

Indoor thermal comfort controls optimized by deducing rules

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Abstract— A novel approach based on an optimization method is developed to deduce the rules of learning human thermal comfort states. In order to achieve a desired thermal comfort level and energy savings, the study constructs a mechanism with varied control strategies by using the deduced rule set. The proposed method is superior to other indoor thermal comfort based controls in that it produces interpretable rules and generates appropriate set-points for control systems. Analytical results of this study demonstrate that the proposed thermal comfort control mechanism can also be implemented with wireless sensor network (WSN) to achieve thermal comfort and energy savings with limited computational resources. In other words, the solution enables the ubiquitous control of indoor thermal comfort.

Keywords—Classification; Predicted mean vote (PMV); Thermal comfort; Rule-based system; Energy saving.

I. INTRODUCTION

A large number of thermal comfort models have been developed to analyze room climates and the control design of HVAC systems [1-10]. Fanger (1973) developed a thermal comfort equation, in which comfort is determined by the response of a large group of individuals, based on air temperature, mean radiant temperature, relative humidity, air velocity, activity level of occupants, and clothing insulation parameters; in addition, the main indices are predicted mean vote (PMV) [3]. Meanwhile, some advanced control models have been developed to enhance the performance of indoor thermal comfort [4,11-14]. However, only a few of these models have been used to evaluate the efficiency of an indoor climate to produce adequate thermal conditions for occupants. Above models are subject to specific processes and complex calculations. For example, a unipolar sigma function is adopted for the neural network as the activation function; a multiple regression equation is relevant to the multiple variables [5]; and a membership function is adopted for the fuzzy algorithm [1,4,12,13,14].

The weaknesses of the conventional thermal comfort control mechanism are described as follows: (i) The Fanger's PMV model involves relatively complex heat transfer processes, in which the mathematical expression is non-linear and necessitates iterative solutions. Owing to the inherent complexity of these processes and unavailability of certain variables, the above models are incompatible with making the designs of thermal comfort control intuitively. (ii) Many

simplified PMV models have been developed to avoid the iterative process in practical applications by using tables and diagrams [6,7,10]. These tables and diagrams can neither determine the relationships among the six parameters nor identify the controlling set-points that are suitable for HVAC systems. (iii) Some modifications of Fanger's PMV equation are made under some assumptions and simplifications, making them applicable only in appropriate conditions. The PMV calculation is inadequate for feedback controls of embedded systems, real-time systems and related applications [4,6].

To overcome these limitations, the present study proposes a method for deducing classification rules for thermal comfort controls to assist users in deploying their HVAC control strategies. The proposed HVAC control mechanism can be implemented with wireless sensor network to achieve the ubiquitous controls of indoor thermal comfort.

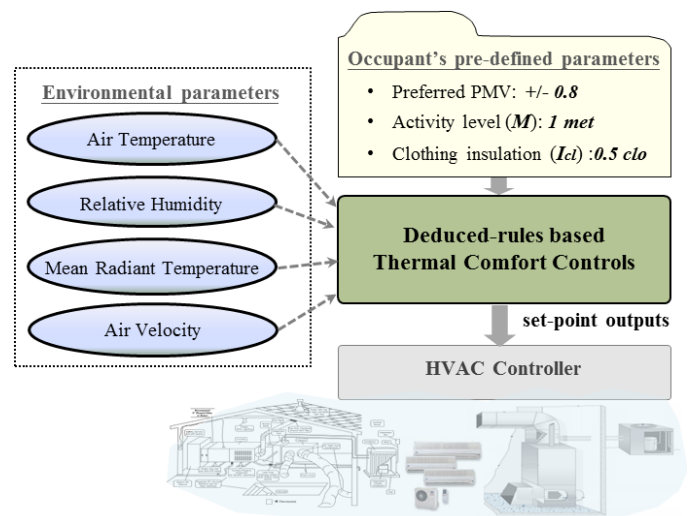


Figure 1. Deduced-rule based control architecture for thermal comfort

II. METHOD

Basic concepts of the rule deducing model are described using supervised learning and classification methods [17]. According to Figure 1, the HVAC systems receive control signals (i.e., set-point outputs) from an inferencing mechanism based on thermal comfort deduced-rules. The rule deducing model induces all rules for classifying target data in a dataset. By using mixed-integer methods, the model identifies separated cubes (i.e., rule set) of various classes, which is an

