A Fuzzy Supervisor for PD Control of Unknown Systems

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Abstract. The design of a fuzzy logic supervisor for PD controllers designed using Ziegler-Nichols tuning rules is carried out in this paper. Since Ziegler-Nichols provide nominal parameter values for the PD controller, the desired system response can not be realized without additional tuning of the controller. A fuzzy supervisor is proposed to reduce the amount of additional tuning. The objective of the fuzzy supervisor is to gradually increase the proportional and derivative gains of the controller, as the system error approaches zero, so as to improve the response of the system. Simulation results are presented, demonstrating improvements in the response of the systems with fuzzy supervisor.

Keywords. PD controller, Ziegler-Nichols rules, fuzzy supervisor, proportional gain, derivative gain.

INTRODUCTION

Conventional controllers, such as proportional-plus-derivative (PD) and proportional-plus-integral-plus-derivative (PID) controllers, have been successfully used in industry. One method of designing a controller for unknown systems is the Ziegler-Nichols tuning rules [7]. Once the initial control parameters are determined by the tuning rules, the controller must then be fine tuned to obtain a desired system response. An alternative to the fine tuning is to supervise the existing controller with a fuzzy system to obtain the desired response. This *fuzzy supervisor* operates in a manner similar to that of the fuzzy logic controller and adds a higher level of control to the existing system. The resulting improvements in the system response are accomplished by making on-line adjustments to the control parameters [2,3].

In this paper, the performance of systems controlled by PD controllers (designed using Ziegler-Nichols tuning rules) is shown to improve with the addition of the Fuzzy Logic Supervisor (FLS). It is shown (through simulation) that a gradual increase in the proportional gain

(K_P) of the controller, as the system error decreases, results in an improved system response. The derivative gain (K_D) is initially determined by multiplying the new proportional gain by the ratio of the original parameters ($\frac{K_D}{K_P}$). Then, as the system error approaches zero, the derivative gain is increased to eliminate oscillations due to the increased value of K_P.

A brief description of the Ziegler-Nichols tuning methods is first given, followed by a short discussion on the basics of fuzzy logic controllers. This is then followed by a discussion on the design of the fuzzy supervisor and finally some simulation results are presented.

ZIEGLER-NICHOLS TUNING METHODS

If a mathematical model of a given system can be derived, then various design techniques may be used to determine the controller parameter values. However, when the system model can not be determined, analytical design methods can not be used. For these systems, experimental methods such as Ziegler-Nichols tuning rules, may be used to design controllers. Let the transfer function of a PID controller be written as

$$G_C(s) = K_P(1 + \frac{1}{s\tau_i} + s\tau_d) \tag{1}$$

where K_P, τ_i, and τ_d are the proportional gain, the integral time, and the derivative time. Initially the derivative and intergral terms are set to zero. The proportional gain is increased from zero to a critical gain value (K_{cr}) where the system exhibits sustained oscillations. Using the value of critical gain (K_{cr}) and the period of oscillation (P_{cr}), the value of parameters K_P, τ_i, and τ_d are determined according to the formulas given in Table 1.

Table 1: Ziegler-Nichols tuning rules based on critical gain and period of oscillation.

Controller	K_P	τ_i	τ_d
P	$0.5K_{cr}$	∞	0
PI	$0.45K_{cr}$	$\frac{1}{1.2}P_{cr}$	0
PID	$0.6K_{cr}$	$0.5P_{cr}$	$0.125P_{cr}$

FUZZY LOGIC CONTROL

Because the basic operation of the FLS is similar to that of the Fuzzy Logic Controller (FLC), this section discusses some of the basic concepts of the FLC (figure 1). Differences between the FLC and the fuzzy supervisor will be addressed in the next section.

