Multi-factorial modelling of comfort in an aircraft cabin considering thermal, noise and vibration metrics

Neil Mansfield, Geetika Aggarwal, Frederique Vanheusden, Steve Faulkner

Department of Engineering, Nottingham Trent University, UK. Neil.mansfield@ntu.ac.uk.

Abstract

Comfort in aircraft cabins is influenced by many ergonomic and physical environment factors. For reasons of sustainability, the fleet of future regional passenger aircraft are expected to have an increased proportion that are propeller powered. Current turboprop regional aircraft have a reputation for being noisy and exposing passengers to vibration. Laboratory studies have simulated the aircraft cabin including noise, vibration and thermal stressors and sought subjective responses from volunteers. These data were used to build multi-factorial models of comfort in an aircraft cabin. Two modelling approaches were used: second order polynomial curve fitting allowed for prediction of subjective ratings from measurements of noise and vibration at discrete temperatures. A multi-factorial model including noise, vibration, and thermal parameters was developed using a linear regression machine-learning approach. This model allows for the prediction of subjective responses within a range of noise, vibration, and temperature levels that are experienced in aircraft.

Keywords: Discomfort, noise, vibration, thermal, aircraft.

Introduction

Air travel is a contributor to carbon emissions and therefore climate change. For regional transportation, turboprop aircraft (i.e. those with a propeller) are more efficient than equivalent jets (Babikian, Lukachko, & Waitz, 2002). Turboprops typically carry less than 100 passengers and include series from De Havilland (formerly Bombardier, Dash 8), Embraer EMB, and ATR42/72. Many future propulsion systems for ultra-low carbon aviation include propeller power units. A barrier to wider acceptance of turboprops has been the perception that they are uncomfortable due to the tonal nature of the noise and vibration. This has been highlighted with the 2022 announcement of a more comfortable ATR model with reduced noise and vibration, including a redesigned propeller (ATR, 2022)

Individual space, the thermal environment, hygiene, noise and vibration are concerns for aircraft passengers (Bouwens, Hiemstra-van Mastrigt, & Vink, 2018; Mansfield, West, Vanheusden, & Faulkner, 2021). To target future aircraft development, manufacturers need a tool by which technological innovation can be prioritized. Improved passenger comfort will lead to improved passenger acceptance and product reputation.

This paper presents the development of a model of the human response to noise, vibration and thermal stimuli. The model allows for the prediction of the response to noise, the response to vibration, the response to the thermal environment and the overall discomfort. It also predicts which of the modalities will be most important in terms of human response.

Methods

Experimental data collection

Data was obtained from a study conducted in an environmental chamber. The details of the study are published elsewhere. 20 volunteers were exposed to combinations of samples of noise and vibration whilst seated in an aircraft seat in an environmental chamber (Figure 1). The vibration was a reproduction of turboprop vibration generated using the 'VibPlate' vibration plate and had magnitudes between 0.75 to 3.0 m/s^2 r.m.s. (unweighted) at the seat. Noise was a reproduction of turboprop noise and reproduced using loudspeakers at levels between 78 and 90 dB(A). The air temperature ranged between 20 and 32 °C. All combinations of noise, vibration and thermal environment were tested. After each sample volunteers were required to rate the noise and the vibration on 11 point (0 to 10) Likert scales, and thermal comfort on the ISO 7730 'PMV' thermal comfort scale (-3 to 3) (International Organization for Standardization, 2005). They were also required to rate their overall discomfort using a modified Borg CR-100 scale (Sammonds, Fray, & Mansfield, 2017). The study was approved by the NTU Ethical Advisory Committee.

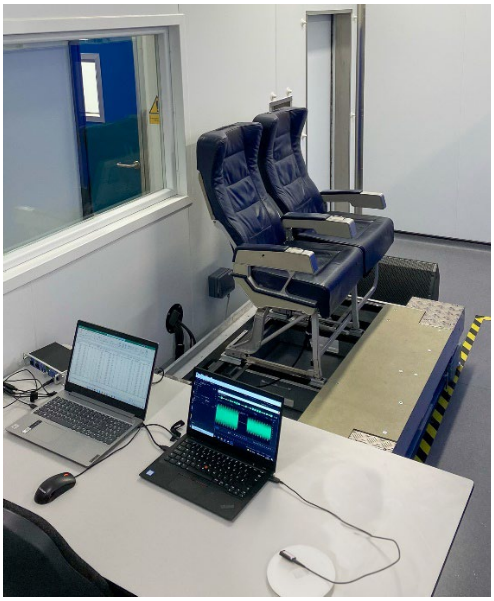

Figure 1. Image of experimental facility used for human data collection.

