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Bicycle Level of Service for Route Choice—A GIS Evaluation of Four Existing Indicators with Empirical Data

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Abstract: Bicycle Level of Service (BLOS) indicators are used to provide objective ratings of the bicycle suitability (or quality) of links or intersections in transport networks. This article uses empirical bicycle route choice data from 467 university students in Trondheim, Norway to test the applicability of BLOS rating schemes for the estimation of whole-journey route choice. The methods evaluated share a common trait of being applicable for mixed traffic urban environments: Bicycle Compatibility Index (BCI), Bicycle Stress Level (BSL), Sixth Edition Highway Capacity Manual (HCM6), and Level of Traffic Stress (LTS). Routes are generated based on BLOS-weighted networks and the suitability of these routes is determined by finding the percentage overlap with empirical route choices. The results show that BCI provides the best match with empirical route data in all five origin–destination pairs, followed by HCM6. BSL and LTS which are not empirically founded have a lower match rate, although the differences between the four methods are relatively small. By iterating the detour rate that cyclists are assumed to be willing to make, it is found that the best match with modelled BLOS routes is achieved between 15 and 21% additional length. This falls within the range suggested by existing empirical research on willingness to deviate from the shortest path, however, it is uncertain whether the method will deliver the comparable findings in other cycling environments.

Keywords: bicycle suitability; route choice; detour rate; level of service; infrastructure evaluation; bikeability; Geographic Information System

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1. Introduction

The promotion of bicycling is increasingly seen as an approach through which towns and cities can become healthier, more equitable, and attractive to live in [1,2]. Whilst many factors are thought to positively influence the levels of bicycling in urban areas, high quality, well-connected bicycle infrastructure is widely considered to be a precondition [3–6]. Since most cities do not meet this criterion, the network of streets and paths available to bicycle users typically varies widely in quality.

In order to improve our understanding of how incomplete bicycle networks are used and valued, many metrics have been developed to assess the bicycle suitability of urban areas. Such metrics typically take account of built environment factors as infrastructure quality, traffic volumes, perceived/actual safety, directness, and attractiveness [7]. A subset of these metrics known as Bicycle Level of Service (BLOS) has been developed along broadly similar principles to the more widely used vehicular Level of Service methods that are commonly used in traffic planning [8].

This research aims to test four existing BLOS methods that consider the bicycle friendliness of mixed traffic urban environments using empirical data from Trondheim, Norway. The empirical data consists of bicycle route preferences of 467 university students to or from their student accommodation to Trondheim Torv, the city square of Trondheim. Five origin–destination pairs are created from the dataset based on geographical midpoints of the students' residence clusters. The objective BLOS methods that are tested are developed based on bicyclists' stated or observed route preferences in the US context. This paper seeks to establish how well BLOS methods, which are used to provide letter-grade or numeric ratings for all streets in the city network, can be used to estimate actual bicycle route preferences in Norway. This is done by generating an optimal route based on a combination of travel time (traditionally the main cost element in route assignment models) and quality of the cycling experience as defined by BLOS. To the authors' knowledge, 'reverse engineering' of BLOS indicators in this manner has not previously been published in the academic literature using the type of empirical data collected (with many unique respondents on a restricted number of origin–destination pairs).

2. Background

Bicycle Level of Service is of interest for many transport planners for evaluating the quality of bicycle networks, however, no consensus on the most suitable method has been reached due to a wide variety of contextual and methodological differences. The term Cycling or Bicycle Level of Service can be used to refer to audit-based categorical metrics (e.g., [9]) and methods relying principally on continuous variables such as speed or traffic volume (e.g., [10]). In this paper, BLOS is used to refer specifically to the latter category, which is primarily related to the quality of the infrastructure and comfort for bicycling and often based on the opinions of many users (cyclists or cycling planners). Although sometimes also referred to as BLOS methods, bikeability indicators, which include destination or area-based variables are excluded from the scope of this paper [11–14].

Many researchers have reviewed existing BLOS methods; however, few if any of these have sought to test BLOS suitability for prediction of route choices. Moudon & Lee evaluated the data requirements of a broad range of assessment tools including 15 instruments referred to by the authors as route quality assessment tools for walking and bicycling [15]. Asadi-Shekeri et al. performed a review of pedestrian and bicycle level of service methods and their associated challenges [16]. Callister & Lowry [7] created a toolbox for ArcGIS users containing three BLOS methods, two of which were used in this research (BSL and HCM6). Parks et al. [17] make a comparison of three BLOS methods for evaluating the changes resulting from bicycle facility installation.

These reviews form the starting point for Table 1, which lists a selection of BLOS methods and the effects of the included component variables. The only criterion for inclusion in the table is that the BLOS method is designed for application to urban mixed-traffic street links or segments (sections of streets between intersections). Supplementary methods to the initial list were found through snowballing of references and searches in the Scopus database. The criterion results in the exclusion of such methods as those that are focused solely on intersections [18], separated bicycle or shared paths [19–21], rural areas [22,23], urban arterials [24], or bicycle lanes [25,26]. Audit-based metrics are also excluded from Table 1, including those in Australia and the UK that use the term "Cycling Level of Service" [9,27,28] and select others that use the term bicycle level of service but are either 'scorecard' based or lack an empirical foundation for the combination of variables [29,30].

Due to different notations for the different forms of BLOS, a higher BLOS is in this paper used to refer to better suitability for cycling (corresponding with A for BCI and HCM6 or 1 for BSL and LTS respectively). With few exceptions, the BLOS indicators are influenced by the component variables in the same manner (e.g., the positive effect of bicycle facility's presence or negative impact of vehicular traffic). There are however two exceptions apparent in Table 1. An increase in the number of traffic lanes for a given Annual Average Daily Traffic (AADT) will normally reduce the number of vehicles in the lane closest to bicycle traffic. This will decrease the number of interactions between vehicles and bicyclists, thereby increasing the BLOS. Level of Traffic Stress, in contrast, is negatively influenced (reduction in LOS) by the number of traffic lanes, presumably because this is connected to higher overall vehicular volumes (or that the nearest lane volume is not considered) [31]. The second exception is found for speed in which the 'Evaluation of Bicycle Suitability' indicator contradicts other research by suggesting that higher speeds are associated with a higher BLOS [32]. The study's authors note that this is due to contextual differences, since the method is applied to highly congested roads in India, in which cyclist accessibility is more positively associated with running speed since this corresponds with traffic flow that allows space for cyclists (as opposed to congestion in which cyclist space disappears).

