Concepts and Models of Knowledge Engineering

SEMINAR PAPER

Topic 5: Car proposes actions based on the current state

Bobko Yuliia, 01349478, a01349478@unet.univie.ac.at

Ligori Armela, 12242736, a12242736@unet.univie.ac.at

Mehran Farkhondeh, 12147525, a12147525@unet.univie.ac.at

Mühlbauer Thomas, 01420689, a01420689@unet.univie.ac.at

Tekhov Oleksii, 01467816, a01467816@unet.univie.ac.at

1. Introduction

The goal of this project is to develop a proof of concept of a fuzzy logic system that can propose actions for the car based on current states. To obtain this goal, we will use a Fuzzy Inference System (FIS) to propose the best actions to the user in the current state. Additionally, the system should include incentives for actions that require the user, e.g., driving to a gas station and refilling the car. This user-centric design ensures a seamless collaboration between the automated system and the rider, promoting a sense of trust and confidence in the technology and increasing the customer experience.

Furthermore, the system is adept at handling ambiguity. By considering a spectrum of possibilities and providing practical suggestions, the fuzzy logic system proves resilient in adapting to unforeseen circumstances. Its ability to analyze and respond to the ever-changing conditions on the road makes it a good solution for a self-driving car scenario.

Another important aspect of the proposed system involves actions arising while driving with a customer. This unique consideration highlights the importance of delivering not only a technically sound solution but also an enjoyable and personalized riding experience. With all these aspects, this FIS will be able to support the whole Car2Go setup with a reliable and user-friendly system.

1.1. Assumptions

We assume that the system is active during the ride. We do not consider variables and actions that happen before or after the ride.

Urban driving: we assume that car rides happen in the city. This also means lower speeds, relatively short trips, and access to city infrastructure.

Car is driverless: we assume the car is intelligent enough to drive independently and follow traffic laws. The car is also assumed to be able to automatically do things like open/close windows, change speed, change headlights intensity, etc.

It is also assumed that the car can communicate with the client (who sits inside) and propose actions with incentives to them, and the client can accept or decline these decisions.

2. Fuzzy Inference System

To solve the presented problem, we use a Mamdani Fuzzy Inference System (FIS). It takes various environmental parameters as input and then outputs several values to define a proposed car action(s).

The chosen input variables allow us to define ranges (degrees) for them that are ambiguous and are more understandable to a human than a machine. For example, “empty fuel tank” or “morning hours”.

First, crisp input goes through fuzzification according to the linguistic variables defined by our team. Then, the rules that we wrote are applied to the fuzzified input to define the membership values of the respective output variable. Output variables are also linguistic variables defined by us. In the end, the values are defuzzified using the center of gravity (COG) method.

The crisp output values can be of two types: they either describe the plausibility of an action (e.g., go to the gas station is 55% plausible or open windows is 91% plausible), or they describe a percentage value unique to them (e.g., adjust headlight intensity by 50% or adjust speed to be 15% of the speed limit).

A broad overview of the system is presented in figure 1.

There are multiple ways to interpret these crisp values to determine the end result, which can either be a single car action or a list of car actions. We plan to use regular logic to achieve this end result. For example, we could say that we always propose “adjust speed” and “adjust headlight intensity” actions, and an extra action with the most plausibility. Another way of doing it would be to propose all actions with plausibility higher than X%, for example, 80%. This system combines fuzzy and regular logic to produce a result. While this paper focuses on the fuzzy logic part, we will flesh out and document the regular logic part (which is significantly smaller in proportion to fuzzy logic) later in the implementation stage.

