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Decision-Making System for Washing Machine using AIFNN

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Abstract: In this paper we proposed Adaptive Intuitionistic Fuzzy Neural Network (AIFNN) based washing machine. Our system consists of five layers, just like adaptive neuro-fuzzy inference system. The proposed decision making system have two inputs, i.e. type of dirt and degree of dirt, and determines clothe washing time. We use intuitionistic fuzzy inference system for representing, and selecting rule. The intuitionistic fuzzy Takagi-Sugeno formula used for defuzzification.

Keywords: Intuitionistic fuzzy set, ANFIS, AIFNN, defuzzification.

1 Introduction

In 1965, Zadeh introduced the notion of fuzzy sets as a method of representing uncertainty, and vagueness [[1]-[3]]. After that, the theory of fuzzy sets has become a robust area of research in several fields. Till now, many applications belonging to different disciplines have been developed using fuzzy logic control systems, some of them are [[4]-[8]]. There are several extensions of basic fuzzy set theory. In 1983, Atanassov [9] introduced the concept of intuitionistic fuzzy sets as a generalization of fuzzy sets [1]. It consists of four basic components: intuitionistic fuzzifier, intuitionistic fuzzy rule base, intuitionistic fuzzy inference engine, and intuitionistic defuzzifier. Intuitionic fuzzifier converts crisp input into linguistic values. Rules may be provided by experts, or can be extracted from numerical data. The inference engine of the intuitionistic fuzzy logic system determines how rules will combine. The intuitionistic defuzzifier maps output sets into crisp numbers [12]. There are several applications of intuitionistic fuzzy logic controller, the readers are referred to [13], [14] and [15].
Neuro-fuzzy system was proposed by Jang [16] as a field of artificial intelligence. It is combination of neural networks, and fuzzy logic, that combines two techniques i.e. human like reasoning with learning that finds the parameters of a fuzzy system (i.e. fuzzy sets, fuzzy rules) by exploiting approximation techniques from neural networks. There are several applications of neuro-fuzzy controller, the readers are referred to [17], [18], [19], [20] and [21].
This paper presents Adaptive Intuitionistic Fuzzy Neural Network (AIFNN) based washing machine controller that makes efficient decision of wash time. Instead of using fuzzy set theory we used intuitionistic fuzzy set theory in artificial neural networks. The system takes two inputs: type-of-dirt and degree-of-dirt, and calculate wash time. AIFNN consists of five layers. Layer one converts crisp input value into linguistic values. Layer two contains IF-Then statements, and determines rules firing strength. Layer three normalizes all firing strengths. Layer four performs defuzzification using Takagi Sugano Kang [22]. Layer five takes sum of all values coming from its previous layer. Block diagram of this model is shown in Figure 1.

Rest of the paper is organizes as follow, in section 2 basic structure of our controller is discussed, in section 3 working of our controller is explained and section 4 describe conclusion.

2 Basic structure of our controller

Generic algorithm of our system

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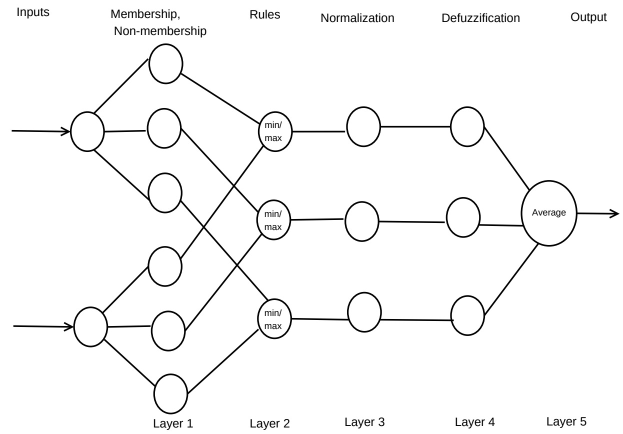

