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Comfort reliability evaluation of building designs by stochastic hygrothermal simulation

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ABSTRACT

Outdoor climate jointly with architectonic design, housing materials, and construction system determine thermal performance of buildings and their ability to deliver comfortable conditions to occupants. Buildings must provide comfortable indoor environment which should be reasonably assured regardless of outdoor weather fluctuations. This paper presents a methodology for quantitatively measuring the hygrothermal discomfort risk of any building design. By combining a numeric model of the building hygrothermal response with stochastic simulation techniques, occurrence probability, expected frequency and duration of discomfort events in each thermal zone can be estimated. The article presents fundamental notions on probabilistic hygrothermal risk assessment, describes the developed numerical simulation models and introduces comfort reliability indexes. In order to illustrate the practicability of the proposed approach in the context of the design process, the methodology was applied to a prototype of a residential house conventionally built and acclimatized. The materials and construction system reflect typical residential housing in the region of study. A bioclimatic variant of the same building design is also evaluated. Monte Carlo simulations of the building's thermal response under stochastic weather conditions allow identifying infrequent but critical situations in which the building is unable to meet comfort requirements. Statistical analysis of simulation results is performed and condensed in meaningful probabilistic indices for objectively measuring comfort reliability. By means of these metrics, shortcoming of the architectonic design can be revealed and properly amended. In addition, comfort reliability and risk indices facilitate the comparison of alternative thermal building designs on a fair basis. The proposed methodology and the developed models are general and they can be applied without constraints to any building design under a wide variety of climates.

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1. Introduction

Buildings are intensive energy consumers in all countries, mainly due to the operation of HVAC equipment [1]. For instance, in Argentina buildings represent 40% of the overall energy consumption of the country, 90% of which is supplied from non-renewable sources [2]. Residential and commercial buildings account for almost 39 percent of total U.S. energy consumption and 38 percent of U.S. carbon dioxide (CO_2) emissions [3]. Nearly all of the greenhouse gas (GHG) emissions from the residential and commercial sectors can be attributed to energy use in buildings for HVAC purposes [3]. The energy consumption for heating and cooling can be reduced principally through the correct morphologic design, favorable orientation and appropriate selection of building envelopes and their components [4]. The implementation of bioclimatic strategies in thermal building design aims at maintaining comfortable indoor conditions as much time as possible while minimizing conventional energy consumption [5].

Over the course of years, a wide variety of conceptual approaches to the thermal design of buildings have been developed. They range from simple design rules to sophisticated numerical models of the building thermal performance.

In practice, the conventional approach to thermal building design is to comply with energy efficiency guidelines and rules contained in applicable construction norms, certification standards, rating systems and building codes [6–10]. Besides standards, norms and codes, bioclimatic design guidelines and recommendations for passive design strategies have been developed based on extensive experience and empirical data [5,11]. However, strict compliance with building codes or bioclimatic design guidelines does not ensure that indoor comfort conditions are consistently achieved with elevated probability in any specific case.

Simple approximate tools to verify thermal performance in early stages of building design have been proposed. Usually, these approaches are mainly based on simplified heat balance calculations [12]. Approaches such as heat degree-day, sol-temperature method, admittance modeling and graphical methods based on psychrometric charts are widely used by practitioners [11–15]. Though useful, these methods are only rough simplifications of physical reality and approximate results are obtained. Unfortunately, the predictive value and accuracy of such tools exceedingly depend on the specific setting as often the underlying assumptions on which they are based do not hold. In addition, these approaches commonly demand highly skilled and experienced designer to judge obtained results.

With the advance in computation technology, chronological simulation models of the thermal building behavior are now readily available and are of widespread use to verify thermal performance of buildings. Some models rests on stating the set of linear differential equations that governs the steady-state thermal dynamic behavior of buildings. An example of this modeling approach is the well-known Transfer Function Method (TFM) [16]. The equation systems are solved by analytical or numerical techniques, e.g. Laplace Transform in continuous time, or Z-Transform in discrete time. Because of the linear properties, very efficient numerical methods can be applied for speeding solutions. However, steady-state and linear assumptions often turn these models inadequate to replicate the thermal dynamics of complex buildings [17]. Furthermore, most modeling approaches assume important simplifications of coupled heat-moisture dynamic phenomena, which are particularly relevant to thermal comfort design.

Presently, models based on computational fluid dynamics (CFD) are increasingly used to overcome limitations of simpler steady-state dynamic models [18]. CFD models formulate the non-linear coupled partial differential equations of mass (Navier–Stokes) and heat flows, which are solved by discrete numerical techniques such as the finite difference method (FDM) or the finite element method (FEM). These models allow for an accurate tri-dimensional description of the thermal transient dynamics in complex geometries. The main drawback of this approach is the vast requirement of computational resources for solving the CFD problem [19].

Most building modeling approaches are deterministic neglecting important sources of uncertainty and their impact on building performance. In fact, a reference or average weather dataset is typically used in simulation models to verify the thermal response of buildings [20]. The Typical Meteorological Year (TMY) is widely used in building thermal simulations as single representative weather time series for long-term energy consumption analysis [21].

However, buildings are pervasively subject to changing meteorological conditions, which frequently significantly depart from the reference climate. Weather variability is stochastic in its very nature and introduces considerable uncertainty in the resulting hygrothermal indoor conditions as well as in the effectiveness of many bioclimatic strategies [22]. Buildings have to reliably preserve indoor comfort regardless of adverse outdoor meteorological events. The problem with many bioclimatic designs is the high dependence of thermal performance on fluctuating weather conditions with the consequent introduction of uncertainty in building behavior. For example, in the use of solar heating, availability of solar radiation and demand for heating are negatively correlated. As consequence, there exists the risk that available solar energy cannot meet the heating demand when needed the most.

Therefore, one of the questions that arises within the bioclimatic design process is how reliable and effective are the bioclimatic strategies for ensuring required comfort conditions under fluctuating and random climatic events, both in terms of severity and duration. Throughout time, there have been many attempts to include uncertainty and stochastic variables, especially meteorological, in hygrothermal building simulations [23]. For instance, Bzowska [24] calculates the mean value and the standard deviation of indoor temperatures with a simple two-node simulation model. This methodology proposes the superposition of deterministic and stochastic components of outdoor climate variables for simulating buildings. In [25], a standard thermal model is combined with Monte Carlo simulation techniques to find the probability distribution of indoor temperatures. Statistical independence of outdoor temperature and solar radiation was assumed to estimate the distribution. Pietrzyk [26] develops an analytic probabilistic model for modeling air infiltration and heat loss in houses. The work emphasizes the importance of considering reliability in the thermal building design.

However, it analyzes the stochastic building behavior without considering the chronology of events, which in turn ignores autocorrelation and serial dependency of meteorological changes. In addition, relevant temporally coupled phenomena, such as the thermal inertia in the thermodynamics of constructions, are disregarded in this fairly simple analytical model. Although analytical reliability models are computationally very efficient, restrictive assumptions and important simplifications are often required to obtain workable solutions. In comparison, simulation models based on Monte Carlo techniques normally allow a very detailed description of reality. However, they have the disadvantage of being expensive in computational calculations [27].

The present paper proposes a new methodology to evaluate the hygrothermal reliability of any building design [28]. By means of a numeric model of the building hygrothermal response and stochastic simulation techniques, expected frequency and duration of discomfort events in each building room can be estimated. This probabilistic analysis allows measuring the ability of the building design to consistently perform as required. Probabilistic metrics enable the proper assessment and comparison of the thermal performance of various design alternatives on the same basis. Furthermore, risk analysis also allows minimizing the overall building costs without deteriorating building's comfort reliability. Proper sizing of HVAC equipment capacity and building insulation is facilitated if hygrothermal risk can be objectively measured.

The reminder of the paper is organized as follows: First, fundamental concepts on thermal reliability evaluation and discomfort risk assessment of buildings are introduced in Section 2. Next, in Section 3, probabilistic reliability indices and discomfort risk metrics for statistically measuring the building thermal performance under critical weather are presented. Necessary numerical models for stochastic hygrothermal simulation are described in Section 4. In Section 5, the practicability of the proposed methodology is illustrated in an exemplary residential dwelling. Finally, concluding remarks on implications of the probabilistic approach to thermal building design as well as avenues for further research are provided in Section 6.

2. Hygrothermal comfort reliability and discomfort risk

Risk assessment and reliability design is an engineering approach widely used for solving system design problems in other fields in which the performed function is important, such as nuclear facilities [29], aerospace [30] and automobile [31] industry, building structures [32], powers systems [33], etc. In this paper, an extension of the reliability-based design approach to the hygrothemal building design is developed.

