Design of a Stable and Dynamic Fuzzy Controller to Achieve Linguistic Closed Loop System Performance Specifications

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Abstract

A method to design a fuzzy controller that tolerates plant parameter changes is given. The controller operates in a closed-loop system. Its inputs are linguistic desired behavior of the plant output and the actual fuzzified plant output. The controller produces a fuzzy output that is defuzzified to control the plant. We assume a linguistic model of the plant, and design an adaptive controller to achieve linguistic closed loop system performance specifications.

Keywords: Fuzzy controller design, Fuzzy closed loop system, Fuzzy system stability, Linguistic performance.

1 Introduction

Since Zadeh's first article on fuzzy sets in 1965 [1], many researchers have contributed to the development of fuzzy set theory. The pioneering research of Mamdani and his colleagues [2, 3] coined fuzzy control, a new approach in control theory [4]. For the last 20 years, fuzzy control theory has been applied to a variety of control problems [5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16].

Even though fuzzy control theory has been successfully applied to control problems, achieving a robust closed loop system is mostly a matter of trial-and-error. It was shown in [17] that stability criteria developed so far for fuzzy closed loop systems described by fuzzy relational equations have no practical application. To achieve a practical stability criterion, the concept of a bounded linguistic variable was introduced [18]. Based on this criterion, the procedure for design of a stable fuzzy controller that achieves linguistic closed loop system performance specifications was presented in [19]. However, even though fuzzy controllers are robust with respect to plant parameter fluctuations compared to classical controllers, drastic changes in plant parameters have a profound effect on

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system dynamical behavior, and control with this behavior is often not known by an expert. In this paper, we present a new technique to design a dynamic fuzzy logic controller that accommodates drastic plant parameter changes. The new technique is implemented for a continuous stirred tank reactor.

The design of the fuzzy controller is based on control knowledge of an expert. The action of the fuzzy controller is determined by a set of linguistic control rules given in the form of IF-THEN statements related by the dual concepts of fuzzy implication and the compositional rule of inference [20]. This form of the fuzzy controller is used here for both analysis and synthesis of the fuzzy closed loop system.

Usually, fuzzy controller synthesis is based on heuristic techniques. Some design methodologies are given in [21, 22, 16, 12, 13]. Almost none of them use predefined performance criteria to synthesize a fuzzy controller. Trial and error methods are used to achieve acceptable performance. Often, problems with tuning a fuzzy controller are related to contradictory information or incomplete control knowledge in the fuzzy rule base of the fuzzy controller. Some design methodologies use prespecified performance objectives of a closed loop system, [22, 23]. However, they are based on fuzzy adaptive algorithms that are not known to be stable nor globally convergent and require much computation.

In this paper we consider closed loop systems as shown in Figure 1, where $V(t)$ is the linguistic input, $U(t)$ is the linguistic output of the fuzzy controller, and $X(t)$ is the linguistic state of the plant. The defuzzifier transforms fuzzy sets into real-valued variables, and the fuzzifier transforms the real-valued state of the plant into fuzzy sets. In [19], a fuzzy controller synthesis algorithm is proposed that is based on linguistically specified performance objectives included in the desired fuzzy rules of the closed loop system.The algorithm is briefly reviewed now.

Given is a linguistic model of a plant in terms of rules such as

$$\begin{array}{lllll}
p_1: & \text{IF} & (X(t) \text{ is } \mathrm{S}_1^1) \text{ and } (\mathrm{U}(\mathrm{t}) \text{ is } \mathrm{S}_2^1) & \text{THEN} & (X(t+1) \text{ is } \mathrm{S}_3^1) \\
p_2: & \text{also IF} & (X(t) \text{ is } \mathrm{S}_1^2) \text{ and } (\mathrm{U}(\mathrm{t}) \text{ is } \mathrm{S}_2^2) & \text{THEN} & (X(t+1) \text{ is } \mathrm{S}_3^2) \\
\vdots & & \vdots & & \\
p_i: & \text{also IF} & (X(t) \text{ is } \mathrm{S}_1^{\mathrm{i}}) \text{ and } (\mathrm{U}(\mathrm{t}) \text{ is } \mathrm{S}_2^{\mathrm{i}}) & \text{THEN} & (X(t+1) \text{ is } \mathrm{S}_3^{\mathrm{i}}) \\
\vdots & & \vdots & & \\
p_{K_p}: & \text{also IF} & \left(X(t) \text{ is } \mathrm{S}_1^{\mathrm{K}}\right) \text{ and } \left(\mathrm{U}(\mathrm{t}) \text{ is } \mathrm{S}_2^{\mathrm{K}}\right) & \text{THEN} & \left(X(t+1) \text{ is } \mathrm{S}_3^{\mathrm{K}}\right)
\end{array} \tag{1}$$

where p_i is the ith fuzzy rule, $X(t) \in \bar{X}$, $X(t+1) \in \bar{X}$ and $U(t) \in \bar{U}$, S_j^i is a linguistic value in the j-th fuzzy proposition of the i-th fuzzy rule and K is the number of fuzzy rules. Fuzzy rules describing the desired dynamic behavior of the closed loop system are given by

$$\begin{array}{lllll}
l_1: & \text{IF} & (X(t) \text{ is } \mathrm{S}_1^1) \text{ and } (\mathrm{V}(\mathrm{t}) \text{ is } \mathrm{S}_2^1) & \text{THEN} & (X(t+1) \text{ is } \mathrm{S}_3^1) \\
l_2: & \text{also IF} & (X(t) \text{ is } \mathrm{S}_1^2) \text{ and } (\mathrm{V}(\mathrm{t}) \text{ is } \mathrm{S}_2^2) & \text{THEN} & (X(t+1) \text{ is } \mathrm{S}_3^2) \\
\vdots & & \vdots & & \\
l_i: & \text{also IF} & (X(t) \text{ is } \mathrm{S}_1^{\mathrm{i}}) \text{ and } (\mathrm{V}(\mathrm{t}) \text{ is } \mathrm{S}_2^{\mathrm{i}}) & \text{THEN} & (X(t+1) \text{ is } \mathrm{S}_3^{\mathrm{i}}) \\
\vdots & & \vdots & & \\
l_{K_l}: & \text{also IF} & \left(X(t) \text{ is } \mathrm{S}_1^{\mathrm{K}}\right) \text{ and } \left(\mathrm{V}(\mathrm{t}) \text{ is } \mathrm{S}_2^{\mathrm{K}}\right) & \text{THEN} & \left(X(t+1) \text{ is } \mathrm{S}_3^{\mathrm{K}}\right)
\end{array} \tag{2}$$

where $V(t) \in \bar{V}$. The synthesized fuzzy controller is described in terms of rules such as

$$\begin{array}{llllllll} c_1: & \text{IF} & (X(t) \text{ is } \mathrm{S}_1^1) & \text{and} & (\mathrm{V(t)} \text{ is } \mathrm{S}_2^1) & \text{THEN} & (U(t) \text{ is } \mathrm{S}_3^1) \\ c_2: & \text{also IF} & (X(t) \text{ is } \mathrm{S}_1^2) & \text{and} & (\mathrm{V(t)} \text{ is } \mathrm{S}_2^2) & \text{THEN} & (U(t) \text{ is } \mathrm{S}_3^2) \\ \vdots & & \vdots & & & & \\ c_i: & \text{also IF} & (X(t) \text{ is } \mathrm{S}_1^i) & \text{and} & (\mathrm{V(t)} \text{ is } \mathrm{S}_2^i) & \text{THEN} & (U(t) \text{ is } \mathrm{S}_3^i) \\ \vdots & & \vdots & & & & \\ c_L: & \text{also IF} & \left(X(t) \text{ is } \mathrm{S}_1^L\right) & \text{and} & \left(\mathrm{V(t)} \text{ is } \mathrm{S}_2^L\right) & \text{THEN} & \left(U(t) \text{ is } \mathrm{S}_3^L\right) \end{array} \tag{3}$$

where L is the number of fuzzy rules in the fuzzy controller rule base using the following algorithm.

