Bikeability and bike-way network design problem

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BIKEABILITY AND BIKE-WAY NETWORK DESIGN PROBLEM

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School of Civil and Environmental Engineering

2021

BIKEABILITY AND BIKE-WAY NETWORK DESIGN PROBLEM

ZHU SIYING

School of Civil and Environmental Engineering

A thesis submitted to the Nanyang Technological University
in partial fulfillment of the requirements for the degree of
Doctor of Philosophy

2021

Statement of Originality

I hereby certify that the work embodied in this thesis is the result of original research, is free of plagiarised materials, and has not been submitted for a higher degree to any other University or Institution.

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I have reviewed the content and presentation style of this thesis and declare it is free of plagiarism and of sufficient grammatical clarity to be examined. To the best of my knowledge, the research and writing are those of the candidate except as acknowledged in the Author Attribution Statement. I confirm that the investigations were conducted in accord with the ethics policies and integrity standards of Nanyang Technological University and that the research data are presented honestly and without prejudice.

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Date

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Asst Prof Zhu Feng

Authorship Attribution Statement

This thesis contains material from 2 paper(s) published in the following peer-reviewed journal(s) / from papers accepted at conferences in which I am listed as an author.

Chapter 2 is published as Zhu, S. and Zhu, F., 2019. Cycling comfort evaluation with instrumented probe bicycle. Transportation Research Part A: Policy and Practice, 129, pp.217-231. DOI: 10.1016/j.tra.2019.08.009.

The contributions of the co-authors are as follows:

- Asst/Prof Zhu conducted methodology discussion and manuscript editing.
- I do the literature review, content planning, result analysis, and manuscript writing.

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ZHU SIYING

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Summary

To achieve the car-lite goal, cycling is increasingly gaining its popularity in recent years as a sustainable and attractive alternative mode of transportation to automobiles. Although bicycle is energy efficient and environmentally friendly, many trips within cycling distance of a commuter's home are accessed via automobiles. Bikeability refers to the extent to which it is conducive and comfort for bicycling. To promote cycling as an alternative mode of transportation to automobiles and have a better understanding of cycling, this thesis aims to investigate the bikeability and bike-way network design problem systematically. In this regard, this thesis contains three sets of models or methods to address the research on bicycle.

For bikeability analysis, to address the cycling comfort level of bicyclists, Chapter 2 derives a Cycling Comfort Index (CCI) as a measure for various types of cycling facilities. For data collection, an Instrumented Probe Bicycle (IPB), equipped with a video camera and a set of sensors is ridden by bicyclist in Singapore. Convolutional neural network (CNN) algorithm is employed for automatic video processing. The extreme gradient boosting (XGBoost) algorithm is applied to calculate CCI based on cycle track characteristics and survey participants' comfort perception ratings. Understanding bikeability can provide valuable information to bike-way network design planning in real-world.

For the bike-way network design problem, the first set of methods in Chapter 3 formulate a multi-objective integer linear programming model to determine the spatial layout of bike-way networks and bike-way link types under space-time accessibility constraint. Four objectives include to maximise the accessibility, minimise the number of intersections, maximise bicycle level of service (BLOS), and minimise total construction cost, with monetary budget and space-time

constraint are considered. Augmented ϵ -constraint method (AUGMECON) is applied as the solution algorithm, and two numerical examples are used to generate non-dominated bike-way network design plans. Then, Chapter 4 addresses the road diet network design problem in consideration of a multi-modal transportation network with bike-and-ride, automobile and bicycle, under stochastic demand scenarios. A mixed integer non-linear bi-level optimisation model is formulated. A path-flow penalty-based branch-and-bound algorithm is applied to derive the optimal road diet plan for upper level, and the method of successive averages is utilised for multi-modal traffic assignment for lower level. Numerical test is utilised to demonstrate the feasibility of model and effectiveness of solution algorithm.

List of Publications

Journal Articles

- **Zhu, S.** and Zhu, F., 2019. Multi-objective bike-way network design problem with space-time accessibility constraint. *Transportation*, pp.1-25.
- **Zhu, S.** and Zhu, F., 2019. Cycling comfort evaluation with instrumented probe bicycle. *Transportation Research Part A: Policy and Practice*, 129, pp.217-231.
- **Zhu, S.**, 2020. Investigation of vehicle-bicycle hit-and-run crashes. *Traffic Injury Prevention*, pp.1-6.
- **Zhu, S.**, 2020. Analysis of the severity of vehicle-bicycle crashes with data mining techniques. *Journal of Safety Research*, In Press.
- **Zhu, S.**, 2020. Multi-objective route planning problem for cycle-tourists. *Transportation Letters*, pp.1-9.

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List of Symbols

CCI	Cycling Comfort Index
BLOS	Bicycle Level of Service
LOS	Level of Service
IPB	Instrumented Probe Bicycle
CNN	Convolutional Neural Network
XGBoost	Extreme Gradient Boosting
GBDT	Gradient Boosting Decision Tree
PMD	Personal Mobility Device
NDP	Network Design Problem
O-D	Origin-Destination
PAB	Power Assisted Bicycle
AUGMECON	Augmented ϵ -constraint method
UE	User Equilibrium
MSA	Method of Successive Averages
MUE	Multi-modal User Equilibrium
DFS	Depth First Search

Chapter 1

Introduction

1.1 Background

To promote sustainable transportation system and achieve the car-lite goal, cycling is an attractive alternative mode of transportation to automobiles. Bicycle provides an energy efficient, environmentally friendly, and healthy way of daily commuting, which can help alleviate congestion and serve as a first-mile and/or last-mile mobility solution. However, many trips are accessed via automobiles even though they are within cycling distance of a commuter's home [97].

Different from car drivers, apart from travel time and distance, a significantly broader range of bikeability factors which influence the comfort level are considered by cyclists when they decide on their routes [50]. It would be necessary to analyse these bikeability factors, in order to increase the share of commuters using bicycle for daily transport. Moreover, to provide suitable cycling infrastructure and attract more people using the sustainable bicycle mode, these bikeability factors can provide valuable information on bicyclists' preference to city planners when designing the bike-way network. Overall, to encourage more citizens to use bicycle for daily commuting and develop bicycle-friendly areas, it is necessary to understand the comfort perception of bicyclists and provide suitable design of bike-way network catering for the interests of various types of stakeholders.

1.2 Motivations

1.2.1 Bikeability

The cycling comfort level on different cycling facilities can significantly affect the mode choice and route choice of bicyclists, which is important to both city planners and bicyclists. In the context of Singapore, conventional cycling comfort level evaluation methods are not suitable due to the unique local environment. For example, the drainage covers which exist on the extensive underground drainage routes for storm water collection degrade the cycling comfort level of bicyclists due to vibration. Moreover, the conventional field data collection method is time-consuming. In addition, regression analysis has been commonly applied in previous research for bicycle facility comfort level evaluation [4]. However, these models relied on strict assumptions and the accuracy was not high.

1.2.2 Bike-way network design problem

There is limited research dedicated to the network design problem (NDP) for bike-way, in comparison with the roadway NDP. Different from automobile drivers, bicyclists consider a broader range of factors when choosing the route. Bicyclists are sensitive to bikeability factors such as slope, pavement condition, which affect the comfort perception of cyclists, apart from travel time and distance. However, in the previous research, the bike-way network design problem was commonly formulated as a single objective optimisation model to minimise the travel time of bicyclists or construction cost. The interests of bicyclists and planners are seldom considered at the same time. Moreover, the concept of accessibility has been commonly used interchangeably with connectivity, regardless of the travel time budget of commuter cyclists.

In addition, although the road diet plans converting motorised lane space to bike-way is a sustainable solution to urban transportation, there is usually insufficient

road space to accommodate bicyclists without affecting the existing automobile traffic negatively [106]. It is necessitated to consider the interests of automobile and public transit users when solving the bike-way network design problem. Moreover, the concept of ‘bike-and-ride’ has been proposed, combining the use of bicycle and public transit service for one trip. The bike-and-ride transit system can help increase the speed and extend the reach of bicycling, as well as increasing the spatial reach of public transit services [90]. In Singapore, the Land Transport Authority aims to make cycling an alternative mode of transportation to automobiles for the first and last mile mobility [62]. However, no quantitative research has investigated the implementation of road diet with the consideration of bike-and-ride. Furthermore, in reality, daily travel demand fluctuation leads to uncertainty in transportation network, while the deterministic network design approach can be sub-optimal when handling stochastic demand. However, the demand uncertainty has not been considered in previous bike-way network design studies either.

1.3 Contributions

Based on the discussion in the previous section, this study aims to analyse bikeability and formulate optimisation models for bike-way network design problem. The results from bikeability analysis is able to provide valuable information and assist in the design of bike-way network in real-world application. Specifically, the contributions of this study are summarised as below:

- (1) Cycling comfort level is evaluated with extreme gradient boosting (XGBoost) method based on survey participants ratings. Convolutional neural network (CNN) algorithm is applied for automatic video processing.
- (2) A multi-objective bike-way network design problem is formulated to cater for the interests of both planners and bicyclists, where the space-time accessibility of commuter cyclist is considered.

(3) A road diet network design problem is formulated, catering for the interests of bike-and-ride commuters, bicyclists and auto-mobile commuters in a congested multi-modal transportation environment under stochastic demand.

The first point on bikeability can provide valuable information on bicyclists' cycling comfort level preferences, which can serve as the inputs when modelling the bikeway network design problem in points 2 and 3.

1.4 Organisation of the report

The contents of the report are organised as below:

Chapters 2 focuses on the investigating the bikeability or comfort level of bicyclists. Gradient boosting algorithm is utilised to evaluate cycling comfort level and convolutional neural network algorithm is applied for automatic video processing.

Chapter 3 and Chapter 4 are on the optimal network design problem for bike-way. Specifically, Chapter 3 is devoted to the multi-objective bike-way network design problem in consideration of the space-time accessibility constraint of commuter cyclists. Chapter 4 formulates a road diet network design problem in a multi-modal network under stochastic demand, where bike-and-ride is considered as an alternative mode of transportation to automobiles. Finally, Chapter 5 concludes the thesis and discusses the future research direction.

Chapter 2

Gradient boosting model for cycling comfort evaluation with convolutional neural network for automatic video processing

2.1 Introduction

Cycling is an important active mobility mode for sustainable transportation system. For densely populated countries with rising congestion level, bicycle can be a good choice to help alleviate congestion, reduce pollution emissions, energy consumption and travel cost. In recent years, cycling infrastructure faces a rapidly changing demographic as more users switch to bicycles as an alternative transportation mode for their first and last mile solutions. The cycling comfort level on different cycling infrastructure can strongly influence the comfort perception of cyclists, their mode choice and route choice. Therefore, cycling comfort level becomes an increasingly important factor for cyclists and city planners. In Singapore, different types of cycling infrastructure have been provided by the government to promote cycling, whose typical layout is as shown in Figure 2.1, including bike path, shared path and footpath.

FIGURE 2.1: Typical layout of cycling facility

While conventional cycling comfort indexes exist for common cycling infrastructure, Singapore's case is out of the norm. For example, pavements in Singapore are designed to coexist with the extensive underground drainage routes (as shown in Figure 2.1b and Figure 2.1c), which are used to collect urban storm water in order to contribute to Singapore's water supply and prevent water stagnation [92]. As such, the existence of drainage covers pose as an additional factor for pavement comfortability, especially for cyclists whose trips are mostly affected by evenness of the pavement.

This study focuses on measuring cycling comfort index (CCI) or bicycle level of service (BLOS) of cycling infrastructure in Singapore. A video processing model is built with convolutional neural network (CNN) algorithm to recognise various cycling infrastructure attributes contributing to cycling comfort index (CCI), such as the existence of drainage covers, bus stops, access points, etc. The model is trained on a series of images collected around Singapore and adjusted to determine the most optimal outcome. Then, extreme gradient boosting (XGBoost) method is employed to build the CCI model based on various explanatory variables and survey participants' comfort perception ratings. Particularly, this study is in the context of Singapore where the cycling comfort measurement of cycling infrastructure differs from conventional BLOS models proposed in literature. Nevertheless, the cycling comfort evaluation method in this research can

also be customized for other countries and cities by including various cycling infrastructure attributes in consideration of different cycling environment.

2.2 Related work

In this research, we seek to evaluate the cycling comfort level of different cycling infrastructure by introducing a cycling comfort index (CCI) and identifying the factors that most significantly affect the CCI. A good design of bicycle infrastructure can encourage more people to cycle [52]. [36] illustrated the significant impact of bicycle infrastructure on bicycle counts. Research that links cycling levels and cycling infrastructure has increased significantly over the last 20 years, especially since 2010 [15]. To effectively and efficiently evaluate whether a road segment can comfortably accommodate bicycle traffic is fundamental to the establishment a bicycle-friendly environment [41, 57].

Level of service (LOS) is a common measure used in transportation engineering to assess the performance of transportation networks. Similar to highways, the LOS of footpath is affected by factors such as traffic volume, road capacity and road quality etc. However, a footpath's LOS varies upon the type of user, which is due to different levels of importance that users attribute to the different characteristics of footpath. For example, a pedestrian may consider safety an important factor when using a footpath, which can be affected by the number of cyclists sharing the footpath with them as well as the probability of a cyclist accidentally crashing into them. On the other hand, cyclists may categorise evenness etc. of the cycling infrastructure as more important factors that affect the quality of their ride. Previous researches [12, 61] have studied the preferences of users of footpaths in order to quantify the LOS provided by footpaths. In particular, the concept of bicycle level of service (BLOS) has been proposed, which serves as a measure for explaining current cycling facilities in streets and evaluates the quality of service [4]. Assessments for bicycle travel have been conducted based on comfort, convenience and safety. It is commonly assumed that BLOS is affected by the joint effect of multiple performance measures,

including traffic conditions, facility characteristics, environment factors, etc. [6, 56, 59, 128]. Many researches have been carried out to evaluate link-based BLOS, such as estimating the BLOS of mid-block bicycle lanes in consideration of mixed traffic flow with e-bikes, e-scooters and bikes [6], measuring the BLOS on off-street and on-street facilities [8], estimating the effect of bike lane buffer type on BLOS [77], measuring the BLOS based on bicycle vibration measurement with GPS-based speed and acceleration data [10, 40, 58], measuring the BLOS based on the perceived satisfaction level of on-street cyclists which is affected by complex bicycle-vehicle interactions [9], evaluating the cyclists' perceptions of satisfaction and comfort on cycling infrastructure [18, 103]. The 2010 edition of Highway Capacity Manual also proposed standards on evaluating BLOS based on the multi-parameter approach which is commonly used in many recent literature [72]. Overall, cycling comfort level is very important in cycling facility planning and cyclists' route choice decisions.

Typically, the perceived comfort level of a linear section of bikeway is rated on a scale, which normally have six levels that range from A to F where BLOS level A represents the best comfort perception [4]. Generally, various attributes of the cycling infrastructure are awarded a certain number of points, which are then combined to calculate a score that categorises the comfort level of cycling infrastructure from desirable to undesirable. Different methods of BLOS evaluation are distinguished with different choices of attributes, different point systems, and how the points are combined, supported by theory and empirical findings [69].

Direct field measurement for different cycling infrastructure attributes is commonly used to gather data about various explanatory variables and the data collection process is time-consuming. Regression analyses is a method commonly adopted in literature to build bicycle infrastructure evaluation model [4]. According to the literature review, it is found that the ordered probit model is most commonly used for the Bicycle Level of Service (BLOS) evaluation as the dependent variable is ordinal [6, 11, 59, 64, 88]. Therefore, the ordered probit model is selected for the comparative analysis in this paper instead of other models to compare with the literature. The model relies on strict assumptions including

normal distribution of random error term and proportional odds assumptions, etc. Furthermore, to the authors' best knowledge, none of the literature focused on improving the accuracy of the BLOS model.

In this study, direct field measurement for data collection is not needed, as convolutional neural network (CNN) algorithm is used for analysing data and gathering information about various explanatory variables. The neural network algorithm has been used in the literature to detect the characteristics of roads. [91] applied the neural network algorithm to process GPS and heart rate signals in order to classify the downhill, uphill and flat cycling segments. [54] applied the CNN based deep learning technique for image processing to identify the attributes of motorised roadway. Instead of ordinal regression techniques commonly used in literature, extreme gradient boosting (XGBoost) method is used in this research to relax the assumptions and improve the accuracy of CCI model. The XGboost algorithm has been applied in the field of cycling. [127] deployed different machine learning techniques including XGBoost algorithm to predict cycling safety at street level in different cycling communities with spatio-temporal analysis based on the open and crowdsourced data. [82] applied different supervised learning techniques including XGBoost method to predict the purpose of cycling trip based on the personal data and GPS traces of bi-cyclists and built-in and social environment characteristics extracted from open datasets which describe the streets cycled.

