Developing A Dynamic Thermal Sensation Model for Outdoor Spaces

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SUMMARY
In an outdoor environment, a person’s thermal comfort changes with the dynamic weather conditions. However, most of the outdoor thermal comfort models are for steady-state conditions. To develop a dynamic thermal comfort model, this study observed the responses of 26 human subjects from West Lafayette, Indiana, USA, and Tianjin, China, to a wide range of outdoor thermal environments. The study monitored the subjects’ skin temperatures, recorded their thermal sensations, and measured several outdoor environmental parameters. Analysis of the test data showed that the thermal load, the mean skin temperature, and the change rate of the mean skin temperature of the subjects tested were the most important parameters affecting their outdoor thermal comfort. These three parameters were integrated as predictor variables into a comfort model for predicting the outdoor thermal sensation. The validity of the model developed in one region was tested with the data obtained from the other region.

INTRODUCTION
The global urbanization rate is expected to reach 66.4% in 2050, according to the United Nations (2014). Outdoor spaces in cities provide the growing urban population with social, health, environmental, and economic benefits (Wooley 2003). Making outdoor spaces used by people by providing greater thermal comfort is an important goal in urban planning and design.

A thermal comfort model is a useful tool for evaluating the comfort in an outdoor space. For instance, Taleghani et al. (2015) employed the physiologically equivalent temperature (PET, Hoppe 1993) model to assess the thermal comfort in five urban settings in the Netherlands in the month of June. They found that courtyards had the most comfortable microclimate because they provided the most shade from solar radiation. However, some studies have questioned the models’ accuracy. For example, Kantor et al. (2012) found that the neutral PET in Hungary differed by as much as 9 K from that in Taiwan (Lin 2009). These discrepancies suggest the need for more accurate thermal comfort models for outdoor spaces.

The development of thermal comfort models for outdoor spaces has followed three different approaches. The first approach uses a regression method to determine outdoor thermal sensation as a function of several climatic parameters (Lai et al. 2014a). Although the approach is simple, it is not based on physical principles, and the validity of such a model is limited to the climate regions where the data was obtained (Hoppe 2002). The second approach develops thermal comfort models by correlating thermal sensation with the thermal load of the human body. However, the thermal load calculated by the model can only predict thermal comfort in a steady-state indoor environment, not a dynamic outdoor environment (Hoppe 2002; Katavoutas et al. 2015). The third approach is based on physiological responses of human subjects. This approach uses the steady state physiological responses and does not consider dynamic effect.

Since no existing outdoor thermal comfort model considered the dynamic feature of outdoor thermal environment, this study aims to develop a dynamic outdoor thermal comfort model. The present paper reports our effort in developing such model based on this approach. The paper also describes the validation of the model.

METHODS
This section describes the procedure for developing a thermal comfort model with a solid physiological and physical foundation. Development of the model required the collection of data by means of human subject tests in outdoor spaces.

Human subject tests
We performed the human subject tests in Tianjin (TJ), China, and West Lafayette (WL), Indiana, USA. The climatic conditions in the two places allowed us to collect data from a wide variety of thermal environments. In addition, we were able to use data from one region to develop the model, and data from the other region to validate the model. The test in Tianjin were conducted from May 21, 2016, to December 14, 2016, and the tests in West Lafayette from March 6, 2016, to September 25, 2016. The air temperature during the test periods ranged from 0 to 35 °C. To collect comparable amounts of experimental data at different outdoor air temperatures, we relied on weather forecasts to arrange the test dates. Our tests involved 26 subjects, satisfying the previously reported sample-size requirement of 25 (Hogg et al. 2014). Each subject participated in the tests between three and five times under different thermal environments. A total of 94 sets of data were obtained, where one set of data consisted of the measured results from one subject in a given test.