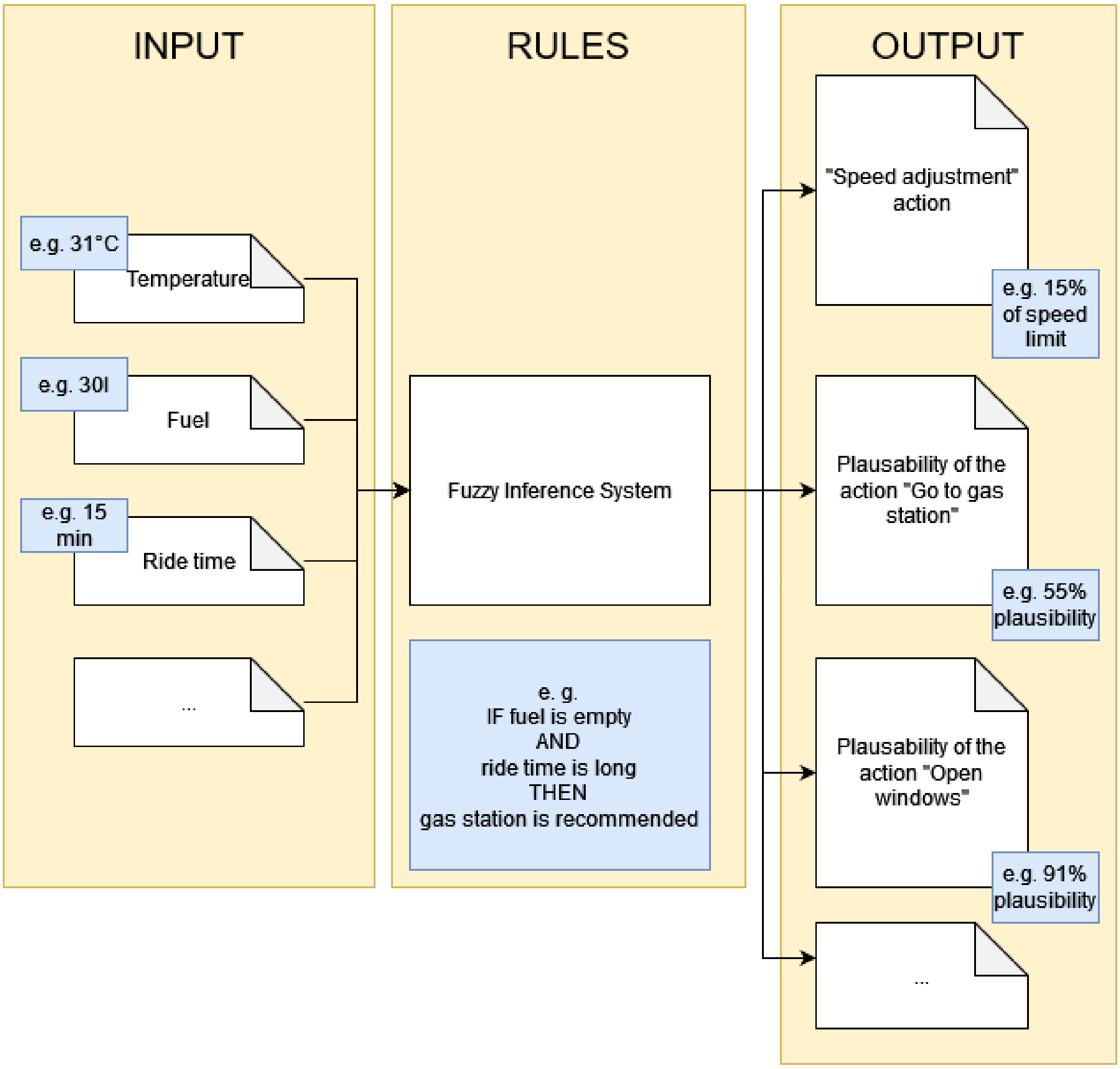


Figure 1: Overview of the system. Fuzzification and defuzzification are implied.

