Reyhane Shahrokhian 99521361

HomeWork4 of Computational Intelligence Course

Dr. Mozayeni

Q1:

A= {(1, 0.5), (2, 0.6), (3, 0.5), (4, 0.7), (5, 0.9)}

B= {(1, 0.9), (2, 0.7), (3, 0.5), (4, 0.7), (5, 0.1)}

C= {(1, 0.8), (2, 0.1), (3, 0.4), (4, 0.2), (5, 0.3)}

According to the roles mentioned in the question, we should calculate both left and right parts of the equation:

1-1:

A AND B = {(1, 0.45), (2, 0.42), (3, 0.25), (4, 0.49), (5, 0.09)}

(A AND B) OR C = {(1, 1), (2, 0.52), (3, 0.65), (4, 0.69), (5, 0.39)}

NOT A = {(1, 0.5), (2, 0.4), (3, 0.5), (4, 0.3), (5, 0.1)}

NOT B = {(1, 0.1), (2, 0.3), (3, 0.5), (4, 0.3), (5, 0.9)}

NOT C = {(1, 0.2), (2, 0.9), (3, 0.6), (4, 0.8), (5, 0.7)}

NOT A OR NOT B = {(1, 0.6), (2, 0.7), (3, 1), (4, 0.6), (5, 1)}

Left part = NOT((A AND B) OR C) = {(1, 0), (2, 0.48), (3, 0.35), (4, 0.31), (5, 0.61)}

Right part=(NOT A OR NOT B) AND NOT C = {(1, 0.12), (2, 0.63), (3, 0.6), (4, 0.48), (5, 0.7)}

The left and right parts are not equal and the reason is that we use different way of Snorm and Tnorm)

1-2:

A OR B = {(1, 1), (2, 1), (3, 1), (4, 1), (5,1)}

(A OR B) AND C = {(1, 0.8), (2, 0.1), (3, 0.4), (4, 0.2), (5, 0.3)}

NOT A = {(1, 0.5), (2, 0.4), (3, 0.5), (4, 0.3), (5, 0.1)}

NOT B = {(1, 0.1), (2, 0.3), (3, 0.5), (4, 0.3), (5, 0.9)}

NOT C = {(1, 0.2), (2, 0.9), (3, 0.6), (4, 0.8), (5, 0.7)}

NOT A AND NOT B = {(1, 0.05), (2, 0.12), (3, 0.25), (4, 0.09), (5, 0.09)}

Left part = NOT((A OR B) AND C) = {(1, 0.2), (2, 0.9), (3, 0.6), (4, 0.8), (5, 0.7)}

Right part=(NOT A AND NOT B) OR NOT C = {(1, 0.25), (2, 1), (3, 0.85), (4, 0.89), (5, 0.79)}

The left and right parts are not equal and the reason is that we use different way of Snorm and Tnorm)

Q2:

We should use the following rules:

$\mu_{true}(v) = v,\ \ \mu_{very\_true}(v) = (\mu_{true}(v))^2,\ \ \mu_{fairly\_true}(v) = (\mu_{true}(v))^{1/2}$

$\mu_{false}(v) = 1 - \mu_{true}(v),\ \ \mu_{very\_false}(v) = (\mu_{false}(v))^2,\ \ \mu_{fairly\_false}(v) = (\mu_{false}(v))^{1/2}$

P	20	30	40	50
High pressure	0.2	0.4	0.7	0.9
Very high pressure	0.04	0.16	0.49	0.81

v	30	50	80	90
Low volume	0.1	0.3	0.8	1
Very low volume	0.01	0.09	0.64	1
Fairly low volume	0.31	0.54	0.89	1
~fairly low volume	0.69	0.46	0.11	0

We also know that if volume is very low then the pressure is very high so:

(here we use minimum)

v\p	20	30	40	50
30	0.01	0.01	0.01	0.01
50	0.04	0.09	0.09	0.09
80	0.04	0.16	0.49	0.64
90	0.04	0.16	0.49	0.81

Now we should compute the membership function for pressure when the volume is not fairly low:

(here we use max-min)

20	30	40	50
min(0.01,0.69)	min(0.01,0.69)	min(0.01,0.69)	min(0.01,0.69)
min(0.04,0.46)	min(0.09,0.46)	min(0.09,0.46)	min(0.09,0.46)
min(0.04,0.11)	min(0.16,0.11)	min(0.49,0.11)	min(0.64,0.11)
min(0.04,0)	min(0.16,0)	min(0.49,0)	min(0.81,0)
max()=0.04	max()=0.11	max()=0.11	max()=0.11

Q3:

3-1:

According to our slides, first of all the input and output variables of the controller should be recognized and linguistic terms should be chosen and express them with suitable fuzzy sets which are usually fuzzy numbers.

