A COMBINED ANALYTIC AND CASE-BASED APPROACH TO THERMAL COMFORT PREDICTION IN BUILDINGS

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ABSTRACT

Despite the obvious importance of thermal comfort in the design of indoor environment, it has not been effectively integrated with design decision support tools. The reasons can be attributed in part to an absence of modular and flexible software architecture that facilitates dynamic data transfer between energy performance, lighting simulation, and thermal comfort modules. Research has shown that the mathematical models of thermal comfort sometimes fail to accurately describe or predict thermal comfort in workplace settings even when the values of environmental and personal parameters are known. Thus, there is a critical need to provide a thermal comfort evaluation framework that, in addition to the algorithmic implementation of mathematical thermal comfort prediction models, would make use of the empirical knowledge base accumulated over the last 20 years from field experiments around the world.

INTRODUCTION

In spite of the widespread implications of thermal comfort on energy use and the perception of indoor environmental quality, architects and systems designer have tended to neglect the climatic, behavioral and adaptive factors affecting thermal comfort requirements at the time of designing buildings, HVAC and control systems. In the process, they miss out on a significant opportunity to save energy and reduce associated emissions and, in most design situations, fall short of providing the optimum environmental settings for thermal satisfaction. Realizing a need for design support, ASHRAE (1994) invited proposals to develop a tool that would provide feedback to designers in evaluating indoor thermal environments. The outcome was an application (Fountain and Huizenga 1996) that can calculate thermal comfort indices based on the user input of environmental and personal parameters. Although this was a good first step, it fell well short of providing an integrated framework for early design support and modification capabilities to meet the stated design objective. One had to wait for the completion of design and then use a separate energy analysis tool to generate input parameters before performing a thermal comfort evaluation. The effort was in line with many other existing building performance evaluation stand alone packages, its use being limited to experts seeking design verification or for standardizing field study calculations (de Dear and Schiller 1998).

SIMULATION ENVIRONMENT

In this paper we describe a combined analytic and case-based approach to address these problems:

1. First, we describe how the thermal comfort module in SEMPER closely collaborates with the energy performance, air flow, and HVAC simulation module to provide real-time feedback to the designer on the status of thermal environment in terms of numeric indicators.

2. Second, we describe the implementation of a knowledge-based expert system support to augment the thermal comfort simulation engine using field studies data.

SEMPER—the computational framework that enables the implementation is an active, multi-performance prototype design environment (Mahdavi 1996, Mahdavi et al. 1996). It incorporates an object-oriented, space-based shared building representation, with dynamic links to different building performance evaluation applications. It is thereby intended to provide computational support for the evaluation of buildings across multiple performance mandates concurrently, with a view toward achieving total building performance and systems integration. SEMPER's primary components are: *i)* a shared object model (SOM), which encapsulates a space-based representation of a building; *ii)* various simulation modules that implement individual domain knowledge using application specific object model representations of the building; *iii)* a database that stores shared object model of the building and facilitates the derivation of domain object models (DOM) and dynamic data transfer between them; and *iv)* a user interface for creating geometric constructs and other widgets for accepting numerical and text values.

To realize the "integration" objective, Thermal Indices for Comfort Module or TICO was designed as part of an integral thermal design environment comprising NODEM (energy simulation), BACH (air flow) and HVAC module.

- TICO implements two algorithms (based on steady-state and two-node model of human body) that are used to predict thermal comfort under a numerical framework. Our perception of thermal comfort and the subsequent evaluation and acceptance of indoor thermal environment depends on the thermal exchange between human body and the environment, and the subsequent physiological strain and perception of thermal sensation (Fanger 1970, Gagge et al. 1971).

In order to accurately predict thermal comfort using the two algorithms, one should be able to calculate the values of the environmental (air and mean radiant temperature, relative humidity, air velocity) and personal (clothing resistance and activity level) parameters. The values of all the variables except mean radiant temperature can either be specified as an input to TICO, or derived from other thermal modules of SEMPER.

