GIS-based Identification of Effective Bicycle Level of Service Improvement in Street Networks

Hartwig H. Hochmair
University of Florida

ABSTRACT

Due to countless benefits of cycling as a means of transportation, planning and policy efforts at all levels of governments aim to increase levels of walking and bicycling. Investment in bicycle facilities to improve the Bicycle Level of Service (LOS) is an important ingredient in the mix of governmental initiatives to increase the number of cyclists. To make best use of limited transportation funds, it is necessary to identify street segments which are most effective to be improved. This research presents a new GIS-based method to do so through taking into account the LOS of existing bicycle route alternatives between trip origin and destination. The applicability of the model is demonstrated on a street network dataset of Broward County, Florida.

KEYWORDS: *Level of service, bicycle demand, transportation planning, network analysis, GIS*

INTRODUCTION: BICYCLE LEVEL OF SERVICE AND BICYCLE DEMAND

With growing concerns over traffic congestion, environmental pollution, and the dramatic increase of obesity in the US during the past 20 years, public policy makers are increasingly promoting bicycling as an alternative for commuting and other utilitarian trip purposes. A key to encouraging bicycling is to provide adequate bicycle facilities, such as wide curb lanes or on-street bike lanes, all of which increase the Bicycle Level of Service (LOS) score. LOS refers to a methodology for estimating the level of comfort or perceived safety experienced by a bicyclist on a specific roadway type (Petritsch et al. 2007; Dowling et al. 2008).

Public planning agencies need to know where in the street network the funding in facility improvement is best invested. Whereas numerous studies analyze how travel behavior, route choice, and bicycle use are affected by the availability of bicycle facilities (Krizek and Johnson 2006; Harvey et al. 2008), only few studies provide guidance as to where to build or improve bicycle facilities, which is the purpose of this paper. A related study by Aultman-Hall et al. (1997), for example, suggests that efforts to accommodate commuter cyclists should be focused on improving cycling conditions on the road network, as high-quality direct off-road paths are used only infrequently by commuting cyclists. The Latent Demand method by Landis and Toole (1996) estimates potential demand for bicycle travel that would occur if a bicycle facility existed on a road segment.

The model proposed in this paper assumes that an origin-destination (O-D) matrix containing the number of existing trips between different analysis zones is available. The problem of obtaining the O-D matrix and predicting travel demand is a challenging and widely discussed research topic on its own (Tamin and Willumsen 1989) and left aside here. Suffice it to say that traffic counts, demographic variables, facility variables, and census commute-to-work shares are common sources to predict bicycle demand (Landis and Toole 1996; Krizek et al. 2006). Our model presumes that the cyclist chooses a compromise route between origin and destination where an increased average LOS along the route is traded off with additional travel distance (detour). This assumption is based on earlier findings in a desktop experiment where potential cyclists frequency applied a compensatory decision rule in their bicycle route choice on maps (Hochmair 2004). That is, testing subjects took into account several optimization criteria at the same time when planning their trip, such as attractive

and fast route. Some research papers quantify the interrelation between LOS and detour. For example, using an adaptive stated preference survey, Tilahun et al. (2007) showed for work commute that with a 20 minute base travel time for fastest route, a bike lane improvement is valued at 16.41 minutes, and a no parking improvement is valued at 9.27 minutes. Other studies observe route detour rates which vary with trip purpose. Thompson et al. (2007) used a human intercept survey with recreational and commuter cyclists. Their study concluded that cyclists are willing to travel an average of 67% additional distance to include an off-street path as part of their route. Based on observed bicycle trips Aultman-Hall et al. (1997) found that commuters divert very little (on average 0.4 km) from the shortest path. Using a GPS-based data collection Harvey et al. (2008) analyzed extra distance bicycle commuters are willing to take to travel their preferred route. Given a trip mean length of approximately 10 km, an average detour of about 1 km (10%) could be observed (after removal of two outliers). These studies do not provide an explicit detour-LOS tradeoff rate.

