QUALITY OF BICYCLE TRAFFIC MANAGEMENT AT URBAN ROAD LINKS AND SIGNALIZED INTERSECTIONS UNDER MIXED TRAFFIC CONDITIONS

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Abstract: This paper deals with the development of bicycle level of service (BLOS) models for urban road links and signalized intersections carrying heterogeneous traffic. For analyses purposes, required data are collected from 74 links and 70 intersection approaches by means of extensive field investigations, video recordings, and perception surveys. Total 22,320 on-site bicyclists have rated the studied sites based on their perceived satisfaction levels (1 = excellent and 6 = worst). These ratings were used as the array of dependent variable in the BLOS model development process. A novel technique namely, multi-gene genetic programming (MGGP) was used to develop the BLOS models for urban road links and signalized intersection approaches. The link model included eight significant variables whereas the intersection model included seven variables. Both models produced reliable prediction performances in the present context with coefficient of determination (R^2) values of above 0.87. It was observed that traffic volume and crossing pedestrians have the highest influences on BLOSs of urban road links and signalized intersections respectively.

Keywords: Roadway link, signalized intersection, mixed traffic, bicycle level of service, multi-gene genetic programming.

INTRODUCTION

In many countries around the world, the developmental stages of road infrastructures have been primarily focusing on the safe management of motorized traffic. Conversely, the perceived comfort levels of bicycle users are being highly neglected. Facilities favorable for bicycle use such as separate bicycle lanes, shared-use paths and wide shoulders are not frequently available on the street segments. As a result, bicyclists are inevitably using the lanes available on the main carriageway to fulfil their mobility requirements. However, these lanes are predominately used by motorists and thus bicyclists are cogently deprived from availing the minimum space desired for a smooth riding. Under such conditions, bicyclists are encountering a very complex interaction with various categories of vehicles widely varying in their sizes and operational characteristics. An in-depth understanding of bicycle operations under such an environment is very much complex and important as well. An innovative approach for the investigation of operational characteristics of bicyclists' measured through comfort ratings is presented in this paper. Researchers in developed countries have made significant effort to explore these concerns under homogeneous traffic flow conditions only.

However, in case of developing countries, the traffic flow on the main-carriageway is highly heterogeneous where vehicle users do not follow the lane discipline. Thus, the findings of previous studies cannot fulfill the mobility requirements under heterogeneous traffic conditions. So far, the modelling of bicyclists' perceived comfort levels under such traffic flow conditions has not been given a systemic approach. These models in fact play vital roles while making any plan of actions for the enhancement of service qualities offered by existing transportation facilities. These models also assist while designing new bicycle-friendly road networks. The present study has primarily focused on the development of "Bicycle Level of Service" (BLOS) models thorough an in-depth investigation of bicycling behavior under prevailing road conditions. For analyses purposes, a large quantity of data sets (roadway geometric details, built environmental characteristics, traffic flow parameters and socio-demographic information of users) were collected from a large number of 60 road segments. These segments are located in different parts of India and well represent the variability and complexities persisting in the bicycling environment. Each studied segment was rated by 150 bicycle users from varying socio-demographic backgrounds based on its ability to satisfy on-street bicyclists. The ratings were collected using a 6-point Likert scale (1 = 'excellent' and 6 = 'worst') and named as BLOS scores. A thorough investigation was carried out to identify which attributes have significant influences on the perceived BLOS in the present context.

BACKGROUND STUDIES

Several studies have been conducted in the recent years to relate roadway geometrics and homogeneous traffic flow conditions with the operational characteristics of bicyclists. Bicycle Safety Index Rating (BSIR) model [2] is the initial model developed to assess the bicycle service criteria of street segments. This model is comprised of two sub-models namely, Roadway Segment Index (RSI) and Intersection Evaluation Index (IEI) model. RSI model is a function of traffic volume, number of lanes, speed limit, width of outside traffic lane, pavement conditions and location factors. This model neglects the influences of percentage of heavy vehicles and on-street parking turn-over, etc. Modified Roadway Condition Index (RCI) model [3] is a modified version of the RSI model. In this model, the location and pavement factors were modified and the lane width term was multiplied by speed limit to place greater weightage on narrow roads with high vehicular speeds. Bicycle Suitability Rating (BSR) model [4] is also a modified version of RSI model which signifies the important roles of traffic volume and traffic speed in BLOS criteria.