Fig. 1: Block diagram

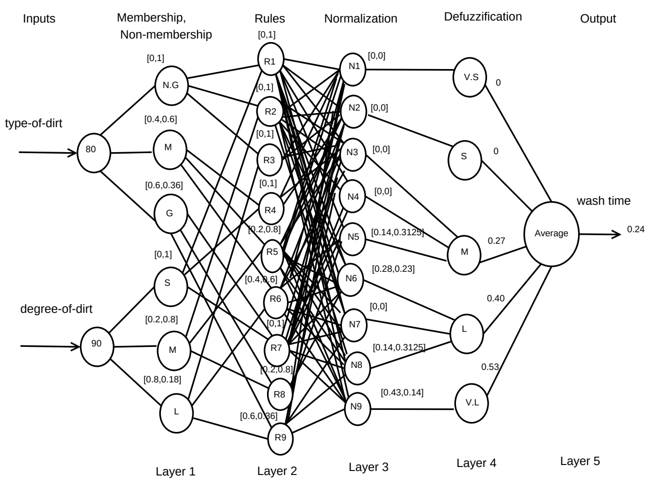

Fig. 2: Proposed controller structure

Algorithm for implementing the AIFNN to control washing machine consists of the following stages:
1. Begin
2. Define intuitionistic neuro-fuzzy inference system
3. Define training data
4. Define linguistic values of input and output variables
5. Read sensor reading to determine type-of-dirt and degree-of-dirt
6. Find degrees of membership and non-membership of type-of-dirt and degree-of-dirt
7. Compute firing strength of all rules
8. Normalize rules firing strength
9. Perform defuzzification for wash time using TS Kang
10. Determine error between desired output and actual output (coming from forward pass).
11.Start learning using back-propagation to minimize error
12.End

3 The proposed controller of washing machine using AIFNN

There are five major processing units of our controller using AIFNN.
1. Fuzzification (Layer 1)
2. Rules fire strength (Layer 2)
3. Normalizing fire strength (Layer 3)
4. Defuzzification (Layer 4)
5. Training network
$O_{l,i}$ is the output of the ith node of the *layer l*, where i=1,2,...
First component of AIFNN is fuzzifier that converts crisp values into linguistic values. The inputs are type-of-dirt and degree-of-dirt, and their ranges are 0-100. The output is wash time, and its range is 0-60. Figure 3 and Figure 4 shows memberships, and non-membership plot of type-of-dirt and degree-of-dirt. The membership and non-membership functions for type-of-dirt and degree-of-dirt are given mathematically as below:

$$\mu_{not-greasy}(x)=\mu_{small}(x)=\begin{cases}\frac{50-x}{50}, & \text{if } x\in[0,50],\\ 0, & \text{else.}\end{cases}$$

$$\mu_{medium}(x)=\begin{cases}\frac{x}{50}, & \text{if } x\in[0,50],\\ \frac{100-x}{50}, & \text{if } x\in[50,100].\end{cases}$$

$$\mu_{greasy}(x)=\mu_{large}(x)=\begin{cases}\frac{x-50}{50}, & \text{if } x\in[50,100],\\ 0, & \text{else.}\end{cases}$$

$$\nu_{not-greasy}(x)=\nu_{small}(x)=\begin{cases}\frac{x}{55}, & \text{if } x\in[0,55],\\ 1, & \text{else.}\end{cases}$$

$$\nu_{medium}(x)=\begin{cases}\frac{50-x}{50}, & \text{if } x\in[0,50],\\ \frac{x-50}{50}, & \text{if } x\in[50,100].\end{cases}$$

$$\nu_{greasy}(x)=\nu_{large}(x)=\begin{cases}\frac{100-x}{55}, & \text{if } x\in[45,100],\\ 1, & \text{else.}\end{cases}$$

Figure 5 and Figure 6 shows memberships, and non-membership plot of wash time. The membership and non-membership functions of wash time are given mathematically as below:

$$\mu_{very-short(x)}=\begin{cases}\frac{x}{8}, & \text{if } x\in[0,8],\\ \frac{12-x}{4}, & \text{if } x\in[8,12],\\ 0, & \text{else.}\end{cases}$$

$$\mu_{short(x)}=\begin{cases}\frac{x-8}{4}, & \text{if } x\in[8,12],\\ \frac{20-x}{8}, & \text{if } x\in[12,20],\\ 0, & \text{else.}\end{cases}$$

$$\mu_{medium(x)}=\begin{cases}\frac{x-12}{8}, & \text{if } x\in[12,20],\\ \frac{40-x}{20}, & \text{if } x\in[20,40],\\ 0, & \text{else.}\end{cases}$$

