

ARTIFICIAL IMMUNE SYSTEM ARCHITECTURE TO MAINTAIN THE THERMAL COMFORT

Borsu Srinivas

Student(M.Tech) , Mechanical Dep
Gokul group of institutions
Visakhapatnam, India

Vommi Pradeep Kumar

ASSOC PROFF, Mechanical Dept
Gokul group of institutions
Visakhapatnam, India

Abstract— Energy management and building comfort are the major tasks for development of information technology. Maximum percentage will be spend by people to the comfort. Hence it is not surprising that they constantly seek to improve comfort in their living spaces. This paper presents an intelligent control system based on artificial immune system architecture to maintain the thermal comfort while reducing energy consumption. Specifically, a residential building is regarded as a human body and a comfortable thermal environment means the healthy state of body. Whenever outside factors disturb this state, which is analogous to the intrusion of pathogens, the immune system will work automatically to eliminate them and therefore to keep the proper state of the body. The experimental results show the advantages of our system comparing with two widely used baseline approaches: two-position control and PI control. **Keywords**— Artificial Immune System; Thermal Comfort.

I. INTRODUCTION

Nowadays most HVAC (Heating, Ventilation and Air Conditioning) systems for residential buildings employ a singlezone, two-position control system which has been simplistic. 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. Corresponding to the increasing demands for environment, energy, and productivity, advanced methods are applied for improving thermal conditions in residential buildings thanks to the dramatically rapid development of information and artificial intelligence technologies. Widespread utilization of personal computers, low cost sensors and actuators, and advanced network technologies make the intelligent control more easily come true. Certainly, this kind of control system is a classic example of Cyber-Physical Systems (CPS), which are integrations of computation with physical processes, where

embedded computers and networks monitor, control and affect the physical processes and vice versa .

[1].Almost all CPS applications are complex and distributed, which call for a novel design and control architecture. The human immune system, that is remarkably efficient to protect human beings against an amazing set of extraneous attacks, offers an extraordinarily suitable option. This system is a complex of cells, molecules and organs, whose complexity is comparable to that of the brain, so makes it sufficient to deal with complex problems. Additionally its distributed property makes it appropriate to cope with CPS applications. Indeed, the cells of the immune system are distributed all over the body and are not subject to any centralized control. In this work, based on the artificial immune system (AIS) theory [2], [3] and its advantageous properties, a building is considered as a human being with a healthy immune system. The outside air temperature and other factors, which will cause the change of comfortable state of the building, are analogous to pathogens (the infectious foreign elements). When a pathogen enters the body, the immune system can recognize it and then eliminate it by immune response to keep the proper state of the body. The objective of this work is to design such an artificial immune system to keep the inside air temperature comfortable while reducing energy consumption.

The contribution of this work is threefold:

- An AIS architecture for intelligent thermal control of residential buildings is proposed, based on which it is more appropriate to build a CPS.
- An adaptive reward function to update the affinities between antibodies and antigens is designed.
- The AIS approach is compared with two widely used baseline control methods, namely two-position control and PI control and their experimental results are analysed.

The rest of this paper is organized as follows. Section 2 overviews related work. Section 3 describes the mathematical building thermal model. Section 4 presents an artificial immune system architecture which is used to control the heating system of the building. Section 5 provides the simulation design. Experimental results and analysis are given in section 6. Finally, we conclude in section 7.

II. RELATED WORK

Many techniques have been used for controlling thermal comfort in buildings, including fuzzy systems, predictive control, artificial neural networks, etc. A fuzzy logic and on-line learning system is proposed in [4], which is capable of adapting to thermal preferences defined by occupants. The comfort level is measured by aggregating several thermal parameters into one single thermal index, which is utilized in the fuzzy rules. Although the system adopts ubiquitous nodes to form a wireless sensor network, it is monitored and controlled by a centralized platform. The authors of [5] presents a hierarchical predictive control system in which the upper layer is dedicated to optimize the indoor air temperature references while the lower layer follows these references by varying the system fan-coil through PID controllers. In a certain environment, the predictive control system may perform well based on the prediction model built in advance, but it is difficult to handle a changing environment and sometimes it is very expensive to build such a model. An on-line artificial neural network controller, which consists of a thermal control logic framework with four thermal control logics (two predictive and two adaptive respectively) and a system hardware framework, is developed and applied in [6] to create more comfortable thermal environments in residential buildings and optimize energy consumption by reducing temperature overshoot and undershoot phenomena in an air conditioning system. However, to fully implement a standard neural network architecture would require lots of computational resources.