optimization process to achieve an optimal solution. This model produces a set of rules to induce rules that maximize the support rate [18] subject to the constraint that the accuracy rate must exceed a threshold value. This method also builds an iterative algorithm to identify the classification rules where the rate of compact is as high as possible [16]. The terms $S_{k,l}$, $P_{k,l}$ and $r_{k,l}$ denote the cube, centroid, and radius of the l -th cube for class k , respectively. The radius of a cube refers to the distance between its centroid point and one of its corner points. The proposed model of classification is formulated below [17]:

$$\text{Maximize } \sum_{l=1}^{q_k} \sum_{i=1}^{n(k)} u_{k,l,i} \quad (1)$$

For a cube (i.e., rule) $S_{k,l}$, the following constraints must be satisfied:

$$\sum_{j=1}^m |a_{i,j} - b_{k,l,j}| \leq r_{k,l} + M(1 - u_{k,l,i}) \quad (2)$$

, $\forall x_i$, where $c_i = k$,

$$\sum_{j=1}^m |a_{i',j} - b_{k,l,j}| > r_{k,l} - Mv_{k,l,i'} \quad (3)$$

, $\forall x_{i'}$, where $c_{i'} \neq k$,

$$AR(R_k) = \frac{\|R_k\| - \sum_{i'=1}^{num(k)} \sum_{l=1}^{q_k} v_{k,l,i'}}{\|R_k\|} \geq \text{Threshold}, \quad (4)$$

where $M =$

$\max\{a_{i,j} \mid \forall i = 1, \dots, n \text{ and } j = 1, \dots, m\}; b_{k,l,j} \geq 0, r_{k,l} \geq 0, u_{k,l,i}, v_{k,l,i'} \in \{0,1\}; a_{i,j} \text{ and } a_{i',j} \text{ are constants.}$

The objective function Eq. (1) is to maximize the support rate [17]. Constraint Eq. (2) describes that an object $x_i = (a_{i,1}, \dots, a_{i,m}; c_i)$ is covered by a cube $S_{k,l} = (b_{k,l,1}, \dots, b_{k,l,m}; r_{k,l})$, implies that if a cube $S_{k,l}$ covers an object x_i of the same class, then $u_{k,l,i} = 1$, and $u_{k,l,i} = 0$ otherwise. Constraint Eq. (3) describes that an object $x_{i'}$ is not covered by a cube $S_{k,l}$, implies that if a cube $S_{k,l}$ does not cover an object $x_{i'}$ of another class, then $v_{k,l,i'} = 0$, and $v_{k,l,i'} = 1$ otherwise. Constraint Eq. (4) ensures that the accuracy rate [18] should exceed a threshold value.

The rule deducing model attempts to use the minimal number of cubes to classify these objects, subjected to the constraints that a cube must cover as many objects of a target class as possible. Next, consider a data set T which has 300 objects $(x_1, \dots, x_{300})$, four attributes (a_1, a_2, a_3, a_4) , and an index of classes c . Each object (i.e., indoor climate condition) described by four attributes (a_1 : air temperature; a_2 : mean radiant temperature; a_3 : air velocity; a_4 : relative humidity) and classified by two classes (1: target; 2: non-target). The data set T is expressed as $T = \{x_i(a_{i,1}, a_{i,2}; a_{i,3}, a_{i,4}; c_i) \mid i = 1, \dots, 300\}$. The domain values of c are $\{1, 2\}$. The attribute values of $P_{k,l}$ are denoted as $(b_{k,l,1}, b_{k,l,2}, b_{k,l,3}, b_{k,l,4})$. A circumstance in which an object $x_i(a_{i,1}, a_{i,2}; a_{i,3}, a_{i,4}; c_i)$ is covered by a cube $S_{k,l}$ is expressed as follows:

$$|a_{i,1} - b_{k,l,1}| + |a_{i,2} - b_{k,l,2}| + |a_{i,3} - b_{k,l,3}| + |a_{i,4} - b_{k,l,4}| \leq r_{k,l}, \quad \forall i = 1, 2, \dots, 300 \quad (5)$$

