FUZZY LOGIC CONTROL VERSUS CONVENTIONAL PID CONTROL FOR CONTROLLING INDOOR TEMPERATURE OF A BUILDING SPACE

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Abstract: A building space and its hot water heating system are simulated. Results are compared with field monitored data obtained from a building in use and an excellent agreement between the two is demonstrated. A fuzzy logic controller (*FLC*) based on if-then control rules is designed and the performance of the *FLC* is compared with a commonly used proportional, integral plus derivative (*PID*) controller. It is found that the *FLC* is more robust and efficient than the *PID* controller in that the *FLC* is much less sensitive to changes in system parameters and results in lower system energy consumption. *Copyright © 2000 IFAC*

Keywords: Heat Exchangers, Temperature Control, Fuzzy Control, PID Controller, Conventional Control, and Modeling.

1. INTRODUCTION

Good control of nonlinear processes is something that is often difficult to achieve. Benefits of good control of heating systems include improved occupancy comfort, increased life span of mechanical equipment, and reduced energy consumption by keeping the system variables efficiently at their setpoint.

There are many different controllers for hot water heating systems. Controllers may be classified by the type of control action or the variable used for the control signal. Control techniques applied to heating systems may be two position *(On/Off)*, modulating (utilizing proportional, integral and differential modes or some combination of these) (Haines, 1988) or more advanced techniques such as predictive control (Georgescu, 1993).

The simplest controller used in heating systems is the *On/Off* type in which the controller output is either "on" or "off" (Haines, 1988; ASHRAE, 1984). In order to avoid excessively rapid cycling, a control differential must be used. Because of the time and thermal lags inherent in heating systems, the operating differential is always greater than the control differential.

Presently, most of the controllers used in industry are based on *PID* control. It is often very difficult to obtain an exact mathematical model of a nonlinear dynamical process. Therefore, the fact that *PID* controllers utilize the error, the integral and the derivative of the error rather than an explicit model of the process has made them quite popular. However, the proportional, integral and derivative gain constants determined by tuning the controller heavily depend on system parameters. Changes in these parameters require retuning of the controller.

An alternative to conventional control is fuzzy logic control. Fuzzy logic control is based on the fact that an experienced human operator can control a process without knowledge of its dynamics (King and Mamdani, 1977). Developing *FLC* is usually easier and cheaper than *PID* controller and *FLCs* are more robust in that they can cover a wider operation range.

In this work a simulation model of a building space and its heating system is developed to which *PID* and *FLC* control are applied. The controllers' parameters are set to values that result in the best performance under likely disturbances and changes in set point.

The thermal dynamic behavior of a building space is described in section 2. Section 3, includes the description of a hot water heating system with nonlinear control valve. Open loop results for the building and heating system model are given in section 4. A Closed loop system based alternately on *PID* and *FLC* are developed in section 5. A comparison between the results under *PID* and *FLC* are given in section 6 and conclusions are drawn in section 7.

2. THERMAL MODEL OF A BUILDING SPACE

The dynamics of a building space depend on outdoor temperature, solar radiation, building construction, internal loads, and the characteristic of the heating system. The thermal model of the building is based on the physical properties of the construction elements (obtainable from standard tables). From a control system perspective, the zone temperature is defined as a process output that has to be controlled. The hot water flow rate is taken to be the manipulated variable, and the other inputs are interpreted as measurable disturbances.

Any construction element can be represented by two "lumped" thermal resistances (R_{ins}, R_{out}), and one thermal capacity (C), as illustrated in figure (1). R_{ins}, R_{out} can be calculated using a method prescribed by (Lorenz and Masy, 1982), as interpreted by (Gouda *et al.*, 2000). The problem specific-state equations can be written for a given building space. This will be demonstrated in section 4.

3. HEATING SYSTEM MODEL

The description of the heating system is divided into two parts. The first part is the description of the heat exchanger and its water connections, and the second part is a description of the nonlinear control valve.

3.1 Heat Exchanger and Its Water Connection.

The type of hot water heat emitter most commonly used in current practice provides natural convection or some combination of natural convection and radiation. The encased natural convector is considered in this work. The dynamics of the heating system are dominated by the thermal capacity of the hot water space and the thermal capacity of the heat exchange material. A full description of the heat emitter model may be found in (Gouda *et al.*, 2000).