Table 1. Overview of factors in urban mixed traffic Bicycle Level of Service indicators. Factors that positively influence BLOS are indicated with a "P" whilst negative effects are indicated with a dash and "X" indicates mixed effects.

Method Name	**Bicycle Safety Index Rating**	**Bicycle Stress Level**	**Florida Roadway Condition Index**	**Bicycle Interaction Hazard Score**	**Bicycle Suitability Rating**	**Real-Time Bicycle LOS**	**Bicycle Compatibility Index**	**Danish Bicycle LOS**	**6th ed. US Highway Capacity Manual**	**Level of Traffic Stress**	**Bicycle LOS—India**	**Evaluation of Bicycle Suitability**
Reference	**Davis, 1987 [33]**	**Sorton & Walsh, 1994 [34]**	**Epperson, 1994 [33]**	**Landis, 1994 [35]**	**Davis, 1995 (Davis, 1995 in [36])**	**Landis et al., 1997 [10]**	**Harkey et al., 1998 [37]**	**Jensen, 2007 [38]**	**TRB, 2016 [8,39]**	**Mekuria et al., 2012 [31,40]**	**Beura et al., 2018 [41]**	**Majumdar& Mitra, 2018 [32]**
Acronym	**BSIR**	**BSL**	**RCI**	**IHS**	**BSR**	**RTBLOS**	**BCI**	**DBLOS**	**HCM6**	**LTS**	**BLOS-I**	**EBS**
AADT	-	-	-	-	-	-	-	-	-	-	-	-
Bicycle Facility Width/Presence						P	P	P	P			
Bicycle Separation from Traffic							P					
Bus Facilities								-			-	
Driveways	-		-	-	-	-			-		-	
Kerb Height/Presence	-				-				-			
Land Use Intensity	-		-	-	-	-	-	X			-	-
Lighting												
Line of Sight	P		P		P							
Median Strip	P		P		P							
Number/Type of Traffic Lanes	P		P	P	P	P	P	P	P	-		
On-street Parking	-		-	-	-	-	-	-	-		-	-
Percentage of Heavy Vehicles				-		-			-			
Road Grade	-		-		-							
Shoulder	P		-		P	P		P	P			
Signage-Bicycles												
Signalised Intersection	-											
Speed	-	-	-	-	-	-	-	-	-	-	-	P
Surface Quality	P		P	P	P	P			P		P	P
Traffic Calming Features												
Turning/Crossing Traffic	-		-									
Vegetation/ Green Space												
Width of outside Lane (inc. Bike lane/shoulder)	P	P	P	P	P	P	P	P	P	P	P	

Bicycle Level of Service methods are typically developed with the intention to rate the bicycle quality of individual road/path links. In this research, the same rating approach is applied at the network scale to consider how well link ratings are reflected in the choice of entire routes. This involves using the BLOS methods to create potential routes for comparison with empirical choices.

Route choice set creation for travel behaviour research is most typically scrutinised on the basis of creating choices that are realistic and representative for any given road user [42]. A method known as labelling is used for route choice creation to optimise a single attribute assumed or known to affect route choice within certain bounds [43]. This study uses a similar approach, however rather than optimising the utility of a single attribute (for example energy expenditure), the authors' take the approach of optimising route choice using the multi-attribute BLOS indicators in combination with travel time. Changing the relative importance of travel time and the 'label' based on BLOS can therefore result in different optimal routes being created.

From Table 1, four methods were selected for evaluation with the empirical data in Trondheim. The selected BLOS methods are chosen based on a balance between their commonality of use and the relative ease with which they can be applied. A key criterion for the selection of indices to be tested is that the score weighting is primarily related to the quality of the infrastructure and comfort for bicycling as opposed to destination accessibility. It was a specific aim to choose methods where most of the GIS data sources necessary could be expected to be found or acquired without additional field data collection. Unfortunately, non-American BLOS methods were not able to be tested due to model complexity of the Danish BLOS method [38] and very different context to the Norwegian test data for two other BLOS methods developed in India [32,41]. The final selection was comprised of (in descending order of complexity):

1. Sixth Edition Highway Capacity Manual BLOS (HCM6) [8,44]
2. Bicycle Compatibility Index (BCI) [37]
3. Level of Traffic Stress (LTS) [40,45]
4. Bicycle Stress Level (BSL) [34]

Each of the four methods is briefly described below.

2.1. Sixth Edition Highway Capacity Manual BLOS (HCM6)

Chapter 18 in the Sixth Edition of the Transportation Research Board's Highway Capacity Manual (hereafter called HCM6) presents a methodology for calculating Bicycle LOS for urban street segments that finds its roots in the Real-Time Bicycle LOS (RTBLOS) method from Landis et al., 1997 [10]. The HCM6 method is unchanged from the 2010 Highway Capacity Manual and was first published in a more detailed report commissioned by the US National Cooperative Highway Research Program in 2008 [8,39]. Whilst the Highway Capacity Manual describes the bicycle LOS in relation to both intersections and links (i.e., linear sections of road between intersections), only the link methodology is used in this paper for comparability with the three other methods described below.

As can be seen in Table 1, there are many similarities in terms of included variables between the RTBLOS method and the HCM6 method. Commercial land use intensity has been excluded from the HCM6 approach, whilst the presence of a street kerb is added to the HCM6 method to adjust the effective lane or bicycle facility width. Parameters have additionally been adjusted in HCM6 which is widely used by transportation practitioners in the USA, where the Highway Capacity Manual was developed. Callister and Lowry [7] developed an ArcMAP toolbox which combines the many equations detailed in the 2010 HCM and HCM6 into the final BLOS link output (a letter grade between A and F), and it is this toolbox that is used to develop a map for the case study area in this paper. The main difference between HCM6 link and HCM6 segment calculations are the consideration of intersections and driveway access points at the segment level which is not accounted for at the link level. Intersections are, however, taken account of using a separate approach that is applied to all four BLOS methods, detailed in Section 3.5. As a result, the link approach of HCM6 is used for this study.

