A Neuro-Fuzzy Sugeno-Style HVAC Control System for Balancing Thermal Comfort and Energy Consumption

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Abstract: Thermal comfort is an environmental state, in which humans enjoy calefactory conditions while being indoor and wearing a normal amount of clothing. To achieve this, the indoor environment's temperature should be adjusted in accordance with the temperature variations of the outdoor space, taking into account the resulting energy costs. We studied this problem by designing a neuro-fuzzy HVAC control system that provides a higher indoor environment comfort while decreasing the corresponding energy consumption. Our controller utilizes a Sugeno-style fuzzy inference system with two sensory inputs: one for temperature and another for occupants' motion. It outputs a signal that represents the mode of the air conditioner and the compressor speed. Simulation results showed that the air conditioner turns off automatically after 10 minutes of the last detected motion. Furthermore, running the simulations for the energy consumption and resulting costs, both variables were shown to fall in the absence of occupants' motion.

1 INTRODUCTION

'Thermal comfort' describes an environmental state, in which a human individual does not suffer from cold or hot temperatures while being indoor and wearing a normal amount of clothing (Canadian Centre for Occupational Health and Safety, 2017). Such a state is important for peoples' health and is expected to increase their personal satisfaction and work productivity. Moreover, out of practical rationale, it is recommended to set the temperature in winter between 21°C and 23°C while in summer it should be set at warmer temperature to decrease the flowing of heat from outdoors to indoors so as to save energy. These temperature settings have been confirmed to meet the needs of 80% of people and, hence, are recommended by American Society of Heating, Refrigerating, and Air Conditioning Engineers (ASHRAE) (Canadian Centre for Occupational Health and Safety, 2017).

Heating, ventilating, and air conditioning (HVAC) is a control technology that aims at improving indoor environment quality by increasing thermal comfort while decreasing energy consumption (Nowak and Urbaniak, 2016). Traditional approaches to regulate the operations of an HVAC system include the use of 'on-off' and 'Proportional Integral Derivative' (PID) controllers.

On-off controllers are the most intuitive and simplest of control techniques. They regulate the underlying process by adjusting the temperature differential between two set values 'low' and 'high' with respect to the desired room temperature. A control process that underlies the on-off principle leads to a rise of room temperature when the heating signal is on (it falls in case of cooling signal) until it hits the value 'high'. The control signal then turns off and the temperature starts falling (it rises in case of cooling) until it reaches the value 'low'. Though easy to implement, control processes utilizing an on-off controller display large fluctuations of temperature and are incapable to control processes with time delays (Afram and Janabi-Sharifi, 2014).

PID controllers were developed to reduce the impact of fluctuations caused by on-off control processes (Song et al., 2015). They achieve accurate control by utilizing error dynamics related to the controlled variable. Despite their relatively promising results, PID controllers, however, need to be frequently tuned in accordance with the operating conditions. This could be time consuming (Wang et al., 2001). Otherwise, performance of the controller will decrease. Moreover, embedding an auto-tuning com-

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ponent (e.g. the Ziegler-Nichols method (Ziegler and Nichols, 1942)) might be helpful for moderating the time complexity given a realistic modeling of the underlying process (Åström and Hägglund, 1984), (Bi et al., 2000). But it doesn't work in all applications (Salsbury, 2005).

Because of the different influences on the overall quality of indoor environment, an HVAC control system has to interrelate several input variables into another set of outputs (Mirinejad et al., 2012). This requires the system to treat numerous elements of uncertainty. Historically, uncertainty has been dealt with by probability theory. Though powerful, probability theory, however, serves well in modeling situations where the primary source of uncertainty is randomness (Jaynes, 2003). Other sources of uncertainty such as vagueness, similarity, or preference as opposed to ambiguity can be dealt with adequately by emulating human cognitive and decision-making processes. The theory of 'fuzzy logic' provides a natural framework to handle *uncertainty* in a natural way. Here, instead of asking *whether* something is true, we ask *how much* it is true (Keller et al., 2016).

