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Evaluation of Runway Bearing Capacity using International Roughness Index

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Abstract

In the airport field, to improve the APMS (Airport Pavement Management System), it may be advantageous, in economic terms, to evaluate "Bearing Capacity" using the International Roughness Index (IRI).

This paper explores the relationship between the bearing capacity (dynamic modulus - HWD) and the IRI; the study was conducted on the Lamezia Terme Airport (IATA: SUF, ICAO: LICA), located near Lamezia Terme in the Calabria region in southern Italy.

Bearing Capacity data (from 2010 to 2014), detected through H.W.D. and data on surface features (in terms of IRI) detected through Laser Profilometer, for the same period, were acquired for the goals of this study.

The data were processed using a series of statistical procedures; in particular two models were obtained: Model 1 by MultiVariate Analysis (MVA) and Model 2 using the Artificial Neural Network (ANN) technique. Comparing the two models, it emerged that Model 2 is better than Model 1 because the total sum of the residual is lower.

In summary, through these two models, knowing simply the IRI, it is possible to indirectly evaluate the "Bearing Capacity" in any point of the runway.

Keywords: APMS, Airport, ANN, MVA.

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1. Introduction

Airport agencies monitor and manage the runway through APMS (Airport Pavement Management System). The APMS (Airport Pavement Management System) includes a set of methods that can help decision makers find cost-effective strategies for providing, evaluating, and maintaining pavements in a serviceable condition. Many researchers have studied this issue in recent years, producing significant results for the improvement of APMS. Khraibani et al. (2012) proposed a mixed-effects logistic model to describe the evolution law of pavement deterioration and the effects of many factors were identified on pavement behavior. This approach made optimum use of the data by taking into account unit-to-unit variability and it was more powerful than traditional regression approaches in establishing the evolution curves. Drewnowski and Uta (1985) made an analysis of the possible causes of the damage to the Kinshasa airport runway, using as a basis the deterioration recorded in the concrete slabs. Deformations caused by the difference of temperature on the top surface of the slabs and the under surface, plus the overloading due to aircraft landing and take-off, were the main causes of deterioration in the Kinshasa airport runway. Greene et al. (2004) suggested how to perform an Airfield Pavement Condition Assessment based on pavement-condition indicators that are determined from measurement of pavement distress, structural capacity, friction, and roughness. Factors addressed in the ratings include the pavement-condition index (PCI), the structural index (ratio between the aircraft classification number (ACN) and the pavement classification number (PCN)) and friction characteristics determined through the use of measuring equipments. Yager et al. (2009) report of the Joint Winter Runway Friction Measurement Program between the National Aeronautics & Space Administration (NASA), Transport Canada (TC), and the Federal Aviation Administration (FAA): the program performed instrumented aircraft and ground vehicle tests aimed at identifying a common number that all the different ground vehicle devices would report. This number, denoted as the International Runway Friction Index (IRFI), will be related to all types of aircraft stopping performance. Kuo, Mahgoub and Hollyday (2014) had developed a study in which a numerical model had been designed to define the impact of load for any landing angle. The results show that the strains of traction at the base of the asphalt layer and those of compression in the upper part of the substrate may be ten times higher than bump under static load. This study shows that during landing the effects due to aircraft's loads have to be considered significant in the design of airfields. De Luca et al. (2016) conducted a study about the surface characteristics decay phenomenon related to contamination from rubber deposits. The experiment was conducted by correlating the pavement surface characteristics, as detected by Grip Tester, to air traffic before and after de-rubberizing operation and two models were constructed for the assessment of functional capacity of the runway before and after the operations de-rubberizing. The goal of this work is a useful criterion for optimizing APMS (Čokorilo et al, 2008). In particular a procedure has been built that allows information on the runway bearing capacity (De Luca et al., 2018) trough a simple reading of IRI.

