Fuzzy Logic Control Optimized by Artificial Immune System for Building Thermal Condition

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Abstract. With the fast development of information technology and increasingly prominent environmental problems, building comfort and energy management become the major tasks for an intelligent residential building system. According to statistical studies, people spend 80% of their lives in buildings. Hence it is not surprising that they constantly seek to improve comfort in their living spaces. This paper presents a fuzzy logic controller optimized by an artificial immune system algorithm aimed at maintaining the thermal comfort while reducing energy consumption. The experimental results show the advantages of our system compared with the widely used baseline: On/Off control approach.

Keywords: energy, fuzzy system, artificial immune system, optimization

1 Introduction

According to statistical studies, people spend 80% of their lives in buildings. This explains why occupants constantly seek to improve comfort in their living spaces. In addition, environmental issues have drawn more and more attention. How to manage energy in a proper way to improve energy efficiency and reduce pollution is a subject of uttermost importance. Meanwhile, the popularization of the concept of home office makes the productivity in residential buildings economically significant.

Among all indoor comfort factors, thermal comfort attracts our special attention. According to [1], thermal comfort is the condition of mind which expresses satisfaction with the thermal environment. This definition leaves open what is meant by *condition of mind* or *satisfaction*, which implies that the judgement of comfort is a cognitive process involving many inputs including physical, physiological, psychological and other processes. Despite not being the only affecting factor, indoor temperature has physically major influence on occupants' feeling comfort. In real world, the operative temperature intervals vary with building location and type. ISO-7730 suggests temperature ranges in different types of buildings and different environmental conditions. For example, for residential buildings of category B in summer, the suggested temperature range is from $23.0°C$ to $26.0°C$, while it is between $20.0°C$ and $24.0°C$ in winter [1].

So far, most Heating, Ventilation and Air Conditioning (HVAC) systems for residential buildings usually employ a single-zone, On/Off control method which is rather simplistic [2]. Corresponding to the increasing demands for environment, energy, comfort and productivity, intelligent control methods are applied for improving thermal conditions in residential buildings [3,4]. Fuzzy control [5] is another type of intelligent control method. Comparing with classical ones, especially like Proportional Integral Derivative control (PID) that is widely used in industrial process control [6,7] due to its simplicity of structure, low-price, relative effectiveness and the familiarity of engineers, but cannot provide good enough performance in highly complex process controlling, fuzzy control can theoretically cope with complex processes [8] and is able to combine the advantages of PID control with human operator experience.

In this work, we first investigate the thermal dynamics of a building. Then a fuzzy control scheme with a meta-heuristic optimization algorithm called CLONALG, is proposed for the heating system of a residential building. This control system can make intelligent decisions of what magnitude of power the physical heating system should adopt at each time step based on the present indoor and outdoor temperatures. Due to empirical picking of fuzzy parameters initially, the target of CLONALG is to optimize these parameters to improve the performance of the fuzzy control system. The remainder of this paper is organized as follows. Section 2 describes the mathematical building thermal model. Section 3 presents the fuzzy controller used to control the heating system. Section 4 provides details about CLONALG algorithm. Section 5 explains the system design and formalizes the fuzzy system optimization process. Experimental results and analysis are given in Section 6. Finally, we conclude in Section 7.

2 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 outside temperature. According to Achterbosch *et al.*[9], 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.

The thermal system of the building can be expressed by Equations (2) - (6):

$$\frac{dT_w}{dt} = \frac{A_w}{C_w}\left[U_{wi}(T_{ai} - T_w) + U_{wo}(T_{ao} - T_w)\right] \tag{2}$$

$$\frac{dT_f}{dt} = \frac{A_f}{C_f}\left[\frac{pQ_s}{A_f} + U_f(T_{ai} - T_f)\right] \tag{3}$$