LOS models refer to individual road segments, arterials including intersections, or both (Petritsch et al. 2007). Davis (1987) developed the bicycle safety index rating (BSIR) which provides a mathematical model for indexing bicycle safety to physical roadway features. The roadway segment index (RSI), a part of the BSIR model, considers average daily traffic, number of traffic lanes, speed limit, width of outside traffic lane, pavement factors, and location factors (angled parking, parallel parking, right-turn lanes, raised median, etc.). Planners in Broward County, Florida, adapted the RSI portion of David's BSIR with no major changes, renamed it the roadway condition index (RCI), and currently use the RCI to assess bicycle suitability on major streets and highways within their jurisdiction.

MODELING APPROACH

The proposed model for identifying street segments where LOS improvements is most effective is shown on Broward County network data. We therefore adapt the Broward County RCI scores. To do so we convert the existing RCI values to an LOS range from 1-6, where LOS of 1 means very poor street conditions for cyclists, and 6 stands for superior street conditions. As the Broward County data set assigns RCI values to major streets and highways only, we assume an LOS value of 6 for local streets.

To identify candidate routes between a chosen trip origin and destination, we use a shortest path search, where travel cost (impedance) along a street segment is based on segment length and segment LOS. A low LOS increases the perceived cost or friction along a segment. Muraleetharan and Hagiwara (2007) use the term "optimized LOS-path" for the route that minimizes a distance weighted, LOS-based impedance score along a route. Different routes can be found by varying the weight of LOS in the segment cost model, and minimizing the total cost c of a route (Eq. 1):

$$c = \sum_{i=1}^{N} d_i \cdot \left(m - s \cdot sLOS_i\right) \qquad \text{Eq. 1}$$

where $sLOS_i$ is the LOS of a segment, m is the maximum $sLOS_i$ found in the network (6 in our case), and s is the weight factor for LOS in cost. N stands for the number of segments along the route, and d_i is the geometric length of the i-th segment. Setting m=6 and s=1 in Eq. 1 gives a related equation used in (Muraleetharan and Hagiwara 2007) for the computation of the optimized LOS-path, i.e., a path with the maximum mean LOS. Setting s=0 (and m to any value>0) retrieves the geometrically shortest path (SP). Through variation of s between 0 and 1, a set of routes with different mean LOS can be found, where the mean LOS of a route (which will be simply referred to as *LOS*) is computed as

$$LOS = \frac{\sum_{i=1}^{N} d_i \cdot sLOS_i}{\sum_{i=1}^{N} d_i} \qquad \text{Eq. 2}$$

Figure 1 shows a set of five routes that were found from point 1 to 2 through variation of s between 0 and 0.90 (s>0.90 yields unacceptably long detours). Table 1 lists related route statistics. Arterial roads in Figure 1 stand out visually through their darker color compared to local and collector streets. To assess the perceived value associated with a route, the LOS value of that route needs to be corrected for the perceived cost of detour, which gives a standardized LOS.
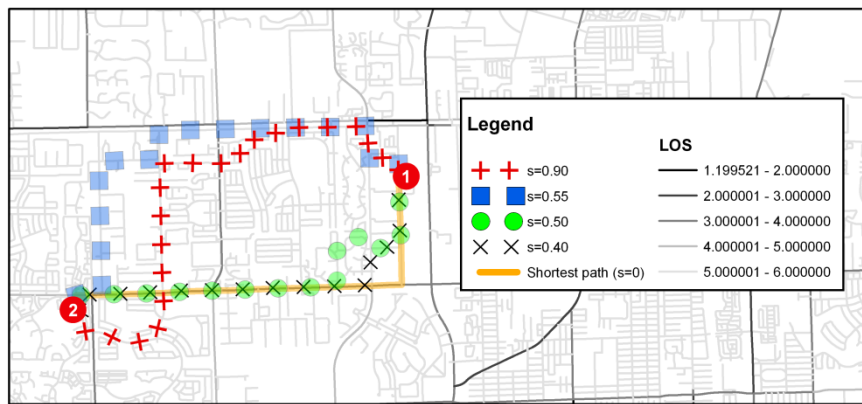

Figure 1: Route set found through variation of weight factor *s*.

