

# **Optimization of indoor air temperature set-point for centralized air-conditioned spaces in subtropical climates**

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## Abstract

Current Building Management System (BMS) does not integrate well with real-time occupant response. In order to fine-tune the system to meet individual demands and to maximize the occupant acceptance of indoor thermal environment, a new notion of Bayesian control algorithm was developed in this study. Control parameters of a weighting function for air temperature control (namely, the control temperature constant  $k_T$  and the probable acceptance of the air temperature set-point  $\lambda$ ) and two prior distribution functions of air temperature set-point, namely the uniform prior and the expert's prior, were examined. Optimum air temperature set-points of air-conditioning systems obtained from certain Hong Kong offices were then used to demonstrate the applicability of the new algorithm for controlling an example air temperature set-point ranged between 0.2°C to 1°C. This algorithm would be useful for adaptive thermal comfort control in a large, post-occupied air-conditioned space.

*Keywords:* Occupant perception, Building Management System (BMS), Thermal comfort, Air temperature set-point

## Nomenclature

BM	benchmark (%)
G	function of
i, j	dummy variables
$k_T$	control temperature constant
$N(\theta, \sigma^2)$	a normal distribution function with mean $\theta$ and variance $\sigma^2$
$N(v, \tau^2)$	a normal distribution function with mean $v$ and variance $\tau^2$
n	number of occupants (ps.)
PPD	predicted percentage dissatisfaction
$T_a$	optimum air temperature set-point (°C)
$T_c$	preferred cool air temperature (°C)
$T_D$	control temperature adjustment (°C)
$T_h$	preferred warm air temperature (°C)
$T_s$	air temperature set-point (°C)
$T_s^*$	expected optimum air temperature set-point (°C)
$T^+$	occupant feedback of ‘Hot’ at the temperature set-point $T_s$
$T^-$	occupant feedback of ‘Cold’ at the temperature set-point $T_s$
$T_{\min}$	lowest air temperature control limits (°C)
$T_{\max}$	highest air temperature control limits (°C)
<i>Greek</i>	
$\lambda$	probable acceptance of the air temperature set-point
$\phi_h$	probability of a complaint of ‘Hot’
$\phi_c$	probability of a complaint of ‘Cold’

$\xi$  a function defined in Equation (2)

*Subscript*

1,2 of conditions 1,2

$\sim$  distribution function

## **Introduction**

An intelligent building management system (BMS) for remote monitoring and control of indoor environment is always a challenge to engineers. In the 1950s, building intelligence was simply a building fire alarm system connected to a municipal reporting system. The fire alarm was tied to a security station system in the 60s while it was coupled with an airside system to shut down supply air fans in the 70s. The energy crisis in 1973 triggered increased use of automated energy management systems. It was not till the 80s that building intelligence, implemented in a BMS designed to provide building occupants a comfortable, safe and sustainable indoor environment as desired, became a salient feature of air-conditioned buildings.

Striking the right balance of interests among the government, developers, engineers and occupants, an effective BMS requires a careful selection of weighting parameters, input/output pairing, decoupling algorithms, pole placement and stability conditions. Computerized algorithms, such as proportional integral derivative (PID) control, fuzzy logic and neural networks, responsive to the indoor environmental parameters were proposed [1-2]. Although complaints about environmental discomfort have been reported in many air-conditioned spaces [3-4], none of the instruments available incorporates records of occupant perception nor integrates real-time occupant response to fine-tune the building services system to meet individual demands in a dynamic manner. Ideally, an environmental parameter set-point of the building services system would be expertly reset in real-time in accordance with the complaints [4-5].

To determine the optimum temperature set-point in a large space, a prior understanding of Bayesian control algorithm is required. Bayesian algorithm is suitable

for combining various kinds of information pertaining to event occurrence and has been applied to predict outdoor environmental parameters [6-8]. It was used in this study for optimizing the acceptance of indoor environment determined from physical measurements and subjective surveys.