1. Given the linguistic model of a plant, obtain the fuzzy relation R_p of the fuzzy plant with

$$R_p(X(t), U(t), X(t+1)) = \bigvee_{i=1}^{K_p} \left(\mu_{X(t)}\left(S_1^i\right) \wedge \mu_{U(t)}\left(S_2^i\right) \wedge \mu_{X(t+1)}\left(S_3^i\right)\right) \tag{4}$$

   where K_p is the number of fuzzy rules in the fuzzy plant.

2. Given information about performance objectives, specify the fuzzy rules of the closed loop system.

3. Based on the fuzzy rules of the closed loop system, obtain the fuzzy relation R_l of the closed loop system with

$$R_{cl}(X(t), V(t), X(t+1)) = \bigvee_{i=1}^{K_l} \left(\mu_{X(t)}\left(S_1^i\right) \wedge \mu_{V(t)}\left(S_2^i\right) \wedge \mu_{X(t+1)}\left(S_3^i\right)\right) \tag{5}$$

   where K_l is the number of fuzzy rules describing the closed loop system.

4. Initialize the fuzzy relation R_c of the controller with degrees of membership values representing "everything" for the given fuzzy input sets and fuzzy output sets of the fuzzy controller to be designed.

5. Do the following for all elements in the fuzzy relation of the initialized fuzzy controller, i.e.

$$\begin{array}{l} \text{if } \{R_c(x_i(t), u_k(t), v_l(t)) \wedge R_p(x_i(t), x_j(t+1), u_k(t))\} > R_{cl}(x_i(t), x_j(t+1), v_l(t)) \\ \qquad \text{then } R_c(x_i(t), u_k(t), v_l(t)) = R_{cl}(x_i(t), x_j(t+1), v_l(t)) \\ \text{otherwise } R_c(x_i(t), u_k(t), v_l(t)) \text{ is not changed.} \end{array} \tag{6}$$

Having obtained the fuzzy relation of a controller, it is easy to obtain its set of fuzzy rules. An advantage of this design procedure is that it inherently includes closed loop system specifications captured in the fuzzy rules of the closed loop system.

Even though a fuzzy controller designed using the above algorithm follows linguistic performance objectives, it is not adaptive enough to accommodate drastic plant parameters changes. In Section 2 we present a dynamic fuzzy controller that accounts for drastic plant parameter changes and makes it follow linguistic performance objectives. In Section 3 we design a controller to control a continuous stirred tank reactor [24] to accommodate a wide feed temperature change.

2 Semi-Dynamic Overlapping Fuzzy Logic Controller

Even though fuzzy logic controllers can be more robust with respect to plant parameter fluctuations than classical controllers, drastic changes in plant parameters can have a profound effect on system dynamical behavior.

EXAMPLE: Consider a fuzzy closed loop system for control of a nonlinear fuel engine [25] shown in Figure 2 that is described by

$$\dot{x} = f(x)\left[u - g(x)\right] \tag{7}$$

where x denotes the speed of the engine, u denotes fuel input and f and g are nonlinear functions shown in Figure 3. The step response of the closed loop system, including a fuzzy logic-controller, for the desired speed of 11 RPS is shown in Figure 4.

In Figure 5, the effect of more than a 200% change in the fuel engine load at $t = 7.5\ s$ is shown. In this case, the desired fuel engine speed of 11 RPS is not achieved after the change in the system's load. The drastic change in the load of the engine also changes its linguistic model. The fuzzy logic controller is trying to control a plant completely different from that for which it was designed.

An approach to have a fuzzy controller that accommodates drastic plant parameter changes would be to include system parameters as part of the set of linguistic variables of a fuzzy rule base. The augmented design procedure can be carried out when required plant parameters are measurable and easy to include in a fuzzy rule base. However, when system disturbances are not accessible, the above method cannot be applied. In order to make a fuzzy closed loop system account for unknown disturbances and plant parameter changes, we propose an overlapping semi-dynamic fuzzy logic controller.

Let us assume that we do not know how and when disturbances and plant parameter changes occur, but, we can roughly estimate the range of these changes. Our goal is to design a fuzzy logic controller that adapts its fuzzy rule base due to disturbances and plant parameter changes. This is obtained by overlapping fuzzy rule bases designed for nominal and extreme parameter values, then properly combined.

The entire procedure consists of the following steps:

- Design a stable fuzzy logic controller for the lower limit of the parameter change, i.e., obtain a fuzzy rule base B_1 of the fuzzy logic controller.
- Design a stable fuzzy logic controller for the upper limit of the parameter change, i.e., obtain a fuzzy rule base B_2 of the fuzzy logic controller.
- Design a stable fuzzy rule base of an overlapping semi-dynamic fuzzy logic controller by using B_1 and B_2 as boundary rules of the new fuzzy rule base. We make the new fuzzy logic controller semi-dynamic by including its previous control action as a part of the antecedent of fuzzy rules. This is explained below.
- Complete the design procedure by choosing a defuzzification method and adding a fuzzification block.

The third step is performed as follows. Let us assume that the control action of a fuzzy logic controller can take on a finite set of linguistic values, i.e., $\mathbf{C} = \{\mathbf{C_1}, \mathbf{C_2}, \ldots, \mathbf{C}_\alpha, \ldots, \mathbf{C_{k-1}}, \mathbf{C_k}\}$. After we design a stable fuzzy logic controller for the lower limit of a parameter change, we obtain its fuzzy rule base. Any fuzzy rule from this base can be represented by

$$c_i: \quad \text{IF} \quad (X(t) \text{ is } \mathrm{S_1^i}) \text{ and } (\mathrm{V}(\mathrm{t}) \text{ is } \mathrm{S_2^i}) \quad \text{THEN} \quad (U(t) \text{ is } \mathrm{S_3^i}) \tag{8}$$

where $X(t) \in \bar{X}$ is a linguistic state of the plant at time t, $V(t) \in \bar{X}$ is an external linguistic input, $U(t) \in \bar{U}$ is a linguistic control action of the fuzzy logic controller, and the S_1^i, S_2^i, and S_3^i are linguistic values defined for designated variables. Notice that $S_3^i \in \mathbf{C}$. Moreover, we can assume that S_3^i is some C_α, where $1 \le \alpha \le k$.

Following the same procedure for the upper limit of the parameter change, we obtain another fuzzy rule base. Any fuzzy rule from this base can also be represented by

$$c_i: \quad \text{IF} \quad (X(t) \text{ is } \mathrm{S_1^i}) \text{ and } (\mathrm{V}(\mathrm{t}) \text{ is } \mathrm{S_2^i}) \quad \text{THEN} \quad (U(t) \text{ is } \mathrm{S_3^i}) \tag{9}$$

but this time S_3^i is some C_β, where $1 \le \beta \le k$. Using both consequences, we create a set of fuzzy rules of the overlapping semi-dynamic fuzzy logic controller. Without loss of generality, let us assume that $\alpha \le \beta$ and create a set of fuzzy rules is given by

$$\begin{array}{llll}
\text{IF} & (X(t) \text{ is } \mathrm{S_1^i}) \text{ and } (\mathrm{V}(\mathrm{t}) \text{ is } \mathrm{S_2^i}) \text{ and } (\mathrm{U}(\mathrm{t}-1) \text{ is } \mathrm{C}_\alpha) & \text{THEN} & (U(t) \text{ is } \mathrm{C}_{\alpha+1}) \\
\text{IF} & (X(t) \text{ is } \mathrm{S_1^i}) \text{ and } (\mathrm{V}(\mathrm{t}) \text{ is } \mathrm{S_2^i}) \text{ and } (\mathrm{U}(\mathrm{t}-1) \text{ is } \mathrm{C}_{\alpha+1}) & \text{THEN} & (U(t) \text{ is } \mathrm{C}_{\alpha+2}) \\
\vdots & & & \\
\text{IF} & (X(t) \text{ is } \mathrm{S_1^i}) \text{ and } (\mathrm{V}(\mathrm{t}) \text{ is } \mathrm{S_2^i}) \text{ and } (\mathrm{U}(\mathrm{t}-1) \text{ is } \mathrm{C}_{\beta-1}) & \text{THEN} & (U(t) \text{ is } \mathrm{C}_\beta) \\
\text{IF} & (X(t) \text{ is } \mathrm{S_1^i}) \text{ and } (\mathrm{V}(\mathrm{t}) \text{ is } \mathrm{S_2^i}) \text{ and } (\mathrm{U}(\mathrm{t}-1) \text{ is } \mathrm{C}_\beta) & \text{THEN} & (U(t) \text{ is } \mathrm{C}_\beta)
\end{array} \tag{10}$$