In reliability engineering, the term reliability is a probabilistic notion and is defined as the ability of a component or system to properly perform its required function [34]. In our setting, the primary function that buildings must perform is to serve as shelter

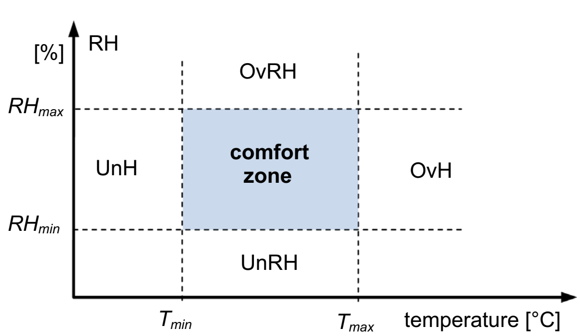

Fig. 1. Target hygrothermal region of human comfort.

from weather to their occupants. Under severe weather, when shelter is needed the most, the proper accomplishment of this function is critical. Under these unfavorable circumstances, buildings are required to behave reliably.

In the context of this work, the Hygrothermal Comfort Reliability (HCR) of a building is defined as the capability of an architectonic design, whether conventional, bioclimatic or hybrid, to maintain prescribed hygrothermal comfort indoor conditions in the presence of random outdoor climate fluctuations. Comfort reliability is therefore the probability that the building preserves hygrothermal indoor conditions within prescribed conditions of human comfort. Contrary, the discomfort risk is the opposite concept and can be defined is the probability of a loss of comfort event. Hygrothermal risk can be stated either in term of an expected cumulated discomfort time or as an expected frequency and duration of discomfort events.

The probability that a building satisfies certain hygrothermal requirements will depend on both, the characteristics (severity) of the local climate and the building thermal design itself. Of both factors, only the latter can be controlled by the designer. Reliability of the building thermal behavior under critical outdoor conditions can be changed by design parameters, such as building topology and morphology, orientation, solar captation surface, constructive materials, fenestration and HVAC installed capacity.

The designer and/or the building user must establish the minimum acceptable comfort reliability level, i.e. the maximum probability of loss of thermal comfort her/he is willing to accept. If the comfort reliability level is set too low, occupants may often suffer uncomfortable conditions when severe weather events happen. On the contrary, if users demand high comfort reliability, i.e. a low discomfort risk, robustness of the thermal design must be enhanced by increasing overall building costs. Therefore, the minimum acceptable reliability level must also be carefully selected in order to avoid adversely affecting the economy of the building.

The desired interval in which indoor conditions can fluctuate have also a significant impact on the probability that the building satisfies the imposed comfort requirement. If indoor conditions are required to be kept unchanged irrespective of meteorological conditions, substantial investment in thermal isolation and/or HVAC equipment will be needed. Hence, the acceptable comfort region must be established cautiously according to the purpose and use of the building (for example: house, office, hospital, museum, library, archive, wine cellar, warehouse, etc.). Depending on the function of each building area and the amount of physical activity typically involved, different acceptable comfort region for each room (e.g. bedroom, reading room, gym, cellar, intensive care room, etc.) may be necessary.

Hygrothermal comfort is a notion that intrinsically accounts for human sense of well-being. In fact, thermal comfort is defined as “the condition of mind that expresses satisfaction with the thermal environment and is assessed by subjective evaluation” [35]. Hygrothermal comfort not only depends on environmental (physical) factors, such as room temperature, relative humidity and air speed, but also on personal factors, such as metabolic rate, clothing type, and to a lesser extent, gender and thermal sensitivity.

For the selection of the hygrothermal comfort region, in this work we use the ASHRAE Standard 55 for which 75% of the population feels comfortable [36]. In practical applications, the ASHRAE Standard 55 is likely the most used comfort criterion. It has been developed based on extensive experimentation in controlled chambers on the subjective thermal sensation of individuals surveyed regarding environmental satisfaction. The comfort region defined by this Standard is constrained by threshold values on temperature and relative humidity, assuming typical values for other environmental and personal parameters (air speed, cloth insulation and metabolic rate). This sets therefore a simple two-dimensional region for assessing the compliance of a given thermal design, which is schematically illustrated in Fig. 1.

Mathematically, the bi-dimensional comfort region is defined by the following two interval inequalities:

$$\text{Condition 1 } (C_1): T_{\min} \le T \le T_{\max} \tag{1}$$

$$\text{Condition 2 } (C_2): RH_{\min} \le RH \le RH_{\max} \tag{2}$$

where the threshold values for temperature are $T_{\min}=19\,^{\circ}\mathrm{C}$ and $T_{\max}=26\,^{\circ}\mathrm{C}$ respectively, and those for relative humidity are $RH_{\min}=30\%$ and $RH_{\max}=70\%$. These parameters define a rectangular area, which is regarded to be a sufficiently broad comfort region. The proposed methodology to assess the building's comfort reliability does not restrict or preclude the use of other values o more sophisticated, multidimensional comfort models.

In addition to the four-sided comfort region depicted in light blue in Fig. 1, the temperature – humidity plane is divided in eight well-defined areas. There are four zones where only one environmental variable is outside the specified limits. These areas (quadrants) are referred in Fig. 1 as Over Heating (OvH), Under Heating (UnH), Over Relative Humidity (OvRH), and Under Relative Humidity (UnRH). In the remaining four areas, simultaneous violations of comfort temperature and relative humidity boundaries take place.

3. Hygrothermal reliability and risk indices

In order to provide a quantitative description of the thermal reliability and the discomfort risk of a building design, a set of probabilistic indicators are developed. These metrics are a convenient way to summarize the statistical hygothermal behavior under critical conditions. The reliability index HCR is normally expressed as a probability in [%], but it can also be given in terms of the expected annual cumulated time, i.e. average hours per annum [h/a], the building satisfies prescribed conditions of hygrothermal comfort.

Sometimes, it is convenient to use the complementary concept of Hygrothermal Discomfort Risk (HDR), defined as the probability that the building is unable to keep indoor conditions within a pre-established comfort region. The risk index HDR is the loss of comfort probability, and as such, it can be expressed as a percentage, or alternatively in terms of a cumulated Expected Discomfort Duration (EDD) per unit period, e.g. in hours per annum [h/a].

Since the building's indoor hygrothermal states can only be assembled in two mutually exclusive states – comfortable or uncomfortable – the HDR index is determined according to the complementary identity:

$$\mathrm{HCR}+\mathrm{HDR}=1 \tag{3}$$

The hygrothermal comfort reliability of a building design can be mathematically expressed as the joint probability that both, the indoor temperature T and the relative humidity RH, at any time h, simultaneously reside within a targeted comfort region delimited by Condition 1 and Condition 2. Mathematically, that is:

$$\mathrm{HCR}=\Pr(T_h \in C_1) \wedge \Pr(\mathrm{RH}_h \in C_2) \tag{4}$$

This probabilistic index can be computed for either, the building as a whole or for each thermal zone individually. The probability HCR can be statistically estimated from stochastic simulations of the thermal building behavior under a sample of R independent chronological realizations of weather, spanning H hours each, as:

$$H\hat{C}R=\frac{1}{N}\sum_{r=1}^{R}\sum_{h=1}^{H}x_h^{(r)} \tag{5}$$

where N is the sample size calculated as N=HR and x is a binary variable that, for the h-th hour and the r-th realization, take values according to the following conditions:

$$x_h^{(r)}=\begin{cases}1 & if\ T_{\min}\le T_h^{(r)}\le T_{\max}\ \wedge\ \mathrm{RH}_{\min}\le \mathrm{RH}_h^{(r)}\le \mathrm{RH}_{\max}\\ 0 & \text{otherwise}\end{cases} \tag{6}$$

The sampled chronological hygrothermal room conditions obtained from the stochastic simulations can be plotted in the temperature – relative humidity (T – RH) plane along with the desired comfort region, as is schematically illustrated in Fig. 2. The HCR index can be interpreted as the ratio of the number of sampled points laying within the comfort region to the total sample size. Analogously, the quotient between the number of points outside this area and the total sampled points is the estimated discomfort risk (HDR). The statistical accuracy of estimations is higher as the number of points increases. This notion sets the basis of the Monte Carlo method for numerically evaluating thermal reliability and discomfort risk.

Although the HDR index objectively measures the occurrence probability of discomfort events, the index itself does not say anything about the magnitude of deviations from the boundaries of the desired comfort region. Therefore, it is appropriate to use the HDR index in conjunction with complementary reliability indicators.

The expected value of indoor temperature and relative humidity during discomfort events are suitable probabilistic parameters to measure the magnitude of such deviations (violations) from the limits of the set comfort region. These indices are called the Expected Over- and Under Heating, denoted as E[OvH] and E [UnH] respectively. The expected value of the overheating and the under-heating temperature can be estimated as the average temperature prevailing during the sampled overheating and under-heating events. Similarly, the expected value of the relative humidity when over and sub-humidification occurs are denoted as E[OvRH] and E[UnRH] respectively and are calculated analogously.

Two further meaningful and complementary indices for providing a whole characterization of the reliability level and the hygrothermal risk of a certain architectonic design are: (1) the Expected Loss of Comfort Frequency (ELCF), expressed, for example, as per year occurrences [a^{-1}], and (2) the Expected Duration of Discomfort Events (EDDE), measured in [h].

