

Hierarchical Genetic Algorithms for Type-2 Fuzzy System Optimization Applied to Pattern Recognition and Fuzzy Control

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Abstract In this chapter a new method of hierarchical genetic algorithm for fuzzy inference systems optimization is proposed. This method was used in two applications, the first was to perform the combination of responses of modular neural networks for human recognition based on face, iris, ear and voice, and the second one for fuzzy control of temperature in the shower benchmark problem. The results obtained by non-optimized type-2 fuzzy inference system can be improved using the proposed hierarchical genetic algorithm as can be verified by the simulations.

1 Introduction

The prudent combination of different intelligent techniques can produce powerful hybrid intelligent systems [15, 30]. These kind of systems have become in part important of investigation, because different new techniques have emerged to help themselves [18, 20, 24, 25]. Some of these techniques are fuzzy logic, neural networks, genetic algorithms, ant colony optimization and particle swarm optimization [9–13]. There are many works where have been used this kind of systems, these works have combined different techniques and they have obtained good results [4, 9, 16, 17, 22, 23]. In this chapter different intelligent techniques are combined such as neural networks, type-2 fuzzy logic and genetic algorithms.

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The proposed method was applied to human recognition based on face, iris, ear and voice, and fuzzy control of temperature in the Shower benchmark problem.

This chapter is organized as follows: The basic concepts used in this work are presented in Sect. 2. Section 3 contains the general architecture of the proposed method. Section 4 presents experimental results for human recognition and fuzzy control and in Sect. 5, the conclusions of this work are presented.

2 Basic Concepts

In this section the basic concepts used in this research work are presented.

2.1 *Modular Neural Networks*

A neural network (NN) is said to be modular if the computation performed by the network can be decomposed into two or more modules. The modular neural networks are comprised of modules which can be categorized on the basis of both distinct structure and functionality which are integrated together via an integrating unit. With functional categorization, each module is a neural network which carries out a distinct identifiable subtask [1, 14]. There is evidence that shows that the use of modular neural networks implies a significant learning improvement comparatively to a single neural network [15].

2.2 *Type-2 Fuzzy Logic*

Fuzzy logic is an area of soft computing that enables a computer system to reason with uncertainty [2]. The concept of a type-2 fuzzy set was introduced by Zadeh (1975) as an extension of the concept of an ordinary fuzzy set (henceforth called a “type-1 fuzzy set”). When we cannot determine the membership of an element in a set as 0 or 1, fuzzy sets of type-1 are used. Similarly, when the situation is so fuzzy that we have trouble determining the membership grade even as a crisp number in $[0,1]$, fuzzy sets of type-2 are used. Uncertainty in the primary memberships of a type-2 fuzzy set, \tilde{A} , consists of a bounded region that we call the “footprint of uncertainty” (FOU). Mathematically, it is the union of all primary membership functions [4, 19]. The basics of fuzzy logic do not change from type-1 to type-2 fuzzy sets, and in general will not change for type- n . A higher type number just indicates a higher degree of fuzziness [3].

2.3 Hierarchical Genetic Algorithms

A Genetic algorithm (GA) is an optimization and search technique based on the principles of genetics and natural selection [8, 21, 26].

Hierarchical genetic algorithm (HGA) is a kind of genetic algorithm [27], but the main difference between HGA and GAs is the structure of the chromosome. The basic idea under hierarchical genetic algorithm is that for complex systems which cannot be easily represented or resolved, this type of GA can be a better choice. The complicated chromosomes may provide a good new way to solve the problem [28, 29].

3 Proposed Method

The proposed hierarchical genetic algorithm performs the optimization of type-2 fuzzy inference system. The proposed method can be used for any application that uses a fuzzy inference system. In this chapter two applications were used, first the human recognition based on face, iris, ear and voice, and the second, the fuzzy control of temperature in the shower benchmark problem.