Research on HVAC control systems has correlated the effectiveness of the PID controllers with the naturalness of the fuzzy logic approaches. For example, Mohindru and Sharma found that a fuzzy controller with two input signals, one for error and another denoting the rate of change along with seven membership functions, performed better than a fine-tuned Ziegler-Nichols-style PID controller (Mohindru and Sharma, 2015). This result was supported by other studies that showed the fuzzy logic controllers' ability to adapt to longer time delays (Kobersi et al., 2013), reduce energy consumption (Dash et al., 2012), and/or provide thermal comfort (Collotta et al., 2014).

In the present work, we set out solve the problem of achieving thermal comfort with possibly reduced energy consumption. To this end, we designed a neuro-fuzzy controller that combines neural networks' ability of generalization (Glüge et al., 2010) and the human-like inference within of the fuzzy logic framework (Keller et al., 2016). Combining information from multiple sensory sources has been shown to facilitate human decision making (Hamid et al., 2010) and model's performance (Hamid, 2015). Our controller achieves a higher indoor environment quality by balancing thermal comfort and energy consumption. The underlying model of the proposed controller utilizes a Sugeno-style fuzzy inference system with two sensory inputs: one for temperature and another for motion. It outputs a signal that represents the mode of the air conditioner and the compressor speed for each mode. The testing of the controller showed that the air conditioner of the controlled HVAC system turns off *automatically* 10 minutes after the last detected motion of room occupants. Accordingly, simulations of the cost levels and energy consumption were shown to fall when the room was empty as justified through the absence of occupants' motion.

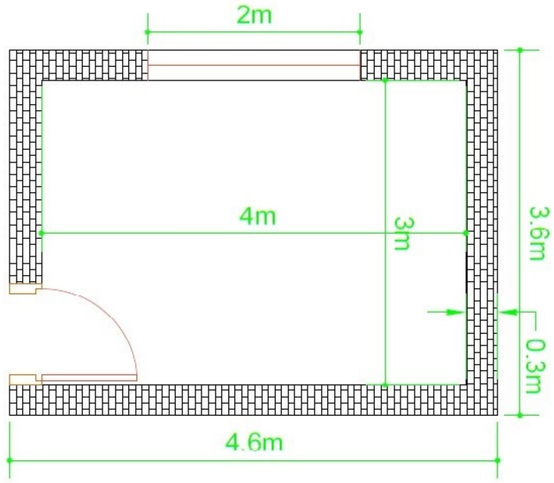

Figure 1: Room geometry.

The remainder of the paper is organised as follows. Section 2 introduces the designed neuro-fuzzy controller and its underlying mathematical model for regulating room temperature. In section 3, we discuss the considered simulation scenarios. Results are presented and discussed in section 4. We finally conclude and portray our plans for future work in section 5.

2 METHODS AND ANALYSIS

2.1 Mathematical Modeling of Indoor Air Temperature

Controlling the temperature of an indoor environment can be affected by various factors including the geometry of the indoor environment as well as the environmental conditions of the corresponding outdoor surroundings. Figure 1 shows the geometric characteristics of the room that served for the control task in our work. The heating and cooling of the room temperature is affected by the efficiency of the air conditioner, the volume of the room, the heat loss and heat gain in winter and summer, respectively. The rate of temperature change of the monitored room can be computed by:

$$\frac{dT_{room}}{dt} = \frac{1}{m_{room-air}.c_{air}} \left[\frac{dQ_{gain}}{dt} - \frac{dQ_{loss}}{dt} \right] \quad (1)$$

where dT_{room}/dt denotes the rate of thermal variation, which is transferred to the room from the air conditioner, in terms of the discrepancy between the rate of energy gain Q_{gain} and that of energy loss Q_{loss} (in joules per seconds). According to Eq. (1), the amount of transferred thermal energy will cool down or heat up the room depending on the constant mass of the air (in kilogram) of the monitored room ($m_{room-air}$) and specific heat capacity (c_{air}) in (joule/kilogram degree). The specific heat capacity of air (c_{air}) in (joule/kilogram degree) for both 20°C and 25°C as initial room temperature is 1005 joule/kilogram degrees. Moreover, the mass of the room's air $m_{room-air}$ depends on air density ρ (in kg/m^3) and the volume V (in m^3) of the room. Hence, the mass of the room's air can be computed as follows.