With a long-term survey of occupant perceptions of the set-point temperature in a typical and large air-conditioned office, a new notion of Bayesian approach to predicting the indoor environmental comfort setting desired via a single environmental parameter set-point was proposed for air-conditioned buildings in a humid and subtropical climate like Hong Kong, while adaptive interface relationship was determined between occupant complaints and indoor environment [4-5]. The new approach updates the set-points selected from the minimum predicted percentage dissatisfaction (PPD) of occupants and enables effective feedback to the occupants. This study further investigated the control parameters through two prior distribution functions of air temperature set-point, namely the uniform prior and the expert's prior.

### **Adaptive air temperature set-point**

The air temperature set-point  $T_s$  (°C) of an air-conditioning system for a large air-conditioned office would be adjusted so that the thermal comfort condition would satisfy most occupants [4-5,9-14]. Assume that the expected air temperature set-points are normally distributed, the optimum air temperature set-point  $T_s^*$  is the expected value of the set-points expected by all occupants ( $n$ ) and approximated by Equation (1) as shown below, where  $T_a$  (°C) is the optimum air temperature set-point of the system

within certain limits from the preferred cool air temperature  $T_c$  (°C) to the preferred warm air temperature  $T_h$  (°C) expected by  $i$  occupants,

$$T_s^* = \langle \tilde{T}_a \rangle = \frac{1}{n} \sum_{i=1}^n T_{a,i} \quad \dots (1)$$

Design guidelines and codes of practice were used as references to determine the system air temperature set-points for some pre-occupied offices [10-13]. However, thermal comfort- related complaints were still reported [4-5]. Defining a complaint made by an occupant at certain level of satisfaction  $\xi$  and an air temperature set-point  $T_s$  ‘Hot’ ( $T_s = T^+$ ) or ‘Cold’ ( $T_s = T^-$ ), a temperature weighting function (Figure 1) that describes the percentage of dissatisfied occupants within an air temperature range is assumed as follows, where  $\lambda$ , set with a minimum PPD between 0.05 and 0.5 for uniform distribution, is an arbitrarily selected parameter indicating the probability of acceptance for  $T_s$ ,

$$\xi(T_s) = \begin{cases} 1-\lambda & ; \quad \begin{cases} T_s < T^+; T_s > T^- \\ T_s \geq T^+; T_s \leq T^- \end{cases} \\ \lambda & ; \quad \begin{cases} T_s < T^+; T_s > T^- \\ T_s \geq T^+; T_s \leq T^- \end{cases} \end{cases} ; 0.05 \leq \lambda < 0.5 \quad \dots(2)$$

With an arbitrary constant  $k_T$  (°C), the boundaries of the weighting function are defined respectively by the lowest and highest air temperature control limits  $T_{\min}$  (°C) and  $T_{\max}$  (°C) deviating from the air temperature set-point such that,

$$T_{\max} - T_s = T_s - T_{\min} = k_T \quad \dots (3)$$

Assume that the complaint made by an occupant  $i$  is a sign of dissatisfaction (to some extent) among all occupants in the space, then the distribution of the optimum air temperature set-point  $T_s^*$  can be approximated by a normal distribution with mean  $\theta$  and variance  $\sigma^2$ , i.e.  $\tilde{T}_s^* = (T_s^* | \theta, \sigma^2) \sim N(\theta, \sigma^2)$ . Based on a ‘prior understanding’ of the optimum air temperature set-point parameterized by the mean  $v$  and variance  $\tau^2$ , i.e.  $(\theta$

$v, \tau^2 \sim N(v, \tau^2)$ , as suggested in certain guidelines [6], the posterior distribution of  $\theta$  given  $T_s^*$  is expressed by,

$$(\theta | T_s^*, \sigma^2, v, \tau^2) \sim N(\theta_1, \tau_1^2); \begin{cases} \theta_1 = \frac{\sigma^2 v + \tau^2 T_s^*}{\sigma^2 + \tau^2} \\ \tau_1^2 = \frac{\sigma^2 \tau^2}{\sigma^2 + \tau^2} \end{cases} \quad \dots (4)$$

