Hybrid supply air controls using fuzzy inference system and neural network fitting models for control and energy efficiencies

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ABSTRACT
This paper presents hybrid supply air control approaches for control and energy efficiencies, using Fuzzy Inference System (FIS) and Artificial Neural Network (ANN) fitting model.
Recently, advanced computing and statistical technologies, such as FIS and ANN algorithm, were introduced to replace the conventional controls for improved energy efficiency in HVAC systems. However, these methods, which were mostly used to control fuel amount or fan motor speed, had lack of the capability of immediate response to the demand of thermal zones.
This paper introduces a zone level hybrid control approach. Simultaneous controls of the amount of supply air and its temperature by FIS and ANN algorithms are developed and tested to evaluate the supply air conditions (mass and temperature) for heating season. The sum of errors, caused by the difference between set-point and actual room temperatures is used as an indicator of energy efficiency. The both FIS and ANN models are compared to typical thermostat on/off baseline controller. The results include the total errors of hybrid models in comparison with the baseline controller. This paper analyzes the effectiveness of hybrid controllers using FIS and ANN models, which can be used to optimize mass and temperature of supply air to meet set-point temperature.

KEYWORDS
Hybrid Heating Control, Fuzzy Inference System, Neural Network Fitting, Control Efficiency, Energy Saving

INTRODUCTION
To test performance of Heating, Ventilating, and Air-Conditioning (HVAC) systems, the fuel amount into the boiler and fan motor speed was commonly adapted as major control factors. Many studies improved the fundamental models to optimize fuel use

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for boiler and its turbine by using control algorithms (Rossiter, Kouvaritakis, & Dunnett, 1991; Zhuang & Atherton, 1993; Wang, Zou, Lee, & Bi, 1997; Tan, Liu, Fang, & Chen, 2004). The development of computing technologies made many researchers improve the models with large amount of data and complex calculations, and the Fuzzy Inference System (FIS) and Artificial Neural Network (ANN) were preferred to deal with them. Fraisse, Virgone, and Roux (1997) developed thermal control through the comparison of the conventional control model and FIS model (Fraisse, Virgone, & Rous, 1997). The signal control efficiency of the FIS model was compared to the conventional rule and developed through Generic Algorithm and HVAC case studies (Zhang, Ou, & Sun, 2003; Alcala, 2003; Fazzolari, Alcala, Nojima, Ishibuchi, & Herrera, 2013). Energy consumption from the various models combining the FIS models was compared for a boiler control (Lianzhong & Zaheeruddin, 2007). Other researchers developed a boiler fuel control model by using both the FIS models (Malhotra & Sodhi, 2011; Soyguder, Karakose, & Alli, 2009). Still others developed control models, such as damper control by combining the FIS and Artificial Neural Network (ANN) model (Soyguder & Alli, 2010; Jin et al, 2013). The control of the combined fan and damper models was tested to meet various demands of three different zones using specific weather data (Koulani, Hviid, & Terkildsen, 2014).

However, most models that dealt with controlling fuel amount or fan motor speed were not appropriate to immediate response to the thermal demand of zone scale level. Also, damper control models were utilized to define the estimated time to meet requirements or explained mass problems to infuse into thermal zones. These approaches had some problems to reflect sensitiveness and promptness.

In this paper, hybrid models for controlling supply air mass and temperature are proposed with FIS, and ANN algorithms. Methodology section describes the structures of the HVAC model, equations, and algorithms used. Result and discussion sections indicate the advantages and disadvantages of FIS and ANN models in comparison with typical thermostat on/off model.

HVAC AND CONTROL MODELS

HVAC model

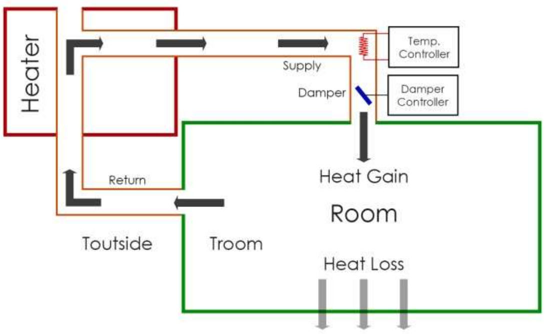

Figure 1 *Diagrammatic flow of HVAC model*

Figure 1 and Table 1 describe the diagrammatic flow and design parameters for the HVAC model used in this paper. This room is an independent module equipped with one heating system with a single duct. The pressure variations of indoor air speed are neglected, as well as air leakage between envelopes and duct systems. Airflow in the zone is homogeneous.

