ANALYSIS OF A NEURAL NETWORK MODEL FOR BUILDING ENERGY HYBRID CONTROLS FOR IN-BETWEEN SEASON

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ABSTRACT: In residential and commercial buildings, programmable thermostats have been practically used to provide appropriate heating and cooling energy to satisfy the thermal conditions. With the help of rapid development of computing technology, recent controllers were able to adopt advanced algorithms such as Fuzzy Inference System (FIS) and Artificial Neural Network (ANN). Several studies for the algorithms were tested to improve the performance of conventional controllers through the large scaled databases associated with hidden interactions between parameters. However, most models focused on the optimization of fuel use for boilers or motor speed for fans, which have some disadvantages to provide sensitive control signals responding to thermal demands in zone scale level.
The advanced FIS and ANN controllers, which deal with simultaneous control of supply air mass and temperature, are tested to optimize supply air conditions for in-between seasons that require both moderate heating and cooling. The controllers are compared with a thermostat on/off model by means of the total control errors and thermal energy consumption. To verify the effectiveness of the controllers, the measures of Integral of Absolute Errors (IAE) and energy consumption results are compared with conventional thermostat on/off controller. The IAE describes the difference between desired and measured room temperature reflects control accuracy, and hourly thermal gain from the system reflects energy efficiency. The ANN mass and temperature simultaneous control algorithm indicates high efficiency for control errors by 5.59% and effectively mitigates energy increase by 3.95% in comparison with thermostat on/off controller. Even though the ANN model can effectively reduce control errors for thermal comfort, it consumes quite less energy than FIS model, and similar amount of energy for thermostat on/off controller. Under building's conditions requiring more sensitive controls and consuming large amount of energy, the ANN controller can be used to effectively optimize the supply air conditions.

KEYWORDS: Building Control, Neural Network Model, Mass & Temperature Control, In-between Season, Energy and Control Efficiency

INTRODUCTION

1.1. Control model

To improve the performance of building energy supply systems, the fuel amount into the boiler and fan motor speed was commonly adapted as major control factors. Many studies improved the mathematical thermal models to optimize fuel use or distribution for boiler and its turbine by using control algorithms like Proportional – Integral – Derivative (PID) algorithm (Rossiter, Kouvaritakis, & Dunnett, 1991; Zhuang & Atherton, 1993; Wang, Zou, Lee, & Bi, 1997; BNP media, 2001; Tan, Liu, Fang, & Chen, 2004). The rapid 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. Several studies for the algorithms were adopted to improve the performance of conventional controllers through the network-based approaches which can effectively deal with large scaled databases and parameters interactions. Some researchers developed hybrid models which combined PID and FIS models in one distribution network. By changing nodes and locations within distribution network, energy consumption was compared through the various models combining the PID and FIS models for a boiler fuel and turbine speed control or wind power systems, and integrated thermal control systems were developed through the comparison of the conventional control theory and FIS genetic algorithm (Fraisse, Virgone, & Rous, 1997; Alcala, 2003; Anderson et al, 2007; Somsai, Oonsivilai, Srikaew, & Kulworawanichpong; 2007). The signal control efficiency of the FIS model was developed by using multi-dimensional genetic algorithm or matrix for HVAC control model of buildings for specific use (Zhang, Ou, & Sun, 2003; Fazzolari, Alcala, Nojima, Ishibuchi, & Herrera, 2013). Energy efficiency from the various scenarios for locations of FIS models associating with PID controller was compared to improve the performance of boiler control (Hamdi & Lachiver, 1998; Lianzhong & Zaheeruddin, 2007; Beinarts, 2013). Also, amount of fuel for boiler or fan motor speed control models adopting refined FIS algorithm were tested to compare conventional PID tuning rule (Malhotra & Sodhi, 2011; Soyguder, Karakose, & Alli, 2009). Still others developed control models, such as damper control by combining the FIS and ANN models (Soyguder & Alli, 2010). Multi-layered genetic algorithm was used to improve the performance of ANN model which might cause overshooting or reduce level of generalization, and the control combining fan motor and damper angle were tested to meet thermal demands of several thermal zones using various weather data (Dounis & Caraiscos, 2009; Dounis Koulani, Hviid, & Terkildsen, 2014; Jovanovic, Sretenovic, & Zivkovic, 2015; Ji, Xu, Duan & Lu, 2016).