Route	s-value	length [m]	detour [%]	LOS	standardized LOS
1	0.00	7114	0	4.36	4.36
2	0.40	7125	0.2	4.44	4.43
3	0.50	7440	4.6	4.79	4.33
4	0.55	8879	24.8	5.82	3.34
5	0.90	9475	33.2	5.93	2.61

Table 1: Characteristics of the five routes in Figure 1.

The cost for detour can be approximately converted to a loss in perceived LOS through a tradeoff function, which is in the simplest case a constant tradeoff rate. The tradeoff rate describes how many % of additional detour a cyclists is willing to accept for an increase of 1 LOS unit, e.g., a 20% detour per gain in 1 LOS unit. The detour of route R is divided by the tradeoff rate to compute its equivalent in LOS units. Subtraction of this equivalent from the route LOS yields the standardized LOS value (*stLOS*) (Eq. 3).

$$stLOS_R = LOS_R - detour_R / tradeoff \qquad \text{Eq. 3}$$

For the shortest route, $stLOS_{SP}=LOS_{SP}$ as its detour is zero. The route with the highest standardized LOS in the origin-destination route set is referred to as the *optimal route*. Leaving aside LOS, it is assumed that the SP is the preferred route option. The ideal situation for a cyclist would therefore be an SP route with an LOS of 6, and this is why we are interested in determining how effective an LOS improvement of the SP to the maximum LOS value 6 is. We introduce a measure called *potential of improvement* (*P*) for a route set between origin and destination. It captures the *additional* perceived value of facility improvement along SP for the cyclist if the LOS of SP would be increased to 6. P depends on the LOS and detour of existing routes. If the optimal route is SP then $P=6-LOS_{SP}$. If a different route is the optimal route (i.e., $stLOS_R>LOS_{SP}$), an improvement of the LOS along SP to 6 will provide less perceived additional benefit, as $P_R=6-stLOS_R<6-LOS_{SP}$. Thus, given the optimal route R, P can be computed as

$$P = 6 - stLOS_R \qquad \text{Eq. 4}$$

Similarly, a *segment potential of improvement* (S_i) can be defined for segments along a SP. If a segments has a current $sLOS_i$ value $< stLOS_R$ (case a), it can gain P LOS units when improved to 6. Any LOS increase up to $stLOS_R$ will not exceed the LOS of the optimal route and thus not cause any perceived improvement. If a segment has a current $sLOS_i$ value $\geq stLOS_R$ (case b), it can gain $6-sLOS_i$ units when improved to 6.

Figure 2a provides a closer look at the situation around the last seven segments of the SP in Figure 1. Numbers on segments indicate the incremental segment IDs up to 38 for this route. Corresponding segment LOS values are shown in brackets. Table 1 indicates that the optimal route for this origin-destination pair is route 2 with $stLOS2=4.43$. It follows from Eq. 4 that $P=1.57$. Figure 2b visualizes the situation in a cross-section. As $sLOS_{32}< stLOS_2$ and $sLOS_{33}< stLOS_2$ (case a) the segment potential of improvement for these two segments amount to $S_{32}= S_{33}=P=1.57$. For the remaining five segments 34-38 with an $sLOS_i>stLOS_2$ (case b), $S_i= 6-sLOS_i=0$. This reflects that these segments cannot be improved.
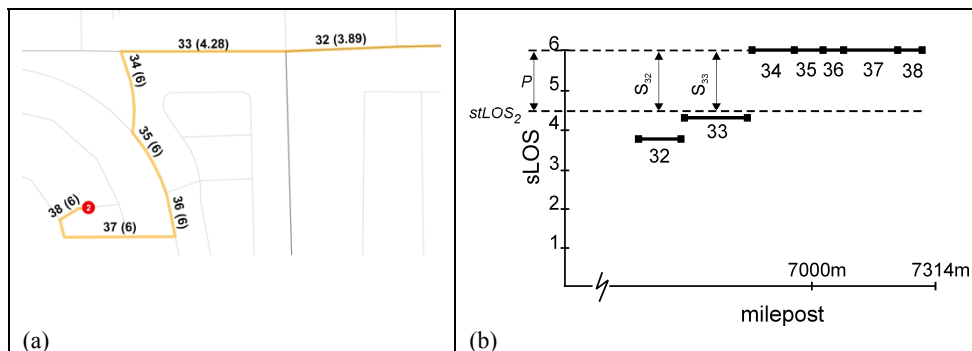

