An improved approach for solving the adaptive coefficient in the aPMV (adaptive Predictive Mean Vote) index

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Abstract

An accurate evaluation of thermal environments in buildings is beneficial not just for occupant comfort but also for reducing unnecessary overheating or overcooling energy. The aPMV (adaptive Predictive Mean Vote) index can take into account occupants' thermal adaptations and is stipulated in Chinese standards for evaluating thermal conditions in free-running buildings. Even though substantial studies have validated the efficiency of the aPMV index, it occasionally exhibits limited performance in certain scenarios. This paper aims to propose a novel algorithm for solving the key adaptive coefficient λ in the aPMV index. Validation was carried out utilizing the public ASHRAE thermal comfort database, which spans 14 climate zones. Results show that the new algorithm-based aPMV index can fit data effectively with low errors, improving average performance by 34.5-37.7% compared to the previous method. The different λ values in the aPMV index are able to quantify specific patterns of occupant thermal adaptations in cold, mild, and hot climates, respectively. Some aPMV outcomes with large deviations can be explained adequately by the specific properties of the original data sources. The code is available at https://github.com/SuDBE/aPMV-calculation.

Keywords: Thermal comfort, PMV, aPMV, Adaptive coefficient, Naturally ventilated buildings

Abbreviations

Af	Tropical rainforest
Am	Tropical monsoon
Aw	Tropical wet savanna
BSh	Hot semi-arid
BSk	Cold semi-arid
BWh	Hot desert
Cfa	Humid subtropical
Cfb	Temperate oceanic
Csa	Hot-summer Mediterranean
Csb	Warm-summer Mediterranean
Csc	Cool-summer mediterranean
Cwb	Subtropical highland
Dfb	Warm-summer humid continental
Dwa	Monsoon-influenced hot-summer humid continental
MAE	Mean Absolute Error
PMV	Predictive Mean Vote
RSME	Root Mean Square Error
TSV	Thermal Sensation Vote
λ	Adaptive coefficient in the aPMV index
λ_N	Proposed algorithm for solving λ in this paper
λ_S	Existing λ optimization method

1. Introduction

Existing international [1] and national [2] standards stipulated Fanger's PMV (Predictive Mean Vote) index for assessing thermal comfort in HVAC (Heating, Ventilation, and Air Conditioning) buildings. While PMV performs well in steady-state conditions [3], its effectiveness is limited in dynamic environments with thermal fluctuations [4], such as naturally ventilated buildings. Given that PMV is defined as a "condition of mind which expresses satisfaction with the thermal environment" [2], considerable studies have concentrated on developing adaptive thermal comfort models that emphasize occupant self-regulation and adaptation, while depending less on HVAC systems. These models have been successfully established and stipulated into international and national standards, such as the graphic-based adaptive mode in EN 16798 [5] and the aPMV index in Chinese GB/T 50785 [6]. The application of adaptive models not only meets occupants' actual thermal needs but also promotes energy efficiency. Research indicates that the models embedded with occupant adaptation can effectively reduce building energy consumption by 18.9-34.4% [7].

To further improve the adaptive comfort theory, several researchers have performed theoretical explorations and extensions on the basis of the PMV index, such as Humphrey's nPMV [8], Fanger's ePMV [9], Yao's aPMV [10], Marcel's ATHB [11], etc. Among these, the aPMV index was first proposed in 2009, with the goal of the development of a framework for quantifying thermal feedback loop based loopsontrol theory. It employs a transfer function to represent occupant adaptations as a negative feedback system. Since its incorporation into the Chinese national standards in 2012 for evaluating thermal environments in free-running buildings (or naturally ventilated buildings), the aPMV index has received substantial academic attention regarding its applicability across varied climates. The adaptive coefficient λ, the key parameter of the aPMV index, has been examined, validated and customized further. These explorations included a wide range of building types, such as residential buildings [12][13][14][15][16][17][18], offices [19][20], classrooms [21][22], activity centers [23], cotton textile factories [24], bus stations [25], railway stations [26], etc. However, because the original aPMV was validated in the context of Chinese climate, with an emphasis on decreasing PMV overestimation in hot and cold conditions, data from too extreme scenario or inappropriate use of the aPMV framework may lead to suboptimal performance. For instance, Chaudhuri et al. [27] found that aPMV exhibited lower accuracy compared to a machine learning-based approach (35.51% vs. 73.14%) and even worse than PMV (35.51% vs. 41.68%) in a study involving 16 buildings in Singapore, but 12 of which were under HVAC operation. They concluded that occupant adaptation in hot and humid weather exhibited an negative λ value (-0.3217), but their calculation method was derived from a non-original source [28]. Notably, the aPMV index has the potential to align with PMV when λ equals zero, raising questions about the rationale behind aPMV's underperformance compared to PMV. Kim et al. [19] found large aPMV deviations from occupant thermal sensation and calculated abnormal negtive λ values in hot conditions. Again, their investigated building was fully air-conditioned rather than naturally ventilated, and subjective voting data also showed a strange trend of more cooler votes when temperatures exceeded 30°C. Certain research, such as [29] [30], have presented optimization methods for solving λ in the aPMV index, but a standardized approach remains elusive. The complexity of the least square method in the aPMV framework could also make computing the best parameter more challenging. Furthermore, there is a lack of comprehensive validation of its performance across various contexts based on large-scale data.

This paper aims to introduce a novel method for solving λ to improve the performance of the aPMV index in data fitting. It also discusses the potential application issues and validates the proposed method using a public thermal comfort database spanning 14 climate zones.

2. Solving adaptive coefficient λ in the aPMV index

2.1 Original solving approach

The aPMV Index is proposed based on Fanger's PMV (Predictive Mean Vote) index, which incorporates negative (adaptive) feedback concept from control theory to account for occupant adaptation in the form of:

$$aPMV = \frac{PMV}{1 + \lambda \times PMV} \tag{1}$$

Where λ is the adaptive coefficient and it can be solved by:

$$\lambda = \frac{1}{n}\sum_{i=1}^{n}(Y_i - X_i) \tag{2}$$

Where n represents the data sum of binned air temperatures, X_i is defined as i^{th} binned $1/PMV_i$, and Y_i is defined as i^{th} binned $1/TSV_i$. The original concept of the aPMV index, its derivation, and the detailed computation can be found in Ref [10].

The aPMV index has been stipulated in the current Chinese National Standard GB/T 50785-2012 [6] and its suggested λ values for the aPMV index are shown Table 1. For evaluating the thermal environment in free-running buildings, the aPMV shall be in accordance with the requirements on the grades of overall thermal comfort indexes as stated in Table 2.

Table 1 Values of λ for the five climate zones in different building types in Chinese National Standard GB/T 50785-2012 [6]

Building climate zone		Residential buildings, shops, hotels, and offices	Education buildings
SC and cold zones	PMV≥0	0.24	0.21
	PMV＜0	-0.50	-0.29
HSCW, HSWW, and mild zones	PMV≥0	0.21	0.17
	PMV＜0	-0.49	-0.28

Note: SC is severe cold zone, HSCW is hot summer and cold winter zone, and HSWW is hot summer and warm winter zone.

Table 2 Grade of thermal environment in free-running buildings [6]

Grade	aPMV
I	-0.5≤aPMV≤0.5
II	-1≤aPMV≤-0.5, or 0.5≤aPMV≤1
III	aPMV<-1, or aPMV>1

2.2 Improved algorithm for solving λ from the published study

While the aPMV index has demonstrated successful applications across various countries, building types, field studies, and Chinese national standards, its fitting results exhibit limitations in certain scenarios. This could be caused by inappropriate utilizations of the aPMV or inadequate solving process for the key coefficient λ. Zhang et al. [29] introduced an improved algorithm for optimizing λ by forcing the target function to the fourth power of the TSV (Thermal Sensation Vote) before calculation, and their improved determination is as follows:

$$\lambda_P = \frac{\sum_{i=1}^{n} TSV_i - \sum_{i=1}^{n} \frac{{TSV_i}^2}{PMV_i}}{\sum_{i=1}^{n} {TSV_i}^2} \tag{3}$$

Detailed deductions can be found in Ref [29] and this method will be marked as λ_P in the following main text and figures to avoid any confusion.

2.3 Proposed algorithm for solving λ

The original computation of λ coefficient and improved λ_P method both involve the reciprocal transformation of TSV and PMV, resulting in the creation of new variables 1/TSV or 1/PMV (assumptions before equation (7) in Ref [10] and equations (11) and (12) in Ref [29]). However, as real-world TSV measurements and calculated PMV values approach zero, these new variables tend to escalate dramatically. In extreme cases of values reaching zero, these new variables can diverge to infinity. To address this concern, this paper introduces an innovative approach for λ determination that circumvents these problematic zero crossings. The original reciprocal transformation in aPMV calculation enables the conversion of the aPMV solving process into a linear equation, which is easy to solve but introduces zero crossings. Here we maintain the same principle and methodology of the aPMV index as outlined in the original paper [10], but solve the λ directly rather than using the reciprocal transformation. The following steps outline the step-by-step procedure:

For original form of aPMV index in equation (1),

Let $x = PMV, f(x) = aPMV$, equation (1) can be transformed to：

$$f(x) = \frac{x}{1 + \lambda \times x} \tag{4}$$

Then import the given set of binned data (x_1,y_1), (x_2,y_2),…, (x_n,y_n), which are also equal to (PMV_1, TSV_1), (PMV_2, TSV_2),…, (PMV_n, TSV_n), the best fitting curve will present the least square error:

$$\delta = \sum_{i=1}^{n} [y_i - f(x_i)]^2 = \sum_{i=1}^{n} \left[y_i - \frac{x_i}{1 + \lambda \times x_i}\right]^2 \tag{5}$$

In search of the minimal δ that yields the partial derivative of λ equating to zero, the following derivation is undertaken:

$$\frac{\partial \delta}{\partial \lambda} = \sum_{i=1}^{n} \left[2\left(y_i - \frac{x_i}{1 + \lambda \times x_i}\right) \times \frac{{x_i}^2}{(1 + \lambda \times x_i)^2}\right] = 0 \tag{6}$$

Multiply $\frac{(1+\lambda \times x_i)^3}{2{x_i}^2}$ to both sides, then we have:

$$\sum_{i=1}^{n} [(y_i(1 + \lambda \times x_i) - x_i)] = 0 \tag{7}$$

The new λ can be solved as：

$$\lambda_N = \frac{\sum_{i=1}^{n} x_i - \sum_{i=1}^{n} y_i}{\sum_{i=1}^{n} x_i \times y_i} \tag{8}$$

Which is also equal to：

$$\lambda_N = \frac{\sum_{i=1}^{n} PMV_i - \sum_{i=1}^{n} TSV_i}{\sum_{i=1}^{n} TSV_i \times PMV_i} \tag{9}$$

The proposed λ_N determination process avoids the use of reciprocal operations, which may help to alleviate the zero crossing concerns. The following sections will validate of its performance by examining data from natural ventilation buildings of 14 climatic regions sourced from the public global ASHRAE thermal comfort database [31].