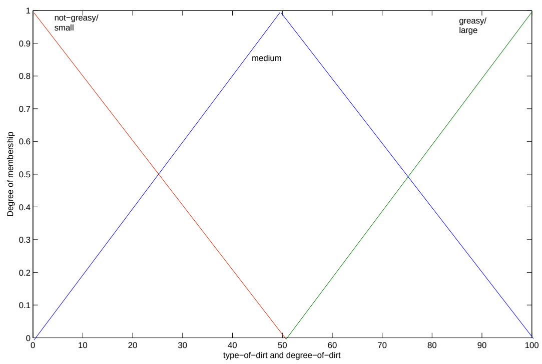

Fig. 3: Membership functions for type-of-dirt and degree-of-dirt

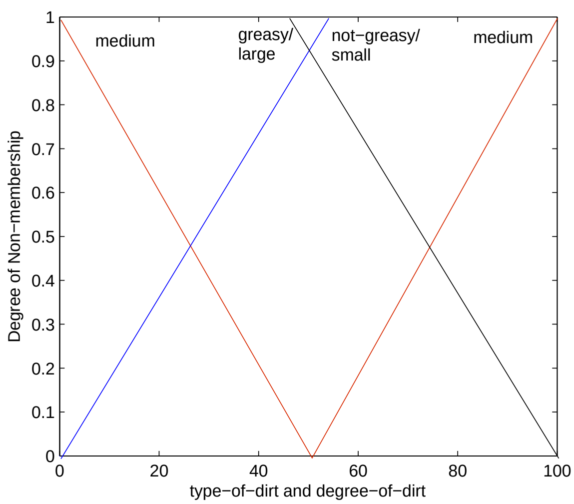

Fig. 4: Non-Membership functions for type-of-dirt and degree-of-dirt

$$\mu_{long(x)} = \begin{cases} \frac{x-20}{20}, & \text{if } x \in [20,40], \\ \frac{60-x}{20}, & \text{if } x \in [40,60], \\ 0, & \text{else.} \end{cases}$$

$$\mu_{very-long(x)} = \begin{cases} \frac{x-40}{20}, & \text{if } x \in [40,60], \\ 0, & \text{else.} \end{cases}$$

$$\nu_{very-short(x)} = \begin{cases} \frac{8-x}{8}, & \text{if } x \in [0,8], \\ \frac{x-8}{9}, & \text{if } x \in [8,17], \\ 1, & \text{else.} \end{cases}$$

$$\nu_{short(x)} = \begin{cases} \frac{12-x}{9}, & \text{if } x \in [3,12], \\ \frac{x-12}{12}, & \text{if } x \in [12,25], \\ 1, & \text{else.} \end{cases}$$

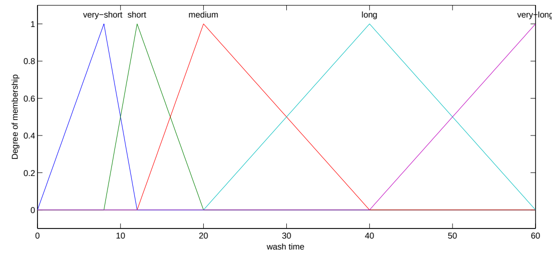

Fig. 5: Membership functions for wash time

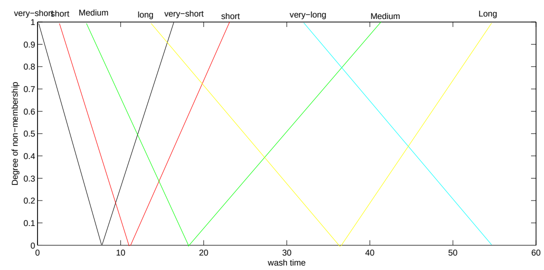

Fig. 6: Non-membership functions for wash time

$$\nu_{medium(x)} = \begin{cases} \frac{20-x}{13}, & \text{if } x \in [7,20], \\ \frac{x-20}{25}, & \text{if } x \in [20,45], \\ 1, & \text{else.} \end{cases}$$

