A Hybrid Intelligent Control System based on PMV Optimization for Thermal Comfort in Smart Buildings

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Abstract. With the fast development of human society, on one hand, environmental issues have drawn incomparable attention, so energy efficiency plays a significant role in smart buildings; on the other hand, spending more and more time in buildings leads occupants constantly to improve the quality of life there. Hence, how to manage devices in buildings with the aid of advanced technologies to save energy while increase comfort level is a subject of uttermost importance. This paper presents a hybrid intelligent control system, which is based on the optimization of the predicted mean vote, for thermal comfort in smart buildings. In this system, the predicted mean vote is adopted as the objective function and after employing particle swarm optimization the near-optimal temperature preference is set to a proportional-integral-derivative controller to regulate the indoor air temperature. In order to validate the system design, a series of computer simulations are conducted. The results indicate the proposed system can both provide better thermal comfort and consume less energy comparing with the other two intelligent methods: fuzzy logic control and reinforcement learning control.

Keywords: thermal comfort, smart building, intelligent control, particle swarm optimization, energy

1 Introduction

United Nations Environment Programme [1] indicates that buildings use about 40% of global energy, 25% of global water, 40% of global resources, and they emit approximately 1/3 of Green House Gas (GHG) emissions. With the development of human society, environmental issues have drawn more and more attention. In this background, buildings can offer a great potential for achieving significant GHG emission reductions in different countries. Furthermore, energy consumption in buildings can be reduced by using advanced technologies and management. On the other hand, people spend greater part of their time in buildings. As the quality of life in home is increasingly considered as of paramount importance, many people constantly seek to improve comfort in their living spaces. Meanwhile, the popularization of the concept of home office makes the productivity in smart buildings economically significant. How to manage buildings in a proper way to improve energy efficiency and comfort level while reducing pollution at the same time is therefore a subject of uttermost importance.

Corresponding to the increasing demands for environment, comfort, energy, and productivity, intelligent computing and control methods are applied for improving comfort conditions in smart buildings thanks to the dramatically rapid development of information technologies. Widespread utilization of low-power, high-capacity, small form-factor computing devices, the proliferation of powerful but low-cost sensors and actuators, and ubiquitous networking technologies make the intelligent control more easily come true.

Many techniques have been used for controlling thermal comfort in smart buildings. Authors in [2] present a model predictive controller, which uses both weather forecast and thermal model , applied to the inside temperature control of real buildings. However, on one hand, it is difficult to obtain accurate thermal models for a variety of buildings. On the other hand, thermal comfort does not only relate to the environmental conditions like room temperature, but also factors about people themselves. In order to describe thermal comfort formally, P.O. Fanger [3] invents a thermal comfort model called Predictive Mean Vote index (PMV). Based on this model, Dounis and Manolakis [4] design a fuzzy logic system, which sets PMV and the ambient temperature as input variables while the heating power as output variables, to regulate the space heating system. But as the authors indicated, the proposed expert system works well only if the knowledge embedded in its rule base is sound. It means that a tuning and optimizing process is needed at the later stage in order to have good results, which is time consuming. In the work of K. Dalamagkidis *et al.*[5], they develop a reinforcement learning controller to achieve thermal comfort in buildings with minimal energy consumption. The reinforcement learning signal is a function of the thermal comfort and the energy consumption. However, the convergence speed of reinforcement learning in this application is very slow.

In this work, we propose a novel hybrid intelligent control system to maintain thermal comfort for occupants. This system utilizes Proportional-Integral-Derivative (PID) to control the heating system regularly at the lower level while employs Particle Swarm Optimization (PSO) to compute near-optimal setpoint inversely from PMV model based on present environmental and personal conditions at the higher level. The contribution of this work is threefold: firstly, the thermal comfort problem is formally described; secondly, a novel hybrid control method is proposed, with which occupants' thermal comfort can be improved and energy consumption can be reduced; thirdly, by conducting experiments and comparing with fuzzy logic control and reinforcement learning control, the better performance of our proposed method is proved. The rest of this paper is organized as follows. Section 2 mathematically describes the thermal comfort problem. Section 3 presents the proposed method in detail. Experimental results and analysis are given in section 4. Finally, we conclude in section 5.