$$m_{room-air} = \rho . V \tag{2}$$

We chose $\rho = 1.225$ kg/m^3 of the standard atmosphere, which is the value of air density at sea level and at 15°C (McCormick, 1995), (Cavcar, 2000). The volume of the room is 36 m^3. Lastly, the energy loss, that is dQ_{loss}/dt, is computed from

$$\frac{dQ_{loss}}{dt} = \frac{\kappa A(T_{room} - T_{outside})}{D} \tag{3}$$

Here, κ is the thermal conductivity (in Joule/sec/m°C) of the insulation materials to conduct energy transfer. It is 0.72 Joule/sec/m° for common brick, 0.78 Joule/sec/m° for glass window, and 0.8 Joule/sec/m° for concrete roof. The term A in Eq. (3) refers to the area. We considered three areas in our calculations, the area of the window A_{window}, that of the roof A_{roof}, and the area of the wall A_{wall}. Finally, D in Eq. (3) represents the thickness of the common brick, double glazed window, and concrete roof, which is in our case 0.3m, 0.01m, and 0.25m, respectively.

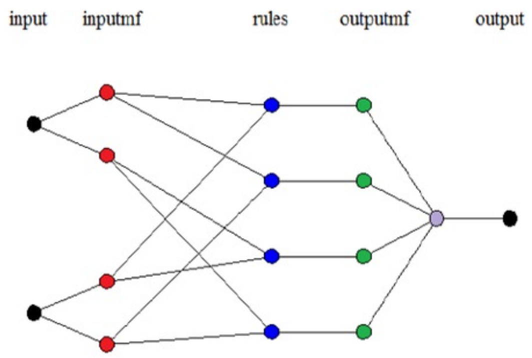

Figure 2: Architecture of the neuro-fuzzy system.

2.2 Modeling the Air Conditioner

Selecting the right size of an air conditioner is crucial for optimizing energy consumption. For example, a bigger sized air conditioner may cool a room faster than a smaller one, but it consumes more energy. On the other hand, choosing the right size of an air conditioner is bedeviled by some factors such as the area and the volume of the room, the number of occupants, the local climate, shading, and the size of windows inside the room. All the same, there is a set of rules that can be used to estimate the proper capacity of an air conditioner. To regulate the room temperature described in Section 2.1, we considered a one ton air conditioner, which corresponds to 3516 Joules/second of energy consumption (Air Conditioning Systems, 2017). The compressor speed for heating and cooling within the air conditioner is not limited to certain values of electricity usage. This implies that the working power of the compressor varies according to the difference between the actual and the desired temperatures (Song et al., 2015). This allows adjusting the compressor to the desired capacity and operating conditions (Engineering 360 Powered by IEEE GlobalSpec, 2017). Thus, the air conditioner will not work with its maximum amount of energy when there is a small amount of differences present between actual temperature of the room and the desired temperature.

2.3 The Neuro-Fuzzy Controller

We modeled the air conditioning using a neuro-fuzzy control system as developed by ANFIS toolbox in Matlab. Figure 2 shows the general architecture of the devised neuro-fuzzy. It consists of five layers with following specifications. The first layer corresponds to input variables, the second layer represents input membership functions (inputmf), the third layer refers to the rule base, the fourth layer is denotes the output membership functions, and the fifth layer refers to the output variable. Importantly, our model utilizes a fuzzy inference system (FIS) with two sensory inputs: one for temperature and another for motion. It then produces an output signal that controls the compressor speed. Specifically, the first input, termed as 'input1', corresponds to the error that results from the discrepancy between the desired and the actual room temperatures. The second input, referred to as 'input2', models the room occupancy, that is, whether or not the sensor detects motion in the room. The output represents the mode of the air conditioner and the compressor speed for each input combination. The error input has three trapezoidal membership func-