The main idea of the proposed method is to perform the optimization of type-2 inference systems that allow us to have better results than fuzzy inference systems non-optimized. In this work some parameters of these type-2 fuzzy inference systems such as the type of system, type of membership functions (Trapezoidal or Gaussian), percentage of rules, the number of membership functions and their parameters. The number of inputs or outputs can be easily establish depending of the application, for this reason the number of inputs or outputs that the fuzzy inference systems will have, depends on the problem or applications.

Figure 1 shows an example of fuzzy integrators. The chromosome of the proposed hierarchical genetic algorithm is shown in Fig. 2.

3.1 Application to Pattern Recognition

In this case, the number of inputs will depend of the number of biometric measures that are being used, here, the responses of each biometric measure are combined by the fuzzy inference systems, for this reason, the fuzzy integrator must have the best architecture in case of a error or failure of some module. In this work, 4 biometric measures are used (face, iris, ear and voice). In Fig. 3, an example of fuzzy integrator for this application is shown. It can notice that each input corresponds to one biometric measure, and the output corresponds to the final answer. The 4 inputs and the inputs have 3 trapezoidal membership functions, an example of these variables are shown in Fig. 4.

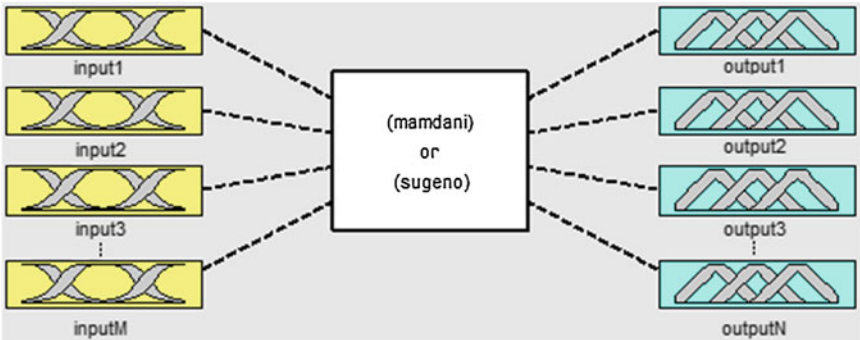


Fig. 1 Example of the type-2 fuzzy inference system

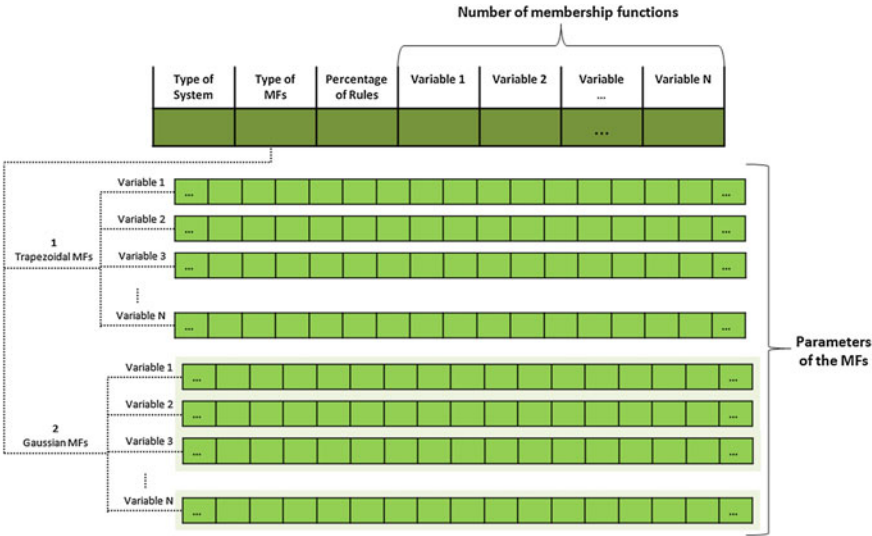


Fig. 2 The chromosome of the hierarchical genetic algorithm for the type-2 fuzzy inference systems

3.1.1 Databases

The databases that were used are described below.