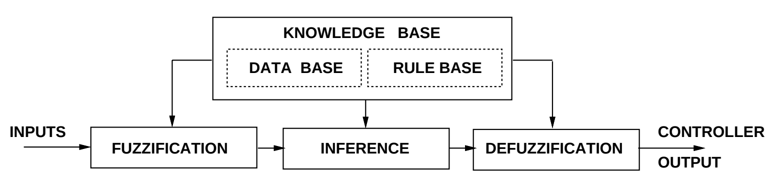


Figure 1: Fuzzy logic controller.

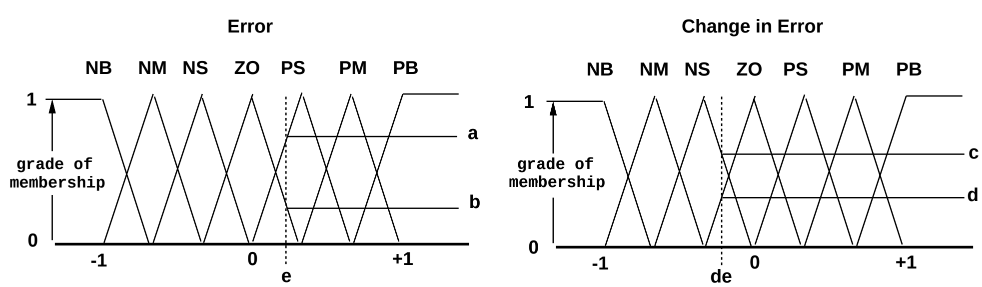
The FLC has four main components: knowledge base, fuzzification, inference, and defuzzification. The knowledge base consists of a rule base and a data base. Fuzzification converts a crisp input signal into a fuzzified signal identified by its level of membership into a fuzzy set. The inference process uses the collection of linguistic statements (rules) relating the input conditions to obtain the fuzzified output. Finally, the process of defuzzification converts the fuzzy outputs into a crisp controlling signals.

Knowledge base

The knowledge base consists of a data base and a rule base. The data base provides information for the proper operation of fuzzification, inference, and defuzzification. This information consists of the input and output membership functions and other information vital to the process logic of the FLC. The rule base is a collection of linguistic statements relating the input signals to desired outputs. Membership sets and the rule base are described in more detail in the following subsections.

Fuzzification

The process of fuzzification receives a crisp input signal, normalizes it and classifies it into membership functions. A grade of membership (a value between zero and one), which measures the compatibility of the signal to the membership function, is assigned to the signal. Each membership function is identified by a linguistic variable like small, large, and very large. The shapes of the membership functions are typically triangular, trapezoidal, or exponential. In this paper, triangular membership functions are used. Figures 2(a) and 2(b) show triangular membership functions for the error and change in error with fuzzy labels NB (negative big), NM (negative medium), NS (negative small), ZO (zero), PS (positive small), PM (positive medium), and PB (positive big).



(a) (b)

Figure 2: Triangular membership functions.

In the case of the triangular functions shown in figure 2(a), the normalized error signal (e) has membership in both the ZO and PS functions, while figure 2(b) shows the change in error signal (de) with membership in the NS and ZO functions. The values of points a and b represent the grade of membership of the error in the ZO and PS functions, and the values of points c and d represent the grade of membership of the change in error in the NS and ZO functions. The sum of a and b, and the sum of c and d, will always be equal to one for triangular membership functions.

The inference process

The basic function of the inference process is to determine the value of the controller output based on the contributions of each rule in the rule base. One method of storing the rule base is the use of the Macvicar-Whelan control matrix [4] (Table 2). This matrix is designed so that if the desired output is realized with zero change in error then the output remains constant. However, if the output is different from the desired response, then the rule matrix produces an output signal based on human knowledge of the operating system. Each element of the matrix describes a rule of the form

$$\text{if } e(t) \text{ is } E_i \text{ and } de(t) \text{ is } dE_j \text{ then } y(t) \text{ is } C_{ij}$$

where $e(t)$ and $de(t)$ are the error and change in error, $y(t)$ is the controller output, E_i and dE_j are the applicable input functions, and C_{ij} is the output function.