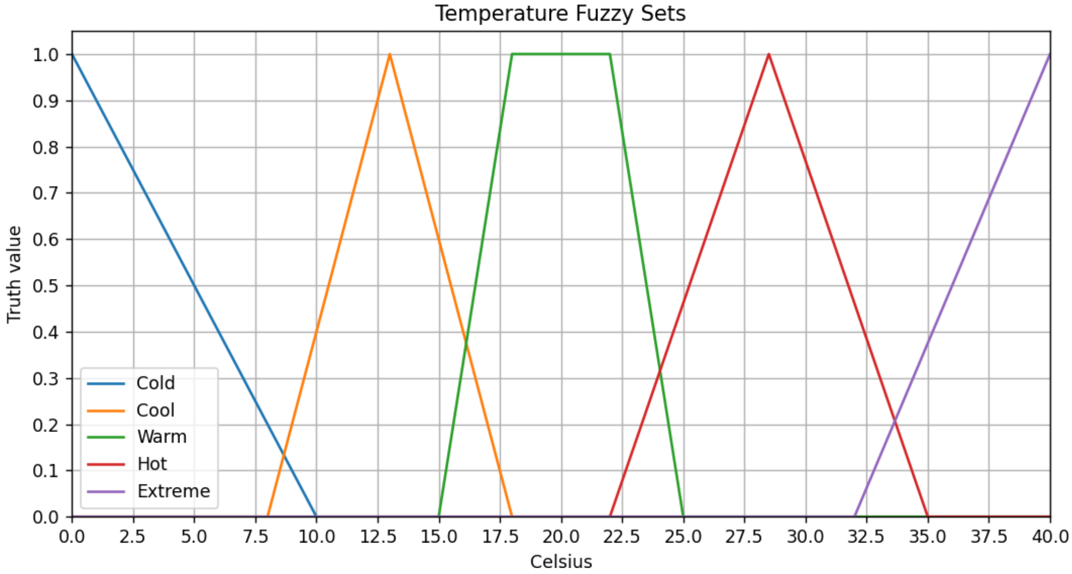
Below, a comprehensive list of linguistic (fuzzy) variables used in our FIS is presented. Each variable includes a list of fuzzy sets.

2.1. Input Variables

Temperature

Linguistic Values	**Ranges**	**Description**
Cold	0-10	degrees Celsius
Cool	8-18	
Warm	15-25	

