Automatic Control System for Thermal Comfort Based on Predicted Mean Vote and Energy Saving

K. L. Ku, J. S. Liaw, M. Y. Tsai, and T. S. Liu

***Abstract*—For human-centered automation, this study presents a wireless sensor network using predicted mean vote (PMV) as a thermal comfort index around occupants in buildings. The network automatically controls air conditioning by means of changing temperature settings in air conditioners. Interior devices of air conditioners thus do not have to be replaced. An adaptive neurofuzzy inference system and a particle swarm algorithm are adopted for solving a nonlinear multivariable inverse PMV model so as to determine thermal comfort temperatures. In solving inverse PMV models, the particle swarm algorithm is more accurate than ANFIS according to computational results. Based on the comfort temperature, this study utilizes feedforward–feedback control and digital self-tuning control, respectively, to satisfy thermal comfort. The control methods are validated by experimental results. Compared with conventional fixed temperature settings, the present control methods effectively maintain the PMV value within the range of ± 0.5 and energy is saved more than 30% in this study.**

***Note to Practitioners*—For advanced control of unitary air conditioners in rooms, air conditioners may have to be retrofitted or connected with extra devices by wire connection, whose processes may be difficult for users, and inappropriate installation may damage original air-conditioning units. This study hence presents a noninvasive method for indoor thermal comfort with a wireless sensor network. The present method facilitates hardware implementation without changing interior devices of the air conditioner. The wireless sensor network measures temperature, air velocity, and humidity around occupants and further transmits temperature commands for air conditioner control. Based on the measured data, a PMV model is adopted to evaluate thermal comfort. Using an inverse PMV model with feedforward–feedback control and self-tuning control, respectively, this study aims to automatically maintain human thermal comfort as well as save energy. The ANFIS model and a particle swarm algorithm are used to solve the inverse PMV model and determine the thermal comfort temperature. Based on that temperature, feedforward–feedback control, and self-tuning control are used to determine appropriate temperature settings in the air conditioner so as to change the cooling capacity and maintain thermal comfort. Experimental results show that the present control method can maintain thermal comfort and saves 30% more energy than the conventional method.**

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K. L. Ku and T. S. Liu are with the Department of Mechanical Engineering, National Chiao Tung University, Hsinchu 30010, Taiwan (e-mail: kunlung.me97g@g2.nctu.edu.tw; tsliu@mail.nctu.edu.tw).

J. S. Liaw and M. Y. Tsai are with Green Energy and Environmental Laboratories, Industrial Technology Research Institute, Hsinchu 31040, Taiwan (e-mail: dreamyatsai@itri.org.tw; JSLiaw@itri.org.tw).

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I. Introduction

Nowadays, most of environmental problems are closely linked to energy consumption. The energy consumed in buildings accounts for 40% of the total energy consumed in the entire world [1]. Moreover, air-conditioning systems consume about 40%–50% of the total electricity use in buildings [1]. Therefore, energy control of air conditioning systems in buildings deserves research.

An air conditioning system is composed of a compressor, a condenser, an expansion valve or a capillary tube, and an evaporator. In order to improve efficiency and maintain indoor thermal comfort, a lot of research has been carried out to control compressors [2]–[4], [6], control the opening of expansion valves [3]–[6], and control fan speeds of air conditioners [2], [4], [6]. For the sake of effectively controlling air-conditioning units, the air conditioners may have to be dissembled and the units of air conditioners may be retrofitted or connected with extra devices by wire connection. The process may be difficult for occupants. In addition, temperature sensors are not always placed at demanded spots around occupants.

By contrast, this paper presents a method by means of transmitting the temperature commands via a wireless sensor network [7] to control air conditioner operation for occupants' thermal comfort. The wireless network is also utilized to obtain environment information including the temperature, humidity, and air velocity at spots around occupants. Therefore, using the proposed control setup does not have to change interior devices of existing air conditioners.

To evaluate thermal comfort, most of researches have used predicted mean vote (PMV) model as the thermal comfort index and PMV is also adopted by ISO 7730 [8]–[10]. PMV takes into account six parameters, namely, metabolic rate, clothing insulation, air temperature, mean radiant temperature, air velocity, and humidity. According to these parameters, PMV values represent the extent of thermal sensation. Since the temperature is the primary variable in controlling air conditioners, an inverse PMV model is developed in this study to determine the thermal comfort temperature dealing with desired PMV values and indoor conditions. However, the inverse PMV model is a nonlinear and multivariable model and it is not easy to find the analytical solution of the inverse PMV model.