The contribution of this study is mainly in the following aspects: 1) For the data collection process, this study only requests the video clips collected by experienced cyclists from the cyclists' perspectives, such that no direct field measurement is required. Therefore, the data collection process is more efficient and less time-consuming. 2) A convolutional neural network (CNN) algorithm which is a class of deep, feed-forward artificial neural networks is applied to classify different cycling infrastructure attributes. 3) Instead of ordinal regression techniques commonly used in literature for BLOS model, extreme gradient boosting (XGBoost) method is applied in this study, providing higher accuracy rate, relaxed assumptions and robustness to multi-collinearity. The accuracy of

XGBoost method is compared with the accuracy of ordered probit model commonly used in literature. The result shows that the overall accuracy of XGBoost method is 11% higher than that of ordered probit model.

2.3 Data

2.3.1 Data collection from Instrumented Probe Bicycle

Data was collected from field studies in the metropolitan area of Singapore, which is constantly moving toward a bicycle-friendly city. The data of road segments is gathered based on video analysis, hence no direct measurement is required in the field. Therefore, the data collection process is more efficient and less time-consuming. The local bicycling environment in Singapore is greatly different from other countries, for example, with the unique layout of public housing, large interlinking network park connectors, existence of drainage covers which may pose as an additional factor for pavement comfortability. Over 80 road segments have been studied and 34 video clips of cycling facilities covering diverse paths and environments are selected and analysed in the study. An Instrumented Probe Bicycle (IPB), which is equipped with video camera and a set of sensors including GPS receiver, accelerometer, gyro sensor, etc., was used for data collection (See Figure 2.2). The common devices make the method for cycling comfort evaluation in this research widely applicable.

2.3.1.1 Video processing

A convolutional neural network (CNN) model is applied for analysing the video recorded from cyclists' perspective during field data collection. The video is firstly partitioned into individual frames with MATLAB, then the stream of frames serve as inputs of the 2D CNN model which can recognise images and classify the features of various explanatory variables. Figure 2.3 shows a most common form of CNN architecture. The first part of CNN architecture is made

(A) IPB

(B) Garmin VIRB camera

FIGURE 2.2: Instrumented Probe Bicycle (IPB)

up of convolutional layers and pooling layers which serve as feature extractors. Units in the convolutional layer are organised in feature maps, in which each unit is connected to local patches in the previous layer's feature maps through the filter bank which is a collection of weights. For example, the input layer in Figure 2.4a is passed through a 3x3 filter (Figure 2.4b) with weights on the diagonal and convolves with a stride of 1 (i.e. moves by 1 unit along the layer). The resulting multiplication and summation of the array gives an output value of three in the next layer. Then, the result of the local weighted sum is passed through an activation layer introducing non-linearity such as a ReLU function. Pooling layers, such as max pooling layers (Figure 2.4c), merge semantically similar features into one, reducing the spatial size and number of parameters to avoid overfitting. Some stages of convolution, non-linearity and pooling are stacked. In the fully connected layer, neurons have full connections to all activations in the previous layer [63]. In this study, softmax loss is used for predicting a single class out of mutually exclusive classes.

Deep convolutional networks started to become mainstream since 2014, yielding substantial gains with different benchmarks. This study adopts Inception-v3 architecture of CNN, introducing inception modules which basically act as multiple convolution filters applied to the same input with pooling. The results are then concatenated into a single output vector forming the input of the next stage,

FIGURE 2.3: Architecture of CNN

FIGURE 2.4: CNN layers

which allows for multi-level feature extraction [110]. The inception-v3 model can lead to high performance vision networks with relatively modest computation cost compared to simpler and more monolithic CNN architectures [111].

To train the CNN model, we utilise a set of images which are separated with different labels so that the CNN model can learn the patterns and features for each class. A minimum of two labels are needed in order to differentiate multiple classes of images. The predictions from CNN model are compared against the actual labels to update the final layer's weights [1]. Features including the number of drainage covers on the road segment, pavement type, buffer type etc. can all be classified with the CNN model multi-class classification.

2.3.1.2 Result of CNN model

This study illustrates the video processing model with the attribute ‘Drainage Cover’ as an example. Firstly, the video recorded from cyclist’ perspective is converted to a stream of frames with frame rate 1 fps with MATLAB, without loss of important information. The number of drainage covers appeared in the video can be counted with CNN classification model. In the same way, data of other attributes include the lane type, presence of curb, pavement type and condition, width, occupancy ratio of drainage cover, separation from pedestrians and motor vehicles, the number of access points, deceleration strips, shelter, bus stop can all be classified.

The model is trained with a dataset containing 500 photos, and a final accuracy of over 90% can be obtained. To test the generalisability of the results, images in the dataset are divided into three sets: training set (60%), validation set (20%) and test set (20%), which is a common practice used for CNN algorithm as cross validation tends to incur high computation cost for deep learning models. The samples in the training set are used to fit the data. Images from the validation set are used as a cross-reference to measure the performance of the model, such that the model is prevented from purely ‘memorising’ the features. The result of validation accuracy with different combinations of parameters are also comparable to the test accuracy, which is around 90%. The test data is used to provide an unbiased evaluation of the final model which is completely trained through the training set and validation set. Analysis of the model is carried out to evaluate the effects of various parameters on the final test accuracy of the model. The values of parameters are varied based on default values, which is set as training batch size 80, learning rate 0.01, and 4000 training steps. The learning rate determines how quickly the model can ascertain the weights for each feature. Training is likely to get stuck at a suboptimal result if the learning rate is too high [94]. Smaller learning rate gives a higher overall precision, as shown in Figure 2.5a. However, when the learning rate is low, longer evaluation time is needed, as Figure 2.5b. Figure 2.5c shows the graph of accuracy against number of training steps while Figure 2.5d shows the graph of evaluation

time against number of training steps. The number of training steps varies from 500 to 4000. It is observed that as the number of training steps increases, the accuracy of the model and time taken for the training process increases. The accuracy peaks at 93% with 4000 training steps used while it takes the longest evaluation time. Figure 2.5e and Figure 2.5f show the graph of accuracy and evaluation time against training batch size respectively. The training batch size is varied from 20 to 120. The accuracy mainly ranges from 91% to 93% while the evaluation time increases with the size of the training batch. Therefore, a lower training batch size can be used here to optimise the efficiency of the model without severely affecting the accuracy.

The accuracy tested for the CNN model is calculated by the following formula:

$$a = 1 - r = 1 - W/A \quad (2.1)$$

where r is multi-class classification error rate, W is the number of wrong cases, A is the number of all cases. The wrong cases refer to all the cases whose results predicted by the model are different from the labels stored in the original image database, i.e. the ground truth labels.

Moreover, the accuracy also varies by class, since images from different classes have different tendency to be misclassified. The accuracy by class can be calculated based on the sensitivity or true positive rate, which represents the proportion of images of certain class s that are correctly classified as:

$$a_s = C_s / (C_s + F_s) \quad (2.2)$$

where C_s represents the number of images of class s that are correctly classified as so, F_s represents the number of images of class s that are wrongly classified. For the classification of the existence of drainage covers, when the default combination of parameters is applied, the overall accuracy is 0.93, while the accuracy by the class ‘no drain’ is 0.96, the accuracy by the class ‘with drain’ 0.90.

FIGURE 2.5: Adjusting CNN parameters

2.3.2 Video-based survey on cyclists' comfort perception

To capture the comfort perception of cyclists on cycling infrastructure, the video-based data collection and rating method is adopted in this study, which is a non-naturalistic data collection approach. In collecting data to evaluate the BLOS, both naturalistic approach and non-naturalistic approach have been applied in the literature. The naturalistic approach allows the researcher to observe the behaviour of subjects in the natural environment without significant interference.

Differently, non-naturalistic approach analyses the subject with an artificial setting. In the literature, non-naturalistic approach has been applied for the data collection process in the field of cycling. [84] investigated the behaviour of cyclists using the cycling simulator with virtual reality technique. Other studies evaluated various cycling environments by analysing pictures or short videos of cycling infrastructure and intersections [7, 25, 38, 77, 114, 126, 137]. The video-based survey method is applied in the paper as the data collection method since the method is more efficient, allowing people to rate conditions not found locally such that a wide range of bicycle facility conditions including the traffic conditions, roadway characteristics, and weather conditions are controlled to be the same for all participants in a particular video clip. The video-based survey method can also provide some comparable results in comparison with field rides [25, 38]. Video clips are processed with Garmin VIRB first to display the grade, velocity, acceleration, precise time, distance and route. The mode of survey is in-person and participants are involved in the survey voluntarily. Participants are well informed about the objective of the study which is to evaluate the cycling comfort level on different types of cycling infrastructure with various environment conditions. Questions on the demographic characteristics of the participants (age, cycling experience) and their cycling comfort perception of different cycling facilities have been asked. Each video clip is about 20 seconds and contains only one road segment which is about 100m long. The road segment in the same video clip have only one type of layout to avoid survey participants' confusion, such that the attributes of the segment are consistent throughout each trip. Survey participants who watch the video clips are exposed to a wide range of bicycle facility conditions while the traffic conditions, roadway characteristics, and weather conditions are controlled to be the same for all participants in terms of a particular video clip [25]. 100 survey participants with different age, gender, and cycling experience are involved in the study to evaluate the cycling comfort level of cycling infrastructure in various video clips on a scale from 1 (least comfortable) to 5 (most comfortable). The responses of the survey are recorded in the database for building the XGBoost model and ordered probit model purpose. The characteristics of various candidate explanatory variables are summarised in Table 2.1. Survey participants' ratings of cycling comfort level are used as

dependent variables ranging from 1 to 5. The total frequency of each attribute adds up to 3400, as there are 100 survey participants and 34 video clips rated by each of them. Therefore, for the whole dataset, the total frequency of physical facility indices and environment conditions is a multiple of 100 and the total frequency of the individual characteristic is a multiple of 34. Please note that video-based survey method can influence the research findings. Due to the non-naturalistic data collection approach, the survey participants cannot experience of road conditions by themselves, such that the influence of factors like slope, presence of shelter can be underestimated due to limited exposure to real-world condition.

TABLE 2.1: Characteristics of candidate explanatory variables

Variable	Description	Frequency
Dependent Variable	CCI ranging from A (most comfortable) to E (least comfortable) numbered 5 to 1 respectively	3400(100%)
Individual characteristics		
Gender	Male~ 0	1734(51%)
	Female~ 1	1666(49%)
Age	Minimum, 16; maximum, 62; Mean, 28.85	3400(100%)
Cycling experience	Attempter~ 0	1598(47%)
	Enthusiast~ 1	1802(53%)
Index of physical facility		
Lane type	Motorized lane~ 0	200(6%)
	Non-motorized lane ~ 1	3200(94%)
Slope	Horizontal ~ 0	2800(82%)
	Presence of slope ~ 1	600(18%)
Presence of curb	No ~ 0	2500(74%)
	Yes~ 1	900(36%)
Pavement type	Concrete ~ 1	1900(56%)
	Tile~ 2	600(18%)
	Asphalt~ 3	900(26%)
Pavement condition	Road with holes or potholes ~ 1	200(6%)
	Cracked or bumpy road~ 2	900(26%)
	No surface deterioration ~ 3	2300(68%)
Drainage cover	Number of drainage covers encountered per 100 m. Minimum, 0; Maximum, 9; Mean, 3.794	3400(100%)
Occupancy ratio of drainage cover	Width of drainage cover divided by the pavement width	

	No ~ 0	1300(38%)
	Low (< 0.3) ~ 1	600(18%)
	Medium (0.3, 0.5) ~ 2	1000(29%)
	High (> 0.5) ~ 3	500(15%)
Turn lanes	No ~ 0	2400(71%)
	Yes ~ 1	1000(29%)
Frequent curves	No ~ 0	3000(88%)
	Yes ~ 1	400(12%)
Number of deceleration strips	Minimum, 0; maximum, 3; mean, 0.2941	3400(100%)
Separation from pedestrians	No segregation ~ 1	2700(79%)
	Visual segregation ~ 2	100(3%)
	Physical segregation ~ 3	600(18%)
Width	[0, 1) ~ 1	300(9%)
	[1, 2) ~ 2	1900(56%)
	[2, 3) ~ 3	900(26%)
	[3, 4) ~ 4	300(9%)
Separation from motor vehicles	No separation ~ 1	500(15%)
	Complete separation ~ 2	300(9%)
	Curb ~ 3	200(6%)
	Fence ~ 4	100(3%)
	Planters ~ 5	2300(67%)
Environment conditions		
Number of access points	The number of access points per 100 m, include the access points to HDB block, other lanes, etc. Minimum, 0; maximum, 3; Mean, 0.7353	3400(100%)
Presence of shelter	No ~ 0	2700(79%)
	Yes ~ 1	700(21%)
Presence of bus stop	No ~ 0	2700(79%)
	Yes ~ 1	700(21%)
Land use	Residential ~ 1	2400(71%)
	Nature ~ 2	200(6%)
	Campus ~ 3	700(20%)
	Commercial ~ 4	100(3%)

2.4 Methodology & Result analysis

In this study, a cycling comfort index (CCI) is introduced to measure the cycling comfort level on different cycling infrastructure, in consideration of different bikeway characteristics. Two bicycle infrastructure CCI evaluation models have been applied in this study, namely, XGBoost model and ordered probit model. Ordered probit model is commonly used in the literature to build a BLOS model. However, ordered probit model relies on strict assumptions which are often violated, for example, assumption that the random error term follows normal distribution and the proportional odds assumption etc. The model development process can be complicated, and it only supports a limited number of cycling facilities [4]. On the other hand, XGBoost method is fast and accurate, which is also good at handling missing values and robust to multi-collinearity among variables. To the authors' best knowledge, the XGBoost method has not been used for the development of BLOS or cycling comfort evaluation model before. This study compares and contrasts the result of XGBoost model and ordered probit model with a case study in Singapore.

2.4.1 XGBoost

2.4.1.1 XGBoost classification algorithm

In this section, we illustrate the principle of classification algorithm XGBoost (eXtreme Gradient Boosting), which is an efficient and scalable machine learning technique based on gradient boosting framework, designed for speed and accuracy [24]. Gradient boosting is an ensemble technique that constructs additive regression models by sequentially fitting a simple parametrised function or base learner to current 'pseudo'-residuals by least squares at each iteration [39]. XGBoost makes a great improvement to the traditional gradient boosting decision tree (GBDT) algorithm in computing speed, generalisation performance and scalability [26].

The optimisation goal of XGBoost algorithm is to construct a tree structure that minimises the target function in each iteration. The tree structure learns from the previous trees' conclusions and residuals which is the difference between the target value and predicted value, fitting a current regression tree. The output of the XGBoost tree ensemble model with K trees for each instance i in the dataset is as below:

$$\hat{y}_i = \sum_{k=1}^K f_k(x_i) \quad (2.3)$$

where each f_k corresponds to an independent tree structure that maps the instance i to the corresponding leaf score.

Given a dataset with n samples, let $\hat{y}_i^{(t)}$ be the prediction of the i -th instance in the t -th iteration of the XGBoost algorithm, and f_t is added to minimise the objective function as below:

$$\mathcal{L}^{(t)} = \sum_{i=1}^n l(y_i, \hat{y}_i^{(t-1)} + f_t(x_i)) + \Omega(f_t) \quad (2.4)$$

where

$$\Omega(f_t) = \gamma T + \frac{1}{2} \lambda \sum_{j=1}^T w_j^2 \quad (2.5)$$

and l represents a convex loss function (e.g., the mean square loss function and logistic loss function). $\Omega(f_t)$ is a regularised term that penalises complex models in order to avoid overfitting. In particular, T is the total number of leaf nodes in the tree; γ and λ are regularised parameters to control the regularisation degree in the regularisation term; w_j represents the weight of each leaf node.

Meanwhile, XGBoost uses both the first and the second order gradient statistics on the loss function to quickly optimise the objective, which is different from traditional gradient boosting algorithm.

$$g_i = \partial_{\hat{y}^{(t-1)}} l(y_i, \hat{y}_i^{(t-1)}) \quad (2.6)$$

Algorithm 1: Greedy algorithm for split finding

Input: Instance set of current nodes I , with I_L and I_R as the instance sets
of left and right nodes after the split

Input: Feature dimension D with total m features

Output: Split with max score

$gain \leftarrow 0$

$G \leftarrow \sum_{i \in I_L} g_i$

$H \leftarrow \sum_{i \in I_L} h_i$

for $k=1$ **to** m **do**

$G_L \leftarrow 0$

$H_L \leftarrow 0$

for j **in** sorted (I , by x_{jk}) **do**

$G_L \leftarrow G_L + g_j$

$G_R \leftarrow G - G_L$

$H_L \leftarrow H_L + h_j$

$H_R \leftarrow H - H_L$

$score \leftarrow \max\{score, \frac{G_L^2}{H_L + \lambda} + \frac{G_R^2}{H_R + \lambda} - \frac{G^2}{H + \lambda}\}$

$$h_i = \partial_{\hat{y}_i^{(t-1)}}^2 l(y_i, \hat{y}_i^{(t-1)}) \quad (2.7)$$

After the second order Taylor expansion of $\mathcal{L}^{(t)}$ and the removal of the constant term, we have the following simplified objective function:

$$\tilde{\mathcal{L}}^{(t)} = \sum_{i=1}^n [g_i f_t(x_i) + \frac{1}{2} h_i f_t(x_i)^2] + \Omega(f_t) \quad (2.8)$$

Finally, XGBoost adopts a greedy algorithm (see Algorithm 1) to split the tree node or iteratively add branches to the tree that start from a single leaf in order to find the best tree structure with minimum value of objective function. Moreover, in many real world problems, when the input x is sparse, for example, with the presence of missing values, sparsity-aware split finding needs to be applied. The details can be found in [24].