Developers of another bicycle service model namely, Interaction Hazard Score (IHS) model [5] identified the important roles of two more influencing variables namely roadside land use intensity and curb cut (on-street parking) frequency. Further, the importance of curb-lane was reflected in Bicycle Stress Level (BSL) model [6]. This model exclusively considers three different parameters of the curb-lane to define the bicycle service criteria such as curb-lane width, curb-lane traffic volume and average traffic speed in the curb-lane. BSL model was further improvised and BCI model [7] was developed. BCI model introduced some new influencing parameters such as bicycle lane parameters and right turning vehicles parameters. HCM (2010) [8] considered a broad range of factors such as effective width of the outside through lane, mid-segment demand flow rate, number of through lanes, motorized vehicle running speed, percentage of heavy vehicles and pavement condition for defining the bicycle service criteria.

Some of the other studies have revealed that, the interference from pedestrians and non-motorized vehicles considerably degrade the bicycle service quality [9] while, well maintained pavement surfaces and the provision of bicycle lanes positively influence the same [7, 10-13]. Frequency of driveways also have considerable negative influence on bicyclists' perceived sense of comfort [2-4, 5, 7]. Traffic volume largely influences bicyclists' perceived comfort levels under heterogeneous traffic flow conditions [14]; and with the provision of separate bicycle lanes, bicyclists gain better confidence to ride further from the edge of roadways [15, 16].

From the above discussions it could be summarized that, several roadway geometric and traffic flow variables have considerable influences on bicyclists' perceived sense of comfort. The role of individual variables changes with the change in roadway environmental conditions. In this regard, an extensive investigation was carried out in this study to identify the influencing variables under heterogeneous traffic flow conditions. In addition to the variables considered in previous studies, the role of few more variables (for an example roadside stoppages of intermittent public transits) were also investigated. Subsequently, a new bicycle service prediction model was developed which is basically a new decision support system for the transportation planners and designers.

MGGP MODELING

MGGP is an extension of GP which is used to develop a mathematical model that is empirical in nature between output and inputs. It is also known as symbolic regression. This model is formed from combination of several trees. The non-linear lower order transformations of input variables represents each tree which is called as a gene. Each gene has specific optimum weights and the summation of weighted genes plus a bias would give the best empirical mathematical model. Genetic Programming principle is used for pattern recognition which is based on the adaptive learning over many data sets. Making use of principles of Genetic Algorithm, it simulates the biological evolution of the living organisms. Using the principle of Darwin natural selection, Genetic programming finds the solution for a problem using symbolic regression technique that uses a computer program. GP can be completely understood by the experimental works of Koza. The extended part of Genetic Algorithm is Genetic Programming. The only difference in between GA and GP is the representation of respective solutions. The solution in GA is represented by string of numbers where as in GP solution is represented by tree structure.

GP model composes of nodes representing a tree structure. Which is commonly known as GP tree. There are 2 sets from which nodes are formed namely functional set and the other is terminal set. Functional set includes arithmetic operators (+, / ,×, -) or Boolean operators (AND, NOT ,OR) or mathematical functions (tanh(.), ln(.), sin(.) or cos(.)),or logical Expressions (IF,or THEN) or any other functions defined by user. Variables like (x_1, x_2, x_3,x_4, etc.) or constants(like2,5,8,etc.) or both can be included in terminal set. A GP tree is formed by randomly selecting functions and terminals. The branches extend from function nodes and finally end in a terminal node. For a defined population size, functions and terminals, initially a group of GP trees are randomly generated. Objective function calculates fitness criteria and the quality of each and every individual in the population which is competing with rest is determined by fitness criteria. Based on the merit of fitness, individuals are selected from the initial population and a new Population is created at each generation. There are three mechanisms those are implemented on the new population which are reproduction, mutation and crossover.