Artificial intelligence strategies such as fuzzy systems, evolutionary algorithms [11], particle swarm algorithms [12], [13], neural networks [14] or the combination of the above strategies are useful for modeling nonlinear characteristic and solving complicated problems. Particle swarm algorithms are inspired by a bird flock and are used to search solutions for complex problems iteratively. Particle swarm algorithms have features of fast searching optimal solutions and easy implementation. An adaptive neurofuzzy inference system (ANFIS) was presented to approximate nonlinear functions [15]. Compared with particle swarm algorithms, the ANFIS algorithm is more complex. However, after training ANFIS can be conducted in real time without iterative computation. Particle swarm algorithms and an adaptive neuro-fuzzy inference system are adopted in this study to solve the inverse PMV model and obtain the desired comfort temperature, respectively.

II. Inverse PMV Model

The inverse PMV model is utilized to generate the desired temperature set point for controllers according to the desired PMV, environments, and human factors. However, the inverse PMV mode is a multivariable nonlinear model and it is difficult to find an analytical solution. In order to solve the problem, ANFIS and particle swarm algorithms, which belong to artificial intelligence approaches, are adopted and their results are discussed.

A. Predicted Mean Vote in Thermal Comfort Model

The thermal comfort PMV model was proposed by Fanger [16] and is used to predict the mean thermal comfort response. Fanger's PMV model establishes the relation between the thermal load on the body and the statistical thermal sensation obtained from numerous people. The thermal load on the body varies with personal factors and environment factors. The personal factors consist of activity and clothing insulation. The environment factors comprise temperature, humidity, air velocity, and mean radiant temperature. The PMV value is calculated by using [16]

$$\mathrm{PMV} = (0.028 + 0.3033\, e^{-0.036M}) \times L \tag{1}$$

where M denotes the metabolism (W/m^2), and L is the human load of the body, defined as the difference between the heat production and the heat loss to the environment [17]. The human load is computed by

$$\begin{aligned} L = {} & M - W - 3.05 \times 10^{-3}[5733 - 6.99(M - W) - P_a] \\ & - 0.42(M - W - 58.15) - 1.7 \times 10^{-5} M(5867 - P_a) \\ & - 0.0014\, M(34 - t_a) - f_{cl} h_c (t_{cl} - t_a) \\ & - 3.96 \times 10^{-8} f_{cl}[(t_{cl} + 273)^4 - (\bar{t}_r + 273)^4]. \end{aligned} \tag{2}$$

The convection heat transfer coefficient h_c is estimated by

$$h_c = \begin{cases} 2.38(t_{cl} - t_a)^{0.25}, & \text{if } 2.38(t_{cl} - t_a)^{0.25} > 12.1\sqrt{V} \\ 12.1\sqrt{V}, & \text{if } 2.38(t_{cl} - t_a)^{0.25} < 12.1\sqrt{V} \end{cases} \tag{3}$$

and the surface temperature t_{cl} of clothing is determined by

$$\begin{aligned} \mathrm{t}_{cl} = {} & 35.7 - 0.028(M - W) - 0.155 I_{cl}\{3.96 \times 10^{-8} \\ & \times f_{cl}[(t_{cl} + 273)^4 + (t_{\mathrm{mrt}} + 273)^4] + f_{cl} \times h_c(t_{cl} - t_a)\} \end{aligned} \tag{4}$$

where M is metabolism (W/m^2); W is the external work (W/m^2), which is equal to zero for most activity; I_{cl} is thermal resistance of clothing (clo), where $1\,\mathrm{clo} = 0.155$ (m$^2 \cdot {}^\circ$C)/W; f_{cl} is the ratio of the surface area of the clothed body to that of the nude body; t_a is the air temperature ($^\circ$C); t_{mrt} is the mean radiant temperature ($^\circ$C); V is the air velocity (m/s); P_a is the partial water vapor pressure (Pa); h_c is the convection heat transfer coefficient (W/m$^2 \cdot \mathrm{K}$); t_{cl} is the surface temperature of the clothing ($^\circ$C).

