A Comparative Study Between Thermostat/Hygrometer-Based Conventional and Artificial Neural Network-Based Predictive/Adaptive Thermal Controls in Residential Buildings

Jin Woo Moon¹ and Seung-Hoon Han*²

¹Professor, Department of Building Services Engineering, Hanbat National University, Korea
²Professor, School of Architecture, Chonnam National University, Korea

Abstract

This study aimed at testing the feasibility of employing artificial neural network (ANN)-based predictive and adaptive control logics to improve thermal comfort and energy efficiency through a decrease in overshoots and undershoots of control variables. Three control logics were developed: (1) conventional temperature/humidity control logic, (2) ANN-based temperature/humidity control logic, and (3) ANN-based Predicted Mean Vote (PMV) control logic. Performance tests were conducted in a thermal chamber for non-application of setback and application of setback of thermal factors. Analysis revealed that the ANN-based predictive temperature/humidity control logic generally provided greater periods of thermal comfort than that of the conventional logic, as well as a reduction in overshoots and undershoots. In addition, the ANN-based PMV control logic provided significantly better PMV conditions than both temperature/humidity based control logics. In more cases, ANN-based control logic demonstrated a reduction in electricity consumption, compared to non-ANN-based control logic, especially for a system with a large time-lag effect such as a radiant water heating system.

Keywords: artificial neural network; predictive controls; adaptive controls; thermal comfort; PMV control

1. Introduction

Because of its simplicity, the most widespread thermal control method for residential buildings has been the thermostat- and hygrometer-based independent temperature and humidity control. However, this conventional method presented two major problems in maintaining a comfortable indoor thermal environment.

The first problem is its inability to take into account the control system's time lag and the building's thermal inertia associated with overshoots and undershoots of thermal factors beyond the specified comfort range. This can lead to thermal discomfort and energy inefficiency. The second problem arises from limiting factors to only two thermal variables (temperature and humidity) as a control variable, thus thermal comfort considering PMV is not yet feasible. Therefore, occupants would feel thermal discomfort even in an indoor space where temperature and humidity are comfortably conditioned.

To address problems caused by overshoots and undershoots, new approaches to predictive control have been studied using artificial intelligence such as ANN (Artificial Neural Network). ANN models were developed for predicting the optimal start time of a heating system for restoring interior temperature to a comfortable level by the start of business hours (Yeo and Kim, 2003) and for predicting the time required for interior temperature to drop to the lower limit of the comfort range (Yang and Kim, 2000). Employing these control logics with the heating system resulted in improved thermal comfort and energy efficiency for test office buildings. For residential thermal controls, ANN models were applied to residential water heating systems and radiant floor heating systems (Morel et al., 2001, Lee et al., 2002). In particular, Fuzzy-ANN incorporation was investigated for a radiant heating device, resulting in a significant reduction of temperature overshoots and energy consumption, compared to the PI controller (Gouda and Danaher, 2006). ANN models also were applied for optimal control of cooling devices using the predicted end-of-setback moment for air-conditioning, resulting in accurate control and ease of use (Ben-Nakhi and Mahmoud, 2002).

1.1 Limitations of Previous Models

Recently developed ANN models regarded indoor air temperature as the only target variable, while other factors such as humidity or PMV were rarely considered. In order to obtain the benefits of regulating building thermal systems based on factors consisting
of thermal comfort including humidity and PMV, Moon et al. investigated PMV control in residential buildings using ANN as a preliminary study (Moon et al., 2009). The researchers developed a thermal control framework and ANN-based advanced logics for conditioning temperature, humidity, and PMV. The performance of control logics for the non-application and application of setback was numerically tested using the IBPT (International Building Physics Toolbox) (IBPT, 2009) incorporated with Matlab (Matrix Laboratory) (MathWorks, 2008). The tests identified potentials for improving thermal conditions using ANN-based environmental controls.

