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A statistical evaluation on flight operational characteristics affecting aircraft noise during take-off

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ABSTRACT

Aircraft noise immission level during the initial phase of take-off is influenced by several parameters, which often produce a significant fluctuation on measured noise levels at the noise monitoring terminal. This fluctuation is not only due to the different aircraft involved in the process, but it is also strongly dependent on the operational settings and characteristics of each take-off, even when the same aircraft type is analysed. The goal of this study is to investigate the relationships between the operational characteristics of flight departure and aircraft noise by means of a statistical approach in order to identify the parameters on which pilots could take action for noise-reduction purposes. The operational settings considered in the present work include actual take-off weight and ground run distance, lift-off aircraft ground speed and ground speed during the initial climb phase. Other variables, for instance source-receiver distance and weather conditions, such as air temperature, air density and headwind were also included in the analysis. The above mentioned parameters of B737-800 flight-departures were collected respectively during 15 days of July 2015 and September 2016. The data collected during the first session is the training set, while the second sample is the test set. Each sample of both datasets was joined with the corresponding noise level provided by the noise monitoring network. Principal Component Analysis and Multiple Linear Regression were performed in order to derive a simplified predictive noise model at a specific point on the ground. This method produced a good Sound Exposure Level estimation. The findings may also be useful to point out the operational characteristics causing the noisiest aircraft flyovers. Consequently, scheduled flight departures could be re-organized by introducing departure-direction and/or departure performance restrictions in order to minimize noise impact on the urban areas.

1. Introduction

Reduction of noise pollution is currently considered one of the most important challenges to be faced in order to ensure a high standard of living for the population in an urban context. The rising influence of globalisation has brought to an increasing need for mobility causing a sharp increase in the usage of air transport. Therefore, noise from airport operations plays a central role in noise concerns of the community. Several studies have indicated that a prolonged exposure to aircraft noise can be directly related with health issues such as cardiovascular diseases [1–5], children impairment [6–8], general annoyance [9,10] and sleep disturbance [11–13]. Flight events generally produce high levels of noise that are also associated with hearing loss [14].

Although significant progress has been made in terms of aircraft noise mitigation, the need to develop and apply new measures to limit its adverse effects persist. The efforts of researches focused on the reduction of aircraft noise at the source have seen considerable progress in the last 60 years with the introduction of quieter propulsion systems accordingly with the ICAO-aircraft-certification classification [15]; moreover, new noise control devices and aerodynamic improvements have been gradually introduced. These developments have led to a noise-emission decrease of about 20 EPNdB [16]. NAMs (Noise Abatement Measures) include specific restrictions for aircraft that are certified in accordance with Chapter 2 and 3 of ICAO Annex 16, Volume I. In the last years many airports have introduced several NAMs which consist, among other things, in Noise Abatement Procedures (NAPs), ground operating restrictions, sound insulation and noise charges as specified in [17,18] and [19]. In particular, NAPs refer to the aircraft noise reduction along the propagation path while sound insulation is normally performed at the receiver. All these measures follow the well-

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known "Balanced Approach" scheme developed by ICAO and re-proposed in the Regulation 598/2014 [20]. Furthermore, noise mapping can be indirectly included in this scheme due to its primary role in the noise action plan development [21]. Noise mapping is a fundamental tool to monitor and predict environmental noise impact generated by airport operations. Noise maps can be produced by means of aircraft noise models [22,23]. These models are normally based on empirical and/or semi-empirical equations [24,25]. Sound emission of the source and sound propagation from the source to the receiver are considered in order to predict noise at a predetermined reference point. With the aid of good-quality input data and for a large sample of aircraft movements corresponding to a typical day based on a yearly average, such models are able to produce accurate representations of the sound level distribution in a given space, even though they can lose prediction accuracy when single flight events are considered as observed in [26]. In fact, aviation noise is a complex subject due to the variability of a large amount of parameters which affect sound generation and propagation. In order to increase the prediction accuracy of the models, above all track radars data are not available, ADS-B (Automatic Dependant Surveillance-Broadcasted) data can be helpful as shown in [27,28]. The information contained in these data are essentially related with aircraft position, velocity and identification.

The purpose of the present work is to provide a simple model for predicting aircraft noise single event in a given reference point by considering ADS-B data as input and taking into account some specific flight-operational characteristics that have prominent effect on noise impact on the ground. The main task of this model is providing to the stakeholders an easy tool based on easy to find flight parameters for a quickly and preventive selection of the noisiest aircraft.

Principal Component Analysis (PCA) [29] has been applied on the independent variables (ADS-B data, aircraft weight and weather parameters) in order to give a qualitative interpretation of their mutual correlations, to reduce the dimensionality of the problem as suggested in [30] and, above all, to avoid multicollinearity. Subsequently, a Multiple Linear Regression (MLR) on the selected principal components has been performed in order to estimate the aircraft noise generated by take-off events.

General information about noise data and ADS-B data collection is presented in detail in Section 2 together with the statistical method discussed above. Section 3 provides the results achieved by performing this classical linear-estimation and includes the results of the validation of the model using a second dataset as test set; the practical utility of this model and noise issue derivations are also highlighted (Section 4). Conclusions and suggestions for future developments based on this work are emphasized in Section 5.

2. Methodology

2.1. Background information

The analysis is based on aircraft noise and track data collected at the Pisa "Galileo Galilei" International Airport. This airport is located along the coast at about 2 km from the city centre of Pisa. Even though the airport consists of two runways, flight departures and approaches occur in the totality of cases from the main runway named 04R-22L. Information about track data and flight performances is provided by an ADS-B system compensating the non-availability of the most common radar tracks [28]. The noise monitoring network consists of 5 stations all equipped with type-1 sound level meters, which are periodically calibrated: 3 of them (P1, P2 and P4) are located almost exactly along the projection of the typical route of take-off from 04R runway (i.e. towards the city, NNE direction), although station P1 is currently out of order.

