TEST RIG DESIGN CONSIDERATIONS TO DETECT VOLATILE ORGANIC COMPOUNDS IN AIRCRAFT CABINS

Christos P. Nasoulis, Stavroula Mantziou, Vasilis G. Gkoutzamanis, Anestis I. Kalfas
Laboratory of Fluid Mechanics and Turbomachinery
Department of Mechanical Engineering
Aristotle University of Thessaloniki
GR-54124, Thessaloniki, Greece
Email: nasoulic@meng.auth.gr

ABSTRACT

This work presents a numerical investigation targeting to simulate the aircraft cabin as an environmental chamber and assist in the design of a test rig assimilating passenger comfort, when exposed to odor effects and high Volatile Organic Compound concentrations. The mixing and transport of chemical species is evaluated using Computational Fluid Dynamics for 800 sec of in-cabin actual flow time and odor measurements are taken every 10 sec, in proximity to passengers' noses. The measurement results are used to create a dataset that trains four different machine learning classifiers, i.e., Random Forest, Support Vector Machine, Logistic Regression, and Naive Bayes, and their performance is compared. Additionally, a simulation using a cabin filtering system is conducted, to evaluate the impact of the molecular weight of the compounds to the residence time variation. Results indicate that the model is insensitive to inlet air mass flow variation, meaning that the impact of the air-conditioning system setting is minor. Moreover, the measurement results are used in a Boruta feature selection algorithm, to determine their importance and form a dataset that will train the machine learning classifiers. The Naive Bayes method outperforms the rest with an accuracy rate of 96 %; thus, it is being selected for the creation of a digital nose model. Furthermore, the comparison between the simulation using the filtering system and the baseline, that has no filtering system, indicates that the Residence Time is independent of the molecular weight of each compound, as they all show equivalent percentile reduction in their times. Finally, in-cabin flow irregularities are present, disrupting the flow symmetry and suggesting that not all passengers share the same traveling experience. This dictates the need to manufacture a full-scale test rig to quantify the impact of the flow asymmetry to the comfort of frequent travelers and aviation professionals.

NOMENCLATURE

CAQ	Cabin Air Quality
CFD	Computational Fluid Dynamics
ECS	Environment Control System
HEPA	High-Efficiency Particulate Air
HVAC	Heat Ventilation Air-Conditioning
VOC	Volatile Organic Compounds
RT	Residence Time

INTRODUCTION

Aviation medicine combines aspects of preventive and environmental medicine to improve the physiology and psychology of human in flight. Apart from the flight conditions, that may impact the passengers' flight comfort, i.e., weather, turbulence etc., odor sense and smell dissipation play a significant role too. On one hand, passengers claim that eating experience during flight may be dissatisfactory. On the other hand, unwanted fumes may be introduced through the aircraft environmental control system, like the bleed air system, thus contributing to the cabin's air contamination. In that direction monitoring Cabin Air Quality – CAQ is essential, to comply with health and safety standards and ensure the in-flight comfort of passengers and crew members. One of the main candidates put under the microscope are Volatile Organic Compounds – VOCs, that should be monitored and controlled efficiently, to maintain the CAQ (Yin et al., 2022).

Odor sensors are neither simple nor inexpensive equipment. Despite that the concept of machine olfactory system goes back to 1961, it remains very complex, mainly focuses on gas detection, and consists of various compartments, such as the sampler, the computing system, the media -where the data is stored-, and the representer, that can reproduce the stored odors (Wen et al., 2018). On the contrary, there is limited research trying to understand the mechanisms that the human olfactory system detects and discriminates odors (Firestein, 2005), and scientists can't yet clearly reach a consensus on whether there is a global methodology that can be applied on that matter.