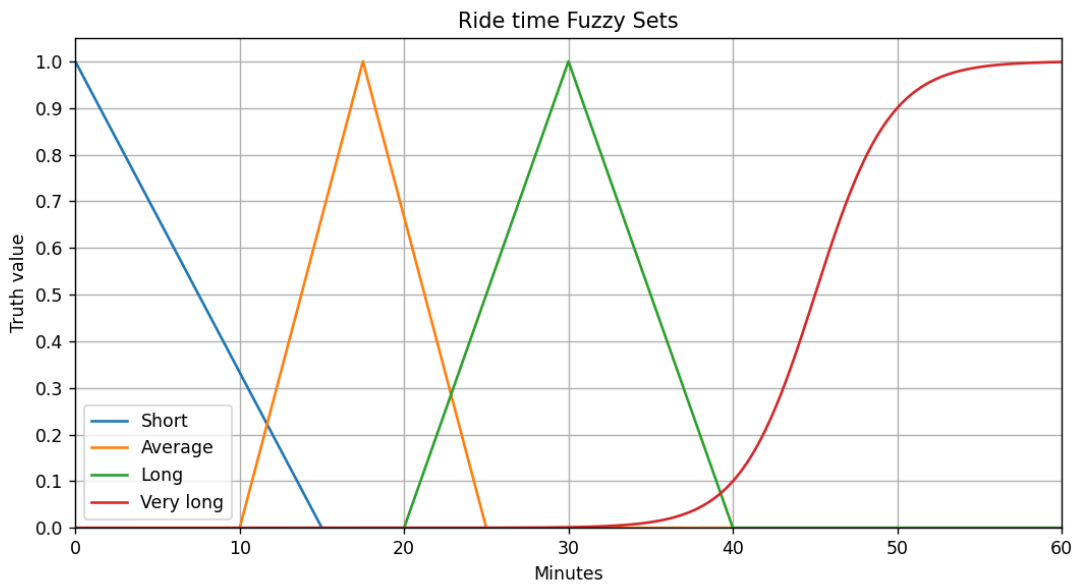
Hot	22-35	
Extreme	32-40	



Ride time

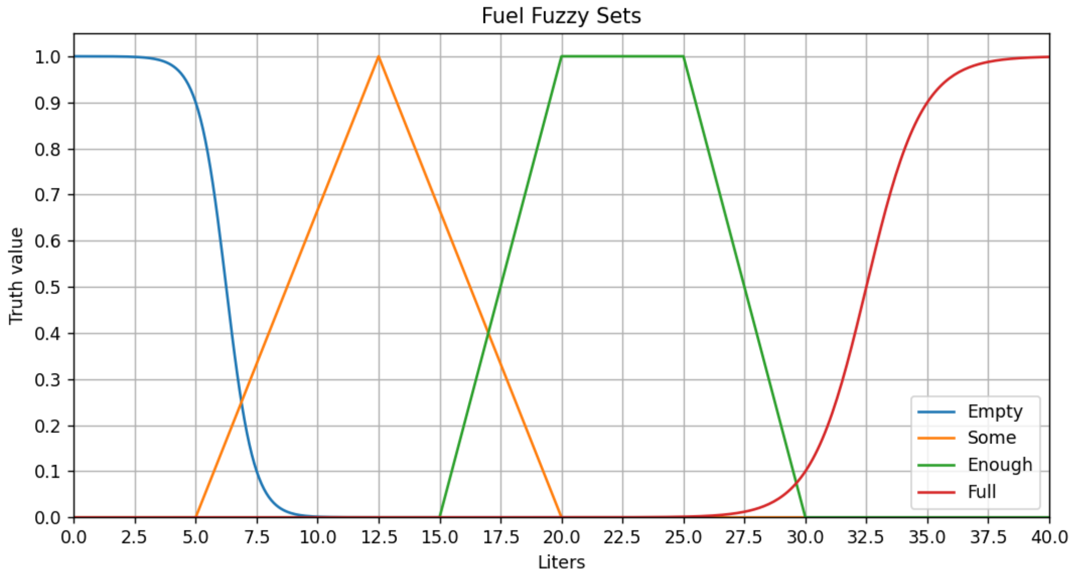
Total time of the trip, in minutes.

Linguistic Values	**Ranges**	**Description**
Short	0-15	minutes
Average	10-30	
Long	20-40	
Very Long	30-60	



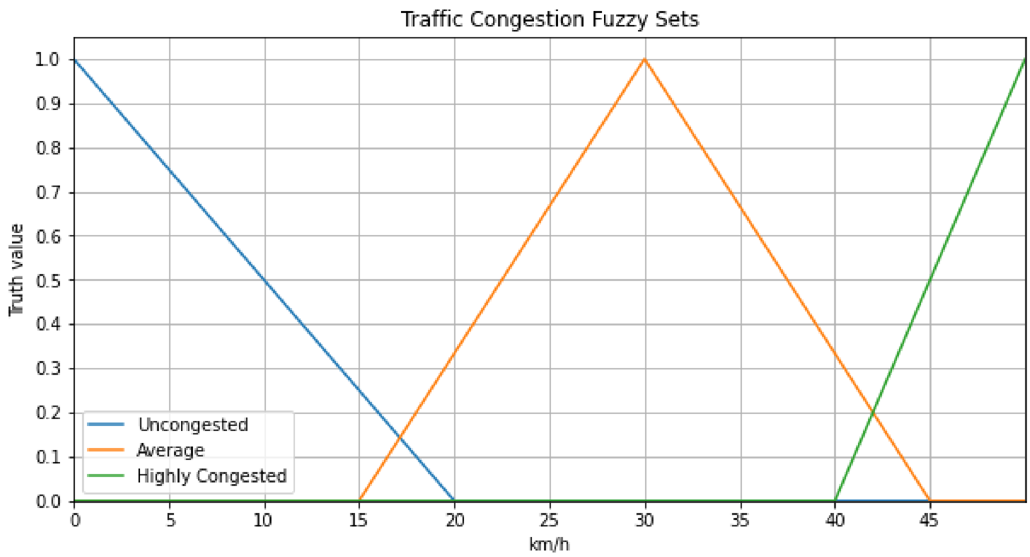
Fuel

Linguistic Values	Ranges	Description
Empty	0-10	liters
Some	5-20	
Enough	15-30	
Full	25-40	



