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ORGINIAL ARTICLE

Enhancing Bicycle Route Selection with Fuzzy Logic: A Case Study in Augsburg

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Abstract

Current bicycle routing applications often rely on numerical metrics. These offer limited support for users seeking more nuanced, human-readable route assessments. This paper explores the use of a fuzzy inference system to enhance route selection. The idea is to model subjective and qualitative characteristics with fuzzy logic. By comparing routes from a set of alternatives for a given origin–destination pair, we demonstrate how fuzzy set theory can translate complex quantitative information into intuitive verbal descriptors (e.g. "long" or "uneven"). A case study in the city of Augsburg exemplarily shows how a fuzzy inference system helps to make a selection from three alternative bike routes. These are based on three exemplary measures (*length, elevation* and *pavement roughness length*). The results document a defuzzyfied measure helping to select the most suitable route. This approach intends to reduce cognitive load, supports informed selection of routes, and aligns more closely with how users perceive real-world biking conditions. Our work contributes a methodological foundation for integrating fuzzy logic into route selection. We thereby intend to offer an alternative to conventional route selection strategies dominated by rigid cost-based models.

Keywords Bikeability · Route selection · Fuzzy logic · Python · Fuzzy inference system

Verbesserung der Fahrradroutenplanung mit Fuzzy Logic: eine Fallstudie in Augsburg

Zusammenfassung

Aktuelle Fahrradroutenplaner basieren häufig auf numerischen Metriken. Solche bieten nur begrenzt Unterstützung für Nutzer, die detailliertere, für Menschen lesbare Routenbeurteilungen suchen. In der vorliegenden Arbeit wird der Einsatz eines Fuzzy Inferenzsystems zur Verbesserung der Wahl zwischen mehreren Routen untersucht. Die Idee ist, subjektive und qualitative Merkmale mit Fuzzy Logic zu modellieren. Durch den Vergleich von Routen aus einer Reihe von Alternativen für ein vorgegebenes Start-Ziel-Paar wird gezeigt, wie die Fuzzy-Set-Theorie komplexe quantitative Information in intuitive verbale Deskriptoren übersetzen kann (z. B. „lang" oder „uneben"). Eine Fallstudie in der Stadt Augsburg zeigt beispielhaft, wie ein Fuzzy Inferenzsystem genützt werden kann, eine Auswahl aus 3 alternativen Fahrradrouten zu treffen. Diese Routen basieren auf 3 exemplarischen Parametern (*Länge, Steigungen* und *unebene Länge des Straßenbelags*). Mit der Hilfe des defuzzifizierten Ergebnisses erstellen wir eine Rangfolge der Routen, um so die am besten geeignete Route auszuwählen. Ziel dieses Ansatzes ist eine Verminderung der kognitiven Belastung, Unterstützung einer informierten Routenplanung und stärkere Annäherung an die Wahrnehmung der realen Bedingungen der Nutzer beim Fahrradfahren. Die vorliegende Arbeit bietet eine methodische Grundlage zur Anwendung von Fuzzy Logic auf die Routenplanung. Ziel dessen ist das Angebot einer Alternative zu konventionellen Routenauswahlstrategien, die von starren kostenbasierten Modellen dominiert werden.

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1 Introduction

Most modern bicycle routing applications present alternative routes. Some user interfaces provide the information on these routes as aggregated values per criteria (travel time, number of turns etc.). When deciding which route to take, we have to manually compare these aggregated values and weight them. Since the number of criteria that routing applications consider is rising, the decision complexity is also increasing.

The characteristics influencing route choice or the use of bicycles are subsumed under the term "bikeability". This field of research is extensive, and different measures determine what is bikeable (Helle et al., 2023; Bres et al., 2023; Hardinghaus and Papantoniou, 2020; Rötzer et al., 2019; Jonietz and Timpf, 2012, Bíl et al., 2015). Established routing applications strive to incorporate these measures, using them as cost factors in shortest-path algorithms like that of Dijkstra (1959) or Yen (1970).

An increasing number of cyclists helps to reduce carbon emissions into the atmosphere (Lee et al., 2023). For some users, the level of detail provided by some routing applications may be overwhelming and potentially confusing. Despite the amount of data available, there is a lack of explanations of trade-offs between different routes that a routing system might suggest. We propose using a fuzzy inference system to facilitate the decision between routes from one origin to a destination.

