ASHRAE Likelihood of Dissatisfaction: a new right-here and right-now thermal comfort index for assessing the Likelihood of Dissatisfaction according to the ASHRAE adaptive comfort model

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Abstract

The assessment of local and short-term thermal discomfort in buildings has been widely investigated, and different metrics are available in the literature to predict the likelihood of dissatisfied people. These metrics are named *right-here* and *right-now* discomfort indexes and constitute the basis for evaluating long-term thermal comfort conditions in buildings. Well-known examples are the Predicted Percentage of Dissatisfied (PPD) part of the Fanger comfort model included in the ISO standard 7730 and the Overheating risk index (NaOR), built upon the EN adaptive thermal comfort model. This study proposes a new index for use with the ASHRAE adaptive thermal comfort model to fill a gap in the literature and standard. It is called the ASHRAE Likelihood of Dissatisfaction (ALD) and is obtained from a logistic regression of the *right-here* and *right-now* thermal comfort field data contained in the 1990s ASHRAE RP-884 database. The recent release of another, more extensive database of thermal comfort field studies, the ASHRAE Global Thermal Comfort Database II, provides an opportunity to validate ALD with an independent dataset and assess its generalisability. The successful external validation of ALD and its agreement with NaOR give support to the reliability of the novel *right-here* and *right-now* index and open to the possibility to use it for assessing short-term thermal comfort conditions in buildings, calculating long-term thermal comfort indices based on the ASHRAE adaptive model, optimising both the design of new buildings and renovations and for assessing the operational thermal comfort performance of existing buildings.

Keywords

Thermal comfort, ASHRAE Standard 55, adaptive comfort, logistic regression, likelihood of dissatisfied

1 Introduction

Thermal comfort analyses have inspired the development of several models in the last fifty years [1,2]. The most adopted thermal comfort models are the so-called rational comfort model developed by Fanger [3], the ASHRAE adaptive comfort model developed by de Dear and Brager [4,5] and the European adaptive comfort model developed by Nicol and Humphreys [6]. Fanger's thermal comfort model, often referred to as the PMV/PPD model, was built on experiments involving exposure of subjects to steady-state conditions in climate chambers and considered the occupants to be passive receptors detecting the surrounding environmental conditions. On the other hand, the adaptive comfort theory has been developed from field studies and considers the building occupants as active agents interacting with their built environment [7]. In particular, the ASHRAE adaptive model is based on the analysis of about 9 000 of the 21 000 sets of raw data compiled from field studies in 160 buildings located in diverse climatic zones across the globe [8], while Nicol and Humphreys' counterpart is based on the EU-funded SCATs project [9], which collected about 1 500 sets of data from 26 field studies carried out in five European countries. These models have already been integrated into several standards, such as ASHRAE 55 [10] and EN 15251 [11] (now EN 16798 [12]), which have also undergone several revisions [13].

The thermal comfort standards offer information for using their respective models in the design phase of new building projects or in the renovation of existing constructions, as well as when assessing the performance of existing buildings. The standards categorise indoor thermal conditions into various comfort categories or classes in both design and assessment applications. For example, the ISO 7730 defines three categories of thermal environments as a function of the value of PMV, which depends on environmental and personal parameters. The ASHRAE Standard 55 evaluates acceptable indoor operative temperatures in occupant-controlled naturally conditioned spaces into two categories of thermal acceptability (80% and 90%, equivalent to 20% and 10% dissatisfied, respectively). The adaptive model within the European standard instead prescribes three different ranges of indoor operative temperatures for buildings without mechanical cooling systems as a function of the outdoor running mean temperature, according to the levels of occupant comfort expectation.

The interpretation and application of the comfort standards have important practical implications. In particular, there is an urgent challenge to strengthen policy actions in the context of summertime conditions under increasingly extreme temperatures [14]: energy use for space cooling is rapidly growing [15], and the summer comfort issues are increasingly difficult to tackle due to climate change and exacerbation of urban heat island [16–18]. In many countries, summer comfort is still poorly considered by the average design practice, especially in the case of energy renovation of buildings for low-income groups (e.g., social and public housing) [19]. In most cases, regulation, and hence everyday design practice, are not taking as a starting point a careful and explicit assessment of the thermal comfort needs of building occupants [20].

Sometimes in the design and operation of space heating and cooling systems, designers and facility managers target the most stringent comfort Category I, expecting that this will assure superior comfort performance for their clients. Nevertheless, Category I was originally intended by EN standards only for fragile persons in hospitals and care centres. Category II was proposed as the appropriate choice for new buildings, and Category III for existing buildings. These misunderstandings are often transferred into building users' expectations and habits [21]. Moving from Category I to Category II theoretically equates to energy savings of 10 to 40%, while moving from Category I to Category III amounts to savings between 20 and 66%, according to [22]. Category

I in EN nomenclature corresponds to Category A in ASHRAE nomenclature. When the concept is expressed with the Fanger comfort model, both Category I and Class A are described as those conditions in which $-0.2 < PMV < 0.2$. Indeed, as referred in Pagliano and Zangheri [2], research is ongoing to ascertain whether people can distinguish among the proposed categories. An analysis of a large volume of data from the ASHRAE global comfort field study database and the European SCAT counterpart [20] concluded that Category A was too narrow to be discriminated by occupants of buildings.

Moreover, an error propagation analysis [23] of the six inputs to the PMV/PPD model concluded that "[…] the PMV range required by A-category can be practically equal to the error due to the measurements accuracy and/or the estimation of parameters affecting the index itself" [24]. The analysis showed that the magnitude of errors in the measurement of the six input parameters, even when strictly complying with the requirements of the international and European standard EN ISO 7726 [25], generates, by error propagation, uncertainties in the PMV output value, which are larger than the width of A (or I) and B (or II) comfort categories. Indeed, ISO 7730 acknowledges that "Owing to the accuracy of instrumentation for measuring the input parameters, it can be difficult to verify that the PMV conforms to the Class A category ($-0.2 < PMV < +0.2$). Instead, the verification may be based on the equivalent operative temperature range, as specified in A.2 and in Table A.5." This is probably equivalent to setting to zero the uncertainties on all PMV input variables other than temperature.

