

Quantification of personal thermal comfort with localized airflow system based on sensitivity analysis and classification tree model

Article

Accepted Version

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Du, C., Li, B., Liu, H., Ji, Y., Yao, R. ORCID: <https://orcid.org/0000-0003-4269-7224> and Yu, W. (2019) Quantification of personal thermal comfort with localized airflow system based on sensitivity analysis and classification tree model. *Energy Building*, 194. pp. 1-11. ISSN 0378-7788 doi: 10.1016/j.enbuild.2019.04.010 Available at <https://centaur.reading.ac.uk/84499/>

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To link to this article DOI: <http://dx.doi.org/10.1016/j.enbuild.2019.04.010>

Publisher: Elsevier

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Abstract

Although local air movement acts as a critical factor to enhance human thermal comfort and energy efficiency, the various factors influencing such movement have led to inconsistent publications on how to evaluate and design localised airflow systems in practice. This study aims to identify the main impacting factors for a localised airflow system and predict a cooling performance based on machine learning algorithms. Three typical localised airflow forms, i.e. an isothermal air supply (IASN), non-isothermal air supply (NIASN), and floor fan (FF), were deployed. The experiments were conducted under a variety of temperature/humidity/air velocity conditions in a well-controlled climate chamber, and a database including 1305 original samples was built. The primary results indicated that a classification tree C5.0 model showed a better prediction performance (83.99%) for a localised airflow system, with 17 input parameters in the model. Through a sensitivity analysis, 8 feature variables were quantified as having significant main effect responses on subjects' thermal sensation votes (TSV), and three environmental factors (temperature, air velocity, and relative humidity) were identified as having the most significant effects. Using the 8 sensitive factors, the C5.0 model was modified with 82.30% accuracy for subject TSV prediction. A tree model demonstrating the decision rules in the C5.0 model was obtained, with air velocity ($=0$ m/s, >0 m/s) as the first feature variable, and root node and temperature (≤ 28 °C, > 28 °C) as the second feature variable and leaf node, respectively. The outcomes that provide the most influential variables and a machine learning model are beneficial for evaluating personal thermal comfort at individual levels and for guiding the application of a localised airflow system in buildings.

Keywords:

Localised airflow system; Influencing factors; Sensitivity analysis; Classification tree model; Thermal sensation prediction.

Nomenclature

| | | | |
|-------|---|-----------------|---------------------------------------|
| PCS | personalised comfort system | $TSV_{overall}$ | overall thermal sensation |
| HVAC | heating, ventilation and air-conditioning | TSV_{head} | thermal sensation for head |
| IASN | isothermal air supply nozzle | TSV_{chest} | thermal sensation for chest |
| NIASN | non-isothermal air supply nozzle | TSV_{back} | thermal sensation for back |
| FF | floor fan | TSV_{hand} | thermal sensation for hand |
| T | Air temperature in the chamber | TSV_{lower} | thermal sensation for lower body part |
| RH | Relative humidity in the chamber | T_{head} | head skin temperature |
| V | Air velocity for the localised airflow system | T_{chest} | chest skin temperature |

| | | | |
|-----|---------------------------|----------------------|----------------------------|
| SA | sensitivity analysis | T_{back} | back skin temperature |
| AD | body surface area | T_{upper} | upper arm skin temperature |
| BMI | body mass index | T_{lower} | lower arm skin temperature |
| SVM | support vector machine | T_{hand} | hand skin temperature |
| ANN | artificial neural network | T_{thigh} | thigh skin temperature |
| SD | Standard deviation | T_{calf} | calf skin temperature |
| | | T_{overall} | Mean skin temperature |

1. Introduction

The personalised comfort system (PCS), which was designed to respond to the energy crisis in the 1970s[1, 2] and to locally change an indoor environment independently from a heating, ventilation, and air-conditioning (HVAC) system, has been acknowledged to benefit both thermal comfort and energy efficiency[3, 4]. The local means of a PCS are targeted to affect the most sensitive body parts to achieve overall comfort, and thus push the boundaries of conventional comfort zones. An extended comfort zone can be achieved from 16 °C to 20 °C with personalised warming, and from 27 °C to 30 °C or more with air velocity adjustments[5]. Most importantly, it consumes a relatively smaller amount of energy. A field study found that through applying personal devices and adjusting HVAC supply air set-points, the occupants' satisfaction increased from 56% to over 80%, while lowering HVAC energy consumption by 60% in heating and 40% in cooling [6]. It is generally estimated that using a PCS can potentially achieve approximately 15%–30% energy savings, with great user satisfaction [7, 8].

A localised airflow system, as a crucial type of PCS, has attracted considerable focus from researchers in both field surveys and lab experiments. Employing a fan to increase airflow indoors is the most frequent behaviour by occupants in buildings to extend their comfort zones in the summer [9, 10]. One on-site observation by Mustapa et al. [11] showed that the use percentage of floor fans was 5.1% in air-conditioned buildings, but up to 19.4% in naturally-ventilated buildings. A higher fan use proportion of 64% was obtained in a long-term case study, and increased in summer with the upper limit of the comfort temperature, up to 28 °C [12]. In-depth research regarding the relationships between air movement and thermal comfort with localised airflow systems has been performed via lab experiments. A variety of operating parameters, such as environmental contexts[13, 14], airflow velocity and turbulence [15–17], the temperature of supplied air [18], the types of different air supply structures [19–21], and locally-exposed body parts [22] were examined as having effects on user comfort, to varying degrees. Additionally, studies [23, 24] that focused on occupant behaviours regarding the local air supply systems further addressed the significant influence of personal controls: the upper acceptable temperature limit was increased when the air supply was accessibly regulated at individual levels. Later, Zhang et al. [7] summarised five typical PCS models reviewed in current studies, and defined a term “corrective powder” to quantify the cooling efficiency of the different PCS models. It was concluded that the offset temperatures ranged from 1 °C to 6 °C for cooling, and from 2 °C to 10 °C for heating. However, these findings are hardly comparable to one another, as variant factors and conditions exist in different experimental designs, all of which remarkably affect the performance of localised airflow systems. As such, no consistent results are available for how to evaluate and design a localised airflow system in building environments[7], which thwarts its real practical application and wider energy saving potential.

42 A machine learning methodology for problem solving has received increased
43 attention in many research fields, thanks to its abilities to improve model prediction
44 performance through continuous learning, and to handle complex and high-dimensional
45 data [25]. Driven by the building technology improvement and wireless sensor-rich
46 environments, researchers have shifted their paradigms to a variety of machine learning
47 algorithms to obtain relationships between human thermal comfort and a number of
48 factors, aiming to achieve better predictions/evaluations on human thermal comfort and
49 applications in buildings. Kim et al. [26] integrated field data of environmental
50 conditions and mechanical system settings as well as occupants' control behaviours on
51 a PCS, and predicted the individuals' thermal comfort responses using six machine
52 learning algorithms. The results indicated that employing a machine learning technique
53 enabled a median prediction accuracy of 0.73, as compared to conventional models
54 (predicted mean vote (PMV), adaptive model) that produced a median accuracy of 0.51.
55 Similarly, Jiang [27] adopted a C-Support Vector Classification (C-SVC) algorithm to
56 predict a personal thermal sensation in a PCS; the results showed a higher predictive
57 accuracy (89.82%) as compared to the PMV model (49.71%), which was beneficial for
58 optimisation control for the PCS. Further, Kim [28] emphasised the new paradigm of
59 using machine learning methods for personal comfort models; such models enable
60 predictions at individual levels instead of the average responses of a large population,
61 and significantly improve the prediction accuracy by approximately 17%–40%,
62 reinforcing the potential of a PCS in real-world applications. Based on real-time
63 feedback and automatic regulation, employing extreme learning machines and neural
64 networks results in a predicted maximum energy saving rate of 30% for air-conditioning
65 and mechanical ventilation systems, while maintaining a pre-defined comfort [29].
66 However, though these works provide valuable insights for using machine learning
67 techniques to improve the prediction performance with a PCS, there is still a paucity of
68 research for gaining a holistic understanding of the various driving factors for a
69 localised airflow system, and identifying an appropriate machine learning model to
70 evaluate personal thermal comfort. Moreover, there has been insufficient examination
71 of how to determine which factors should be considered for localised airflow systems,
72 to what degree the model inputs affect the target variable, and how to guide the
73 evaluation and designs of such localised airflow systems in real-life buildings.