The criteria describing the routes are subjective and their impact is difficult to estimate. Lotfi Zadeh (1965) introduces fuzzy logic as a mathematical framework that allows active handling of vague and imprecise information. It is a generalization of the traditional set theory (Bellman & Zadeh, 1970). Based on that, Mamdani & Assilian (1975) develop fuzzy inference systems to make this framework applicable. A fuzzy inference system maps multiple inputs onto an output value (Takagi & Sugeno, 1985). We apply such a system to a set of routes, inferring one value for each of them. These values rank the routes from best to worst on the basis of all criteria. According to this ranking, we can propose "the most fitting" route.

We start by summarizing relevant aspects of the fuzzy logic field. After introducing the study area, we give the origins of the routes. The main part comprises the setup of the fuzzy inference system. Then we present and discuss the results based on a case study from Augsburg, Germany.

2 Theory of Fuzzy Inference Systems

In the following, we outline the background of fuzzy logic and how it is connected with our case study. We thereby discern vagueness from uncertainty, as it helps to explain the advantage of fuzzy logic together with bikeability.

2.1 Fuzzy Logic and Vagueness

Humans do not perceive their environment in terms of binary logic but rather in more imprecise, vague or relative concepts. At this point it is important to discern vagueness from uncertainty, because it clarifies the connection of fuzzy logic and "bikeability". At first glance, the difference between uncertainty and vagueness can be difficult to grasp due to their similarities (e.g. often given in percent). Uncertainty is lack of knowledge about some event, which is eliminated by recording its results (Bezdek, 1993 Novák et al., 1999). It is a statistical description of an event's likelihood of happening. However, bikeability is vague and not uncertain, since it is subjective for each cyclist, situation, type of bicycle etc. Fuzzy logic was invented as a means to work with such concepts.

The mathematical framework of fuzzy logic allows active handling of the vague or imprecise (Zadeh, 1965), which is achieved by connecting degrees of truth to assertions (Zadeh et al., 2015; Bellman and Zadeh, 1970; Kalinic and Krisp, 2019). Different people have diverse perceptions of bikeability. Additionally, the situation of bike use needs to be considered. For instance, the type of bicycle (racing-, cargo-, mountain bike) that is used can change the requirements of the level of service the route provides (Yager, 2003; Dane et al., 2020).

Fuzzy sets are a generalization of Boolean logic and classical set theory (Zadeh, 1965; Zadeh, 1973; Kalinic and Krisp, 2019). A fuzzy set is not defined by associating "true" with all items that belong in it or "false" otherwise (Bellman and Zadeh, 1970). Instead, it is defined by a membership function μ that provides a degree for each item: $\mu(x) \rightarrow [0, 1]\ \forall x \in X$, with $X = \{\text{all routes}\}$. Usually the degrees are between 1 (does belong to the set) and 0 (does not belong to a set). For example, a certain route x belongs to the fuzzy set of short routes X_{short} to degree 0.9. Depending on the membership function, we expect it to be very short. The membership functions μ(x) can be designed freely. The most used versions are triangle, trapezoid and Gaussian, but other designs are possible as well. They usually take on simple forms because of ease of computation.

2.2 Fuzzy Inference Systems

Among the first appearances of an applied fuzzy inference system was the implementation of Mamdani and Assilian (1975). It is used to encompass human decision-making based on rules of thumb or vague concepts into a deterministic controller. Takagi and Sugeno (1985) build upon that and create a different type of system that is more efficient.

Often the inference of a crisp value called defuzzification is computationally costly. That is because the graph it describes can become complex. The most common example is the centre of gravity that we also use. However, we use the pithier Mamdani style in our case study. These systems model the different dimensions (distance, height etc.) of routes with so-called variables or domains. Each of them is defined by a number of fuzzy sets with their membership functions. For instance, the domain representing the *distance* dimension could comprise two fuzzy sets *long* and *short*. When we look at the length of a route we can now determine whether a route belongs more to the short or the long routes (Mamdani and Assilian, 1975). Since we use fuzzy logic, it is possible that a route belongs to some degree to both sets (Zadeh, 1973).