Due to the small distances occurring between the main runway and the region of interest taking into account in the present work, the initial flight path can be considered straight and the lateral dispersion of the backbone track negligible (see Fig. 1). More details of Pisa airport can be found in [27,28].

2.2. Dataset description

2.2.1. Noise data

Noise data corresponding to the Sound Exposure Levels (SELs) generated by the B737-800 aircraft flyovers and recorded by the P2 fixed-noise-monitoring terminal (installed near the airport area along the ground projection of the typical take-off path) were considered. Two different dataset of flight departures, which occurred from 04R runway, were analysed. The first set of noise data, consisting of $m = 143$ samples, was composed by a subset of the dataset already used in [28], and it was used as the training set. The second one was composed by 115 samples of noise events recorded from the 15th to the 30th of September 2016 and it was used as test set in the validation process. Each dataset included only take-off events during a period of 15 days of two different years as resumed in Table 1. The SEL of each measured event, i.e. the constant sound level that has the same amount of energy in one second as the original noise event [31], was calculated following the threshold method.[1] The obtained values were considered to be affected by a total uncertainty of $\pm$ 1.2 dB(A) as suggested in [32] and investigated in [33], by considering only the uncertainties due to the instrumentation and SEL calculation. In order to minimize variability due to difference in noise emission among aircraft type it was chosen to consider only the B737-800 aircraft model in the analysis, because its use is prevalent at Pisa airport.

2.2.2. ADS-B data, flight performance estimation and weather parameters

In order to build up the matrix X of the independent variables (or predictors) an ADS-B data elaboration was necessary. For each take-off event the variables directly derived from ADS-B data were considered together with the event-associated weather conditions. Moreover, the Take-Off Ground Run Distance (TGRD) was calculated by using the geo-coordinates provided by the ADS-B system every 0.5 second [28] and the Actual Take-Off Weight (ATOW) corresponding to the gross weight of the aircraft during the departure procedure was also collected. A total of $n = 9$ variables were used in order to describe each flight event and they are resumed as follows:

- X_1: Actual Take-Off Weight (ATOW): the aircraft gross weight at the moment of releasing its brakes;
- X_2: Take-off Ground Run Distance (TGRD): the distance covered by aircraft from the brake-release to the rotation phase;
- X_3: Headwind (HW): the component of wind velocity vector in the direction of the aircraft motion. Conventionally, headwind has positive values when its direction is opposite to the direction of the aircraft motion;
- X_4: Aircraft ground speed (V_{TO}) when the aircraft reaches the rotation point (or take-off point);
- X_5: Altitude reached by the aircraft at the end of the runway during take-off (H_{22L});
- X_6: Aircraft altitude (H_{P2}) above the ground when its flight path projection on the ground reached the minimum distance from the P2 reference point;
- X_7: Aircraft ground speed of the aircraft when its flight path projection on the ground reached the minimum distance from the P2 reference point (V_{P2});
- X_8: Air density (ρ);
- X_9: Air temperature (T).

[1] When the aircraft sound level exceeds a given threshold for a minimum of time. SEL is usually calculated by considering the time interval in which the sound level exceeds the threshold level. In this case the value of threshold consists in subtracting 10 dB(A) from the maximum value recorded with the $L_{AS,max}$ metric (the so-called "10 dB(A) down" rule).