Figure 2: sLOS values for selected route segments on shortest route (a), and corresponding segment potential of improvement (b).

This segment analysis is done for the shortest path within the route set for each O-D pair. If a street segment is located on more than one shortest path (from different O-D pairs), this segment will be assigned different S_i values, and several statistics can be used to capture the nature of these assigned values. The mean of assigned segment potentials ($\underline{S}_i$) estimates the additional value that a cyclist would perceive on average on this segment when following all the shortest paths including that segment after the LOS on these shortest paths has been maximized to 6. As opposed to this, the total over all assigned segment potentials (Σ_i) provides a measure for the overall impact of an increased

LOS value to 6 on that segment. Σ_i takes into account the expected bicycle demand and is therefore a more powerful statistics for planning purposes than the mean, but also more prone to errors in the O-D matrix.

DESIGN OF SHOWCASE

This section describes the design of the showcase used to demonstrate the applicability of the proposed model. The street data with their bicycle LOS values were provided by Broward County Metropolitan Planning Organization. For demonstration purposes it suffices to create fictive O-D trip count information. To do so, we created a set of 72 stop locations randomly distributed over the test area, which serve as trip generators and attractors at the same time (Figure 3). These stops can also be seen as centroid of analysis zones between which the bicycle demand is known.
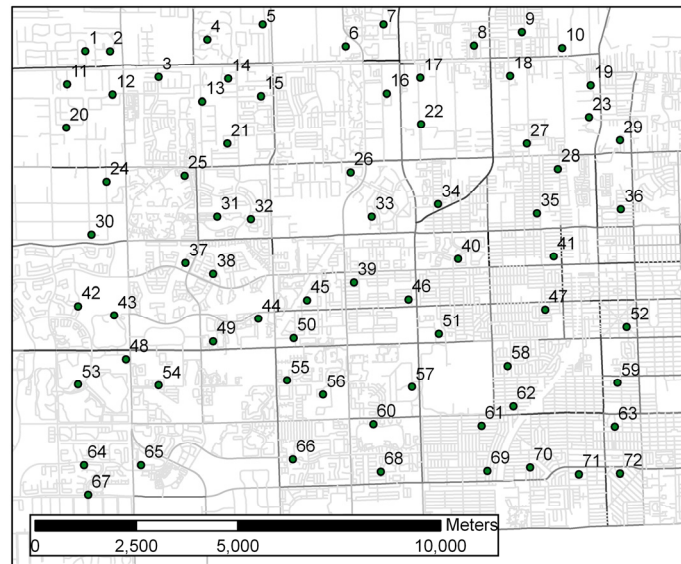

Figure 3: Trip origins and destination used for model testing.

For the assignment of trips between zones we adapt the structure of the gravity model commonly used in transportation research to predict travel demand (Khisty and Lall 1997). It is assumed that the number of trips $T_{i,j}$ between two zones i and j is inversely related to the separation between the zones described as the straight line distance $d_{i,j}$ (Eq. 5).

$$T_{i,j} = \frac{T_{def} \cdot d_{def}}{d_{i,j}} \qquad \text{Eq. 5}$$

T_{def} stands for an assumed bicycle trip number between two zones separated by a default distance d_{def}. For the model demonstration we set T_{def}=5 and d_{def}=1000m. This means that zones that are, for example, 1000m apart have a bicycle demand of 5 trips in both directions between them. When the O-D matrix is built from trip counts $T_{i,j}$ observed in the real world, Eq. 5 is not required.