1.2 Objectives

This study aimed at experimentally testing the performance of three control logics developed by Moon et al. (2009) and to identify the optimal logic in terms of thermal comfort and energy efficiency. The tested control logics were: (1) conventional temperature/humidity control logic, (2) ANN-based temperature/humidity control logic, and (3) ANN-based PMV control logic. Experimental data from this study coupled with the previous study's computational analysis can provide further evidence of the potential of proposed logics for residential thermal control.

2. Methods

2.1 Development of Control Logics

(1) Conventional Temperature/Humidity Control Logic

Conventional control logic controls temperature and humidity using a thermostat and hygrometer. Control algorithm flow consists of two primary parts: one for temperature control, the other for humidity control (Fig.1.). To deduct these devices' new operation, current operation (e.g., heating, cooling, humidifying, and dehumidifying) and current temperature/humidity conditions are employed as determinants.

(2) ANN-Based Thermal Control Logics

Two ANN-based predictive and adaptive logics were developed as proposed logics. The first proposed was an ANN-based temperature/humidity control logic (Fig.2.), designed to control temperature and humidity independently based on predicted values from two ANN models: predicted temperature (∆Temperature) and predicted humidity (AHumidity). At every minute, ANN models predicted the maximum amount of rise or drop of thermal factor when the current operating mode of the control device was changed. For example, in the heating season, ∆Temperature is the maximum rise of temperature after stopping the currently working heating device. By employing these predicted values as determinants for deducting the devices' operation, climate control device operation could be predetermined before thermal conditions reached comfortable condition boundaries. Thus, thermal conditions could be more comfortably stabilized within the specified comfort range (Fig.3.).
The second proposed logic was an ANN-based PMV control logic which conditions the interior PMV using the predicted PMV values ($\Delta$PMV) from an ANN model (Fig.4.). More diverse climate factors (e.g., interior air velocity and Mean Radiant Temperature - MRT) and occupant conditions (e.g., clothing level and activity) need to be considered for calculating PMV. Heating/humidifying systems and cooling/dehumidifying systems work together to increase and decrease the PMV, respectively.

The features of employed ANN models are described in Table 1. Three structurally identical ANN models were developed. Since there is no fixed scientific solution for the design of an optimal ANN model, this study employed empirical solutions proven in previous studies (Datta et al., 1997, Kalogirou and Bojic, 2000, Lee et al., 2002, MathWorks, 2008, Moon et al., 2009, Yang and Kim, 2000, Yang et al., 2003, Yang et al., 2005).

### 2.2 Performance Tests

(1) Description of a Thermal Chamber

Developed control logics were tested in a thermal chamber built inside a climate-controlled building. Fig.5. illustrates the thermal chamber layout and Table 2. describes the composition details. The south perimeter wall of the climate-controlled building served as the south wall of the thermal chamber. This wall had a large window, which was covered with rigid insulation to block any sunlight from entering the interior space. The other walls of the thermal chamber were built inside the climate-controlled space. The interior and exterior thermal conditions were monitored and transmitted to the control panel by sensors. Comparing with a different sensor (HOBO12 Temp/RH/Light/External Data Logger) (MicroDAQ, 2008) as a standard method, the exterior and interior temperature and humidity sensors were calibrated in the pretest. The exterior sensors were doubly-covered with galvanized iron cases to block direct sunlight, with openings for adequate ventilation.

The sensors and thermal control systems of the applied system were connected to the control panel through the data acquisition system EZIO board (NIQ, 2006) for signal conversion incorporated with the Data Acquisition Toolbox in Matlab. Control logics were developed using Matlab, particularly the Neural Network toolbox for developing ANN-based control logics.