Recently, inspired by immunology, an emerging metaheuristic method called artificial immune system (AIS) [2], [3], [7] has been developed and applied as a new branch of computational intelligence to a variety of theoretical research, such as function optimization [8], [9], [10], [11] and classification [12], [13], [14]. With its gradually maturing, it has been applied to more complex engineering applications. In [15], [16], [17], [18], [19], [20], artificial immune system is employed to control robots, while in [21], [22] and in [23], [24] AIS is used to deal with computer security and anomaly detection problems separately. Although much work has been done in many scientific and technological fields and has proven its success, little attempt is undertaken in residential building science and technology, which demonstrates the significance of our work.

III. BUILDING THERMAL MODEL

The general system design is depicted in Figure 1. A heating system perceives states (including indoor and

outdoor temperature) of the building environment and according to the decisions made by AIS control system, the heating system can perform specific actions (heating the building in a certain power) to the environment. In this section, we mainly concentrate on the thermal model of the building environment. 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.[25], the heat balance of a building can be expressed as

where ϕ_h is the heat supplied by all internal heat sources; ϕ_s is the heat gained by solar radiation; ϕ_t is

$$\phi_h(t) + \phi_s(t) = \phi_t(t) + \phi_c(t) \quad (1)$$

the heat loss through external contact; ϕ_c is the heat retained by the building. Before deriving state-space equations of the building, two definitions should be mentioned:

$$\phi = A \times U \times (T_1 - T_2) \quad (2)$$

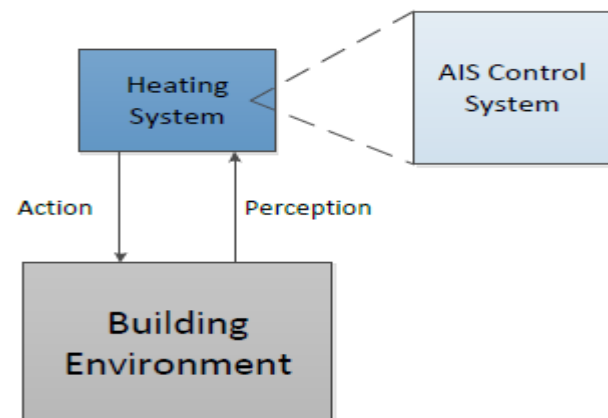


Fig. 1: General system design and its context

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.

$$C = \frac{\Delta Q}{\Delta T} \quad (3)$$

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 can be expressed by Equations (4) - (8):

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

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

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

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

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

In above equations, the inputs are:

Qe heat gained by using electrical equipments,
 Qs solar radiation through glazing,
 Tao outside air temperature,
 Tai inside air temperature,
 U thermal transmittance,
 C thermal capacitance,
 p fraction of solar radiation entering floor. and the output is: Qp heat supplied by the heating system,
 Above equations can be stacked using the state-space notation:

$$\dot{x} = Ax + Bu \quad (9)$$

where \dot{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}), A, B are matrices of coefficients, x is a vector of states and u is a vector including Q_p, Q_e, Q_s and T_{ao} . 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 [26].

IV. ARTIFICIAL IMMUNE SYSTEM ARCHITECTURE

The human immune system is a complex of cells, molecules and organs that represents an identification mechanism capable of perceiving and combating dysfunction from our own cells (infectious self) and the action of exogenous infectious micro-organisms (infectious nonself) [2]. There are two interrelated systems by which the body identifies foreign material: the innate immune system and the adaptive immune system. The innate immune system exists with one's birth, which is not interesting for us. This article is largely concerned with the adaptive immune system.

Recent studies on immunology have clarified that each antibody has also its antigen determinant part called idiotope, as shown in Figure 2, which means that an antibody can not only recognize antigens, but also other antibodies if its paratopes can match their idiotopes. This self-organizing property enables the immune system to maintain an effective dynamic set of antibodies in order to deal with antigens. Based on this fact, N. K. Jerne proposed a model called Jerne's Idiotypic Network [27]. The network is defined by stimulation/suppression links between antibodies and the degrees of correlation are measured by affinities.

