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A prediction model of the coefficient of friction for runway using artificial neural network

Modelo de previsão do coeficiente de atrito para pista de pouso e decolagem com uso de redes neurais artificiais

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ABSTRACT
Runway surface conditions are fundamental to ensure safety during landing and takeoff operations of aircrafts. In this manner, airport operators are required to monitor the coefficient of friction and macrotexture of runways to maintain its safety and plan maintenance and rehabilitation strategies when appropriate, since both these parameters get deteriorated with time. Thus, to assist aerodrome operators and regulatory agencies in the decision-making process for conservation and monitoring of airfield pavements, this study aimed to develop a prediction model for runway friction using Artificial Neural Network. Our results were satisfactory and may contribute to the decision-making process in the context of the Airport Pavement Management System.

RESUMO
As condições superficiais de uma pista de pouso e decolagem (PPD) são fundamentais para a garantia da segurança das operações das aeronaves que a utilizam. Nesse sentido, operadores de aeródromos devem manter atenção especial ao coeficiente de atrito e à macrotextura, para que possam promover uma PPD segura, planejar estratégias de manutenção e reabilitação em momentos oportunos, à medida que esses parâmetros se deterioram. Dessa forma, com o intuito de auxiliar operadores de aeródromo e a agência reguladora na tomada de decisão acerca do monitoramento e dos serviços de conservação de pavimentos aeroportuários, este trabalho tem o objetivo de desenvolver um modelo de previsão do coeficiente de atrito medido numa PPD, por meio de Redes Neurais Artificiais. Os resultados apresentaram-se satisfatórios e, assim, tem-se potencial de aplicação do modelo para contribuir na tomada de decisão no contexto de um Sistema de Gerência de Pavimentos Aeroportuários.

1. INTRODUCTION

The tire-pavement adherence – represented by the macrotexture and by the coefficient of friction – are essential for the safety of the operations on the runways. They make it possible for the aircraft to slow down after landing as they allow the airplane tire to roll until it reaches the speed to takeoff (Fwa *et al*., 1997) and also, they act in the draining of the water on the runway. Therefore, the importance of their monitoring in order to help making decisions regarding maintenance measures taken by the airport operators and the inspection of the National Civil Aviation Agency of Brazil (ANAC) are highlighted.

In Brazil, ANAC (2019), establishes that the airport operators should keep the runway in condition to operate safely in order to guarantee: (*i*) skid resistance, (*ii*) the directional control of the airplanes, and (*iii*) the integrity of the aeronautical equipment. Hence, among the aspects that must be monitored, the ones in evidence are the coefficient of friction, the macrotexture, and the rubber accumulation from the airplane tires. So, the frequency for monitoring the parameters mentioned above is established according to the average number of daily landings. Consequently, the more landings, the more measurements should be made, and therefore, as these measurements are made, more data that composes the Pavement Management System (PMS) are generated, which is one of the main characteristics of a modern PMS for Haas *et al*. (2015).

Nevertheless, according to Federal Aviation Administration (FAA) (2014), airport operators do not always make the best rational decisions regarding pavement maintenance and rehabilitation using an approach that allows them to evaluate alternative strategies and lead to an efficient usage of the resources available. Many times, decisions are based on an immediate need or in the experience of past services, in a subjective way (Fwa *et al*., 1997; Chen *et al*., 2008).

It is fundamental for a PMS to have tools that are capable of foreseeing the surface conditions of the pavements with the objective of helping the airport operators and the regulatory agencies in decision making in order to guarantee the safety of the operations and the efficiency to allocate resources. Thus, Artificial Neural Networks (ANN) can be useful for this purpose because they are able to detect nonlinear patterns in data bases. Moreover, the ANNs are tools that have been successfully used in various areas, including Transportation Engineering.

According to the aforementioned, this paper has the objective of developing a prediction model using Artificial Neural Networks, for the coefficient of friction measured in a runway. The International Airport of Fortaleza, in the state of Ceará, Brazil, was used as the study case and for applying the model in focus.