2.2. Bicycle Compatibility Index (BCI)

The BCI methodology was developed by Harkey et al. in 1998 for urban and suburban roadway segments (in this case, the same as links), making it suitable for comparison with the HCM6 bicycle approach and for application to the mixed traffic environment of the case study area [37]. The methodology has a much simpler form than the HCM6 approach, being a single linear equation comprised of nine variables as displayed in Equation (1) below. In the same manner as the link BLOS used for HCM6, intersections are not treated directly by the BCI method but are performed independently as discussed in Methods.

$$\begin{aligned} BCI = 3.67 - 0.966BL - 0.410BLW - 0.498CLW + 0.002CLV \\ + 0.0004OLV + 0.022SPD + 0.506PKG - 0.264AREA \end{aligned} \tag{1}$$

where:

BL = presence of a bicycle lane or paved shoulder > 3.0 ft no = 0 yes = 1
BLW = bicycle lane width in feet (to the nearest tenth)
CLW = curb lane width in feet (to the nearest tenth)
CLV = curb lane vehicles per hour in the travel direction
OLV = other lane(s) volume in travel direction
SPD = 85th percentile vehicle speeds miles/h
PKG = presence of a parking lane with more than 30 percent occupancy; no = 0, yes = 1
AREA = type of roadside development; residential = 1 other type = 0
AF = adjustment factor for truck volumes, parking turnover and right-turn volumes

To ensure compatibility with the HCM6 and its previous editions, the numeric BCI value (where a lower number corresponds to a higher bicycle standard) is converted to an A to F letter grading system using percentile scores. The percentile boundaries are as follows: A/B—5th, B/C—25th, C/D—50th, D/E—75th and E/F—95th.

2.3. Level of Traffic Stress (LTS)

Level of Traffic Stress (LTS) is a four-level BLOS method loosely based on the Dutch CROW Design Manual for Bicycle Traffic [46]. The original methodology was developed in connection with a report from Mekuria et al. in 2012 for the California Department of Transportation and received minor modifications in 2018 [31,40]. Criteria for allocation to each category is made according to the posted speed limit, number of lanes, AADT, and the provision of separate infrastructure, such as bicycle lanes and paths. The four levels of traffic stress are linked to a classification of cyclists into four categories from Geller in 2006: "interested but concerned"—split into two groups representing suitability for children (LTS 1) and adults (LTS 2), "enthused and confident" (LTS 3), and "strong and fearless" (LTS 4) whilst the final group "No Way No How" is not classified into any of the LTS levels [47,48].

LTS levels 1 and 2 are intended to represent the lowest stress and good cycling conditions, with separation from traffic in the form of bicycle-specific infrastructure or only occasional interactions with vehicular traffic at low speeds. Network links graded as LTS 1 or 2 are considered by the methodology developers to be acceptable for the majority of adults [31]. The original methodology stresses the importance of connectivity for any pair of points, defined as "the ability to get between the two points without exceeding a specified stress threshold and without exceeding the specified level of detour" [Ibid., p. 8]. The level of detour, referred to in this paper as the detour rate (the percentage additional distance of a route compared to the shortest path between origin and destination) is applied for route choice optimisation discussed in Section 3.6.

2.4. Bicycle Stress Level (BSL)

The Bicycle Stress Level method was developed by Sorton and Walsh in 1994 to quantify the intensity of the traffic in terms of speed and hourly vehicular volumes which, in combination with outside lane width, are presented as the main sources of traffic stress to cyclists [34]. The BSL method uses a 5-point scale scoring system for each of the three aforementioned criteria which are then averaged to give a stress level between 1—very low and 5—very high. The hourly traffic volume is proposed to be superior to AADT but is not generally collected in connection with evaluations of bicycle suitability at the network level. As a result, a standard estimation for hourly traffic volume is made based on the 10 percent of the AADT as recommended by Sorton and Walsh in cases where hourly volumes have not been measured or estimated [34]. With only three explanatory variables, the method omits many other environmental and psychological factors that are proposed to influence BLOS (see Table 1). It is included in this study to assess whether simple indicators like this are sufficient for the purpose of route choice estimation in the same way as more complex BLOS methods. Although the three parameters necessary to produce the BSL rating can be easily aggregated via attribute tables in GIS, the ArcMAP toolbox used earlier for HCM6 also contained a tool for BSL calculation, and this was therefore employed for this paper [7].

3. Methods

3.1. Survey and Mapping API

The primary empirical data source used in this paper was obtained through a web-based mapping survey where university students were asked to draw their preferred route by bicycle between their student residence complex and the Trondheim City Square. By choosing the centre of Trondheim, the presumption is that students would be familiar with the location and several potential routes to get there given it is near to many common destinations and is frequently used as a meeting place. In November 2015, approximately 3000 students across four university-managed residence complexes were emailed an invitation to the study by the Student Welfare Organisation in Trondheim. The largest student complex Moholt houses approximately 2000 students and was therefore considered as two separate origins due to its larger geographical footprint. This meant that route choices were mapped along five origin–destination pairs based on geographical midpoints of the students' residence clusters and the Trondheim city square.

Although the focus was on bicycle travel behaviour, the survey invitation was titled "student travel behaviour study" in order to receive responses from non-cyclists and cyclists alike. This was done to avoid response bias towards those who already cycle [49,50]. This assist to ensure that the sample is generally representative of the overall (student) population, an important consideration compared to most bicycle travel behaviour studies that are focused primarily on existing cyclists (whose potential to cycle more is limited) [51]. As a motivation for completing the survey, participants were given the chance to win a gift card worth €50. The online survey contained 20 general questions concerning participants' socio-demographic characteristics and personal travel behaviour both at the beginning of the 2015 autumn semester and at the time of answering the survey (early winter with some snow).

Upon completion of the survey form made in Jotform.com, participants were redirected to a second webpage that contained a Google Maps mapping Application Programming Interface (API), built upon the same principles detailed in Snizek et al., 2013 [52]. The survey generated a unique identifier for each participant which was sent to the second webpage via the Hypertext Transfer Protocol (HTTP) POST request method. The POST request method requires the receiving web server to accept data contained within the request message (in this case a user ID number) and is often used in connection with file uploads or a customised "thank you" message following survey submission. The redirect URL for this paper had the form http://trondheim.routr.dk/?user_id={ID} in which trondheim.routr.dk was the web host whilst {ID} was received directly from Jotform upon survey completion. This allowed the matching of survey responses and the mapping API webpage. The mapping API webpage was specifically created for the study and contained a Google Maps background map centred on Trondheim, a polyline drawing tool and instructions to draw a single preferred bicycle route between their student residence and the city square, illustrated below in Figure 1.

