Empirical validation of infiltration models based on different wind data

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ABSTRACT

By 2050, the European council proposed to achieve total decarbonization in buildings. In this way, building energy models are key factors to predict the energy consumption in the design, use and retrofit stages. However, these models may present a relevant gap between predicted and measured energy performance, which should be minimised by cutting uncertainties with real data. Air leakage is one of the main uncertainties and causes of increasing building loads by renovating the indoor air in an uncontrolled way. Nevertheless, many energy modellers do not have a solution for this parameter.

Therefore, the two main goals of this study are to find the most accurate dynamic infiltration model and to verify if it can be extrapolated to different periods and wind data. For this reason, an experiment of tracer gas with CO2 was carried out in the south room of a flat in Pamplona, Spain. The experiment was conducted for 40 days, 18 in summer (9 for training and 9 for checking), 11 in winter and 11 in spring for checking. The Design Flow Rate EnergyPlus object was chosen to calculate infiltration, which, in turn, fed the multi-points decay equation to generate the simulated CO2 curve. Then, to find the best coefficients of this object, the performance of multi-variable regressions was done based on the objective function of minimising the mean absolute error between predicted and measured CO2 concentrations. As wind plays an important role in the calculation of air leakage, this process was made using different wind data: one from in-situ sensor and three from a nearby meteorological station (a global wind with all directions, a westbound wind and an eastbound wind), in order to analyse which one was the best to predict the air leakage. The most precise training model was applied in the checking periods to test its robustness to time and wind data. To evaluate these models, the ASTM D5157 Standard Guide for Statistical Evaluation of Indoor Air Quality Models and Taylor Diagrams were used.

As a result, the models created from the in-situ data and from the west wind of the weather station best represent the measured CO2. They present 14% better performance than the model generated with the global wind from the weather station, the latter usually applied in building energy simulations. The in-situ wind data developed coefficients specific to the test space that can be extrapolated to other seasons and weather conditions without losing their quality. Even models that did not meet ASTM D5157 criteria in the training period passed the standard with in-situ coefficients. This study is a step forward in reducing the infiltration uncertainty and corresponds to a cost-effective solution, since with only 9 days of training, it is possible to obtain coefficients that generate accurate air leakage values at other seasons and with wind from the weather station, which is easier to collect than in field measurements.

KEYWORDS

Infiltration modelling, Tracer gas test, Decay method, Wind data, Empirical validation.

1 INTRODUCTION

The European Commission proposed to achieve climate neutrality by 2050, which means to reduce buildings energy consumption. In this context, building energy demand should be minimised by applying passive strategies, improving the construction systems and preventing any cause of increasing building loads. One of independent agents that can affect the building energy demand is air leakage, that can increase heating demand by 13-30% and cooling demand by 4-14%, as it uncontrollably renews indoor air (Raman et al., 2014; Persily et al., 1999). The air tightness improvement in a building envelope could enhance indoor air quality (IAQ), people's comfort, long-term durability of buildings, as well as, reduce carbon emissions (Pérez-Lombard et al., 2008), in the case of buildings that use fossil energy sources.

Usually, buildings energy consumption is predicted in building energy models (BEMs) which require many input parameters, air leakage being one of them. However, air leakage is difficult to measure and inserting inaccurate values can lead to misleading results. The difference between the estimated and measured energy of a building is called building energy performance gap (BEPG) (De Wilde, 2014). Reducing this gap will allow for more precise predictions and give investors more confidence in retrofit projects.

This study is built on previous calibration knowledge of reducing the BEPG based on inverse modelling approach, grey box models and optimization performed in EnergyPlus (EP) and JePLUS+EA (Ruiz et al., 2016; Fernandez et al., 2017). The calibration process is carried out to accurately estimate the energy at each time step. For this purpose, studies have concluded the number of parameters needed to calibrate the building envelope and the impact of their input in the BEPG (González et al., 2020; Lucas Segarra et al., 2019; González et al., 2020; Du et al., 2019). Nevertheless, the calibration process developed by Fernández et al. still presents uncertainties about the thermal inertia and air leakage values.

Therefore, this study attempts to verify a new methodology of modelling dynamic infiltration to resolve this uncertainty in the calibration process using EnergyPlus as a simulation engine. For this reason, the EP object: ZoneInfiltration: DesignFlowRate (DOE, 2021) was used to calculate infiltration. This object is composed by an equation with five coefficients (Idesign, A, B, C, and D) that can be found by a multi-variable regression or can be provided by energy analysis programs.