PMV values are enacted based on thermal sensation scales listed in Table I. It is recommended that the value of PMV should lie within the range of $[-0.5, 0.5]$ to ensure indoor thermal comfort.

Experiments were carried out in an office in summer. The metabolic rate and the clothing insulation of people are difficult to measure in real time. In general, the values of the metabolism and the clothing insulation are assumed as constants. The metabolic rate is assumed as 60 W/m^2 for the office activity and the clothing insulation is assumed as 0.57 clo for short-sleeved shirt with trousers [17]. In some research, the mean radiant temperature was assumed to equal the air temperature due to the requirement of multiple sensors and the difficulty of measurement [10]. Thus, the above assumptions are used in both solving the inverse PMV model and evaluating the PMV value in this study.

TABLE I
Thermal Sensation Scale of PMV

PMV	Sensation
+3	Hot
+2	Warm
+1	Slightly warm
0	Neutral
-1	Slightly cool
-2	Cool
-3	Cold

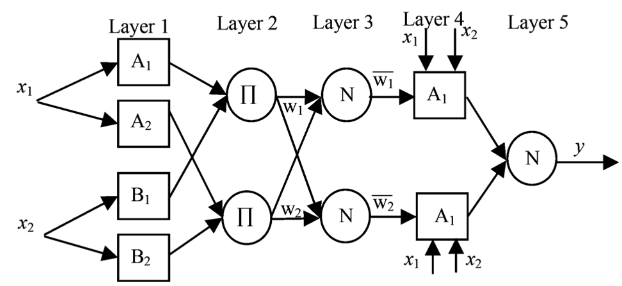

Fig. 1. ANFIS architecture with two rules and two inputs.

B. ANFIS for Inverse PMV

ANFIS belongs to a neurofuzzy system [15]. ANFIS can deal with nonlinear behavior and create inverse models through input/output data [18]. Based on the input–output data, the learning capability of neural networks is used to tune membership functions parameters and consequent parameters in fuzzy models. The ANFIS architecture is depicted in Fig. 1.

The ANFIS model for modeling the inverse PMV model is constructed in this study by using a Sugeno fuzzy model [15]. To implement the ANFIS model, first of all, the training data are generated from the PMV model. Initial values of parameters in the ANFIS model are in turn guessed. Finally, one applies an offline training technique to tune the ANFIS parameters until meeting requirements of the error tolerance.

Fig. 2 shows the absolute thermal comfort temperature error between the ANFIS output and the inverse PMV data. It can be observed that the maximum absolute error is less than 0.015°C, which is sufficiently small for temperature control.

C. Particle Swarm Algorithm for Inverse PMV

In a particle swarm, each moving particle in a swarm is treated as a potential solution. Each particle has memory functions, and it can memorize its current own best position and group's best position. Like bird flocking, each bird adjusts its position according to its own information and group information. The velocity of each particle in a standard particle swarm is limited in the range of $[-v_{\max}, v_{\max}]$ and is updated by [13]

$$\begin{aligned} v_i(t+1) = {} & w \cdot v_i(t) + c_1 r_1 [P\_\mathrm{best}_i - X_i(t)] \\ & + c_2 r_2 [G\_\mathrm{best} - X_i(t)] \end{aligned} \tag{5}$$

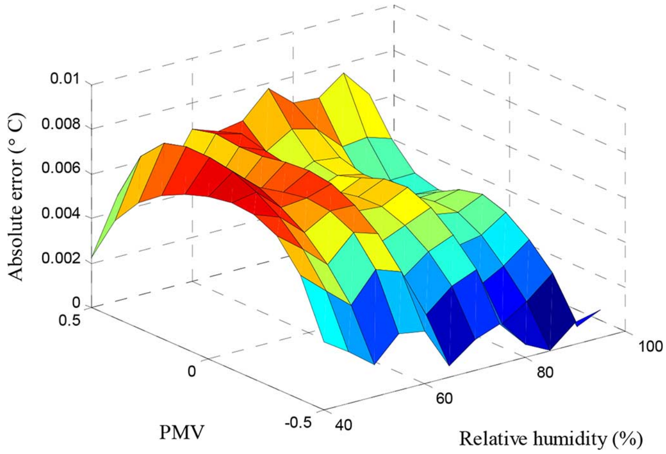

Fig. 2. Absolute temperature error between ANFIS and inverse PMV data under various PMV and relative humidity given $\mathrm{metabolic\ rate} = 60$ W/m2, $\mathrm{air\ velocity} = 0.05$ m/s, and $\mathrm{clothing\ insulation} = 0.57$ clo.