2 Problem Description

2.1 Building Thermal Model

The room temperature is affected not only by auxiliary heating / cooling systems and electric appliances, but also by the solar radiation and the ambient temperature. According to [6], the heat balance of a building can be expressed as

$$\phi_h(t) + \phi_s(t) = \phi_t(t) + \phi_c(t) \tag{1}$$

where ϕ_h is the heat supplied by all internal heat sources; ϕ_s is the heat gained by solar radiation; ϕ_t is the heat loss through external contact; ϕ_c is the heat retained by the building.

In order to analyze the thermal dynamics of a building, we can consider it as a thermal network, which is analogous to an electric circuit network by regarding heat flows as electric current, temperature as voltage and treating thermal transmittance (U) and thermal capacitance (C) as electric resistance and electric capacitance respectively, as shown in Fig.1. In the figure, there are two nodes which represent the temperature inside and outside the room, and six sub-circuits which indicate physical components of the room, including room air, internal partitions, ceiling, floor and external walls.

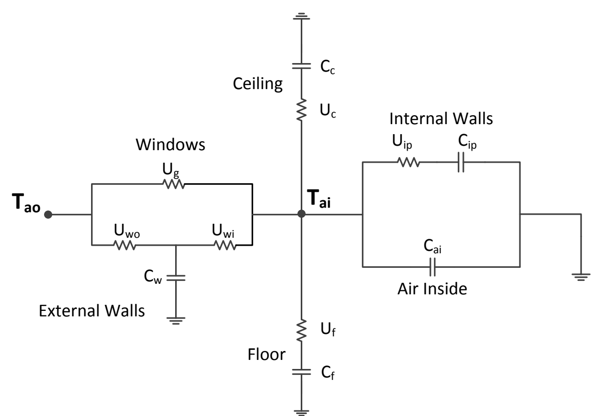

Fig. 1. Thermal Network

Before deriving state-space equations of the building, two definitions should be mentioned:

$$\phi = A \times U \times (T_1 - T_2) \tag{2}$$

where ϕ is the heat transfer in watts, A is the area in square metres, U is the thermal transmittance, T_1 is the temperature on one side of an object and T_2 is the temperature on the other side of the object.

$$C = \frac{\Delta Q}{\Delta T} \tag{3}$$

where C is the thermal capacitance, ΔQ is the change of heat and ΔT is the change of temperature.

Now the thermal system of the building depicted in Fig.1 can be expressed by Equations (4) - (8), except the sub-circuit of windows, because of its so tiny thermal mass that we assume windows have not the property of thermal capacitance to store heat:

$$\frac{dT_w}{dt} = \frac{A_w}{C_w}\left[U_{wi}(T_{ai} - T_w) + U_{wo}(T_{ao} - T_w)\right] \tag{4}$$

$$\frac{dT_f}{dt} = \frac{A_f}{C_f}\left[\frac{pQ_s}{A_f} + U_f(T_{ai} - T_f)\right] \tag{5}$$

$$\frac{dT_c}{dt} = \frac{A_c}{C_c}\left[U_c(T_{ai} - T_c)\right] \tag{6}$$

$$\frac{dT_{ip}}{dt} = \frac{A_{ip}}{C_{ip}}\left[\frac{(1-p)Q_s}{A_{ip}} + U_{ip}(T_{ai} - T_{ip})\right] \tag{7}$$

$$\begin{aligned}\frac{dT_{ai}}{dt} = \frac{1}{C_{ai}}\Big[&Q_p + Q_e + (A_g U_g + U_v)(T_{ao} - T_{ai}) \\ &+A_w U_{wi}(T_w - T_{ai}) + A_f U_f (T_f - T_{ai}) \\ &+A_c U_c (T_c - T_{ai}) + A_{ip} U_{ip}(T_{ip} - T_{ai})\Big]\end{aligned} \tag{8}$$

In above equations,

- Q_p heat supplied by the heating system in W,
- Q_e heat gained by using electrical equipments in W,
- Q_s solar radiation through glazing in W,
- T temperature in K,
- U thermal transmittance in $W/(m^2 \cdot K)$,
- C thermal capacitance in J/K,
- p fraction of solar radiation entering floor.

Subscripts:

- w external wall,
- wi inside part of external wall,
- wo outside part of external wall,
- f floor,
- c ceiling,
- ip internal partition,
- ao outdoor air,
- ai indoor air,
- v ventilation
- g glazing

Above equations can be stacked using the state-space notation:

$$\dot{\mathbf{x}} = \mathbf{A}\mathbf{x} + \mathbf{B}\mathbf{u} \tag{9}$$

where $\dot{\mathbf{x}}$ is a vector of derivatives of temperatures of external walls(T_w), floor(T_f), ceiling(T_c), internal partitions(T_{ip}) and air inside(T_{ai}), $\mathbf{A}$, $\mathbf{B}$ are matrices of coefficients, $\mathbf{x}$ is a vector of states and $\mathbf{u}$ is the input vector, including Q_p, Q_e, Q_s and T_{ao}. The area of each component of the building is known after choosing a physical building model, and the properties of different building materials can be obtained from [7].

