# Fuzzy Estimation of Link Travel Time from a Digital Elevation Model and Road Hierarchy Level

J. Stötzer, S. Wursthorn and S. Keller
*Institute of Photogrammetry and Remote Sensing, Karlsruhe Institute of Technology, Germany*

Keywords: OpenStreetMap, Link Travel Time, Digital Elevation Model, Fuzzy Control System, Routing.

Abstract: Link travel time is crucial for finding the fastest path in a road network which is an issue in many fields of research. Readily available data sources like OpenStreetMap (OSM) often lack information about the maximum speed of a road which is needed to calculate link travel time. In rural regions, the average speed of a road depends mainly on two parameters: slope and road quality. In this paper, we develop a fuzzy control system (FCS) which estimates link travel time based on these two input parameters. The OSM road network and a digital elevation model (DEM) serve as free-to-use and worldwide available input data. Google Directions API data provides a reference for the link travel time. The setup of the FCS as well as its tuning and validation is described in detail. Furthermore, two approaches to derive slope from a DEM are presented and compared. The FCS is applied exemplary for the BioBío region in central Chile. The results of the case study reveal the potential of this approach. Link travel times are estimated by the FCS with an $R^2$ of at least 87.8 %. In future work, the FCS can be designed with more input parameters to achieve an even better performance.

## 1 INTRODUCTION

Finding the fastest path in a road network is important for many applications such as route planning, disaster risk management or transport of goods. To calculate the fastest path, an associated link travel time is assigned to every edge in the road network. The link travel time is the average time a vehicle spends travelling an edge in the road network Stanojevic et al. (2018). Especially in studies on critical road infrastructure and accessibility, link travel time often serves as a cost factor for the road network Knoop et al. (2012); Li et al. (2011); Scott et al. (2006).

Many of these approaches use OpenStreetMap (OSM) data. The OSM project provides free road network data with global coverage. OSM data is collected by volunteers worldwide and can be edited by anyone. The representation of the road network in OSM is more than 80 % complete Barrington-Leigh and Millard-Ball (2017). Furthermore, 40 % of countries worldwide have a fully mapped road network. Many approaches using OSM data raised the question of data quality which caused a number of investigations on that topic. To summarize the results, OSM can be highly accurate and complete and in some regions even better than commercial or administrative datasets Cipeluch et al. (2010); Girres and Touya (2010); Haklay (2010); Neis et al. (2011); Jackson et al. (2013); Dorn et al. (2015); Demetriou (2016). Even in some developing countries the completeness of the road network is high at a national level Ludwig et al. (2011); Mahabir et al. (2017).

While the quality of the OSM road network itself is satisfying for most approaches, routing applications need additional metadata. Although the possibility to include maximum speed information in OSM is given, most roads lack this information. Figure 1 shows the proportion of the total length of the upper level roads (defined in Table 1) with maximum speed information per country. Worldwide, only 7.5 % of all road elements in OSM feature a maximum speed information. However, to compute link travel time and consequently fastest paths, speed information for every edge in the road network is crucial.

The influencing factors on link travel time in urban and in rural areas differ a lot. While traffic, turn restrictions, one way streets and traffic signals have a huge impact on travel time in the city, other factors dominate in rural areas. Especially in developing countries, the road quality has a considerable impact on the link travel time. Asphalted roads allow for a higher velocity than unsealed gravel or mud roads. Also, the wider a road is and the more lanes it has, the faster a vehicle can drive. Another big influenc-



Stötzer, J., Wursthorn, S. and Keller, S.
Fuzzy Estimation of Link Travel Time from a Digital Elevation Model and Road Hierarchy Level.
DOI: 10.5220/0007655800150025
In *Proceedings of the 5th International Conference on Geographical Information Systems Theory, Applications and Management (GISTAM 2019)*, pages 15-25
ISBN: 978-989-758-371-1

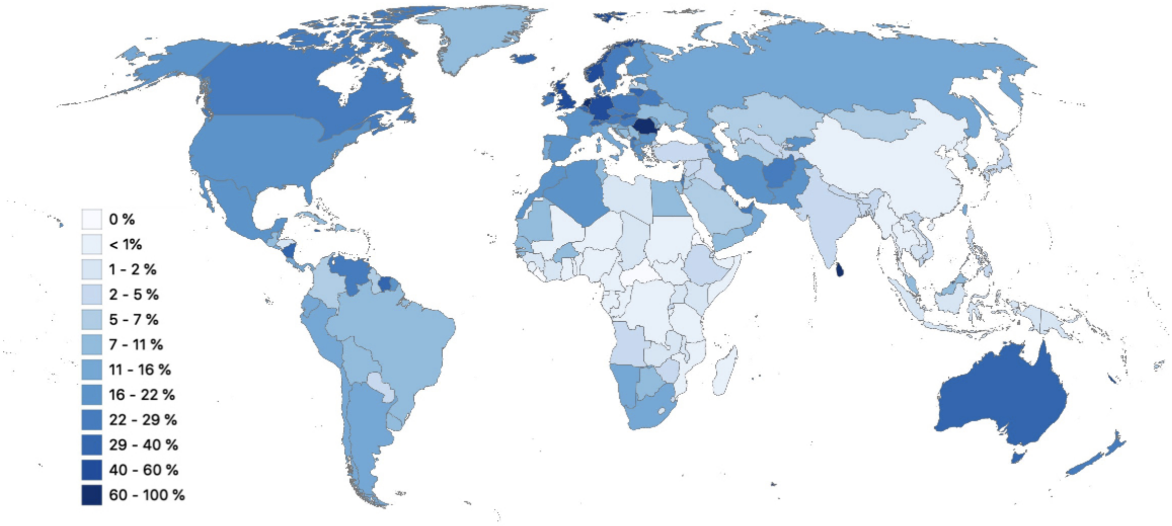


Figure 1: Proportion of the total length of all roads (road classes in Table 1) with maximum speed information in OpenStreetMap (`maxspeed` tag) per country. Only 7.5 % of all road elements stored in the OSM world dataset have information on maximum speed.

ing factor is the topography of the terrain Collischonn and Pilar (2000). The slope of a road limits the driving speed, both by an increase in sinuosity and by the slope itself.