The aPMV theory aims to reduce the deviation between PMV prediction and actual TSV on the 7-voting scale from -3 to +3, representing “cold”, “cool”, “slightly cool”, “neutral”, “slightly warm”, “warm”, and “hot”. The smaller absolute λ value indicates lower capacity of adaptation, and the aPMV index is equal to the PMV index when λ is zero. On the hot side, the lowest available vote for occupants is +1 (slightly warm). Assuming that PMV overestimates the +1 (slightly warm) to the highest level, which is +3 (hot) by two orders of magnitude, the λ value will be +0.66. Meanwhile, the λ value will be -0.66 when PMV underestimates actual hot sensation by two orders of magnitude. Similarly, when the PMV index overestimates or underestimates the cold sensation by two orders of magnitude, the λ value is -0.66 or +0.66, respectively. If the absolute value of λ is greater than 0.66, it indicates that the PMV index overestimates or underestimates the sensation magnitude by more than 2, which lacks practical meaning under 7-voting scale. Therefore, it is suggested that any λ values greater than +0.66 and less than -0.66 should be modified to the nearest +0.66 or -0.66 value that best fits the practical data. The detailed steps for solving λ_N are outlined in Appendix A.

2.4 Evaluation indicators

The model estimation errors in this paper have been calculated by two popular indicators MAE (Mean Absolute Error) and RSME (Root Mean Square Error):

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|e_i| \tag{10}$$

$$RMSE = \left[\frac{1}{N}\sum_{i=1}^{n}|e_i|^2\right]^{\frac{1}{2}} \tag{11}$$

Where e_i is individual model prediction error defined as $e_i = P_i - O_i$, P_i is specific model prediction, and O_i is its matched observation. In this paper, P_i is equal to $aPMV_i$, and O_i is equal to TSV_i.

Willmott and Matsuura [32] criticized RSME as a misleading indicator for representing average model performance compared with MAE, because RSME tends to inflate disproportionately relative to MAE when the magnitudes of the errors within the distribution vary. However, Chai and Draxler [33] argued that RMSE can be more appropriate than MAE when error distribution is expected to be Gaussian. To comprehensively evaluate the λ performance, this paper used both MAE and RSME as evaluation indicators.

3. Validation using public Comfort Database

The ASHRAE Global Thermal Comfort Database II (short name: Comfort Database) is an accessible online dataset, which includes 81,846 data points of 52 field studies from 160 buildings worldwide [31] and 22,000 records from the RP-884 project which aims to supplement the adaptive comfort theory [34]. This paper employs the Comfort Database to validate the proposed algorithm for solving λ in the aPMV index. Although this database harmonized the raw data with a high and uniform standard, some anomalies still remain. For example, radiant temperature of 148.1°C (record No. 53,128) and air velocity of 56.16 m/s (record No. 17,533). Therefore, the Boxplot rule [35] was employed to eliminate these outliers. After filtering the data from naturally ventilated buildings, 22,785 data points from 14 climate zones have been selected for further analysis under Köppen climatic classification [36], as shown in Table 3, Fig 1 and Fig.

2. The meanings of Köppen climatic symbols are presented in Table 4.

Table 3. Statistical information of variables in selected data for λ validation

Climate	Air temperature (℃)	Radiant temperature (℃)	Relative humidity (%)	Air velocity (m/s)	Clothing level (Clo)	Metabolic rate (Met)	PMV	TSV	Sum
Af	30.2±1.42	30.34±1.33	71.82±6.36	0.2±0.13	0.25±0.11	1.08±0.09	1.4±0.72	0.46±1.3	1060
Am	27.14±2.26	27.14±2.26	63.53±5.18	0.22±0.13	0.41±0.09	1.18±0.06	0.44±0.83	0.41±0.94	1626
Aw	28.9±2.27	28.98±2.31	65.86±11.19	0.22±0.13	0.59±0.14	1.13±0.08	1.39±0.71	0.64±1.09	801
BSh	24.76±4.68	24.76±4.68	46.03±19.55	0.19±0.13	0.61±0.23	1.06±0.09	-0.3±1.51	-0.2±1.14	1271
BSk	24.22±5.43	24.22±5.43	57.56±10.76	0.13±0.06	0.62±0.22	1.11±0.09	-0.03±1.48	0.4±1.05	156
BWh	25.81±5.02	25.8±5.05	51.96±16.71	0.15±0.13	0.71±0.24	1.09±0.1	0.47±1.34	0.33±0.92	2580
Cfa	27.4±3.21	27.86±3.06	60.4±12.45	0.25±0.11	0.47±0.19	1.17±0.08	0.73±0.91	0.43±1.22	1321
Cfb	23.35±2.72	23.49±2.78	43.37±9.25	0.1±0.09	0.62±0.18	1.16±0.08	-0.38±0.85	0.37±1.18	2240
Csa	23.76±2.98	23.77±2.92	37.78±10.92	0.07±0.09	0.69±0.2	1.19±0.08	-0.02±0.72	0.19±1.25	7194
Csb	22.43±2.34	25.02±2.79	54.9±7.43	0.06±0.05	0.87±0.21	1.21±0.06	0.36±0.46	0.11±0.85	140
Csc	23.83±1.32	24.08±1.24	47.87±10.24	0.11±0.07	0.62±0.19	1.09±0.1	-0.36±0.57	0.3±1.08	456
Cwb	23.79±2.57	23.79±2.57	60.51±19.74	0.04±0.05	0.71±0.17	1.14±0.09	0.04±0.61	0.09±0.56	436
Dfb	22.21±1.89	22.83±2.01	57.79±8.35	0.09±0.03	0.58±0.15	1.2±0	-0.47±0.56	0.57±1.58	2928
Dwa	24.44±2.45	22.57±2.51	37.64±11.31	0.17±0.11	0.78±0.23	1.1±0	-0.24±0.64	-0.03±0.71	576

Note: several empty radiant temperature values were replaced with air temperature to enrich the data sum. Af: Tropical rainforest; Am: Tropical monsoon; Aw: Tropical wet savanna; BSh: Hot semi-arid; BSk: Cold semi-arid; BWh: Hot desert; Cfa: Humid subtropical; Cfb: Temperate oceanic; Csa: Hot-summer Mediterranean; Csb: Warm-summer Mediterranean; Csc: Cool-summer Mediterranean; Cwb: Subtropical highland; Dfb: Warm-summer humid continental; Dwa: Monsoon-influenced hot-summer humid continental.

Table 4. Description of Köppen climatic symbols [36]

1st	2nd	3rd	Description
A			Tropical
	f		-Rainforest
	m		-Monsoon
	w		-Savannah
B			Arid
	W		-Desert
	S		-Steppe

		h	-Hot
		k	-Cold
C			Temperate
	s		-Dry Summer
	w		-Dry Winter
	f		-Without dry season
		a	-Hot Summer
		b	-Warm Summer
		c	-Cold Summer
D			Cold
	s		-Dry Summer
	w		-Dry Winter
	f		-Without dry season
		a	-Hot Summer
		b	-Warm Summer
		c	-Cold Summer
		d	-Very Cold Winter
E			Plar
	T		-Tundra
	F		-Frost

The tropical climatic zones (Af, Am, Aw) have the highest temperature values, with means ranging from 27.14°C to 30.34°C. The Csa and Dwa zones have the lowest relative humidity levels with mean values below 40%. Wind speeds average between 0.1 and 0.2 m/s, with the exception of the Csa, Csb, Cwb, and Dfb zones, where they fall below 0.1 m/s. This suggests that airflow is being intentionally utilized to regulate occupants' thermal comfort in naturally ventilated buildings. Clothing levels tend to be lower in tropical regions, while other areas demonstrate a more uniform distribution. Given that most data in the Comfort Database come from office buildings, the values of metabolic rate keep stable, ranging from 1 to 1.4 met, since occupants often assume to conduct office activities, such as reading, typing, filing, standing, etc. Moreover, as A to E in the Köppen climatic classification correspond to Tropical, Arid, Temperate, Cold, and Polar, respectively, the outdoor climate will follow a descending trend. This tendency corresponds to the fluctuation in PMV values shown in Fig. 2.