$$\frac{dT_c}{dt} = \frac{A_c}{C_c}\left[U_c(T_{ai} - T_c)\right] \tag{4}$$

$$\frac{dT_{ip}}{dt} = \frac{A_{ip}}{C_{ip}} \left[\frac{(1-p)Q_s}{A_{ip}} + U_{ip}(T_{ai} - T_{ip}) \right] \tag{5}$$

$$\begin{aligned} \frac{dT_{ai}}{dt} = \frac{1}{C_{ai}} \Big[& Q_p + Q_e + (A_g U_g + U_v)(T_{ao} - T_{ai}) \\ & + A_w U_{wi}(T_w - T_{ai}) + A_f U_f (T_f - T_{ai}) \\ & + A_c U_c (T_c - T_{ai}) + A_{ip} U_{ip} (T_{ip} - T_{ai}) \Big] \end{aligned} \tag{6}$$

In above equations: Q_e is the heat gained by using electrical equipments, Q_s is the solar radiation through glazing, Q_p is the heat supplied by the heating system, T_{ao} is the outside air temperature, T_{ai} is the inside air temperature, U is the thermal transmittance, C is the thermal capacitance, A is the area of the component, p is the fraction of solar radiation entering floor, and w, ip, f, c means external wall, internal partition, floor and ceiling respectively.

The area of each component is known after choosing the physical building model, and the properties of different building materials can be obtained from ASHRAE Handbook [10].

3 Fuzzy Logic Controller

Fuzzy Logic Controllers (FLC) have gained more and more prominence in recent years because of its ability to control devices which imitate the decision making of human being. Moreover, a FLC is efficient to cope with continuous states with the help of membership function (MF) and IF-THEN rules. In general, a FLC contains four parts: fuzzifier, rules, inference engine and defuzzifier. Firstly, a crisp set of input data is gathered and converted to a fuzzy set using fuzzy linguistic variables, fuzzy linguistic terms and membership functions. This step is known as fuzzification. Afterwards, an inference is made based on a set of rules. Lastly, the resulting fuzzy output is mapped to a crisp output using the MFs in the defuzzification step.

Specifically, in aforementioned building model the inputs include 4 elements: Q_p, Q_e, Q_s and T_{ao} and in order to simplify the problem, let's assume that Q_e and Q_s are both constant. T_{ao} can be simulated by using former weather data. Hence, the variable we need to control by our FLC is Q_p, which is the input of the building model but the output of the FLC. We define $eTai$ as the error between the indoor temperature T_{ai} and the setpoint T_{set}, and $eTao$ as the error between the outdoor temperature T_{ao} and T_{set}. Setpoint is the comfortable temperature that occupants prefer. To set the input variable(s) of the FLC there are two options: one is to consider $eTai$ solely, like common air-condition, which is naive but still possible; the other one is to take $eTai$ and $eTao$ into account together, which gathers more information and therefore performs better. In our study, we prefer the latter. Therefore, we have two input variables, $eTai$ and $eTao$ separately and one output variable, Q_p.

In practice, there are different forms of MFs such as triangular, trapezoidal, piecewise linear, Gaussian, singleton, etc. They are curves which define how each crisp input point is mapped to a degree of membership between 0 and 1. Actually, these functions can be arbitrary curves whose shapes suit us from the point of view of simplicity, convenience, speed or efficiency under the only condition of their value between 0 and 1. In our study we capitalize on the Gaussian symmetrical function (GMF), Z-shape function (ZMF) and S-shape function (SMF) [11] because of their smoothness and concise notation that each of them can be defined by two parameters. Each fuzzy linguistic variable is expressed by three MFs, namely negative, zero and positive.

In fact, choosing MF types is not a tough job which is often out of empirical analysis. However, it is difficult to choose optimal fuzzy parameters for these MFs to design an optimal FLC. Usually people do this empirically too. In this study, we will use an AIS algorithm to find a near optimal set of parameters for the FLC. The proposed method involves arbitrarily picking an initial set of parameters and then finding a set of near optimal parameters by shifting the peak locations and tuning the deviations of fuzzy sets of antecedent MFs and consequent MF. We will discuss how to implement it in detail in Section 5.