74 With new devices and technologies of localised airflow systems being increasingly
75 accessible for indoor building environments, identifying the most significant factors
76 and an appropriate evaluation model covering all these factors is of great importance,
77 before such systems are applied in buildings to achieve building energy savings. As a
78 result, this study is based on a collective database of several lab experiments for
79 localised airflow systems and conducts a rigorous process to explore the influencing
80 factors and evaluate models for local airflow conditions. The aims of this study are to
81 quantify the relative significance of factors by referring to sensitivity analysis and
82 identify a prediction model of personal comfort based on the advantages of machine
83 learning algorithms. This work is expected to provide an in-depth understanding of

84 factor interactions in a localised airflow system and enable a more informed appraisal
85 of localised airflow system design in practice. The outcomes can aid in guiding data
86 monitoring and collection efforts when a localised airflow system is applied in
87 buildings in the future to improve personal thermal comfort prediction and energy
88 efficiency in buildings.

89 2. Methods

90 We conducted multiple laboratory experiments to examine the relationships
91 between local air supply and human thermal comfort in warm and hot environments
92 and built a database. For personalised ventilation, it has been found that airflow is
93 preferred by people when it is directed against the upper parts of the body (e.g. face,
94 head, chest)[30, 31] and that a transverse flow improves thermal comfort. Therefore,
95 we selected three typical localised airflow systems, i.e. isothermal air supply nozzle
96 (IASN), non-isothermal air supply nozzle (NIASN), and floor fan (FF). The difference
97 between the IASN and NIASN systems is the temperature difference of the supplied air.
98 The FF was considered as a common local airflow device in buildings to increase air
99 movement, wherein the air supply type differed from the IASN system. All experiments
100 were performed during the summer season in different periods from 2014 to 2017 and
101 covered the main factors we aimed to explore for a localised airflow system. An
102 introduction is briefly presented as follows, to support an improved understanding of
103 the experiments and the database used.

104 2.1 Climate chamber

105 All three series of experiments were performed in a climate chamber with a size
106 of 4 m × 3 m × 3 m (L×W×H). The air temperature (T) and relative humidity (RH) in
107 the chamber were managed by an automatic control system with a temperature range
108 of 10 °C–40 °C (accuracy: ±0.3 °C) and RH range of 10%–90% (accuracy: ±5%). The
109 handled air was sent to the chamber using a perforated ceiling, such that the ambient
110 air velocity in the chambers not generated by the local airflow system did not exceed
111 0.1 m/s during experiments. This ensured a uniform surrounding environment and a
112 lack of disturbances of the airflow during experiments. A special insulation construction
113 of the chamber ensured conditions such that the mean radiant temperature was equal to
114 the room air temperature. In addition, the climate chamber was connected to an air-
115 conditioned room that was controlled at a neutral thermal environment (26 °C/50% RH)
116 for preparation work before each test.

117 2.2 Subjects

118 The subjects in experiments were recruited from college students. Before the
119 experiments, a *priori power* analysis in G*Power 3 [32] was conducted to determine
120 the sample capacity, according to the designs in each series of experiments. All
121 participants were volunteers between 20 and 25 years of age, with healthy conditions,
122 e.g. no colds or fever. They were paid to participate in all of the design conditions in
123 each series of experiments. Before enrolment in the tests, each subject received verbal
124 and written explanations of the study. Written informed consent was obtained from the

125 subjects. The basic information of participants was collected at the first time they
 126 attended the test, as summarised in Table 1. In addition, uniform summer clothes (cotton
 127 short-sleeved T-shirt, thin trousers, and slippers, with clothing insulation of 0.4 clo[33])
 128 were provided to subjects in the experiments, to minimise the effect of clothing
 129 insulation on subjective thermal perceptions.

130 Table 1 Basic anthropometric data of subjects(mean±SD)

| Conditions | Number | Sex | Age(years) | Height(cm) | Weight(kg) |
|---|--------|--------|------------|------------|------------|
| Isothermal air supply nozzle (IASN) | 18 | male | 24.5±1.2 | 174.2±5.2 | 62.6±5.5 |
| Non- isothermal air supply nozzle (NIASN) | 8 | male | 23.6±1.4 | 175.1±6.1 | 70.0±10.5 |
| | 8 | female | 23.4±1.2 | 161.5±6.4 | 51.3±4.8 |
| Floor Fan (FF) | 8 | male | 23.7±0.9 | 174.2±6.1 | 63.3±5.9 |
| | 8 | female | 23.7±0.7 | 162.2±1.3 | 49.8±4.6 |

131 **2.3 Experimental designs**

132 Among all three types of localised airflow systems, local air was directly supplied
 133 in front of the subjects. As shown in Figure 1, the IASN and NIASN systems were made
 134 of a ventilation duct with plastic batches (d=150 mm) and equipped with a nozzle
 135 (d=100 mm)[34]. Variable nozzle types and sizes were exclusively considered in this
 136 study. The supply-air outlet was placed 30–40 cm from the subjects, with an adjustable
 137 angle to aim at a subject's face and head horizontally, or to aim in a slightly downward
 138 slope, e.g. to aim at the neck and chest. The FF was located 1.5 m horizontally in front
 139 of the subjects and was placed approximately 0.9 m above the floor level, and it directed
 140 a forced airflow to the head and chest region. A general view of the local airflow system
 141 used in the experiments is shown in Figure 1.

142



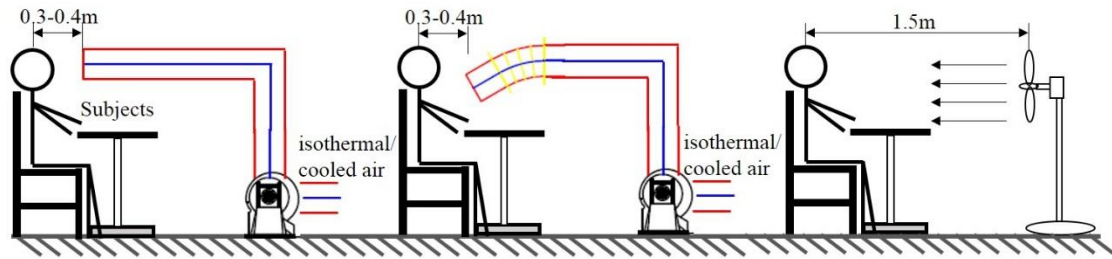


Figure 1 Schematic of the three localised airflow systems

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Considering that local airflows given to upper body parts were more sensitive and efficient for cooling[35, 36], we mainly focused on three factors for airflow, i.e. the V at locations where subjects were exposed, temperature of the supplied air, and body parts exposed to the airflow. In addition, as air velocity has been acknowledged to offset temperature increases in warm settings, all of the experiments were designed in warm/hot environments, with T ranging from 26 °C to 32 °C, and RH from 50% to 90%. The design conditions in the three series of experiments are summarised in Table 2.

For the NIASN system, the temperature of the supplied air shown in Table 2 was controlled by a constant temperature-humidity air-conditioned system in an adjacent room, and the cooled air at the designed levels was supplied to the chamber through plastic ducts; for the IASN system, the supplied air was circulated by fans from ambient air in the chamber. The designed V in Table 2 for the NIASN system was slightly lower than that for the IASN system, in accordance with the cooling effect of the low temperature of the air supplied in IASN system. The different body parts exposed to airflow were achieved by regulating the angles of the supply air outlet (see Figure 1) in these two systems. It should be noted that the V given in Table 1 for all three localised airflow systems are designed values referring to places where subjects were located, rather than at the outlets (see the lower part of Figure 1). This was to determine a comfortable V for subjects. The V under each condition was regulated and measured during preparation work, with no subjects. The regulations were recorded, and before each test, the V would be preset at the designed level.