A tracer gas test was done according to Sherman and Standard ASTM E741 (Sherman, 1990; ASTM 11, 2017) to analyse empirically the infiltration values calculated. The experiment was based on the decay multi-point method (ASHRAE, 2017). Some studies using the decay method were carried out to calculate air leakage (Cui et al., 2015; Taddeo et al., 2018). However, they refer to infiltration as a constant value, and it should be dynamic for accurate energy predictions. In addition, the experiment using CO2 also allowed us to find the coefficients of the EP object by realising a multi-variable regression of the measured data.

As wind plays an important role in the calculation of air leakage and as the last two coefficients (C and D) are multiplied by the wind speed values, the regression process was made using different wind data: one from the in-situ sensor and three from a nearby meteorological station (a global wind with all directions, a westbound wind and an eastbound wind). The objective was to analyse which wind speed data was the best at predicting air leakage. As far as the authors know, this study has not been done before.

The infiltration rates were evaluated according to the American Society for Testing Material D5157: Standard Guide for Statistical Evaluation of Indoor Air Quality Model (ASTM, 2019). The standard presents statistical instruments to assess the agreement and bias of measured and predicted CO2 concentration. ASTM D5157 requires two different data to generate and check the models. In this study, we have overcome this requirement, as four distinct periods were used to evaluate the models: 9 days in summer for model training, and 31 days for model checking: 9 in summer, 11 in winter and 11 in spring. Taylor diagrams were also used to assess the models.

In summary, this research aims to achieve two main objectives. 1) To find the most accurate EnergyPlus dynamic infiltration model, validated on 18 summer days and based on different wind speed data, and 2) To verify if this best model can still comply with ASTM D5157 criteria when extrapolated to different periods and wind data.

The next sections are organised as follows. Section 2 describes the experimental procedure. Section 3 explains the methodology. Section 4 presents the results and discussion, and section 5 the conclusions.

2 EXPERIMENTAL PROCEDURE

2.1 Test space and instrumentation

The experiment was carried out in the living room of an attic of 29.50 m² in a 7 floors apartment building in Pamplona, Spain. We selected this space because it was unoccupied throughout the experiment and because we could access the monitored data. It is a building from 1992 and its exterior walls, from the outer to the inner layer, are made of perforated brick (115 mm), air cavity (30 mm), expanded polystyrene (50 mm), hollow brick (70 mm) and plaster (15 mm). The southeast façade has two openings, and the southwest façade has one window, all of them made of aluminium. The interior walls are constructed with hollow brick (75 mm) between two layers of plaster (20 mm each) and the interior doors are made of wood.

Tracer gas test. The method chosen for the tracer gas test is the concentration decay, which consists of injecting CO2 and mixing it with the room air (Remion et al., 2019). The procedure consists of injecting the CO2 twice in the room by using a 5 kg fire extinguisher during three seasons, summer, winter and spring:

- P_1_T: Training period with 9 days between June 20th and July 2nd 2021.
- P_2_C: Checking period with 9 days between July 2nd al July 14th 2021.
- P_3_C: Checking period with 11 days between December 10th and January 9th 2022.
- P_4_C: Checking period with 11 days between March 24th and April 24th 2022.

CO2 concentration. We installed two types of sensors to measure the CO2 concentration (ppm): 1) HOBO (data logger model Delta OHM HD37VBTV.1), and 2) EXTECH (data logger model CO210). The sensors are in different places in the room (see Fig. 1) to check the uniformity of the CO2 in the whole test space. Both types of sensors have an accuracy of +-5%, but only the HOBOs are integrated into the monitoring system, which facilitates data management. Therefore, we chose the HOBO data to calculate air leakage.

To measure the outdoor CO2 concentration, a sensor model Delta OHM HD37VBTV.1 was installed on the southeast façade (see Fig. 1). All sensors recorded CO2 data at one-minute intervals.