3.2 Control Valve.

Mathematical models of control valves for liquids are generally based on expressing the relationship between the flow rate passed by the valve and the position of the valve stem (Underwood and Edge, 1995). Thus the valve can be expressed by an "inherent characteristic", G_{inh} leading to an "installed characteristic", G_{ins}, (N is the Valve authority, and G_o is the valve let-by):

$$G_{inh} = G_o^{(1-u)} \tag{1}$$

$$G_{ins} = \left[1 + N(1/G_{inh}^2 - 1)\right]^{-1/2} \tag{2}$$

This nonlinear characteristic is "shaped" in an attempt to compensate for nonlinearities in the radiator emission characteristics.

The heating system model is summarized as shown in figure (2) in which the hot water supply from central boiler is delivered at constant temperature.

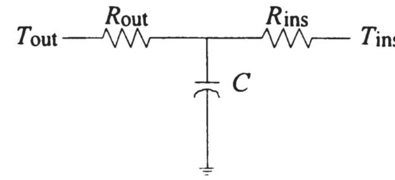

Fig. 1. "Lumped-parameter" Construction Element.

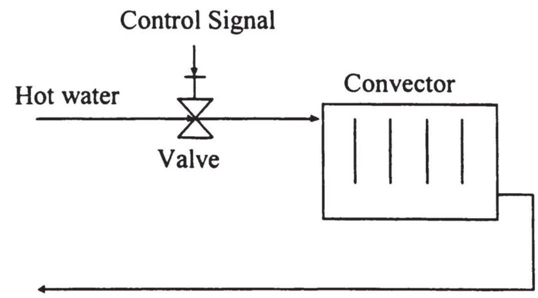

Fig. 2. Heating System.

The valve controls the water flow rate, which is applied to the radiator to produce the heating.

4. OPEN LOOP RESULTS

The combined building and heating system model was applied to a sample space in a campus building at the University of Northumbria. This building is of high thermal capacity and has been the subject of extensive research into photovoltaic cladding and is thus well documented in the literature (Horne, 1998). A north-facing room was selected at a period in which the room was known to be heated but not in use, enabling a simpler validation test scenario. It has two external walls, an internal floor, internal ceiling and two partitions (figure (3)).

The heating system consists of an encased finned natural convector which is controlled from a room temperature sensor and a three-port diverting valve which seeks to vary the hot water flow rate in response to room temperature. A state-space model of the building space can thus be written as:

$$\begin{aligned} \dot{X} &= AX + BU \\ Y &= CX + DU \end{aligned} \tag{3}$$

Where: X is the state vector: $[T_1\, T_2\, T_3\, T_4\, T_5\, T_i]^T$; U is the input vector $[T_o\, Q_s\, Q_p\, Q_g\, Q_r\, T_{z1}\, T_{z2}\, T_{z3}]^T$ and Y the output vector (in this case the indoor space temperature, T_i). Details of the model parameters can be found in (Gouda *et al.*, 2000). The measured data sample consists of a one-week (approximate) time series at 15-minute intervals of space dry bulb temperatures and heating control valve signals. The external temperature time-series was applied directly, and then filtered in order to smooth out some unacceptable noise spikes. The final model was initially implemented using the open loop realization shown in figure (4).