The boundary conditions of training data for reducing indoor thermal comfort rules are listed in Table 1. By using

the proposed method, Table 2 shows the deduced classification cubes, centroid points, radius, PMV and PPD. Fanger also provided an index of discomfort levels, in which a given predicted percentage of dissatisfied (PPD) maximum value is constructed and the corresponding PMV range of acceptability is established [3]. Table 2 contains a rule set. The rule set (i.e., R_1) is the union of 14 rule-cubes (i.e., $S_{1,1} \cup S_{1,2} \cup S_{1,3} \cup \dots \cup S_{1,14}$). This can be expressed as “if an object x_i is covered by cube $S_{1,1}, S_{1,2}, S_{1,3}, \dots$, or $S_{1,14}$ then x_i belongs to class 1”. The circumstance in which the thermal comfort classification (i.e., class 1, $-0.8 \leq \text{PMV} \leq +0.8$) is implied as follows:

if {
|air temperature – 25.60| + |mean radiant temperature – 28.90| + |air velocity – 0.27| + |relative humidity – 48| ≤ 4.95
or
...
or
|air temperature – 30.10| + |mean radiant temperature – 26.79| + |air velocity – 0.33| + |relative humidity – 48| ≤ 4.24}
then
{The thermal environment is comfortable (target).}
else
{The thermal environment is uncomfortable (non-target).}

Evaluation results of the rule-based classification model are also compared with Fanger’s PMV equation. In this work, the accuracy rate of a rule indicates that the rule fitting a class should not cover the objects of other classes. The support rate of a rule indicates that the rule fitting a class should be supported by a large number of objects in the same class [18]. Owing to the proposed method, the rule set of R_1 performs excellently in terms of accuracy rate (0.98) and support rate (0.98). Analytical results indicate that the proposed approach performs high quality in classification accuracy when learning with a larger training data set to classify specific PMV levels.

TABLE 1. BOUNDARY CONDITIONS OF COLLECTING DATA FOR RESIDENCES AND OFFICE BUILDINGS

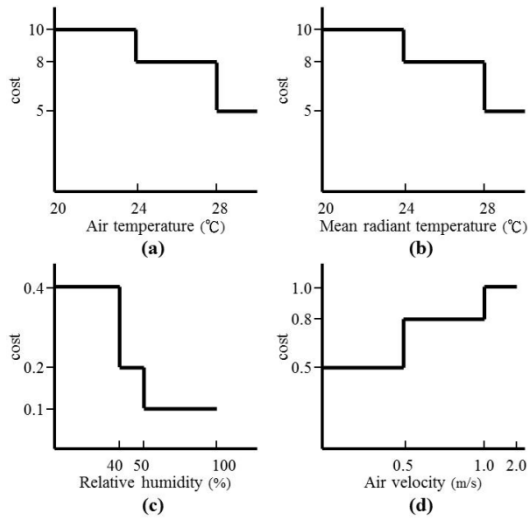
Parameter	Symbol	Range	Unit
Activity level	M	1.0	met
Clothing insulation	I_{cl}	0.5	clo
Air temperature	t_a	24 ~ 34	°C
Mean radiant temperature	tr	24 ~ 34	°C
Air velocity	v_a	0 ~ 0.8	m/s
Air humidity	RH	30 ~ 70	%

