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Fuzzy neural network based energy efficiencies control in the heating energy supply system responding to the changes of user demands

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Abstract. *This paper presents hybrid control approaches for heating air supply in response to changes in demand by using the Fuzzy neural network. Some advanced computing and statistical tools were introduced in improving control and energy efficiency to replace conventional control models. Among these tools, The FIS and ANN algorithms were used as control models to predict precise thermal performance. This paper introduces the Fuzzy neural network (FNN) to control simultaneously the amount of supply air and its temperature. The differences between the set-point and actual room temperature and their sums indicate control efficiency, and the energy consumption level is defined by the heat gains into a room and their sums. It is concluded FNN controller work in a highly efficient manner while maintains the desired room temperature.*
Keywords: Energy efficiency, Control accuracy, Fuzzy neural network, User thermal demand changes

1. **Introduction.** There is much focus on improving Heating, Ventilating, and Air-Conditioning (HVAC) system to maintain the desired temperature in thermal zones. The Proportional-Integral-Derivative (PID) algorithm has been proposed to improve control technologies to meet various conditions in HVAC models. However, most technologies developed in the PID algorithm focus on controls were used to optimize fuel usage and fan motor speed. These models are only useful when they are used in large-scaled HVAC system, plants, and buildings; however, when applied to small, sensitive thermal models requiring immediate response they have many disadvantages. Recent some computing and statistical technologies which make controllers more sensitive have been rapidly developed.

In order to control coal and oil based plants effectively, several models and some specific structures in boiler turbine or distribution controls are developed [1, 2, 3, 4, 5, 6] . With the help of computing applications, some more refined control methods and PID tuning algorithms were proposed to deal with sensitive parameters and thresholds [7, 8, 9, 10, 11, 12].

In large-scaled buildings and district level, heating control models were developed in terms of reduction of gas emission, to improve energy, and to optimize design distribution network [13, 14, 15, 16, 17, 18]. On some so called advanced HVAC systems, rule-based supervisory controllers [19, 20] are implemented which use the operator knowledge and apply it to reduce the energy and operating cost such as appropriate start/stop time of HVAC, night set-back, precooling and preheating etc.

As energy related databases were accumulated, advanced statistics algorithms focused on dealing with large databases by applying computing technology. Artificial Neural Network (ANN) was applied to evaluate energy performance of buildings which equipped various energy conservation measures [21]. Device control models with combining PID and FIS through ANN were developed [22, 23]. By using Fuzzy Neural Network, prediction of automobile air condition system performance was performed more accurately [24].

Although there has been many researchers of ANN applications in air-conditioning system, quite a few studies being done on AAC with fuzzy neural network. It is well known that Fuzzy neural network (FNN), which incorporates the advantages of fuzzy inference and neuron learning, has been exploited by many researchers. FNN combine the human inference style and natural language description of fuzzy systems with the learning and parallel processing of neural networks.

Several algorithms and tools have been developed in terms of control methods and applications. In order to meet the thermal demands in buildings, conventional PID control schemes were typically utilized in practice. However, this method is useful when it is used to measure fuel usage in boiler operations or electricity usage for fan motor. These kinds of methods have some disadvantages to produce immediate response for thermal demands with respect to human comfort. Also, the thermostat on/off controllers typically used in practice unable respond to immediate changes in thermal demands that are directly related to human comfort and energy efficiently. Damper control models only consider the estimated time to meet the requirement and explain the mass problem to infuse into thermal zones without considering temperature control. These conventional methods are not appropriate to sensitive and immediate control.

This paper proposes a comparative analysis of supply heating air controllers dealing with amount of mass and air temperature by using FNN. The main purpose of the comparison is to define effectiveness of FNN that control supply air mass and temperature in both cases of fixed T_{fix} and changed T_{chg} as users demand.

2. design strategy.

This section discusses the structure and mode of HVAC and design strategy.

2.1. The Structure of HVAC.

A simplified structure is designed for the HVAC model as shown in Fig.1. Suppose that this room is an independent module equipped with one heating system and a single duct. We neglect the indoor air speed variations and their relation to pressure, because they are thought as are leakages between envelopes and duct systems. The zones airflow is homogeneous.