Using certain distribution function of the expected temperature set-point  $G(T_s^*)$  obtained from the results of thermal comfort studies or field measurements [4,14], the temperature set-point benchmark by request of an occupant is determined by the following equation, where  $BM \leq 1$  and  $BM = 100$  are the lowest and highest desired temperature set-points of the indicative group of occupants respectively,

$$BM = 100 \times \int_{-\infty}^{\theta_1} G(T_s^*) dT_s^* \quad \dots (5)$$

## Review of occupant feedback

Occupant complaints of thermal discomfort (i.e. hot or cold) were recorded in a typical Hong Kong Grade A office building [4]. This 53-storey building was located in the central business district, with a 2-storey basement car-park and a total building area of 70,000 m<sup>2</sup> designed for 7,500 occupants. These complaint records were collected in the same period of a thermal comfort survey study in 61 offices, with thermal responses of 422 occupants were collected in summer and winter of a year. It was noted that the complaints were recorded in summer and ((not necessary from the interviewed occupants????)). For each of the complaints, the local thermal environmental condition



was measured and the air temperature set-point was professionally adjusted to meet occupant satisfaction [4]. A total of 183 complaints, of which 113 claiming ‘Hot’ at air temperature set-points between 22.8°C and 28°C, and 72 ‘Cold’ between 20°C and 22.2°C, were reported within two months of summer period.

By assuming there would be thermal discomfort beyond the desired temperature set-point range, the probabilities of a ‘Hot’ complaint  $\phi_h$  and a ‘Cold’ one  $\phi_c$  were approximated ( $p < 0.0001$ ),

$$\begin{cases} \phi_h = \frac{1}{1 + \exp(2155 - 95.8T_s)}; T_s \notin T_s^* \\ \phi_c = 1 - \phi_h \end{cases} \quad \dots (6)$$

The operative temperature, approximately equals the average of air temperature and mean radiant temperature, is considered an effective temperature in an occupied space with air velocity less than  $0.4 \text{ ms}^{-1}$ ; and the ‘neutral temperature’ is defined as the operative temperature which corresponds closest to a mean thermal sensation vote of zero [12-14]. It was reported that the post-occupied mean expected temperature of the air-conditioning system was adjusted to 22.8°C to settle all the complaints that summer. Indeed, not a single complaint was recorded for temperatures set to 21.4°C and 23.6°C in summer and winter respectively [3-5].

## Results and discussions

For Bayesian predictions, a prior understanding of the optimum temperature set-point is required. Two expressions of prior distribution were considered. The first one,

approximated by a normal distribution, was a uniform prior distribution of air temperature set-point:

$$\tilde{T}_s^* = \frac{1}{T_h - T_c} \sim N(v, \tau^2); \begin{cases} v = \frac{T_c + T_h}{2} \\ \tau^2 = \frac{(T_c + T_h)^2}{12} \end{cases}; T_c \leq T_s^* \leq T_h \quad \dots (7)$$

This prior distribution was  $N(v=23, \tau=13.3)$  for arbitrary set-point limits between 13°C and 33°C as shown in Figure 2.

The second one was an expert's prior determined from the PPD for typical office thermal environment; it was  $N(v=23.2, \tau=3.7)$  as shown in Figure 2.

