10 Experimental Study of Intelligent Controllers Under Uncertainty Using Type-1 and Type-2 Fuzzy Logic

Uncertainty is an inherent part in controllers used for real-world applications. The use of new methods for handling incomplete information is of fundamental importance in engineering applications. This chapter deals with the design of controllers using type-2 fuzzy logic for minimizing the effects of uncertainty produced by the instrumentation elements. We simulated type-1 and type-2 fuzzy logic controllers to perform a comparative analysis of the systems' response, in the presence of uncertainty.

10.1 Introduction

Uncertainty affects decision-making and appears in a number of different forms. The concept of information is fully connected with the concept of uncertainty. The most fundamental aspect of this connection is that the uncertainty involved in any problem-solving situation is a result of some information deficiency, which may be incomplete, imprecise, fragmentary, not fully reliable, vague, contradictory, or deficient in some other way (Klir and Yuan, 1995). The general framework of fuzzy reasoning allows handling much of this uncertainty, fuzzy systems employ type-1 fuzzy sets, which represents uncertainty by numbers in the range [0, 1]. However, when something is uncertain, like a measurement, it is difficult to determine its exact value, and of course type-1 fuzzy sets make more sense than using crisp sets (Zadeh, 1975). However, it is not reasonable to use an accurate membership function for something uncertain, so in this case what we need is another type of fuzzy sets, those, which are able to handle these uncertainties, the so called type-2 fuzzy sets (Mendel, 2000). So, the amount of uncertainty in a system can be reduced by using type-2 fuzzy logic because it offers better capabilities to handle linguistic uncertainties by modeling vagueness and unreliability of information (Karnik and Mendel, 2001).

Recently, we have seen the use of type-2 fuzzy sets in fuzzy logic systems to deal with uncertain information (Mendel, 1998). So we can find some papers emphasizing on the implementation of a type-2 Fuzzy Logic System (FLS) (Karnik and Mendel, 1999); in others, it is explained how type-2 fuzzy sets let us model and minimize the

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effects of uncertainties in rule-base FLSs (Mendel and John, 2002). Some research works are devoted to solve real world applications in different areas, for example, in signal processing type-2 fuzzy logic is applied in prediction in Mackey-Glass chaotic time-series with uniform noise presence (Mendel, 2000). In medicine, an expert system was developed for solving the problem of Umbilical Acid-Base (UAB) assessment (Ozen and Garibaldi, 2003). In industry, type-2 fuzzy logic and neural networks was used in the control of non-linear dynamic plants (Hagras, 2004) (Melin and Castillo, 2004).

This chapter deals with the advantages of using type-2 fuzzy sets in the implementation of a Fuzzy Logic Controller (FLC), for a real system. It is a fact, that in the control of real systems, the instrumentation elements (instrumentation amplifier, sensors, digital to analog, analog to digital converters, etc.) introduce some sort of unpredictable values in the information that has been collected (Castillo and Melin, 2001). So, the controllers designed under idealized conditions tend to behave in an inappropriate manner. Since, uncertainty is inherent in the design of controllers for real world applications, we are presenting how to deal with it using type-2 FLC to diminish the effects of imprecise information. We are supporting this statement with experimental results, qualitative observations, and quantitative measures of errors. For quantifying the errors, we utilized three widely used performance criteria, these are: Integral of Square Error (ISE), Integral of the Absolute value of the Error (IAE), and Integral of the Time multiplied by the Absolute value of the Error (ITAE) (Sepulveda et al., 2007).

This chapter is organized as follows: section 10.2 presents an introductory explanation of type-1 and type-2 FLCs and the performance criteria for evaluating the transient and steady state closed-loop response in a computer control system. In section 10.3, we are showing details of the implementation of the feedback control system used in this work, we are presenting some experimental results and a performance comparison between type-1 and type-2 fuzzy logic controllers.

10.2 Fuzzy Controllers

In the 40's and 50's, many researchers proved that many dynamic systems can be mathematically modeled using differential equations. These previous works represent the foundations of the Control theory which, in addition with the Transform theory, provided an extremely powerful means of analyzing and designing control systems. These theories were being developed until the 70's, when the area was called System theory to indicate its definitiveness (Mamdani, 1993). Its principles have been used to control a very big amount of systems taking mathematics as the main tool to do it during many years. Unfortunately, in too many cases this approach could not be sustained because many systems have unknown parameters or highly complex and nonlinear characteristics that make them not to be amenable to the full force of mathematical analysis as dictated by the Control theory.