A data center is used as an example for the thermal model which includes its geometry and operation of the room model. Accurate controls are required by a data center to satisfy temperature conditions for data servers and workers comfort level. The 2011 ASHRAE TC9.9 updated its recommended temperature rage to be from 18°C to 27°C. General recommendations suggest that the temperature of room should go above 10°C or below 21°C. However, in practice, the temperature over 21°C jeopardize sever safety and comfort. Fig.1 shows a schematic diagram of a simplified heater and heat transfer model. One reference model and three control models are tested using the assumptions

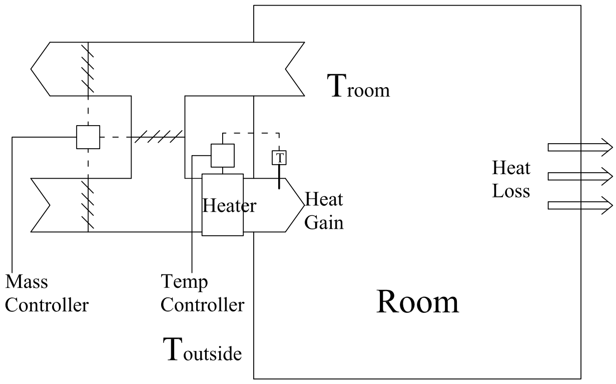

FIGURE 1. Schematic diagram of HVAC system used

to define the effectiveness of each controller. A conventional thermostat on/off controller with deadband setup ±1 is used as baseline model. The thermostat controller use FNN as control algorithms which contain three different control methods for heating air supply: Mass only (M), Temperature only (T), and Mass and Temperature simultaneously (M+T), Table 1 summarizes the four different controllers used in the simulation.

TABLE 1. Design strategies

		Heating air control	abbreviation
1	Baseline	Thermostat On/Off	On/Off
2	Fuzzy Neural Network (FNN)	Mass Only	FNN-M
3		Temperature Only	FNN-T
4		Mass and Temperature	FNN-M+T

2.2. **HVAC model.** We use a heating system and its relationship to a room: Thermal characteristics of a house and a heater, and Outdoor and Indoor temperature. Total chemical energy is contained within objects which are defined by temperature, mass, and characteristic of materials. According the thermodynamic first law, the thermal energy transfer of Fig.1 is given by:

$$Q_{gain} + Q_{loss} = \frac{du}{dt} \tag{1}$$

Where heat Q_{gain} is transfer from heater to room and Q_{loss} is heat transfer from room to outside. U is internal energy, and t is time.

From the conduction through the walls and windows, thermal energy loss of room Q is given by:

$$Q_{loss} = \frac{(T_{room} - T_{outside}) * A}{R} \tag{2}$$

$$R = \frac{1}{\alpha_{out}} + \frac{\delta}{\lambda} + \frac{1}{\alpha_{in}} \tag{3}$$

Where α_{out} and α_{in} are heat transfer coefficients, λ is transmission coefficient, A is area, δ is depth of envelope.

From the mass flow rate and enthalpy, suppose that there is no work in the system, thermal energy gain of room, Q_{gain} is given by:

$$Q_{gain} = \dot{m}_{in} * h_{in} - \dot{m}_{out} * h_{out} \tag{4}$$

According the law of conservation of mass and the assumption that there is no change in the flow rate, mass flow rate into a room and out from a room, and from a heater are:

$$\dot{m}_{in} = \dot{m}_{out} = m_{heat} \tag{5}$$

From Eqs. (4) and (5), Q_{gain} is transformed:

$$Q_{gain} = \dot{m}_{heat} * C_p * (T_{heat} - T_{room}) \tag{6}$$

The rate of internal energy is given by:

$$\frac{du}{dt} = m_{room} * C_v * \frac{dT_{room}}{dt} \tag{7}$$

From Eqs.(2),(3), and (7), Eq.(1) is rewritten:

$$\frac{dT_{room}}{dt} = \frac{1}{m_{room} * C_v} * \left\{ \frac{(T_{room} - T_{out}) * A}{1/\alpha_{out} + \delta/\lambda + 1/\alpha_{in}} + [\dot{m}_{heat} * C_p * (T_{heat} - T_{room})] \right\} \tag{8}$$

Geometry parameters used as follow:

$$A_{wall} = 680m^2, \delta_{wall} = 0.24m, \lambda_{wall} = 0.035w/m.k;$$

$$A_{window}{=}10m^2, \delta_{window} = 0.02m, \lambda_{window} = 0.77W/m.k$$

Based on the assumptions, parameters, and Eq.(8), all program codes for simulation were generated by the MATLAB program.