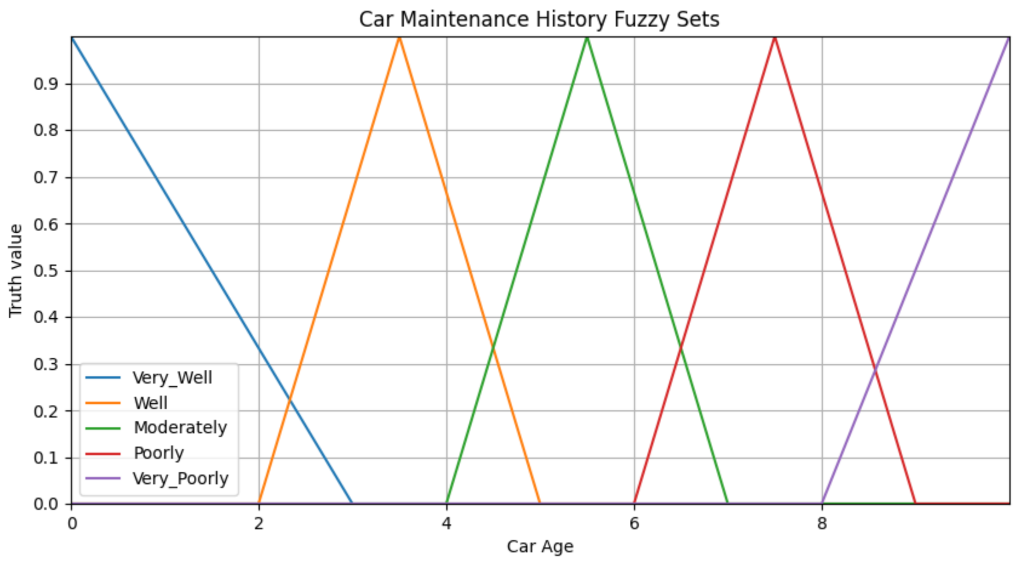
Traffic congestion

Linguistic Values	Ranges	Description
Uncongested	>40	Mean average speed for the selected route in km/h
Average	15-45	
Highly congested	<20	



Car's maintenance history

Linguistic Values	Ranges	Description
Very Well Maintained	0 - 3	The car is in excellent condition, with all maintenance tasks performed regularly and no known issues.
Well Maintained	2 - 5	The car is in good condition, with most maintenance tasks performed on time, and only minor issues if any.
Moderately Maintained	4 - 7	The car has been maintained to a reasonable degree, but some maintenance tasks may have been delayed or skipped.
Poorly Maintained	6 - 9	The car has missed several important maintenance tasks and may have some unresolved mechanical issues.
Very Poorly Maintained	8 - 10	The car has been neglected in terms of maintenance, likely leading to significant mechanical problems and reliability issues.



Nearby Points of Interest (POI)

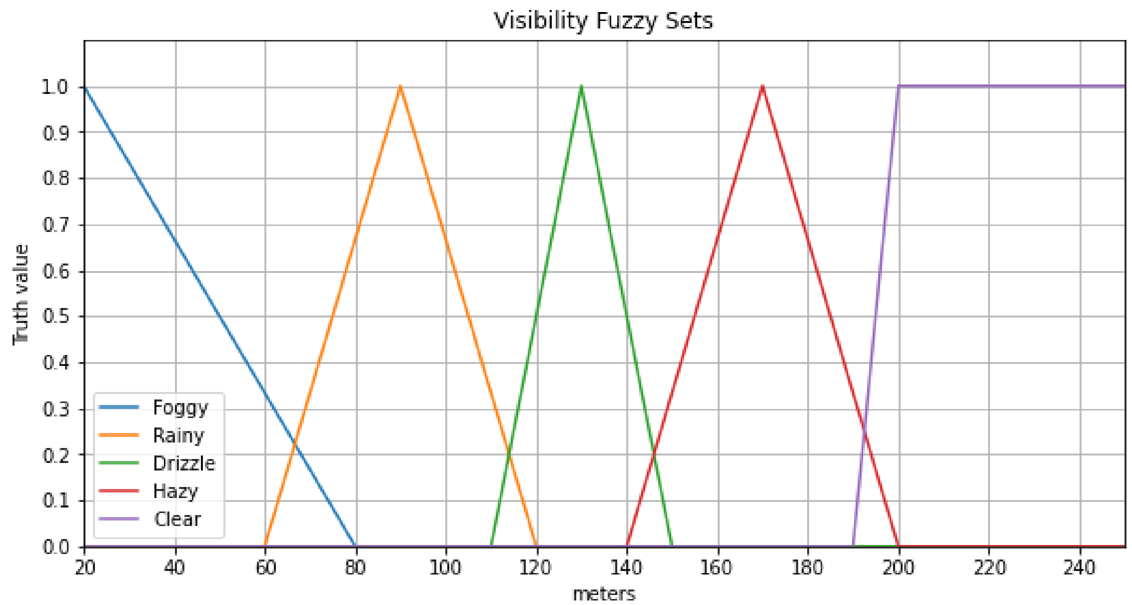
Linguistic Value	Ranges	Description
Abundant	0.8 - 1.0	Numerous points of interest are close by, offering variety.
Many	0.6 - 0.8	Good number of points of interest within reasonable distance.
Moderate	0.4 - 0.6	Moderate number of points, some options available.
Few	0.2 - 0.4	Limited points of interest, very few options
Scarce	0.0 - 0.2	Almost no points of interest in the vicinity.