Soft computing techniques have become a research topic, which is applied in the design of controllers (Jang et al., 1997). These techniques have tried to avoid the abovementioned drawbacks, and they allow us to obtain efficient controllers, which utilize the human experience in a more related form than the conventional mathematical approach

(Zadeh, 1971). In the cases in which a mathematical representation of the controlled systems cannot be obtained, the process operator should be able to express the relationships existing in them, that is, the process behavior.

A FLS, described completely in terms of type-1 fuzzy sets is called a type-1 fuzzy logic system (type-1 FLS). It is composed by a knowledge base that comprises the information given by the process operator in form of linguistic control rules, a fuzzification interface, who has the effect of transforming crisp data into fuzzy sets, an inference system, that uses them in conjunction with the knowledge base to make inference by means of a reasoning method, and a defuzzification interface, which translates the fuzzy control action so obtained to a real control action using a defuzzification method.

In this chapter, the implementation of the fuzzy controller in terms of type-1 fuzzy sets, has two input variables such as the error $e(t)$, the difference between the reference signal and the output of the process, as well as the error variation $\Delta e(t)$,

$$e(t) = r(t) - y(t) \tag{10.1}$$

$$\Delta e(t) = e(t) - e(t-1) \tag{10.2}$$

so the control law can be represented as in Fig. 10.1.

A FLS described using at least one type-2 fuzzy set is called a type-2 FLS. Type-1 FLSs are unable to directly handle rule uncertainties, because they use type-1 fuzzy sets that are certain (Mendel and Mouzouris, 1999). On the other hand, type-2 FLSs, are very useful in circumstances where it is difficult to determine an exact certainties, and measurement uncertainties (Mendel, 2000).

It is known that type-2 fuzzy sets let us to model and to minimize the effects of uncertainties in rule-based FLS. Unfortunately, type-2 fuzzy sets are more difficult to use and understand than type-1 fuzzy sets; hence, their use is not widespread yet. In (Sepulveda et al., 2007) were mentioned at least four sources of uncertainties in type-1 FLSs:

1. The meanings of the words that are used in the antecedents and consequents of rules can be uncertain (words mean different things to different people).
2. Consequents may have histogram of values associated with them, especially when knowledge is extracted from a group of experts who do not all agree.
3. Measurements that activate a type-1 FLS may be noisy and therefore uncertain.
4. The data used to tune the parameters of a type-1 FLS may also be noisy.

All of these uncertainties translate into uncertainties about fuzzy set membership functions. Type-1 fuzzy sets are not able to directly model such uncertainties because their membership functions are totally crisp. On the other hand, type-2 fuzzy sets are able to model such uncertainties because their membership functions are themselves fuzzy. A type-2 membership grade can be any subset in [0,1], the primary membership, and corresponding to each primary membership, there is a secondary membership (which can also be in [0,1]) that defines the possibilities for the primary

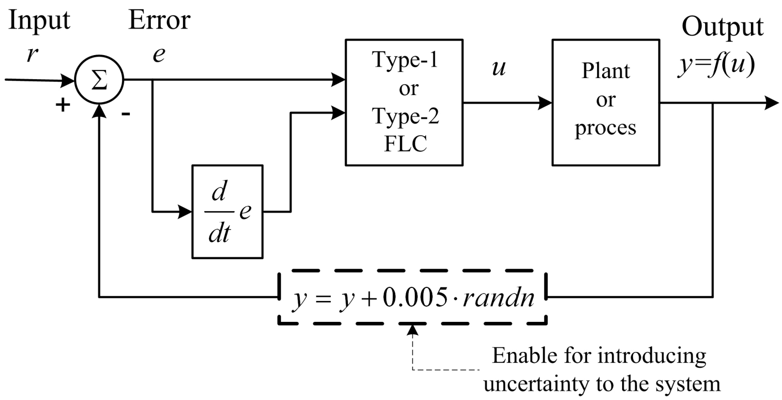

Fig. 10.1. Block diagram of the fuzzy control

membership. A type-1 fuzzy set is a special case of a type-2 fuzzy set; its secondary membership function is a subset with only one element, unity.