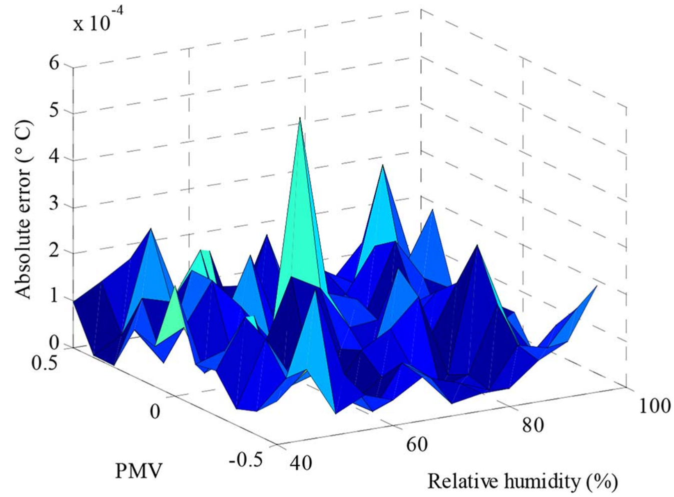

Fig. 3. Absolute temperature error of the particle swarm algorithm given $\mathrm{metabolic\ rate} = 60$ W/m^2, $\mathrm{air\ velocity} = 0.05$ m/s, and $\mathrm{clothing\ insulation} = 0.57$ clo.

where $v_i(t+1)$ and $v_i(t)$ are the next velocity and the current velocity of individual i, respectively; X_i is the current position of individual i; P_best_i and G_best denote the individual best position of individual i and the global best position, respectively; c_1 represents the acceleration weight that pushes the particle towards P_best_i; c_2 represents the acceleration weight that pushes the particle towards G_best; r_1 and r_2 are uniformly distributed random numbers in the range $[0, 1]$; w is the inertia weight. To balance global search and local search, a linearly deceasing inertia weight is used and described as

$$w = w_{\max} - \frac{w_{\max} - w_{\min}}{T_{\max}} t \tag{6}$$

where $w_{\max}$ and $w_{\min}$ are the maximum and minimum values of the inertia weight, respectively; t is the number of the current iteration; $T_{\max}$ is the number of maximum iteration.

The position of each particle is limited in the range $[X_{\min}, X_{\max}]$ and represented as

$$X_i(t+1) = X_i(t) + v_i(t+1). \tag{7}$$

In the present particle swarm algorithm, $c_1 = c_2 = 2, w_{\max} = 1.2, w_{\min} = 0.8$, the number of particles are 40, and the maximum number of iterations is 30. The fitness value is the absolute error between the desired PMV and the PMV calculated by a candidate solution.

The metabolic rate is prescribed as 60 W/m^2 and the clothing insulation 0.57 clo. The computational time is less than 1.4 s. Fig. 3 shows temperature errors between the algorithm result and actual value. The results show that the maximum error is less than 6×10^{-4}°C. The particle swarm algorithm is more accurate than ANFIS, as depicted in Table II. Particle swarm algorithms have to calculate iteratively while a well-trained ANFIS calculates the desired temperature directly without the need of iteration.

III. Control Methods

In order to maintain building occupants' thermal comfort and avoid wasting energy, this study utilizes an inverse PMV model with a feedforward–feedback controller and with a digital self-tuning controller, respectively. The humidity and air velocity measured through the wireless sensor network are used in the inverse PMV model, whereas the measured temperature via the wireless sensor network is used in the feedback controller.