Many studies and routing applications rely on fixed speed profiles for every road class defined by various input parameters. This leads to jumps at the class borders. A fuzzy control system (FCS) is able to fuzzify these input parameters and provides a more continuous, nonlinear output. Furthermore, as it is based on expert knowledge, it does not rely on nonexistent reference data to learn its behaviour.

Focusing on rural road networks, in this paper we develop a FCS to estimate link travel time from two input parameters: road hierarchy level and slope. The OSM road network and SRTM (Shuttle Radar Topography Mission) data serve as input data for the FCS. We use the Google Directions API (GD-API) as reference data to tune and to validate the FCS. Two approaches to derive road slope from a digital elevation model (DEM) are presented. The FCS is set up with membership functions for the input parameters slope and hierarchy level and for the output parameter velocity. Then, it is tuned and validated with GD-API data. A case study is performed in the BioBío region in Chile.
The main contributions of this paper are summarized in the following:

- development of a FCS with slope and hierarchy level as input and velocity as output parameters;
- validation of the developed concept with GD-API data;
- enrichment of the rural OSM road network with estimated link travel times;
- usage of open source and worldwide available data (OSM, SRTM);
- exemplary case study for the BioBío region in Chile.

In this paper, we first provide an overview of the related work on link travel time in OSM in Section 2.1 and introduce the concept of Fuzzy Control in Section 2.2. The input and reference datasets are described in Section 3. In Section 4.1 two approaches to calculate slope are presented. Then, the setting up, tuning and validation of the FCS is explained in Section 4.2. A description of the case study (Section 5.1), the results (Section 5.2) and the discussion (Section 5.3) are presented. Finally, a conclusion and an outlook are given in Section 6.

## 2 RELATED WORK

In this section, we briefly introduce the related work on two topics. First, we investigate how link travel time is calculated in other approaches that rely on OSM data. Then, we introduce the concept of Fuzzy Control, its advantages and how other studies apply this concept.

### 2.1 Link Travel Time in OSM

Many routing applications exist that compute fastest paths, and consequently link travel time, and base on

OSM data. Popular examples are the OpenRouteService ORS (2018), the Open Source Routing Machine (OSRM) Luxen and Vetter (2011), the OpenTripPlanner OTP (2018) and YOURS YOURS (2018). The latter three are open source applications and use the maximum speed information in OSM to calculate link travel time if available. If not, the OSM Wiki OSM Wiki (2016) contains default speed limits for some countries (24 countries worldwide) which are processed and applied by these routing applications. The applications also include other metadata like the road type and the number of lanes (if available) to derive fixed speed profiles for every road class. The algorithm for the OpenRouteService is not accessible by public. But it seems more complex than the other routing applications as it provides additional information like the slope and type of a route. However, like many commercial routing applications such as Google Maps or Bing Maps the exact calculation is not transparent.

Few studies address the issue to derive link travel time from the OSM road network. Stanojevic et al. (2018) present a methodology to calculate link travel times based on origin-destination and timestamp information generated by a taxi fleet and OSM data. They estimate travel times in urban regions with 60 % lower errors than OSRM. A lot of related work concentrates on urban regions and how to improve the estimation of travel time in trafficed networks. Steiger et al. (2016) include real-time traffic data into the OpenRouteService application.

As mentioned in Section 1, the important factors for routing in urban and rural areas differ considerably. In the design standards of Asian highway routes, the assigned maximum speed of a road in a rural region is directly dependent on the slope of the terrain Behera (2008). Brabyn and Skelly (2001) model access to public hospitals and calculate shortest and fastest paths. To estimate the link travel time, they consider if the road is inside or outside an urban area, the number of lanes and the sinuosity of a road. The sinuosity of a road is calculated with a sinuosity index. They categorize the roads by these factors and assign fixed velocities for every combination.

This study aims at filling some of the existent gaps in the related work. Most routing applications with OSM focus more on the city than the rural areas and only include country wide speed limits in their travel time calculation. Few studies focus on the calculation of link travel time. The ones that do, rely on self-collected or commercial datasets. To our knowledge, a fuzzy control system has never been applied to estimate link travel time with different parameters.

## 2.2 Fuzzy Control Systems

FCSs work on linguistic terms and partial memberships which are able to express fuzziness. A FCS takes crisp input values and fuzzifies them with the help of membership functions. In a second step, a rule base provides the basis for the inference mechanism. A defuzzification generates crisp and continuous output values.

The idea of Fuzzy Control was first introduced by Mamdani and Assilian (1975) for a steam engine and boiler combination. Since then, Fuzzy Control has been applied successfully in various research areas: in the environmental research e.g. for flood simulation Wang et al. (2011), in remote sensing e.g. for classification of multispectral data Shackelford and Davis (2003) or in analytic chemistry Hayward and Davidson (2003). Das and Winter (2018) employ fuzzy logic to detect the transport mode in an urban environment.

Fuzzy Control allows for many input and many output parameters. Such parameters can be combined in an if-then rule Jantzen (2007). The two greatest strengths of fuzzy control are the ability to reason with uncertainty and its utilization in complex ill-defined processes without much knowledge of their underlying dynamics Mahmoud (2018).

# 3 DATASETS

To create and evaluate a FCS, both input and reference data are required. The input dataset consists of two datasets: OSM and SRTM. The reference data for the Fuzzy Control System is provided by the GD-API. In the following section the input and reference data are described.