Face

The database of human iris from the Institute of Automation of the Chinese Academy of Sciences was used [6]. It contains of 5 images per person, and it consists of 500 persons, but in this work only 77 persons are used. The image dimensions are 640 × 480, BMP format. Only the first 77 persons were used. Figure 5 shows examples of the human iris images from CASIA database.

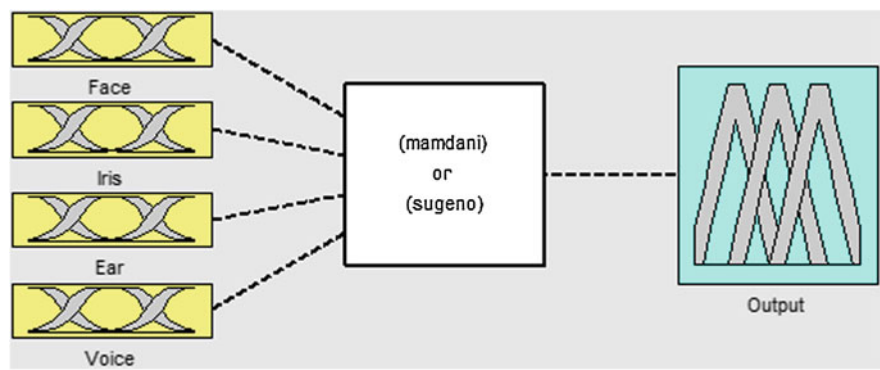


Fig. 3 The architecture of proposed method for the modular neural network

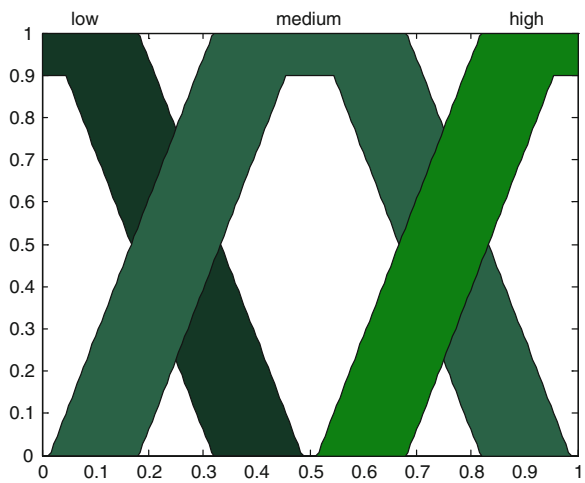


Fig. 4 Example of variable

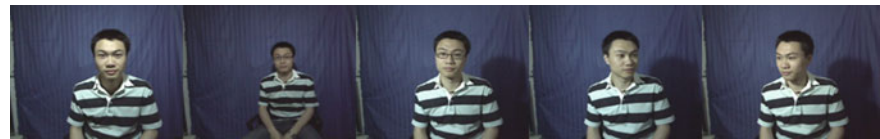


Fig. 5 Examples of the face images from CASIA database

Ear

The database of human iris from the Institute of Automation of the Chinese Academy of Sciences was used [7]. It contains of 14 images (7 for each eye) per person, and it consists of 99 persons. The image dimensions are 320 × 280, JPEG

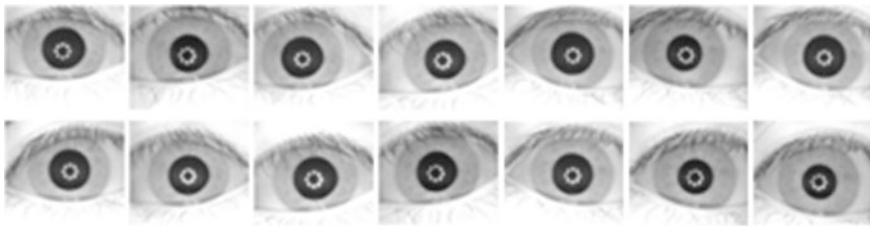


Fig. 6 Examples of the human iris images from CASIA database



Fig. 7 Examples of ear recognition laboratory from the University of Science and Technology Beijing (USTB)

format. Only the first 77 persons were used. Figure 6 shows examples of the human iris images from CASIA database.