Initial studies were limited to a small number of flights (Fox, 2000), however, in the recent years, effort has been put to broaden the flight spectrum, include more flights, and create complete aircraft cabin models to assess CAQ (Spengler et al., 2012). In this direction, Gao et al., and Wang et al., led independent studies to model VOCs in detail (Wang et al., 2014), (Gao et al., 2015), whereas Schuchardt conducted measurements in 194 flights, focusing on the relation between VOCs and odor experiences (Schuchardt et al., 2019). The subject was broadened by Pei et al., and Yin et al., who performed comparative studies to identify common VOCs in aircraft cabins and household apartments and created databases of most commonly measured VOCs in both locations, with tetrachloroethylene, styrene and naphthalene being among the compounds with a detection rate of 70 % or greater (Pei et al., 2020), (Yin et al., 2021), (Yin et al., 2022).

A typical air-conditioning unit in civil aviation uses recirculated air, 50 % of which is bleed air from the gas turbines -the main source of VOCs- that is cooled by the Environmental Control System – ECS, prior to entering the cabin, and the rest is recycled and filtered through the aircraft filtering unit (Hunt et al., 1995). Moreover, according to the inlet and outlet positioning inside the cabin, the ventilation system can be divided into three variants, namely the under-floor displacement ventilation, the mixing ventilation, and the personalized ventilation (Farag and Khalil, 2015). For the under-floor displacement ventilation, cooled air enters the cabin through the floor vents, creating an iso-surface of cold air that interacts with body heat and creates an upward stream that exits through the outlet vents located at the cabin ceiling. In this type of ventilation, air contaminants are concentrated close to the outlet vents, that are far from passengers' nasal area. Aircraft manufacturers gain interest in this ventilation system, as it preserves Cabin Air Quality with lower air inlet velocity, compared to other ventilation variants (Maier et al., 2017). Considering the mixing ventilation, that is the most common type in aviation, high-velocity inlets are located on the cabin ceiling, both above and beneath the storage compartments, that allows for inlet air to mix and remove contaminants prior to reaching the passengers. Then, the mixed air exits through the outlet vents located close to the cabin floor. However, this system enables the spread of contaminants from one passenger to another, as the air mixing occurs closer to the passengers' heads, compared to the under-floor system. Finally, the personalized ventilation provides fresh air directly to each passenger via individual jets located above the passenger headroom, that creates a curtain of decontaminated air around each passenger. However, due to the high jet velocity, the passenger thermal comfort is often compromised after several minutes of exposure.

Aircraft Environment Control System – ECS is used to provide clean air during flight to maintain a healthy environment for passengers and aviation professionals. It consists of ventilation, pressure regulation, contamination dissipation control, and flow regulation control systems, that determine air distribution and recirculation. The operation of ECS is dictated by both American and European Aviation Associations and it is supplemented by the American Society of Heating, Refrigerating, and Air Conditioning – ASHRAE, dictating bounds for acceptable operating conditions that preserve the high standards of passenger comfort. For example, the air inlet velocity should be between 0.1 and 0.4 m/s to ensure high levels of passenger comfort (ASHRAE, 2003). In order to properly filter the recycled air that passes though the ECS, High-Efficiency Particulate Air – HEPA filters are commonly used to remove airborne pathogens, that remove 99.97 % of particles with diameter up to 0.3 μm, including particles exhaled from the human respiratory system. Maintaining the recirculated air quality is of utmost importance, since it is used to regulate in-cabin pressure, temperature, and humidity conditions (Zee et al., 2021).

In short, air quality evaluation and monitoring inside the aircraft cabin is a pre-requisite, to provide a comfortable and healthy in-flight experience, both for passengers and aviation professionals. In this direction, odor sensors must be distributed inside the cabin to provide local measurements giving feedback to the ECS to maintain the in-cabin air quality. In the work of Zhang et al., (Zhang et al., 2007), a computational model is set, considering a slice of a large Boeing 767-300 cabin, aiming to optimize the location and determine the minimum number of sensors required to monitor the CAQ. However, the question of how the olfactory system receives the odor signal remains unanswered, especially in smaller aircraft cabins, where odor dissipation gets more intense due to the confined space. Therefore, the scope of this work is to simulate the air-condition flow in a small aircraft cabin, and to monitor the effect of variation of cooled air mass-flow and VOC concentrations on the overall VOC residence time inside the cabin, using measuring sensors located in proximity to the passengers' nasal area. Then, the computational data is used to train four different machine learning classifiers and compare their performance, with aim to create a digital nose model. That model will predict the fractions of various in-cabin compounds, like the VOCs, and define the limits beyond which, the concentration of each compound becomes effective for the passengers. Moreover, a direct comparison of two air-conditioning systems; one with and one without a filtering system is performed, to determine the impact of the mass fraction of VOCs on the overall Residence Time – R. T., inside the cabin. Finally, the feasibility of manufacturing a full-scale test rig for odor testing is discussed.