Table 1 *Design parameters*

No.	*Factor*	*Value*
1	Set-point temperature (T_{set})	20ºC
2	Wall area (A_{wall})	711.6 m^2
3	Wall thickness (D_{wall})	15 cm
4	Wall thermal conductivity (k_{wall})	136.8 j/m-hr-ºC
5	Window area (A_{window})	12m^2
6	Window thickness (D_{window})	2cm
7	Window thermal conductivity (k_{window})	2,808.0 j/m-hr-ºC
8	Mass flow rate into room	3,600 kg/hr
9	Weather condition	Raleigh Durham Int'l AP

From the thermodynamic first law, equation below is obtained:

$$\frac{dT_{room}}{dt} = \frac{1}{m_{roomair} * c_{air}} * \left(\frac{dQ_{gain}}{dt} - \frac{dQ_{loss}}{dt}\right)$$

Thermostat on/off model

The thermostat On/Off controller operates within the deadband setup. If the difference between set-point and room temperature is larger than a specified value, the control model sends the run or stop signal to the heater. As a reference to compare to other control models, the initial values of deadband are +1'C and -1'C. For instance, a set-point and room temperature are 20'C and 18'C, respectively, wherein the heater supplies hot air into room because the difference between two is 2'C.

Fuzzy Inference System (FIS) model

The purpose of the FIS models used in the three cases is to determine the optimal values of the mass and the temperature of the supply heating air, which depends on the difference between the set-point and room temperature. Figure 2 shows the FIS membership rule with two input variables: wherein the temperature differences between the set-point and room (E) are derivative of the temperature difference (ER).

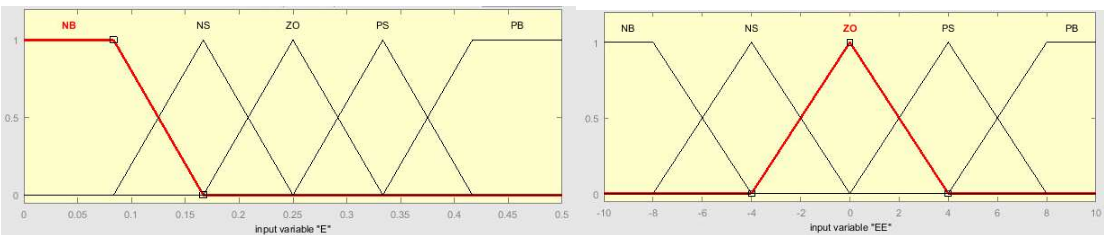

Figure 2 *FIS membership graphs for mass and temperature control signals*

In this paper, the new method uses five membership functions for each input variable with universal of discourse 0 to 0.5 and -10 to 10; respectively, Negative Big (NB), Negative Small (NS), Zero (ZO), Positive Small (PS), and Positive Big (PB). The method also uses an output of control signal of 0 (0% output) to 1 (100% output).

Artificial Neural Network (ANN) model

ANN consists of a large class of several structures, and the appropriate selections of a nonlinear mapping function x with a network are required (Heikki, 2008). In this paper, the network used in function approximation is the Multilayer Perception (MLP) which consists of two input layers, 10 hidden layers, and an output layer. The ANN fitting models are performed through the two inputs of E and ER from each simulation output of the FIS model with the deadband setup from -1'C to +1'C, and 10 the single nodes in MLP network used as hidden layers within two inputs and an output. Table 2 shows the simulation configuration and iteration information for the ANN fitting model in the paper.

Table2 *ANN fitting model configuration*

No.	*Simulation configuration*	
1	# of training sets	60,480
2	# of testing and validating sets	25,920
3	# of hidden layers	10
4	Algorithm	Scaled conjugated gradient
5	Max iterations in 1 Epoch	1,000

Simulation model

By using the assumptions and design parameters, one reference model and six controllers are tested. The reference model is a typical thermostat on/off controller. The FIS controls of mass only, temperature only, and mass and temperature simultaneously are tested. Also, these are performed by the ANN algorithm. Figure 3 describes the diagrammatic structure of the MATLAB simulation model.

