4 A Method for Type-2 Fuzzy Inference in Control Applications

A novel method of type 2 fuzzy logic inference is presented in this chapter. The method is highly efficient regarding computational time and implementation effort. Type-2 input membership functions are optimized using the Human Evolutionary Model (HEM) considering as the objective function the Integral of Squared Error at the controllers output. Statistical tests were achieved considering how the error at the controller's output is diminished in presence of uncertainty, demonstrating that the proposed method outperforms an optimized traditional type-2 fuzzy controller for the same test conditions.

4.1 Introduction

In engineering as well as in the scientific field is of growing interest to use type-2 fuzzy logic controller (FLC). It is a well documented fact that type-2 FLC had demonstrated in several fields their usefulness to handle uncertainty which is an inherent characteristic of real systems. Because uncertainty and real systems are inseparable characteristics the research of novel methods to handle incomplete or not too reliable information is of great interest (Mendel, 2001). Recently, we have seen the use of type-2 fuzzy sets in Fuzzy Logic Systems (FLS) in different areas of application. From those including fuzzy logic systems, neural networks and genetic algorithms, to some papers with emphasis on the implementation of type-2 FLS; in others, it is explained how type-2 fuzzy sets let us model and minimize the effects of uncertainties in rule-base FLS (Mendel and John, 2002). Also, a paper that provides mathematical formulas and computational flowcharts for computing the derivatives that are needed to implement steepest-descent parameter tuning algorithms for type-2 fuzzy logic systems (Mendel, 2004). 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 of the Mackey-Glass chaotic time-series with uniform noise presence (Karnik and Mendel, 1999). 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

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non-linear dynamic plants (Melin and Castillo, 2004); also we can find interesting studies in the field of mobile robots (Hagras, 2004).
Although, the use of a type-2 FLC can be considered as a viable option to handle uncertainty, also it is well known all the deficiencies and requirements that the use of this technology implies.

In this work we are presenting a method whose goal is to simplify the implementation of a type-2 FLC without any loss of reliability in the results. In fact, this novel method reduces some of the stressful difficult to implement the traditional type-2 FLC.

The organization of this work is as follows: In section 2 is explained step by step how to implement this proposal and the method used to optimize the traditional as well as the proposed type-2 FLC. Section 3 is devoted to explain the kind and classification of experiments that were achieved, also in this section are given the experimental results. In section 4 is performed a discussion about the obtained results. Finally, in section 5 we have the conclusions.

4.2 Proposed Method to Implement Type-2 FLC

It is proposed to use two type-1 fuzzy systems (FS) to emulate a type-2 FS. The membership functions (MF), fuzzification process, fuzzy inference and defuzzification are type-1. The MFs are organized in such a way that they will be able to emulate the footprint of uncertainty (FOU) in a type-2 FS. To obtain the best parametric values for the MF the proposed method uses the optimized MFs, and we used the Human Evolutionary Model (HEM) to achieve the optimization.

To validate the proposed method, we made several comparative experiments using type-1 fuzzy traditional systems, as well as type-2 interval FS in accordance to those worked by (Mendel, 2001). The tests were achieved in the experimental base shown in Figure 4.1 which is a closed loop control system. The control goal is to make a tracking of the input signal r, which is applied to the systems summing junction. Note that we are using an adaptive fuzzy controller that needs to be optimized. In the feedback, with the aim of proving the proposal, we are considering two situations. One is to directly connect the system output to one summing junction. The second is to introduce noise to simulate uncertainty in the feedback data. At the summing junction output we have the error signal, which is applied to the input of the fuzzy controller, from the error signal we are obtaining a derivative signal; i.e., the change of error vs. time, which also is applied to the controllers input.