Iris

The database of the University of Science and Technology of Beijing was used [5]. The database consists of 77 people, which contain 4 images per person, the image dimensions are 300×400 pixels, the format is BMP. Figure 7 shows examples of the human ear images from the University of Science and Technology Beijing.

Voice

In the case of voice, the database was made from students of Tijuana Institute of Technology, and it consist of 10 voice samples (of 77 persons), WAV format. The word that they said in Spanish was “ACCESAR”. To preprocess the voice the Mel Frequency Cepstral Coefficients were used.

3.2 Application to Fuzzy Control

In this case, the fuzzy control of temperature in the shower benchmark problem was used. The variables of this problem are shown in Fig. 8. This problem has 2 inputs (Temp and Flow) and 2 outputs (Cold and Hot). In Fig. 9, an example of fuzzy integrator for this application is shown.

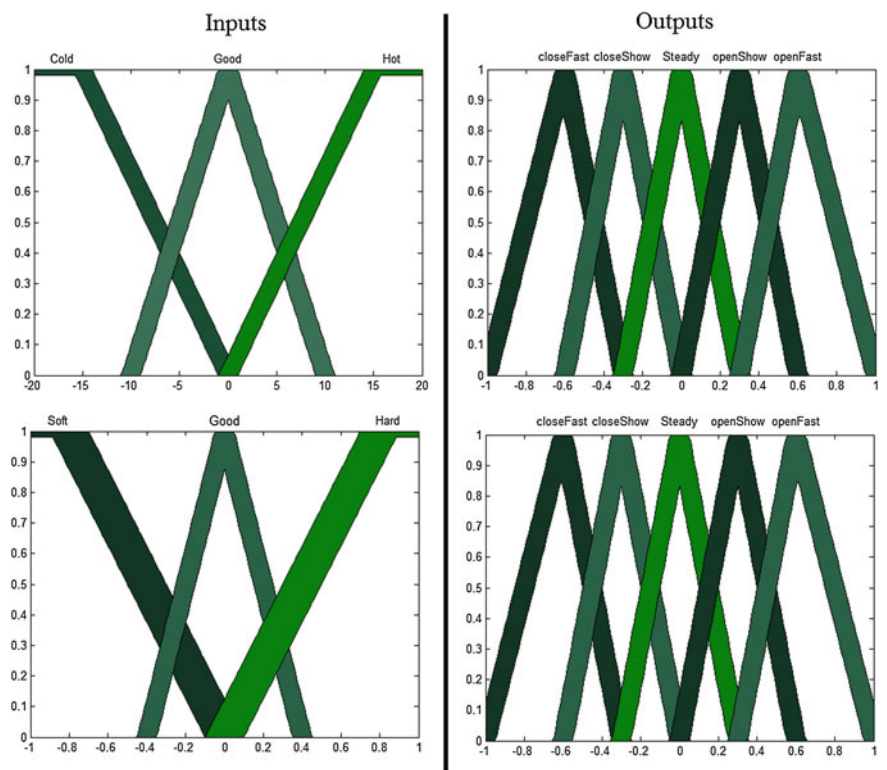


Fig. 8 Variables of the fuzzy control of temperature in a shower

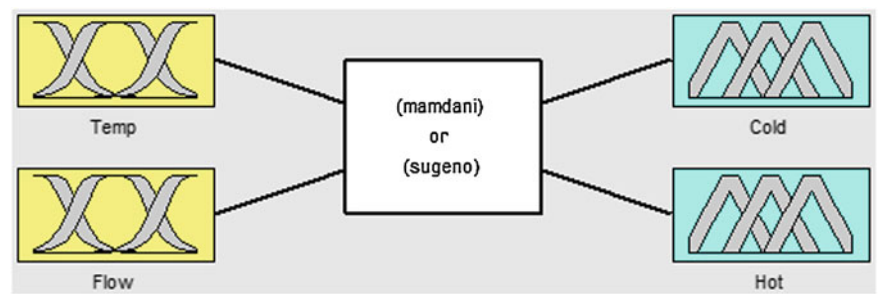


Fig. 9 Example of the fuzzy inference systems

4 Experimental Results

The results obtained (in applications, human recognition and fuzzy control) are presented in this section.