TABLE II
Comparison Between ANFIS and Particle Swarm Algorithm

	Max error (℃)	Advantage	Disadvantage
ANFIS	0.015	No iteration	Inaccurate
Particle swarm algorithm	6×10^{-4}	Accurate	Iteration

A. Feedforward–Feedback Control

Fig. 4 depicts the control block diagram of feedforward–feedback control. The overall control action that determines the temperature setting equals the sum of the feedforward control output and the feedback control output. The feedforward control simply serves to generate a thermal comfort temperature setting. It is desired that the output value in feedforward control is the same as the thermal comfort temperature evaluated by an inverse PMV model. Therefore, the gain of the feedforward controller is prescribed as 1. However, the temperature sensor that has been embedded in air conditioners cannot reflect the temperature at spots around occupants. Therefore, the feedback controller is responsible for automatically adjusting the indoor temperature, compensating the difference between the temperature measured by wireless sensor network around occupants and the temperature sensed by the air conditioners, and preventing the temperature around occupants from overcooling or overheating. In this study, fuzzy control and Proportional-Integral-Derivative (PID) control are respectively adopted as the feedback controller.

B. PID Controller

A PID controller is the most commonly used feedback controller in industrial processes. Because the control algorithm is implemented by a computer, the PID controller is written in discrete form

$$u_{\mathrm{PID}} = K_p e(nT) + K_D \frac{\Delta e(nT)}{T} + K_I \sum_{k=0}^{n} e(nT) \tag{8}$$

where $e(nT)$ denotes the difference between the desired temperature and the temperature around occupants.

C. Fuzzy Control

Fuzzy control based on the fuzzy set theory [19] was developed initially by Mamdani [20]. Fuzzy control was also adopted to improve the performance of air conditioning systems [2].

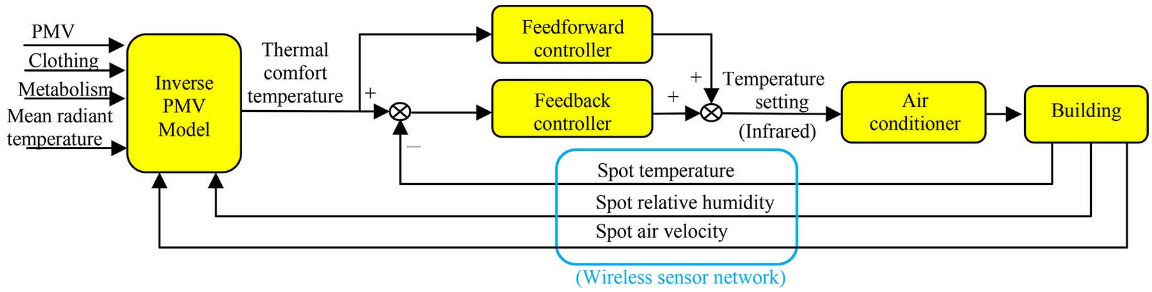

Fig. 4. Control block diagram of inverse PMV model with feedforward–feedback control.

In this study, input variables are the temperature error (E) and the temperature error change (CE). The difference between the desired and the indoor measured temperatures is E. The CE is computed by $(\mathrm{e(n)} - \mathrm{e(n-1)})/\mathrm{T}$, where e(n) is the current temperature error, $\mathrm{e(n-1)}$ is the previous temperature error and T is the sampling time. The output variable is the temperature change in temperature setting.

D. Digital Self-Tuning Control

A digital self-tuning controller belongs to an adaptive controller and is suitable for time-varying system or a system whose parameters are not completely known [21].

A regression model is employed in this study for self-tuning controller designs and the model is expressed as

$$y(k) = \mathbf{\Theta}^T(k)\mathbf{\Phi}(k-1) + n(k) \tag{9}$$

where $y(k)$ is the plant output at the k sample interval, $n(k)$ is the nonmeasurable random component, $\mathbf{\Theta}^T(k)$ is the parameter vector described as $\mathbf{\Theta}^T(k) = [a_1, a_2, \ldots a_{na}, b_1, b_2, \ldots, b_{nb}, d_1, d_2, \ldots, d_{nd}]$, and $\mathbf{\Phi}(k-1)$ is the regression vector described as $\mathbf{\Phi}^{\mathrm{T}}(k-1) = [-y(k-1), -y(k-2), \ldots, -y(k-na), u(k-1), u(k-2), \ldots, u(k-nb), v(k-1), v(k-2), \ldots, v(k-nd)]$ where $u(k-1)$ is the controller output at the $(k-1)$ sample interval and $v(k-1)$ is measurable disturbance. In addition, assume that $n(\mathrm{k})$ has zero-mean value and constant covariance.