Table 1. Environmental conditions tested in the study.

Noise (dB(A))	**Vibration (m/s^2 r.m.s.)***	**Temp (ºC)**
78	0.75	20
82	1.50	24
86	2.25	28
90	3.00	32

*vibration are reported as band-limited unweighted, 0.63-100 Hz.

Data analysis and modelling approach

Data were analyzed using data visualization tools in MATLAB, curve fitting tools in MATLAB, and statistical analysis in SPSS.

Polynomial digital models

Individual models were generated for each of the four temperatures tested, and to predict noise, vibration, thermal, and overall ratings. These models were designed to indicate the expected response of the participants for any combination of noise and vibration within the range of experimental conditions tested. Second order polynomial models were used in MATLAB (Poly22)

Expressions were generated in the form:

$$f(x, y) = p00 + p10x + p01y + p20x^2 + p11xy + p02y^2$$

Where x represents the noise level, and y represents the magnitude of the vibration. The x and y variables are transformed using the mean of 84 and standard deviation 4.479 for noise, and 1.875 and 0.8398 for vibration. Coefficients *p* represent the first and second order polynomial coefficients (Table 2).

Table 2. Descriptors for polynomial coefficients

Coefficient	**Description**
p00	Constant value
p10	Linear coefficient (noise)
p20	Second order coefficient (noise)
p01	Linear coefficient (vibration)
p02	Second order coefficient (vibration)
p11	Coefficient of interaction between noise and vibration

Models were generated on the full data set of responses from participants (i.e. 20 responses for each combination of noise, vibration and temperature representing the 20 participants).

Machine learning digital models

The k-fold cross-validation machine learning (KFML) technique was used to generate an overall multifactorial model including noise, vibration, and thermal stressors. Data were randomly allocated to one of 5 test sets, each comprising 256 (20%) test conditions. Five training sets comprised the 1024 (80%) non-allocated data points. Multiple linear regression for each training set was conducted in SPSS, to generate model coefficients for that set. The overall model was generated by taking the mean coefficients across the 5 tests.

Models were generated in the form:

$$f(x, y, z) = q000 + q100x + q010y + q001z$$

where x represents the noise level, y represents the magnitude of vibration and z represents the temperature. Variables were not transformed. Coefficients are described in Table 3.

Table 3. Descriptors for multiple linear coefficients

Coefficient	Description
q000	Constant value
q100	Linear coefficient (noise)
q010	Linear coefficient (vibration)
q001	Linear coefficient (temperature)

Results

Summary experimental data

In summary, discomfort due to noise increased with noise level but not with vibration or temperature; discomfort due to vibration increased with vibration but not with noise level or temperature, showing no cross-modal interaction (i.e. no masking or synergistic effect). Overall discomfort increased with noise and vibration showing and additive effect (Figure 2). Overall discomfort also increased as the temperature increased.

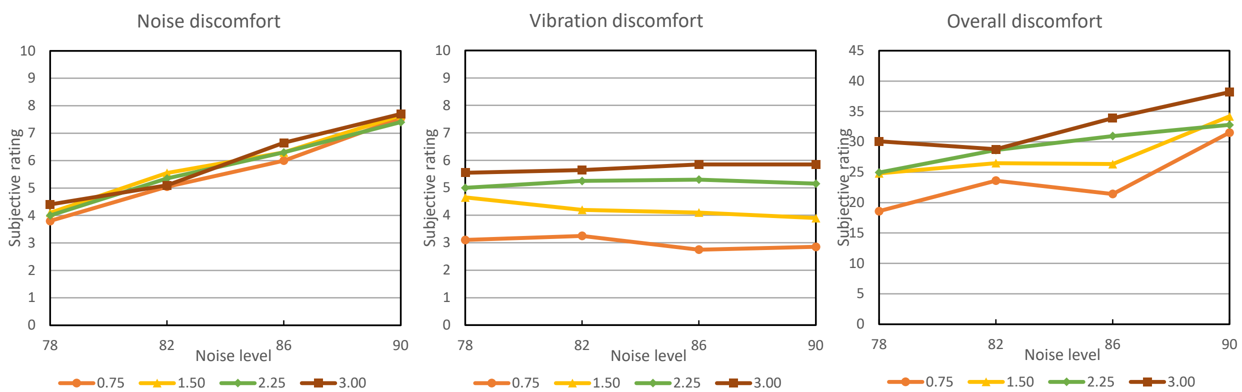

Figure 2. Mean data from laboratory study at 24 deg C showing subjective ratings of noise (*left*), vibration (*centre*) and overall discomfort (*right*) with changes in noise and vibration.