THE DISCREPANCY BETWEEN PREDICTED AND OBSERVED VALUES

After completing a comprehensive review of the existing literature in the field of thermal comfort (Mahdavi and Kumar 1996), it was clear that the numerical framework for calculating thermal comfort indices needed refinement and enrichment in order to capture certain complex aspects of thermal comfort. The most serious shortcoming of these models is their problems with accurately describing or predicting thermal comfort in a variety of settings outside the climate chamber even when the values of environmental and personal parameters are known (de Dear and Auliciems 1985, Schiller et. al. 1988, Busch 1992). The challenge was to come up with a framework that is in closer agreement with the field studies conducted all over the world, but especially in the natural ventilated buildings of tropical climates where these discrepancies are most pronounced.

Many researchers have stated the need for a knowledge-based system to address the inherent deficiencies in the numerical models (Auliciems and de Dear 1978, Baker et al. 1994, Nicol et al. 1995, Mahdavi and Kumar 1996, de Dear and Schiller 1998). The development of such a framework using the results of the field studies is an effort in this direction. The knowledge-based support in TICO has been developed to complement thermal comfort indices derived from the heat balance models of human body. Taking advantage of the modular architecture of SEMPER, and the dynamic data exchange capability accorded by it between various modules (TICO, NODEM, BACH, and HVAC), an active support mechanism has been used to develop a richer set of controls with the aim of maximizing occupant satisfaction.

A FIELD STUDY BASED EVALUATIVE APPROACH

This approach fine tunes the results derived from the classical thermal comfort algorithms by working in tandem with a database of field studies made available under ASHRAE RP-884 (de Dear 1998). The strategy to find one or more suitable cases from the search domain (ASHRAE database) is outlined below. The pre-processing of the database was important to abstract the relevant information required for developing a strategy to offer an *expert advice* to the users. Furthermore, to help the users judge the quality of the recommendations, a rating criteria has been developed. The key variables involved in the analysis are:

1. **Climate/Geographical Location**: Based on the information gathered from the weather file, the design is grouped into one of the following nine climatic regions of the world. The climatic regions with examples are listed below:

- *Continental Subarctic* (Montreal, Helsinki, etc.)
- *Desert* (Las Vegas, Cairo, Karachi, etc.)
- *Humid Midlatitude* (Beijing, Moscow, etc.)
- *Humid Subtropical* (Sydney, Dhaka, etc.)
- *Mediterranean* (Athens, Rome, etc.)
- *Semi-arid Midlatitude or Semi-desert* (Peshawar)
- *Temperature Marine or West Coast Marine* (Vancouver, London, Melbourne, etc.)
- *Tropical Savanna* (Bangkok, Sao Paolo, etc.)
- *Wet Equatorial* (Jakarta, Singapore, Manila, , etc.)

2. **Environmental Control System**: There is a distinct correlation between the level of thermal comfort desired by occupants in a building and the controls system in place for regulating the environmental parameters inside a building. The three alternatives are: active controls, passive controls, and a combination of active and passive controls

3. **Season**: Hourly values of environmental parameters, together with thermal comfort indices for each zone can be further divided by season to facilitate a more detailed season-specific analysis. This option is provided because of the dependence of thermal comfort perception on the prevailing season. The three seasons used in the analysis are: Summer, Winter, and Swing (Spring, Fall)

DATA ABSTRACTION

The field studies made available under ASHRAE RP-884 store large amount of data, not all of which is directly relevant for the task at hand. After careful consideration, key parameters that affect thermal comfort and energy performance were selected from this database and are shown in *Table 1*. Three variables DIFF (ASH - PMV) - also referred to as ΔPMV, $T_{neutral}$ (Humphreys), and PMV (Humphreys) were not originally in the database and were calculated for each of the 46 field studies during pre-processing of data. The sequence of steps that was followed is:

- The six factors affecting thermal comfort, outdoor temperature, ASH or people's thermal sensation on the 7-point ASHRAE scale, PMV, DIFF (ASH - PMV) or difference between the observed value and predicted value, and PPD are selected. Critical information pertaining to the climate, ventilation and season type and the year in which the study was conducted is also selected from the list of variables for detailed reporting purposes.
- For each study, mean values of all the identified variables are calculated so that each study ends up with one set of average values (the first data row in *Table 1*). Total number of subjects and total number of data points are stored for each study (fifth row in *Table 1*) to be used for finding out the statistical significance of experiments.
- The maximum and minimum values and the standard deviation of the sample set for each of the variables affecting thermal comfort are also calculated and stored (second, third and fourth row of the *Table 1*).
- One noteworthy point about the entire analysis is the assumption of a normal distribution of thermal sensation votes (ASH), which is also the basis of the PMV-PPD model.
- A new index, DPMV (ASH - PMV) is derived. The plot in *Figure 1* shows the discrepancies between observed and predicted values. If this plot is top heavy (DPMV is positive), then it is a clear indication that majority of the population is warmer (or not as cold depending on the actual thermal sensation values) than what is currently being predicted by Fanger's PMV. By the same token, if the plot is bottom-heavy (DPMV is negative), the average thermal sensation of the population is colder (or not as warm depending on the actual thermal sensation values) in comparison to the values predicted by Fanger's model. If either of these situations is true, as happens in 39 out of 46 field studies, a clear inference can be drawn from the field studies, and a corresponding correction factor can be applied to the computed value of PMV. In the remaining 7 cases, there is no clear indication since almost half the population feels warmer and the other half feels colder than what is being predicted by the model. Instead of modifying the predicted PMV in such a case, no correction factor is applied. *Figure 2* shows the discrepancy between observed and predicted values using DPMV for benchmarking all the field studies. It also shows that the discrepancies are more pronounced in free running buildings (8% as compared to 16%) and the PMV model seem to exaggerate thermal discomfort on the warmer side.

METHODOLOGY

The methodology adopted is outlined below:

- For a specific design situation, an hourly simulation is run to calculate thermal comfort indices (PMV, SET*, TSENS, DISC). Consequently, for example, an average value of PMV together with the mean of environmental and meteorological parameters are, either inherited from NODEM and other SEMPER modules (air temperature, air velocity) or calculated

TABLE 1: Matrix following data abstraction for each field study

ASHRAE Scale (empirical)	PMV (calculated)	PMV (Humphreys)	DIFF (ASHRAE-PMV)	PPD	Air Temperature	MRT	Air Velocity	Relative Humidity	Outdoor Air Temperature	$T_{neutral}$ (Humphreys)	
0.66	1.33	0.80	-0.67	0.42	29.4	29.8	0.22	73	27.4	25.4	**Avg.**
N/A[a]	N/A	N/A	N/A	N/A	26	26.8	0.05	57.9	26.9	N/A	**Min.**
N/A	N/A	N/A	N/A	N/A	31.9	31.9	0.58	97.8	27.4	N/A	**Max.**
N/A	N/A	N/A	N/A	N/A	1.2	1.2	0.12	6.6	0.07	N/A	**Std. Dev.**

Climate	System Type	Researcher	City	Year	Season	Data pts.
Wet Equatorial	Naturally Ventilated	de Dear et al.	Singapore	1991	Summer	583

a. The min., max., and standard deviation row were used for calculating "reliability index" and hence calculated for thermal comfort variables and not for any performance indices

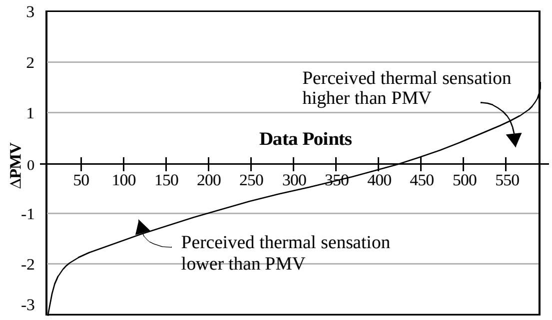
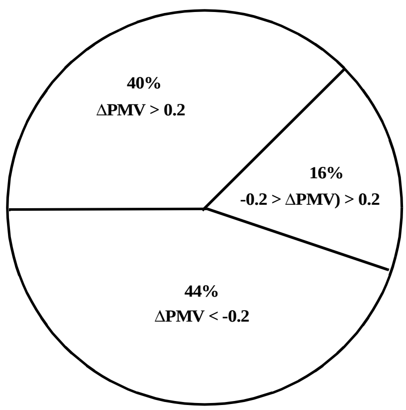
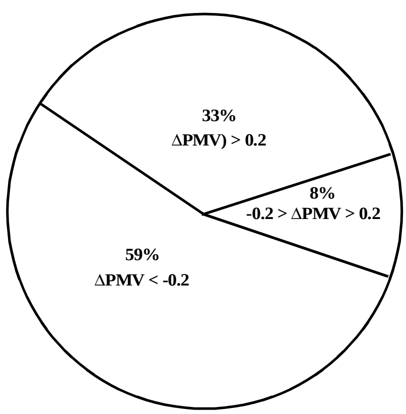


Figure 1: ΔPMV plotted for *Table 1*



For all field studies



For field studies in free running buildings

Figure 2: Range of discrepancy between predicted and observed values

inside TICO (mean radiant temperature). For analysis purposes, the mean values of the parameters are calculated based on either the number of occupancy hours or a 24 hour period.