4.1 Human Recognition

The architecture of each training and the percentage of data for training were established randomly. Thirty trainings for each biometrics were performed and the results of each biometric are presented below.

4.1.1 Face

The first 5 results for face are shown in Table 1. The training #1 is the best training where a 87.01 of rate of recognition (0.12987 of error) is obtained.

4.1.2 Iris

The first 5 results for iris are shown in Table 2. The training #10 is the best training where a 98.27 of rate of recognition (0.01732 of error) is obtained.

4.1.3 Ear

The first 5 results for ear are shown in Table 3. The training #5 is the best training.

4.1.4 Voice

The first 5 results for voice are shown in Table 4. The training #7 is the best training where a 93.18 of rate of recognition (0.06818 of error) is obtained.

4.1.5 Non-optimized Fuzzy Integration

Different trainings were combined and 3 cases were performed. The fuzzy integrator with 4 trapezoidal membership functions in each variable (inputs and output) is used, of Mamdani type, an example of variable is shown in Fig. 4. The result for each case is shown in column 6 of the Table 5.

4.1.6 Optimized Fuzzy Integration

Fifteen evolutions for each case were performed and the results are shown in Table 6.

In Fig. 10, the best fuzzy integrator for the case #2 is shown, it is a fuzzy integrator of Sugeno type, and with Gaussian Membership Functions.

Table 1 The first 5 results for face

Training	Images for training (%)	Persons per module	Recognition rate
FT1	77	Module #1(1–25)	68.83 %
		Module #2(26–32)	0.31169
		Module #3(33–47)	
		Module #4(48–57)	
		Module #5(58–77)	
FT2	69	Module #1(1–12)	85.71 %
		Module #2(13–22)	0.14286
		Module #3(23–35)	
		Module #4(36–37)	
		Module #5(38–42)	
		Module #6(43–44)	
		Module #7(45–58)	
		Module #8(59–61)	
		Module #9(62–66)	
		Module #10(67–77)	
FT3	19	Module #1(1–6)	52.92 %
		Module #2(7–17)	0.47078
		Module #3(18–19)	
		Module #4(20–29)	
		Module #5(30–35)	
		Module #6(36–47)	
		Module #7(48–56)	
		Module #8(57–67)	
		Module #9(68–77)	
FT4	11	Module #1(1–21)	45.78 %
		Module #2(22–34)	0.54221
		Module #3(35–53)	
		Module #4(54–55)	
		Module #5(56–73)	
		Module #6(74–77)	
FT5	49	Module #1(1–15)	60.17 %
		Module #2(16–24)	0.39827
		Module #3(25–36)	
		Module #4(37–51)	
		Module #5(52–53)	
		Module #6(54–66)	
		Module #7(67–77)	

4.2 Fuzzy Control

The Simulation plant for the fuzzy control of temperature for the shower in Matlab is shown in Fig. 11.

Table 2 The first 5 results for face

Training	Images for training (%)	Persons per module	Recognition rate
IT1	19	Module #1(1–37)	79.10 %
		Module #2(38–64)	0.20897
		Module #3(65–69)	
		Module #4(70–77)	
IT2	73	Module #1(1–24)	96.10 %
		Module #2(25–77)	0.03896
IT3	71	Module #1(1–77)	90.91 % 0.09091
IT4	16	Module #1(1–21)	63.20 %
		Module #2(22–42)	0.36797
		Module #3(43–66)	
		Module #4(67–77)	
IT5	80	Module #1(1–10)	98.27 %
		Module #2(11–18)	0.01732
		Module #3(19–28)	
		Module #4(29–39)	
		Module #5(40–52)	
		Module #6(53–64)	
		Module #7(65–77)	

Using the non-optimized fuzzy integrator presented in Fig. 9, an error of 0.1589 is obtained. Fifteen evolutions were performed and the best result is shown in Table 7. In Fig. 12, the best fuzzy inference system obtained is shown.