METHODOLOGY

The aircraft considered in this study is a hybrid-electric commuter aircraft with a maximum payload capacity of 19 passengers that is sized using in-house tools tailored for novel propulsive architectures (Gkoutzamanis et al., 2021), (Nasoulis et al., 2022). The cabin selected for this configuration is a single-aisle cabin, with single seats per side, the characteristics of which are shown in Table 1.

Table 1 Test case cabin dimensions

No of rows	9	-
Seat pitch	0.77	m
Seat length	0.5	m
Seat width	0.5	m
Aisle width	0.6	m
Cabin length	6.93	m
Cabin height	1.8	m
Cabin width	1.95	m

Part of this work aims to understand the evolution of the flow inside the cabin and capture the mass transfer phenomena of VOCs caused by the operation of the aircraft air-conditioning system. Therefore, a CFD computational domain is prepared, that will be used in a transient Heat Ventilation Air-Conditioning – HVAC analysis inside the aircraft cabin. To reduce the size of the computational domain, a cabin slice of 2m is selected, including a single row of seats and two manikins -one on each side-. The topology of the cabin slice is shown in Figure 1. Each manikin is positioned to a seat and a standard siting position is assumed. The outlets of the air-conditioning system are attached to the fuselage side wall, next to the seats and close to each passenger's feet, whereas the inlets are above the cabin storage compartments. The size of the inlet and outlet grills are selected to be similar to aircraft of the same class and the final dimensions are shown in Table 2. Finally, a sensor is attached to each manikin's nose, to detect particle concentrations.

Table 2 Air-Conditioning grills dimensions

Name	Length	Width
Inlet vents	0.75 m	0.045 m
Outlet vents	0.5 m	0.09 m

The domain is discretized by a polyhedral mesh, with polyhedral layers on all walls. Different grid sizes are tested, ranging from 1.4 mi. elements to 6.7 mi. elements and for a grid size of approximately 4.2 mi. elements, the solution is considered sufficiently accurate at an acceptable computational cost. To compare the different grids, an auxiliary cut plane is created, that is normal to the z-axis, at the sensors' height. As it can be seen in Table 3, the average plane velocity difference between the 4.2 and 6.7 mi. elements grid sizes is approximately 1 %, therefore the solution is considered grid independent. Numerous other parameters tested, showed the same trends, thus the 4.2 mi. elements grid size is selected for the evaluation.

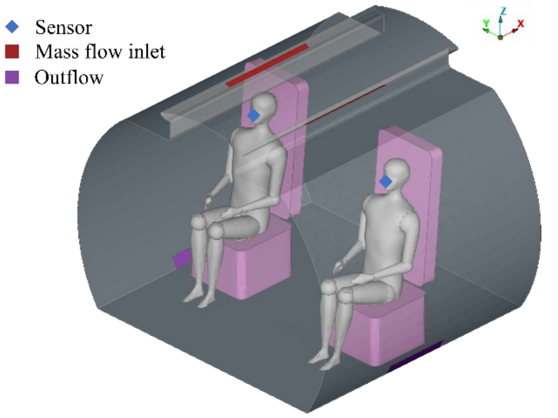

Figure 1 Manikin position and cabin air-conditioning system

Table 3 Average plane velocity versus grid size

Grid size [elements]	Average plane velocity [m/s]	Difference [%]
1,412,649	0.0208	5.66 %
4,261,596	0.0199	1.01 %
6,767,836	0.0197	-

