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Estimation of link-cost function for cyclists based on stochastic optimisation and GPS traces

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Abstract: The objective of this work is the calibration of a generalised cost function for the bicycle network links to be used in conjunction with assignment methods for uncongested networks, as cyclists are generally much less delayed by traffic congestions with respect to auto-traffic. The calibration's goal is to find a coefficient vector for a linear link-cost function that maximises the overlap between routes obtained with a minimum cost routing of cyclists' demand and the relative cyclists' chosen routes, identified by a map-matching procedure of recorded global positioning system (GPS) traces. The calibration focuses on minimising an objective function through different established evolution-based optimisation algorithms, thus avoiding the generation of route choice sets. Link cost functions are calibrated for a modified Openstreet network of Bologna, Italy, using GPS data from the European cycling challenge and Bella Mossa campaign. Results show an improvement of up to 30% of overlapping routes with respect to pure distance-based routing. It is also demonstrated that the calibrated link-costs are transferable to a different scenario.

1 Introduction

1.1 Problem definition

Most traffic assignment models use several attributes including travel time and distance as link-costs of a road network, as these are the most significant attributes for drivers to select the preferred route. Instead, cyclists perceive link-costs differently: safety, physical fatigue, health and build-environments are important issues in the cyclists' path choice. On the other hand, cyclists are generally much less delayed by traffic congestions with respect to auto-traffic [1] – as long as the road remains sufficiently permeable. In fact, even in cities with high bike mode share, bicycle congestions may play a minor role, as investigated in [2] for the greater Copenhagen area. The present study is an effort to quantify the cyclists' link-costs of the road network concentrating on known road attributes.

The scope of this paper is to calibrate parameters of a generalised cost function of road network links, to be used in conjunction with either deterministic or stochastic assignment methods of uncongested networks for solving bicycle traffic assignment problems.

1.2 Literature review

In the literature, many studies deal with the identification of road attributes that affect the cyclists' path choice and different models have been calibrated to quantify their respective influence [2–10]. In particular, the studies in [3, 6–10] have compared the cyclist's route choice with the shortest route in order to find attributes that cause the users to deviate from the shortest path: for example, in [10] the shortest path has been used to split the global positioning system (GPS) recorded traces in a set of detour-classes. Moreover, Rupi *et al.* [8] calibrated a binominal logit-model able to predict if a cyclist will choose either the shortest route or a non-overlapping alternative, based on route-links attributes.

A major problem of such route choice models is the determination of the choice set among which cyclists can select their routes – it is generally unknown which routes a cyclist considers as alternatives between a specific origin and destination, and in particular how users can detour from the shortest path. Empirical data on detours have been calculated in different ways, see for example Rupi *et al.* [8], Park and Akar [10], Pritchard *et al.* [11] and Griffin and Jiao [12]. For example, Park and Akar [10], in Ohio, found that most bicycle trips (91.1%) include a detour and that these are 13.5% longer on average than their shortest alternatives, with large variations. Moreover, Rupi *et al.* [8], in Italy, found that detours are 20.7% longer on average with respect to the shortest path.

A related problem is that alternative routes are mutually overlapping or cyclists choose a route only because it is the single feasible alternative. However, different procedures have been proposed to generate the route choice set, for example, in [13] the problem is analysed with a data-driven approach, where the route choice set is defined by effectively chosen routes; another method eliminates consecutively links on the shortest path and performs a rerouting after each iteration [4]. Broach *et al.* [14] have used a labelling method for generating bicyclist route choice sets, incorporating unbiased attribute variation. Additionally, Koch *et al.* [15] compared the observed routes to those created by a double stochastic generation function method. Hood *et al.* [16] used as a similar method of choice set generation: a network-based automatic calibration of the 'doubly stochastic' method of Bovy and Fiorenzo-Catalano [17].

Generally, traffic congestions do not seem to alter cyclists' travel times which greatly simplifies the assignment procedure. Even for bicycle cities like Copenhagen, the congestion effects on bikes seem limited: Paulsen and Nagel [2] have shown that, even by assigning more than a million bicycle trips to the Copenhagen bike network, travel times of cyclists do not increase significantly.

