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An alternative statistical approach to estimate the level of airtightness of existing residential buildings: Influencing factors from measured data

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ABSTRACT

Estimating the level of airtightness of a building can offer valuable information for energy performance simulation tools or decision-making during retrofitting processes. However, it remains a challenge given the great variability of the variables involved, the complexity of addressing some of these variables, and some context-specific features. Based on previous research in this direction, this paper proposes an alternative predictive model based on Generalized Linear Models (GLIM) and validated using cross-validation that involves 13 main effects and 4 interactions. This leads to a substantial enhancement in predictive capacity, accounting for nearly 50% of the response variability. A detailed set of variables fully described offers the opportunity to transcend region-specific applicability and opens a window for other populations. The model provides more reliable estimates of airtightness and expands its applicability to a broader range of construction conditions, while maintaining the statistical significance of its predictors and achieving a satisfactory fit.

1. Introduction

Building airtightness is a key factor in the energy performance and Indoor Air Quality (IAQ) of residential buildings. Uncontrolled air leakage can account for 10–30 % of the heating demand in winter [1–8] and may lead to moisture and durability issues. This is key in a context in which great efforts are being made towards the decarbonization of the building stock.

Given the importance of controlling air infiltration, regulatory airtightness requirements have been set in numerous countries in recent years [9]. However, in-situ tests (e.g., pressurization tests) are not always performed due to their cost and complexity and are often replaced by theoretical reference values that may lack accuracy. Alternatively, predictive models can assess building envelope performance before and after construction or retrofitting actions.

In this context, predictive airtightness models have gained relevance as support tools for estimating building envelope permeability based on building characteristics. Various models of this type have been developed [10–17]; however, differences in building systems and local practices often limit their applicability outside the context for which they were created. The same is true in Spain, where, until recently, available predictive models focused on particular regions or typologies, limiting their usefulness to the national level [17–20]. Consequently, there is a need to develop models that, based on standardized construction principles, transcend borders to establish precise and generalizable principles regarding the airtightness of residential buildings.

Other challenges in developing airtightness predictive models have been identified [21], including:

- Lack of standardization: inconsistencies in measurement methods, nomenclature, and data presentation hinder the comparison and generalization of results across different studies [22,23].
- Complexity and user-friendliness: many existing models, while statistically sound, are too complex for practical use by designers and contractors who require quick, reliable estimates during the decision-making process.
- Influence of workmanship and supervision: factors such as construction quality and on-site installation variability are difficult to quantify yet have a significant impact on airtightness [24,25].

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In a previous study [20], the authors proposed a predictive airtightness model for the Spanish residential sector, employing a General Linear Model (GLM) that was calibrated using a representative database of residential buildings. The original model took into account variables such as the climate zone, period of construction, typology (single-family or multifamily), retrofitting state, specific construction systems (e.g., window materials), and dimensional values, in order to estimate the air leakage rate (n_{50} value) of the envelope. First-order interactions between key variables were also explored. Subsequently, an enhancement of the model was proposed [26], incorporating the heating system and the number of bathrooms as additional variables, which improved the model's predictions.

This paper presents a novel predictive model based on Generalized Linear Models (GLIM). To the authors' knowledge, this methodology has not been previously used in airtightness predictive models; however, its application is promising, allowing a response variable (n_{50} value) without transformation and yielding improved results. The current study addresses some of the identified gaps by proposing an improved predictive model that:

- Combines detailed experimental data with comprehensive statistical analyses.
- Uses a detailed database with standardized measurements and available data presentation.
- Is adaptable to different residential building stocks, transcending region-specific applicability. A detailed description of the variables used makes it possible to assimilate the model into other contexts by adapting building characteristics.
- Enhances airtightness estimates using an improved statistical framework that does not need to transform the response, includes cross-validation to select the explanatory variables and evaluate the performance of the model, and accounts for interactions among variables.

2. Methodology

The statistical methodology considered in this work is based on an extension of the linear models called Generalized Linear Models. It is easy to check that in our problem, the response variable is non-normal. This issue was treated using a response variable transformation in [20] but, according to [27] pp. 233–234, "when the response is non-normal, it may be impossible for the same transformation to create distributed random errors, to stabilize the variance and to lead to a linear model". The GLIM models overcome these problems, as constant variance is not an issue in these models, as they base their analysis on the natural variance of the data's distribution. Moreover, they keep the principal elements and advantages of the linear models, such as variable selection, diagnostic tools and ease of interpretation and, as shown in the examples provided in [27] pp. 234–240, usually provide shorter confidence intervals for the response when compared with the usual linear models, thus leading to more useful prediction intervals for the response.

Moreover, as the number of variables considered in the model is large, a variable selection procedure has been performed and validated using cross-validation. Cross-validation has also been used in the final validation of the model to avoid overfitting. These statistical procedures, together with the airtightness measure methodology considered in the paper, are briefly explained below.

2.1. Generalized linear models

Generalized Lineal Models [28], commonly denoted as GLIM, are a generalization of Linear Models designed to cope with non-normal response variables while keeping the straightforward interpretation and helpful diagnosis tools (such as, for example, residual analysis and influential points detection) available for Linear Models.

Given a response variable Y and a set of explanatory variables $X_1,\ldots, X_k$, instead of directly relating the mean of the response to a linear combination of the explanatory variables, GLIM models relate these values through a link function g so that $E(Y) = g^{-1}\left(\sum_{i=1}^{k}\beta_i X_i\right)$. Full details on the implementation of these models and the extension of the usual linear model tools to GLIM models can be found in McCullagh & Nelder [29] or Agresti [30].

Particularly relevant points when considering a GLIM model in practice are the selection of an appropriate variable distribution for the response variable and a suitable link function for the model as, although there is a canonical link function for each response distribution, there may be a better one for the problem at hand. The selection of a distribution for the response variable may be performed considering goodness-of-fit tests. The most commonly considered in practice may be the Kolmogorov-Smirnov, Anderson-Darling, and Cramer-von Mises tests (see D'Agostino & Stephens [31] for a full monograph on goodness of fit). For the selection of the link function with a continuous response variable, McCullagh & Nelder [29] propose studying the deviance of the model under a power link function, and Dunn & Smyth [32] check this selection considering the analysis of trends in the residual plots.

The uncertainty of the estimations in these models is computed taking into account that iteratively reweighted least squares are used to fit the model. Details on the computations appear in Agresti [30] and Dunnn & Smyth [32]. Both references recommend initially working in the linear predictor scale and then transforming the results to the response variable scale. Appendix A in this paper describes these computations.

2.2. Model selection criteria

When a large set of possible explanatory variables is considered, it is common for some of them to be statistically insignificant. In these cases, the problem of variable selection is a relevant one. Several methods have been proposed to deal with this problem. In this work, we will consider stepwise selection. There are two primary methods for performing stepwise selection. One of them is forward selection. This method begins with an empty model, and at each step, the variable that most improves the model, according to a predefined criterion, is included until no significant improvement is obtained by adding more variables to the model. The second method is backwards elimination. This method begins by including all possible variables in the model, and at each step, the variable whose elimination yields the most significant improvement to the model is eliminated. The method stops when eliminating any of the variables in the model does not improve it according to the predefined criterion.

Several criteria can be used for this stepwise variable selection. The most common one is the p-value criterion. A p-value limit, usually between 0.05 and 0.15, is fixed. For forward selection, the variable not in the model with the lowest p-value under that limit is included in each step. For backwards elimination, the variable in the model with the highest p-value over that limit is dropped in each step. Other selection criteria are based on information criteria such as AIC [33] or BIC [34], or fitting quality measures such as adjusted R^2 (Adjr2). They work in a similar way, including or excluding the variable that improves the most the corresponding criterion in each step.

2.3. Cross-validation for model selection and validation

A common problem appearing in statistical model selection and validation is overfitting. It is usual to consider the complete set of data to fit the model and to assess its performance. This clearly overestimates the model's performance, as the dataset is used both for fitting and evaluating the model, and the model will likely perform worse than expected on a new, independent dataset. Cross-validation is a method, independently introduced by Allen [35], Stone [36], and Geisser [37], to avoid this problem and improve the predictions that can be obtained with a statistical model. The most common method of performing cross-validation is known as K-fold cross-validation. The data sample is randomly split into K equal-sized subsamples. One of these subsamples is kept aside (test sample), and the rest of the data (training sample) is used to fit the model, and then this model is evaluated in the test sample. This is done with each of the K subsamples, and all results obtained are finally combined to give a final model and estimate its performance. It is important to note, as observed in Krstajic et al. [38], that this process must be performed not only when evaluating the model's performance but also in the variable selection process.

2.4. Airtightness measurement

Airtightness was measured by performing pressurization tests according to ISO 9972 [39] and preparation of the building as in Method 2, with all intentional openings sealed. The response variable is the air change rate at a 50 Pa pressure difference, n_{50} [h^{-1}]. For more details, refer to [20].

3. Variables selected

Variables related to location, age of the building, type of building, building state, building systems, and dimensions were considered. To improve the readability of the document, the complete list can be consulted in Appendix B.

Although a large number of variables were initially considered, the statistical methodology enabled the selection of a limited number of variables that were ultimately used to build the model. From the initial 53 variables in the dataset, the final model includes 13 main effects and 4 interactions among them. These variables are objective and easily identifiable in order to avoid misinterpretations during the characterization process.

Despite the geographical limitation of the study to dwellings in Spain, each variable in the final model is explained in detail below, allowing the model to be applied to other countries based on the numerous common and comparable aspects found in buildings constructed since 1945. These are the 13 variables selected for the model, described in detail.

3.1. Location variables

3.1.1. ***Climate zone*** *(Categorical variable)*

The climate was considered in accordance with the classification system used for Spanish energy regulations. Each standardised climate delineates the representative outdoor boundary conditions for a typical year through a set of parameters (temperature, humidity, solar radiation, etc.) that are indicative of a specific climatic zone.