The computational domain is solved in Ansys Fluent commercial solver. The Reynolds-Averaged Navier-Stokes - RANS equations are solved with the k-omega SST turbulence model. Additionally, the energy equation is enabled, as well as the species solver for the mass transfer of VOCs. The inlets of the model are specified as mass flow inlets, whereas the outlets are set as outflows, in order to calculate the species concentrations on the outlet plane. The inlet mass flow is calculated to be 0.01 kg/sec according to ASHRAE recommendation and inlet vent dimensions for inlet velocity of 0.25 m/s, while the inlet temperature from the air-conditioning system is 291 K. As mentioned in the introduction, the Volatile Organic Compounds that are used in this model are tetrachloroethylene (C_2Cl_4), naphthalene ($C_{10}H_8$), and styrene (C_8H_8), since they are among the highly detected compounds in a cabin. Additionally, VOCs from essential oils are also considered, like Limonene ($C_{10}H_{16}$) that is the major component in the oil of citrus peels. Moreover, Linalool ($C_{10}H_{18}O$), and Citral ($C_{10}H_{16}O$), are included, commonly found in flowers and spice plants and oils of several plants like lemon myrtle respectively, to explore the impact of food-related odors in the passenger's eating experience. The approximation of the VOCs mass fractions along with air mass fractions are included in Table 4. Finally, the initial pressure of the cabin is set to 75 kPa.

A transient analysis with a variable time step, ranging from 10^{-4} to 10^{-2} sec, is solved, while the actual flow simulation time is 800 sec; the time needed to renew the air inside the cabin slice completely. Subsequently, the mass of the VOCs and air compounds detected by the model's sensors is used to create a dataset that will train a digital nose model. Mass measurements for each VOC are exported every 10 sec of actual flow time and stored in the dataset, along with the respective mass fractions and partial pressures, adding up to 22 columns of data per writing interval. Additionally, an odor sensing threshold is set to be of the order of micrograms, meaning that if the mass of any VOC is less than 1 μg, it is assumed undetected, an assumption that is based on applications of Electronic Olfaction Systems (Campagnoli et al, 2013). Finally, a feature selection Boruta based algorithm, (Kursa and Rudnicki, 2010), is used in the dataset to determine which dataset attributes i.e., masses, mass fractions and partial pressures, are more significant than others. Finally, the dataset is used to train the machine learning-assisted digital nose model, where four different classifiers are tested, namely the Random Forest, Support Vector Machine, Logistic Regression, and Naive Bayes, and their performance is compared. The Random Forest method uses feature randomness when building individual trees to create an uncorrelated forest whose prediction by committee is more accurate than of any individual tree. Moreover, the trees are trained on different sets of data and use different features to make decisions. For this study, various number of trees were tested and an overall number of 200 trees was selected. Considering the Logistic Regression, it is a statistical method for analyzing a dataset where there are independent variables that define an outcome. This method is selected as it is easy to implement, interpret and very efficient to train, whereas it performs well when the dataset is linearly separable. Finally, the Naive Bayes method is used, that is based on the Bayes Theorem for probabilities, as it is easy to implement and fast to predict.

Table 4 Volatile Organic Compounds and cabin air mass fractions

Compound	Mass Fraction
Oxygen (O_2)	0.17
Nitrogen (N_2)	0.83
Tetrachloroethylene (C_2Cl_4)	$4.8 \cdot 10^{-6}$
Styrene (C_8H_8)	$2.71 \cdot 10^{-6}$
Naphthalene ($C_{10}H_8$)	$2.12 \cdot 10^{-6}$
Limonene ($C_{10}H_{16}$)	$3.13 \cdot 10^{-6}$
Linalool ($C_{10}H_{18}O$)	$3.54 \cdot 10^{-6}$
Citral ($C_{10}H_{16}O$)	$3.5 \cdot 10^{-6}$

Lastly, the cabin filtering system is modeled through proper boundary conditions. It is assumed that 50 % of the incoming air is from outside and contains the VOCs, whereas the other 50 % passes through the cabin filtering unit. The filtration of the VOCs leads to an overall reduction of their in-cabin mass by 50 %, after a full filtration cycle. One full cycle occurs every 180 sec and the Residence Time of each VOC is monitored until the end of the filtration, with a 10 sec reporting interval.

