Assessment of Latent Bicycle Demand in Street Networks

Hartwig H. HOCHMAIR

Abstract

Due to numerous benefits of bicycling as a means of transportation, planning and policy efforts at all levels of governments aim to increase levels of bicycling. In order to decide where to best invest tax payer's money in bicycle facilities, many cities and regional planning agencies base their decisions on bike counts at the present. However, in areas of poor bicycle infrastructure, this tends to lead to negative feedback loops in policy making and planning, as fewer bicycle counts also means less investment. This paper presents a new GIS- and network-based method that identifies on which network portions an improvement of bicycle facilities can create most additional bicycle demand. These network portions may also be segments of currently low bicycle use.

1   Introduction

Because of growing concerns over traffic congestion and environmental pollution, public policy promotes use of bicycling as an alternative for commuting and other utilitarian trip purposes. Insufficient bicycle infrastructure, such as lack of bicycle lanes, discourages use of bicycles (DILL & CARR 2003). It is therefore important to know where investment in bicycle facility improvement helps to increase the total number of cyclists in an area. When a cyclist plans a trip, he or she will decide in an initial screening process which of the available route alternatives between trip origin and destination are feasible and meet the cyclist's minimum expected level of comfort. The level of comfort experienced by a cyclist on a specific roadway type is often described through a Bicycle Level of Service (LOS) (PETRITSCH et al. 2007). The criteria used by a cyclist to determine whether a route is feasible or not are referred to as eliminatory constraints. In some situations of poor bicycle infrastructure, i.e., low LOS, none of the existing route alternatives between trip origin and destination may satisfy all eliminatory constraints, so that the traveler may use another mode of transportation, e.g., car, instead. In general, the difference in bicycle demand under current and improved bicycle facility conditions is referred to as latent demand (LANDIS & TOOLE 1996).

Eliminatory constraints in individual bicycle route planning are manifold and include various criteria, such as avoidance of heavy traffic, steep slopes, or stairs (HOCHMAIR & RINNER 2005). Most of these constraints can be grouped into two more general constraints, namely a minimum acceptable LOS, and a maximum acceptable detour a cyclist is willing to travel to find better travel conditions. This paper demonstrates how these constraints can be included in a latent demand model that predicts the increase in bicycle demand based on improved bicycle facility conditions. First results of a model implementation will be given

at the end of this paper. The street data used were provided by Broward County, Florida. Planners in Broward County use a roadway condition index (RCI) as a measure of Level of Service to assess bicycle suitability on major streets and highways within their jurisdiction.

2   Related Work

LANDIS & TOOLE (1996) developed a GIS based Latent Demand Score (LDS) model which uses basic GIS functions, such as spatial buffering and spatial queries. The LDS Model estimates the probability of bicycle travel on individual street segments based on their proximity, frequency, and magnitude of adjacent bicycle trip generators and/or attractors. The model does not require network coding and trip computations, and does therefore also not take into account existing nearby high-LOS alternative routes. This may lead to an overestimated latent demand score. Further, no formal framework is provided as to how the LDS model can be combined with supply-side facility analysis methods, such as bicycle LOS measures, to indicate network portions with the greatest need for improvement.

As route detour is a determining factor in route choice, knowledge about accepted detour thresholds among cyclists is relevant for demand modeling. Various field studies show that trip purpose impacts route detour. An empirical study by HARVEY et al. (2008) identifies for bicycle commuters an approximate mean detour of 10 % for trips with a mean distance of about 10 km (after removal of two outliers). Longer detours were identified in a survey with recreational and commuter cyclists (THOMPSON et al. 2007) which concluded that cyclists are willing to travel an average of 67 % additional distance to include an off-street path as part of their route. A tradeoff rate describes the percentage of additional detour a cyclist is willing to accept for an average increase of one LOS unit along the route, which varies between different trip purposes. The cited studies provide information on the magnitude of observed detours, but do not discuss the corresponding gain in LOS. Also, no study is known to the author that provides explicit information on the minimum LOS a cyclist is willing to accept along a potential route.

3   Modeling Approach

The model proposed in this paper assumes that an origin-destination (O-D) matrix containing the number of potential trips between different analysis zones with their trip purposes is available. Such information can, for example, be derived from a combination of demographic information, trip generators and attractors, and trip generation rates from Trip Generation Manuals (LANDIS & TOOLE 1996).