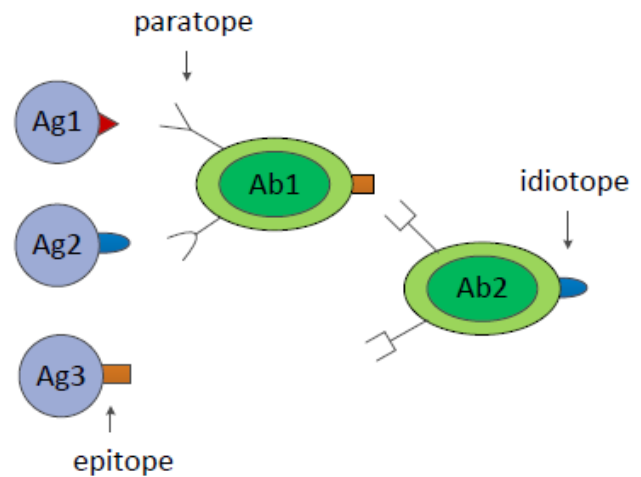


Fig. 2: Antibody and Antigen Recognition and Binding Mechanism

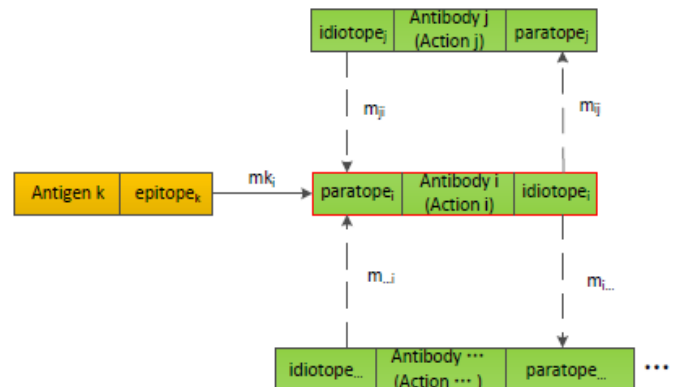


Fig. 3: Idiotypic Network

Jerne's Idiotypic Network has been widely used and our immune-system-based architecture is an interpretation of Jerne's theory. The main principle of this architecture is that each antibody represents a possible action of the system, its paratopes mean the preconditions under which the action is stimulated, and its idiotopes interlink other antibodies as a network to memorize some knowledge (the degree of the linkage is expressed by affinity). In other words, it is an arbitration mechanism that allows the choice of an action according to antigens, knowledge learnt and the continuous computation of affinities among these antibodies.

An example of the idiotypic network is presented in Figure 3. In this figure, the direction of arrows indicates stimulation while the reverse direction of arrows indicates suppression. In addition, the solid arrow means stimulation/suppression between antibody and antigen while the dashed arrows represent stimulation/suppression among antibodies (the affinity is denoted by m). Therefore antibody i is stimulated by antigen k , antibody j and other antibodies, while antibody j and other antibodies are suppressed by antibody i . The population of antibody is expressed by the concept of concentration. In [28], authors propose the Equations (10) and (11) to compute the concentration of the antibody i , denoted by a_i . In Equation (10), the first and second part of the right hand side denote the stimulation and suppression from other antibodies respectively, where m_{ji} and m_{ik} are affinity values between 0 and 1. The third term indicates the stimulation directly from an antigen and the fourth term denotes the antibody's natural death. Equation (11) aims at normalizing the concentration between 0 and 1. For a given antigen, the probability of selecting an antibody increases with its current