Using more compact notation, we can write

$$\text{IF} \quad (X(t) \text{ is } \mathrm{S_1^i}) \text{ and } (\mathrm{V}(\mathrm{t}) \text{ is } \mathrm{S_2^i}) \text{ and } (\mathrm{U}(\mathrm{t}-1) \text{ is } \mathrm{C}_\alpha \to \mathrm{C}_\beta) \quad \text{THEN} \quad (U(t) \text{ is } \mathrm{C}_\alpha \to \mathrm{C}_\beta) \tag{11}$$

where $C_\alpha \to C_\beta$ represents all linguistic values between the lower and upper limits. Doing the same for each pair of fuzzy rules with the same antecedents from both upper and lower limit fuzzy rule bases, we obtain a complete set of fuzzy rules of the overlapping semi-dynamic fuzzy rule base of the fuzzy logic controller.

The overlapping semi-dynamic fuzzy logic controller algorithm accounts for unpredictable system disturbances and parameter changes, and ensures that the overall fuzzy closed loop system is always globally stable [17]. We implemented this algorithm for the nonlinear fuel engine fuzzy controller. Two fuzzy logic controllers were obtained for two extreme values of load. The step response of the overlapping semi-dynamic fuzzy closed loop system of the nonlinear engine is shown in Figure 6. We see that after an unknown 200% load change, at $t = 7.5s$, the fuzzy closed loop system is driven back toward its desired speed of 10 RPS. Figure 7 shows how the overlapping semi-dynamic fuzzy logic controller updates its output in order to meet linguistic specifications.

We call this fuzzy logic controller semi-dynamic because it uses only a part of its fuzzy rule base depending on the last control action. The great advantage of the overlapping semi-dynamic fuzzy logic controller design procedure over the stable fuzzy logic controller design algorithm is that it has learning abilities, and it adapts its fuzzy rule base according to actual behavior of the system parameters. Since its fuzzy rule base is static, it can be downloaded into a fuzzy microcontroller memory [26], and used for practical applications.

3 Continuous-Stirred-Tank-Reactor Control

Some strongly nonlinear processes, such as chemical reactors, have such wide dynamic behavior in the open-loop that even SISO control system design can be very difficult [24]. Even though these nonlinearities are often sufficiently weak so that model approximations or local linearization followed by application of linear multivariable design procedures result in practical control systems, there are many types of chemical processes (usually chemical reactors) that have especially strong nonlinear behavior, and often do not respond well to standard linearized control system analysis. Among them, there is a Continuous-Stirred-Tank-Reactor (CSTR).

A CSTR in which a single, first order, exothermic irreversible reaction is taking place, is shown in Figure 8. V is the volume of the reactor, F is the feed rate, c_{Af} and T_f are the inlet reactant concentration and temperature, respectively, and c_A and T are their values in the reactor. The quantity T_c is the jacket coolant temperature.

We must control the reactor temperature, T, in the face of disturbances in feed temperature, T_f, by adjusting the coolant temperature, T_c, in a boiling liquid jacket. It is assumed that the coolant concentration c_A will ultimately settle down to the desired value if the reaction temperature is controlled properly.

The CSTR can be mathematically described by

$$\begin{aligned} \frac{dx_1}{dt} &= -x_1 + Da\,(1-x_1)\,e^{G(x_2)} \\ \frac{dx_2}{dt} &= -x_2 + BDa\,(1-x_1)\,e^{G(x_2)} - \beta\,(x_2 - x_{2c}) + d + \beta u \end{aligned} \tag{12}$$

with

$$G\,(x_2) = \frac{x_2}{1+\frac{x_2}{\gamma}} \tag{13}$$

Da is the Damkőhler number, x_1, x_2 represent dimensionless reactant conversion and temperature defined as

$$\begin{aligned} x_1 &= \frac{c_{Af}-c_A}{c_{Af}} \\ x_2 &= \left[\frac{T-T_{fo}}{T_{fo}}\right]\left[\frac{E}{RT_{fo}}\right] \end{aligned} \tag{14}$$

and

$$x_{2c} = \frac{T_{co}-T_{fo}}{T_{fo}}\left[\frac{E}{RT_{fo}}\right] \tag{15}$$

Also, T_{fo} and T_{co} are nominal design values for inlet feed temperature and coolant temperature, respectively. The variables d and u are dimensionless deviations for feed temperature disturbance

$T(t+1)$		$T_c(t)$				
		$A270$	$A280$	$A290$	$A300$	$A310$
$T(t)$	$A270$	$A270$	$A280$	$A280$	$A290$	$A300$
	$A280$	$A270$	$A280$	$A280$	$A290$	$A300$
	$A290$	$A270$	$A280$	$A280$	$A290$	$A300$
	$A300$	$A270$	$A280$	$A280$	$A290$	$A300$
	$A310$	$A270$	$A280$	$A280$	$A290$	$A300$

Table 1: CSTR linguistic model for $T_f = 270\ K$

(T_f), and control (T_c) given by

$$d = \left[\frac{T_f - T_{fo}}{T_{fo}}\right]\left[\frac{E}{RT_{co}}\right]$$

$$u = x_{2c}(T_c) - x_{2c}(T_{co}) = \frac{T_c - T_{co}}{T_{fo}}\left[\frac{E}{RT_{fo}}\right] \tag{16}$$

Overall, the fuzzy closed loop system of the CSTR can be represented by Figure 9.

Due to nonlinearities in the system mathematical model, the problem is not well suited for for application of most controller design methods. According to our fuzzy logic controller design procedure, we have to obtain a linguistic model of the CSTR. This can be done in three different ways, e.g.,

- by interviewing an operator who can control the CSTR manually,
- by using a linguistic model identification algorithm
- by system simulation

Here, the last method was used. Based on the system description and control goals, which are to keep the *"current temperature"* close to the *"desired temperature"*, regardless of feed temperature, T_f, changes within the range $275K - 300K$ (This range of feed temperature change is 5 times wider than the $5K$ range considered in [24].), we defined three linguistic variables, i.e., $T_r(t)$, $T(t)$, and $T_c(t)$ meaning *"desired temperature"* at time t, *"current temperature* at time t and *"coolant temperature* at time t, respectively. For each linguistic variable we defined eight linguistic values, i.e., $LT260$ meaning *"less than 260"*, $A270$ meaning *"about 270"*, $A280$ meaning *"about 280"*, $A290$ meaning *"about 290"*, $A300$ meaning *"about 300"* , $A310$ meaning *"about 310"*, $A320$ meaning *"about 320"*, and $A350$ meaning *"about 350"*. Their fuzzy sets are shown in Figure 10.

Using CSTR linguistic variables, we roughly identified two linguistic models of the CSTR for two extreme values of T_f, i.e., $T_f = 270K$, and $T_f = 310K$. Their fuzzy rule bases are given in Table 1 and Table 2, respectively.