Similar to a type-1 FLS, a type-2 FLS includes fuzzifier, rule base, fuzzy inference engine, and output processor. The output processor includes type-reducer and defuzzifier; it generates a type-1 fuzzy set output (from the type-reducer) or a crisp number (from the defuzzifier). A type-2 FLS is again characterized by IF-THEN rules, but its antecedent or consequent sets are now type-2. Type-2 FLSs, can be used when the circumstances are too uncertain to determine exact membership grades such as when training data is corrupted by noise. In our case, we are simulating that the instrumentation elements (instrumentation amplifier, sensors, digital to analog, analog to digital converters, etc.) are introducing some sort of unpredictable values in the collected information.

In the case of the implementation of the type-2 FLC, we have the same characteristics as in type-1 FLC, but we used type-2 fuzzy sets as membership functions for the inputs and for the output.

For evaluating the transient closed-loop response of a computer control system we can use the same criteria that normally are used for adjusting constants in PID (Proportional Integral Derivative) controllers. These are (Deshpande and Ash, 1988):

1. Integral of Square Error (ISE).

$$\mathrm{ISE} = \int_0^\infty [e]^2 \, dt \tag{10.3}$$

2. Integral of the Absolute value of the Error (IAE).

$$\mathrm{IAE} = \int_0^\infty | e | \, dt \tag{10.4}$$

3. Integral of the Time multiplied by the Absolute value of the Error (ITAE).

$$\mathrm{ITAE} = \int_0^\infty t \, | e | \, dt \tag{10.5}$$

The selection of the criteria depends on the type of response desired, the errors will contribute different for each criterion, so we have that large errors will increase the value of ISE more heavily than to IAE. ISE will favor responses with smaller overshoot for load changes, but ISE will give longer settling time. In ITAE, time appears as a factor, and therefore, ITAE will penalize heavily on errors that occur late in time, but virtually ignores errors that occurs early in time. Designing using ITAE will give us the shortest settling time, but it will produce the largest overshoot among the three criteria considered. Designing considering IAE will give us an intermediate result, in this case, the settling time will not be so large than using ISE nor so small than using ITAE, and the same applies for the overshoot response. The selection of a particular criterion is depending on the type of desired response.

10.3 Experimental Results

We are showing in Fig. 10.1, the feedback control system that was used for achieving the results of this paper. It was implemented in Matlab where the controller was designed to follow the input as closely as possible. The plant was modeled using equation (10.6)

$$y(i)=0.2\cdot y(i-3)\cdot 0.7y(i-2)+0.9\cdot y(i-1)+0.005u(i-1)+0.5\cdot u(i-2) \tag{10.6}$$

The controller's output was applied directly to the plant's input. Since we are interested in comparing the performance between type-1 and type-2 FLC system, we tested the controller in two ways:

1. One is considering the system as ideal, that is, we did not introduce in the modules of the control system any source of uncertainty. See experiments 1, and 2.
2. The other one is simulating the effects of uncertain modules (subsystems) response introducing some uncertainty. See experiments 3, and 4.

For both cases, as is shown in Fig. 10.1, the system's output is directly connected to the summing junction, but in the second case, the uncertainty was simulated introducing random noise with normal distribution (the dashed square in Fig. 10.1). We added noise to the system's output $y(i)$ using equation (10.7), which in turn was introduced to the summing junction of the controller system.

$$y(i)=y(i)+0.05\cdot randn \tag{10.7}$$

We tested the system using as input, a unit step sequence free of noise, $r(i)$. For evaluating the system's response and compare between type 1 and type 2 fuzzy controllers, we used the performance criteria ISE, IAE, and ITAE. In table 10.1, we summarized the values obtained for each criterion considering 400 units of time. For calculating ITAE we considered a sampling time $T_s = 0.1$ sec.

For Experiments 1, 2, 3, and 4 the reference input r is stable and noisy free. In experiments 3 and 4, although the reference appears clean, the feedback at the summing junction is noisy since we introduced deliberately noise for simulating the overall existing uncertainty in the system, in consequence, the controller's inputs e (error), and $\frac{\Delta}{\Delta t}e$ contains uncertainty data.