From an international standpoint, direct equivalence can be established by implementing the methodology outlined in the reference document [40]. However, it should be noted that the correspondence with the international Köppen-Geiger climate classification is not direct, as they are based on different criteria. The Spanish classification is specifically tailored to energy design, whereas the Köppen-Geiger classification encompasses a broader range of global climate characteristics, based on temperature and precipitation. When considering the specific locations of the cases, the following equivalences can be established in the Köppen-Geiger climate classification [41]: A3 = Csa; B4 = BSk-Csa; C1 = Csb-Cfb; C2 = Csa, C3 = BSk; D2 = Csb; α3 = BSh.

3.2. Building state variables

3.2.1. ***Improvement of the envelope*** *(Categorical variable)*

It is estimated that approximately 35 % of the EU's buildings are over 50 years old, and almost 75 % of the building stock is energy inefficient [42]. In this regard, the Energy Performance Building Regulations (EPBR) include policies and measures that aim to improve the energy performance of the existing building stock.

The majority of current passive retrofitting strategies for the building envelope involve the replacement of windows and the addition of thermal insulation to façades and roofs. Insulation is typically achieved through the installation of injected insulation in the wall cavity, external thermal insulation systems, or interior lining insulation [43]. These measures, primarily aimed at enhancing thermal transmittance, often have an indirect impact on airtightness [44,45].

The variable in question makes reference to the condition and state of the envelope in relation to retrofitting. The examined cases were divided into two classifications: those with the original envelope and those in which the thermal envelope had undergone retrofitting to enhance its energy performance. This retrofitting process involved adding an insulation layer to the opaque part of the envelope, either on the interior or exterior surface. It was observed that in none of the cases studied, the objective of the retrofitting was to reduce air permeability, thereby confining its impact.

3.2.2. ***Bathroom refurbishment*** *(Categorical variable)*

Interior refurbishment actions were also considered through the characterisation of several kinds of actions in different rooms or construction systems of the dwellings under study. This variable refers to cases in which at least one bathroom has undergone complete renovation, encompassing wall tiling, flooring, interior finishes, replacement of hydraulic seals or traps in plumbing systems, and sanitaryware, irrespective of their inclusion in the thermal envelope. It is acknowledged that wet areas exhibit distinct airtightness behaviours, attributable to the concentration of building services (see information about the variable "Share of wet areas").

3.3. Building systems variables

3.3.1. ***Windows permeability*** *(Categorical variable)*

The air permeability of windows was assessed in accordance with the EN 12207 guidelines [46]. The classification system is based on the air permeability relative to the overall area of the window, measured at a reference pressure of 100 Pa. It is important to note, however, that this information was not always available and could be estimated from visual inspection based on window operation type [47] and its state:

- Class 1 (up to 50 m^3/hm^2): sliding or casement joinery where air penetration is noticeable by touch. It includes windows in poor condition.
- Class 2 (up to 27 m^3/hm^2): sliding or casement joinery, where wind pressure can be detected.
- Class 3 (up to 9 m^3/hm^2): new windows with casement joinery with airtight seals.
- Class 4 (up to 3 m^3/hm^2): new casement joinery of excellent quality with an airtight seal.

In accordance with the Spanish regulations [48], the air permeability of windows is subject to limitations depending on the designated winter climate zone. Class 2 is designated for zones α, A and B, while Class 3 is designated for the rest of the zones. It is noteworthy that, since 2017, the determination of permeability values must be undertaken with consideration for the shutter box, where applicable.

This variable is also incorporated into the model for determining the air permeability of buildings, using reference values stipulated in the regulation as mentioned above.

3.3.2. ***Window material*** *(Categorical variable)*

The evolution of window frame materials and glazing has been a subject of interest in the field of architectural history, particularly in terms of their impact on the overall performance of the building envelope. It has been noted that, historically, these elements were often considered the weakest link in terms of thermal performance and airtightness. A case in point is the transition from wooden swing windows with monolithic glass before the 1940 s to the adoption of folding steel windows in the 60 s. The utilisation of wooden windows was often hindered by their susceptibility to expansion and contraction, which was contingent on the prevailing climate conditions [49]. The system underwent an evolution to aluminium sliding frames [50] until concerns regarding energy usage emerged, prompting the development of more airtight solutions. Casement aluminium, machined wood, PVC, or mixed windows with thermal bridge breaks, combined with argon-filled triple glazing, became the prevailing option.

A relationship between window frame material and the level of global airtightness has been identified in previous research [25,49]. However, it is essential to avoid biased conclusions when the sample used was scarce or the material is correlated with age. Almeida et al. [25] demonstrated that windows, particularly in Southern European heavy construction, exhibit a significant variability in leakage performance due to factors such as frame material and sealing details.

The variable categorises the window frame material as follows: aluminium, PVC, wood or steel. In instances where multiple window types were identified within a case, the most representative type was considered.

3.3.3. ***Shutter position*** *(Categorical variable)*

Rolling shutters, commonly found in conjunction with windows, are a prominent architectural element in Spain. Both cultural tradition and the climatic conditions characteristic of Mediterranean regions influence their incorporation into building design. Historically, traditional architecture in these areas was shielded from the sun by means of folding blinds, rope shutters, or booklet blinds [51]. These were primarily employed in residential buildings as a means of mitigating solar radiation, regulating light, and enhancing ventilation and thermal performance. However, shutters have also been traditionally utilised for the purpose of enhancing privacy and security.

These shutters experienced a period of widespread use during the 1950 s, when novel construction systems incorporated them into the building envelope, superseding the traditional methods. The integration of rolling shutters within the inner layer of the envelope became a widespread practice, offering numerous advantages, including interior operation, insulation, regulation, and enhanced security [51].

However, issues arose concerning their integration when envelope systems reduced their thickness. The system became widespread in most residential buildings, generally without thermal insulation or airtight joints. In the 1990 s, built-on shutters and prefabricated box shutters were introduced. Current technical solutions focus on addressing the limitations of the system in terms of thermal transmission and airtightness, as encouraged by energy codes' requirements. In this regard, the Spanish energy code considers the shutter box to be part of the window system when determining airtightness requirements [48].

From a thermal perspective, integrating rolling shutters into a building's design can lead to a substantial enhancement in its thermal performance, particularly in reducing solar heat gain during summer months and heat loss during winter periods [52]. Conversely, rolling shutters are often identified as a primary component that can impede the overall airtightness of windows and, consequently, the entire building envelope. The shutter box has been identified as a critical point of air leakage if not adequately sealed or insulated [17,53], although good design and workmanship can achieve airtight systems [25]. Conversely, the utilisation of completely closed roller shutters as an infiltration control strategy has been demonstrated to be effective, particularly during nocturnal periods in winter and diurnal periods in summer [52].

This variable was based on the position of rolling shutters, including non-integrated shutters (P.01), external shutters (P.02), internal shutters (P.03), and the absence of shutters (P.04), as shown in [20]. The predominant solution is the integration of external shutters within the inner layer of the envelope (P.02), while non-integrated shutters (P.01) refer to cases where shutters were not initially present.

3.3.4. ***False ceiling*** *(Categorical variable)*

This particular variable pertains to suspended or dropped ceilings, which involve creating an air chamber between a secondary ceiling and the underlying structure. The development of false ceilings is a recent phenomenon, originating in the 20th century as a response to the expanding prevalence of building services, which necessitated their concealment [54]. The design objective of false ceilings is to enhance aesthetics, control acoustics, provide thermal insulation, and, most notably, conceal various building services, such as HVAC systems, ductwork, and recessed luminaires. This practical application is evidenced by the prevalence of false ceilings in wet areas and corridors, which often contain plumbing and ventilation systems.

In terms of airtightness, gaps between the false ceiling and structural elements, vertical walls, and installation pathways can become pathways for air infiltration that are difficult to locate. In this regard, installation pathways from common areas, recessed luminaires (a feature of many recent buildings), and sanitation pipes from the upper floor beneath the floor slab and bathtubs are of particular concern. For the study, a simplified classification was proposed, considering dwellings with no false ceiling (FC0), dwellings with a false ceiling only in the corridor and wet areas (FC1), and dwellings with a false ceiling in all rooms (FC2).

3.3.5. ***Ductwork*** *(Categorical variable)*

Ductwork is associated with ventilation and conditioning systems, and the introduction of air conditioning systems in residential buildings began in the mid-20th century as a consequence of housing modernisation and rising standards of living. However, it was not until the 1980 s that centralized systems with ductwork became more common.

In dwellings, ductwork is generally hidden by false ceilings (see above). Despite the stipulation in Method 2 [39] that openings for mechanical ventilation or air conditioning systems must be sealed, the presence of ductwork invariably creates connections between rooms, as well as between the false ceiling and rooms. Moreover, ductwork connecting a central unit to the exterior often involves leaky joints in inaccessible spaces.

The impact of ductwork on the airtightness of buildings' envelopes has been extensively documented in the literature. Dickerhoff et al. [55] estimated the impact of ductwork to be approximately 13 %, although some authors have argued that this figure underestimates the actual impact due to the significantly higher pressure differentials across duct leaks during system operation when compared to envelope leaks [56].

Recent regulatory frameworks underscore the significance of airtightness in ductwork and mandate rigorous testing and inspection protocols to minimise duct leakage and ensure compliance with energy performance standards. The categorisation of cases was based on the presence or absence of ductwork.

3.3.6. ***Kitchen hood exhaust*** *(Categorical variable)*

The purpose of a kitchen hood exhaust is to act locally to remove contaminants, grease particles, and odours generated in the kitchen cooking area. The first hood exhausts appeared in dwellings in the mid-20th century in the USA and Europe. In Spain, they became popular during the 1960 s and 1970 s due to the need for adequate kitchen ventilation (although initially, they did not include an electric fan). A significant milestone was marked by the introduction of the Technical Building Code [57], which included specific mechanical extraction systems in kitchens. In most cases, the hood is connected to a vertical chimney; however, it is frequent to find buildings constructed before the 1980 s without vertical chimneys. In such cases, recirculating range hoods are often used in original dwellings without kitchen exhaust. When retrofitting, the preferred option is to connect the hood to a duct that expels the air through an opening in the building façade (when allowed). However, for the past few years, highly energy-efficient homes with voluntary standards have utilised carbon filters for recirculating air to prevent the penetration of the envelope.