2.2 Thermal Comfort

Thermal comfort is the condition of mind that expresses satisfaction with the thermal environment and is assessed by subjective evaluation [8]. The Predictive Mean Vote index (PMV) derived by P.O. Fanger [3] stands among the most recognized thermal comfort models, which predicts the mean value of the votes of a large group of persons on the 7-point thermal sensation scale, based on the heat balance of the human body. The 7-point thermal sensation scale separately indicates -3 for cold, -2 for cool, -1 for slightly cool, 0 for neutral, +1 for slightly warm, +2 for warm, and +3 for hot. Moreover, the ISO recommends maintaining PMV at level 0 with a tolerance of 0.5 as the best thermal comfort. The calculation of PMV is non-linear and non-convex [10]. It is affected by six factors, four environmental-dependent: air temperature T_{ai}, mean radiant temperature (MRT) T_{mrt}, air velocity v_{air}, and relative humidity h_r and two personal-dependent: occupant's clothing insulation I_{cl} and activity level M, as given below:

$$PMV = F(T_{ai}, T_{mrt}, v_{air}, h_r, I_{cl}, M) \tag{10}$$

In our problem, based on other parameters and an optimal PMV value we need to inversely calculate the optimal air temperature as a proper preference for the heating controller. This can be mathematically expressed as:

$$T_{ai} = G(PMV^*, T_{mrt}, v_{air}, h_r, I_{cl}, M) \tag{11}$$

3 Proposed Method

In order to solve the thermal comfort problem presented in the last section, we propose a novel hybrid intelligent control method, as can be seen in Fig.2. In this figure, occupants set PMV preference (recall that 0 represents comfort), and according to the present sensing data from the environment, the Inverse PMV Optimization module can provide a proper indoor temperature setpoint. Based on this setpoint and the sensing indoor temperature, the PID controller can calculate an applicable heating power for the space heating system.

In the Inverse PMV Optimization module, it has been proved that the PMV calculation is non-linear and non-convex [10], so classic optimization tools are

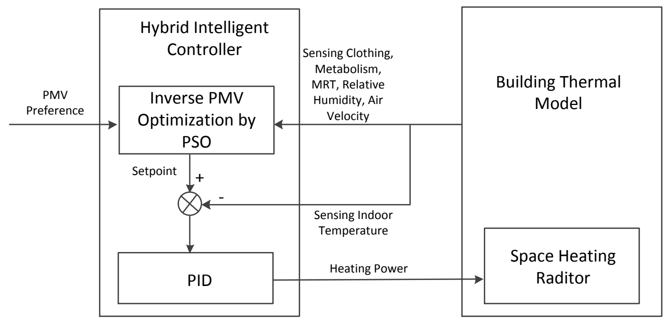

Fig. 2. Hybrid Intelligent Controller Diagram

not suitable. In this research, we use PSO to search for the near-optimal solutions. Particle Swarm Optimization (PSO), which is derived from simulating social behavior as a stylized representation of the movement of organisms in a bird flock or fish school, is originally proposed and developed by [11,12]. It is a metaheuristic algorithm that has been turned out to be powerful to solve the complex non-linear and non-convex optimization problems [13]. Moreover, it has several other advantages, such as fewer parameters to adjust, easier to escape from the local optimal solutions, and so on.

In PSO, a population of candidate solutions, here dubbed particles that include position vector $\mathbf{x}$ and velocity vector $\mathbf{v}$, is randomly generated around the search-space initially. After that they are iteratively updated to simulate the movement around the search-space according to mathematical formulae over the particles' position and velocity, as expressed below:

$$\begin{aligned} \mathbf{v}_i^{k+1} = & w \cdot \mathbf{v}_i^k + c_1 \cdot rand() \cdot (\mathbf{p_{best}}_i^k - \mathbf{x}_i^k) \\ & + c_2 \cdot rand() \cdot (\mathbf{g_{best}}^k - \mathbf{x}_i^k) \end{aligned} \tag{12}$$

$$\mathbf{x}_i^{k+1} = \mathbf{x}_i^k + \mathbf{v}_i^{k+1} \tag{13}$$

where w is inertia weight, c_1 and c_2 are acceleration constants, $rand()$ generates random value between 0 and 1, $\mathbf{p_{best}}_i^k$ is the local best position, $\mathbf{g_{best}}^k$ is global best position, i is the particle index, and k is the iteration index. For Equation 12, the first part expresses particle's inertia of previous action, the second part reflects particle's cognition that stimulates the particle to minish errors, and the last part is called social part, which indicates the information sharing and cooperation among particles.