For each input of the type-1 FLC, we defined three type-1 fuzzy Gaussian membership functions: negative, zero, positive. The universe of discourse for these membership functions is in the range [-10 10]; their mean is -10, 0 and 10 respectively, and their standard deviation are 9, 2 and 9 respectively.

For the output, we have five type-1 fuzzy Gaussian membership functions: NG, N, Z, P and PG. They are on the interval [-10 10], their means are -10, -4.5, 0, 4, and 10 respectively; and their standard deviations are 4.5, 4, 4.5, 4 and 4.5 respectively.

In the type-2 FLC, for each input we defined three type-2 fuzzy Gaussian membership functions: negative, zero, positive. In this case the fuzzy membership functions have uncertain mean and fixed standard deviation on the interval [-10 10]. For the upper membership functions we have -10.5, -1, and 9.5 uncertain means; for the lower membership functions we have -9.5, 1, and 10.5 uncertain means respectively; for the fixed standard deviations 9, 2 and 9 respectively.

For computing the output we have five type-2 fuzzy Gaussian membership functions with uncertain mean and fixed standard deviations: NG, N, Z, P and PG, on the interval [-10 10]. For the upper membership functions we have -10.25, -4.75, -0.25, 3.75 and 9.75 uncertain means; for the lower membership functions we have -9.75, -4.25, 0.25, 4.25 and 10.25 uncertain means respectively. The fixed standard deviations: 4.5, 4, 4.5, 4 and 4.5 respectively.

For the type-2 FLC, the inputs and the output have interval type-2 membership functions. In all of the experiments, we used a dash-dot line for illustrating the system's response and behavior of type-1 FLC, in the same sense, we used continuous line for type-2 FLC. The reference input r is shown with a dot line.

Experiment 1. Ideal system using a type-1 FLC.
In this experiment, we did not add uncertainty data to the system, the system response is illustrated in Figure 10.2. Note that the settling time is in about 140 units of time; i.e., the system trends to stabilize with time and the output will follow accurately the input. In Table 10.1, we listed the obtained values of ISE, IAE, and ITAE for this experiment. We are showing in Fig. 10.3, 10.4 and 10.5 the ISE, IAE, and ITAE behavior of this experiment.

Experiment 2. Ideal system using a type-2 FLC.
Here, we used the same test conditions of Experiment 1, but in this case, we implemented the controller's algorithm with type-2 fuzzy logic, its output sequence is illustrated in Fig. 10.2, and the corresponding performance criteria are listed in Table 10.1. By visual inspection, we can observe that the output system response of the Experiment 1, and this one, are very similar, they are almost overlapped.

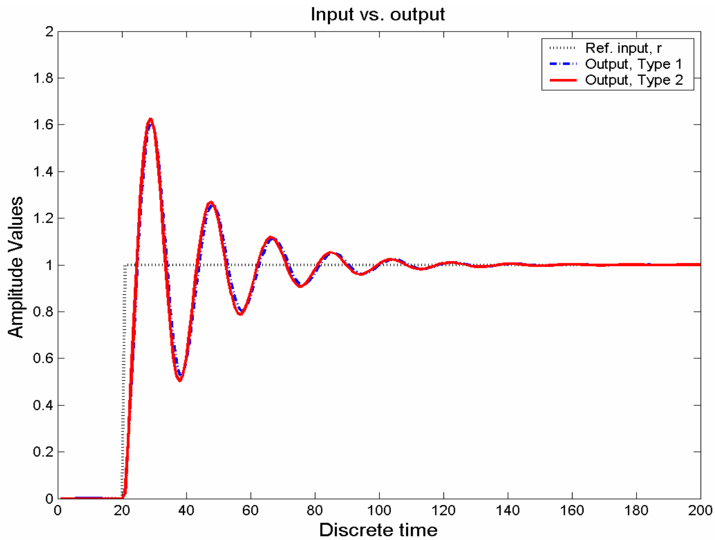

Fig. 10.2. This graphic shows the system's response to a unit step sequence. The input reference *r* is shown with pointed line, for type 1 the systems's output *y*(*i*) is shown with dash dot line; and for type-2, the system's output *y*(*i*) with continuous line. Note, that both responses are very similar, although, in this case the lower errors were obtained with type-1 FLC.

