Cold Regions Science and Technology 117 (2015) 43–51

Contents lists available at ScienceDirect

Cold Regions Science and Technology

journal homepage: www.elsevier.com/locate/coldregions

A decision support model to assess the braking performance on snow and ice contaminated runways

Alex Klein-Paste [a,*], Hans-Jørgen Bugge [b,1], Arne Bang Huseby [c,2]

[a] Norwegian University of Science and Technology, Dept. of Civil and Transport Engineering, Hoegskoleringen 7A, 7491 Trondheim, Norway
[b] Atkins, Postboks 438, 1327 Lysaker, Norway
[c] University of Oslo, Dept. of Mathematics, Postbox 1053 Blindern, Oslo 0163, Norway

ARTICLE INFO

Article history:
Received 13 March 2015
Received in revised form 8 May 2015
Accepted 5 June 2015
Available online 10 June 2015

Keywords:
Winter contaminated runways
Friction measurements
Braking action
Braking performance

ABSTRACT

Pilots need accurate predictions on the quality of runway surface conditions when operating on snow/ice contaminated runways. These predictions are typically made by friction measurements, or by expert judgments of runway inspectors. This study presents a decision support model (the IRIS runway model) for runway inspectors that interprets descriptive data from SNOWTAM reports and predicts the braking action on the common scale from 1 to 5, ranging from "poor" to "good". The model is tested on two airports in Norway during the winter seasons 2008/2009 to 2010/2011. Two other predictors of the braking action (assessments by runway inspectors and friction measurements) were also included. Analyses of 1261 friction-limited landings of commercial airplanes were used to compare predicted and measured braking actions.

The IRIS runway model was found to be more conservative than the assessments of Norwegian runway inspectors, and even more conservative than friction measurements. In 86% of the landings, the IRIS runway model predicted the conditions within ±1 category of what the airplanes experienced, compared to 77% achieved by the runway inspectors. The predictions by the friction measurement devices were the least conservative and predicted the conditions within ±1 category in 61% of the landings. The model is now implemented in 15 airports in Norway.

1. Introduction

Before pilots can land on snow/ice contaminated runways, they need accurate information on the prevailing surface conditions. Hence, reporting the surface conditions is an important task for winter maintenance personnel at airports. During winter operation, a ground vehicle regularly drives over the runway and the runway inspector collects visual information like the type and depth of the snow/ice contamination, percentage of coverage of the contaminant and the presence of sand and chemicals. In addition it is common to perform friction measurements during these inspections, using a ground friction measurement device (GFMD). All this information is transmitted to the pilots in a so-called SNOWTAM report (ICAO, 2013).

Pilots refer to slipperiness of the runway as the braking action, or braking performance. They typically use a scale of five categories ranging from "poor" to "good". Sometimes a sixth category "NIL" is used, meaning it is very slippery and is considered unsafe to land. GFMDs have been used since the 1950s to predict the braking action (Norheim, 2004). Throughout the world, many different models and makes are operative at airports and their readings are often directly reported to the pilots. Unfortunately, different GFMDs do not always give consistent readings on the same surface (Sinha, 2004) and large efforts have been devoted to correlate devices with each other and to airplane braking performance (Andrássy, 1999; Boccanfuso, 2004; Croll, 2004). Despite these efforts, there still seems to be no consensus on how to interpret these readings and the quality of their predictions.

The use of friction measurement devices has been debated (Norheim, 2004; Norheim et al., 2001) and several aircraft accidents have occurred where the conditions were significantly worse than measured by the GFMDs (AIBN, 2011). One of the reasons why it is so difficult to get a valid prediction with GFMDs is that the test tires form scaled tribosystems, compared to the aircraft tire. Parameters like the travel speed, tire characteristics, normal load, braking mode and contact time differ significantly between the GFMDs and the aircraft tires. During braking the rotational speed of the tire is less, compared to a free-rolling tire, inducing slip. As the tire rolls and slides friction is created by hysteresis within the rubber (Bowden and Tabor, 1954; Moore, 1975), by deformations within the snow/ice (Klein-Paste and Sinha, 2010b; Tusima, 1977) and by the creation and destruction of interfaces at the contact points (Makkonen, 2012). The high sliding speeds can induce frictional melting

---

[*] Corresponding author. Tel.: +47 73 59 46 13; fax: +47 73 59 70 21.
E-mail addresses: kleinpas@ntnu.no (A. Klein-Paste), hans.jorgen.bugge@terramar.no (H.-J. Bugge), arne@math.uio.no (A.B. Huseby).
[1] Tel: +47 97 66 50 66.
[2] Tel: +47 22 85 58 60.

http://dx.doi.org/10.1016/j.coldregions.2015.06.002

(Higgins et al., 2008) and loose material (water, slush, wet or dry snow) has to be squeezed out of the contact area before friction can be obtained. The interactions of these multiple friction and lubrication mechanisms act simultaneously on different length scales. This makes it extremely difficult, if not practically impossible, to realistically recreate all these processes during a measurement with a scaled test tire, compared to the aircraft tire. Recent modeling efforts on tire–pavement interactions (Gerthoffert et al., 2015; Makkonen and Tikanmäki, 2014; Michael et al., 2015) help to further understand how different tribosystems behave on a given contaminated surface. But to the best of the authors' knowledge, these models have not yet reached a stage where they have been successfully applied to correct predictions of GFMDs for aircraft braking performance in operational winter conditions.