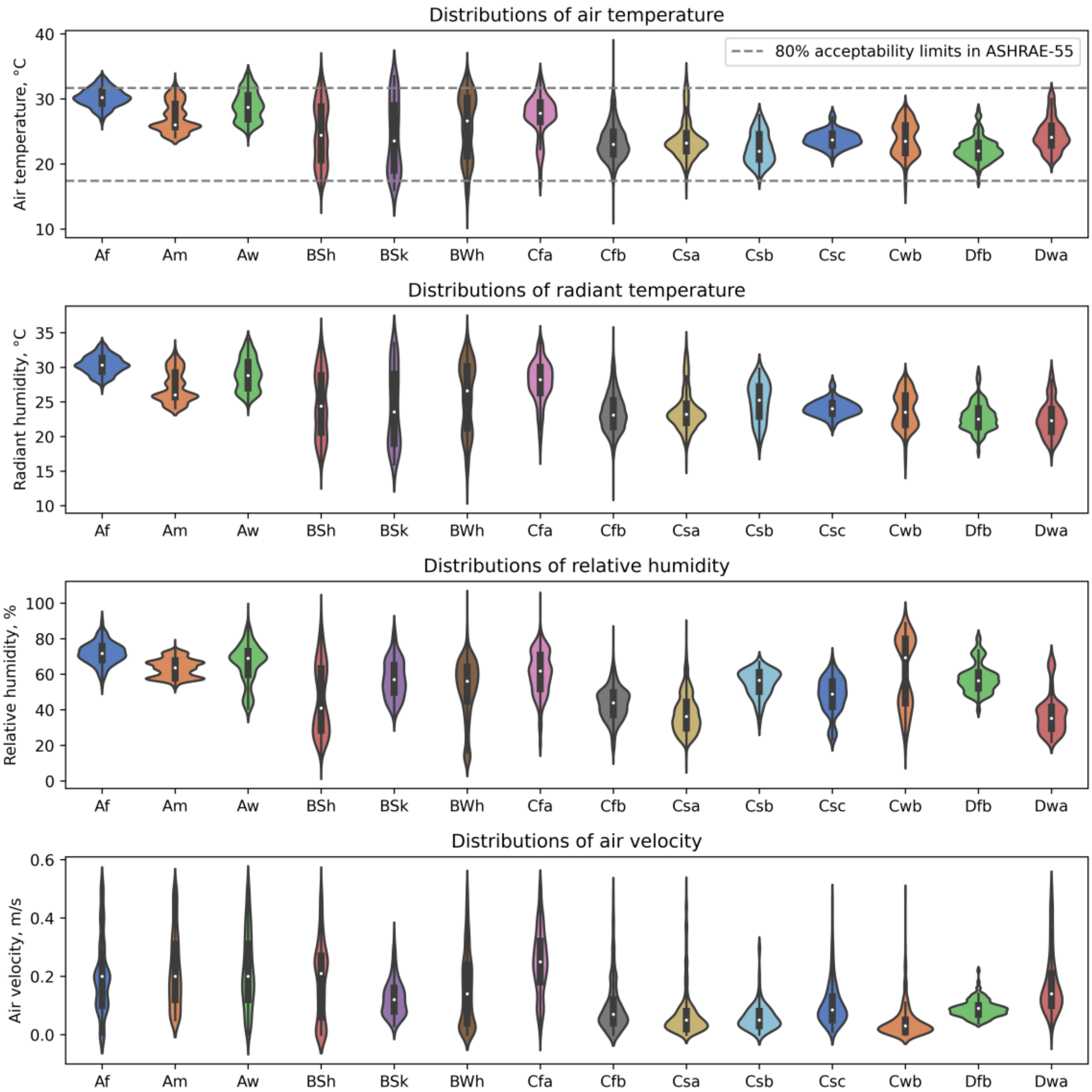


Fig.1 Variable distributions of environmental data grouped by climate

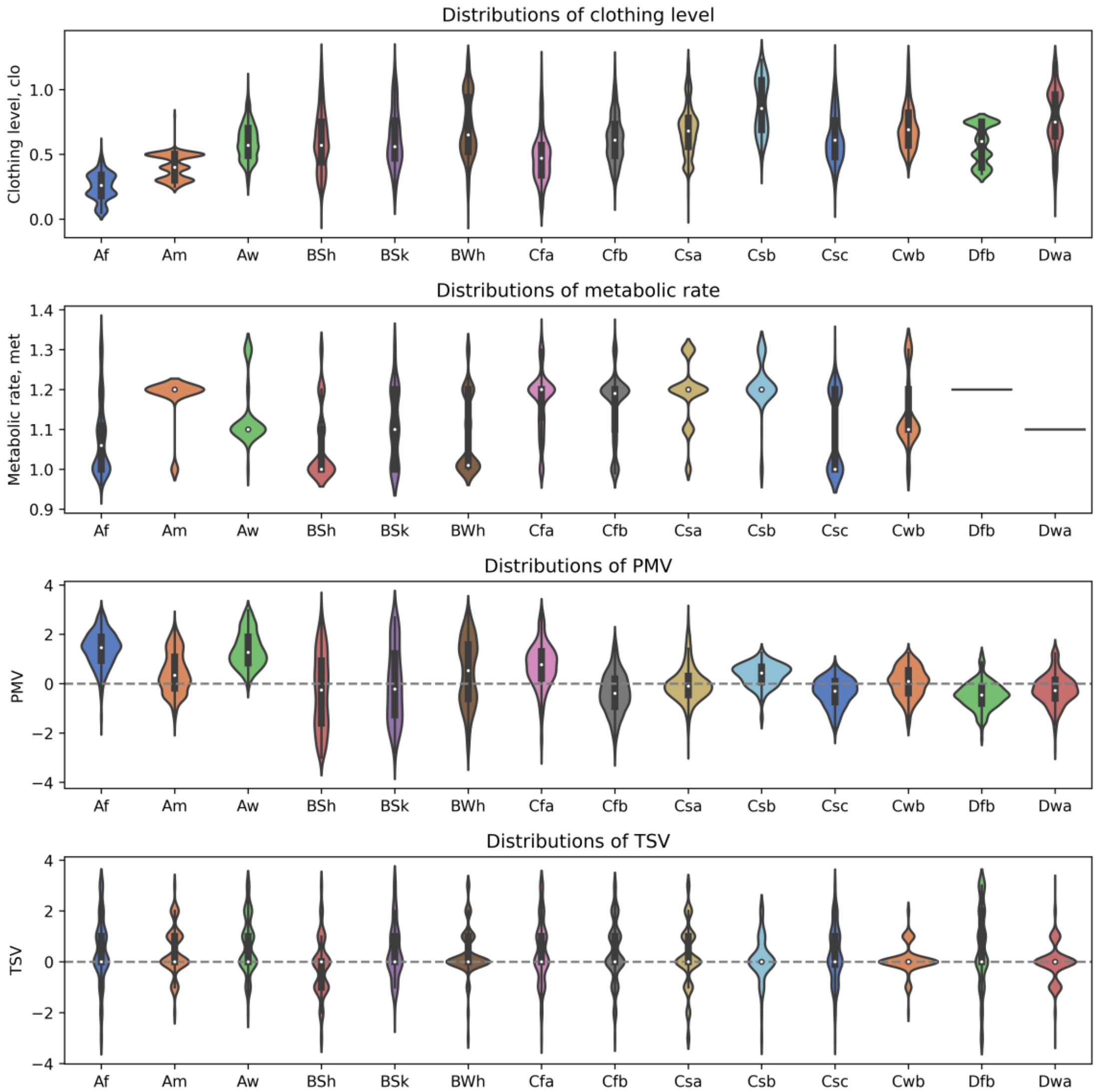


Fig.2 Variable distributions of subjective data, PMV and TSV grouped by climate

Table 5 shows the λ values obtained through our proposed algorithm (λ_N) and Zhang's algorithm (λ_P). It is evident that the absolute values of λ_N are generally higher, with a mean excess of 0.08 on the cold side and 0.06 on the hot side. To guarantee that the outputs are meaningful, any aPMV prediction greater than +3 was limited to +3, while any aPMV prediction less than -3 was limited to -3. Fig. 3 and Fig. 4 present the predictive errors of aPMV under the two λ scenarios, measured using both MAE and RMSE. It is clear that λ_N-based aPMV index demonstrates superior performance, as evidenced by lower predictive errors in both MAE and RMSE across the majority of cases, with the mean improvements of 34.5% in MAE and 37.7% in RMSE as shown in Table 6.