Table 2 Design conditions of the three series of experiments

| Conditions | T*(°C) | RH(%)* | V(m/s)* | Supply Air Temperature(°C)** | Local Body Parts |
|------------|-------------|--------|-------------------|------------------------------|------------------|
| IASN | 28 | 55 | 0/1.4 | 28 | head |
| | | | | 28 | chest |
| | 30 | | 0/1.8 | 30 | head |
| | | | | 30 | chest |
| | 32 | | 0/2.2 | 32 | head |
| | | | | 32 | chest |
| | 0/1/1.4/1.8 | | 28 | head+chest | |
| | | | 30 | head+chest | |
| | | | 32 | head+chest | |
| NIASN | 26 | 75 | 0/0.6/0.8/1.0/1.2 | 25 | head |

| | | | | |
|----|----|----|-------------------|------------|
| | | | | 26 |
| | 28 | | 0/0.6/0.8/1.0/1.2 | 25 |
| | | | | 22 |
| | 30 | | 0/0.8/1.0/1.2/1.4 | 25 |
| | | | | 22 |
| | | 50 | 0/1.1/1.3/1.9 | |
| | 28 | 70 | 0/1.1/1.3/1.9 | 28 |
| | | 90 | 0/1.1/1.9/2.4 | |
| | | 50 | 0/1.1/1.9/2.4 | |
| | 30 | 70 | 0/1.1/1.9/2.4 | 30 |
| | | 90 | 0/1.3/1.9/2.4 | |
| FF | | 50 | 0/1.3/1.9/2.4 | head+chest |
| | 32 | 70 | 0/1.9/2.4/2.8 | 32 |
| | | 90 | 0/1.9/2.4/2.8 | |

166 Note:

167 * the T and RH are the designed ambient temperature and humidity in the climate chamber, which
168 are controlled by the chamber automatic control system; the V is the designed air velocity at subject
169 location, with the equal height to the jet axis in localised airflow system.

170 ** the supply air temperature is the measured temperature at the air outlet.

171

172 Table 3 shows the measured thermal environments during tests, using the average
173 values of all samples in each condition in each series of experiments in Table 2. It is
174 observed that the measured environmental T and RH met the designed conditions (Table
175 2) well. The V fluctuated around the designed levels, with small standard deviations.
176 The strictly controlled environment minimised the errors caused by the designs and
177 ensured the quality of the experimental data.

178

179 Table 3 Measured thermal environment parameters during experiments (mean±SD)

| Conditions | Temperature (°C) | RH (%) | Air Velocity (m/s) | Supply Air Temperature(°C)* |
|------------|---------------------|-----------|---|--------------------------------|
| IASN | 28.0±0.1 | 56.2±0.4 | 0/1.40±0.02 | 28.5±0.2 |
| | 29.9±0.2 | 55.7±0.9 | 0/1.81±0.02 | 30.5±0.2 |
| | 32.1±0.2 | 56.2±1.3 | 0/2.20±0.09 | 32.5±0.5 |
| | 28.0±0.1 | 56.1±0.5 | 0/1.02±0.06/1.41±0.02/1.81±0.02 | 28.4±0.1 |
| | 29.9±0.1 | 56.4±0.4 | 0/1.04±0.06/1.40±0.03/1.81±0.02 | 30.3±0.3 |
| | 32.1±0.1 | 56.1±1.0 | 0/1.00±0.04/1.41±0.01/1.80±0.05 | 32.5±0.2 |
| NIASN | 25.9±0.2 | 74.2±1.5 | 0/0.61±0.05/0.79±0.03/1.01±0.05/1.21±0.03 | 24.9±0.3 |
| | 26.1±0.1 | 75.4±1.2 | 0/0.57±0.08/0.81±0.05/0.98±0.07/1.20±0.02 | 26.1±0.2 |
| | 28.1±0.1 | 75.1±0.8 | 0/0.60±0.07/0.81±0.05/1.0±0.03/1.22±0.04 | 25.2±0.3 |
| | 27.9±0.2 | 75.5±0.4 | 0/0.62±0.03/0.79±0.06/0.99±0.04/1.18±0.05 | 22.1±0.4 |
| | 30.0±0.2 | 75.3±0.6 | 0/0.81±0.08/1.02±0.02/1.21±0.05/1.42±0.06 | 24.9±0.5 |
| | 39.9±0.2 | 74.8±1.0 | 0/0.80±0.04/1.01±0.05/1.23±0.02/1.39±0.04 | 22.2±0.4 |

| | | | | |
|----|----------|----------|---------------------------------|----------|
| | 28.0±0.2 | 50.5±1.0 | 0/1.13±0.07/1.32±0.05/1.90±0.09 | 28.0±0.2 |
| | 27.9±0.2 | 69.6±0.8 | 0/1.1±0.1/1.29±0.08/1.91±0.08 | 27.9±0.2 |
| | 28.1±0.2 | 89.5±1.2 | 0/1.08±0.1/1.90±0.08/2.42±0.05 | 28.1±0.2 |
| | 30.2±0.1 | 49.8±1.0 | 0/1.11±0.1/1.88±0.07/2.4±0.10 | 30.2±0.1 |
| FF | 29.9±0.2 | 70.4±0.9 | 0/1.12±0.07/1.93±0.05/2.39±0.1 | 29.9±0.2 |
| | 30.1±0.2 | 89.5±1.1 | 0/1.31±0.06/1.91±0.04/2.43±0.05 | 30.1±0.2 |
| | 27.9±0.2 | 51.2±0.8 | 0/1.29±0.13/1.85±0.11/2.41±0.08 | 27.9±0.2 |
| | 27.9±0.1 | 70.5±1.2 | 0/1.92±0.08/2.38±0.11/2.82±0.1 | 27.9±0.1 |
| | 28.1±0.2 | 91.2±0.9 | 0/1.88±0.1/2.4±0.13/2.82±0.1 | 28.1±0.2 |

180 Note:

181 * the temperature of the supplied air in IASN and NIASN systems was measured at outlets using
 182 thermocouples (range: -20 °C-+85 °C, accuracy: ± 0.1 °C, PyroButton-T, Oplus, US); the
 183 temperature of the supplied air in FF system was defaulted to ambient air temperature.

184

185 2.4 Variables and measurements

186 Many factors influence the cooling effect of local airflow on human thermal
 187 comfort. With the aim of identifying significant variables, we classified possible factors
 188 into four categories, namely environmental, individual, physiological, and
 189 psychological, and selected representative parameters in each category for further
 190 analysis.

191 A thermal comfort monitoring station instrument was used to measure the real-
 192 time T and RH in the chamber (MI6401, Germany, Accuracy: T ±0.2 °C, RH ±2%), to
 193 ensure that the experimental environments met the designed demands. The instrument
 194 was placed in the central chamber, at a height of 0.6 m above the floor and 0.5 m away
 195 from subjects. Before each test, when no subject was present, the V at the subject
 196 exposing location was pre-regulated and measured to reach the designed level in Table
 197 2, using an Air Distribution Measuring System (AirDistSys 5000, Sensor Electronic,
 198 Poland, range: 0.05 m/s–5 m/s, accuracy: ±0.02 m/s ± 1% reading data). To evaluate an
 199 environmental air velocity for thermal comfort, a weighted average of the indoor air
 200 velocity was calculated. The weighted average was calculated based on measurements
 201 performed at levels representing heights of ankles, abdomen, and neck (0.1, 0.6 and 1.1
 202 m for seated occupants, respectively) during tests, and according to the American
 203 Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE)
 204 Standard 55 [33] and European standards [37, 38]. A portable hot wire anemometer
 205 (VT110, France, 0.15 m/s–30 m/s, ±3% reading data with ±0.05 m/s) was used every 5
 206 min repeatedly, to verify whether the actual V met the designed level in Table 2. The
 207 values at the three levels were then averaged to represent the mean air velocity in the
 208 room when necessary.