2.4.1.2 Result of XGBoost method

This study uses XGBoost package with R to generate cycling comfort index(CCI) evaluation model. The XGBoost method can handle various predictors, fit complex nonlinear relationships, and automatically handle the multicollinearity effect with high accuracy, as it is an ensemble of tree models. Although the XGBoost model is robust to multicollinearity effect among variables, it is a good practice to remove redundant features from the dataset; otherwise, there can be a lot of instability in the variable importance ranking as the model uses the variables somewhat interchangeably.

For the XGBoost model, to optimise the model and avoid over-fitting, a five-fold cross-validation procedure is applied to determine the optimal combination of parameters. The dataset is randomly partitioned into five samples, and each of them is used as the test set while the remaining sub-samples serve as the training set. We fit the XGBoost model with different combinations of shrinkage value (0.001, 0.01, 0.1, 0.3), regularisation parameter γ (0, 0.1, 0.2, 0.3) and depth of tree (4, 6, 8, 10). The maximum number of iterations is set to 20000, and the optimal number of iterations will be automatically found in the XGBoost process. The shrinkage value or learning rate is introduced to reduce the influence of each individual tree structure and leave space for future trees for improving the model [25, 39]. The lower learning rate can lead to longer computation time. The regularisation parameter γ is to prevent overfitting and higher γ value leads to higher regularisation. As the depth of tree increases, the complexity of the model is increased, and the chance of overfitting becomes higher. The multi-class classification error rate serves as the performance measurement the XGBoost. After the cross-validation process, we find that the error rate varies between 0.21 and 0.24 with various combinations of parameter settings. The parameter combination with shrinkage value as 0.001, γ as 0 and depth of tree as 8 is finally chosen, with 1000 iterations.

XGBoost is an improved algorithm based on GBDT algorithm, constructing the boosted trees to intelligently obtain the feature importance ranked with gain. The gain after each split in XGBoost method can be calculated with the equation

below, giving an indication on how a feature is important in making a branch of a decision tree purer [24].

$$Gain = \frac{1}{2} \left[\frac{(\sum_{i \in I_L} g_i)^2}{\sum_{i \in I_L} h_i + \lambda} + \frac{(\sum_{i \in I_R} g_i)^2}{\sum_{i \in I_R} h_i + \lambda} - \frac{(\sum_{i \in I} g_i)^2}{(\sum_{i \in I} h_i)^2 + \lambda} \right] - \gamma \quad (2.9)$$

where I_L and I_R are the instance sets of left and right nodes after the split, $I = I_L \cup I_R$. The first term represents the score of left child, the second term represents the score of right child, the third item represents the score if we do not split, and the last term represents the complexity cost if an additional leaf is introduced.

It can be seen that the importance ranking is consistent for top features since those features are used across most of the boosted trees. The less useful features will get used less and have a lot more variability. Therefore, the XGBoost method works better in top feature selection. Figure 2.6 presents the relative contribution rankings or relative importance of explanatory variables in predicting CCI, and the total contribution adds up to 100%.

The most significant predictors that affect CCI include pavement type (asphalt), the number of drainage covers on the road segment, the type of lane (motorised or non-motorised lane), width of lane, separation from pedestrians. The pavement type and the number of drainage covers can significantly affect the vibration felt by cyclists. Separation from pedestrians, and width of lane mainly affect cycling comfort by varying effective riding space. Cycling on motorised or non-motorised lane mainly affect cyclists' safety perception. The result of XGBoost method is mostly consistent with literature, with additional significant feature 'Drainage Cover' that affect cycling comfort level considered in Singapore context.

How the important variables affect the CCI rating (positively or negatively) and how one would apply the CCI measure to a given facility segment can be explained by the partial dependence plot as below: XGBoost which is based on gradient boosting framework can illustrate the non-linear effects of independent variables [32]. Different from traditional linear regression models whose sensitivity analysis can only evaluate one single variable at one time while the

FIGURE 2.6: Relative importance of explanatory variables

association between other variables is ignored, XGBoost models can generate partial dependence plots which measure the relation between CCI and a set of predictors. Partial dependence plots can illustrate the marginal effects of each predictor on the target variable, which taking the average influences of all other independent variables into account [32, 98]. The marginal effects of the top five predictors are demonstrated with partial dependence plots, as shown in Figure 2.7, where the y-axis represents the relative logit contribution of the predictor on the probability of CCI level 4 and 5 (relatively desirable cycling comfort level) from the perspective of the model, and detailed explanation can be found in [39].

Figure 2.7a and Figure 2.7b show that when the pavement type is asphalt, the likelihood that the CCI level is 4 or 5 increases, i.e. the pavement type (asphalt) positively affects the CCI level. The asphalt cycling paths are mostly dedicated cycling path or park network connectors near natural reserves constructed in recent years with better surface condition and enjoyable surroundings. Figure 2.7c and Figure 2.7d illustrate that the number of drainage covers greater than eight significantly reduces the likelihood of relatively satisfactory cycling comfort level with CCI level evaluated as 4 or 5. Drainage covers commonly coexist with the paths in Singapore for water storage and draining away water during storm, increase the level of vibration and create noise when cycling, thereby reducing the cycling comfort level. Figure 2.7e and Figure 2.7f demonstrate that the non-motorised lane positively affects the CCI rating in comparison with the motorised lane, and the result is consistent with the literature, which argued that the cycling comfort level significantly increases when the cyclists are physically separated from the motor vehicles due to safety concern [6, 55, 64]. Figure 2.7g and Figure 2.7h illustrate the impact of width of the pavement on the CCI levels. Generally, as the width of the cycling path increases, the cycling comfort level is more likely to be satisfiable, as more riding space is available to the cyclists, which is consistent with the literature [6, 25, 64]. Figure 2.7i and Figure 2.7j show that the cycling comfort level increases as the cyclist is separated from the pedestrians, and the result is consistent with [64]. The pedestrians with lower speed create conflicts between the two parties during interaction and tend to raise safety concerns, which negatively affect the cycling comfort level.

2.4.2 Ordered probit model

Ordered probit model is a regression technique commonly used in literature as the dependent variable BLOS or CCI is an ordinal variable. An unobserved variable y_i^* is introduced as a function of each observation i :

$$y_i^* = x_i\beta + \epsilon_i \quad (2.10)$$

FIGURE 2.7: Partial dependence plots

where β is a vector of coefficients, x_i is a vector of independent variables, and ϵ_i is a random error term which follows normal distribution. The value of CCI is represented by y , which ranges from 1 (least comfortable) to 5 (most comfortable). Various cut-points are computed to categorise different y values. Parameters in the ordered probit model is estimated with maximum log-likelihood function, coded with R. Correlation test is carried out to exclude explanatory variables with high collinearity. The model coefficient and statistical parameters of the ordered probit model is summarised in Table 2.2. P-value will be used to select the most significant predictors of cycling comfort index (CCI).

TABLE 2.2: Results of ordered probit model

Variable		Coefficient	Std	P-value
Gender		0.062	0.045	>0.10
Age		-0.010	0.027	>0.10
Cycling experience		0.056	0.045	>0.10
Lane type		1.357	0.192	<0.01
Slope		-0.144	0.007	<0.01
Pavement type	Tile vs concrete	0.358	0.085	<0.01
	Asphalt vs concrete	0.693	0.127	<0.01
Drainage cover		-0.159	0.016	<0.01
Occupancy ratio of drainage cover		-0.640	0.571	>0.10
Turn lanes		-0.896	0.078	<0.01
Frequent curves		-0.310	0.099	<0.01
Number of decelera- tion strips		-0.505	0.057	<0.01
Width		1.283	0.067	<0.01
Separation from pedes- trians		1.028	0.075	<0.01
Separation from motor vehicles	Complete separation vs no separation	2.180	0.172	<0.01
	Curb vs no separation	2.048	0.179	<0.01
	Fence vs no separation	-0.003	0.207	>0.10
	Planters vs no separation	2.607	0.122	<0.01
Number of access points		-0.035	0.003	<0.01
Presence of shelter		-0.349	0.110	<0.01
Presence of bus stop		-0.414	0.070	<0.01

According to Table 2.2, it is seen that with the provision of non-motorised lane, increasing width of road and separation from pedestrians, the CCI level increases in the ordered log-odds estimate when the other variables are kept constant, at the significance level of 0.01. The increment in CCI can be explained by the increment in effective riding space for the cyclists. Moreover, cyclists feel more

comfortable and safe when they are separated from other road users whose traveling speed and behaviour is different from cyclists. When separation between the cyclists and motor vehicles are provided, the ordered log-odds estimate for CCI generally increases, except when fence is provided as a type of buffer between cyclists and motor vehicles. The CCI level also increases when the pavement type is asphalt or tile in comparison with concrete. Asphalt and tile pavement can commonly be found near nature reserve or inside campus with lower level of vibration, relatively good pavement condition and enjoyable surroundings. On the other hand, with the presence of slope (upslope), drainage cover, shelter, access points, bus stop, frequent curves and turn lanes, reductions in the ordered log-odds estimate for CCI can be observed when the other variables are kept constant at the significance level of 0.01. The result shows that cyclists feel uncomfortable when they are disturbed by the upslope, access points, bus stop, which is consistent with the literature [6, 64]. The existence of frequent curves, turn lanes and drainage covers are also identified to negatively affect cyclists cycling experience. Interestingly, shelter is found to affect CCI negatively. In reality, shelter can protect cyclists under adverse weather condition, thereby provide better level of service. However, the survey in this paper was based on video clips collected under sunny daylight conditions, in which case the shelter can only block the visibility range, which constitutes a limitation. The result of ordered probit model is consistent with the result of XGBoost method for top feature selection. Furthermore, the assumptions that the ordered probit model relies on are also addressed here. It is assumed that the random error term is normally distributed across all observations with mean value as zero and variance as one [6]. The strict assumption lies in the nature of the ordered probit model, and it cannot be proven to be violated for the particular case. Moreover, it is assumed that the coefficients on all independent variables are equal for each category of dependent variable, i.e. the relationship between each pair of groups is the same, which is called the parallel regression assumption [125]. We evaluate the assumption by applying a series of binary probit regressions with different cut-points on the target variable to check the equality of coefficients across cut-points, and it is found that this assumption is violated.

2.4.3 Performance comparison of XGBoost and Ordered probit model

The overall accuracy rate of the model is computed as:

$$a = 1 - r = 1 - W/A \quad (2.11)$$

where r is multi-class classification error rate, W is the number of wrong cases, A is the number of all cases. Wrong cases refer to all the cases whose results predicted by the model are different from the labels stored in the CCI rating database. To compute the accuracy of the ordered probit model and XGBoost model, the dataset is randomly partitioned into training set (80%) and test set (20%), such that the data used for training is never used in the test set which is used for the final verification, with test accuracy rate as the performance measure.

The accuracy of each individual CCI level j is calculated based on the sensitivity or true positive rate, which represents the proportion of cases of CCI level j that are correctly classified as:

$$a_j = C_j / (C_j + F_j) \quad (2.12)$$

where C_j represents the number of cases of CCI level j that are correctly classified as so, F_j represents the number of cases of CCI level j that are wrongly classified.

The overall accuracy rate of XGBoost method is 78%, while ordered probit model's accuracy rate is 67%. For the XGBoost and ordered probit model, the accuracy rate for the overall model and for individual CCI levels are summarised in Table 2.3.

In general, it is seen that the accuracy rate of XGBoost model is higher than the ordered probit model, demonstrating better performance of XGBoost model. Moreover, for both the XGBoost model and ordered probit model, the classification accuracy of CCI level 1 and level 5 is observed to be higher than the

TABLE 2.3: Accuracy of XGBoost and ordered probit model

Accuracy rate	XGBoost model	Ordered probit model
Overall	0.78	0.67
Level 1	0.84	0.86
Level 2	0.68	0.56
Level 3	0.74	0.62
Level 4	0.76	0.59
Level 5	0.89	0.74

accuracy of level 2 to 4. This is because the dependent variable of CCI model is based on survey participants' comfort perception ratings. Survey participants' opinion toward extremely good or bad cycling infrastructure comfort condition is more consistent while their opinion varies when the cycling infrastructure comfort condition is moderate. Overall, the XGBoost method outperforms the ordered probit model with 11% improvement in accuracy for evaluating CCI.

2.5 Conclusions

In this study, we seek to evaluate cycling comfort level of different cycling infrastructure by introducing a cycling comfort index (CCI) and identify the factors that most significantly affect the CCI. There are three major contributions of this study: 1) For the data collection process, this study only requires the video clips collected by experienced cyclists from the cyclists' perspective and no direct field measurement is needed. The data collection process is more efficient and less time-consuming. 2) This study automates data processing and cycling infrastructure feature extraction process. A Convolutional Neural Network (CNN) algorithm is applied to classify different cycling infrastructure features with high accuracy. 3) Instead of ordinal regression techniques commonly used in literature, this research applies XGBoost method for computing CCI with relatively high accuracy rate, relaxed assumptions and robustness to multi-collinearity. Features that significantly affect the CCI are also identified, including pavement type, the number of drainage covers on the road segment, the type of lane (motorised or non-motorised lane), separation from pedestrians, and width of

the lane. The result of XGBoost method is mostly consistent with literature, with additional significant feature ‘Drainage Cover’ considered in the Singapore context. The method and result of this research help individual cyclists make their route choice decisions and help city planner evaluate and improve existing cycling infrastructure to facilitate cycling in a sustainable city. In particular, this study is suitable for Singapore context, which cannot adopt existing BLOS models in the literature directly. Nevertheless, the inclusion or exclusion of various explanatory variables can be adjusted accordingly based on the local cycling environment when applying the methodology of this study to other countries and cities.

Limitations of the paper and the future study direction are discussed as below. For the data collection method, the drawbacks of the video-based survey method exist due to the non-naturalistic data collection approach. The respondents did not actually experience themselves traffic environment on the target and the psychological and physiological responses of participants that occur in the natural setting should be considered under different weather and light conditions. For further study, we would like to investigate the subject in his or her natural mobility environment without any significant interference with field riding experiment to provide more complete immersion for the participants. Moreover, this paper focuses primarily on the effects of different cycling facility types and built environment conditions on cycling comfort level. Traffic volume is also an important factor for estimating the cycling comfort level, which should be included in further cycling comfort evaluation study from a more complete perspective. In addition, this paper applies the ordered probit model which is commonly used in the literature to build BLOS model for comparative analysis with the XGBoost algorithm. Future studies should develop and apply more advanced econometric models for the comparative analysis. Furthermore, further studies can be carried out to evaluate cycling infrastructure comfort level based on GPS and 3-axis sensor data. The comfort perception of different types of PMD users may also be added into consideration. The scope of study can also extend from link-based cycling comfort level evaluation to the whole cycling network, considering the effect of intersections. In the future, more advanced

statistical models, such as hierarchical ordered probit model, random parameter logit model should be explored, in order to cater for problems such as the interdependence and heterogeneity.

Chapter 3

Multi-objective bike-way network design problem with space-time accessibility constraint

3.1 Introduction

Cycling is a healthy, environmentally friendly, energy efficient and economical alternative transportation mode of travel to auto-mobiles [96]. Cycling enables travellers to integrate the regular physical activity and form healthy living habits, and reduce pollutants emitted by vehicles. Expansion of bike-way network is carried out in many cities to enhance connectivity among residential areas and major amenities in order to promote cycling to the public. However, many trips that are within cycling distance of a traveller's home, are often accessed via auto-mobile [97]. The most challenging task in developing bicycle-friendly areas is to promote demand not only for recreational cycling but also for commuting. Therefore, it is highly desirable to optimise bike-way network design problem.

The most significant factors that influence cycling demand are proximity and connectivity [86]. Therefore, accessibility which is an essential performance measure for transportation systems, defined as the ability of reaching important destinations is considered as the primary goal in this paper [118]. Unlike commuter drivers, commuter cyclists also consider the suitability of a route to

be important, including cycling comfort and safety. In order to promote cycling behaviour, it is important to understand how to enhance different design-based factors to provide safe, continuous and well-maintained non-motorised lanes separated from vehicles. Although the transportation network design framework in terms of motorised roadway networks has been well studied, the research on the bike-way network design problem for commuter cyclists is limited.

Bike-way network design problem is commonly formulated as a single objective model to minimise bike-way construction cost or travel time while the interest of multiple stakeholders including planners and cyclists are rarely taken into consideration at the same time. Moreover, in many literature, accessibility is used interchangeably with connectivity which is not comprehensive as travel time budget of commuter cyclists, representing the amount of time that commuter cyclists are willing to spend on cycling out of the day between each origin-activity location pair, is not taken into consideration. To the authors' best knowledge, there are only two papers [67] and [66] that formulated multi-objective bike-way network design optimisation model until now. Nevertheless, both studies applied the concept of accessibility interchangeably with connectivity and neither of them catered for the travel time budget of commuter cyclists.

