2012-XX-XXXX

Classification of Aircrafts using Artificial Neural Networks

Alejandro Osses
Laboratory of Acoustics, Sociedad Acustical S.A..
CP 7770563, Ñuñoa, Santiago, Chile
e-mail: aosses@acustical.cl

Ismael Gómez, Max Glisser, Christian Gerard
Gerard Ingeniería Acústica SpA – Control Acústico
CP 7770563, Ñuñoa, Santiago, Chile

Ricardo Guzmán
Dirección General de Aeronáutica Civil, DGAC
CP 9020588, Pudahuel, Santiago, Chile

ABSTRACT

In this paper an algorithm for the classification of aircrafts composing the commercial fleet currently operating in the Chilean airspace is described. This classification is based on certain acoustic descriptors obtained at a specific noise monitoring point, which are used as inputs for a Feed-Forward Artificial Neural Network. As a result, determined classification groups for the evaluated aircraft models are obtained, so that aircrafts of similar size and technology belong to the same group.

INTRODUCTION

For implementing environmental management plans for airports it is required to define procedures for reducing the emissions of the involved air pollutants, among which are aircraft noise. For this end it is important to have a certain amount of noise monitoring points. In addition, it is necessary to identify each aircraft and its characteristics of operation, usually provided by the secondary RADAR system(s) related to the evaluated airport. When having this, integrated with noise monitoring terminals it results in a high-cost system from the point of view of acquisition and also of implementation.

There are several papers studying the recognition of aircraft noise event based on the self-contained information in the time history of different acoustic descriptors [1, 2, 3]. Inspired in these methodologies, in the present paper, the classification of aircrafts using noise data by means of an algorithm based on Artificial Neural Network (ANN) is presented.

For achivieng the objectives specific ANN are used, the so-called Feed Forward Networks, which are computational structures able to relate a certain amount o input parameters with their respective outputs. In this case, the outputs are four classification groups. In the following sections a theoretical review of the main used concepts and the assumptions considered are reviewed.

AIRCRAFT NOISE FEATURES

CHAPTER 2 AND CHAPTER 3 AIRCRAFTS

Large aircrafts could be classified considering their certificated noise levels, according to the document *'Standards and Recommended Practices – Aircraft Noise: Annex 16 to the Convention on International Civil Aviation'* emitted by the International Civil Aviation Organization (ICAO), into 2 categories: a) Type **Chapter 2** characterised by being the current loudest aircrafts, with a low bypass ratio (BPR) turbofan engines and the early high bypass ratio and b) Type **Chapter 3**, aircrafts with an high bypass ratio quiter and more modern aircrafts.

CONFORMATION OF THE CLASSIFICATION GROUPS

For this study, seven (7) aircraft models were considered, being the more representative aircrafts conforming the current commercial fleet operating in the Santiago's International Airport SCEL: Two (2) Airbus models having a narrow fuselage and 2 engines, A318 and A319. In addition, five (5) Boeing models are considered, one of them belonging to the Chapter 2 category, the B737-200, designed for short and mid-range flights with fuel autonomy of approximately 4 hours. Besides, 3 variants to this model were considered, nevertheless they are chapter 3 aircrafts: B737-300 Classic series, having CFM-56 engines instead of the original JT8D engines; B737-700 and B737-800 Next Generation Series, having CFM 56-7 engines, with an increment in the fuel consumption and the new design of the wing. Finally, the Chapter 3 B767-300 was considered which has bi-engine system with medium fuselage, with fuel autonomy of over 7,000 Km.

To achieve the target of the study, it was necessary to segment the aircrafts in four (4) groups; whereby the first criterion was to separate chapter 2 from chapter 3 aircrafts, thus forming a first group integrated by the Boeing 737-200. The second criterion was the aeronautical factory company, thus separating the Airbus from Boeing. Finally Boeing aircrafts chapter 3 where divide between the different streams of B737 and the B767-300.

In table 1 is shown a summary of the criteria used and groups formed.

Table 1: Criterion of aircrfats segmentation groups.