Once the appropriate comfort model and category have been explicitly chosen, the assessment of thermal comfort performance in simulated or actual buildings can be addressed. Reliable performance metrics provide valuable operational and design decision support. For example, genetic algorithms were used to optimise the thermal design and control strategies of buildings based on the Fanger comfort metrics [26,27] and on the adaptive comfort models [28–30]. Similarly, Delgarm *et al.* [31] presented a multi-objective optimisation procedure to simultaneously enhance building energy and thermal comfort performance with Fanger's model. Ascione *et al.* [32] showed a multi-step and multi-objective optimisation refurbishment process of an educational building to simultaneously minimise energy demand and thermal discomfort assessed in terms of percentage of discomfort hours. Zhang *et al.* [33] presented an optimisation method to reduce energy use while maximizing thermal and visual comfort, using the adaptive thermal comfort model of ASHRAE Standard 55 for evaluating the duration of summertime thermally acceptable indoor conditions. Most indices were developed to assess localised and instantaneous hygrothermal conditions inside a built space according to specific thermal comfort models, hence the name *right-here and right-now indexes*. Examples include the Predicted Percentage of Dissatisfied (PPD) derived from Fanger's comfort model [3], the overheating risk index (NaOR) proposed by Nicol *et al.* [34] derived from the EN adaptive thermal comfort model, and the Robinson and Haldi's overheating risk index [35] based on the conceptualization of human thermal stress as an electrical capacitor. However, to date, there is not any *right-here and right-now* index proposed for use with the ASHRAE Standard 55 adaptive thermal comfort model.

This paper proposes, hence, a novel *right-here and right-now* index for use with the ASHRAE Standard 55 adaptive thermal comfort model. It is based on the same underlying logic and assumptions embedded in de Dear and Bragers' [4,5] adaptive model in order to maximise coherence with the reference thermal comfort approach. The new performance index is named ASHRAE Likelihood of Dissatisfaction (ALD), and its formulation is presented in section 2. In section 3, we externally validate ALD against the thermal comfort data collected in the ASHRAE Global Thermal Comfort Database II [36]. The fourth section reports a comparison between ALD (related to the ASHRAE adaptive model) and the already existing adaptive *right-here and right-now* index NaOR (which can only be used with the EN adaptive model) through the evaluation of the likelihood of (thermal) dissatisfaction in real case studies.

2 Index development

The value of being able to predict the likelihood that people will be uncomfortable in a building is widely acknowledged [37–40], and different metrics and tools are available to drive comfort optimisation algorithms [41–43]. The prediction accuracy relies on the quality of the data recorded during the surveys and on the approach used for the prediction [44].

The model developed by Fanger to predict thermal comfort in steady-state conditions is based on climate chamber experiments with 1296 subjects, mainly college-aged students [3]. The model uses an analytical heat balance of the body and two linear approximations of the relationships between respectively the mean value of skin temperature and sweat secretions, as a function of the activity level of the subjects, to construct two indices and propose them for application in mechanically conditioned buildings:

- the *Predicted Mean Vote* (PMV), which estimates the mean value of the sensation votes that would be expressed on the standard thermal sensation scale (-3 cold, -2 cool, -1 slightly cool, 0 neutral, +1 slightly warm, +2 warm, +3 hot) by a large group of people exposed to a given combination of the personal and environmental variables, and
- the *Predicted Percentage of Dissatisfied* (PPD), where "decidedly dissatisfied people" are defined by Fanger as those voting ≥ 2 or ≤ -2 on the thermal sensation scale under the same given combination of the personal and environmental variables [3].

The model expresses PPD as a function of PMV through the equation (Eq. 1):

$$PPD_{Fanger}^{ISO}(PMV) = 100 - 95e^{-0.03353 \cdot PMV^4 - 0.2179 \cdot PMV^2} \in (5, 100). \quad (1)$$

That is symmetrically distributed around the neutral vote at PMV = 0.

Several analyses [45–47] have questioned the validity of this model, particularly in environments displaced away from neutrality (Fanger himself emphasised caution and restricted its validity to the range between ±2 [3]). Based on an analysis of the ASHRAE Global Comfort Database II, Cheung *et al.* [47] concluded PMV has low predictive skill, especially for conditions far from neutrality, but also that "if the observed mean vote is known then the PPD curve is not very accurate but still a useful predictive tool". Also, they stated that "in many contexts the inaccuracies are not in the PPD model itself but rather the PMV model and its prediction of thermal sensation. If OMV [Observed Mean Vote, authors' note] is known then the PPD model accuracy improved significantly in many contexts" [47].

Nicol *et al.'s* Overheating risk (NaOR) [34], on the other hand, is built upon the EN adaptive thermal comfort model [6] and is intended for application in buildings without a mechanical cooling system in operation. It proposes that thermal dissatisfaction is not anchored to a fixed indoor temperature value but rather to the difference, ΔT, between the actual indoor operative temperature at a given time and the EN 15251 adaptive optimal operative temperature T_c, the latter being a function of outdoor running mean temperature, T_{rm}. The NaOR index, which is derived from logistic regression, is asymmetric and predicts the percentage of individuals, $P(\Delta T)$, voting +2 (warm) or +3 (hot) on the ASHRAE thermal sensation scale, as described in equation (Eq. 2):

$$P(\Delta T) \equiv \frac{\exp\,(0.4734 \cdot \Delta T - 2.607)}{1 + \exp\,(0.4734 \cdot \Delta T - 2.607)} \in [0.069;\, 1) \qquad (2)$$

Where the optimal operative temperature $T_{c,EN}$ (in °C) is calculated using the formula:

$$T_{c,EN} = 0.33 \cdot T_{rm} + 18.8 \qquad (3)$$

To date, the ASHRAE adaptive thermal comfort model does not have a *right-here and right-now index* of dissatisfaction, although it does give 80% and 90% acceptability threshold temperatures on either side of the adaptive comfort temperature optimum, which, like its EN 15251 counterpart (recently superseded by EN 16798 [12,13]), is a function of outdoor running mean temperature. Therefore, the purpose of the current work is to show the development and validate a new index built upon the ASHRAE adaptive thermal comfort model to estimate the predicted percentage of dissatisfied people according to the above model.
The first step is a statistical analysis of the ASHRAE RP-884 Global Thermal Comfort Database [8], which contains *right-here and right-now* thermal questionnaire responses from occupants of naturally ventilated (NV) buildings across diverse global climate zones. The analysis aims to derive the predicted percentage of dissatisfaction as a function of the deviation of the actual operative temperature from the optimal comfort temperature estimated by the ASHRAE adaptive thermal comfort model. Since the ASHRAE adaptive model was developed from observations collected in NV buildings, we extracted from ASHRAE RP-884 Database only the data collected in such buildings for our analysis.
The statistical procedure adopted to derive acceptability ranges (range of operative temperature for which the predicted percentage of dissatisfaction is smaller than a specified value) as a function of actual thermal sensation votes is similar to the one used in [4,5]. Thermal sensation votes averaged over temperature bins and calculated from the observations gathered in the ASHRAE RP-884 Database are indicated in this paper with ASH.