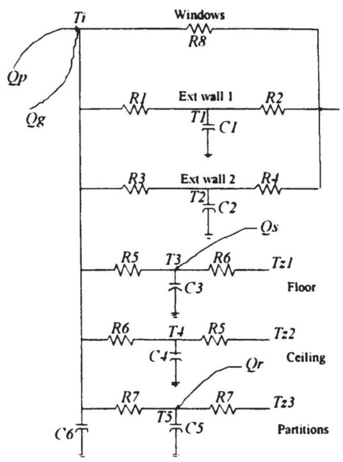

Fig. 3. Model Realisation of the Sample Space

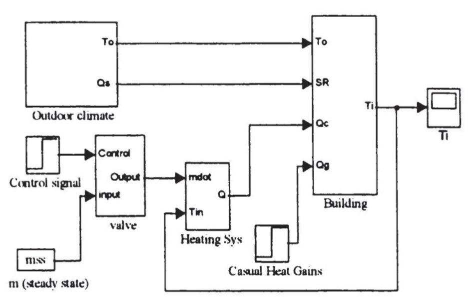

Fig. 4. Block Diagram of the Open Loop Model

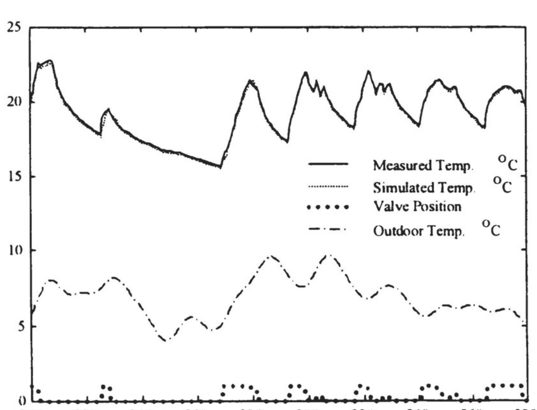

Fig. 5. Comparison of the Model and Monitored Data

The building space model, which was expressed as a state-space block (equation (3)), was solved with the nonlinear differential equations forming the heating system model using a variable step Runge-Kutta scheme selected from within the solver library of the software used. The model was implemented in Matlab-Simulink (MathWorks, 1993). In figure (5), the response to several cycles of heating is compared with field measurement data. The initial period represents a weekend whilst the 5 cycles of heating and cooling represent Monday to Friday. Results based on the model and field-measurements compare very favourably.

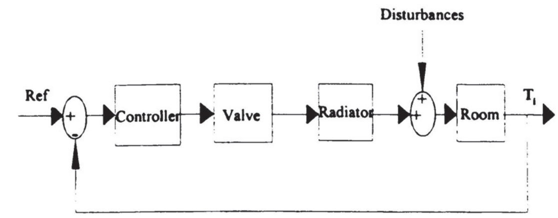

Fig. 6. Closed Loop System.

The overall root-mean-square error between the model and measured temperatures being approximately 0.1K.

5. CLOSED LOOP MODEL

A controller and feedback path were added in order to close the open loop system described above. The controlled variable (T_i) is compared with the user reference temperature and the resulting temperature error is applied to the controller. Outdoor temperature, solar radiation and casual heat gains act as disturbances, as shown in figure (6).

5.1. PID Controller.

PID control is commonly used in heating systems (Haines, 1988; and ASHRAE, 1984). Although a *PID* controller is reliable and efficient, its parameters require precise adjustment to obtain optimal performance, and they are heavily dependent on system parameters. The output of a *PID* is given by:

$$u(t) = k_p e(t) + k_i \int_0^t e(t) + k_d \frac{de(t)}{dt} \tag{4}$$

Where $e(t)$ is the error, u is the control signal and k_p, k_i, k_d are proportional, integral and derivative gain constants, respectively.

The *PID* controller described by equation (4) was applied to the system. The actual parameters of the controller in the sample building space (k_p, k_i, k_d) are $0.1K^{-1}$, $0.01K^{-1}s^{-1}$, and $0.5sK^{-1}$ respectively and these were initially applied. This produced a reasonable response but with overshoot (figure (10)), leading to more energy consumption and thermal discomfort for the occupants.

A tuning algorithm was adopted to adjust the controller parameters in order to eliminate this overshoot. In practice, Ziegler Nichols rules (Ziegler and Nichols, 1943) or similar tuning rules are used for predicting *PID* controller settings. These are based on achieving favourable response criteria of a hypothetical linear low-order system and, thus, have limited utility other than in the precise region of plant operation in which the tuning was carried out.