2. FACTORS INFLUENCING THE COEFFICIENT OF FRICTION

The tire-pavement adherence is fundamental, besides other factors, for the landing or taking off to happen safely, and it is strongly affected by the quality of the contact area. Therefore, the presence of contaminants, such as water, is an important aspect to be taken into consideration. It is possible to reach a good tire-pavement interaction due to macrotexture and adequate draining, since a wet runway facilitates hydroplaning, or aquaplaning, a phenomenon in which there is the loss of traction, resulting in an inefficient breaking, with the possibility of losing the directional control and causing accidents (Silva, 2008).

The microtexture is responsible for breaking the water film that is present in the surface and consequently, for allowing the reestablishment of the tire-pavement contact. This parameter depends, basically, on the roughness or smoothness of the superficial aggregates. So, it is desirable, according to Aps (2006), that the surface is composed of aggregates that are rough enough to break the water film. In spite of this, ANAC (2019) does not require the microtexture of the runways be measured in the airports of Brazil. The reason for this may be substantiated in Bernucci *et al*. (2008), when they affirm that this parameter, despite being a very important characteristic to promote the tire-pavement contact, acts at low speed, of up to 40km/h.

The macrotexture is one of the main characteristics of the tire-pavement adherence, mostly for speeds higher than 50km/h, being one of the factors that predominantly interfere in friction (Bernucci *et al*., 2008). Due to the importance of macrotexture in the maintenance of the tire-pavement adherence, the ANAC (2016) determines that the macrotexture depth on the pavement must be of at least 0,60mm and measured by the volumetric sand patch test. The measurements are one-off events that take place three meters away from the runway centerline, and alternately every 100 meters, to the left and to the right of the centerline (ANAC, 2019).

Like the macrotexture, the friction forces between the tire and the pavement are also important for the safety of the airplane, especially in smaller runways, in which the extension available is close to the necessary amount for braking. The friction forces form the main way to stop the airplane after the takeoff or the landing is interrupted because the engine reversal is considered a mere complement, although it may contribute significantly considering low friction runways (Rodrigues Filho, 2006).

Although macrotexture is an important factor for airplanes to brake, for it helps draining the water from the surface of the pavement, this feature was not used in this paper for two main reasons: (*i*) its measurements are isolated, whereas the measurements of the coefficient of friction are done continuously; and (*ii*) the initial results have shown a weak correlation between the values of macrotexture measured using the sand patch method and the values of the coefficient of friction using the Grip Tester, according to what has been observed by Bezerra Filho and Oliveira (2013) and Ramos *et al*. (2015).

As for the ways of measuring the coefficient of friction, ANAC (2019) establishes a classification of equipment, speeds, water depth and measurement frequencies that aerodrome operators can adopt. The results are reported in 100-meter segments and the limit values, according to the type of equipment and measurement speed. In this paper, a Grip Tester equipment was used, with a speed of 65 km/h, whose maintenance planning level of the coefficient of friction value is 0.53 and the minimum level of the coefficient of friction value is 0.43.

Besides this, the measurements of the coefficient of friction always take place within a 1,0mm water level layer in order to simulate a situation of wet pavement, a condition in which the friction between the airplane tire and the pavement is reduced. Regarding the frequency of the measurements, it is established according to the average of landing of fixed-wing aircrafts with reaction engines per day, on the predominant threshold, during the past year. This way, the frequency of the measurements of the coefficient of friction, defined by the ANAC (2019), may vary from 15 to 360 days.

Several characteristics and factors influence the coefficient of friction on a pavement, namely: the types of surface layer, texture, traffic, time, the presence of contaminants, the weather conditions, among others. Regarding the type of pavement, Aps (2006) compared the coefficients of friction measured in different kinds of asphalt surfaces: a draining one (Porous Friction Course – PFC), a cold premix asphalt, and an asphaltic concrete. It has been noticed that, in general, the PFC has shown the best results of coefficient of friction, and the asphaltic concrete, the worst results.

McDanniel *et al*. (2010) also investigated the performance of the coefficient of friction in some parts of North American roads, which were composed of three types of surfaces: the conventional asphalt concrete, Stone Matrix Asphalt (SMA), and PFC. The monitoring began when the runway started operating and continued for five years. It has been noticed that, after the action of traffic, the asphalt concrete section has shown the lowest friction values among the surfaces being investigated.