In general, the proposed solution to substitute the Mendel's type-2 FS consists in using the average of two type-1 FS, and to achieve this is necessary to follow the next steps:

1. To substitute each type-2 MF with two type-1 MFs. For doing this, the FOU of each MF is substituted with two type-1 MFs. In Fig. 4.2, the error signal (input fuzzy variable) e consists of three linguistic variables, they have been substituted as was explained obtaining the fuzzy sets that are shown in Fig. 4.3 where each fuzzy set is a type-1 MF. The first type-1 FLC (FLC1) is constructed using the upper MFs, and the second one (FLC2) with the lower MFs.

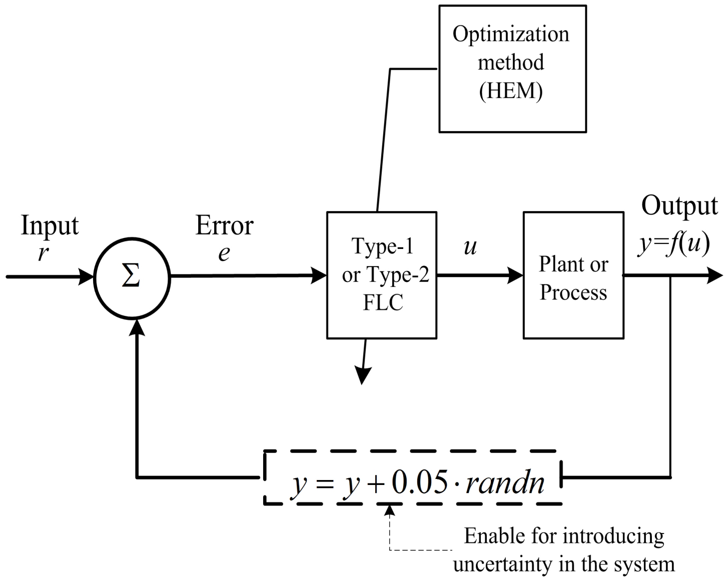

Fig. 4.1. Block diagram of the system used to test the proposal solution

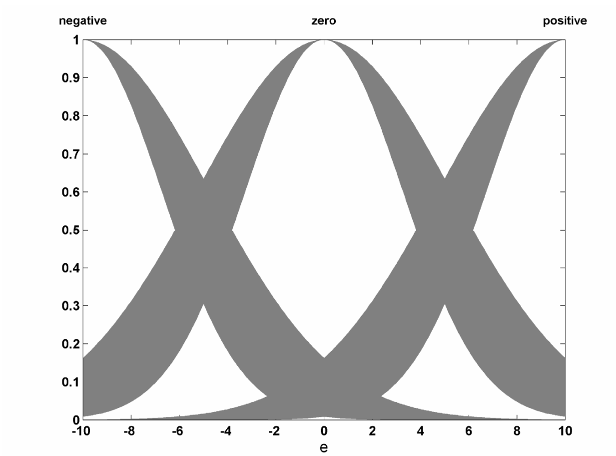

Fig. 4.2. Type-2 MF for the error input

2. To substitute the type-2 inference system, it is necessary to obtain the inference of each type-1 system in the traditional way. 1

3. To substitute the type reduction and defuzzification stages of a type-2 FS, it is necessary to obtain the defuzzification of each system as is traditionally done, and average them.

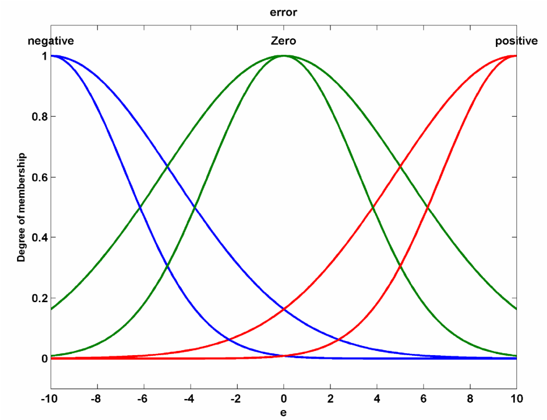

Fig 4.3. Substitution of the type-2 MFs of the error input using type-1 MFs

Performance Criteria

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 (Sepulveda et al., 2007):