At the lower level of the proposed method, we use PID to regulate the heating power regularly. There are three reasons that we choose it: firstly due to the huge thermal mass of the building, the indoor temperature change is a rather slow process, that means it does not need an exquisite control method; secondly the work of Paris *et al.*[14] has proved that PID is already good enough to regulate the indoor temperature comparing with other hybrid methods such as PID-FLC and PID-MPC; thirdly, PID can be implemented easily which only needs three scalar parameters. A typical equation, that describes a PID regulator, is the following:

$$Q_p(t) = K_p e(t) + K_d \frac{de(t)}{dt} + K_i \int e(t)dt \tag{14}$$

where K_p is the proportional parameter, K_d is the derivative parameter, and K_i is the integral parameter.

4 Experimentation

In experiments, we compare our proposed hybrid intelligent control approach, denoted as HIC, with fuzzy logic control (FLC) and reinforcement learning control (RLC). In PSO part of HIC, inertia weight $w = 0.4$, acceleration constants $c_1 = c_2 = 2$, particle number is 30, and maximum iteration number is 150. In PID part, proportional gain is 2000, integral gain is 0.5, and derivative gain is 0. The maximum power of the electric heating radiator is $2000W$.

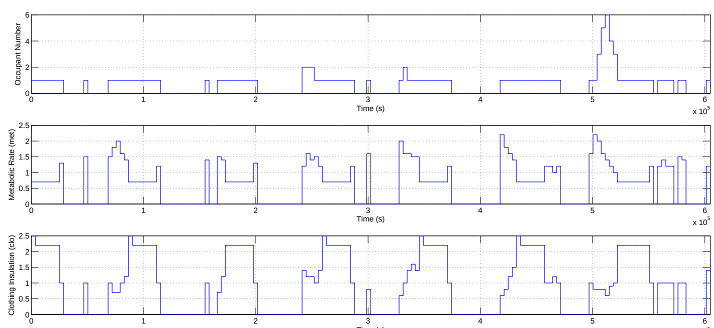

Fig. 3. Simulation of Occupant's Number, Metabolic Rate, and Clothing Insulation of One Week

The simulations of occupant number, metabolic rate, and clothing insulation are shown in Fig. 3, which depict the general life of a person who works or studies during the daytime, has lunch at home sometimes, and returns home cooking, taking exercise, watching TV, etc. in the evenings regularly on weekdays, and invites friends to have a party at weekend.

Fig. 4 show the simulation results of our proposed method. The simulation environment is assumed in Oslo with a duration of one week in winter from 08/01/2014 00:00 to 14/01/2014 11:59, 604800 seconds in total. The ambient