- An initial screening is performed using climate and control types to reduce the sample size of the field studies in the database. The premise being that both thermal comfort and energy usage are closely linked to these two variables and at a minimum, a match is needed against them before conducting a more complex analysis.
- From this reduced pool of field studies, a compensation factor ΔPMV is derived based on the range specified for individual thermal comfort variables. A *reliability index* is associated with each ΔPMV term by following the matrix shown in *Table 2*. The analysis behind the evolution of this rating is described below.

Table 2 lays out the criteria for deriving the *reliability index* of expert advice. After a match has been found based on control type and the climate in which the simulated building is located, the four environmental variables under current design conditions are compared against the corresponding value of the variable for the field study, and points are allocated that can range (in case of air temperature) from a maximum of 35 to a minimum of 3. This schema is based on the multiple parametric runs of Fanger's comfort equation to evaluate the influence of the four environmental variables on the PMV. The points reflect the relative importance of the variables in the determination of thermal comfort. The range of rating for any advice can vary from a maximum of 100 (best) to a minimum of 15 (worst).

TABLE 2: Reliability Index for the "expert" advice derived from field study data

	Within ±1 Std. Dev.	Within Min/ Max value	Outside Min/ Max range
Air Temp.	35	15	3
MRT	25	10	3
Air Velocity	25	12	4
Rel. Humidity	15	8	5
Total	100	45	15

This reliability index provides a quantitative framework to adjust the value of thermal comfort indices (PMV, in this case). In *Equation 1*, ΔPMV is the adjustment resulting from the analysis, which should be made to the value of PMV calculated in TICO. W_1, W_2, etc. are the *reliability indices* and ΔPMV_1 and ΔPMV_2 are the compensation factors associated with matching field studies. $PMV_{modified}$ can be interpreted as a term that has accounted for the discrepancy found in observed and predicted values.

$$\Delta PMV = \frac{W_1 \times \Delta PMV_1 + \ldots + W_n \times \Delta PMV_n}{\sum W} \quad (1)$$

$$PMV_{modified} = PMV_{simulated} + \Delta PMV \quad (2)$$

This adjusted value ($PMV_{modified}$) is used as the starting point for providing feedback to NODEM so that changes at the system level (in conjunction with BACH and HVAC module) or design level (SEMPER) can be made.

BI-DIRECTIONAL FUNCTIONALITY

The results of this analysis to modify PMV can now be used to:

1. design an indoor thermal environment that satisfies more people and is energy-efficient as well;

2. provide better and optimized controls for the indoor thermal environment that will result in a still higher satisfaction level for the occupants.

Past research has established the concept of a bi-directional simulation environment to facilitate the interactive and simultaneous modification of properties and the observation of changes in various building design and performance variables (Mahdavi 1993, Mahdavi and Berberidou-Kallivoka 1993). In a bi-directional simulation environment, designers modify and observe both *design and performance* variables at different levels of abstraction. The bi-directional approach can increase the effectiveness of computational design support environments in at least two ways: 1) by reducing the number of parametric variations of design variables a designer may need to explore as the performance goal is defined at the outset, and 2) by enhancing the designer's understanding of the complex and dynamic interactions between various design and performance variables.

In most design problems, however, the design variables are constrained by building codes, contextual parameters, technological limitations, and designers' preferences. A bi-directional analysis tool incorporating such constraints can support performance responsive design generation and modification. In the current situation, it entails recognizing performance (PMV or PPD) and design variables (air temperature, air velocity etc.) and evolving a quantitative framework to implement the active support algorithm.

As noted earlier, since the performance-to-design mapping process is an ambiguous one, the same performance (e.g. optimizing PMV or minimizing PPD) can be achieved by passive design configurations (window dimensions/properties, ventilation or shading characteristics of design, varying thermal mass and insulation, etc.) or evolving a control strategy for HVAC systems (controlling the supply air temperature or regulating the temperature of radiant panels, incorporating enthalpy controls, etc.). As a result, the actual implementation of a bi-directional inference tool requires a clear decision-making process that can be applied unambiguously at any stage of design. Instead of relying completely on a preference mechanism, a hybrid approach (both preference and heuristic based) that involves the formalization of various external or internal constraints and preferences (such as code and standard requirements or results of field studies) is implemented here to achieve the desired performance.