A fuzzy inference system deterministically maps input to output values using fuzzy logic. It can be structured into four different parts:

1. *Fuzzification*: In this part a measured crisp value is related to fuzzy sets via membership functions. These functions model how strong the connection between the input value and each fuzzy set is.
2. *Knowledge base*: The knowledge of each system is represented by the membership functions and the fuzzy "IF–THEN" rules. With these rules the relations of the fuzzy input and output sets are defined.
3. *Interference engine*: The interference is achieved by applying the rules to the fuzzified input values. The result of this are fuzzy outputs.
4. *Defuzzification*: This part is optional and only necessary when a fuzzy output set is not fit to act upon. Especially for control systems, the resulting function is reduced to a crisp value by applying a descriptive method.

3 Example Set of Bikeability Routes in Augsburg

Fuzzy logic is a theoretical framework. Because we want to make it more understandable, it is applied in a study area to an example set of routes. In the following, we provide the reasoning for why we select Augsburg and how we obtain the routes.

3.1 Augsburg as the Study Area

The case study focuses on the Jakobervorstadt district in Augsburg, Germany. The city has been striving to become a "bicycle city" (*Fahrradstadt*)[1] since 2012 and received the "bicycle friendly" certificate from the state in 2020. Further, it is the object of scientific research, and its university actively promotes bikeability analysis. Previous research ranges from the question of which factors contribute to improving bikeability and how can they be measured (Krisp et al., 2021; Rötzer et al., 2019; Löw and Krisp, 2024) to the modelling thereof (Jonietz and Timpf, 2012).

However, the area was originally selected for its diverse street network. That is important, because it ensures differences between routes and provides relevance for our methodology. The Jakobervorstadt features various road surface types, such as gravel, asphalt and cobblestones. Its southern part is more of a living quarter, with small cobblestone streets and parks. The northern part is a commercial space with points of interest like hospitals, cinemas or an old brewery. The routes connect both parts to simulate travelling to work over different road types.

3.2 Routes and Their Origins

We compute the set of three routes, as shown in Fig. 1. The basis for this is a street network with OSMnX[2] (Open Street Map NetworkX). The networks are based on volunteered geographic information from OpenStreetMap and processed for routability. These data are generally reliable, especially in densely populated areas (Boeing, 2024; Alsudais, 2021). Then we use the OSMnX implementation of the Dijkstra algorithm in combination with the edge length as cost factor to obtain the first route. Since the algorithm minimizes the cost factor when travelling from origin to destination, this is the shortest route (compare green route in Fig. 1). The orange route uses a cost factor of a pavement roughness index (Löw & Krisp, 2024).

The green route uses an elevation-based index as a cost factor. High-resolution elevation data (1×1 m) sourced by the Bavarian State Office for Digitalization, Broadband, and Surveying[3] form the data basis for the index and are of high quality. First, we assign each node its absolute elevation. The elevation changes that are both up- and downhill along the edge are disregarded (rise-over-run). The network is directional and has potentially separate edges representing each direction of a road. This configuration allows us to differentiate whether the road segment leads up- or downhill. We divide the grades by that of the steepest edge of the network and add one to derive an index. Adding one is necessary to have strictly positive numbers, as negative ones cannot be used in a cost function for Dijkstra's algorithm.

[1] https://www.augsburg.de/buergerservice-rathaus/verkehr/radverkehr/ziel-fahrradstadt; last access: 18.12.2024.

[2] https://github.com/gboeing/osmnx; last access 25.08.2025.

[3] https://geodaten.bayern.de/opengeodata/OpenDataDetail.html?pn=dgm1; last access 24.06.2025.