209 The parameters that were considered influential for individuals were sex, body
 210 surface area (AD), and body fat ratio, which were believed to affect body heat
 211 generation and heat loss and thus affect the sensation of airflow. As shown in Table 1,
 212 the first time subjects attended the tests, each subject's weight and height were

213 measured. The AD values for each subject were calculated by Equation (1)[39]. The
214 body fat ratio was indirectly calculated using body mass index(BMI), referring to
215 Equation (2).

$$216 \quad A_D = 0.202 W_b^{0.425} H_b^{0.725} \quad (1)$$

$$217 \quad BMI = W_b / H_b^2 \quad (2)$$

218 Where H_b is the body height, m; W_b is the body weight, kg.

219 In warm/hot environments, body heat dissipation commonly occurs through two
220 major mechanisms, namely cutaneous vasodilation and sweating, which affect skin
221 temperatures and convective and evaporative heat transfer from the core to the skin[40].
222 During experiments, the local skin temperatures from eight parts of the body (i.e.
223 forehead, left chest, left back, left upper arm, left lower arm, left hand, right anterior
224 thigh, and anterior calf), were measured by thermocouples (TSD202B, BIOPAC, US,
225 temperature range: 0–70 °C, accuracy: ± 0.1 °C), while using surgical, water permeable,
226 adhesive tapes. The data were recorded at 0.5/s and logged by a multi-channel
227 physiological acquisition system (MP150-SKT100C, BIOPAC, US). The mean skin
228 temperature (T_{overall}) was calculated using an area-weighted eight-point method
229 (Equation (3)) [41].

$$230 \quad T_{\text{overall}} = 0.07T_{\text{head}} + 0.175T_{\text{chest}} + 0.175T_{\text{back}} + 0.07T_{\text{upper}} + 0.07T_{\text{lower}} + 0.05T_{\text{hand}} + 0.2T_{\text{thigh}} + 0.19T_{\text{calf}} \quad (3)$$

231
232 where the T_{overall} is the mean skin temperatures, °C; T_i is the local skin temperature of
233 the head, chest, back, upper arm, lower arm, hand, thigh, and calf, °C.

234 Studies had previously suggested that a whole body thermal sensation was a result
235 of the integrated effect of whole and local thermal responses, where the local body parts
236 took significant proportions in affecting the whole body thermal sensation under local
237 airflow environments [35, 36, 42, 43]. Therefore, we considered the interactions of
238 subjects' whole and local thermal perceptions and designed questionnaires for both
239 whole and local thermal evaluation. The most common thermal sensation vote (TSV)
240 scale was used: -3 cold, -2 cool, -1 slightly cool, 0 neutral, +1 slightly warm, +2 warm,
241 and +3 hot, as described in the ASHRAE 7-point scale[33]. Subjects were asked to
242 evaluate a thermal sensation on the whole body, head, chest, back, hand, and lower body,
243 under local airflow conditions. In some situations, when the subjects had difficulties in
244 expressing judgements, he/she was allowed to use middle votes between the above
245 values (e.g. +1.5 between +1 and +2). Additional questions were also involved in the
246 questionnaire to evaluate subjects' sensation to humidity, air velocity, environmental
247 expectations, environmental acceptability, and so on. Considering this study concerns
248 the offset of a local airflow on acceptable temperature limits, the main dependent
249 variable being focused on is the thermal sensation. Therefore, these indices were
250 exclusively analysed in the following parts.

251 2.5 Experimental protocols

252 The experiments complied with the guidelines in the Declaration of Helsinki[44].
253 Participants were counselled to withdraw from the experiments at any point in time if
254 they were not comfortable during the tests.

255 For each test, subjects were asked to arrive at the adjacent room 30 min in advance,
256 to change into uniform clothes, attach thermocouples, and stabilise their metabolic rates.
257 During this period, the details of experimental process and questionnaires were
258 explained to them.

259 The formal experiment began after the subjects entered the chamber and were
260 seated at desks. For each test, they experienced different conditions, with and without
261 a local air supply. Blind to the experimental settings, the subjects were exposed to two
262 or three levels of V for 20 min, and intermittent recovery for 15–20 min (without air
263 supply) during each test. The different air velocities in each condition were regulated
264 by experimenters according to the preset measurements, and were supplied in a random
265 way during the whole experimental process. The T and RH in the chamber were kept
266 constant, at the designed levels. Over the period of testing, the local skin temperatures
267 of each subject were measured continuously; meanwhile, they were asked to fill in
268 identical questionnaires every 5 min to report their thermal perceptions. During the
269 whole experiment, the subjects performed standardised office work while avoiding
270 walking, talking, and other intensive activities.

271 2.6 Statistical analysis

272 2.6.1 Data collection

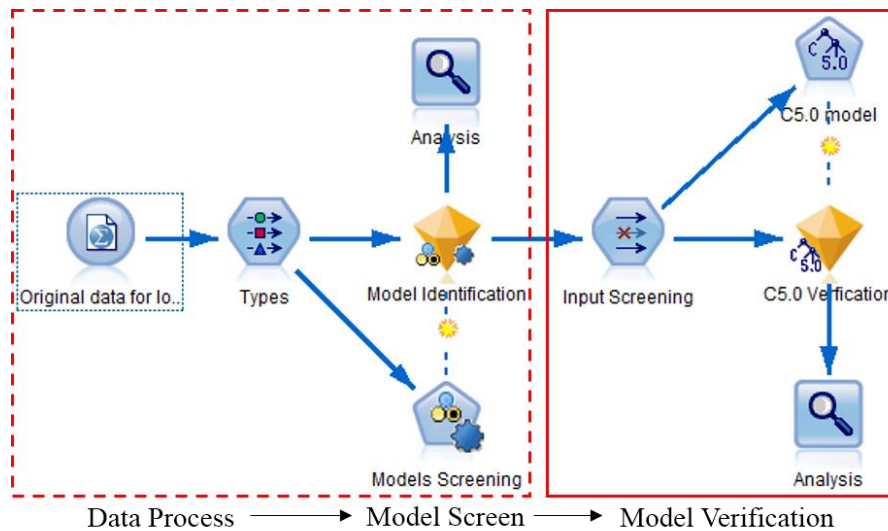
273 The experiments adopted 17 variables to comprehensively identify the significant
274 influencing factors. They included 3 individual factors (i.e. sex, AD, BMI), 5
275 environmental factors (i.e. T, RH, V, supplied air temperature, and local exposed body
276 parts), 9 physiological factors (i.e. T_{head} , T_{chest} , T_{back} , T_{upper} , T_{lower} , T_{hand} , T_{thigh} , T_{calf} , and
277 T_{overall}). In addition, 6 subjective indices (TSV_{overall} , TSV_{head} , TSV_{chest} , TSV_{back} , TSV_{hand} ,
278 and $TSV_{\text{lower body}}$) were also investigated using questionnaires. The original
279 experimental data were collected and saved in SPSS 22.0 software. As the study mainly
280 focused on subjects' stable thermal responses to local airflow, a repeated measure of
281 analysis of variance (ANOVA) was firstly performed for subjects' skin temperatures, to
282 determine the stable time of subjects' thermal responses during tests under each
283 condition. The stable time was determined as that having no significant difference
284 between subject' skin temperatures at one-time point and thereafter. The results showed
285 that majority of subjects' skin temperatures stabilised quickly, during the initial 10 min
286 when they were exposed to airflow. Then, all of the data for each subject were averaged
287 (mean \pm SD) for the last 10 min at each stage during the tests, either with airflow or
288 without airflow. The new database included 1305 sample cases, which were built and
289 used for the following analysis. To explore the correlation and interaction between
290 variables, a Pearson correlation coefficient analysis was employed for continuous
291 variables, and Spearman correlation coefficients were employed for categorical
292 variables. A p-value below 0.05 indicated statistical significance during the analysis.