1.3 Research contribution

The calibration of the link-costs in combination with assignment method for uncongested networks allows calculating the most likely route choice while avoiding the problem of choice set definition. This work presents an unconventional direct method to calibrate the parameters of a general link-cost function for cyclists. The method can be applied in a city where GPS traces of bike trips are available. Once the link-costs are calibrated, they can be used for uncongested deterministic or stochastic traffic assignments of cyclist Origin to Destination (OD) demand, reproducing the most similar flows. Clearly, the calibrated link-costs could be used in 'all or nothing' assignments or as deterministic component in stochastic link-cost models, such as the Probit assignment method.

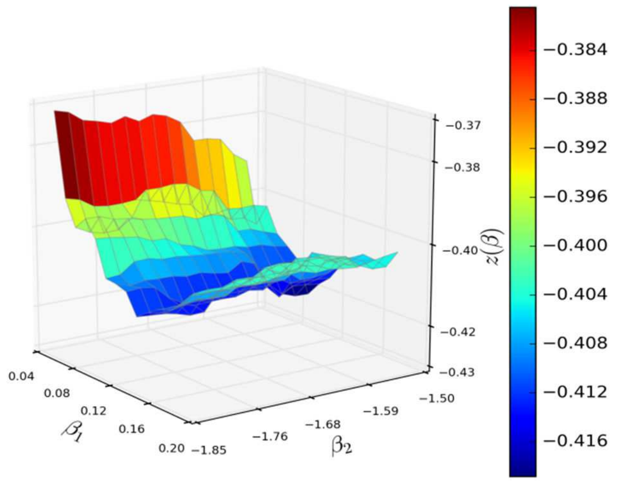

Fig. 1 *Illustration of the surface of the objective function $z(\boldsymbol{\beta})$. For illustration purposes the beta vector is only two-dimensional: β_1 is the coefficient for the link length and β_2 for the exclusive bikeway attribute. The plot has been computed with the GPS traces from the ECC in Bologna 2015, for details see Section 3*

The calibration method is applied to the road network of Bologna (Italy), using GPS traces from 2014 to 2017.

2 Methodology

The methodology requires the definition of a link cost function and a scalar objective function to quantify the overlap between chosen and modelled routes. Furthermore, stochastic optimisation methods are used to find a parameter vector of the link cost function that maximises the overlap.

2.1 Objective function

Prior to the calibration of the generalised disutility function for cyclists, a road network must be available, where each network link a has the link attributes $\boldsymbol{x}_a$ (e.g. link length, exclusive bike access, number of lanes etc.). The routes chosen by the cyclists must also be known, where each route r_i is a sequence of network links connecting an OD pair. The chosen route r_i can be identified by a map-matching process [18]: for each trip i, a cyclist has recorded a sequence of GPS points via a dedicated smartphone application; the map-matching process matches these geo-referenced points to a sequence of links of the respective road network. Successively, a cost function $c_a(\boldsymbol{\beta}, \boldsymbol{x}_a) = \boldsymbol{\beta}' \boldsymbol{x}_a + \alpha$ of link a is defined as a linear combination between parameter vector $\boldsymbol{\beta}$ and link attribute vector $\boldsymbol{x}_a$, where $\boldsymbol{\beta}$ is to be calibrated by minimising the objective function $z(\boldsymbol{\beta})$ and α is an arbitrary, non-zero constant. In this work, this objective function is the negative normalised sum of the length of overlapping links between each chosen route r_i and the respective model route q_i, over all routes. The model route q_i is obtained by a Dijkstra routing, connecting the first and the last link in r_i, while assuming the link costs $c_a = c_a(\boldsymbol{\beta}, \boldsymbol{x}_a)$. Let the overlapping length of route i be defined as $Q_i(\boldsymbol{\beta}) = \sum_{\forall a} L_a \delta_{ai}(\boldsymbol{\beta})$ where $\delta_{ai}(\boldsymbol{\beta}) = 1$ if $a \in r_i \cap a \in q_i$ (i.e. link a is contained in chosen route r_i and in model route q_i), otherwise $\delta_{ai}(\boldsymbol{\beta}) = 0$.