(2) Variables and Schedule

Logics were tested for (1) non-application of setback and (2) application of setback. Non-application of setback adopted the constant comfort range of

---

### Table 1. Descriptions of Developed ANN Models

| Structure          | Input Layer                                                                 |
|--------------------|------------------------------------------------------------------------------|
|                    | ► Number of neurons: 8                                                       |
|                    | i) exterior temperature                                                      |
|                    | exterior temperature change                                                  |
|                    | ii) from the preceding hour                                                  |
|                    | iii) interior humidity                                                       |
|                    | iv) exterior humidity change                                                 |
|                    | from the preceding hour                                                      |
|                    | v) interior temperature                                                      |
|                    | vi) interior temperature change                                               |
|                    | from the preceding ten minutes                                               |
|                    | vii) interior humidity                                                       |
|                    | viii) interior humidity change                                                |
|                    | from the preceding ten minutes                                               |

| Hidden Layer       | ► Number of Layers: 1                                                        |
|--------------------|► Number of neurons: 17                                                      |
|                    | using $N_h = 2 \times N_i + 1$                                               |
|                    | $N_i$: number of hidden neurons                                              |
|                    | $N_o$: number of input neurons                                               |

| Output Layer       | ► Number of neurons: 1                                                       |
|--------------------|► (DeltaTemperature, DeltaHumidity, and $\Delta$PMV, respectively)           |

| Training Method    | ► Number of data sets: 160                                                   |
|--------------------| using $N_d = (N_i - (N_i + N_o)/2)^2$                                        |
|                    | $N_d$: number of data sets                                                   |
|                    | $N_i$: number of input neurons                                               |
|                    | $N_o$: number of output neurons                                              |
|                    | ► Obtained from the pre-test                                                 |
|                    | ► Type: sliding-window method                                                 |
|                    | ► Training goals:                                                           |
|                    | 0.1°C for temperature                                                       |
|                    | 0.1% for humidity                                                           |
|                    | 0.1 for PMV                                                                 |
|                    | ► Epoch: 1,000 times                                                        |
|                    | ► Learning rate: 0.75                                                        |
|                    | ► Momentum: 0.9                                                             |
|                    | ► Algorithm: Levenberg-Marquardt                                             |

---

Fig.4. ANN-Based PMV Control Logic

Fig.5. Plan of the Thermal Chamber
the thermal factors as recommended by ASHRAE (American Society of Heating, Refrigerating, and Air-Conditioning Engineers) (ASHRAE, 1992) for the whole experimental periods, as shown below.

- Heating Devices: 20–23°C
- Cooling Devices: 23–26°C
- Humidifying Devices: 30–45%
- Dehumidifying Devices: 45–60%
- PMV Increasing Devices: -0.5–0.0
- PMV Decreasing Devices: 0.0–0.5

On the other hand, application of setback, applied for conserving energy, employed night-time and daytime setback of thermal factors. Fig.6. shows the new comfort ranges and periods by setback for temperature, humidity, and PMV.

Performance tests were conducted for two seasons: heating & humidifying season and cooling & dehumidifying season for five days each (Table 3.).

3. Results and Discussion

Control logic performances were analyzed regarding (1) duration of comfort period, (2) magnitude of overshoots and undershoots, and (3) energy consumption. Since weather conditions were not identical for each test, the period having the most similar enthalpy conditions of exterior and surrounding interior spaces was extracted for comparison.

3.1 Non-application of setback

(1) Background thermal conditions

Average thermal conditions of exterior and surrounding spaces for the extracted periods (38 hours in the heating & humidifying season and 48 hours in the cooling & dehumidifying season) were summarized for both seasons (Table 4.). Sampled periods were selected which did not have a positive effect on the ANN-based temperature/humidity control logic when its performance was compared with that of the non-ANN-based logic. For the heating and humidifying season, the enthalpy condition for the ANN-based temperature/humidity control logic was slightly lower than those for other logics, which may have led to the use of more energy for heating and humidifying during the sampled period. Similarly, the ANN-based temperature/humidity control logic was tested under the highest enthalpy conditions during the cooling and dehumidifying seasons, thus more cooling and dehumidifying energy was required.