$$\nu_{long(x)} = \begin{cases} \frac{40-x}{25}, & \text{if } x \in [15,40], \\ \frac{x-40}{20}, & \text{if } x \in [40,60], \\ 1, & \text{else.} \end{cases}$$

$$\nu_{very-long(x)} = \begin{cases} \frac{60-x}{25}, & \text{if } x \in [35,60], \\ 1, & \text{else.} \end{cases}$$

To better understand working of proposed controller; consider a hypothetical value and execute all stages. Let type-of-dirt is 80, and degree-of-dirt is 90, then the first layer output is as follows:

$$\mu_{not-greasy}(x) = 0, \mu_{medium}(x) = 0.4, \mu_{greasy}(x) = 0.6$$

$$\nu_{not-greasy}(x) = 1, \nu_{medium}(x) = 0.6, \nu_{greasy}(x) = 0.36$$

$$\mu_{small}(x) = 0, \mu_{medium}(x) = 0.2, \mu_{large}(x) = 0.8$$

$$\nu_{small}(x) = 1, \nu_{medium}(x) = 0.8, \nu_{large}(x) = 0.18$$

Second layer deals with rules firing strength. Take min in case of membership, and max in case of non-membership [23]. There are total nine rules. These rules are same as describe in [24].

R1:if type-of-dirt is not-greasy and degree-of-Dirt is small then wash time is very-short
R2:if type-of-dirt is not-greasy and degree-of-dirt is medium then wash time is short
R3:if type-of-dirt is not-greasy and degree-of-dirt is large then wash time is medium
R4:if type-of-dirt is medium and degree-of-dirt is small wash time is medium
R5:if type-of-dirt is medium and degree-of-dirt is medium then wash time is medium
R6:if type-of-dirt is medium and degree-of-dirt is large then wash time is long
R7:if type-of-dirt is greasy and degree-of-dirt is small then wash time is long
R8:if type-of-dirt is greasy and degree-of-dirt is medium then wash time is long
R9:if type-of-dirt is greasy and degree-of-dirt is large then wash time is very-long

Against our input values, rule 5,6,8 and 9 gives some membership, and non-membership values, remaining rules gives ”0” contribution in case of membership, and ”1” in case of non-membership that means there is no chance of triggering rule 1,2,3 and 4. Therefore, layer 2 output is:
$medium \wedge medium = 0.4 \wedge 0.2 = 0.2$
$medium \wedge large = 0.4 \wedge 0.8 = 0.4$
$greasy \wedge medium = 0.6 \wedge 0.2 = 0.2$
$greasy \wedge large = 0.6 \wedge 0.8 = 0.6$
In case of non-membership:
$medium \vee medium = 0.6 \vee 0.8 = 0.8$
$medium \vee large = 0.6 \vee 0.18 = 0.6$
$greasy \vee medium = 0.36 \vee 0.8 = 0.8$
$greasy \vee large = 0.36 \vee 0.18 = 0.36$
According to ANFIS layer 3 normalizes memberships firing strength on each node. Now in case of AIFNN layer 3 also normalizes memberships firing strength, and non-memberships firing strength. Here, $O_{3,i}$ denotes the output of the ith node of the *layer 3*, where i=1,2,... For membership layer 3 output is:

$$O_{3,5} = \frac{0.2}{0.2+0.4+0.2+0.6} = 0.14$$
$$O_{3,6} = \frac{0.4}{0.2+0.4+0.2+0.6} = 0.28$$
$$O_{3,8} = \frac{0.2}{0.2+0.4+0.2+0.6} = 0.14$$
$$O_{3,9} = \frac{0.6}{0.2+0.4+0.2+0.6} = 0.43$$

