the transit phase.

The thrust reversal system is almost always in use when landing on Nordic airports, as it contributes to shorter landing distances and reduces wear on the brakes. On slippery runways, the use of thrust reversal is of major importance to avoid accidents. The thrust reversal is eventually turned off when the aircraft's speed has slowed down. This is because of the high decrease in the effect of the thrust reversal when the aircraft's speed is low, and that using it on a slower moving vehicle could inflict damage as a consequence of pushing debris into the engine, as described in Oda et al. (2010).

To investigate the relevance of the different phases for calculating the friction coefficient, we look at the normal development of brake pressure during a landing, where a typical example is given in Figure 6. We find a tendency for the highest brake pressures to occur during the phase when the thrust reversal system is in use, as seen in Table 8. The column *% of total* shows the distribution of the total occurrences of high pressure, distributed on the three different phases. We see that approximately 75% of the high pressure values occur during the thrush reversal phase, as well as 72% of the extreme values, meaning this is the phase which affects the calculation of the friction coefficients the most. The column *% of time* shows the percentage of time each phase has high brake pressures. We find that 7.9% of the time in the phase with thrust reversal, we have a brake pressure higher than 1000 psi. This happens for only 1.5% of the time with no thrust reversal used.

Table 8. Summary of occurrence of high brake pressure, giving the distribution of the total occurrences of high pressure, and amount of time each phase has high pressure.

Phase	% of total	% of time
Bpr $\geq$ 1000 psi		
No thrust reversal	15.1%	1.5%
Thrust reversal	74.6%	7.9%
In transit	10.3%	5.1%
Bpr $\geq$ 2000 psi		
No thrust reversal	20.0%	0.4%
Thrust reversal	71.8%	1.7%
In transit	8.1%	0.9%

It would seem that the transit phase does not have larger variations or more extreme values in the brake pressure, as only 5.1% of the brake pressures in this phase is above 1000 psi, a lower number than for the thrust reversal phase. In addition, this phase contributes to only 11% of the high pressure values and 8.1% of the extreme values. As the calculations of the friction coefficients depends mostly on the high pressure values, it would seem that this phase does not have the highest contributions to the calculations. Nevertheless, as the stability of these measurements has been questioned for some time, we verify this result by investigating the effect of filtrating out the transit phase, to see how large impact this has on calculating the friction coefficient. This is done by calculating the friction coefficient for four different kinds of filtration:

- No filtration
- Filtration of the transit phase only
- Filtration of the transit phase and one second on each side
- Filtration of the transit phase and two seconds on each side

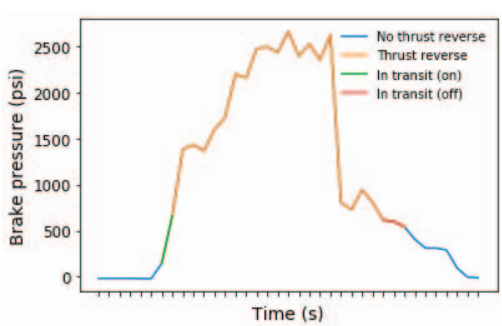

Fig. 6. A typical example of brake pressure after touchdown with color marking according to phase.

The result of this is shown in Table 9, where it can be seen that there is not much difference in the friction coefficients' mean for the different kind of filtrations, where the largest absolute relative difference is 0.30%. The P-values are quite large, giving no signs of significant differences in the means. The largest variation is seen in number of friction limited landings, which decreases from 5.63% to 5.37%. The results indicates that the transit phase does not have instability problems that affect the calculations of the friction coefficients, and that it is appropriate to use data from all phases of the landing in the calculations.

Table 9. Summary of mean values for different kind of filtration. *Difference* is the relative difference between the mean of that filtration method and the mean of using no filtration, Difference $= (\mu_{\text{filter}} - \mu_{\text{none}})/\mu_{\text{none}}$. *P-value* is the P-value for the difference in mean in relation to using no filtration, and *FricLim* refers to the percentage of landings which are classified as friction limited.

Filtration	Mean	Difference	P-value	FricLim
None	0.1209	0%	1	5.63%
Only transit	0.1212	0.24%	0.602	5.58%
One second	0.1213	0.30%	0.520	5.52%
Two seconds	0.1207	-0.21%	0.654	5.37%

5. Conclusions and future work

In this paper we have discussed some of the challenges with converting time series of measurements of flight data into reliable estimates of runway friction. We have shown how to calibrate the acceleration measurements to account for bias in the measurements, both using the measured initial velocity and without using it. We have also shown the effect the calibration has on the estimated friction coefficient and the evaluation of the accuracy of SNOWTAM reports.

We found that the calibrated friction coefficient is at average lower and more scattered than the uncalibrated friction coefficient, which leads to an increase in the number of friction limited landings. Furthermore, the changes made on the friction coefficient has a significant impact on the evaluation of the accuracy of the SNOWTAM reports, as they will be considered less accurate than they would if the uncalibrated coefficients were considered the truth. In addition, we have shown the behavior and stability of the measurements of brake pressure during the flight landing in conjunction with using thrust reversal.

This work is a small part of a large study with the main goal of providing pilots and airport operators with accurate and timely information about the actual runway surface condition, to support in safe and economic operations of airports. In addition to verifying existing warning models, the estimates of runway frictions will be used as a response variable when using machine learning to predict the runway surface conditions, based on weather forecasts. Further work will also include exploring methods for evaluating the different approaches for estimating the friction coefficient.

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