Integral of Square Error (ISE).

$$\mathrm{ISE} = \int_0^\infty [e(t)]^2\, dt \tag{4.1}$$

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

$$\mathrm{IAE} = \int_0^\infty |\, e(t)\, |\, dt \tag{4.2}$$

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

$$\mathrm{ITAE} = \int_0^\infty t\, |\, e(t)\, |\, dt \tag{4.3}$$

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 errors that occur late in time, but virtually ignores errors that occur early in time.

4.3 Experiments

The experiments were divided in two classes:

1. The first class was to find, under different ranges for the FOU, the optimal values for the parameters of the interval type-2 MFs of the type-2 FLC of the non-linear control plant.
2. On the second class of experiments; it was realized the same as in the first class, but considering the average of the two type-1 FLC.

Class 1. Experiments with type-2 FLC

It is a fact that type-2 FLCs offer better conditions to handle uncertainty, so the purpose of the experiments of class 1, were to find the optimal parameters of the interval type-2 MFs to control the plant in a better way.

It was used a novel evolutive algorithm; Human Evolutionary Model (Montiel et al., 2005), to find those optimal values and to analize the influence of the FOU, we realized several tests for different ranges of it, beginning with the thinner and finally with the broader one. Once the optimal values were found, it was tested the behavior of the type-2 FLC, for different noise levels, from 8 db to 30 db.

Class 2. Experiments with average of two FLCs

To control the plant, we used the proposal solution of using the average of two type-1 FLC to simulate a type-2 FLC. For these experiments, it was considered that one type-1 FLC manage and fixed the upper MFs, and the other the low MFs. Here, in the same way as in experiments of class 1, from the optimal values found for the MFs, it was tested the behavior of the average of two type-1 FLC, for different noise levels, from 8 db to 30 db.

4.4 Results

The HEM was the optimization method that we used (Montiel et al., 2005). The initial setting for each range of the FOU for this evolutionary method were:

Initial population of individuals =20
Low bound of individuals=10
Upper bound of individuals=100
Number of variables=6 (Standard deviation of each of the MFs of the inputs).
Number of generations=60

The search process was repeated 30 times, always looking for the optimal parameter values to obtain the lowest ISE value.

Class 1

In figures 4.4 and 4.5 it can be seen the optimized MFs that obtained the best results in the control of the plant.

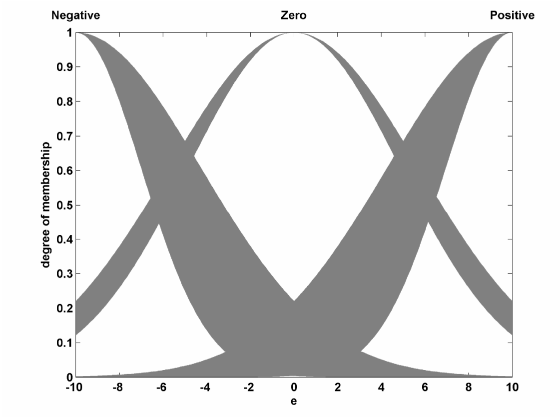

Fig. 4.4. Optimized MFs of the input error *e* of the type-2 FLC, for a 2.74 to 5.75 range of the FOU

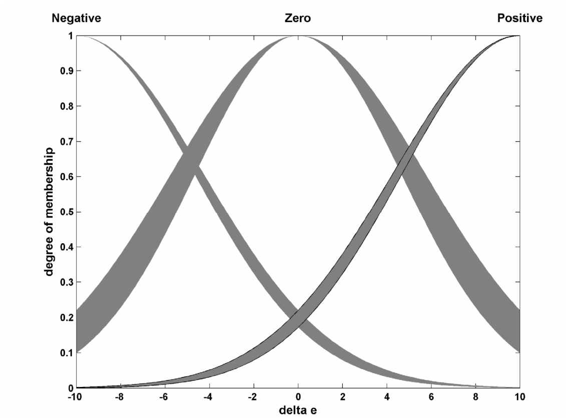

Fig. 4.5. Optimized MFs of the input delta-*e* of the type-2 FLC, for a 2.74 to 5.75 range of the FOU

Class 2

In figures 4.6 and 4.7, we can see the optimized MFs of the average of two type-1 FLCs, here as in Class 1, the best results were obtained in the broader range search.