Regarding the influence of traffic and time on pavements, Skerrit (1993) affirms that friction on new pavements noticeably comes from macrotexture, since the aggregates are still covered by an asphalt binder coating. Nevertheless, as vehicles move, this coating disappears and the aggregates become exposed to polishing. Occasionally, all the aggregates on the surface abrade until they reach a condition of balance. This usually happens after the traffic of one to five million passenger vehicles, or after a period of two years.

Therefore, the polishing of the aggregates is directly associated to traffic intensity and commercial vehicles contribute the most in this process. However, the geometry of the pavement also represents another factor that contributes for the polishing to happen. Consequently, regions with a high number of vehicles demand more attention concerning friction (Chelliah *et al.*, 2002).

Another important factor that also influences the friction available on runways is the amount of rubber accumulated on the surface of the pavement originated from the airplane tires during operations, mainly landings. This rubber accumulated on the touchdown zone of the runways can be very extensive and fill all the texture of the pavement surface, leading to the loss of braking capacity and the directional control when the runway is wet. Hence, the main reason of attention to the accumulation of rubber is the safety of the landing and takeoff operations on the runway (Chen *et al.*, 2008).

Chen *et al.* (2008) studied the effect of rubber accumulation on a runway of the International Airport of Kaohsiung. According to the authors, after the initial 200m, from the threshold end, it is already possible to observe the presence of rubber deposits. However, it is between the 500m and 1,000m stretches that the biggest rubber accumulation can be noticed and, as a result, the lowest friction coefficient values. Besides this, Chen *et al.* (2008) also observe that, in general, each landing contributes for the increase of 0,05 μm in the thickness of the rubber deposited. This accumulated rubber goes through a compaction process as a result of the heat and weight of the airplanes during their landing, thus becoming a layer of rubber that covers the runway surface, impairing the contact between the tire and the pavement reducing the coefficient of friction.

Finally, the pavement surfaces also suffer the influence of the weather conditions. Regarding friction, there are different patterns of seasonal variations on the skidding resistance levels. This variation is more noticeable during the summer months, according to Masad *et al.* (2009), because these are times of higher temperatures when the lower levels of skidding resistance are observed, mainly due to the accumulation of a large quantity of small particles and detritus. Consequently, there is a faster polishing of the surface of the pavement and for this reason, the skidding resistance is reduced. Chelliah *et al.* (2002) observed an alteration of approximately 30% of the friction between a minimum in summer and a peak during winter.

Anupam *et al.* (2013) studied the influence of temperature of the pavements, of the air and of the air inside the tire, on the friction, in three different types of asphaltic pavements: draining pavement, SMA and ultra-thin surface. The results have shown that friction is inversely proportional to temperature, no matter the type of pavement surface.

Several studies have been developed with the objective of estimating the pavement surface conditions. These models use variables that influence them or are related to these parameters, such as data related to the type of pavement, to the aggregates, to the road geometry, to traffic and to the weather conditions (Cerezo *et al.*, 2012; Santos *et al.*, 2014; Beckley, 2016; Oliveira, 2017; Susanna *et al.*, 2017; Hossain *et al.*, 2019; Yao *et al.*, 2019).

In these models, several techniques were employed to predict, from multiple linear regression, nonlinear regression to Artificial Neural Networks. This last technique outstands the others and will be approached in this article due to its efficient capacity of data processing and patterns detection in big amounts of data.

3. ARTIFICIAL NEURAL NETWORKS

ANN are techniques inspired by the functioning of the human brain. For this reason, distributed parallel systems composed by simple processing units are used, known as nodes or neurons, that calculate certain mathematical functions, that are usually nonlinear. These units are disposed in one or more layers and are interconnected by a significant amount of connections (Ribeiro, 2013).

A neuron, according to Haykin (2009), is an information processing unit that is fundamental for the operation of a neural network. Multilayer Perceptrons (MLP) networks are some of the most employed and best-known models. This type of network consists of a set of sensorial units that form an input layer, one or more hidden – or intermediate – layers and an output layer. The input signals are propagated layer after layer through the network in a positive direction, that is, from input to output, as illustrated in Figure 1 (Bocanegra, 2002).