After that, the fuzzy function is introduced for each input variable that illustrates the uncertainty of measurement (fuzzification).

Then, by the help of an expert we should formulate the knowledge of the given control problem in terms of a set of fuzzy inference rules.

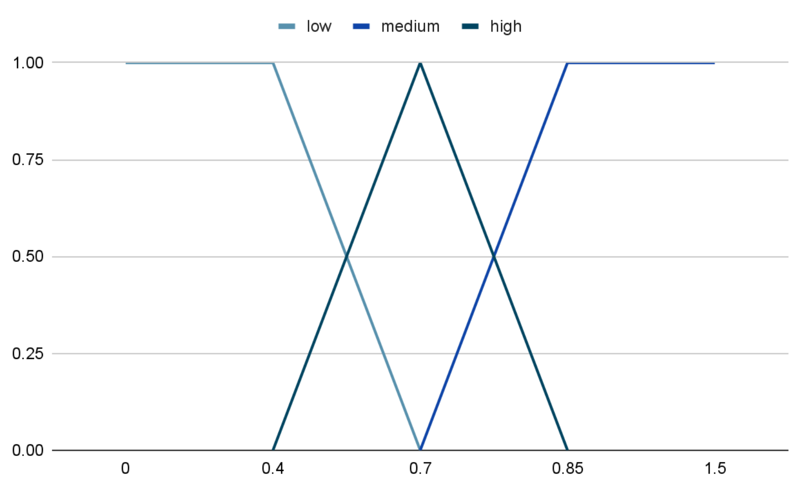
Next, the inference engine is designed using the fuzzy rules to combine measurements of input variables.

At the end, one of the defuzzification methods is chosen to convert the fuzzy conclusions into a real number.

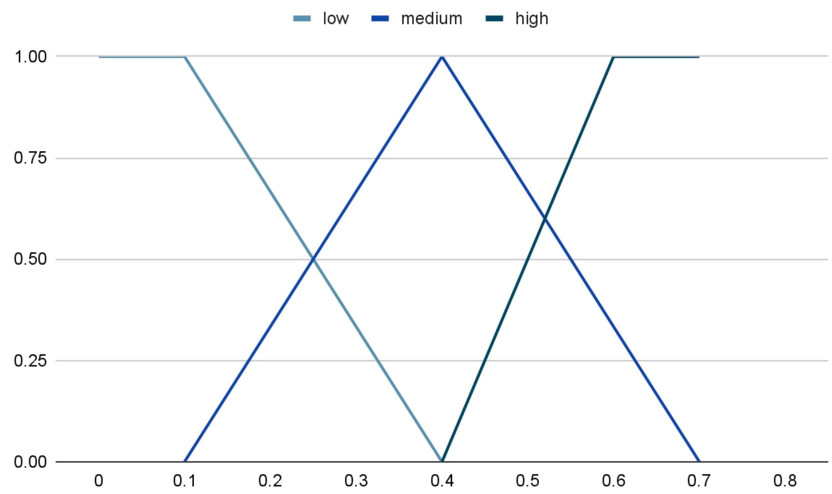
3-2:

According to the given functions, the membership charts are drawn:

x1:



x2:



3-3:

First of all the membership value of both inputs are calculated:

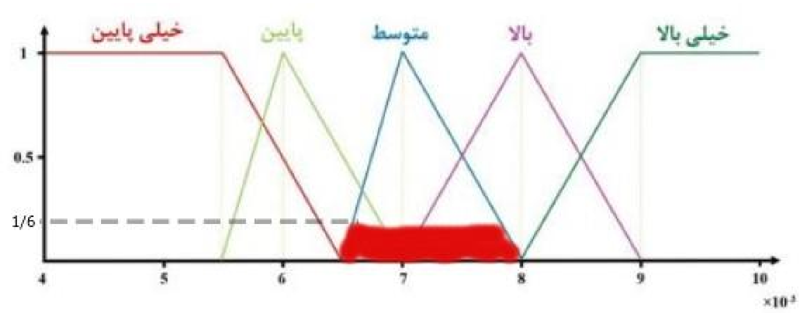
Distance: $\mu_{low}(0.65) = \frac{1}{6}$, $\mu_{medium}(0.65) = \frac{5}{6}$, $\mu_{high}(0.65) = 0$

Slippery: $\mu_{low}(0.5) = 0$, $\mu_{medium}(0.5) = \frac{2}{3}$, $\mu_{high}(0.5) = \frac{1}{2}$