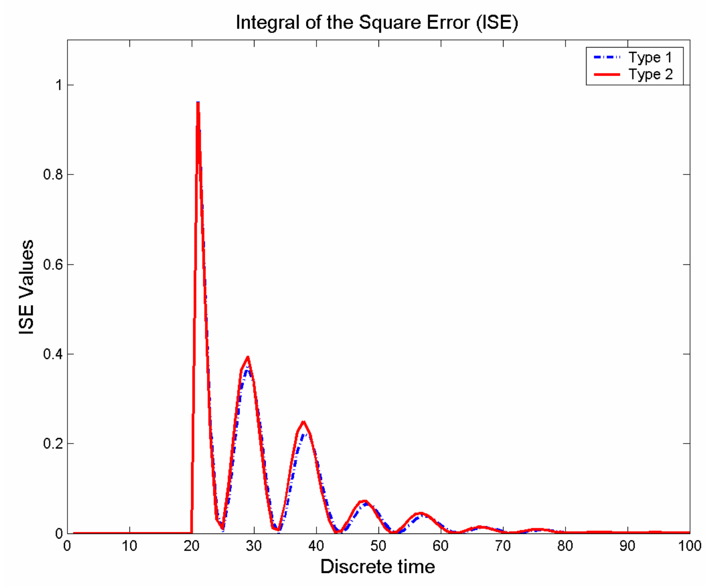

Fig. 10.3. In uncertainty absence, the ISE values are very similar for type-1 and type-2 FLCs

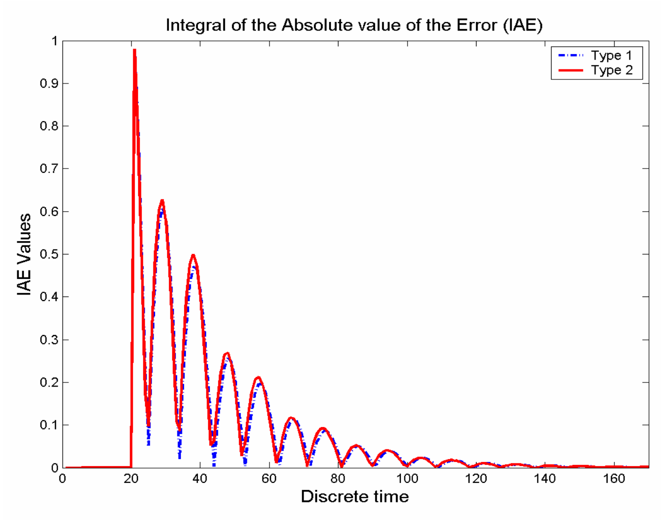

Fig. 10.4. In uncertainty absence, the IAE values obtained at the plant's output are very similar for type-1 and type-2 FLCs, here is more evident that a type-1 FLC works a little better than in Fig. 10.3

Using the performance criteria we can get a quantitative comparison, where we can observe small differences favoring Experiment 1, i.e., the results obtained using a type-1 FLC.

We can observe in Fig. 10.3, 10.4, and 10.5 that using a type-1 FLC we got the lower errors.

Experiment 3. System with uncertainty using a type-1 FLC.
In this case, we simulated using equation (7), the effects of uncertainty introduced to the system by transducers, amplifiers, and any other element that in real world applications affects expected values. We are showing in Fig. 6, the system's response output. In Fig. 10.7, 10.8, and 10.9 are plotted the performance criteria ISE, IAE, ITAE.

Experiment 4. System with uncertainty using a type-2 FLC. In this experiment, we introduced uncertainty in the system, in the same way as in Experiment 3. In this case, we used a type-2 FLC and we improved those results obtained with a type-1 FLC (Experiment 3).

We can easily appreciate in Fig. 10.6, that the lower overshoot and the best settling times were reached using a type-2 FLC.

Using Fig. 10.7 and 10.8, we can see that with a type-2 FLC the overshoot error decreases very quickly and remains lower than using a type-1 FLC. In Fig. 10.9, we can observe that through the time the lower errors are obtained using a type-2 FLC.