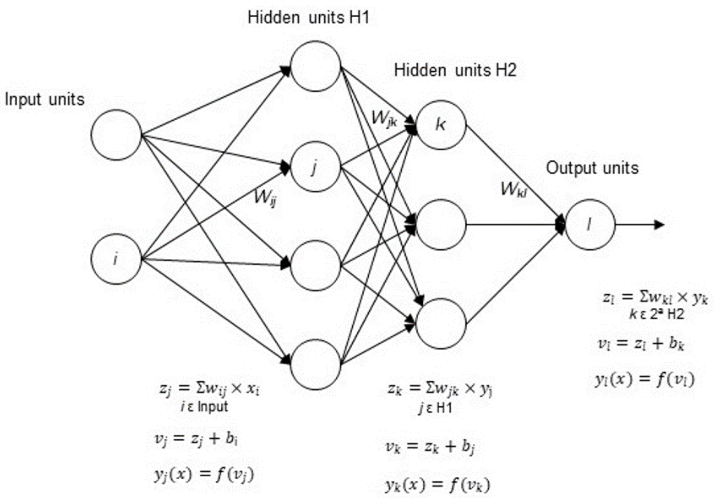

Figure 1. Process of Positive Propagation (input-output)

The neuron, according to Haykin (2009), can be mathematically represented by equations 1, 2 and 3:

$$z_j = \sum w_{ij} \times x_i \quad (1)$$

$$v_j = z_j + b_j \quad (2)$$

$$y(x) = f(v_j) \quad (3)$$

where: z_j is the addition of the outputs, x_i are the input signals, w_{ij} are the respective synaptic weights of neuron j, $y(x)$ is the signal for the output neuron, $f(.)$ is a nonlinear activation function and b_k is bias.

In order to go from one layer to the next, a set of neurons calculates the sum of the weights of the previous layer and the result comes out from a nonlinear function. In previous decades, the neural networks used to use the sigmoid activation functions or the hyperbolic tangent functions. However, nowadays, one of the most popular nonlinear activation functions is the rectified linear function (ReLU), because, in general, ReLU learns faster in networks with many layers (Lecun *et al.*, 2015).

After propagating the input signals in a positive direction the algorithm analyzes the errors in the output and verifies how much each neuron, in the previous hidden layer, contributed to the error in the output and so on and so forth, until the algorithm reaches the input layer. Géron (2017) synthesizes this process the following way: for every training example, the backpropagation algorithm makes a prediction, checks the error and passes by every layer in the opposite direction to analyze the contribution of the error of each connection and, finally, makes small adjustments on the weights of the connection to minimize the error, Figure 2.

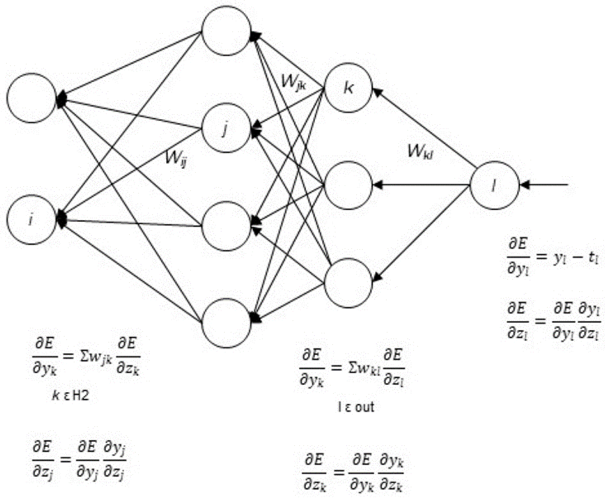

Figure 2. Backpropagation process (from the output to the input)

The backpropagation algorithm can be summarized by the following steps: (*i*) first, a vector with input data is applied in the network and propagated through the network in order to find the activation of all hidden and output neurons; (*ii*) next, the errors that were obtained between the desired and estimated values are evaluated; (*iii*) so, the error is propagated in the inverse direction to analyze the error in each neuron; (*iv*) and last, the weights are adjusted by the derivates of the neuron activation functions (Bishop, 2006).