Using the global stability theorem [17], we divide the universe of discourse of $T(t)$ and $\bar{T}$, into stable and unstable parts. The unstable part includes two boundary linguistic values, i.e., $LT260$,

$T(t+1)$		$T_c(t)$				
		$A270$	$A280$	$A290$	$A300$	$A310$
	$A270$	$A290$	$A300$	$A310$	$A310$	$A310$
	$A280$	$A290$	$A300$	$A310$	$A310$	$A310$
$T(t)$	$A290$	$A290$	$A300$	$A310$	$A310$	$A310$
	$A300$	$A290$	$A300$	$A310$	$A310$	$A310$
	$A310$	$A290$	$A300$	$A310$	$A350$	$A350$

Table 2: CSTR linguistic model for $T_f = 310\ K$

$T(t+1)$		$T_r(t)$				
		$A270$	$A280$	$A290$	$A300$	$A310$
	$A270$	$A280$	$A280$	$A290$	$A290$	$A300$
	$A280$	$A280$	$A280$	$A290$	$A300$	$A300$
$T(t)$	$A290$	$A280$	$A280$	$A290$	$A300$	$A300$
	$A300$	$A280$	$A280$	$A290$	$A300$	$A300$
	$A310$	$A280$	$A280$	$A290$	$A300$	$A300$

Table 3: Fuzzy closed loop system linguistic model of CSTR for $T_f = 270\ K$

and $A350$. The stable part of the universe of discourse includes all internal linguistic values. Based on these assumptions, we specify two sets of fuzzy closed loop system linguistic objectives. These are given in Table 3 and Table 4.

Using both sets of fuzzy closed loop system specifications and both linguistic models of the CSTR, we synthesize two fuzzy logic controllers. Their fuzzy rule bases are given in Table 5 and Table 6.

Having synthesized the fuzzy logic controllers for upper and lower limits of the T_f change, we obtained the overlapping semi-dynamic fuzzy logic controller. Its fuzzy rule base is given in Table 7. We completed the overlapping semi-dynamic fuzzy logic controller design by adding a fuzzification block and the Center of Gravity defuzzification block. Then, we constructed the fuzzy closed loop system using the CSTR mathematical model described earlier. The CSTR closed loop control system was tested for different desired temperatures with a wide range of T_f changes.

The fuzzy closed loop system dynamic behavior is shown in Figure 11, where the dashed line is the actual behavior $T(t)$ of the fuzzy closed loop system, the solid line is $T_f(t)$, and the dashed-dotted line is the desired temperature, $T_r(t)$. Wee see that the feed temperature starts at 280^o and then changes to 290^o, 300^o, 285^o and down to 275^o at time points not known by the controller. Even though the range of the feed temperature is so wide, the fuzzy closed loop system tracks the desired temperature changes. Small deviations between the desired temperature and the actual temperature are achieved by a totally fuzzy logic approach to the design of the fuzzy closed loop

$T(t+1)$		$T_r(t)$				
		$A270$	$A280$	$A290$	$A300$	$A310$
$T(t)$	$A270$	$A290$	$A290$	$A290$	$A290$	$A310$
	$A280$	$A290$	$A290$	$A290$	$A300$	$A310$
	$A290$	$A290$	$A290$	$A290$	$A300$	$A300$
	$A300$	$A290$	$A290$	$A290$	$A300$	$A310$
	$A310$	$A290$	$A290$	$A290$	$A300$	$A300$

Table 4: Fuzzy closed loop system linguistic model of CSTR for $T_f = 310\ K$

$T_c(t)$		$T_r(t)$				
		$A270$	$A280$	$A290$	$A300$	$A310$
$T(t)$	$A270$	$A280$	$A290$	$A300$	$A300$	$A310$
	$A280$	$A280$	$A290$	$A300$	$A310$	$A310$
	$A290$	$A280$	$A290$	$A300$	$A310$	$A310$
	$A300$	$A280$	$A290$	$A300$	$A310$	$A310$
	$A310$	$A280$	$A290$	$A300$	$A310$	$A310$

Table 5: Fuzzy logic controller of CSTR for $T_f = 270\ K$

$T_c(t)$		$T_r(t)$				
		$A270$	$A280$	$A290$	$A300$	$A310$
$T(t)$	$A270$	$A270$	$A270$	$A270$	$A270$	$A310$
	$A280$	$A270$	$A270$	$A270$	$A280$	$A310$
	$A290$	$A270$	$A270$	$A270$	$A280$	$A310$
	$A300$	$A270$	$A270$	$A270$	$A280$	$A310$
	$A310$	$A270$	$A270$	$A270$	$A280$	$A310$

Table 6: Fuzzy logic controller of CSTR for $T_f = 310\ K$

$T_c\,(t)$		$T_r\,(t)$				
		$A270$	$A280$	$A290$	$A300$	$A310$
$T\,(t)$	$A270$	$A270 \to A280$	$A270 \to A290$	$A270 \to A300$	$A270 \to A300$	$A310 \to A310$
	$A280$	$A270 \to A280$	$A270 \to A290$	$A270 \to A300$	$A280 \to A310$	$A310 \to A310$
	$A290$	$A270 \to A280$	$A270 \to A290$	$A270 \to A300$	$A280 \to A310$	$A310 \to A310$
	$A300$	$A270 \to A280$	$A270 \to A290$	$A270 \to A300$	$A280 \to A310$	$A310 \to A310$
	$A310$	$A270 \to A280$	$A270 \to A290$	$A270 \to A300$	$A280 \to A310$	$A310 \to A310$

Table 7: Fuzzy rule base of the overlapping semi-dynamic fuzzy logic controller of CSTR

system, and all closed loop system specifications were stated in terms of linguistic variables.In a fuzzy sense, the fuzzy closed loop system fully meets prespecified performance objectives. Figure 12 shows the overlapping semi-dynamic fuzzy logic controller output(the dashed line) for different desired temperatures (the solid line) and drastic changes in T_f (the dashed-dotted line).

4 Conclusions

A method to design a closed loop system fuzzy logic controller that accommodates drastic plant parameter changes has been given. The method is based on prescribing linguistically desired closed loop system performance. A fuzzy model of the plant is required, with knowledge of plant parameter range limits. An illustrative example of a semi-dynamic fuzzy logic controller that controls a Continuous-Stirred-Tank Reactor shows that the design procedure is feasible for practical applications.

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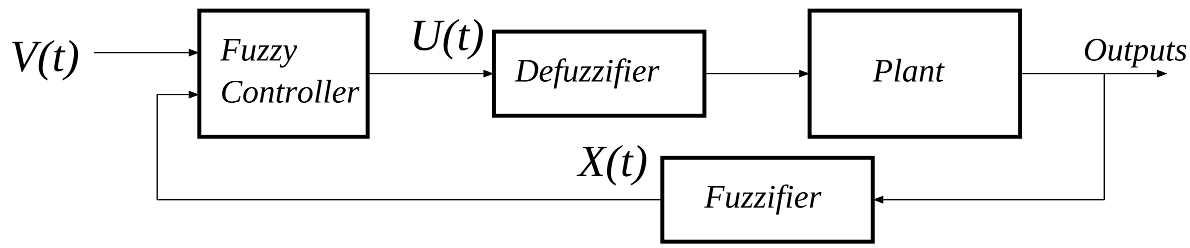

Figure 1: Block diagram of a closed loop system.