TABLE 2. CENTROID POINTS OF DEDUCED CLASSIFICATION CUBES

Cubes #	Air temperature	Mean radiant temperature	Air velocity	Relative humidity	Radius	PMV	PPD
$S_{k,l}$	$b_{k,l,1}$	$b_{k,l,2}$	$b_{k,l,3}$	$b_{k,l,4}$	$r_{k,l}$		
$S_{1,1}$	25.60	28.90	0.27	48	4.95	-0.11	5.3%
$S_{1,2}$	29.20	27.02	0.16	36	5.69	0.53	11.1%
$S_{1,3}$	25.00	29.05	0.28	63	4.67	-0.15	5.5%
$S_{1,4}$	26.35	24.10	0.08	50	6.09	-0.23	6.1%
$S_{1,5}$	26.50	32.34	0.36	34	6.00	0.43	9.0%
$S_{1,6}$	26.19	24.10	0.12	69	6.54	-0.22	6.0%
$S_{1,7}$	28.14	26.65	0.32	59	5.03	0.31	7.0%
$S_{1,8}$	28.30	28.00	0.37	44	4.94	0.35	7.5%
$S_{1,9}$	24.12	31.30	0.48	54	4.59	-0.53	10.8%
$S_{1,10}$	26.19	32.80	0.48	66	5.12	0.48	9.8%
$S_{1,11}$	26.49	25.00	0.03	36	5.73	-0.17	5.6%
$S_{1,12}$	29.50	31.89	0.50	33	6.72	1.00	28.0%
$S_{1,13}$	24.40	31.47	0.26	50	5.04	0.03	5.0%
$S_{1,14}$	30.10	26.79	0.33	48	4.24	0.78	17.8%

III. THERMAL COMFORT CONTROL MECHANISM

Suppose the experimental values of the pre-defined parameters (i.e., 0.5 clo, 1.0 met, and preferred PMV +/- 0.8) and the environmental parameters detected by sensors are inserted into the deduced-rule based control mechanism for thermal comfort controls (Fig. 1). Several environmental parameters (i.e., indoor climate conditions) are obtained from air temperature (t_a), mean radiant temperature (t_r), air velocity (v_a) and relative humidity (RH) sensors within residence and office buildings. Each set of the control results gives a unit cost based on Fig. 2.

**Figure 2.** Unit costs of system controls

During the thermal comfort controls, the varied energy costs among each evaluation cases are calculated. The distance between the observed indoor climate condition ($y_{k,i,m}$) and the cube centroid ($b_{k,l,m}$) in 4-dimensional space is the sum of the distances in each dimension (Eq. (6)). Next, consider R_1 with l^{th} rule cube. Each rule cube has m attributes and belongs to a class k ($k=1$: $-0.8 \leq \text{PMV} \leq +0.8$; $k=2$: $\text{PMV} < -0.8$, or $\text{PMV} > +0.8$). There are i observed indoor climate conditions

(i.e., indoor environments). Additionally, the attribute values of centroid of l^{th} cube are denoted as ($b_{1,1,1}$, $b_{1,1,2}$, ..., $b_{k,l,m}$), where $k \in \{1, 2\}$, $l \in \{1, \dots, 14\}$, and $m \in \{1, \dots, 4\}$. Notably, the centroid of cube $S_{1,12}$ is not covered by the occupant's pre-defined PMV, the centroid of cube $S_{1,12}$ is subsequently ignored by the thermal comfort control rules. Based on Fig. 2, the given unit cost associated with each attribute is denoted as w_m .