The test procedures were approved by the Purdue IRB (institutional review board) for human subject experimentation. Before the start of the tests, the subjects were informed of the research objectives and procedures. Each subject signed a consent form before participating in the tests. During the tests, the subjects remained in a neutral indoor chamber for 30 minutes to achieve a stable thermal state. They then walked to an outdoor space and stood there for 60 minutes. The air temperature and relative humidity in the indoor chamber was controlled at around 24 °C and 50%, and the air movement was kept at a minimum. As shown in Figure 1, this investigation monitored the skin temperature of the subjects, recorded their thermal sensation and clothing level, and measured several outdoor environmental parameters.
The skin temperature was measured by attaching thermocouples to the head, face, thorax, abdomen, left upper arm, left lower arm, left hand, left upper leg, left lower leg, and left foot of each subject. The thermocouples were connected to portable data loggers. With continuous measurements of skin temperature, the change rates of the skin temperature can be easily obtained. At the same time, we used a questionnaire to collect information about the subjects' clothing and thermal sensation. The clothing information was converted to clothing resistance (CR) with the use of garment insulation values from the ASHRAE Handbook (ASHRAE 2009). The subjects recorded their thermal sensation vote (TSV) according to the ASHRAE (2009) seven-point scale, where -3 = cold, -2 = cool, -1 = slightly cool, 0 = neutral, 1 = slightly warm, 2 = warm, and 3 = hot. We allowed the subjects to rate their thermal sensation continuously along this scale. During the one-hour outdoor exposure, the subjects recorded their thermal sensation every five minutes. Thus, 12 thermal sensation values were obtained for each subject during a given outdoor test. To reduce the uncertainty caused by solar radiation in the outdoor spaces, the subjects stood with their backs to the sun. The recorded outdoor thermal environmental parameters included air temperature, T_a; relative humidity, RH; global radiation, G; and wind speed, V_a. Table 1 provides information about the instruments used in the subject tests.

Table 1. Sensors used to measure thermal environmental parameters and skin temperature

<table>
<thead>
<tr>
<th>Param.</th>
<th>Sensor</th>
<th>Range</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>T_a</td>
<td>S-THB-M002</td>
<td>-40 to 75 °C</td>
<td>±0.2 K at 20°C</td>
</tr>
<tr>
<td>RH</td>
<td>S-THB-M002</td>
<td>0 to 100%</td>
<td>±3%</td>
</tr>
<tr>
<td>V_a, WL</td>
<td>WM4</td>
<td>0.35 to 40 m/s</td>
<td>±3%</td>
</tr>
<tr>
<td>G, WL</td>
<td>SPN1</td>
<td>0 to 2000 W/m²</td>
<td>±5% or ±10 W/m²</td>
</tr>
<tr>
<td>V_a, TJ</td>
<td>S-WSET-A</td>
<td>0–45 m/s</td>
<td>±1.1 m/s</td>
</tr>
<tr>
<td>G, TJ</td>
<td>S-LIB-M003</td>
<td>0–1280 W/m²</td>
<td>±10 W/m² or ±5%</td>
</tr>
<tr>
<td>T_sk</td>
<td>TT-K-30</td>
<td>0 to 350°C</td>
<td>±1.1°C or ±0.4%</td>
</tr>
</tbody>
</table>

The thermal load (TL) of the subjects were calculated by using the T_a, RH, G, V_a, CR, and metabolic heat production rate (MET). The thermal load per unit of skin area is defined as the rate of heat gain or loss by an individual when his or her skin temperature is maintained at a neutral level and sweating is kept to a minimum:

\[
TL = (M - W + R_s) - (C + R_T + E_{sk} + C_{res} + E_{res})
\]  

where M is the rate of metabolic heat production (W/m²), W the rate of mechanical work (W/m²), R_s the rate of short-wave radiative heat gain (W/m²), C the rate of convective heat loss (W/m²), R_T the rate of long-wave radiative heat loss (W/m²), E_{sk} the rate of evaporative heat loss from the skin (W/m²), and C_{res} and E_{res} the rates of convective and evaporative heat loss, respectively, from respiration (W/m²). The calculation of each term is based on the human heat transfer model developed by Lai and Chen (2016).