The offsets from optimal comfort temperature were calculated not only in correspondence of PPD values equal to 10% and 20% currently embedded in the ASHRAE Standard 55 [10] but also for a larger number of values of PPD to derive a smooth function correlating acceptability ranges in terms of ΔT with PPD.

As a basis for the procedure, the assumptions adopted are the same used in [4,5]: (i) normality and equality-of-variance are applied across the database; (ii) the Fanger's relationship between PPD and PMV (Eq. 1) was used to relate the predicted percentage of dissatisfied with ASH ; (iii) a linear dependence of thermal sensation vote on operative temperature is assumed. A consequence of these assumptions is that the relationship between indoor operative temperature and adaptive PPD is symmetric around the optimal comfort temperature (neutrality). The first phase of the analysis consisted of determining the statistical significance of the data collected for each building of the sample to exclude from further analysis those buildings characterised by few observations or rather small variations of indoor temperatures with respect to outdoor variations. From the full set of 45 buildings in the RP-884 database classified as naturally ventilated, one was excluded since the thermal sensation votes were missing. Then, the statistical significance of the remaining samples was tested using the F-test. The linear regression models of eight buildings failed to achieve a residual probability, p, related to F, smaller than 0.05 and those buildings were also eliminated by the set of data. A summary of the statistical analysis is reported in Table 1.

Table 1 Summary of the weighted linear regression coefficients of the average thermal sensation votes of each bin on indoor operative temperature

Description	Value
Total number of naturally ventilated buildings of ASHRAE RP-884 database	45
Number of building with missing values	1
Number of building with linear regression model failing 95% significance	8
Number of buildings with linear regression model achieving 95% significance	36 (80.0% of total buildings)
Mean model y-intercept (± standard deviation)	-6.22 (± 3.098)
Mean model gradient (± standard deviation)	0.26 (± 0.122)

For each of the remaining 36 buildings, the ASHs were averaged within 0.5 °C temperature bins, and each pair of data (average ASH and mean value of the temperature bin) was weighted by the number of observations contained in each bin to minimise the impact of those outliers that correspond to a low number of observations. Binning process causes some diversity loss since it represents a distribution of data within each temperature bin by just its average value. These average values represent, hence, the average thermal response of a representative population and cannot be used for predicting the thermal sensation perceived by one individual person in a given building; it is in the nature of all global thermal comfort models to aim at predicting the average response of a group of people exposed to the same thermal conditions. We decided to adopt the bin method also because we intended to maximise the compatibility of the new metric with the ASHRAE adaptive model, which was developed using the bin method as described in the ASHRAE RP-884 report. Therefore, the main goal of the new metric is to assess the likelihood of dissatisfaction perceived by “a majority of the occupants within the space” [10].

For each building a linear regression was conducted for modelling the relationship between the mean indoor operative temperature values of each bin and the mean thermal sensation votes (ASH) of each bin. Each point was repeated as many times as the observations fell in each bin. An example is reported in Figure 1. The regression models for every building were verified with respect to the graphs reported in Appendix 1 of the ASHRAE RP-884 report [48].

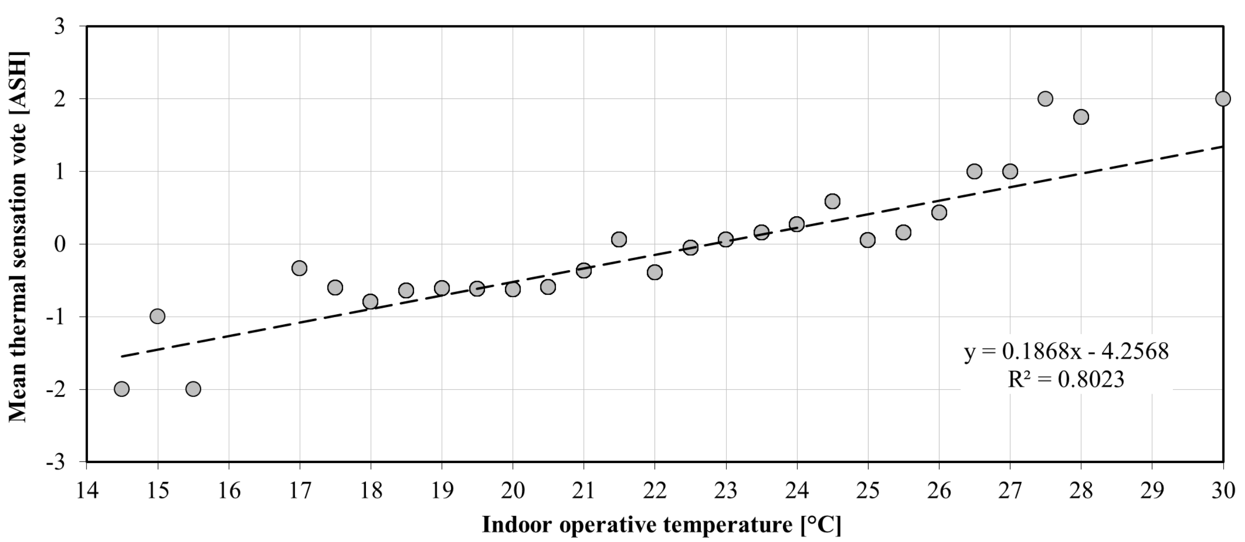

Figure 1 Example of a correlation between the mean thermal sensation vote (ASH) and the indoor operative temperature for one building of the ASHRAE RP-884 database: Oxford UK (summer), NV building #1

Assuming that ASHs are distributed around the zero value (neutral sensation) with the same variance embedded in the PMV model, Fanger’s PPD/PMV relationship can be used to calculate the two values of the ASH (one positive and one negative) corresponding to a given PPD. Hence, we obtained, for each building, an array formed by the two values of ASH for each PPD value of the series 5%, 7%, 10%, 20%, 30%, 40%, 50%, 60%, 70%, 80%, 90% and 99%. Then, for each building, using its own linear regression model (e.g., Figure 1), operative temperatures were derived from each ASH value inside the array. Finally, the two operative temperatures corresponding to the same value of PPD, one warmer-than-neutral and the other cooler-than-neutral, were subtracted to obtain the acceptability range (in degrees Celsius) for a given PPD. Each half-range represents the offset in Celsius from the optimal comfort temperature per every value of the PPD in the array. The offsets in Celsius from the optimal comfort temperature calculated for each building were averaged for each PPD value obtaining the mean offset in Celsius from the optimal comfort temperature in correspondence with each value of the PPD in the array.

