Applied Computational Intelligence

Project 1 - Fuzzy Systems and Neural Networks

Report

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1 Fuzzy System

1.1 Application

The first part of the project consists of building a Fuzzy Inference System (**FIS**) to control the percentage of the computing load assigned for edge computing. This is achieved by controlling the CLPVariation, the mentioned percentage should be increased, maintained or decreased. A lot of different inputs where provided but, to handle the problem of the exponential growth of rules, it was decided to use four inputs in a number of hierarchically connected Fuzzy Systems. Memory Usage, Processor Load, Available Output Bandwidth and Latency was chosen to represent the whole set of inputs. The membership functions were decided to be trapazodial.

To be found below in Figure 1 is the correlation between the CLPVariation and the individual input values upon which the logic for the rule bases has been built.

Variable	High Latency	High Processor Load	High Available Output Bandwidth	High Memory Usage
Effect	Increase CLPVar	Decrease CLPVar	Increase CLPVar	Decrease CLPVar

Figure 1: Effect on CLP Variation from input variables

1.1.1 Fuzzy system 1

The first fuzzy system uses Latency and Processor Load as inputs which was chosen to represent the how favorable local processing of data would be. For both inputs the linguistic terms were chosen to be low, medium and high. The trapezoidal membership functions for Latency and Processor Load can be found below in Figures 2 and 3.

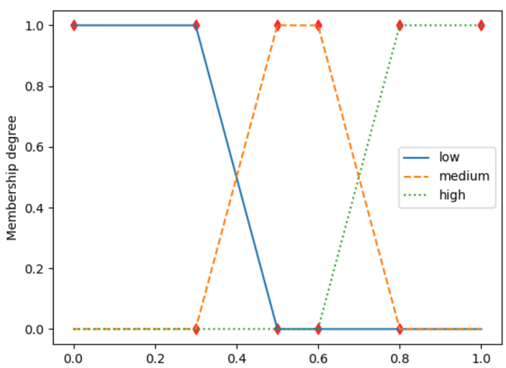

Figure 2: Latency

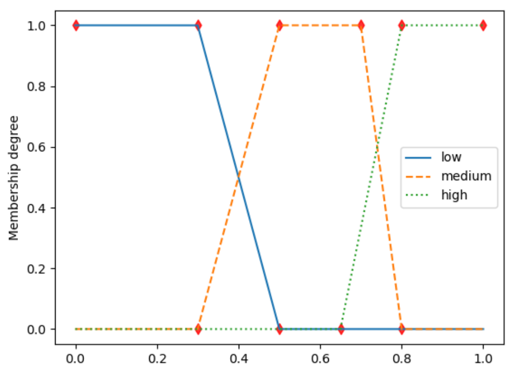

Figure 3: Processor Load

The rule base for the linguistic variables Latency and Processor Load is presented in Table 1 below.

		Latency		
		Low	**Medium**	**High**
Processor Load	**Low**	Okay	Good	Good
	Medium	Bad	Okay	Good
	High	Bad	Bad	Bad

Table 1: Rule Base Fuzzy System 1

The membership functions for the resulting output 1 is presented in Figure 4 below. The linguistic values for the output is Bad, Okay, Good and is an intermediate step, and estimation to the desired output CLPVariation.

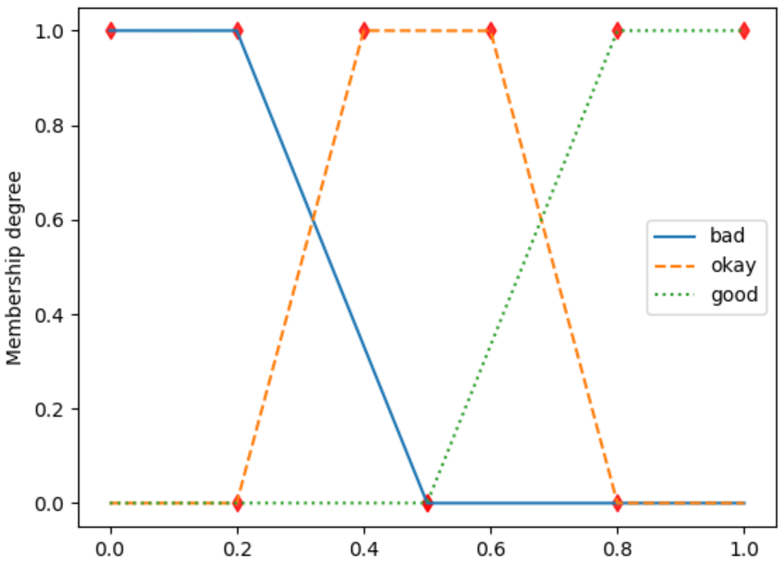

Figure 4: Output 1

1.1.2 Fuzzy system 2

The second fuzzy system uses Available Output Bandwidth and Memory Usage as inputs which was chosen as they was found out to be highly correlated with the output CLPVariation. For both inputs the linguistic terms were chosen to be low, medium and high. The trapezoidal membership functions for Available Output Bandwidth and Memory Usage can be found below in Figures 5 and 6.