3.1   Search for Route Alternatives

To model current and latent bicycle demand between trip origin and destination, a set of route candidates must be found which covers those alternatives a cyclists would consider in trip planning. As the model implementation is shown along with Broward County network data, we adapt the Broward RCI values and convert them to an LOS range from 1-6. An LOS of 1 means very poor street condition for cyclists, whereas 6 stands for superior street condition. As the Broward County data set provides RCI values for major streets and highways only, we assign an LOS value of 6 for local streets.

A common method to computationally generate a set of route alternatives is to use a single criterion shortest path search, where travel cost (impedance) along a street segment is based on segment length and segment LOS. Different routes can be found through a variation of the weight of LOS in the segment cost model, and minimizing the total cost c of a route

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

where m is the maximum LOS used on any segment i ($sLOS_i$), i.e., 6 in our case, and s is the weight of LOS, with $0 \leq s \leq 1$. 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 gives a path with the maximum mean LOS. Setting s=0 (and m>0) retrieves the geometrically shortest path (SP).

3.2   Detour and Minimum LOS as Eliminatory Constraints

Fig. 1 demonstrates the concepts used in the further description of the latent demand model. Trip origin (O) and destination (D) are connected through four routes A-D. Whereas A is the shortest route, routes B and C have a 10 % detour, and route D has a 20 % detour. The LOS_R values to the left denote the mean LOS value of each route, whereas values to the right indicate the lowest LOS value found on any segment along a route R ($sLOSmin_R$). Route D is assumed to run entirely along local streets with all $sLOS_i$ having a value of 6. Depending on the cyclist's subjective thresholds for minimum LOS (*LOSminT*) and maximum detour, the cyclist may exclude some of the available routes from further consideration. Once a set of feasible routes is determined, the cyclist uses mean LOS and detour of included routes to decide which route to choose for the bike trip.
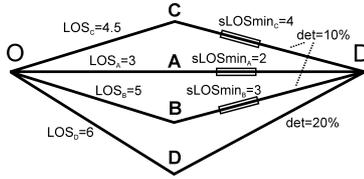

Fig. 1:   Set of route alternatives with detour, mean LOS, and lowest segment LOS

Whereas the actually applied *LOSminT* threshold may vary for an individual in repeated identical choice situations, each cyclist's decision behavior will reveal an average *LOSminT* value. We assume that the average thresholds are approximately normally distributed among a homogenous group of cyclists, such as commuting cyclists. Fig. 2a shows part of the probability density function of the normal distribution for an assumed average minimum threshold (μ=3) for a group and the standard deviation of minimum thresholds (σ=0.5). These parameters are also used in the model demonstration. Letters A-D in Fig. 2 refer to sample routes in Fig. 1. As the normal distribution function has no closed form, the logistic distribution is often used as its approximation. Let $\Delta LOS = sLOSmin_R - \mu$. Assuming that *LOSminT* and detour threshold vary among individuals, a larger ΔLOS (i.e., a higher minimum LOS value) will result in a higher percentage of cyclists that consider R as a feasible route alternative. This percentage value, or probability, is

$$P(\Delta LOS, s) = \frac{1}{1 + e^{-\Delta LOS/s}}$$
Eq. 2

where s is the standard deviation of the logistic regression with $s = sqrt(3) * \sigma / \pi$. An overlay of normal and logistic distribution function reveals their similar shapes (Fig. 2b).
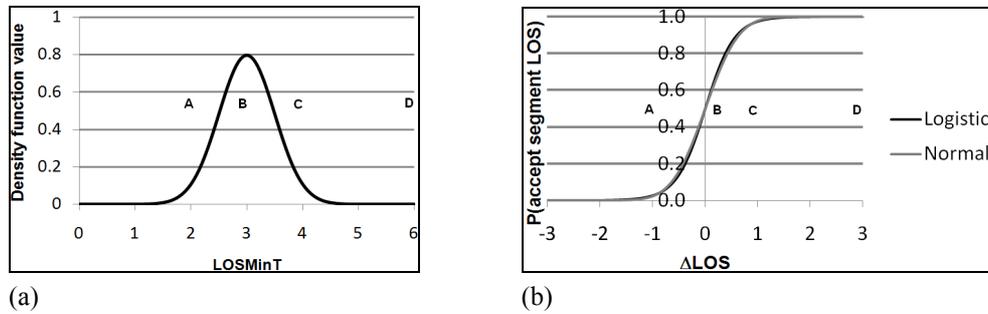

(a)

(b)

Fig. 2: Probability density function of the normal distribution for µ=3 and σ=0.5 (a). Comparison of corresponding normal and logistic distribution function (b).