2. Technique used in the study

Two different types of techniques are used for the analysis in this study: *MultiVariate Analysis* (MVA) and *Artificial Neural Network* (ANN). The first description is omitted because it is present for many years in the technical literature. The second, more recent, follows the basic principles shown below:

2.1 The Artificial Neural Network multilayer approach

Inspiration for the structure of the (ANNs) is taken from the structure and operating principles of the human brain. It is made of interconnected artificial neurons that mimic some properties of biological neurons. The function of a biological neuron is to add its input and produce an output. This output is transmitted to subsequent neurons, through the synoptic joints, only if the transmitted signal is high (i.e., greater than a predetermined value), otherwise, the signal is not transmitted to the next neuron. In the network, therefore, a neuron calculates the weighted sum, using Eq (1) (considering the input x_i and weights w_i) and compares it with a threshold value.

$$I = \sum_{i=1}^{n} w_i x_i, \tag{1}$$

where I − the weighted sum (dimensionless); w_i − the weight (dimensionless); x_i − the input (dimensionless).

If the sum is greater than the threshold value, the neuron lights up and the signal is transmitted. Otherwise, the neuron does not turn on and the flow stops.

The activation value u_j rather than u_j, connected to weight w_{ij}, is a function of the weighted sum of the input. This function may take various forms. In this study, a function as Eq (2) is used.

$$\mathbf{u_j} = \frac{\mathbf{1}}{\mathbf{1+e^{-(\Sigma(i) w_{ij} \cdot u_i + \theta_j)}}} \tag{2}$$

where θ_j − the bias unit (dimensionless); u_i − the degree of sensitivity of u_j when it receives an input signal from u_j; w_{ij} − the weight between the connection of the neuron i with the neuron j (dimensionless).

In particular in this study, a neural network with Multi-Layer Perceptron (MLP) architecture is used; moreover, training is carried out using the Back Propagation (BP) algorithm (De Luca, 2016).

3. Data Collection and instruments used to survey

The International Civil Airport of Lamezia Terme (ICAO: LICA, IATA: SUF) is equipped with a 4D class runway (Moretti et al, 2018) named RWY 10/28 of approximately 145,000 square meters, built with flexible pavement whose structural characteristics are identified by the code: PCN 58/F/B/W/T.

Geographic coordinates and altitude on the average sea level are as follows:

- Latitude: 38°54'30" North; Longitude: 16°14'30" East; Altitude: 12.31 m on the a.s.l..

The runway has a flexible pavement with a dense asphalt wearing surface and the following layers:

- *Surface*: 4 cm in dense asphalt
- *Binder*: 4 cm in dense asphalt
- *Base*: 38 cm in dense asphalt
- *Subgrade*: 40 cm in "mixed crushed rock"

Fig. 1 Lamezia Terme International Civil Airport

The following data were collected in three different surveys from 2010 to 2014:

1) Bearing Capacity data using H.W.D. (Heavy Falling Weight Deflectometer) - ICAO regulation, Annex 14, 3th Edition, July 1999, "Aerodrome Design Manual and Operations";
2) Surface Characteristic, in terms of IRI (International Roughness Index), using Laser Profilometer -ICAO regulation, Annex 14, 3th Edition, July 1999, "Aerodrome Design Manual and Operations" (Ivković et al, 2018);

3.1 Bearing Capacity data using HWD

The HWD data were measured according to the "measurement lines" shown in Figure 2; ie with a 5m step along the ***y*** axis and with a 25m step along the ***x*** axis (Runway axis). In particular, the paving has been schematized as follows:

- Layer 1 (Surface +Binder + Base): Dense asphalt, with complex module $\mathbf{E_1}$*
- Layer 2 (Sub Grade): mixed crushed rock, with Dynamic module $\mathbf{E_2}$.
- Layer 3 (Compacted Sub Grade/Natural Sub Grade): with dynamic module $\mathbf{E_3}$.

The data collected were organized as shown in table 1.