For the scenario testing, mean potential ($\underline{S}_i$) and total potential (Σ_i) of improvement are computed for segments that are part of an SP. For the demonstration case, we assume a 10% detour-per-LOS-unit tradeoff rate for all trips. This average rate would correspond to the commuter behavior observed in (Harvey et al. 2008), assuming that a cyclist is willing to "pay" an improvement of 1 LOS unit with a detour of 10%. If the trip purpose is available for origin destination pairs, different tradeoff rates can be applied for origin destination pairs. For the showcase we use, however, a constant rate for all trips. As tradeoff rates determined from field studies may not always be accurate, we assess the sensitivity of model results in dependence of the chosen detour-per-LOS-unit tradeoff rate. That is, all computations are made for 0%, 10%, 15% and 20% tradeoff rates, where 0% indicates that a cyclist would always take the shortest path. The model has been implemented in the ESRI ArcObjects framework using VBA scripting.

RESULTS AND INTERPRETATION

This section analyzes computed mean and total effectiveness (potential) of improvement for segments. The following figures show only a zoomed-in part of the network for the 10% and 20% tradeoff rates to improve legibility.

Figure 4 shows the mean potential of improvement for street segments ($\underline{S}_i$). The numbers outside brackets result from a 10% tradeoff rate and the ones in brackets from a 20% tradeoff rate. A smaller tradeoff rate causes a steeper decline of standardized LOS for longer routes than larger tradeoff rates. As a result, the chance that an alternative route other than the SP route is the optimal route, decreases, which, in turn, increases the mean potential for segments along a SP. This explains why in Figure 4 the mean potential values associated with the 10% tradeoff rate are higher than the ones with the 20% tradeoff rate. High mean potential values can be found where the SP routes run mainly on arterials, and where no high-LOS alternative routes are available. Note that this map does not reflect the expected bicycle demand on street segments.
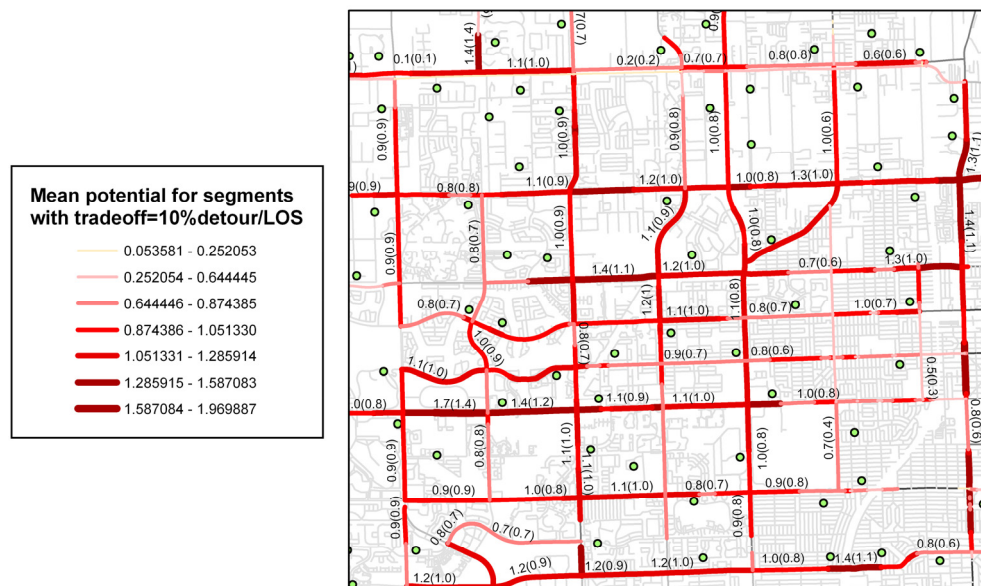