(2) Duration of comfort period

Figs.7. and 8. show the duration that the three
control logics were able to maintain the comfort range. Compared to conventional logic, the ANN-based temperature/humidity control greatly improved the comfort period of temperature (from 69.8% to 86.8%) and to a lesser degree humidity (from 97.3% to 97.6%), in the heating and humidifying season but not significantly in the cooling and dehumidifying season (same 98.3% of temperature and 100.0% of humidity for both logics). This difference between heating and cooling operations was due to the greater time lag of the radiant heating system compared to the cooling system.

Improvement of the humidity comfort period during the heating and humidifying season, which was a 0.3% increase, does not prove predictive logic superiority, because there could be some sensor errors (i.e., ±2% error by the employed humidity sensor). To reduce sensor data errors, the normal averaging method needs to be applied in future research.

Since PMV was the target control variable, the ANN-based PMV control conditioned PMV more comfortably (74.6% comfort period in the heating and humidifying season and 15.8% comfort period in the cooling and dehumidifying season) than did the temperature- and humidity-based control logics (Figs. 7 and 8). On the other hand, the comfort periods of temperature and humidity decreased because temperature and humidity values generally were maintained higher than the specified comfort ranges to keep the PMV within the comfort range.

There are two reasons why the comfort periods of PMV by the ANN-based PMV control logic were generally smaller than those of temperature and humidity by the Temp/Humid Control logics. Firstly, the specified comfort ranges for PMV were narrower than those for temperature and humidity. Thus, the overshoot and undershoot of PMV went beyond the comfort range more frequently and for longer compared to those of temperature or humidity. Secondly, the significantly low percentage of PMV comfort periods in the cooling and dehumidifying season (15.8%) was due to cold interior conditions even without operating A/C and dehumidifier.

(3) Magnitude of overshoots and undershoots

The magnitude of overshoots and undershoots for temperature and humidity were analyzed using Equation (1). Using this criterion, the stability of thermal comfort factors were compared.

$$M (°C \times minutes or °F \times minutes) = \sum(\Delta \times t) \quad (1)$$

Where,

- $M$: magnitude of overshoots or undershoots out of the specified comfort range
- $\Delta$: degree of overshoots or undershoots out of the specified comfort range
- $t$: duration time of overshoots or undershoots out of the specified comfort range

The magnitudes for temperature using the ANN-based predictive logic were reduced in all cases except for the magnitude of overshoots in the cooling and dehumidifying season, where the magnitude was increased (Table 5). The first reason for this increase was the insignificant time lag of the air conditioner, in which predictive control based on the ANN model was less effective in reducing overshoots. The second reason might be the higher enthalpy conditions of the exterior and surrounding space during the sampled period of the predictive logic. A higher enthalpy condition could still raise interior temperature more easily at the moment when, or shortly after, the A/C is

| Table 4. Average Thermal Conditions of Exterior and Surrounding Interior Space for the Sampled Period: Non-Application of Setback |
|-----------------|-----------------|-----------------|-----------------|
| Seasons         | Location & Sampled Periods | Enthalpy (Btu/lb of dry air) | Conventional Temp/Humid Control | ANN-based Temp/Humid Control | ANN-based PMV control |
| Heating & Humidifying | Exterior | 7.24 | 7.23 | 7.31 |
|                  | Surrounding Interior | 18.08 | 17.65 | 17.79 |
|                  | Sampled Period | (Dec. 19, 1am~ Dec. 20, 15pm, 2007) | (Dec. 28, 1am~ Dec. 29, 15pm, 2007) | (Dec. 31, 1am, 2007~ Jan. 01, 15pm, 2008) |
| Cooling & Dehumidifying | Exterior | 16.76 | 16.78 | 16.76 |
|                  | Surrounding Interior | 19.51 | 19.54 | 19.53 |
|                  | Sampled Periods | (Aug. 11, 0am~ Aug. 12, 24pm, 2008) | (Aug. 14,0am~ Aug. 15, 24pm, 2008) | (Jun. 24, 0am~ Jun. 25, 24pm, 2008) |
turned on. Thus, overshoots went beyond the comfort range more easily.