Based on Fanger's comprehensive calculation of PPD for an air-conditioned space [10,14], studies showed that typical air temperature set-points for air-conditioned offices in Hong Kong could be approximated by a normal distribution with a mean at  $23 \pm 2^\circ\text{C}$  [4-5]. To demonstrate different responses of the proposed algorithm, this study took the extreme cases of initial air temperatures set at 17°C and 29°C into account, i.e. 3 standard deviations from the mean set-point or 1% exception in the population. If any feedback of 'Hot' ( $\phi_h > \phi_c$ ) or 'Cold' ( $\phi_h < \phi_c$ ) as described in Equation (6) was reported, predicted optimum air temperature set-points would be determined. It was expected that, via Equation (6), the algorithm would reset the air temperature set-point to 22°C-23°C.

Figure 3 shows the predicted air temperature set-points for the two initial air temperatures and subsequent predictions against a number of occupant feedback entries  $j$ ; effects of the two prior distributions with control parameters  $\lambda$  ( $= 0.15$  and  $0.45$ ) and  $k_T$  ( $= 5^\circ\text{C}$  and  $10^\circ\text{C}$ ) as shown were examined. The results illustrated that, as expected, in comparison with the expert's prior, the uniform prior distribution was associated with a larger variance and thus a slower convergence of the predicted air temperature set-

points. For a small number of occupant feedback entries, the prior distribution using PPD (i.e. the expert's) was more representative and yielded better predictions. However, the differences between the two distributions would diminish if the number of entries was large enough, e.g.  $>15$ .

Apparently, both the choices of  $\lambda$  and  $k_T$  demonstrated effects on set-point adjustment. It was reported that the proposed algorithm would give a rapid response of large adjustment with a small  $\lambda$  yet over-react and fail to attain the 'target' air temperature set-point range (i.e. 22°C-23°C) when the set-point was shifting from 'Cold' to 'Hot'. For  $\lambda = 0.45$ , nevertheless, the exhibited predictions were excellent after a number of feedback entries. Hence, with carefully selected control parameters, this algorithm could be incorporated into some single set-point real-time feedback systems of adaptive thermal comfort control for large, post-occupied air-conditioned environments.

Temperature set-point benchmarks meeting occupant feedback were determined according to the expert's prior distribution, i.e.  $G(\mu, \sigma) \sim N(23.2, 3.7)$ . Example benchmarks taking  $\lambda = 0.45$  from Figure 3(b) are shown in Figure 4. As expected, the benchmark would be less than 50 after certain feedback entries because the preferred temperature set-point of the surveyed office was 22.8°C [4].

An occupant might still respond to a set-point within the 'target' range. An adjustment allowance of 'not larger than the target range' was thus enforced to ensure the system stability. The final set-point adjustments  $T_D$  (°C) were studied using both prior distributions with various parameters  $\lambda$  and  $k_T$ . Figure 5 shows those adjustments triggered by at least 20 occupant responses (i.e.  $j \geq 20$ ) for  $k_T = 5^\circ\text{C}-15^\circ\text{C}$ .

It was reported that the air temperature set-point might ‘surge’ outside the target range with some  $\lambda$ - $k_T$  sets. For practical control, a large adjustment is considered ‘inappropriate’. From the results exhibited in Figure 5, an example of small adjustment  $T_D = 0.2^\circ\text{C}$ - $1^\circ\text{C}$  illustrated that both  $\lambda = 0.45$  and  $\lambda = 0.35$  in between  $5^\circ\text{C}$  and  $15^\circ\text{C}$  would be suitable choices for the two prior functions.

As the air temperature set-point has significant energy impact in air-conditioned offices of Hong Kong. It was reported that a 2% energy saving in offices adopted a temperature control of  $20^\circ\text{C}$ - $25.5^\circ\text{C}$  as compared with offices at the same average air temperature [15,16]. This was corresponding to an improvement of occupant’s thermal acceptance of 0.6%, which results would gain in office work productivity [17,18].

## Conclusions

Complaints about environmental discomfort have been reported in many air-conditioned spaces, but none of the systems available integrates well with the real-time occupant response. For centralized air-conditioning systems with a single temperature set-point, this study developed a Bayesian control algorithm to optimize air temperature of a space in accordance with the occupant feedback. This new algorithm maximizes the occupant acceptance of an indoor thermal environment by making use of the minimum PPD.