1.2. Problem statement

However, most PID and FIS models which dealt with controlling fuel amount or fan motor speed were not appropriate to immediate response to the thermal demand of zone scale level. Also, most control models for damper and valve were utilized to define time collapse to satisfy thermal demands or optimize amount of supply heating water into thermal zones, respectively. These approaches had some disadvantages that controllers cannot operate sensitively and promptly corresponding to outdoor temperature conditions.

In this research, network-based control models for supply air mass and temperature are proposed by using FIS and ANN algorithms. Design strategy section describes the structures of the HVAC model, equations, and FIS and ANN algorithms used. Result and discussion sections indicate the advantages and disadvantages of FIS and ANN models in comparison with typical thermostat equipped in most buildings in the US.

Nomenclature

A	area (m2)	h_{out}	specific enthalpy (J/kg)
D	depth of envelope components (m)	h	convection heat transfer coefficient (J/m2·°C)
m_{in}	mass flow-rate into room (kg/h)	k	transmission coefficient (J/m· °C)
m_{out}	mass flow-rate out from room (kg/h)	r	thermal resistivity (m·h·°C /J)
m_{heater}	mass flow-rate of heater (kg/h)	R	thermal resistance (h·°C /J)
$m_{roomair}$	mass of room air (kg)	Cv	specific heat capacity at constant volume (J/kg·°C)
Q_{loss}	convection and transmission heat loss (J)	Cp	specific heat capacity at constant pressure (J/kg·°C)
Q_{gain}	convection and transmission heat gain (J)	u	internal energy (J)
T_{ht}	air temperature entered into room (°C)	W	work (J)
T_{room}	room temperature (°C)	t	time
T_{out}	outdoor temperature (°C)	E	error (°C)
T_{set}	set-point temperature (°C)	ΔE	derivative of error
h_{in}	specific enthalpy (J/kg)	R2	fraction of variance

2.0. DESIGN STRATEGY

2.1. HVAC model

Figure 1 describes the diagrammatic flow for the HVAC model used in this research. 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, and also, airflows in the zone are de-stratified.

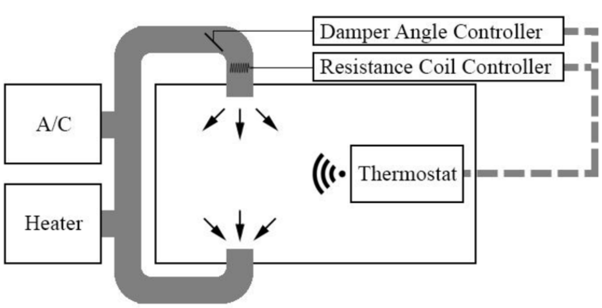

Figure 1 : Diagrammatic flow of HVAC model

The heating system describes a heating system and its relationship to a room for thermal characteristics of a house and a heater, and outdoor and indoor temperature. Total thermal energy is contained within any objects is defined by temperature, mass, and characteristics of materials. From the thermodynamic first law, the thermal energy transfer is given by:

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

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

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

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

$$R = \frac{1}{h_{out} * A} + \frac{D}{k * A} + \frac{1}{h_{in} * A} \tag{3}$$

where h_{out} and h_{in} are heat transfer coefficients, *k* is transmission coefficient, A is area, D is depth of envelope. From the mass flow rate and enthalpy, assuming that there is no work in the system, thermal energy gain of room, Q_{gain} is given by:

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

From the law of conservation of mass and the assumption of no change in the flow rate:

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

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

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

The rate of internal energy is given by:

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

From the equations above, Eq. (8) for simulation is obtained:

$$\frac{dT_{room}}{dt} = \frac{1}{m_{room} C_v} * \left(\left(\frac{T_{room} - T_{out}}{\frac{1}{h_{out} * A} + \frac{D}{k * A} + \frac{h_{in}}{A}}\right) + \left(\dot{m}_{ht} * C_p * (T_{heater} - T_{room})\right)\right) \tag{8}$$

Based on the equations and scenarios, initial input parameters are assigned, and Table 1 summarizes the factors and assigned values used in the simulation test (ASHRAE TC9.9, 2011; Steinbrecher & Schmidt, 2011; Mathworks, 2016).