4 Artificial Immune System Architecture

It has been proved that the human adaptive immune system possesses three capabilities: recognition, adaptation and memory [12]. When the human body is invaded by a specific pathogen or antigen, it will be recognized and bound by specific immunoglobulins or antibodies, which are secreted by B cells, to be tagged for attack by other part of the immune system or neutralised to death.

Figure 1 shows the antigen recognition and clonal selection process. An antibody, Ab, can recognize and bind an antigen, Ag, when Ab matches the structure of Ag. The regions of the antibodies that match the antigens are called paratopes, while the counterpart regions of the antigens are called epitopes. In this figure, Ab1 can match Ag1 but not Ag2, while Ab2 can neither match Ag1 nor Ag2, so Ab1 has higher affinity than Ab2 for encountering antigens. Higher affinity means higher probability of being selected and higher strength of clone and mutation. By continuous cloning and mutating existing ones, new generation of antibodies will be produced and among them new types of antibodies which may better match existing or new antigens are generated, for example Ab1' which can match both Ag1 and Ag2. This presents the adaptation capability of the immune system. Even if all antigens are destroyed, some relevant B cells will differentiate into memory cells. Therefore, if the same antigens reappear, the immune response will act sooner.

Inspired by the properties of human immune system, a variety of algorithms, such as Negative Selection, Clonal Selection, Immune Networks, and Dendritic Cell, have been designed to tackle different problems. The CLONALG algorithm [12], which belongs to Clonal Selection, we use to search the near optimal fuzzy parameters for the FLC is described below:

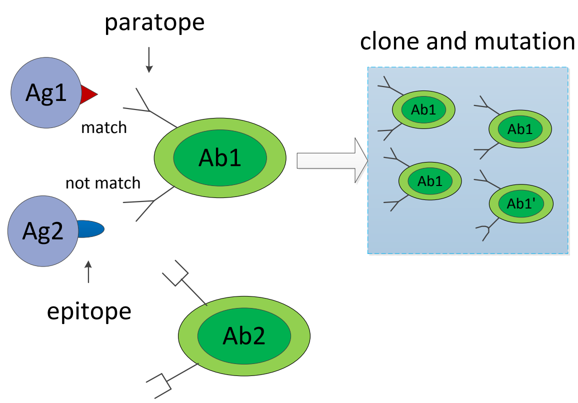


Fig. 1. Antigen Recognition, Clone and Mutation of Antibody

(1) Generate a set (P) of candidate solutions, composed of the subset of memory cells (M) added to the remaining (Pr) population (P = Pr + M);
(2) Determine (Select) the n best individuals of the population (Pn), based on an affinity measure;
(3) Reproduce (Clone) these n best individuals of the population, giving rise to a temporary population of clones (C). The clone size is an increasing function of the affinity with the antigen;
(4) Submit the population of clones to a hypermutation scheme, where the hypermutation is proportional to the affinity of the antibody with the antigen. A maturated antibody population is generated (C*);
(5) Re-select the improved individuals from C* to compose the memory set M. Some members of P can be replaced by other improved members of C*;
(6) Replace d antibodies by novel ones (diversity introduction). The lower affinity cells have higher probabilities of being replaced.