The impact of this approach on airtightness is associated with the variable nature of “Ductwork”, given that the exhaust process involves a penetration of the building envelope, which can result in air leaks if not adequately sealed. In preparation for a pressurisation test in accordance with ISO 9972 (2015), Method 2, it is essential to seal this category of openings, specifically the hood.

The cases under study were classified as follows: “vertical chimney”, “Recirculating units”, and “exhaust to the façade·.

3.4. Building dimensions variables

3.4.1. **Envelope area** $\left[m^2\right]$ (Continuous variable)

The building envelope is defined as the boundary or barrier that separates the interior of the building or part of the building subject to the test from the outside environment or another building or part of the building [39]. The envelope area A_E $\left[m^2\right]$ is defined as the total area of the envelope (i.e. façades, walls, ceilings, floors, and internal partitions) that encloses the internal volume of the measured extent, irrespective of the heat exchange performance ($A_E = \sum A_{Ei}$).

According to ISO, 2015, the overall internal dimensions should be used, with no deductions made for the area where the internal walls, floors, and ceilings meet the exterior walls, floors, and ceilings. The envelope area of an apartment in a multi-story building includes the floors, walls, and ceilings that are shared with neighbouring apartments.

However, the calculation of this variable may introduce a significant source of error due to the variation in energy codes across countries [58]. This can lead to differing conventions in the assessment of internal or external dimensions, including or excluding the volume of partitions and floors, the volume of window openings, etc. [59].

In this sense, the utilisation of this variable in country codes will necessitate the integration of the entire envelope or merely a portion of it, taking into account the thermal envelope. To illustrate this point, the calculation in the Spanish energy code [60] deviates from the ISO standard. The CTE (Technical Building Code of Spain) conceptualises the envelope area as the aggregate of surfaces involved in thermal exchange with the external air or the ground of the thermal envelope. Consequently, floors, walls and ceilings in contact with other buildings, neighbouring apartments, or adjacent spaces outside the thermal envelope are excluded. It is noteworthy that other countries also assess the thermal envelope in different ways. For instance, in Belgium, the code refers to the thermal envelope area based on exterior dimensions, including the area in contact with the exterior environment, adjacent unheated spaces, or the ground [61]. However, in France, the basement floor area is excluded [62]. Errors in the calculation of volume or envelope area are sources of uncertainty in the derivation of airtightness-related quantities or measurement results, such as the specific leakage rate at 50 Pa Q_{50} $\left[m^3/h\,m^2\right]$, based on the average air leakage rate and the envelope area of the building.

The fact that the envelope area is calculated in different ways hinders comparability and the application of the proposed model, so it is important to take into account the calculation method in each case.

3.4.2. **Form factor FF** $\left[{m^2}/{m^3}\right]$ (continuous variable)

This variable refers to a geometric relationship that describes the ratio between the envelope area of a building, denoted by A_E, and its enclosed volume or internal volume of the dwelling, denoted by V. It is a quantitative measure of the proportion of the external surface area that is exposed per unit of internal volume. This is expressed as:

$$FF\left[{m^2}/{m^3}\right] = \frac{A_E}{V}$$

This ratio is closely related to compactness, being the inverse measure of compactness.

The form factor is a key indicator of a building’s energy efficiency, as it significantly impacts the building’s thermal performance and heat exchange with its surroundings. A reduced form factor, characterised by a smaller surface area relative to volume, generally results in diminished heat exchange with the environment. Consequently, energy codes and guidelines frequently underscore the importance of optimising the form factor or compactness of a building to minimise energy demand.

Since the envelope area and volume can be calculated in different ways depending on the context (see above), it is crucial to use homogeneous criteria. For the purposes of this study, A_E $\left[m^2\right]$ and V $\left[m^3\right]$ were calculated according to ISO 9972 [39].

3.4.3. **Share of windows** [%] (Continuous variable)

The share of windows [%] is the sum of the areas of doors and windows located on the building envelope A_w $\left[m^2\right]$ related to the total envelope area A_E $\left[m^2\right]$:

$$Share\ of\ windows\,[\%] = \frac{\sum A_{wi}}{A_E}$$

This parameter is important when considering airtightness, since windows and doors have been reported to have a substantial impact on the total leakage [25,53,63,64]. This is because windows introduce a discontinuity to the envelope, meaning that joints must be well sealed to avoid leakages, both between the wall and the window and between the openable part and the frame. Other components, such as rolling shutters included in the window’s system, may add leakages to it.

It is noteworthy that the Spanish energy code [60] considers $\sum A_{wi}$ when determining the air change rate by means of reference values, a practice previously employed in developed models [65].

It is important to note that this variable is derived from A_E, which is often calculated using different criteria.

3.4.4. **Share of wet areas** [%] (Continuous variable)

This variable makes reference to the ratio between the volume of bathrooms, the kitchen, or the laundry room V_W $\left[m^3\right]$, and the internal volume of the dwelling $V\left[m^3\right]$:

$$Share\ of\ wet\ areas\,[\%] = \frac{\sum V_{Wi}}{V}$$

In this respect, some authors have reported divergent airtightness behaviour between dry and wet areas. The exclusion of vents and other functional openings resulted in a higher leakiness in dry areas, which can be attributed to the larger share of window area and building service penetrations [19,63].

4. Results

The statistical model is built based on the INFILES airtightness database, which consists of around 400 cases considered representative of the residential built stock in Spain [20]. Data collection was performed according to the methodology explained in Section 2.4. Cases were chosen according to their climate zone, construction year, and typology. Each case was evaluated in terms of both the airtightness of the envelope and its building characteristics. More than 50 parameters

Table 1
Descriptive study for the variables and observations in the final model.

Continuous variables		Mean	Std. Dev.
Response variable: n_{50}		7.14	3.98
Envelope area		292.73	117.43
Form factor		1.29	0.20
Share of windows		5.19	2.04
Share of wet areas		18.54	4.88
Categorical variables	Value	N	%
Climate zone	A3	33	8.5 %
	B4	85	21.9 %
	C1	47	12.1 %
	C2	83	21.3 %
	C3	111	28.5 %
	D2	16	4.1 %
	α3	14	3.6 %
Improvement of the envelope	Yes	9	2.3 %
	None	380	97.7 %
Bathroom refurbishment	Yes	186	47.8 %
	None	203	52.2 %
Window permeability	Class 0 or 1	45	11.6 %
	Class 2	195	50.1 %
	Class 3	116	29.8 %
	Class 4	33	8.5 %
Window material	Aluminium	263	67.6 %
	Wood	53	13.6 %
	PVC	70	18.0 %
	Steel	3	0.8 %
Shutter position	0P.01	19	4.9 %
	0P.02	289	74.3 %
	0P.03	20	5.1 %
	0P.04	61	15.7 %
False ceiling	FC0	85	21.9 %
	FC1	242	62.2 %
	FC2	62	15.9 %
Ductwork	Yes	60	15.4 %
	None	329	84.6 %
Kitchen hood exhaust	Vertical chimney	226	58.1 %
	Exhaust to the façade	124	31.9 %
	Recirculating units	39	10.0 %

were characterized for each dwelling. This allowed the creation of a detailed and standardized database.

4.1. Descriptive study

The outlier detection procedure developed in Poza-Casado et al. [20] resulted in the elimination of 8 observations that had anomalous n_{50} values, possibly due to measurement errors. Considering the results obtained in that paper, three more observations were deleted due to high leverage values. Therefore, this work considers 389 observations. Table 1 contains a descriptive study of the response and explanatory variables in the final model.

4.2. Response variable distribution and link function selection

As mentioned in Section 2.1, the first modelling step was the selection of the response variable (n_{50}) distribution. Several classical goodness-of-fit tests, such as Kolmogorov-Smirnov (KS), Cramer-von Mises (CvM), and Anderson-Darling (AD) were performed using the goftest [66] R package. As can be seen in Table 2, the null hypotheses of a Gamma distribution was not rejected for any of them with p-values close to or over 0.5. The lowest one was that for the Kolmogorov-Smirnov test (0.494). Graphical methods showed in Fig. 1 such as frequency histogram or quantile plot also show a good fit.

Table 2
P-values for goodness of fit test for testing the null hypotheses of Gamma distribution for n_{50}.

Test	KS	CvM	AD
p-value	0.4979	0.8884	0.8355

For the link selection, as described in Section 2.1, the power family of links was considered, and the deviance of the models under λ powers between −1 and 1 was computed. Fig. 2 shows the graph of the deviance under the powers between 0 and 0.8. The minimum deviance appears at $\lambda = 0.24$. The usual link functions for Gamma response are the inverse ($\lambda = -1$), the log ($\lambda = 0$) and the identity ($\lambda = 1$) links. Since the closest significant value is $\lambda = 0$ the logarithm was chosen as link function. This is a common choice for gamma models.

4.3. First step of model selection: Main effects selection

Since we are considering a large number of possible explanatory variables, we first performed a selection of main effects only. In other words, interactions were not considered in this step, as their inclusion would have multiplied the number of coefficients, yielding an unstable or even non-adjustable model. Since many of the initial variables were not significant in the model, we performed stepwise forward and backward selection (see Section 2.2), considering different selection criteria based on p-values, ACI, BIC and Adjr2 and using cross-validation (see Section 2.3) with the cross-validation cv [67] R package. Ten-fold cross-validation was performed for the model selection under each of the criteria, and when selecting the final first step model among the ones obtained for each criterion. The model selected in this step is the one obtained from the complete model using a backward selection procedure based on a p-value of 0.15 as the selection criterion. The ANOVA table for this model appears in Table 3. Notice that, according to the 0.15p-value criteria, all variables in the model are significant at the 0.15 level.