**General procedure for development of the model**

The data obtained from the human subject tests was used to develop the outdoor thermal sensation model. As shown in Figure 2, this investigation assumed that thermal sensation is determined by three groups of parameters: the heat transfer parameters (T_a, RH, G, V_a, CR, MET, and TL); the skin temperatures T_{sk,m} at different body segments and the mean skin temperature T_{sk,m}; and the change rates of the skin temperatures, dT_{sk,m}/dt and dT_{sk,m}/dt. We obtained the mean skin temperature T_{sk,m} by weighting the skin temperatures at different body parts. When the mean skin temperature has been determined, the change rate of mean skin temperature can be easily calculated.

**Figure 1. Parameters obtained in the human subject tests**

**Figure 2. Three groups of parameters related to thermal sensation**

The first step in development of the model was to select the most significant parameters from the three groups as the predictor variables. The model should involve the smallest number of variables that can adequately represent the influences on outdoor thermal sensation. To select the predictor variables, this investigation used the Spearman correlation coefficient (Dowdy et al. 2004), r_s, to study the correlations between the influencing parameters and thermal sensation. The coefficient is a non-parametric measure of the strength and direction of association between two variables. The value of r_s ranges between -1 and 1, and a higher absolute value indicates a stronger association. The statistical software program R (R development core team 2008) was used to determine r_s. This investigation selected the parameters with high r_s from the three groups.

After the most significant parameters had been selected, the next step was to determine the function form of the model.
According to our observation, the logistic function (Zhang et al. 2010) could represent the thermal sensation and the predictor variables. The general form of the logistic function can be written as:

\[ y = A \left(1 - \frac{2}{1 + \exp\left(\sum B_i \cdot x_i\right)}\right) \]  

(2)

where \( A \) is the limit coefficient and \( B \) is the slope coefficient. As shown in Figure 3, the relationship between \( x \) and \( y \) is linear when the value of \( x \) is small. As \( x \) increases or decreases, the value of \( y \) reaches the upper limit of \( A \) or the lower limit of -\( A \). This study selected the logistic function as a candidate because it can mimic the limits of thermal sensation. Furthermore, we can see that a function with a larger \( B \) has a greater slope. For this application, \( y \) is thermal sensation and \( A \) represents the limits of thermal sensation.

![Figure 3. Illustration of the logistic function](image)

### RESULTS

This section describes our development of the outdoor thermal sensation model and validation of the model. First, we selected the predictor variables on the basis of the correlation analysis described above. We then determined and validated the mathematical expression of the model.

#### Selection of predictor variables

Table 2 shows the values of the Spearman correlation coefficient, \( r_s \), for the correlations between the heat transfer parameters and thermal sensation. The \( r_s \) values for clothing resistance, relative humidity, and wind speed were negative, which indicates that increases in these parameters were associated with a decrease in thermal sensation. The thermal load had the highest \( r_s \) 0.85, among the heat transfer parameters. Thermal load is an artificial parameter that indicates the imbalance of heat in a human body with hypothetical neutral skin temperature and sweat secretion. If this neutral human body has a thermal load, it means that heat exchange exists between the environment and the body. As a result, the body will deviate from the neutral state. The larger the thermal load, the greater the deviation. Because of the high level of correlation between thermal load and thermal sensation, we selected TL as a predictor variable in the outdoor thermal sensation model. Although the \( r_s \) for the correlation between \( T_s \) and thermal sensation is 0.83, we did not include it in our model. This is because the \( r_s \) for the correlation between TL and \( T_s \) is as high as 0.86. The high correlation between two predictor variables can cause multicollinearity (Dowdy et al. 2004) problem, which will make the coefficient estimate unstable and difficult to interpret.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>TL</th>
<th>T_s</th>
<th>CR</th>
<th>G</th>
<th>RH</th>
<th>V_a</th>
</tr>
</thead>
<tbody>
<tr>
<td>( r_s )</td>
<td>0.85</td>
<td>0.83</td>
<td>-0.74</td>
<td>0.41</td>
<td>-0.28</td>
<td>-0.19</td>
</tr>
</tbody>
</table>