The factor $\delta_{ai}(\boldsymbol{\beta})$ clearly depends on the link costs and indirectly on the link-cost parameter $\boldsymbol{\beta}$. Then the objective function to be minimised can be written as:

$$z(\boldsymbol{\beta}) = -\frac{\sum_{\forall i} Q_i(\boldsymbol{\beta})}{\sum_{\forall i} \sum_{a \in r_i} L_a} \qquad (1)$$

where the numerator represents the total overlap and the denominator represents the total distance of all routes, as L_a is the geometric length of the link a. The objective function can be interpreted as the negative relative overlap of all routes. In the ideal case, when all model routes are equal to the chosen routes, then $z(\boldsymbol{\beta}) = -1$, while if all links are not overlapping, then $z(\boldsymbol{\beta}) = 0$. The calibration problem is to find the parameter vector $\boldsymbol{\beta} = \hat{\boldsymbol{\beta}}$ which minimises $z(\boldsymbol{\beta})$. Unfortunately, this is not a simple optimisation problem due to the following reasons: the objective function is neither convex nor continuous and there are multiple local minima, see Fig. 1 for an example of an objective function from the dataset explained in Section 3. One can clearly see the irregular surface with many local minima, but within this rough surface one can also observe a valley which contains a global minimum. Due to the many local minima, all optimisation algorithms based on gradients or Hessians fail to find a global minimum. For this reason, stochastic optimisation algorithms are employed to solve this optimisation problem.

2.2 Stochastic optimisation algorithms

Stochastic optimisation algorithms are based on a population of different parameter vectors which seek to find the function minimum employing an iterative process. The general principle is that the more successful members of the parameter population will influence the parameter values of other members of the population. In this way, it is hoped that with each iteration at least one member of the population can decrease the objective function with respect to the previous step. The location of parameter-vectors can be constrained in a parameter space defined by minimum parameter values $\boldsymbol{\beta}_{\min}$ and maximum parameter values $\boldsymbol{\beta}_{\max}$.

Different stochastic optimisation algorithms have different strategies to generate the next iteration (or with evolutionary algorithms also called generations) of parameter vectors. For the present problem, three optimisation algorithms have shown good performance.

The differential evolution (DE) [19] is based on a scheme for generating trial parameter vectors. DE generates children parameter vectors by adding a weighted difference vector between two population members to a third member. If the resulting vector yields a lower objective function value than a predetermined population member, the newly generated vector will replace the vector with which it was compared in the following generation.

The particle swarm optimisation (PSO) [20–22] has its origin in the simulation of a bird flock in search for a corn-field. In an abstract version of the original algorithm, a ‘swarm’ of agents, each representing initially random parameter vectors, are trying to optimise a scalar function. Each agent evaluates the objective function with respect for its own parameter value. In addition, each agent knows also the parameter vector of the best agent, the one who has achieved the lowest objective function of all agents. During an iteration, each agent is changing its parameter vector by adding an incremental vector. The direction of the incremental vector points into the direction of the best agent, whereas the size of the increments takes some random values. The increment corresponds to the speed with which agents of the swarm change their ‘positions’ in the parameter space.

The covariance matrix adaptation (CMA) evolution strategy considers a population of agents, where each agent represents a parameter vector of an objective function. Each member of the population will have a certain number of children. The parameters of the children are multinomial distributed with a mean value which is equal to the parameters of the parent. Successively only children with a lower objective function with respect to their parent are considered. The parameter vector of the parent is also updated by adding a zero mean, multinomial noise value. The particularity is that the variances of the single noise components depend on the parameter values of the component of the best-performing children. This means the family will improve with each generation. For details, see [23].