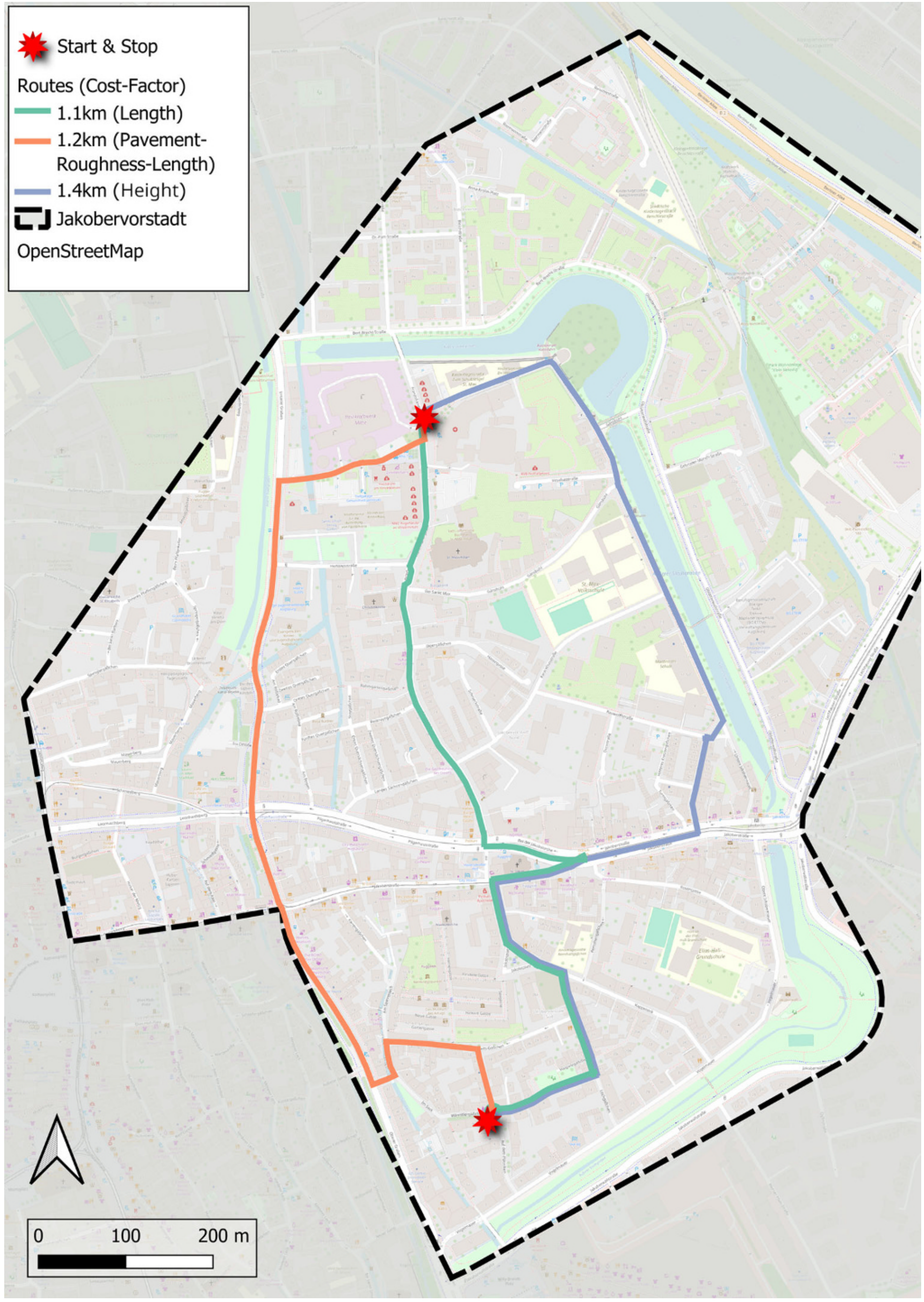

Fig. 1 Three exemplary routes with the same start and endpoint based on the Dijkstra algorithm in combination with three different cost factors (*length, pavement-roughness-length, elevation*)

3.3 Data Normalization

Starting with this example set of three routes, we now calculate characteristic values used as input for the fuzzy inference system. The following two steps are conducted for each route. The first step is to calculate the cumulative sum per cost factor (length, elevation index, roughness index) along the edges that the route uses. Since these sums vary proportionately to the distance between origin and destination, we apply min–max normalization in the second step. The normalization is relative to the cost factor and has the target range [0, 1]. In this way, the system can be set up independently of the origin–destination pair. The normalized values are the starting point for the inference process.