For non-membership layer 3 output is:

$$O_{3,5} = \frac{0.8}{0.8+0.6+0.8+0.36} = 0.3125$$
$$O_{3,6} = \frac{0.6}{0.8+0.6+0.8+0.36} = 0.23$$
$$O_{3,8} = \frac{0.8}{0.8+0.6+0.8+0.36} = 0.3125$$

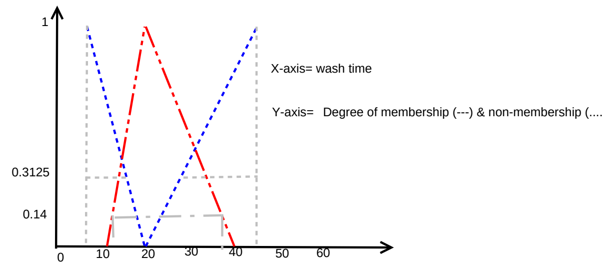

Fig. 7: R5:wash time will be medium with degree of truth 0.14 and degree of falsify 0.3125

$$O_{3,9} = \frac{0.36}{0.8+0.6+0.8+0.36} = 0.14$$

Fourth layer performs defuzzification. Figure 7,8,9 and 10 shows the combined profile of membership, and non-membership against R5, R6, R8 and R9 respectively. According to rule 5 wash time will be medium.

$$\mu_{medium(x)} = \frac{x-12}{8}$$
$$0.14 = \frac{x-12}{8}$$
$$x = 13.12$$
$$\mu_{medium(x)} = \frac{40-x}{20}$$
$$0.14 = \frac{40-x}{20}$$
$$x = 37.2$$
$$\nu_{medium(x)} = \frac{20-x}{13}$$
$$0.3125 = \frac{20-x}{13}$$
$$x = 15.6$$
$$\nu_{medium(x)} = \frac{x-20}{25}$$
$$0.3125 = \frac{x-20}{25}$$
$$x = 27.8125$$

According to rule 6 wash time will be long.

$$\mu_{long(x)} = \frac{x-20}{20}$$
$$0.28 = \frac{x-20}{20}$$
$$x = 25.6$$
$$\mu_{long(x)} = \frac{60-x}{20}$$

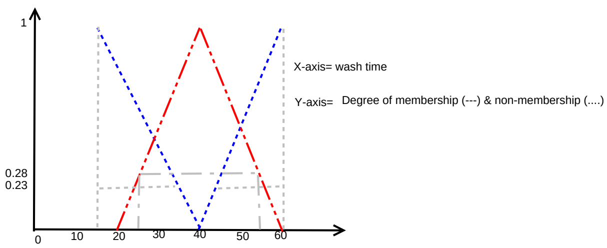

Fig. 8: R6:wash time will be long with degree of truth 0.28 and degree of falsify 0.23

$$0.28 = \frac{60-x}{20}$$
$$x = 54.4$$
$$\nu_{long(x)} = \frac{40-x}{25}$$
$$0.23 = \frac{40-x}{25}$$
$$x = 34.25$$
$$\nu_{long(x)} = \frac{x-40}{20}$$
$$0.23 = \frac{x-40}{20}$$
$$x = 44.6$$

According to rule 8 wash time will be long.

$$\mu_{long(x)} = \frac{x-20}{20}$$
$$0.14 = \frac{x-20}{20}$$
$$x = 22.8$$
$$\mu_{long(x)} = \frac{60-x}{20}$$
$$0.14 = \frac{60-x}{20}$$
$$x = 57.2$$
$$\nu_{long(x)} = \frac{40-x}{25}$$
$$0.3125 = \frac{40-x}{25}$$
$$x = 32.1875$$
$$\nu_{long(x)} = \frac{x-40}{20}$$
$$0.3125 = \frac{x-40}{20}$$
$$x = 46.25$$