The common property of all three algorithms is that they have the capacity to find a global optimum because the search is spread over some predefined parameter space. There are several limitations of the proposed algorithms: it is not guaranteed that the global minimum of the objective function will be found, especially if the dimensions of the parameter space increases; it is possible to

Fig. 2 *Bologna SUMO transport network (in blue), overlapped with GPS traces from the ECC (yellow) recorded in 2015. The graphics are generated by the GUI from SUMOPy*

Table 1 Link cost calibration results. All stochastic optimisation methods use a population size of 26 as recommended by the Stochopy documentation [17] for a two-dimensional optimisation problem

Method	$\hat{\beta}$ Calibrated with ECC 2014	$z(\hat{\beta})$ ECC 2014	Improvement ECC 2014, %
DE	[1.5314, −0.449]	−0.44356	16.72
PSO	[0.2429, −0.4289]	−0.46227	21.65
CMA	[0.7156, −0.1216]	−0.45963	20.96

increase the population size in order to improve the exploration of all the parameter space, but then computation time increases and the convergence becomes slower.

Regarding the specific application to link-cost estimations, it is not clear how much the optimal bike link costs improve the correct identification of the chosen bike path and whether the calibrated parameters are transferable to a different scenario. Such questions are addressed in the next section where the stochastic optimisation methods are used to calibrate a link cost model for bike routes in Bologna, Italy.

3 Results

The proposed calibration method is applied to the road network of Bologna, Italy. The road network is extracted from *Openstreet* data and the GPS traces are taken from different years: the European Cycling Challenge (ECC) for the years 2014, 2015 and 2016, and Bella Mossa (BM) in the year 2017. The recording period is the month of May of the respective year. Details on the data processing and map-matching can be found in [6]. The *Openstreet* network is converted into a SUMO transport network [24] and edited/completed manually with a special editor. The software environment SUMOPy [25] allows to import the *Openstreet* network in SUMO, import the GPS traces, do the map-matching and run the Dijkstra routing. Fig. 2 represents the SUMO transport network in the software SUMOPy, overlapped with GPS traces of the ECC of the year 2015. The main calibration script is implemented in Python, using the stochastic optimisation algorithms from the *stochopy* package [26].

In a first step, the performances of the three stochastic optimisation methods have been determined. For this purpose, only two road link attributes are considered as attribute vector $\boldsymbol{x'}_a = [L_a, L_aB_a]$: the link length L_a and the exclusive bikeway attribute B_a (where $B_a = 1$ if link a is an exclusive bikeway, otherwise $B_a = 0$) The constant α has been fixed to one. The constant is meant to account for all not considered costs per link.; the most important not included variable is likely to be the waiting time at junctions. Note that α is constant but the parameters $\boldsymbol{\beta}$ of the other attributes will adjust their value relative to α during the optimisation. All elements of $\boldsymbol{\beta}_{\min}$ were initially set to -2, and all elements of $\boldsymbol{\beta}_{\max}$ are set to $+2$. The definition of the parameter-space has been found after some initial estimation trials, clearly the larger the parameter space, the longer it takes for the algorithms to converge. The cost functions have been calibrated with 2619 trips from the ECC 2014. The performance of the calibrated link cost functions has been quantified by measuring the improvement of the objective function with respect to the simple shortest path routing, which is equivalent to link cost functions with parameters $\boldsymbol{\beta}_{\text{SP}} = [1, 0]$: for the ECC 2014, the objective function results in $z(\boldsymbol{\beta}_{\text{SP}}) = -0.380$ in this case. As shown in Table 1, the objective function value becomes more negative when routing with the calibrated link cost functions. The improvements are 21% with respect to the shortest routes when link-costs are calibrated with the PSO method, see Table 1. Comparable improvements are obtained by calibrating with the CMA method. Note that the signs of the estimated parameters are reasonable for all optimisation methods: the first parameter is positive as an increased link length increases the perceived costs, while the second parameter is negative because in case the link is a reserved bikeway then the perceived link cost is reduced. However, the parameter vectors from the different optimisation methods vary considerably because each method does apparently find different local minima of the objective function. An increase of the population could improve the results, forcing the algorithms to find the same, global minima for all methods.

Successively only PSO has been considered to perform further calibrations with different parameter vectors.

In general, it has been found that a parameter space greater than three dimensions did not improve the results, or the algorithm gets trapped in an insignificant local minimum. This limitation may be overcome by optimising the algorithm-internal parameters, as described in [21], which would be the first step to pursue in future works.