2.3. **Controller model.** In thermostat on/off control, Initial set-point temperature T_{fix} is 18°C, so the deadband setup ±1°C which the thermostat on/off control model operates within. That is say if T_{room} goes over 19°C, so the difference between T_{fix} and T_{room} goes to -1°C, then a controller sends turn-off signal to a heater. Suppose that the room temperature is below 17°C, so the difference goes up to ±1 , then a controller send turn-on signal to a heater.

The fuzzy neural network combines the advantages of fuzzy control and artificial neural network, so this paper based on fuzzy neural network to design a control system of thermostat heater controller.

3. **Design of Fuzzy Neural Network.** In this paper, the purpose of FNN models used in three cases in to determine the optimal values of the mass and temperature of supply heating air that depends on the difference between T_{fix} and T_{room} .

Input variables temperature difference T_{fix} and $T_{room}(E)$ network and derivative of the temperature difference (ΔE) as input of the network. Calculate the parameters of the membership function and the corresponding fuzzy rules by using the learning ability, so as to obtain an output that are output signals of the amount of mass and the supply air temperature. The whole fuzzy neural network structure is shown in figure 2. The input of this fuzzy neural network is:

$$x_1 = e(t) = T_{fix} - T_{room}, x_2 = \Delta E = \frac{e(t + \Delta t) - e(t)}{\Delta t} \tag{9}$$

In the Eq, e(t) is the current temperature, e(t) is the rate of change of temperature. Assuming that each input has n membership, the fuzzy neural network in each layer of the relationship between input and output is as follows.

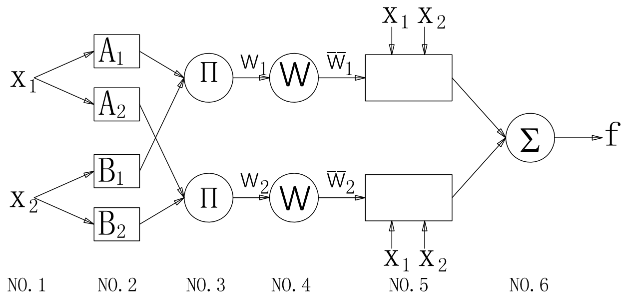

FIGURE 2. Structure of Fuzzy Neural Network

(1) The first layer is the input layer. The x1 and x2 respectively represent the temperature error and the rate of error change. Each input variable transfers to the next layer without any treatment, the input of this layer and the output unit respectively are:

$$I_i^{(1)} = x_i \ \ i = 1, 2. \tag{10}$$

$$O_{ij}^{(1)} = I_i^{(1)} \qquad i = 1, 2.; j = 1, 2, ..., n. \tag{11}$$

(2) The second layer is a layer of language. Each note represents a linguistic variable; using gauss function as membership function, blur the input variables, and calculate the fuzzy membership of the input variables. The input unit and output unit of this layer respectively:

$$I_{ij}^{(2)} = -\frac{\left(O_{ij}^{(1)} - c_{ij}\right)}{\sigma_{ij}^2} \quad i = 1, 2; j = 1, 2, ..., n. \tag{12}$$

$$O_{ij}^{(2)} = \mu(A_{ij}) = exp(I_{ij}^{(2)}) \tag{13}$$

In the Eq, σ_{ij} and c_{ij} respectively represent the width and center of the Gauss function.

(3) The third layer is the rule layer. Each node represents a fuzzy rule, and one correspondence, which can obtain the input unit and output unit of this layer respectively are:

$$I_{j(n+l)}^{(3)} = O_{1j}^{(2)} \times O_{1l}^{(2)} \quad j = 1, 2, \cdots, n; l = 1, 2, \cdots, n. \tag{14}$$

$$O_i^{(3)} = \omega_i = I_i^{(3)} \ \ i = 1, 2, \cdots, m. \tag{15}$$

In the Eq, m = n^2. The layer can be any AND operator with T paradigm, the excitation intensity of each fuzzy rule can output by operation, which is ω_i in the Eq.