In 2009, the Norwegian Civil Aviation Authority changed the legislation and prohibited that readings from GFMDs are directly reported to pilots (CAA-Norway, 2009). Instead, trained and authorized runway inspectors (typically the team leaders of the winter maintenance staff) have to estimate the braking action on the scale from 1 to 5 ("poor" to "good"). They are still allowed to use a GFMD, but only as a decision support tool to come to his/her estimate. This change in legislation placed more value on the expert judgment of runway inspectors and less focus on friction measurements. This focus shift is also reflected in the latest SNOWTAM format (ICAO, 2013) which no longer facilitates for reporting measured friction values.

But it also created a need for additional decision support systems. The Norwegian airport operator Avinor had started a large R&D project to develop an Integrated Runway Information System (IRIS). All relevant weather and runway data was collected, together with landing data from two commercial airliners. An airplane braking model was utilized to calculate the aircraft braking coefficient (Klein-Paste et al., 2012). The goal was to develop a decision support system that provided winter maintenance personnel all relevant weather information (to help them making the right winter maintenance decisions) and help runway inspectors to asses the runway condition (the braking action).

In this paper we present the IRIS runway model, which is the decision support tool to assess runway conditions. For this model we used the approach to directly relate the characterization of the contaminants to airplane braking performance (Norheim et al., 2001), without using GFMD readings. In essence it is an expert model that judges the visual information collected during an inspection to predict the braking action. A similar approach was explored by Federal Aviation Administration (FAA) through its Take-off and Landing Performance Assessment — Aviation Rulemaking Committee TALPA-ARC (Subbotin and Gardner, 2013).

In this study we compare three different predictors (IRIS model, runway inspector assessments and friction measurements) with the measured airplane braking coefficient of landings on winter contaminated runways. Therefore, Table 1 introduces a common scale, which relates the different predictors to each other.

2. Description of the model

The IRIS model evaluates a set of information given in the SNOWTAM report and prevailing weather data and returns the prediction P on a scale from 1 to 5, according to Table 1. The model does not predict 0, because SNOWTAM reports are only issued in Norway when the runway is open for air traffic. Hence during very poor conditions the runway is closed and there is no input data available for the model. An overview of the model's input and output is given in Fig. 1.

The model evaluates seven different factors that influence the quality of surface conditions. The mathematical structure of the model is given in Eq. (1).

$$P = x_1 + x_2 + x_3 + x_4 + x_5 + x_6 + x_7 \tag{1}$$

where x_1 to x_7 represent the factors described in Table 2. Variable x_1 can be considered as the base prediction and its value ranges between 1 and 5 and is based on the observed type of contamination that is present on the runway. Variables x_2 to x_7 are the additional factors that either downgrade or upgrade the base prediction. Their values range from -2 to $+2$ and it reflects the number of categories that are either downgraded ($-$) or upgraded ($+$). When P exceeds 5 it is set to 5 and when it becomes lower than 1 it is set to 1. This is done to ensure that P stays within the range from "poor" to "good". Note that there are no weighing coefficients used in Eq. (1) to adjust the relative sensitivity of the different factors. This "weighing" is performed within the factor by adjusting how quickly the factor upgrades, or downgrades the prediction P.

2.1. Type of contamination, x_1

The SNOWTAM format (ICAO, 2003) defines nine different contamination codes K, given in Table 3. Reporting multiple layers is allowed, for example 47, meaning dry snow on ice. The multiple layers consist of maximum one "loose layer" like rime, dry snow, slush, or water, and maximum two "solid layers" like ice, compact snow, or frozen ruts. To reduce the number of possible combinations, the multiple layers involving ruts are grouped together with the multilayers involving compact snow. When the contamination consists of both ice and compact snow, it is considered as ice.

A look-up table was created that classifies the different types of contamination and assigns a value of x_1 to them (see Table 4). The choice of classification is based on experience from winter maintenance personnel, earlier published classifications (Subbotin and Gardner, 2013) and evaluations of braking performance during operational conditions (Klein-Paste et al., 2012). Note that wet snow is judged more slippery than slush in Table 4, which is in accordance with measurements on Norwegian runways (Klein-Paste et al., 2012). This aspect can be physically explained because slush is easier being squeezed out to the contact area, compared to wet snow which is still a compressible material (Colbeck et al., 1978) but it can also be caused by the fact that slush is reported in 3 mm intervals whereas wet snow is reported in 6 mm intervals.

Groups of contamination codes have been defined to assist selection of conditions in the later parts of the model. The following groups have been defined:

$\mathit{notContaminated} = [0\ 1\ 2]$
$\mathit{dryContaminated} = [3\ 4\ 7\ 8\ 9\ 37\ 38\ 47\ 48\ 78\ 87]$
$\mathit{wetContaminated} = [5\ 6\ 27\ 28\ 57\ 58\ 67\ 68]$

Table 1
Scales to express the tire–pavement friction of runway surfaces.

Braking action	Descriptive braking action	Airplane braking coefficient (Klein-Paste et al, 2012)	Estimated friction (ICAO, 2013)	IRIS model P	Measured Friction coefficient (ICAO, 2003)
5	Good	$\mu_B > 0.2$	5	5	≥0.4
4	Medium-good	$0.2 \geq \mu_B > 0.15$	4	4	0.36 to 0.39
3	Medium	$0.15 \geq \mu_B > 0.10$	3	3	0.30 to 0.35
2	Poor-medium	$0.10 \geq \mu_B > 0.075$	2	2	0.26 to 0.29
1	Poor	$0.075 \geq \mu_B > 0.05$	1	1	≤0.25
0	NIL	$0.05 \geq \mu_B$			