This first step model keeps 15 of the initial variables. Table 3 also shows the values of the fitting criteria. It is interesting to note that the pseudo-R^2 value, computed using the R pscl [68] package, of this model without interactions has risen to 0.457, whereas the value obtained in Poza-Casado et al. [20] in a normal linear model with interactions was 0.385.

4.4. Second step of model selection: Interaction selection

In this second step, we start with the model selected in the previous section and consider the possible interactions between the 4 continuous and 11 categorical variables in that model. Therefore, the starting model in this step contains a total of 15 main effects plus 4 interaction terms. From this model, we performed again a selection procedure under the same conditions as in the first step, i.e., stepwise selection under several different criteria using cross-validation. In this case, the model selected after the stepwise and cross-validation steps was the one obtained using forward selection and AIC as selection criteria. The model was selected in 6 out of the 10 folds used in the 10-fold cross-validation. Table 4 shows the ANOVA table and fitting criteria for this model, while Table 5 includes all the coefficients of the model and their significance.

From Table 4 it can be seen that two of the main effects ("Share of opaque envelope" and "Windows opening system") have been dropped from the model and that, although in this case the p-value 0.15 criteria is not the one considered and the variable is not present in any of the interactions, the main effect "Envelope Area" has a p-value over 0.1. This has been a consequence of the cross-validation selection procedure considered, i.e., the model without this variable was also considered in the second step of the cross-validation model selection procedure. However, the model including this effect was still selected. Fig. 3 shows in a graphic way the process followed to develop the model.

The final model then has 13 main effects plus 4 interactions. It is also noteworthy that the pseudo-R^2 value increases from 0.457 to 0.496, bringing it closer to 0.5, and there is an improvement of more than 28 % over the 0.385 R^2 value reported in Poza-Casado et al. [20]. Moreover, both the deviance and the AIC value have been significantly reduced in

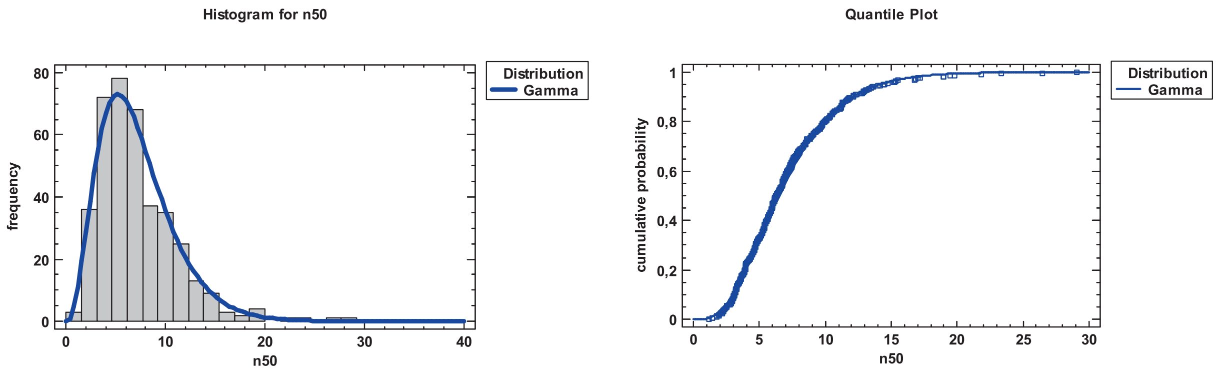

Fig. 1. Frequency histogram and quantile plot showing the good fit between the data and the Gamma distribution.

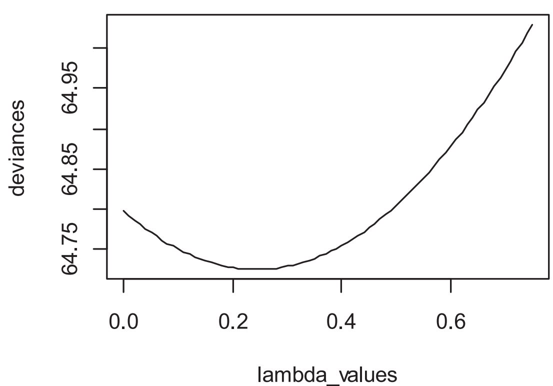

Fig. 2. Model deviance function for $\lambda \in [0, 0.8]$.

Table 3
Type III ANOVA table and fit criteria for the model selected in the first step.

	LR Chisq	Df	Pr(>Chisq)
Climate Zone	47.711	6	1.350e-08 ***
Ductwork	19.400	1	1.060e-05 ***
Share of Windows	18.870	1	1.400e-05 ***
Window permeability	24.855	3	1.655e-05 ***
Form factor	17.594	1	2.734e-05 ***
False ceiling	13.960	2	0.0009302 ***
Kitchen hood exhaust	12.624	2	0.0018141 **
Bathroom refurbishment	8.713	1	0.0031594 **
Shutter position	12.756	3	0.0051943 **
Share of wet areas	4.551	1	0.0328944 *
Window material	7.835	3	0.0495571 *
Envelope area	3.122	1	0.0772232.
Improvement of the envelope	2.807	1	0.0938367.
Windows opening system	2.675	1	0.1019303
Share of opaque envelope	2.173	1	0.1404330
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1			
Deviance	AIC	BIC	r2ml
60.86646	1872.359	1991.266	0.45698

this second step. In contrast, the BIC value of this model is slightly higher because it includes a larger number of variables.

The residual analysis for this final model is presented in Fig. 4. The first panel of the figure displays the typical residual versus predicted value graph, where no significant deviations or high residuals are observed. According to Dunn & Smyth [32], the lack of trends in this plot also confirms the choice of the log link function. The second panel shows the standardized Pearson residuals vs leverage values. Again, no significant pattern is observable. The highest-leverage points have been individually studied, and no significant change has been observed when they are deleted.

Then, the final equation for estimating the n_{50} values using the model is: $\widehat{n_{50}} = exp\left(\sum_i \widehat{\beta}_i X_i\right)$ where the X_i are the values of the variables (or interactions) included in the final model for the building whose n_{50} value is to be estimated, and the $\widehat{\beta}_i$ are the coefficients of those variables appearing in Table 5.

5. Discussion

The model proposed addresses the impact of a limited number of building characteristics on the airtightness performance of the envelope. The results show that most of the effects can be considered as expected (e.g., PVC windows, usually newer, are associated with more airtight envelopes than dwellings with steel windows). In this line, windows emerged as a critical factor influencing multiple variables, including "Share of windows", "Window permeability", "Window material", and "Shutter position". These elements significantly impact overall airtightness, highlighting the need for further investigation into window-related airtightness interventions.

The results for other variables, however, are not that immediate or need further discussion:

- Ductwork has been associated with leaks as a result of joints and connecting air chambers [55,69]. The model results, when considering the variable "Ductwork", apparently point in the opposite direction, as the "Ductwork yes" coefficient is negative (−0.632). However, when the interaction of "Ductwork" with "Form Factor" is considered (see Fig. 4) it can be checked that for the values of "Form Factor" in the sample (the minimum value of "Form Factor" is 0.665) "Ductwork yes" implies a higher value of the linear predictor of n_{50} and obviously of n_{50} as the link function is a monotone increasing function.
- The variable "Kitchen hood exhaust" also needed further analysis. Cases with recirculating units are expected to be more airtight because the system does not involve any discontinuity of the envelope. However, these cases were found to be generally leakier. Cross-tabulation analysis (Table 6) suggests that extractor type may serve as an indirect indicator of building age and renovation status (both variables excluded from the final model). Recirculating units are more dominant in buildings constructed before the 1990 s. Almost 80 % of the cases (31 out of 39) with recirculating units were dwellings in their original state. In contrast, an important share of the refurbished buildings (more than 90 %, 112 out of 120) installed the exhaust to the façade or to a vertical chimney. It is worth noting that the model was not fitted for extremely airtight recent cases,

Table 4
Type III ANOVA table and fit criteria for the model selected in the second step.

	LR Chisq	Df	Pr(>Chisq)
Climate Zone	58.314	6	9.896e-11 ***
Share of Windows	24.739	1	6.565e-07 ***
Kitchen hood exhaust	17.024	2	0.0002011 ***
False ceiling	16.730	2	0.0002329 ***
Bathroom refurbishment	11.114	1	0.0008566 ***
Window permeability	15.597	3	0.0013715 **
Window material	12.216	3	0.0066801 **
Share of wet areas	4.236	1	0.0395647 *
Form factor	3.155	1	0.0757059.
Shutter position	6.243	3	0.1003611
Envelope area	2.534	1	0.1114495
Ductwork	2.382	1	0.1227305
Improvement of the envelope	2.280	1	0.1310893
Form factor: Window permeability	10.796	3	0.0128817 *
Form factor: Ductwork	4.876	1	0.0272303 *
Form factor: Shutter position	8.489	3	0.0369222 *
Improvement of the envelope: Share of wet areas	3.591	1	0.0581091.
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 '' 1			
Deviance	AIC	BIC	r2ml
56.60926	1855.445	1998,134	0.49588

Table 5
Coefficients of the model selected in the second step.