Two modes of bi-directional support have been implemented. In the first case, the user can specify her performance requirements by requesting SEMPER to *a)* maximize thermal satisfaction and/or *b)* minimize energy use or minimize total energy cost in the current design. In such a situation, the thermal suite of applications in SEMPER takes necessary actions and suggests design changes to the user, which would help in achieving the performance requirements of the design. An example that shows how NODEM, BACH and TICO work together to maximize thermal satisfaction is shown later.

In the second case, the inherent intelligence embedded in TICO is used to guide the HVAC module to achieve the environmental conditions that would satisfy the performance objectives of the design. The bi-directional process, in this case, can be viewed as a two-step process. In the first step, a target value of PMV, let us call it the first-order performance variable, is either specified by the designer or suggested by TICO after analyzing field study data. The environmental parameters such as, air temperature, mean radiant temperature, relative humidity and air velocity, which can all be theoretically controlled by HVAC systems are the design variables that can be modified to bring about the desired changes in the performance variable. A methodology outlined below, which relies on the knowledge ingrained in TICO is used to suggest changes in the design variables that will bring the performance variable closer to its final value. In the second step, the design variable, say air temperature, becomes the performance variable that can be modified by the HVAC module. The HVAC module can bring about this change by taking appropriate controls actions such as, changing the chilled water temperature, modifying the economizer settings or changing the speed and volume of supply air in the distribution system. The first stage of this bi-directional strategy has been implemented in TICO and the second step will become functional once the HVAC module is integrated with the SEMPER framework.

The first stage of the bi-directional thermal comfort inference mechanism entails:

1. Identifying *performance variables* such as *PMV* and *PPD*, and define the objective function such as *Min* (PMV) at TICO level that would drive the optimization process.

   Predicted Mean Vote (PMV): Hourly values of PMV calculated in TICO is used to arrive at the initial value of PMV. Subsequently, PMV in a space is assessed by taking a mean value of the hourly values over an entire season or year. Optimizing PMV is the major goal of the bi-directional analysis. A user can specify an acceptable range for PMV in which case the bi-directional inference mechanism makes sure that the value of PMV remains in the specified range by constraining the values of the design variables.

2. Identifying relevant *design variables*, such as air temperature, mean radiant temperature, and air velocity etc. and then assigning boundary conditions and default values to them.

   For each of the design variables, an allowable range is set by defining the minimum and maximum values, and an ordered set of discrete values within the allowable range is determined using a fixed increment value. In the current implementation, four design variables have been defined. *Table 3* identifies the design variables along with their boundary conditions and default values in deriving the preference attributes for them. In the case of air temperature, the minimum, maximum and default values are 18°C, 30°C and 24°C respectively as shown in *Table 3*. However, the user has the flexibility of setting one or all three values for all the design variables.

TABLE 3: Design variables with their min, max and default values

Design Variables	Min.	Max.	Default	Increment
Air Temp.	18°C	30°C	24°C	0.6°C
MRT	18°C	30°C	24°C	0.6°C
Air Vel.	0	$0.5\ m \cdot s^{-1}$	$0.15\ m \cdot s^{-1}$	$0.02\ m \cdot s^{-1}$
Rel. Hum.	30%	70%	50%	2%
Activity	N/A	N/A	$60\ W \cdot m^{-2}$	N/A
Clothing	N/A	N/A	$0.155\ m^2 \cdot K \cdot W^{-1}$	N/A

3. Deriving the *normalized distance (D)* attribute for each of the variables identified above. The normalized distance attribute of the design variables is proportional to the difference between the current and default value. As shown in *Figure 3*, the normalized distance for an air temperature of 19.5°C is 0.6. This means that the air temperature will be incremented by this value at the end of the current iteration. In other words, the normalized distance is a dummy attribute for calculating the increment or decrement term for various variables. Call it I.