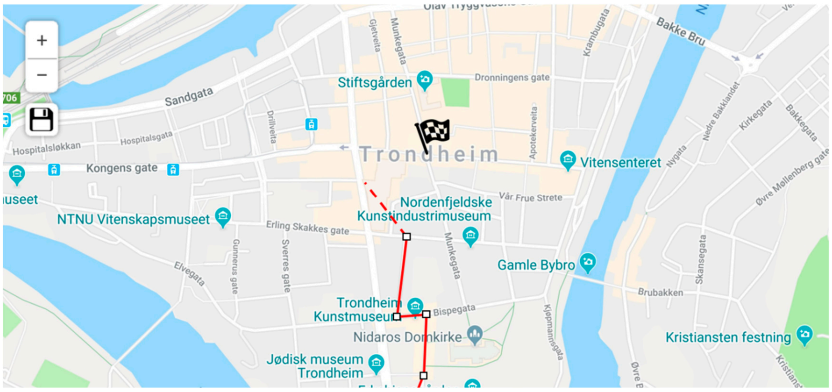


Figure 1. Google Maps based mapping API used to collect participant responses on bicycle route choice. The end point, Trondheim City Square, is indicated to users with a flag.

Early in the data collection process, it was discovered that the route data received via the mapping API was highly variable in quality and that this was likely due to the poor functionality of the mapping website on smartphone browsers. In particular, the drawing, navigation, and zoom functions were found to respond poorly to touch screen input. The respondents that this applied to were asked to repeat the mapping task using a personal computer. In total, 677 routes were gathered by the mapping API and stored for further data processing, as described below.

Despite the commonality of web-based mapping applications, this data-collection method is seldom applied to studies of bicycle route choice [51]. It does, however, offer insights from a large respondent population without the need for more time and cost-intensive Global Positioning System (GPS) methods, whilst avoiding the need for digitisation of hand-drawn or verbally described routes. It should be noted that web-based mapping applications are subject to the same limitations as other mapping tools, particularly with respect to imperfect user knowledge (both of maps generally and of their local environment)—making data collection in this manner less reliable than methods which track movements such as GPS or ride-along interviews.

3.2. Network Information

In addition to the data gathered from the mapping API described above, there were several other data sources that needed to be utilised in order to develop a complete bicycle network upon which the analysis of the data could be performed. These are detailed below in Table 2.

3.3. Data Preparation

The first stage of empirical data processing involved removal of duplicate route responses, which may have been the result of participants refreshing the mapping API webpage. From a total of 677 routes drawn, 611 remained after duplicate responses were removed, giving a response rate of 20%. For the purpose of determining route choice, the data received in the mapping API had to be both complete and relatively detailed. In the cases where route choice was not possible to determine from the raw data, the routes were removed from further analysis, leading to a dataset with 518 responses. Map-matching was performed on the routes using ArcMAP 10.6. The process involved the creation of a 50-metre buffer around each route which was found to provide the optimum level of matching (incrementing buffer size by 10 metres each time) without excessive false positive matches to neighbouring streets. The maximum buffer width is a function of the urban structure of the city—particularly the length of city blocks or distance between parallel streets. Thereafter, two further datasets were created containing the origins and destinations for the corresponding route. A shortest path search (based on non-modified link lengths) from origin to destination on the transport network contained within the 50-m buffer was performed. 467 routes were able to be matched using this procedure.

Table 2. Data sources for the GIS transport network.

Data Source	Input Data Set	Data Type
Norwegian Mapping Authority & Norwegian Public Roads Administration	Street network including paths and topography (Norwegian "elveg" database)	Geodatabase—centrelines of roads
Norwegian National Road Database	AADT traffic volumes, speed limit and lane width data	ArcMAP API toolbox
Authors, kart.finn.no aerial photography	Missing links for pedestrians and bicycle users. Supplementary information for the network (parking, bicycle lanes, kerb presence)	Geodatabase (manual editing)
Survey respondents	Mapped bicycle route choice (mapping API)	Geographic JavaScript Object Notation (GeoJSON)

3.4. Network Impedance Based on BLOS

Bicycle Level of Service methods are used to generate potential route choices using a modification of the approach from Cervero et al., 2019 in which a Level of Traffic Stress (LTS)-classified transport network is used to allocate additional impedance (together with travel time) for streets and intersections poorly suited for cycling [53]. The approach involves the distribution of impedance (as an additional length) based on BLOS score.

Links in the transport network with poorer standard as defined by the various BLOS methods are the least attractive and are therefore allocated a higher impedance (up to the maximum detour rate bicyclists are considered willing to take). Impedance is allocated in two stages: as a multiplicative impedance factor for link length, and as an additional penalty length added to the links as they enter intersections.

The first stage of allocating impedance to link lengths applies Cervero et al.'s method for LTS to all four BLOS methods. This method applies the maximum level of impedance to the links with LTS4, and zero impedance to the links with LTS1. Cervero et al. allocate a maximum impedance factor (to be multiplied by link length) of 1.15, which stems from the assumption that a 15% detour rate is considered to be acceptable for cyclists. Since LTS2 and LTS3 street links are of a standard in between links classified as LTS1 and LTS4, they are allocated impedance factors of 1.05 and 1.10 respectively. This method, limited to link impedance, has previously been applied to generate bicycle routes using an impedance factor of 1.20 (or 20% detour rate) on a network classified according to LTS [54].

The second stage of Cervero et al.'s impedance allocation occurs at intersections. This approach creates buffers of varying sizes around intersections in order to transfer the LTS attributes of the poorest standard link in an intersection to the buffer length of other links in the intersection [53]. The rationale behind this is to transfer some of the traffic stress involved in crossing an intersection onto the links in the intersection with lower traffic stress. The largest buffer of 25 m corresponds to links with the highest traffic stress, LTS4. Thus, if a quiet bicycle path (LTS1) intersects an LTS4 road, 25 m of its length nearest the intersection is replaced by an LTS4 standard link, thereby receiving an increased impedance when the link impedance factor is applied as described earlier. Whilst Cervero et al. use unevenly distributed buffer sizes of 0, 10, 15, and 25 m for the LTS categories 1 to 4 respectively, this paper uses evenly distributed buffer sizes of 0, 8.33, 16.67, and 25 m (for the same LTS categories). The even distribution of buffer sizes (between 0 and a maximum of 25 m) extends the principle used in the link allocation stage and ensures that all four BLOS methods receive the appropriate share of intersection impedance.