RESULTS AND DISCUSSION

Prior to exploring the results, it is essential to perform a sensitivity analysis to the model input parameters to determine possible correlations between them. Therefore, each VOC mass fraction is altered by $\pm 10\%$, and the model is re-evaluated, this time in steady state, to capture any VOC concentration variations in the sensor positions. The same $\pm 10\%$ variation is applied in the mass flow inlet, to quantify the impact of air-conditioning inlet air mass flow to the in-cabin mass transfer phenomena.

A selection of the sensitivity analysis results is presented in Table 5, namely the variation analysis for the mass flow inlet and the variation for the mass fraction for one of the six VOCs that are present in the model. Regarding the inlet mass flow variation, it is observed that the concentration of VOCs that is measured by the sensors remains unaffected, compared to the reference case of 0.01 kg/s of inlet air mass flow. The measured difference between the reference value and the $\pm 10\%$ mass flow variation cases is less than 0.1 % for all 6 VOCs, meaning that the measurements are independent of the air-conditioning system fan speed setting. Moreover, the measurements for Limonene are also presented in Table 5. The mass fraction of Limonene at the air-conditioning inlet is altered by $\pm$ 10 %, compared to the reference case, that is shown in Table 4, and measurements are taken by the sensors close to the manikins. It is observed that the measurements of the other 5 VOCs remain unaffected by the variation, with the difference between them being less than 1 %, for all compounds. Additionally, it is observed that for a 10 % reduction of the mass fraction at the inlet, the sensor measures 7.41 % less Limonene mass, compared to the reference. The exact opposite measurement is taken for the 10 % increase of the inlet mass fraction. The same analysis performed for the rest of the VOCs, namely, Tetrachloroethylene, Styrene, Naphthalene, Linalool, and Citral, and the same trends are observed.

Having concluded the sensitivity analysis of the model to the input parameters, the feature selection-based Boruta algorithm is used, to determine the most important variables of the time-transient model

Table 5 Input parameters sensitivity analysis for the cabin model

		C_2Cl_4 mass [mg]	$C_{10}H_{18}O$ mass [mg]	$C_{10}H_{16}O$ mass [mg]	$C_{10}H_{16}$ mass [mg]	$C_{10}H_8$ mass [mg]	C_8H_8 mass [mg]
Mass	-10%	4.679 *(+0.086 %)*	1.898 *(+0.053 %)*	3.324 *(-0.06 %)*	2.669 *(-0.037 %)*	1.998 *(-0.05 %)*	2.299 *(-0.043%)*
	Ref.	4.675	1.897	3.326	2.7	1.999	2.3
	10%	4.677 *(+0.043 %)*	1.898 *(+0.053 %)*	3.328 *(+0.06 %)*	2.702 *(+0.074 %)*	2 *(+0.05 %)*	2.302 *(0.087 %)*
Limonene	-10%	4.66 *(-0.32%)*	1.88 *(-0.9%)*	3.31 *(-0.48%)*	2.5 *(-7.41%)*	1.998 *(+0.45 %)*	2.29 *(-0.43%)*
	Ref.	4.675	1.897	3.326	2.7	1.989	2.3
	10%	4.699 *(+0.51%)*	1.915 *(+0.95%)*	3.34 *(+0.42%)*	2.9 *(+7.41%)*	2 *(+0.55%)*	2.31 *(+0.43%)*

that affect odor detection. The dataset is copied and the rows in each column are shuffled. These values are called shadow features (Shadow Min, Mean, and Max colored in blue in Figure 2) and are used by the algorithm to decide the importance of each variable. In addition, the red and green bars are the features