Visibility (v1)

Linguistic Values	Ranges	Description
Foggy	20-80	Distance to see in meters
Rainy	60-100	
Clear	>200	

Visibility (v2)

Linguistic Values	Ranges	Description
Foggy	20-80	Distance to see in meters. The range at which various sensors of the driverless car can detect and interpret the surrounding environment.
Rainy	60-120	
Drizzle	110-150	
Hazy	140-200	
Clear	>190	



Daytime

Linguistic Values	Ranges	Description
Dawn	04:30-06:30	Daytime categorized in hours of the day
Morning	06:00-08:30	
Day	08:00-19:00	
Evening	18:00-22:00	
Night	21:30-05:00	

2.2. Output Variables

Our FIS output variables are car actions that might be proposed by the system. Some actions include incentives.

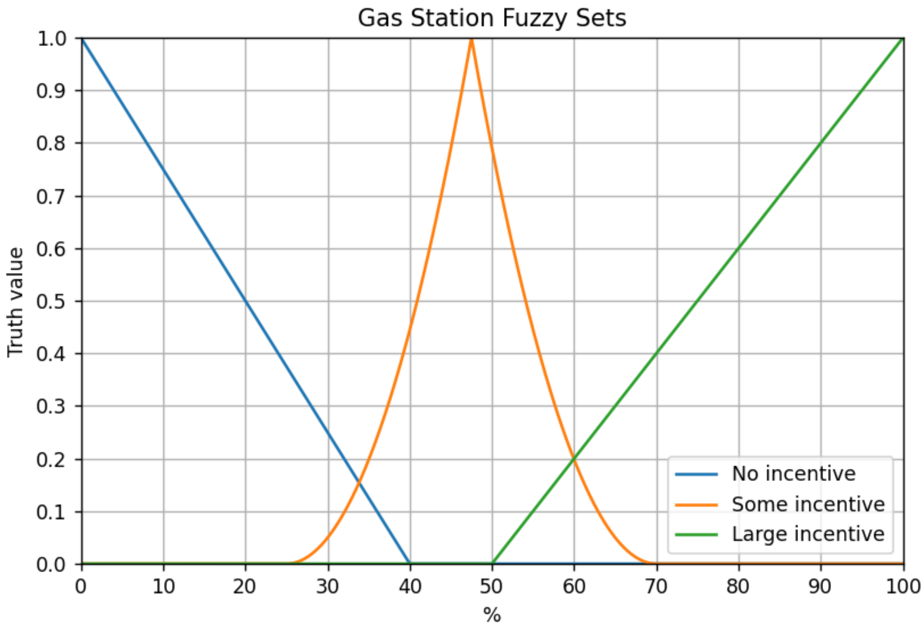
<u>Gas station</u>

Propose car action “Stop by a gas station to refuel”. Includes incentives for the client.

Linguistic Values	Ranges	Description
No Incentive	0-33	Propose action without incentive.
Some Incentive	20-70	Propose action and a 10% discount for the next ride.
Large Incentive	66-100	Propose action and a 10 EUR gift card.

Rules:

Traffic/Fuel	Empty	Some	Enough	Full
Uncongested	Large	Some	Some	No
Average	Large	Some	No	No
Highly Congested	Some	No	No	No