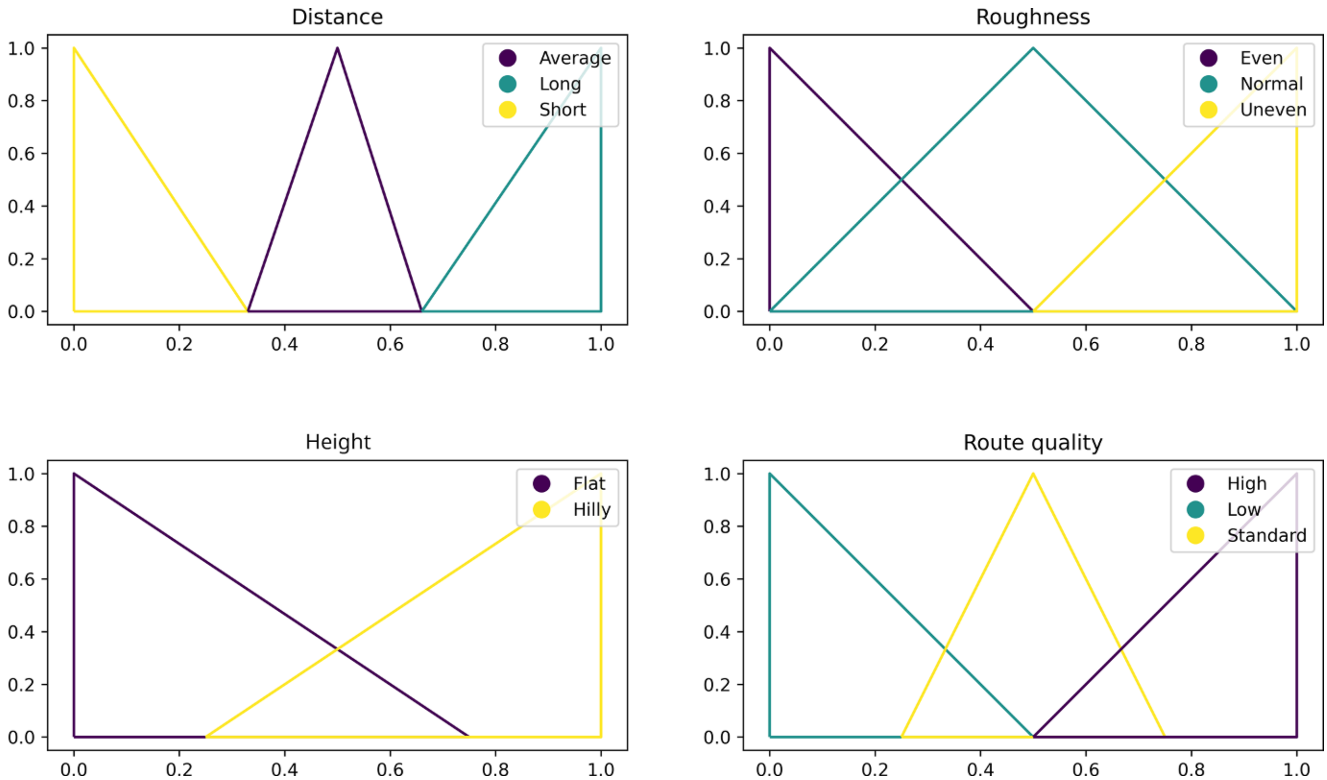

Fig. 2 Full fuzzy system featuring the triangle-shaped membership functions of the fuzzy sets for distance, roughness and elevation and the resulting route quality

4 Fuzzy Inference Systems—Design and Application

We set up an example fuzzy inference system to rank the three routes introduced in the previous section. The system fuzzifies the normalized values per fuzzy set. With a Mamdani fuzzy inference system, the sets are subsumed to variables. This configuration allows for many design decisions. We provide an outline of the decisions behind the system applied for this study.

4.1 Variables and Their Fuzzy Sets

Figure 2 shows the structure of the exemplary Mamdani-style fuzzy inference system. The system comprises eight fuzzy sets organized in variables for the fuzzification of the input values. Per cost factor in the routing part, we use one variable. That variable covers the range of the min–max normalization [0, 1].