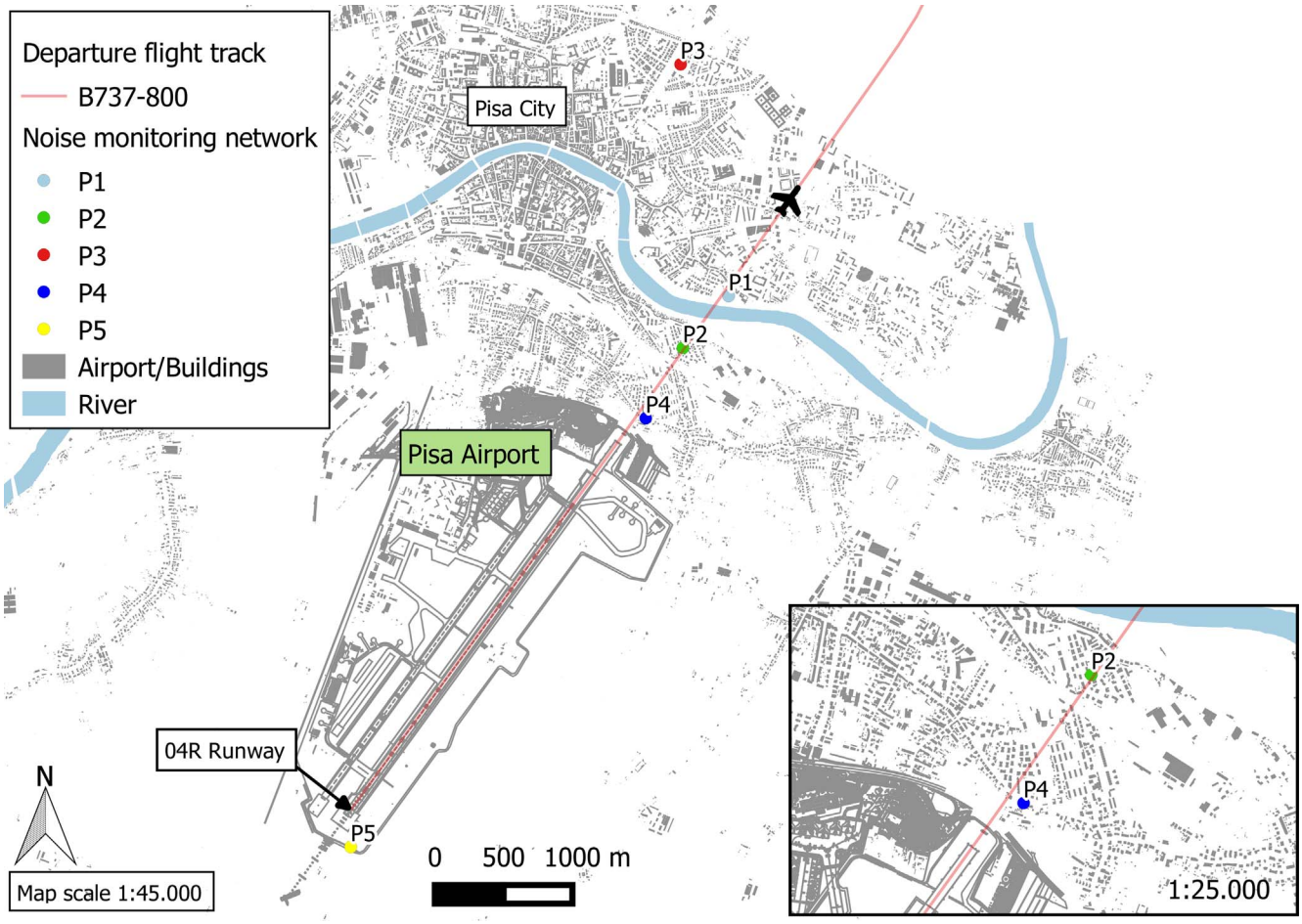

Fig. 1. Aircraft noise monitoring network at Pisa (Italy).

Air density and temperature were included as atmospheric factors in the model because of their non-negligible roles in the flight performance during take-off: reduced density causes a decrease in lifting capability; temperature affects both the propulsion system performance and noise propagation.

2.3. Principal component analysis and multiple linear regression

Principal component analysis (PCA) enables to extract the important information from the multivariate data sample and to express this information as a set of new variables called Principal Components (PCs) [34].

The principle of PCA used in a multiple regression is to replace the original predictors by their PCs, which are mutually orthogonal and are composed by a linear combination of all the original variables, corresponding to the eigenvectors of the covariance matrix of the original dataset. The purpose of applying PCA is to provide a qualitative interpretation of the investigated phenomena by identifying directions along which the data variation is maximal, that is to say the direction of maximum variance. Furthermore, PCA resolves the problem related to multicollinearity among predictors: the original set of correlated variables is transformed into a set of uncorrelated components.

PCA multiple regression develops a model for the Y (SEL) using as independent variables the built PCs. Thanks to the mutual orthogonality of PCs, regression results (coefficients b) are robust. The inversion of the linear combination used to build the PCs, enables to obtain the model equation for Y as a function of the original variables to point out their role on the noise generation event (see Eq. (1)).

$$Y = Y_0 + \sum_{k=1}^{n\leq 9} b_k PC_k \rightarrow Y_0 + \sum_{j=1}^{9} \alpha_j X_j \tag{1}$$

In order to evaluate the model performance, the R^2 (adjusted R-squared coefficient) was taken into account. Furthermore, the obtained model has been tested on the above mentioned samples of the test set for a validation. Model results obtained for the two datasets have been compared by means of the MAE (mean absolute error) and RMSE (root mean square error).

The statistical treatment of the data was performed with R open-source software [35].

Table 1
Basic description of the noise data samples of B737-800 take-offs considered in the present work.

Dataset ID	Time-period	Year	Flight procedure	Runway	#Samples	Aircraft type	Noise monitoring terminal	Mean temperature [°C]	Mean air density [kg/m^3]
1	1–15 July	2015	Take-off	04R	143	B737-800	P2	28.0	1.166
2	15–30 Sept.	2016	Take-off	04R	115	B737-800	P2	20.9	1.199

Table 2
Variance-covariance matrix S of the standardized variables (i.e. the correlation matrix).

	ATOW	TGRD	HW	V_{TO}	H_{22L}	H_{P2}	V_{P2}	P	T
ATOW	1.00								
TGRD	0.06	1.00							
HW	−0.14	−0.11	1.00						
V_{TO}	0.38	0.51	−0.38	1.00					
H_{22L}	−0.11	−0.85	0.24	−0.39	1.00				
H_{P2}	−0.15	−0.73	0.24	−0.22	0.87	1.00			
V_{P2}	0.61	0.19	−0.61	0.51	−0.30	−0.39	1.00		
ρ	−0.26	0.16	0.51	−0.25	−0.06	−0.06	−0.36	1.00	
T	0.21	0.02	−0.48	0.34	−0.09	−0.02	0.32	−0.95	1.00

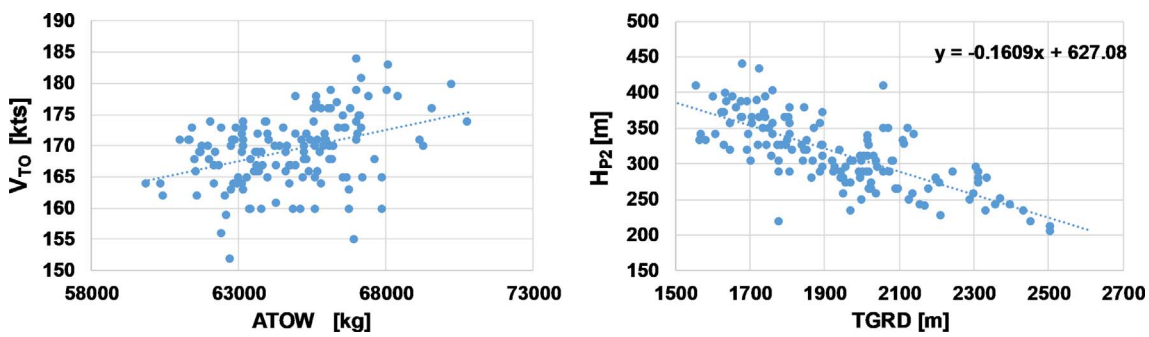

Fig. 2. Take-off ground speed vs. ATOW (left) and distance source-receiver at P2 vs. TGRD (right).