In the initial step of genetic programming, various GP trees are produced by arbitrarily selecting user characterized functions and terminals. Initial population is formed from these GP trees. Initial population is generated by randomly selecting m individuals which forms the first generation. Based on fitness function depending on m inputs an output will be evaluated which describes how nearer were these m individuals close to our demand. Of the above fittest individuals a new generation N is formed. This process of forming generation N and iterating N+1 generations is carried till good performance is satisfied. Breeding is the formation of offspring based on the fittest individual from previous generations. The genetic operations involved in breeding are reproduction, mutation and crossover. From generation N, one individual is selected from the fittest individuals which changes most of its characteristics swapping with the other one. The offspring formed gets over next generation. This process is called mutation and is represented as P_m. From generation N, two are selected from the fittest individuals, randomly chooses characteristics of first individual to be replaced by the second one such that characteristic won't change. Two offspring's are created which belongs to the new generation. This process is called crossover and the probability is defined as P_c. From generation N, one is selected from the fittest individuals and pass it over next generation N+1 without making any changes. This process is called reproduction and its probability of occurrence is P_s. The above mechanisms are iterated until the threshold of fitness is reached or the maximum generations is satisfied. Based on fitness value that appears in any of the generation is taken as the best fit GP model.

DATABASE PREPARATION

In this study required data are collected form 74 road links and 70 signalized intersection approaches. These sites are located in the following cities of India:

1. Bhubaneswar, Odisha state (29 links, 25 intersection approaches);
2. Lucknow, Uttar Pradesh state (14 intersection approaches);
3. Rajahmundry, Andhra Pradesh state (11 links);
4. Nagpur, Maharashtra state (7 intersection approaches);
5. Tirupati, Andhra Pradesh state (12 intersection approaches);
6. Kottayam, Kerala state (12 links);
7. Rourkela, Odisha state (19 links, 6 intersection approaches);
8. Kurnool, Andhra Pradesh state (3 intersection approaches);
9. Anantapur, Andhra Pradesh state (3 intersection approaches).

Quantitative Data

Quantitative data sets basically include geometric, traffic and other built-environmental attributes. During the inventory survey, geometric attributes such as: width of carriageway, shoulder, parking lane, sidewalk, median kerb and gutter were measured using measuring tapes. The pavement surface conditions were rated using a 5-point scale where, 5 = excellent and 1 = worst. Roadside land-use pattern was rated using a 3-point scale where, 1 = highly commercial, 0.5 = moderately commercial, and 0 = minimal or non-commercial. The operating speed of motor vehicles on Indian roads under mixed traffic conditions is not as high as in developed countries; and a large variation exists among speeds of vehicles. Hence the speed measures such as: spot speed or space mean speed that are normally calculated for homogeneous traffic, should not be considered for mixed traffic situations. In this regard, the mid-segment traffic flow on each segment was videotaped during the peak hours (i.e., either morning 8:30-11:00 AM or evening 4:00-6:30 PM) over a longitudinal trap of 30 meter. The average time taken by motor-vehicles to cross this trap was extracted with an accuracy of 0.1 second. Subsequently, the average traffic speed on each segment was calculated by dividing the crossing distance (30 meter) by the average crossing time of motor-vehicles. Other variables collected during inventory study and visual inspections are: total number of driveways connecting the segment; approximate vehicular ingress volume (veh/h) to each driveway during the peak hours; and interruptions caused from authorized/un-authorized stoppages of intermittent public transits (1 = high, 0.5 = medium, 0 = minimal).

Recorded video clips were also used to extract several other parameters such as traffic volume, pedestrian volume (ped/h), percentage of heavy vehicles (%), average vehicular ingress-egress to the on-street parking area (veh/h/km) and average headway of on-street vehicular encounters (min). In this study, the running average method was used to determine the peak hour traffic volume on each segment. In order to bring all categories of motor-vehicles into a single measuring unit, Passenger Car Unit per hour (PCUs/h), volumes of different categories of motor-vehicles were multiplied by corresponding PCU values recommended by Indian Road Congress (IRC)-106.