Through the control parameters and two prior distribution functions of air temperature set-point, namely the uniform prior and the expert’s prior, temperature control of the algorithm was examined in terms of sensitivity and stability. Application of the algorithm to certain Hong Kong offices demonstrated that, together with properly

selected control parameters, effective system feedback could be attained in the form of a desired temperature set-point ‘benchmark’. This study would be a useful source of reference in determining the control constants of a system using the HABIT.

## **Acknowledgement**

The work described in this paper was partially supported by a research grant from the Research Grants Council of the HKSAR, China (B-Q11W) and a grant from The Hong Kong Polytechnic University (Project A/C code: G-YX1Y).

## **References**

- [1] M.M. Eftekhari, L.D. Marjanovic, Application of fuzzy control in naturally ventilated buildings for summer conditions, *Energy and Buildings* 35 (7) (2003) 645-655.
- [2] W. Franco, M. Sen, K.T. Yang, R.L. McClain, Dynamics of thermal-hydraulic network control strategies, *Experimental Heat Transfer* 17 (3) (2004) 161-179.
- [3] K.W. Mui, Energy policy for integrating the building environmental performance model of an air conditioned building in a subtropical climate, *Energy conversion and Management* 47 (15-16) (2006) 2059-2069.
- [4] K.W. Mui, L.T. Wong, Neutral temperature in subtropical climates – a field survey in air-conditioned offices, *Building and Environment* 42 (2) (2007) 699-706.

- [5] L.T. Wong, K.W. Mui, N.K. Fong, A humanized adaptive baseline information technology (HABIT) algorithm for building management system, *Building Services Research and Technology* 27 (4) (2006) 341-347.
- [6] P.M. Lee, *Bayesian statistics*, 3<sup>rd</sup> Edition, Hodder Arnold, New York, 2004.
- [7] L.E. Sucar, J. Perez-Brito, J.C. Ruiz-Suarez, E. Morales, Learning structure from data and its application to ozone prediction, *Applied Intelligence* 7 (4) ( 1997) 327-338.
- [8] L.T. Wong, K.W. Mui, K.Y. Law, P.S. Hui, Epistemic assessment of radon level of offices in Hong Kong, *Atmospheric Environment* 40 (8) (2006) 1441-1451.
- [9] G.J. Rios-Moreno, M. Trejo-Perea, R. Castaneda-Miranda, V.M. Hernandez-Guzman, G. Herrera-Ruiz, Modelling temperature in intelligent buildings by means of autoregressive models, *Automation in Construction* 16 (5) (2007) 713-722.
- [10] ISO. International Standard 7730-1994: Moderate thermal environments - determination of the PMV and PPD indices and specification of the conditions for thermal comfort, International Standard Organization, Geneva, Switzerland, 1994.
- [11] Committee of European Normalization (CEN), Ventilation for Buildings: Design criteria for the indoor environment, Commission of the European Communities, Directorate General for Science, Research and Development Joint Research Centre – Environment Institute, Brussels, Luxembourg, CR1752, 1998.
- [12] American Society of Heating, Refrigerating and Air-Conditioning Engineers, ANSI/ASHRAE 55-1992, Thermal Environmental Conditions for Human Occupancy, Atlanta: American Society of Heating, Refrigerating and Air-Conditioning Engineers, Inc., 1992.
- [13] American Society of Heating, Refrigerating and Air-Conditioning Engineers, ANSI/ASHRAE 55a-1995, Addendum to Thermal Environmental Conditions for

Human Occupancy, Atlanta: American Society of Heating, Refrigerating and Air-Conditioning Engineers, Inc., 1995.