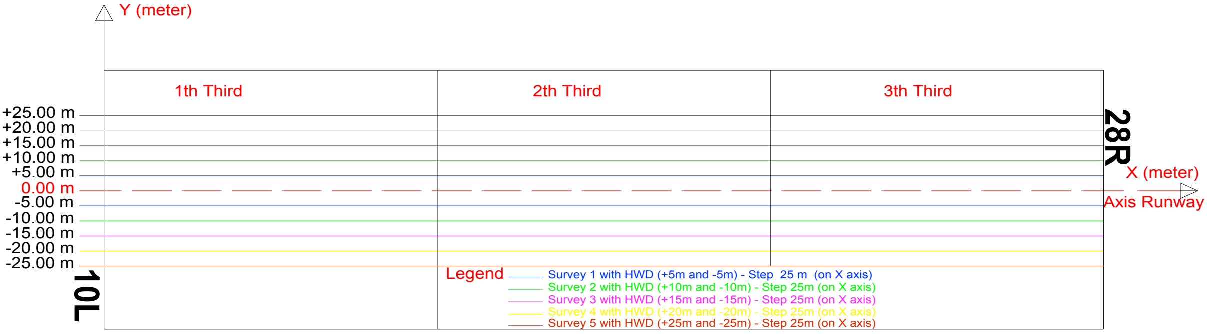

Fig. 2 Layout of "HWD" Surveys

Table 1. HWD data Collection organization (Case *y=5m* and *0<x<2400m*)

x(m)	y (m)	E_1^*(Mpa)	E_2(Mpa)	E_3(Mpa)
0	5	4859	648	75
25	5	2984	1090	133
50	5	3543	1229	111
…..	…..	……	……	…..
2400	5	2242	1235	133

3.2 Surface characteristic in terms of IRI.

The IRI data were measured according to the "measurement lines" shown in Figure 3 and table 2; ie with a 25m step along the ***x*** axis (Runway axis) and with a 3m step along the y axis.

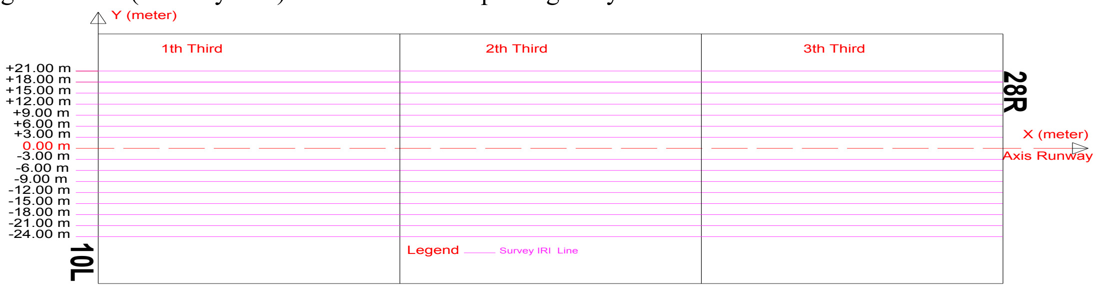

Fig. 3 Layout of "IRI" Surveys

Table 2. IRI data Collection organization

X(m)	-24<y<-21 IRI (mm/m)	-21<y<-18 IRI (mm/m)	…..	-6<y<-3 IRI(mm/m)	3<y<0 IRI(mm/m)	3<y<6 IRI(mm/m)	…..	21<y<24 IRI (mm/m)
25	1.73	1.27	…..	1.57	3.10	3.80	…..	2.70
50	1.60	1.24	…..	1.66	2.69	3.62	…..	1.50
75	1.45	2.12	…..	1.55	2.75	2.4	…..	2.02
100	1.51	2.14	…..	1.42	2.62	2.30	…..	1.77
…..	…..	…..	…..	…..	…..	…..	…..	…..
……	……	……	……	……	……	……	……	……
2375	1.82	2.17	…..	1.9	1.29	1.05	…..	1.86
2400	2.57	2.48	…..	2.11	1.69	1.02	……	1.43

4. Data Collection and data Analysis

The IRI values taken on the runway were organized into 19 classes using the central values of each class as a basis, the average value of the E_1*, E_2 and E_3 associated (see Table 3).

Table 3 IRI data Collection organization

Class Number	IRI Amplitude class (mm/m)	IRI Central Value (mm/m)	E_1* (MPa)	E_2 (MPa)	E_3 (MPa)
1	0.6<IRI<0.76	0.68	4397	550	103
2	0.76<IRI<0.92	0.84	3759	589	118
3	0.92<IRI<1.08	1.00	3671	547	116
4	1.08<IRI<1.24	1.16	3319	527	116
5	1.24<IRI<1.40	1.32	3122	488	116
6	1.40<IRI<1.56	1.48	2871	501	114
7	1.56<IRI<1.72	1.64	2988	527	114
8	1.72<IRI<1.88	1.80	2721	448	114
9	1.88<IRI<2.04	1.96	2603	468	115
10	2.04<IRI<2.20	2.12	2887	499	118
11	2.20<IRI<2.36	2.28	2306	473	122
12	2.36<IRI<2.52	2.44	2864	395	118
13	2.52<IRI<2.68	2.60	1823	380	129
14	2.68<IRI<2.84	2.76	2361	545	110
15	2.84<IRI<3.00	2.92	2338	478	111
16	3.00<IRI<3.16	3.08	2508	334	106
17	3.16<IRI<3.32	3.24	1714	167	124
18	3.32<IRI<3.48	3.40	1937	317	97
19	3.48<IRI<3.64	3.56	2252	315	118