Starting with two dimensions, the general link cost attribute $\boldsymbol{x'}_a = [L_a, X_a]$ has been tested, where X_a has taken one of the following link attributes: exclusive bikeways, bikeways with pedestrian access, road width, maximum allowed speed, low-priority roads, presence of traffic lights, number of entering roads at the entry node of the link and number of incoming roads from the right side. The outcome has been that all attributes but the 'exclusive bikeway' attribute showed only minor improvements of the overlap. It could not be clarified why the optimiser has not been sensible to many of the tried road attributes. It may be due to inconsistent network information (for example intersections with minor, irrelevant roads), or the optimisation is not able to identify the parameters due to the roughness of the objective function. Note that slopes have not been considered as they play a marginal role in most parts of Bologna, but may be relevant in hilly cities. The attribute which delivered the best results remained the presence of exclusive bikeways.

For the following investigation, two different attribute vectors have been taken into consideration: the attribute vector with a constant exclusive bikeway $\boldsymbol{x}_a^{\text{C}} = [L_a, B_a]'$ and $\boldsymbol{x}_a^{\text{P}} = [L_a, L_aB_a]'$ where the exclusive bikeway attribute is proportional to the link length L_a, in accordance with other studies [4, 8, 27].

The calibration of the link-cost functions with both attribute vectors and for different data sets is summarised in Table 2. For example, the calibration with attribute vector $\boldsymbol{x}_a^{\text{C}}$ using the GPS traces from ECC 2016 achieved a minimum objective function of −0.39468, which means that 39% of the length of all model routes do overlap with the effectively chosen route.

In general, the overlaps for the two attribute vectors $\boldsymbol{x}_a^{\text{C}}$ and $\boldsymbol{x}_a^{\text{P}}$ are similar for the same data set, where the attribute vectors $\boldsymbol{x}_a^{\text{P}}$ generally result in slightly better overlaps. However, the different data sets show considerable differences in overlap and improvements with respect to the shortest distance routing. The parameter vectors $\hat{\boldsymbol{\beta}}$ calibrated for different years using attribute vectors $\boldsymbol{x}_a^{\text{C}}$ are similar in magnitude. The parameter vectors using attribute vectors $\boldsymbol{x}_a^{\text{P}}$ are more variable, especially the 2017 data set shows diverse parameters with respect to the other data sets. As the

Table 2 Link cost calibration results using both attribute vectors x_a^C and x_a^P and improvements with respect to the shortest path routing, see text for definitions

Data set, year	Attribute vector type	$\hat{\beta}$ (transposed)	$z(\beta_{SP})$	$z(\hat{\beta})$	Improvement over shortest path, %
ECC, 2014	x_a^C	[0.3031, − 1.1545]	−0.3800	−0.4407	15.98
ECC, 2014	x_a^P	[0.2429, − 0.4289]	—	−0.4623	21.65
ECC, 2015	x_a^C	[0.5857, − 1.6071]	−0.3305	−0.3807	15.19
ECC, 2015	x_a^P	[0.2050, − 1.2343]	—	−0.3887	17.62
ECC, 2016	x_a^C	[0.2018, − 1.3182]	−0.3269	−0.3947	20.74
ECC, 2016	x_a^P	[0.6539, − 0.1969]	—	−0.4274	30.74
BM, 2017	x_a^C	[0.1992, − 1.2397]	−0.3775	−0.4644	23.02
BM, 2017	x_a^P	[1.9991, − 0.3522]	—	−0.4733	25.38

Population size equals 26 for all calibrations.