As opposed to minimum acceptable LOS values on segments, route detours are not normal distributed. Fig. 3a shows the distribution of the extra distance bicycle commuters accept to travel their preferred route (HARVEY et al. 2008). After removal of the two outliers, the histogram shows a skew to the right, as negative detours are not possible. A visual comparison of relative frequency for two different trip purposes is given in Fig. 3b. Due to lack of observed field data, the accepted detour rates for the recreational trip purpose are taken from the commuting curve and multiplied by two.
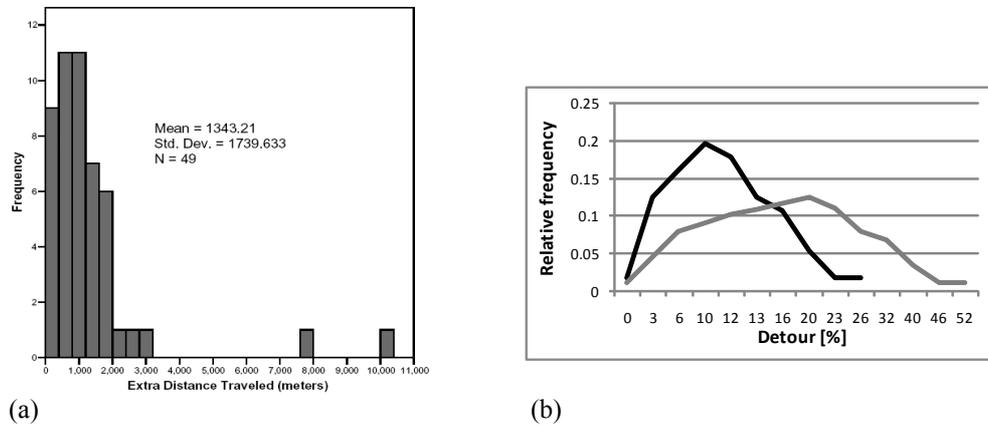

(a)

(b)

Fig. 3: Extra distance traveled during commute (a) (HARVEY et al. 2008). Density function for commuter (black line) and recreational cyclists (gray line) (b).

The observed variation in detour within a group of cyclists with the same trip purpose can be explained in several ways. First, the availability of high LOS routes on daily commute may vary between individuals due to an irregular distribution of bicycle facilities in the network structure. In a relatively homogeneous test region, which Fig. 3a is based on, this seems to play a minor role. Second, cyclists could use different detour-to-LOS tradeoff rates. A smaller tradeoff rate would lead to routes with smaller extra trip distance, and no explicit detour threshold would be considered. Third, cyclists share the same tradeoff rate but apply different maximum detour thresholds. The latter two explanations lead to different parameters to be considered in latent demand modeling. This paper uses the third explanation as basis for the model.

Due to the skewed distribution of detour thresholds, the percentage of cyclists that accept a route up to a certain detour threshold is rather modeled through an empirical distribution function than through a normal distribution function. Fig. 4 shows the cumulative distribution function (cdf) for commuters derived from Fig. 3. This is the basis for modeling the probabilities $P(det)$ that a cyclist accepts a detour that is smaller than or equal to a given threshold value (triangles). These data points are approximated through a fourth-order polynomial curve to get a continuous distribution function. The curve indicates that a higher detour leads to a smaller percentage of cyclists accepting the route. Circles show the approximate probabilities for observed detours using the polynomial function.
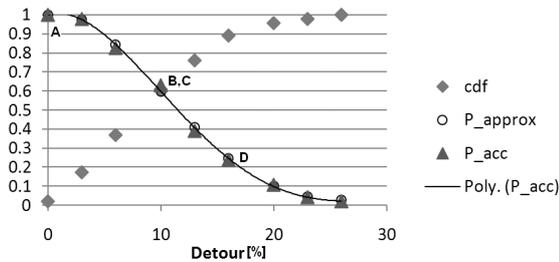