The ELCF is the mean number of discomfort events per time period, e.g. one year, calculated over the simulated sample. The expected duration of discomfort events EDDE can be estimated as the average duration of discomfort events sampled in the Monte Carlo simulation. The mean frequency of discomfort events (ELCF), the expected duration of discomfort events (EDDE) and the

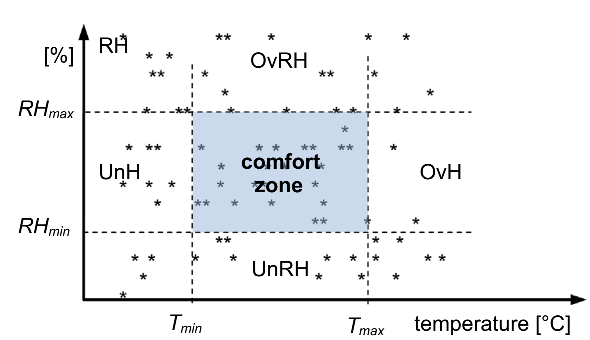

Fig. 2. Sampled indoor hygrothermal conditions and targeted comfort zone.

cumulated expected discomfort duration (EDD) relates as follows:

$$\text{EDD} = \text{ELCF} \times \text{EDDE} \tag{7}$$

From Eq. (7) follows that different combinations of occurrence frequency and duration of discomfort events yield the same hygrothermal risk. Therefore, for the same expected total discomfort duration EDD (or, equivalently for the same discomfort risk HDR) the designer might decide if on average it is preferable accepting a greater number of discomfort events but of shorter expected duration, or accepting fewer but longer discomfort periods (such as 2 or 3 continuous days). The decision criteria will highly depend on subjective considerations as well as the purpose and function of the building under study. Expected frequency and duration of discomfort events relates to the building's comfort reliability level HCR by multiplying Eq. (3) by the period basis H, e.g. one year, expressed in [h] and replacing Eq. (7) in Eq. (3), as follows:

$$\text{HCR} \times H + \text{HDR} \times H = H \tag{8}$$

$$\text{HCR} \times H + \text{EDD} = H \tag{9}$$

$$\text{HCR} \times H + \text{ELCF} \times \text{EDDE} = H \tag{10}$$

$$\text{HCR} = 1 - \frac{1}{\text{H}}(\text{ELCF} \times \text{EDDE}) \tag{11}$$

The indices of expected frequency and duration of loss of comfort events can be further disaggregated in eight specific indices to indicate the cause of occurrence and the deviating direction regarding each limit of the defined comfort zone. Therefore, there will be in total a set of four individual indices of the mean frequency for the violation of upper and lower limits of temperature and relative humidity. Similarly, the expected durations of discomfort events occurring in the OvH, UnH, OvRH, and UnRH quadrants also define a set of four separate indices.

Each of these reliability and risk indices can be estimated for the whole year or for a specific time period of interest, e.g. a season, individual months or certain hours of the day. The disaggregation by time and/or quadrant of the proposed probabilistic indices provides relevant information about the type and cause of comfort reliability problems in the building design. Thereby, this disaggregation facilitates the identification of solutions in the design optimization process.

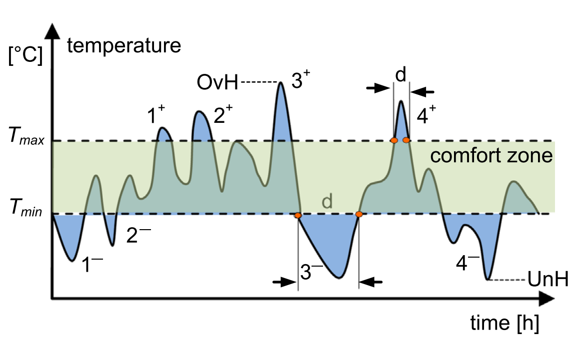

Fig. 3. Graphical representation of temperature violations of the comfort interval. Discomfort events are numbered according to the chronological occurrence. The signs (+) and (−) indicate overheating and low-temperature events.

The rationale behind these probabilistic indices and the way they are calculated in the context of stochastic simulations of building thermal performance is illustrated in Fig. 3. For a few days, this figure schematically depicts the indoor time-varying temperature in a thermal zone. Though the prevailing air temperature mostly resides within the allowable comfort interval, there are short periods in which indoor conditions violates the established temperature limits, causing uncomfortable situations to occupants. The diagram shows the existence of intervals in which either, the upper temperature limit is exceeded due to overheating, or the room temperature is colder than the minimum acceptable limit. At those times, a thermal discomfort event takes place whose duration is d and its deviation magnitude from the comfort temperature limits are denoted by OvH and UnH, for the cases of overheating or under-heating respectively.

3.1. Definition of comfort reliability requirements

Depending on purpose and function of the building under design, the reliability requirement to maintain indoor environment within specified hygrothermal conditions may be highly different. As risk and building economics are inversely related and must be traded off, the maximum discomfort risk the designer and/or the user is willing to accept will also depend on subjective preferences and risk aversion. In fact, the number y duration of expected discomfort events may be reduced at the expense of increasing initial investments (more thermal isolation, larger HVAC equipment, etc.) and/or incurring in higher energy costs for acclimatization during the building's service lifetime.

After extensive experimentation with a variety of house designs and a survey of user preferences we suggest in Table 1 threshold values for most reliability and risk indices developed in the previous section. This reliability and risk values were considered as design criteria in the exemplary building assessed in Section 5. In those cases in which there is a continued use of the building, the guiding criteria would impose a high reliability requirement, do not deviate much from the comfort limits and reasonably avoid the likely occurrence of discomfort events of long duration.

For instance, the minimum comfort reliability level is suggested to be HCR=0.95. This requirement means that the building must provide hygrothermal conditions to its occupants within the targeted comfort region with a probability of 95%. On average, the building will therefore perform its function according to the comfort constraints 95% of the time, or 8322 h per annum. Equivalently, the user can express the requirement in terms of the maximum acceptable loss of comfort probability by imposing a maximum discomfort risk of HDR=0.05. This risk level implies accepting an annual expected discomfort duration of EDD=438 h.

Due to the continued use of the house, it might be possible to admit several discomfort events but of short duration. If a 5% probability is set as the maximum acceptable hygrothermal risk and we admit a mean frequency of discomfort events (ELCF) of 75 events per year, by applying Eq. (7) the expected duration of each discomfort occurrence is 5.84 h. If expected discomfort frequency and/or duration are regarded too high for the function of the building under study, a higher comfort reliability level must be established, for instance a HCR index equal to 99%.

Table 1
Suggested threshold values of comfort reliability and risk indices for a residential house.

Interval	HCR (%)	HDR (%)	EDD (h/a)	EDDE (h)	ELCF (1/a)	EUnH (°C)	EOvH (°C)	EUnRH (%)	EOvRH (%)
Min	95	0	0	0	0	18.9	26.1	29	71
Max	100	5	438	5.84	75	15.9	29.1	20	80

4. Stochastic hygrothermal simulation model

In order to identify and sample possible occurrences of discomfort events in a building design that will be exposed to uncertain weather conditions, a chronological numerical model of the indoor hygrothermal dynamics under stochastic meteorological fluctuations is needed.

The thermal building model must properly reproduce thermodynamics phenomena such as heat transfer (conduction, convection, and radiation) and mass transport (ventilation and people traffic). Moreover, the simulation model must account for heat accumulation in the building mass (thermal inertia), which dampens the influence of outdoor weather fluctuations on room conditions and originates temporal coupling between adjacent time intervals. Ideally, the model should also consider both, the dependence of relative humidity on room temperature, and the cyclical phenomenon of accumulation and release of moisture stored in hygroscopic materials such as furniture, curtains, wood, papers, etc.

Due to its open source design, the HAMBASE building simulation model has been selected for this study. HAMBASE [37] is a multi-zone coupled heat and moisture chronological numerical model of the hygrothermal building behavior, which has been developed and coded in Matlab.[1] Besides hourly weather data, building features such as: number of rooms, morphology, volume, orientation, materials, fenestration, and glazing can be entered as input data. Capacity and control settings of heating and cooling equipment are also data considered in simulations. Thermal loads due to occupants, ventilation and use patterns can also be accounted for. Time series of hourly room temperature and relative humidity in each thermal zone, as well as energy consumption for heating and cooling can be obtained as a result of chronological hygrothermal simulations.

For a given thermal design, occurrence number, duration, and magnitude of discomfort events will depend on the particular meteorological year used as input data in the simulation. If the weather time series used as input corresponds to a mild year, few, in any, discomfort events will be sampled in the simulation. On the contrary, an uneconomical thermal design will likely arise if building is designed to withstand the most severe meteorological year in records. Instead of using a single weather realization, an ensemble with a large number of sample meteorological years must be considered order to obtain statistically meaningful results. This allows exploring the building's thermal behavior under infrequent but severe climatic conditions, acknowledging the low occurrence probability of extreme weather. If length of available climate date on the location of interest is not enough, a synthetic climate database must be generated based on the existent observational records. Statistical evaluation of hourly hygrothermal indoor conditions simulated under a massive set of annual meteorological scenarios enable the accurate estimation of reliability and discomfort risk of the thermal building design.