In this paper, an Artificial Neural Network of Multilayer Perceptron type with the use of the backpropagation algorithm was used.

3.1. ANN application in the Management of Pavements

Flintsch *et al.* (1996) elaborated a model using ANN to help in the choice of road sections that were to go under maintenance, and reduce the subjectivity in this process. For this, data related to the pavement condition, the location, and the costs of maintenance services were used. The authors obtained as outcome a model capable to correctly predict 76% of the output for the testing examples.

Regarding the Airport Pavement Management System, Fwa *et al.* (1997) developed an ANN model to define the necessity or not of maintenance services on runways and to decide if a rubber removal operation should be done. Concerning the results, the model reached a success rate of 90.0% during the testing phase. As the Fwa *et al.* (1997) model, the model developed in this article tried to develop a tool using ANN to estimate the coefficient of friction, as of environmental variables, number of operations, rubber removal operations, among others, thus contributing to decision making process related to the runway maintenance.

Two models of ANN were created by Bosurgi and Trifirò (2005) to collaborate in decision making regarding the choice of maintenance services and to determine the most economical solution with the highest coefficient of friction. The results of the model for predicting the coefficient of friction presented a Mean Squared Error (MSE) of 0.072 in the testing phase. Concerning the second model, which was developed to estimate the number of accidents on the selected roads, it reached MSE of 0.063 in the testing phase.

Ribeiro *et al.* (2018) presented a low-cost methodology for geotechnical mapping applied to paving with the use of ANN. The model developed by the authors showed a precision of 0.98 hence, being a potential tool to be used in infrastructure projects.

Yang *et al.* (2018) built a prediction model using ANN for the coefficient of friction based on data about the pavement texture, and as a consequence, better understand the relation between these two parameters. Yao *et al.* (2019), in their turn, elaborated models to predict the deterioration of the pavement conditions, among which the coefficient of friction is highlighted and the Coefficient of Determination (R^2) was of 86.1% during the testing phase.

An alternative model for retroanalysis of Resilient Modulus (RM) of pavements, an important mechanical property of the paving material, was developed by Celeste and Oliveira (2019). The results of this module reached a R^2 of 99.9% among the RM observed and estimated values.

4. RESEARCH METHOD

The methodology used in this paper can be divided into five stages. The first stage regards the choice of the airport to be used; in the second stage, data was collected; in the third stage this data was treated; in the fourth stage a model of Artificial Neural Network was trained; and last, in the fifth stage the results of the model, Coefficient of Determination (R^2), and errors were analyzed.

When choosing the airport, the International Airport of Fortaleza was chosen with a 2,545m runway of asphalt concrete and with no grooving. This was the airport that had the biggest amount of data available for the authors during the period from 2015 to 2019.

The following features were collected: coefficient of friction, rubber removal, number of operations (landings and takeoffs), relative humidity, and the age of the runway. The data related to the coefficient of friction were obtained from technical reports provided by the Superintendency of Airport Infrastructure from the National Civil Aviation Agency (SIA/ANAC).

The data related to the coefficient of friction was taken from 19 technical reports measured from 21/02/2015 to 14/08/2019. The measurements of the coefficient of friction were made using a Grip Tester, three meters away from the centerline at 65 km/h, and the acceleration distance was 100 meters. It is important to point out that the measurements of the coefficient of friction are made on a water film of 1.0 mm. Besides this, some pieces of information related to the maintenance of the pavement conditions were also included in the aforementioned reports, such as the date of the last rubber removal on the runway. It should be pointed out that the measurements of the coefficient of friction were discriminated every 100 m of segment measured. In general, 2,300 m to 2,400 m of the runway is measured, considering the length of the International Airport of Fortaleza. This way, about 46 values of coefficient of friction per measurement were found, considering a report of 2,300 m and both the right and left sides of the runway.

Regarding the climatic data, these were acquired on the website of the climatological data base of the Institute of Air Space Control (ICEA). The information collected at ICEA refers to the monthly hour average. The reports of the coefficient of friction measurement also contain information on the relative humidity of the air at the time the measurements were taken.