Finally, we performed a logistic regression over the data-pairs constituted by the mean deviations from the optimal comfort temperature expressed in Celsius and the corresponding Predicted Percentage of Dissatisfied

(PPD) values (Figure 2). The resulting interpolating logistic function PPD (ΔT) is what we call ASHRAE Likelihood of Dissatisfaction (ALD).

In order to avoid overfitting, we identified three conditions that were used to select the appropriate fitting expression. The objective is that ALD extends the current recommendations included in ASHRAE 55 for the two acceptability classes of 90% and 80% and approaches to PPD = 5% when in theoretical comfort conditions (i.e. when the offset from theoretical comfort temperature is nil, ΔT = 0), which is the minimum PPD value for PMV = 0. Based on the above three desiderata, the three criteria used to select the best-fit nonlinear logistic expression among those statistically significant to an F test for model fit ($p \leq 0.05$) are:

1. PPD (ΔT_{op} = 0 K) ≈ 5%
2. PPD (ΔT_{op} = 2.5 K) ≈ 10%
3. PPD (ΔT_{op} = 3.5 K) ≈ 20%

We tested three logistic expressions with the exponent being linear, quadratic and cubic. Table 2, Table 3 and Table 4 show the parameter estimates, the mean square error, the R^2 and the percentage deviation from the three criteria for the three logistic expressions.

Table 2 Parameter estimates, goodness-of-fit and percentage deviation from criteria for the logistic expression $ALD(\Delta T_{op}) = \frac{e^{A+B\,\Delta T_{op}}}{1+e^{A+B\,\Delta T_{op}}}$

		95% Confidence interval	
Parameter	Estimate	Lower bound	Upper bound
A	-3.305	-3.445	-3.165
B	0.510	0.489	0.531
Mean square error	1.929		
R^2	0.999		
PPD (ΔT_{op} = 0 K)	3.5% (Deviation = -1.5% ; Relative error = 30.0%)		
PPD (ΔT_{op} = 2.5 K)	11.6% (Deviation = +1.6% ; Relative error = 16.0%)		
PPD (ΔT_{op} = 3.5 K)	17.9% (Deviation = -2.1% ; Relative error = 10.5%)		

Table 3 Parameter estimates, goodness-of-fit and percentage deviation from criteria for the logistic expression $ALD(\Delta T_{op}) = \frac{e^{A+B\,\Delta T_{op}+C\,\Delta T_{op}^2}}{1+e^{A+B\,\Delta T_{op}+C\,\Delta T_{op}^2}}$

		95% Confidence interval	
Parameter	Estimate	Lower bound	Upper bound
A	-3.057	-3.261	-2.853
B	0.419	0.350	0.487
C	0.007	0.002	0.013
Mean square error	1.286		
R^2	0.999		

PPD (ΔT_{op} = 0 K)	4.5% (Deviation = -0.5% ; Relative error = 10.0%)
PPD (ΔT_{op} = 2.5 K)	12.3% (Deviation = +2.3% ; Relative error = 23.0%)
PPD (ΔT_{op} = 3.5 K)	18.2% (Deviation = -1.8% ; Relative error = 9.0%)

Table 4 Parameter estimates, goodness-of-fit and percentage deviation from criteria for the logistic expression $ALD(\Delta T_{op}) = \frac{e^{A+B\,\Delta T_{op}+C\,\Delta T_{op}^2+D\,\Delta T_{op}^3}}{1+e^{A+B\,\Delta T_{op}+C\,\Delta T_{op}^2+D\,\Delta T_{op}^3}}$

		95% Confidence interval	
Parameter	Estimate	Lower bound	Upper bound
A	-3.299	-3.590	-3.008
B	0.578	0.414	0.742
C	-0.022	-0.051	0.007
D	0.002	4.325E-6	-0.003
Mean square error	0.965		
R^2	1.000		
PPD (ΔT_{op} = 0 K)	3.6% (Deviation = -1.4% ; Relative error = 28.0%)		
PPD (ΔT_{op} = 2.5 K)	12.3% (Deviation = +2.3% ; Relative error = 23.0%)		
PPD (ΔT_{op} = 3.5 K)	18.9% (Deviation = -1.1% ; Relative error = 5.5%)		

Based on these outcomes, we selected the nonlinear regression using the logistic fitting function of the second order since it fits well the data and offers a better overall match with the three evaluation criteria (see relative errors in Table 2, Table 3 and Table 4). The expression of our proposed ASHRAE Likelihood of Dissatisfaction (ALD) is hence:

$$ALD(\Delta T_{op}) = PPD(\Delta T_{op}) = \frac{e^{-3.057+0.419\Delta T_{op}+0.007\Delta T_{op}^2}}{1+e^{-3.057+0.419\Delta T_{op}+0.007\Delta T_{op}^2}} \quad (4)$$

where $\Delta T_{op} = |T_{op,in} - T_{c,ASHRAE}|$ is the offset from the ASHRAE optimal operative temperature $T_{c,ASHRAE}$ (°C), which is derived from the prevailing mean outdoor air temperature $t_{pma(out)}$ and is calculated as

$$T_{c,ASHRAE} = 0.31 \cdot t_{pma(out)} + 17.8 \quad (5)$$

Figure 2 compares the averaged observations from the ASHRAE RP884 Database with ALD and its 95% confidence interval.