4.1 MVA - Multivariate Analysis Model

The technique of MVA has been applied to the data contained in Table 3 using IRI as the dependent variable and the other variables as predictors (E_1*, E_2, E_3). The expression of the model obtained is the following:

$$IRI = \beta_O + \beta_1 E_1^* + \beta_2 E_2 + \beta_3 E_3 \tag{3}$$

The model (3) was characterized by a coefficient of determination $\rho^2 = 0.87$ and a significance more than 95% (see table 4)

Table 4. Model parameters

Parameter	Estimate	Std. Error	Significance
β_o	9.007E0	1.463	.000
β_1	-9.608E-4	.000	.000
β_2	-2.294E-3	.001	.050
β_3	-2.793E-2	.012	.031

4.2 ANN- Artificial Neural Network Model

The ANN technique has been applied to the data contained in Table 3. The model has been obtained with the technique of ANN as given in Section 2.1. The variables that were considered and used in the model are listed in Table 3 (i.e. IRI, E_1*, E_2 and E_3). The 70% of the data was used to train the network, and the remaining part of the data was used for verification. Different configurations were considered for the architecture of the neural network. Fig. 4 presents the best network architecture. Table 5 gives values of the estimated parameters.

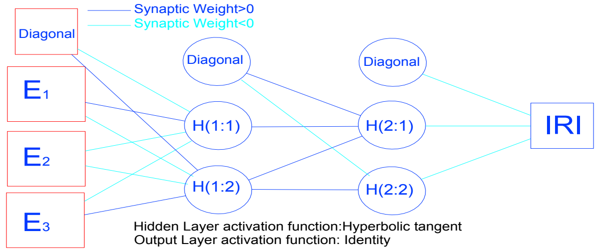

Fig. 4. Architecture of ANN model

Table 5. Parameters of ANN model

Predictor		Predicted				
		Hidden layer 1		Hidden layer 1		Output layer
		H(1:1)	H(1:2)	H(2:1)	H(2:2)	IRI
Input layer	(Bias)	1.115	-.566			
	E1	1.057	.989			
	E2	.560	.221			
	E3	.587	-.522			
Hidden layer 1	(Bias)			-.156	.027	
	H(1:1)			-.485	-.500	
	H(1:2)			-.542	-.453	
Hidden layer 2	(Bias)					.217
	H(2:1)					.916
	H(2:2)					1.234

4.3. ANN Model Versus the MVA Model

Figure 5 and table 6 shows the comparison between the two models and it denotes that Model 2 is better than Model 1 because the residual has a lower total sum.