## 3.1 Input Data

**OpenStreetMap** road data includes a hierarchic classification of the road network that is described in Table 1. The mentioned road classes and their respective link roads (meaning roads that lead to or from the respective road) build up the road network. Other existing road classes, such as residential and service roads or special road types like living streets, are not considered.

The **Shuttle Radar Topography Mission** was a joint mission by National Imagery and Mapping Agency and the National Aeronautics and Space Administration (NASA) to collect an open source global elevation dataset. We use the SRTM void-filled, 1 arc-

Table 1: Road Classes in the OSM road network.

| Road Class | Description |
|---|---|
| Motorway | Restricted access, major divided highway. |
| Trunk | Most important roads in a country's system that are not motorways. |
| Primary | Major highways, linking large towns. |
| Secondary | Highways, not part of a major route, form a link in the national route network, often link towns. |
| Tertiary | Connect smaller settlements and minor streets to more major roads. |
| Unclassified | Minor public roads, lowest level of the network, often link villages and hamlets. |

second global data NASA and USGS (2013) with a resolution of approximately 30 m.

Due to this resolution, it has to be taken into account that one pixel of the SRTM raster may be the average of the road itself as well as possible hills beside that road. Therefore, we consider the slope of the surrounding terrain, which is, in most cases, higher than the actual road slope.

### 3.2 Reference Data

The **Google Directions API** is a service that calculates routing directions and travel times between locations. GD-API data includes the distance in meter, the travel time in seconds with and without traffic at a given time and the coordinates of the points on a road closest to the input point coordinates.

The GD-API relies on Google Maps and its underlying road and traffic data. The quality of Google Maps data is difficult to assess, especially in developing countries. During our studies, both roads that exist in OSM and not Google Maps and vice versa have been detected. Cipeluch et al. (2010) compare the accuracy of Bing Maps, OSM data and Google Maps data in Ireland and their results support our observations. They found that although some areas are better served by one data source than by the others, no single data source proves to have better overall coverage. As for the travel time and traffic data, there is no data available to evaluate the quality of Google Maps. We employ GD-API travel time as reference data while keeping in mind that this might, in some cases, be untrue.

The GD-API data is split into a dataset for tuning the model and a dataset used to validate the model. The tuning subset contains about 1000 roads and is randomly selected to display a representative subset of the complete dataset. The representative tuning subset contains the same kilometer percentage of every OSM road class like the entire dataset. The validation subset excludes the data used to tune the subset and consists of 5000 representative roads.

## 4 METHODS

This section is divided in two parts. First, two approaches to derive road slope from a DEM are presented. Afterwards a FCS is set up, tuned and validated. The road slope value calculated in the first part of the sections serves as input for the FCS in the second part.

### 4.1 Slope Calculation

We compare two approaches to derive the slope of the road from the DEM. As mentioned in Section 3 both approaches calculate a mix of road slope and terrain slope rather than the exact road slope due to the resolution of the DEM dataset. With this in mind we refer to the results as road slope in the following.

In the first approach, referred to as **Slope Approach 1** (SA-1), a slope percentage raster is created from the original DEM by applying the Horn algo-

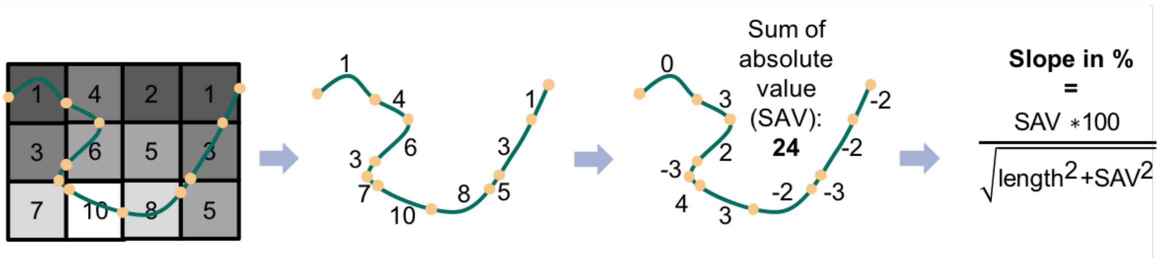


Figure 2: Schema of the SA-2 to calculate road slope directly of the DEM. The numbers of the grid cell symbolize the hight values of the terrain (in meter). In the equation length means the road segment length.

rithm Horn (1981). Then, the OSM road network is overlaid with the slope raster. Every road segment intersects multiple pixels of the slope raster. The average of all intersecting pixels is assigned as road slope value to the road segment.

The second approach is herein referred to as **Slope Approach 2** (SA-2) and is visualized in Figure 2. First, the OSM road network is overlaid with the DEM raster. Every road segment is cut in smaller pieces by the 30 m raster pixels of the DEM. Then, the height difference of every road segment to the road segment before is calculated. The absolute value of these differences along the original road segment is summed up. Finally, the slope of the road in percent is calculated according to the equation in the last step of Figure 2.

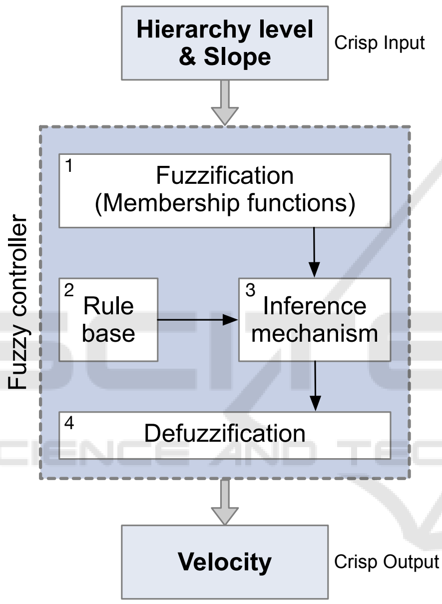


Figure 4: Schema of the Fuzzy Control System.