$$\text{Dist} = \sum_{m=1}^4 |y_{k,i,m} - b_{k,l,m}| \quad (6)$$

$$\text{Cost} = \sum_{m=1}^4 w_m \times (y_{k,i,m} - b_{k,l,m}) \quad (7)$$

The key principle of Eq. (6) used for thermal comfort control is the efficient to achieve the set-points by using the minimal distance (i.e., L2 distance). Eq. (7) is considered to achieve both effective thermal comfort control and higher energy efficiency (i.e., minimalized cost). Suppose a value of 33.1°C is detected for t_a , a value of 33°C is detected for t_r , a value of 0.5 m/s is used for v_a , and a value of 48% is detected for RH . Notably, this observed indoor climate condition $y_{1,1}$ is not covered by any cube of the deduced PMV rule-cubes listed in Table. 2, and is regarded as an indoor climate condition out of the occupant's pre-defined PMV levels. The general formula for calculating the L2 distance between $y_{k,i,m}$ (i.e., indoor climate condition) and centroid $b_{k,l,m}$ of $S_{k,l}$ is shown as Eq. (6). Therefore, if $y_{1,1} = (33.1, 33, 0.5, 48)$ and $b_{1,10} = (26.19, 32.8, 0.48, 66)$, the L2 distance between $y_{1,1}$ and $b_{1,10}$ is $|33.1-26.19| + |33-32.8| + |0.5-0.48| + |48-66| = 25.13$. The equation for evaluating the energy cost between indoor climate condition $y_{1,1}$ and centroid $b_{1,10}$ of $S_{1,10}$ is as Eq. (7), is described as $5 \times (33.1-28) + 8 \times (28-26.19) + 5 \times (33-32.8) + 0.5 \times (0.5-0.48) + 0.1 \times (50-66) + 0.2 \times (48-50) = 38.99$. When minimal cost (MC) control strategy is used, the thermal comfort control mechanism should select the cube centroid $b_{1,10}$ of $S_{1,10}$ due to the energy cost is the lowest among rule cubes. The superiority for decision alternatives is $S_{1,10} > S_{1,5} > \dots > S_{1,4}$, where $S_{1,10} > S_{1,5}$ implies that $S_{1,10}$ dominates $S_{1,5}$. Then, the suggested set-points for HVAC are $t_{a_sp}=26.19^\circ\text{C}$, $t_{r_sp}=32.8^\circ\text{C}$, $v_{a_sp}=0.48$ m/s, and $RH_{sp}=66\%$. Similarly, when minimal distance (MD) control strategy is used, the superiority for decision alternatives is $S_{1,14} > S_{1,1} > \dots > S_{1,6}$, the control mechanism should select the cube centroid $b_{1,14}$ of $S_{1,14}$ due to the control path is the shortest among other rule cubes. The suggested set-points for HVAC are $t_{a_sp}=30.1^\circ\text{C}$, $t_{r_sp}=26.79^\circ\text{C}$, $v_{a_sp}=0.33$ m/s, and $RH_{sp}=48\%$. Table 3 summarizes the evaluated results for selecting the optimal control rule.

TABLE 3. EVALUATION RESULTS OF MC AND MD CONTROL STRATEGIES

Control Strategy	MC	MD
Cube Order	$S_{1,10} > S_{1,5} > \dots > S_{1,4}$	$S_{1,14} > S_{1,1} > \dots > S_{1,6}$
Suggested Set-Point	$t_{a_sp} = 26.19^\circ\text{C}$ $t_{r_sp} = 32.8^\circ\text{C}$ $v_{a_sp} = 0.48 \text{ m/s}$ $RH_{sp} = 66\%$	$t_{a_sp} = 30.1^\circ\text{C}$ $t_{r_sp} = 26.79^\circ\text{C}$ $v_{a_sp} = 0.33 \text{ m/s}$ $RH_{sp} = 48\%$

IV. EXPERIMENT AND RESULTS

Having developed the thermal comfort control mechanism, we present one of the applications, using the deduced rules to regulate the trade-off between human thermal comfort and energy cost. Assume that a user, wants to set up a controllable indoor thermal comfort system; he/she is first required to enter the preferred PMV condition (e.g., PMV between -0.8 and +0.8 was used in this study). The system subsequently detects the air temperature, mean radiant temperature, relative humidity, and air velocity among the indoor environment. Fig. 3 summarizes the experimental results obtained using each proposed control strategy. This comparison is based on three factors: (i) Unit cost hypothesis (i.e., Fig. 2) is in determining varied energy costs. (ii) The predicted percentage of dissatisfied thermal comfort (i.e., PDD) is determined below 18.5%. (iii) The PMV control strategies (i.e., PMV_{MC} , and PMV_{MD}) are considered here by using proposed “minimal cost (MC)”, and “minimal distance (MD)” control mechanisms.