Regarding the age of the pavement surface of the runway, on its turn, it was gotten from the Brazilian Airport Infrastructure Company (INFRAERO).

The information concerning landings and takeoffs came from the SIA/ANAC. The number of operations was calculated by the amount of operations, considering all the landings and takeoffs that happened in between the procedures of rubber removal and the moment when the coefficient of friction was measured. Since more than 98% of the operations in the International Airport of Fortaleza take place on the predominant threshold, considering the average of the period from 2015 to 2018, the option was for considering all the operations that occurred on this threshold.

Categoric features were also used to indicate (*i*) the side of the runway where the coefficient of friction was measured and (*ii*) proceeding or not of the rubber removal process. For this matter, 0 indicates no rubber removal was done since the last measurement and 1, indicates the opposite. It is observed that going through this procedure was considered only for the first one-third of the runway, a section where there is predominance of landings and takeoffs; regarding the side on which the coefficient of friction was measured, 0 was determined for the left side and 1, for the right side.

Next, the data was normalized, that is, each value was subtracted from its average and then, divided by their standard deviation. When applying this method, the features present average 0 and variance 1. This is a common procedure for an ANN; otherwise, it may present unsatisfactory results, mainly if the individual features bear no similarity to the standard data that is normally distributed. So, it points out all resources are centralized around 0 and have their variation in the same order or are between [0, 1] or [-1, 1].

For training the model, which was written in the Python programming language, the Scikit-Learn library were used to test several parameters simultaneously. Among the parameters that were tested, the ones highlighted were: ANN architectures with up to two hidden layers; of 1 to 100 neurons; activation functions: sigmoid, hyperbolic tangent and rectified linear; alpha, a regularization term to prevent excessive adjustments, from 0.001 to 1; number of iterations between 200 and 1.0000; two ways of optimizing weights, using the Stochastic Gradient Descent and the L-BFGS, an optimizer of the quasi-Newton family.

As for the data set, two proportions were tested: 80% / 20% and 90% / 10%; the first portion of the proportion relating to training and the second, to the test. The data were, then, randomly divided without repetition. It was noticed that the division 90%/10% was the one that showed the most relevant results. Finally, the model that was analyzed by its success rate, measured by the Coefficient of Determination (R^2) among the observed and estimated values. In order to measure the errors, we used the Mean Squared Error (MSE) and the Mean Absolute Error (MAE).

5. RESULTS AND DISCUSSION

The 19 technical reports on measurements of the coefficient of friction resulted in 894 observations, from which 804 were used in the training phase and 90 in the testing phase. The ANN architecture that reached the best results is formed by two hidden layers with 94 and 73 neurons; Rectified Linear Unit (ReLU); L-BFGS weight optimizer; alpha equal to 0.1; and a maximum of 600 iterations.

The input features adopted were (*i*) distance of measurement; (*ii*) side of measurement; (*iii*) rubber removal; (*iv*) age of the pavement surface; (*v*) relative humidity; and (*vi*) number of operations between removals. In relation to the output feature of the model, this is an estimate of the coefficient of friction measured by the equipment Grip Tester at the speed of 65km/h, three meters away from the runway centerline.

The success rates, Coefficient of Determination (R^2), and the errors measured by the Mean Squared Error (MSE) and the Mean Absolute Error (MAE) are shown on Table 1.

Table 1 – Model Results

Phase	Coefficient of Determination	MSE	MAE
Training	77.63%	0.0018	0.0327
Test	77.51%	0.0021	0.0364

The input variable "distance of measurement" was the one that influenced the model the most. There are sections on the runway that are more used than others, such as the touchdown zone of the airplanes during the landing operations, where there is more rubber accumulation due to the fact that the tire-pavement contact happens more intensely in this area. The results of the Coefficient of Determination (R^2) were similar on the training and testing phases (Table 1). Regarding the errors, both phases have also shown similar MSE and MAE, although the training phase slightly superior to the testing phase. Figure 3 shows the scatter plot between the coefficient of friction observed and the coefficient of friction estimated by the model for the training and testing phases.