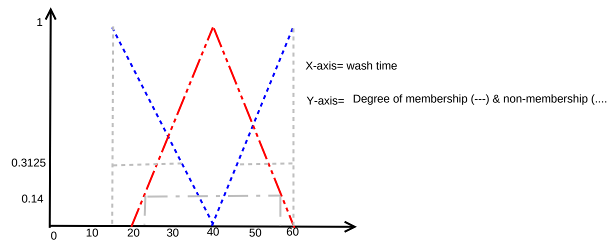

Fig. 9: R8:wash time will be long with degree of truth 0.14 and degree of falsify 0.3125

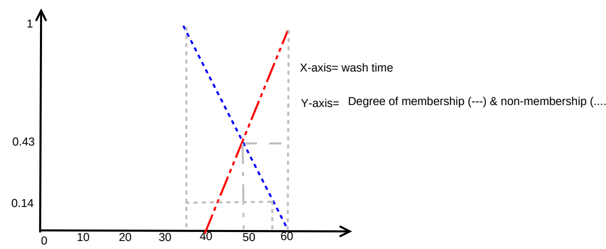

Fig. 10: R9:wash time will be very long with degree of truth 0.43 and degree of falsify 0.14

According to rule 9 wash time will be verylong.

$$\mu_{verylong(x)} = \frac{x-40}{20}$$
$$0.43 = \frac{x-40}{20}$$
$$x = 48.6$$
$$\nu_{verylong(x)} = \frac{60-x}{25}$$
$$0.14 = \frac{60-x}{25}$$
$$x = 56.5$$

We apply Takagi Sugani formula [22] for defuzzification. Let x be an element in intuitionistic fuzzy set A, and μ_A and ν_A are degree of membership, and non-membership of x in A. If M are few sample spaces in A. x^j represents the jth sample space in M. If a number of rules (i.e. n) give same output membership function, then we take minimum out of all membership value, and maximum out of all non-membership values. Takagi Sugani's formula is:

$$x = \frac{\sum_{j=1}^{M} x^j((1-\pi_{Aj})\mu_{Aj} + \mu_{Aj}\pi_{Aj})}{\sum_{j=1}^{M}((1-\pi_{Aj})\mu_{Aj} + \mu_{Aj}\pi_{Aj})},$$

where,

$$\mu_{A^j} = \wedge_{i=1}^{n}, \mu_{A_i^j}(x)$$

$$\nu_{A^j} = \vee_{i=1}^{n}, \nu_{A_i^j}(x)$$

$$\pi_{A^j} = 1 - \mu_{A^j} - \nu_{A^j}$$

According to Takagi Sugeno Kang's formula take minimum of memberships, and maximum of non-memberships from table 1 and table 2.

Table 1: Membership and Non-membership values of long (according to rule 6)

sample space (x)	μ_x	ν_x
15	0	0.23
20	0	0.23
25	0.25	0.23
30	0.28	0.23
35	0.28	0.2
40	0.28	0
45	0.28	0.23
50	0.28	0.23
55	0.25	0.23
60	0	0.23

Table 2: Membership and Non-membership values of long (according to rule 8)

sample space (x)	μ_x	ν_x
15	0	0.3125
20	0	0.3125
25	0.14	0.3125
30	0.14	0.3125
35	0.14	0.2
40	0.14	0
45	0.14	0.23
50	0.14	0.3125
55	0.14	0.3125
60	0	0.3125

Result of long is=$\frac{39.76}{0.994}$=40, result of medium is=$\frac{19.305}{0.715}$=27, and result of very long is=$\frac{25.74}{0.429}$=53.37345478. The resultant wash time is 24 minutes, which is average of all incoming values from layer 4.Let us assume according to training data output against input value wash time should be 23. In order to reduce this error, we use back-propagation technique [25]. Following formula used to calculate error of output neuron.