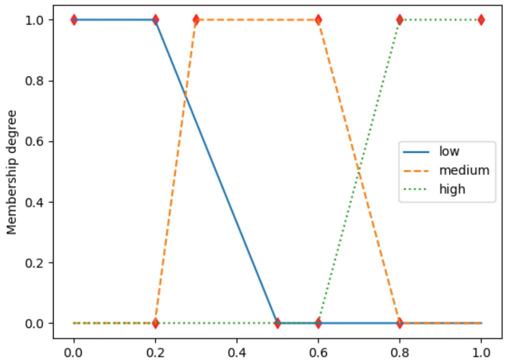

Figure 5: Available Output Bandwidth

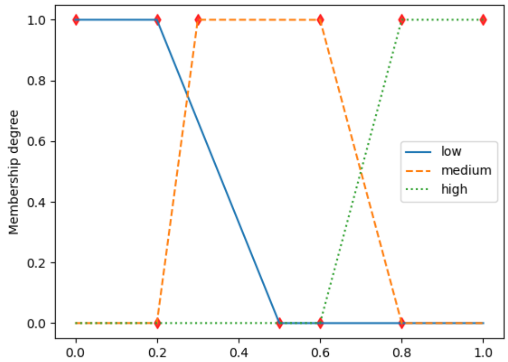

Figure 6: Memory Usage

The rule base for the linguistic variables Avalilable Output Bandwidth and Memory Usage is presented in Table 2 below.

		Available Output Bandwidth		
		Low	**Medium**	**High**
Memory Usage	**Low**	Okay	Good	Good
	Medium	Bad	Okay	Good
	High	Bad	Bad	Bad

Table 2: Rule Base Fuzzy System 2

The membership functions for the resulting output 2 is presented in Figure 7 below. The linguistic values for the output is once more Bad, Okay and Good.

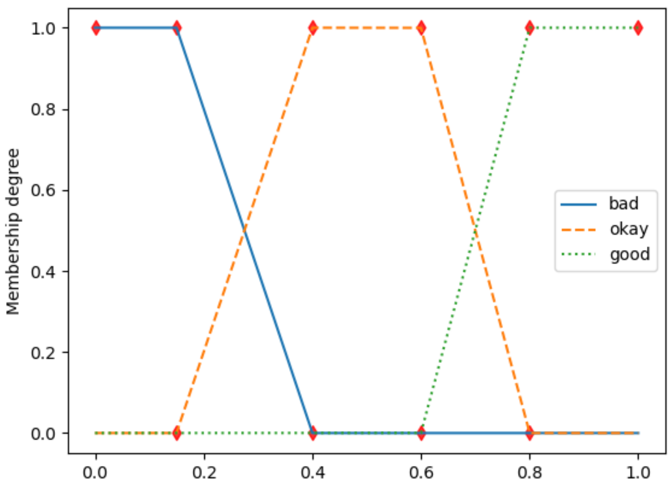

Figure 7: Output 2

1.1.3 Fuzzy system 3

The third and last fuzzy system uses the previous outputs as inputs. The output from the third fuzzy system is the desired CLP Variation. For both inputs the linguistic terms were chosen to be low, medium and high. he trapezoidal membership functions for Input 1 and Input 2 can be found below in Figures 8 and 9.