Figure 4*: Mean potential of improvement for segments.*

Figure 5 visualizes differences between mean potentials resulting from the two tradeoff rates. As expected, the magnitude of differences is correlated with the absolute size of the mean potential (we refer to the 10% tradeoff rate here), although the correlation is relatively small (Pearson's $r=0.395$, $p=0.000$). This means that, to some extent, the sensitivity of the predicted mean potential caused by an incorrect tradeoff rate grows with the mean potential itself. Only segments with a mean of assigned potentials>0 were used for the computation of the correlation.
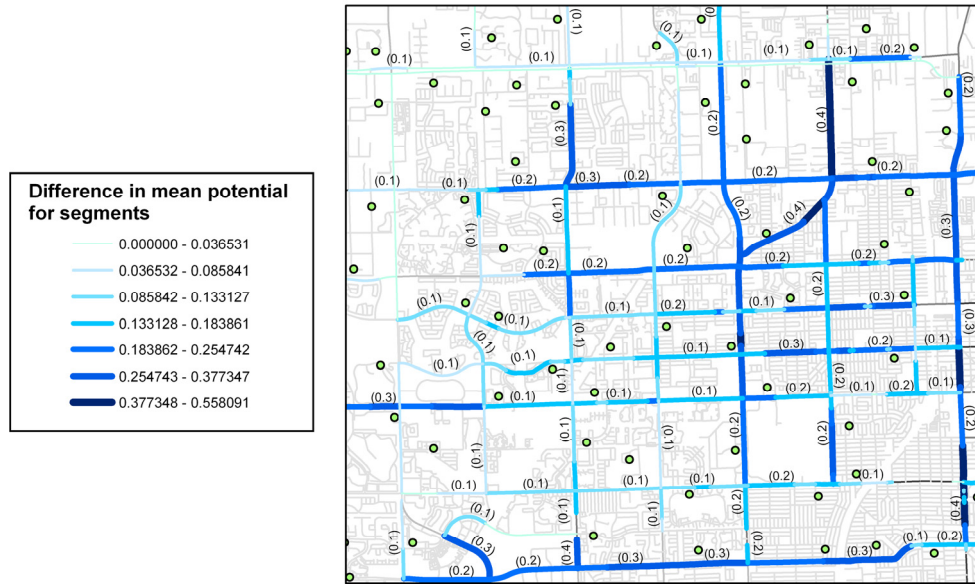

Figure 5: Difference in mean potential between 10% and 20% detour-per-LOS-unit tradeoff rate.

Figure 6 visualizes the total potential of improvement (Σ_i) for both tradeoff rates. Total potentials are positively correlated with mean potentials for segments (10% tradeoff rate: Pearson's $r=0.209$, $p=0.000$; 15% tradeoff rate: Pearson's $r=0.267$, $p=0.000$; 20% tradeoff rate: Pearson's $r=0.290$, $p=0.000$). However, as the total potential considers besides the mean potential also the bicycle demand on segments, the relation between mean and total potential is not linear (Pearson's $r<1$). This result can be informally checked through visual comparison of color values between corresponding segments in Figure 4 and Figure 6.
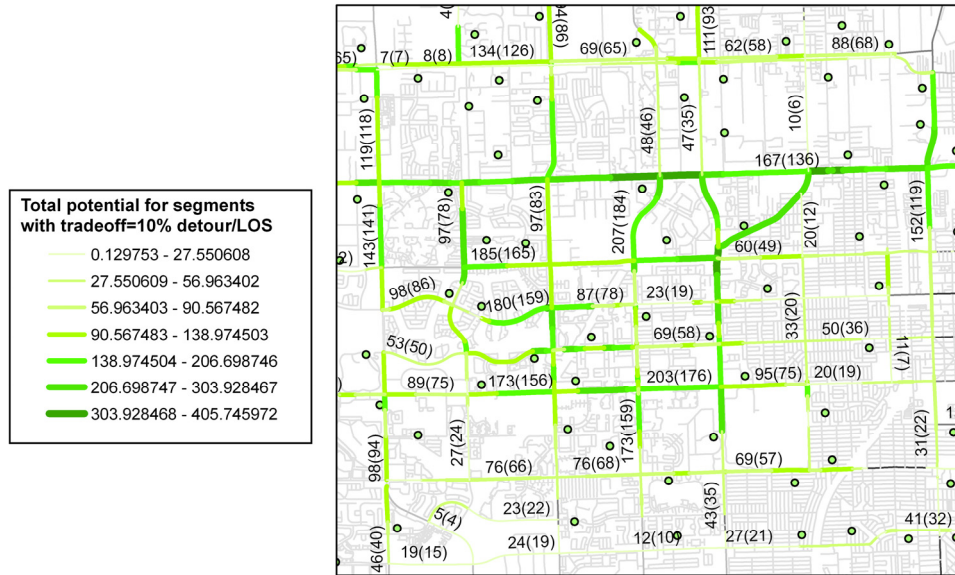
Figure 6: Total potential of improvement for segments.