Table 1 : Design factors and values

No.	*Factor*	*Value*
1	Set-point temperature (T_{set})	20 °C for Heating, 25.5 °C for Cooling
2	Wall width x height	19.5 m x 4.4 m
3	Wall thickness (D_{wall})	0.15 m
4	Wall thermal conductivity (k_{wall})	136.8 J/m·h·°C
5	Window width x height	1.5 m x 1.0 m
6	Window thickness (D_{window})	0.02 m
7	Number of windows	8
8	Window thermal conductivity (k_{window})	2,808.0 J/m·h·°C
9	Mass flow rate into room	3,600 kg/h
10	Weather data	Incheon Int'l Airport in South Korea

2.2. Thermostat on/off model

The thermostat on/off controller operates within the dead-band setup. If the difference between T_{set} and T_{room} 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, T_{set} and T_{room} are 20°C and 18°C, respectively, wherein the heater turns on and starts to supply hot air into room because the difference is 2°C.

2.3. 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 T_{set} and T_{room}. Figure 2 shows the FIS membership rule with two input variables: wherein the temperature differences between T_{set} and T_{room} (E) are derivative of the T difference (ΔE).

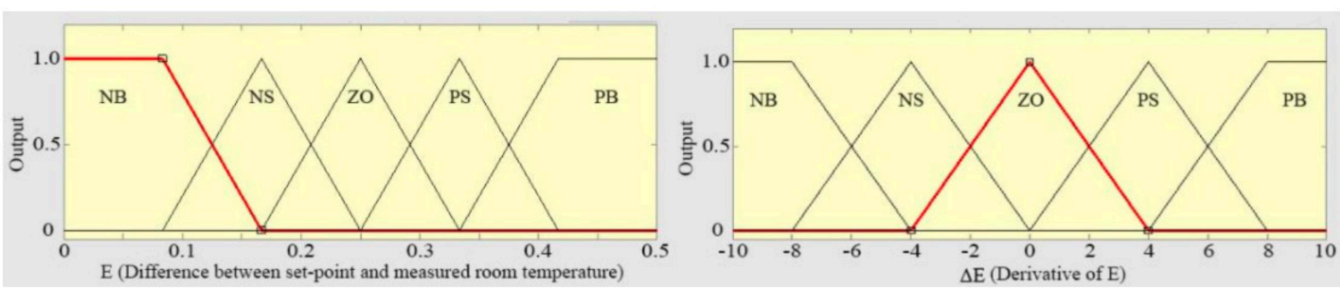

Figure 2 : FIS membership graphs for mass and temperature control signals

In this research, 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).

2.4. Artificial Neural Network (ANN) model

The ANN consists of a large class of several structures, and the appropriate selections of a nonlinear mapping function with a network are required (Politechnika Wroclawska, 2016). Figure 3 indicates diagram for typical multiple nodes within the neural network function (Politechnika Wroclawska, 2016). The function in the network used in this research consists of two input layers, 10 hidden layers, and an output layer.

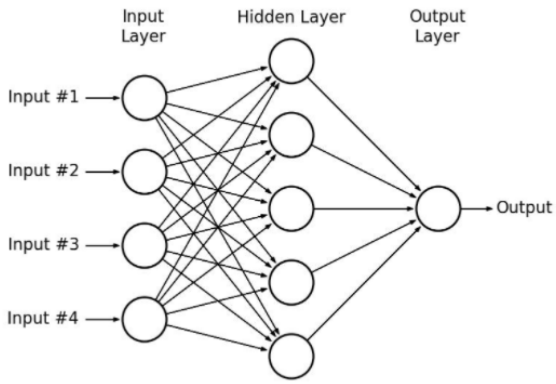

Figure 3 : Structure of ANN node

The inputs of x_1,...x_k to the neuron are multiplied by weights and summed up with the constant bias. The resulting is the input to the activation function. Then, results from activation function were summed up goes to output y_k. The ANN models in this research are performed through the two inputs: Error (E) is temperature difference between T_{set} and T_{room}, and ΔE is derivative of the error. Table 2 describes the configuration used for ANN simulation in this research.

Table 2: ANN configuration

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

2.5. Simulation model

By using the assumptions and design strategy, one reference model and two controllers are tested. The reference model is a typical thermostat on/off controller. By using fuzzy logic, the FIS controls for mass and temperature simultaneously are tested. Also, the results from the FIS are trained by the ANN regression fitting model, which generates the ANN controller. Figure 4 describes the diagrammatic structure of the MATLAB simulation model. In the case of the FIS and ANN models, when the difference between the lower limit temperature of cooling T_{set} setting and the upper limit of heating T_{set} is +1 ° C, a switch for automatically limiting the supply is activated like the thermostat on/off model.