Although thermal load can indicate the general direction and magnitude of thermal sensation, it does not take into account the dynamic influence of weather conditions on the body’s thermal state. Skin temperature is a good indication of this influence because the thermoreceptors in the skin sense the skin temperature and send a signal to the brain, which interprets the signal as thermal sensation in real time (Zhang et al. 2010). Table 3 shows the values of \( r_s \) between the thermal sensation and the skin temperatures, including the mean skin temperature \( T_{sk,m} \) and the skin temperatures at different body parts. The face, head and hand, which were exposed to the outdoor environment, had higher \( r_s \) than the thorax and abdomen, which were not exposed. Because of high thermal inertia and clothing insulation, the responses of the non-exposed body parts to the dynamic outdoor thermal environment were not as fast as the responses of the exposed body parts. The mean skin temperature had the highest \( r_s \) among all the skin temperatures because it integrated the thermoreceptors’ signals from all over the body. As a result, this investigation selected \( T_{sk,m} \) as another predictor variable in the model.

<table>
<thead>
<tr>
<th>( T_{sk} )</th>
<th>Mean skin</th>
<th>Face</th>
<th>Head</th>
<th>Hand</th>
</tr>
</thead>
<tbody>
<tr>
<td>( r_s )</td>
<td>0.85</td>
<td>0.84</td>
<td>0.81</td>
<td>0.79</td>
</tr>
<tr>
<td>( T_{sk} )</td>
<td>Lower leg</td>
<td>Upper leg</td>
<td>Upper arm</td>
<td>Feet</td>
</tr>
<tr>
<td>( r_s )</td>
<td>0.78</td>
<td>0.77</td>
<td>0.68</td>
<td>0.63</td>
</tr>
<tr>
<td>( T_{sk} )</td>
<td>Lower arm</td>
<td>Thorax</td>
<td>Abdomen</td>
<td></td>
</tr>
<tr>
<td>( r_s )</td>
<td>0.50</td>
<td>0.24</td>
<td>0.14</td>
<td></td>
</tr>
</tbody>
</table>

Weather conditions also have a dynamic effect on the change rate of skin temperature. The thermoreceptors in the skin respond to changing skin temperature at a higher stimulating rate than to steady skin temperature (Hensel 1982). For example, a person feels colder when his or her skin temperature is decreasing than when the skin temperature is constant. Table 4 lists the \( r_s \) values for the correlations between the change rates of skin temperatures and the thermal sensation. Although the \( r_s \) was not as high as that for thermal load and skin temperatures, the value for the change rate of mean skin temperature show moderate correlations. Because the change rate of \( T_{sk,m} \) had the highest \( r_s \) among the values shown in the table, we selected it as the third predictor variable in the model.

<table>
<thead>
<tr>
<th>( dT_{sk}/dt )</th>
<th>Mean skin</th>
<th>Feet</th>
<th>Upper leg</th>
</tr>
</thead>
<tbody>
<tr>
<td>( r_s )</td>
<td>0.51</td>
<td>0.47</td>
<td>0.44</td>
</tr>
<tr>
<td>( dT_{sk}/dt )</td>
<td>Hand</td>
<td>Upper arm</td>
<td>Lower leg</td>
</tr>
<tr>
<td>( r_s )</td>
<td>0.43</td>
<td>0.38</td>
<td>0.36</td>
</tr>
<tr>
<td>( dT_{sk}/dt )</td>
<td>Face</td>
<td>Lower arm</td>
<td>Head</td>
</tr>
<tr>
<td>( r_s )</td>
<td>0.33</td>
<td>0.32</td>
<td>0.13</td>
</tr>
<tr>
<td>( dT_{sk}/dt )</td>
<td>Abdomen</td>
<td>Thorax</td>
<td></td>
</tr>
<tr>
<td>( r_s )</td>
<td>0.10</td>
<td>0.08</td>
<td></td>
</tr>
</tbody>
</table>
Thus, on the basis of the above correlation analysis, this study selected thermal load (TL), mean skin temperature ($T_{sk,m}$), and the change rate of mean skin temperature ($dT_{sk,m}/dt$) as the three predictor variables for determining an outdoor thermal sensation, $TS$, expressed as:

$$TS = f(TL, T_{sk,m}, \frac{dT_{sk,m}}{dt})$$

(3)