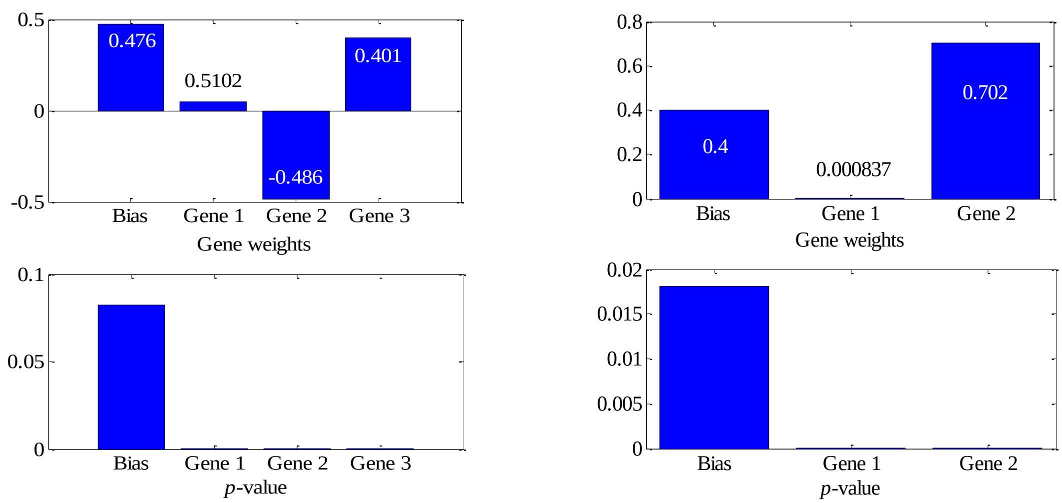
Qualitative data
Assessment of BLOS being the primary aim of this study, a perception survey was carried out to assess the perceived satisfaction levels of bicyclists. Face-to-face interactions with on-site bicyclists was carried out with a large number of bicyclists. Participants were chosen from widely varying demographic characteristics, geographic origins, and social, economic and educational backgrounds. Diversities in various characteristics of the participants as observed in the survey sample are presented in Table 1. Any bicyclist who hardly ride a bicycle through the urban intersections may result in erroneous responses in the perception survey due to lack of adequate bicycling experiences. In this regard, users having at least a year of cycling experience on the city roads were only requested for participation. The frequency of bicycling through the urban signalized intersections as reported by the participants varied from once in a week to twice a day. Thus, it was ensured that the participants have gone through similar situations many times and have enough experience with bicycling at urban road intersections. Thus, each of them was believably capable of giving reliable responses on each studied intersection approach, even if he/she has not ridden bicycle through a particular intersection investigated in this study.

TABLE 1 Characteristics of survey participants

Attribute	**Distribution**	**Percentage**
Gender	Female	43.75
	Male	56.25
Age group	Young (< 25 years old)	23.60
	Middle-aged (25–60 years old)	66.10
	Elderly (> 60 years old)	10.30
Educational attainment	Matriculation or less	18.70
	Intermediate	32.00
	Graduate	41.30
	PG or above	8.00
Household size	1	4.37
	2	14.38
	3	31.25
	4	43.75
	More than 4	6.25
Working type	Full time worker	34.38
	Part-time worker	12.50
	Un-employed	5.62
	Student	47.50
Approximate bicycling distance (km/day)	< 5	28.7
	5–10	55.30
	11–20	14.00
	> 20	2.00
User type	Regular bicyclist	42.60
	Occasional bicyclist	57.70

MODEL DEVELOPMENT

The Spearman's correlation analysis concluded that bicyclists in the present context perceive similar kind of services under a particular set of road conditions irrespective of their socio-demographics and travel characteristics. Thus, the BLOS models were made to predict an overall BLOS score of a particular site. Overall perceived scores obtained at individual sites were used as the array of output variable. Separate models are developed for links and intersections. The MGGP algorithm was coded in MATLAB R2014b to estimate the link model parameters (genes and bias). The objective was to minimize the root mean square error (RMSE) between overall perceived and predicted BLOS scores. The best BLOS model road links was obtained with a population size of 800 individuals at 400 generations, G_{max} of 3, d_{max} of 4, reproduction probability of 0.02, crossover probability of 0.84, and mutation probability of 0.14. Similarly, the best BLOS model for signalized intersection approaches was obtained with a population size of 1200 individuals at 400 generations, G_{max} of 2, d_{max} of 4, reproduction probability of 0.02, crossover probability of 0.84, and mutation probability of 0.14. Weights and significances of genes and bias obtained for these models are shown in Figure 1.



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

FIGURE 1 Weights and significances of (a) link model (b) intersection model parameters.