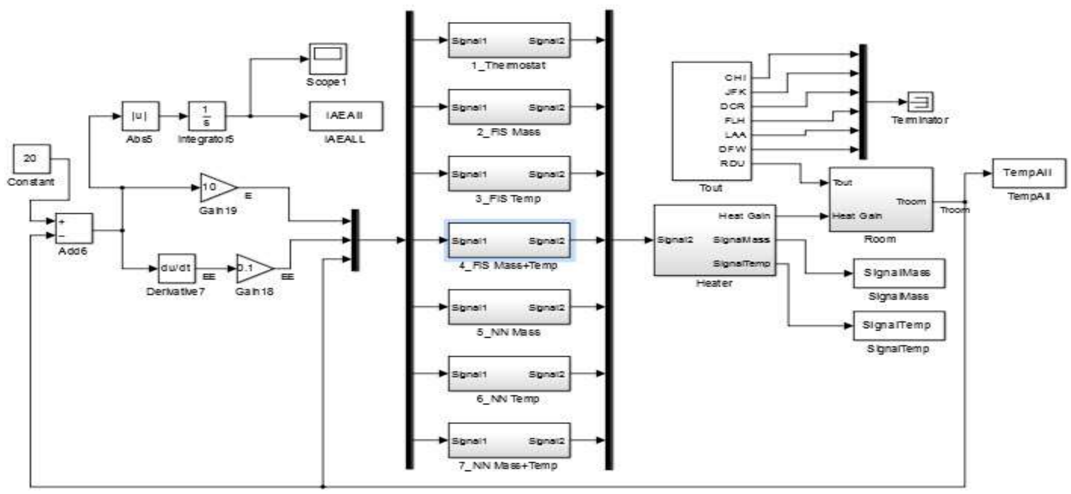

Figure 3 *Diagrammatic structure of simulation model*

RESULTS

Table 3 shows the performance of ANN fitting using E and ER as inputs, and FIS control signals as targets to respond to changes in Temperature Outside (T_{out}).

Table3 *ANN fitting results and regressions*

No.	*Results & Regression (R)*	*Mass Control*	*Temp Control*
1	# of iterations	138	587
2	Gradient	0.001	0.214
3	Validation checks	6	6
4	R of training set	0.9954	0.9975
5	R of validating set	0.9951	0.9975
6	R of testing set	0.9951	0.9974
7	R of all data set	0.9953	0.9975

Figure 4 shows the results of seven control strategies. From 11:00 to 18:00, the T_{out} was over 19’C, meeting the set-point temperature. This confirms that T_{room} follows T_{out} with time delays because the controller stops at the time range.