Fifteen evolutions for each case were performed and the results are shown in Table 7.

In Fig. 12, the best fuzzy integrator obtained is shown; it is a fuzzy integrator of Mamdani type, and with Gaussian Membership Functions. In both applications the fuzzy inference systems obtained have Gaussian membership functions.

5 Conclusions

In this work a new hierarchical genetic algorithm was presented, the main idea of this HGA is to perform the optimization of type-2 fuzzy systems. For this reason the optimization of parameters was performed (type of system, type of membership functions (Trapezoidal or Gaussian), percentage of rules, the number of membership functions and their parameters). As the results show, better results can be obtained when a optimization is performed. This HGA was tested in two different applications (combination of responses of modular neural networks for human recognition and fuzzy control of the temperature of a shower) but this HGA

Table 3 The first 5 results for face

Training	Images for training (%)	Persons per module	Recognition rate
ET1	74	Module #1(1–5)	94.81 %
		Module #2(6–15)	0.05195
		Module #3(16–26)	
		Module #4(27–30)	
		Module #5(31–43)	
		Module #6(44–49)	
		Module #7(50–58)	
		Module #8(59–71)	
		Module #9(72–77)	
ET2	66	Module #1(1–21)	77.92 %
		Module #2(22–34)	0.22078
		Module #3(35–45)	
		Module #4(46–64)	
		Module #5(65–77)	
ET3	51	Module #1(1–3)	79.22 %
		Module #2(4–11)	0.20779
		Module #3(12–17)	
		Module #4(18–33)	
		Module #5(34–50)	
		Module #6(51–55)	
		Module #7(56–61)	
		Module #8(62–75)	
		Module #9(76–77)	
ET4	81	Module #1(1–12)	97.40 %
		Module #2(13–14)	0.02597
		Module #3(15–23)	
		Module #4(24–43)	
		Module #5(44–58)	
		Module #6(59–77)	
ET5	56	Module #1(1–27)	82.47 %
		Module #2(28–52)	0.17532
		Module #3(53–55)	
		Module #4(56–77)	

can be used in other applications because can be easily adaptable. In human recognition, the main objective was the minimization of the error of recognition and, in the case of fuzzy control, the minimization of the error of simulation. In the future the combination of membership functions in a same variable will be implemented, waiting of obtaining better results in any application that uses type-2 fuzzy inference systems.

Table 4 The first 5 results for face

Training	Images for training (%)	Persons per module	Recognition rate
VT1	38	Module #1(1–5)	92.86 %
		Module #2(6–12)	0.07143
		Module #3(13–23)	
		Module #4(24–32)	
		Module #5(33–35)	
		Module #6(36–42)	
		Module #7(43–50)	
		Module #8(51–58)	
		Module #9(59–67)	
		Module #10(68–77)	
VT2	57	Module #1(1–23)	91.88 %
		Module #2(24–31)	0.08117
		Module #3(32–52)	
		Module #4(53–77)	
VT3	58	Module #1(1–32)	91.23 %
		Module #2(33–53)	0.08766
		Module #3(54–77)	
VT4	37	Module #1(1–38)	86.36 %
		Module #2(39–77)	0.13636
VT5	64	Module #1(1–13)	93.18 %
		Module #2(14–26)	0.06818
		Module #3(27–32)	
		Module #4(33–37)	
		Module #5(38–50)	
		Module #6(51–52)	
		Module #7(53–66)	
		Module #8(67–68)	
		Module #9(69–77)	