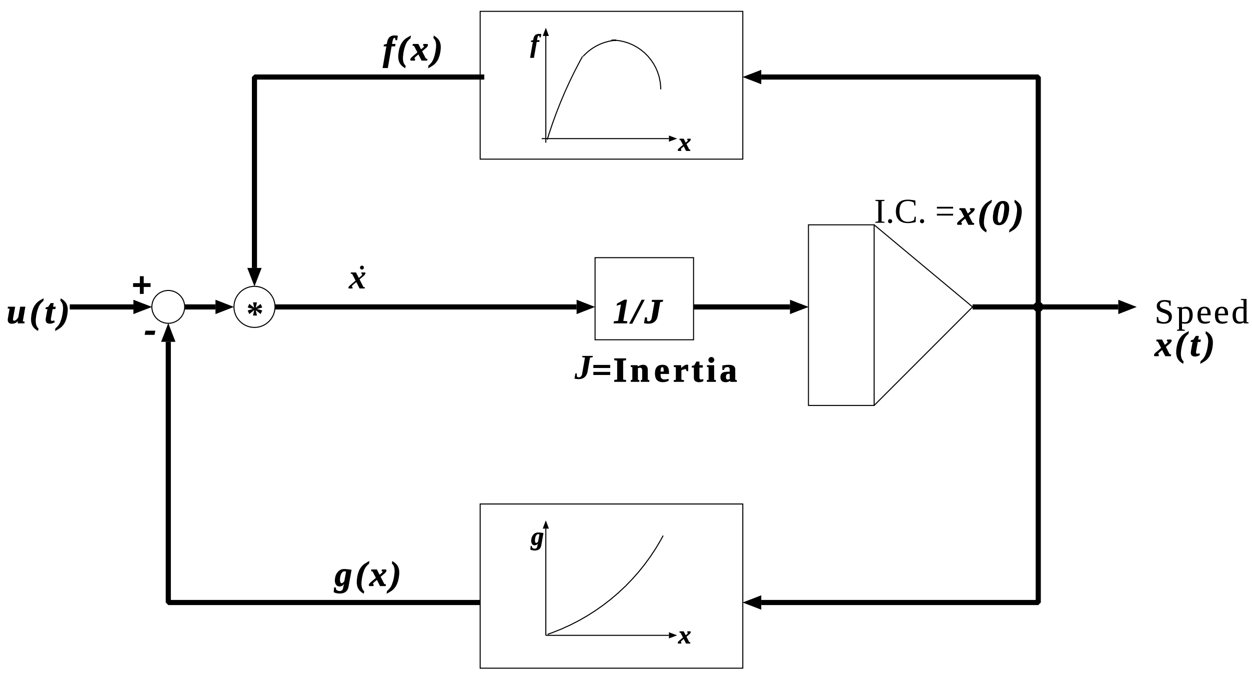

Figure 2: Block diagram of a nonlinear fuel engine

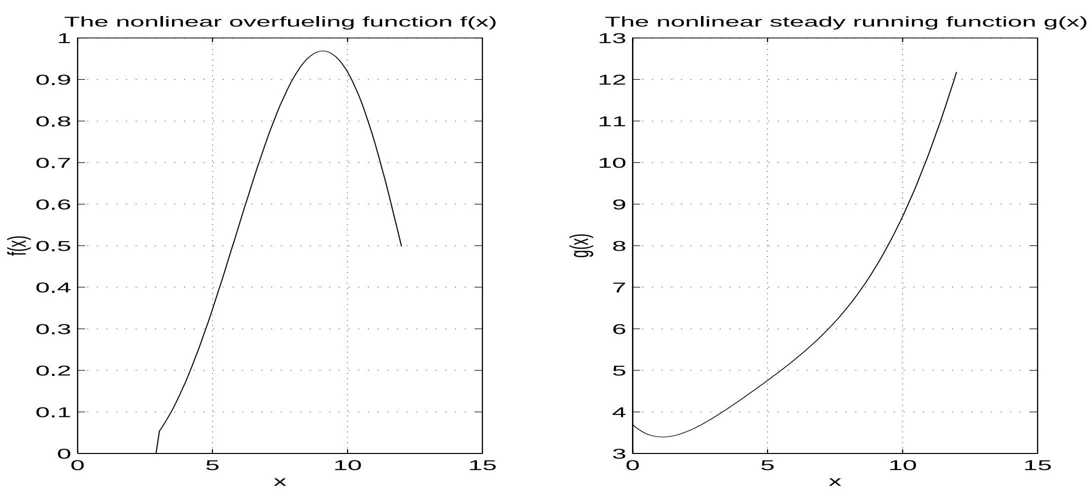

Figure 3: Nonlinear functions of the fuel engine.

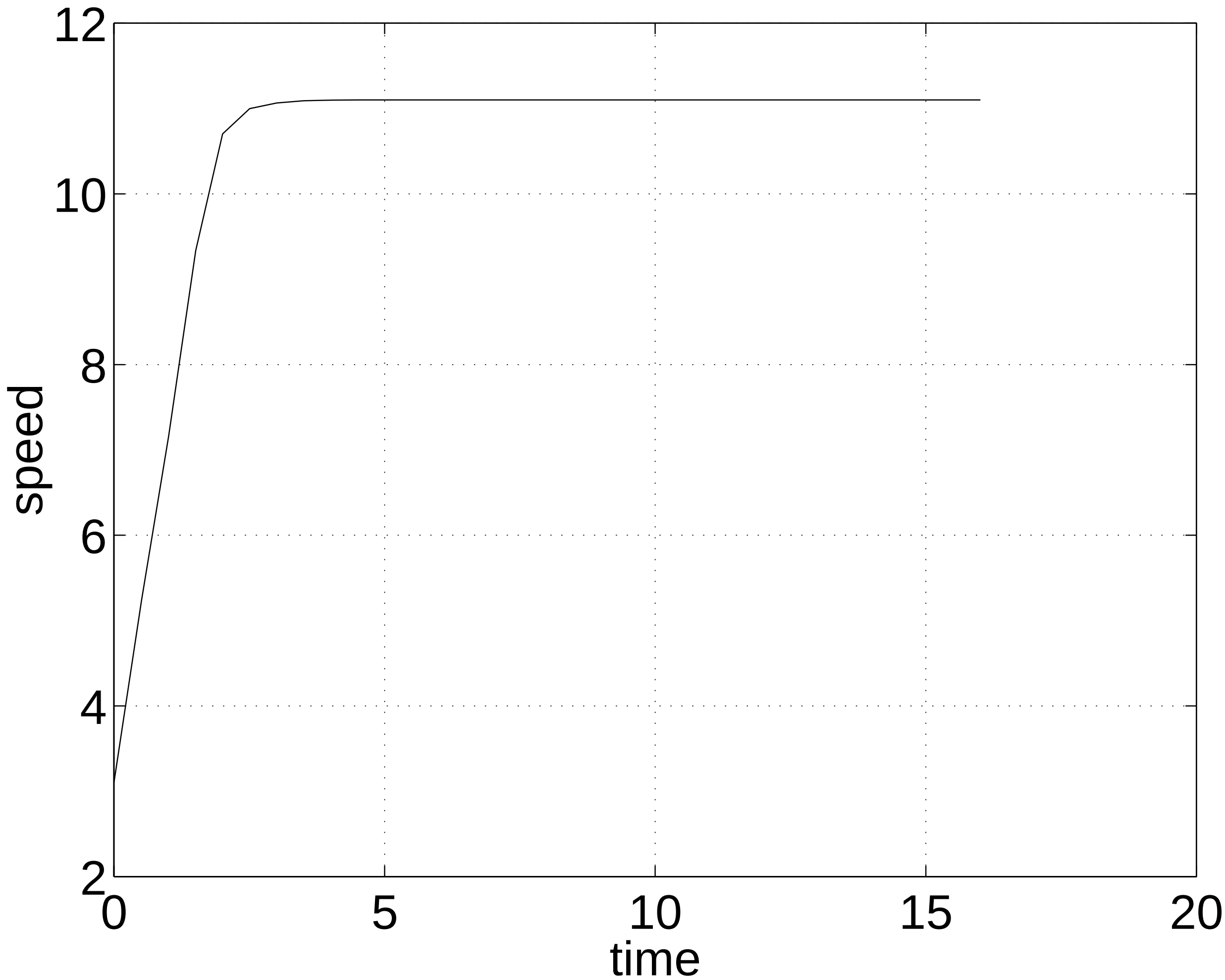

Figure 4: Step response of a nonlinear fuel engine fuzzy closed-loop system.