Table 5. Calculated λ_N and λ_P for selected climate zones

Climate	λ_N		λ_P	
	PMV<0	PMV>0	PMV<0	PMV>0
Af	0.66	0.66	0.66	0.11
Am	-0.66	0.46	-0.66	0.15
Aw	-	0.36	-	0.21
BSh	-0.56	0.66	0.15	0.51
BSk	-0.66	0.09	-0.66	-0.32
BWh	-0.66	0.34	-0.54	0.21
Cfa	0.1	0.41	0.19	0.38
Cfb	-0.41	-0.23	0.22	-0.46
Csa	-0.66	0.29	-0.53	-0.4
Csb	-0.25	0.55	-0.26	-0.66
Csc	-0.66	-0.66	-0.66	-0.66
Cwb	-0.66	0.55	-0.31	0.33
Dfb	-0.66	-0.66	-0.66	-0.66
Dwa	-0.66	-0.07	-0.66	-0.28
Absolute mean	0.57	0.44	0.49	0.38

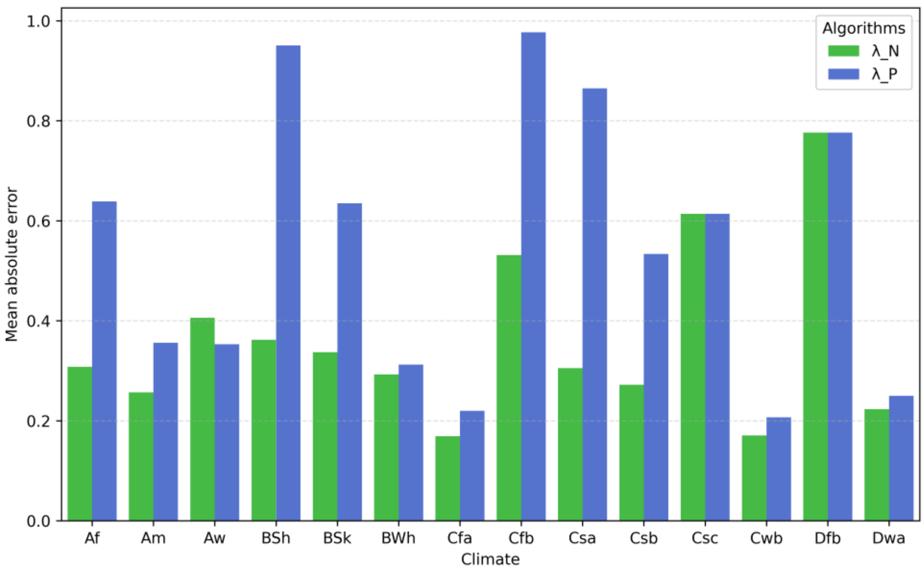


Fig. 3 MAE (Mean Absolute Error) for aPMV performance using λ_N and λ_P across 14 climate zones

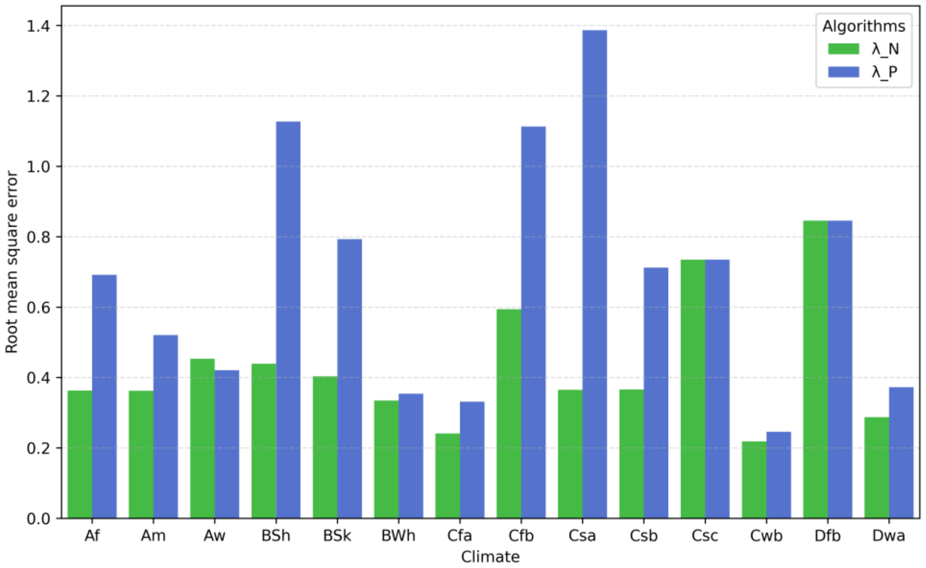


Fig. 4 RMSE (Root Mean Square Error) for aPMV performance using λ_N and λ_P across 14 climate zones

Table 6. Statistical information of MAE and RMSE on λ_P-based aPMV and λ_N-based aPMV

Building type	Indicator		λ_P-based aPMV	λ_N-based aPMV	Improvements of λ_N method compared to λ_P method
Naturally ventilated buildings	MAE	Min	0.21	0.17	19.0%
		Mean	0.55	0.36	34.5%
		Max	0.98	0.78	20.4%
	RMSE	Min	0.25	0.22	12.0%
		Mean	0.69	0.43	37.7%
		Max	1.39	0.85	38.8%

To examine calculation outcomes at the climate level, two climatic zones, hot semi-arid (BSh) and cold semi-arid (BSk), were chosen for further investigation since they had the longest temperature ranges. The appendix has detailed results for each climate zone. According to Fig.5, λ_N-based aPMV curves (green lines) fit better with actual TSV points compared with λ_P-based aPMV ones. The λ_P-based aPMV underestimates occupants' tolerance for cold conditions (red line, PMV<0 parts) in climate BSh, and it also underestimates occupants' tolerance for warm conditions (red line, PMV>0 parts) in climate BSk. In contrast, λ_N-based aPMV curves present more adequate performance when fitting data from these two climates.

Fig. 6 shows the actual TSV votes, PMV, λ_N-based aPMV, and λ_P-based aPMV predictions at one-temperature binned intervals. In Fig. 6(a), for climate BSh, the absolute PMV values (blue squares) consistently surpass TSV values (black circles). This suggests that using PMV for thermal comfort prediction tends to underestimate people's heat tolerance in naturally ventilated buildings. However, both λ_N-based aPMV (green triangles) and λ_P-based aPMV (red diamonds) can effectively align the predicted points on the right side (warm conditions) with the actual TSV values. However, on the left side (cool conditions) of Fig. 6(a), λ_P-based aPMV exhibits considerable overestimation that even performs slightly worse than the original PMV, nearing or exceeding -3. In comparison, the proposed λ_N-based approach in this paper better fits the TSV. Nonetheless, for points at 14°C and 34°C, the absolute values of λ_P-based predictions lie lower than users' actual TSV, approaching a difference of nearly one scale. This indicates a potential risk of overestimating human tolerance under extreme conditions using λ_P-based approach. Fig. 6(b) shows similar trends, where PMV and TSV deviate, and λ_N-based aPMV is capable of correcting this discrepancy on both the cold and warm conditions, whereas λ_P-based aPMV falls short in rectifying the deviation on one side (warm conditions).

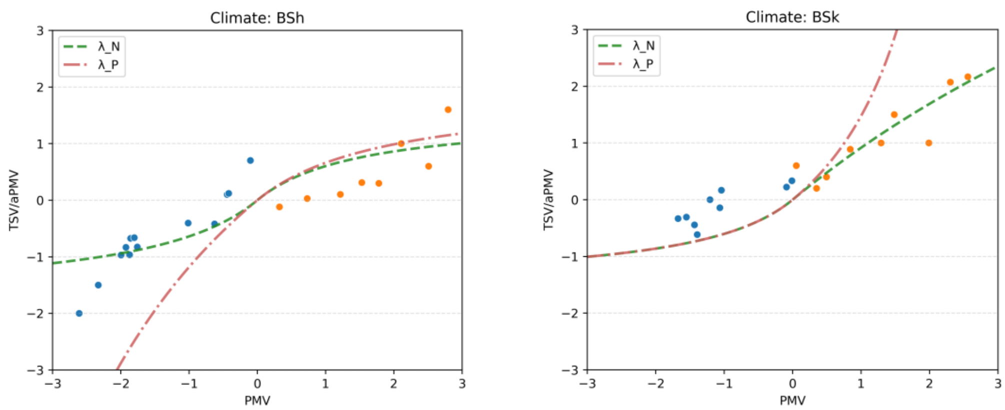
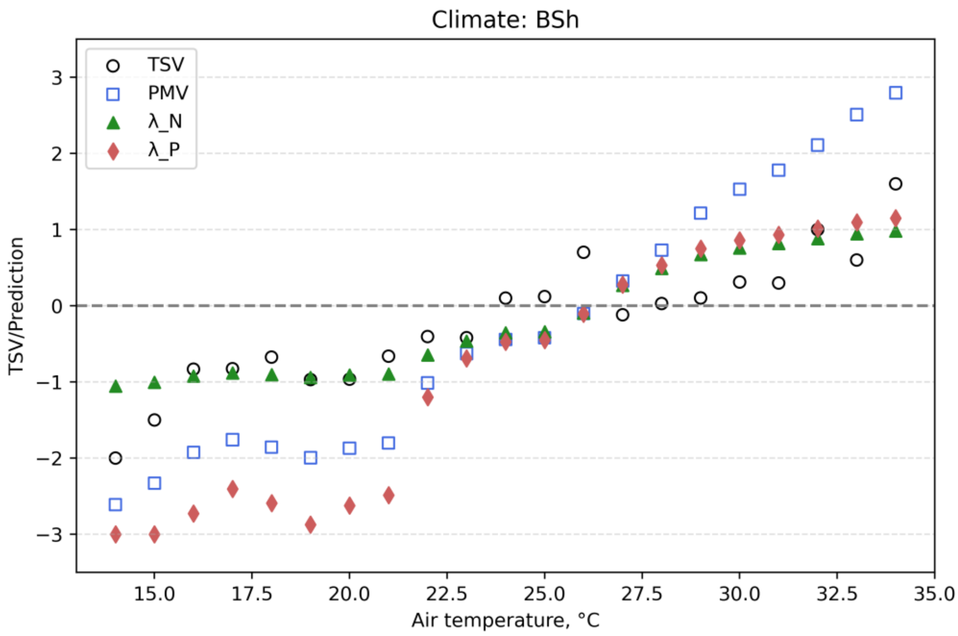
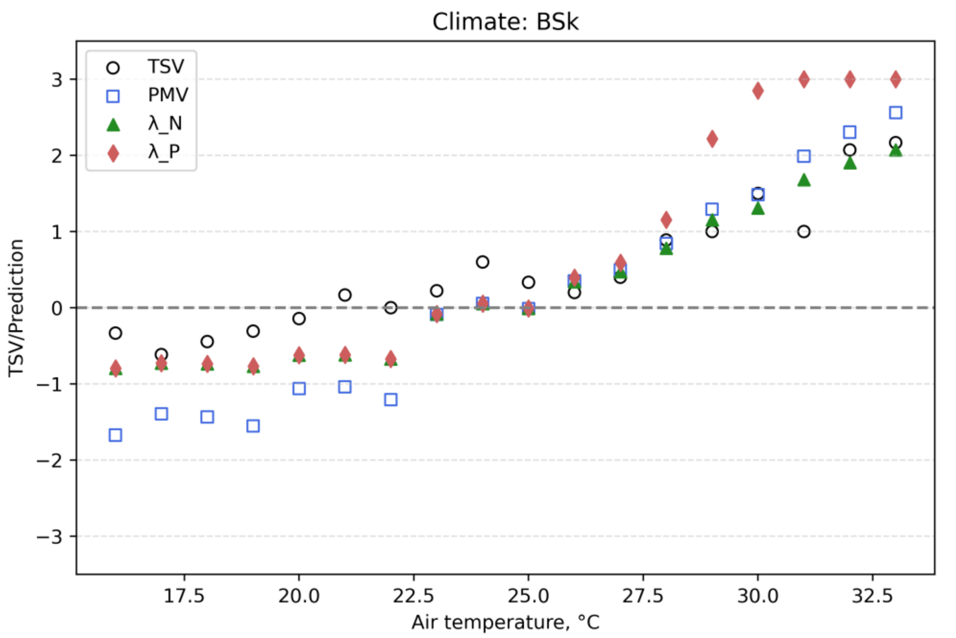