In this paper, the multiple buffers are converted into an additional 'penalty length' measured in metres to be added to all links that cross a higher level of traffic stress link. The maximum penalty length is the additional length added to a link of the highest standard which crosses one of the lowest standards (such as LTS1 with LTS4) and is described by Equation (2) below. Using a length rather than multiple concentric buffers simplifies the GIS requirements of intersection impedance allocation (especially since BSL has five rather than four levels whilst BCI and HCM6 have six levels each). The penalty length is allocated to links at intersections using 10-centimetre radius buffers. Such small buffers are used to avoid issues with closely spaced intersections, including intersections of bicycle paths with roads [54].

$$Penalty\ length_{max} = (Impedance\ factor) \cdot (virtual\ buffer\ length) - (virtual\ buffer\ length) \quad (2)$$

Table 3 below displays impedance factors (for link length multiplication) in column 2 and maximum penalty length (for links entering intersections) in column 4 for the LTS method based on a sample maximum detour rate of 15%. The same principle applies for the three other BLOS methods. The maximum penalty length applies only to LTS1 links (since they have no impedance from the link impedance allocation). For other links which cross a link of higher LTS, the penalty length applied is reduced. For example, at the intersection of an LTS2 and LTS3 link, the penalty length applied to the LTS2 link would be equal to the difference in maximum penalty lengths, i.e., 1.67 − 0.42 = 1.25 m (using the sample numbers from Table 3). The LTS3 link in this example is the link with the highest level of traffic stress and will therefore receive no additional penalty length, in the same manner as the original method from Cervero et al. [53].

Table 3. Lookup table for maximum additional 'penalty length' at intersections in the bicycle network with different Levels of Traffic Stress. The impedance factor in the second column is multiplied with link lengths in addition to give a 'perceived link length'. Similar tables can be made for the BCI, BSL and HCM6 methods.

LTS Level	Impedance Factor for Links (for Max Detour Rate of 15%)	Virtual Buffer Length (in Metres)	Maximum Penalty Length (in Metres)
1 (best)	1	0	0
2	1.05	8.33	0.42
3	1.10	16.67	1.67
4 (worst)	1.15	25	3.75

The only difference in replicating Table 3 above for the other BLOS methods is the number of rows (equal to the number of classification categories in the method). Both the impedance factor and the virtual buffer length are evenly distributed into (up the max impedance factor defined by the max detour rate and to 25 m for virtual buffer lengths).

The additional lengths or travel distances generated by this approach means that a shortest path search on the network will be less likely to make use of links with poor quality (such as those with LTS4). This paper replicates the approach outlined above for all four BLOS methods in order to generate route choices that take account of bicycle infrastructure quality, described in greater detail below.

3.5. Detour Rate

Empirical data on detour rates does exist however and is reported and calculated in many ways. A route choice model from Portland, USA that found that cyclists perceived distance to be 16% shorter on bicycle paths compared to regular routes, all else being equal [55]. This is equivalent to a willingness to cycle 19% longer for a commuting journey if they are able to use a bicycle path for the whole journey: 1/(1 − 0.16) = 1.19. Other literature from Ohio uncovered a mean detour rate of 13.5% [56]. A small sample of 50 cyclists in Indiana was found to have a similar detour rate of 13% [57]. A Brazilian study of the same size found that cyclists travelled on average 14.6% longer than the shortest path [58]. One smartphone application used in Bologna found a mean detour rate of 14% from 4272 bicycle commuting journeys, which the authors claim are generally more direct than other journeys made by bike [59]. Aultman-Hall performed a study using recalled hand-drawn route choices from 397 participants in Ontario, Canada and found that individuals were willing to divert 0.4 km from the shortest path for trips that averaged 3.7 km (i.e., 10.8% detour) [60].

Although many of these values for detour rates are similar, arriving at a maximum acceptable detour rate is troublesome due to heterogeneity of users, contexts and approaches, as indicated by the wide range of means starting from 6% [61] and up to as much as 67% [62].

Norwegian cyclist route behaviour is very appropriate for the consideration of detour rates due to the hilly topography and urban form common to many Norwegian cities. Hulleberg et al. found that for 721 GPS users in Oslo, a mean detour rate of 21% was observed whilst the median was approximately 12% longer than the shortest path [63]. This study demonstrates how skewed the distribution of detours from the shortest path can be. Since most literature suggests that cyclists are not willing to cycle more than 50% longer than the shortest path, this was used as an upper limit for the iteration of the detour rate. This corresponds with impedance factor intervals of 0.05, this meant that 11 iterations were performed between 1.00 and 1.50. The intention of this procedure was to create multiple optimal routes which can subsequently be checked for association with the empirical route choice data.

The maximum impedance factor of 1.15 used in Table 3 is not empirically founded, and is used to demonstrate the procedure for calculating penalty length [53]. The impedance factor to be multiplied with link length is shown for Level of Traffic Stress in Table 4 below as a function of the 11 detour rates. For links intersecting other links with lower BLOS standard, a second table is required to summarise the additional 'penalty length' (in metres) for each detour rate iteration. An example for application to LTS is shown in Table 5, which extends on the principles explained in Table 3 and Section 3.4. All possible combinations of links with a higher standard intersecting those with a lower standard are shown in this table, whilst the original figures from Table 3 and the 15% detour rate are marked with asterisks. Tables 3–5 are used for illustration purposes for LTS, but they have also been created for BCI, BSL, and HCM6 in order to produce the results presented in this paper.

Table 4. Level of Traffic Stress link impedance factors (to multiply with length) to create the 'perceived link length'.

	Detour Rate (Percentage Additional Length)										
LTS level	**0**	**5**	**10**	**15**	**20**	**25**	**30**	**35**	**40**	**45**	**50**
1 (best)	1	1	1	1	1	1	1	1	1	1	1
2	1	1.02	1.03	1.05	1.07	1.08	1.10	1.12	1.13	1.15	1.17
3	1	1.03	1.07	1.10	1.13	1.17	1.20	1.23	1.27	1.30	1.33
4 (worst)	1	1.05	1.10	1.15	1.20	1.25	1.30	1.35	1.40	1.45	1.50

Table 5. Level of Traffic Stress penalty length (in metres) for all links at intersections (applies to all network links with LTS lower than the maximum LTS in the intersection). The asterisks indicate the connection with the final column in Table 3.