Output error δ= (target-output) (1-output)output

The "output (1-output) term is necessary in the equation because of the sigmoid function; if we were only using a threshold neuron it would just be (target−output) [[25]-[27]]. Output neuron error δ=0.23-0.24=-0.01

New weights for output layer:

$$w_{next} = w_{old} + \eta(target - output)x$$

$$w_1, w_2 = 0$$

$$w_3 = 0.26784$$

$$w_4 = 0.3974$$

$$w_5 = 0.52784$$

Now we calculate error for hidden layers:

$$\delta_1, \delta_2 = 0$$

$$\delta_3 = \delta \times w_3 = -0.01 \times 0.2678 = -0.002678$$

$$\delta_4 = \delta \times w_4 = -0.01 \times 0.3974 = -0.003974$$

$$\delta_5 = \delta \times w_4 = -0.01 \times 0.52789 = -0.0052789$$

New weights for hidden layer 1-2 for membership:

$$w_i = w_i(old) + (\eta) \times (\delta) \times (input)$$

$$w_1, w_1^{'}, w_2, w_2^{'}, w_3, w_3^{'}, w_4, w_4^{'}, w_7, w_7^{'} = 0$$

$$w_5 = 0.398$$

$$w_5^{'} = 0.198$$

$$w_6 = 0.397$$

$$w_6^{'} = 0.797$$

$$w_8 = 0.597$$

$$w_8^{'} = 0.197$$

$$w_9 = 0.596$$

$$w_9^{'} = 0.796$$

New weights for hidden layer 1-2 for non-membership:

$$w_1, w_1^{'}, w_2, w_2^{'}, w_3, w_3^{'}, w_4, w_4^{'}, w_7, w_7^{'} = 0$$

$$w_5 = 0.598$$

$$w_5^{'} = 0.798$$

$$w_6 = 0.597$$

$$w_6^{'} = 0.177$$

$$w_8 = 0.357$$

$$w_8^{'} = 0.797$$

$$w_9 = 0.356$$

$$w_9^{'} = 0.176$$

Table 3: Defuzzification of long using TS formula

sample space (x)	μ_x	ν_x	π_x	$A=(1-\pi_x)\mu_x$	$B=\pi_x\mu_x$	$A+B$	$x*(A+B)$
15	0	0.3125	0.6875	0	0	0	0
20	0	0.3125	0.6875	0	0	0	0
25	0.14	0.3125	0.5455	0.064539	0.077461	0.142	3.55
30	0.14	0.3125	0.5455	0.064539	0.077461	0.142	4.26
35	0.14	0.2	0.658	0.048564	0.093436	0.142	4.97
40	0.14	0	0.858	0.020164	0.121836	0.142	5.68
45	0.14	0.23	0.628	0.052824	0.089176	0.142	6.39
50	0.14	0.3125	0.5455	0.064539	0.077461	0.142	7.1
55	0.14	0.3125	0.5455	0.064539	0.077461	0.142	7.81
60	0	0.3125	0.6875	0	0	0	0
						0.994	39.76

Table 4: Defuzzification of medium using TS formula

sample space (x)	μ_x	ν_x	π_x	$A=(1-\pi_x)\mu_x$	$B=\pi_x\mu_x$	$A+B$	$x*(A+B)$
7	0	0.313	0.687	0	0	0	0
12	0	0.313	0.687	0	0	0	0
17	0.143	0.23	0.627	0.053339	0.089661	0.143	2.431
22	0.143	0.08	0.777	0.031889	0.111111	0.143	3.146
27	0.143	0.28	0.577	0.060489	0.082511	0.143	3.861
32	0.143	0.313	0.544	0.065208	0.077792	0.143	4.576
37	0.143	0.313	0.544	0.065208	0.077792	0.143	5.291
42	0	0.313	0.687	0	0	0	0
45	0	0.313	0.687	0	0	0	0
						0.715	19.305

Table 5: Defuzzification of very long using TS formula

sample space (x)	μ_x	ν_x	π_x	$A=(1-\pi_x)\mu_x$	$B=\pi_x\mu_x$	$A+B$	$x*(A+B)$
35	0	0.139	0.861	0	0	0	0
40	0	0.139	0.861	0	0	0	0
45	0.25	0.139	0.611	0.09725	0.15275	0.25	11.25
50	0.429	0.139	0.432	0.243672	0.185328	0.429	21.45
55	0.429	0.139	0.432	0.243672	0.185328	0.429	23.595
60	0.429	0.139	0.432	0.243672	0.185328	0.429	25.74
						1.35	69.25