Table 2: Macvicar-Whelan fuzzy rule matrix.

dE \ E	NB	NM	NS	ZO	PS	PM	PB
NB	NB	NB	NB	NB	NM	NS	ZO
NM	NB	NB	NB	NM	NS	ZO	PS
NS	NB	NB	NM	NS	ZO	PS	PM
ZO	NB	NM	NS	ZO	PS	PM	PB
PS	NM	NS	ZO	PS	PM	PB	PB
PM	NS	ZO	PS	PM	PB	PB	PB
PB	ZO	PS	PM	PB	PB	PB	PB

Defuzzification

Choosing triangular membership functions, for the input signals, ensures that a maximum of four rules apply for the error shown in figure 2(a) and the change in error shown in figure 2(b). To determine the output value, a weighted average of the active rules is used. This method is illustrated in figure 3 with the crisp output realized as

$$y(t) = \frac{a * c * PS \; + \; a * d * ZO \; + b * c * NS \; + \; b * d * ZO}{a * c \; + \; a * d \; + \; b * c \; + \; b * d} \tag{2}$$

where a and b represent the membership values for the error, c and d represent the membership values for the change in error, and the terms NS, ZO, and PS are the peak values of the output membership functions. It should be noted that the denominator in (1) will be one when the triangular functions are symmetric.

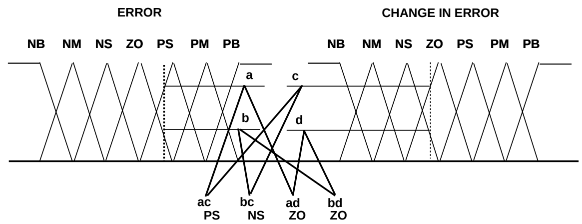


Figure 3: Fuzzy output generation.

THE FUZZY SUPERVISOR

Conventional PD and PID controller are widely used in many industrial processes. However, when the plant dynamics are not known precisely, the design of the controller is difficult. Tuning rules, such as Ziegler-Nichols methods, have been useful in the design of a nominal PID controller. However, the results of the tuning method is usually a coarse approximation of the controller and more fine tuning is required to obtain a desired system response. The addition of a higher level of control, through a fuzzy logic supervisor, reduces the difficulty of fine tuning the controller and improves the system response under normal operating conditions and when uncertainties are introduced. A general block diagram of a fuzzy supervised system is shown in figure 4. System control is still accomplished by the Ziegler-Nichols tuned controller, however, the gain values K_P and K_D are now controlled by the FLS. The general structure of the fuzzy logic supervisor is similar to that of the FLC (figure 1). The differences are in the rule base and the supervisor outputs. The supervisor rule base is not designed for PD control as with the Macvicar-Whelan rule matrix, and the supervisor outputs (ΔK_P and ΔK_D) are the incremental changes to be made to the existing parameters.

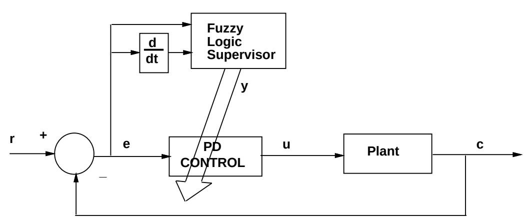


Figure 4: PD control with fuzzy supervisor.

While the basic operation of the fuzzy supervisor is similar to that of an FLC, it is not designed to provide the total controlling action. Instead, the FLS is designed to provide incremental changes based on how a human would operate the system.

Supervisor control matrix

It has been shown, for conventional PD fuzzy controllers [5], that a gradual increase in the proportional gain as system error decreases, reduces the overshoot of the system. This concept is used for the design of fuzzy supervisor. The development of the supervisor control matrix is based on the observation of a typical step response shown in figure 5.