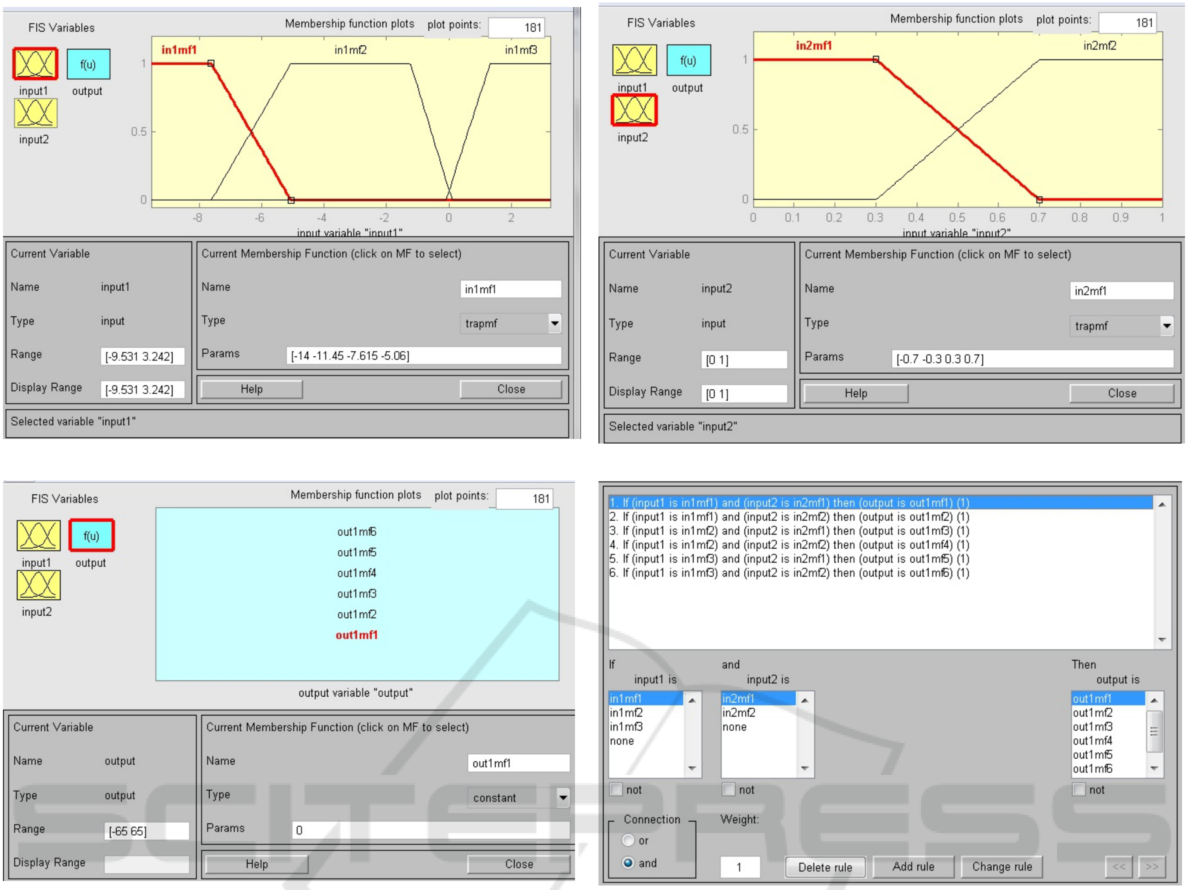

Figure 3: Modeling the Neuro-Fuzzy Controller with Matlab ANFIS toolbox.

tions, the motion input has two trapezoidal membership functions, and the output has six membership functions. We tested the devised FIS with different input combinations, ranging from -9.531°C to 3.242°C for ‘input1’ and from 0 to 1 for ‘input2’ as illustrated in the upper left and upper right plots of Fig. 3, respectively). The range of output membership function lies within the interval [-65, 65] as shown in the bottom left plot of Fig. 3. Finally, the rule base of a Sugeno-style FIS is demonstrated in the bottom right plot of Fig. 3.