Compared to the conventional logic, the ANN-based logic reduced the magnitude of overshoots and undershoots for humidity in the heating and humidifying season (Table 5.). However, it was impossible to compare those for a dehumidifying device since there were no dehumidifying operations.

(4) Energy consumption

Electricity consumption for thermal conditioning was compared using the amount (Wh) calculated by multiplication of power (Watt) and operating time (h). Compared to the conventional logic, the ANN-based temperature/humidity control saved energy for heating by 0.7% (from 21,350 to 21,200 Wh) and for humidifying by 26.9% (from 1,042 to 762 Wh) in the heating and humidifying season (Fig.9.) while consuming more electricity for cooling by 10.5% (from 832 to 919 Wh) in the cooling and dehumidifying season (Fig.10.). The increase may be due to two factors: (1) no time lag effect by the air conditioner and (2) higher enthalpy in the exterior- and interior-surrounding spaces.

PMV control with ANN consumed more energy in both seasons than the temperature- and humidity-based control logic (Figs.9. and 10.). In the heating and humidifying season, the specified comfort range of PMV was higher than those of temperature and humidity; therefore the PMV-based control logic required more heating and humidifying operations. On the other hand, increase in energy consumption in the cooling and dehumidifying season was due to the narrow range of PMV comfort. Specified comfort ranges of PMV were -0.5~0.0 in the heating and humidifying season and 0.0~0.5 in the cooling and dehumidifying season. When a PMV was over 0.5 in the cooling and dehumidifying season, the air conditioner and dehumidifier worked to cool the interior. When PMV reached 0.0, systems were turned off. However, PMV was still apt to be reduced a certain degree to reach -0.5, which required heating and humidifying. This resulted in unnecessary heating and humidifying leading to additional energy consumption. Therefore, a function must be added to the algorithm in future research to prevent the unnecessary operation of devices.

3.2 Application of setback

(1) Background thermal conditions

Period of similar thermal conditions of exterior and

| Seasons            | Types of Shoots | Conventional Temp/Humid Control | ANN-based Temp/Humid Control |
|--------------------|-----------------|---------------------------------|-------------------------------|
|                    | Magnitudes of Shoots (˚C × minutes, % × minutes) |                                |                               |
|                    | Overshoots      | Undershoots                     | Overshoots                   | Undershoots                   |
| Heating &         | Temperature     | 260.74                          | -26.08                       | 48.12                         | -19.71                       |
| Humidifying       | Overshoots      | 13.87                           | -13.28                       | 9.14                          | -8.33                        |
|                    | Undershoots     | -8.95                           | -7.39                        |                               |                               |

Fig.9. Energy Consumption (Wh) in the Heating and Humidifying Seasons: Non-Application of Setback

Fig.10. Energy Consumption (Wh) in the Cooling and Dehumidifying Season: Non-Application of Setback

Fig.11. Comfort Periods in the Heating and Humidifying Season: Application of Setback

Fig.12. Comfort Periods in the Cooling and Dehumidifying Season: Application of Setback
surrounding spaces were extracted for 24 hours in the heating/humidifying season and for 8 hours in the cooling/dehumidifying season (Table 6). As with the non-application of setback, lower enthalpy conditions for the heating and humidifying season, and higher enthalpy conditions for the cooling and dehumidifying season were given for the ANN-based temperature/humidity control.

(2) Duration of comfort period

For the application of setback mode as well, the ANN-based predictive logic showed improvement in temperature and humidity control (Figs. 11. and 12.). The comfort temperature period was improved from 86.2 to 91.3% in the heating and humidifying season, and from 93.1 to 93.4% in the cooling and dehumidifying season. The amount of increase was less significant in the cooling and dehumidifying season because of less time lag effect by the air conditioner. Although not significant, humidity conditions also improved, from 98.0% to 98.2% in the heating and humidifying season. For the cooling and dehumidifying season, both logics created 100% of comfort period for humidity although there were no dehumidifying operations.