	Detour Rate (Percentage Additional Length)										
LTS_{link} to LTS_{max}	**0**	**5**	**10**	**15 ***	**20**	**25**	**30**	**35**	**40**	**45**	**50**
1 to 2	0	0.14	0.28	0.42 *	0.56	0.69	0.83	0.97	1.11	1.25	1.39
1 to 3	0	0.56	1.11	1.67 *	2.22	2.78	3.33	3.89	4.44	5.00	5.56
1 to 4	0	1.25	2.50	3.75 *	5.00	6.25	7.50	8.75	10.00	11.25	12.50
2 to 3	0	0.42	0.83	1.25	1.67	2.08	2.50	2.92	3.33	3.75	4.17
2 to 4	0	1.11	2.22	3.33	4.44	5.56	6.67	7.78	8.89	10.00	11.11
3 to 4	0	0.69	1.39	2.08	2.78	3.47	4.17	4.86	5.56	6.25	6.94

3.6. Route Choice Generation and Evaluation with Empirical Data

The procedure detailed below was used to generate routes using the four BLOS methods described in Section 2 and subsequently assess their association with empirical map-matched route choices.

1. Collect necessary transport and land use GIS parameters in the area of interest from existing data sources (see Table 2) or field data.
2. Combine the necessary parameters to produce the BLOS index value for each link in the transport network area using GIS attribute tables.
3. Create a range of plausible detour rates and corresponding impedance factors (for different BLOS levels) from the shortest path (e.g., 0 to 50% in this paper). See example in Table 4 for LTS.
4. Create a new parameter for each link 'perceived link length' by multiplying the link length with the impedance factors from step 3.
5. Create a new parameter 'perceived intersection length' for intersections with three or more links and variability in BLOS amongst links (see lookup example in Table 5 for LTS).
6. Combine the two components for each link to produce a new parameter 'perceived length'. This is the sum of 'perceived link length' and the relevant 'perceived intersection length' lookup value for cases in which the link intersects another link with a lower (poorer standard) BLOS.
7. Calculate a new parameter 'perceived travel time' using 'perceived length' and the underlying topography (in this study, performed using Network Analyst in ArcGIS). For this paper, travel time is dependent on cycling speed which is a direct function of link gradient the Norwegian Area and Transport Planning (ATP) model. The ATP model is an ArcGIS extension which performs a variety of functions and includes a simple speed model for different gradients. On slopes with a gradient of −10% or more (downhill), a maximum speed of 40 kph is used. Similarly, above 8% gradient (uphill), a constant speed of 3 kph is used. On level ground, cyclists are assumed to cycle at 16 kph. Speed is linearly decreased as the gradient increases from 0 to 8% and is linearly increased when the (downhill) gradient approaches −10% (from 0% gradient). Note that the original link gradient is assumed to apply to the 'perceived length'.
8. Now, for each OD pair and detour combination, find the optimal route which minimises the perceived travel time (these are hereafter called generated routes). Since there are 11 different detour rates iterated in this example, each OD pair will have 11 (not necessarily unique) generated routes.
9. For each OD pair, find the degree of overlap between the empirical map-matched routes and the generated routes. Since there are very few empirical routes that use the entirety of the generated route, we can measure instead the number of cyclists on each link of the shortest path to give a 'length-weighted' number of cyclists on a generated route according to the numbers of cyclists found to use its component links. This is described using the notation in step 10.
10. Say that there are n unique generated routes of interest $R_1, \ldots, R_n$. For each $j \in \{1, \ldots, n\}$ we have m_j links, and the lengths of these links are denoted by $L_{1,j}, L_{2,j}, \ldots, L_{m_j,j}$. The total length of the jth route would then be $L_{tot,j} = \sum_{i=1}^{m_j} L_{i,j}$. Now let C_i be the number of cyclists recorded on link i. Then the number of 'weighted cyclists' (denoted by W_i) on link i within route j is therefore $W_{i,j} = C_{i,j}\frac{L_{i,j}}{L_{tot}}$. The percentage of cyclists on a specific generated route is then the sum of weighted cyclists along that route's component links divided by the total number of participant-drawn routes (which we know from Section 3.3 to be 467) as given by Equation (3)

$$\textit{Percentage cyclists using generated route } R_j = \frac{\sum_{i=1}^{m_j}\left(C_{i,j}\frac{L_{i,j}}{L_{tot,j}}\right)}{467} \quad (3)$$

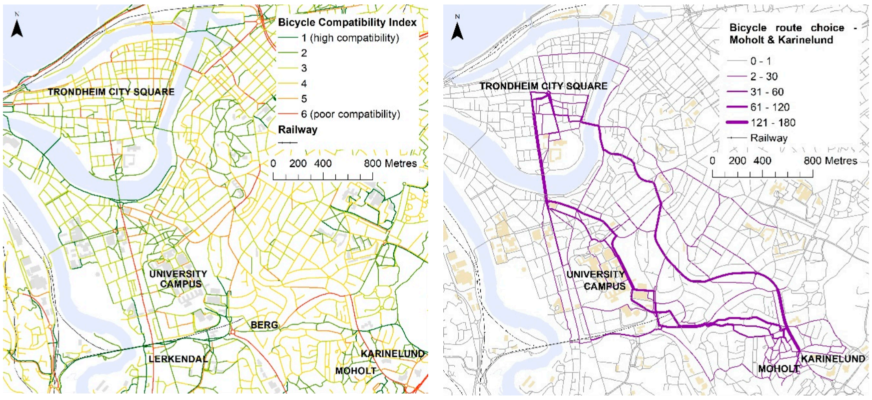
11. Plot the percentage cyclists on each generated route R_j against the iterated detour rates (on the x-axis. The optimal value (highest percentage match on the y-axis) provides an empirical indicator

of willingness to deviate from the shortest path to use high-quality infrastructure (in terms of bicycle suitability in relation to surrounding options).

4. Results

4.1. BLOS Map Creation and Empirical Route Choices

The intention of the study was to assess the suitability of BLOS methods for the creation of realistic bicycle route choices. Following the procedure outlined in steps 1 and 2 of Section 3.6, four BLOS maps were produced for each of the different methods: BCI, BSL, HCM6, and LTS. In Figure 2a below, the map of the Bicycle Compatibility Index in the study area is shown, and similar maps were created for the three other BLOS methods. In Figure 2b, the empirical routes for the two student residences Moholt and Karinelund are shown, which represent three of the five OD pairs since the largest student village was subsequently split into Moholt North and Moholt South. The paper then attempts to uncover whether there is an association between each BLOS method and the empirical route choices by following the steps 3 to 10 from Section 3.6.