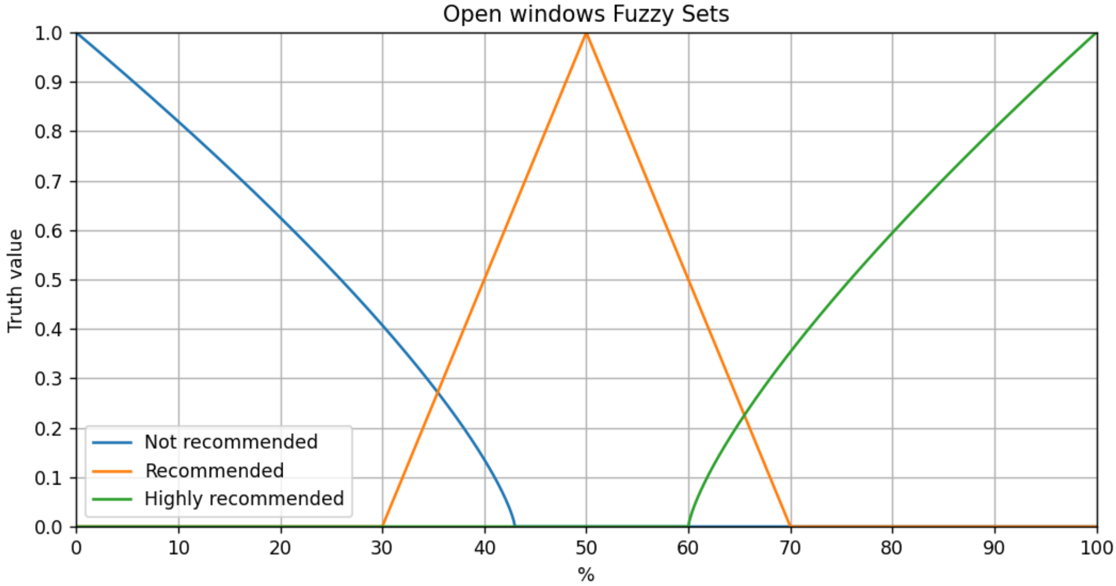


Open windows

Linguistic Values	Ranges	Description
Not Recommended	0-43	
Recommended	30-70	
Highly Recommended	60-100	

Rules:

POI/Visibility v2	Clear	Hazy	Drizzle	Rainy	Foggy
Scarce	No	No	No	No	No
Few	Rec	No	No	No	No
Moderate	Rec	Rec	No	No	Rec
Many	Highly	Rec	Rec	No	Rec
Abundant	Highly	Highly	Rec	Rec	Rec



<u>Route recalculation</u>

Linguistic Values	Ranges	Description
Not Recommended	0-35	
Recommended	30-70	
Highly Recommended	60-100	

Rules:

Ride time/ Traffic congestion	Uncongested	Average	Highly congested
Short	No	No	Rec
Average	No	No	Highly
Long	No	Rec	Highly
Very Long	No	Rec	Highly

Supply customer with a snack and water

Linguistic Values	Ranges	Description
Not recommended	0-35	
Recommended	30-70	
Highly recommended	60-100	

Rules:

Temperature/ Ride time	Short	Average	Long	Very Long
Cold	No	No	Rec	Highly
Cool	No	No	Rec	Highly
Warm	No	No	Rec	Highly
Hot	Rec	Rec	Highly	Highly
Very Hot	Highly	Highly	Highly	Highly

Speed adjustment

Determining the appropriate speed category, assuming real-time data on traffic congestion and weather conditions that affect visibility. The legal speed limit for urban areas in Vienna is 50 km/h.

Linguistic Values	Ranges	Description
Very slow	0-25% of the legal speed limit	Significantly below the usual speed, prioritizes safety
Slow	20-55% of the legal speed limit	Below the average speed
Moderate	50 - 85% of the legal speed limit	Around the average speed for the given area

Fast	80 - 100% of the legal speed limit	Close to the maximum legal speed for the current area

Rules:

Traffic Congestion/ Visibility v2	Clear	Hazy	Drizzle	Rainy	Foggy
Uncongested	Fast	Fast	Moderate	Moderate	Slow
Average	Moderate	Moderate	Moderate	Slow	Very slow
Highly Congested	Slow	Slow	Slow	Very slow	Very slow

<u>Car goes for maintenance</u>

Linguistic Values	Ranges	Description
Not recommended	0-35	
Recommended	30-70	
Highly Recommended	60-100	

Rules:

Ride Time/ Car's maintenance history	Very Well Maintained	Well Maintained	Moderately Maintained	Poorly Maintained	Very Poorly Maintained
Short	Highly	Highly	Rec	Rec	No
Average	Highly	Highly	Rec	No	No
Long	Highly	Highly	Rec	No	No

Very Long	Highly	Highly	No	No	No

Output: Recommendation for Stopping

Linguistic Value	Ranges	Description
Not Advised	0-35	Stopping is not recommended due to scarce options.
Optional	30-70	Stopping is optional, some points of interest
Advised	60-100	Advised to stop, many relevant and useful points of interest.