In order to monitor slow changes in the parameters of the identified process, the technique of adaptive directional forgetting is used. The parameter vector can be estimated when minimizing the criterion

$$J(\hat{\mathbf{\Theta}}) = \sum_{i=k_0}^{k} \varphi^{(k-i)} \hat{e}^2(i) \tag{10}$$

where k_0 is the initial identification time, $0 < \varphi(k) \leq 1$ is the adaptive directional forgetting factor, and $\hat{e}(i) = y(i) - \mathbf{\Theta}^T(i)\mathbf{\Phi}(i-1)$ is the prediction error. According to a recursive approach [22], the parameter vector is computed by

$$\hat{\mathbf{\Theta}}(k) = \hat{\mathbf{\Theta}}(k-1) + \frac{\mathbf{C}(k-1)\mathbf{\Phi}(k-1)}{1+\zeta(k-1)} \tag{11}$$

where $\zeta(k-1) = \mathbf{\Phi}^{\mathrm{T}}(k-1)\mathbf{C}(k-1)\mathbf{\Phi}(k-1)$ is an auxiliary scalar and $\mathbf{C}$ is a rectangular covariance matrix. If $\zeta(k-1) > 0$, then $\mathbf{C}(k)$ is computed by the recurrent algorithm

$$\mathbf{C}(k) = \mathbf{C}(k-1) - \frac{\mathbf{C}(k-1)\mathbf{\Phi}(k-1)\mathbf{\Phi}^{\mathrm{T}}(k-1)\mathbf{C}(k-1)}{\varepsilon^{-1}(k-1) + \zeta(k-1)} \tag{12}$$

where

$$\varepsilon(k-1) = \varphi(k) - \frac{1-\varphi(k)}{\zeta(k-1)}. \tag{13}$$

If $\zeta(k-1) = 0$, then $\mathbf{C}(k) = \mathbf{C}(k-1)$. The value of adaptive forgetting factor $\varphi(\mathrm{k})$ is updated by the relation

$$\varphi(k) = \Bigg\{1 + (1+\rho)[\ln(1+\zeta(k-1))] + \left[\frac{(\nu(k-1)+1)\eta(k-1)}{1+\xi(k-1)+\eta(k-1)} - 1\right]\frac{\zeta(k-1)}{1+\zeta(k-1)}\Bigg\}^{-1} \tag{14}$$

Fig. 5. Photo of a room employed for experiments. The red circle indicates the place where a ZigBee module is located.

where $\eta(k) = \hat{e}^2(k)/\lambda(k)$, $\nu(k) = \varphi(k)[(v(k-1)+1)]$ and

$$\lambda(k) = \varphi(k)\left[\lambda(k-1) + \frac{\hat{e}^2(k-1)}{1+\zeta(k-1)}\right]. \tag{15}$$

are auxiliary variables, ρ is constant $(0 \leq \rho \leq 1)$. The initial conditions for recursive identification are $\mathbf{C}(0) = 10^3\mathbf{I}$, $\varphi(0) = 1$, $\lambda(0) = 0.001$, $\vartheta(0) = 10^{-6}$, and $\rho = 0.99$. Assume that $na = nb = 3$ and $nd = 0$ in this study.

Takahashi's PID controller [22] is employed in experiments of the digital self-tuning control

$$u(k) = K_p\Bigg\{-y(k) + y(k-1) + \frac{T_0}{T_i}[w(k) - y(k)] + \frac{T_d}{T_o}[2y(k-1) - y(k) - y(k-2) + u(k)]\Bigg\}. \tag{16}$$

where $w(k)$ is the reference value, T_o is a sampling period, K_p is the proportional gain, T_i is the integral time constant, and T_d is the derivative time constant. K_p, T_i, and T_d are tuned in real time and are determined by

$$\mathrm{K}_p = 0.6K_{pu}\left(1 - \frac{T_0}{T_u}\right), T_i = \frac{K_pT_u}{1.2K_{pu}}, T_d = \frac{3K_{pu}T_u}{40K_p} \tag{17}$$

where K_{pu} is the ultimate gain at which the output of the control loop oscillates with a constant amplitude and T_u is the ultimate period. The calculation of parameters of K_{pu} and T_u are based on identified model parameters.

IV. Experimental Setup

The room size of the office selected for executing experiments is 6 m in length, 5.8 m in width, and 2.8 m in height. The photo of the room is shown in Fig. 5. Furthermore, there are three people in the room when performing experiments. A unitary air conditioner with a nominal cooling capacity of 7.3 kW is employed for experiments.