This paper focuses on the optimisation of the bike-way network design process, including accessibility measures, bicycle level of service (BLOS), number of intersections and total construction cost, taking into account the space-time constraints and monetary budget, to meet the interests of multiple stakeholders including planners and cyclists, through the optimisation of location and type of bike-ways. This paper can assist city planners in bike-way network design; nevertheless, the final bike-way construction plan should be consistent with other socio-economic and institutional considerations, including citizen's will, maintenance cost, construction rules, etc.

3.2 Related work

In the field of operations research and transportation planning, the network design problem (NDP) aims to find an optimal allocation and utilisation of resources to achieve the objective [28]. The optimisation objectives of NDP in transportation including to increase the accessibility of network, to improve the mobility of travellers, and to reduce the risk of accidents, etc. In the transportation engineering field, the concept of accessibility was firstly proposed by [47] as the potential of opportunities for traveller interaction, serving as one of the most significant goals of transportation network construction and management. Currently, there is no unified method to evaluate accessibility since the concept is defined and measured from various perspectives. Some of the commonly used accessibility measures is summarised as below. (1) Cumulative opportunity measures count the number of potential opportunities that can be reached by each location within a given travel distance or time budget as accessibility measurement [122]. (2) Gravity-based of potential accessibility measures firstly introduced by [47] weight the attractiveness of opportunities by travel impedance function. (3) Utility-based or log-sum accessibility measures adhere to travel behaviour theories. The measure which can directly include the utility of choice options and capture the random nature of users' preferences is commonly used as an accessibility indicator, especially for the public transport system. [45] evaluated zonal accessibility as performance indicators in the urban public transport facility planning process. [83] developed a utility-based travel impedance measure for public transit modes, capturing the behaviour and subjective perceptions of impedance of travellers, with log-sum accessibility defined in a general logit choice model. However, this log-sum accessibility evaluation method also have some drawbacks, for example, the expected utility used in the log-sum indicator may differ from experienced utility, and using willingness to pay to calculate utility is disputed [119]. (4) Topological-based accessibility measures evaluate network connectivity. [20] analysed the accessibility impacts for the first and last mile transport connectivity to or from the major transit line using two most common feeder transit services, namely fixed route transit

and demand responsive transit. [89] incorporated externalities (safety, pollution) and accessibility measured by total travel time in the multi-objective NDP as objectives in designing sustainable networks, while the constraints like monetary budget were not considered and the decision making task is left entirely to the policy makers. Furthermore, the concept of space-time accessibility has been proposed, which considers not only spatial but also temporal accessibility. [115] presented a linear integer programming model to maximise end-to-end accessibility within space-time constraints for motorised roadway network.

Classic survey papers on NDP has been reviewed. [71] reviewed the the application of network design models in transportation planning, which addressed the integer-programming based models, as well as some discrete and continuous choice models and solution algorithms. [85] presented a structured survey on the hub network design problem for the hub-and-spoke configurations. [14] provided an analytical review on the hub-and-spoke network design problem for the air transportation, in which the hub location problem and its variants are analysed. [129] provided a structured review on the road network design which aims to make optimal investment to minimise then total travel time in the network, in consideration of the travel behaviour of road users. [44] reviewed the related works on transit network design problem, which focused on the design and scheduling of the transit network. [37] provided a comprehensive survey on the urban transportation network design problem, which contains both the road network design problem and the public transit network design problem. [28, 124] reviewed different service network design modelling methods and maths programming developments for freight transportation. [107] focused on the review of multimodal freight transportation planning, presenting relevant models and solution algorithms.

Although many studies on NDP have focused on roadways for auto-mobiles, the NDP of non-motorised lanes like cycle lanes are seldom addressed. In addition, traditionally, the accessibility literature has not focused much on short distances and slow modes, like cycling [119]. In contrast to car drivers, cyclists consider a significantly broader range of factors while deciding on their routes. Other than travel time and distance, cyclists are also sensitive to bicycle level

of service (BLOS) factors including slope, turn frequency, etc., which influence the safety and comfort perception of cyclists [50]. The majority of bike-way network design problems apply the gravity-based accessibility measures, which represent zonal or macro-scale accessibility, weighting the attractiveness of opportunities according to a travel impedance function [53, 69, 70, 118]. However, the transportation needs between each origin and activity location pairs are not considered. [138] derived a utility-based accessibility measure from a bike route choice model using GPS data. The utility-based accessibility measure focuses on demand-side management with cyclists' behaviour. Nevertheless, to meet existing demand can lead to a chicken-and-egg problem such that regions with good cycling infrastructure improve while regions with poor ones are neglected [35]. Topological-based accessibility measures have been incorporated in some other works which consider node-to-node connectivity of all O-D pairs as the accessibility measure which commonly serve as constraints in the bike-way network design optimisation problem. However, the time budget which is significant to commuter cyclists is not considered in the accessibility measure. Then, the literature on the optimisation of bike-way network design problem is summarised as below: [23, 35] focused on the minimisation of the cost associated with improving the bike-ways to create suitable paths between each OD pair. [79] formulated a bi-level optimisation model where the benefits of cyclists and car users are considered at the upper level and traffic and bike demand assignment is modelled at the lower level. The objective of the model was defined by a weighted sum of total travel time for private car users versus the total travel distance on bike lanes for bicyclists. [75] also formulated an optimisation model to minimise the travel cost of users while satisfying the monetary budget of planners, and a metaheuristic algorithm was applied to solve the model. [22] constructed a bike-way network improvement model for an existing bike-way network system to minimise cyclist travel times, meeting related restrictions for bike-way construction, but other BLOS factors which are significant to cyclists were not considered. To the authors' best knowledge, there are only two papers that formulated multi-objective bike-way network design optimisation model until now. [67] developed a multi-objective bike-way network design model for urban areas involving various stakeholder concerns while [66] emphasised on recreational

bicycling in scenic areas. Both studies applied the concept of accessibility interchangeably with connectivity, which may not be rigorous as travel time budget of commuter cyclists was not taken into consideration. In this study, the concept of time budget is introduced between each origin-activity location pair (e.g., home and school, market place, hospital, job locations nearby, etc.), representing the amount of time that traveler are willing to spend on cycling.

Compared with motorised roadway network design problem, there is less research on bike-way network design problem. Bike-way network design optimisation problem is commonly formulated as single objective optimisation model to minimise bike-way construction cost or travel time. Moreover, most literature use the concept of accessibility interchangeably with connectivity which is not comprehensive or rigorous as travel time budget of commuter cyclists is not taken into consideration. In this study, the concept of time budget is applied between each origin-activity location pair which represents the amount of time that travellers are willing to spend on cycling out of the day between each origin-activity location pair, for example, between home and school, market place, hospital, job locations nearby, etc. The value of time budget should be decided by city planner or policy maker when apply the optimisation model in order to better promote cycling. It is assumed that reasonable commuter cyclists would not take the trip by bicycle if the travel time between two locations exceed the travel time budget.

The major contribution of this study is to address bike-way network design problem based on a multi-objective optimisation algorithm which maximises the accessibility and bicycle level of service (BLOS) of the bike-way network and minimises the total number of intersections and total construction cost subject to space-time constraints and monetary budget. The key indicators are chosen to cater for the conflicting interests of different stakeholders involved in the bike-way network design process. Related works have also been reviewed for the key indicator selection process. First, the travel time between origin and activity location is significant to commuter cyclists. [75] and [22] formulated a bike-way network improvement model for an existing bike-way network system to minimise cyclist travel times while meeting related restrictions for bike-way

construction. Therefore, in this paper we apply the concept of space-time accessibility to maximise commuter cyclists' accessibility level within the travel time budget to cater for the need of commuter cyclists. Second, intersections can pose safety risk and cyclists may prefer connected bikeway networks to fragmented ones [66, 67], hence we also introduce the objective to minimise the number of intersections in the bike-way network. Third, the objective to maximise the Bicycle Level of Service (BLOS) on the bike-way network is also considered, as the cycling comfort level on different cycling infrastructure can strongly influence the comfort perception, mode choice, and route choice of cyclists. As cycling comfort level becomes an increasingly important factor for cyclists and city planners, the importance of BLOS has been addressed in the literature [4, 6, 10, 18, 77], and it is also included in this paper as an indicator. Different from indicator 2 which focuses more on the safety level of bicyclists, the indicator 3 focuses more on the cycling comfort level, for example, the level of road unevenness. Fourth, one of the major concerns of the planners is the monetary bike-way network construction cost. [35] and [23] aimed to minimise the construction cost associated with improving the bike-ways to create suitable paths between each OD pair. Therefore, the objective of minimisation of bike-way construction cost is included in this paper. Note that the objectives considered in the paper are usually competing, for example, higher BLOS condition provided are usually associated with higher bike-way construction cost. The four objective functions are also assumed to be independent. Therefore, we formulated a multi-objective optimisation model to address the trade-offs among different objective functions at the same time, such that a set of non-dominated bike-way network design alternatives are generated.

Augmented ϵ -constraint method (AUGMECON) is applied to solve the multi-objective bike-way network design problem, which generates a set of non-dominated solutions. The non-dominated bike-way design plans represent that the selection of each one of the alternative plans to replace another can always improve the performance of at least one objective function at the cost of sacrificing the performance of at least one other objective function, addressing the trade-offs

FIGURE 3.1: Bike-way types

among objective functions. Two numerical examples are used to demonstrate feasibility of the multi-objective bike-way network design model.

3.3 Methodology

The research problem is to optimise bike-way locations and types for a specified planning area with a set of candidate links in order to maximise the accessibility and bicycle level of service and minimise the number of intersections and total construction cost subject to space-time constraints and monetary budget. Three types of bike-way classifications are applied in this study according to Singapore context: bike path, shared path and footpath as shown in Figure 3.1. Bike paths are defined as a dedicated bike lane completely separated from motorised traffic and pedestrians; shared paths including Park Connectors and cycling paths, are designed for use by bikes, pedestrians etc., with speed limit of 25 km/h; footpaths are similar to shared paths except that footpaths disallow Power-Assisted Bicycles (PAB) and have a lower speed limit of 15 km/h [105]. The three different types of bike-ways provide significantly different Bicycle Level of Service (BLOS) conditions due to the different pavement condition, different widths of road, different volumes and types of users on them.

3.3.1 Space-time network

In comparison with the common connectivity measure, the space-time accessibility measure considers both spatial and temporal accessibility. Additional inputs include time-varying congestion levels associated with specific departure times at the origin and activity locations, total travel time budget and required activity location [80]. In this study, we modify and simplify the traditional space-time accessibility measure applied for roadway network design problem to make it more suitable for the bike-way network design problem. The notations of parameters used are summarised in Table 3.1.

TABLE 3.1: Notations

Symbol	Definition
Q	Set of nodes in the space-time network
A	Set of links in the space-time network
A^T	Set of space-time traveling arcs in the space-time network, $A^T \in A$
A^W	Set of waiting arcs in the space-time network, $A^W \in A$
A^{ap}	Set of activity-performing arcs in the space-time network, $A^{ap} \in A$
A^v	Set of virtual traveling arcs in the space-time network, $A^v \in A$
N	Set of nodes in the physical bike-way network or the simplified space-time network
N^a	Set of origin and activity location nodes in the physical network, $N^a \in N$
i, j	Indices of nodes in the physical bike-way network, $i, j \in N$
t, s	Indices of different time stamps
(i, j, t, s)	Index of space-time arcs in the space-time network indicating the actual movement at entering time t and leaving time s on link (i, j) , arc $(i, j, t, s) \in A$
PR	Set of origin-activity location pair(s)
(o, a)	Origin-activity location pair, $(o, a) \in PR$
$T(o, a)$	Total time budget for origin-activity location pair (o, a)
Ω	Set of discretionary activity locations
M_o	The opportunity set of valued activity locations from location o
$c_{ijts}(o, a)$	Inaccessibility cost of space-time arc (i, j, t, s) in the space-time network for origin-activity location pair (o, a) , takes the value of 1 for space-time virtual traveling arcs and $t_{ij}/T(o, a)$ otherwise
$t(o, a)$	Travel time between origin-activity location pair (o, a)
T_a	Activity performing time at activity location a
E	Set of all links to in the simplified space-time network
E^n	Set of all non-existing physical candidate links which can be newly constructed in the simplified space-time network
E^p	Set of all physical links to in the simplified space-time network

E^v	Set of virtual traveling arcs in the simplified space-time network
(i, j)	Index of the simplified space-time network links, connecting adjacent nodes i and j , $(i, j) \in E$
$\Gamma(i)$	The set of node $j \in \Gamma(i)$ such that a link (i, j) exists, $(i, j) \in E$
t_{ij}	Travel time on candidate link (i, j) , $(i, j) \in E$
$c_{ij}(o, a)$	Inaccessibility cost of arc (i, j) in the simplified space-time network for origin-activity location pair (o, a) , takes the value of 1 for virtual travelling arcs; takes the value of $t_{ij}/T(o, a)$ for physical links, $(i, j) \in E$
y_{ij}	Coefficient of arc (i, j) , which takes the value of 1 for all non-existing physical candidate links to be constructed and 0 otherwise, $(i, j) \in E$
n_{ij}	Number of intersections on link (i, j) , $(i, j) \in E$
d_{ij}	Distance of link (i, j) , $(i, j) \in E$
k	Bike-way types, which is ranked according to cyclists' right of way: bike path ($k=3$)>shared path ($k=2$)>footpath ($k=1$)
s_{ijk}	Suitability score of paving bike-way type k along candidate link (i, j) , $(i, j) \in E$
B	Total construction cost budget
C_{ijk}	Cost for constructing link (i, j) with bike-way type k , $(i, j) \in E$, $k \in \{1, 2, 3\}$
n_{oa}	Number of origin-activity location pair(s) considered in the simplified space-time network
$P_{o,a}$	Feasible path between origin-activity location pair (o, a)
M	The minimum number of candidate links (i, j) chosen to be constructed or improved, $(i, j) \in E$
U	Set of feasible solutions for the optimisation model formulated in this study
u	The vector representing decision variables
δ_{ijk}	Takes the value of 1 if bike-way type k is chosen to be newly constructed or the current bike-way type is to be improved to type k on candidate link (i, j) , $(i, j) \in E$; and 0 otherwise
$x_{ij}(o, a)$	Takes the value of 1 if a link (i, j) , $(i, j) \in E$ is used in the tour for origin-activity location pair (o, a) in the direction of i to j and 0 otherwise

For the bike-way NDP considered in this paper, we do not incorporate the dynamic opportunity effects commonly used in the space-time network accessibility analysis, i.e. the congestion effect on bike-way network is not considered. Thereby, the activity performing duration at activity location is also excluded. In this study, the accessibility measure focuses on the trip between origin and activity location where travel time is used as a major influencing factor.

Given the time budget $T(o, a)$ between origin o and activity location a regardless of departure time, the opportunity set M_o of valued activity locations from

location o is:

$$M_o = \{a \in \Omega | t(o, a) \leq T(o, a)\} \quad (3.1)$$

That is, the opportunity set contains all locations a which are accessible from the origin o in a space-time network if the total travel time budget is greater than or equal to the travel time $t(o, a)$. Modified based on [115], Algorithm 2 illustrates the process of building a modified space-time network for origin-activity location pair (o, a) , with two considerations: (1) ensure travel time budget constraint; (2) connect the space-time arcs with the existing physical links or physical links to be constructed. Different type of arcs used in the algorithm are explained as below: Basically, all the arcs in the space-time network represent cyclists' time-dependent movements or trajectories based on the physical bike-way network. The space-time traveling arc is defined to connect two different nodes in the physical bike-way network at two different time stamps. The activity performing arc is only introduced to the space-time network when the cyclist arrives at the activity location earlier than the travel time budget. In other words, activity performing arc is defined to represent the activity participation time at the same node in the physical network. The virtual traveling arc represents the length of cyclists' travel time budget between certain origin and activity location node in the dimension of time, and it connects the origin to the activity location node in the dimension of physical network. To ensure flow balance conditions at each vertex, virtual traveling arcs are added to connect origin node and activity location node at different time stamps, i.e. to connect the super source vertex with the super sink vertex from the beginning time 0 to the end time $T(o, a)$ which represents the time budget for origin-activity location pair (o, a) . If the traveler cannot arrive at the activity location node within the travel time budget, the virtual traveling arc is to be chosen instead of the space-time traveling arc and activity performing arc to ensure the flow balance. Figure 3.2 illustrates the space-time network and physical network with an example that contains two overlapping space-time networks connecting the same origin node o to activity location a_1 and a_2 . 6-dimensional binary variables $x_{ijts}(o, a)$ need to be introduced to indicate that the space-time arcs (i, j, t, s) are used in the tour for origin-activity location pair (o, a) .