Aircraft	Criterion 1. Etapa	Criterion 2. Aeronautical company	Criterio 4. Model	Group
B732	Chapter 2[1]	Boeing		Group 1
B733	Chapter 3		Streams of Boeing B737[2]	Group 2
B737				
B738				
B763			Boeing 767-300[3]	Group 3
A318		Airbus[4]		Group 4|
A319				

[1] GROUP 1 – Aircrafts chapter 2
[2] GROUP 2 – Aircrafts chapter 3, streams of Boeing B737
[3] GROUP 3 – Aircrafts chapter 3, model Boeing B767-300.
[4] GROUP 4 – Aircrafts chapter 3 from Airbus company

ACOUSTICS DESCRIPTORS

The use of specific acoustic descriptors allows the identification, definition and classification of noise sources. Low frequencies provide important information regarding the acoustic recognition of aircrafts. Many studies have shown the difference between each aircraft having the same global level, but with differences in the noise spectra and its corresponding influence in human perception and community annoyance. Considering this, 1/1 Octave Bands between 31.5 and 1 kHz in dB(Z) were considered. In addition the Equivalent Continuous Noise Level LAeq in dB(A); Maximum Sound Pressure Level LASmax in dB(A) Slow and Peak Sound Pressure Level LZpeak dB(Z), were used.

In Figure 1 the characteristics (including the dispersion of the data) of the average level in 1/1 octave frequency bands for each classification group are shown. In the same way, in Figure 2, the characteristics of the global acoustic descriptors are shown also emphasising the dispersion of the measured data.

Figure 1: Box-plot for the 1/1 octave band spectra between 31.5 Hz and 1,000 Hz for each aircraft classification group.

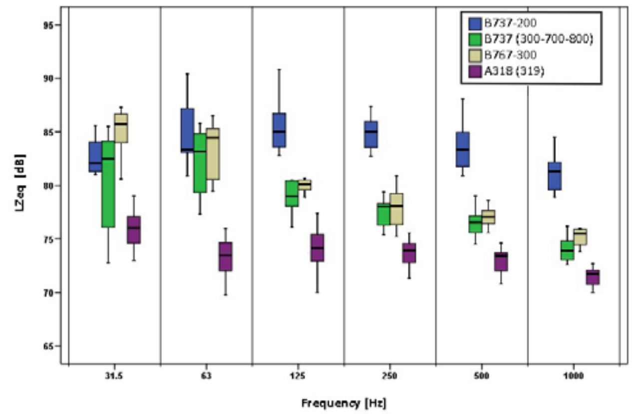
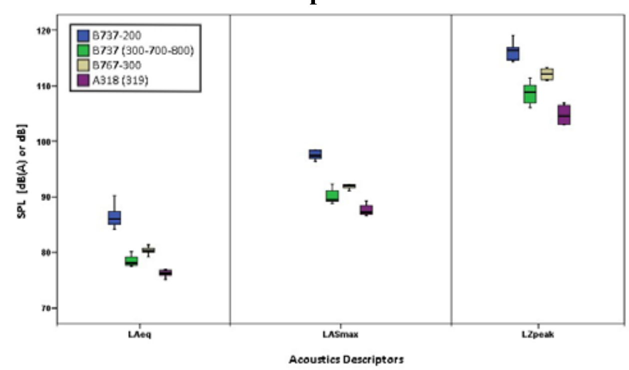


Figure 2: Box-plot for the global acoustic descriptors for each aircraft classification group: LAeq, LASmax and LZpeak.



ARTIFICIAL NEURAL NETWORKS

An artificial neural network (ANN) is a computational structure which emulates the processing carried out by human neurones having the capacity to learn how to relate a determined input to its expected response allowing the generalisation of this behaviour (extrapolation of information based on experience).

The learning process for an ANN is codified into several numeric vectors and functions related to each artificial neurone, generally combined considering simple arithmetic operations (sums and products).