Compared with wire-based measurement and control systems, wireless systems [23] have the advantage of easy installation, convenience of relocation, and expansion for equipment. Wireless technologies applied in building automation systems include ZigBee (IEEE 802.15.4 protocol), Wi-Fi (IEEE 802.11 protocol standard), Bluetooth, etc., we

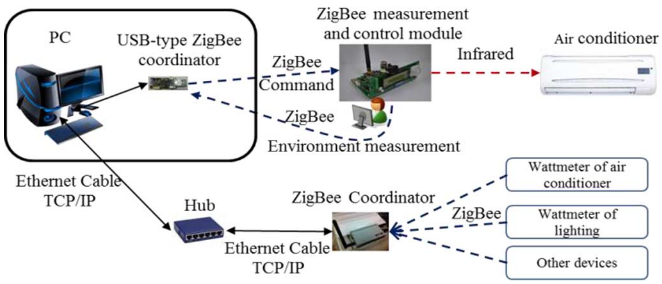

Fig. 6. Signal transmission among devices in the wireless control network.

use a ZigBee module including an infrared emitter for air conditioner remote control and environment sensors that can measure temperature, humidity, air velocity, illuminance, and CO_2 concentration. In addition, the real-time environment information can be displayed on the monitor in the ZigBee module. However, only the temperature, air velocity, and humidity functions are employed for thermal comfort control in this study. The ZigBee module is placed on the desk around occupants and located at the red circle shown in Fig. 5.

Fig. 6 depicts signal transmission among devices in the overall wireless network. And it has two coordinators: one is USB-type coordinator and it is connected to the ZigBee measurement and control module, and the other is connected to other devices including wattmeter of the air conditioner, lightings, and printer, and other devices.

V. Experimental Results

Experiments were performed for four control methods in Taiwan, where the climate is a hot and subtropical humid. The first control method is the conventional method, i.e., fixed temperature setting at 26 °C. The other three control methods belong to the inverse PMV model with the feedforward-fuzzy feedback control, with feedforward-PID feedback control, and with digital self-tuning control. The air conditioner is operated to track the thermal comfort temperature by the last three controllers. The inverse PMV model computes thermal comfort temperature in real time based on the desired PMV, measured air velocity, and humidity. In order to ensure PMV in the range of $[-0.5, 0.5]$ and reduce energy consumption, this study prescribes the PMV input in the inverse PMV model depicted in Fig. 4 as 0.25 in the summer, during which experiments were conducted for 4.5 hours. By contrast, in the winter the PMV input of -0.25 is suggested due to energy saving consideration.

Performances of the four methods are compared based on PMV response curves shown in Fig. 7. The PMV value of the conventional method changes more severely than the other three controllers. According to Fig. 7, the PMV values of the three nonconventional controllers maintain between 0 and 0.5. The three perform better than the conventional method because the inverse PMV model can real time generate proper comfort temperatures, which are in turn continuously tracked by each of three controllers. Furthermore, according to the measured indoor temperature around occupants and the thermal comfort temperature, the three nonconventional controllers appropriately change the temperature setting in the air conditioner, which is equivalent to adjusting cooling capacities at any time.

Table III compares performances among control methods. The percentage of the period lying within PMV $[-0.5, 0.5]$ is defined as the ratio of periods during which the PMV value lies within $[-0.5, 0.5]$ to the total time from the time at which the PMV first enters within $[-0.5, 0.5]$ to the end time. The percentages of periods lying within PMV $[-0.5, 0.5]$ of the inverse PMV model with the three nonconventional controllers are larger than the conventional one. And the standard deviations of the three are smaller than the conventional method. The inverse PMV model with these three controllers can better satisfy

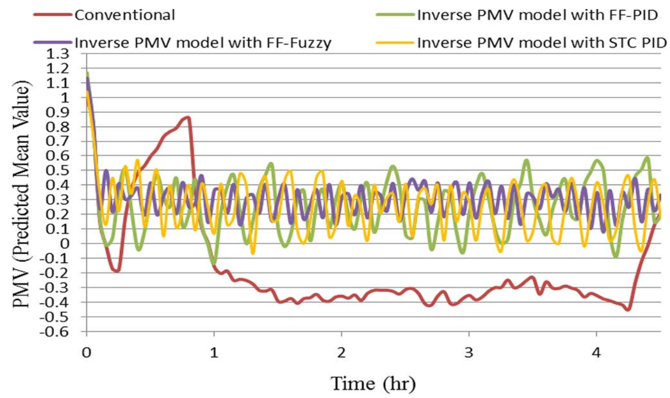

Fig. 7. Measured PMV responses of the conventional method, the inverse PMV model with feedforward-fuzzy feedback control and self-tuning control.