293 2.6.2 Machine learning models

294 Research has provided robust evidence for the application of a variety of machine
295 learning algorithms, to better predict human thermal comfort[28] at individual levels.
296 These algorithms include the adaptive stochastic model[45], classification tree [46, 47],

297 Bayesian network [48], Gaussian process [49], support vector machine (SVM) [27, 50],
 298 and artificial neural network(ANN) [51]. These models enable using a variety of factors
 299 to solve the complexity of variant variables in models, and concentrate exclusively on
 300 the target output. This is an advantage in PCS studies, which have a large number of
 301 confounding factors.

302 One objective of this study is to deploy the advantages of the machine learning
 303 methods to explore an appropriate model to predict the personal comfort for a localised
 304 airflow system. The SPSS Modeler 20.0, as a data mining tool, offers multiple machine
 305 learning techniques and supports a variety of classification and regression models[52].
 306 Given many algorithms exist in machine learning[25], this study first employed the
 307 SPSS Modeler 20.0 to select the well-matched generative and deterministic machine
 308 learning models according to the experimental database. One benefit of the SPSS
 309 Modeler is that it can provide an intuitive graphical interface to help visualise each step
 310 in the data mining process as part of a stream. Figure 2 shows the primary analysis
 311 processing in SPSS Modeler, including experimental data processing and model
 312 screening. After those steps, 11 models are further examined in the following parts:
 313 logistic regression, discriminative model, Bayesian network, ANN, Lagrangian SVM
 314 (LSVM), C5.0, Tree-AS, chi-squared automatic interaction detection (CHAID),
 315 classification and regression tree (C&RT), Quest, and Random Tree.



316

317 Figure 2 Analysis process in SPSS Modeler using experimental data

318 2.6.3 Sensitivity analysis (SA)

319 As nearly 20 impacting factors were considered in this study for a localised airflow
 320 system, it is impractical to cover all of these data in models for a building application.
 321 Therefore, it is necessary to first identify significant variables, e.g. those with better
 322 explanations of human thermal comfort under local airflow conditions. A sensitivity
 323 analysis (SA) is a targeted method that enables determination of how the variation of
 324 the output in a model can be apportioned among the inputs[53]. The SA has been widely
 325 applied in academic research, and has been used in practical application in a variety of
 326 fields [54]. The method has also been considered as a powerful tool for building

327 optimisation in building design, and for exploring influencing variables on a specific
328 target in a building energy simulation[55, 56]. However, as there are several methods
329 to perform the SA, less attention has been paid to explore the application in multiclass
330 classification, and in particular with the various categorical and numerical features in a
331 thermal comfort evaluation for a PCS. In this study, we referred to a variance-based SA
332 methodology based on a Bayesian treed Gaussian process model in the “tgp” package,
333 [57] and conducted the analysis via R software (ver. 3.3.2). The outcomes enable us to
334 understand and quantify the main effects of variables on a dependent variable, as well
335 as the first order and total sensitivity indices among the input variables. The
336 significance level was set at 95% ($p < 0.05$).
337

338 3. Results analysis

339 Based on the dataset of 1305 original samples from the three series of experiments,
340 the following section aims to explore which models are superior for thermal comfort
341 evaluation in a localised airflow system at individual levels, as well as the
342 representative factors that have the most significant effects on personal thermal comfort.

343 3.1 Machine learning models identification for localised airflow system

344 Although both local and whole thermal sensations of subjects were measured
345 during the experiments, an interactive effect exists among these indices. Therefore, we
346 employed the typical whole body (overall) thermal sensation $TSV_{overall}$ as the target
347 dependent variable to examine its relation to the variant independent variables and build
348 models.

349 After determining the 17 input variables (see Section 2.4) and the target output,
350 the dataset was randomly split into training and testing sets (80% and 20%), and all of
351 the 11 machine learning models mentioned in Section 2.6.2 were tested using the SPSS
352 Modeler 20.0. Figure 2 depicts the conducting process in the SPSS Modeler. In that
353 regard, this study does not discuss the detailed process of data training and parameter
354 tuning in these algorithms. Instead, we focused on comparing the prediction
355 performance among these models to identify the appropriate model. Table 4
356 summarises the preferred five models from the set of 11 models and lists their prediction
357 performances. From Table 4, it can be seen that the C5.0 model displays the highest
358 prediction performance of 83.99% when all 17 variables are included, followed by
359 59.69% for the CHAID model, and 57.47% for the C&RT model. The Quest and ANN
360 models were worse than the first three classification tree models, with their predictive
361 performances at 53.56% and 44.9%, respectively. As the C5.0 model takes the
362 information gain as a standard to optimise the partition process and favours outcomes
363 with a higher information gain, the results indicate that the C5.0 model is superior for
364 predicting subjects’ thermal sensations under local airflow conditions. Therefore, we
365 give priority to the C5.0 model in the following analysis to profile the relationship
366 between subjects’ thermal sensations and variant input features in localised airflow
367 systems.

368

369

Table 4 Preferred machine learning models

| Models | Prediction Performance | Number of Input Variables |
|--------|------------------------|---------------------------|
| C5.0 | 83.99% | 17 |
| CHAID | 59.69% | 9 |
| C&RT | 57.47% | 14 |
| Quest | 53.56% | 10 |
| ANN | 44.91% | 17 |

370

371 3.2 SA for impacting factors in localised airflow system

372 3.2.1 Feature variable screening

373

374 From Table 4, it is not surprising that the C5.0 model possesses a better prediction
375 performance, as too many variables are involved in the model. Practically speaking,
376 owing to the difficulties and expenses of monitoring all influential variables, choosing
377 a good model is not only based on accuracy, but also on the validity and explanatory
378 ability of the selected data [26]. Therefore, it may be difficult to capture all the relevant
379 information for the C5.0 model to develop a comfort prediction; otherwise, it is
380 necessary to correlate the comfort prediction with highly representative variables. In
381 fact, some variables in the dataset interact with each other to influence subjects' thermal
382 sensations, and some are negligible for model prediction. Therefore, we first conducted
383 a correlation analysis to examine the 17 variables in the C5.0 model, to possibly reduce
384 the number of input variables.

385 First of all, because of the limited distance (30–40 cm) between the supplied air
386 outlet and the subjects in the IASN system, both the head and chest of subjects were
387 exposed to air movement in the experiments, which made the boundaries fuzzy in
388 distinguishing the body areas exposed to airflow. In that case, the factors of different
389 exposed parts for the body are exclusively considered. Moreover, some previous
390 studies[58, 59] confirmed that the temperature difference between the supplied air from
391 a nozzle and the surroundings was negligible when the air reached the subjects,
392 resulting from the diffusing effect of the supplied air. The measurements of the air flow
393 field during pre-experiments had also found that the temperature of the cooled air
394 attenuated quickly in a NIASN system, being equal to the ambient temperatures in
395 warm and hot conditions. Thus, the temperature variable of supplied air is also removed
396 when evaluating the cooling effect of local air movement. After that, the environmental
397 parameters were reduced to three: T, RH, and V.

398 As for physiological variables, Dai et al. [50]discussed that the curse of
399 dimensionality may occur with additional local body skin temperatures as inputs for
400 thermal demand predictions, based on a SVM classifier. Therefore, a Pearson
401 correlation analysis was performed first, and the correlation metrics of these
402 physiological indices are illustrated in Table 5. From Table 5, it can be seen that there
403 were no significant correlations between the skin temperatures of the chest and other

404 parts. During experiments, the thermocouples were placed at the upper left part of the
 405 chest, and were directly exposed to the air and V. Therefore, it was reasonable that the
 406 subjects' chest skin temperatures were more sensitive to local airflow than other body
 407 parts (see Figure 1). In addition, the correlation coefficients in Table 5 (marked in grey
 408 colour) show that the T_{overall} was significantly related to local skin temperatures. As a
 409 result, the mean skin temperature T_{overall} can be a feature selected to represent the local
 410 skin temperatures. After analysis, the physiological variables can be reduced to two:
 411 T_{overall} and T_{chest} .