Fig. 5 Fitted aPMV curves in climates hot semi-arid (BSh) and cold semi-arid (BSk)

using λ_N and λ_P along with corresponding PMV-TSV values



(a) Validation for climate hot semi-arid (BSh)



(B) Validation for climate cold semi-arid (BSk)

Fig. 6 Validation of proposed λ_N-based aPMV, pervious λ_P-based aPMV, TSV, and PMV for naturally ventilated buildings in climates hot semi-arid (BSh) and cold semi-arid (BSk)

4. Discussion

4.1 Are adaptive opportunities always available in naturally ventilated buildings?

One key concept in adaptive thermal comfort theory is that individuals can actively adjust environmental surroundings and personal factors to restore their own comfort, particularly in naturally ventilated buildings [37]. Fitting results of aPMV curves based on the Comfort Database show strong alignment across the majority of climates. However, for climate warm-summer humid continental (Dfb), both λ_P-based and λ_N-based aPMV models perform limited with high MAE and RMSE values, with corresponding predictions shown in Fig. 7. A high proportion of PMV and aPMV values are approximately one scale lower than the actual TSV of occupants (black circles), indicating frequent warm discomfort.

After further exploring the dataset, these data points were found originated from a study conducted in 2011 concerning non-heating periods in classrooms for children aged 7 to 11 in the UK [38]. The authors mentioned that thermal environments in the surveyed classrooms were generally controlled by teachers and students can only adjust clothing levels. Notably, even among students who indicated a thermal sensation of +3 and +2, they (15% and 25%) continued to wear jumpers (0.25 clo). Some teachers also reported the observations that some students appeared to be visibly hot, yet they did not remove their jumpers or seek for help.

In the Comfort Database, the naturally ventilated buildings in climate Dfb are not the commonly investigated offices but rather classrooms. The majority of occupants, in this case, students, did not have the authority to control the thermal surroundings in the classrooms and were not always able to actively adapt themselves by taking off jumpers to restore thermal comfort. These departures from the adaptive thermal comfort theory gives rise to distinct characteristics in data distribution, which may ultimately result in constrained effectiveness during aPMV model fitting.

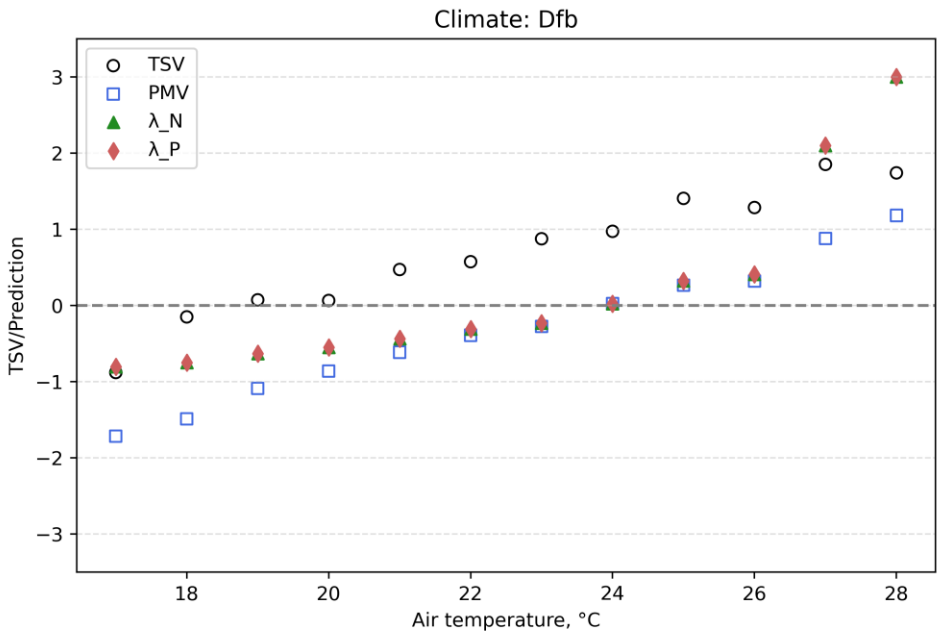
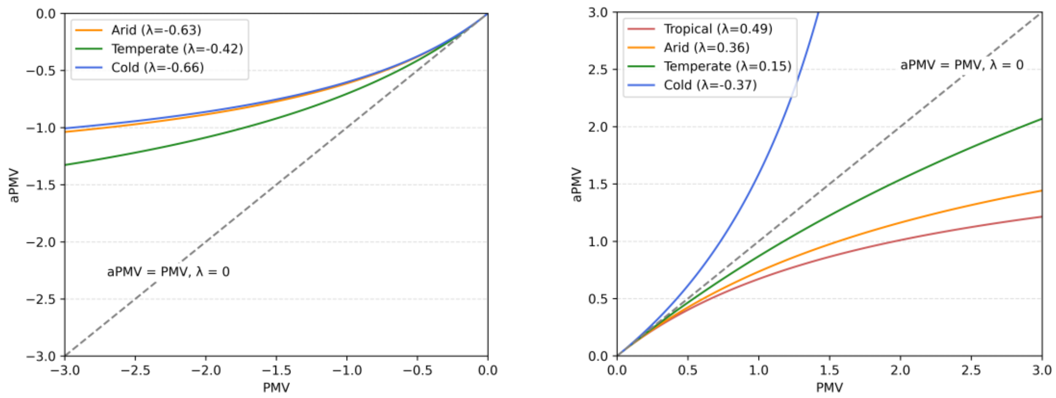


Fig. 7 Validation of predictions in climate warm-summer humid continental (Dfb)

4.2 aPMV fitting curves under the 1st level of Köppen climatic classification

The average MAE obtained for the λ_N-based aPMV models is 0.34 (Table 6), which signifies that the absolute value of the average prediction deviation is roughly 0.34 scale units, indicating that the aPMV index has a robust predictive capacity. To further investigate the thermal adaptability represented by λ, we combine the data within distinct 1st levels of Köppen climatic classification. Specifically, we calculate the averages of λ values for each of the initial letters A to D (corresponding to Tropical, Arid, Temperate, and Cold climates) and generate aPMV fitting curves for 1st level, as shown in Figure 8.

According to the original concept of aPMV [10], when λ equals 0, aPMV corresponds to PMV, indicating that PMV can adequately provide accurate evaluations of thermal comfort with very limited thermal adaptations (black dashed line in Fig. 8). In cold conditions, λ generally tends to be less than 0, aligning the curve close to the x-axis, demonstrating higher cold tolerance. Conversely, in hot conditions, λ tends to be greater than 0, also resulting in a curve close to the x-axis, indicating enhanced heat tolerance. Furthermore, the magnitude of λ influences this phenomenon: the larger λ absolute value, the greater the individuals' tolerance, leading to a curve that lies closer to the x-axis.



(a) PMV<0 (b) PMV>0

Fig. 8 λ_N-based aPMV fitting curves under 1st level of Köppen climatic classification: Tropical, Arid, Temperate, and Cold

Fig. 8 depicts the aPMV fitting curves under 1st level of Köppen climatic classification, and several key findings emerge:

- Tropical climates: individuals exhibit the highest tolerance for hot conditions (red lines), but for cold conditions, three tropical climates (Af, Am, and Aw) only contribute three binned data points that are just slightly below PMV=0 (Appendix B). Therefore, there is insufficient data representation for cold adaptation in tropical climate regions, and its PMV<0 curve was not depicted in Fig. 8.
- Arid climates: there is a notable resilience to both cold and hot conditions (orange lines).
- Temperate climates: tolerance levels fall within intermediate ranges (green lines).
- Cold climates: people have the strongest cold tolerance, yet display an unusual trend with λ values below 0 for hot conditions (blue lines). This implies a stricter cooling demand in hot conditions when compared to PMV estimation. Considering the

substantial amount of data from Cold climates originating from climate Dfb, this observation (λ<0 in hot conditions) correlates with the findings discussed in the preceding section 4.1, where occupants within the Dfb climate struggled with uncontrolled environments and non-active self-regulation.

More detailed findings under the 3rd level of Köppen climatic classification can be found in Appendices B and C.