Two variables, *distance* and *roughness,* each feature three fuzzy sets (Fig. 2). Having three sets is intuitive to the user, since it features a clear middle and two extremes. If we use more sets per variable, the results of the system would be less differentiated and thus less helpful for a decision. The variable *height* has two fuzzy sets. We implement this alteration to show the adaptability of the rulesets of fuzzy inference systems. The membership functions are all triangle shaped for ease of computation. Experience shows that triangle functions are solid choices and do not deviate much from e.g. Gaussian shapes. In some places they overlap, while in others they leave space open. Such design decisions can later help to model user preferences and need to be optimized for a real use case. We can fuzzify every potential input value with this arrangement of membership functions. The effect of overlaps can be tracked to the result table.

4.2 The Knowledge Base (Ruleset)

The ruleset determines how the fuzzy inference system combines the fuzzified values. These rules mirror the preferences of the user and can be adapted accordingly. The setup of rules we use for the case study is exemplary and basic. In their sense, a good route is short, flat and even; a bad one is long, hilly and uneven; and a standard one is average distance wise, the elevation difference is not important and the pavement is neither even nor uneven.

An intriguing characteristic of fuzzy inference systems is that this configuration can be easily altered. The foundation (variables, fuzzy sets) of the system can stay the same, but when the rules are adapted, the system mirrors different user preferences. The rules contain the information of the

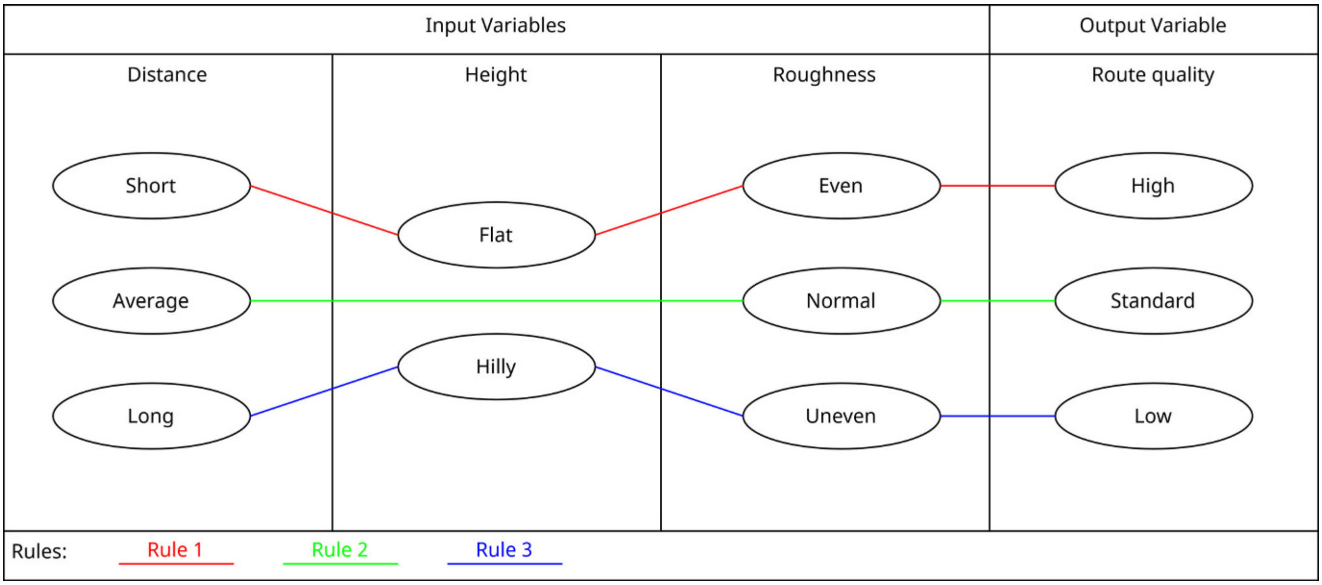

Fig. 3 Structure of the Mamdani fuzzy inference system. It consists of three input- and one output variable. Except for height, each features three fuzzy sets that are connected by one of three rules

user and can be seen as the knowledge base of our system. The example for the case study comprises three IF–THEN rules that are not yet optimised. As an example, consider the verbal definition of rule 1:

> "If the route is short, flat and even the route quality is high"

The red, green and blue lines in Fig. 3 show how the single fuzzy sets are connected. Each fuzzy set is considered exactly in one rule. That makes it easier to understand their single contribution to the results. The variable *height* has only two fuzzy sets, and rule 2 ignores the variable. Mamdani fuzzy inference systems use output variables for the calculation of a crisp defuzzified value. We name it *route quality* and define it with three fuzzy sets (Figs. 2 and 3). For this final step, we use the centre-of-gravity method to calculate a defuzzified number between 0 and 1. The higher it is, the better the corresponding route is from the perspective of the ruleset.