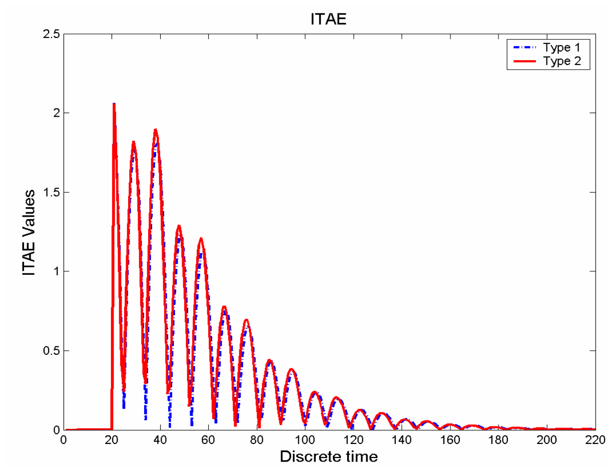

Fig. 10.5. In uncertainty absence, the ITAE values obtained at the plant's output are very similar for type-1 and type-2 FLCs, in accordance with Figure 10.13, it is evident a type-1 FLC works a little better

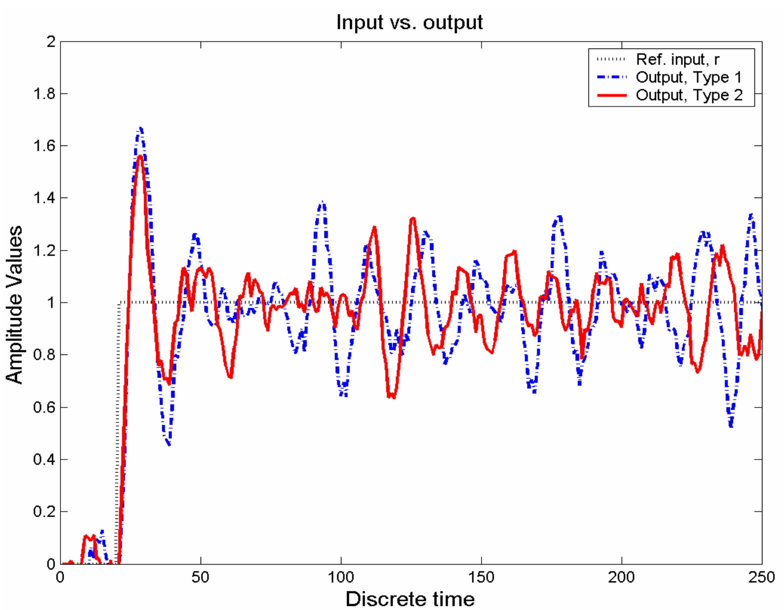

Fig. 10.6. This graphic was obtained with uncertainty presence; compare the system's outputs produced by type-1 and type-2 FLCs. Note that quite the opposite of Figure 10.2, a type-2 FLC works much better than a type-1 FLC when the system has uncertainty. The overshoot error is lower for a type-2 FLC.

Table 10.1. comparison of performance criteria for type-1 and type-2 fuzzy logic controllers. Values obtained after 400 samples.

Performance Criteria	Type-1 FLC		Type-2 FLC	
	Ideal System	Syst. with uncertainty	Ideal System	Syst. with uncertainty
ISE	5.2569	15.1143	5.4479	9.5516
IAE	13.8092	57.9542	14.204	45.4106
ITAE	59.9589	1111.2	61.636	877.5299