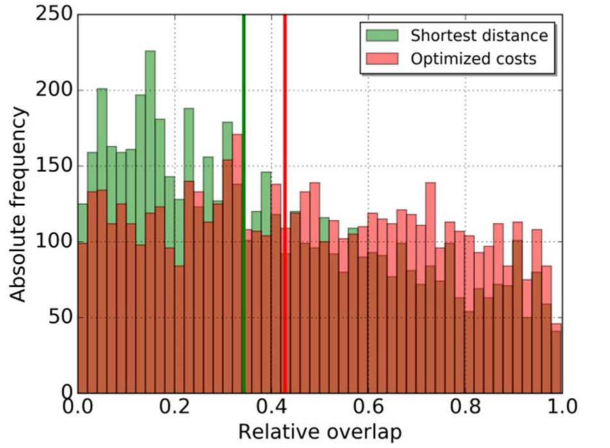

Fig. 3 *Route frequencies of the relative overlaps $\tilde{z}_i(\beta)$ using the bin width of 0.01. The green distribution represents the routes modelled with the simple shortest path parameters $\tilde{z}_i(\beta_{SP})$, while the red distribution is modelled with the calibrated link cost function $\tilde{z}_i(\hat{\beta})$ using $\hat{\beta}$ = [0.6539, − 0.1969]'. The dark area represents the intersection of both distributions. The green vertical bar shows the negative objective function with shortest distance $z(\beta_{SP})$ while the red vertical bar shows the negative objective function $z(\hat{\beta})$. Calibrated with data set ECC 2016 and attribute vector x_a^P*

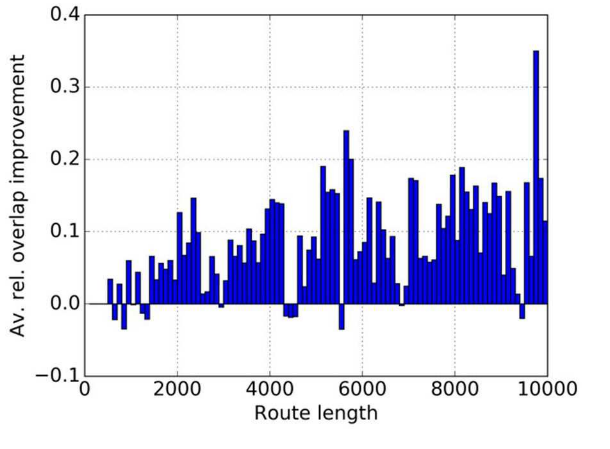

Fig. 4 *Overlap improvement Δ_i over route length (m). The overlap improvements have been averaged within length intervals of 100 m. Calibrated with data set ECC 2016 and attribute vector x_a^P*

first parameter of $\hat{\beta}$ for BM 2017, using x_a^P, is close to the parameter boundary of 2.0, this boundary has been extended to 5.0 for this particular estimation. However the extended parameter space did not result in an improvement of the overlap. Note that the objective function is spiky and even a close point in the parameter space may result in a very different overlap. The surface of the objective function seems to be even rougher than suggested in Fig. 1 because its relatively low space resolution has a smoothing effect.

In an attempt to further increase the overlap, another attribute has been added: the attribute vector $x_a^P = [L_a, L_aB_a, \ L_aW_a]'$ has been used, where W_a corresponds to the road width of link a. The parameter vector obtained from calibration with data set ECC 2014 becomes $\hat{\beta}' = [1.1851, \ -0.2521, \ 4.0629]$ resulting in a $z(\hat{\beta}) = -0.4610$, which is marginally below the overlap found without considering the road width. Running the same calibration with the BM 2017 data set, the parameters $\hat{\beta}' = [1.1614, \ -0.2364, \ 4.1972]$ have been obtained and $z(\hat{\beta}) = -0.47987$, which is slightly better than the overlap using the cost function without the road width. Also, note that the two-parameter vectors are similar.

Before interpreting these results it is interesting to look into some statistical analysis of the improved overlaps. The relative overlap $\tilde{z}_i$ of a single route i by can be defined by the overlapping length over the total route length, hence

$$\tilde{z}_i(\beta) = \frac{Q_i(\beta)}{\sum_{a \in r_i} L_a}. \qquad (2)$$

The following analysis refer to the data set ECC 2016 calibrated with x_a^P (link length proportional bikeway attribute). Other data sets showed qualitatively the same results. The frequency of the routes over the relative overlap is shown in Fig. 3, for both models: the simple shortest path model and the calibrated link cost model. The figure shows clearly that using the simple shortest distance model, there is a high share of trips with low overlap (green distribution below 40%). Instead, with the calibrated link cost model, there are more routes with high relative overlaps (red distribution). However, even with the calibrated link cost model, there is an almost even distribution of trips from zero to total overlap, with a reduced frequency at the total overlap ($\tilde{z}_i = 1$).