412
 413 Table 5 Correlation analysis of subjects' physiological indices

| Variiances | T_{head} | T_{chest} | T_{back} | T_{upperarm} | T_{lowerarm} | T_{hand} | T_{thigh} | T_{calf} | T_{overall} |
|-----------------------|-------------------|--------------------|-------------------|-----------------------|-----------------------|-------------------|--------------------|-------------------|----------------------|
| T_{head} | 1.00 | 0.008 | 0.253** | 0.097** | 0.017 | 0.023** | 0.445** | 0.173** | 0.283** |
| T_{chest} | | 1.00 | 0.012 | 0.013 | -0.001 | 0.000 | 0.033 | 0.001 | 0.023 |
| T_{back} | | | 1.00 | 0.086** | -0.014 | 0.048 | 0.329* | 0.001 | 0.246** |
| T_{upperarm} | | | | 1.00 | 0.017 | 0.012 | 0.108** | 0.001 | 0.147** |
| T_{lowerarm} | | | | | 1.00 | -0.001 | 0.000 | -0.006 | 0.51* |
| T_{hand} | | | | | | 1.00 | 0.032 | 0.010 | 0.871** |
| T_{thigh} | | | | | | | 1.00 | 0.134** | 0.319** |
| T_{calf} | | | | | | | | 1.00 | 0.283** |
| T_{overall} | | | | | | | | | 1.00 |

414 (Note: ** $p < 0.01$; * $p < 0.05$, (two-tailed))

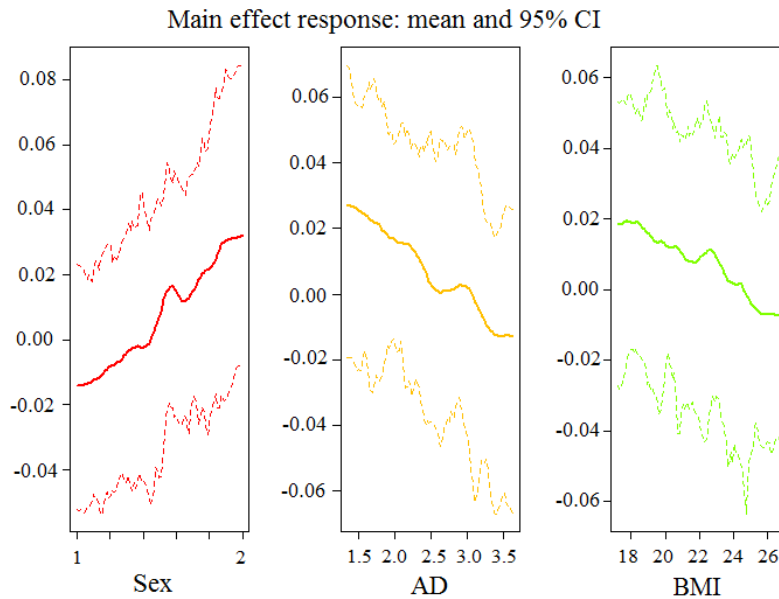
415 In summary, we identified the featured variables, and reduced the number of
 416 variables from 17 to 8, i.e. sex, AD, BMI, T, RH, V, T_{chest} , and T_{overall} . These 8 variables
 417 are examined for sensitivity.

418 3.2.2 SA of the feature variables

419 Although the correlation analysis allows us to simplify the features in the C5.0
 420 model, there is still a need to examine the degree to which these factors affect thermal
 421 sensation, and how to quantify their effects. To correctly interpret the results in the right
 422 perspective, we divided the 8 variables into three categories (i.e. environmental,
 423 individual, and physiological), and conducted a global SA to evaluate their effects.
 424 Figures 3–5 plot the main effects of the 8 features, respectively. The slopes of different
 425 inputs in Figures 3–5 give the information on whether the output of TSV is an
 426 increasing or decreasing function of the corresponding inputs; the solid lines are the
 427 mean values, and the dotted lines are the 95% intervals.

428 ① Individual features

429 It was observed that the TSV showed linear change trends with the 8 variables
 430 increasing, as can be seen from Figures 3–5. Specifically, in Figure 3, the main effect
 431 differed in sex, with 1 being defaulted as female and 2 as male. In addition, with the
 432 increase of body AD and BMI, the main effects caused by increasing AD and BMI
 433 decreased slightly, suggesting the effects of individual differences of AD and BMI on
 434 subjects' TSV changes were attenuated under such conditions.



435

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Figure 3 Sensitivity analysis (SA) results for three individual factors

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② Environmental features

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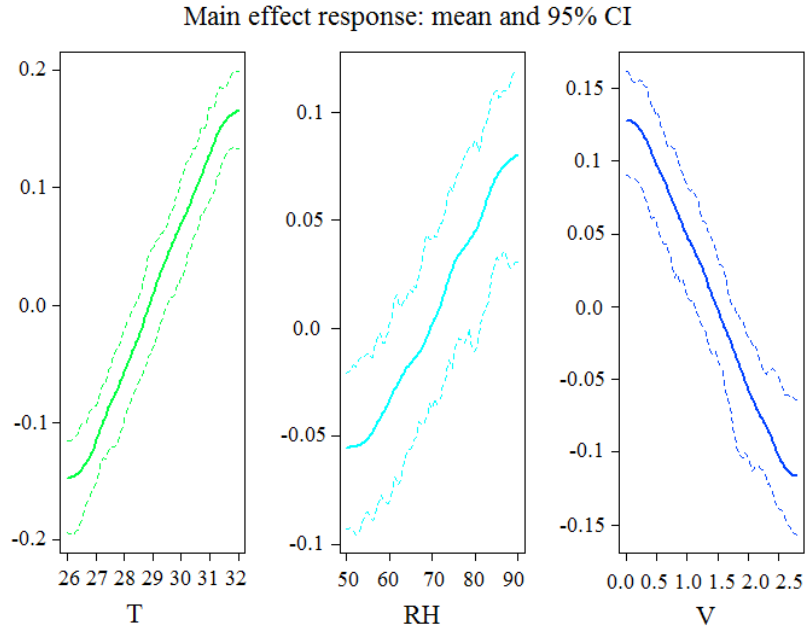
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The main effects of environmental parameters of T, RH, and V on TSV are plotted in Figure 4. From Figure 4, larger main effects of T and RH were observed on the TSV responses. Especially for T, it revealed that with T increasing, the effect of increasing 1 °C on the TSV would be more significant. In addition, an in-depth observation on Figure 4 showed that the main effect responses tended to be stable when the T and RH were approximately 26 °C/50% RH, and above 31 °C/80% RH. This allows us to infer that when the T and RH are in a moderate zone, the thermal environment is neutral, such that the changes of T and RH have slight effects on subject thermal sensation. As the thermal sensation is limited to seven scale values with a maximum of +3 for hot, when the T and RH are high, subjects' TSV may stabilise at +3, and can be higher for longer. As a result, the effect caused by T and RH changes on TSV responses is slight. Conversely, the V in Figure 4 displays an opposite trend of the main effect response, i.e. increasing V has positive effects on a subject's thermal sensation, and produces a decrease in TSV. Moreover, the values of the main effect responses for V were much higher in Figure 4, indicating that the elevated V in a localised airflow system has a significant cooling effect on subjects' TSV.