Table 5 Non-optimized results

Case	Face	Iris	Ear	Voice
1	FT4	IT5	ET5	VT2
	45.78 %	98.27 %	82.47 %	91.88 %
2	FT1	IT4	ET2	VT1
	87.01 %	63.20 %	77.92 %	91.77 %
3	FT2	IT2	ET4	VT5
	85.71 %	96.10 %	97.40 %	93.18 %

Table 6 Non-optimized results

Case	Non-optimized	Best	Average
1	85.06 %	99.02 %	97.73 %
	0.1494	0.0097	0.0227
2	79.11 %	93.72 %	92.76 %
	0.2089	0.0628	0.0724
3	92.21 %	100 %	99.77 %
	0.0779	0	0.0023

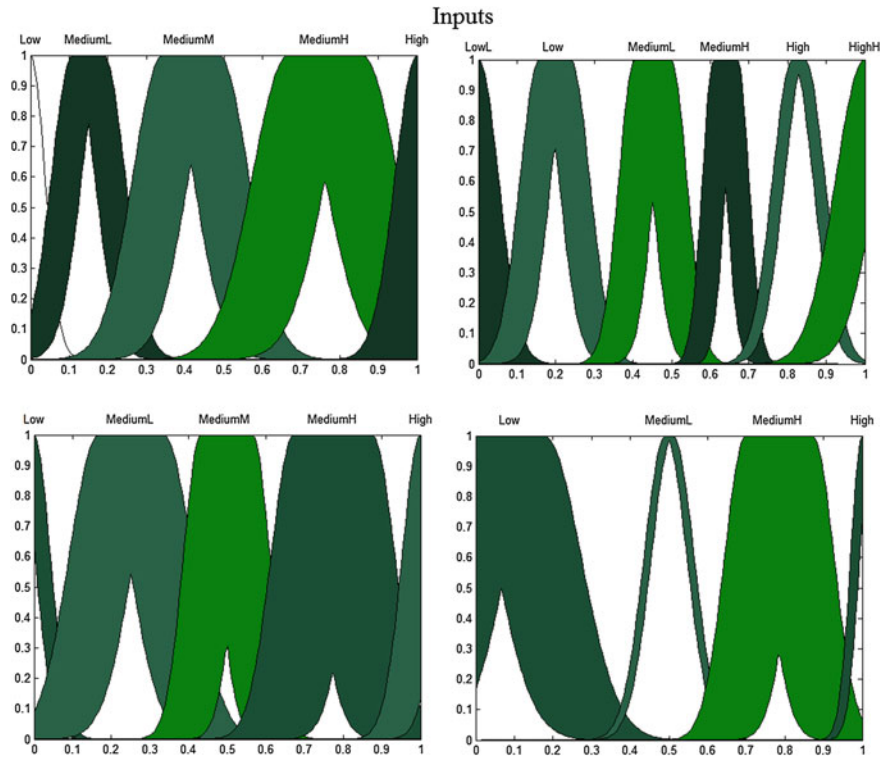