The advantage of stochastic simulation techniques (Monte Carlo method) with respect to analytical approaches is that the reliability problem can be solved without major simplifications and/or restrictive hypotheses. The difficulty is the intensive requirement of computational resources. However, this disadvantage has been progressively mitigated due to the rapid growth of computing power. Furthermore, because the Monte Carlo method is a loosely coupled computation technique amenable to distributed computing, multi-core architecture of modern processors can be advantageously exploited for drastically reducing calculation time.

The proposed methodology required the development of several computing routines and synthetic climatic databases for its implementation. For this purpose, a stochastic simulation model named sHAMs (stochastic Heat And Moisture simulation) was conceived. With this model, the comfort reliability of a building design – irrespective if conventional, bioclimatic or hybrid – can be determined. In order to facilitate integration with the thermal simulation engine (HAMBASE), the numerical model sHAMs has been developed in the same programming platform (MatLab). MatLab facilitates the numerical and graphical processing of the masive data volume resulting from stochastic simulations. sHAMs allows adding modules to perform integrated energetic and economic analysis of thermal design variants. This enables the further algorithmic optimization of the building design to find the least-cost building design subject to reliability requirements.

5. Application: thermal reliability assessment of a residential house

5.1. Case study description

With the purpose of demonstrating the applicability and practicability of the proposed approach, hygrothermal reliability and discomfort risk of a residential dwelling is assessed. The first design under study is named ConvHouse, in which construction as well as heating and cooling systems are conventional. The ConvHouse design is in compliance with the currently applicable building code. In addition, a modified thermal design variant referred as BioHouse, which incorporates some bioclimatic strategies, such as enhanced isolation and a controllable humidifier, is also considered for the sake of comparison. Both building designs are subject to a dry hot summer and a dry cold winter representing the continental climate prevailing in the City of San Juan, Argentina (31°32′S 68°31′W).

The basic layout of the ConvHouse design is portrayed in Fig. 4. It is a paired dwelling and the West wall is modeled as adiabatic. All rooms (excluding bathroom and kitchen) are well-oriented toward the north façade, which receives significant solar gain (12.5% useful surface). East and West orientation are blocked to solar radiation and North orientation is protected against the high solar radiation in summer. Also, there is protection from cold winds from South by means of regular windows with shutters.

A typical family of three members is considered. Occupancy patterns during daytime and night have been accounted for in internal thermal load estimations. Heat and moisture released during cooking are also entered as input at breakfast, lunch and dinner time. Well-behaved operation of windows for solar gain and natural ventilation is assumed.

The building model is divided in two hygrothermal zones: the day room (Z_1) and the bedroom (Z_2). Total thermal mass is 4.41 kWh/K and 2.19 kWh/K for Zone 1 and Zone 2 respectively. Table 2 provides basic data on construction features, materials, thermal transmittance U, and calculated global loss coefficients G. From Table 2, modifications of the conventional design introduced to the BioHouse variant become evident.

5.2. Stochastic simulation of hourly weather data

During lifetime, buildings are subjected to highly fluctuating weather conditions, including sporadic but critical meteorological circumstances that threaten indoor comfort. To estimate the failure probability of a thermal building design to keep comfortable conditions under severe weather, meteorological records of substantial

[1] Matlab is an efficient programing environment for scientific purposes speeding the development phase. Matlab platform provides powerful statistic and graphic processing capabilities. In addition, it allows the easy treatment of input/output data in other formats commonly used.

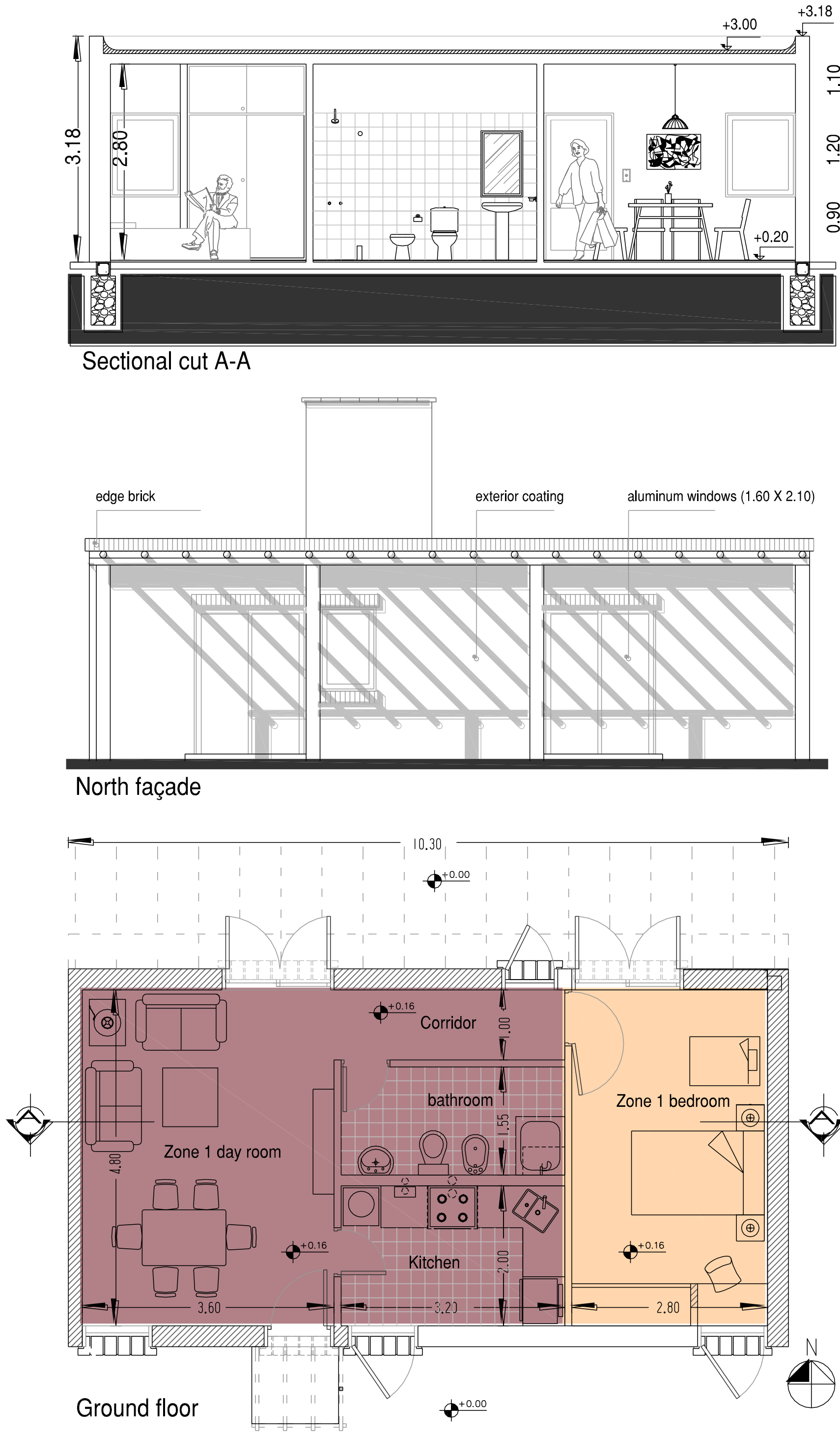

Fig. 4. Sectional cut, north façade and, plan of the exemplary residential house.

length are necessary. On most sites, extent of available climatic observations is insufficient for computing accurate and statistically meaningful estimations of the discomfort risk. For this reason, synthetic climate datasets based on observational records are often needed for performing risk assessments. The generated weather time series must accurately replicate distributional and stochastic dynamical properties of the weather measurements. Next, we outline a method for constructing such a synthetic weather dataset.

Basically, weather fluctuations can be thought to be the additive superposition of a deterministic and a stochastic component. The deterministic part describes regular and predictable patterns, mostly due to astronomical cycles, such as seasonal and daily cycles. The stochastic component explains random weather changes. Each relevant meteorological variable, e.g. temperature, humidity, solar radiation, etc., can therefore be decomposed in these two components.

To identify regular cycles embedded in weather time series, a non-parametric filter is applied to each meteorological variable. The approach consists of an array of 24 separate moving-average filters applied to each day hour. To estimate the deterministic component, each filter has a sliding window that spans 30 days of data. In order to avoid introducing a lag when identifying the

Table 2
Description of constructive characteristics of the ConvHouse and BioHouse design.