Coefficients:	Estimate
(Intercept)	2.1556581
Climate zone. A3	−0.308213***
Climate zone. B4	−0.021683
Climate zone. C1	−0.309688***
Climate zone. C2	0[a]
Climate zone. C3	−0.082913
Climate zone. D2	−0.597692***
Climate zone. α3	−0.848767***
Share of Windows	0.054648***
Kitchen hood exhaust. Vertical chimney	−0.341092***
Kitchen hood exhaust. Exhaust to the façade	−0.236577**
Kitchen hood exhaust. Recirculating units	0[a]
False ceiling. FC0	−0.009354
False ceiling. FC1	0[a]
False ceiling. FC2	0.2522201***
Bathroom refurbishment. Yes	−0.148709***
Bathroom refurbishment. None	0[a]
Window permeability. Class 0 or 1	2.3430266***
Window permeability. Class 2	1.3879695**
Window permeability. Class 3	0.783767
Window permeability. Class 4	0[a]
Window material. Aluminium	−0.314518
Window material. Wood	−0.139812
Window material. PVC	−0.443981·
Window material. Steel	0[a]
Share of wet areas	−0.090312*
Form factor	1.1760779·
Shutter position. P01	0[a]
Shutter position. P02	−0.273984
Shutter position. P03	0.7788937
Shutter position. P04	0.6553915
Envelope area	−0.000367·
Ductwork. Yes	−0.632335·
Ductwork. None	0[a]
Improvement of the envelope. Yes	0[a]
Improvement of the envelope. None	−1.219845
Form factor: Window permeability.Class 0 or 1	−1.480941**
Form factor: Window permeability.Class 2	−0.889299*
Form factor: Window permeability.Class 3	−0.470269
Form factor: Window permeability.Class 4	0[a]
Form factor: Ductwork Yes	0.6885442*
Form factor: Ductwork None	0[a]
Form factor: Shutter position. P01	0[a]
Form factor: Shutter position. P02	0.1622378
Form factor: Shutter position. P03	−0.933482
Form factor: Shutter position. P04	−0.616728
Improvement of the envelope.Yes: Share of wet areas	0[a]
Improvement of the envelope.None: Share of wet areas	0.0832804*
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 '' 1	
a. This parameter is set to 0 as it corresponds to the reference class of the variable.	

which include recirculating units; therefore, further refinement of this variable may be necessary if applied to other datasets.

- Higher "Form factor" values (envelope area and volume ratio) generally correspond to poorer airtightness levels, although this effect is not significant at the usual 0.05 level. Moreover, this is the effect of this variable alone. Yet, the statistical coefficients of the interactions of this variable with "Window permeability" and "Shutter position" lead to an even much lower effect when the interaction coefficients are negative, and the effect of "Form factor" can even be the opposite (i.e. better airtightness results) when "Window permeability" is in class 0 or 1 (see Fig. 5). This means that there is a more complex relationship that needs to be assessed.
- Dwellings without rolling shutters are not always more airtight (Fig. 7), although this element has been proven to be a source of leaks [17,53]. This effect can be explained by considering that cases without shutters were generally older (Fig. 6). This must be taken into account if the model is to be applied to other regions or to recent buildings without shutters.
- A greater share of wet areas is associated with a lower n_{50} value, in line with previous research [19,63], as dry areas usually involve a larger share of window area and building service penetrations. Here, the effect of it could be nearly compensated in cases that have undergone no "Improvement of the envelope".

The potential relationship between the variables "Form factor" and "Envelope area" was also studied. Even though the form factor is a derived quantity from the envelope area, they represent distinct physical attributes of the dwellings, and their inclusion does not introduce multicollinearity issues as their correlation is not high (−0.481). This negative correlation also indicates that buildings with a higher Envelope area were also the most compact (probably due to the influence of single-family dwellings). According to the model, greater envelope areas lead to better airtightness, although the effect is not statistically significant.

It is noteworthy that the new methodology employed has resulted in an expansion of the variables chosen for this model in comparison with those initially selected by Poza et al. [20]. These variables are easy to determine in situ for each building by visual inspection and dimension' measurement, so that the model can be easily applied. Thus, a compromise between complexity and fitting quality has been determined. All the variables in the model play a statistically significant role in the model fitting.

The final model then has 13 main effects plus 4 interactions. As shown in Table 7, several variables from the previous model were retained due to their consistent predictive power, namely "Climate

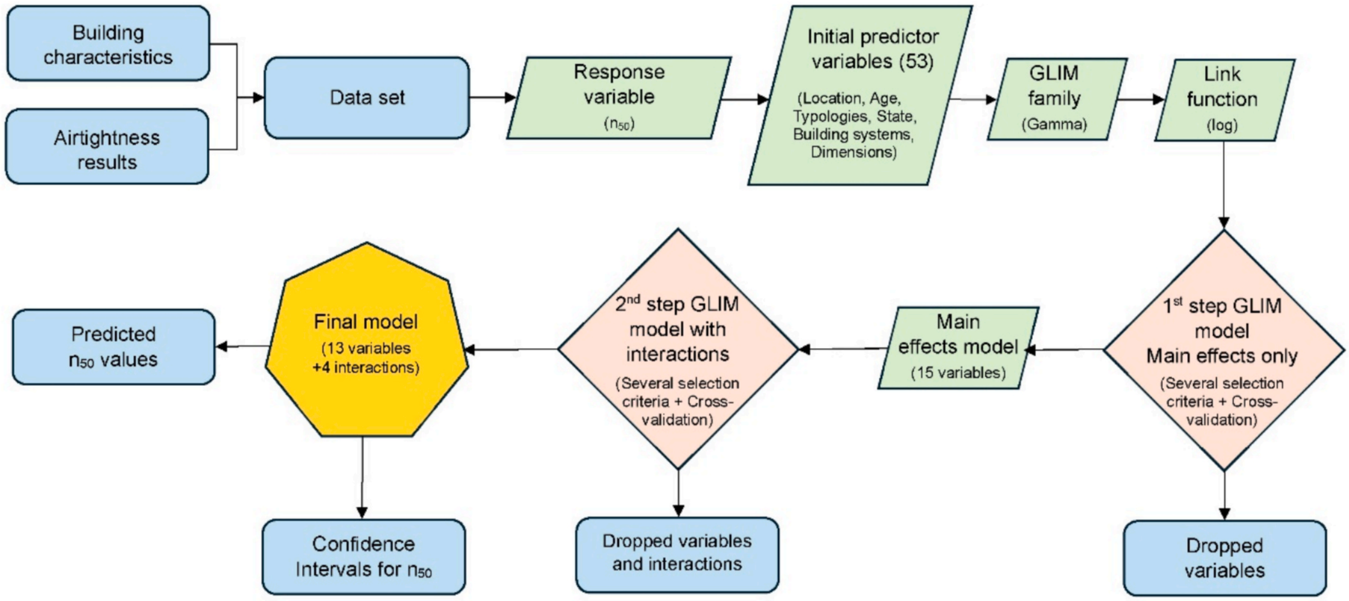

Fig. 3. Flowchart of the process of the model development. Tabular data is represented by blue rectangles, calculations by red diamonds, choices by green parallelograms, and diagnostic outcomes by orange heptagons. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

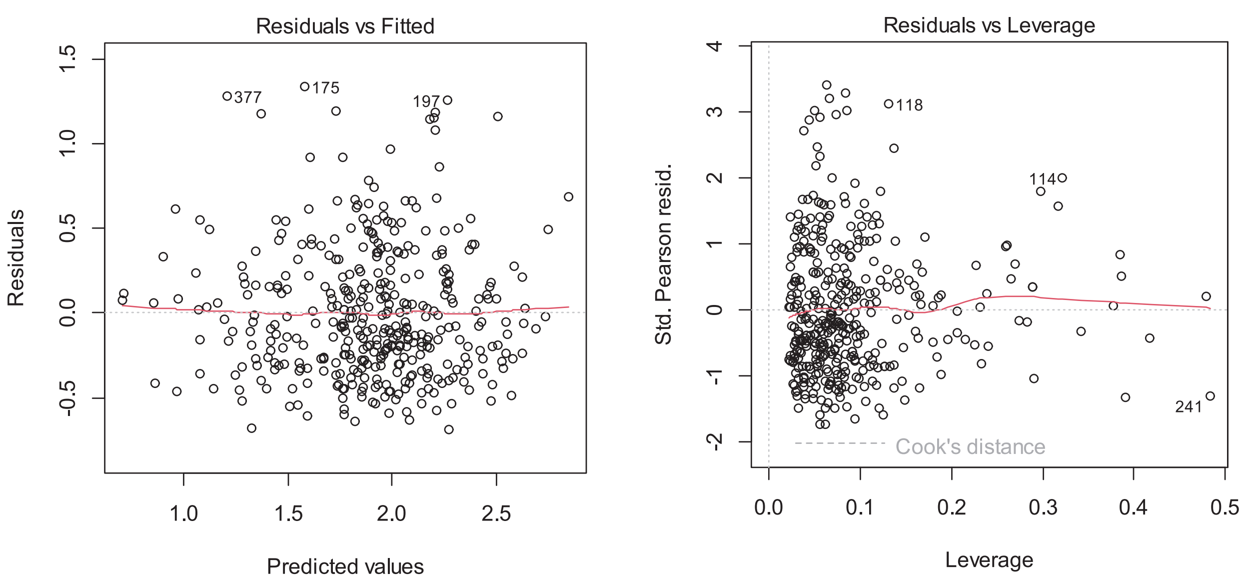

Fig. 4. Residual analysis for the final model.

Table 6
Relationship between the Retrofitting state and their Kitchen Hood exhaust type of the cases addressed.

Retrofitting state	Kitchen hood exhaust			Total
	recirculating units	*vertical chimney*	*exhaust to the façade*	
Original	31	160	78	**269**
Retrofitted	8	66	46	**120**
Total	**39**	**226**	**124**	**389**

zone", "Window permeability", "Window material", "Share of windows", "False ceiling", and "Shutter position". These factors continue to demonstrate relevance in predicting airtightness levels. On the other hand, some variables were excluded from the final model, despite their potential relevance. Notably, the year or "Period of construction" and "Dwelling typology" were removed due to a lack of significant impact on airtightness predictions. In any case, the effect of these variables may be included in other variables.

In comparison with existing models and other approaches in the literature, this approach includes typical variables such as the climate zone, dimensional and window-related variables, ductwork, etc. Other common variables already mentioned were dropped during the cross-validation process, namely the "Year of construction" or "Typology". Furthermore, the comprehensive set of variables allowed for the inclusion of other variables that are not typically included, such as the "Shutter position", the "Kitchen hood exhaust", or the "Share of wet areas", as well as 4 interactions, which are not commonly found in other models developed.