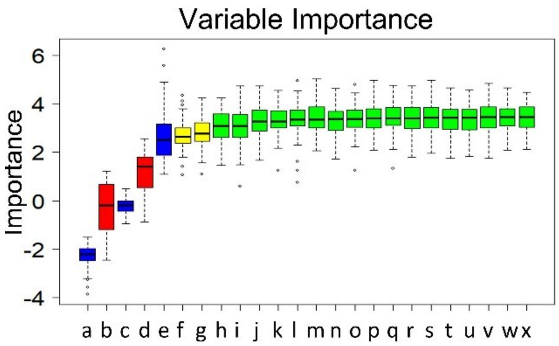

Figure 2 Importance of each variable according to the Boruta feature selection algorithm

Table 6 Cross-reference of horizontal abscissa of Figure 2

Symbol	Name	Symbol	Name
a	Shadow Min	m	N_2 R
b	Pressure R	n	$C_{10}H_{16}O$ L
c	Shadow mean	o	$C_{10}H_{16}O$ R
d	Pressure L	p	Time
e	Shadow Max	q	O_2 L
f	C_2Cl_4 R	r	m_{air} R
g	O_2 R	s	m_{air} L
h	$C_{10}H_{18}O$ L	t	$C_{10}H_{16}$ R
i	$C_{10}H_{18}O$ R	u	C_8H_8 L
j	$C_{10}H_{16}$ L	v	$C_{10}H_8$ R
k	N_2 L	w	C_8H_8 R
l	C_2Cl_4 L	x	$C_{10}H_8$ L

that are rejected as less important and accepted as important respectively (Szul et al., 2021). In addition, the Residence Time is calculated, according to Eq. 1 and Eq. 2, where $m_{VOC,i}$ is the mass of each VOC at the mass flow inlet, ψ is the mass fraction of each VOC, and $\dot{m}_{out}$ is the total mass flow at the outlet. The cross-references of the horizontal abscissa on Figure 2 is shown on Table 6.

The result of the Boruta evaluation is shown in Figure 2, where the variables are sorted from the least important (left) to the most important (right). It is observed that the mass of all compounds and the actual flow time show equivalent importance, according to the algorithm's criteria, whereas the pressure difference measurements are classified as not important. Furthermore, since the in-cabin flow is not symmetric in the XZ plane, there are differences in the measurements of the two sensors, that affect the characterization of the importance of each variable. In other words, it is suggested that not all passengers share the same odor experience during flight, due to in-cabin flow irregularities. Finally, the variables that stand out, according to the Boruta selection algorithm, namely, the Styrene and Naphthalene mass on both sides, and the total in-cabin air mass on the right side, are summarized in Table 7, along with their mean importance.

$$\psi = \frac{m_{VOC,i}}{\sum_{i=0}^{n} m_{VOC,i}} \qquad \text{Eq. 1}$$

$$R.T. = \frac{\psi}{\dot{m}_{out}} \qquad \text{Eq. 2}$$

Table 7 Boruta algorithm feature selection synopsis

Name	Mean Importance
$m_{C_{10}H_8}$ L	3.479
$m_{C_{10}H_8}$ R	3.477
$m_{C_8H_8}$ L	3.470
m_{air} R	3.463
$m_{C_8H_8}$ R	3.454

The created dataset derived from the Boruta feature selection algorithm is used as an input by four different machine learning classifiers. The first evaluation is performed using the Random Forest classifier with 200 trees, that appears to have the best performance of the four, as shown in Table 8.