ConvHouse description	**Thickness** [m]	**Surf.** [m²]	**U** [W/K/m²]	
1	Brick wall 0.17 m + plaster in both faces	0.20	47.4	1.97
2	Inner non supporting partition	0.12	37.5	–
3	Pre-stressed ceramic slab + 0.02 m concrete with polystyrene beads	0.22	47	2.64
4	Ceramic floor, subfloor, natural land (perimeter 29.80 m)	0.20	47	1.38
5	Doors (pine wood)	0.04	1.80	2.30
6	Single glass 6 mm windows	0.05	10.60	5.70
7	Single glass with closed shutter	0.01	12.8	2.80
8	Natural ventilation, heating and AC 2000 W per zone	**G** [W/m³/K]	**1.72**	
BioHouse variant				
1	Identical to ConvHouse + 0.05 m polystyrene 15 kg/m² + edge brick 0.07 m	0.32	34/13.4	0.53
3	Identical to ConvHouse + 0.08 m concrete with polystyrene beads	0.30	47	0.83
8	Identical to ConvHouse + humidification	**G** [W/m³/K]	**1.43**	

x=9.30 m; y=4.80 m; z=2.80 m.
Volume: 94.10 m³ (Zone 1) and 37.6 m³ (Zone 2).
Covered surface: 46.08 m² (internal) and 52.52 m² (external).

cyclical component, the sliding time window is centered at the relevant hour to be estimated. Hence, the time-varying mean is computed across a dynamical sample constituted by values of the variable in the same day hour within an interval comprising 15 days backward and 15 days forward the hour to be estimated and for all years of recorded data.

In the context of an additive model of weather fluctuations, the stochastic component of the climatic variability can be obtained by subtracting to each recorded time series the estimated deterministic component. First-order distributional features of random weather fluctuations can be entirely captured by estimating the probability density function (PDF). Second-order statistics, which describe dynamical properties of observed random fluctuations, are characterized by either calculating the autocorrelation function (ACF) or estimating the power spectral density (PSD) of the stochastic component. By virtue of the Wiener–Kintchine theorem, both descriptions are equivalent and contain the same information on the stochastic dynamics of time series.

Statistical tests on an exemplary climate datasets reveal that stochastic fluctuations of meteorological variables are typically non-Gaussian and non-stationary. Indeed, the probability distribution of time series notably deviates from normality and the variance of the process is time-varying (inhomogeneous random process). The local time-varying variance of the random process can be estimated by using the same sliding window method used to estimate the time-varying mean, i.e. the deterministic component of the random process.

A non-parametric simulation algorithm based on the spectral representation method is used to generate a synthetic ensemble of the stochastic component of weather fluctuations according to prescribed observational properties [38]. Parameter-free approaches are general in their very nature, as they do not make any assumption on the distributional and the dynamical properties of the generating process. Thus, non-parametric models do require neither the postulation of a model structure nor the calibration of model parameters to the specific dataset. Therefore, they provide a very flexible modeling framework that can be applied to simulating weather time series at any site, irrespective from its specific statistical and stochastic properties. Besides eliminating the optimization problem related to the estimation of model parameters, the proposed method is computationally very efficient because it takes advantage of Fast Fourier Transform (FFT) techniques. In order to reproduce the non-Gaussian features of the weather fluctuations, a non-linear memoryless transformation and an iterative procedure for correction of the introduced spectral distortion are applied [39]. The non-stationary behavior of variance can be obtained by modulating the simulated processes by an appropriate envelope function. The generating process of meteorological variables is assumed to be uniformly modulated, i.e. time-varying spectral properties only changes in amplitude. This preserve computational efficiency as FFT techniques can still be exploited [40].

A detailed description of the stochastic algorithm of weather data can be found in [41], where performance is tested in the context of stochastic simulation of spot prices of electricity which are random processes well-known by their complexity and difficulty to be properly replicated. More recently, the algorithm has also been used to the stochastic simulation of non-stationary non-Gaussian wind speeds [42]. It can be demonstrated that the simulated ensemble of the random component of weather variables holds simultaneously the target non-Gaussian probability distribution, the target power spectrum and the non-stationary variance observed in the meteorological records. This ensures that occurrence probability, recurrence rate and time persistence of simulated severe (but rare) weather events are nicely replicated as they are a key influencing factors in risk assessment. The last step for generating synthetic weather time series is adding the identified deterministic component to each synthetic realization of the stochastic component.

A sample dataset of 1000 annual realizations of synthetic hourly meteorological conditions has been generated by the spectral-based simulation algorithm according to the target distributional and spectral observational weather characteristics. Weather was characterized by an available 5-year dataset of 30-min averaged weather measurements in the City of San Juan, Argentina. Temperature, relative humidity, atmospheric pressure, wind intensity and direction and solar radiation were continuously recorded in the period spanning Jan/2003 to Dec/2007. Main descriptive statistics of the prevailing climate at the site are provided in Table 3. For the stochastic component of each meteorological variable, deterministic mean, local variance, probability distribution, and power spectrum have been estimated. Cross-correlation between temperature and relative humidity has also been taken into consideration.

The statistical analysis of the simulated weather dataset indicates that the mean temperature across a sample of 1000 annual realizations of hourly temperatures is 18.8 °C, which is in excellent agreement with observations (cf. Table 3). Similarly, the average relative humidity of the simulated weather ensemble is 45%, fitting well the observed behavior of climate in the site. Absolute minimum and maximum temperatures in the synthetic 1000-year dataset are −10.3 °C and 49.6 °C respectively. At a first look, these extreme values significantly deviate from the available measurements. However, we

Table 3
Five-year weather statistics of the City of San Juan, Argentina.

Temperature [°C]						**Relative humidity**	**Solar radiation**	**Mean wind speed**	**Mean max. wind speed**
Month	**Mean min.**	**Abs. min.**	**Mean**	**Mean max.**	**Abs. max.**	[%]	[W/m²]	[km/h]	[km/h]
Jan	21.5	9.7	26.8	32.0	40.9	41	330.2	10.4	20.1
Feb	20.2	10.8	25.1	30.3	37.4	36	301.4	9.2	18.0
Mar	17.9	9.2	22.6	27.5	38.2	49	249.1	8.5	16.4
Apr	13.2	4.2	17.7	22.3	33.0	54	181.0	7.1	13.7
May	8.4	0.5	12.6	17.0	28.9	55	132.9	6.2	12.3
Jun	6.7	1.0	11.2	16.1	31.7	56	109.3	5.5	11.2
Jul	5.6	−1.9	10.4	15.6	30.4	48	118.5	6.2	12.6
Ago	6.5	−0.4	11.5	16.7	28.8	42	149.0	6.9	13.9
Sep	10.9	2.4	16.3	21.5	34.2	38	211.4	8.3	16.1
Oct	15.0	7.6	20.6	25.9	36.7	35	272.8	9.2	18.4
Nov	17.2	7.6	22.7	27.9	38.7	34	304.5	9.9	20.0
Dec	20.3	13.1	25.9	31.3	39.0	34	340.3	11.3	22.6
Annual	**13.6**	**5.3**	**18.6**	**23.7**	**34.8**	**43**	**225.0**	**8.2**	**16.3**

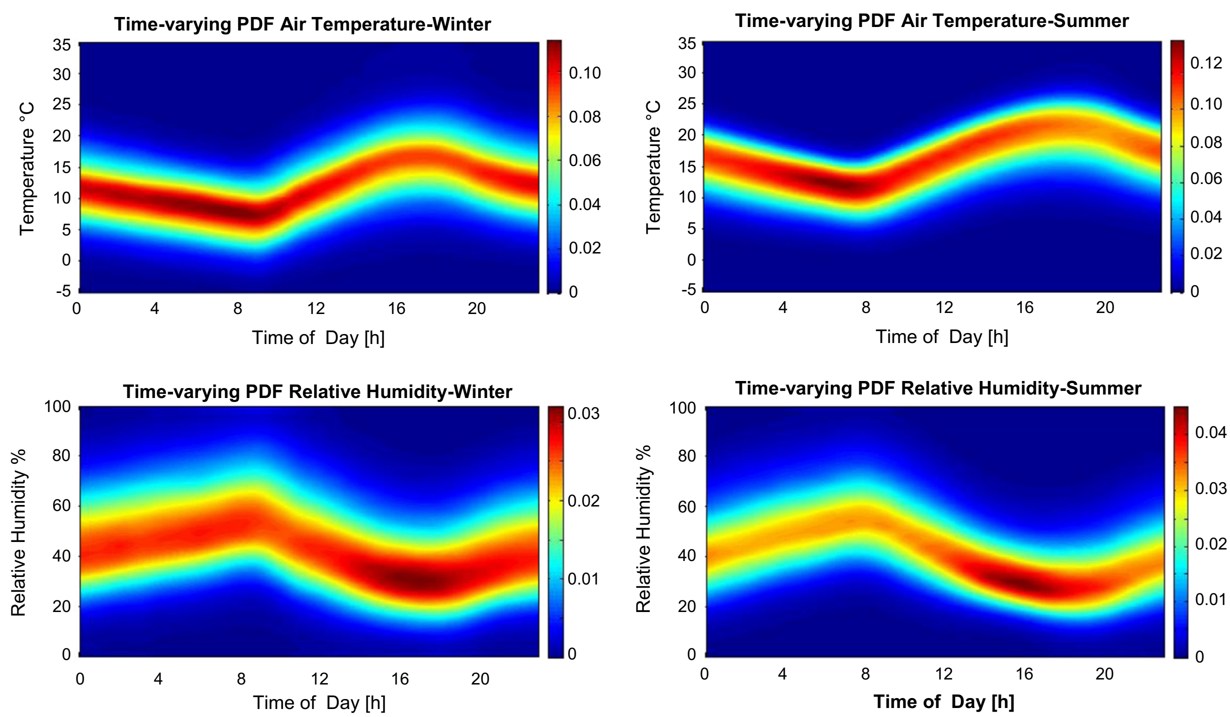

Fig. 5. Time-dependent PDF of temperature and relative humidity for summer and winter computed from 1000 hourly realizations.

must recall that available records span only five years, which is a too short time period for characterizing extreme weather. Much longer temperature records measured by the National Weather Service in the nearby airport indicates absolute extreme values of −9.2 °C and 44.3 °C within a period spanning 30 years from 1961 to 1991.