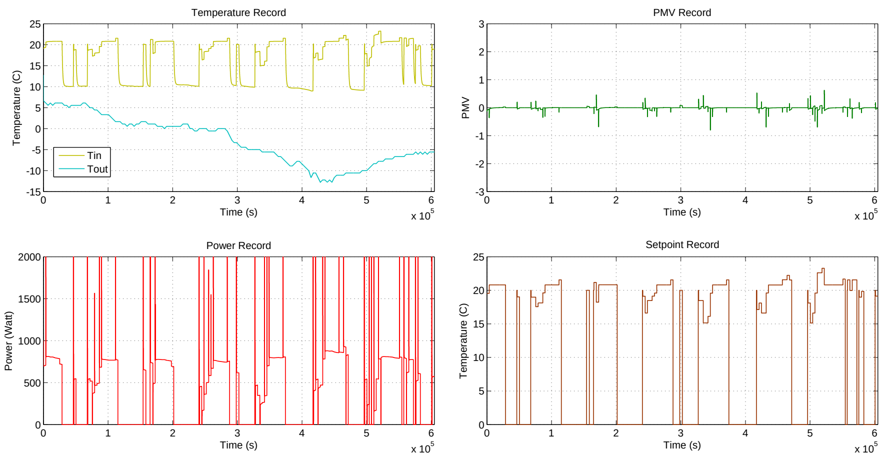

Fig. 4. Simulation Results of HIC Method

weather data is obtained from [15]. The upper-left subfigure records the variations of indoor and outdoor air temperature, in yellow line and blue line respectively. When the occupant is at home, the system will compute an optimal setpoint by PSO according to the present conditions, and based on this setpoint the PID controller can tune the power of the heating system to have the room temperature access to the setpoint. Because the occupant may do different activities like sitting, cooking, sleeping, etc. and wear different clothes with different insulation values, the room temperature has to change to obtain good thermal comfort. When the occupant leaves the room, the heating system will turn off to save energy. This makes the indoor temperature drop to about $10°C$. Due to the huge thermal mass of the building, although the outdoor temperature drops below $0°C$, the indoor temperature can be kept around $10°C$, and this is called thermal flywheel effect [16].

The upper-right subfigure shows the PMV record. It defines that when there is no one in the room, the PMV is set to 0. From the subfigure, it can be seen that the PMV can be kept between +0.5 and -0.5 to assure excellent thermal comfort, except a few minutes' slight cool or warm feeling, which are caused by (1) leaving and then returning home in extremely cold weather, in which case the heating system is unable to warm the room instantly; and (2) the arriving of a mount of visitors from whom the metabolism and thermal radiation make the room over warm. The two bottom subfigures indicate the output heating power and the intelligent setpoint picking during this simulation.

Fig. 5 is the simulation results using FLC and RLC separately. By comparing these 4 figures with Fig. 4, it can be found that our proposed method can provide much better thermal comfort than these two methods, for they sometimes overshoot and have considerable vibrations. For FLC, the performance is

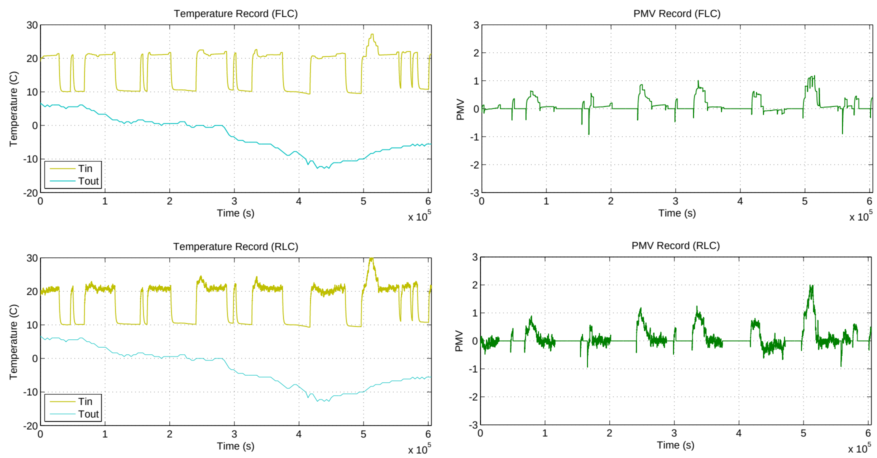

Fig. 5. Simulation Results of FLC Method and RLC Method

tightly related to the designing of membership functions and rules, which are often done empirically. Through optimizing these factors, the results may be better, but due to the complexity of PMV calculation it is hard for this expert system to outperform our proposed method. For RLC, because we discretize the action space, it causes the indoor temperature and PMV value vibrate continually within some extent. By using some techniques may handle this problem, but it is time consuming. The total energy consumed by employing our HIC method is $2.4817 \times 10^8 J$, while they are $2.7393 \times 10^8 J$ and $2.7236 \times 10^8 J$ for FLC and RLC respectively.

5 Conclusion

Nowadays, smart buildings not only mean providing a more comfortable living environment, but also dedicate to reduce the energy cost and environmental pollution. In order to achieve this goal, this paper proposes a hybrid intelligent control system. In detail, a traditional Proportional-Integral-Derivative (PID) controller is used to directly regulate the heating system, while a Particle Swarm Optimization (PSO) method is employed to compute near-optimal setpoints for the PID controller based on present environmental and personal conditions. The advantages of this approach are threefold: (1) better thermal comfort, (2) less energy cost, (3) easier to implement. The experimental results have proved these points and indicated that it outperforms the other two control methods: fuzzy logic control and reinforcement learning control.

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