Fig. 4: Percentage of commuter cyclists that accept a given route detour

3.3 Generation of Route Sets

The probability curves in Fig. 2b and Fig. 4 can be used to compute compound probabilities by multiplication. That is, $P(R)=P(sLOSmin_R) \times P(det_R)$, where $P(R)$ denotes the percentage of cyclists that consider route R to be feasible. For example, route B would be accepted by $P(B)=0.50 \times 0.59 \approx 30\%$ of cyclists. Based on this, one can estimate which route subsets C_i will be considered by which percentage of cyclists in trip planning. The following procedure is used:

(1) sort all n route alternatives between trip origin and destination from highest to lowest P, which gives a sorted route set {R1, R2…Rn}

(2) compute the probability of the empty route set C0={} as $P(C0)=1-P(R1)$

(3) go one by one through routes Ri $\in$ {R1…Rn-1}
    – set Ci=Ci-1 $\cup$ {Ri}
    – set $P(Ci)= P(Ri)-P(Ri+1)$

(4) set the complete set Cn=Cn-1 $\cup$ {Rn} and set $P(Cn)=P(Rn)$

Fig. 5 shows three route sets with their individual route probabilities printed in boldface. Routes in Figure a are identical, routes in Figure b vary solely in *sLOSmin* values, and routes in Figure c vary both in detour and minimum *sLOS* value.
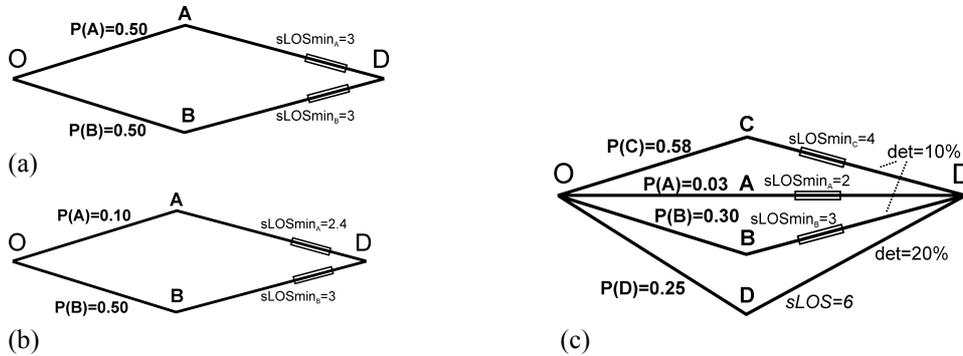

Fig. 5:   Sets of route alternatives with their individual route probabilities

Table 1 lists the resulting route subsets with their computed probabilities. Multiplication of $P(C_0)$ by the theoretical demand between origin and destination describes the latent demand.

Table 1:   Probabilities of subsets from route alternatives visualized in Figure 5

Situation	i	R_i	C_i	$P(R_i)$	$P(R_{i+1})$	$P(C_i)$	Remarks
Fig. 5a	0	-	{}	-	0.50	**0.50**	empty set
	1	A or B	{A} or {B}	0.50	0.50	**0**	
	2	B or A	{A,B}	0.50	-	**0.50**	complete set
Fig. 5b	0	-	{}	-	0.50	**0.50**	empty set
	1	B	{B}	0.50	0.10	**0.40**	
	2	A	{A, B}	0.10	-	**0.10**	complete set
Fig. 5c	0	-	{}	-	0.58	**0.42**	empty set
	1	C	{C}	0.58	0.30	**0.28**	
	2	B	{B,C}	0.30	0.25	**0.05**	
	3	D	{B,C,D}	0.25	0.03	**0.22**	
	4	A	{A,B,C,D}	0.03	-	**0.03**	complete set