Mathematical expression of the model

To determine the mathematical expression for the outdoor thermal sensation model, we examined scatter plots of the thermal load, mean skin temperature, and change rate of mean skin temperature with respect to thermal sensation. As shown in Figures 4(a), 4(b), and 4(c).

$$3(1-2/(1+\exp(B_1 \times TL + B_2 \times \Delta T_{sk,m} + B_3 \times \frac{dT_{sk,m}}{dt}))$$

(4)

where $T_{sk,m}$ is replaced by $\Delta T_{sk,m}$, the difference between the actual and neutral $T_{sk,m}$. The neutral $T_{sk,m}$ was 32.73°C, which was obtained by averaging the $T_{sk,m}$ when the subjects voted for neutral in the outdoors. The TL, $\Delta T_{sk,m}$, and $dT_{sk,m}/dt$ act as the stimuli for outdoor thermal sensation. The TS is neutral if these stimuli are absent. When the stimuli are positive or negative, the resulting TS is on the warm or cold side. The $B_1$, $B_2$, and $B_3$ are coefficients for TL, $\Delta T_{sk,m}$, and $dT_{sk,m}/dt$, respectively. The data plotted in Figures 4(d), 4(e), and 4(f) reveals asymmetries in warm and cold sensation. For example, in Figure 4(d), the thermal sensation approaches the cold limit faster than the warm limit. Table 5 lists the coefficients that reflect the asymmetry for cold and warm sensation. The $R^2$ value of the model is 0.811, which indicates a very good fit of the model to the data.

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>$B_1$ (m²/W)</th>
<th>$B_2$ (1/K)</th>
<th>$B_3$ (min./K)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cold (TL &lt; 0)</td>
<td>0.0124</td>
<td>0.40</td>
<td>0.80</td>
</tr>
<tr>
<td>Warm (TL &gt; 0)</td>
<td>0.0102</td>
<td>0.35</td>
<td>0.35</td>
</tr>
</tbody>
</table>

Table 5. Model coefficients $B_1$, $B_2$, and $B_3$

Figure 5 is a graphical interpretation of the model. Larger stimuli result in a greater deviation from zero (neutral). If the stimuli have very large positive values, the right term in the parentheses in Eq. (4) vanishes and the TS is 3. If the stimuli have very large negative values, the exponential of the linear combination in the equation is zero and the TS is -3. As shown in Figure 5, when $T_{sk,m}$ is at its neutral level ($\Delta T_{sk,m} = 0$ K) and the mean skin temperature is stable ($dT_{sk,m}/dt = 0$ K/min.), the model is a function only of thermal load, and TS is represented by the solid line in the figure. Because of fluctuating wind speed and the broad ranges of the outdoor thermal environmental parameters, the skin temperature usually deviates from the neutral level ($\Delta T_{sk,m} \neq 0$ K) and is constantly changing ($dT_{sk,m}/dt \neq 0$ K/min.). When the $T_{sk,m}$ changes, the thermal sensation changes correspondingly. This contributes to the transient aspect of the model. Figure 5 shows that when $T_{sk,m}$ deviates from the neutral level by 3 K, TS changes by an amount ranging from 0.6 to 1.6. The figure also demonstrates that the effect of the change rate of $T_{sk,m}$ is minor. A rate of 0.2 K/minute changes the TS by an amount ranging from 0.1 to 0.2.

Figure 5. Graphical representation of the outdoor thermal sensation model

Validation of the model

Our development of the model above was based on data from Tianjin. We then used the model to predict subjects’ thermal sensations in West Lafayette and compared them with the actual data in order to validate the model. This investigation first compared the actual and predicted mean thermal sensation.
sensation. The mean thermal sensation was obtained by averaging the thermal sensation values within a certain range of TL and $T_{sk,m}$. The TL, $T_{sk,m}$, and $dT_{sk,m}/dt$ within the same interval were averaged to calculate the predicted mean thermal sensation, which was then compared with the actual mean thermal sensation. Figure 6 compares the 31 eligible cases. The error bars indicate the standard deviations of the actual thermal sensations. Although the model slightly overpredicted the mean thermal sensation, the predictions were still within the ranges of the error bars. The average difference between the actual and predicted thermal sensation was 0.40, while the standard deviation of that difference was 0.27. In light of the wide ranges and frequent fluctuations of thermal environmental parameters in outdoor spaces, the performance of the model in predicting the outdoor thermal sensation is acceptable.