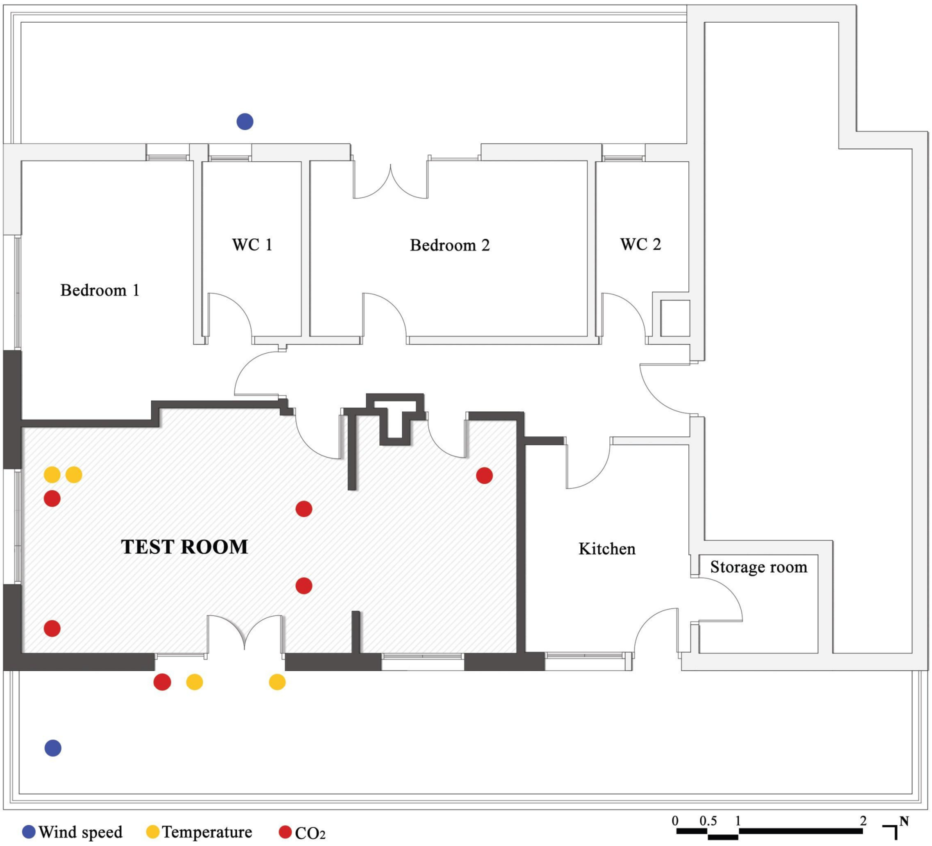


Figure 1: Apartment floor plan.

Temperature recording. Two data loggers model HOBO ZW-006 were installed in the test space to measure the indoor temperature (ºC). One at 0.80 m above the ground and the other at 1.75 m, in order to have accurate data according to temperature stratification. On the southeast façade, two sensors were installed to measure the outdoor temperature (ºC) using the same data logger model. Temperature recording was done in one-minute time-steps.

Wind data. In this study, we used four types of wind speed data to calculate infiltration (see Fig. 2). One related to the in-situ measurement recorded with an interval of one minute and one related to the data recorded at a nearby meteorological station (at ten-minute time-steps):

1. South wind in-situ (SW_INSITU). This wind is collected on the southeast façade of the test space by a wind speed sensor (m/s) model AHLBORN FVA 615-2.
2. Wind from the weather station (W_MET). This wind speed comes from all directions, and we identified it as W_MET.
3. East wind from the weather station (EW_MET). The W_MET was divided into east and west based on its direction. The EW_MET refers to the wind speed data from 0º to 180º according to the north.
4. West wind from the weather station (WW_MET). The WW_MET ranges directions from 181º to 360º.

In order to standardise the data collected, all data were applied at ten-minute intervals.