Daily time-dependent probability density function of indoor temperature and relative humidity in both, summer and winter have been computed from the entire synthetic weather dataset. These functions are illustrated in Fig. 5. The daily and seasonal patterns (deterministic cycles) in temperature and relative humidity can be easily recognized in the synthetic ensemble. The typical negative correlation between air temperature and relative humidity is also captured in the simulated weather dataset.

Fluctuations around the time-varying mean represent the random component of climate variability. It is easy to observe that stochastic fluctuations of the generated weather ensemble are asymmetric with respect to the seasonal mean, deviating from the Gaussian distribution. Furthermore, the local variance of the synthetic time series depends on the daytime and the season as well, which properly reproduces the observed non-stationary variance in records. For instance, uncertainty on temperatures in winter is higher than in summer and variability at 9:00 is much less than at 17:00 in both seasons.

5.3. Simulation result

5.3.1. ConvHouse

In this section, the discomfort risk assessment of the conventionally acclimatized house (ConvHouse) is performed by applying stochastic hygrothermal simulations. In Fig. 6 the simulated hourly room temperature (left) and relative humidity (right) of the ConvHouse along a single sample year is illustred together with the prevailing weather. Although indoor temperatures are mostly acceptable, the Zone 1 often undergoes loss comfort during winter and, to a lesser extent, also in summer. Indoor relative humidity decreases in winter because of the heating system, whereas it coincides with outdoor peaks in summer adding considerable instability.

The main comfort reliability and risk indices of the ConHouse design are provided in Table 6. The bivariate probability density

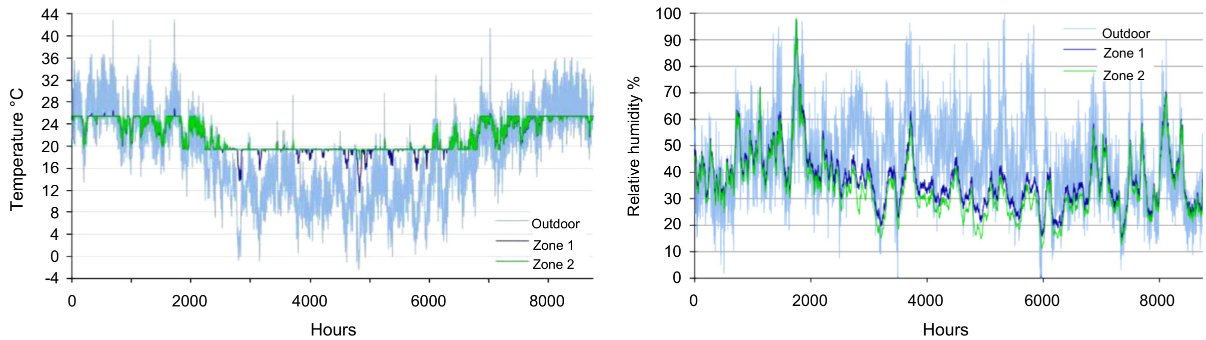

Fig. 6. Sampled annual simulation of hourly indoor conditions in the ConvHouse along with the prevailing outdoor weather.

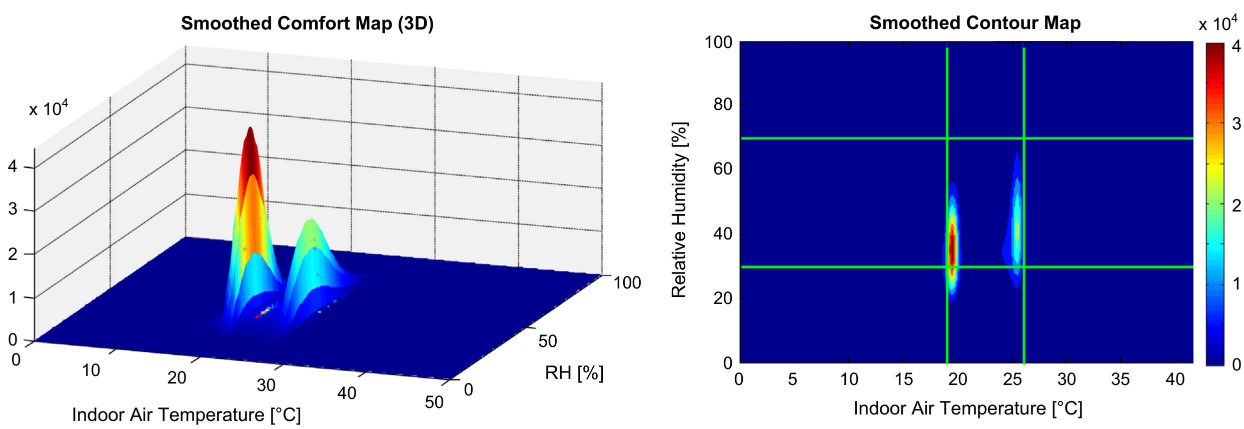

Fig. 7. Probabilistic comfort map estimated for thermal Zone 1 of the conventional house design.

functions of the indoor temperature and relative humidity estimated from the simulated sample is depicted in Fig. 7. The color 3D comfort map is a useful visualization tool to facilitate interpreting the massive data generated by stochastic simulations in a single chart. In the T–RH plane, the acceptable limits of the targeted comfort region are plotted. The estimated joint probability density that the building resides in each state of the T–RH plane can be read in the *z*-axis. The estimation is carried out by evenly discretizing the T–RH plane, computing the bivariate histogram from the simulated dataset of indoor conditions, and further applying interpolation and smoothing techniques.

It is worth noting the low reliability level achieved through conventional acclimatization with a HCR = 71.5%. With a risk index HDR = 28.5%, there is over 2500 h/a during which the house is unable to maintain indoor comfort conditions in all thermal zones due to violations of the established temperature and relative humidity limits, either individually or simultaneously. From stochastic simulations, the mean duration of discomfort events (EDDE) is estimated in 33 h and the expected annual frequency of discomfort events (ELCF) is 76.5 a^{-1}. Because the operation of the heating and cooling systems, indoor environment spreads over two long and thin areas close to the upper and the lower temperature limits, but extending across almost the whole admissible relative humidity interval.

In the context of Monte Carlo simulations, the accuracy of estimations improves as the sampled space increases. Statistical convergence in the discomfort risk estimation of each thermal zone for increasing sample size is shown in Fig. 8. It can be observed that there is a substantial difference in the estimated discomfort risk of the two modeled thermal zones, which can be explained because of the disparate exposed wall surface with respect to the room volume. Therefore, the loss of comfort probability is substantially higher in Zone 2 than in Zone 1, i.e.

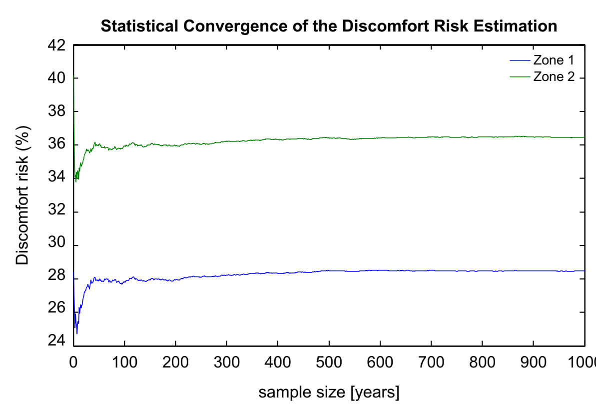

Fig. 8. Statistical convergence of the discomfort risk estimation for increasing number of sampled meteorological years.

Zone 2 is considerably less reliable with respect to human thermal comfort than Zone 1.