It is also interesting to note that the pseudo-R^2 value improves by

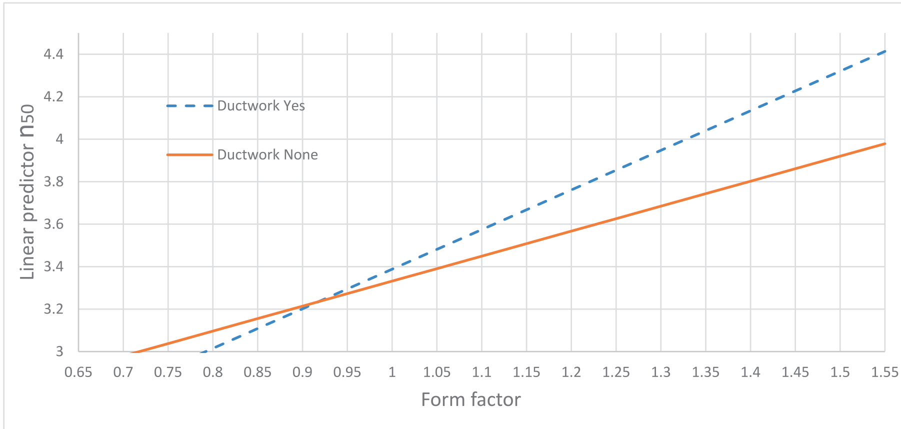

Fig. 5. Interaction plot between "Form factor" and "Ductwork" showing how the effect of "Form factor" on the linear predictor of n_{50} changes for the different values of "Ductwork".

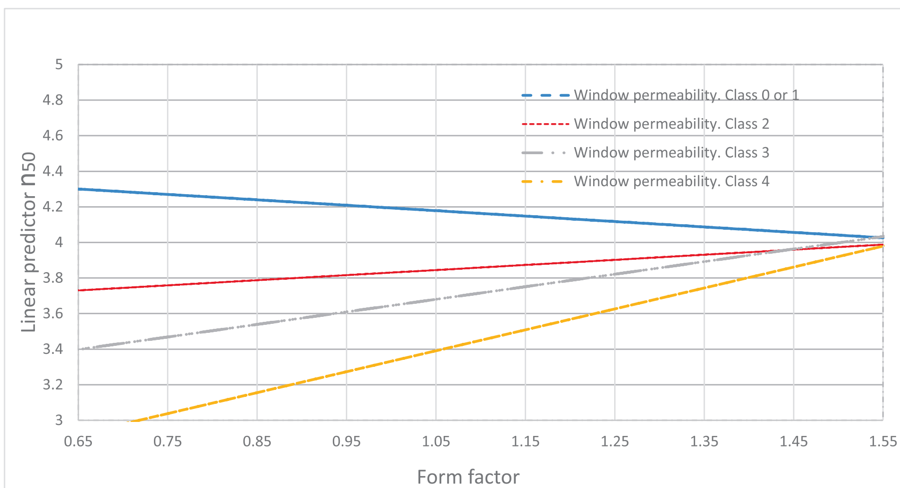

Fig. 6. Interaction plot between "Form factor" and "Window permeability" showing how the effect of "Form factor" changes for different values of "Window permeability".

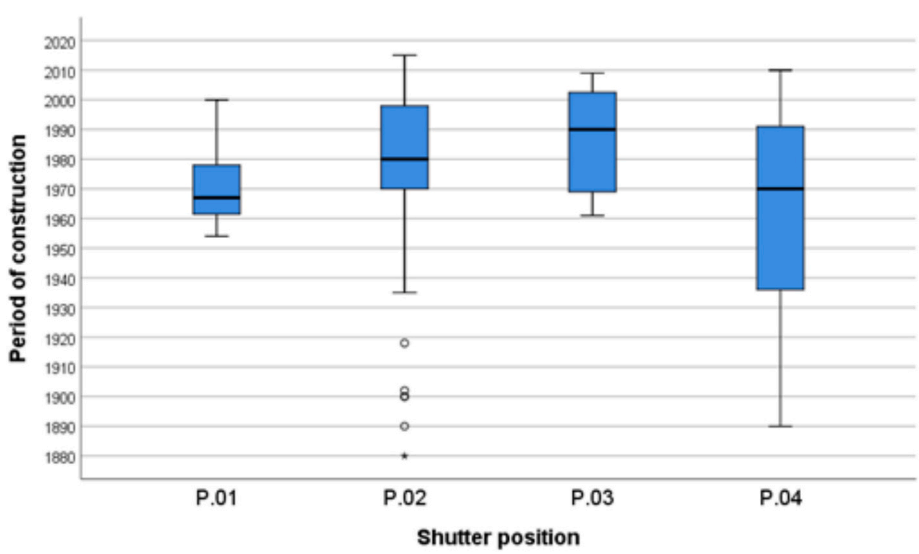

Fig. 7. Box plot relating "Shuter position" and the "Period of construction" of the cases addressed.

Table 7
Comparison of the variables of the original model and the model proposed through this research.

Model proposal	**Original model** (Poza-Casado et al., 2022)
Climate zone	Climate zone
	Period of construction (Before-Since 1980)
	Typology
	Retrofitting state
Improvement of the envelope	
Bathroom refurbishment	
Window permeability	Window permeability
Window material	Window material
Shutter position	Shutter position
False ceiling	False ceiling
Ductwork	
Kitchen hood exhaust	
Envelope area *(continuous variable)*	
Form Factor *(continuous variable)*	
Share of Windows *(continuous variable)*	Share of windows *(continuous variable)*
	Share of opaque envelope *(continuous variable)*
Share of wet areas *(continuous variable)*	
	Period of construction * Share of opaque envelope
	Typology * Share of opaque envelope
Form factor * Window permeability	
Form Factor * Ductwork	
Form Factor * Shutter position	
Improvement of the envelope *Share of wet areas	

more than 28 % compared to the R^2 value reported in [20]. The model explains almost 50 % of the variability. This outcome is relatively high compared to previous approaches summarized in [20] when the sample comprises a heterogeneous population. Higher R^2 values can be found in other models only when those apply only to specific sets of cases, as in [19].

6. Conclusions

A predictive model is proposed to estimate the level of airtightness in existing dwellings, aiming to provide a valuable tool for designers and contractors. The model has been developed based on GLIM and involves 13 main effects and 4 interactions, selected considering several variable selection criteria and validated using cross-validation, thus offering reliable estimates of airtightness. Cross-validation ensures that overfitting is limited so that the results are not excessively dependent on the sample considered in the dataset, and the reliability of the predictive outcomes is improved. The proposed methodology is uncommon in airtightness predictive models, but its results demonstrate its potential, yielding improved results compared to those obtained with typical normal linear models. In addition, this tool overcomes previously identified challenges such as the lack of standardization and a limited applicability to a specific extent. In this sense, a detailed standardised database has been used, and each parameter has been thoroughly described and classified so that the model can be applied to other datasets. Variables were measurable and easily assessed through inspection, offering the possibility to transcend region-specific airtightness estimation.

The findings reinforce the importance of windows, ventilation systems, construction features, and building dimensions in determining airtightness levels. The effect of building characteristics, however, is not a straightforward matter due to the fact that interactions add complexity and need to be analysed closely. For some variables, interactions may reinforce the effect of the original variable, but in other cases, they can lead to the opposite result.

A pertinent question is whether artificial intelligence techniques, such as neural networks, can be utilised to enhance the results. Some work has already been done in this line [13,65]. However, the number of buildings considered is limited and the results obtained are not better than the ones reported here, while the usual black-box problem in this sort of techniques makes the interpretation of the results more difficult. Moreover, since the data collection in our problem is not of a dynamic nature, there is no need to use artificial intelligence methods that need a considerable amount of data, such as [70], or the use of these techniques to recover lost information in data acquisition, as in [71,72]. A possible future direction of research could certainly be to check whether the use of neural networks may improve the results obtained here by increasing the size of the database.

In addition, it is worth noting that some challenges still remain and are difficult to address, such as the difficulties in considering workmanship and supervision. This has been pointed out by other authors associated with on-site installation variability, which seems difficult to address unless prefabricated construction systems are imposed. In addition, the model could be improved if the database was expanded, including further representative data. This expansion would also be helpful for further model validation and checking of the model's predictive outcomes. In any case, it must be noted that the authors understand that estimations can never replace on-site testing to measure the actual level of airtightness.

All things considered, the model provides valuable insights into the airtightness of dwellings and the key factors affecting their performance. It also raises new research questions and avenues for further exploration. Future research should focus on refining interactions between key variables, exploring the role of renovation interventions, and validating results with additional datasets to enhance model robustness.

CRediT authorship contribution statement

Miguel Fernández-Temprano: Writing – review & editing, Writing – original draft, Formal analysis, Conceptualization. **Irene Poza-Casado:** Writing – review & editing, Writing – original draft, Conceptualization. **Pilar Rodríguez-del-Tío:** Validation, Formal analysis, Data curation. **Alberto Meiss:** Supervision, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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APPENDIX A. Calculation of uncertainty and confidence intervals

Consider the GLIM model $E(Y) = g^{-1}\left(\sum_{i=1}^{k}\beta_i X_i\right)$. To compute the 100(1-α) % confidence intervals of the response Y (n_{50}) at specific values of the explanatory variables $X_1,\ldots,X_k$, the standard deviation around the mean value is needed. For these GLIM models, it is recommended, see Agresti

(2015) and Dunn & Smyth (2018), to perform the computations on the linear predictor scale $\eta = \sum_{i=1}^{k} \beta_i X_i$ and then transform the results using the link function g.

Let $\mathbf{X}_g$ be a vector containing given specific values of the explanatory variables. According to Dunn & Smyth (2018), p. 252, the variance of $\widehat{\eta}$ is estimated as $\widehat{var[\widehat{\eta}]} = \widehat{var\left[\mathbf{X}_g \widehat{\beta}\right]} = \mathbf{X}_g (\mathbf{X}'\mathbf{W}\mathbf{X}) \mathbf{X}'_g \widehat{\phi}$ where $\mathbf{X}$ is the design matrix of the model, $\mathbf{W}$ is the diagonal matrix of working weights and ϕ is a dispersion parameter of the model that is estimated in the model estimation process.