(**a**) (**b**)

Figure 2. (**a**) Bicycle Compatibility Index for Trondheim. (**b**) Heat map of the student route preferences from the student villages Moholt (n_{north} = 140, n_{south} = 100) and Karinelund (n = 57).

4.2. Route Generation

By subsequently iterating the level of impedance allocated to links based on their BLOS, it was possible to generate a variety of 'shortest path' routes. With 4 BLOS methods, 5 OD pairs, and 11 iterations of detour rate, this meant that 220 routes were generated in total. Despite the relatively large range of detour rates trialled (0–50%), the variation in routes generated was relatively small. With only 23 unique generated routes from 220 iteration runs, the effect of the iteration steps was lower than expected. Each OD pair had between 2 and 6 unique routes generated by the alternative approaches. The maximum percentage difference in length between any generated routes on a single OD pair was 4.3% (for Moholt North).

The quality of the route generation approach was determined by taking the average percentage overlap between empirical routes and the generated route. For each combination of four BLOS methods and five OD pairs, the route with the highest overlap with empirical routes is selected, giving a total of 20 best-generated routes. These are displayed in Figure 3 below. Immediately apparent is the high degree of coincident routes generated. For example, from the westernmost student residence Lerkendal, all of the routes generated have the same 'best' route. For this example, the generated route overlaps with on average 52% of the empirical routes (see step 9, Section 3.6). For the four other OD pairs, a larger variety of empirical route choices is observed, and the percentage overlap is therefore also lower (Berg: 16%, Moholt North: 20%, Moholt South: 28% and Karinelund: 24%).

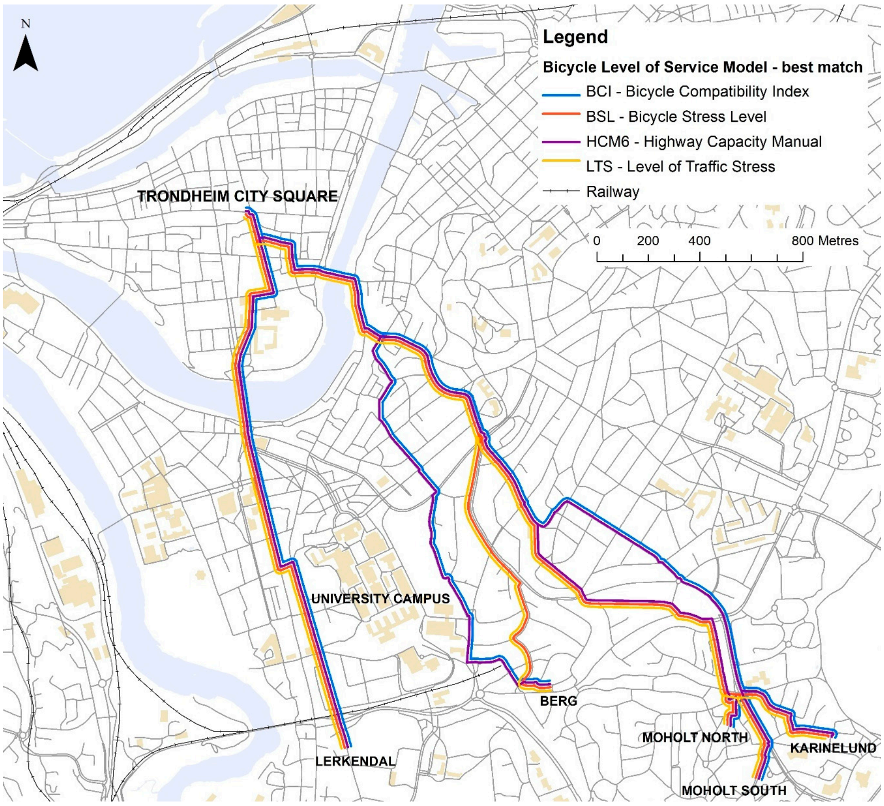


Figure 3. Best routes generated (across all iterations of detour rate) along five OD pairs using four BLOS methods.

4.3. BLOS Model Comparison

The four BLOS models' performance is compared by percentage route overlap with the empirical route choice data in Figure 4 below. The plotted data is the average percentage overlap from each of the five origin–destination pairs (which each have a minimum of 50 route preference responses). The figure shows relatively similar performance between the methods, despite the different BLOS method inputs, with route overlap for the alternative approaches ranging between 20 and 27% across the full range of detour rates. This suggests that the importance of the shortest travel time may be more dominant than the effect of the different levels of service, which is supported by the low degree of generated route variety in Figure 3. Alternatively, this may be the result of a significant degree of overlap between simple methods such as BSL with more complex methods like HCM6. The two methods with fewest parameters, BSL and LTS, have identical best route geometry with three and four parameters respectively. The similarity is also reflected by the similarity of the percentage route overlap in Figure 4. BCI and HCM6 each produce 16 route suggestions for the group of 5 OD pairs, whilst LTS and BSL produce only 8 route suggestions.

The method that performs best across all iterations of detour rate is BCI, with eight explanatory parameters. Trends in relation to detour rate are not immediately obvious, and therefore the average of the four methods is depicted in green together with a line of best fit. The line of best fit shows a local maximum for detour rate of approximately 15%. The tendency for a global maximum to form around this value is expected given empirical research on detour rates (see Section 3.5), but this trend is not as clearly evident in the individual BLOS methods, lending some uncertainty as to whether this finding is significant.