3.4   Route Choice from a Route Set

The next step in identifying travel demand between trip origin and destination is to determine the probability of a cyclist choosing a specific route from a set of feasible routes. Probabilistic choice models aim to explain inconsistent and non transitive choice behavior and are an appropriate means to model observed inconsistencies between individuals. Inconsistencies in choice behavior arise in empirical applications when several individuals with identical choice sets, route attributes, and socioeconomic characteristics select different alternatives (BEN-AKIVA & LERMAN 1985). Instead of identifying one alternative as the chosen option, probabilistic choice models assign to each alternative a probability to

be chosen. In the constant utility approach utilities of alternatives are presumed constant and choice probabilities for an individual are functions parameterized by those utilities. For distinct alternatives the probability of a decision maker choosing alternative i from choice set C_n can be defined as

$$P(i \mid C_n) = \frac{U_{in}}{\sum_{j \in C_n} U_{jn}}$$ Eq. 3

where U_{in} may be interpreted as the utility of alternative i in choice set n, with the utility being positive and defined on a ratio scale which is unique up to multiplication by a unique constant (LUCE 1959). In the context of this paper, route utility can be modeled as a quantity based on average LOS and detour of a route. The cost, i.e., disutility, for route detour can be approximately converted to a loss in perceived LOS through a tradeoff function, which in the simplest case is a constant tradeoff rate. Subtraction of this equivalent from the route mean LOS yields the standardized LOS value (*stLOS*), so that *stLOS=LOS-detour/tradeoff*. As the *stLOS* measure considers perceived cost of route detour, it provides a comparable LOS measure for all routes in a route set.

In the case of significantly correlated, i.e., partially overlapping, alternatives, all utilities in Eq. 3 need to be multiplied by an individual overlap factor f_r as otherwise the probability of choosing one of the correlated alternatives would be overestimated and non-intuitive. An overlap factor f_r for route r can be computed as (DAAMEN et al. 2005)

$$f_r = \sum_{a \in r} \frac{l_a}{L_r} \frac{1}{N_a}$$ Eq. 4

where a is the index of a link (i.e., route segment) connecting O and D, l_a is the length of link a that is a part of route r, and L_r is the length of route r. N_a is the number of alternatives in the choice set which contain link a. In the example in Fig. 6, all routes are presumed identical, i.e., $U_A = U_B = U_C$, and the length of the small rectangle is neglectable. Eq. 3 leads to a choice probability of 1/3 for each route, which is counter-intuitive, as routes B and C are perceived as one alternative. Eq. 4 leads to f_A=1, and f_B=f_C=0.5. These values, if multiplied by corresponding utilities in Eq. 3, lead to the expected probabilities, which are P(A)=0.5, and P(B)=P(C)=0.25.
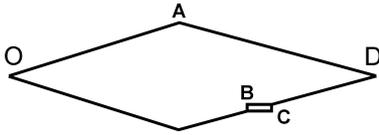

Fig. 6: Route set with three identical choice options

Combining route set probability (section 3.3) and choice probability of a route within a route set (Eq. 3, Eq. 4), provides the probability of choosing route i between origin and destination. This value multiplied by the travel demand T between trip origin and destination provides the travel demand D_r on Route r so that

$$D_r = T \sum_{i=1}^{n} P(r \mid C_i) \cdot P(C_i)$$ Eq. 5

where *n* is the number of route sets C_i for a given origin destination pair. For example, for route B in Fig. 5c the term to the right of the summation symbol in Eq. 5 is:

$$P(B|\{B,C\}) \times P(C_{\{B,C\}}) + P(B|\{B,C,D\}) \times P(C_{\{B,C,D\}}) + P(B|\{A,B,C,D\}) \times P(C_{\{A,B,C,D\}}) =$$
$$= P(B|\{B,C\}) \times 0.05 + P(B|\{B,C,D\}) \times 0.22 + P(B|\{A,B,C,D\}) \times 0.03$$