4. Deriving the *effectiveness (E)* attribute for each design variable. Under the *bi-directional* approach, the ability to bring about a change in PMV is termed as the *effectiveness* of a design variable. To derive *E*, an incremental change is made in the variable and the change in the value of the performance variable is recorded. The increment for each design variable was shown in *Table 3*. For example, *E* for air temperature is given by:

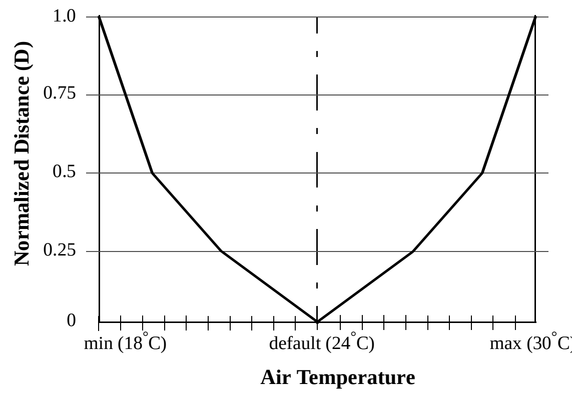


Figure 3: Illustration showing the derivation of normalized distance attribute

$$E_t = \frac{PMV_{t_i} - PMV_{t_{(i+1)}}}{\Delta t} \quad (3)$$

5. Deriving a *relative normalized distance* (D_{rel}) attribute for each of the four design variables. To calculate $D_{rel, i}$, the *normalized distance* attribute for each variable $D_1 \ldots D_n$ (calculated using the stepped curve function derived earlier) will be used. The $D_{rel, i}$ for any variable is then given by:

$$D_{rel, i} = \frac{D_i}{Max(D_1 \ldots D_n)} \quad (4)$$

6. Deriving a *relative effectiveness* (E_{rel}) attribute for each of the four design variables. $E_{rel, i}$ (relative effectiveness of nth design variable), is derived using the individual effectiveness (E) of design variables calculated in step 4. For any design variable, it can now be calculated using *Equation 5*.

$$E_{rel, i} = \frac{E_i}{Max(E_1 \ldots E_n)} \quad (5)$$

7. Calculating the *preference* (P) index for each of the variables at each design stage as shown in *Equation 6*.

$$P = w_E \times E_{rel} + w_D \times D_{rel} \quad (6)$$

   E_{rel} and D_{rel} for each of the design variables have been defined in step 5 and 6 respectively. w_E and w_D are the corresponding weighting factors for these two attributes. For the purpose of the current implementation, a value of $w_E = w_D = 0.5$ has been used, which means that P must lie between 0 and 1.

8. In the case of an active design, the design variable with the highest preference index is passed to the

HVAC module. In a passive design situation, the ordered list of design variables is passed to NODEM. The design variable with the highest preference index will be modified by adding or subtracting I, calculated in step 3. If design limitation does not allow NODEM to bring about the change using the design variable with the highest preference index then the next design variable in the sorted list will be selected. This process will go on till NODEM modifies one of the design variables or a better performance cannot be achieved under the current set of design conditions.

9. Repeating steps 3-8 till the objective function is satisfied or a better performance cannot be achieved.

AN ILLUSTRATIVE EXAMPLE

The sequence of steps for modifying PMV based on matching field studies is shown below:

- *Figure 4* shows the schematic design of a building along with the space and grid information. NODEM interacts with TICO by passing the geometric attributes of spaces with thermal parameters as arguments. As NODEM iterates through the spaces, it calls TICO and the resulting grid of mean radiant temperature and PMV is shown in *Figure 4*. This capability to simulate mean radiant temperature and thermal comfort values for each cell in a building can help in devising a better control strategy, which is one of the goals of the current exercise.

Based on the methodology evolved earlier, NODEM communicates the climatic region and the environmental control system type for the current design to TICO. In this case, they are—*Climatic region*: Singapore (Wet Equatorial) and *Environmental Control System*: Natural Ventilation (passive).