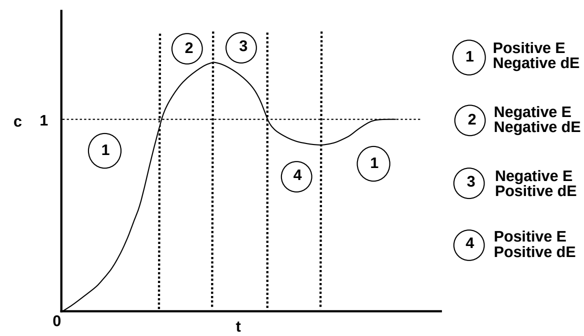


Figure 5: Typical step response.

The step response (figure 5) is divided into four general regions, each determined by the sign of the error and change in error. The regions are

Region 1: Positive error, negative change in error
Region 2: Negative error, negative change in error
Region 3: Negative error, positive change in error
Region 4: Positive error, positive change in error

A fifth region (the zero region) is used when both the error and change in error values are near zero and is not dependent on the sign of the signals. The resultant supervisor control matrix is shown in Table 3. A total of nine membership functions for both input and output signals are used. The membership functions are described as NL (negative large), NB (negative big), NM (negative medium), NS (negative small), ZO (zero), PS (positive small), PM (positive medium), PB (positive big) and PL (positive large).

Table 3: Fuzzy supervisor rule matrix.

		E								
		NL	NB	NM	NS	ZO	PS	PM	PB	PL
	NL	NL	NL	NL	NL	PB	PB	PB	PM	PM
	NB	NL	NL	NL	NB	PB	PB	PB	PM	PM
	NM	NL	NL	NB	NM	PB	PB	PM	PM	PS
	NS	NL	NB	NM	NS	PL	PB	PM	PS	PS
dE	ZO	ZO	NS	NM	NB	PL	PB	PM	PS	ZO
	PS	PS	PS	PM	PB	NL	NS	NM	NB	NL
	PM	PS	PM	PM	PB	NB	NM	NB	NL	NL
	PB	PM	PM	PB	PB	NB	NB	NL	NL	NL
	PL	PM	PM	PB	PB	NB	NL	NL	NL	NL

Initially the error is one (PB) and the change in error is zero (ZO). This condition is identified by the linguistic statement

if e(t) is PB and de(t) is ZO, then y(t) is ZO, which states that the supervisor output is zero and no changes are made to the existing control parameters. As the error begins to decrease toward zero and the change in error increases in a negative direction (region 1), the supervisor output is gradually increased from zero towards a maximum of one. Using the supervisor output (y(t)), the incremental changes are calculated as

$$\Delta K_P = y(t) * K_P \tag{3}$$

$$\Delta K_D = y(t) * K_D \tag{4}$$

Equations (3) and (4) ensure that the original ratio $\frac{K_D}{K_P}$ is maintained. When the system error becomes negative (region 2), the system needs to be slowed down to reduce the overshoot. This is accomplished by decreasing the value of the control parameters. The supervisor output in this region is a negative value. As the overshoot reaches a peak value, the change in error of the system becomes a positive value (region 3). Once again the controller gains are increased in value until the response enters region 4. In region 4, the error is again positive, but the signal is moving away from the desired steady-state value. To reduce the overshoot, the parameter values are gradually decreased until the response is moving toward the desired response. The process continues until both the error and change in error values are classified in the zero membership region.

SIMULATION RESULTS

Ziegler-Nichols tuning rules were developed to assist in the design of controllers for unknown systems, however, the techniques may also be applied to systems with known transfer functions. To demonstrate the effect of the fuzzy supervisor in this paper, the Ziegler-Nichols method is implemented on two systems with known transfer functions. The first system (a type-1 system) is a liquid-level control system. The second example (a type-0 system) is a single link flexible arm.

Liquid-level control system

The first system tested was a liquid level control system with the transfer function given by $G(s) = \frac{1}{s(s+1)(s+5)}$. A PD controller was first designed using Ziegler-Nichols tuning methods and the values of the controller parameters were found to be $K_P = 18$ $K_D = 6.32$. These parameters values were also supplied to the fuzzy supervisor. Figure 6 shows a comparison of the two systems (with and without the FLS) showing that the fuzzy supervisor actually improves the system response reducing the overshoot from 25% to less than 5%, reducing the settling time from 4 seconds to two seconds, and decreasing the rise time from .505 seconds to .475 seconds.