4.3 Setup of the System With a Custom Python Package

We use a custom python package[4] to construct and evaluate the fuzzy inference system. The following pseudo-code outlines the setup the system (Fig. 4).

[4] https://git.rz.uni-augsburg.de/loewpabl/fuzzy_polygons.

5 Results and Interpretation

Some may find the results of fuzzy inference systems that are subdivided into fuzzification and defuzzification not intuitive. We provide the three stages (value, fuzzified value, defuzzified value) of the approach and interpret them in the light of the ruleset.

5.1 Defuzzification and Fuzzification Metrics

All three routes (Fig. 1) have the same start and endpoint but use different cost factors. That can be seen in the example

Table 1 Comparative metrics

Fuzzy inference	Green route	Blue route	Orange route
Length [m]	*1146*	*1393*	*1182*
Short	1.00	–	0.56
Average	–	–	–
Long	–	1.00	–
Elevation [unitless]	*37.42*	*33.72*	*42.48*
Flat	0.44	1.00	–
Hilly	0.23	–	1.00
Roughness [unitless]	*1205*	*1426*	*1053*
Even	0.34	–	1.00
Normal	0.66	–	–
Uneven	0	1.00	–
Ranking (median)	*0.67*	*0.17*	***0.81***

The cumulative sum of the categories is shown in the italicised rows next to the cost factor. The rows below the cost factor show the fuzzified value per fuzzy set. In the bottom rows is the ranking of the routes in dependence of the function used in the ruleset

Fig. 4 Pseudo Code for constructing the example fuzzy inference system with the custom python package

Pseudo code	Explanation
	The following is done accordingly for all three input domains (roughness, height, distance)

`even: [0, 0, 0.5]`
`normal: [0, 0.5, 1],`
`uneven: [0.5, 1, 1]`
	Defines the fuzzy sets even, normal and uneven for the respective intervals [0;0.5], [0,1] and [0.5,1]
	The second number in the pseudo code defines the peak of the triangle function

`rou: InputDomain(`
`'Roughness',`
`[even, normal, uneven]`
`)`
	Create an input domain
	Name it 'Roughness'
	Add the 3 fuzzy sets

	The output domain is similar, but we also add the three input domains:

`low: [0, 0, 0.5],`
`standard: [0.25, 0.5, 0.75],`
`high: [0.5, 1, 1]`
	Defines the fuzzy sets low, standard and high for the respective intervals

`rqu: OutputDomain(`
`‘Route quality’,`
`[low, standard, high],`
`[dis, hei, rou]`
`)`
	Create an output domain
	Name it 'Roughness'
	Add the 3 fuzzy sets
	Add the reference of the 3 input domains (distance: dis, Height: hei, Roughness: rou) to the output domain

`For each route in routes do`	Iterate through the routes:
`route[relative_length]:` `route[length]/max(routes[length])`	Calculating the relative-length normalized by the longest route. That is done accordingly for relative-elevation and relative-roughness

`Route Quality(`
`rqu,`
`COG,`
`[route[relative_length],`
`Route[relative_elevation],`
`route[relative_roughness]])`
	Calculate the route quality with the center of gravity (COG) method based on the characteristics of each route

of the different lengths of the routes in Table 1, where the italicised rows contain the cumulative values.

The green route in the middle leading straight northward uses length as a cost factor. Accordingly, it is the shortest route, with a length of 1146 m. The blue route minimizes the *elevation* per edge and does not consider length. Therefore, it is the longest route with 1393 m. The orange route minimizes *pavement roughness* as well as *length* and is 1182 m long. The Dijkstra algorithm successfully keeps the cumulated cost factor along the route low. That works even if the cost factor is a compound of length and pavement roughness (compare orange route).