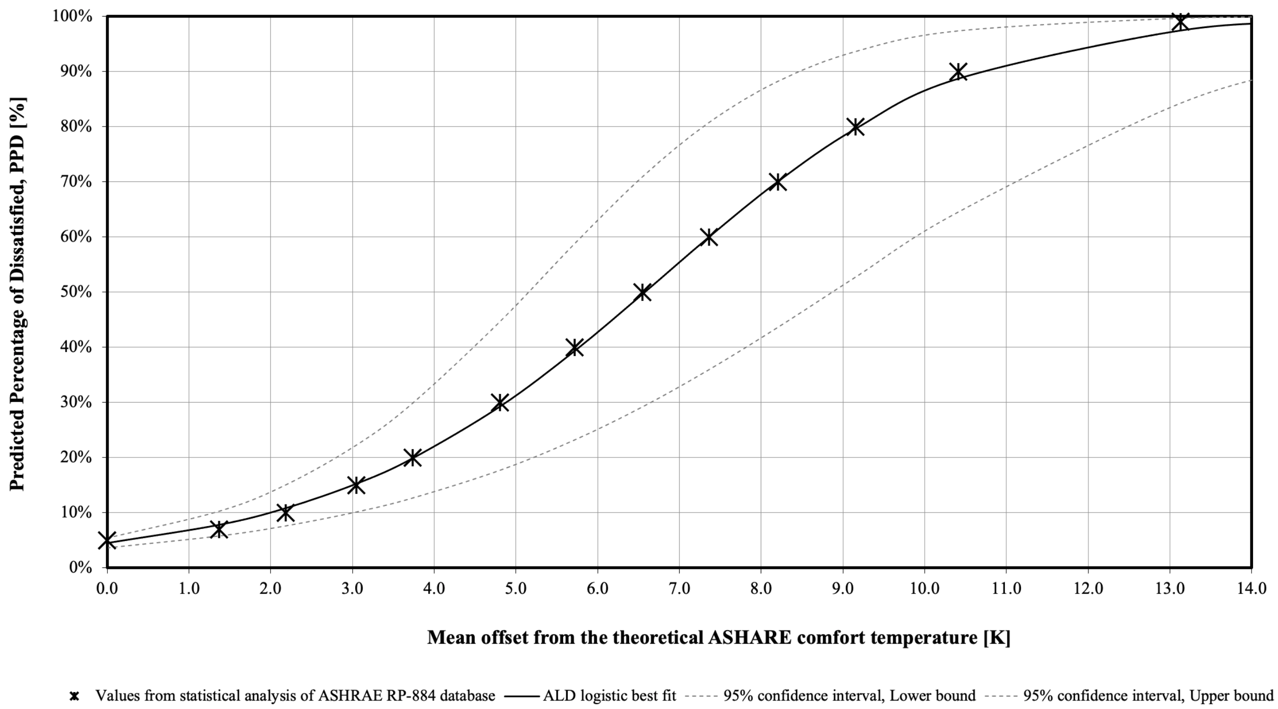

Figure 2 Predicted Percentage of Dissatisfied (PPD) versus the mean offset from comfort temperature obtained by the elaboration of data from ASHRAE RP-884 database. The interpolating logistic curve is the proposed ASHRAE Likelihood of Dissatisfaction (ALD)

Figure 3 shows the extension of acceptability classes from 10% to 90%, in steps of 10% acceptability increase. Compared to the result of the analysis performed in the ASHRAE RP-884 project [4,5], which was limited to 90% and 80% acceptability, the analysis developed here provides the relationship between PPD and the temperature offset across the entire range of PPDs.

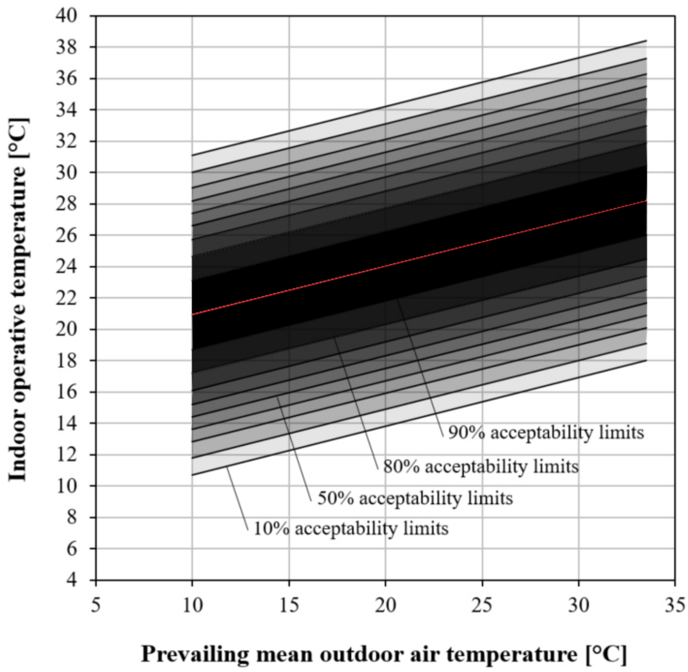

Figure 3 Acceptable operative temperature ranges for occupant-controlled naturally conditioned spaces

3 Model validation

External validation is used to assess the reproducibility of the model on a sample different from the one used to develop the ALD model and thus its generalisability, or transportability, on a different dataset.

3.1 Selection of records in the database

The validation of the ALD model has been performed using the data contained in the ASHRAE Global Thermal Comfort Database II [36]. This is an online open data repository, which includes records of raw data of paired subjective thermal sensation votes and objective instrumental measurements of thermal environmental parameters, published in 2018. In order to validate ALD, data stored in the ASHRAE Global Thermal Comfort Database II needed to be filtered to meet conditions similar to the ones under which the ASHRAE adaptive comfort model, and consequently the ALD, were developed [48]. The required assumptions are:

1. Since the ASHRAE RP-884 database was incorporated into the sequel database 20 years later [36], we have excluded all RP-884 data for validation in order to ensure the independence of validation dataset (external validation), which resulted in 81 967 records.
2. Since the ASHRAE adaptive model is exclusively addressed to naturally ventilated buildings, only the data referred to this type of cooling strategy were used for a total of 35 215 records.
3. In accordance with RP-884, among the different available building types, only the offices have been selected, which reduced the number of surveys to 17 920.
4. The database contains information about thermal acceptability (0 = unacceptable, 1 = acceptable) and the ASHRAE thermal sensation vote (TSV) from -3 that means cold to +3 that means hot, but not all the records presents both data. In ASHRAE RP-884, a proxy inferred from thermal sensation votes had been considered to include the whole set of records. The report defined the criterion for thermal acceptability as a thermal sensation vote falling in the interval $-1.5 < TSV < +1.5$. In agreement with RP-884 while maintaining also the information coming from thermal acceptability, we selected only the cases where both data were available, and we analysed only those records in which the two complementary responses were matching, that is in which either the condition “acceptable AND $-1.5 < TSV < +1.5$” or “unacceptable AND ($TSV \leq 1.5$ OR $TSV \geq +1.5$)” are met. In 11 998 records, the correspondence between the binary acceptability and the acceptability inferred from thermal sensation vote falling in the interval $-1.5 < TSV < +1.5$ was verified.