FEED FORWARD ARTIFICIAL NEURAL NETWORKS

A feed forward artificial neural network corresponds to a topology in which the neurone connections are always between contiguous layers, without feedback connections. For this work, 3-layer networks were considered. The first layer handles the 9 acoustics input parameters to the second layer (or hidden layer) implemented with a sigmoid activation function and composed by *n* neurones. The third layer has 2 output neurones with a threshold activation function, obtaining an Artificial Neural Network for classification ends, as shown in Figure 3.

Figure 3: Diagram for a 3-layer feed forward artificial neural network.

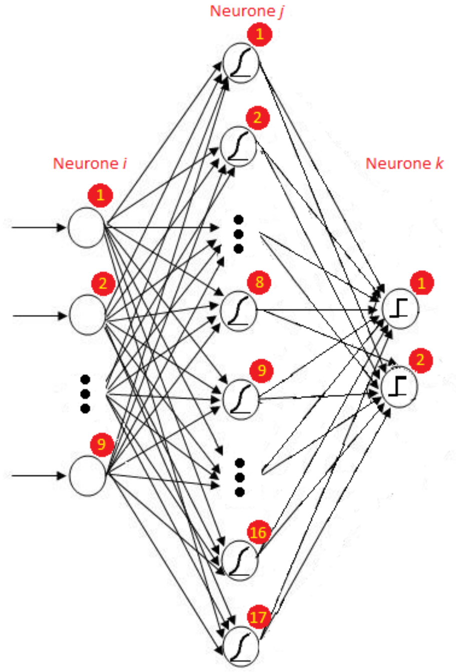


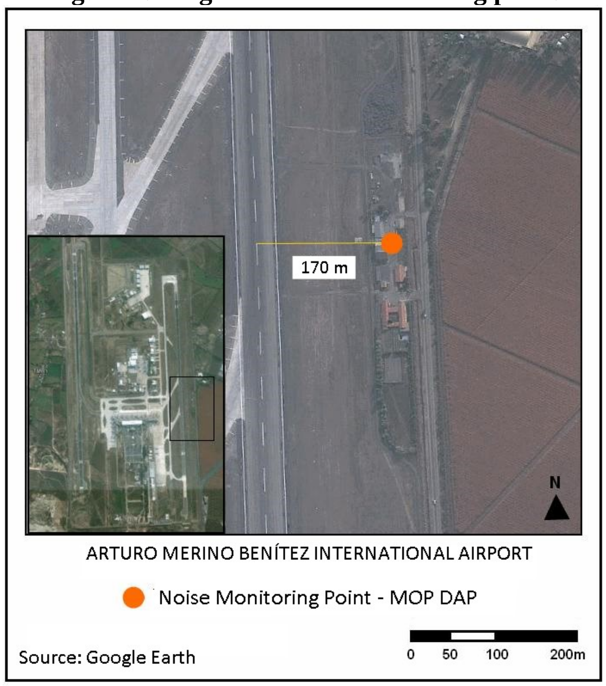
Table 2: Assigned outputs for each aircraft classification group.

Group Nº	Aircraft	Output	
		Neurone 1	Neurone 2
1	Boeing B737-200	0	0
2	Boeing B737 (300-700-800)	0	1
3	Boeing B767-300	1	0
4	Airbus A318-A319	1	1

DATA PROCESSING

The Artificial Neural Network (ANN) was trained considering data measured at one monitoring site located 170 m away of one runway (17L/35R) of the mayor airport in Chile, the Santiago International Airport SCEL, as shown in (Figure 2). The election of this point was based on the favourable condition for detecting aircrafts due to the preponderance of aircraft noise (low background noise), as a result of the distance respect to the runway. The acoustic descriptors were obtained considering 1-minute periods for known aircraft noise events at the monitoring site (take-off operations) with a time history stored at a rate of 8 samples per second. A 48-events data set was considered (12 aircrafts for each classification group), divided into 1 data block (50% of the data) for training and 1 data block (50% of the data) for testing and validating the ANN.

Figure 4: Diagram of noise monitoring point.