$$A = \begin{bmatrix} \frac{-A_{w1}}{C_{w1}} [U_{w11} + U_{w01}] & 0 & 0 & 0 & 0 & \frac{A_{w1}U_{w01}}{C_{w1}} \\ 0 & \frac{-A_{w2}}{C_{w2}} [U_{w12} + U_{w02}] & 0 & 0 & 0 & \frac{A_{w2}U_{w02}}{C_{w2}} \\ 0 & 0 & \frac{-A_f U_f}{C_f} & 0 & 0 & \frac{A_f U_f}{C_f} \\ 0 & 0 & 0 & \frac{-A_c U_c}{C_c} & 0 & \frac{A_c U_c}{C_c} \\ 0 & 0 & 0 & 0 & \frac{-A_{ip} U_{ip}}{C_{ip}} & \frac{A_{ip} U_{ip}}{C_{ip}} \\ \frac{A_{w1}U_{w01}}{C_a} & \frac{A_{w2}U_{w02}}{C_a} & \frac{A_f U_f}{C_a} & \frac{A_c U_c}{C_a} & \frac{A_{ip} U_{ip}}{C_a} & \frac{-A_g U_g - U_a}{C_a} \dots \dots \frac{-A_{ip} U_{ip}}{C_a} \end{bmatrix}$$

$$B = \begin{bmatrix} 0 & 0 & 0 & \frac{A_{w1}U_{w01}}{C_{w1}} \\ 0 & 0 & 0 & \frac{A_{w2}U_{w02}}{C_{w2}} \\ 0 & 0 & \frac{p}{C_f} & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & \frac{(1-p)}{C_{ip}} & 0 \\ \frac{1}{C_a} & \frac{1}{C_a} & 0 & \frac{A_g U_g + U_a}{C_a} \end{bmatrix}$$

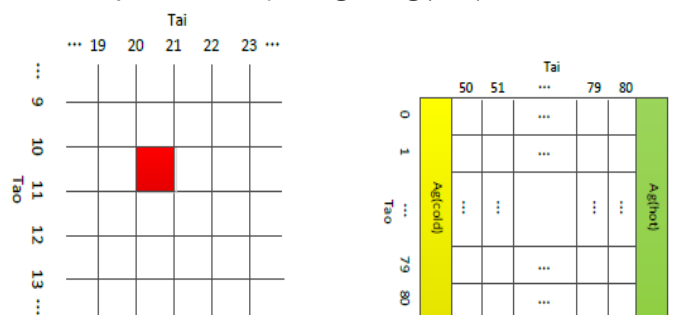
concentration.

$$\frac{da_i(t)}{dt} = \left(\alpha \frac{1}{N} \sum_{j=1}^N m_{ji} a_j(t) - \alpha \frac{1}{M} \sum_{k=1}^M m_{ik} a_k(t) + \beta m_i - k_i \right) a_i(t) \tag{10}$$

$$a_i(t+1) = \frac{1}{1 + \exp(0.5 - a_i(t))} \tag{11}$$

By taking advantage of the idiotypic network as a arbitration mechanism or intelligent decision-making mechanism, the heating system of buildings is able to maintain the indoor thermal comfort regardless of the outside weather condition. That is to say, for specific inside air temperature and outside air temperature, the heating system can select an optimized magnitude of power by applying idiotypic network to not only make room temperature comfortable but also consume less

energy. To achieve these two goals, antigens and antibodies for this system must be defined properly and the idiotypic network need to be constructed. Additionally, a critique mechanism that evaluates the effect of antibodies must be designed carefully. The rest of this section depicts how they are done in detail. Firstly we treat the combination of present inside air temperature and outside air temperature as antigens, denoted by $Ag(tai; tao)$. The temperature values are real. Because the idiotypic network can only exploit discrete values, we need to discretize the space spanned by these temperatures. For example, assuming that tai and tao range from 0_F to 90_F and from 0_F to 80_F respectively, and that every space dimension is discretized by regular intervals of 1 degree, $Ag(20; 10)$ indicates all possible inside air temperature in [20.0, 21.0) and all possible outside air temperature in [10.0, 11.0), as shown in Figure 4 (a). The total number of antigen is $91 * 81 = 7371$. This number can be further reduced by introducing some knowledge. For example, when the room temperature is too cold (when $tai < 50_F$ for instance), the same decision is likely to be carried out irrespective of the outside temperature. This situation can be represented by one single antigen $Ag(cold)$. Another decision could be carried out when the room temperature is too hot (when $tai > 80_F$ for instance), irrespective of the outside temperature. This situation can be represented by antigen $Ag(hot)$. In this case,



a) The Red Part is $Ag(20, 10)$ (b) Reducing Antigen Number

Fig. 4: Antigen Definition

2513 (see Figure 4 (b)). The second step consists in defining antibodies. In this system, we assume that the total number of antibodies is N . When N is large, the idiotypic network constructed will become complex, so the arbitration process will take more time, and vice versa. Each antibody contains information including ID, concentration, action, natural death rate and affinities with others. The action of each antibody represents the magnitude of the heating system power. Once the action of an antibody has been selected, how to evaluate its effect and how to update the affinity between the antibody and the antigen? We can do these by Equations (12) and (13) separately