Although a fast statistical stabilization of the HDR index is noticed for the ConvHouse in Fig. 8, the simulation of at least 500 sample years is still necessary for accurately estimating the discomfort risk in more reliable thermal designs. Indeed, in reliable designs discomfort events seldom occur and more simulated years are thus necessary to obtain a statistical meaningful sample of uncomfortable situations. In this work, the thermal building performance has been simulated in hourly resolution for an ensemble of 1000 sample meteorological years. The calculation time is 118 min in a desktop PC with an AMD Phenom II X6 3.2 GHz processor and 16 GB RAM. The CPU time can drastically reduced to 23 min when computations are distributed into the

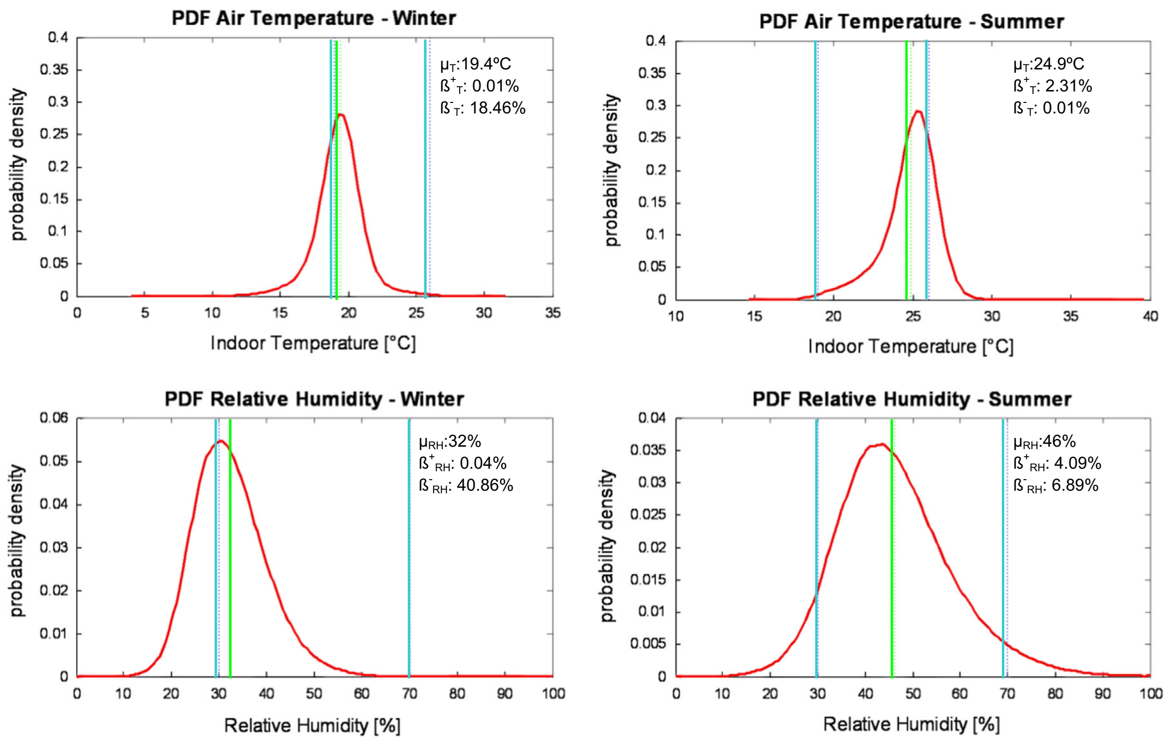

Fig. 9. Seasonal probability density functions of indoor temperature and relative humidity for the ConvHouse design.

Table 4
Expected yearly energy consumption for heating (H) and cooling (C) estimated from 1000 annual meterological realizations.

Design	Zone 1		Zone 2		Total annual consumption					
	H [kWh]	**AC** [kWh]	**H** [kWh]	**AC** [kWh]	**H** [kWh]	**AC** [kWh]	**Total** [kWh]	**H** [kWh/m²]	**AC** [kWh/m²]	**Total** [kWh/m²]
ConvHouse	6150	2201	3697	1421	9847	3622	13,469	214	79	292
BioHouse	2074	1314	941	836	3015	2150	5165	65	47	112

six-core processor. This implies a speed up of 5.13 when the stochastic simulations are deployed in a distributed computing environment.

In most cases, discomfort risk is not evenly distributed in the year. Tipically, performance of building designs considerably differs under cold or hot weather conditions. Therefore, it is often necessary to compute disagregate reliability and risk indices for each season. For this reason, the univariate probablity density function (PDF) of indoor temperature and relative humidity for winter and summer have been computed and are depicted in Fig. 9. Density functions are estimated from the simulated hourly dataset by means of the kernel smoothing method [43]. The mean value of the density functions, denoted as μ, are ploted along with the admissible comfort intervals. The probability of either not reaching the minimum or exceeding the maximum threshold values of the target comfort region is denoted by β (see inset). Seasonal PDFs enable the discriminated detection and diagnosis of deficiencies in the building design to realiably sustain indoor comfort under hot or cold weather.

For instance, the loss of comfort in Zone 1 is mainly due to low relative humidity in winter with almost 41% probability of not reaching the targeted lower limit. According to Table 4, the expected value of relative humidity when it violates the lower limit is E[UnRH]=25.3%. For correcting this situation, the addition of a controllable humidifier is required to meet humidity conditions within the desired comfort region. The probability of exceeding the maximum admissible relative humidity in winter is negligible. In summer, the probability of not reaching the minimum relative humidity is only about 7% and the probability of exceeding the maximum acceptable value is 4.1%.

Table 5
Estimated comfort reliability level and discomfort risk in Zone 1 of the ConvHouse design.

Index	HCR	HDR	EDD	EUnH	EOvH	EUnRH	EOvRH	EDCE	EDDE	ELCF
Units	%	%	h/a	°C	°C	%	%	h	h	1/a
Value	71.5	28.5	2496	17.4	27.1	25.3	77.2	82	33	76.5

With a probability of about 18.5%, low indoor temperature during winter is the second most likely cause of discomfort. The PDF is symmetric about the mean and the shape is similar to the normal distribution. The expected indoor temperature during winter is 19.4 °C: a value close to the lower allowable temperature limit. However, the mean temperature when the targeted comfort conditions are not reached is 17.4 °C (cf. the expected underheating index EUnH in Table 4), i.e. only 1.6 °C below the set lower limit of 19 °C. Increased use of warm clothing or minor changes in the thermal design, e.g. heating capacity, insulation thickness, solar gains, could readily improve comfort reliability.

In summer, comfort reliability is considerably higher than in winter although there is a higher dispersion of temperature and humidity, which might cause discomfort to occupants if these variations occur within short periods of time. To summarize, even though the building has been carefully designed in compliance with the currently applicable building code, the comfort reliability of this conventionally acclimatized house is not acceptable.

5.3.2. *BioHouse*

In this section, thermal comfort reliability and discomfort risk of a bioclimatic design variant (BioHouse) of the house analyzed in the previous section is evaluated. Energy performance of this design has improved considerably. The overall expected annual energy consumption for heating and cooling of the BioHouse is estimated in 5165 kWh. For the sake of comparison, the expected consumption of the ConvHouse under the same meteorological ensemble is 13,469 kWh/a. The introduction of bioclimatic strategies to the thermal design of the building drastically reduces the energy consumption for climatization by about 61%. Table 5 provide dissagregated figures of the expected annual energy consumption for heating and cooling in both house designs.

Fig. 10 shows the behavior of the simulated indoor temperature and relative humidity in Zone 1 of the BioHouse design for the same sample year used in the thermal simulation depicted in Fig. 6. On the one hand, there is absence of hours outside the targeted comfort temperature interval. On the other hand, there is controlled humidity in the lower limit of the comfort region established. However, it is necessary to revise the thermal design to avoid discomfort events caused by an excess in relative humidity since, for this sample year, it reaches 97% in one day in March and recurrently exceeds 70%. Table 5 provides the comfort reliability and risk indices of the bioclimatic design variant. Fig. 11 portrays the comfort map of the BioHouse, in which indoor temperatures mostly moves along two linear zones inside and close to the comfort limits. It is noteworthy the fact that due to the operation of the controlled humidifier, indoor conditions reside within a very sharp (concentrated) area around 20 °C and 31% humidity with the highest probability. This architectonic bioclimatic design has a higher comfort reliability than the conventional design achieving a HCR = 98.5%. The discomfort risk is only 1.5%, which means an expected cumulated duration of discomfort events of EDD = 128 h per year. Loss of comfort is most likely due to overheating and excess of relative humidity during summer. Table 6.

Seasonal probability density functions of indoor temperature and relative humidity for the BioHouse are illustrated in Fig. 12. In a sample of 1000 synthetic meteorological years, temperature never falls below the lower comfort in winter and exceeds the upper temperature limit in summer with a probability of 0.07%. Accordingly, the bioclimatic design keeps indoor temperatures within the comfort limits with a reliability of 99.93%. Expected temperature values are 19.8 °C and 24.9 °C in winter and summer respectively. In winter, the probability density function is highly right-skewed with a very sharp concentration just above the lower limit. The relative humidity is within the comfort interval more than 99.6% of the time during winter, whereas in summer the

Table 6
Estimated comfort reliability level and discomfort risk in Zone 1 of the BioHouse design.