The resulting ANN corresponds to a Feed Forward topology with 1 hidden layer implemented in MATLAB® [4]. The number of neurons *n* in the hidden layer was considered as a variable. The transfer function related to the entire ANN was the logsig function, nevertheless, after the training process a threshold function was applied to the outputs in order to obtain only binary values. The optimal configuration found for the ANN is a 9-17-2 setup, which means that the hidden layer has 17 neurones and 9 input parameters and 2 outputs were considered. Regarding the training, the ANN classifies correctly all the events, while for the validation and test data only 1 error is presented.

RESULTS AND ANALYSIS

The results obtained using the trained Artificial Neural Network (ANN) along with the expected values (targets) for the 24 aircraft events used for testing and validation are shown in Table 4.

It is possible to observe that 23 of 24 aircraft events are correctly classified. This corresponds to a 4.17% of error (1 incorrect classification).

Table 3: Comparison between the obtained values (network outputs) and their targets

Event N°	1	2	3	4	5	6	7	8	9	10	11	12
Target	1 0	0 1	0 0	1 1	1 0	0 1	0 0	1 1	1 0	0 1	0 0	1 1
Obtained output	1 0	0 1	0 0	1 1	1 0	0 1	0 0	1 1	1 0	0 1	0 0	1 1
Event N°	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
Target	1 0	0 1	0 0	1 1	1 0	0 1	0 0	1 1	1 0	0 1	0 0	1 1
Obtained output	1 0	0 1	0 0	1 1	1 0	0 1	0 0	1 0	1 0	0 1	0 0	1 1

Considering that a typical error related to an ANN is due to the absence –during the training process– of all the possible cases that could be fed into the network, it is possible that the misclassified event may contain spurious sounds at any of their 9 inputs (e.g. bark dogs, horns, etc.). For solving this kind of problems only would be necessary to add these unfavourable conditions to the ANN training process in such a way to optimise the results.

FUTURE WORK

This paper presents a classification methodology of aircrafts (take-off operations) using the results obtained in a continuous measurement point located less than 200 meters from the nearest runway, where the main noise source were aircraft take-off operations. It is proposed a generalisation of the method to others monitoring points where could present a "less favorable environment" for the doing classification of aircraft. In addition, It would be desirable to test the methodology for both take-off and landing tracks (or profiles), in areas further from the SCEL airport, such as in the commune of Maipú, over 5000 meters of the runways.

Furthermore, we propose to study the use of additional descriptors such as the Sound Exposure Level (SEL), and the use of the whole 1/1 octave bandwidth (at least up to 10 kHz) and to determine if it could be possible to improve the results when using a higher frequency resolution (e.g. one-third octave bands).

It is also suggested to consider other aircraft models, expanding and reorganising the classification groups or to refine the aircraft classification proposed along this article. Finally, it is also possible to evaluate the influence of the "duration of the event" variable, decreasing or increasing the 60 seconds for the events considered in this study, and test new types and configurations of ANN, varying the number of hidden layers and the number of neurones therein.

SUMMARY/CONCLUSIONS

From measurements obtained in a continuous noise monitoring point, values of acoustic descriptors were determined for 48 events (aircraft take off), considering one (1) minute duration for each of them.

From these values, 24 were entered as input to an ANN-based algorithm to train the network and to find the optimal configuration to obtain the minimum classification error of aircraft models.

The proposed classification of aircraft models was based on their technological differences, the various aircraft companies and the several aircraft models considered.

Then, from the remaining events, the results of the ANN produced a classification error of 4.17%, corresponding to one event misclassified from 24 events.

It thus proved the utility of acoustic information contained in the time history of acoustic descriptors to classify certain types of aircraft using ANN based algorithm.

Finally, the generalization of the method was proposed incorporating other variables such as distance to the runway (other monitoring points), aircraft landing operations, other acoustic descriptors, other aircraft models, another duration for the event, and new types and configurations of ANN.

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ACKNOWLEDGMENTS

This research was granted by the companies *Control Acústico* and *Acustical*, making possible the publication of this paper. We also acknowledge the technical support of the Chilean Directorate General for Civil Aviation DGAC, particularly the Engineer Ricard Guzmán.