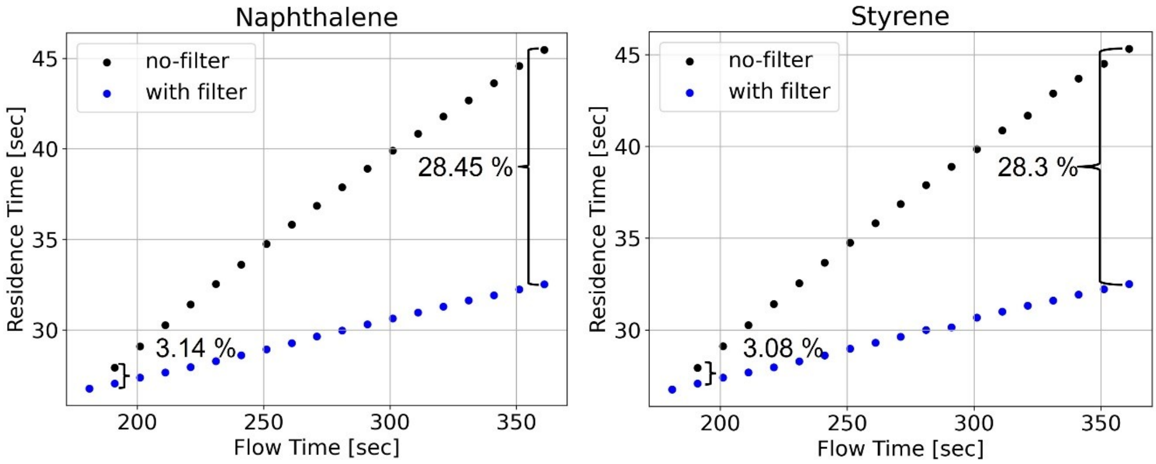

Figure 3 Cabin air quality monitoring with and without filtering system for Naphthalene and Styrene compounds

Table 8 Performance assessment of four machine learning classifiers

Random Forest / Support Vector Machine			**Logistic Regression**			**Naive Bayes**		
Confusion Matrix			**Confusion Matrix**			**Confusion Matrix**		
Prediction	False	True	**Prediction**	False	True	**Prediction**	False	True
False	27	0	False	16	1	False	25	2
True	0	23	True	2	14	True	0	23
Statistics			**Statistics**			**Statistics**		
Accuracy	100 %		**Accuracy**	90.9 %		**Accuracy**	96.0 %	
Sensitivity	1.00		**Sensitivity**	0.89		**Sensitivity**	1.00	
Specificity	1.00		**Specificity**	0.93		**Specificity**	0.92	

Considering the confusion matrix there are no mispredictions in the data, whereas the sensitivity and the specificity of the model are equal to 1. Additionally, the performance accuracy of the algorithm is 100 %. Then, the Support Vector Machine algorithm is tested, aiming to optimize a cost objective function, based on prediction accuracy, showing performance metrics matching those of the Random Forest. Moving on to the Logistic Regression method, it has the worst performance, with an accuracy of 90.9 %, a sensitivity of 0.89, and a specificity of 0.93. The model seems to detect odors in cases where it shouldn't, as some False signals are interpreted as True, according to the confusion matrix. In addition, some odors are not detected during the training, as some True signals are interpreted as False. Finally, the Naive Bayes classifier has the second-best prediction performance, with an accuracy of 96 %, a sensitivity of 1, and a specificity of 0.92. Again, this method also detects odors in cases where it shouldn't, according to the confusion matrix in Table 8. From the classifiers' comparison, the Random Forest and the Support Vector Machine methods show superior performance compared to the rest. However, since Boruta is a feature ranking and selection algorithm based on Random Forest, the results may be biased. This can be supported by the fact that the methods have 100 % accuracy and make no mistakes during the training phase. For this reason, the second-best candidate will be selected to for the digital nose model, namely the Naive Bayes, with 96 % accuracy.