Rules:

Relation Between Temperature and Nearby Points of Interest (POI)

Temperature/ Nearby POI	Abundant	Many	Moderate	Few	Scarce
Cold	Optional	Optional	Optional	Not Advised	Not Advised
Cool	Advised	Optional	Optional	Not Advised	Not Advised
Warm	Advised	Advised	Advised	Optional	Not Advised
Hot	Advised	Optional	Not Advised	Not Advised	Not Advised
Extreme	Optional	Not Advised	Not Advised	Not Advised	Not Advised

Headlight intensity

Linguistic Values	Ranges	Description
High	70-100	Rules require a high headlight intensity
Medium	30-80	Rules require a medium headlight intensity

Low	0-40	Rules require a low headlight intensity

Rules:

Visibility v1/Daytime	**Clear**	**Foggy**	**Rainy**
Dawn	High	High	High
Morning	Medium	High	Medium
Day	Low	Medium	Medium
Evening	Medium	Medium	Medium
Night	High	High	High

Recommend ride-sharing:

Following action provides an incentive for customers if the customer chooses to share the ride.

Linguistic Values	**Ranges**	**Description**
not recommended	0-40	No action is proposed, therefore no incentive is issued.
recommended	30-70	Propose action and 10% for the ride.
highly recommended	60-100	Propose action and 25% for the ride.

Rules:

Daytime/ Traffic	**Uncongested**	**Average**	**Congested**
Morning	Rec	Highly	Highly
Dawn	No	Rec	Rec
Day	Rec	Rec	Rec

Evening	No	Highly	Highly
Night	No	No	Rec

Following table shows the interconnectivity between inputs and outputs. Our goal was to have as many overlapping inputs as possible, to ensure ambiguity of the proposed actions.

Inputs	**Temperature**	**Ride time**	**Fuel**	**Traffic**	**Mainte-nance**	**POI**	**Visibility**	**Daytime**
Temperature		Snack				Stopping		
Ride time	Snack			Route recalculation	Mainte-nance			
Fuel				Gas station				
Traffic		Route recalculation	Gas station				Speed	Ride sharing
Maintenance		Maintenance						
POI	Stopping						Open windows	
Visibility				Speed		Open windows		Headlight
Daytime				Ride sharing			Headlight	

3. Development and Technology Stack

Our Fuzzy Logic system is designed as a web service that facilitates interaction through a REST-like interface. A Python-based web application built with *Flask* framework handles API requests and delivers responses in a stateless manner. The input data, representing the car's current state, is sent as a JSON payload. The system analyzes the data using the described fuzzy inference process and returns the corresponding set of proposed actions, also encoded in a JSON format.

The fuzzy inference process is developed using the *fuzzy logic* library for Python. It provides the necessary tools for membership function creation, input fuzzification, rule creation, and output defuzzification. To visualize the relationship between membership functions, we use the Matplotlib library.

We containerize our application using *Docker*. Docker containers encapsulate the entire application, including the Python environment, Flask web service configurations, and any other dependencies. This makes it portable and easy to deploy across various environments.

The corresponding versions and documentation of the tech stack used are provided in the table below.

Technology	**Version**	**Link**
Python	=> 3.7 (3.10.11)	https://www.python.org
Flask	3.0.0	https://flask.palletsprojects.com/en/3.0.x/
fuzzylogic	1.2.0	https://pypi.org/project/fuzzylogic/
Matplotlib (pyplot)	3.8.2	https://matplotlib.org/
Docker	=> 4 (4.26.1)	https://www.docker.com/

4. Conclusion

This seminar paper thoroughly explores the development of a nuanced Fuzzy Inference System (FIS), demonstrating its capability to customize car actions under varying circumstances. Emphasizing a user-centric approach, this system is designed to enhance trust and enrich the customer experience. Key inputs such as fuel level, traffic dynamics, and car maintenance history are intelligently processed to yield actionable outputs like maintenance recommendations, significantly bolstering customer safety and overall driving experience. This system's proficiency in handling varied inputs and producing relevant outputs underscores its immense potential in the autonomous vehicle domain.

Future enhancements include incorporating dynamic factors like live traffic and car behavior and leveraging advanced AI techniques such as machine learning for deeper user needs analysis and improved driver-system interaction, steering towards a more integrated and user-friendly system.