Improving the forecast of aircraft icing conditions

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Icing is a critical danger for aeroplanes. Here, we aim to improve the forecast of in-flight icing environments. We develop a new icing index using the AROME model. The comparison of scores calculated for the operational icing index and the new one shows an improvement in icing detection.

1 Introduction

Icing refers to the phenomenon of supercooled water drops turning into ice when impacting the plane's wings, probes or even engines. This may result in alterations of the aerodynamics of the plane, and breakdowns of the navigation systems or the engines. In these conditions, the plane may crash. Therefore, even if planes have de-icing systems, it is crucial for meteorologists to reliably forecast the danger zones, so that the pilots can avoid them.

During these few months, I have completed and validated the design of a new icing forecast index with the operational model AROME (Seity et al. [2011]) and icing observations from a data base of an airline company.

2 The new icing index

The currently operational index is calculated as an empirical linear combination of temperature and relative humidity. We chose to build our new index as a probability density function (PDF) of several variables of AROME using inflight icing observations.

2.1 Index building

2.1.1 Observed and modelled data

The observations were gathered on airliners between October 2013 and September 2015, mainly over France. Every icing occurrence corresponds to the trigger of the de-icing system during an icing event.

In order to match the simulated conditions with the observations, we interpolate them in time and space, using the nearest AROME forecasts.

2.1.2 Method

We then use these processed data to compute PDFs as icing probability histograms built as a functions of a variable of the model. We sort the values of the variable into bins, so that each bin contains the same amount of observations. We can compute these PDFs for several variables. Figure 1 shows the two-dimensional icing PDF for modelled temperature and specific humidity.

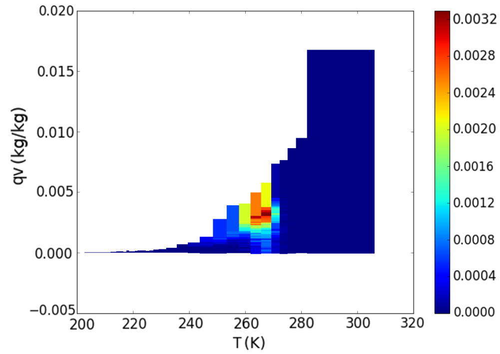

Figure 1: *2D PDF for temperature and specific humidity (qv) of the model.*

To design the new index, we need to select the variables to be used in the PDF computation. A study about the dependencies of icing on different variables was previously led by Coustau [2016]. S. Riette wrote an iterative algorithm to perform the selection, that works as described in figure 2: a score is calculated for every combination of the already selected variables with each remaining one, the variable with the best score is added as a new dimension to the PDF.

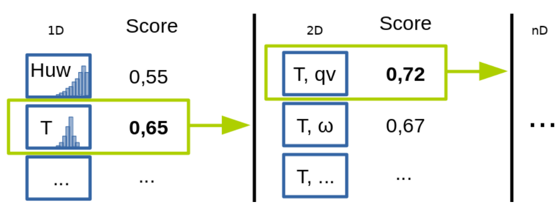

Figure 2: *The algorithm selecting the variables for the index.*

In order to choose the most appropriate score for the selection, I studied the properties of many scores thanks to the CAWCR Website, and the book of Jolliffe and Stephenson [2012] in particular. I have decided to use the Peirce Skill Score (PSS), which has all the desirable properties for our use, such as equitability (random and other unskilled forecasts are rewarded with a null score). This score requires the calculation of a contingency table, which involves the choice of a threshold to distinguish the icing occurrence forecasts from the non-occurrence ones. Whereas the other appropriate scores involve a complicated time-consuming iterative process to calculate their optimal threshold, the PSS is maximal when this threshold is simply equal to the icing occurrence probability, which we approximate here with the ratio of observed icing occurrences.

I also decided to split the dataset into a "learning" period (about 75% of the data) on which the index will be built, and a "control" period to check the relevance of the choices made by the algorithm.

2.2 Results

Figure 3 shows which variables the algorithm selected in one of our trials (the same variables were chosen in most of our trials). Each one of the first three selected variables, temperature, specific humidity (qv) and relative humidity over ice (Hui) improves the scores of the PDF on both learning and control periods. However, the last variable (pressure, P) seems to lower the control scores, meaning that selecting this variable as a fourth one in the PDF would be overfitting. That is why we keep only the first three variables, T, qv and Hui to calculate the PDF.

To find the best PDF, I ran numerous sensitivity tests for various parameters, such as the number of bins (13), the order of the variables (T, qv, Hui), or by introducing a limit on the difference between modelled and observed temperature (unnecessary). Table 1 compares the new index with the operational one using PSS, hit rate and false alarm rate.

The new index shows better detection of icing events when both indices have the same false alarm rate, and vice versa. A first step towards the operational use of the new index has been taken by making an internal website available for the forecasters, where they can daily visualise the icing forecasts of both index.

	PSS	H	F	PSSc	Hc	Fc
Oper. Index.	0.47	0.52	0.05	0.54	0.61	0.07
[T,qv,Hui] maxPSS	0.81	**0.97**	**0.16**	0.78	**0.96**	**0.17**
[T,qv,Hui] same F	0.63	**0.68**	**0.05**	0.66	**0.73**	**0.07**
[T,qv,Hui] same H	0.48	**0.51**	**0.03**	0.51	**0.56**	**0.04**

Table 1: *Scores of both operational and new index for different decisional thresholds. First three columns: learning scores, last three: control scores. NB:* $PSS = H - F$

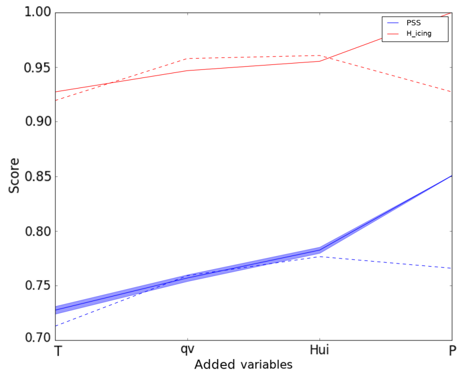

Figure 3: *Building the PDF. Blue: PSS, red: icing hit rate. Solid lines and colour filled areas: learning scores with uncertainty, dashed lines: control scores. X-axis: PDF with T, PDF with (T, qv), PDF with (T, qv, Hui) and PDF with (T, qv, Hui, P).*

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