Fig. 10 The best fuzzy integrator for the case #2

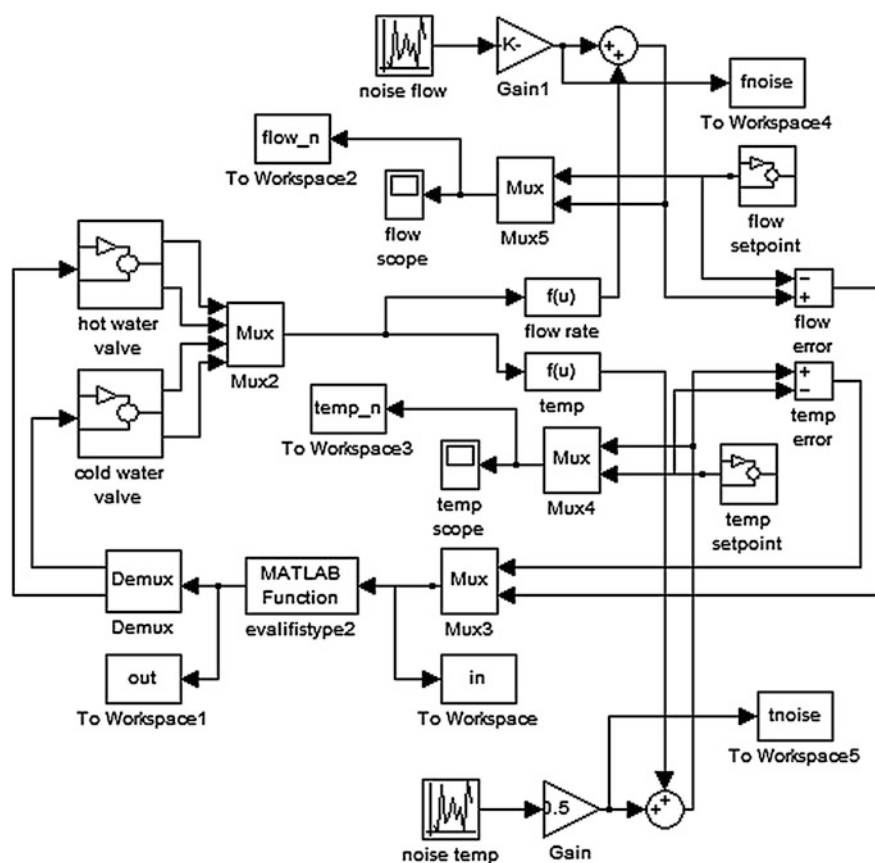


Fig. 11 Simulation plant for the fuzzy control of temperature in the shower

Table 7 Comparison between non-optimized and optimized results

Non-optimized	Best	Average
0.1589	0.00075	0.0040

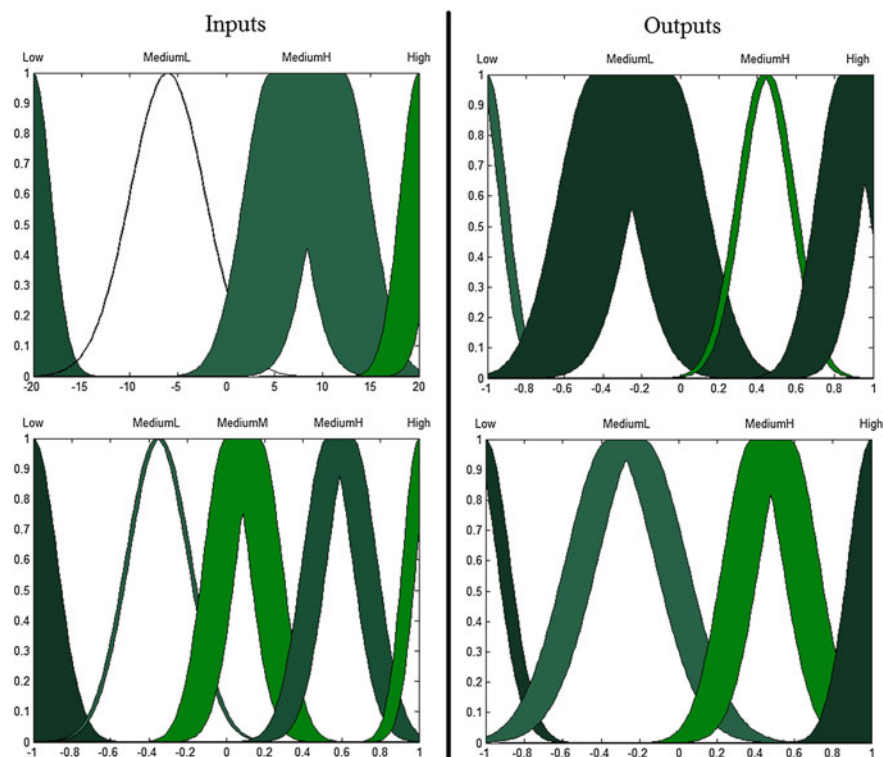


Fig. 12 The best fuzzy inference system for the fuzzy control of temperature of a shower

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