The confidence interval in the linear predictor scale is then: $\widehat{\eta} \pm z_{\alpha/2} \sqrt{\widehat{var[\widehat{\eta}]}}$ where $z_{\alpha/2}$ is the corresponding percentile of the standard normal distribution. Now, as we are considering the log link function, g^{-1} is the exponential function and the 100(1-α) % interval for the response is

$$exp(\widehat{\eta}) \bullet exp\left(\pm z_{\alpha/2} \sqrt{\widehat{var[\widehat{\eta}]}} \right)$$

APPENDIX B. Variables considered

Table 8 includes a list of the variables included in the database, which were considered for the development of the model. The variables are related to location, age of the building, building typology, state, building systems, and dimensions. The variables included in the model are also specified.

Table 8
Database variables considered for the development of the model.

Type of variable	Variables in the final model	Variables dismissed in the final model
Location	Climate zone	City Winter severity climate Summer severity climate Simplified climate zone
Age of the building		Year of construction Period of construction Decades of construction Applied regulations
Type of building		Typology Position within the building Dwelling height Number of floors Property developer Number of rooms/bathrooms Layout of the floor plan
Building state	Improvement of the envelope Bathroom refurbishment	Retrofitting state Improvement of thermal bridges Identified cracks Closed balconies Integrated balconies Kitchen refurbishment
Building systems	Window permeability Window material Shutter position False ceiling Ductwork Kitchen Hood exhaust	Envelope layer composition Outer cladding Insulation of the envelope Air chamber Windows opening system Double window Shutter type Partitioning system Heating system Cooling system Ventilation system Adventitious openings
Dimensions	Envelope area Form Factor Share of windows Share of wet areas	Floor area Height Volume Share of opaque envelope Windows joint length Window area Share of joint length

Data availability

The authors do not have permission to share data. Data may be available under request.

References

[1] X. Zheng, E. Cooper, M. Gillott, C.J. Wood, A practical review of alternatives to the steady pressurisation method for determining building airtightness, Renew. Sustain. Energy Rev. 132 (2020) 110049, https://doi.org/10.1016/j.rser.2020.110049.

[2] J. Jokisalo, J. Kurnitski, M. Korpi, T. Kalamees, J. Vinha, Building leakage, infiltration, and energy performance analyses for finnish detached houses, Build. Environ. 44 (2009) 377–387, https://doi.org/10.1016/j.buildenv.2008.03.014.

[3] R. Simson, T. Rebane, M. Kiil, M. Thalfeldt, J. Kurnitski, The impact of infiltration on heating systems dimensioning in Estonian climate, in: 12th Nord, Symp. Build. Phys. (NSB 2020) (2020), https://doi.org/10.1051/e3sconf/202017205004.
[4] S. Domínguez-Amarillo, J. Fernández-Agüera, M.Á. Campano, I. Acosta, Effect of airtightness on thermal loads in legacy low-income housing, Energies 12 (2019) 1–14, https://doi.org/10.3390/en12091677.
[5] J. Huang, J. Hanford, F. Yang, Residential heating and cooling loads component analysis, Berkeley, USA, 1999 https://basc.pnnl.gov/library/residential-heating-and-cooling-loads-component-analysis.
[6] B. Jones, P. Das, Z. Chalabi, M. Davies, I. Hamilton, R. Lowe, A. Mavrogianni, D. Robinson, J. Taylor, Assessing uncertainty in housing stock infiltration rates and associated heat loss: English and UK case studies, Build. Environ. 92 (2015) 644–656, https://doi.org/10.1016/j.buildenv.2015.05.033.
[7] T. Kalamees, Air tightness and air leakages of new lightweight single-family detached houses in Estonia, Build. Environ. 42 (2007) 2369–2377, https://doi.org/10.1016/j.buildenv.2006.06.001.
[8] I. Poza-Casado, A. Meiss, M.Á. Padilla-Marcos, J. Feijó-Muñoz, Airtightness and energy impact of air infiltration in residential buildings in Spain, Int. J. Vent. (2020), https://doi.org/10.1080/14733315.2020.1777029.
[9] N. Hurel, V. Leprince, AIVC Technical Note 73 Overview of the trends in building and ductwork airtightness in 16 countries, 2024 https://www.aivc.org/news/overview-trends-building-and-ductwork-airtightness-16-countries.
[10] M. Ismaiel, M. Gouda, Y. Li, Y. Chen, Airtightness evaluation of Canadian dwellings and influencing factors based on measured data and predictive models, Indoor Built Environ. 32 (2023) 553–573, https://doi.org/10.1177/1420326X221121519.
[11] J. Mcwilliams, M. Jung, Development of a Mathematical Air-Leakage Model from Measured Data, 2006 https://escholarship.org/uc/item/4rm0j6hf.
[12] W.R. Chan, J. Joh, M.H. Sherman, Analysis of air leakage measurements of US houses, Energy Build. 66 (2013) 616–625, https://doi.org/10.1016/j.enbuild.2013.07.047.
[13] H. Krstić, Ž. Koški, I.I. Otković, M. Španić, Application of neural networks in predicting airtightness of residential units, Energy Build. 84 (2014) 160–168, https://doi.org/10.1016/j.enbuild.2014.08.007.
[14] C.N. Bramiana, A.G. Entrop, J.I.M. Halman, Relationships between Building Characteristics and Airtightness of Dutch Dwellings, Energy Procedia 96 (2016) 580–591, https://doi.org/10.1016/j.egypro.2016.09.103.
[15] W. Pan, Relationships between air-tightness and its influencing factors of post-2006 new-build dwellings in the UK, Build. Environ. 45 (2010) 2387–2399, https://doi.org/10.1016/j.buildenv.2010.04.011.
[16] B. Khemet, R. Richman, A univariate and multiple linear regression analysis on a national fan (de)Pressurization testing database to predict airtightness in houses, Build. Environ. 146 (2018) 88–97, https://doi.org/10.1016/j.buildenv.2018.09.030.
[17] J. Fernández-Agüera, S. Domínguez-Amarillo, J.J. Sendra, R. Suarez, Predictive models for airtightness in social housing in a Mediterranean region, Sustain. Cities Soc. 51 (2019) 101695, https://doi.org/10.1016/j.scs.2019.101695.
[18] M.I. Montoya, E. Pastor, F.R. Carrié, G. Guyot, E. Planas, Air leakage in Catalan dwellings: developing an airtightness model and leakage airflow predictions, Build. Environ. 45 (2010) 1458–1469, https://doi.org/10.1016/j.buildenv.2009.12.009.
[19] J. Fernández-Agüera, S. Domínguez-Amarillo, J.J. Sendra, R. Suárez, An approach to modelling envelope airtightness in multi-family social housing in Mediterranean Europe based on the situation in Spain, Energy Build. 128 (2016) 236–253, https://doi.org/10.1016/j.enbuild.2016.06.074.
[20] I. Poza-Casado, P. Rodríguez-del-Tío, M. Fernández-Temprano, M.-Á. Padilla-Marcos, A. Meiss, An envelope airtightness predictive model for residential buildings in Spain, Build. Environ. 223 (2022) 109435, https://doi.org/10.1016/j.buildenv.2022.109435.
[21] M. Prignon, G. Van Moeseke, Factors influencing airtightness and airtightness predictive models: a literature review, Energy Build. 146 (2017) 87–97, https://doi.org/10.1016/j.enbuild.2017.04.062.
[22] B. Moujalled, B. Kölsch, A. Mélois, V. Leprince, Quantitative correlation between buildings air permeability indicators: Statistical analyses of over 400,000 measurements, Energy Build. 298 (2023) 113566, https://doi.org/10.1016/j.enbuild.2023.113566.
[23] I. Poza-Casado, V.E.M. Cardoso, R.M.S.F. Almeida, A. Meiss, N.M.M. Ramos, M.Á. Padilla-Marcos, Residential buildings airtightness frameworks: a review on the main databases and setups in Europe and North America, Build. Environ. 183 (2020) 107221, https://doi.org/10.1016/j.buildenv.2020.107221.
[24] J. Laverge, M. Delghust, N. Van Den Bossche, A. Janssens, Airtightness Assessment of Single Family Houses in Belgium, Int. J. Vent. 12 (2014) 379–390, https://doi.org/10.1080/14733315.2014.11684031.
[25] R.M.S.F. Almeida, N.M.M. Ramos, P.F. Pereira, A contribution for the quantification of the influence of windows on the airtightness of southern European buildings, Energy Build. 139 (2017) 174–185, https://doi.org/10.1016/j.enbuild.2017.01.012.
[26] I. Poza-Casado, P. Rodríguez-del-Tío, M. Fernández-Temprano, M.Á. Padilla-Marcos, A. Meiss, Airtightness predictive model from measured data of residential buildings in Spain, 2023 https://www.aivc.org/resource/airtightness-predictive-model-measured-data-residential-buildings-spain.
[27] R.H. Myers, D.C. Montgomery, G.G. Vining, T.J. Robinson, Generalized Linear Models, Wiley (2010), https://doi.org/10.1002/9780470556986.
[28] J.A. Nelder, R.W.M. Wedderburn, Generalized Linear Models, J. R. Stat. Soc. Ser. A 135 (1972) 370, https://doi.org/10.2307/2344614.
[29] P. McCullagh, J.A. Nelder, Generalized Linear Models, 2nd ed., Routledge, 1989. https://doi.org/10.1201/9780203753736.
[30] A. Agresti, Foundations of Linear and Generalized Linear Models, John Wiley Sons, INC., 2015, p. 473, https://www.wiley.com/Foundations+of+Linear+and+Generalized+Linear+Models-p-9781118730034 (accessed November 17, 2025).
[31] R.B. D'Agostino, M.A. Stephens, Goodness-of-Fit Techniques, Routledge (1986), https://doi.org/10.1201/9780203753064.
[32] P.K. Dunn, G.K. Smyth, Generalized Linear Models with examples in R, Springer New York, New York, NY (2018), https://doi.org/10.1007/978-1-4419-0118-7.
[33] H. Akaike, A New Look at the Statistical Model Identification, in: Springer, New York, NY, 1974: pp. 215–222. https://doi.org/10.1007/978-1-4612-1694-0_16.
[34] G. Schwarz, Estimating the Dimension of a Model, Ann. Stat. 6 (1978) 461–464, https://www.jstor.org/stable/2958889.
[35] D.M. Allen, The Relationship between Variable selection and Data Agumentation and a Method for Prediction, Technometrics 16 (1974) 125–127, https://doi.org/10.1080/00401706.1974.10489157.
[36] M. Stone, Cross-Validatory Choice and Assessment of Statistical predictions, J. R. Stat. Soc. Ser. B 36 (1974) 111–133, https://doi.org/10.1111/J.2517-6161.1974.TB00994.X.
[37] S. Geisser, The Predictive Sample Reuse Method with applications, J. Am. Stat. Assoc. 70 (1975) 320–328, https://doi.org/10.1080/01621459.1975.10479865.
[38] D. Krstajic, L.J. Buturovic, D.E. Leahy, S. Thomas, Cross-validation pitfalls when selecting and assessing regression and classification models, J. Cheminform. 6 (2014) 1–15, https://doi.org/10.1186/1758-2946-6-10/FIGURES/16.
[39] ISO, ISO 9972. Thermal performance of buildings. Determination of air permeability of buildings. Fan pressurization method (ISO 9972:2015), (2015). https://www.iso.org/standard/55718.html.
[40] Fomento. Ministerio de, Gobierno de España, Documento descriptivo climas referencia, Spain, 2017. https://www.codigotecnico.org/pdf/Documentos/HE/20170202-DOC-DB-HE-0-Climas%20de%20referencia.pdf.
[41] Agencia Estatal de Meteorología (AEMET), Atlas climático ibérico (Iberian climate atlas), Ministerio De Medio Ambiente y Medio Rural y Marino De España, 2011.
[42] F. Filippidou, J.P. Jimenez Navarro, Achieving the cost-effective energy transformation of Europe's buildings, 2019. https://doi.org/10.2760/278207.
[43] Ministerio de, Transportes Movilidad y Agenda Urbana, ERESEE 2020. Update of the long-term Strategy for Energy Rehabilitation in the Building Sector in Spain, 2020. https://cdn.mitma.gob.es/portal-web-drupal/ERESSE/ERESEE_2020version_ingles.pdf.
[44] J. Fernández-Agüera, S. Domínguez-Amarillo, C. Alonso, F. Martín-Consuegra, Thermal comfort and indoor air quality in low-income housing in Spain: the influence of airtightness and occupant behaviour, Energy Build. 199 (2019) 102–114, https://doi.org/10.1016/j.enbuild.2019.06.052.
[45] T. Blázquez, R. Suárez, S. Ferrari, J.J. Sendra, Improving winter thermal comfort in Mediterranean buildings upgrading the envelope: an adaptive assessment based on a real survey, Energy Build. 278 (2023) 112615, https://doi.org/10.1016/j.enbuild.2022.112615.
[46] European Committee for Standardization, EN 12207:2016. Windows and doors - Air permeability - Classification, (2016).
[47] J.L. Weidt, J. Weidt, S.E. Selkowitz, Field Air Leakage of newly Installed Residential Windows | Smarter small buildings, accessed January 10, 2025, ASHRAE Trans. 85 (1979), https://www.aivc.org/sites/default/files/members_area/medias/pdf/Airbase/airbase_00458.pdf.
[48] Ministerio de Vivienda y Agenda Urbana. Gobierno de España, Código técnico de la Edificación (CTE). Documento básico HE: Ahorro de energía, 2022. https://www.codigotecnico.org.
[49] A. González Cáceres, C. Recart, R. Espinoza, A. Bobadilla, Simple Tool to Evaluate Airtightness in Chilean Homes, Sustainability 8 (2016), https://doi.org/10.3390/su8101000.
[50] Existent Experiences in Spain (2011). http://episcope.eu/fileadmin/tabula/public/docs/scientific/ES_TABULA_Report_IVE.pdf.
[51] N. Martí, R. Araujo, R. Araujo, La persiana enrollable, Revisión del sistema constructivo y sus requisitos medioambientales, Inf. La Construcción. 67 (2015) e113, https://doi.org/10.3989/ic.14.069.
[52] M. Roca-Musach, E. Garcia-Nevado, C. Alonso-Montolio, I. Crespo-Cabillo, H. Coch-Roura, Comparison of the Thermal Effect of Two Automatic Controls of Roller Shutters in an Academic Space, Smart Innov. Syst. Technol. 336 SIST (2023) 261–270, https://doi.org/10.1007/978-981-19-8769-4_25.
[53] F. d'Ambrosio Alfano, M. Dell'Isola, G. Ficco, F. Tassini, Experimental analysis of air tightness in Mediterranean buildings using the fan pressurization method, Build. Environ. 53 (2012) 16–25, https://doi.org/10.1016/j.buildenv.2011.12.017.
[54] E. Prieto González, La cultura del bienestar. Poéticas del confort en la arquitectura de los siglos XIX y XX, Cuad. Proy. Arquit. (2013) 22–31. https://polired.upm.es/index.php/proyectos_arquitectonicos/article/view/2003.
[55] D.J. Dickerhoff, D.T. Grimsrud, R.D. Lipschutz, Component Leakage Testing in Residential Buildings, (1982). http://escholarship.org/uc/item/03q2t8d3#page-18.
[56] M.P. Modera, Residential duct system leakage: magnitude, impacts and potential for reduction, Prepr. Ashrae Trans. 95 (1989) 9, https://www.aivc.org/resource/residential-duct-system-leakage-magnitude-impacts-and-potential-reduction.
[57] Ministerio de Vivienda. Gobierno de España, Código técnico de la Edificación (CTE). Documento básico HS 3: Calidad del aire interior, Spain, 2006. https://www.codigotecnico.org/index.php/menu-salubridad.html.
[58] B. Kölsch, A. Mélois, V. Leprince, Improvement of the ISO 9972: proposal for a more reliable standard to measure air leakage rate using fan pressurisation method, in: 13th Int. BUILDAIR Symp., Hannover, Germany, 2023. https://www.researchgate.net/publication/371732492_Improvement_of_the_ISO_9972_proposal_for_a_