In Equation (12), we use a reward function to evaluate the antibody's action: after the heating system carries out an action, the inside air temperature is captured and the less difference with the setpoint, the more reward it gains. The affinity between the antigen and the antibody is updated proportionally to the reward. For the reason that an antigen actually represents different combinations of real inside and outside air temperatures as we mentioned above, the mean value of the rewards obtained, which is calculated in an adapted mechanism, is used to indicate the affinity, as expressed in Equation (13). The affinities between antibodies could be updated by a reinforcement signal to deal with some special situation, i.e. during the high pricing period of using electricity or emergency. But in order to simplify the problem, we assume the affinities between antibodies are constant.

$$reward = \frac{1}{1 + abs(T_{ai} - setpoint)} \quad (12)$$

$$m_i(t + 1) = \frac{reward}{n} + \frac{(n - 1)m_i(t)}{n} \quad (13)$$

V. SIMULATION DESIGN

The differential equations representing the thermal model within a building have been implemented under a Matlab / Simulink environment [29]. Furthermore, for the purpose of taking advantages of multi-agent system, one of the most widely used multi-agent development framework named JADE has been employed. In our application, the heating system is regarded as an intelligent decision-making agent. However, Simulink models can not communicate directly with Java programs. In order to deal with this difficulty, a middleware named MACSimJX [30] has been utilized. It acts as an agent in JADE environment and provides services of getting and sending data from/to Simulink models. Moreover, actual recorded weather data for Golden, CO in January 1999 (totally 744 hours) obtained from EERE [31] is used as the outside air temperature.

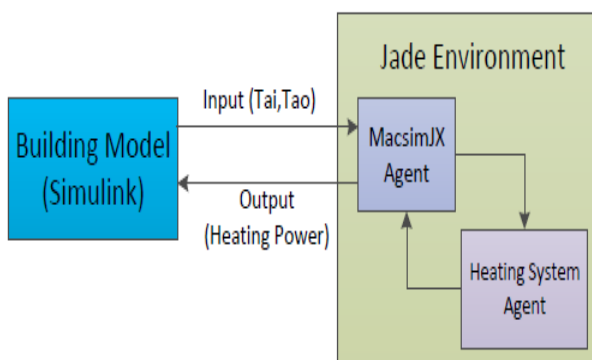


Fig. 5: Interface of the System

The interface of the system is shown in Figure 5. In this figure, building thermal model is simulated in Simulink environment. At every certain time intervals, the thermal sensors of the building can record the present indoor and outdoor temperature and packaging them as an input send to MacsimJX Agent. This agent then repackages it as an antigen and sends it to Heating System Agent, which contains the idiotypic network and can operate the immune response mentioned above. After the arbitration process, the heating system in Simulink environment will be notified with a magnitude of power.

As discussed before, the decision-making architecture of the heating system is an idiotypic network which is composed of defined antibodies. When the Heating System Agent performs, it feeds an antigen to the idiotypic network. Then this network inform all antibodies the newcome antigen. According to Equation (10) and (11), these antibodies update their concentrations and a winner is selected by a greedy or roulette wheel selection strategy based on their present concentrations. Once chosen, the winner can perform its defined action to the environment and will be rewarded or penalized by Equation (12). Its affinity with the antigen will be updated by Equation (13).

VI. EXPERIMENTS

The property values of our building model are listed in Table 1, which can be obtained from ASHRAE Handbook[26]. In addition, the general experimental parameters and the antibody configuration are listed in Table 2 and Table 3 separately. In Table 2, NorCon represents the initial normalized concentration of antibodies and other parameters are explained in Equation (10). In Table 3, thirteen antibodies are defined and each antibody has its concentration. The action value of antibody indicates the output power of the heating system. By implementing AIS, through thirty episodes' training, a good experimental result can be obtained (see Figure 6). This figure shows the variations of the outside air temperature (red line) and the inside air temperature (blue line) of Golden, CO in January 1999 (totally 744 hours). From the figure, after 5 days' very cold weather, the inside air temperature is maintained at 72_F almost steadily. This is because the idiotypic network is organized with different antibodies and after being stimulated by the antigens a number of times, it can evolve into a good decision-making structure.