(4) The fourth layer is one layer. Every note of this layer are denoted by W, by normalization of relevance grade of each rules, to calculate the ratio of incentive intensity at i point and incentive intensity of all rules. The input unit and output unit respectively are:

$$I_i^{(3)} = O_i^{(3)} = \omega_i \ \ i = 1, 2, \cdots, m. \tag{16}$$

$$O_i^{(3)} = \bar{\omega}_i = \frac{\omega_i}{\sum\limits_i \omega_i} \ \ i = 1, 2, \cdots, m. \tag{17}$$

(5) The fifth layer is the rule of output layer. This layer is used to calculate the output of each fuzzy rule, which can obtain the input unit and output unit respectively are:

$$I_i^{(5)} = O_i^{(5)} = \bar{\omega}_i \qquad i = 1, 2, \cdots, m. \tag{18}$$

$$O_i^{(5)} = \bar{\omega}_i f_i = \bar{\omega}_i(p_i x_1 + q_i x_2 + r_i) \qquad i = 1, 2, \cdots, m. \tag{19}$$

In the Eq, p_i, q_i, r_i are conclusion parameters of the linear system. And f_i is a linear combination value of the conclusion parameter.

(6) The sixth layer is the overall output level. The unit of the layer is a fixed node, the sum of all input signal as the output. The input unit and output unit of the layer are respectively:

$$I_i^{(6)} = O_i^{(5)} = \bar{\omega}_i f_i \;\; i = 1, 2, \cdots, m. \tag{20}$$

$$o_i^{(6)} = \sum \bar{\omega}_i f_i = \frac{\sum\limits_i \omega_i f_i}{\sum\limits_i \omega_i} \;\; i = 1, 2, \cdots, m. \tag{21}$$

(7) For this fuzzy neural network, after determine the initial membership functions, the total output of the system is linear combination of conclusion parameters. For many parameters used in the network, so a hybrid learning algorithm is used, that increases the least square method on the basis of gradient descent method [25] .

Among them, i=1, 2; j=1, 2, $\cdots$, 5; is the local gradient layer, is the concrete actual output.

4. **Discussions.** The models are simulated under the conditions from an outdoor dry bulb temperature at simulation. The results consist of room temperature, mass and temperature signals of each controller, Integral (Sum) of Absolute Error (IAE), and energy consumption for heating (Heating). The IAE is the sum of the absolute value of difference between T_{fix} and T_{room} , and the Heating is energy consumption for heating room. Each simulation for thermostat on/off, FNN is performed under the two scenarios for set-point temperature.

$$T_{fix} = 18°C \qquad (t : 00 : 00 - 04 : 00)$$

and

$$T_{chg} = 18°C \qquad (t : 00 : 00 - 01 : 00)$$
$$T_{chg} = 20°C \qquad (t : 01 : 00 - 02 : 00)$$
$$T_{chg} = 19°C \qquad (t : 02 : 00 - 04 : 00)$$

Fig 3-6 compares the results of Integral of Absolute Error (IAE) and Energy Consumption for Heating from four different controllers. The FNN-M and FNN-M+T controllers show very high control efficiency. The control efficiency is highly related to human feel of comfort. Because that mean the temperature of room should be changed immediately and maintained consistently to meet changes in users demands.

As shown in figs3 and 4, we can see that the control efficiency of FNN-T is not so well. The reason come from the difference between output signals to operate a damper for air mass and a heater for air temperature.

In the case of mass control(or damper control), if room temperature is goes over set-point temperature, the controllers send a 0 signal (i.e., no air supply for heating) to a damper, and room temperature immediately starts to decrease since there is no air (mass) is provided.

For the case of temperature control, the controlled range of supply heating air temperature is between 40°C and 70°C. That means if FNN-T controller sent 0 signal to a heater, the minimum heating air of 40°C is still supplied to a room. The result is even room temperature reaching the set-point, it is still continually increases, and as a consequence, the control efficiency is not improved much.

Figs.4 and 5 show different aspects of Heating. For the case of the exception of FNN-M and FNN-M-T controllers, they show similar energy consumption patterns. It indicate that the FNN algorithm has strong advantages in energy efficiency even though it produces sensitive control signals to maintain consistent room temperature directly related to human comfort.