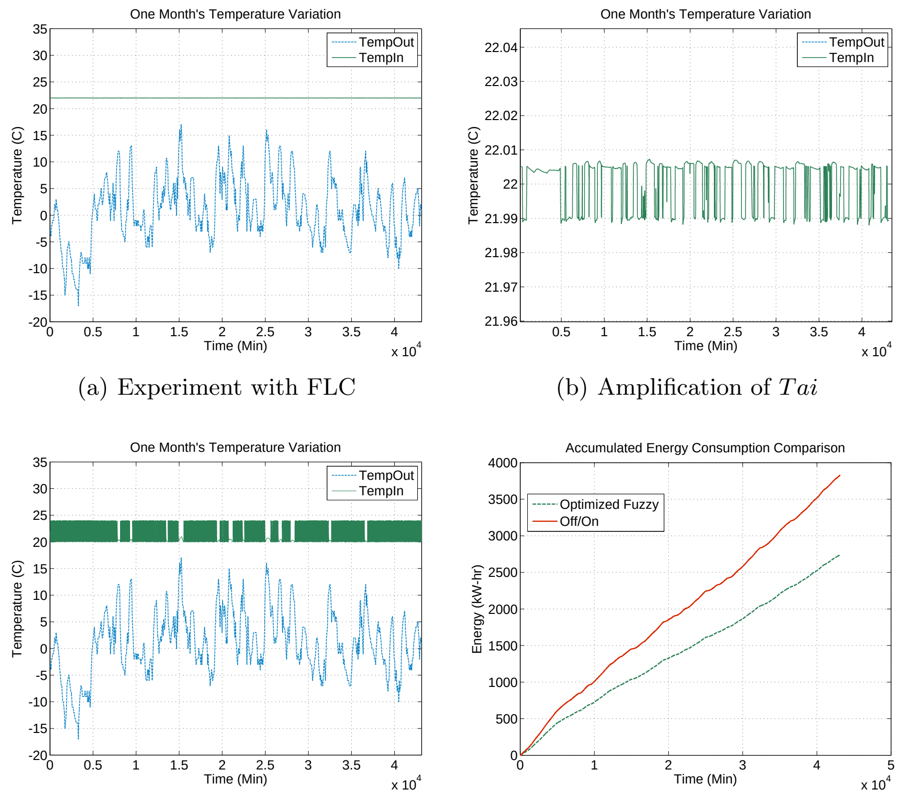
5 System Design and Optimization

Based on the aforementioned model and technique, in this section we discuss the system design and the optimization of the fuzzy system. At every certain time interval, the thermal sensors of the building can record indoor and outdoor temperatures and sent them as inputs to the fuzzy controller. According to the MFs and rules of the fuzzy controller, after the fuzzifier-inference-defuzzifier process the physical heating appliance in the building will be notified a magnitude of heating power. Because the MFs defined empirically can not perform very well, therefore optimizing the fuzzy controller is a must step and this is the target of the artificial immune system, which in this application is a meta-heuristic algorithm named CLONALG. For the reason that the variation of outdoor temperature is continuous and rather slow, we can capitalize on a specific sinusoidal curve to simulate one day's outdoor temperature variation, and use CLONALG to tune fuzzy controller to make good decisions for general real-time weather situations.

Now we move on to this optimization problem formalization. Assume that there are m input variables $[x_1, x_2, ..., x_m]$ and one output variable y. The total number of fuzzy sets N is calculated as follows: $N = \sum_{i=1}^{m} n_i + n_o$, where m is the number of input variables, n_i and n_o are the number of fuzzy sets for ith linguistic input variable and the linguistic output variable. A set P with size of $2N$ contains the peak location and deviation of every fuzzy set, that is: $P = [\boldsymbol{\mu}_{in}, \boldsymbol{\sigma}_{in}, \boldsymbol{\mu}_{out}, \boldsymbol{\sigma}_{out}]$, where $\boldsymbol{\mu}_{in} = [\mu_1^1, \mu_2^1, ..., \mu_{n_1}^1, ..., \mu_{n_i}^i]$, $\boldsymbol{\sigma}_{in} = [\sigma_1^1, \sigma_2^1, ..., \sigma_{n_1}^1, ..., \sigma_{n_i}^i]$, $\boldsymbol{\mu}_{out} = [\mu_1^o, ..., \mu_{n_o}^o]$, and $\boldsymbol{\sigma}_{out} = [\sigma_1^o, ..., \sigma_{n_o}^o]$, for all $i = 1, 2, ..., m$. The objective of the method is to minimize the difference between the inference output y and the desired output y^*, in our case are controlled Q_p and desired Q_p separately, with respect to P: $C = \min_P (y - y^*)^2$, where: $y = f(x_1, x_2, ..., x_m, P)$, and $y^* = f(x_1, x_2, ..., x_m)$. We can see that the objective function C depends not only on P but also the inputs. In order to eliminate the dependence of the inputs, we use the Root Mean Square Error (RMSE), such that: $RMSE(y) = \sqrt{E((y_t - y_t^*)^2)} = \sqrt{\frac{\sum_{t=1}^{T} (y_t - y_t^*)^2}{T}}$, where T is the number of points of the whole trajectory. Therefore the objective function becomes: $C = \min_P \left[\alpha \sqrt{\frac{\sum_{t=1}^{T} (y_t - y_t^*)^2}{T}} \right]$. All else being known, at a time t indoor temperature only depends on the output power of the heating system (we can see this in Equation (6)). Therefore at every time t, indoor temperature is a function of the output power of the heating system, recorded as: $T_{ai}^t = g^t(Q_p^t)$. Moreover, because $g^t(\cdot)$ is linearly monotonically increasing, the final objective function can be expressed as follows: $C = \min_P \left[\alpha \sqrt{\frac{\sum_{t=1}^{T} (g^t(y_t) - g^t(y_t^*))^2}{T}} \right]$. Hence, after the minimization process, the FLC with fuzzy parameters in P is optimized.