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Figure 4 SA results for physical factors

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③ Physiological features

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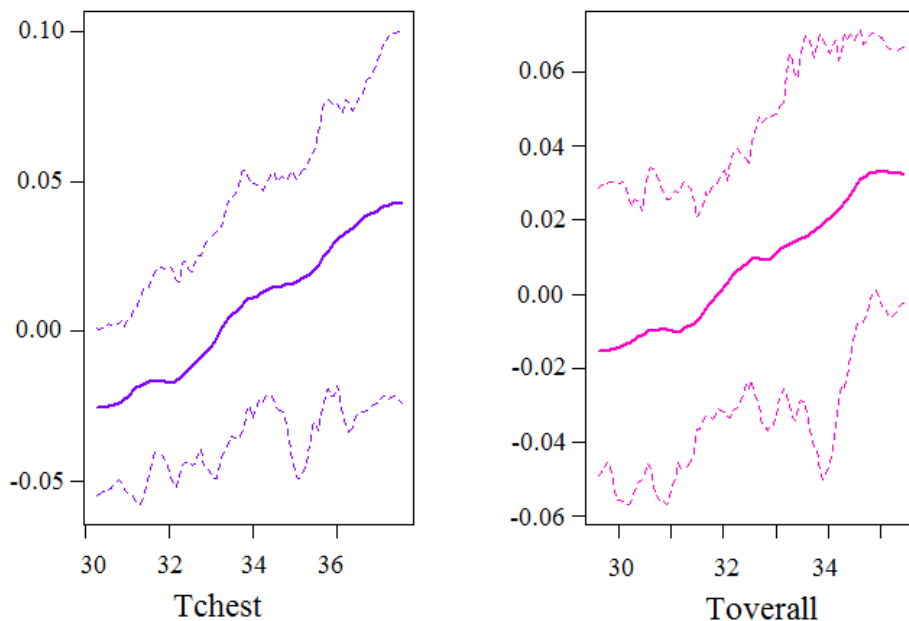
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As compared to the environmental factors shown in Figure 4, the main effects of T_{overall} and T_{chest} changes on the TSV responses in Figure 5 were slight in cases where skin temperatures were lower than approximately 32 °C. However, the main effects increased remarkably when the skin temperatures increased above 32 °C. Considering the comfort limits for skin temperatures, this indicates that when the skin temperatures of subjects are lower than the thresholds (e.g. 32 °C in this study), the TSV is in a comfortable range, and is slightly affected by skin temperatures. When the skin temperatures increase beyond the comfort zones, the TSV of subjects tends to increase significantly.

Main effect response: mean and 95% CI



466

467

Figure 5 SA results on physiological factors

468

④ Global effects

469

To display the main effects for all parameters using a single plot, Figure 6 further summarises the first-order sensitivity and the total effect sensitivity of the 8 indices. In Figure 6, the first-order sensitivity indices quantify the changes of output variables respectively caused by individual input variables, and the total effect sensitivity indices reflect the interactive effects of all of the input variables on the output variable. From Figure 6, it is clearly observed that T is a major contributor, leading to the most sensitive TSV responses with increasing T. The V and RH are ranked as the second and third contributors to the TSV changes, respectively. This is to some degree different from the individual effects depicted in Figure 5, which may be explained by the coupled effects of T, RH, and V. By contrast, the individual and physiological features are roughly the same, sharing the small values of sensitivity responses to TSV. However, for the total sensitivity, a remarkable change is found in Figure 6. Although the overall distribution trend of the 8 variables remains, the total effects increase when considering the interactions among 8 variables, especially for T. That the sensitivity indices do not sum to one indicates that the interactive effects between two or more variables are important for individual thermal sensation evaluation under local airflow conditions. Overall, Figure 6 gives a visual impression of the effects of the selected 8 feature variables on the variation of TSV, and quantifies their individual and coupled effects, which are believed to be beneficial for the evaluation and design of localised airflow systems in buildings.

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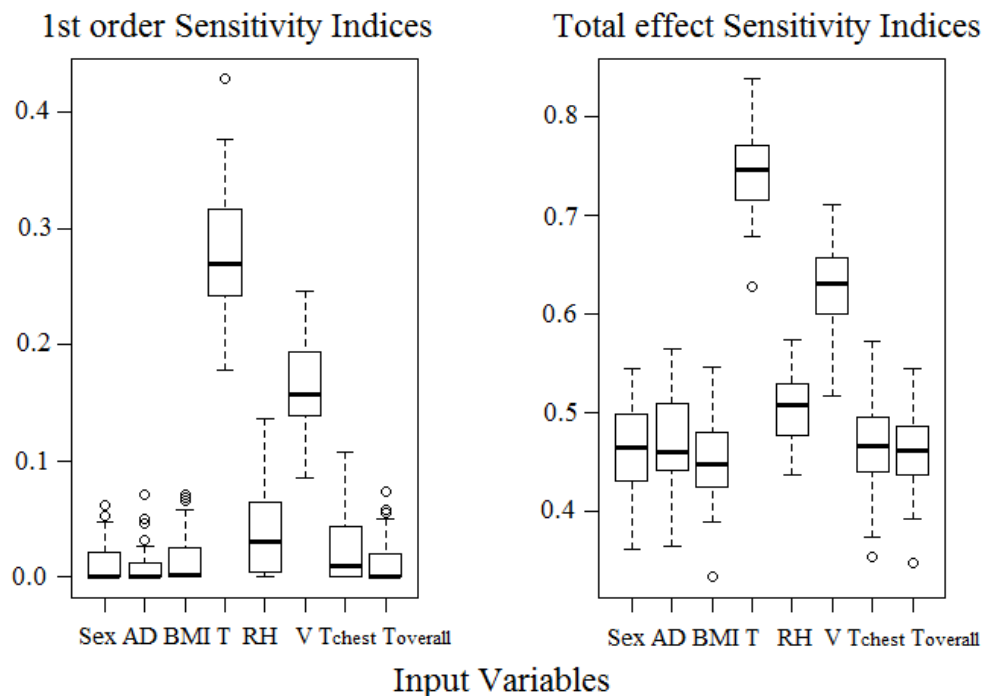
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Figure 6 Full SA results for all feature variables

492 3.3 Model verification

493 Here, further discussion is provided as to whether and to what degree the reduction
494 of input variables might compromise the prediction performance of the obtained C5.0
495 model, as compared to the iteration using e.g. 17 variables. A new database with 8
496 feature variables and 1 output variable is created via inputs filtering, as shown in Figure
497 2 in solid red lines. Using the same settings as in Section 3.1, the data are also divided
498 into training and testing sets, and the predictive performance of the obtained C 5.0
499 model is examined and verified. The result shows that the new C5.0 model using 8
500 inputs has a high predictive performance of 82.30%, even though it is slightly lower
501 than the aforementioned performance of 83.99% using 17 variables as shown in Table
502 4. This indicates that the C5.0 model is better for predicting human thermal comfort in
503 a local airflow system with as few as 8 variables, which is expected to simplify the C5.0
504 model to facilitate its use in applications.

505 One additional advantage of choosing the C5.0 model is that it can generate a
506 interpretable model to understand how the model implements rules and can run faster
507 with a large database, as compared with some complex models such as Random forest
508 and SVM[26]. Therefore, we demonstrate the decision rules in the C5.0 model and
509 simplify the process using the first four layers as example, as shown in Figure 7.
510 Consistent with the sensitivity analysis, the model in Figure 7 adopts the environmental
511 parameters as the prior feature nodes, to divide different categories and layers. With or
512 without a local air velocity, the C5.0 model first takes V as the root node of the tree, as
513 seen in Figure 7. In particular, the C5.0 model only follows a rule of binary
514 classification for features, from the root node to leaf node. Therefore, the original
515 division splits V into two categories of ≤ 0 m/s and > 0 m/s. However, it is
516 unreasonable in reality for V to be under 0 m/s. Therefore, we fine-tune the
517 classification tree in Figure 7 with $V=0$ m/s. Starting from root node, the data are split
518 into two categories, using a T baseline of 28 °C in the second layer. The third layer
519 introduces RH as the feature, and divides according to the baselines of 75% and 55%
520 for $T \leq 28$ °C and $T > 28$ °C, respectively. The fourth layer further adopts RH and BMI
521 as leaf nodes. By contrast, the classification rule is slightly different from that when V
522 is above 0 m/s. That is, with $V > 0$ m/s, the T and RH are adopted as feature variables
523 in the third layer for classification. When T is equal to or under 28 °C, T is introduced
524 for the third layer ($T \leq 26$ °C(neutral) and $T > 26$ °C(warm)). When T is above 28 °C,
525 the RH is adopted in the third layer, with $RH \leq 75\%$ and $RH > 75\%$. This suggests that
526 the effect of RH on human thermal comfort is coupled with T , and plays a dominant
527 role under higher T values and humidity.