The ANN-based PMV control worked better to control PMV conditions (85.3% and 58.7% in the respective seasons) than did the temperature- and humidity-based control logic. The comfort periods of temperature and humidity decreased for the same reasons as the non-application of setback.

(3) Magnitude of overshoots and undershoots

As with the non-application of setback, the magnitudes of overshoots and undershoots for temperature using the ANN-based predictive logic were reduced in both seasons except for overshoots in the cooling and dehumidifying season, in which the increase was from 1.80 to 2.03 °C × minutes (Table 7.).

In addition, predictive logic reduced the magnitude of overshoots and undershoots for humidity in the heating and humidifying season (Table 7.). There were no dehumidifying operations in the cooling and dehumidifying season, thus it was impossible to compare the magnitude of humidity for a dehumidifying system.

(4) Energy consumption

Compared to the conventional logic, the ANN-based temperature/humidity control logic saved energy in both seasons: 11.3% (from 10,425 to 9,250 Wh) for heating and 14.0% (from 300 to 258 Wh) for humidifying in the heating and humidifying season (Fig. 13.), and 11.7% (from 962 to 849 Wh) for cooling in the cooling and dehumidifying season (Fig. 14.).

As with the non-application of setback, the ANN-based PMV control logic consumed more energy in both seasons than did the two temperature- and

| Seasons | Location & Sampled Periods | Temperature Enthalpy (Btu/lb of dry air) | Conventional Temp/Humid Control | ANN-based Temp/Humid Control | ANN-based PMV control |
|---------|-----------------------------|----------------------------------------|-------------------------------|-----------------------------|----------------------|
| Heating & Humidifying | Exterior | 7.00 | 6.78 | 6.94 |
| | Surrounding Interior | 17.70 | 17.68 | 17.80 |
| | Sampled Period | (7/17, 0am ~ 24pm, 2008) | (7/14, 0am ~ 24pm, 2008) | (7/28, 0am ~ 24pm, 2008) |
| Cooling & Dehumidifying | Exterior | 20.46 | 20.63 | 21.40 |
| | Surrounding Interior | 19.51 | 19.96 | 19.38 |
| | Sampled Periods | (7/12, 16pm ~ 24pm, 2008) | (8/22, 16pm ~ 24pm, 2008) | (8/3, 16pm ~ 24pm, 2008) |

| Seasons | Thermal Factors | Types of Shoots | Magnitudes of Shoots (°C × minutes, % × minutes) | Conventional Temp/Humid Control | ANN-based Temp/Humid Control |
|---------|-----------------|-----------------|-----------------------------------------------|-------------------------------|-----------------------------|
| Heating & Humidifying | Temperature | Overshoots | 29.43 | 9.21 |
| | | Undershoots | -10.34 | -9.17 |
| | Humidity | Overshoots | -2.55 | -2.06 |
| | | Undershoots | -3.66 | -2.75 |

| Seasons | Temperature | Overshoots | Undershoots |
|---------|-------------|------------|-------------|
| Heating & Humidifying | 1.80 | 2.03 |
| Cooling & Dehumidifying | -3.66 | -2.75 |
humidity based control logics due to the higher specified PMV comfort range in the heating and humidifying season; and dehumidification in the cooling and dehumidifying seasons.

4. Conclusions

This study aimed to experimentally test the performance of three control logics and to identify optimal logic in thermal comfort and energy efficiency. The tested control logics were: (1) conventional temperature/humidity control logic, (2) ANN-based temperature/humidity control logic, and (3) ANN-based PMV control logic, as predictive and adaptive methods. Experimental data from this study, collected in the thermal chamber, coupled with the previous study's computational analysis, can provide further evidence of the potential of the proposed logics for residential thermal control. The findings from this study are:

- Predictive temperature/humidity control logic using ANN maintained temperature more comfortably with increased comfort periods within the specified comfort ranges than did the conventional control logic. In particular, the ANN-based method was more effective for a device with larger thermal lag effect, such as a radiant water heater.