2.4 Cost Calculation

Total energy cost was calculated as the product of the amount of energy consumed and the cost for one energy unit. The amount of energy consumed in time unit is computed from

$$\frac{dQ}{dt} = Q.t \tag{4}$$

with Q representing the energy in Joule unit and t referring to time in seconds.

3 SIMULATION SCENARIOS

Once the devised neuro-fuzzy controller is setup, the simulation for regulating room temperature can start. We set our target temperatures at 22°C for winter and 24°C for summer. Our choice of these temperature values was motivated by research results on ‘thermal comfort’ (Caldo, 2015) and international standards along with a sense of practical rationale. A place with relatively high temperature will cause its occupants to feel tired and exhausted, whereas they will become restless and distracted, if the temperature is relatively low. Consequently, the simulation runs with the target temperatures of 22°C for winter and 24° for summer. We used different initial room temperature at the start of the simulation for summer and winter. Temperature variation is generated from the differences between the current and the desired room temperatures. Once the rate of temperature differences are fed into the controller, the system outputs the mode of the air conditioning, which will be selected automatically, and the amount of energy given to the air conditioner

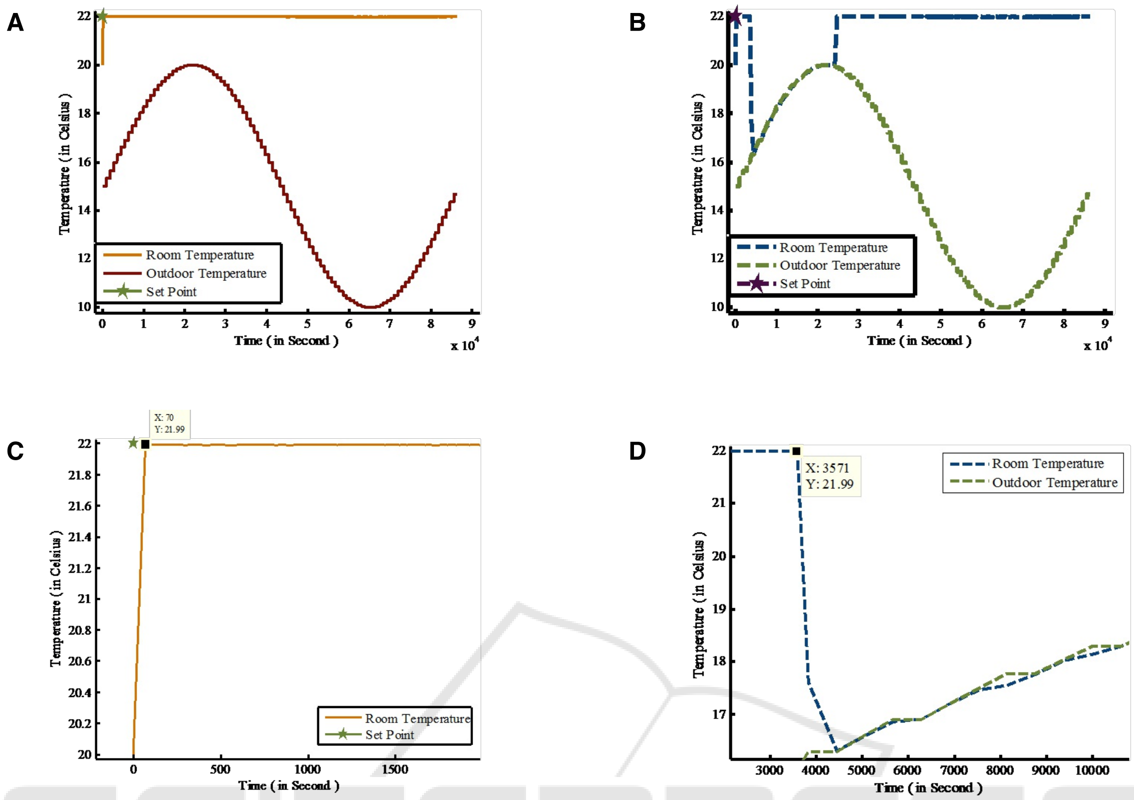

Figure 4: Simulation results. The first column corresponds to the presence of motion, whereas the second simulates the absence of motion. In each column, the rows from up to down show the neuro-fuzzy controller's output response and the controller's speed.

to control the compressor speed. The second input, which represents the signal provided by the motion sensor, detects whether there is moving occupants to ensure that the air conditioner turns on only if there is motion and off 10 minutes after the last observed motion.