## 4.2 Developing a Fuzzy Control System

We develop a FCS that calculates the velocity with the two road parameters hierarchy level and road slope. In the following section, a methodology to construct, tune and validate a FCS is presented. A schema of the applied FCS is presented in Figure 4.

### 4.2.1 Setup of the FCS

Road hierarchy level and road slope serve as input parameters to calculate the velocity by car and the travel time, subsequently. Fuzzy logic introduces the concept of partial membership. In a classical or crisp set, members of a crisp set would only be members if their membership was full or complete. In fuzzy sets, however, elements can have varying degrees of membership Mahmoud (2018). Membership functions that are defined on an interval of 0 (not a member) to 1 (full member) characterize the membership of the three parameters slope, hierarchy level and velocity (see Figure 3). Linguistic terms for road hierarchy range from very low to very high and serve as a fuzzification of the classes in Table 1. The terms for slope include level, rolling, mountainous and steep. The output parameter velocity varies from very slow to very fast. The membership functions convert crisp input and output values into fuzzy sets (Figure 4, Step 1).

We use a Mamdani fuzzy inference system Mamdani and Assilian (1975) which has a rule base where every rule contains an antecedent (`IF`) part and a consequent (`THEN`) part (Figure 4, Step 2). Antecedent

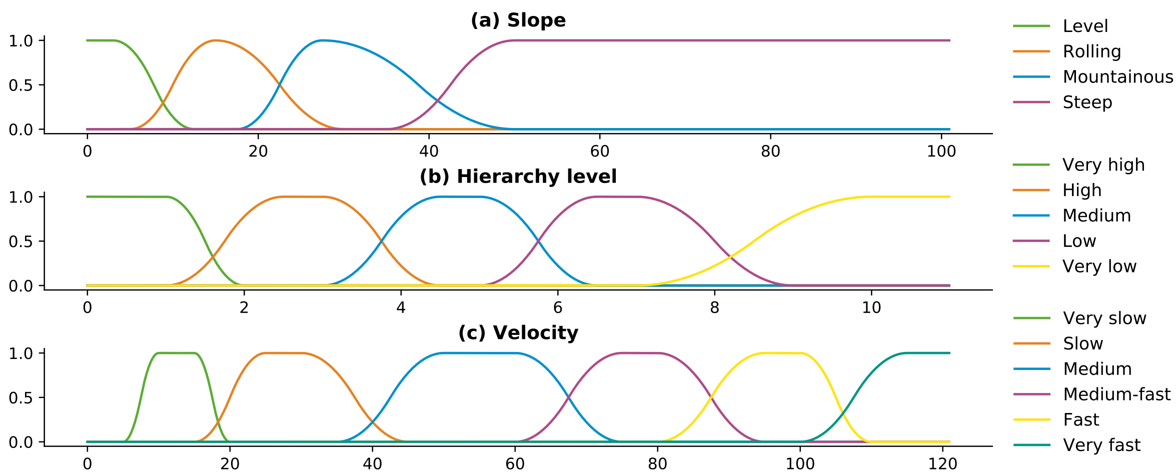


Figure 3: Membership functions of the parameters (a) Slope, (b) Hierarchy level and (c) Velocity.

and consequent variables can be aggregated using an AND-operator. The rule base and the membership functions for this FCS are build based on the design standards of Asian highway routes Behera (2008). These design standards are transferable to Chile as they describe similar road characteristics. A slightly lower velocity was assumed as Behera (2008) describes speed limits and not actual travel speed. 19 rules have been developed with two antecedents and one consequent each. Two exemplary rules are:

- IF slope is level AND road hierarchy level is very high THEN velocity is very fast.
- IF slope is mountainous AND road hierarchy level is very low THEN velocity is slow AND very slow

The final step of a FCS is the defuzzification (Figure 4, Step 4) which converts fuzzy output to crisp output. We tested several defuzzification methods like centroid, bisector and mean-, minimum- and maximum- of maximum. A centroid-based defuzzification (see Mahmoud (2018)) fits our problem best, as it results in a more smooth distribution. The output of the initial FCS is illustrated in Figure 5.

#### 4.2.2 Model Tuning

In order to adapt the initial FCS to produce better outputs, the output is compared to data generated by the GD-API. As described in section 3.2, a subset of approximately 1000 roads is used to tune the FCS.

Some obstacles exist when comparing the output of the FCS to the GD-API output. As mentioned in Section 3, both the Google data and the OSM data may contain errors. Furthermore, as the GD-API always takes the shortest path, it may take a different path between the two input coordinates than the road from which we want to compare the velocity. Also, the output of travel time of the GD-API is whole seconds. Therefore, short road segments with a travel time of only few seconds may be less accurate due to rounding. An exemplary output from the GD-API of 4 s for a 100 m road segment can signify a velocity of 81 km/h (for 4.4 s) or 102 km/h (for 3.5 s).

Four types of possible errors or large inaccuracies are captured automatically and are excluded of the comparison:

- the distance between either the start or the end points on the road in OSM and in Google is larger than 50 m;
- the lengths of the road in OSM and in Google differ in more than 20 %;
- the road is shorter than 200 m;
- the request to the GD-API returns an error or an empty result set.

The FCS is tuned with the knowledge gained by the comparison with the GD-API. The membership functions and the defuzzification methods are not changed. Only the rule base is adapted to better fit the tuning subset.

#### 4.2.3 Validation

Finally, the data is validated with the GD-API. The validation subset with approximately 5000 roads is used to validate the FCS (see Section 3.2). Possible errors described above are deleted from the validation subset and evaluated to obtain the error statistics.