5. Online package release for calculating the λ_N-based aPMV index

In order to reinforce the reproducibility of this study and facilitate more efficient computations with the λ_N-based aPMV index, we have uploaded our proposed method (Python codes) to GitHub at https://github.com/SuDBE/aPMV-calculation. The website interface is shown in Fig. 9, meanwhile the used Python packages, along with their respective versions and functions, are detailed in Table 7.

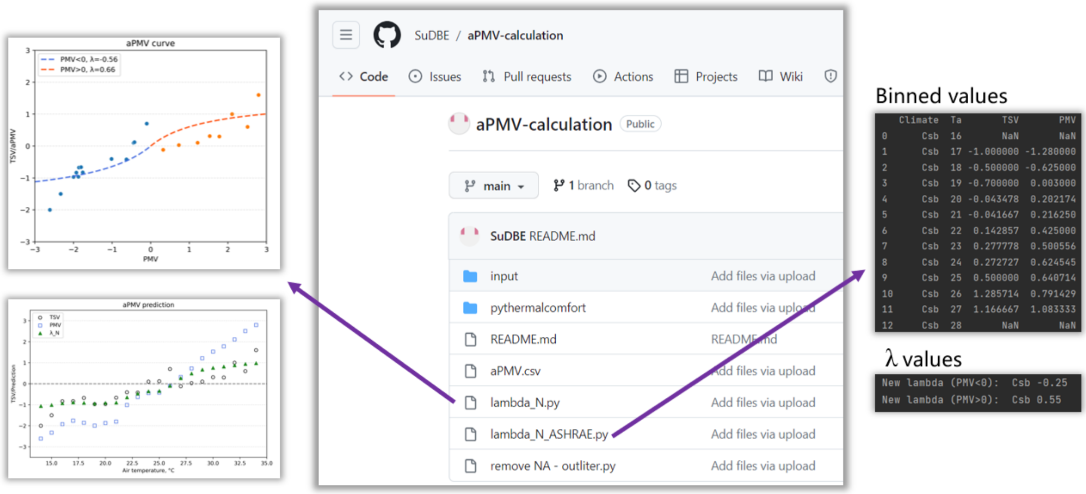


Fig. 9 GitHub interface and code execution results

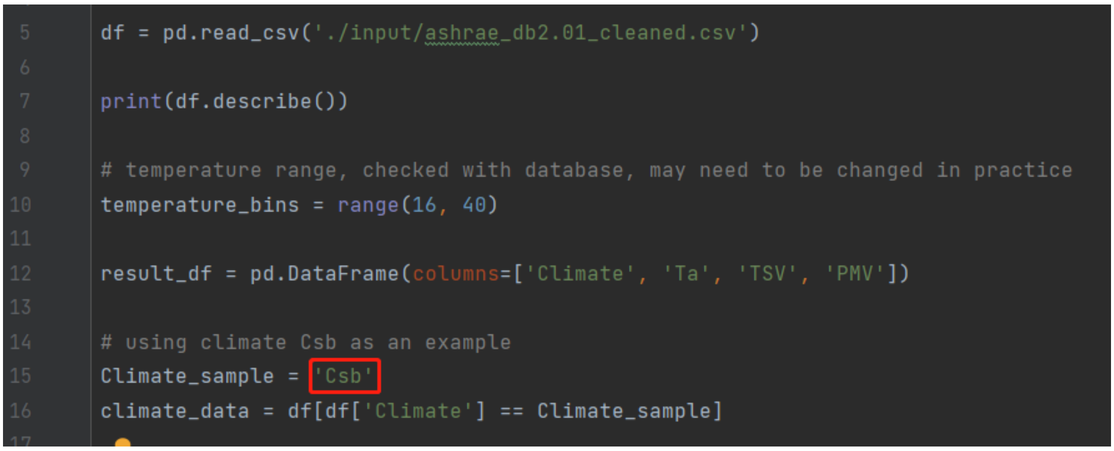
Table 7. Python packages and their versions and functions

Package	Version	Function
pandas	1.4.3	Data analysis and manipulation
numpy	1.23.1	Computation
sklearn	1.3.0	Calculate error

matplotlib	3.5.2	Data visualization
seaborn	0.12.2	Data visualization
pythermalcomfort	2.8.4	Calculate PMV

5.1 Content reproduction

The original Comfort Database was preprocessed using the "*remove NA - outliter.py*", which involves filtering qualified data and removing outliers. The cleaned dataset was stored in folder "*input*". The "*lambda_N_ASHRAE.py*" utilizes this cleaned dataset to calculate the λ values by the method propsoed in this study. By default, the program assumes a "*Csb*" climate zone, as indicated in code line 15 (Fig 10). Users can modify this setting to compute λ values for other climate zones, thus facilitating validation and reproducibility.



```
5   df = pd.read_csv('./input/ashrae_db2.01_cleaned.csv')
6
7   print(df.describe())
8
9   # temperature range, checked with database, may need to be changed in practice
10  temperature_bins = range(16, 40)
11
12  result_df = pd.DataFrame(columns=['Climate', 'Ta', 'TSV', 'PMV'])
13
14  # using climate Csb as an example
15  Climate_sample = 'Csb'
16  climate_data = df[df['Climate'] == Climate_sample]
```

Fig. 10 λ_N calculations using the Comfort Database in Python 3.9

5.2 General approaches for solving λ_N

To provide a more general way of sovling λ_N, we have developed "*lambda_N.py*" to compute λ_N when a csv file named "*aPMV.csv*" with accurate column names is given at the same file directory. Detailed descriptions can be found on our shared GitHub site. This program has several functions, including PMV calculation, temperature binned computation, λ_N calculation, aPMV curve plotting, and aPMV prediction compared with TSV/PMV.

For the convenience of users who do not have Python installed, we have also compiled this code into an executable (.exe) file. It can run on 64-bit Windows systems without requiring Python installation. The download link and input file template can also be found on our GitHub site. Its functionality is illustrated in Fig. 11.

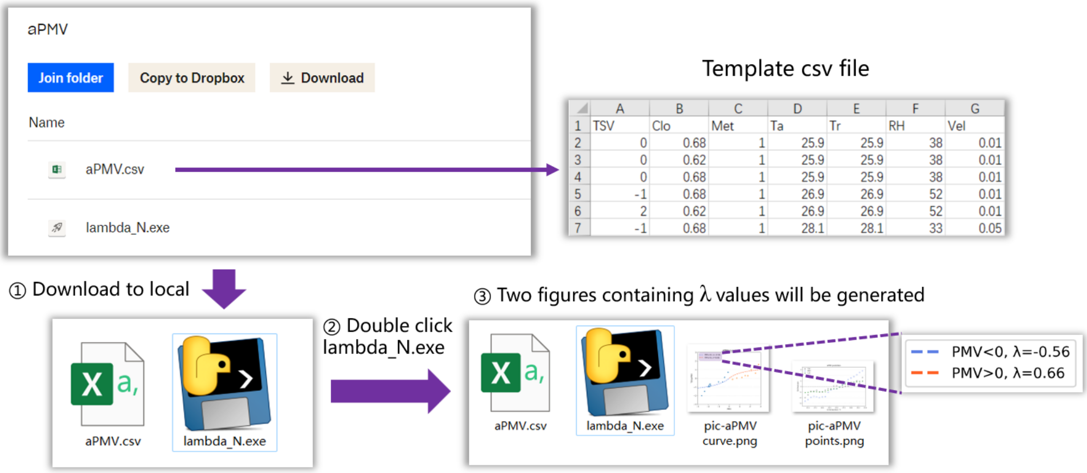


Fig. 11 Steps of using executable EXE file for solving $\lambda_N$without Python installation

6. Conclusions

The aPMV index has been extensively validated and used by research community over last 15 years since its initial publication. This study introduces a novel solving algorithm for adaptive coefficient λ in the aPMV index. It can effectively avoid the issue of some abnormal intermediary values resulting from previous aPMV calculations, especially the problematic near-zero data points. A package containing the original Python code and an executable file for this approach has also been shared on GitHub to facilitate better dissemination and reproducibility. We emphasize that, in accordance with the concept and purpose of original aPMV index, it should be careful when employing aPMV in scenarios involving a high proportion of cases with neutral TSV or PMV. This is due to the fact that the goal of aPMV is to correct predicted biases on the hot and cold conditions, rather than to discover adaptive patterns in neutral environments.

We validate the proposed λ solving algorithm for aPMV fitting across 14 climate zones based on the ASHRAE public database after providing constraints on the border of adaptive coefficients λ and prediction outputs. The results demonstrate that new aPMV curves can better fit actual TSV and significantly reduce predictive deviations in various temperature ranges. Compared to the previously published λ_P optimization method, our approach presents lower Mean Absolute Error and Root Mean Square Error values, with average performance improvements of 34.5% and 37.7%, respectively.

The aPMV fitting curves for the 1st level of Köppen climatic classification demonstrate the following trends: in hot climates, occupants have highest heat tolerance; in cold climates, their heat tolerance decreases while their cold tolerance is high. The adaptive coefficient λ can efficiently quantify the degrees of these tolerances. Certain Cold climate evidence suggests that when people are in naturally ventilated buildings with minimal environmental control and non-active self-regulation, they develop demanding heat preferences, which can also be captured by the λ in the aPMV index.

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Appendix

Appendix A

Suggested solving steps for adaptive coefficient λ_N in the aPMV index

The least-square method is employed to minimize errors in solving adaptive coefficient λ in the aPMV index, and the calculation process proposed in this paper is recommended as:

(1) Gather binned values (average value at a certain interval) of indoor air intemperate with corresponding PMV_i and TSV_i. PMV_i is the mean value of PMV_i at i^{th} binned range, and TSV_i is the mean value of occupants' thermal sensation vote at i^{th} binned range.