Furthermore, ALD is a function of the difference between the calculated operative temperature, obtained from measurements within the occupied zone of the building, and the ASHRAE optimal operative temperature, calculated using equation (5). Therefore, to carry out the validation of the novel index, the following assumptions were also required:

1. Since the Comfort Database does not contain the values of prevailing mean outdoor temperature, according to the exception 5.4.2.1.3 of the ASHRAE Standard 55 [10], we used the outdoor monthly average temperature to calculate the ASHRAE optimal operative temperature.
2. Since the operative temperature is available only in 1 653 records, the air temperature was used otherwise, without a detrimental impact on thermal comfort estimations [49]. Records, where neither operative temperature nor air temperature was available, were eliminated.

Under the above assumptions, the number of records used for the external validation resulted in 11 659.

3.2 Validation procedure

The validation procedure was carried out by comparing the likelihood of dissatisfaction calculated with ALD (derived from the ASHRAE RP-884 database) with the dissatisfaction rate actually observed in the ASHRAE Global Thermal Comfort Database II (test values).

To calculate the dissatisfaction rate, the thermal acceptability inferred from thermal sensation votes (-1.5 < TSV < +1.5) of each selected survey from the ASHRAE Global Thermal Comfort Database II (11 659 records) has been binned in relation to the absolute value of the difference between the measured indoor operative (or air) temperature and the ASHRAE adaptive comfort temperature, in one-degree increments. The number of dissatisfied for each bin has been counted, and the Percentage of Dissatisfied is obtained as the ratio of dissatisfied over the total records within each bin.

Figure 4 shows the comparison of the likelihoods of dissatisfaction as a function of the difference between the operative (or air) temperature and the ASHRAE comfort temperature in the occupied zone.

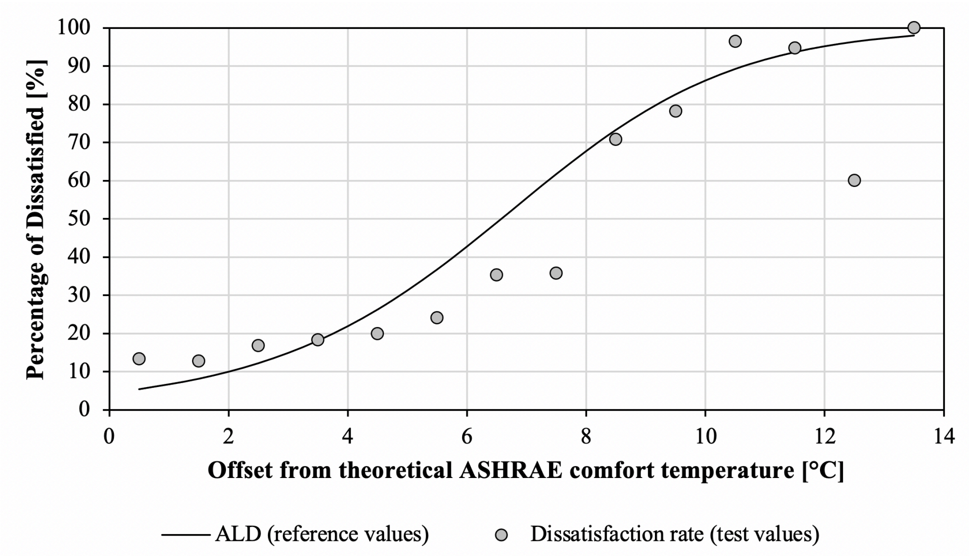

Figure 4 Comparison between the percentage of dissatisfied calculated with ALD – ASHRAE Likelihood of Dissatisfaction (reference values) and the dissatisfaction rate calculated from actual thermal acceptability from the ASHRAE Global Thermal Comfort Database II (test values)

The agreement between the reference values and the test values has been assessed using the coefficient of determination R^2, as represented in Figure 5.

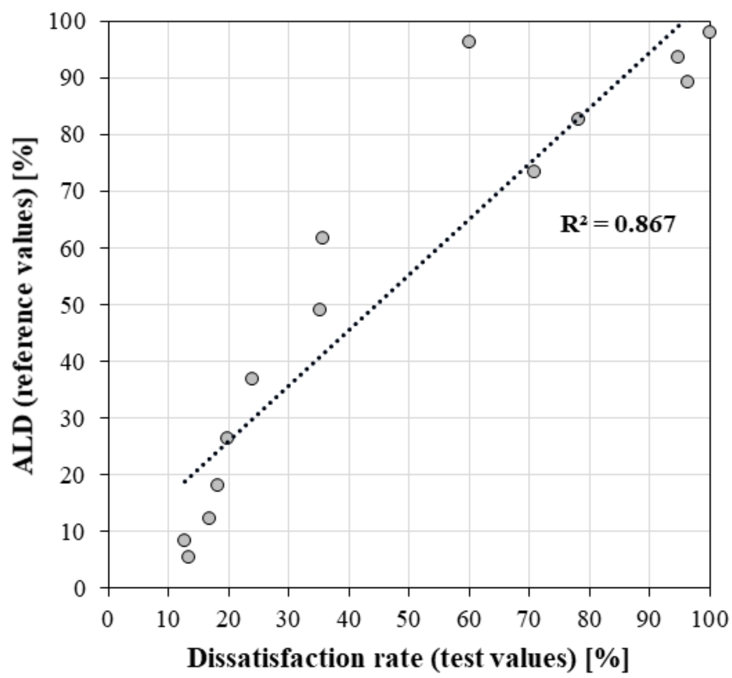

Figure 5 Correlation between the ALD - ASHRAE Likelihood of Dissatisfaction (reference values) and the Dissatisfaction rate (test values)

The resulting value of R^2 equal to 0.867 indicates that the ALD model, which is obtained from a logistic regression analysis on the ASHRAE RP-884 Database, approximates the data points from the independent ASHRAE Global Thermal Comfort Database II quite well. The novel discomfort index has proved reliable to predict the percentage of dissatisfied people in a broader set of data.

4 Discussion

After having tested the accuracy of the proposed index by performing validation against the data contained in the new ASHRAE Global Thermal Comfort Database II, we have compared ALD with the already existing *right-here and right-now* overheating risk index developed and proposed by Nicol et al., hereby indicated with NaOR and described in detail in section 2. NaOR index was derived from a completely different dataset, is asymmetric (defined only for warm sensations) and predicts the percentage of individuals voting on the warm side of the ASHRAE thermal comfort scale [34]. On the contrary, the ALD index is symmetric and applicable to both summer and winter assessment.