3. Results

3.1. Principal component selection and interpretation

In a PCA analysis, the set of PCs that enable to describe the multidimensional space defined by the original variables is calculated thanks to the orthogonalization of the variance-covariance matrix S (Table 2). The variance-covariance matrix is also useful to highlight the relationship among variables due to the take-off procedure. For example, a positive correlation between ATOW and V_{TO} can be observed: the heavier the aircraft is, the more lift force is needed to balance the weight, and lift is directly proportional to the square of the speed (Fig. 2 on the left). Moreover, the longer the take-off ground run is, the lower the altitudes reached both at the end of the runway and at the reference point P2 are (Fig. 2 on the right).

This last correlation is due to the take-off procedure adopted by the pilots and is well explained in Eq. (2) and Fig. 3.

$$H = V_{\uparrow}\cdot\Delta T = V_{\uparrow}\cdot\left(\frac{L-TGRD}{V_{\longrightarrow}}\right) \approx -\frac{V_{\uparrow}}{V_{\longrightarrow}}\cdot TGRD = -tan(\theta)\cdot TGRD \tag{2}$$

where H is the height reached by aircraft in a ΔT time interval (in this case H_{P2}), $V_{\uparrow}$ is the rate of climb, $V_{\longrightarrow}$ is the ground speed (V_{TO} at the rotation point) and θ is the climb angle. From Fig. 2 (right side) it can be noticed that the average climb angle is about 9°.

The selected principal components can be expressed as a linear combination of the standardized original data (X_j) using the loadings a_j (Eq. (3)) provided by the PCA (Table 3):

$$PC_k = \sum_{j=1}^{9} a_{jk}X_j \tag{3}$$

3.2. The prediction model

In order to select the number of principal components for the regression model a threshold level of 95% of the explained variance of the original variables was established [30]. To achieve this task, the first five principal components were selected (see Table 4), which correspond to a percentage of explained variance of 95.3%.

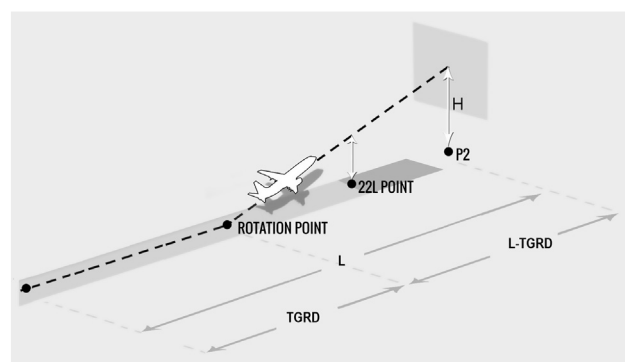

Fig. 3. Take-off procedure scheme. L is the distance between the start-rolling point and P2 reference point.

A first multiple linear regression model using the first five PCs has been performed and the obtained results are resumed in the left side of Table 5. As far as model assumptions are concerned, the residual terms follow a normal distribution centred on zero (p-value = .11 > .05 using the Shapiro-Wilk normality test), but it was observed heteroscedasticity and a slight positive autocorrelation of the errors. Moreover, all the coefficients had a p-value of t-statistic test much lower than the significance level of 5%, except for PC_2 that resulted non-significant. Thus, a second multiple linear regression was performed without PC_2 and using an algorithm that provides a robust estimation of the standard errors of the regression coefficients.[2]

The summary of the second multiple linear regression, which also contains the estimation of the coefficients of the resultant regression model, is presented in right side of Table 5.

The validation of the prediction model was performed on a second dataset of 115 samples (test set). In this case, RMSE was 0.51 and the adjusted R-squared was 0.69. Thus, the model provides a good estimation of the SEL also for the test set, showing that the model does not

[2] The second multiple linear regression was performed using the generalized least square method (GLS).

Table 3
Loadings of the selected principal component.

Standardized variables Original variables	X_1 ATOW	X_2 TGRD	X_3 HW	X_4 V_{TO}	X_5 H_{22L}	X_6 H_{P2}	X_7 V_{P2}	X_8 ρ	X_9 T
PC_1	−0.26	−0.33	0.34	−0.37	0.37	0.35	−0.4	0.25	−0.29
PC_2	−0.15	0.43	0.22	−0.01	−0.4	−0.38	−0.14	0.49	−0.42
PC_3	0.69	−0.16	0.16	0.17	0.19	0.11	0.4	0.3	−0.39
PC_4	0.15	0.29	0.55	0.55	0.01	0.29	−0.36	−0.1	0.25
PC_5	0.42	−0.06	0.47	−0.57	−0.16	−0.34	−0.08	−0.27	0.24

Table 4
Summary of the principal component analysis carried out on the standardized matrix X of the independent variables.

	PC_1	PC_2	PC_3	PC_4	PC_5	PC_6	PC_7	PC_8	PC_9
Proportion of variance	0.402	0.272	0.124	0.082	0.073	0.022	0.012	0.009	0.003
Cumulative proportion	0.402	0.674	0.798	0.881	0.953	0.975	0.987	0.997	1.000

Table 5
Summary of the multiple linear regression results.