The differences between total potentials found from the two different tradeoff rates are visualized in Figure 7. The magnitude of differences between the total potentials is more strongly correlated with the total potential of the segment (Pearson's r=0.840, p=0.000) than with the mean potential (Pearson's r=0.238).
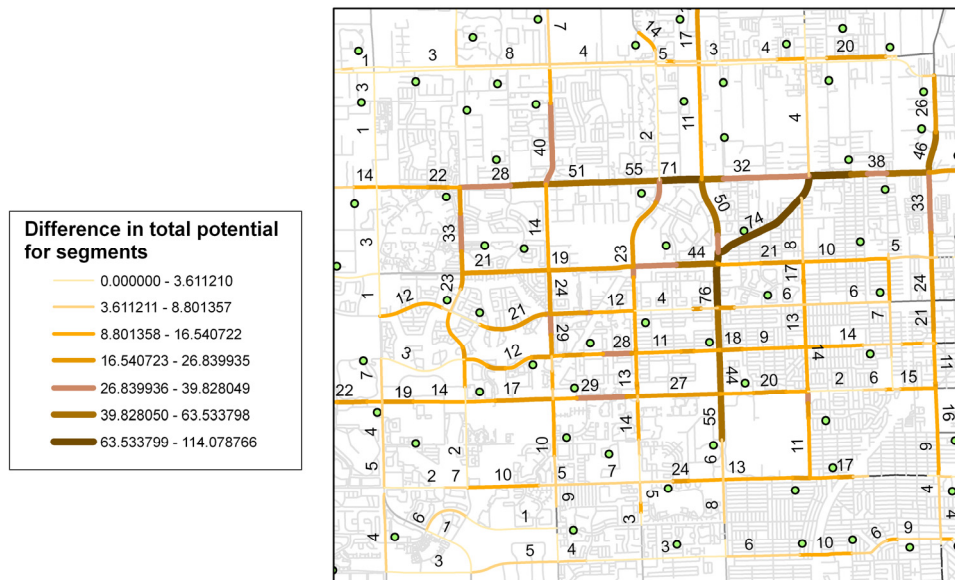

Figure 7: Difference in total potential between 10% and 20% detour-per-LOS-unit tradeoff rate.

In reference to Figure 5 and Figure 7, Table 2 provides some descriptive statistics on the observed differences in mean and total segment potentials. These differences originate from a change in the tradeoff rate from 10% to 20%, from 10% to 15%, and from 0% to 10%. When comparing two models with tradeoff-rates>0 (10% vs. 20% and 10% vs. 15%), differences in mean and total potential between the two models (1) increase, and (2) get more dispersed with a larger difference between used tradeoff rates. The first finding indicates that larger tradeoff rates cause smaller mean and total potentials on average than smaller tradeoff rates. The second observation indicates that besides this systematic effect, the error band for predicted potentials increases with a larger difference between the used tradeoff rates. Table 2 further shows that the predicted potentials are about 2-3 times as sensitive to a 0% to 10% change in tradeoff rate than to a 10% vs. 20% change. This indicates that the sensitivity of estimated potentials does not grow linearly with change in tradeoff rates, and that a model with the simplified assumption of cyclists using exclusively using shortest paths (i.e., a tradeoff rate 0%), can lead to disproportionally high distortions of estimates.