4 SIMULATION RESULTS OF THE NEURO-FUZZY CONTROLLER

4.1 In The Presence of Motion

Simulation results of the neuro-fuzzy controller in the presence of motion are shown in the first subplot columns of figures 4 and 5. Subplot **A** of figure 4 represents the indoor temperature change according to the outdoor temperature and the target temperature. The starting indoor temperature is 20°C for simulating the outdoor temperature in winter. The system starts at 08:00 AM and the indoor temperature raised fast by 70 seconds and was brought to around the set point of 22°C as it is shown in subplot **C** of figure 4. This time for reaching the set point will be shorter if the initial indoor temperature is higher or the target temperature is lower. The lower target temperature is easier to achieve since it is closer to the outdoor temperature whenever the system is starting to work. This means that the room temperature is well controlled by the proposed neuro-fuzzy controller. Then the indoor temperature remains relatively steady and keeps around the set point. However, there is a temperature fluctuation which is because of the outdoor temperature reaches to the lowest temperature during this time periods or evening time. As a result of that the conduction of heating flow from indoor to outdoor is increasing but the controller has the capability of regulating room temperature. Therefore, there are some variations due to outdoor temperature during 24 hours or 86400 seconds. Although the proposed intelligent temperature controller is able to rise the indoor temperature back to the set point, there is a small fluctuation occurred which is variant between 21.98 and 21.99.

While providing a comfortable indoor temperature, it is important to consume less energy. The more