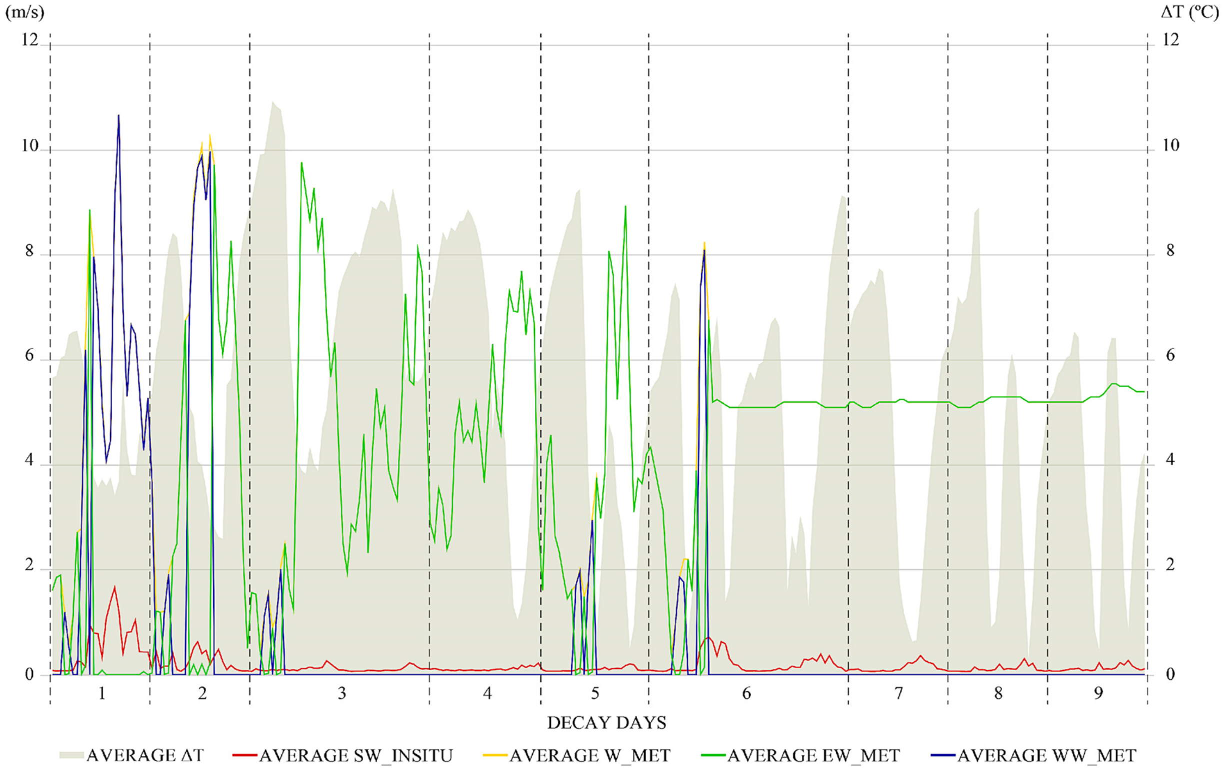


Figure 2: Weather conditions during P_1_T.

3 METHODOLOGY

We used the object of EnergyPlus: ZoneInfiltration: DesignFlowRate (DOE, 2021) to calculate the infiltration of the test space. This object is composed by an equation of five coefficients (i.e., Idesign, A, B, C, and D). The ABC equation is as follows:

$$I = (Idesign)\ (Fsch)\ [A + B^*|(Tzone\text{-}Todb)| + C^*(WS) + D^*(WS2)] \quad (1)$$

Where:
Idesign is the design infiltration rate;
Fsch is the infiltration schedule;
Tzone and Todb are, in this study, the average indoor ambient temperature and the average outdoor ambient temperature in ºC, and
WS is the wind speed in m/s.

In addition, we implemented a multi-point decay method, as it is more accurate than the two-point decay. According to ASHRAE Fundamentals (ASHRAE, 2017), the decay equation is as follows:

$$Ct = (C0 – Cbg)\ e^\wedge(–It) \quad (2)$$

Where:
Ct = estimated CO2 concentration;
C0 = average of measured indoor CO2 concentration;
Cbg = average of measured exterior CO2 concentration;
t = time in s; and
I = infiltration of each time-step in air changes/hour.

We calculated the in-situ coefficients for the P_1_T by performing a multi-variable regression. The objective function was to reduce the mean absolute error (MAE) between measured and estimated CO2 concentration. This methodology is explained in Fig. 3:

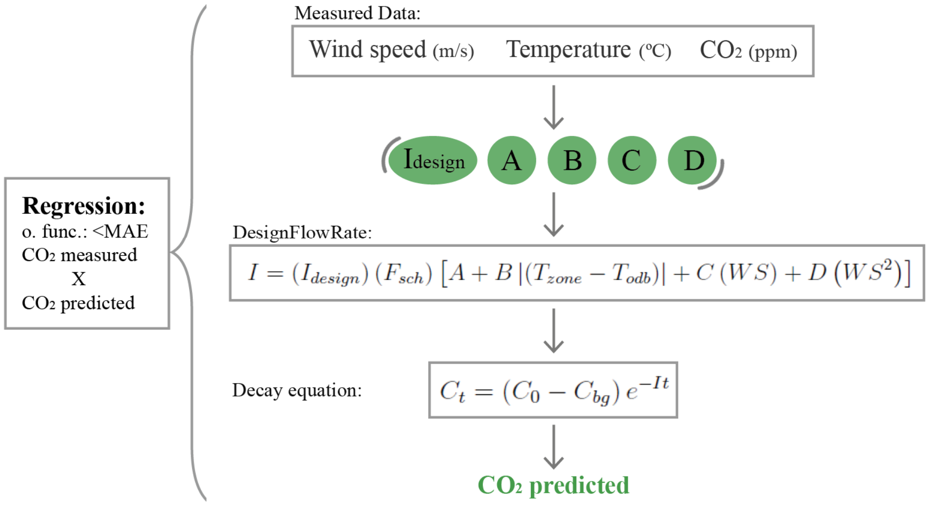


Figure 3: Methodology applied to find the best coefficients in-situ.

We applied the ASTM D5157 Standard Guide for Statistical Evaluation of Indoor Air Quality Models (ASTM, 2019) to assess the models. The standard gives three statistical instruments for evaluating accordance between estimations and measurements (i.e., R^2, NMSE and the line of regression). Also, the slope of the line of regression, m, should be from 0.75 to 1.25 and the intercept of the average measured concentration, b/Co $\leq$ 25%. Moreover, there are two statistical tools for assessing bias (i.e., FB and FS). These values should be in the limitation presented in Table 1, to determine if the model performance is accurate.

Table 1: ASTM D5157 Standard requirements.

	Description	Limitation
R^2	Square of the correlation of predictions and measurements.	≥ 90
NMSE	Normalised mean square error.	≤ 0.25
FB	Normalised or fractional bias of the mean concentration.	≤ 0.25
FS	Fractional bias based on the variance.	≤ 0.50

This standard requires two independent data for model evaluation, which means that the data used for training should be different from the checking. In this study, we have overcome this standard requirement, as we chose four different periods for model evaluation. The four models generated with ABC and each of the wind data are evaluated in two steps. The first is to find the model that best represents the infiltration of the test space. The second is the application of the coefficients of the most accurate model (from the first stage) to each wind data in two different periods (see Fig. 4).

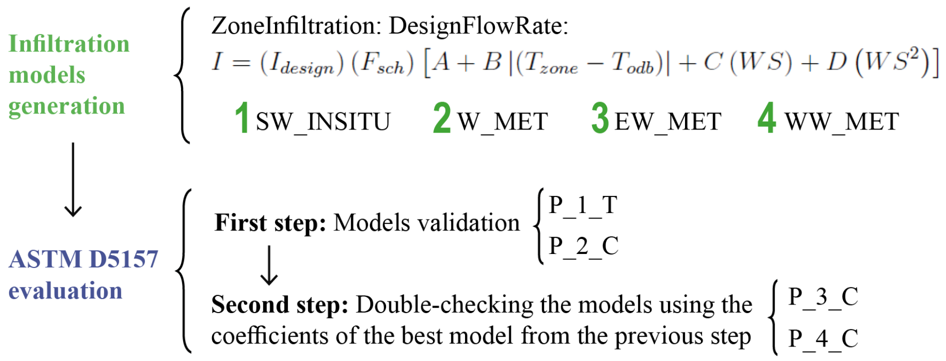


Figure 4: Scheme of the evaluation methodology.

In addition to ASTM D5157 evaluation, we also used Taylor diagrams to assess the models in P_1_T and P_2_C. Taylor diagram focuses on the similarity between models and their distance from the observed measurement. For this purpose, two statistical tools different from the standard are applied: centred root-mean-square difference (CRMSD) and standard deviations (Taylor, 2005). In addition, R^2 values equal to those of ASTM D5157 are also analysed.

4 RESULTS AND DISCUSSIONS

The results of the infiltration models according to ASTM D5157 are presented below. As shown in Table 2, each wind speed generates a set of coefficients specific to the test space. The coefficients Idesign and B, present similar values in all models. However, the other three coefficients (i.e. A, C, and D) are very different, mainly when referring to SW_INSITU and WW_MET.