	Multiple linear regression - 1				Multiple linear regression - 2			
	Estimate	Std. error	t value	$Pr > (\|t\|)$	Estimate	Std. error	t value	$Pr > (\|t\|)$
Y_0	93.15315	0.03497	2663.833	< 0.0001	93.15848	0.04555	2045.3995	< 0.0001
b_1	−0.29478	0.01845	−15.977	< 0.0001	−0.31559	0.01938	−16.2859	< 0.0001
b_2	−0.0152	0.02244	−0.677	0.499	–	–	–	–
b_3	0.47422	0.03317	14.295	< 0.0001	0.46823	0.03247	14.4210	< 0.0001
b_4	−0.1959	0.04074	−4.809	< 0.0001	−0.18341	0.03836	−4.7811	< 0.0001
b_5	0.24591	0.04338	5.669	< 0.0001	0.20369	0.03983	5.1142	< 0.0001
RMSE	0.41				0.41			
MAE	0.32				0.32			
adj-R^2	0.78				0.77			

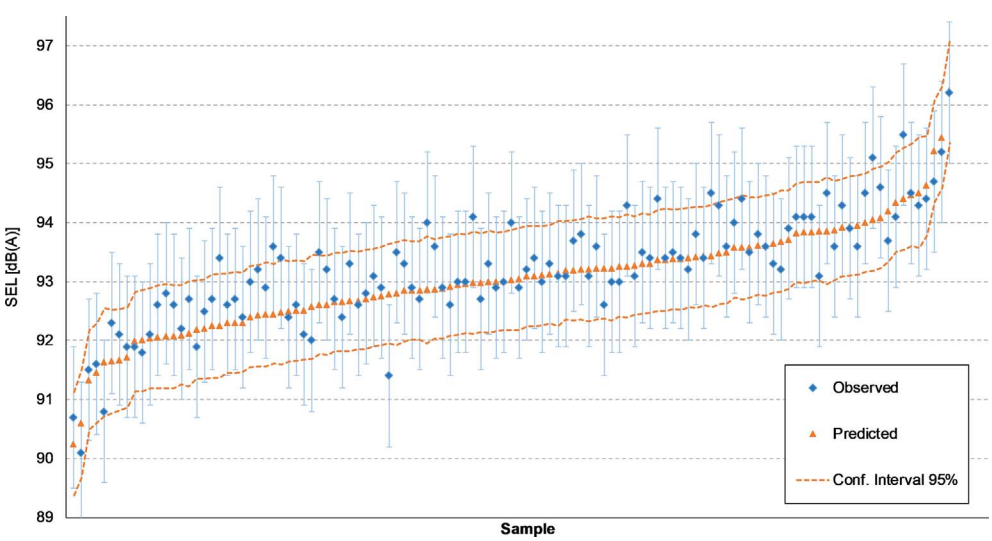

Fig. 4. Predicted and measured values of SEL for each sample of the test set (dotted lines show confidence intervals for predicted values). For the sake of simplicity and clarity, samples are sorted by their predicted value.

depend on the dataset used to obtain the coefficients. The result of the comparison among predicted and observed noise levels is shown in Fig. 4.

4. Discussion

In order to use the results of the multiple linear regression for the estimation of a flight event SEL from the ADS-B data, the ATOW data and the weather parameters, it was necessary to use the original variables, as shown in Eq. (4):

$$SEL_i = Y_0 + \sum_k b_k PC_k = Y_0 + \sum_k \sum_{j=1}^{9} b_k a_{jk} X_j = Y_0 + \sum_j \alpha_j X_j \tag{4}$$

In this way, the analysis of the coefficient of each variable provides insight on the importance of a variable for this model. In order to select the most significant variables affecting noise level, the coefficients associated to the standardized variables were taken into account, as resumed in Table 6.

Based on the normalized coefficient weights it can be observed that the most important variables affecting noise level at the NMT (Noise Monitoring Terminal) are ATOW, H_{P2} and V_{P2}. Fig. 5 shows SEL

Table 6
Summary of the multiple linear regression results obtained for the original variables.

	Normalized coefficient $\tilde{\alpha}_j$	Coefficient α_j
Intercept (Y_0)	93.16 ± 0.05	93.16 ± 0.05
ATOW	0.46 ± 0.03	0.00022 ± 0.00003
TGRD	−0.04 ± 0.01	0.00017 ± 0.00013
HW	−0.04 ± 0.03	−0.01851 ± 0.02760
V_{TO}	−0.02 ± 0.03	−0.00339 ± 0.01137
H_{22L}	−0.06 ± 0.01	−0.00175 ± 0.00065
H_{P2}	−0.18 ± 0.02	−0.00372 ± 0.00078
V_{P2}	0.36 ± 0.02	0.06661 ± 0.00747
ρ	0.02 ± 0.01	1.75983 ± 2.24732
T	−0.09 ± 0.02	−0.02553 ± 0.01134

dependence on ATOW, H_{P2}, V_{P2} and TGRD, taking into account the SEL corrected for all the remaining variables at their mean values.

From Fig. 5a, aircraft noise level at the NMT is directly proportional to the ATOW: a heavier aircraft needs to increase engine thrust in order to reach take-off speed, and therefore the minimum lift enabling the flight, as already seen in Section 3.1 (Fig. 2). Engines are the main noise source during the initial take-off phase and increasing the thrust means increasing the noise. In order to minimize noise impact on urban areas, scheduled flight departures could be re-organized by introducing departure-direction restrictions based on aircraft ATOW. For instance, Pisa airport could restrict the heaviest aircraft to the SSW direction (i.e. departure from 22L runway) for take-off procedures. Furthermore, flight departures could be optimized by adopting the Continuous Climb Operations (CCO) technique, which would allow the execution of a take-off aimed at increasing the aircraft performance in terms of noise and fuel consumption.

Fig. 5b shows that source-receiver distance at reference point P2 (H_{P2}) is inversely proportional to noise. This is easily explained taking into account the geometric divergence of the sound waves. Higher heights over the reference point H_{P2} are likely to be obtained with shorter TGRDs, since H_{P2} and TGRDs are highly correlated, due to their dependence on the climb angle, as seen in Section 3.1 (Fig. 2).