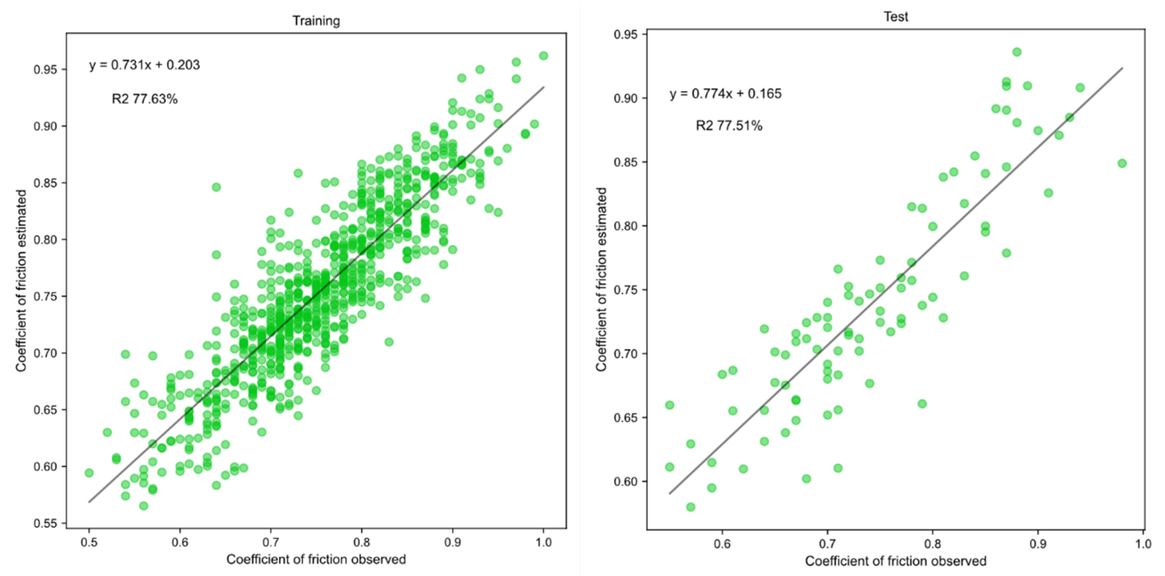

Figure 3. Scatter plots of the coefficient of friction in the training and testing phases

Although the graphs in Figure 3 show significant dispersion in both phases, it should be emphasized that the coefficients of friction show the same tendency to dispose the values close to the diagonal, that is, to the trendline. A summary of the results of the testing phase is presented in Table 2. Therefore, the importance of analyzing the errors histogram, shown in Figure 4, is highlighted, to better check these results.

Table 2 – Summary of the accuracy score of the testing phase

Estimated Coefficient of Friction	Observed Coefficient of Friction					
	0.5	0.6	0.7	0.8	0.9	1
0.5	2	0	0	0	0	0
0.6	4	13	9	0	0	0
0.7	0	9	25	4	0	0
0.8	0	0	2	12	5	0
0.9	0	0	0	4	1	0
1	0	0	0	0	0	0