TABLE I: Property Values of Building Components [26]

Parameters	Area (ft ²)	U (W/ft ² ·° F)	U _i	U _o	C (BTU/° F)
Wall 1 (w ₁)	700	-	0.056	2.60	1346.8
Wall 2 (w ₂)	200	-	0.056	2.60	1128.6
Floor (f)	1400	0.14	-	-	3300
Ceiling (c)	1400	0.08	-	-	2700
Partitions(ip)	1450	0.06	-	-	1200

TABLE II: General Experimental Parameters

Parameter	α	β	NorCon	Death Rate	m _{ij}	m _i
Value	0.8	0.2	0.5	0.1	0.5	1.0

TABLE III: Antibody Configuration

Antibody ID	0	1	2	3	4	5	6
Action Value	0	300	600	900	1200	1500	1800
Antibody ID	7	8	9	10	11	12	
Action Value	2100	2400	2700	3000	3300	3500	

The sequential decisions of this episode is shown in Figure 7. It can be found that due to the low outside air temperature the heating system employed the maximum power of 3500 BTU/hour with more opportunity during the first 5 days, and after that the choices of power from 1200 BTU/hour to 2100 BTU/hour are taken during most part of this episode which means these choices of power are suitable for maintaining the room temperature at the setpoint (72_F) in the weather condition. The system turned off only 7 times and the total energy consumed during this episode is 1,464,000 BTU.

Figure 8 and Figure 9 reveal experimental results of two-position control and PI control respectively. For two-position control, the output power is 3500 BTU/hour when the heating system turns on, otherwise it equals 0. In order to keep a comfort temperature, the heating system has to turn on and off frequently, which may damage the physical system. The total energy consumed is 1,491,000 BTU. For PI control (Proportional = 1000, Integral = 100), it can make rooms most comfortable by managing the temperature at 72_F. However, the maximum power has to be at least 7000 BTU/hour. If we use the same maximum power of 3500 BTU/hour as artificial immune system and two-position control, a huge overshoot of inside air temperature (about 90_F) will occur. For this reason, it requires physical equipments with much greater output power and therefore costs more energy (1,593,000 BTU).

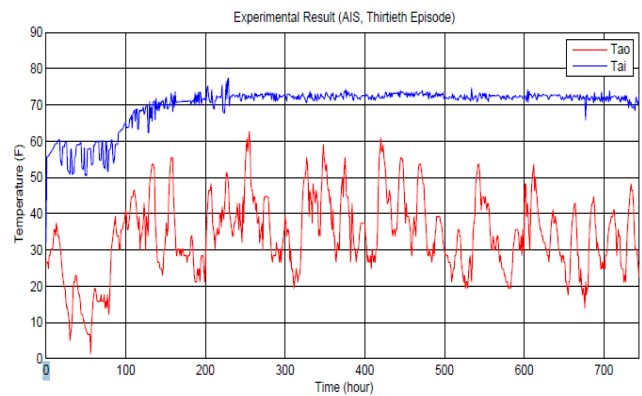


Fig. 6: Experimental Result (AIS, Thirtieth Episode)

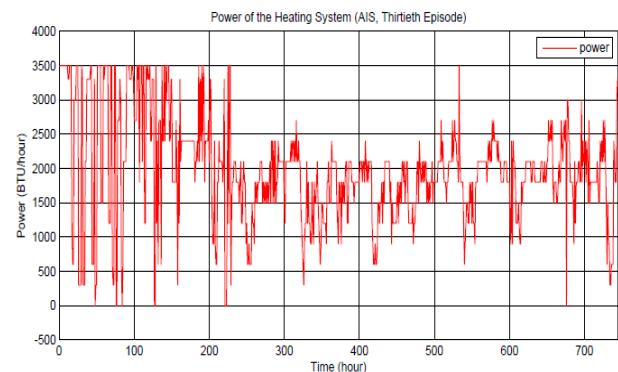


Fig. 7: Sequential Decisions (AIS, Thirtieth Episode)