6 Experiments

We first empirically pick μ and σ for all MFs of input and output variables. Then these parameters are optimized by CLONALG. Due to CLONALG can not guarantee to obtain optimal values, we run CLONALG for 30 times and take their mean values as near-optimal parameters for the fuzzy controller: $\boldsymbol{\mu}_{in} = [0, -0.4, 0, 0, -0.54, 0]$, $\boldsymbol{\sigma}_{in} = [-0.61, 0.1, 0.508, -6.952, 5.333, 6.426]$, $\boldsymbol{\mu}_{out} = [22, 18, 22]$, and $\boldsymbol{\sigma}_{out} = [10.89, 1.889, 26.24]$. In Figure 2(a), actual recorded weather data obtained from EERE [13] is used as the outdoor air temperature, which is depicted by a dashed blue line. From the simulation result, it can be found that during this period, the indoor temperature, which is delineated by a green line, is able to be kept at $22°C$. Even during the first three days' extremely cold weather, the indoor temperature is retained at the setpoint. Figure 2(b) shows the amplification of the room temperature, and one can see that the variation of



(a) Experiment with FLC

(b) Amplification of Tai

(c) Experiment with On/Off

(d) Energy Comparison

Fig. 2. Experimental Results

this temperature is almost within $\pm 0.01°C$. Moreover, the simulation result with On/Off control is described in Figure 2(c). For this control method, the heating system turns on when the room temperature is below $20°C$, while it turns off when above $24°C$. In order to keep a comfort temperature, the heating system has to turn on and off frequently, which will jeopardize the physical system and reduce its service life. Finally, the accumulated energy consumption comparison between the optimized FLC and the On/Off control is shown in Figure 2(d). We can see that compared with the On/Off control which uses 3830 $kW \cdot hr$ in total, the optimized FLC uses 2742 $kW \cdot hr$ in total, so that it consumes 1088 $kW \cdot hr$ less energy.

7 Conclusion

This paper has presented a fuzzy logic controller optimized by an artificial immune system algorithm to keep thermal comfort while consuming less energy in residential buildings. The experimental results show that by employing this controller, the indoor temperature can be more stable and thus more comfortable than the classical On/Off control and consumes less energy. However, the work conducted here is still a preliminary step towards a completely autonomous HVAC system. In future work, the comparison with other optimization algorithms like PSO will be made. Furthermore, other systems such as a lighting system and a ventilation system, will be taken into account together. Certainly this is also a good application for multi-agent paradigm. Based on the multi-agent framework, agent-to-agent communication, cooperation and coordination can be employed to provide a more comfortable residential environment and consume less energy.

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