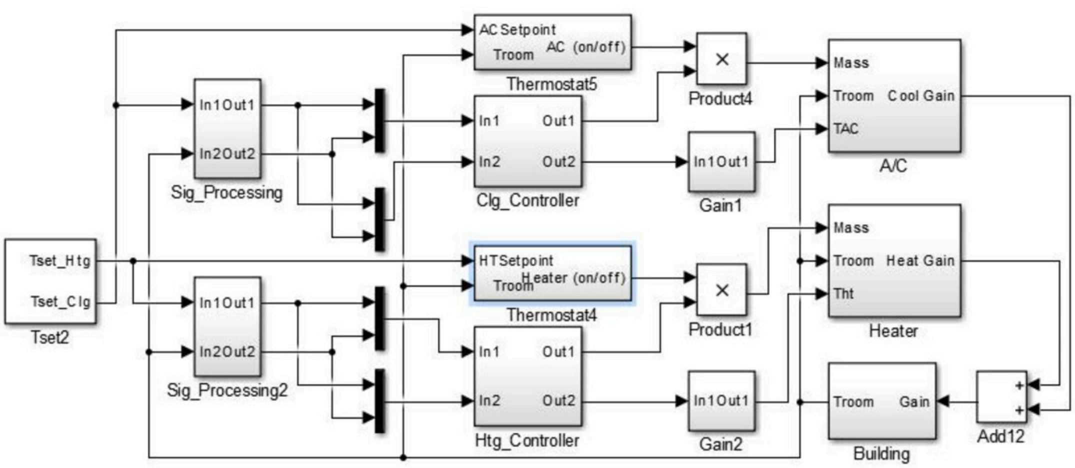

Figure 4: Diagrammatic structure of simulation model

RESULT AND DISCUSSION

Table 3 shows the performance of ANN fitting model trained by inputs of E and ΔE, and a target of FIS output signals to respond to changes in T_{out}. As indicated in the R^2 values for training and validating, the regression of ANN for mass and temperature controls is significant.

Table 3: ANN fitting results and regressions

No.	*Results*	*Mass Control*	*Temp Control*
1	# of iterations (maximum 1000)	138	587
2	Gradient	0.001	0.214
3	Validation checks	6	6
4	R^2 of training set	0.9954	0.9975
5	R^2 of validating set	0.9951	0.9975
6	R^2 of testing set	0.9951	0.9974
7	R^2 of all data set	0.9953	0.9975

Figure 5 describes the results of three control strategies. From 10:00 to 14:00 and from 19:00 to 24:00, the Tout is in between the upper and lower dead-bands of T_{set}. This confirms the fact that T_{room} follows T_{out} with time delays because the controller stops at the time range.

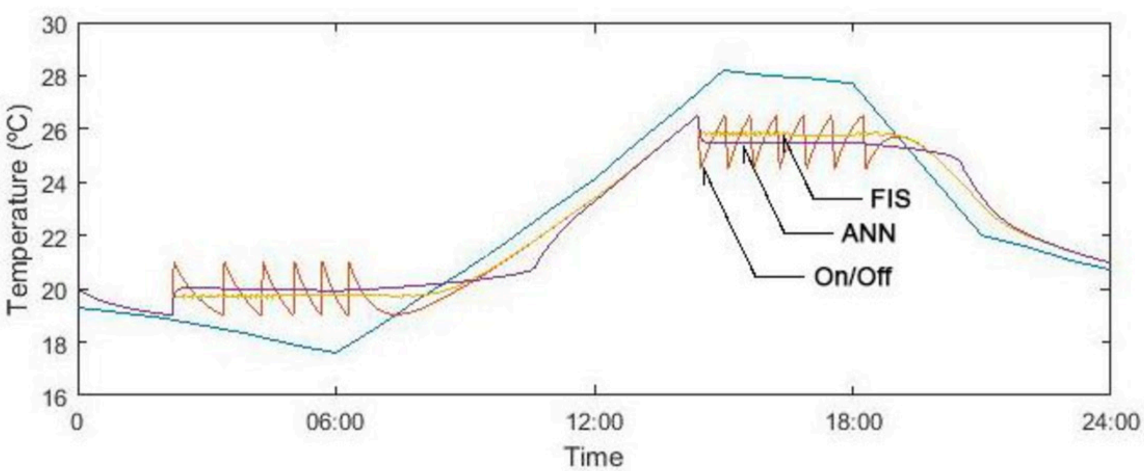

Figure 5: T_{out} vs. T_{room} by three controllers

Temperature controlled by FIS and ANN show similar trajectories as compared to thermostat on/off controller. The FIS controller reduces overshoot which can be seen in thermostat on/off controls, but it is confirmed that the ANN controller reduces more than the level of FIS. Simultaneous control of mass and temperature by ANN shows the highest performance in terms of control accuracy for T_{room}.