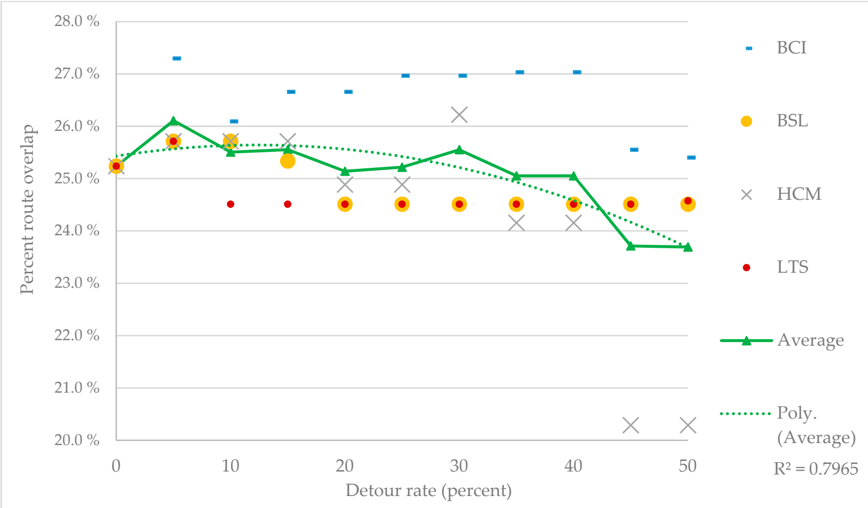


Figure 4. Percentage route overlap between empirical and generated routes for four BLOS models. The line of best fit is indicated by the dashed line.

An alternative means by which the detour rates can be compared is considering the mean level of detour needed for each method and OD pair combination to achieve the best match with empirical data. For Moholt North, the best match is achieved by BCI, for Moholt South, Berg, and Karinelund, both BCI and HCM6 produce the same best match result, whilst for Lerkendal, all methods produce the same best match route. The average detour rate of these 11 best match results across the 5 OD pairs is 21% (additional length). This figure is also within the range expected by the existing empirical research on detour rates.

5. Discussion

This paper seeks to establish how well BLOS methods, which are used to provide letter-grade or numeric ratings for all streets in the city network, can reflect actual route preferences. To the authors' knowledge, this is the first 'reverse engineering' of BLOS indicators in the academic literature using OD route choice data. BCI performs the best of the four methods across all iterations of detour rate, achieving the highest percentage overlap with empirical routes. HCM6 performs equally as well for four of the five OD pairs, and together with BCI has the most explanatory factors. Both HCM6 and BCI have factor coefficients that are empirically determined. The two remaining methods, BSL and LTS, have only three and four explanatory factors respectively and equation coefficients that are not based on the empirical evidence potentially explaining the lower percentage match with the empirical route preferences.

The comparison of generated routes with empirical routes gave a considerably different percentage overlap for the Lerkendal student residence compared to the three other student residences. Variation between different OD pairs in terms of percentage overlap is a natural function of variability in actual route choices (assuming the methods work equally well in different network configurations). It is also shown that the two best-performing BLOS methods, BCI and HCM6, also produce double as many routes compared to BSL and LTS. The greater number of routes generated increases the chances of achieving a higher match. It should be noted however that route choice generation algorithms should ideally create the fewest false positives possible whilst also covering the breadth of empirically chosen route options [42].

Two different approaches were used to compare the BLOS methods in relation to detour rate. The first approach considers the average performance of all four models for the five OD pairs, with a line of best fit revealing a local maximum for iterated detour rate of between 10 and 15%. The second approach takes the average iterated detour rate of the 11 equally best matches for each of the five OD pairs is 21% (additional length). These figures show the optimum detour rate used in achieving the best match with empirical data. Whilst empirical research on detour rates suggests that cyclists are willing to travel approximately 15% longer compared to the shortest path, the route generation process does not create routes with this level of detour. Indeed, the maximum difference in length for generated routes on any OD pair was 4.3%. This small difference is surprising given that the maximum detour rate of 50% was used for all BLOS models.

There are several factors that could explain this discrepancy. The perceived travel time of any given link is increased by the value of the detour rate only if it has the lowest level of service for the corresponding BLOS model. If the link has anything greater than the lowest level of service, the detour rate applied is reduced, as detailed in Table 4. Since the network has few links with the lowest BLOS, the effective maximum change in detour rate of 50% is only applied to these select links. Another explanatory factor relates to the way impedance values are added at intersections; by affecting only links crossing those with a lower level of service. This is a simplification of the reality since interactions with crossing traffic will occur even if travelling on the link least suited for cycling or when entering an intersection where all links have the same BLOS value. Future research may seek to explore the penalty lengths that should be applied to links in intersections with equal or lower BLOS than other incoming links. Finally, if the shortest path has a relatively high BLOS (high quality), then alternatives are less likely to be created since this paper finds the optimum cycling route, based on BLOS weighted travel time.

Given that a 50% detour rate in the link penalty approach does not give a 50% longer route compared to the shortest path, future research should modify to the approach used through the consideration of the factors above. Alternatively, much higher detour rates than 50% could be trialled for generation of additional routes provided it is understood that this detour rate does not reflect the typical additional detour length of routes generated.

The low route variation in the modelling process adopted is not uncommon in reviews of the route generation literature [64,65]. In order to generate a route choice set which better reflects the typical range of bicycle route choices, there are a number of alternative approaches that can be used such as labelling, stochastic methods, link elimination, and link penalty as summarised by Ton et al. [42]. This study's route choice generation is a form of link penalty, in which multiple attributes are combined through the adoption of existing BLOS methods and used to allocate link impedance or cost. The assumption is that BLOS methods combine attributes considered important to users and that this therefore should reflect the likelihood of selection. The assumption is supported by empirical data which suggests that cyclists tend to choose routes that optimise the combination of distance, time, and safety but not any one objective singularly [66].

The objective BLOS methods tested are based upon bicyclists' route preferences in the US context. Whether or not contextual differences are important is difficult to assess since no non-US BLOS methods were tested. Future research may seek to use other methods for the purposes of contextual comparison such as the Danish model of BLOS from Jensen, which represents a considerably different cycling environment [38].

6. Conclusions

The methodology adopted in this paper demonstrates that BLOS methods are able to assist in the generate of bicycle route choices, but that the number of unique routes generated is low. The iterated impedance factor demonstrates a tendency to develop optimal routes at between 15 and 21%, however the overall match rate is lower than expected (<30% match when averaging across the five OD pairs). This is partly because the iteration of the multiplicative impedance factor (between 1.0 and 1.5) used in this paper does not lead to an equivalent variation in the length of generated routes. Given that the maximum difference in length between any two routes on a single OD pair was less than 5%, the maximum impedance factor should be increased if the intention is to generate routes that are up to 50% longer than the shortest path. In addition to modifications of the detour approach, future research may seek to use alternative BLOS methods, or make comparisons with alternative route generation approaches including commonly used internet mapping applications. Wayfinding literature, in which route choices tend to be preferred if they reduce navigational complexity, may also be considered by future research [67].

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