Based on the simulation results, the immune system has successfully achieved the reduction of energy consumption (1.81% less than two-position control and 8.10% less than PI control). Besides, by comparing with two-position control, it can definitely prolong equipments' service life. Although it seems that PI control can reach a more smooth temperature curve, it has to pay more price. When it requires strict thermal control or in some special situations, PI control may be considered as more suitable. But when discussing in the residential scope and considering its advantage of distributed capability, the immune system prevails

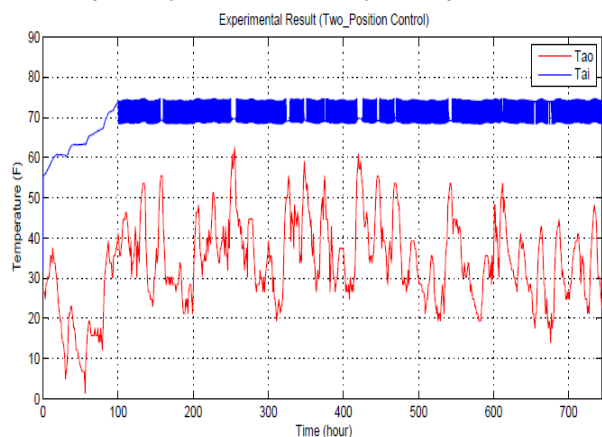


Fig. 8: Experimental Result (Two Position Control)

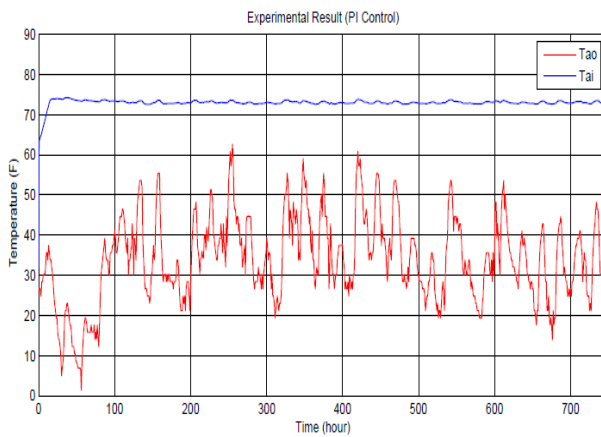


Fig. 9: Experimental Result (PI Control)

CONCLUSION

This paper has presented an intelligent control system based on artificial immune system architecture to keep thermal comfort while consuming less energy in residential buildings. A mathematical thermal model of a building was developed in the Simulink/Matlab environment. Additionally the intelligent system was developed in a Java based multi-agent system framework named JADE, and a middleware software, MACSimJX, was utilized to connect the system and the simulation environment. The experimental results show that by employing this intelligent system, the inside air temperature can be more stable and thus more comfortable than the two-position control and it consumes less energy than PI control. However, the work here is a preliminary step: only thermal systems are considered, making the current use of multi-agent systems not as efficient as they could be if other energy systems are not taken into account. Moreover, the presented idiotypic networks can only exploit discrete values, which may be inconvenient when dealing with practical problems. In future work, other components, such as lighting systems and ventilation systems, can be considered together. Based on the multi-agent framework, agent-to-agent communication, cooperation and coordination can be achieved. And function approximators will be utilized to solve problems with continuous decision.