Tables 4 and 5 show the results of Integral of Absolute Error (IAE: sum of absolute errors derived from the difference between T_{set} and T_{room}) and energy consumption as Energy Use Intensity (EUI: kWh/m2·year) for heating air supply derived from the simulations of three design strategies. The ANN controller through the simultaneous control of mass and temperature shows higher control efficiency than other two controllers. This result can be derived from the effective reduction of overshoot at the time when the controllers turn on from 02:00 to 07:00 and from 14:00 to 19:00.

Table 4: Comparisons of IAE

Controller	*IAE*			*Comparison*
	Cooling	*Heating*	*Total*	
Thermostat On/Off	81.45	62.55	144.00	-
FIS	80.02	61.50	141.52	-1.72%
ANN	77.96	57.99	135.95	-5.59%

In the U.S. market, typical thermostat controllers are operated in the deadband set up of ±2°F (about 1.1°C). The result describes the 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, as indicated in Figure 5, the ANN controller supplies unnecessary heating energy from 09:00 to 10:30, and cooling energy from 19:00 to 20:00 to maintain T_{room} inside T_{set}. This can be one of the reasons why energy consumption is increasing. Table 5 summarizes the energy consumption level as EUI for three different controllers.

As indicated in Table 5, thermostat on/off controller shows higher efficiency in energy consumption as compared to the FIS and ANN controllers. This is directly related to the control sensitivity to maintain a desired T_{room}, which may increase energy consumption during heater and cooler turned on. In spite of the probable deficiencies, the ANN model shows higher efficiency rather than the FIS controller by about 60%, and also, it effectively mitigates energy consumption increase by 3.95% as compared to thermostat on/off controller. If the algorithm in the ANN is improved to rectify unnecessary signals from 02:00 to 07:00 and from 14:00 to 19:00, the energy efficiency can be improved rather than the result. This can be considered as one of follow-up studies. As indicated in Tables 4 and 5, the FIS model shows a much larger increase in energy consumption in comparison with the improvement of control efficiency. This implies a fact that the algorithm of the fuzzy membership function uses unnecessary energy to sensitively maintain T_{room}, and more precise configuration for membership function is required.

Table 5: Comparisons of energy consumption

Controller	*Energy Use Intensity (kWh/m2·year)*			*Comparison*
	Cooling	*Heating*	*Total*	
Thermostat On/Off	29.04	22.85	51.89	-
FIS	39.69	43.62	81.31	+60.57%
ANN	28.79	25.14	53.93	+3.95%

In brief, thermostat on/off controller is still effective in terms of energy consumption only. However, it makes inconsistent T_{room} which directly related to thermal dissatisfaction for occupants. The ANN simultaneous mass and temperature controller can effectively maintain desired T_{room} by minimizing control errors, and also, it just consumes energy 3.95% 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 hospitals and laboratories requiring huge energy and sensitive T_{room} control.

In order to implement this ANN model to actual buildings, it needs to be considered that each control signal is converted into physical signals. The mass signals from the ANN are used to adjust fan motor speed in a heater and an air conditioner, or to change damper angle in ducts or diffusers. The temperature signals from the ANN are used to control temperature controllers of a heater and an air conditioner, or to operate resistance coils in ducts or diffusers. Therefore, a comprehensive simulation or experimental analysis for total energy costs including electricity used to drive the devices will be performed as a follow-up study.

CONCLUSION

In this research, neural network controller for heating and cooling supply air was introduced with simultaneous control of the amount of supply air and its temperature in-between season. In order to verify the effectiveness of the advanced controller, thermostat on/off and FIS controllers are tested, and the measures of IAE and heat and cooling gains a day were used.

The result concludes advantages of the ANN controller which effectively optimizes the supply air conditions to reduce control errors by 5.59% and mitigate energy consumption increase by 3.95%, respectively. Under conditions requiring more sensitive control and consuming large amount of energy such as hospitals and laboratories, the ANN controller can be used to effectively optimize the supply air condition as it relates to workability and productivity. Despite its sensitive and accurate control, the ANN controller maintains an energy consumption level as low as a conventional thermostat on/off controller. Another advantage is that the model can also be used for other colder or hotter areas without any major changes or modifications because working properly at low temperature below T_{set} and higher temperature above T_{set} was confirmed.