(2) Choose data whose PMV≥0 to calculate λ in warm conditions, choose data whose PMV<0 to calculate λ in cool conditions.

(3) Find out the binned sum of data sets "n", suggest to bin air temperature at 1°C integer intervals for better reproductivity, such as [25.0°C, 26°C), [26°C, 27.0°C), etc.

(4) Let each

$$X_i = PMV_i, Y_i = TSV_i$$

(5) Calculate λ:

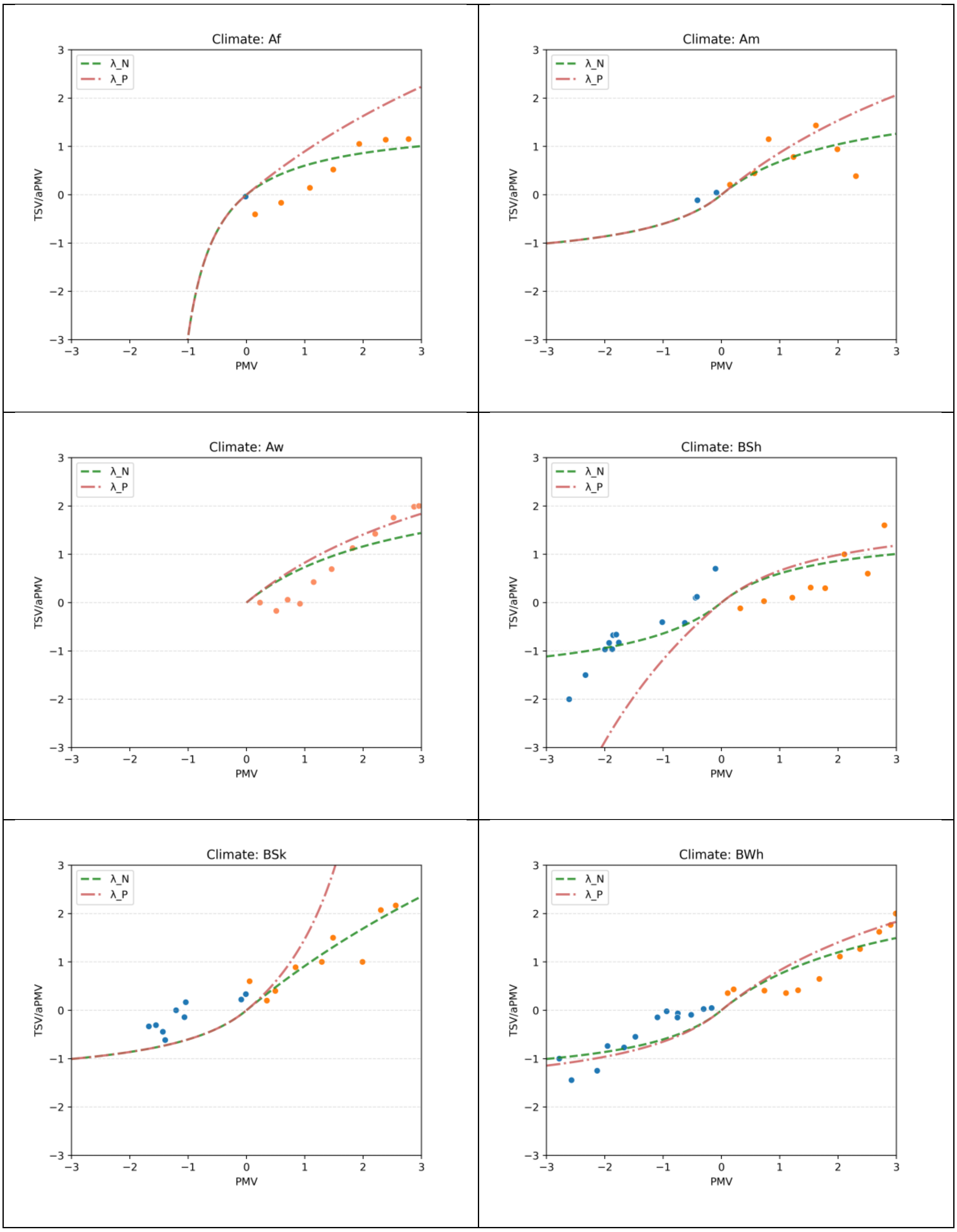
$$\lambda_N = \frac{\sum_{i=1}^{n} PMV_i - \sum_{i=1}^{n} TSV_i}{\sum_{i=1}^{n} TSV_i \times PMV_i}$$

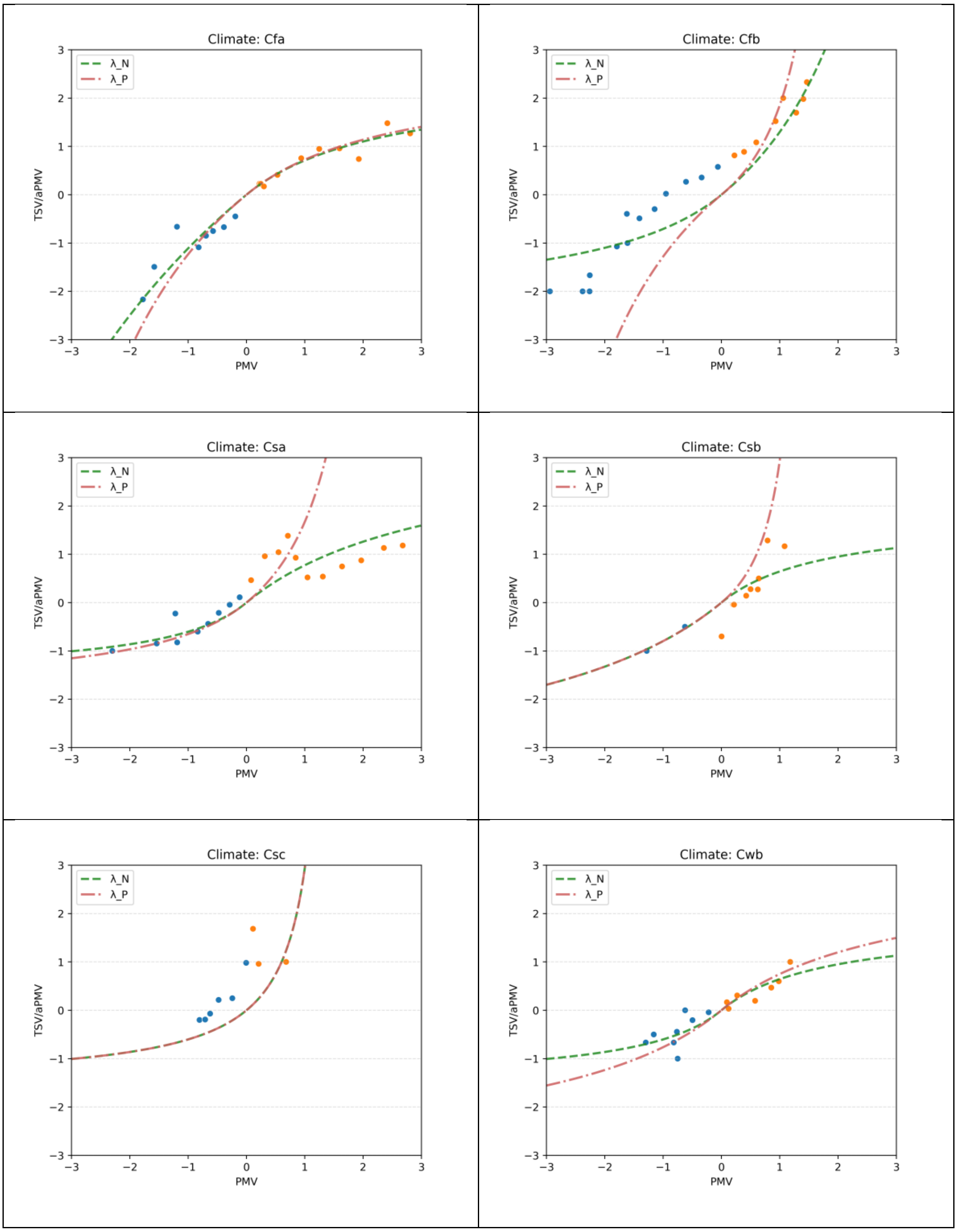
(6) For λ values greater than +0.66 or less than -0.66, the λ should be +0.66 or -0.66, depending on which can give a smaller sum of squared errors.

(7) For aPMV predictions greater than +3 or less than -3, it is suggested to constrain the acceptable aPMV values to +3 or -3. Specifically, values that are greater than +3 should be adjusted to +3, and values that are less than -3 should be adjusted to -3.