Following indications of ASHRAE 55 and EN 16798 that allow the use of adaptive models also in residential buildings, we have calculated the predicted percentage of dissatisfaction according to the two indices in a real case study of an inhabited residential building with an office room. The house, certified Passivhaus and located in Sicily, Italy, is constantly monitored for research purposes by means of sensors, as shown in Figure 6 [50,51].

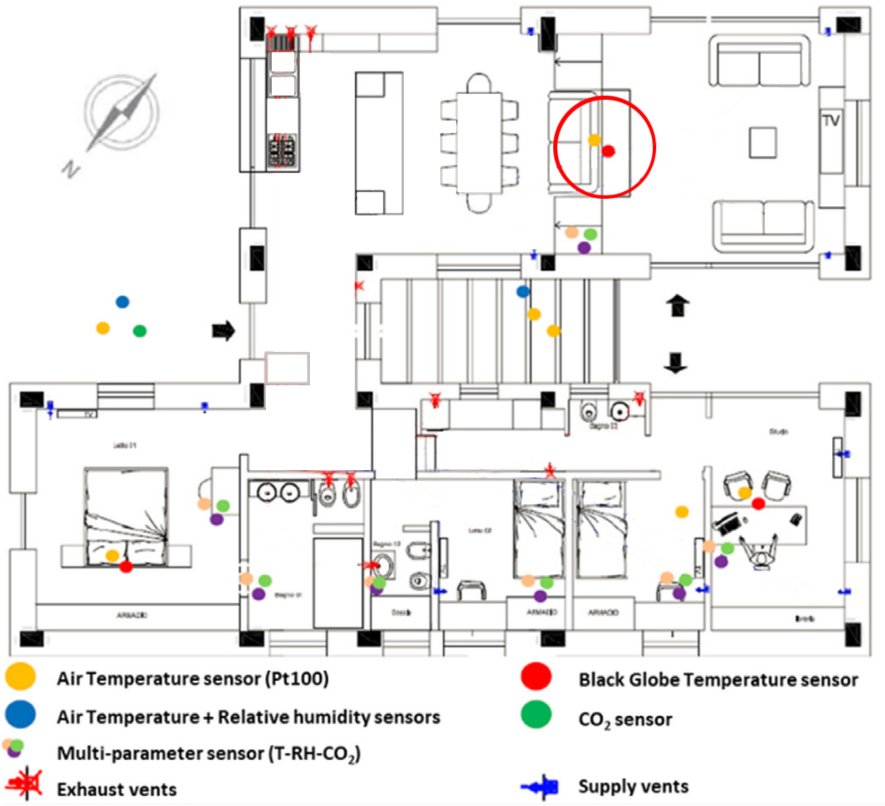

Figure 6 Plan of the building and sensors' location. The sensors selected for the analysis are circled in red

The thermal comfort analysis has been carried out choosing the data acquired in the living/dining room from the 8th of June 2019 until the 22nd of June 2019, when the building was naturally ventilated (Figure 7).

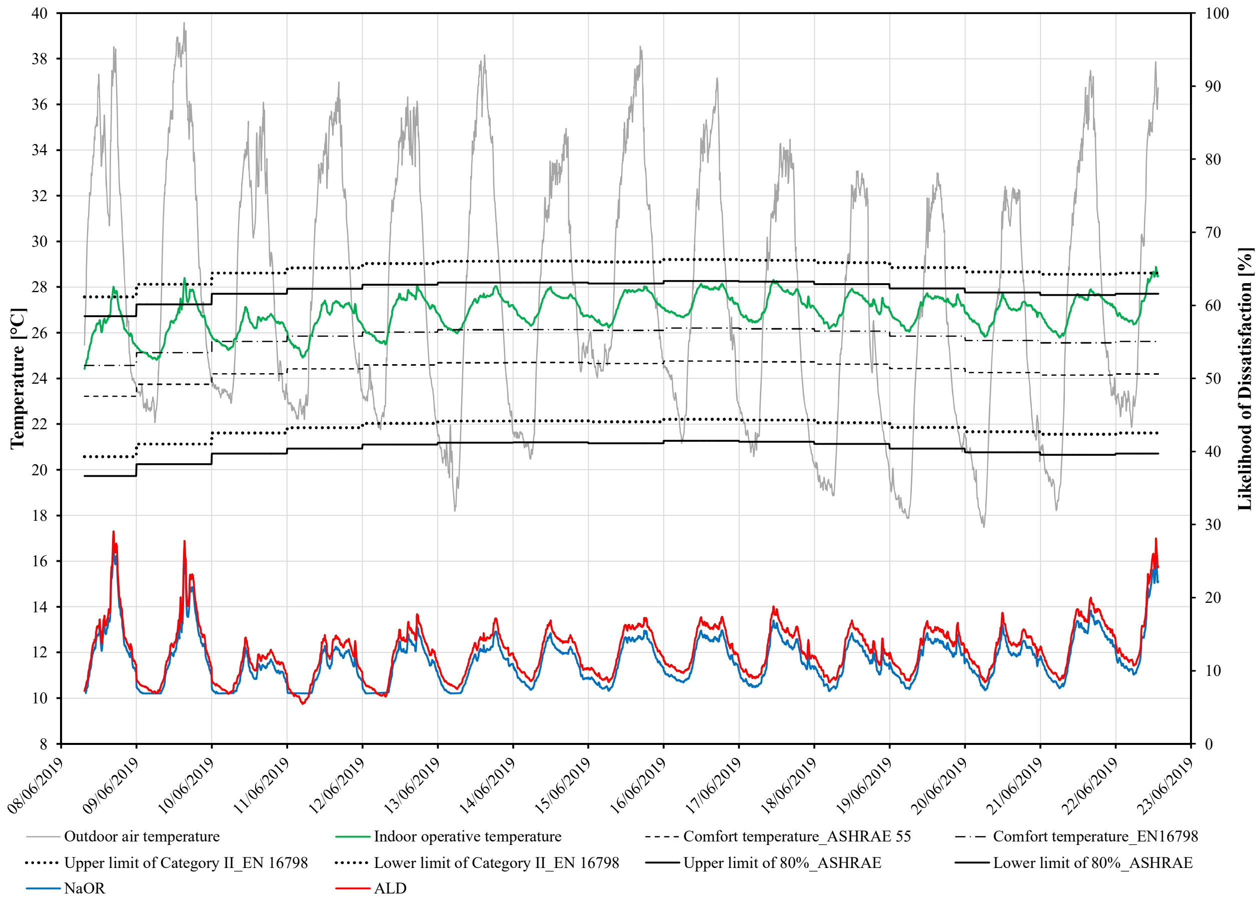

Figure 7 Indoor operative temperature distribution, comfort temperature thresholds (left scale), according to EN 16798 (PPD < 10%) and ASHRAE 55 (80% acceptability limit) and the predicted percentage of dissatisfied (right scale) obtained applying the NaOR and ALD indexes, respectively.