REFERENCES

Alcala, R. 2003. Fuzzy Control of HVAC Systems Optimized by Genetic Algorithms. *Applied Intelligence*, 155-177.

Anderson, M., Buehner, M., Young, P., Hittle, D., Anderson, C., Tu, J., et al. 2007. An experimental systems for advanced heating, ventilating and air conditioning control. *Energy and Buildings*, 136-147.

ASHRAE TC9.9. 2011. ASHRAE TC9.9: *Data Center Networking Equipment - Issues and Best Practices*. Atlanta, GA: ASHRAE.

Beinarts, I. 2013. Fuzzy Logic Control Method of HVAC Equipment for Optimization of Passengers' Thermal Comfort in Public Electric Transport Vehicles. *EUROCON 2013* (pp. 1180-1186). Zagreb: IEEE.

BNP media. 2001, November 12. *An Early History Of Comfort Heating*. Retrieved March 27, 2016, from The NEW Magazine: http://www.achrnews.com.

Dounis, A., & Caraiscos, C. 2009. Advanced control systems engineering for energy and comfort management in a building environment - A review. *Renewable and Sustainable Energy Reviews* , 1246-1261.

Fazzolari, M., Alcala, R., Nojima, Y., Ishibuchi, H., & Herrera, F. 2013. A Review of the Application of Multiobjective Evolutionary Fuzzy Systems: Current Status and Further Directions. *Fuzzy Systems*, 45-65.

Fraisse, G., Virgone, J., & Rous, J. 1997. Thermal control of a discontinuously occupied building using a classical and a fuzzy logic approach. *Energy and Buildings*, 303-316.

Hamdi, M., & Lachiver, G. 1998. A Fuzzy Control System Based on the Human Sensation of Thermal Comfort. *Fuzzy Systems* (pp. 487-492). NJ: IEEE.

Ji, Y; Xu, P; Duan, P; Lu, X. 2016. Estimating hourly cooling load in commercial buildings using a thermal network model and electricity submetering data. *Applied Energy*, 309-323.

Jovanović, R, Sretenović, A & Živković, B. 2015. Ensemble of various neural networks for prediction of heating energy consumption. *Energy and Buildings*, 189-199.

Koulani, C., Hviid, C., & Terkildsen, S. 2014. Optimized damper control of pressure and airflow in ventilation systems. *10th Nordic Symposium on Building Physics* (pp. 822-829). Lund: Lund University.

Lianzhong, L., & Zaheeruddin, M. 2007. Hybrid fuzzy logic control strategies for hot water district heating systems. *Building Services Engineers*, 35-53.

Malhotra, R., & Sodhi, R. 2011. Boiler flow control using PID and fuzzy logic controller. *IJCSET*, 315-319.

Mathworks. 2016, March 28, Documentation: *Matlab examples*, Retrieved March 31, 2016, from Mathworks: https://www.mathworks.com.

Politechnika Wroclawska. 2016, March 28. *Chapter 2 Introduction to Neural network*. Retrieved March 28, 2016, from Politechnika Wroclawska: www.ii.pwr.edu.pl.

Rossiter, J., Kouvaritakis, B., & Dunnett, R. 1991. Application of generalised predictive control to a boiler-turbine unit for electricity generation. *Control Theory and Applications* (pp. 59-67). NJ: IEEE.

Somsai, K., Oonsivilai, A., Srikaew, A., & Kulworawanichpong, T. 2007. Optimal PI Controller Design and Simulation of a Static Var Compensator Using MATLAB's SIMULINK. *7th WSEAS International Conference on Power Systems* (pp. 30-35). Beijing: WSEAS.

Soyguder, S., & Alli, H. 2010. Fuzzy adaptive control for the actuators position control and modeling of an expert system. *Energy and Buildings*, 2072-2080.

Steinbrecher, R., & Schmidt, R. 2011. Data center environments. *ASHRAE Journal*, 42-49.

Tan, W., Liu, J., Fang, F., & Chen, Y. 2004. Tuning of PID controllers for boiler-turbine units. *ISA Trans*, 571-583.

Wang, Q., Zou, B., Lee, T., & Bi, Q. 1997. Auto-tuning of multivariable PID controllers from decentralized relay feedback. *Automatica*, 319-330.

Zhang, J., Ou, J., & Sun, D. 2003. Study on Fuzzy Control for HVAC Systems. *ASHRAE*, 13-36.

Zhuang, M., & Atherton, D. 1993. Automatic tuning of optimum PID controllers. *Control Theory and Applications*, 216-224.