Figure 11 shows the updated weight of our system. Again we pass through forward pass in order to determine new output and error; the layer 2 output is:

$$O_{2,1}, O_{2,2}, O_{2,3}, O_{2,4}, O_{2,7} = 0$$
$$O_{2,5} = 0.398 \wedge 0.198 = 0.198$$
$$O_{2,6} = 0.397 \wedge 0.797 = 0.397$$
$$O_{2,8} = 0.597 \wedge 0.197 = 0.197$$
$$O_{2,9} = 0.596 \wedge 0.796 = 0.596$$

For non-membership layer 2 output is:

$$O_{2,1}, O_{2,2}, O_{2,3}, O_{2,4}, O_{2,7} = 0$$
$$O_{2,5} = 0.598 \vee 0.798 = 0.798$$
$$O_{2,6} = 0.597 \vee 0.177 = 0.597$$
$$O_{2,8} = 0.357 \vee 0.797 = 0.797$$
$$O_{2,9} = 0.356 \vee 0.176 = 0.356$$

Layer 3 output for membership:

$$O_{3,1}, O_{3,2}, O_{3,3}, O_{3,4}, O_{3,7} = 0$$
$$O_{3,5} = \frac{0.198}{0.198+0.397+0.197+0.596} = 0.14$$
$$O_{3,6} = \frac{0.397}{0.198+0.397+0.197+0.596} = 0.28$$
$$O_{3,8} = \frac{0.197}{0.198+0.397+0.197+0.596} = 0.14$$
$$O_{3,9} = \frac{0.596}{0.198+0.397+0.197+0.596} = 0.43$$

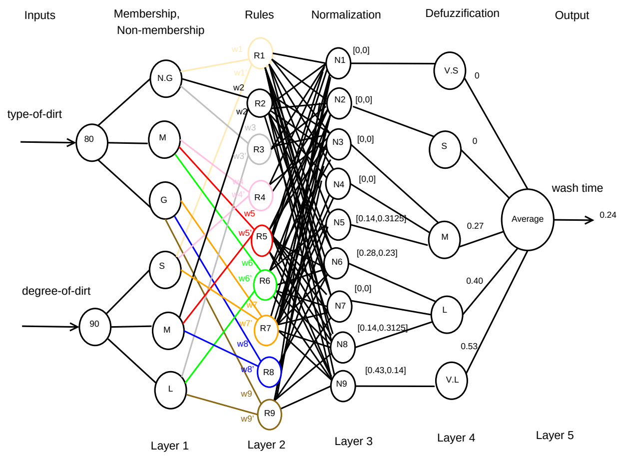

Fig. 11: Updated weight of our system

For non-membership layer 3 output is:

$$O_{3,1}, O_{3,2}, O_{3,3}, O_{3,4}, O_{3,7} = 0$$

$$O_{3,5} = \frac{0.798}{0.798 + 0.597 + 0.797 + 0.356} = 0.31$$

$$O_{3,6} = \frac{0.597}{0.798 + 0.597 + 0.797 + 0.356} = 0.23$$

$$O_{3,8} = \frac{0.797}{0.798 + 0.597 + 0.797 + 0.356} = 0.31$$

$$O_{3,9} = \frac{0.356}{0.798 + 0.597 + 0.797 + 0.356} = 0.14$$

Fourth layer perform defuzzification. From layer 3 results we can see the there is not a big different between new and old weights of layer 3. After defuzzification we again get output value 24. Thus, we concluded that further membership and non-membership tuning is not possible.

4 Conclusion

An adaptive intuitionistic fuzzy neural network is a control system based on neural network and intuitionistic fuzzy logic, which deals with membership, and non-membership parts, and train neural network in order to tune membership, and non-membership to get desire output. It combines two techniques i.e. human like reasoning with learning that finds the parameters of a fuzzy system (i.e. fuzzy sets, fuzzy rules) by exploiting approximation techniques from neural networks. In this paper we calculate wash time of washing machine by using AIFNN, and conclude that our proposed that washing machine is more automatic compare to those that use simple fuzzy logic or the traditional control system design methodology.

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