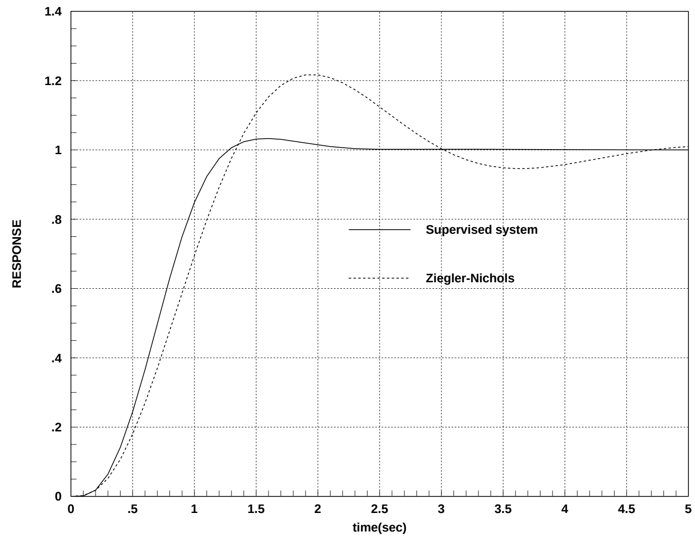


Figure 6: Response of liquid level control system with and without FLS.

Flexible arm

The next system tested is a type-0, single link flexible arm. The transfer function for this system is given by $G(s) = \frac{43.75}{(s^2+43.75)}$. Ziegler-Nichols tuning methods were used to design a PD controller with parameter values as $K_P = 100$ and $K_D = 1.25$. Figure 7 shows the results of the simulation. The supervised system improved the response by reducing the overshoot to zero, decreasing the rise time by .02 seconds, and decreasing the settling time from .13 seconds to .03 seconds. In addition, the steady-state error is reduced as the proportional gain is increased.

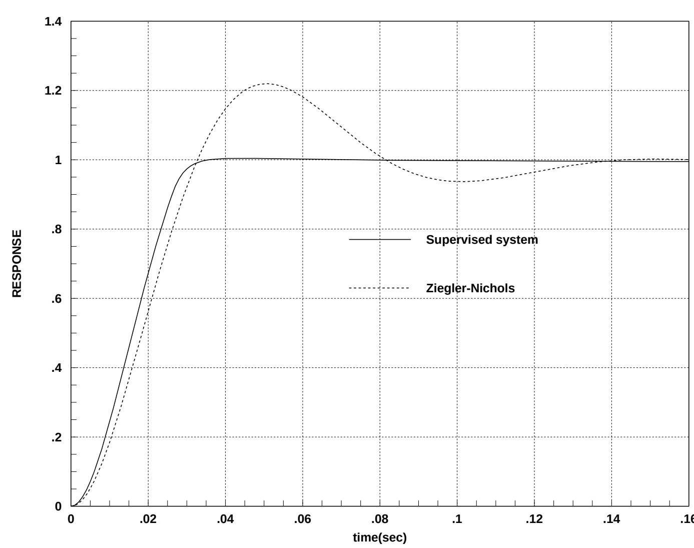


Figure 7: Response of flexible arm system with and without FLS.

CONCLUSIONS

The application of a fuzzy supervisor to nominal controllers designed using Ziegler-Nichols tuning rules is studied in this paper. It is shown that the addition of a fuzzy logic supervisor improves the response of an nominal PD controlled system. The design of the fuzzy supervisor is based on human observation of a typical step response. Gradual increase in the controller gains, as the error approaches zero, provide improved system response. The advantage of the fuzzy supervisor is its ability to simplify the design of a controller by reducing the amount of tuning required. The supervisor, however, does not completely eliminate the need for fine tuning. Some additional tuning, may be needed to accomplish a desired response.

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