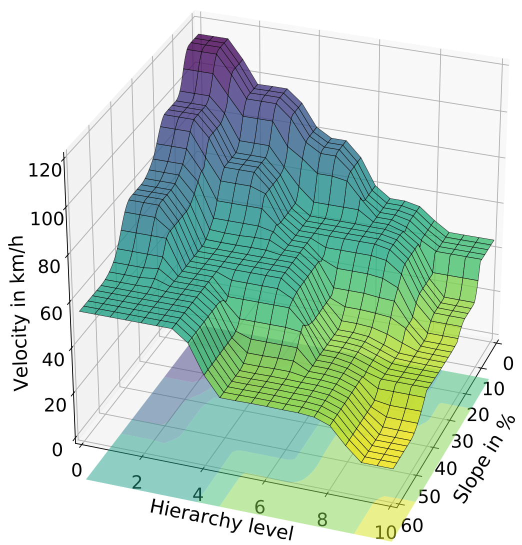

Figure 5: Fuzzy Control System.

## 5 CASE STUDY, RESULTS AND DISCUSSION

### 5.1 Study Region

The model is applied exemplary for the BioBío region in central Chile. The road infrastructure of Chile is typical of a developing country. The upper level road network mainly consists of paved roads. But a lot of minor roads in the category of tertiary roads or unclassified roads are gravel or even mud roads. The BioBío region has a characteristic topography with the coastal mountain range in the west and the Andes in the east. Large areas of the region are rural and not densely populated. This makes the region an ideal candidate to apply the developed FCS. It offers

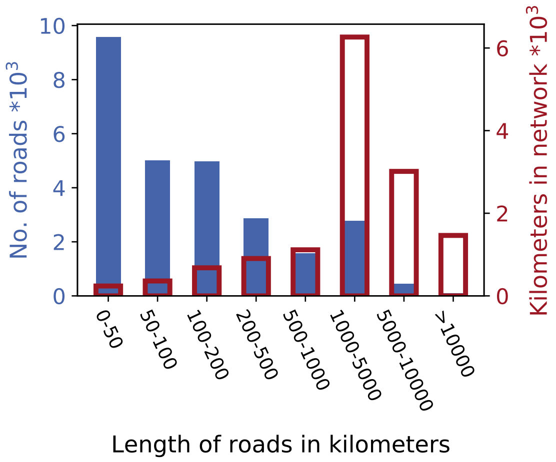


Figure 6: Road segment length in OSM.

a wide range of hierarchy levels and slopes. Furthermore, only 2.6 % of the roads in Chile (5.5 % of the kilometers in the network) have corresponding speed information in OSM, which underlines the need to calculate velocity from another source.

The OSM data for the BioBío region consists of about 14 040 km of road network. The road network is classified as follows: 53 % tertiary roads, 18 % unclassified roads, 12 % primary roads, 10 % secondary roads, 6 % motorways and 1 % trunks. Figure 6 illustrates the distribution of road segments of specific lengths: once in relation to the number of roads and once in relation to the kilometers in the road network. This figure states clearly that there are many road segments shorter than 200 m. But their percentage in respect to the kilometers in the road network is low which renders them insignificant.

Before applying the FCS, the hierarchy level of every road class in the region has to be assigned. The fuzzy input hierarchy level ranges from 0 (very high) to 10 (very low). Based on expert knowledge, roads were assigned the following values: motorways 1.8, trunks 4.3, primary roads 5, secondary roads 7, tertiary roads 8.7 and unclassified roads 10. The hierarchy levels have to be chosen for every region while taking into account its specific level of infrastructure development.

## 5.2 Results

The initial FCS achieves an $R^2$ of 89.3 % for the SA-1 and 87.8 % for the SA-2 (see Table 2). The FCS performs best for motorways, followed by unclassified roads. The tuned FCS reaches a slightly higher $R^2$ of 89.5 % for the SA-1 and 88.3 for the SA-2. The road classes motorway and unclassified decrease their $R^2$ in the tuned FCS slightly while the others perform better.

Figure 7 shows the deviation percentage from GD-API seconds of the kilometer-wise largest road classes tertiary, unclassified and primary for the initial (left) and for the tuned (right) FCS. Negative percentages signify that the FCS estimates lower travel times than the GD-API. With the initial FCS (Figure 7, left), the estimated travel time is generally lower than the one of the GD-API. With the tuned FCS (Figure 7, right), the average and median of the deviation percentage is around zero for all road classes and most of the data ranges from −25 % to 25 %. The interquartile range of the results of the tuned FCS is wider than with the initial FCS. Furthermore, the interquartile range and the total range is generally smaller for the SA-2 than for the SA-1. The deviation percentage of the SA-1 is, in most cases, slightly larger than for SA-2.

A map of the deviation percentage with the tuned FCS and SA-1 is illustrated in Figure 8. The deviation percentage in the central plains of the study region is larger than in the coastal mountain range in the west. In the center of the region, link travel times that are underestimated by the FCS (dark red) and link travel times that are overestimated by the FCS (dark blue) are often spatially close to each other. This also occurs more often near urban centers. Within the urban centers, the FCS mostly calculates lower travel times than the GD-API.