- On the other hand, the comfort period of humidity was not improved significantly by the predictive logic. This may have been due to the reduced time-lag effect of the humidity control systems.

- The ANN-based PMV control logic better maintained PMV conditions than did the temperature/humidity based control logics. However, the comfort periods of temperature and humidity decreased, since temperature and humidity values were generally maintained higher than the specified comfort ranges for comfortably maintaining PMV.

- The ANN-based predictive temperature/humidity control logic better stabilized thermal conditions than did the conventional logic. The magnitudes of overshoots and undershoots of temperature and humidity were reduced by the predictive logic.

- The ANN-based predictive temperature/humidity control logic was generally more energy efficient for equipment with a higher thermal lag.

- The PMV-based control logic consumed more energy than the temperature/humidity based control logics for both seasons.

In conclusion, the predictive control of temperature/humidity using ANN models has great potential for enhancing thermal comfort and energy efficiency in residential buildings. In addition, the predictive control of PMV using the ANN model improved overall thermal comfort, but its energy efficiency was lower than that of the temperature/humidity-based logics. Thus, further study is warranted to investigate the value of improving thermal comfort (i.e. increased productivity) at the expense of increased energy consumption.

Acknowledgements

This work was supported by the Grant of the Korean Ministry of Education, Science and Technology (The Regional Core Research Program/Biohousing Research Institute) and by the Biohousing Research Center. This research was supported by the Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education, Science and Technology (2011-0010519).