Table 2: DesignFlowRate coefficients of each wind data found in the training period.

Model	Wind	Idesign	A	B	C	D
ABC	SW_INSITU	0.97817	0.00068	0.00008	0.00002	0.00244
	W_MET	0.96016	0.00028	0.00007	0.00000	0.00003
	EW_MET	1.12101	0.00004	0.00008	0.00003	0.00002
	WW_MET	0.93913	0.00092	0.00006	0.00006	0.00012

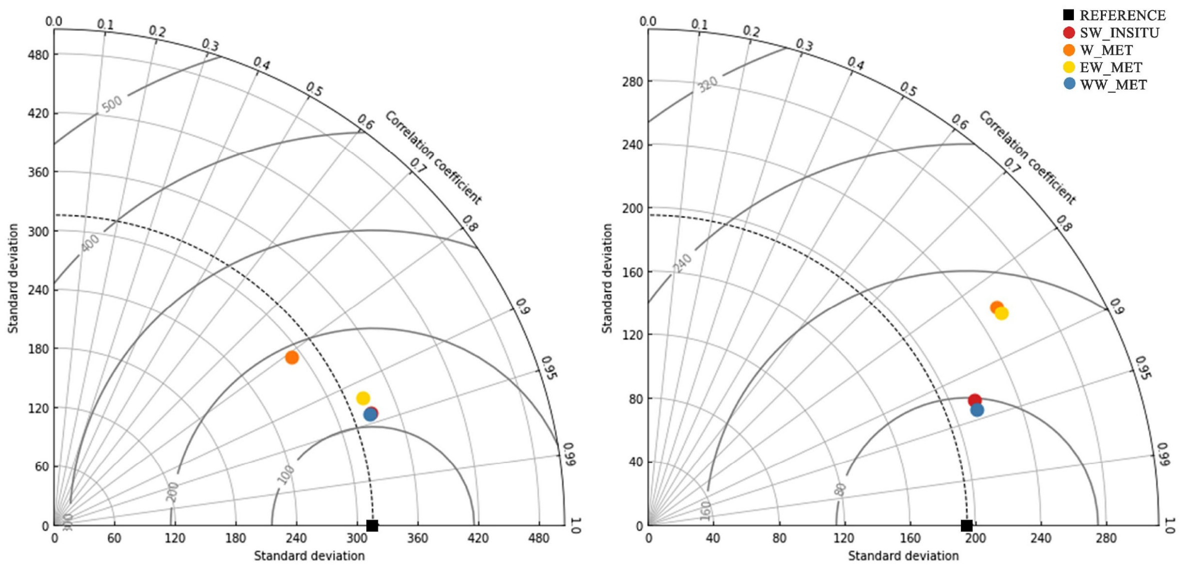
In the first step of model validation, the models created from the SW_INSITU and WW_MET data best represent the measured CO2 based on ASTM D5157 criteria. Table 3 shows that both models present small differences in performance between them. On the other hand, W_MET and EW_MET do not meet the requirements of the standard, as all statistical instruments must be within the limitation proposed by the standard in all periods. The difference in the wind data generated different coefficients, which could be the reason why some models pass ASTM 5157 and others do not. In addition, the SW_INSITU model is 14% better than the model developed with the global wind from the weather station (W_MET), the latter commonly applied in building energy simulations.

Table 3: Model validation according to Standard ASTM D5157 requirements. In red models and values which do not comply with the standard.

Wind	Period	Co (ppm)	Cp (ppm)	R^2	m	b	b/Co (%)	NMSE	FB	FS

SW_INSITU	P_1_T	613.87	637.80	0.94	1.03	8.34	1.36%	0.018	0.038	0.111
	P_2_C	502.96	504.05	0.93	1.06	-29.64	-5.89%	0.013	0.002	0.095
W_MET	P_1_T	613.87	663.98	0.81	0.83	155.88	25.39%	0.053	0.078	-0.164
	P_2_C	502.96	353.52	0.84	1.19	-243.46	-48.41%	0.193	-0.349	0.260
EW_MET	P_1_T	613.87	624.21	0.92	1.01	5.65	0.92%	0.023	0.017	0.097
	P_2_C	502.96	357.47	0.85	1.20	-244.35	-48.58%	0.181	-0.338	0.261
WW_MET	P_1_T	613.87	633.65	0.94	1.02	8.62	1.40%	0.019	0.032	0.102
	P_2_C	502.96	518.66	0.94	1.06	-15.41	-3.06%	0.012	0.031	0.092