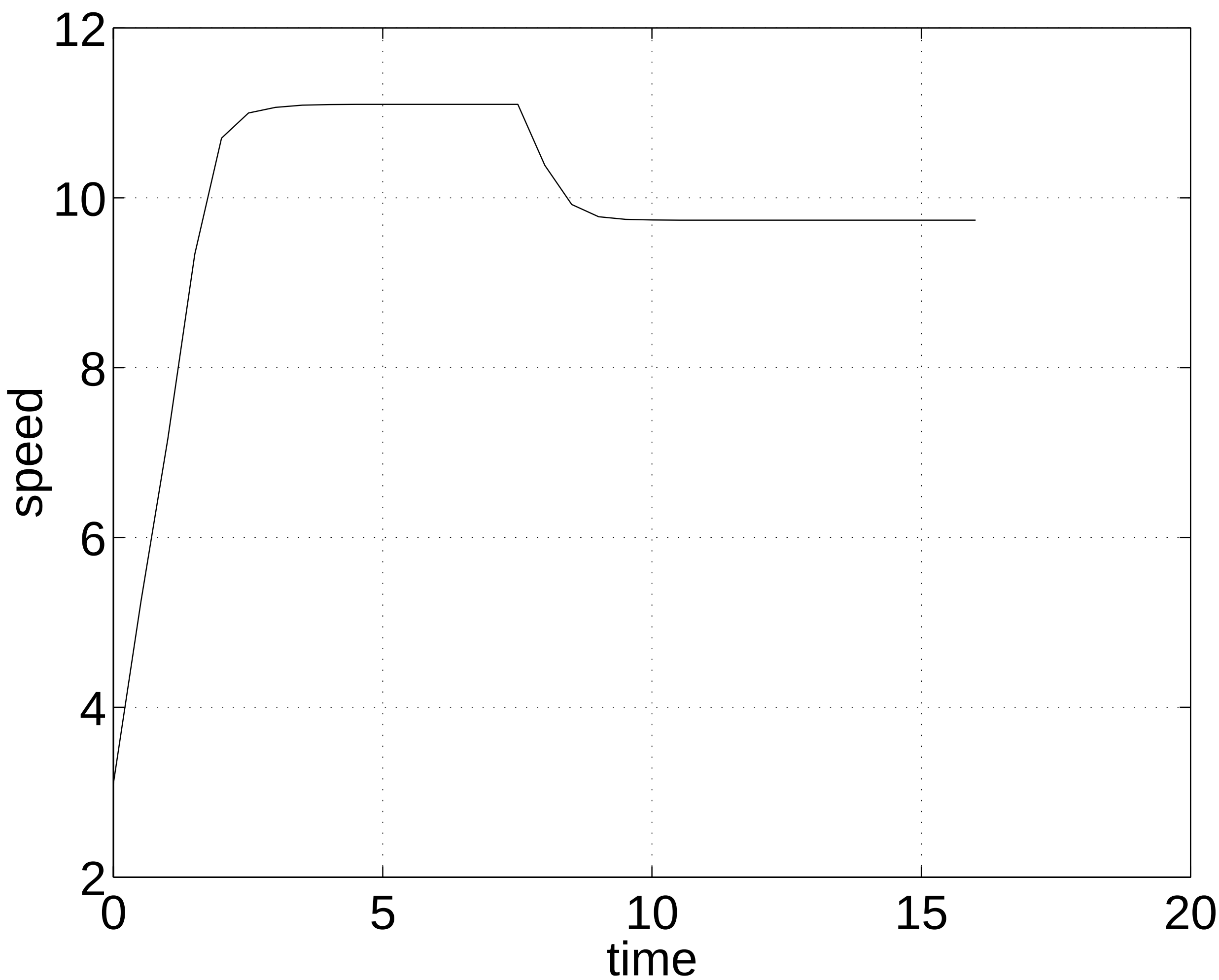

Figure 5: Step response of the stable closed loop system with a load change at 7.5s.

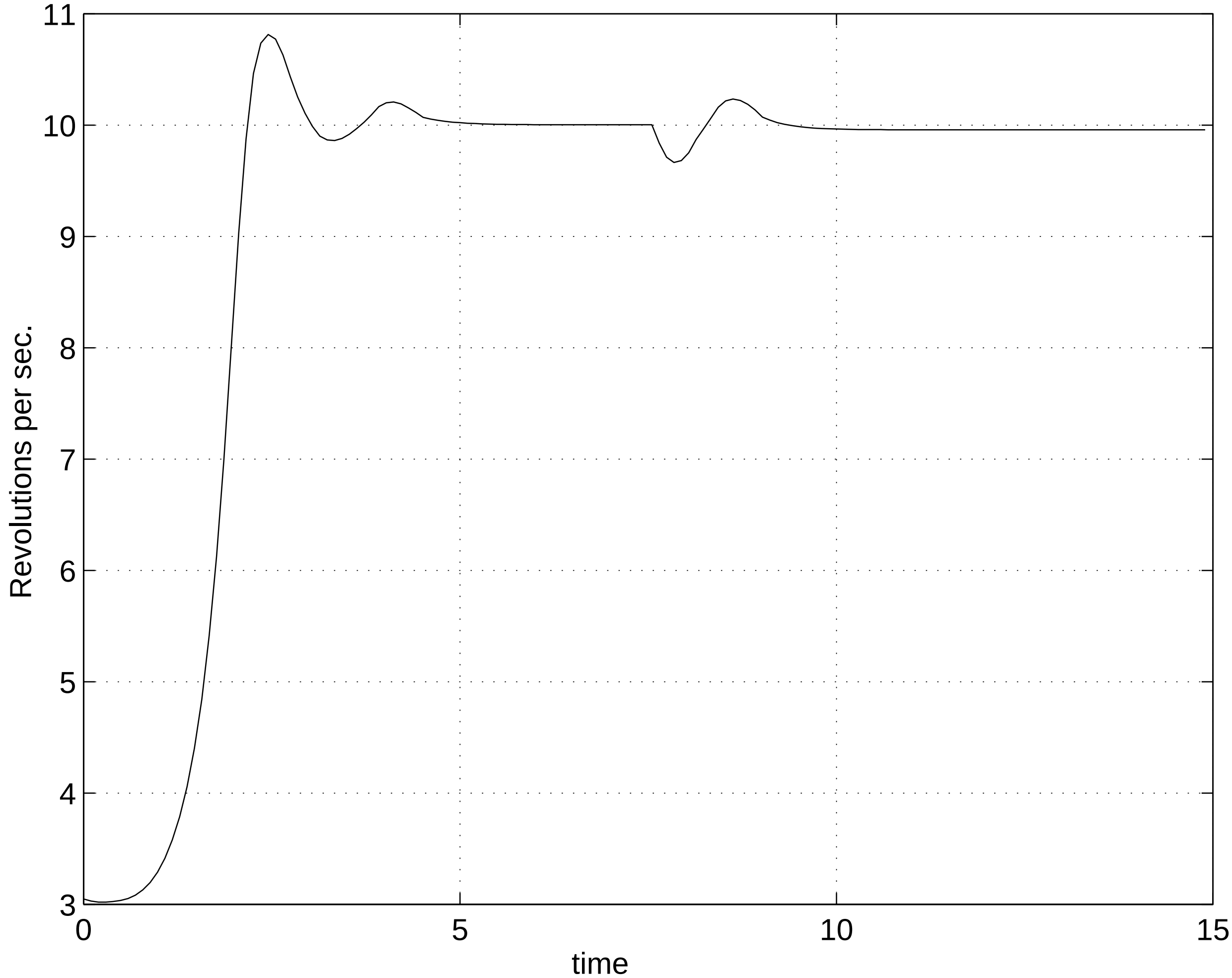

Figure 6: Step response of the overlapping semi-dynamic FCLS.