\[ y = 1.2135x + 0.0429 \]
\[ R^2 = 0.9376 \]

![Figure 6. Comparison between the actual and predicted mean thermal sensation](image)

Please note that the above validation used the mean thermal sensation. It is also worthwhile to evaluate the model’s performance in predicting individual thermal sensations. Figure 7 compares the individual actual thermal sensations in West Lafayette with the predicted values.

The results show that in 79.6% of the cases, there was a difference of less than one between the predicted and measured thermal sensation. The $R^2$ between the actual and predicted values in Figure 7 was 0.766, which was only 0.045 less than the model $R^2$ of 0.811. The closeness of these $R^2$ values indicates that the Tianjin model did not lose accuracy when applied to West Lafayette. Thus, our model has been validated.

**DISCUSSION**

**Comparison with the Predicted Mean Vote (PMV) model**

The PMV model (Fanger 1970) employs thermal load to predict thermal sensation in an indoor environment. This study collected thermal load and thermal sensation data in an outdoor environment, and it was worthwhile to compare this data with the results predicted by the PMV model. Since the outdoor data was collected from human subjects who were in a standing position, we assumed a metabolic rate of 70 W/m² when calculating the PMV. It can be seen in Figure 8 that the thermal sensation predicted by the PMV model is almost two times the outdoor value. This finding is in accordance with previous results from Nikolopoulou et al. (2004), and Lai et al. (2014b). In their field studies, the PMV model over-predicted the outdoor thermal sensation considerably.

![Figure 8. Relationship between thermal load and thermal sensation in the outdoor study and as predicted by the PMV model](image)

**Limitations of this study**

Outdoor activities typically include sitting, standing, walking, and various levels of exercise, whereas our human subject tests considered only standing activities. However, this study has provided a procedure for developing an outdoor thermal sensation model. In future studies, the model can be further developed for all kinds of outdoor activities. The metabolic rate in our study for a standing person is assumed to be 70 W/m². However, the actual metabolic rate may deviate from 70 W/m². This caused uncertainty in the thermal load calculation.

The core temperature of the human body is an important physiological parameter that influences thermal comfort. However, the large inter- and intra-personal variability of the core temperature (Zhang et al. 2010) and the difficulties in measuring it in open outdoor conditions prevented us from studying its impact in this study.

Note that the weather conditions in Tianjin and West Lafayette were similar. According to the Koppen climate classification system (Kottek et al. 2006), both cities are in “hot summer continental” climates. It is necessary to validate our model for use in other climates.
CONCLUSIONS
This study developed a dynamic outdoor thermal sensation model by conducting tests on 26 human subjects in West Lafayette, Indiana, USA, and Tianjin, China. The study led to the following conclusions:

The investigation monitored the skin temperature of the subjects, recorded their thermal sensation and clothing level, and measured several outdoor environmental parameters. This study found that the thermal load, the mean skin temperature, and the change rate of the mean skin temperature were the three most important parameters influencing thermal sensation. The thermal load represents the impact of the thermal environment on the thermal sensation, while mean skin temperature and its change rate are indicators of the dynamic influences of the environment on the body’s thermal state.

By analyzing the data, this investigation found that the thermal comfort model for outdoor environments can be described by a logistic function. With the use of the thermal load, the difference between the actual and neutral skin temperature, and the change rate of the mean skin temperature, this investigation developed a thermal comfort model for predicting the outdoor thermal sensation.

This study found that the thermal comfort model developed from the test data from Tianjin can reasonably predict the thermal sensation of subjects in West Lafayette. The model was developed with the use of data from subject tests in hot summer continental climates, and its validity for other climate types needs to be verified.

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