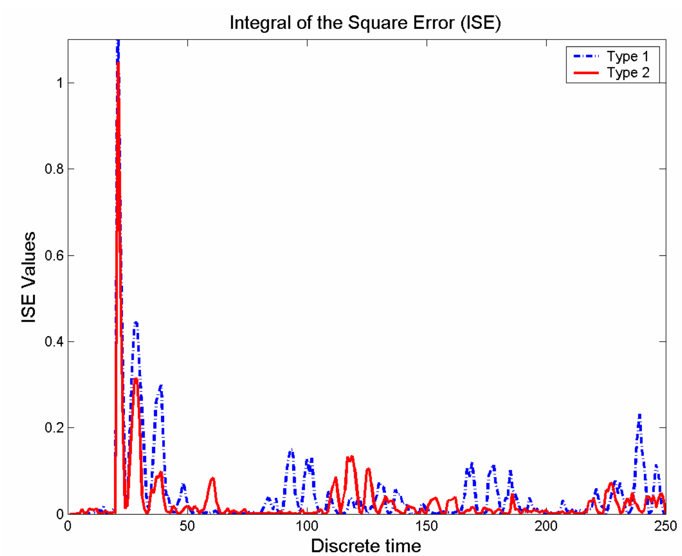

Fig. 10.7. Here we can see that a type-2 FLC produces lower overshoot errors, quantitatively the ISE overall error of using type-2 is 9.5516 against 15.1143 of the overall error produced by the type-1 FLC

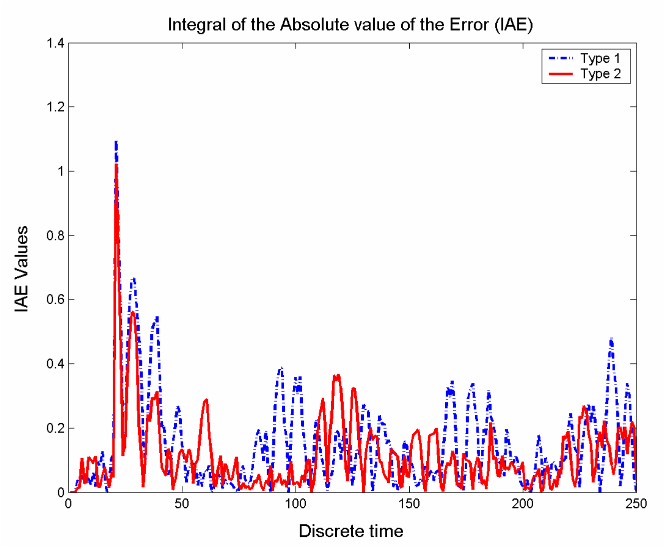

Fig. 10.8. In accordance with Fig. 10.6, IAE confirms that we obtained the best system response using a type-2 FLC with uncertainty presence. Moreover, the error of the settling time and steady state is lower using a type-2 FLC.

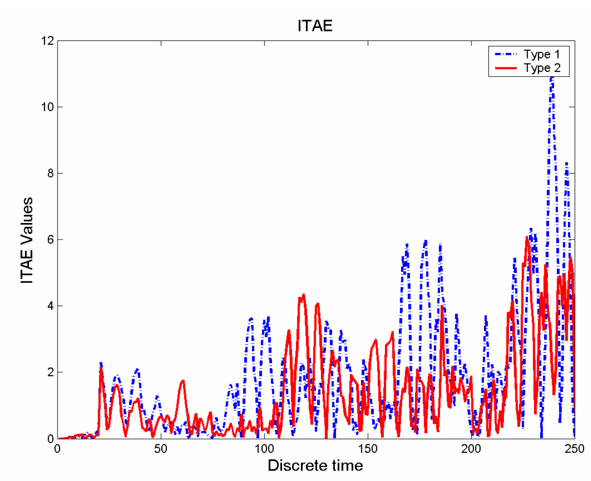

Fig. 10.9. Here we can see that the steady state error of the system produced by a type-2 FLC is lower than the error produced by a type-1 FLC with uncertainty present. ITAE will punish heavily all those errors produced with time.

10.4 Summary

We observed and quantified using performance criteria such as ISE, IAE, and ITAE that in systems without uncertainties (ideal systems) is a better choice to select a type-1 FLC since it works a little better than a type-2 FLC, and it is easier to implement it. It is known that type-1 FLC can handle nonlinearities, and uncertainties up to some extent.

Unfortunately, real systems are inherently noisy and nonlinear, since any element in the system contributes with deviations of the expected measures because of thermal noise, electromagnetic interference, etc., moreover, they add nonlinearities from element to element in the system.

For real systems, systems with uncertainty, we observed and quantify that the lower overshoot errors and the best settling times were obtained using a type-2 FLC.

We are concluding that using a type-2 FLC in real world applications can be a better choice since the amount of uncertainty in real systems most of time is difficult to estimate.