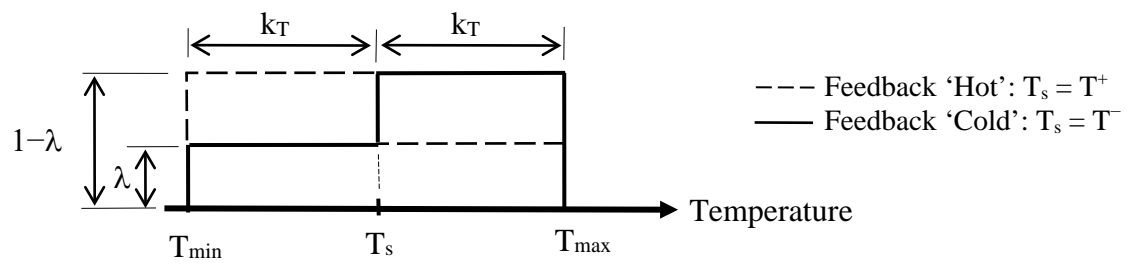
[14] P.O. Fanger, Thermal comfort, McGraw-Hill, NY, USA, 1972.

[15] L. T. Wong, K. W. Mui, K. L. Shi, Energy impact of indoor environmental policy for air-conditioned offices of Hong Kong, Energy Policy 36 (2) (2008) 714-721.

[16] L. T. Wong, K. W. Mui, K. L. Shi, P. S. Hui, An energy impact assessment of indoor air quality acceptance for air-conditioned offices, Energy Conversion Management 49 (10) (2008) 2815-2819.

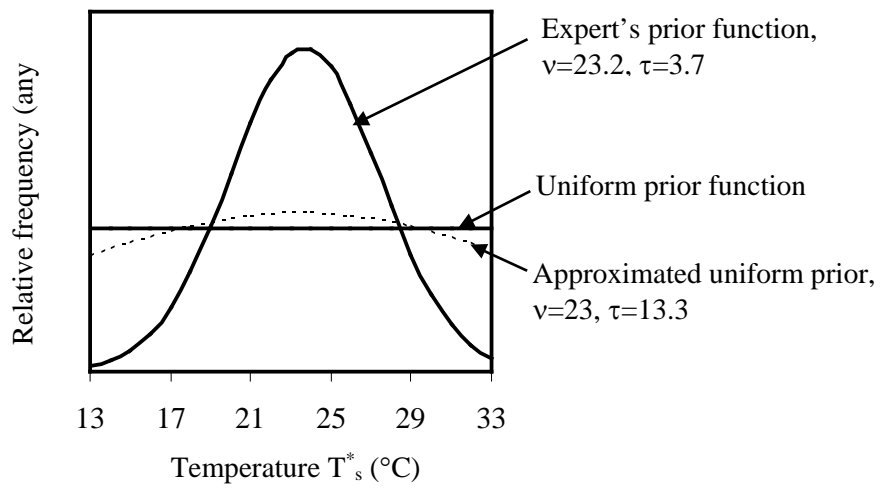
[17] L. T. Wong, K. W. Mui, An energy performance assessment for indoor environmental quality (IEQ) acceptance in air-conditioned offices, Energy Conversion and Management 50 (5) (2009) 1362-1367.

[18] L. T. Wong, K. W. Mui, Efficiency assessment of indoor environmental policy for air-conditioned offices in Hong Kong, Applied Energy 86 (10) (2009) 1933-1938.