For the *PID* controller described in this work, the Matlab nonlinear control design blockset was used (MathWorks, 1993). This adopts a gradient search method that seeks to minimise a cost function. To give initial estimates of the controller parameters, an error mapping method was used as shown in figures (7, 8, and 9). Using the initial mapped values to initiate the tuning algorithm, tuned controller parameters of $1.527K^{-1}$, $0.005K^{-1}s^{-1}$, and $0.050sK^{-1}$ respectively were obtained for k_p, k_i, k_d. The response of the system under tuned *PID* controller is shown in figure (10).

The tuned *PID* controller gives good results at the precise conditions for which it has been designed. However, as will be seen later, when these conditions change performance is less favourable unless the controller is re-tuned.

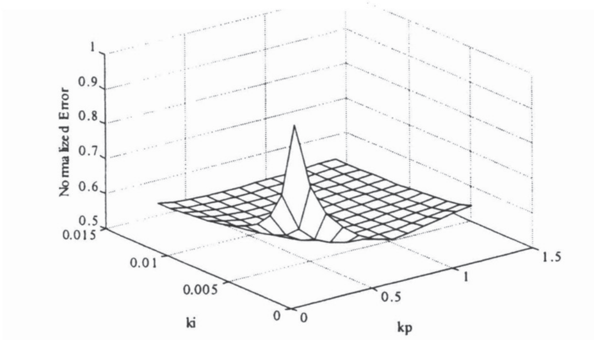

Fig. 7. Normalized Error vs k_p, k_i

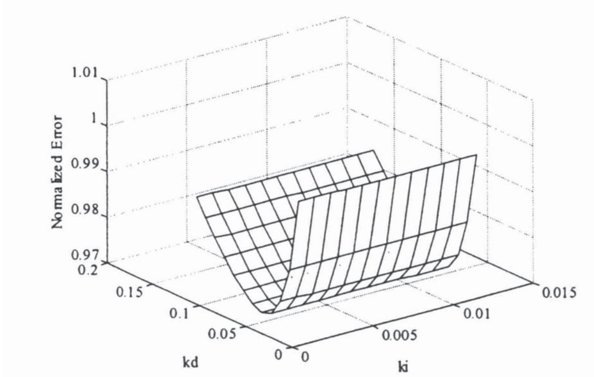

Fig. 8. Normalized Error vs k_d, k_i

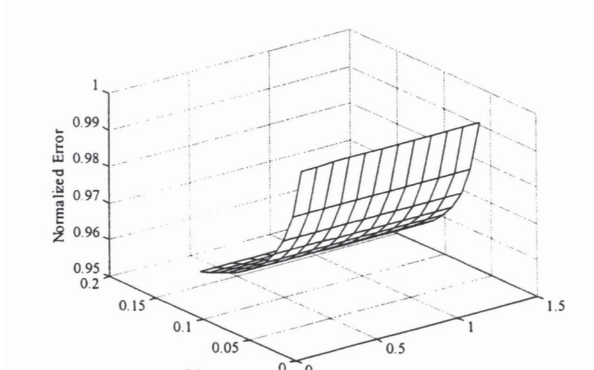

Fig. 9. Normalized Error vs k_p, k_d

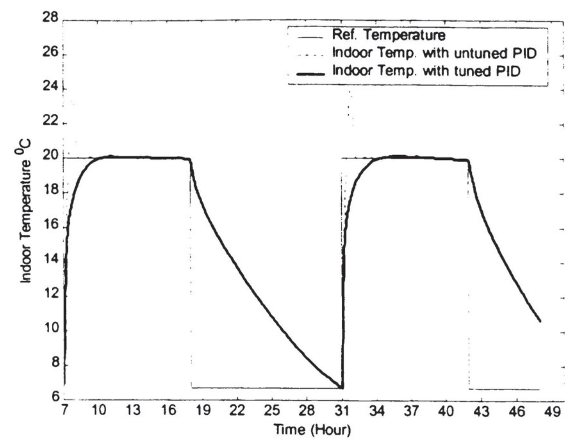

Fig. 10. Closed Loop Response with Tuned and Untuned *PID* Control

5.2. Static Fuzzy Logic Controller (FLC).

Since fuzzy control theory is somewhat new to those involved in building systems; it is appropriate to review some of the basic concepts. The reader interested in a more comprehensive review of the subject will find (Lee, 1990a, b; Gouda, *et al.* 1997) helpful. In this section, the basic structure of the fuzzy controller, which is shown in figure (11), will be developed. The static fuzzy controller consists of four main functional blocks: fuzzification interface; fuzzy control rules; inference engine, and defuzzification interface.