Table 4.1, shows a comparison of the ISE values obtained for each FLC with its optimized MFs. As can be seen, with the proposal of two optimizedtype-1 FLCs, the ISE error is lower in all the search ranges.

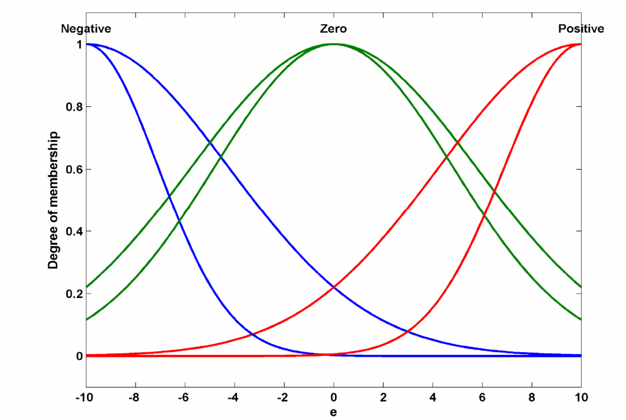

Fig. 4.6. Optimized MFs of the input error e of the average of two type-1 FLC, for a 2.74 to 5.75 range of the FOU

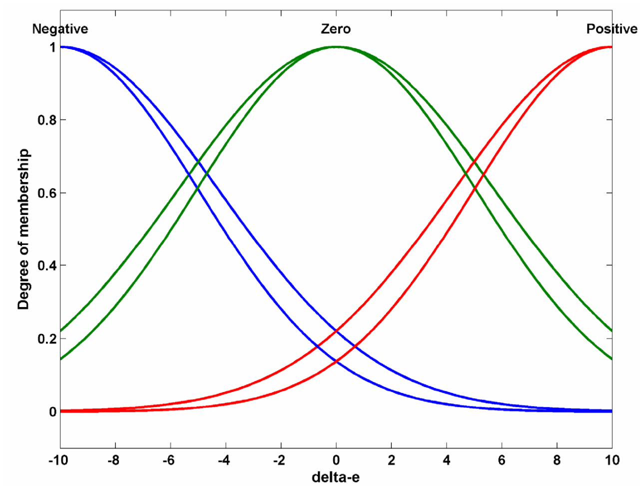

Fig. 4.7. Optimized MFs of the input delta-*e* of the two type-1 FLC, for a 2.74 to 5.75 range of the FOU

Table 4.1. Comparison values between Type-2 FLC and average of two type-1 FLCs

	TYPE-2 FLC		AVERAGE TYPE-1 FLCs	
Search range	Best ISE	AVERAGE ISE	Best ISE	**AVERAGE ISE**
3.74-4.75	4.761	4.9942	4.5619	**4.7701**
3.24-5.25	4.328	4.5060	4.2024	**4.4009**
2.74-5.75	**4.3014**	**4.4005**	**4.1950**	**4.346**

4.5 Summary

Based on the results of the experiments, we can conclude that the proposed method, that consists in using two optimized type-1 FLCs instead of a optimized traditional type-2 FLC, is a convenient and viable alternative because it offers advantages such as a highly efficient regarding computational time and implementation effort. The type-2 FLCs need to realize a complex task in each step of the process, specially in the type reduction case. With the proposed method it is easier to optimize the parameters of the MFs of a type-1 FLC than an interval type-2 FLC.