Reliability of Developed Models

Prediction performances of developed models with both training and testing data sets were assessed through the application of various statistical parameters such as R^2, RMSE and the mean absolute percentage error (MAPE). Obtained results are presented in Table 2. As observed, both models have produced very high R^2-values in the present context and minimal prediction errors. Thus, both models are highly reliable for their applications in the present context.

TABLE 2 Prediction Results of BLOS Models

BLOS Model	Data	R^2	RMSE	MAPE (%)
MGGP-based link model	Training	0.87	0.25	6.28
	Testing	0.87	0.29	7.05
MGGP-based intersection model	Training	0.91	0.30	7.52
	Testing	0.92	0.31	6.41

Ranges of BLOS Classes (A–F)
A service scale has been defined as follows to convert predicted BLOS scores into letter-graded service classes (A = excellent through F = worst):

- BLOS A: score ≤ 1.5
- BLOS B: 1.5 < score ≤ 2.5
- BLOS C: 2.5 < score ≤ 3.5
- BLOS D: 3.5< score ≤ 4.5
- BLOS E: 4.5 < score ≤ 5.5
- BLOS F: score > 5.5

CONCLUSIONS

Most of the existing BLOS models are applicable to homogeneous traffic flow conditions only. Few models available for heterogeneous traffic conditions are very much complex in their structures. Thus, this study has developed highly reliable and easy to implement BLOS models for the later context. As observed from the Spearman's correlation analysis, the BLOS of road links is decided by eight quantitative variables, and that for intersection approaches include seven variables. Using these variables, BLOS models of respective facilities are developed through the application of the MGGP technique. Both models have produced highly reliable performances in the present context with R^2 values of above 0.87. It was observed that traffic volume and crossing pedestrians have the highest influences on BLOSs of urban road links and signalized intersections respectively. Further, the field implementations of the models revealed that, above 95% of the total investigated sites are offering average to very poor service levels in the present scenario. Thus, the utmost important variables identified in this study should be largely prioritized to enhance the service qualities of these facilities. Developed models do not address the influences of bicycle lane parameters as bicycle lanes were not available at the study locations. Thus, the same could be investigated in the future studies.

REFERENCES

1. Koza, J. R. *Genetic Programming: On the Programming of Computers by Means of Natural Selection*, MIT Press, 1992.
2. McPhee, N. F., R. Poli, and W. B. Langdon. *A Field Guide to Genetic Programming*, Lulu Enterprises, UK Ltd., 2008.
3. Davis, J. *Bicycle Safety Evaluation*. Auburn University, City of Chattanooga and Chattanooga-Hamilton County Regional Planning Commission, TN, 1987.
4. Epperson, B. Evaluating Suitability of Roadways for Bicycle Use: Toward a Cycling Level-of-Service Standard. *Transportation Research Record: Journal of the Transportation Research Board*, No. 1438, 1994, pp. 9–16.
5. Landis, B. W. Bicycle Interaction Hazard Score: A Theoretical Model. *Transportation Research Record: Journal of the Transportation Research Board*, No. 1438, 1994, pp. 3–8.
6. Sorton, A., and T. Walsh. Bicycle Stress Level as a Tool to Evaluate Urban and Suburban Bicycle Compatibility. *Transportation Research Record: Journal of the Transportation Research Board*, No. 1438, 1994, pp. 17–24.
7. Davis, J. Bicycle Test Route Evaluation for Urban Road Conditions. In *Transportation Congress: Civil Engineers—Key to the World Infrastructure*, ASCE, San Diego, CA, 1995, pp. 1063–1076.
8. Harkey, D. L., D. W. Reinfurt, and M. Knuiman. Development of the Bicycle Compatibility Index. *Transportation Research Record: Journal of the Transportation Research Board*, No. 1636, 1998, pp. 13–20.
9. Landis, B. W., V. R. Vattikuti, and M. T. Brannick. Real-Time Human Perceptions: Toward a Bicycle Level of Service. *Transportation Research Record: Journal of the Transportation Research Board*, No. 1578, 1997, pp. 119–126. https://doi.org/10.3141/1578-15.
10. Jensen, S. U. Pedestrian and Bicycle Level of Service on Roadway Segments. *Transportation Research Record: Journal of the Transportation Research Board*, No. 2031, 2007, pp. 43–51. https://doi.org/10.3141/2031-06.
11. *Highway Capacity Manual.* Transportation Research Board, National Research Council, Washington, D.C., 2000.
12. *Highway Capacity Manual*. Transportation Research Board, National Research Council, Washington, D.C., 2010.
13. Kang, K., and K. Lee. Development of a Bicycle Level of Service Model from the User's Perspective. *KSCE Journal of Civil Engineering*, Vol. 16, Issue 6, 2012, pp. 1032–1039. https://doi.org/10.1007/s12205-012-1146-z.
14. Chellapilla H., S. K. Beura, and P. K. Bhuyan. Modeling Bicycle Activity on Multi-Lane Urban Road Segments in Indian Context and Prioritizing Bicycle Lane to Enhance the Operational Efficiency. In *Transportation Planning and Implementation Methodologies for Developing Countries*, IIT Bombay, India, 2016.
15. Beura, S. K., and P. K. Bhuyan. Modeling Quality of Bicycle Accommodations on Urban Road Segments Using Functional Networks and Multivariate Adaptive Regression Spline Techniques. In *96th Annual Meeting of the Transportation Research Board*. CD-ROM. TRB, National Academies, Washington, D.C., 2017, 20p.
16. Beura, S. K., H. Chellapilla, and P. K. Bhuyan. Urban Road Segment Level of Service Based on Bicycle Users' Perception under Mixed Traffic