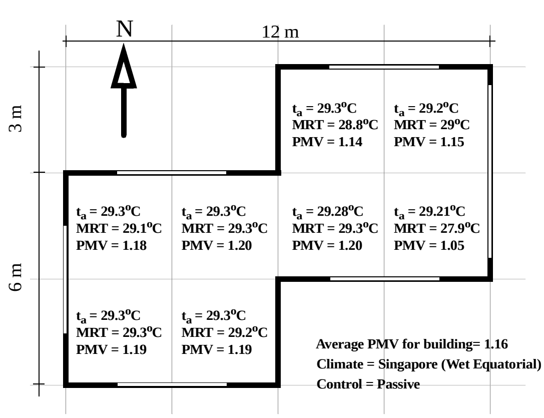


Figure 4: Results of running TICO on a building in Singapore in tandem with NODEM

The two parameters identified above are passed on as arguments to the TICO module for field study evaluation. It performs a search on the database and selects the studies that satisfy the search criteria. In this case, two matching field studies are found and their summary information is displayed below in *Table 5*.

TABLE 4: Adjustment factor for PMV and the associated reliability indices

Comparison	Averages	Variance (Min, Max, SD)
Design values (Base Case)	t_a = 29.3°C, RH = 81%, PMV = 1.16	Not Required
Field Study 1 (RI = 90)	t_a = 30.3°C RH = 72%	t_a = 28°C, 32°C, 1.0°C, RH = 69%, 79%, 3.15%, ΔPMV = **-0.52**
Field Study 2 (RI = 80)	t_a = 29.4°C RH = 74%	t_a = 26°C, 31.9°C, 1.2°C , RH = 58%, 98%, 6.65% ΔPMV = **-0.67**

Once the relevant field studies have been identified, the discrepancy between Fanger's predicted PMV and thermal sensation (ΔPMV) experienced by people is recorded. *Table 4* shows the environmental parameters recorded in field studies and compares it with the values in the current design situation. The reliability index developed in *Table 2* for applying a ΔPMV term to Fanger's PMV, is shown in the 3rd column of *Table 4* for the two field studies. If all the short-listed field studies show the same ΔPMV sign, as is the case above (both point to a negative adjustment to the simulated PMV), an adjustment is made based on *Equation 2 on page 4*.

TABLE 5: Field studies matching the climate and controls specified in the current design

City	Climate	Control	Researcher
Jakarta	Wet Equatorial	Passive	Karyono
Singapore	Wet Equatorial	Passive	de Dear

This results in a final value of -0.60 for ΔPMV. The simulated PMV value (1.16) must be adjusted by this factor to take into account the results from the two field studies as shown in *Figure 5*. With the derivation of the weighted ΔPMV term, the field study based analysis and subsequent modification of PMV is complete.

CONCLUSIONS

It has been demonstrated that thermal comfort calculations can be integrated in a computer-aided architectural design environment just like any other performance simulation and can play a major role in optimizing energy use and enhancing thermal comfort in a building. This has been done by exploiting the inherent structural homologies between space-based design representation and node-based "thermal zone" representation. The technical contribution in terms of implementation of TICO are:

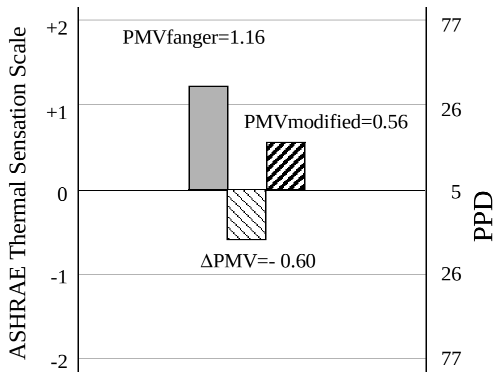


Figure 5: Modifying Fanger's PMV with field studies findings to maximize satisfaction

1. *Simultaneous evaluation of thermal and energy performance with thermal comfort.*
   Using Predicted Mean Vote (PMV) to propose a richer set of environmental control strategies that go well beyond the conventional, mono-dimensional (thermostat based) control options currently available.

2. *Field study based analytical support to fine tune thermal environment during early design stage.*
   The knowledge based analytical capability of TICO was developed using the most comprehensive database of empirical experiments conducted to evaluate indoor thermal environments. The coupling of inferences from the field studies to comfort evaluation using classical thermal comfort algorithms helped formulate a flexible framework that can be used to perform a contextual thermal comfort analysis in a variety of settings.

3. *Enhanced preference-based performance-to-design mapping in the domain of thermal performance.*
   A set of heuristics that looks at the complex relationship between environmental parameters and their influence on integrated thermal comfort index was used to refine the design. This was done by using the knowledge ingrained in TICO to recommend changes in the environmental parameters to improve indoor thermal environment.

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