Algorithm 2: Build a modified space-time network for origin-activity location pair (o, a)

Step 1: Build space-time vertex set Q

Add vertex (i, t) to Q for $i \in N$ and each t

Step 2: Build space-time arc set A

Step 2.1: Add a set of space-time traveling arcs A^T for a pair of vertices $(i, t), (j, t + t_{ij})$ to A for link $(i, j) \in A$, where t_{ij} is the link travel time from node i to node j

Step 2.2: Add a set of space-time virtual traveling arcs A^v for a pair of vertices $(o, 0), (a, T(o, a))$ to A

Step 2.3: Add a set of space-time activity-performing arcs A^{ap} for a pair of vertices $(a, t), (a, t + T_a)$ if arriving at activity location earlier than time budget.

$$\sum_{(i,j) \in A^T} t_{ij} + T_a = T(o, a) \quad (3.2)$$

Step 3: Set arc cost structure

Step 3.1: Set $c_{ijts}(o, a) = 1$ for space-time virtual traveling arc $(i, j, t, s) \in A^v$

Step 3.2: Set $c_{ijts}(o, a) = t_{ij}/T(o, a)$ for space-time traveling arc $(i, j, t, s) \in A^T$ for a pair of vertices $(i, t), (j, t + t_{ij})$

We further convert the space-time accessibility network to an equivalent bike-way network with space-time constraint such that it consists of physical bike-way links and virtual traveling arcs which are used to maintain flow balance as in Figure 3.3, where the values of $T(o, a)$ and travel cost t_{ij} on each link (i, j) are labeled as weight. A feasible tour exists in physical network that connects origin o to activity location a_1 within the travel time budget, hence node a_1 is accessible. Node a_2 is not accessible through the physical network within travel time budget, thus virtual traveling arc that corresponds to a_2 is selected to ensure the flow balance constraint. Virtual arcs indicate the inaccessible level of certain origin-activity pairs within a travel time budget constraint. In other words, if the resulting travel time is greater than travel time budget, then the virtual traveling arc is automatically selected due to the objective of inaccessibility cost minimisation and flow balance constraint. The process of building the equivalent bike-way network with space-time constraint is illustrated with Algorithm 3, which is feasible since time-dependent travel time or congestion effect is not

FIGURE 3.2: Space-time network & physical network

considered for bike-way network design problem in this study. Dimensionality is reduced by introducing 4-dimensional binary variables $x_{ij}(o, a)$ to indicate that arcs (i, j) are used in the tour for origin-activity location pair (o, a) , where the time dimension is incorporated with the travel cost of each arc.

In this study, total time budget $T(o, a)$ for each origin-activity location pair (o, a) is applied to represent the amount of time that travellers are willing to spend on cycling out of the day between each origin-activity location pair (o, a) , for example, between home and school for children who may be escorted by parents [49], between home and market place, hospital, job locations nearby, etc. The value of $T(o, a)$ is decided by city planner or policy maker when apply the bike-way design optimisation in order to encourage cycle behaviour. In this study, it is assumed that reasonable cyclists would not take the journey by bicycle if the travel time between two locations exceed the travel time budget.

FIGURE 3.3: Simplified network

Algorithm 3: Equivalent bike-way network with space-time constraint

Step 1: Build vertex set N

Add vertex i for $i \in N$

Step 2: Build arc set E

Step 2.1: Add a set of physical links E^p for a pair of vertices (i, j) to E

Step 2.2: Add a set of virtual traveling arcs E^v for a pair of vertices (o, a) to E , $(o, a) \in PR$

Step 3: Set arc cost structure

Step 3.1: Set $c_{ij}(o, a) = 1$ for virtual traveling arc $(i, j) \in E^v$; set

$c_{ij}(o, a) = t_{ij}/T(o, a)$ for physical links

Step 3.2: Set $y_{ij}(o, a) = 1$ for non-existing physical links to be constructed $(i, j) \in E$

3.3.2 Bike-way network design model

3.3.2.1 Notations and assumptions

Given node set N with a set of activity locations N^a and link set E . The notations of parameters and decision variables used in the bike-way network design model are summarised in Table 3.1.

Assumptions: (1) All sets and parameters have been precisely determined before model analysis. (2) The bike-way network is an undirected graph such that a node i is accessible with the selection of link (i, j) or (j, i) . (3) All origin and activity location pairs in the modified space-time network are connected. (4) In the modified space-time network, it is assumed that the congestion effect on different types of bike-way links is not considered and all types of bike-way links have sufficient capacity to handle the traffic. (5) In the modified space-time network, the travel cost on each candidate link is approximated by the summation of link travel time and intersection delays, different travel speed of different cyclists on different type of bike-way types is not taken into account. (6) If the travel time between the two locations exceeds the travel time budget, it is assumed that a reasonable cyclist does not travel by bicycle. (7) Similar to [66], we assume that only one type of bike-way can be provided along a roadway section. (8) A pre-existing candidate site and a set of candidate links have been selected

by the government for bike-way network design model development during the pre-modelling process. The set of initial candidate links should be evaluated and selected based on different built environment characteristics and criteria, including the traffic volume, slope, road width, etc.

3.3.2.2 Objective functions of the formulation

Objective 1 is to minimise the inaccessibility level in terms of travel time and unreachable activity locations given travel time budget $T(o, a)$ between each origin-activity location pair.

$$Z_1 = \sum_{(o,a) \in PR} \sum_{(i,j) \in E} c_{ij}(o, a) \cdot x_{ij}(o, a) \quad (3.3)$$

where $c_{ij}(o, a) = 1$ for virtual traveling arc $(i, j) \in E^v$ indicating that the activity location a is unreachable from location o within travel time budget $T(o, a)$; and $c_{ij}(o, a) = t_{ij}/T(o, a)$ represents the travel time on certain link (i, j) between origin and activity location (o, a) relative to the travel time budget. For simplification purpose, it is assumed that all origins have the same number of activity locations. The value of travel cost t_{ij} on each candidate link is approximated by the summation of link travel time and intersection delays. The maximum possible value of the objective Z_1 is equal to the number of origin-activity location pairs (o, a) that are taken into account in the network design process, and the value of Z_1 can approximate the number of inaccessible locations. In the space-time network, different weights can also be given to various O-D pairs to show varying degrees of importance in meeting the travel budget between different origin-activity location pairs (o, a) . In this study, it is assumed that reasonable cyclists would not take the journey between origin-activity location pair (o, a) by bicycle if the travel time budget $T(o, a)$ is exceeded. To measure the space-time accessibility, it is simply assumed that the cyclists will choose the shortest path here. The effect of the level of comfort and other factors that affect the route choice behaviour has not been considered.

Objective 2 is to minimise the number of intersections on the candidate links (i, j) in the bike-way network in order to minimise the number of interruptions and safety risk induced to cyclists as in Figure 3.4.

$$Z_2 = \sum_{(i,j) \in E} n_{ij} \cdot \left(\sum_{k=1}^3 \delta_{ijk} \right) \quad (3.4)$$

FIGURE 3.4: Intersections

Objective 3 is to maximise the bicycle level of service (BLOS), which measures the safety and comfort perception of cyclists. For each candidate link, right-of-way is ranked as bike path ($k=3$) > shared path ($k=2$) > footpath ($k=1$). In the context of Singapore, bike path, shared path and footpath are the three most commonly used bikeway types. The three different types of bikeway provide significantly different Bicycle Level of Service (BLOS) conditions due to different pavement conditions, different widths of road, different volumes and types of users on them (due to different ranks of right-of-way), which affects the objective. Generally, the BLOS of bike path is better than shared path, and footpath is the worst. The objective to maximise BLOS is equivalent to minimise the following equation, which multiplies link BLOS score with link distance [69].

$$Z_3 = \sum_{(i,j) \in E} \sum_{k=1}^3 s_{ijk} \cdot \delta_{ijk} \cdot d_{ij} \quad (3.5)$$

where s_{ijk} can be calculated with [72] method.

According to [72], the calculation for link-based BLOS score s_{ijk} is based on the following ten attributes: width of outside lane, width of bike lane, width of shoulder, proportion of occupied on-street parking, vehicle traffic volume, vehicle speeds, percentage of heavy vehicles, pavement condition, presence of curb and

TABLE 3.2: BLOS score and letter grade

BLOS score	Letter grade
< 2.00	A
2.00-2.75	B
2.75-3.5	C
3.5-4.25	D
4.25-5	E
> 5	F

number of through lanes. Different design and operating features of bike-way are combined to calculate a numeric score to categorise the BLOS from most desirable (letter grade A) to most undesirable (letter grade F), as in Table 3.2. Other types of BLOS evaluation measure may also be used to generate a score that describe the suitability of the cycling infrastructure.

Objective 4 is to minimise the total construction cost of locating candidate links (i, j) with bike-way type k in the bike-way network.

$$Z_4 = \sum_{(i,j) \in E} \sum_{k=1}^3 C_{ijk} \cdot \delta_{ijk} \quad (3.6)$$

3.3.2.3 Constraints of the formulation

Flow balance constraint ensures that at least one path can be used to connect origin-activity location pair (o, a) in the modified space-time network.

$$\sum_{j \in \Gamma(i)} x_{ij}(o, a) - \sum_{j \in \Gamma(i)} x_{ji}(o, a) = \begin{cases} 1 & i = o \\ -1 & i = a \\ 0 & \forall i \in N \setminus \{o, a\} \end{cases} \quad \forall (o, a) \in PR \quad (3.7)$$

Coupling constraints between modified space-time network and physical bike-way network express the relationship between the physical candidate link to be located and modified space-time transportation network arc used between each

origin-activity location pair (o, a) , which ensures that cyclists cannot travel on a bike-way link that is not constructed.

$$x_{ij}(o, a) \cdot y_{ij} \leq \sum_{k=1}^3 \delta_{ijk}, \quad \forall o, a \in N^a, (i, j) \in E \quad (3.8)$$

$$x_{ji}(o, a) \cdot y_{ij} \leq \sum_{k=1}^3 \delta_{ijk}, \quad \forall o, a \in N^a, (i, j) \in E \quad (3.9)$$

Construction budget constraint ensures that the total construction cost does not exceed the budget.

$$\sum_{(i,j) \in E} \sum_{k=1}^3 C_{ijk} \cdot \delta_{ijk} \leq B \quad (3.10)$$

Bike-way type constraint ensures at most one type of bike-way can be located on a certain candidate link.

$$\sum_{k=1}^3 \delta_{ijk} \leq 1, \quad \forall (i, j) \in E \quad (3.11)$$

Bike-way construction constraint ensures the minimum number of bike-way links (i, j) to be constructed or improved.

$$\sum_{(i,j) \in E} \sum_{k=1}^3 \delta_{ijk} \geq M, \quad \forall (i, j) \in E \quad (3.12)$$

Binary constraints limit decision variables to binary variables.

$$\delta_{ijk} \in \{0, 1\}, \quad \forall (i, j) \in E, k = 1, 2, 3 \quad (3.13)$$

$$x_{ij}(o, a) \in \{0, 1\}, \quad \forall o, a \in N^a, (i, j) \in E \quad (3.14)$$

All the objective functions and constraints in this study satisfies the requirement of integer linear programming model, hence for each objective function, the

property should be integer linear programming model. Overall, the property of the whole model with four objective functions is multi-objective integer linear programming model.

3.3.3 Algorithms

3.3.3.1 Multi-objective optimisation

In this study, we obey the principle for an ideal multi-objective optimisation procedure as suggested by [29] with two steps, where the first step is to find multiple trade-off optimal solutions with a wide range of values for objectives and the second step is to choose one of the solutions obtained from the first step using higher-level information. A decision maker who can express preferences among different solutions, or city planner and policy maker in the case of bike-way network design problem will be involved in the process of choosing a desirable solution out of the Pareto-optimal set, which is the non-dominated set of the entire feasible decision space.

The concept of dominance is used to determine the goodness of solutions to the multi-objective optimisation problem. A solution u' is defined to dominate another solution u if the following two conditions are satisfied for the minimisation of S objective functions:

1. u' is no worse than u for all objectives, $f_s(u') \leq f_s(u)$, $\forall s \in \{1, 2, \dots, S\}$
2. u' is strictly better than u for at least one objective, $f_{\bar{s}}(u') < f_{\bar{s}}(u)$, $\exists \bar{s} \in \{1, 2, \dots, S\}$

A solution u^* is a non-dominated solution or Pareto-optimal solution if and only if there is no other solution u' that dominates u^* .

3.3.3.2 Augmented ϵ -constraint method–AUGMECON

ϵ -constraint method can be adopted to overcome the sensitivity issues and optimality issues of traditional weighted-sum approach. ϵ -constraint method preserves one of the objectives while the rest of the objectives are converted to constraints, such that they are restricted within user-specific ϵ values [76]. No weight is required as a set of non-dominated bike-way design solutions are explicitly generated by the ϵ -constraint method. There are various forms of ϵ -constraint method in the literature, and the solution of the algorithm largely depends on the selection of ϵ vector. In this study, we apply the augmented ϵ -constraint method (AUGMECON) which avoids the production of weakly non-dominated solutions which can be generated with the original form of ϵ -constraint method and speeds up the whole process by avoiding redundant iterations [76]. With augmented ϵ -constraint method (AUGMECON), the original multi-objective optimisation problem [P1] (as in Equation 3.15) is converted to [P2] (as in Equation 3.16), where the first objective Z_1 for the minimisation of inaccessibility level is retained to be solved, with slack variables sl_2, sl_3, sl_4 introduced to represent inequality constraints $Z_s \leq \epsilon_s, \forall s = \{2, 3, 4\}$. The augmented ϵ -constraint method (AUGMECON) produces non-dominated solutions, excluding weakly non-dominated solutions which can be computed with simple ϵ -constraint method.

$$[P1] \quad \min Z_1; \min Z_2; \min Z_3; \min Z_4; \\ u \in U \quad (3.15)$$

$$[P2] \quad \min Z_1 - eps * (sl_2/r_2 + sl_3/r_3 + sl_4/r_4); \\ s.t. \quad Z_2 + sl_2 = \epsilon_2, \\ Z_3 + sl_3 = \epsilon_3, \\ Z_4 + sl_4 = \epsilon_4, \\ u \in U \quad (3.16)$$

where eps is an adequately small value usually ranges from 10^{-6} to 10^{-4} , and r_2, r_3, r_4 represent the range of objective 2, 3, 4 respectively, i.e. the maximum value minus the minimum value, which are used for normalisation. $\epsilon_s = Z_s^- +$

$b/(\mathcal{B} - 1) \cdot (Z_s^+ - Z_s^-)$, $\forall s \in \{2, 3, 4\}$. ϵ_s ($s \in \{2, 3, 4\}$) represents an upper bound of the value of Z_s ($s \in \{2, 3, 4\}$), which is not necessarily a small value close to zero. Z_s^- and Z_s^+ represents the minimum value and maximum value that could be taken by Z_s respectively. With the parametrical variations in the ϵ_s values of the constrained objective functions, Equation 3.16 is solved repeatedly for different $b \in \{1, 2, \dots, \mathcal{B} - 1\}$, which provides at most $3^{\mathcal{B}}$ non-dominated solutions. The $\mathcal{B}$ value indicates the number of grid points within the range of each objective function, which controls the total number of the generated efficient solutions [76], and the b value indicates each grid point, $b \in \{1, 2, \dots, \mathcal{B} - 1\}$. Algorithm 4 illustrates the process of generating the Pareto-optimal set $\hat{P}$. $\hat{Z}_2, \hat{Z}_3, \hat{Z}_4$ represent sets of different values that can be taken by objectives Z_2, Z_3, Z_4 respectively, denoted by Z_2^p, Z_3^q, Z_4^g . At each iteration, ϵ value pair $(\epsilon_2, \epsilon_3, \epsilon_4)$ for which [P2] has a feasible solution is solved for optimality, giving an optimal solution $u^* = \text{opt}((Z_1 - \text{eps} * (sl_2/r_2 + sl_3/r_3 + sl_4/r_4)), \epsilon_2, \epsilon_3, \epsilon_4)$. For each Z_2^p, Z_3^q, Z_4^g value of $\epsilon_2, \epsilon_3, \epsilon_4$, solution u^* is a Pareto-optimal solution if it has not been found in the previous iterations [2].

Algorithm 4: ϵ -constraint method

```

 $\hat{P} \leftarrow \emptyset$ 
for  $p=1$  to  $|\hat{Z}_2|$  do
    for  $q=1$  to  $|\hat{Z}_3|$  do
        for  $g=1$  to  $|\hat{Z}_4|$  do
             $\epsilon_2 = \hat{Z}_2^p, \epsilon_3 = \hat{Z}_3^q, \epsilon_4 = \hat{Z}_4^g$ 
            while  $P(\epsilon_2, \epsilon_3, \epsilon_4)$  has a feasible solution do
                 $\epsilon_2^* \leftarrow \epsilon_2, \epsilon_3^* \leftarrow \epsilon_3, \epsilon_4^* \leftarrow \epsilon_4;$ 
                 $u^* \leftarrow \text{opt}((Z_1 - \text{eps} * (sl_2/r_2 + sl_3/r_3 + sl_4/r_4)), \epsilon_2^*, \epsilon_3^*, \epsilon_4^*)$ 
                 $\hat{P} \leftarrow \hat{P} \cup \{u^*\}$ 
for  $u^* \in \hat{P}$  do
    if  $u^* = \hat{u}$ , for  $\forall \hat{u} \in \hat{P}$ , then
         $\hat{P} \leftarrow \hat{P} \setminus \{u^*\}$ 
return  $\hat{P}$ 

```

Since the first objective for the maximisation of accessibility is retained in this study, we have the following remark with regard to the decision variable $x_{ij}(o, a)$ and the virtual traveling arc.