It is further interesting to ask whether this improvement in relative overlap depends on the route length. The improvement in overlap for each trip can be quantified by $\Delta_i = \tilde{z}_i(\hat{\beta}) - \tilde{z}_i(\beta_{SP})$. The average improvements over the route length are shown in Fig. 4 for the data set ECC 2016. It can be seen that there is no improvement in overlap for short distances of less than ∼500 m. This can be explained by the fact that simple short routes have typically few route choices and deviations from the shortest path are less likely. Otherwise, it appears from Fig. 4 that the improved overlap with the calibrated link costs are independent of the route length. These results are confirmed applying the same analysis to all other data sets.

The question of whether the proposed link-cost model is transferable can be addressed in two approaches:

(i) If the parameter vectors calibrated with different data sets from different scenarios are similar, then it can be assumed that the

Table 3 Improvements of the objective function $z(\hat{\beta})$ with $\widehat{\beta'} = [0.6539, -0.1969]$ relative to the overlap with shortest path routing $z(\beta_{SP})$

Data set, year	Number of routes	$z(\beta_{SP})$	$z(\hat{\beta})$	Improvement
ECC, 2014	2619	−0.3800	−0.4553	19,81%
ECC, 2015	3280	−0.3305	−0.3842	16.25%
ECC, 2016	5626	−0.3269	−0.4274	30.34%
BM, 2017	16,646	−0.3775	−0.4726	25.19%

The vector $\hat{\beta}$ has been calibrated using the PSO method, the length proportional bikeway attribute and the data set from ECC 2016 (in bold letters).

model is transferable. Looking at Table 2 one can see that the parameters calibrated with the same attribute vectors are similar – the parameters calibrated with x_a^C are identical in sign and similar in magnitude; the parameters calibrated with x_a^P differ more, but have the same size and are in the same order of magnitude. The differences can be explained, in part that the data sets are different (e.g. different participants) and in part that the algorithm converged into different local minima.

(ii) The model calibrated for ECC 2016 has been applied to other data sets and networks from different years (ECC 2014, ECC 2015, ECC 2016 and BM 2017). Table 3 summarises the outcomes and improvements. The improvements between 16 and 25% of scenarios from four consecutive years show that the link cost model is transferable. Note that not only the data sets but also the network has changed throughout the years as new bikeways have been constructed and added to the model. As the cost-function has been calibrated for the year 2016, it is obvious that ECC 2016 results in the highest improvement with respect to shortest path routing.

4 Conclusions

A novel calibration method has been proposed that allows to determine a link cost function for cyclists based on routes from map-matched GPS traces. The link costs have been calibrated and validated with an OpenStreetmap-based network from Bologna, Italy, and GPS-traces recorded in four consecutive years.

The main result has been that the calibration method can improve the correctness of bicycle routing by approximately 16–30% in terms of overlapping route length between the modelled and effective route, with respect to the simple shortest path. With the calibrated link costs, the relative overlaps are approximately equally distributed from zero (no overlap) to one (complete overlap), while a simple shortest path routing generates a higher share of routes with low overlap between shortest route and effectively chosen route. It has further been shown that the improvements in overlap do not depend on the route length, except for routes shorter than ∼500 m.

There is strong evidence that the obtained link cost functions are transferable to three different data sets from different years but from the same city, Bologna. This means the same link cost function may be usable for deterministic or stochastic traffic assignments in other cities. However, the present method does not estimate the dispersion parameter needed to perform stochastic traffic assignments.

In comparison with conventional, likelihood-function based calibration methods, the present calibration method does not require route choice set generation. However, one important disadvantage is the impossibility to determine p values which would allow validating the significance of single model parameters.

One of the biggest current restriction of the employed stochastic optimisation methods is their poor convergence for parameter spaces greater than three. Adding a third attribute to the cost function has hardly improved the overlap. In future research, the objective function could be smoothed by spatial filtering with the effect that the number of local minima is reduced. This would improve the speed of convergence and allow the consideration of more than three-parameter dimensions. Another possibility is to optimise the parameters of the stochastic optimisation algorithms such as population size and spread of the particle population.

5 Acknowledgments

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