5.2.1. Fuzzification Interface.

The fuzzification interface consists of the following operations:

(1) Compute the input variables (crisp values of error and change of error).

(2) Perform a scale mapping that transfers the input variable ranges into a corresponding universe of discourse *(quantization/normalization)*.

(3) Perform the fuzzification strategy that converts crisp input data into suitable linguistic variables, which may be viewed as labels of fuzzy sets.

The fuzzification strategy converts the crisp input data into fuzzy sets (linguistic variables) such as, positive very big *(PVB)*, negative very small *(NVS)*, positive big *(PB)*, negative small *(NS)*, zero *(ZE)* and so on. The fuzzification action consists of a set of analogue membership functions, describing the input linguistic terms. The membership function can be of a variaety of shapes (e.g. triangle, trapezoid, etc.).

5.2.2. Fuzzy Control Rules.

The dynamic behavior of a fuzzy system is characterized by a set of imprecise conditional statements, which form a set of decision rules.

The process can be expressed linguistically as a set of linguistic decision rules of the form: If *(Conditions are satisfied)* Then *(Action can be inferred)*.

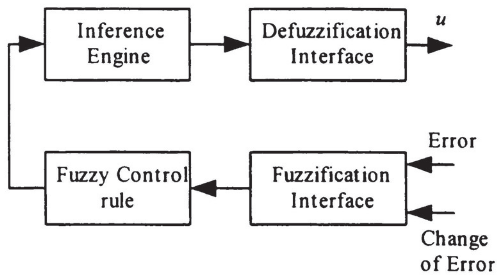

Fig. 11. Structure of a Fuzzy Logic Controller

There are four ways to derive fuzzy control rules (Mamdani, 1974; Sugeno, 1985). They may be derived by referring to human operators' experiences and knowledge. They may be derived by modeling or observing the human operator's control actions. They may be derived from a fuzzy model of the process or the rules may be learnt by the controller (self-organization).

5.2.3. Inference Engine.

There are in general four methods of fuzzy reasoning (Lee, 1990b). One of the most common methods is used in this work–Mamdani's minimum operation method. The inference mechanism involves the following two functions:

1) Determine for any fuzzy controller input (error and change of error) which rules are applicable.
2) Determine the fuzzy control action by using fuzzy reasoning.

5.2.4. Defuzzification Strategies.

The output of inference engine is a fuzzy set. As a process usually requires a non-fuzzy control signal (i.e. a crisp value), a defuzzification strategy is needed. There are several methods for defuzzifying to a crisp value (Pedrycz, 1989); the maximum criterion method (*MCM*); mean of maximum method (*MOM*) and the center of gravity method (*COG*). The *COG* method is probably the most common method and is used in this work. This method is based on taking the average of the control action values weighted by the grade of membership.

A fuzzy control algorithm has been developed after some trials in order to verify the fuzzy control rules, membership functions, scaling factors and defuzzification strategy. The detailed structure of the fuzzy controller contains the scaling factors of the error, and the change of error (g_e, g_{ce}).

So the input variables are quantized using different scaling factors of error and change of error $(EN=g_e*E,$ and $CEN=g_{ce}*CE)$. A similar relationship holds for the control signal which results from defuzzification $(U_p=g_u*U)$. In this application, a fuzzy set is defined by assigning its membership function to seven fuzzy sets (*NB, NM, NS, ZE, PS, PM, PB*) as shown in table (1).

Table 1. Applied Fuzzy Control Rules

OUTPUT

	Change of Error						
Error	NB	NM	NS	ZE	PS	PM	PB
NB	NB	NB	NB	NB	NM	NS	ZE
NM	NB	NB	NB	NM	NS	ZE	PS
NS	NB	[illegible]	NM	NS	ZE	PS	PM
ZE	NB	NM	NS	ZE	PS	PM	PB
PS	NM	NS	ZE	PS	PM	PB	PB
PM	NS	ZE	PS	PM	PB	PB	PB
PB	ZE	PS	PM	PB	PB	PB	PB

Overlapping triangular membership functions were used for inputs (fuzzification) and output (defuzzification), the difference between them being corresponding scaling factors.