Remark 1. By solving problem [P2] with Algorithm 4, no non-dominated solution can generate a vector of decision variable $x_{ij}(o, a)$ such that the total travel time on a feasible path $P_{o,a}$ between origin-activity location pair (o, a) is greater than travel time budget $T(o, a)$.

Proof. For the origin-activity location pair (o, a) with travel time budget $T(o, a)$, we consider u^* with $u^* = \text{opt}(Z_1 - \text{eps} * (sl_2/r_2 + sl_3/r_3 + sl_4/r_4), \epsilon_2^*, \epsilon_3^*, \epsilon_4^*)$. We suppose, for the sake of contradiction, that a non-dominated solution u^* generates a vector of $x_{ij}(o, a)$ that satisfies $\sum_{(i,j) \in P_{o,a}} t_{i,j} > T(o, a)$. Let $\tilde{u}$ be a solution with virtual traveling arc selected, hence $Z_1(\tilde{u}) < Z_1(u^*)$. Meanwhile, we can have $Z_2(\tilde{u}) = Z_2(u^*)$, $Z_3(\tilde{u}) = Z_3(u^*)$, $Z_4(\tilde{u}) = Z_4(u^*)$, since the selection of virtual traveling arc does not affect the value of Z_2 , Z_3 , and Z_4 which is dependent on the decision variable δ_{ijk} . Therefore, the assumption that u^* is a non-dominated solution with $Z_1(u^*) - \text{eps} * (sl_2/r_2 + sl_3/r_3 + sl_4/r_4) < Z_1(u) - \text{eps} * (sl_2/r_2 + sl_3/r_3 + sl_4/r_4)$, $\forall u \in U$ is contradicted as u^* is dominated by $\tilde{u}$. □

To sum up, the flowchart in Figure 3.5 shows an overview of the methodology section. In the first stage, we try to build a network for the study area. Algorithm 2 [115] is used to build a space-time network for the bike-way network. Then Algorithm 3 is further proposed to simplify the space-time network such that the dimension of decision variable is reduced from 6-dimensional to 4-dimensional. In the second stage, we formulate a multi-objective integer linear programming model based on the study network generated from Algorithm 3, with the objective functions (Equation 3.3-3.6) and constraints (Equation 3.7-3.14). In the third stage, augmented ϵ -constraint method (AUGMECON) has been applied to generate a set of non-dominated bike-way design alternatives. The weighted-sum method which is commonly used in the literature has also been applied to compare with AUGMECON adopted in this paper in the first numerical example.

FIGURE 3.5: Overview flowchart

3.4 Numerical studies

Two numerical examples are applied to demonstrate the properties and effectiveness of the multi-objective integer linear programming model and the solution algorithm. First, we use a small 6-node network to illustrate the trade-offs between different objectives. Then, a hypothetical study area (Figure 3.7) at Jurong Lake district in Singapore which consists of 32 nodes and 47 links is used to demonstrate the feasibility of the proposed model and solution algorithm in reality.

3.4.1 Example 1

For ease of explanation, we use a simple network as Figure 3.6. The network consists of 10 links, including 1 virtual traveling arc and 9 physical links. Among the 6 nodes in the network defining candidate links, node 1 is an origin node

and node 4 is an activity location node. The parameters used here include construction cost C_{ijk} of different types of bike-ways, number of intersections n_{ij} , bicycle level of service (BLOS) score s_{ijk} , travel time t_{ij} , indicator of non-existing physical links y_{ij} of candidate links (i, j) , inaccessibility cost $c_{ij}(o, a)$, and travel time budget $T(o, a)$ between each origin-activity location pair (o, a) . Those parameters are set with some random example values within reasonable ranges, such that no bike-way can be located on the links which are not physical candidate links and no existing bike-way types can build repeatedly on the same link. In Figure 3.6, the weight on each physical link indicates the travel cost between two nodes, while the weight on the virtual traveling arc indicates the travel time budget between origin-activity location pair (1,4). The parameters used in the numerical examples are hypothetical values without units, and the link length, construction cost, travel time for each link are given in Table 3.3. The travel time budget is set to 3.5 and construction budget is set to 15. The hypothetical values are set according to rules like the construction cost for bike path is usually higher than shared path, then higher than the footpath; the value of link length and travel cost should be positively correlated. ‘Inf’ represents infinity value, which is introduced if certain type of bike-way is not allowed to be constructed. The link length of virtual traveling arcs is set to 0 as it is not a physical bike-way link to be constructed, and the time cost of the virtual traveling arc is equal to the travel time budget between certain origin-activity location pairs.

FIGURE 3.6: Simple numerical example

TABLE 3.3: Information on each link

link(i,j)	Link length	Construction cost			Time cost
		k=1	k=2	k=3	
(1,2)	2	Inf	5	6	2
(1,3)	2	Inf	1	2	2
(1,5)	1	5	6	7	1
(5,6)	1	3	6	9	1
(6,3)	1	1	2	3	1
(3,4)	2	Inf	4	7	2
(2,5)	1	1	2	4	1
(6,4)	1	3	4	5	1
(2,4)	2	Inf	2	6	2
(1,4) ^v	0	Inf	Inf	Inf	3.5

^a ^v represents virtual traveling arcs

3.4.1.1 Result of augmented ϵ -constraint method

With augmented ϵ -constraint method (AUGMECON), five sets of non-dominated solutions are given when B value is set to 4, with running time 0.80 sec. The result of candidate bike-way links and bike-way types selected are summarised in Table 3.4, with different δ_{ijk} values listed. The objective values and performances of Z_1 , Z_2 , Z_3 , Z_4 are summarised in Table 3.5 to address the trade-offs between the minimisation of the four objective functions Z_1 , Z_2 , Z_3 , Z_4 . The performance of the minimisation of objectives can be measured with the following formula [67]:

$$performance = (Max - OV)/(Max - Min) \quad (3.17)$$

where Max represents the maximum objective value, Min represents the minimum objective value, and OV represents the objective value of a particular non-dominated solution.

From Table 3.5, we can see five non-dominated bike-way network design alternatives, i.e. the selection of each one of the alternative plans to replace another can always improve the performance of at least one objective function at the cost of sacrificing the performance of at least one other objective function. For

TABLE 3.4: Result of 6-node network (augmented ϵ -constraint method)

link(i,j)	Plan 1	Plan 2	Plan 3	Plan 4	Plan 5
(1,2)	0	0	0	0	0
(1,3)	0	0	1 (k=2)	0	0
(1,5)	0	1 (k=3)	0	1 (k=1)	0
(5,6)	1 (k=1)	0	0	1 (k=1)	0
(6,3)	0	1 (k=3)	1 (k=1)	0	1 (k=1)
(3,4)	0	0	0	0	0
(2,5)	0	1 (k=2)	1 (k=1)	0	1 (k=1)
(6,4)	1 (k=1)	0	0	1 (k=1)	1 (k=1)
(2,4)	1 (k=2)	0	0	0	0
(1,4) ^v	0	0	0	0	0

^a ^v represents virtual traveling arcs

TABLE 3.5: Objective values of non-dominated solutions

Non-dominated alternative plans	Objective values & performances			
	Z_1	Z_2	Z_3	Z_4
Plan 1	1 (0 %)	11 (100 %)	20 (0 %)	8 (44 %)
Plan 2	1 (0 %)	20 (35 %)	3 (100 %)	12 (0 %)
Plan 3	1 (0 %)	25 (0 %)	8 (71 %)	3 (100 %)
Plan 4	0.8571 (100 %)	14 (78 %)	13 (41 %)	11 (11 %)
Plan 5	1 (0 %)	16 (64 %)	9 (65 %)	5 (22 %)
Existing network	1	-	-	-

the first objective to minimise the inaccessible level, plan 4 has performed the best as shown in percentage in the table, while the performance of other plans are the same. Thereby, the plan can be chosen when the decision maker values the space-time accessibility. Plan 1 has the best performance for the second objective to minimise the number of intersections, while it performs the worst for the third objective to minimise the Bicycle Level of Service (BLOS) score. The plan should be selected when the decision make consider the safety level as most important. Plan 2 performs the best for the third objective to minimise the

BLOS score, while it performs the worst for the fourth objective to minimise the total construction cost of bike-way. The plan should be chosen when the cycling comfort level is considered as most important. Plan 3 has the best performance in the objective to minimise the total construction cost, but its performance in objective two is the worst. The plan should be selected when the monetary cost is most important to the decision maker. Plan 5 have moderate performance level in comparison with the other alternative plans for Objective two, three and four, and its performance level for each objective function has also been shown with the percentage in the table, where 0% represents the worst performance and 100% represents the best. The decision maker can choose desired bike-way design plan out of the table according to preference and judgment based on the performance of each objective in each plan.

3.4.1.2 Result of weighted-sum method

Weighted-sum method is commonly used in literature to solve multi-objective optimisation problem, which is also adopted here to compare with AUGMECON. For each given weight combination, the weighted-sum method converts the multi-objective optimisation problem into a single objective optimisation problem, which generates one optimal bike-way network design solution as Equation 3.18 [42].

$$\min \sum_{s=1}^4 w_s Z_s, \quad u \in U \quad (3.18)$$

where $w_s \geq 0$ and $\sum_{s=1}^4 w_s = 1$, U represents the set of decision variables. The weights w_s of objectives can be set to reflect the preferences of decision makers more accurately through the transformation of each objective function such that they all have similar magnitudes and do not naturally dominate the aggregate objective function [73]. Therefore, the values of Z_1, Z_2, Z_3, Z_4 in Equation 3.18 are normalised by r_1, r_2, r_3, r_4 which represent the range of each objective function respectively.

In this study, multiple Pareto-optimal bike-way design solutions are found by iterating over different weight combinations. The weight of each objective varies with an incremental step size 0.1, giving 196 solutions, including 20 dissimilar solutions. Many repeated solutions have been obtained since huge jumps in optimal solution can be resulted from slight changes in weights. Weight of objectives should be chosen by decision maker in proportion to the relative importance of objectives. When the weight of each objective function is set to 0.25, the solution is as Plan 4 in Table 3.4.

Remark 2. The comparison between the weighted-sum method and augmented ϵ -constraint method adopted in this paper is illustrated as follows. Both the weighted-sum method and the augmented ϵ -constraint method are classical scaling methods for solving the multi-objective optimisation problem. However, for the weighted-sum method, decision makers need to choose the weights w_s of objectives in proportion to the relative importance of objectives, and multiple bike-way network design solutions can be generated by varying the weight combinations. Nevertheless, it can be difficult to set the weight vectors to obtain a Pareto-optimal solution in a desired region in the objective space as slight changes in weights can result in huge jumps in optimal solution, and the optimal solutions are usually corner solutions of the Pareto-optimal set which are rarely desirable in practical. Augmented ϵ -constraint method is applied as it overcomes the sensitivity issues and the difficulty in setting weights to reflect the preference of decision makers. ϵ value which is within the minimum or maximum value of each objective function is introduced such that the algorithm search the entire feasible space. As the weighted-sum method applied in the numerical example is problematic, the augmented ϵ -constraint method is selected to solve the problem.

3.4.2 Example 2

The hypothetical study area (Figure 3.7) of the bike-way network design problem is at Jurong Lake district in Singapore which is the second Central Business

District of the country. Currently, new cycling path network are constructed in the Jurong Lake district such that citizens can cycle from residential area to public transportation nodes, amenities and offices in the neighbourhood more safely and seamlessly. Hypothetical candidate links and parameters for the bike-way design problem are set and a set of non-dominated solutions are generated which serve as alternative bike-way network design plans. The hypothetical bike-way design network consists of 32 nodes and 47 links, which include both directed physical bike-way links and virtual traveling arcs. Five set of origin-activity location pairs are considered in this numerical example, where HDB (short for Housing & Development Board, referring to the public residential area in Singapore) blocks serve as the origins of trips and the activity locations include market and food centre, park, school, hospital and MRT station serve as the destination of trips. In the modified space-time network, physical bike-way links are directed with five additional virtual traveling arcs between each origin-activity location pair.

FIGURE 3.7: Hypothetical study area

Since there are too many parameters to be listed here, only estimations and sources of parameter values are elaborated. In the hypothetical candidate bike-way network, some random values are assigned to various parameters such that they reasonably reflect the BLOS condition and construction cost of different types of bike-way links to be constructed or improved. For the bike-way link types that cannot be located on certain candidate links and virtual traveling arcs, the construction cost, BLOS score and number of intersections values are set to be extremely large such that they cannot be chosen to build. In reality, the construction budget limit should be based on the development plan of government, and the construction cost of individual bike-way links should also be estimated based on local condition. The number of intersections on candidate links can be directly counted with updated digital map like Google Map. The Bicycle Level of Service score can be calculated with [48] method, and the value of various bike-way infrastructure characteristics can be obtained from field studies. There are also many other different methods to calculate BLOS score in the literature which can be adopted, and the BLOS evaluation measures should be adjusted according to local bicycling environment before application. The travel cost on each bike-way link is approximated by the summation of travel time on each link and intersection delay, and the average cycling speed can be approximated by a certain value like 15 km/h. It is assumed that there is no congestion on bike-way links and the capacity of each candidate link is large enough to handle the traffic volume. Different cycling speed of different cyclists on different types of bike-way is also not considered.

With augmented ϵ -constraint method (AUGMECON), four non-dominated solutions are generated with running time 16.13 seconds when $B = 5$. The alternative bike-way network design plans are summarised in Figure 3.8, where the value of the link side tag indicates the type of bike-way link k ($k \in \{1, 2, 3\}$) to be located. The trade-offs between the space-time accessibility, the number of intersections, Bicycle Level of Service (BLOS), and construction cost of the candidate bike-way links is addressed and summarised in Table 3.6. When B is set to 4 and 3, only one non-dominated solutions, i.e. Plan 1, with running time 10.07 seconds and 5.56 seconds receptively, which depicts the choice of value of

B is a trade-off between running time and the accuracy of the Pareto-optimal set where the more the number of non-dominated solutions generated, the more accurate the Pareto-optimal set is.

FIGURE 3.8: Alternative bike-way network design plans

Based on the performance table computed (Table 3.6), decision makers can filter different conditions to select the most desirable bike-way design alternative. Among the four bike-way network design alternatives, Plan 3 gives the best performance on the first objective to maximise the space-time accessibility, while there is no difference among the performance of Plans 1, 2 and 4. Thereby, when

TABLE 3.6: Multiple objectives trade-offs

Non-dominated alternative plans	Objective values & performances			
	Z_1	Z_2	Z_3	Z_4
Plan 1	2.93 (0%)	36 (100 %)	52 (88%)	15 (0 %)
Plan 2	2.93 (0%)	37 (97%)	50 (100%)	15 (0 %)
Plan 3	2.53 (100%)	69.5 (8%)	67 (0%)	12 (100 %)
Plan 4	2.93 (0%)	72.5 (0 %)	61 (35%)	12 (100 %)
Existing network	5	-	-	-

the decision maker indicates that the space-time accessibility is most important, Plan 3 should be highly recommended. Plan 1 performs the best in the second objective to minimise risk of cyclists due to intersection and the number of interruptions incurred to the cyclists. Moreover, the BLOS condition provided by the plan is also relatively good. However, the highest construction cost in comparison with other alternatives has been incurred. Plan 2 provides the most comfortable bike-way network as it has the best BLOS score, and relatively good performance on the objective to provide bike-way links with minimal number of intersections, while the plan also gives the highest construction cost among all plans. When the decision maker values the safety level and cycling comfort level, Plans 1 and 2 should be suitable choices. Among the two plans, Plan 1 should be selected when the safety level is considered as more important, while Plan 2 should be chosen when the BLOS condition is valued. Plan 3 and 4 both gives lower construction cost, but the performance of Plan 4 is relatively poor in other objective functions. When the decision maker values the total construction cost most, as well as the BLOS condition, Plan 4 can be selected. It should be noted that the final bike-way construction plan should be consistent with other socio-economic and institutional considerations (e.g, citizen's will, maintenance cost, construction rules, etc).

3.5 Conclusions

Although the expansion of bike-way network is carried out in many cities around the world, there is less research on bike-way network design problem in comparison with the motorised roadway network design problem. The optimisation of bike-way network design problem is commonly formulated as single objective integer linear programming model to minimise bike-way construction cost or travel time. To the authors' best knowledge, [67] and [66] are the only two papers that formulated multi-objective bike-way network design optimisation model until now. Both studies applied the concept of accessibility interchangeably with connectivity, which may not be rigorous as travel time budget of commuter cyclists was not taken into consideration. In this study, the concept of time budget is introduced between each origin-activity location pair (e.g., home and school, market place, hospital, job locations nearby, etc.), representing the amount of time that travellers are willing to spend on cycling. In order to promote cycling, time budget value between each origin-activity location pair can be determined and set by city planner.