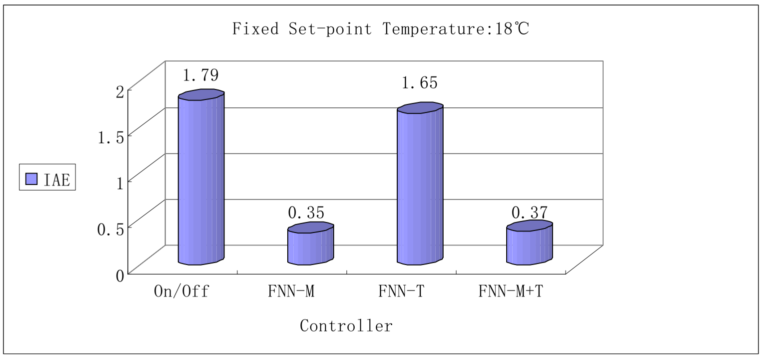

Figure 3. Comparison of IAE at Fix temperature

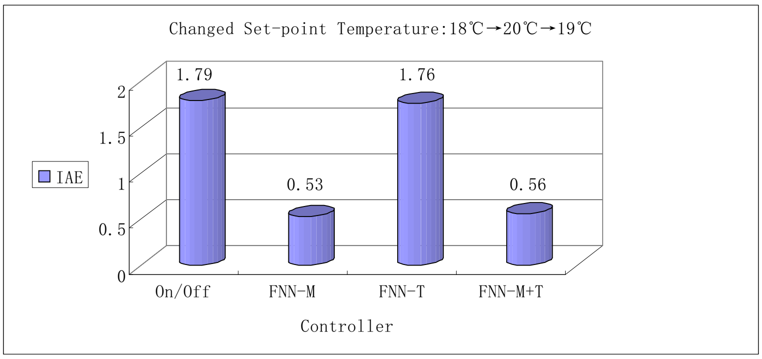

Figure 4. Comparison of IAE at changed temperature

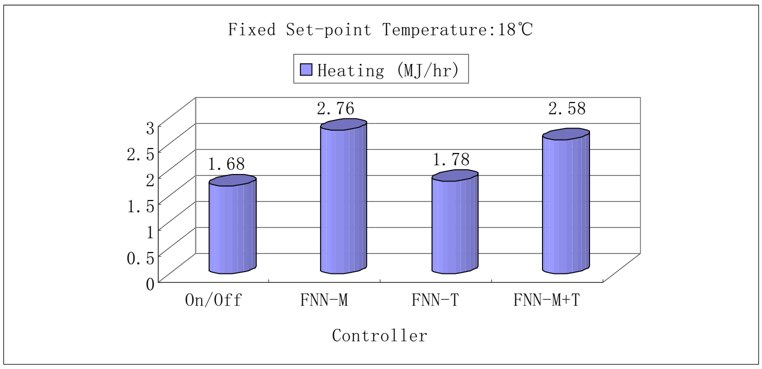

Figure 5. Comarision of Heating at Fixed temperature

5. **Conclusions.** This paper introduces FNN heating air supply controllers with controlling amount of supply air and its temperature. In comparison with conventional On/off controller, the sum of control errors caused by the difference between room temperature and the set-point temperature indicates that the control accuracy, further energy consumption for heating of controllers shows energy savings.

The FNN models have advantages in control efficiency directly related with human comfort in comparison with typical On/off. The reason is the effectiveness of heating air controllers based the machine learning tools using FNN. So this kind of model can be used to optimize heating supply air conditions to meet the set-point temperature effectively in conditions requiring sensitive controls and huge energy consumption such as data centers,

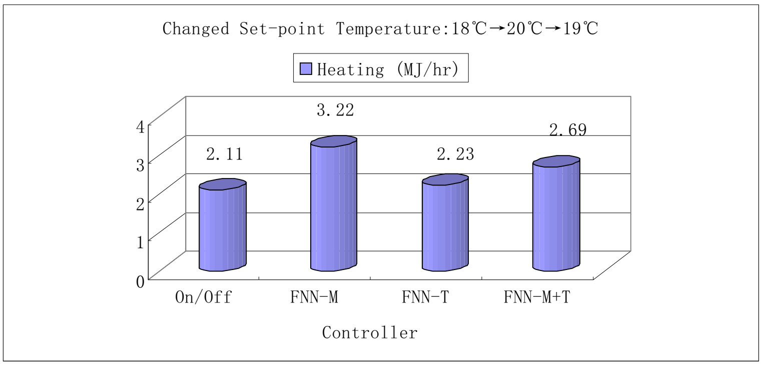

Figure 6. Comparision of Heating at changed temperature

hospital, laboratories. The model also is applied in the case of requiring frequent changes to temperature based on users demands.

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