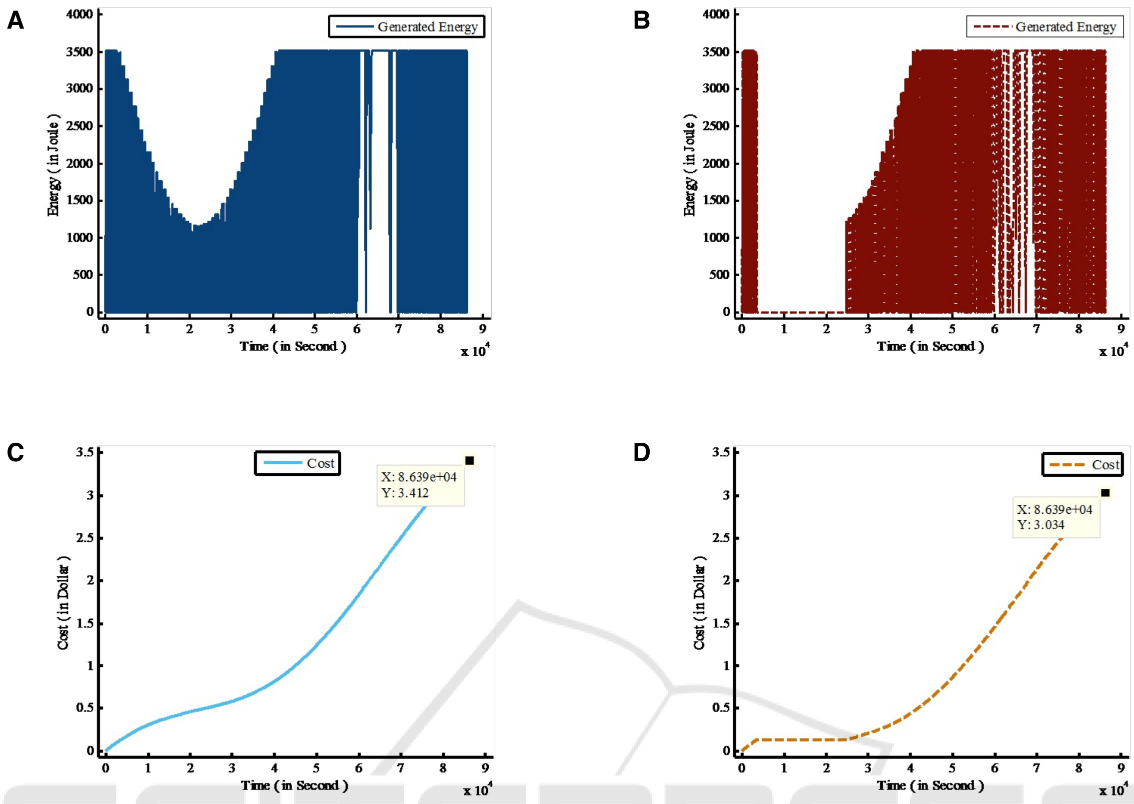

Figure 5: Simulation results. The first column corresponds to the presence of motion, whereas the second simulates the absence of motion. In each column, the rows from up to down show the amount of energy consumed by the controller and the corresponding total cost.

energy consumed will result in increasing the emission of greenhouse gases like carbon dioxide. The validation of the neuro-fuzzy controller according to energy consumption is shown in subplot **A** of figure 5. The measurements indicate that the maximum of energy is consumed when there is a huge difference between indoor temperature which is affected by outdoor temperature and set temperature. On the other hand, the energy consumed decreases when the system is relatively steady, since the variation of temperature has decreased. This is applied in the first period of the day which is from 08:00 AM to 08:00 PM or every twelve hours of a day. Therefore, the variation of the amount of energy consumed will results in the variation of electric power consumed. The amount of consumed electricity over a specific time period is the cost of consumed energy. As we can see in subplot **C** of figure 5, the cost of electric power is stable during the period of (08:00 AM) to (08:00 PM) which indicates the period of saved energy. On the other hand, in the period between the (08:00 PM) to (08:00 AM) the cost increases because of the increasing energy consumption. This results in a total cost of energy consumption of $3.412.

4.2 In the Absence of Motion

Analogously, the simulation results in the absence of occupants' motion are given in the second subplot columns of figures 4 and 5. Specifically, the system is tested for assuming that there is no motion in the room in the period from 2938 seconds to 29978 seconds while the set point temperature is 22°C (subplot **B** of figure 4). The HVAC system will turn off after 10 minutes or 600 seconds at point 3538 seconds of no occupants in the room. On the other hand, as soon as the room is occupied at 29978 seconds, the air conditioning system will start to work and it controls the indoor temperature to be back on track of rising up to reach the set point. The measurements shown in subplot **D** of figure 4 illustrate that the system will cool down or reach around the outdoor temperature of about 16°C by 867 seconds. Nevertheless, there are some small differences between the outdoor and indoor temperatures because of the wall and window insulations.

Importantly, one of the aims of our controller's design is to automatically turn off the air conditioner when there is no occupants, so as to save energy and decrease the cost of electricity used. The result of saving energy can be seen clearly in subplot **B** of figure 5. When there is no room occupancy, the amount of energy consumed becomes zero. As a result,the total cost of electricity decreases to \$3 as shown in subplot **D** of figure 5.

5 CONCLUSIONS

We have designed a neuro-fuzzy HVAC control system for regulating room temperature. Our controller achieves a higher indoor environment quality by balancing thermal comfort and energy consumption. The underlying model of the proposed controller utilizes a Sugeno-style fuzzy inference system with two sensory inputs: one for temperature and another for motion. It outputs a signal that represents the mode of the air conditioner and the compressor speed for each mode. The testing of the controller showed that the air conditioner of the controlled HVAC system turns off *automatically* 10 minutes after the last detected motion of room occupants. Accordingly, simulations of the cost levels and energy consumption were shown when the room was empty as justified through the absence of occupants' motion.

For the future, we aim at expanding the number of environmental factors to be considered compared with only one variable, that is, the room temperature in the current analysis. Also, we shall deploy the controller to monitor a whole house rather than merely one room.