Virtual traveling arcs are introduced in a modified space-time network in order to reflect the inaccessible level between each origin-activity location pair within the time budget. Augmented ϵ -constraint method (AUGMECON) is used for solving the multi-objective integer linear programming model, which generates a set of non-dominated bike-way network design alternative plans. Two networks are selected as numerical examples to demonstrate the feasibility of the multi-objective model and solution algorithm. The first network is a small 6-node network which contains one origin-activity location pair. The other network is based on a hypothetical study area at Jurong Lake district in Singapore which is the second Central Business District of the country, to demonstrate the feasibility of this study for larger networks in reality. Hypothetical parameters have been set within reasonable range such that their values reflect the characteristics of different types of bike-way links and candidate bike-way links can be chosen only if it is indicated as feasible by the city planner. Four non-dominated alternative bike-way design plans are generated whose objective values and objective

performances indicate the trade-offs between different objectives. Decision makers select the most desirable bike-way design alternative based on their judgment with the performance table computed. It should be noted that the final bike-way construction plan should be consistent with other socio-economic and institutional considerations, including citizen's will, maintenance cost, construction rules, etc.

Further research on the congestion effects on bike-ways can be made, which have a greater impact on the shared path. Moreover, the route choice decisions of cyclists can also be incorporated into the space-time network and bike-way network design problem, to cater for the effect of not only time, but also the level of comfort and other factors that affect the route choice behaviour. This study is also limited as the intra-connectivity issue in the bike-way network is not considered. Under the current NDP derived, multiple sub-networks disconnected with each other co-exist. As city planners usually expect a connected bikeway network without isolated sub-networks in reality, constraints should be added in the future work to address intra-connectivity issue of bike-way network.

Chapter 4

Road diet network design with bike-and-ride in a multi-modal network under stochastic demand

4.1 Introduction

With the growth of the urban economy and car ownership, the sustainable development of urban transportation system is vital [93]. The concept of road diet has been applied to reduce the number or width of motorised lanes and use the space for bicycle lanes, sidewalks, or on-street parking, such that the roads become cleaner, safer, more efficient, and more productive with the integration of multiple travel modes into the roadway network design [16]. Empirical studies have been carried out to illustrate the impact of road diet plans, and the results suggested that the crash rate was reduced after the implementation of road diet [51, 87], and the road diet can benefit bicyclists without compromising the interests of automobile drivers [43].

In order to promote bicycling and develop bicycle-friendly area, previous research has been conducted to solve the road diet¹ network design problem (NDP) for bike-way. [23, 35, 75] aimed to minimise the cost of improving the bike-ways to create paths between various OD pairs. [22, 104] formulated road diet NDPs

¹In this study, similar to [106], the phrase ‘road diet’ refers to the free-up of motorised roadway space for the dedicated use of bicyclists.

for improving existing bike-way network to minimise cyclist travel times, under bike-way construction restrictions such as demand coverage and construction budget. [66, 67, 136] formulated multi-objective bike-way NDPs to address the concerns and interests of various types of stakeholders, such as the cycling comfort level of commuter cyclists and the monetary budget of planners. However, these studies focused primarily on the interests of bicyclists when formulating the NDP, without considering the traffic assignment in the congested multi-modal network. In reality, the existing road space was usually insufficient to accommodate bicyclists without negative influence on existing auto-mobile traffic [106]. Thereby, the road diet NDP has also been formulated to address the trade-off between benefits and costs of road diet with multi-modal traffic assignment and find the optimal road design pattern [5, 34, 79, 106].

While many studies on road diet NDP have been done, few study has addressed the concept of ‘bike-and-ride’ when defining the problem. Cycling is a suitable alternative transportation mode for the first-mile and/or last-mile mobility when the public transit station is beyond the walkable range or have limited car parking capacity [112]. The concept of ‘bike-and-ride’ has been proposed which refers to the combined use of bicycle and public transport for one trip [74]. In the bike-and-ride transit system, public transit helps increase the speed and extend the reach of bicycling. Similarly, bicycle can also facilitate the increase in the spatial reach of public transit services, as an access mode [90]. [46] suggested that bicycle trips with longer distance to destinations reduce the likelihood of cycling. The problem can be overcome by the bike-and-ride public transit system. In countries like Singapore, the government aims to make cycling an alternative mode of transportation to automobile as the first and last mile solution to achieve the ‘car-lite’ goal [62]. In the tropical region, it is also unrealistic for bicyclists to do bicycling for the whole long-distance trip due to the hot and humid weather condition. Both aggregate cross-sectional studies [19, 95, 120] and disaggregate level studies [13, 78, 121] have suggested that the implementation of road diet led to increasing bicycle use due to the reduced travel time, improved comfort and safety level, etc. In order to develop bicycle-friendly area and promote bike-and-ride for daily commuting in a sustainable

transportation system with the implementation of road diet plan, it is necessary to quantify the benefits and risks with respect to the travel utility, such that benefits on bike-and-ride users and bicyclists are maximised while the harm to the motorists is also controlled.

Besides, fewer literature on road diet NDP have addressed the uncertainty which exist in the problem, i.e. deterministic modelling approach has commonly been applied. However, the uncertainty in travel demand exists in nature [37]. Modelling with deterministic approach which ignores the uncertainty effects can result in inaccurate network performance evaluations and investment decision making. To design the road diet plan, the realisation of uncertain demand needs to be considered, as it is not sensible to expect the travel cost of travellers remains the same due to demand fluctuation. Many studies have addressed the travel demand uncertainty in transportation NDP. [21, 30, 60, 100, 101, 116, 117, 132] considered demand uncertainty with scenario-based models. [31, 102, 109, 123] formulated NDPs with travel time reliability requirement. [27, 33, 132] formulated min-max model to address demand uncertainty within an uncertainty set and provided an optimal solution for the worst case. Similar to [116], in this paper, the traffic assignment model is applied to derive the flow pattern under user equilibrium condition for each demand realisation in the road diet NDP and a compact objective function needs to be formulated.

Overall, this paper seeks to solve a road diet NDP which considers the interests of auto-mobile users, bicyclists and bike-and-ride users in a congested multi-modal transportation system under stochastic demand. For bike-and-ride commuters, bike trips are incorporated into the first-mile and/or last-mile of the whole trip and integrated with public transport. The contributions of this paper are summarised as follows: (1) In comparison with the roadway NDP for automobiles and public transit, less research has addressed the road diet NDP for bike-way specifically. (2) For bike-way NDP, this paper incorporates the bike-and-ride public transport system where bicycle is integrated into trips as first-mile and/or last-mile mobility mode instead of being utilised for the whole journey, which has not been considered in the literature. (3) The stochastic demand between

each OD pair which has rarely been addressed in previous road diet NDP either is taken into consideration.

The remainder of the paper is organised as follows: Section 4.2 explains the model formulation: A new road diet network design problem with bike-and-ride as an alternative mode of transportation in a congested multi-modal network under stochastic demand. A mixed integer non-linear bi-level optimisation model is formulated, where the objective of the upper level is to minimise the share of commuters using automobile as the transportation mode, and the objective of the lower level is to assign traffic flow under multi-modal user equilibrium (UE) condition under stochastic demand scenarios. Section 4.3 is on the solution algorithm for solving the problem: The depth first search algorithm is applied to generate feasible paths. Then a path-flow penalty-based branch-and-bound algorithm is applied to generate the optimal road diet plan, and the method of successive averages (MSA) is utilised for multi-modal traffic assignment, where the stochastic demand scenarios are generated with Latin hypercube sampling method. Section 4.4 provides a numerical example to examine the validity of the model and the effectiveness of the solution algorithm: The effects of maximum bike-way links constraint, minimum average auto speed constraint, various demand levels, and stochastic demand are examined. The trade-offs between the maximum number of bike-way links allowed to be constructed (monetary budget) and the reduction in automobile share, between the average speed of automobiles and the reduction in automobile share due to the implementation of road diet plan are investigated. In the end, Section 4.5 states some conclusions.

4.2 Model formulation

4.2.1 Notations and assumptions

Given a road transportation network $G = (N, E)$, where the nodes in node set N are connected with links in link set E . The road network can be expanded as a multi-modal network, consisting of three sub-networks, where automobiles,

buses and bicycles are allowed to travel on respectively, as illustrated in Figure 4.1. Please note that a bus link should possibly pass over multiple bike links and nodes for the bike-and-ride paths. Figure 4.1 which only shows that one bike-link is passed over by a bus-link is for simple illustration purpose. The notations of parameters and decision variables used in the road diet network design model are summarised in Table 4.1. Similar to [102], in the multi-modal network, the set of auto links E^R , the set of bike links E^B and the set of bus links E^T are ordered such that each link in these sub-networks corresponds to the same physical street with the same traffic flow direction.

FIGURE 4.1: Multi-modal network representation

The model's assumptions are stated as below: (1) Bicycle travel times on all links are flow independent, i.e., not affected by the flow; (2) Bicyclists can travel on links both with and without road diet implementations, and the speed is higher on links with a road diet than without a road diet, whose value is assumed to be fixed [106]; (3) Bus can access neither the origin nor the destination of a certain trip; (4) The stochastic demands between OD pairs are independent and follow a specific known probability distribution.

TABLE 4.1: Notations

Symbol	Definition
N	Set of nodes in the road transportation network
E	Set of links in the road transportation network

E^R	Set of auto links
E^B	Set of bike links
E^T	Set of bus links
W	Set of OD pairs in the network
i, j	Indices of nodes in the network, $i, j \in N$
w	Indices of OD pair, $w \in W$
Ω	The support of the demand distribution
e	Subscript associated with variables for certain demand realisation
C	Total construction cost budget
c_{ij}	Construction cost of road diet on link (i, j)
s_{ij}	BLOS condition on candidate link (i, j)
$\bar{s}$	The minimum average BLOS requirement of road diet plan
M	Set of all transportation modes, $M = \{a, c, d\}$: a =auto, c =bike, d =bike-and-ride
$P^{w,m}$	Set of paths connecting OD pair w by mode m , $m \in M$
l_{ij}	Length of link (i, j)
$T_{p,e}^m$	Travel time on route p by mode m , for demand realisation e , $m \in M$, $p \in P^{w,m}$
$t_{ij,e}^a$	Travel time on link (i, j) by automobile, for demand realisation e
$t_{ij,e}^b$	Travel time on link (i, j) by bus, for demand realisation e
$t_{ij,e}^c$	Travel time on link (i, j) by bike, for demand realisation e
δ_{ij}^p	Binary indicator variable; it takes the value of 1 if link (i, j) is used on route p , and takes the value of 0 otherwise, $p \in P^{w,m}$
$v_{ij,e}^a$	Traffic volume of auto on link (i, j) , for demand realisation e
$v_{ij,e}^b$	Traffic volume of bus on link (i, j) , measured in terms of equivalent passenger car units, for demand realisation e
$\bar{V}^a$	Free flow speed of auto
$\bar{V}^b$	Free flow speed of bus
$\bar{V}_1^c$	Free flow speed of bicycle on links without road diet
$\bar{V}_2^c$	Free flow speed of bicycle on links with road diet
μ, α	Positive parameters used in BPR function
$\bar{K}_{ij}$	Capacity of link (i, j) before road diet implementation
ζ	The percentage reduction in capacity on roadway link with road diet
K_{ij}	Capacity of link (i, j) after road diet implementation
$T_{p,e}^{b1}$	In-vehicle travel time by bus on bike-and-ride route p , for demand realisation e
F_{ij}^b	Bus frequency on link (i, j)
σ	A parameter to convert the traffic volume of bus to equivalent passenger car units
$W_{p,e}^b$	The waiting time for bus along bike-and-ride route p , for demand realisation e
N_1	The set of waiting or transfer nodes
$\hat{t}_{i,e}$	The waiting time at node i , for demand realisation e
γ	Calibration parameter, depending on distributions of headway & passenger arrival

$T_{p,e}^b$	Total travel time by bus along bike-and-ride route p , for demand realisation e
$T_{p,e}^{c1}$	Total travel time by bicycle on bike-and-ride route p , for demand realisation e
$T_{w,e}^{m*}$	The intuitively minimum path travel time between OD pair w by mode m , for demand realisation e
$\bar{v}^l$	The minimum average speed threshold of auto mode
θ	Parameter for modal split function
$prob_e$	Probability of demand scenario e
$p_{s,e}^{w,m}$	Shortest path between each OD pair w by mode m , for demand realisation e
$x_{p,e}^m$	Flow on path p by transportation mode m , for demand realisation e
$d_{w,e}^m$	Demand by transportation mode m between OD pair w , for demand realisation e
D_e^w	Total demand between OD pair w , for demand realisation e
y_{ij}	1 if link (i, j) is reduced in the road diet plan; 0 otherwise
y	A vector of decision variables y_{ij}

4.2.2 Travel time of different modes

4.2.2.1 Auto

In this paper, the stochastic travel demand distribution is discretised into several discrete demand scenarios, and the travel time by auto on route p for each demand realisation e is calculated as below:

$$T_{p,e}^a = \sum_{(i,j) \in E^R} t_{ij,e}^a(v_{ij,e}^a, v_{ij,e}^b, y_{ij}) \cdot \delta_{ij}^p, \quad \forall p \in P^{w,a}, \quad w \in W, \quad e \in \Omega \quad (4.1)$$

where traffic volume of auto $v_{ij,e}^a$ and bus $v_{ij,e}^b$ is measured in terms of equivalent passenger car units. $v_{ij,e}^b$ is assumed to be fixed based on service frequency (Eq.4.9), for demand realisation e . Ω represents the support of the demand distribution. δ_{ij}^p indicates whether road link (i, j) is used on route p or not.

The auto volume $v_{ij,e}^a$ is calculated with the following equation:

$$v_{ij,e}^a = \sum_{w \in W} \sum_{p \in P^{w,a}} x_{p,e}^a \cdot \delta_{ij}^p, \quad \forall (i, j) \in E^R, \quad e \in \Omega \quad (4.2)$$

Since public transit (bus) and auto share the same road, the travel time of auto on roadway link is affected by both the traffic volume of bus and auto according to BPR function [17], as shown below:

$$t_{ij,e}^a(v_{ij,e}^a, v_{ij,e}^b, y_{ij}) = \frac{l_{ij}}{\bar{V}^a} [1 + \mu (\frac{v_{ij,e}^a + v_{ij,e}^b}{K_{ij}})^\alpha], \quad \forall (i, j) \in E^R, \quad e \in \Omega \quad (4.3)$$

where $\frac{l_{ij}}{\bar{V}^a}$ represents the free flow travel time of automobiles on link (i, j) ; μ and α are positive parameters; K_{ij} represents the capacity of link (i, j) after road diet implementation:

$$K_{ij} = \bar{K}_{ij} \cdot (1 - y_{ij} \cdot \zeta), \quad \forall (i, j) \in E^R \quad (4.4)$$

where ζ represents the percentage reduction in capacity on road link with road diet, $\bar{K}_{ij}$ represents the capacity of link (i, j) before road diet implementation. Please note that according to the sub-network concept mentioned in subsection 4.2.1, the road diet design variable y_{ij} which corresponds to the directional physical street of the multi-modal subnetwork is applied here.

4.2.2.2 Bicycle

The total travel time by bicycle on bike route p between OD pair w for demand realisation e is derived as:

$$T_{p,e}^c = \sum_{(i,j) \in E^B} t_{ij,e}^c(y_{ij}) \cdot \delta_{ij}^p, \quad \forall p \in P^{w,c}, \quad w \in W, \quad e \in \Omega \quad (4.5)$$

$$t_{ij,e}^c(y_{ij}) = \frac{l_{ij}}{(1 - y_{ij}) \cdot \bar{V}_1^c + y_{ij} \cdot \bar{V}_2^c}, \quad \forall (i, j) \in E^B, \quad e \in \Omega \quad (4.6)$$

where $\bar{V}_1^c$ represents the free flow speed of bicycle on link (i, j) without road diet; $\bar{V}_2^c$ represents the free flow speed of bicycle on link (i, j) with road diet.

4.2.2.3 Bike-and-ride

For the bike-and-ride transit system, the travel time on each path $p \in P^{w,d}$ contains two parts, namely, the travel time by bus and by bike.

Bus mode:

Similar to auto mode, the in-vehicle travel time by bus on bike-and-ride route p for demand realisation e is calculated as:

$$T_{p,e}^{b_1} = \sum_{(i,j) \in E^T} t_{ij,e}^b(v_{ij,e}^a, v_{ij,e}^b, y_{ij}) \cdot \delta_{ij}^p, \quad \forall p \in P^{w,d}, \quad w \in W, \quad e \in \Omega \quad (4.7)$$

The travel time of bus on roadway link is affected by both the traffic volume of public transit and auto according to BPR function, as shown below:

$$t_{ij,e}^b(v_{ij,e}^a, v_{ij,e}^b, y_{ij}) = \frac{l_{ij}}{\bar{V}^b} [1 + \mu (\frac{v_{ij,e}^a + v_{ij,e}^b}{K_{ij}})^\alpha], \quad \forall (i,j) \in E^T, \quad e \in \Omega \quad (4.8)$$

The volume of bus traffic $v_{ij,e}^b$ is measured in terms of equivalent passenger car units:

$$v_{ij,e}^b = \sigma \cdot F_{ij}^b, \quad \forall (i,j) \in E^T, \quad e \in \Omega \quad (4.9)$$

where F_{ij}^b represents the bus frequency on link (i,j) , σ is a parameter to convert to equivalent passenger car units.