Table 1 shows the impact of the min–max normalization. It is best observed in the elevation domain. Here the blue route performs best (flat = 1.00), corresponding to the minimum of the three routes. The orange route is the maximum (Hilly = 1.00) and thus the worst. Coincidentally, the green one is around the middle but skewed slightly towards flat. The min–max normalization spreads the values between 0 and 1, causing this distribution. To achieve a better spread in the ranking, we use the median of the fuzzified values per rule instead of the more common maximum. The selection of this function is important and potentially changes the ranking.

5.2 Qualitative Reasoning

The fuzzy inference system creates the ranking (shown in Table 1) and also provides a reasoning. The ranking suggests that the orange route is the most suitable, while the blue is the worst. The green route is in between, but closer to the orange route. We can look at the membership degrees of the routes to the fuzzy sets when seeking explanations. The reasoning of the system behind the ranking can be summarized into a sentence. That sentence can be structured according to the rules:

> "The blue route has the lowest route quality even though it is flat, because it is uneven and long"

Descriptions like this can be derived in a straightforward way, such that it could be automated. We can add more information by translating the membership degrees into adverbs (e.g. very ≥ 0.8, averagely ≈ 0.5) highlighting the fuzzy character of bikeability:

> "The orange is the best because it is comparably short, very even, despite being hilly"

These verbal descriptions help to understand the ranking and have a similar structure to the rules. The ruleset defines which routes the system ranks high or low. Individualizing the rules offers a way of adapting the whole system and the results to a specific user. They can help the casual user to understand why a certain route is the best.

6 Discussion and Conclusion—How Do Fuzzy Inference Systems Help with Route Selection?

The results demonstrate how a fuzzy inference system can aid route selection. We achieve that by creating a ranking that incorporates multiple bikeability-relevant factors like length and elevation. Additionally, the fuzzification step provides a reasoning behind that ranking in a new and different way. Depending on the situation, the membership degrees can be included to give an understanding of the strength with which a route belongs to a set.

With this system, we intend to help users that are not familiar with sophisticated bike measures. Fuzzy logic is thought to avoid arbitrary classifications by substituting them with degrees. A common critique is that defining membership functions is also just as arbitrary. Since we use the fuzzy inference system for giving route descriptions, the routing part is unaffected. With these membership functions we have more options for adjustment. The creation and presentation of membership functions openly describes potentially arbitrary decisions and makes them visible and debatable.

An important reason to use fuzzy logic is that it helps to adapt a system to vague concepts like bikeability. Whether a route is perceived as bicycle friendly or not is dependent on many factors. Examples include the individual riding the bike, the bike that is used and the purpose of the travel. The fuzzy inference system allows us to avoid fixed thresholds that define at which point a route is bikeable. Instead, we can set up a membership function that gives a degree instead of yes or no. The ranking does not make an absolute assertion but gives an idea of how different the routes are.

This fuzzy logic approach mediates between different inputs like indexes or meters. Usually those are very difficult to weigh against each other. For instance, how much shorter must a route be to be favourable compared to a route that has an elevation index 30 lower? This is complex and becomes more difficult if the route planner considers more characteristics. Inference systems can be set up and optimized. This can be challenging. But our results show that it helps with the decision between routes.

With this paper, we explore the effect of applying a deterministic fuzzy inference system to the data that are available for an exemplary set of bike routes. Among the results of the system are the crisp defuzzified *route quality* values that rank the routes and facilitate decisions. In combination with the fuzzification information, one can explain why a certain route is valued more highly than another.

Often the ruleset of a fuzzy inference system is called a knowledge base. It contains information about the connections between the fuzzy sets. When the rules are changed, the system provides different results. This offers a simple way to adapt the system to a user. Mamdani constructed his system such that it stores and resembles expert knowledge in the ruleset. In our case, this means that if we enable users to restructure the rules, they can adapt how the system ranks routes to their preferences. Thus, we can avoid one challenging step of optimization, and users have room to customize the system.

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Data Availability The python package used for the fuzzy inference system can be found under: https://git.rz.uni-augsburg.de/loewpabl/fuzzy_polygons

Conflict of interest P.S. Löw, J.M. Krisp and A. Keler declare that they have no competing interests.

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