conditions. *Journal of Modern Transportation*, Vol. 25, Issue 2, 2017, pp. 90–105. https://doi.org/10.1007/s40534-017-0127-9.

17. Crider L. B., J. Burden, and F. Han. *Multimodal LOS-Point Level of Service Project*, *Final Report*. Department of Urban and Regional Planning, University of Florida, Gainesville, Florida, 2001.
18. Landis, B., V. Vattikuti, R. Ottenberg, T. Petritsch, M. Guttenplan, and L. Crider. Intersection Level of Service for the Bicycle Through Movement. *Transportation Research Record: Journal of the Transportation Research Board*, No. 1828, 2003, pp. 101–106. https://doi.org/10.3141/1828-12.
19. Carter, D., W. Hunter, C. Zegeer, J. Stewart, and H. Huang. Bicyclist Intersection Safety Index. *Transportation Research Record: Journal of the Transportation Research Board*, No. 2031, 2007, pp. 18–24. https://doi.org/10.3141/2031-03.
20. Jensen, S. U. Pedestrian and Bicycle Level of Service at Intersections, Roundabouts and Other Crossings. In *92nd Annual Meeting of the Transportation Research Board*. CD-ROM. TRB, National Academies, Washington, D.C., 2013, 19p.
21. Strauss, J., L. F. Miranda-Moreno, and P. Morency. Cyclist Activity and Injury Risk Analysis at Signalized Intersections: A Bayesian Modelling Approach. *Accident Analysis & Prevention*, Vol. 59, 2013, pp. 9–17. https://doi.org/10.1016/j.aap.2013.04.037.
22. Searson, D. P., D. E. Leahy, and M. J. Willis. GPTIPS: An Open Source Genetic Programming Toolbox from Multi-Gene Symbolic Regression. In *International Multi-Conference of Engineers and Computer Scientists*, Vol. I, Hong Kong, 2010.
23. *Guidelines for Capacity of Urban Roads in Plain Areas*, Indian Road Congress, IRC: 106, New Delhi, 1990.
24. *Driveway Geometrics*, Engineering Policy Guide, EPG 940.16, Missouri Department of Transportation, Missouri, 2010. http://epg.modot.org/.
25. *A Policy on Geometric Design for Streets and Highways*, American Association of State Highway and Transportation Officials, Washington, D.C., 2011.
26. Bai, L., P. Liu, C. Y. Chan, and Z. Li. Estimating Level of Service of Mid-Block Bicycle Lanes Considering Mixed Traffic Flow. *Transportation research part A: policy and practice*, Vol. 101, 2017, pp. 203–217. https://doi.org/10.1016/j.tra.2017.04.031.
27. Cochran, W. G. *Sampling Techniques*. John Wiley & Sons, Inc., New York, 1997.