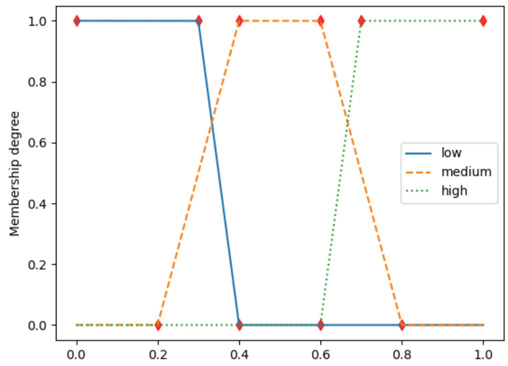

Figure 8: Input 1

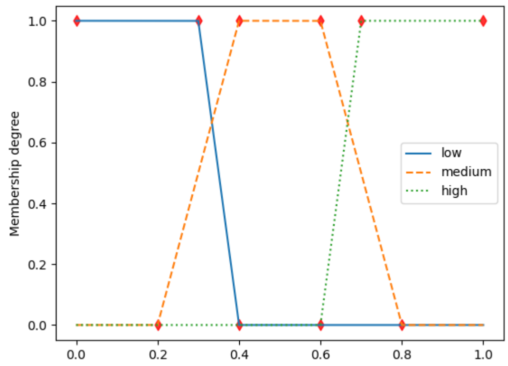

Figure 9: Input 2

The rule base for the linguistic variables Input 1 and Input 2 can be found in Table 3 below.

		Input 1		
		Low	**Medium**	**High**
Input 2	**Low**	Decrease	Decrease	Decrease
	Medium	Decrease	Maintain	Increase
	High	Decrease	Increase	Increase

Table 3: Rule Base Fuzzy System 3

The membership functions for the resulting output CLP Variation is presented in Figure 10 below. The linguistic values for the output is decrease, maintain and increase.

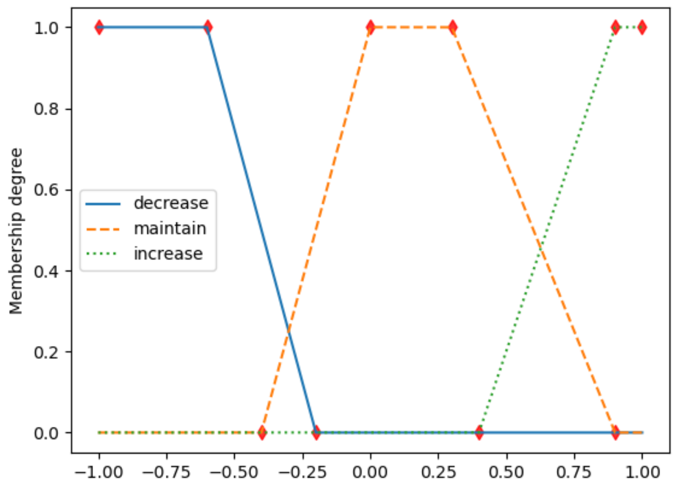

Figure 10: CLP Variation

1.2 Modification and tuning

Throughout the development of the fuzzy system, modification and tuning has been conducted. Initially other input variables were chosen, but when unable to make the system yield sufficient result, the input variables was changed to the current ones. Another thing which was changed are the membership functions. A lot of effort went into tuning the membership functions so that the had sufficient overlap. To choice to use trapezoidal membership functions were taken because a specific "best" value was unable to be pinpointed. Still, the use of the trapezoids has been in constant evaluation upon discovering that the can yield the exact same output for different inputs. That in and of itself mustn't be a negative thing so it was kept.

1.3 Results

The system was evaluated primarily on the example data with the reasoning that similar results to the provided ones was desirable. The dataset, generated by the fuzzy system was also inspected and was deemed reasonable.

2 Neural Network

The Neural Network was built and trained upon the data set generated by the fuzzy system. The data set was generated to contain 1000 data points, each consisting of the 12 input variables and the output from the fuzzy system. The network was created to replicate at worst, and outperform the fuzzy system at best. It consists of an input layer with 12 neurons along with two hidden layers with 16, and 36 neurons respectively. The output layer has a single neuron.

The parameters of the Neural Network, built as a Multi Layer Perceptron regressor using just sklearn library, are: solve as default (”adam”) because it works well with large data sets, ”relu” activation, alpha parameter value equal to 0.00001 and max iterations as 2000, this model optimizes the squared error using stochastic gradient descent. The train data set (”fuzzy dataset”) was separated in 70% train set, 15% validation set and 15% test set. The validation score was made before, to improve the R-squared, which means the proportion of the variance for a dependent variable that's explained by an independent variable in a regression model, i.e. if this value is close to 1, it means that the variation in the outputs of fuzzy systems 1 and 2 are explained by the independent variables chosen to formulate the fuzzy systems and that the model perfectly predicts the output.

Therefore, using the data set given for example for project, the Rsquared value is 89,2% for the test, and has 22,4% as RMSE, which means that the model can predict the CLP Variations pretty well.