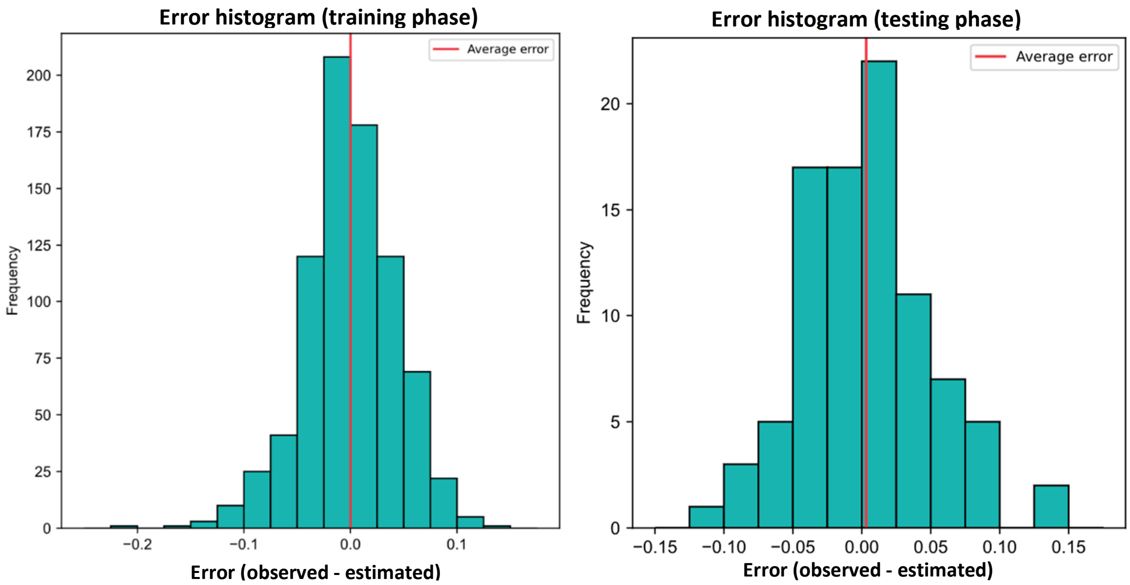

Figure 4. Error histograms in the training and testing phases

It is noticeable that, in the training phase, most of the errors are in the gap between -0.05 and +0.05, mainly between -0.025 and 0.0. Moreover, the average of errors in the training phase is 0.0 and the standard deviation is of 0.04. We found that 50.87% of the results had values below 0, that is, the model estimated the coefficient of friction above the observed rates. This situation, under the perspective of operational safety, would be the most unwanted, since it could transmit to the National Civil Aviation Agency – ANAC and to the airport operator (the decision maker), who is responsible for the runway maintenance, a coefficient of friction superior to the real one.

Regarding the testing phase, the errors are mainly between -0.05 and +0.025, notably on the gap from 0.0 to +0.025. Moreover, 52.22% of errors are superior to zero, indicating that, in general, the estimated coefficients of friction are lower than the ones observed and, consequently, they do not present a risky scenario to the safety of the landing and takeoff operations, since the model estimates more adverse scenarios than the ones observed, and hence, stimulates the airport operator to measure of the coefficient of friction on the runway.

It should be emphasized that estimates of the coefficient of friction lower or equal to 0.60 must be closely observed because, according to the scatter plots in Figure 3 and the errors histograms in Figure 4, such estimates may reflect values close to 0.50. So, in order to guarantee the safety in the operations on the runway, when the model estimates results close to 0.60, it is suggested the airport operator measures the coefficient of friction on site, since the ANAC (2019) establishes both the minimum and the maintenance values are, respectively, 0.43 and 0.53 for measurements of the coefficient of friction using the equipment Grip tester at 65km/h.

This tool might help the airport operator to have better a control of the runway condition of friction and thus, plan on site measurements in more appropriate moments, as well as indicate maintenance strategies, obeying the frequency established by the National Civil Aviation Agency (ANAC, 2019). That being so, one hopes to have contributed for the increase and guarantee of the safety in the landing and takeoff operations.

6. CONCLUSIONS

This paper developed a model to estimate the coefficient of friction measured on the runway of the International Airport of Fortaleza. The results present a feasible model with a coefficient of determination of 77,5% to implement and monitor the conditions of operational safety.

The model may contribute to the airport operator when making decisions related to making measurements of the coefficient of friction on site or taking measures of maintenance and rehabilitation, reducing the subjectivity of these procedures. Moreover, the model proposed may monitor the conditions of friction on the runway by the National Civil Aviation Agency.

Among the limitations inherent to this paper, it can be mentioned that it was developed using data exclusively from the International Airport of Fortaleza and therefore, it might not be adequate for other airports. The prediction model estimates the coefficient of friction measured with the equipment Grip tester at 65km/h, 3m away from the runway centerline, so, situations out of this scope may lead to errors. Furthermore, scenarios that present features that are either too low or that exceed the values used for training by far, also may lead to errors.

Finally, it is important to clarify that the measurements that take place on the runways cannot be abandoned because models are managerial, but measurements are verifications *in loco*, that is to say, they are real measures. Nevertheless, it is expected the model developed in this research may offer a helping tool for an Airport Pavement Management System with the intent to guarantee the safety of the landing and takeoff operations in the Brazilian airports.

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