Of the 5023 roads considered for validation, approximately 13 % were excluded due to the errors described in section 4.2.2. The errors occurred when the road distance between the OSM and the GD-API data differed in more than 20 % (50 % of the errors) and when the start or endpoints differ in more than 50 m (46 % of the errors). In 17 cases the GD-API

Table 2: $R^2$ in % for the initial and for the tuned FCS and for both slope calculation methods.

| | | Motorway | Trunk | Primary | Secondary | Tertiary | Unclassified | **Total** |
|---|---|---|---|---|---|---|---|---|
| Initial | SA-1 | 98.0 | 76.0 | 81.1 | 87.1 | 88.1 | 89.5 | **89.3** |
| | SA-2 | 97.7 | 78.0 | 82.2 | 85.0 | 88.3 | 88.2 | **87.8** |
| Tuned | SA-1 | 97.8 | 78.5 | 83.0 | 89.6 | 89.1 | 89.0 | **89.5** |
| | SA-2 | 97.5 | 80.1 | 83.7 | 86.3 | 88.6 | 87.4 | **88.3** |

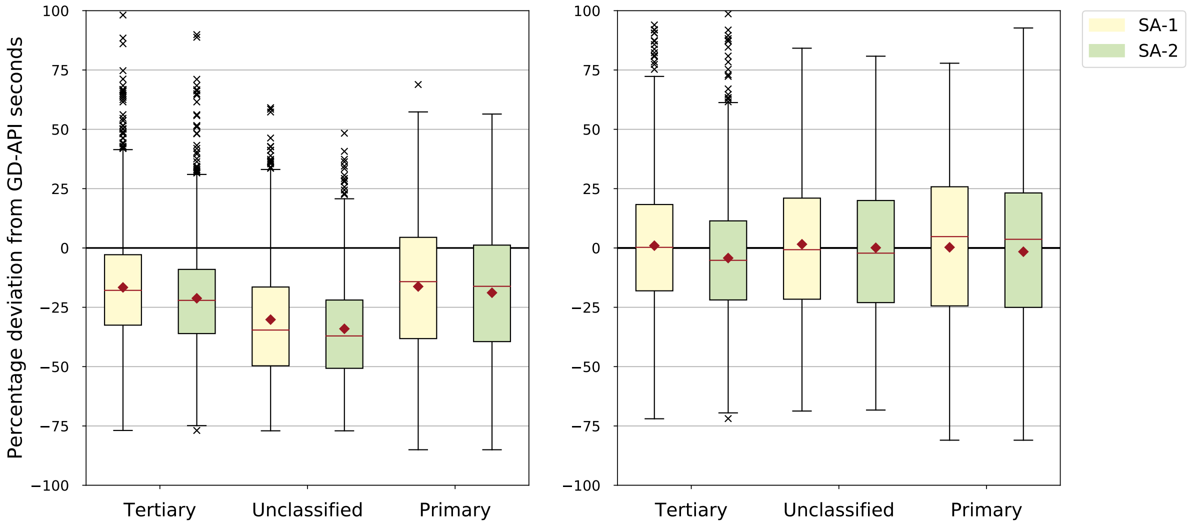


Figure 7: Deviation percentage of the three largest road classes in the initial (left) and in the tuned FCS (right) and respectively for both slope calculation methods.

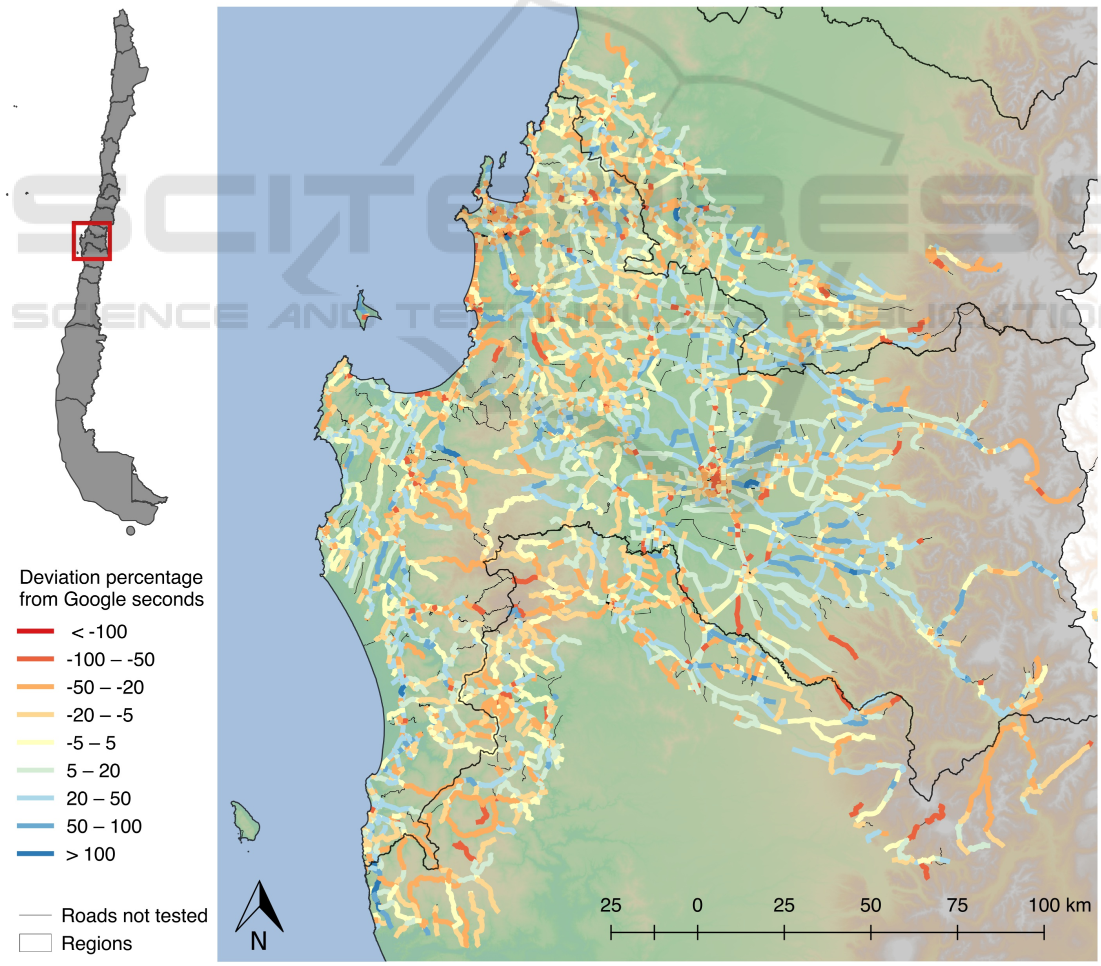


Figure 8: Map of deviation percentage in the tuned model with SA-1. If the percentage is negative (yellow - red), the calculated travel time is lower than the reference travel time of the GD-API.

responded with an error, for 5 roads it gave an empty result.