Polynomial digital models

Polynomial digital models of the human were created for noise discomfort, vibration discomfort, and overall discomfort. Models were fitted to individual data points, whereas RMS error (%RMSE) was calculated to the mean data.

For noise and vibration discomfort, RMS errors were less than 4% in all cases (Table 4). Models followed patterns as expected in the data, showing increases in discomfort with noise and vibration (Figure 2). Data in Figure 3 are for 20 degrees C, similar trends were obtained for other temperatures.

Table 4. Polynomial parameters for models of noise and vibration discomfort at four different temperatures.

Temp deg C	**Model type**	**p00**	**p10**	**p01**	**p20**	**p11**	**p02**	**%RMSE**
20	Noise	5.797	1.284	0.046	-0.106	0.037	0.043	2.45
	Vibration	4.342	-0.071	1.020	-0.027	-0.066	-0.231	3.27
24	Noise	5.814	1.293	0.106	0.024	-0.031	-0.031	3.01
	Vibration	4.759	-0.056	1.027	-0.024	0.124	-0.212	3.64
28	Noise	5.659	1.291	0.050	0.063	-0.119	-0.047	2.55
	Vibration	5.006	0.000	1.047	-0.110	0.044	-0.204	3.94
32	Noise	5.387	1.341	0.073	0.157	-0.088	-0.063	2.32
	Vibration	4.944	0.029	1.093	-0.051	0.068	-0.216	2.72