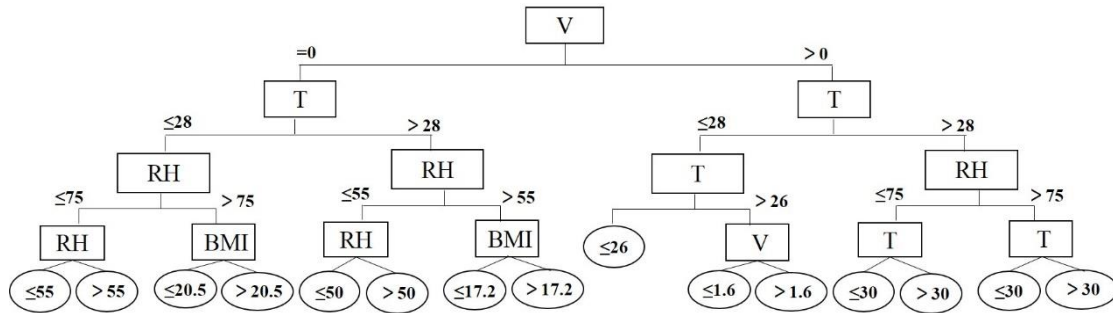


Figure 7 Classification Tree C5.0 model for localised airflow evaluation

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529

530 4. Discussion and limitations

531 The above analysis (depicted in Figure 7) identifies the most significant features
532 affecting TSV at each layer of the tree with different discriminative approaches, and is
533 superior to some other models. Kim[26] compared the performance of six typical
534 machine learning algorithms used to develop personal comfort models; he argued that
535 although algorithms with capabilities to control high dimensions and noise in the data
536 (e.g. Random forest, regularised logistic regression, kernel SVM (kSVM)) could
537 produce higher accuracy, they were more computationally expensive. In light of this,
538 the C5.0 model in the current study significantly reduces the numbers of feature
539 variables; meanwhile, it still predicts the individual thermal sensations well (higher than
540 80%). Most important, the machine learning models are superior at continuously and
541 automatically improving themselves through repeated learning and training [26]. It is
542 thus believed that by performing an incremental restoration of data, the prediction
543 performance of the C5.0 model for predicting personal thermal comfort with 8 input
544 variables could be improved, i.e. more in-depth. In this way, this work can be referred
545 to for comfort evaluation for a localised airflow system and guide application of such a
546 system, in parallel with reduced dependence on HVAC systems and more energy-saving
547 potential.

548 However, although this study identifies the significant influencing variables in
549 localised airflow systems and builds an appropriate classification tree model based on
550 C5.0, some limitations should be discussed for the current study, to make better
551 interpretation of the results and inspire further studies. The results in this study are
552 based on a database including three local air supply forms, where subjects were exposed
553 to airflow for 20 min, and recovered for 15–20 min between two different V levels. As
554 under warm/hot conditions, the inner body heat storage of subjects would increase over
555 the periods without airflow, the study may exaggerate the subjects' real thermal
556 sensation on the cooling effect of air velocity, when the airflow is subsequently given.
557 This would have effects on the obtained database. However, some experiments
558 designed without recovery periods, or with a short recovery time [60–63], could cause
559 the inclusion of subjects' thermal memories from a previous thermal experience,
560 potentially resulting in deviations for the subjective evaluations. Therefore, balancing

561 the variant factors in a localised airflow system and the contradictions between time,
562 cost, and experimental designs for different purposes should be considered for future
563 studies.

564 The preferred air velocity of occupants is believed to have a “time and fatigue”
565 effect, as the demand for air velocity for people would differ from short-term exposure
566 to long-term exposure[64, 65]. The lab experiments used in this study were designed to
567 explore the cooling effect of air movement for a localised airflow system and the
568 exposure durations were limited, with the time-dependent variations of subject thermal
569 sensations being thus exclusively considered. The term “alliesthesia” has been paid
570 increasing attention in the dynamic thermal comfort field, and describes a sensation of
571 pleasantness that occurs only with dynamic thermal stimuli on a human skin surface[66,
572 67]. As for long-term exposure to airflow in real building environments, the annoyance
573 caused by a constant air velocity may increase over time[64]. An air velocity over 1 m/s
574 may exert extra pressure on the human body surface[68]and cause eye irritation [69];
575 moreover, the high air velocity may cause thermal draught for occupants in hot
576 environments [15, 65]. In that case, a new database including a time variable should be
577 built, to retrain the current C5.0 model for long-term comfort evaluation.

578 In addition, to achieve such ‘temporal alliesthesia’ for people, the local air supply
579 system should be regulatory for occupants. According to some studies exploring the
580 personal control of localised air supply systems[23, 70], the expected air velocity
581 decreases and the acceptable temperature limits increase when providing personal
582 control to occupants. However, considering that occupants’ demands and regulations
583 on air velocity as integrated with a time factor remain incompletely understood, subjects
584 in these three series of experiments were restricted from regulating the local airflow
585 system. Therefore, some deviations may exist when the C5.0 model is applied to a
586 personally-controlled system. As the occupant behaviours play dominant roles for
587 thermal comfort and energy consumption in buildings, in-depth research should be
588 conducted for the effects of personal control on localised air supply systems and the
589 corresponding demands.

590 From a practical perspective, the challenges ahead model application would
591 depend upon some factors[71]: (1) the quality and importance of the monitored
592 parameters; (2) the availability of devices to monitor these parameters; and (3) the
593 operation and cost for long term measurements. The current study identifies 8 features
594 for C5.0 model prediction, but some individual parameters and physiological indices
595 may be difficult for data monitoring and collection in buildings. Future studies for
596 application of the localised airflow system in buildings should select more accessible
597 variables, or alternative indices, without compromising the prediction performance of
598 the C5.0 model.

599 5. Conclusions

600 This work, based on three series of experiments with localised airflow systems, i.e.
601 IASN, NIASN, and FF, identifies the appropriate machine learning model - the

602 classification tree C5.0 model, which has the highest prediction performance of 83.99%
603 with 17 original variables.

604 The sensitivity analysis quantifies the main effects of 8 major variables in a
605 localised airflow system. T is the major contributor leading to the most sensitive
606 response of TSV, followed by V and RH. The total effects increase using global
607 sensitivity analysis, indicating significant interactive effects.

608 The C5.0 model is then modified with the 8 sensitive features, and displays a better
609 prediction performance (82.3%). A tree model is obtained to demonstrate the decision
610 rules in the C5.0 model. The model employs V ($=0$ m/s, >0 m/s) as the first feature
611 variable and root node, and T (≤ 28 °C, >28 °C) as the second feature variable and leaf
612 node. This is highly interpretable, and responds to the sensitivity analysis. With the
613 lowered cost of sensors and ubiquitous wireless connectivity, it is believed that the C5.0
614 model will be further improved, thanks to its continuous learning and ability to
615 automatically train itself.

616 Acknowledgements

617 This work was supported by the National Key R&D Program of China (Grant No:
618 2016YFC0700301) supported by the Ministry of Science and Technology of China.
619 The authors would also thank for all the participants in these experiments.

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