### 5.3 Discussion

Two approaches to calculate road slope from a DEM, presented in Section 4.1, are applied within the scope of this paper. The initial expectation was that SA-2 performs better because it approximates the actual road slope more accurately by considering only the pixels of the DEM that the road intersects. In contrast, the SA-1 calculates the slope by including neighbouring pixels on all sides, thus including possible hills beside the road. When comparing both approaches, the results are surprising: the FCS with SA-1 performs slightly more accurate, both regarding the $R^2$ and regarding the deviation percentage. But, as the interquartile range and the total range of the data is smaller in the SA-2, the SA-2 is more precise while less accurate than SA-1.

Regarding the $R^2$ of the initial FCS versus the tuned FCS, the improvement is insignificant. From the deviation percentage (see Figure 7) we gather that the accuracy increases significantly in the tuned FCS. However, the precision decreases as the interquartile range and the total range widens. When applying the generated travel times for routing, the choice of FCS is dependent on the requirements of the application. The initial FCS should be chosen if an overestimation of travel time needs to be avoided. If a more accurate result is desired and a possible overestimation is of little consequence, we suggest the tuned FCS. For complete routes, road segments are summed up and positive and negative deviations from the GD-API nearly cancel each other out.

For some road classes, the FCS performs better than for others. Motorways are estimated with a very high $R^2$ (>97.5 %). A motorway features a mostly homogeneous velocity and little slope variation and the class contains little variety within. Both aspects facilitate the estimation of travel time. On the other side, primary roads represent a very inhomogeneous class with some roads having two lanes and others that are only just asphalted. This poses a challenge to the FCS which is recognizable by the lower $R^2$ and the high interquartile range. The two largest road classes tertiary and unclassified are underestimated in the initial FCS. Probably this results from the fact that road conditions of the lower road classes in Chile are worse than expected. The road class trunk has the lowest $R^2$ value which is due to the fact that this road class is very uncommon in Chile. Roads that are classified as trunks in other countries are probably tagged as primary roads in Chile.

The presented fuzzy estimation of link travel time is designed for rural application. In urban and suburban regions traffic, number of turns or local speed limits play a much bigger role for the estimation of travel time than slope and hierarchy level. Therefore, travel times in urban centers estimated with the developed FCS should be treated with caution.

To tune and to validate the FCS, GD-API data is applied. As mentioned in Section 3.2 some differences exist between the Google Maps data and the OSM data. The error statistics emphasize this issue. Some errors can not be caught and are treated as reference data which falsifies the tuning and the validation. Thus, the GD-API data is only suitable to some extend as valid reference data. However, other reference datasets that are readily available and feature worldwide coverage do not exist.

## 6 CONCLUSIONS

We develop a FCS to estimate link travel time from the two parameters road slope and road hierarchy level. The open source and worldwide available datasets OSM and SRTM serve as input data. The FCS is validated with GD-API data. An exemplary application on a case study for the BioBío region in Chile is performed successfully.

The developed FCS offers the advantages of Fuzzy Control. It includes fuzzy input parameters and a reasoning process of a human operator. Both enable a relatively clean and fast design process. Especially in comparison to the common use of fixed speed profiles, a FCS produces a more continuous output. In contrast to machine learning approaches, training data is not needed as it is based on expert knowledge. For our FCS this is a crucial benefit as real training data is unavailable. However, it has to be considered that the ability of a FCS to perform well, highly depends on its design. A FCS is much more susceptible to false assumptions than for example a machine learning model would be.

The findings of this study can be used in many different applications. Most routing engines could benefit from the introduction of Fuzzy Control to combine their various input parameters in order to obtain a more continuous output. Furthermore, road slope could also be included as one of these input parameters to improve the accuracy in rural regions for these routing engines. Many studies on critical road infrastructure rely on commercial travel time data as a cost factor in the road network. They could benefit very much from estimated link travel times in rural regions.

The fuzzy estimation of link travel time has great potential for future development. A FCS can take multiple input parameters so that more of the existing metadata in OSM could be included in the speed calculation. Also, the sinuosity of a road is a big influencing factor on link travel time and could be an additional input parameter. In order to state which of the presented slope calculation approaches is to be used in which cases, further analyses in many different study areas are needed. Another inquiring approach could be to combine our proposed fuzzy methodology with approaches like machine learning. A neuro-fuzzy system could improve the estimations of the FCS using appropriate reference data.

## ACKNOWLEDGEMENTS

We thank Prof. Dr.-Ing. Stefan Hinz head of the Institute of Photogrammetry and Remote Sensing at the Karlsruhe Institute of Technology for the funding of this work.

## REFERENCES

Barrington-Leigh, C. and Millard-Ball, A. (2017). The world's user-generated road map is more than 80% complete. *PLOS ONE*, 12(8):1–20.

Behera, S. K. (2008). *Connecting India's North East with Bangladesh: a study of transport linkages*. PhD thesis, Scholl of International Studies, Jawaharlal Nehru University, India.

Brabyn, L. and Skelly, C. (2001). Geographical Access to Services, Health (GASH): Modelling Population Access to New Zealand Public Hospitals. In *The 13 th Annual Colloquium of the Spatial Information Research Centre*, page 11, Dunedin, New Zealand.