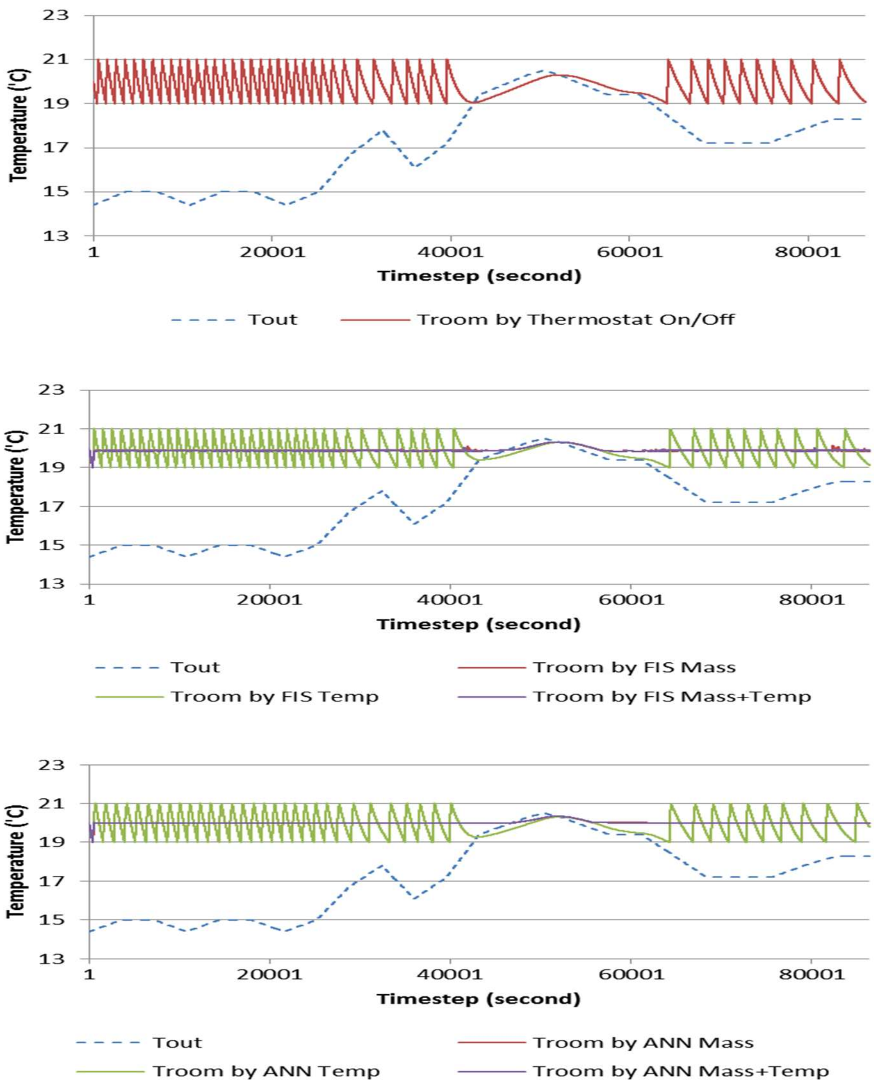

Figure 4 *Outdoor Temperature (T_{out}) vs. Room Temperature (T_{room}) by 7 controllers*

Temperature controls by FIS and ANN show similar patterns of thermostat on/off controller, but mass controls show quite different patterns. FIS control reduces overshoot which can be seen in thermostat and temperature controls, and ANN reduces more than the level of FIS. Simultaneous control of mass and temperature by ANN shows the highest performance in terms of control accuracy.

DISCUSSIONS

Table 4 shows the results of Integral of Absolute Error (IAE) and energy consumption for heating air supply derived from the simulations of 7 design strategies. In all cases, the ANN model through the simultaneous control of mass and temperature as a hybrid model shows higher control efficiency than any other controls. Most FIS and ANN control models reduced the overshoot of temperature changes as compared to the thermostat on/off control as indicated in Figure 4.

Table4 *Comparisons of IAE and energy consumption*

	Controller		Value	Eff. (%)
IAE	Thermostat On/Off		11.64	-
	FIS	Mass	3.03	-74.0%
		Temp	11.18	-4.0%
		M+T	3.17	-72.8%
	ANN	Mass	0.71	-93.9%
		Temp	11.44	-1.8%
		M+T	0.65	-94.4%

	Controller		Value	Eff. (%)
Energy Consumption (MJ/hr)	Thermostat On/Off		6.13	-
	FIS	Mass	10.09	64.5%
		Temp	6.21	1.3%
		M+T	10.00	63.1%
	ANN	Mass	6.59	7.4%
		Temp	6.38	4.1%
		M+T	6.58	7.3%

In the U.S. market, typical thermostat controllers are operated in the deadband setup of ±2’F (about 1.1’C). The result describes a fact that most FIS and ANN models can improve control efficiency as compared to typical thermostat on/off controller equipped in U.S. buildings. However, temperature control models show less efficiency in comparison with mass controllers, which implies facts that more sensitive configurations are required, and that controlling temperature for supply air cannot be appropriate for practical applications.

The thermostat on/off controller shows higher efficiency in energy consumption as compared to FIS and ANN controllers. This is directly related to the control sensitivity to maintain a desired room temperature, which may increase energy consumption derived from continuous operation. And also, there might be additional energy consumption, especially electricity, of motor for controlling damper angle and resistance coil for heating supply air. However, these energy consumptions can be neglected in comparison with huge direct heat gain relatively.

As a consequence, the thermostat on/off controller is still effective in terms of energy consumption only. However, it makes inconsistent T_{room} which fluctuates from 19ºC to 21ºC. The ANN simultaneous mass and temperature controller can effectively maintain desired T_{room} by minimizing control errors. And also, to control T_{room} consistently, it just consumes energy 7.3% more than thermostat on/off controller. Regarding the result, the ANN simultaneous controller can be used for some rooms or buildings with specific use such as Data Center, Intensive Care Unit in hospital, and Biology Lab. In addition, improved comfort level derived from consistent T_{room} can increase productivity in Factory and Distribution Center.

CONCLUSION

In this paper, the hybrid supply air control is introduced with simultaneous control of the amount of supply air and its temperature, and the FIS and ANN algorithms are used to compare with conventional thermostat on/off controller. To verify the effectiveness of the hybrid controls, the measures of IAE and hourly heat gain are used. The IAE caused by the difference between set-point and actual room temperatures reflects control accuracy, and hourly heat gain from the HVAC system reflects energy consumption.

The ANN simultaneous mass and temperature controller as a hybrid controller shows high control efficiency of over 90% reductions of control errors in comparison with conventional thermostat on/off controller. Although sensitive and accurate controls are performed, it consumed quite less energy than the FIS, and its energy consumption is quite similar to the thermostat on/off. The hybrid ANN controller can be used to optimize the supply air condition under conditions requiring more sensitive T_{room} controls and to improve human comfort which can be directly related to productivity.

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