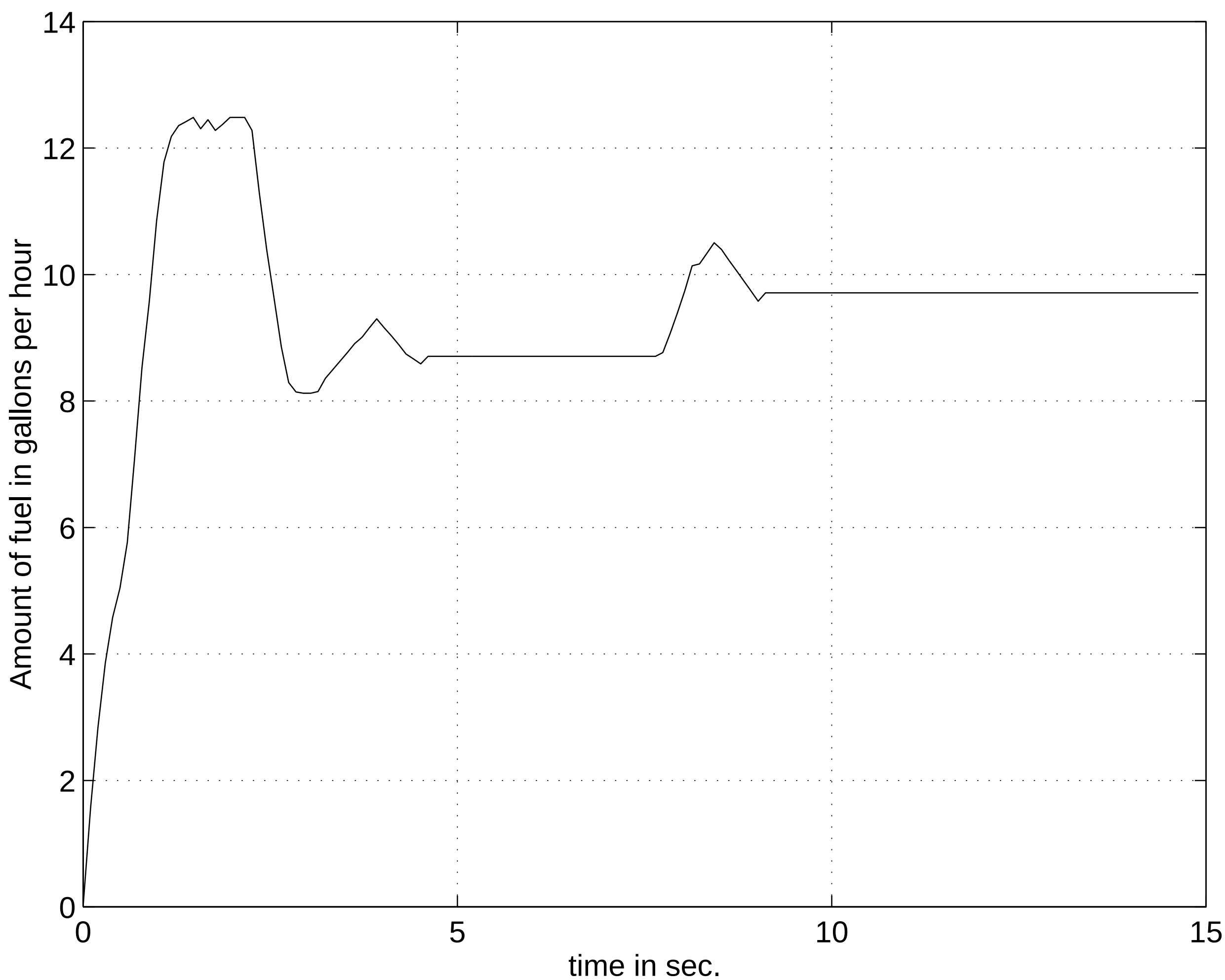

Figure 7: Control action of the overlapping semi-dynamic fuzzy logic controller.

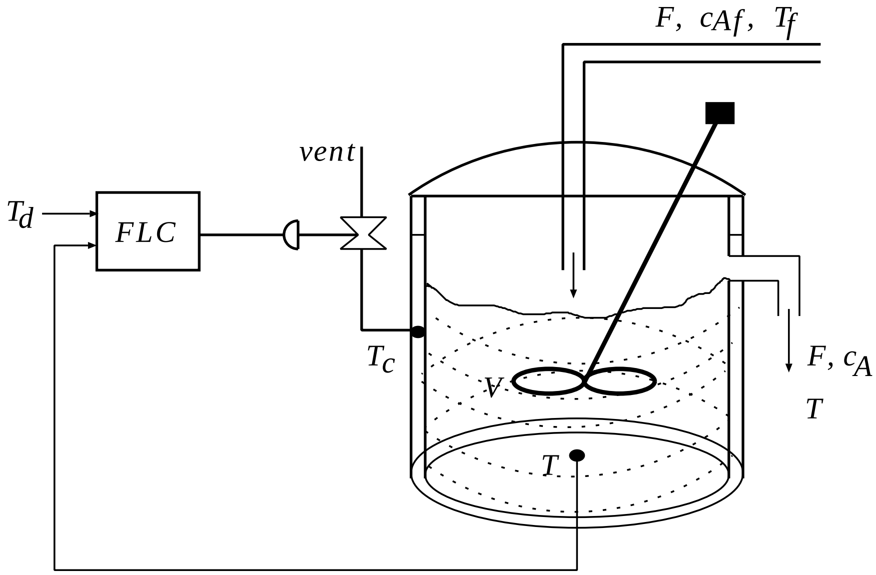

Figure 8: Simple schematic of a CSTR.

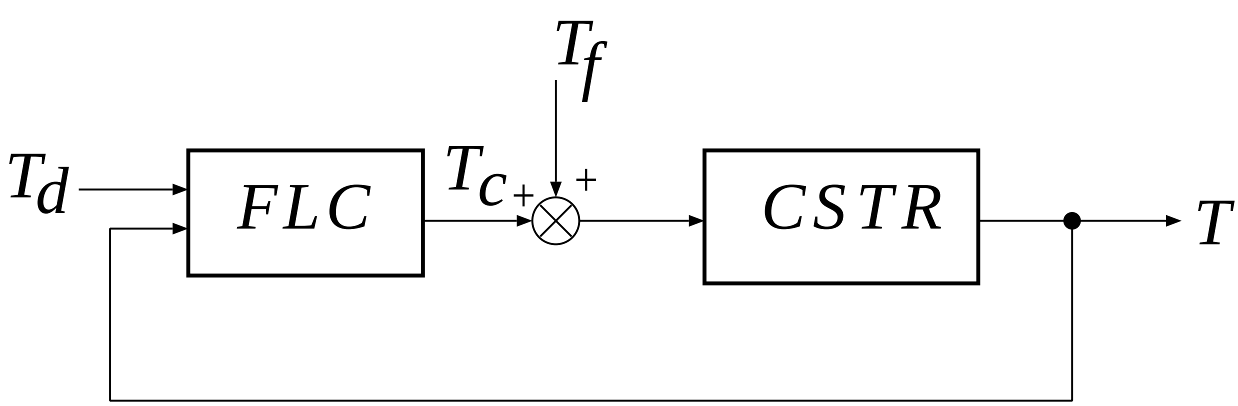

Figure 9: A complete fuzzy closed-loop system of the CSTR.

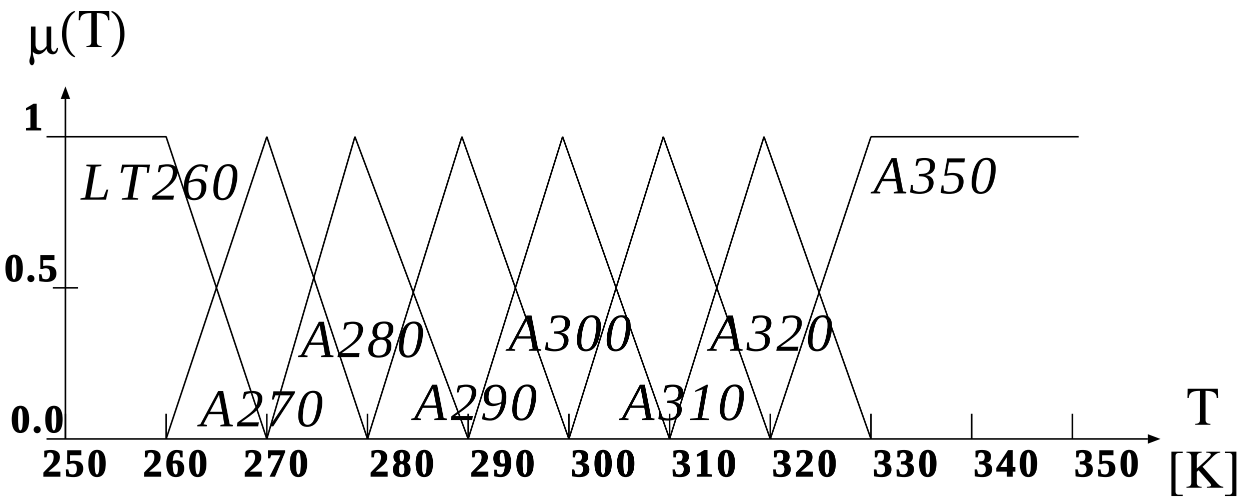

Figure 10: Fuzzy sets defined for CSTR linguistic variables.