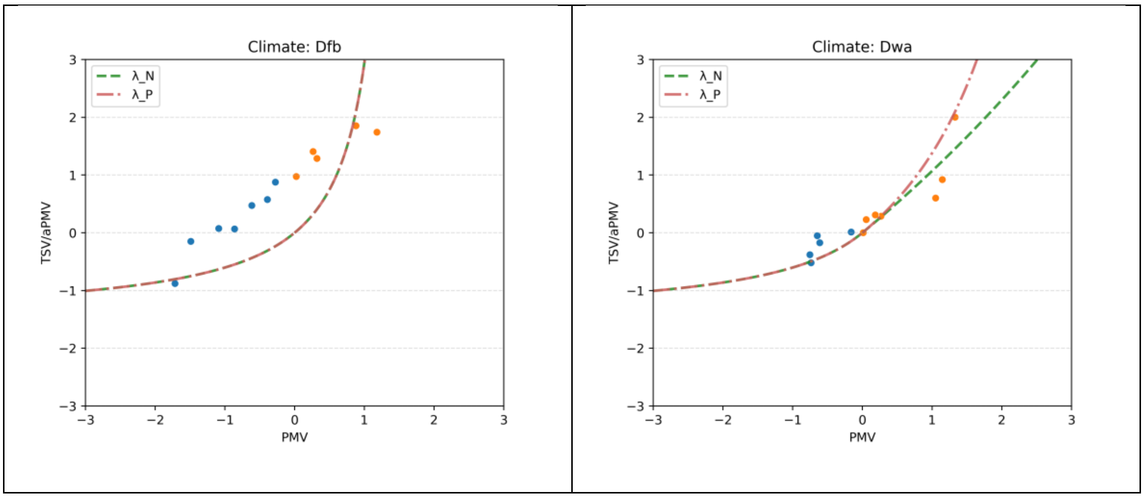
Appendix B

Fitted aPMV curves using λ_N and $\lambda_P$in 14 climate zones based on Comfort Database


Climate: Af
Climate: Am
Climate: Aw
Climate: BSh
Climate: BSk
Climate: BWh
λ_N
λ_P
TSV/aPMV
PMV

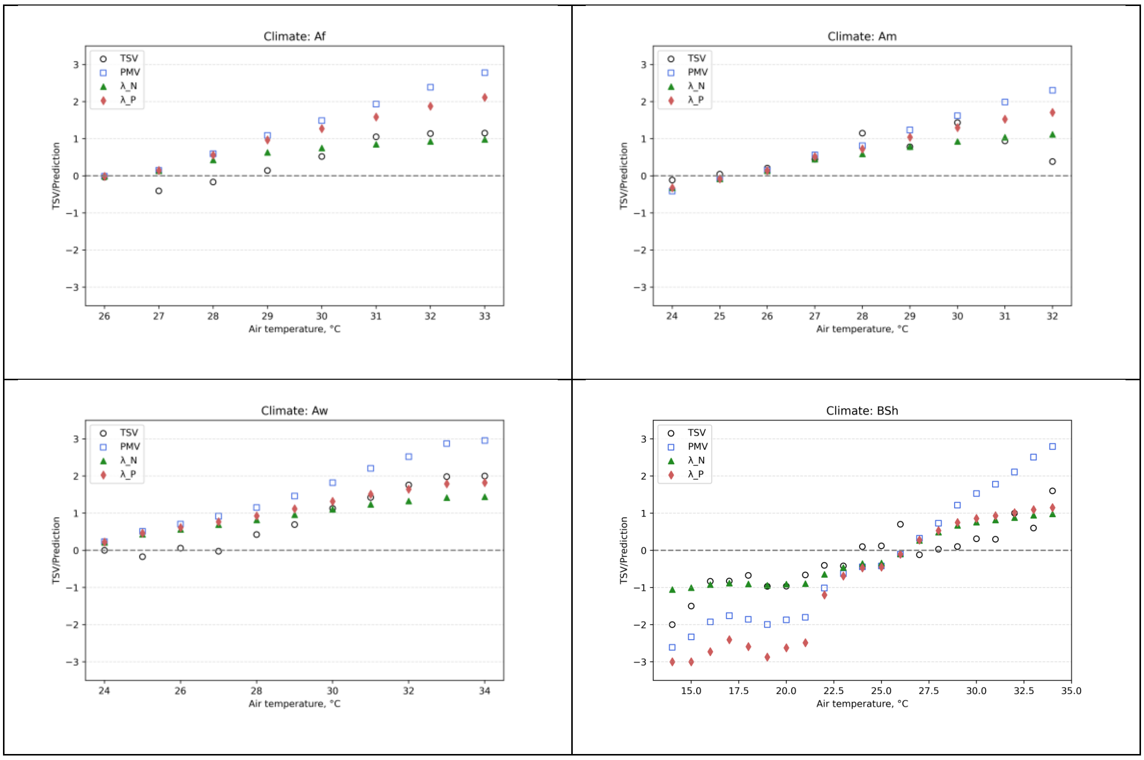


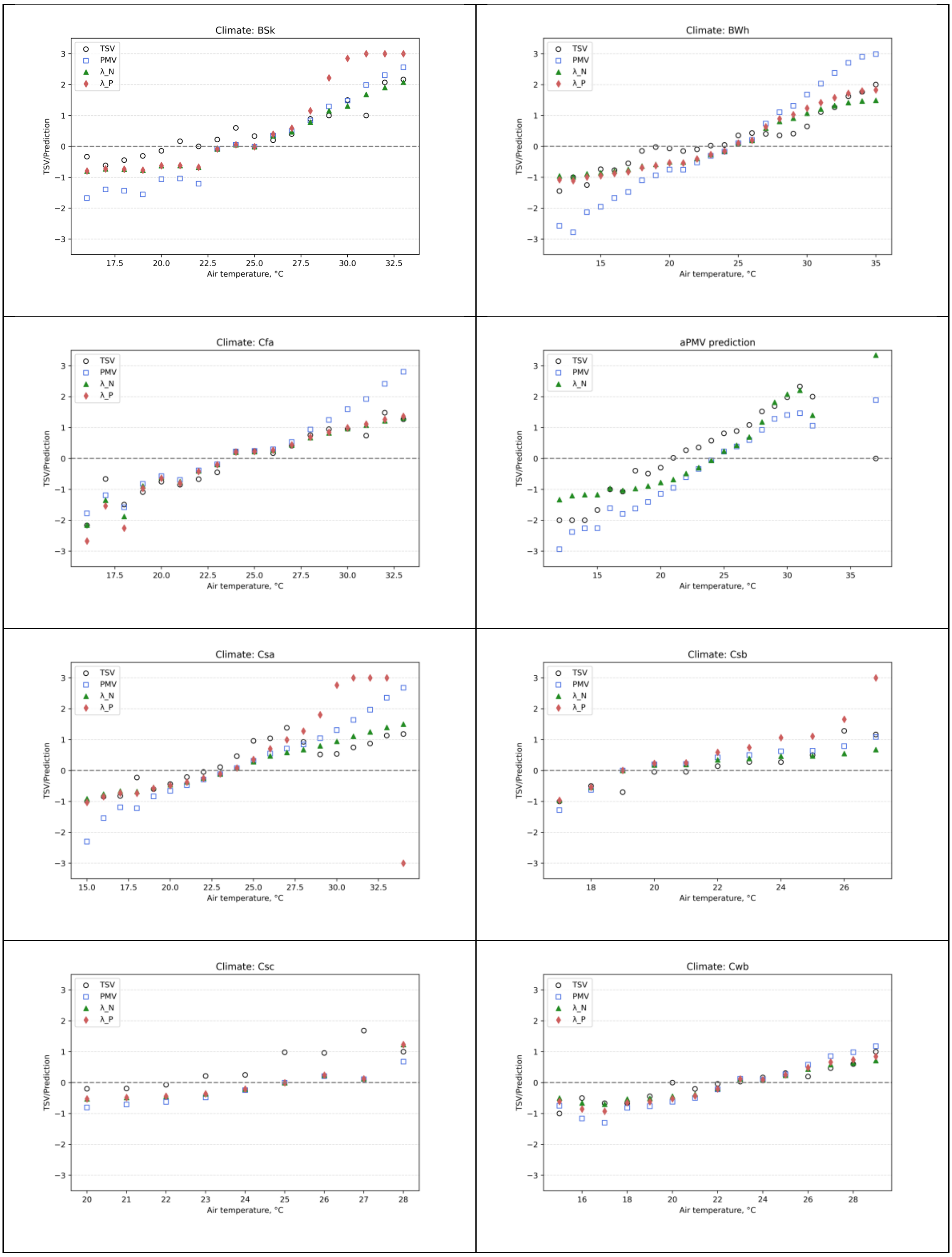
Climate: Cfa
Climate: Cfb
Climate: Csa
Climate: Csb
Climate: Csc
Climate: Cwb
λ_N
λ_P
TSV/aPMV
PMV

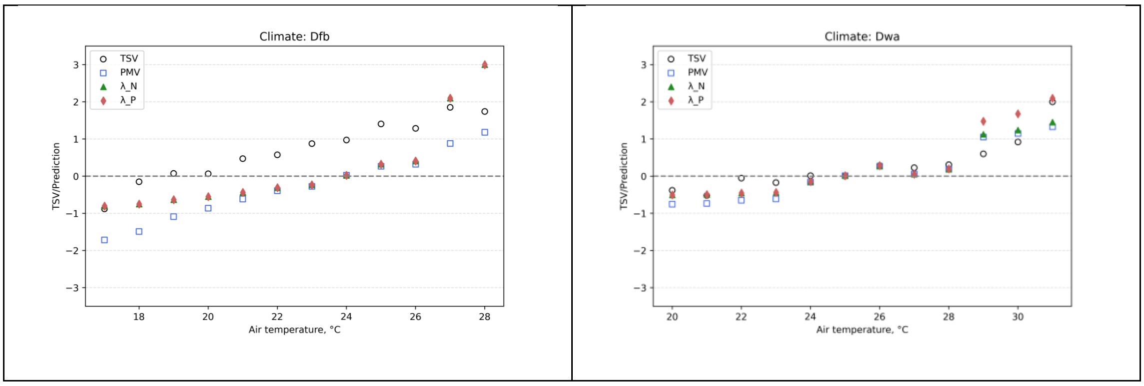


Appendix C

Validation of proposed and previous algorithms on aPMV in 14 climate zones based on Comfort Database




Climate: BSk
Climate: BWh
Climate: Cfa
aPMV prediction
Climate: Csa
Climate: Csb
Climate: Csc
Climate: Cwb
TSV
PMV
λ_N
λ_P
TSV/Prediction
Air temperature, °C



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