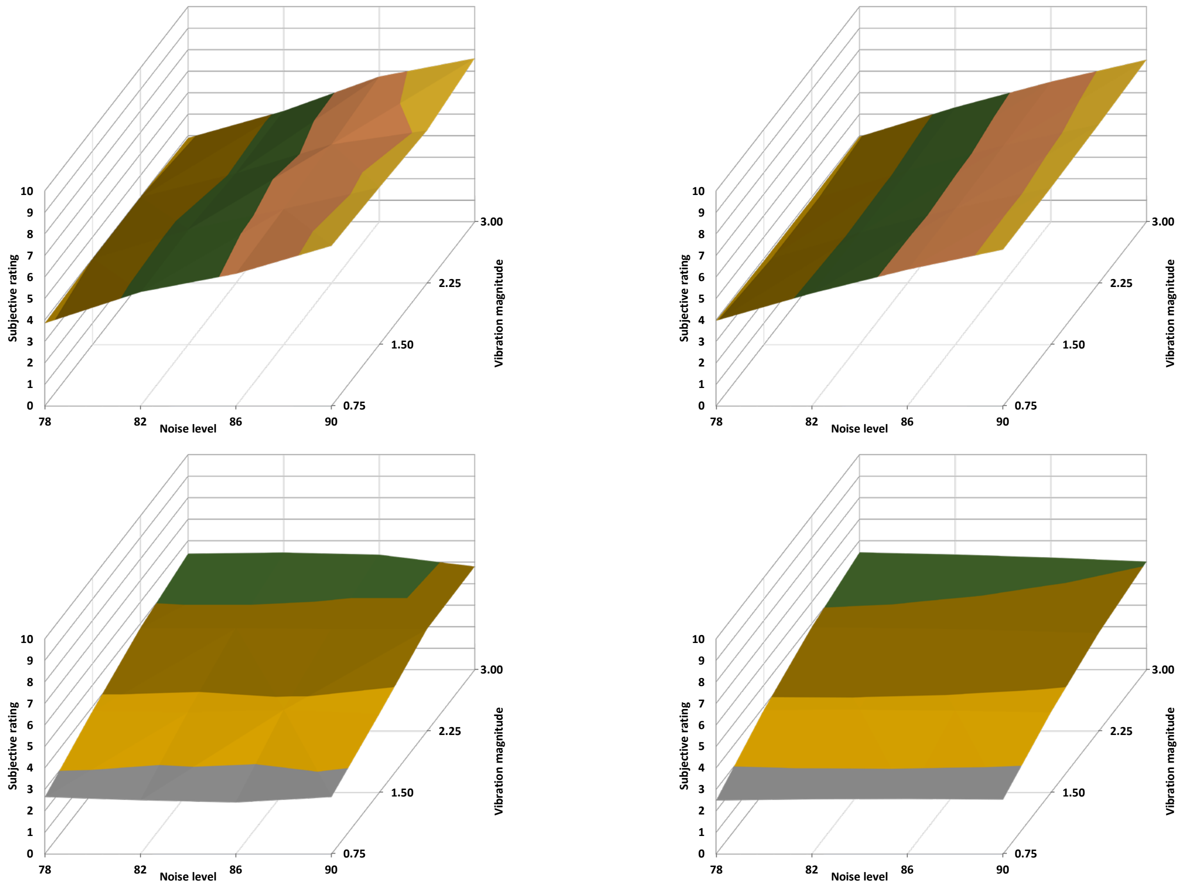

Figure 3. Mean data from laboratory study (left column) and polynomial model output (right column). Example data are shown for 20 degree C, *noise* discomfort (top row) and *vibration* discomfort (bottom row).

Overall discomfort was measured using a different scale to individual modality discomfort. Model parameters (Table 5) were therefore not directly comparable to those in Table 4. Results showed that the overall discomfort was a function of the temperature, the noise and the vibration (Figure 4).

Table 5. Polynomial parameters for models of overall discomfort at four different temperatures.

Model type	**Temp deg C**	**p00**	**p10**	**p01**	**p20**	**p11**	**p02**	**%RMSE**
Overall	20	25.460	3.744	2.381	0.499	-0.879	-0.250	4.68
Overall	24	27.530	3.358	3.158	1.174	-0.293	-0.242	6.30
Overall	28	31.430	3.090	3.051	0.496	-0.718	-0.025	4.47
Overall	32	38.320	3.518	2.977	0.312	-0.257	-0.382	2.15