3.5   Selection of Route to be Improved

Eq. 5 can be used to compute the current bicycle demand on a route. For bicycle facility improvement, it is intuitive to select that route from a given set of alternatives that minimizes the latent demand percentage P{} between trip origin and destination, with *P{}=1-max[P(A),P(B),...P(N)]*. If the possible LOS up to which a street segment can be technically increased through facility improvement (*possLOS*) is equal for the whole network, this route will be the shortest route. Otherwise, which is more realistic, any route in the complete route set could be the one that minimizes P{}. For the selected route, LOS values are increased to *possLOS* if they are lower than *possLOS*. After this fictive improvement of the selected route, Eq. 5 is re-applied to estimate the new travel demand for all route alternatives between trip origin and destination. This step allows to examine the increase in travel demand on the improved route, and the change in travel demand on the other routes. The net gain in demand over all route alternatives is a measure of satisfied latent demand for a given origin destination pair. If a street segment is part of routes of several origin- destination pairs, the changes in demand can be added for each segment for visualization in a map. In addition to this, a map that shows how often a segment has been part of a route that has been identified to minimize latent demand allows to visually grasp the location of hot spots for LOS improvement. The previously described model steps are summarized in the flow diagram in Fig. 7. Model steps are annotated with section numbers of this document where each step has been described in more detail.
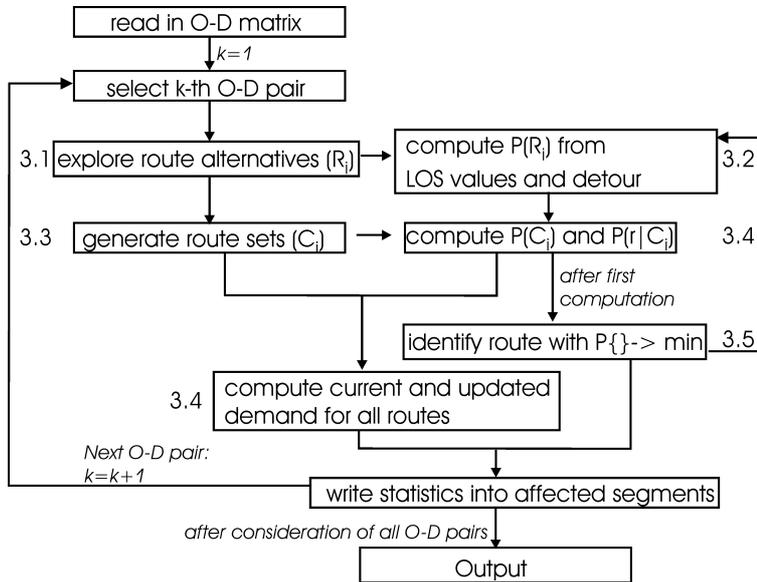

Fig. 7:   Conceptual model of latent demand computation

4   Showcase

This section shows part of results from applying the proposed model (Fig. 7) on a sample data set, which serves as a proof of concept. The model has been implemented in the ESRI ArcObjects framework using VBA script and the Network Analyst extension. For the demonstration, we used a fictive O-D travel demand table for 72 stop locations that were randomly distributed over the test area (round dots in Fig. 8). These locations serve as trip generators and attractors at the same time. Travel demand between stops was modeled inversely related to the straight line distance between stops, where stops 1000 m apart were assumed to have a theoretical demand of five bicycle trips in-between.

Fig. 8a shows the additional demand on segments based on fictive LOS improvement for selected routes between origin and destination where *possLOS*=5 was assumed for the complete network. Demand changes on alternative routes (side roads) are not visualized here to keep the map legible. Two sets of constraint parameters are tested, where both sets use the same *LOSMinT* acceptance curves from Fig. 2 but vary in detour acceptance curves. The first set uses a detour acceptance curve that is more closely related to commuter behavior with a tradeoff rate of 10 % (black curve in Fig. 3b), whereas the second set represents rather a recreational cyclist with a tradeoff rate of 20 % (gray curve in Fig. 3b). The two sets of numbers on segments (outside and inside brackets) in Fig. 8a refer to the commuter and recreational data set. It can be observed that with an increased acceptance of longer detour the latent demand generally decreases. This is because the cyclist will accept longer routes in search for a route that satisfies the minimum LOS. Fig. 8b uses the first set of parameters and shows for segments with an LOS<5 how often a segment was part of a route selected for LOS improvement.