Fig. 3(a) depicts the states of the original PMV (i.e., non-controlled indoor climate conditions), PMV_{MC} (i.e., based on minimal cost controls), and PMV_{MD} (i.e., based on minimal distance controls). For instance, the indoor climate condition is detected at time #40, the non-controlled PMV level is around 2.6, and the indoor environment is too hot for occupants. In the meantime, by using MC control strategy, while the set-point outputs are defined as the centroid of $S_{1,10}$ (see Fig. 3(c)) the PMV level is improved to +0.5 (i.e., PMV_{MC}). Thus, the optimal set-points $t_{a_sp} = 26.19^\circ\text{C}$, $t_{r_sp} = 32.8^\circ\text{C}$, $v_{a_sp} = 0.48 \text{ m/s}$, and $RH_{sp} = 66\%$ are suitable to HVAC controller at time #40. The cost is around 39.1 units (see Fig. 3(b)). Similarly, by using MD control strategy, the PMV level is improved to +0.8 (i.e., PMV_{MD}) while the set-point outputs are configured as the centroid of $S_{1,14}$. Thus, the optimal set-points of PMV_{MD} are $t_{a_sp} = 30.1^\circ\text{C}$, $t_{r_sp} = 26.79^\circ\text{C}$, $v_{a_sp} = 0.33 \text{ m/s}$, and $RH_{sp} = 48\%$, and the cost of MD control strategy is around 49.7 units at time #40. Fig. 3(a) depicts that the overall non-controlled PMV is ranged between -1.6 and 2.6. While enabling the proposed thermal comfort controls, the overall PMV_{MC} and PMV_{MD} are adapted between -0.8 and +0.8. More specifically, the PMV_{MC} is kept around 0.5, the PMV_{MD} is ranged between -0.5 and +0.8. Therefore, the human thermal comfort states are in neutral. Analytical results demonstrate that the proposed method generates a set of rule cubes to predict the thermal comfort levels and initiate control strategies with simplified computations. The method can be used in rule-based systems, real-time controls and embedded systems with limited computing resources.

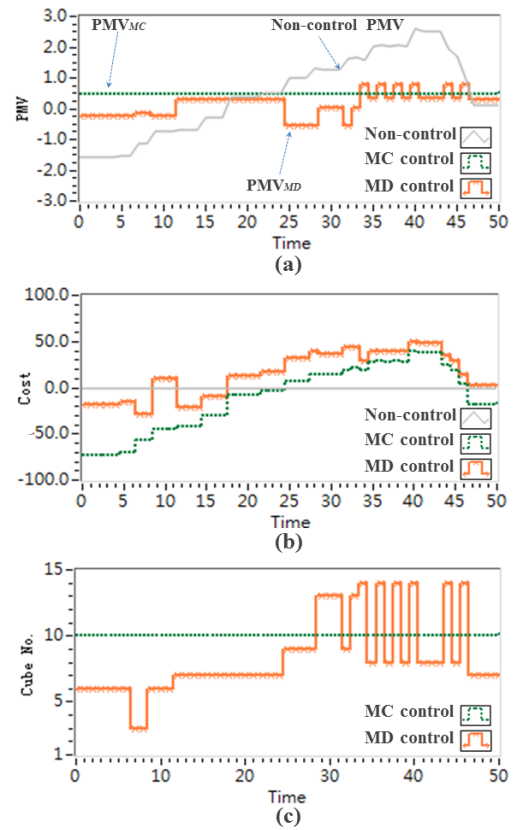


Figure 3. PMV states and control costs by using varied control strategies

V. CONCLUSIONS

This work develops a mechanism to estimate and regulate the state of thermal comfort without a complex computing and iterative process. The proposed method is superior to other PMV based thermal controls in that it produces interpretable rules or logic statements for control systems. Based on our results we conclude the following. First, by using proposed machine learning method, Fanger's PMV can be modeled as set of rule cubes for use in predicting thermal comfort levels. Second, as expected, the deducing classification rules can provide clear guidelines for devising control strategies. Third, the proposed control mechanism can also be implemented to achieve thermal comfort, energy savings, and reduce computational costs. Furthermore, our results can be integrated into a sensor based control system, enable the sensory-feedback controls for guaranteeing occupants' thermal comfort in real time. We recommend that future research attempt to improve the experimental set-up and another round of proof-read for ubiquitous applications.

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