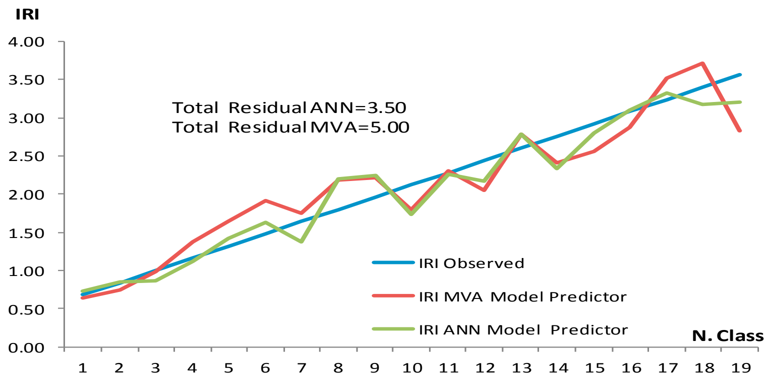

Figure 5. Graphical comparision ANN Versus MVA

Table 6. ANN Versus MVA

N. Class	IRI Observed	IRI MVA Model Predictor	IRI MVA Model Predictor
1	0.68	0.64	0.73
2	0.84	0.75	0.85
3	1.00	0.99	0.87
4	1.16	1.37	1.12
5	1.32	1.65	1.42
6	1.48	1.92	1.63
7	1.64	1.74	1.37
8	1.80	2.18	2.20
9	1.96	2.22	2.24
10	2.12	1.79	1.74
11	2.28	2.30	2.26
12	2.44	2.05	2.17
13	2.60	2.78	2.79
14	2.76	2.42	2.33
15	2.92	2.56	2.80
16	3.08	2.87	3.10
17	3.24	3.51	3.33
18	3.40	3.71	3.17
19	3.56	2.83	3.21

5. Result

MVA and ANN models were used to construct an abacus (Čavka et al, 2018) for the indirect estimation of Et (Bearing Capacity). To construct the abacus the following hypothesis was made: Layer 1, characterized by E_1*, contributes in terms of bearing capacity about 80%; layer 2, characterized by E_2, contributes about 15%; layer 3, characterized by E_3, contributes about 5%; in addition, the reference temperature is 20 ° C. In particular the IRI values were organized into 5 classes (amplitude equal to 0.8); the abacus was built using the central values of each class and the average value of E_1 *, E_2 and E_3 (see Table 7 and figure 6). For example, if IRI on runway is 1.65 mm/m, you can read on abacus that *Bearing Capacity* is judged Sufficient (i.e. if IRI=1.60 mm/m then Et=3800 Mpa).

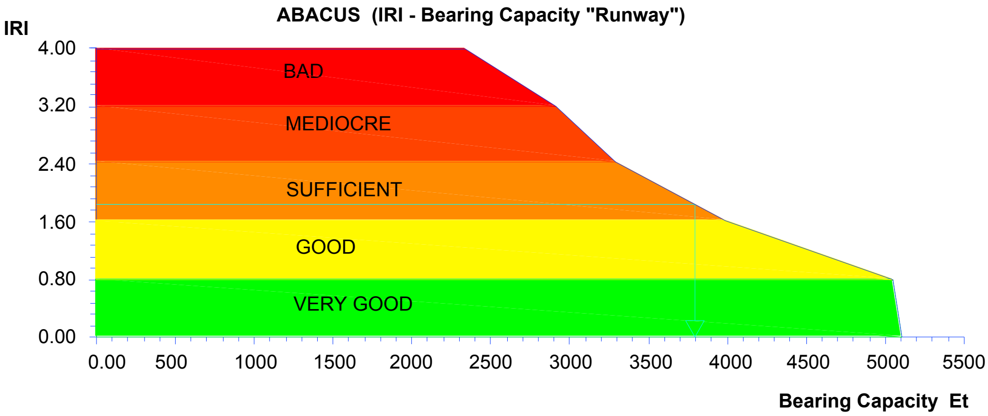

Figure 6 - Abacus IRI - Bearing Capacity

Table 7 IRI- Bearing Capacity Values

Judgment	IRI Class	$Et=(0.8E_1*+0.15E_2+0.05E_3)$
Very Good	0<IRI<0.80	5050
Good	0.80<IRI<1.60	3994
Sufficient	1.60<IRI<2.40	3300
mediocre	2.40<IRI<3.20	291
Bad	3.20<IRI<4.00	2347

Conclusion

This study proposes a procedure to estimate the capacity (dynamic modulus - HWD) through IRI. The study was conducted on the Lamezia Terme Airport (IATA: SUF, ICAO: LICA), located near Lamezia Terme in the Calabria region in southern Italy.

The data were acquired through a series of surveys (from 2010 to 2014) in three different phases. From the analysis of the data, through the MVA and ANN technique, two models were obtained for the estimation of the load-bearing capacity of the runway through the IRI. Comparing the two models, it is evident that Model ANN is better than Model MVA because it has a lower total residual.

Subsequently, with the procedures indicated in chapter 4.5, an Abacus allows, through a simple measure of IRI, to have immediate information on the "Bearing Capacity" of the runway also in quantitative terms. Tests are currently trying to transfer this methodology to other roads with similar characteristics. Although in the initial phase, the assessment is providing very interesting results.

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