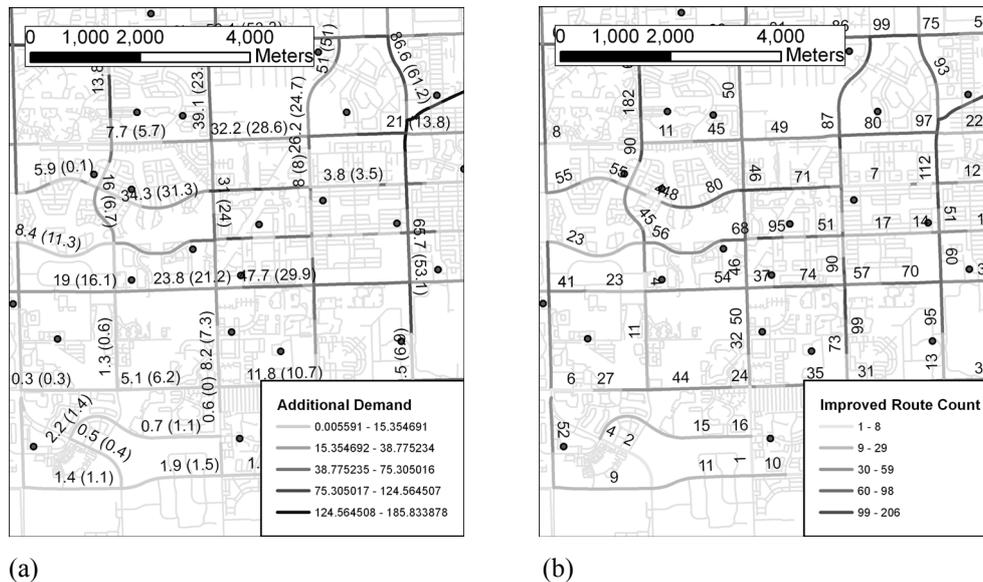(a)   (b)

Fig. 8:   Additional demand on segments along routes chosen for LOS improvement (a), and number of times a segment was part of an improved route (b).

5 Summary and Outlook

This paper proposed a model for the prediction of latent demand on street segments based on bicycle LOS improvements on selected streets. For future work we will explore how this model can be combined with other approaches that identify the street segments with the greatest need for improvement based on LOS and current bicycle demand (HOCHMAIR 2009). In the implementation presented, mostly fictive threshold values were used. Future work will therefore also aim to identify appropriate field procedures that allow determining more precise model parameters for different bicycle trip purposes. As the generation of the O-D matrix is a complex, but necessary task the model is based on, we will for this task also explore the possibility to use trip origins and destinations extracted from user requests in Web based bicycle trip planners.

References

BEN-AKIVA, M. & LERMAN, S. R. (1985), Discrete Choice Analysis: Theory and Application to Travel Demands. Cambridge, MA, MIT Press.

DAAMEN, W., BOVY, P. H. L., HOOGENDOORN, S. P. & REIJT, A. V. D. (2005), Passenger Route Choice concerning Level Changes in Railway Stations. Transportation Research Board – 84th Annual Meeting, Washington, D.C. Transportation Research Board of the National Academies.

DILL, J. & CARR, T. (2003), Bicycle Commuting and Facilities in Major U.S. Cities: If You Build Them, Commuters Will Use Them – Another Look. Transportation Research Record: Journal of the Transportation Research Board, 1828, pp. 116-123.

HARVEY, F., KRIZEK, K. J., & COLLINS, R. (2008), Using GPS Data to Assess Bicycle Commuter Route Choice. Transportation Research Board – 87th Annual Meeting, Washington, D.C. Transportation Research Board of the National Academies.

HOCHMAIR, H. H. (2009). GIS-based Identification of Need for Bicycle Level of Service Improvement in Street Networks. 12th AGILE International Conference on Geographic Information Science, Hannover, Germany.

HOCHMAIR, H. H. & RINNER, C. (2005), Investigating the Need for Eliminatory Constraints in the User Interface of Bicycle Route Planners. In: COHN & MARK (Eds.), Conference on Spatial Information Theory (COSIT'05) (LNCS 3693, pp. 49-66). Berlin, Springer.

LANDIS, B. & TOOLE, J. (1996), Using the Latent Demand Score Model to Estimate Use, ProBike ProWalk 96: Resource Book, The Ninth International Conference on Bicycle and Pedestrian Programs (pp. 320-325). Portland, ME.

LUCE, R. (1959), Individual Choice Behavior: A Theoretical Analysis. New York, Wiley.

PETRITSCH, T. A., LANDIS, B. W., HUANG, H. F., MCLEOD, P. S., LAMB, D., FARAH, W. & GUTTENPLAN, M. (2007), Bicycle Level of Service for Arterials. Transportation Research Record: Journal of the Transportation Research Board, 2031, pp. 34-42.

THOMPSON, K., KRIZEK, K. J. & EL-GENEIDY, A. M. (2007), A detailed analysis of the influence of an urban trail system on travel behavior. Transportation Research Board – 86th Annual Meeting, Washington, D.C. Transportation Research Board of the National Academies.