TABLE III
Comparison of Measured PMV Performances in Four Control Methods

Control Methods	Average PMV	Standard Deviation PMV	Max PMV	Min PMV	Percentage of Period within PMV [-0.5, 0.5]
Conventional	-0.17	0.34	0.86	-0.45	90.5%
Inverse PMVmodel with FF-PID[a]	0.27	0.18	0.58	-0.13	94%
Inverse PMV model with FF-Fuzzy[b]	0.30	0.11	0.50	0.08	100.0%
Inverse PMV model with self-tuning control	0.25	0.16	0.57	-0.07	99.2%

[a,b]FF-PID and FF-Fuzzy denote the feedforward-PID feedback and feedforward-fuzzy feedback, respectively.

thermal comfort and yields smaller variation of PMV than the conventional method.

Among these three controllers, the feedforward-fuzzy feedback controller has the largest percentage of periods lying within PMV $[-0.5, 0.5]$ and the smallest variation of PMV than the other controllers. Comparing between the feedforward-PID feedback controller and the digital self-tuning controller. Table III shows that the digital self-tuning controller performs better than the feedforward-PID feedback controller in terms of the percentage of the period lying within PMV $[-0.5, 0.5]$ and the PMV variation. Table III also shows that the effective tuning of the self-tuning control parameters results in better control performance than the feedforward-PID feedback controller. Furthermore, among these controllers, the average PMV of the digital self-tuning controller is closest to the PMV input than the other controllers.

Table IV compares the energy consumptions among the four methods. The energy saving is calculated according to

$$\eta = \frac{E_{\mathrm{conv}} - E_{\mathrm{ctrl}}}{E_{\mathrm{conv}}} \times 100\% \tag{18}$$

where E_{conv} is the energy consumption of the conventional method, and E_{ctrl} is the energy consumption of the ANFIS with the three control methods. According to Table IV, the inverse PMV model with feedforward-fuzzy feedforward-PID or with digital self-tuning control indeed outperform the conventional method by 34.7%, 37.3%, and 32.9%, respectively, in energy saving. The inverse PMV model with the feedforward-fuzzy feedback control saves the most energy among the three methods.

TABLE IV
COMPARISON OF MEASURED ENERGY CONSUMPTION AND ADVANTAGES AMONG FOUR CONTROL METHODS

Methods	Energy Consumption (kWh)	Energy Saving (%)	Advantage
Conventional	3.89	---	Simple
Inverse PMV model with FF-PID[a]	2.57	34.7	Model-free design
Inverse PMV model with FF-Fuzzy[b]	2.44	37.3	Easy realize
Inverse PMV model with self-tuning control	2.61	32.9	Adaptive

[a,b]FF-PID and FF-Fuzzy denote the feedforward-PID feedback and feedforward-fuzzy feedback, respectively.

VI. CONCLUSION

Experiments have been carried out by using four control methods. As shown in Fig. 7, PMV response curves of every controller fluctuates due to 1 °C increment of air-conditioner temperature commands. Therefore, it remains to develop methods and devices to maintain PMV near 0 and smooth responses while saving energy. In addition, since the comfort range of PMV may vary with different people's feeling, it may be required to modify the comfort range of PMV according to the questionnaire of occupants' preference or develop other thermal comfort indices for occupants. In this study, the values of the metabolic rates and the clothing insulation are assumed as constants and are estimated from tables in [17]. For accurate estimation, the clothing insulation can be determined by measurement on heated mannequins, and the metabolic rates can be estimated from measuring CO_2 and O_2 in a person's expired air [17]. Moreover, human activity changes with time. However, estimating metabolic rates and clothing insulation is not trivial. Therefore, it is desired in future work to devise wearable or non-contact sensors to measure the values of metabolic rates and clothing insulation and improve the human factor measurement process.

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