The following Taylor diagrams for P_1_T (Fig. 5a) and P_2_C (Fig. 5b) easily show the accuracy of the models, and which one is closer to the reference value. SW_INSITU and WW_MET, as mentioned before, have similar performance in the training and checking periods, with WW_MET being slightly more accurate than the other. Furthermore, it is clear that W_MET and EW_MET do not generate adequate models to represent the reality.



(a) P_1_T models. (b) P_2_C models.

Figure 5: Taylor diagrams for training and checking periods.

In the second step of the model evaluation, we chose to verify the robustness of the SW_INSITU coefficients by applying it to two other periods (P_3_C and P_4_C) and to other wind data. As a result, the best coefficients of the dynamic infiltration model can be extrapolated to other stations without losing their quality, even if they are checked with W_MET and EW_MET that do not pass the model validation.

Table 4: Results of infiltration models according to Standard ASTM D5157 based on different wind data.

Wind	Period	Co (ppm)	Cp (ppm)	R^2	m	b	b/Co (%)	NMSE	FB	FS
SW_INSITU	P_3_C	613.87	637.80	0.94	1.03	8.34	1.36%	0.018	0.038	0.111
	P_4_C	502.96	504.05	0.93	1.06	-29.64	-5.89%	0.013	0.002	0.095

W_MET	P_3_C	613.87	466.28	0.98	1.02	-101.39	-18.13%	0.047	-0.181	0.027
	P_4_C	502.96	614.80	0.92	1.07	-58.64	-9.34%	0.020	-0.021	0.110
EW_MET	P_3_C	613.87	466.28	0.98	1.02	-101.39	-18.13%	0.047	-0.181	0.027
	P_4_C	502.96	614.80	0.92	1.07	-58.64	-9.34%	0.020	-0.021	0.110
WW_MET	P_3_C	613.87	475.89	0.98	1.02	-91.84	-16.42%	0.039	-0.161	0.026
	P_4_C	502.96	627.13	0.93	1.07	-41.91	-6.68%	0.018	-0.001	0.102

5 CONCLUSIONS

In this study, a tracer gas decay test was conducted in a controlled environment to accurately calculate air leakage of the test space using ZoneInfiltration: DesignFlowRate EnergyPlus object. In addition, this in-situ test makes it possible to do an empirical evaluation of the models by comparing the measured and estimated CO2 concentrations. The test was realised during four different periods which allowed to verify if the models trained in one period could be checked in the other three and present high performance according to ASTM D5157 Standard requirements. Moreover, as infiltration can be wind-driven, we tested distinct wind speed data to see which one is the best to predict the air leakage of the test space. The four-wind data used to generate the infiltration models are: one from in-situ sensor placed on the southeast façade of the test space (SW_INSITU) and three from a nearby meteorological station (a global wind with all directions – W_MET, a westbound wind – WW_MET and an eastbound wind – EW_MET). The W_MET is usually applied to building energy models.

The results show that there are two best models validated in 18 days of summer (trained for 9 days and checked the other 9 days): SW_INSITU and WW_MET. These models meet the ASTM D5157 criteria as both presented R^2 values of 0.94 and NMSE equal to 0.018 and 0.019 in the training period, when the limits are ≥ 0.90 and ≤ 0.25. The W_MET model was not able to represent the actual air leakage of the test space, which raises doubts about the use of this wind for energy simulations.

Moreover, the SW_INSITU model develops coefficients proper of the test space, then it can be extrapolated to other seasons and weather conditions without losing its quality. SW_INSITU' coefficients were applied to other period and wind data and still approved the ASTM D5157 requirements, even when applying the coefficients in the winds that did not pass the first step of model validation.

This study is a step forward in reducing the infiltration uncertainty and corresponds to a cost-effective solution, since with only 9 days of training, it is possible to obtain coefficients that generate accurate air leakage values at other seasons and with wind from the weather station, which is easier to collect than in field measurements. Future work should be done to verify these results in other test spaces.

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