REFERENCES

- [1] E. A. Lee, "Cyber-physical systems-are computing foundations adequate," in Position Paper for NSF Workshop On Cyber-Physical Systems: Research Motivation, Techniques and Roadmap, vol. 2. Citeseer, 2006.
- [2] L. N. de Castro and F. J. Von Zuben, "Artificial immune systems: Part i-basic theory and applications," Universidade Estadual de Campinas, Dezembro de, Tech. Rep, 1999.
- [3] L. N. De Castro and F. J. Von Zuben, "Artificial immune systems: Part ii-a survey of applications," FEEC/Univ. Campinas, Campinas, Brazil, 2000.
- [4] P. Bermejo, L. Redondo, L. de la Ossa, D. Rodríguez, J. Flores, C. Urea, J. A. Gmez, and J. M. Puerta, "Design and simulation of a thermal comfort adaptive system based on fuzzy logic and on-line learning," *Energy and Buildings*, vol. 49, no. 0, pp. 367 – 379, 2012.
- [5] M. Castilla, J. Alvarez, M. Berenguel, F. Rodríguez, J. Guzmán, and M. Pérez, "A comparison of thermal comfort predictive control strategies," *Energy and Buildings*, vol. 43, no. 10, pp. 2737 – 2746, 2011.
- [6] J. W. Moon and J.-J. Kim, "Ann-based thermal control models for residential buildings," *Building and Environment*, vol. 45, no. 7, pp.1612 – 1625, 2010.
- [7] J. Al-Enezi, M. Abbod, and S. Alsharhan, "Artificial immune systemsmodels, algorithms and applications," *International Journal*, 2010.
- [8] K. Tan, C. Goh, A. Mamun, and E. Ei, "An evolutionary artificial immune system for multi-objective optimization," *European Journal of Operational Research*, vol. 187, no. 2, pp. 371 – 392, 2008.
- [9] S. Omkar, R. Khandelwal, S. Yathindra, G. N. Naik, and S. Gopalakrishnan, "Artificial immune system for multi-objective design optimization of composite structures," *Engineering Applications of Artificial Intelligence*, vol. 21, no. 8, pp. 1416 – 1429, 2008.
- [10] M. Gong, L. Jiao, and X. Zhang, "A population-based artificial immune system for numerical optimization," *Neurocomputing*, vol. 72, no. 1C3, pp. 149 – 161, 2008, *machine Learning for Signal Processing (MLSP 2006) / Life System Modelling, Simulation, and Bio-inspired Computing (LSMS 2007)*.
- [11] J. Gao and J. Wang, "Wbmoais: A novel artificial immune system for multiobjective optimization," *Computers & Operations Research*, vol. 37, no. 1, pp. 50 – 61, 2010.
- [12] J. Timmis, M. Neal, and J. Hunt, "An artificial immune system for data analysis," *Biosystems*, vol. 55, no. 1C3, pp. 143 – 150, 2000.
- [13] Secker, A. A. Freitas, and J. Timmis, "Aisec: an artificial immune system for e-mail classification," in *Evolutionary Computation, 2003. CEC'03. The 2003 Congress on*, vol. 1. IEEE, 2003, pp. 131–138.

- [14] P. van der Putten, L. Meng, and J. Kok, "Profiling novel classification algorithms artificial immune systems," in Cybernetic Intelligent Systems, 2008. CIS 2008. 7th IEEE International Conference on. IEEE, 2008, pp. 1–6.
- [15] V. Hilaire, A. Koukam, and S. Rodriguez, "An adaptative agent architecture for holonic multi-agent systems," ACM Trans. Auton. Adapt. Syst., vol. 3, no. 1, pp. 2:1–2:24, Mar. 2008.
- [16] Y. Watanabe, A. Ishiguro, and Y. Uchikawa, "Decentralized behaviour arbitration mechanism for autonomous mobile robot using immune network," in Artificial Immune Systems and Their Applications, D. Dasgupta, Ed. Springer Berlin Heidelberg, 1999, pp. 187–209.
- [17] W. W. Godfrey and S. B. Nair, "An immune system based multi-robot mobile agent network," pp. 424–433, 2008.
- [18] S. Ozcelik and S. Sukumaran, "Implementation of an artificial immune system on a mobile robot," Procedia Computer Science, vol. 6, no. 0, pp. 317 – 322, 2011, complex adaptive systems.
- [19] Whitbrook, U. Aickelin, and J. Garibaldi, "An id tecture for mobile robots," in Artificial Immune Systems. Springer, 2008, pp. 266–278.
- [20] Ko, H. Y. Lau, and N. M. Lee, "Ais based distributed wireless sensor network for mobile search and rescue robot tracking," in Artificial Immune Systems. Springer, 2008, pp. 399–411.
- [21] D. Dal, S. Abraham, A. Abraham, S. Sanyal, and M. Sanglikar, "Evolution induced secondary immunity: An artificial immune system based intrusion detection system," in Computer Information Systems and Industrial Management Applications, 2008. CISIM'08. 7th. IEEE, 2008, pp. 65–70.