From Fig. 5d, using a similar approach as for the analysis of the ATOW results, noise at the reference point is directly proportional to the speed of the aircraft, due to the higher propulsive thrust needed to reach higher speeds.

Thus, at a fixed value of the Actual Take-Off Weight (ATOW), the aircraft flyovers reaching the highest altitudes (H_{P2}) above the reference point with the lowest speeds (V_{P2}) are the quietest ones.

From Fig. 5c, no clear relationship appears between SEL and TGRD. Indeed, all these variables are related to the take-off procedures adopted by pilots, as clearly shown in Fig. 6, where a 3D-scatterplot shows the speed and the altitude over the P2 reference point and the take-off ground run distance for each take-off of the dataset (coloured dots highlights the TGRD values, from the minimum in red to the maximum in black; grey dots represent projections of each event in a 2D perspective, in order to simultaneously show the three different

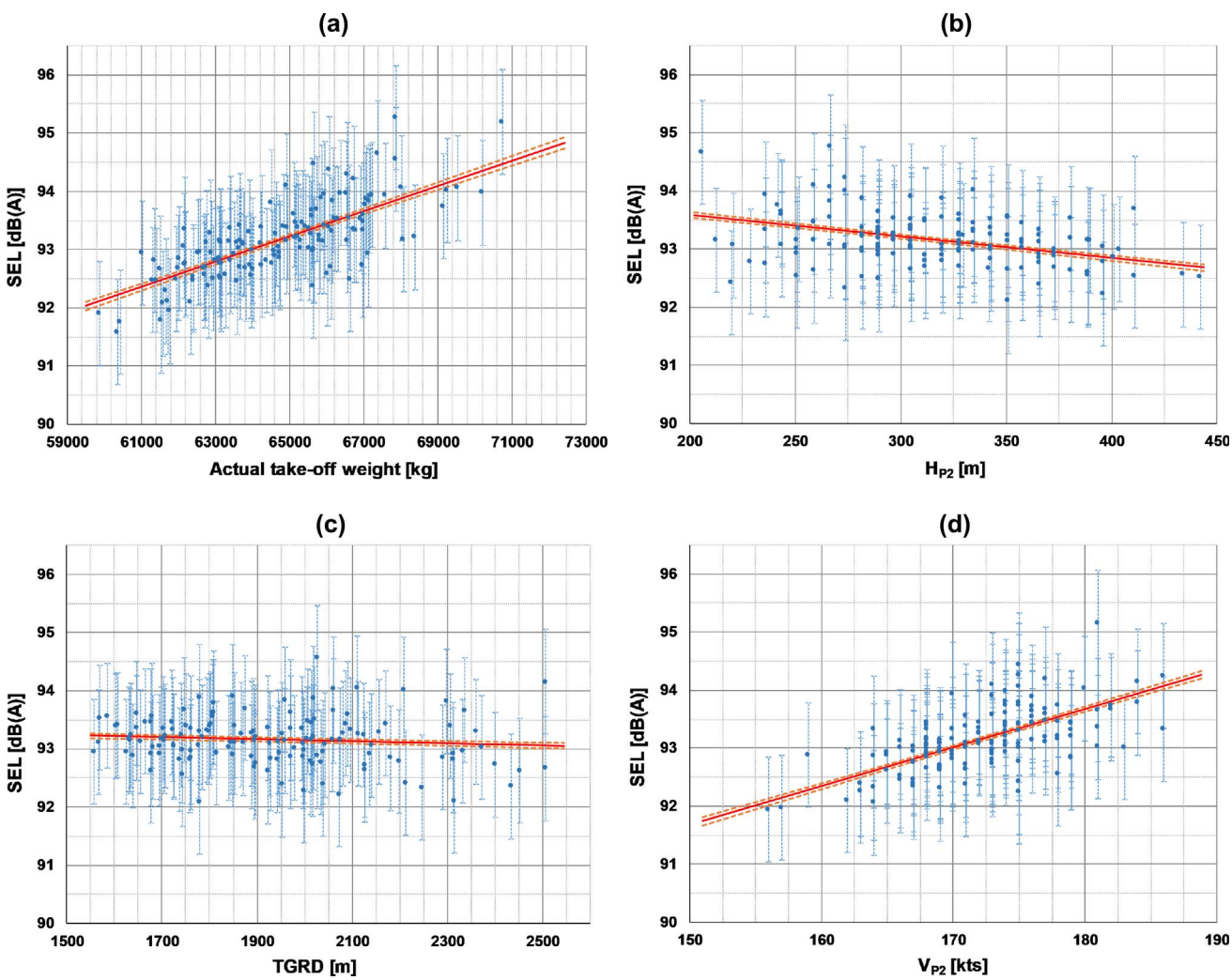

Fig. 5. SEL dependence on one variable for ATOW, H_{P2}, V_{P2} and TGRD, taking into account SEL corrected for all the remaining variables at their mean values.