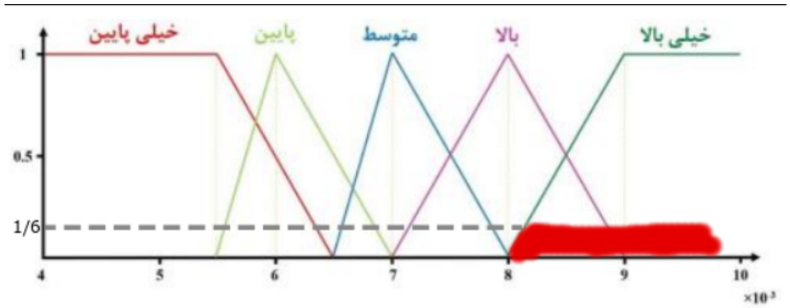
As two of the membership values are 0, so only 4 rules are left for us. Their chart of membership functions are drawn:

(According to Mamdani rules I use minimum of them)

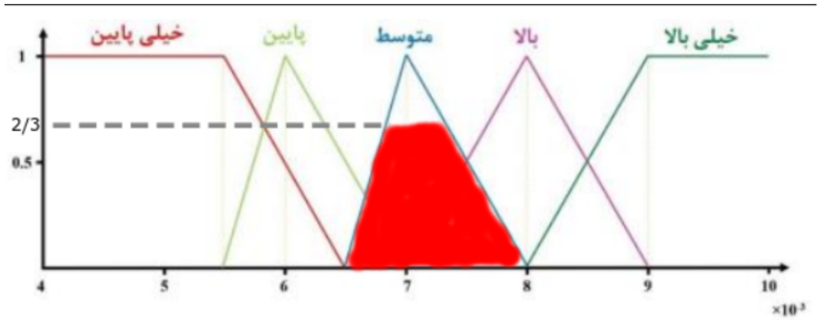
1) If the distance value is low and the slippery is medium then the pressure value is medium.



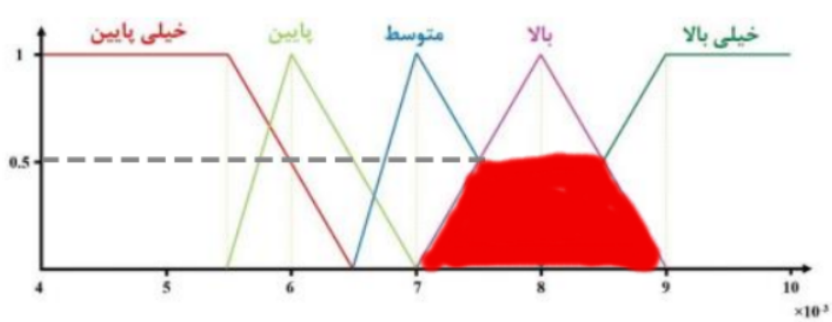
2) If the distance value is low and the slippery is high then the pressure value is very high.



3) If the distance value is medium and the slippery is medium then the pressure value is medium.



4) If the distance value is medium and the slippery is high then the pressure value is high.



Now it's the time to use one of the defuzzification methods to find the output.

I chose the center average method:

$$y^* = \frac{\sum_{l=1}^{M} \bar{y}^l w_l}{\sum_{l=1}^{M} w_l} = \frac{7.25\times\frac{2}{3}+8\times\frac{1}{2}+9\times\frac{1}{6}}{\frac{2}{3}+\frac{1}{6}+\frac{1}{2}} = 7.75$$

Q4:

There are various defuzzification methods, each with its own set of pros and cons.

- Center of Gravity (COG):

  Pros:

  Provides a crisp value that represents the center of mass of the fuzzy set.

  Takes into account both the width and height of the fuzzy set.

  Widely used and well-understood method.

  Cons:

  Sensitive to outliers, as extreme values can heavily influence the center.

- Center of Sums (COS):

  Pros:

  Consider the centroids of individual fuzzy rules and combine them.

  Suitable for systems with multiple rules, addressing complexity.

  Cons:

  More complex and computationally intensive compared to some other methods.

  May not perform optimally with simple rule bases.

- Center of Area (CA):

  Pros:

  Provides a single crisp value based on the weighted average of the fuzzy set's support.

  Take into account the entire area under the fuzzy set.

  Applicable to a wide range of fuzzy sets.

  Cons:

  Sensitive to noise, outliers, and variations in the fuzzy set's shape.

The accuracy may be compromised in the presence of irregular fuzzy sets.

- Mean of Maxima (MOM):

  Pros:

  Identifies the maximum membership values and takes their mean.

  Robust to outliers, as it focuses on the most significant regions of the fuzzy set.

  Cons:

  May not accurately represent the center of mass for certain fuzzy sets.

  Can be affected by noise in the fuzzy set.