	10% vs. 20%		10% vs. 15%		0% vs. 10%	
	m. p.	t. p.	m. p.	t. p.	m. p.	t. p.
mean	0.182	15.451	0.109	8.892	0.463	38.493
median	0.158	9.698	0.093	5.487	0.421	28.634
Standard dev.	0.128	18.503	0.084	11.058	0.333	36.796
maximum	0.558	114.079	0.369	68.520	1.435	176.675
Match rate (M)	88.98%	97.01%	93.30%	98.20%	73.70%	91.58%

Table 2: Statistics on differences in predicted mean (m. p.) and total potentials (t. p.) of segments.

Prioritization, i.e., the ordering (ranking) of street segments with regard to the need for facility improvement is one of the applications of the proposed model. In this context it is of interest to assess the sensitivity of the ordering of computed potentials on street segments in response to a change in tradeoff rate. For this assessment, we first compute a binary relation ($<$, $>$, $=$) of predicted potential values for all segment pairs of the reference data set, where only segments with a mean potential>0 are considered. The left models in the tradeoff pairs in Table 2 (i.e., 10% and 0% tradeoff rate) serve as reference data sets here. The same step is repeated for the comparison data sets (right models). The binary relations are compared for all corresponding segment pairs between the reference and the comparison data set. Based on this, a ranking match statistics M is computed (last row in Table 3).

Reference dataset				Comparison dataset		
seg1 ID#	relation	seg2 ID#		seg1 ID#	relation	seg2 ID#
1	>	2		1	<	2
1	=	3		1	=	3
..		..	compare	..		..
2	>	1	↔	2	>	1
2	<	3		2	=	3
..				..		
n-1	>	n		n-1	<	n
			ranking match			

Table 3: Scheme for comparing two data sets using inequalities of potentials on segments.

M is computed as the number of relation matches divided by the total number of compared relations. If $M =1$ then corresponding segments in both datasets have the same rank, and a changed tradeoff rate does not impact the ordering between segments. A decreasing M indicates a higher distortion in the ordering. In the test network, each dataset provides a total of 942x941=886422 binary

relations, which are pairwise compared between different datasets. Two observations can be made: First, M decreases with a higher difference between tradeoff rates. Thus, higher errors in used tradeoff rates lead to more distorted prioritizations of segments. Second, the ranking match statistics is higher, i.e., better, for total potentials than for mean potentials. A value of over 97% for a change between 10% and 20% tradeoff rate indicates that the ordering of predicted total potentials is relatively insensitive to a 10% change in the tradeoff rate. However, the comparatively low values associated with match rates between 0% and 10% tradeoff rates of 73.70% and 91.58%, respectively, indicate that complete neglect of non-SP route alternatives in the model can lead to disproportionally high distortions in segment prioritization.

CONCLUSIONS

This research proposed a model to identify network segments where facility improvement is effective. The model requires both an O-D trip matrix and an existing LOS model. For demonstration purposes we used a constant tradeoff rate between detour and LOS, although in the model, modified tradeoff rates could be used for different trip purposes. It was found that errors in estimated tradeoff rates have a relatively small impact on predicted total potentials of segments, whereas the total exclusion of alternatives to shortest paths (i.e., a zero tradeoff rate), leads to larger differences in potential predictions and segment prioritization. A further simplification in the presented showcase was the use of random origin destination pairs. Future work will therefore explore the feasibility of using trip origins and destinations from trip planning requests on Web based bicycle route planners to derive the bicycle demand and trip purpose between different regions, which might be an alternative method to using demographic information, explicit trip generators and attractors, and trip generation rates from Trip Generation Manuals, as suggested by Landis and Toole (1996). We also plan to look into combining the presented model with another recently developed model that predicts latent bicycle demand under consideration of LOS and network structure (Hochmair 2009).

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