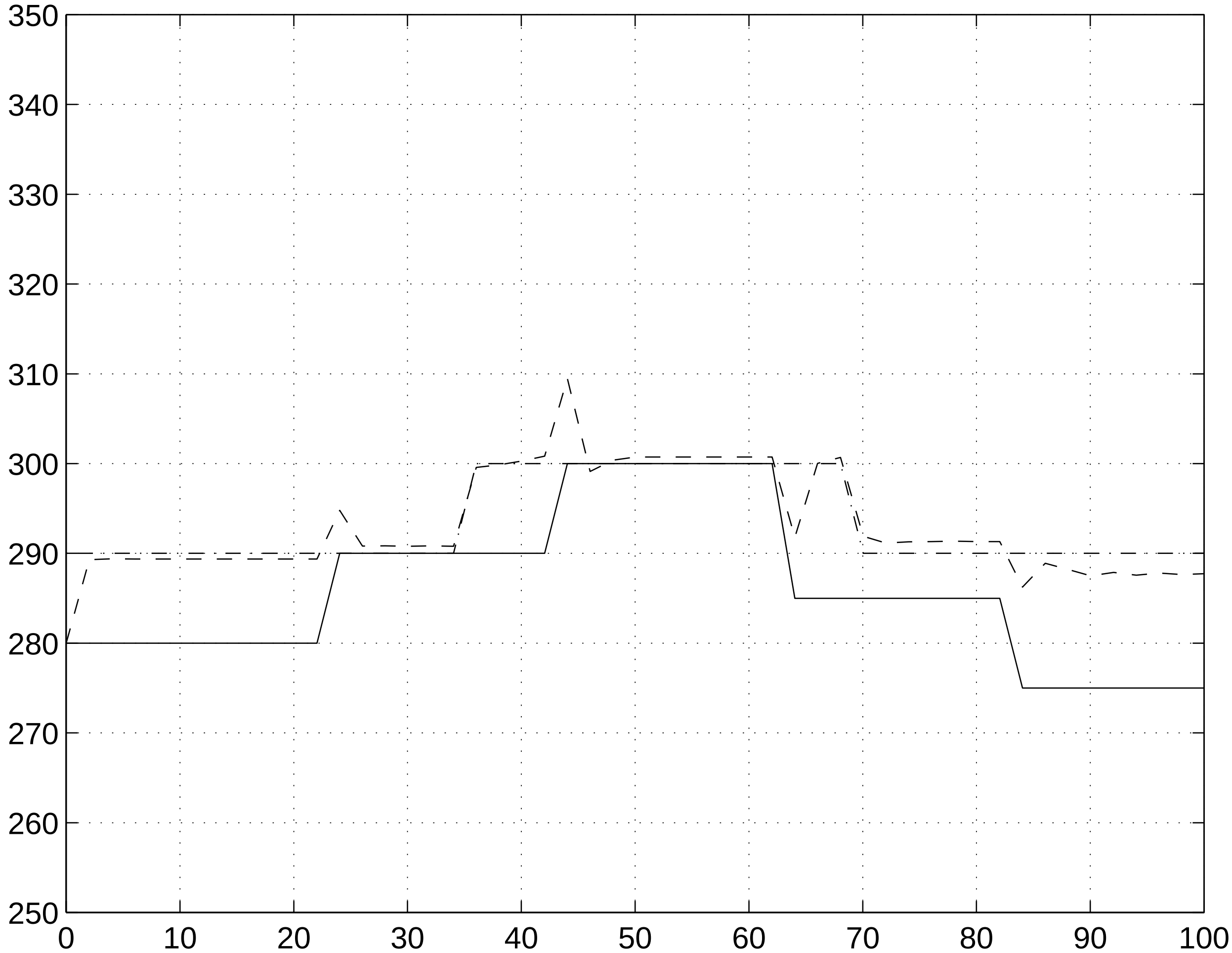

Figure 11: Dynamic behavior of the CSTR fuzzy closed loop system.

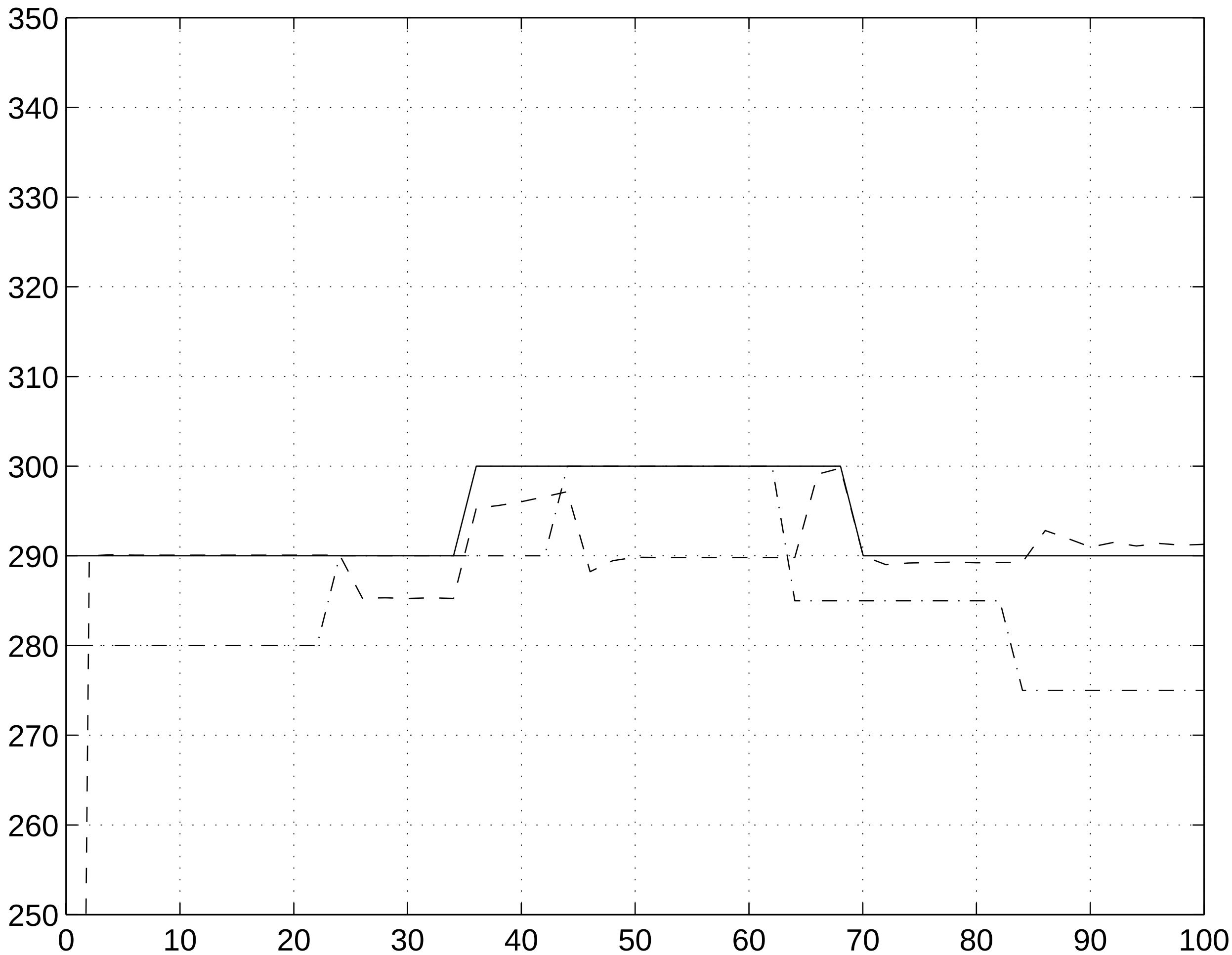

Figure 12: Control action of the overlapping semi-dynamic fuzzy logic controller in the CSTR closed loop system.