The previous analysis concerns a typical air-conditioning unit, without an additional air filtering treatment. However, it is common practice to use novel filtering systems to clear the air inside the cabin, as mentioned in the introduction. These filters have a high filtration effectiveness and maintain the Cabin Air Quality within acceptable limits, as defined by health standards. Therefore, a second study is performed to capture the impact of the filters on the in-cabin air quality and assess the effect of the molecular weight of VOCs on their residence time. These filters are applied to the air-conditioning system, where 50 % of the incoming air is from the outside, including VOCs, whereas the rest 50 % is being recycled air that passes through the filter. The air filtration and mixing of the system occurs every 3 minutes and the residence time is calculated for a full filtration cycle. The difference between the residence time for the case with and without the filter, for Naphthalene and Styrene, is shown in Figure 3. It is observed that for the filter case, the residence time is reduced, compared to the no-filter case. Moreover, this difference increases with the transient flow progress, starting from 3.14 % and 3.08 % to 28.45 % and 28.3 % for the Naphthalene and Styrene respectively, for the 190 and 360 sec of flow time correspondingly. Furthermore, the slope of the residence time as function of the simulation time is reduced compared to the no-filter case. The same measurements are performed for the other VOCs and similar trends are observed. Finally, the evaluation of residence time for all VOCs indicates that it is independent of the molecular weight of the compounds since they all show equivalent percentile reduction.

Considering the flow irregularities that disrupt the in-cabin flow symmetry, the next step towards quantifying the magnitude of the asymmetry is to manufacture a full-scale test rig and recreate the experiment in real conditions, instead of simulation. However, the cost of equipment and construction of the rig should be considered. Since the cabin is small (Table 1), as it is derived from the commuter aircraft class, there is greater potential for construction as the production cost is significantly lower, and the room requirements are smaller. The preliminary assessment of the cabin slice simulation results indicates that a cabin slice of 3 rows (approximately 2.5 m in length), is adequate to capture the in-cabin flow field and overall passenger odor experience, at a low production cost. Towards this direction, a small-scale Environmental Control System is required, in terms of equipment, able to monitor and maintain in-cabin conditions, so they are in harmony with the actual cabin environment during flight. Moreover, the system must be versatile, to recreate all possible pressure and temperature conditions, throughout a typical flight mission. Also, an odor controlling system must be introduced, able to create and dissipate multiple types of ingested odors through the ventilation system. Besides, the odor sensors will be positioned appropriately in proximity to the passengers' noses, to capture odors in a similar way to the human olfactory system. Furthermore, a few odor sources will be scattered in the test rig seats, to account for the passengers' inhale and exhale function, and assess the breathing impact of others to the odor experience of an individual. Additionally, test campaigns will be set up including questionaries, to evaluate different individuals exposed to different scents, to assess the robustness of human odor perception. In conclusion, these are some of the major challenges to be addressed during the design and manufacturing of a full-scale test rig to assess the in-flight passenger odor experience.

CONCLUSIONS

A Computational Fluid Dynamics - CFD cabin slice simulation for a commuter aircraft was performed, to investigate the impact of odor effects and high Volatile Organic Compounds – VOCs concentrations on passenger comfort. A grid independent transient flow simulation of 800 sec of actual flow time was solved, to obtain real-time measurements of odors, using sensors located at the passengers' noses. Additionally, variation analyses were performed to determine the model sensitivity to changes in the input parameters. The air inlet mass flow of the air-conditioning system and the mass of the VOCs at the inlet were varied by $\pm$ 10 % of their nominal value, and the model was proven to be insensitive to the inlet mass flow variation. Also, the variation of mass of a certain VOC did not affect the measurements of the others during the simulation. Subsequently, the measurements from the 800 sec of real flow time were evaluated using a Boruta feature selection algorithm, to determine the importance of each measurement, and select those that were used to train the machine learning classifiers. Four classifiers were considered, namely, the Random Forest, Support Vector Machine, Logistic Regression and Naive Bayes, and their performance was compared, with the Naive Bayes having a prediction accuracy of 96 %, that was eventually selected for the digital nose model. Furthermore, the addition of cabin filters was considered, to compare two different air-conditioning systems, one with the filters and one without, and determine the impact of the molecular weight of VOCs to their respective in-cabin Residence Time. It was observed that the Residence Time is independent of the molecular weight, as all 6 VOCs showed almost equal reduction in Residence Time, compared to the no-filter case. Finally, the simulated flow showed irregularities that disrupted the symmetry of the field, suggesting the possibility that passengers share different in-cabin odor experiences, thus mandating the construction of a full-scale cabin test rig, consisting of at least three seat rows.

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