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REFERENCES

Afram, A. and Janabi-Sharifi, F. (2014). Theory and applications of hvac control systems–a review of model predictive control (mpc). *Building and Environment*, 72:343–355.

Åström, K. J. and Hägglund, T. (1984). Automatic tuning of simple regulators with specifications on phase and amplitude margins. *Automatica*, 20(5):645–651.

Bi, Q., Cai, W.-J., Wang, Q.-G., Hang, C.-C., Lee, E.-L., Sun, Y., Liu, K.-D., Zhang, Y., and Zou, B. (2000). Advanced controller auto-tuning and its application in hvac systems. *Control Engineering Practice*, 8(6):633–644.

Caldo, R. B. (2015). FLC-based indoor air quality assessment for ashrae standard conformance. In *Industrial Engineering, Management Science and Applications 2015*, pages 711–718. Springer.

Cavcar, M. (2000). The international standard atmosphere (isa). *Anadolu University, Turkey*, 30:1–7.

Collotta, M., Messineo, A., Nicolosi, G., and Pau, G. (2014). A dynamic fuzzy controller to meet thermal comfort by using neural network forecasted parameters as the input. *Energies*, 7(8):4727–4756.

Dash, S. K., Mohanty, G., and Mohanty, A. (2012). Intelligent air conditioning system using fuzzy logic. *International Journal of Scientific & Engineering Research*, 3(12):1–6.

Glüge, S., Hamid, O. H., and Wendemuth, A. (2010). A simple recurrent network for implicit learning of temporal sequences. *Cognitive Computation*, 2(4):265–271.

Hamid, O. H. (2015). A model-based markovian context-dependent reinforcement learning approach for neurobiologically plausible transfer of experience. *International Journal of Hybrid Intelligent Systems*, 12(2):119–129.

Hamid, O. H., Wendemuth, A., and Braun, J. (2010). Temporal context and conditional associative learning. *BMC neuroscience*, 11(1):45.

Jaynes, E. T. (2003). *Probability theory: The logic of science*. Cambridge university press.

Keller, J. M., Fogel, D. B., and Liu, D. (2016). *Fundamentals of computational intelligence*. Wiley-IEEE Press.

Kobersi, I. S., Finaev, V. I., Almasani, S. A., and Abdo, K. W. A. (2013). Control of the heating system with fuzzy logic. *World Applied Sciences Journal*, 23(11):1441–1447.

Air Conditioning Systems (2017). Air Conditioning Calculations. (online accessed: 2017, January 27).

Canadian Centre for Occupational Health and Safety (2017). Thermal Comfort for Office Work. (2017, February 17).

Engineering 360 Powered by IEEE GlobalSpec (2017). HVAC - Ventilation. (online accessed: 2017, January 27).

McCormick, B. W. (1995). *Aerodynamics, aeronautics, and flight mechanics*, volume 2. Wiley New York.

Mirinejad, H., Welch, K. C., and Spicer, L. (2012). A review of intelligent control techniques in hvac systems. In *Energytech, 2012 IEEE*, pages 1–5. IEEE.

Mohindru, P. and Sharma, G. (2015). Simulation performance of pid and fuzzy logic controller for higher order system. *Simulation*, 1(7).

Nowak, M. and Urbaniak, A. (2016). Application of predictive control algorithms for thermal comfort and energy saving in the classroom. In *Carpathian Control Conference (ICCC), 2016 17th International*, pages 527–532. IEEE.

Salsbury, T. I. (2005). A survey of control technologies in the building automation industry. *IFAC Proceedings Volumes*, 38(1):90–100.

Song, Y., Wu, S., and Yan, Y. (2015). Control strategies for indoor environment quality and energy efficiencya review. *International Journal of Low-Carbon Technologies*, 10(3):305–312.

Wang, Y.-G., Shi, Z.-G., and Cai, W.-J. (2001). Pid auto-tuner and its application in hvac systems. In *American Control Conference, 2001. Proceedings of the 2001*, volume 3, pages 2192–2196. IEEE.

Ziegler, J. G. and Nichols, N. B. (1942). Optimum settings for automatic controllers. *trans. ASME*, 64(11).