References

1) ASHRAE (1992) ANSI/ASHRAE Standard 55-1992, Thermal Environmental Conditions for human occupancy. American Society of Heating, Refrigerating, and Air-Conditioning Engineers.
2) Ben-Nahlki, A.E. and Mahmoud, M.A. (2002) Energy conservation in buildings through efficient A/C control using neural networks. Applied Energy, 73, pp.5-23.
3) Datta, D., Tassou, S.A., and Marriott, D. (1997) Application of neural networks for the prediction of the energy consumption in a supermarket. In: Proc. of CLIMA 2000 Conf, Brussels (Belgium), pp.98-107.
4) DWYER (2008) HU-1142. Available from: http://oemcontrols.com/lists/DwyerRb.htm; 2004-10-15:17:35.
5) National Semiconductor, LM35 Precision Centigrade Temperature Sensors, Available from: www.national.com; 2008-11-29-11:00.
6) Global Controls (2005) E70 Series. Available from: http://images.google.com/imgres?imgurl=http://www.global-controls.net/home/images/Airtest/Airtest%2520Velocity/E70.gif&imgrefurl=http://www.global-controls.net/air_velocity.html&h=264&w=375&sz=35&bih=35&biw=264&qc=3&hl=en&sa=X&ti=Air%2520test&tbm=isch&biw=264&bih=35&sa=X&tbm=isch&ei=964702410&rlz=1q%3Den&hl=en&lr=&tbnh=83&tbnw=118&start=12&prev=/images%3Fq=%3DDec%26hl%3Den%26sa=X%26ie=UTF-8%26oe=UTF-8%26rlz%3D1Q801%26iact=rc&sig2=JbhOvOu6mtOJ&bih=83&biw=118&start=12&prev=/images%3Fq=%3DDec%26hl%3Den%26sa=X%26ie=UTF-8%26oe=UTF-8%26rlz%3D1Q801%26iact=rc&sig2=JbhOvOu6mtOJ&bih=83&biw=118&start=12&prev=/images%3Fq=%3DDec%26hl%3Den%26sa=X%26ie=UTF-8%26oe=UTF-8%26rlz%3D1Q801%26iact=rc&sig2=JbhOvOu6mtOJ&bih=83&biw=118&start=12&prev=/images%3Fq=%3DDec%26hl%3Den%26sa=X%26ie=UTF-8%26oe=UTF-8%26rlz%3D1Q801%26iact=rc&sig2=JbhOvOu6mtOJ&bih=83&biw=118&start=12&prev=/images%3Fq=%3DDec%26hl%3Den%26sa=X%26ie=UTF-8%26oe=UTF-8%26rlz%3D1Q801%26iact=rc&sig2=JbhOvOu6mtOJ&bih=83&biw=118&start=12&prev=/images%3Fq=%3DDec%26hl%3Den%26sa=X%26ie=UTF-8%26oe=UTF-8%26rlz%3D1Q801%26iact=rc&sig2=JbhOvOu6mtOJ&bih=83&biw=118&start=12&prev=/images%3Fq=%3DDec%26hl%3Den%26sa=X%26ie=UTF-8%26oe=UTF-8%26rlz%3D1Q801%26iact=rc&sig2=JbhOvOu6mtOJ&bih=83&biw=118&start=12&prev=/images%3Fq=%3DDec%26hl%3Den%26sa=X%26ie=UTF-8%26oe=UTF-8%26rlz%3D1Q801%26iact=rc&sig2=JbhOvOu6mtOJ&bih=83&biw=118&start=12&prev=/images%3Fq=%3DDec%26hl%3Den%26sa=X%26ie=UTF-8%26oe=UTF-8%26rlz%3D1Q801%26iact=rc&sig2=JbhOvOu6mtOJ&bih=83&biw=118&start=12&prev=/images%3Fq=%3DDec%26hl%3Den%26sa=X%26ie=UTF-8%26oe=UTF-8%26rlz%3D1Q801%26iact=rc&sig2=JbhOvOu6mtOJ&bih=83&biw=118&start=12&prev=/images%3Fq=%3DDec%26hl%3Den%26sa=X%26ie=UTF-8%26oe=UTF-8%26rlz%3D1Q801%26iact=rc&sig2=JbhOvOu6mtOJ&bih=83&biw=118&start=12&prev=/images%3Fq=%3DDec%26hl%3Den%26sa=X%26ie=UTF-8%26oe=UTF-8%26rlz%3D1Q801%26iact=rc&sig2=JbhOvOu6mtOJ&bih=83&biw=118&start=12&prev=/images%3Fq=%3DDec%26hl%3Den%26sa=X%26ie=UTF-8%26oe=UTF-8%26rlz%3D1Q801%26iact=rc&sig2=JbhOvOu6mtOJ&bih=83&biw=118&start=12&prev=/images%3Fq=%3DDec%26hl%3Den%26sa=X%26ie=UTF-8%26oe=UTF-8%26rlz%3D1Q801%26iact=rc&sig2=JbhOvOu6mtOJ&bih=83&biw=118&start=12&prev=/images%3Fq=%3DDec%26hl%3Den%26sa=X%26ie=UTF-8%26oe=UTF-8%26rlz%3D1Q801%26iact=rc&sig2=JbhOvOu6mtOJ&bih=83&biw=118&start=12&prev=/images%3Fq=%3DDec%26hl%3Den%26sa=X%26ie=UTF-8%26oe=UTF-8%26rlz%3D1Q801%26iact=rc&sig2=JbhOvOu6mtOJ&bih=83&biw=118&start=12&prev=/images%3Fq=%3DDec%26hl%3Den%26sa=X%26ie=UTF-8%26oe=UTF-8%26rlz%3D1Q801%26iact=rc&sig2=JbhOvOu6mtOJ&bih=83&biw=118&start=12&prev=/images%3Fq=%3DDec%26hl%3Den%26sa=X%26ie=UTF-8%26oe=UTF-8%26rlz%3D1Q801%26iact=rc&sig2=JbhOvOu6mtOJ&bih=83&biw=118&start=12&prev=/images%3Fq=%3DDec%26hl%3Den%26sa=X%26ie=UTF-8%26oe=UTF-8%26rlz%3D1Q801%26iact=rc&sig2=JbhOvOu6mtOJ&bih=83&biw=118&start=12&prev=/images%3Fq=%3DDec%26hl%3En...