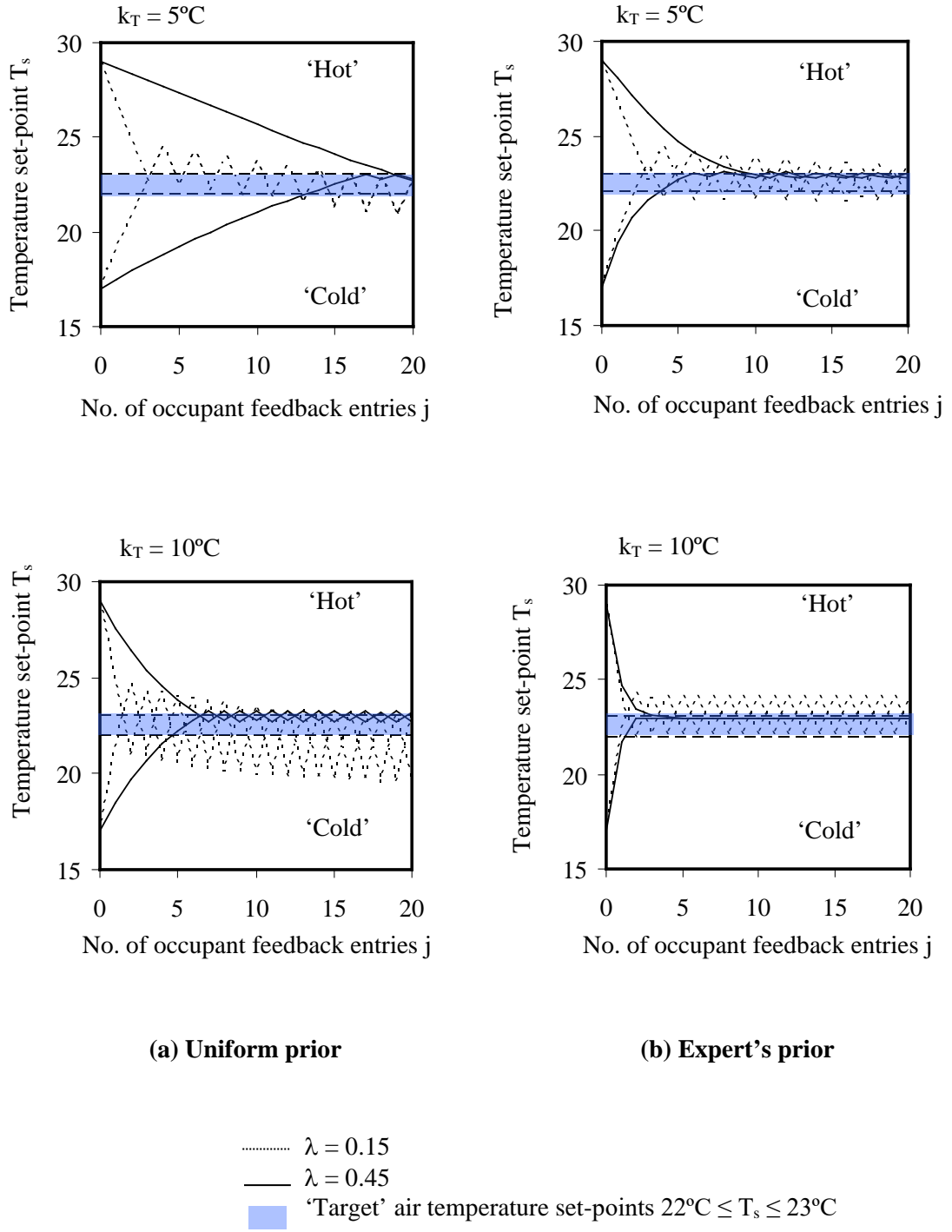


**Figure 1: Temperature weighting function**

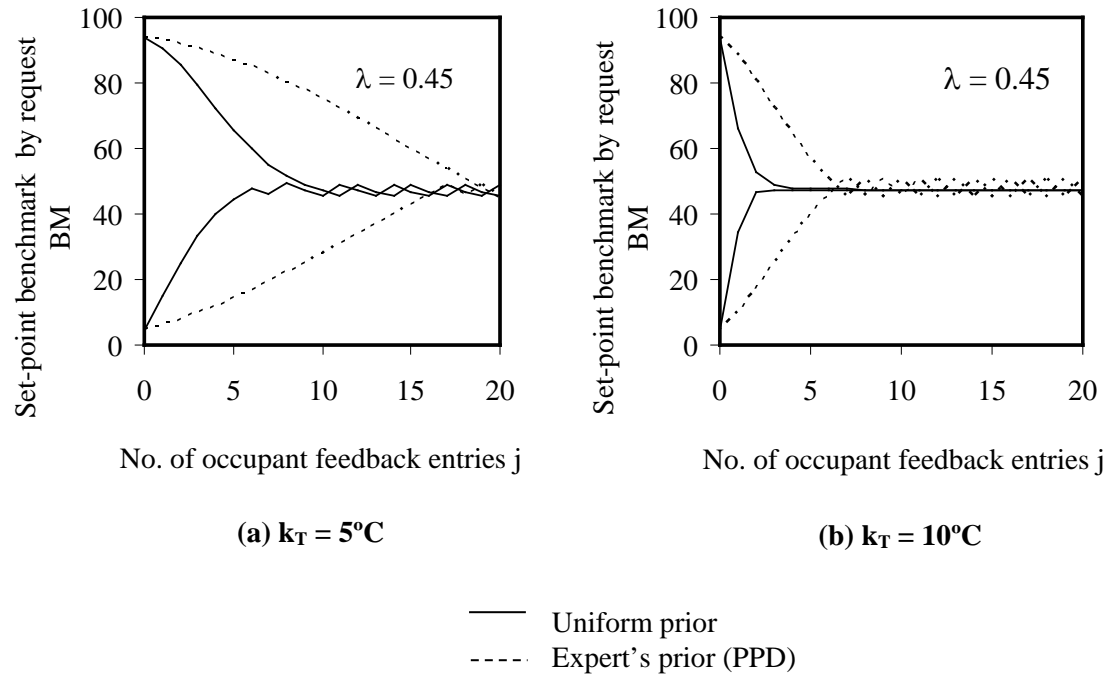




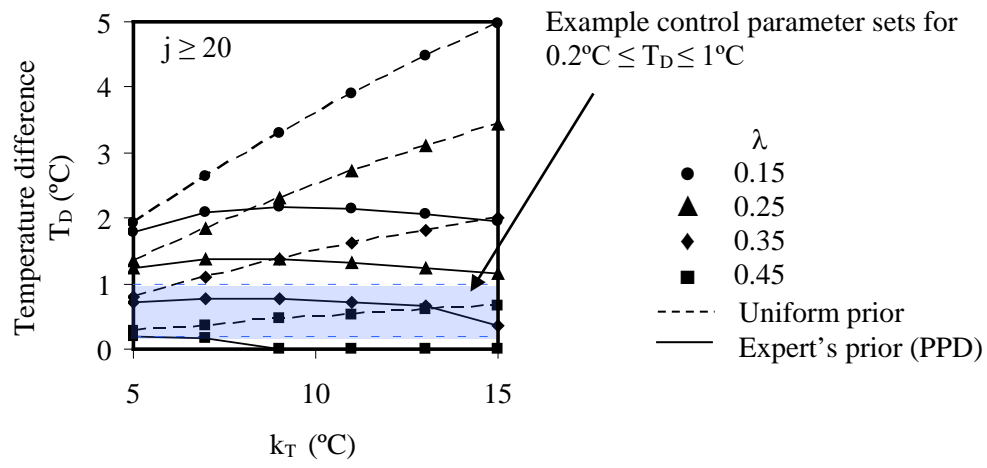
**Figure 2: Expert and uniform prior distribution functions**



**Figure 3: Predicted air temperature set-points against occupant feedback**



**Figure 4: Example temperature set-point benchmarks by request ( $\lambda=0.45$ ,  $k_T = 5^\circ\text{C}$  &  $10^\circ\text{C}$ )**



**Figure 5: Final set-point temperature adjustment  $T_D$  for occupant responses  $j \geq 20$**