more_reliable_standard_to_measure_air_leakage_rate_using_fan_pressurization_method.

[59] S. Caillou, N. Van Den Bossche, C. Delmotte, D. Van Orshoven, L. Vandaele. Measurement of Building Airtightness in the EPB Context: specific Procedure and sources of Uncertainties, in Build. Phys. Symp. (2008) 29–31.

[60] Ministerio de, Vivienda y Agenda Urbana. Gobierno de España, Código técnico de la Edificación (CTE). Documento básico HE 1: Limitación de la demanda energética.

[61] L. Van Gelder, M. De Strycker, C. Delmotte, J. Arnold, Trends in building and ductwork airtightness in Belgium, Vent. Inf. Pap. AIVC. 48.1 (2024) 1–17. https://www.aivc.org/resource/vip-481-trends-building-ventilation-requirements-and-inspection-spain?volume=33977.

[62] AFNOR, FD P50-784:2016 - Guide d'application de la norme NF EN ISO 9972, 2016.

[63] J. Fernández-Agüera, S. Domínguez-Amarillo, M.Á. Campano, Characterising Draught in Mediterranean Multifamily Housing, Sustainability 11 (2019) 2433, https://doi.org/10.3390/su11082433.

[64] D.T. Harrje, G. Born, Cataloguing air leakage components in houses, Proc. Am. Counc. an Energy-Efficient Econ. Summer Study Energy Effic. Build. (1982). https://www.aivc.org/resource/cataloguing-air-leakage-components-houses.

[65] H. Krstić, I.I. Otković, P. Kosiński, R. Wójcik, Validation of neural network model for predicting airtightness of residential and non-residential units in Poland, Energy Build. 133 (2016) 423–432, https://doi.org/10.1016/j.enbuild.2016.10.011.

[66] J. Faraway, G. Marsaglia, J. Marsaglia, A. Baddeley, goftest: Classical Goodness-of-Fit Tests for Univariate Distributions, CRAN Contrib. Packag. (2021). https://doi.org/10.32614/CRAN.package.goftest.

[67] J. Fox, G. Monette, cv: Cross-Validating Regression Models, CRAN Contrib. Packag. (2024). https://doi.org/10.32614/CRAN.package.cv.

[68] S. Jackman, pscl: Classes and Methods for R Developed in the Political Science Computational Laboratory, (2024). https://github.com/atahk/pscl/.

[69] J. Fernández-Agüera. Caracterización de la estanqueidad al aire de la vivienda social en Andalucía, Universidad de Sevilla, 2018 https://hdl.handle.net/11441/77154.

[70] Z. He, Generative Adversarial Network for Optimizing Air Flow and Particulate Dissipation in Buildings, in: 2024 IEEE MIT Undergrad. Res. Technol. Conf., IEEE, 2024: pp. 1–5. https://doi.org/10.1109/URTC65039.2024.10937621.

[71] X. Hu, H. Zhang, D. Ma, R. Wang, Hierarchical pressure Data Recovery for Pipeline Network via Generative Adversarial Networks, IEEE Trans. Autom. Sci. Eng. 19 (2022) 1960–1970, https://doi.org/10.1109/TASE.2021.3069003.

[72] X. Hu, H. Zhang, D. Ma, R. Wang, A tnGAN-based Leak Detection Method for Pipeline Network considering Incomplete Sensor Data, IEEE Trans. Instrum. Meas. 70 (2021) 1–10, https://doi.org/10.1109/TIM.2020.3045843.