The upper part of Figure 7 shows the distribution of indoor operative temperature, which has been calculated according to the standard EN ISO 7726 [25] as the mean value of air and mean radiant temperature. These have been measured using an air temperature probe and a black globe sensor (D = 0.15 m, $\varepsilon_g = 0.95$). The figure also reports the calculated optimal operative temperatures and the upper and lower limits according to the Category II of EN 16798 and 80% acceptability of ASHRAE 55.

The lower part of the figure reports the two predicted percentage of dissatisfaction obtained applying the NaOR and ALD indexes. They show a similar trend, which follows the distribution of the indoor operative temperature, despite the independence of their data sources [8,9] and the differences in their analytical derivation.

The scatterplot in Figure 8 shows a high agreement between the two indexes (coefficient of determination R^2 almost equal to 1) and highlights a slight difference (average +11.0%, min +6.2%, and max +14.5%) in the values of ALD with respect to NaOR.

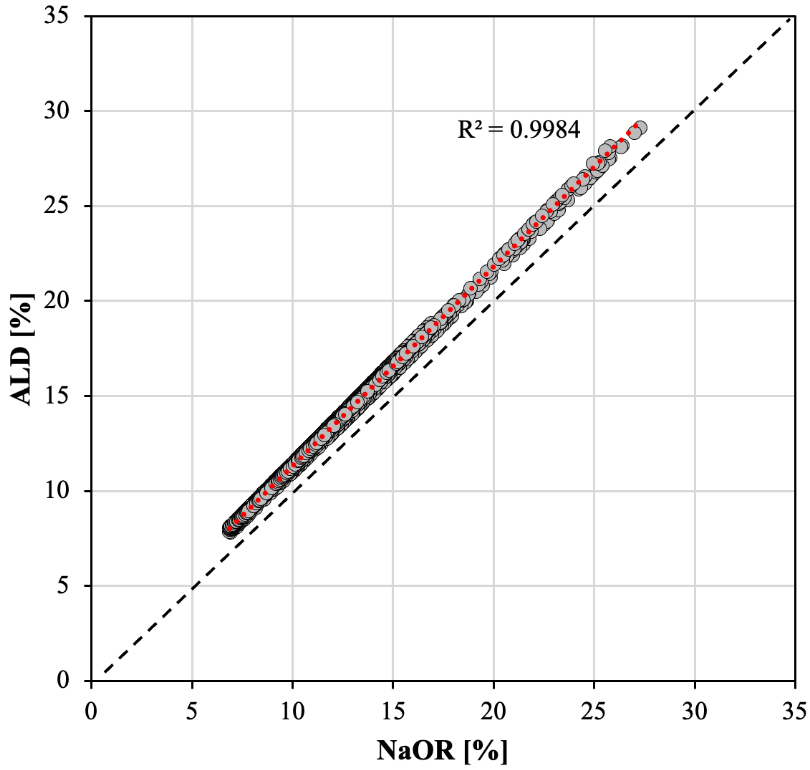

Figure 8 Scatterplot of ALD and NaOR indexes concerning the presented case study and the red dotted interpolation line.

We might also note that the predicted percentage of dissatisfied remains low (mostly between 10 to 15%) even under challenging outdoor temperatures (32 to 38°C during the day and only a limited number of nights where temperature drops below 20°C), with no active conditioning, thanks to the building geometry, highly insulated envelope and external movable solar protections automatically controlled.

5 Conclusions

A prediction of the percentage of dissatisfied people under specified personal and environmental conditions in indoor spaces can be used in building design optimisation and for the assessment of thermal condition in existing buildings. *Right-here* and *right-now* thermal acceptability indices (or their counterpart, percentage of dissatisfaction indices) are available in the literature and standards for Fanger's model and the European adaptive comfort model, as presented in the European standard EN 15251 and its update EN 16798. To date, a *right-here* and *right-now* thermal acceptability index is not available for use with the ASHRAE adaptive comfort model as presented in the ASHRAE Standard 55. This paper proposes a new *right-here and right-now* thermal comfort index to assess the likelihood of dissatisfaction according to the ASHRAE adaptive comfort model, in order to fill this gap in the literature. We name it the ASHRAE Likelihood of Dissatisfaction (ALD). It has been created from an analysis of the ASHRAE RP-884 Global Thermal Comfort Database and has been validated on independent data from the ASHRAE Global Thermal Comfort Database II. In addition, we have compared the ALD distribution with the Overheating risk presented by Nicol and al. [34] (NaOR), which estimates the percentage of dissatisfaction based on the EN adaptive comfort model and hence it is applicable only when using that model. ALD is meant to be used with the ASHRAE adaptive model and hence adds a tool previously missing. We found broadly consistent results between the two indices, despite the different reference datasets used for model development and underlying models (EN adaptive vs ASHRAE adaptive) used for deriving them.

The successful validation of ALD on the independent ASHRAE Global Thermal Comfort Database II and the agreement with NaOR give support to the reliability of the novel ALD index and open to the possibility to use it for assessing short-term thermal comfort conditions in buildings, for calculating long-term thermal comfort indices based on ASHRAE's adaptive model, for optimising both the design of new buildings and renovations and for assessing the operational thermal comfort performance of existing buildings. In a situation where more and more data, detailed in space and time, are available due to the increasing number of sensors deployed in buildings, there is a need to assign a weight also to situations far from comfort and of low acceptability, since are those that are relevant in the process of assessment of the quality of a building and the subsequent plan of amelioration. Similarly, in an optimisation process, a quantitative weight is necessary for all situations in order to evaluate objective functions to be maximised or minimised. The new ASHRAE Likelihood of Dissatisfaction may constitute a potential candidate for inclusion in a future update of the ASHRAE Standard 55.

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