Index	HCR	HDR	EDD	EUnH	EOvH	EUnRH	EOvRH	EDCE	EDDE	ELCF
Units	%	%	h/a	°C	°C	%	%	h	h	1/a
Value	98.5	1.5	128	18.9	26.9	–	77.5	1176	17	7.3

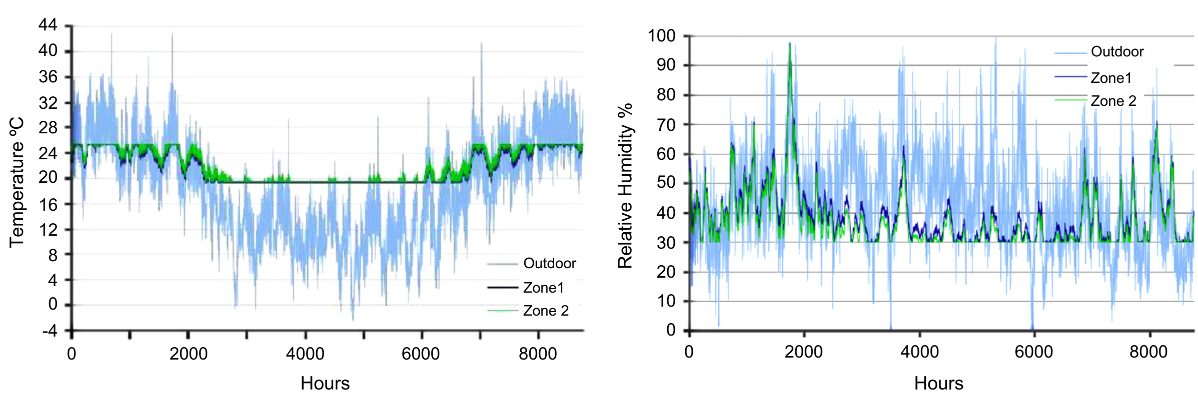

Fig. 10. Sampled annual simulation of hourly indoor conditions in the BioHouse design along with the outdoor prevailing weather.

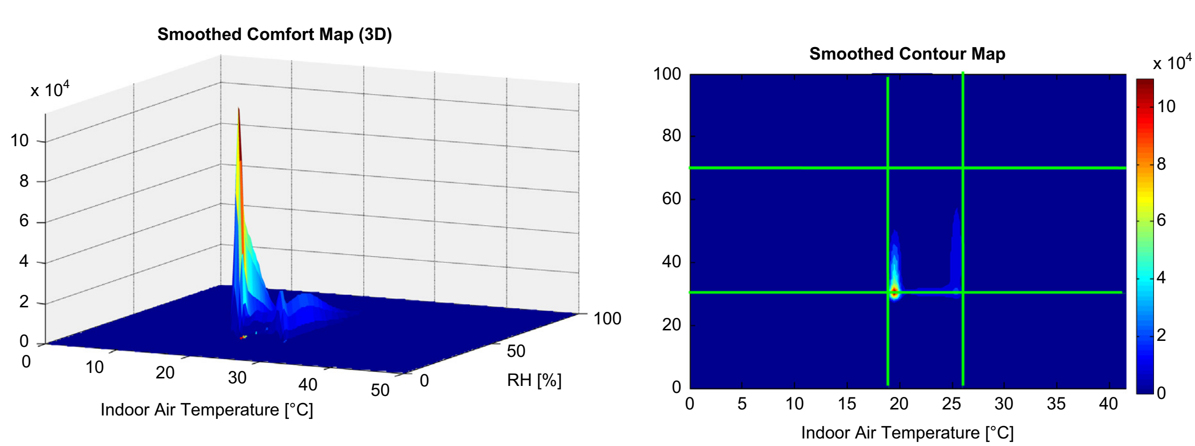

Fig. 11. Probabilistic comfort map estimated for thermal Zone 1 of the bioclimatic house design.

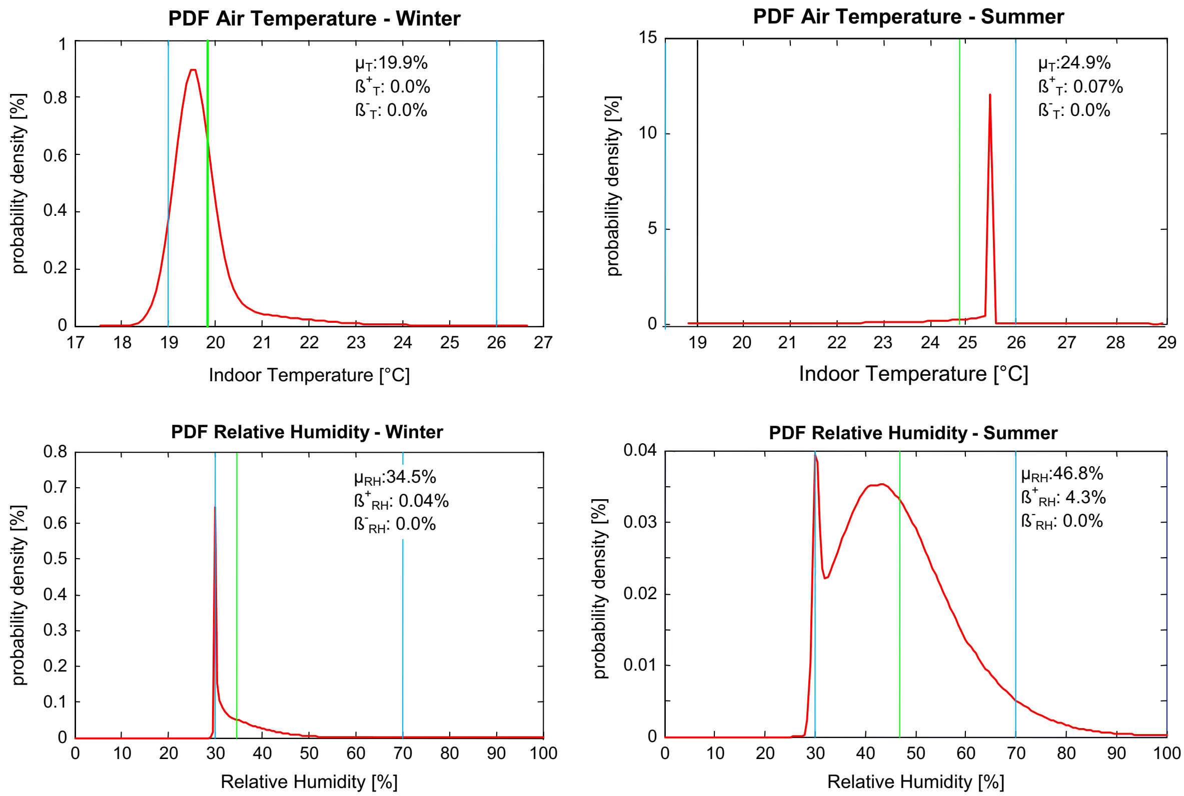

Fig. 12. Seasonal probability density functions of indoor temperature and relative humidity for the BioHouse design.

upper limit is exceeded with a probability of 4.7%. It can be presumed that by adding a dehumidifier – usually built in standard cooling equipment – and provided the equipment and power supply cannot fail, the hygrothermal comfort reliability of the bioclimatic house design could reach 100%.

As illustrated in the preceeding example, the thermal discomfort risk of building may be very sensitive to modifications in the hygrothermal design.

6. Conclusion

A major function of buildings is to provide sheltering to their occupants. Confortable indoor environment must be reasonably preserved regardless of prevailing (uncertain) meterological conditions. However, random weather events introduce uncertainty on the building thermal performance and its ability to perform as required.

Presently, the conventional approach to thermal design is to comply with a set of guiding rules established in building codes and standards. Due to several factors such as local weather, specific design features, selected materials, etc., compliance with applicable norms does not guarantee that any specific building at any given location is capable to provide indoor comfort conditions with some pre-established (elevated) probability. Likewise, verification of building thermal performance by means of numerical simulation under typical climate (e.g. TMY) provides little information on hygrothermal risks associated to weather events that deviate from average climate. A thermal building design must satisfy comfort requirements not only under typical weather, but also when severe meteorological events occurs and shelter is needed the most. Nevertheless, designing buildings to keep indoor comfort conditions even under the worst credible or recorded weather event in the location might be exceedingly uneconomical. Hence, severity, persistence, and occurrence probability of adverse weather events are factors that must be properly considered in the design methodology.

The present paper proposes a methodology to objectively meassure the reliability of a building thermal design to perform its main function, i.e. to sustain indoor hygrothermal comfort conditions under weather uncertainty. The assessment of comfort reliability is accomplished by stochastic chronologic simulation of the building hygrothermal behavior. In the stochastic simulation setting, the building is exposed to a massive number of random meterological scenarios, which conform with the probabilistic properties of the local climate. Thereby, a statistically meaningful sample of indoor uncomfortable conditions can be obtained for further analysis. The developed approach allows the designer to quantify the uncertainty in building indoor conditions and to estimate the discomfort risk of a proposed building configuration subject to the random nature of the local climate.

A number of probabilistic measures have been conceived to describe the hygrothermal reliability level and the risk of discomfort of any building design. The proposed reliability and risk indices are convenient metrics to condense and summarize in a few parameters the statistical behavior of indoor hygrothermal conditions under uncertain severe weather. Threshold values on these indices can be used as constraints or performance criteria to be met when design is optimized.

By quantitatively measuring comfort reliability, designers can minimize overall building costs without exceeding a maximum acceptable value for discomfort risk. Within this probabilistic framework, the problem of thermal design of buildings could be restated as to find the least-cost configuration (in terms of both, initial investment and future energy costs) without deteriorating comfort reliability below a minimum threshold value. Reliability-based thermal design combined with risk-constrained optimization of building economics is hence an important avenues of investigation that are currently being adressed.

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