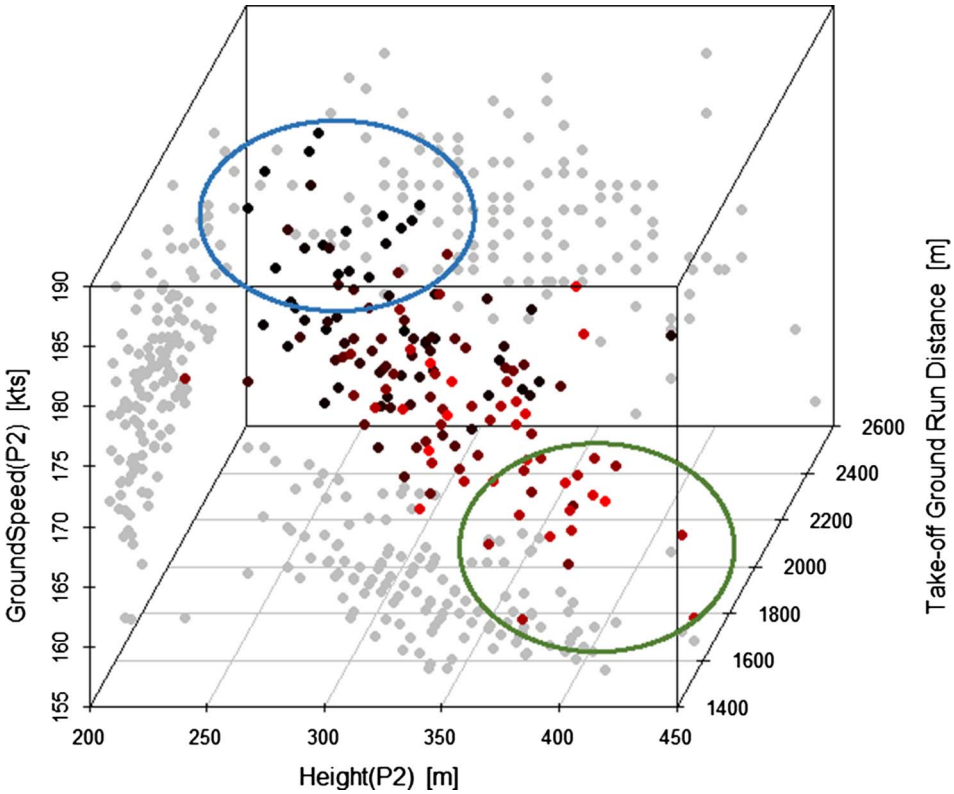

Fig. 6. 3D-scatterplot shows the speed and the altitude over the P2 reference point and the take-off ground run distance for each take-off of the dataset.

relationships among pairs of the used variables).

A heavier aircraft not necessarily needs to cover longer take-off ground run distances: in order to reach the minimum speed for taking off (V_{TO}) the engine thrust could be increased. Longer distances on the ground are probably related to fuel saving policies. However, based on the observed data, aircraft that cover longer take-off ground run distances reach lower altitudes above the receiver (i.e. the NMT) with a larger ground speed and consequently they produce higher noise levels. In fact, the blue and green circles in Fig. 6 pinpoint the highest and lowest values of TGRD; it can be easily inferred that their related SEL difference is about 1.5 dB(A).

5. Conclusions

A principal component analysis was performed on a set of variables composed of ADS-B data related to flight performance parameters, actual take-off weights and weather parameters. The main goal of applying PCA was to avoid multicollinearity. In fact, PCA yields the orthogonal variables to use as input of the multiple linear regression. The multiple linear regression was applied in order to specify the model coefficients, which enabled to predict aircraft noise level, due to single take-off event at a reference point on the ground.

The regression coefficients related to each independent variable were determined for a well-defined point of space. This choice was based on its proximity to the airport infrastructure and the pre-existence of a noise monitoring station. This point is a representative spot for noise exposure in nearby residential areas due to the presence of the airport. In fact, the airport operator's policies in the evaluation of noise impact are based on recorded levels in noise-affected areas. Specific spatial and temporal distribution of air traffic and/or choice of aircraft or their flying operating conditions are used to follow this goal.

The results show that the percentage of the variance of the response variable explained by the linear model is about 77%. This means that the variables contain sufficient information for the prediction of sound exposure level with good accuracy. Subsequently, the predictive noise model was validated by using a test set providing an adjusted R-squared of 0.69 and a RMSE of 0.51 dB(A). An evaluation of the main parameters affecting aircraft noise levels based on the values of the estimated coefficients of the regression model was also performed. From the results of the statistical analyses it was possible to select the variables causing the largest noise level variation: the findings show that actual take-off weight and both aircraft ground speed and altitude (when ground tracks were located at minimum distance from the reference point) most significantly affected noise-immission level. Therefore, a qualitative evaluation was performed in order to estimate the obtainable noise reduction level, which could be achieved acting on the parameters previously selected.

One of the possible applications of the developed method is to provide operational guidance to the airport operator for the definition of mitigation actions. A tool for managing air traffic operations could be developed, permitting a full-scale analysis of the flight operational conditions for a careful planning of air traffic. The operational conditions must also take into account noise impact on the territory. Usage of this tool will increase operator's awareness to aeronautical events that could possibly produce the greatest noise impact during take-off.

Global international air traffic is due to increase in the next years. Pisa airport also follows this trend, and, therefore an increase of the number of flights is expected. Following these considerations, since noise reduction at source will likely be effective in the medium or long term, short-term noise-mitigation actions are necessary in order to contain aircraft noise impact. Among these actions, the possibility to reduce take-off ground run distance by increasing engine thrust is a viable option. This measure inevitably leads both to an increase in the direct costs related to the fuel consumption and to a decrease in the indirect costs associated with the potential health effects on the community. Moreover, direct costs for the airlines could be amortized by the expected increase of the number of flights permitted by noise reduction at the ground using the suggested noise-reduction measures.

In the future, it could be possible to apply a similar approach,

reiterating this proposed method to other locations and applying it also for landing operations, and therefore providing additional useful information to the operators in order to prepare further noise-mitigation actions or improve them.