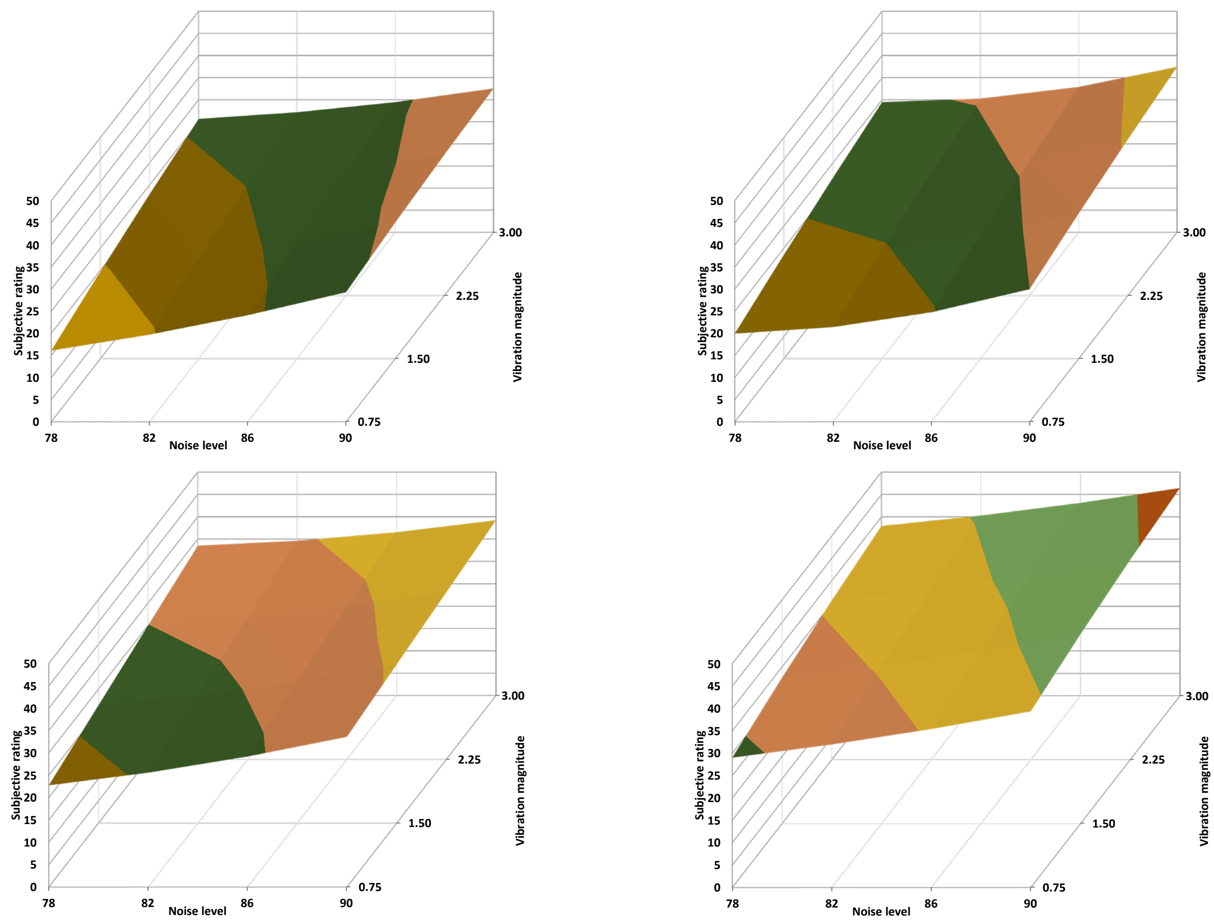

Figure 4. Polynomial model output for human model of *overall* discomfort at four different temperatures. Top row 20 and 24 deg C, bottom row 28 and 32 dec C.

Multiple linear regression machine-learning digital models

Five linear regression machine-learning (LRML) models were developed on 80% of the full data set and tested on 20% of the data. Model parameters are shown in Table 6. The RMS errors in comparison to mean data were 6.44 to 6.99%, with mean model error of 6.40% across all combinations of temperature, noise, and vibration.

Table 6. Linear regression machine-learning model parameters for overall discomfort.

Model	**q000**	**q100**	**q010**	**q001**
k-fold LRML 01	-61.98	0.69	3.18	1.10
k-fold LRML 02	-73.31	0.84	3.41	1.04
k-fold LRML 03	-58.70	0.66	3.43	1.06

k-fold LRML 04	-73.86	0.86	3.83	1.00
k-fold LRML 05	-64.02	0.77	3.36	0.93
k-fold LRML MEAN	**-66.37**	**0.77**	**3.44**	**1.03**

Discussion and conclusions

Digital models of the response of the human to aircraft environments have been shown to successfully fit to experimental data. For models that are designed to represent noise discomfort and vibration discomfort the polynomial model parameters were dominated by those addressing the modality of interest, indicating little cross-modal interaction. Future development of the models could remove those parameters that have little influence on the predicted values. All parameters were important for the overall discomfort model. The polynomial model was not comprehensive and needed parameters redefining for each temperature.

A linearized general model was developed using a machine learning algorithm. This method allowed for the prediction of the overall discomfort on the basis of 4 model parameters. Testing the model on mean data from 20 participants showed an RMS error of 6.4%.

The source data for the development of the model was obtained within a pre-determined range of temperatures, noise and vibration. Simulated cabin temperatures were designed to be in a comfortable range. Application of the model outside of the range may not be valid. For example, the predicted discomfort reduces in the model if the temperature reduces. However, if the temperature falls below 20 degrees, participants could feel discomfort due to cold.

Acknowledgments

This study was supported by EU CleanSky ComfDemo project — H2020-CS2-CFP08-2018-01.

References

ATR. (2022, May 18). *ATR paves way for next generation of its best-selling aircraft.* Retrieved from atr-aircraft.com: https://www.atr-aircraft.com/presspost/atr-paves-way-for-next-generation-of-its-best-selling-aircraft/

Babikian, R., Lukachko, S. P., & Waitz, I. A. (2002). The historical fuel efficiency characteristics of regional aircraft from technological, operational, and cost perspectives. *Journal of Air Transport Management*, 389-400.

Bouwens, J., Hiemstra-van Mastrigt, S., & Vink, P. (2018). Ranking of human senses in relation to different in-flight activities contributing to the comfort experience of airplane passengers. *International Journal of Aviation, Aeronautics, and Aerospace, 5*(2), 1-15. doi:10.15394/ijaaa.2018.1228

International Organization for Standardization. (2005). *ISO 7730 Ergonomics of the thermal environment.* Geneva: International Organization for Standardization.

Mansfield, N. J., West, A., Vanheusden, F., & Faulkner, S. (2021). Comfort in the Regional Aircraft Cabin: Passenger Priorities. *Congress of the International Ergonomics Association* (pp. 143-149). Vancouver: Springer.

Sammonds, G. M., Fray, M., & Mansfield, N. J. (2017). Effect of long term driving on driver discomfort and its relationship with seat fidgets and movements (SFMs). *Applied Ergonomics*, 119-127. doi:10.1016/j.apergo.2016.05.009