The fuzzy control rules are derived by referring to the human operator experience and knowledge. There are two selected fuzzy sets each for error and change of error. Therefore, four rules only can be applied which represented by the intersection of two rows and two columns in table (1).

Using Mamdani's minimum operator method for inference, the control action is a fuzzy set which requires a defuzzification strategy to obtain the crisp control signal via the method of centre of gravity *(COG)* to convert from fuzzy values to crisp values. A scaling factor (g_u) is used to convert the crisp control signal from the normalized discourse to the applied range of actual control signals, which can then be applied to the nonlinear valve.

6. COMPARISON OF CONTROLLERS

The resulting FLC was applied to the building space and its heating system. Figure (12), shows the system response under tuned *PID* and *FLC*. As can be seen, the performance of the *FLC* is superior to *PID* controller in terms of good tracking of the reference point, and, hence system energy usage and comfort criteria.

In order to test the controllers' performance when system parameters change, the building construction data were changed to those representing a very low thermal capacity structure while keeping the overall thermal transmittance of each element constant. This would have the effect of making the system much more responsive (and, hence control more "difficult"). The controller specifications remained unchanged.

Figure (13) reveals that the fuzzy controller maintains excellent tracking of the reference condition whereas the tuned *PID* gives a reasonable response but with overshoot. Thus a certain amount of robustness of the *PID* controller is lost requiring it to be re-tuned. Thus the robustness characteristic of the *FLC* is superior to that of the tuned *PID* for this application.

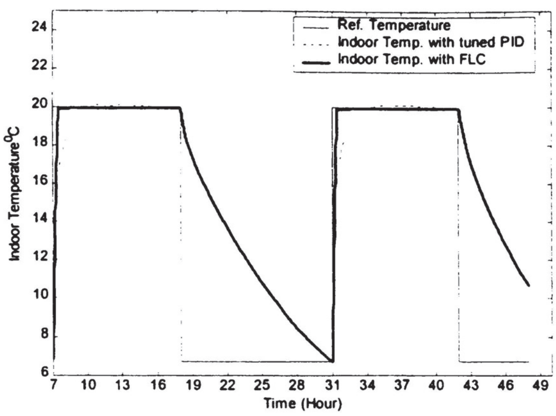

Fig. 12. Comparison of Tuned *PID* and *FLC*

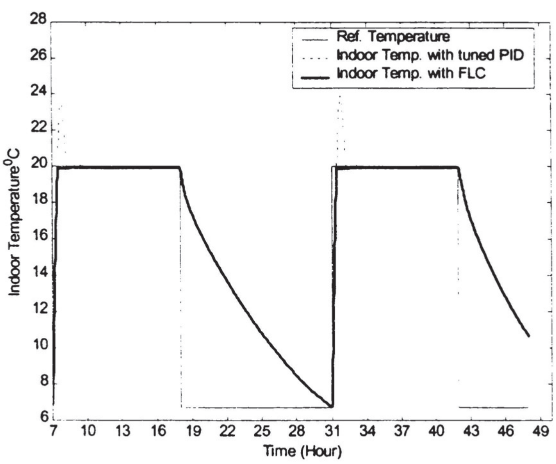

Fig. 13. Low Thermal capacity Building's Space with tuned *PID* and *FLC*.

7. CONCLUSIONS

Most current space heating system controllers continue to be based on the conventional *PID* regulator. These controllers require 3 tuning parameters which are difficult to optimise *a priori* and which, in any event, are only suited to a finite range of plant response when the plant has nonlinear characteristics.

A fuzzy logic controller has been developed based on a 49-rule rulebase. The *FLC* was found to give better tracking of the reference control condition than a comparative tuned *PID* controller as well as better robustness properties when the parameters of the system under control were changed. The *FLC* has the advantage of requiring no mathematical model of the plant or measurements of plant response as would be required to achieve satisfactory tuning of the *PID* controller.

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