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References

[1] Huss Anke, et al. Aircraft noise, air pollution, and mortality from myocardial infarction. Epidemiology 2010;21(6):829–36.
[2] Jarup Lars, et al. Hypertension and exposure to noise near airports: the HYENA study. Environ Health Perspect 2008;116(3):329.
[3] Ancona Carla, et al. Valutazione dell'impatto del rumore aeroportuale sulla salute della popolazione residente nelle vicinanze di sei aeroporti italiani. Epidemiol Prev 2014;38(3–4):227–36.
[4] Bruno Rosa Maria, et al. Increased central pressure augmentation is associated with reduced sleep duration in individuals exposed to aircraft noise pollution: the SERA-CV study. Artery Res 2016;16:85.
[5] Evrard Anne-Sophie, et al. Does exposure to aircraft noise increase the mortality from cardiovascular disease in the population living in the vicinity of airports? Results of an ecological study in France. Noise Health 2015;17(78):328.
[6] Stansfeld Stephen, Clark Charlotte. Health effects of noise exposure in children. Curr Environ Health Rep 2015;2(2):171–8.
[7] Klatte Maria, Bergström Kirstin, Lachmann Thomas. Does noise affect learning? A short review on noise effects on cognitive performance in children. Front Psychol 2013;4.
[8] Kaltenbach Martin, et al. Health impairments, annoyance and learning disorders caused by aircraft noise. Int J Environ Protect 2016;6:15–46.
[9] Miedema Henk ME, Vos Henk. Exposure-response relationships for transportation noise. J Acoust Soc Am 1998;104(6):3432–45.
[10] World Health Organization. Burden of disease from environmental noise: quantification of healthy life years lost in Europe. Burden of disease from environmental noise: quantification of healthy life years lost in Europe; 2011. p. 126–126.
[11] Kwak Kyeong Min, et al. The effect of aircraft noise on sleep disturbance among the residents near a civilian airport: a cross-sectional study. Ann Occup Environ Med 2016;28(1):38.
[12] Janssen Sabine A, et al. The effect of the number of aircraft noise events on sleep quality. Appl Acoust 2014;84:9–16.
[13] Kim Soo Jeong, et al. Exposure–response relationship between aircraft noise and sleep quality: a community-based cross-sectional study. Osong Public Health Res Perspect 2014;5(2):108–14.
[14] Basner Mathias, et al. Auditory and non-auditory effects of noise on health. Lancet 2014;383(9925):1325–32.
[15] Dickson Neil. ICAO noise standards. In: ICAO symposium on aviation and climate change, vol. 202; 2013. Retrieved from < http://www.icao.int/Meetings/Green/Documents/day%201pdf/session > .
[16] Casalino D, et al. Aircraft noise reduction technologies: a bibliographic review. Aerosp Sci Technol 2008;12(1):1–17.
[17] Netjasov Fedja. Contemporary measures for noise reduction in airport surroundings. Appl Acoust 2012;73(10):1076–85.
[18] Ganic Emir M, Netjasov Fedja, Babic Obrad. Analysis of noise abatement measures on European airports. Appl Acoust 2015;92:115–23.
[19] Girvin Raquel. Aircraft noise-abatement and mitigation strategies. J Air Transp Manage 2009;15(1):14–22.
[20] Regulation (EU) no. 598/2014 of the European Parliament and of the Council of 16 April 2014 on the establishment of rules and procedures with regard to the introduction of noise-related operating restrictions at Union airports within a Balanced Approach and repealing Directive 2002/30/EC. OJ L 173/65; 12.6.2014.
[21] Directive EU. Directive 2002/49/EC of the European parliament and the Council of 25 June 2002 relating to the assessment and management of environmental noise. Off J Eur Commun 2002;189(12):0012–26.
[22] Doc, ECAC CEAC. 29, Report on standard method of computing, noise contours around civil airports, volume 2: technical guide. In: European civil aviation conference; 2005.
[23] Society of Automotive Engineers, Committee A-21, procedure for the calculation of airplane noise in the vicinity of airports, aerospace information report, no. 1845. Warrendale (PA): Society of Automotive Engineers A-21 Committee; 1986.
[24] Boeker Eric R et al. Integrated noise model (INM) version 7.0 technical manual. No. FAA-AEE-08-01; 2008.
[25] Ahearn Meghan et al. Aviation environmental design tool (AEDT) technical manual version 2b service pack 3. No. DOT-VNTSC-FAA-16-11; 2016.
[26] Miller Nicholas P et al. Integrated noise model accuracy for general aviation aircraft. No. ACRP 02-37; 2014.
[27] Licitra Gaetano et al. Noise mitigation action plan of Pisa civil and military airport and its effects on people exposure. Appl Acoust 2014;84:25–36.
[28] Gagliardi Paolo et al. ADS-B system as a useful tool for testing and redrawing noise management strategies at Pisa Airport." Acta Acustica united with Acustica 2017;103(4):543–51.
[29] Torija Antonio J, Ruiz Diego P, Ramos-Ridao AF. Use of back-propagation neural networks to predict both level and temporal-spectral composition of sound pressure in urban sound environments. Build Environ 2012;52:45–56.
[30] Torija Antonio J, Ruiz Diego P. A general procedure to generate models for urban environmental-noise pollution using feature selection and machine learning methods. Sci Total Environ 2015;505:680–93.
[31] ISO 1996-1. Acoustics – description, measurement and assessment of environmental noise – Part 1: basic quantities and assessment procedures. International Organization for Standardization; 2016. p. 1–28.
[32] Bütikofer Rudolf, Thomann Georg. Uncertainty and level adjustments of aircraft noise measurements. In: INTER-NOISE and NOISE-CON congress and conference proceedings, vol. 2009, no. 7. Institute of Noise Control Engineering; 2009.
[33] Flores Rodrigo et al. A case study of the influence of the urban morphology on aircraft noise. Acoust Aust 2017:1–13.
[34] Jolliffe Ian T. Principal component analysis and factor analysis. Principal component analysis. New York: Springer; 1986. p. 115–28.
[35] R Core Team. R: a language and environment for statistical computing. Vienna (Austria): R Foundation for Statistical Computing; 2014. p. 3–36.