Cipeluch, B., Jacob, R., Winstanley, A., and Mooney, P. (2010). Comparison of the accuracy of OpenStreetMap for Ireland with Google Maps and Bing Maps. In *In Proceedings of the Ninth International Symposium on Spatial Accuracy Assessment in Natural Resuorces and Enviromental Sciences*, page 4, Leicester, UK.

Collischonn, W. and Pilar, J. V. (2000). A direction dependent least-cost-path algorithm for roads and canals. *International Journal of Geographical Information Science*, 14(4):397–406.

Das, R. D. and Winter, S. (2018). A fuzzy logic based transport mode detection framework in urban environment. *Journal of Intelligent Transportation Systems*, pages 1–12.

Demetriou, D. (2016). Uncertainty of OpenStreetMap data for the road network in Cyprus. In Themistocleous, K., Hadjimitsis, D. G., Michaelides, S., and Papadavid, G., editors, *Fourth International Conference on Remote Sensing and Geoinformation of the Environment*.

Dorn, H., Törnros, T., and Zipf, A. (2015). Quality Evaluation of VGI Using Authoritative Data – A Comparison with Land Use Data in Southern Germany. *ISPRS International Journal of Geo-Information*, 4(3):1657–1671.

Girres, J.-F. and Touya, G. (2010). Quality Assessment of the French OpenStreetMap Dataset: Quality Assessment of the French OpenStreetMap Dataset. *Transactions in GIS*, 14(4):435–459.

Haklay, M. (2010). How Good is Volunteered Geographical Information? A Comparative Study of OpenStreetMap and Ordnance Survey Datasets. *Environment and Planning B: Planning and Design*, 37(4):682–703.

Hayward, G. and Davidson, V. (2003). Fuzzy logic applications. *Analyst*, 128:3.

Horn, B. (1981). Hill shading and the reflectance map. *Proceedings of the IEEE*, 69(1):14–47.

Jackson, S., Mullen, W., Agouris, P., Crooks, A., Croitoru, A., and Stefanidis, A. (2013). Assessing Completeness and Spatial Error of Features in Volunteered Geographic Information. *ISPRS International Journal of Geo-Information*, 2(2):507–530.

Jantzen, J. (2007). *Foundations of Fuzzy Control*. John Wiley & Sons, Ltd, Chichester, UK.

Knoop, V. L., Snelder, M., van Zuylen, H. J., and Hoogendoorn, S. P. (2012). Link-level vulnerability indicators for real-world networks. *Transportation Research Part A: Policy and Practice*, 46(5):843–854.

Li, X., Zhao, Z., Zhu, X., and Wyatt, T. (2011). Covering models and optimization techniques for emergency response facility location and planning: a review. *Mathematical Methods of Operations Research*, 74(3):281–310.

Ludwig, I., Voss, A., and Krause-Traudes, M. (2011). A Comparison of the Street Networks of Navteq and OSM in Germany. In *Advancing Geoinformation Science for a Changing World*, pages 65–84. Springer, Berlin, Heidelberg.

Luxen, D. and Vetter, C. (2011). Real-time routing with OpenStreetMap data. In *Proceedings of the 19th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems - GIS '11*, page 513, Chicago, Illinois. ACM Press.

Mahabir, R., Stefanidis, A., Croitoru, A., Crooks, A., and Agouris, P. (2017). Authoritative and Volunteered Geographical Information in a Developing Country: A Comparative Case Study of Road Datasets in Nairobi, Kenya. *ISPRS International Journal of Geo-Information*, 6(1):24.

Mahmoud, M. S. (2018). *Fuzzy Control, Estimation and Diagnosis*. Springer International Publishing, Cham.

Mamdani, E. H. and Assilian, S. (1975). An experiment in linguistic synthesis with a fuzzy logic controller. *International Journal of Man-Machine Studies*, 7(1):1–13.

NASA and USGS (2013). Shuttle Radar Topography Mission. 1 Arc second void-filled. https://earthexplorer.usgs.gov. Downloaded 25 May 2018.

Neis, P., Zielstra, D., and Zipf, A. (2011). The Street Network Evolution of Crowdsourced Maps: OpenStreetMap in Germany 2007-2011. *Future Internet*, 4(1):1–21.

ORS (2018). OpenRouteService: The spatial services api with plenty of features. https://openrouteservice.org/. Accessed 30 November 2018.

OSM Wiki (2016). Using OpenStreetMap: OpenStreetMap Wiki. http://wiki.openstreetmap.org/. Accessed 25 November 2018.

OTP (2018). OpenTripPlanner – Multimodal Trip Planning. http://www.opentripplanner.org/. Accessed 30 November 2018.

Scott, D. M., Novak, D. C., Aultman-Hall, L., and Guo, F. (2006). Network Robustness Index: A new method for identifying critical links and evaluating the performance of transportation networks. *Journal of Transport Geography*, 14(3):215–227.

Shackelford, A. and Davis, C. (2003). A combined fuzzy pixel-based and object-based approach for classification of high-resolution multispectral data over urban areas. *IEEE Transactions on Geoscience and Remote Sensing*, 41(10):2354–2364.

Stanojevic, R., Abbar, S., and Mokbel, M. (2018). W-edge: weighing the edges of the road network. In *Proceedings of the 26th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems - SIGSPATIAL '18*, pages 424–427, Seattle, Washington. ACM Press.

Steiger, E., Rylov, M., and Zipf, A. (2016). Echtzeitverkehrslage basierend auf OSM-Daten im OpenRouteService. *AGIT Journal*, 2:264–267.

Wang, X. J., Zhao, R. H., and Hao, Y. W. (2011). Flood Control Operations Based on the Theory of Variable Fuzzy Sets. *Water Resources Management*, 25(3):777–792.

YOURS (2018). YourNavigation - Worldwide routing on OpenStreetMap data. http://yournavigation.org. Accessed 30 November 2018.