The average waiting time of commuters for bus along bike-and-ride path p is calculated as:

$$W_{p,e}^b = \sum_{i \in N_1} \hat{t}_{i,e} \cdot \delta_{ij}^p, \quad \forall p \in P^{w,d}, \quad w \in W, \quad e \in \Omega \quad (4.10)$$

where N_1 represents the set of waiting nodes, $\hat{t}_{i,e}$ represents the waiting time at node i :

$$\hat{t}_{i,e} = \frac{\gamma}{F_{ij}^b}, \quad \forall i \in N_1 \quad (4.11)$$

where γ is a calibration parameter which depends on the distributions of headway and passenger arrival.

Then, the total travel time by bus mode along bike-and-ride route p is calculated as:

$$T_{p,e}^b = T_{p,e}^{b_1} + W_{p,e}^b, \quad \forall p \in P^{w,d}, \quad w \in W, \quad e \in \Omega \quad (4.12)$$

Bike mode:

Similar to Eq.4.5, the total travel time by bicycle on bike-and-ride route p between OD pair w for demand realisation e is derived as:

$$T_{p,e}^{c1} = \sum_{(i,j) \in E^B} t_{ij,e}^c(y_{ij}) \cdot \delta_{ij}^p, \quad \forall p \in P^{w,d}, \quad w \in W, \quad e \in \Omega \quad (4.13)$$

Bike-and-ride mode:

The total travel time on bike-and-ride path $p \in P^{w,d}$ is computed as:

$$T_{p,e}^d = T_{p,e}^b + T_{p,e}^{c1}, \quad \forall p \in P^{w,d}, \quad w \in W, \quad e \in \Omega \quad (4.14)$$

where bus is integrated with bicycle for the first mile and last mile mobility.

4.2.3 Upper-level model

With the implementation of road diet plan, it is a desirable condition for the entire society whereby the use of automobiles is discouraged. Similar to [106], which aims to minimise the share of commuters using automobile as the mode of transportation, the upper-level problem of this paper is to minimise the expectation of the share of commuters travelling by auto under stochastic demand distribution:

$$\underset{y}{Min} \quad \underset{e}{E} \left[\frac{\sum_{w \in W} \sum_{p \in P_w^a} x_{p,e}^a}{\sum_{w \in W} \sum_{m \in M} \sum_{p \in P_w^m} x_{p,e}^m} \right] \quad (4.15)$$

where e is associated with each specific demand realisation to calculate the value of the expectation term.

The constraints of the formulation are listed below:

Construction budget constraint ensures that the total construction cost of the road diet plan does not exceed the budget:

$$\sum_{(i,j) \in E} (c_{ij} \cdot y_{ij}) \leq C \quad (4.16)$$

where c_{ij} represents the construction cost of road diet on link (i, j) , and C represents the monetary budget.

Speed constraint is introduced as the existing road space in most metropolitan areas is usually not sufficient to accommodate more non-motorised traffic without negatively affecting auto users under road diet plan [106]. The expectation of the average speed of auto mode is required to be greater than a minimum speed threshold $\bar{v}^l$, in order to ensure that the service level for the remaining auto users under the road diet plan is acceptable.

$$\underset{e}{E} \left[\frac{\sum_{(i,j) \in E} (v_{ij,e}^a \cdot l_{ij})}{\sum_{(i,j) \in E} [v_{ij,e}^a \cdot t_{ij,e}^a (v_{ij,e}^a, v_{ij,e}^b, y_{ij})]} \right] \geq \bar{v}^l \quad (4.17)$$

Bicycle level of service (BLOS) constraint is applied as the cycling comfort and safety level on the candidate bike-way links should be ensured [135]:

$$\sum_{(i,j) \in E} (s_{ij} \cdot y_{ij}) \geq \bar{s} \cdot \sum_{(i,j) \in E} (y_{ij}) \quad (4.18)$$

where s_{ij} represents the BLOS condition on candidate link (i, j) and $\bar{s}$ represents the minimum average BLOS requirement.

Binary constraint limits the decision variable y_{ij} to be binary, indicating whether link (i, j) is selected for road diet implementation or not:

$$y_{ij} \in \{0, 1\}, \forall (i, j) \in E \quad (4.19)$$

4.2.4 Lower-level model

To obtain the flow variables used in the upper-level problem, multi-modal user equilibrium (MUE) model is formulated in the lower-level problem with asymmetric link impedance functions. Under stochastic travel demand, it is not sensible to find the MUE flow pattern while expecting that the travel cost keeps the same. Instead, we aim to derive the MUE traveller flow pattern for each demand realisation. The MUE condition include two aspects: first, all utilised paths of the same travel mode have the same travel cost between each OD pair w and the travel costs of all unutilised paths are not lower than the travel costs of any utilised paths for the same travel mode; second, commuters' mode choice decisions are based on the multinomial logit model [134].

For each demand realisation e which satisfies the demand distribution given ($e \in \Omega$), under the first MUE condition, for all the car paths, the following constraints need to be satisfied:

$$(T_{p,e}^a - T_{w,e}^{a*}) \cdot x_{p,e}^a = 0, \forall p \in P^{w,a}, w \in W, e \in \Omega \quad (4.20)$$

$$d_{w,e}^a = \sum_{p \in P^{w,a}} x_{p,e}^a, \forall w \in W, e \in \Omega \quad (4.21)$$

$$T_{p,e}^a - T_{w,e}^{a*} \geq 0, \forall p \in P^{w,a}, w \in W, e \in \Omega \quad (4.22)$$

$$x_{p,e}^a \geq 0, \forall p \in P^{w,a}, w \in W, e \in \Omega \quad (4.23)$$

where $T_{p,e}^a$ represents the travel time by mode a (automobile) on path p and $T_{w,e}^{a*}$ represents the intuitively minimum path travel time between OD pair w by mode a ; $x_{p,e}^a$ represents the flow on path p by transportation mode a ; $d_{w,e}^a$ represents the demand by transportation mode a between OD pair w . According to the constraints, when flow is assigned on path p ($x_{p,e}^a > 0$), the path travel time $T_{p,e}^a$

is the same as the shortest path travel time $T_{w,e}^{a*}$ by travel mode a between OD pair w ; if path p is not utilised between OD pair w ($x_{p,e}^a = 0$), the path travel time $T_{p,e}^a$ is never less than $T_{w,e}^{a*}$.

Similarly, for all the bike paths as the travel time by bike $T_{p,e}^d$ is assumed not to be affected by the volume of bicyclists for simplification purpose in this paper, all bicyclists are assigned to the shortest path $p_{s,e}^{w,c}$ between each OD pair w . In other words, under the assumption, the following constraints (eqs.4.24-4.26) need to be satisfied:

$$d_{w,e}^c = x_{p_{s,e}^{w,c}}, \forall w \in W, e \in \Omega \quad (4.24)$$

$$T_{w,e}^{c*} = T_{p_{s,e}^{w,c}}, \forall w \in W, e \in \Omega \quad (4.25)$$

$$x_{p,e}^c = 0, \forall p \in P^{w,c} \setminus p_{s,e}^{w,c}, w \in W, e \in \Omega \quad (4.26)$$

For all bike-and-ride paths, when the bike-and-ride system is planned as an integrated system, similar to the bus lane NDP, the model can be simply extended to include the bus frequencies or bus lane allocation strategy, etc., as decision variables, affecting the lower-level traffic assignment. As this paper focuses on road diet NDP, for simplification purpose, the fixed bus frequency has been applied such that the bike-and-ride commuters are also assigned to the shortest path $p_{s,e}^{w,d}$ between each OD pair w given the traffic volume of auto, where the following constraints (eqs.4.27-4.29) need to be satisfied:

$$d_{w,e}^d = x_{p_{s,e}^{w,d}}, \forall w \in W, e \in \Omega \quad (4.27)$$

$$T_{w,e}^{d*} = T_{p_{s,e}^{w,d}}, \forall w \in W, e \in \Omega \quad (4.28)$$

$$x_{p,e}^d = 0, \forall p \in P^{w,d} \setminus p_{s,e}^{w,d}, w \in W, e \in \Omega \quad (4.29)$$

Under the second MUE condition, as the modal split is based on the logit function, the travel demand of auto, bicycle and bike-and-ride can be formulated as

below:

$$d_{w,e}^a = \frac{D_e^w}{1 + e^{\theta(T_{w,e}^{a*} - T_{w,e}^{c*})} + e^{\theta(T_{w,e}^{a*} - T_{w,e}^{d*})}}, \quad \forall w \in W, e \in \Omega \quad (4.30)$$

$$d_{w,e}^c = \frac{D_e^w}{1 + e^{\theta(T_{w,e}^{c*} - T_{w,e}^{a*})} + e^{\theta(T_{w,e}^{c*} - T_{w,e}^{d*})}}, \quad \forall w \in W, e \in \Omega \quad (4.31)$$

$$\begin{aligned} d_{w,e}^d &= \frac{D_e^w}{1 + e^{\theta(T_{w,e}^{d*} - T_{w,e}^{a*})} + e^{\theta(T_{w,e}^{d*} - T_{w,e}^{c*})}} \\ &= D_e^w - d_{w,e}^c - d_{w,e}^a, \quad \forall w \in W, e \in \Omega \end{aligned} \quad (4.32)$$

where D_e^w represents the total demand between OD pair w under demand realisation e .

With the preceding analysis, $(T_{p,e}^a - T_{w,e}^{a*}) \cdot x_{p,e}^a \geq 0$ is given by Eqs.4.22 and 4.23. Modified based on bi-modal traffic assignment [131], the lower level model (Eqs.4.20-4.32) which includes separate flows for auto-mobile, bicycle and bike-and-ride commuters can be reformulated to minimise the objective function as follows:

$$\begin{aligned} &\sum_{w \in W} \sum_{p \in P^{w,a}} (T_{p,e}^a - T_{w,e}^{a*}) \cdot x_{p,e}^m + \sum_{w \in W} \left\{ d_{w,e}^a - \frac{D_e^w}{1 + e^{\theta(T_{w,e}^{a*} - T_{w,e}^{c*})} + e^{\theta(T_{w,e}^{a*} - T_{w,e}^{d*})}} \right\}^2 \\ &+ \sum_{w \in W} \left\{ d_{w,e}^c - \frac{D_e^w}{1 + e^{\theta(T_{w,e}^{c*} - T_{w,e}^{a*})} + e^{\theta(T_{w,e}^{c*} - T_{w,e}^{d*})}} \right\}^2 \end{aligned} \quad (4.33)$$

subject to Eqs.4.1-4.14, 4.21-4.23, 4.24-4.26, 4.27-4.29, 4.32. To satisfy the MUE condition, a solution $\{T_{w,e}^{m*}, d_{w,e}^m, x_{p,e}^m\}$ to the lower level model (Eqs.4.20-4.32) can be derived only if the value of the optimal objective function (Eq.4.33) is zero, as each term in Eq.4.33 is non-negative.

4.3 Solution algorithm

4.3.1 Find all feasible paths

The first step is to generate the set of all feasible paths $P^{w,m}$ between OD pair w by mode m . The problem can be formulated as an all simple paths problem to find all non-cyclical paths between OD pair w , which is based on Depth First Search (DFS) algorithm (Algorithm 5) [113]. As the number of simple paths in a graph can be very large, to ensure the efficiency of the algorithm, a cut-off value can be predefined as the depth to stop the search such that only the paths with length less than the cut-off value are returned [99]. Additional filtering technique is then applied such that bicycle is only used as the first-mile and/or last-mile mobility mode for bike-and-ride trips.

Algorithm 5: Depth First Search Algorithm

Input: A graph $G = (V, E)$, with start vertex s .

Output: A sequence of visited nodes $visited[]$

Data Structure: Stack S for the storage of nodes (last-in-first-out)

$S = \emptyset$; $visited[] = \emptyset$;

Add s to S ;

while $S \neq \emptyset$ **do**

 Pop the first vertex v from S ;

if $v \notin visited[]$ **then**

 Add v to $visited[]$;

for all w adjacent to v **do**

if $w \notin visited[]$ **then**

 Add w to the top of S ;

4.3.2 Latin hypercube sampling method

Monte Carlo sampling method has been commonly applied in the literature to simulate problems with random variables, which requires relatively large sample size and result in computational inefficiency [3]. In this paper, to reduce the sample size, we apply Latin hypercube sampling method, which is a type

of stratified Monte Carlo sampling method to simulate the stochastic demand between various OD pairs. A set of independent demand scenarios are generated, and demand scenario e corresponds to a probability $prob_e > 0$, such that $\sum_e prob_e = 1$. More details on Latin hypercube sampling method can be found in [108].

4.3.3 Upper level: branch-and-bound algorithm

In the upper level of the bi-level optimisation algorithm, we employed a path-flow penalty-based branch-and-bound algorithm, which is modified based on [133]. The depth first search with complete branching method is applied in this paper, which explores the problem structure by choosing the next child sub-problem as the one with the best upper bound value. As the decision variables in the upper level of the road diet NDP are all binary, the branching factor is small, hence the memory usage is unlikely to increase significantly [81]. As the number of candidate roadway links in the study area is $|E|$, there should be $2^{|E|}$ number of possible road diet plans. The branch-and-bound algorithm is applied due to the discrete nature of the road diet network design problem, and the procedure is shown in Algorithm 6.

The constrained optimisation problem in the upper level model can be represented by the following general form:

$$\begin{aligned} & \text{Min } f(x) \\ & \text{s.t. } g_i(x) \leq 0, \text{ for inequality constraints} \\ & \quad h_i(x) = 0, \text{ for equality constraints} \end{aligned} \tag{4.34}$$

To penalise the solutions according to the distance to feasibility, the following fitness function is employed instead of the objective function in Eq. 4.34:

$$\text{Min } f_p(x) = f(x) + \sum_i C_i \cdot d_i \tag{4.35}$$

Algorithm 6: Path-flow penalty-based branch-and-bound algorithm

Step 0: Initialization & network loading

- (a) Set up the parameters
- (b) Load the multi-modal transportation network
- (c) Let $k=0$, the road diet network design plan is initialised as $y^{(0)} = \{y_{ij} = 0 | (i, j) \in E\}$, such that there is no dedicated bicycle lane over the whole network.

Step 1: Feasible path identification

Identify the set of feasible paths with depth first algorithm (Algorithm 5)

Step 2: Calculation

Input $y^{(k)}$ into the network. The path flows are identified based on the method of successive averages (Algorithm 7).

Step 3: Evaluation with penalty function

The fitness value which sums up the objective function (Eq. 4.15) and the penalty function incorporating constraints 4.16-4.18 is calculated for $y^{(k)}$. The mechanism of calculating the fitness value is illustrated in Eqs. 4.34-4.36.

Step 4: Branch-and-bound

$k = k + 1$; let the k^{th} element of $y^{(k-1)}$ be 1 to obtain $y^{(k)}$.

Step 5: Update

The fitness value of $y^{(k)}$ is evaluated according to step 3. If the fitness values of $y^{(k)}$ is not lower than $y^{(k-1)}$'s, then $y^{(k)} = y^{(k-1)}$;

Otherwise, proceed to step 6.

Step 6: Iteration

The algorithm is terminated when meeting the stopping criteria, i.e. $k = |E|$;

Otherwise, repeat steps 4-5.

where

$$d_i = \begin{cases} g_i(x) \cdot H(g_i(x)) & \text{for inequality constraints} \\ |h_i(x)| & \text{for equality constraints} \end{cases} \quad (4.36)$$

d_i is the distance to feasibility of constraint i . $H(g_i(x))$ is the modified Heaviside step function, which returns 1 if the value is positive and 0 otherwise. C_i is the penalty multiplier approaching ∞ , which should be replaced by a large value in computer implementation [68, 130], and the value is set as 10^5 here. The objective function (Eq. 4.15) is penalised when the constraints (Eqs. 4.16-4.18) are not satisfied.

4.3.4 Lower level: method of successive average

The method of successive averages (MSA) is applied to solve the lower level multi-modal user equilibrium model whose objective function (Eq. 4.33) is non-linear and not convex. For each demand realisation e ($e \in \Omega$), in each iteration, we firstly evaluate which mode of transportation has lower demand than the value calculated with the multinomial logit model, for each OD pair w . All-or-nothing traffic assignment is then conducted at each iteration which creates auxiliary path flows to update current path flows. The algorithm is terminated when it reaches the maximum number of iterations. The method is shown in Algorithm 7, which is modified based on [131, 133].

4.4 Numerical example

4.4.1 Test instance

To demonstrate the validity of the road diet network design model and the effectiveness the solution algorithm in a multi-modal transportation system, a multi-OD network is applied in this paper as the numerical example. The example network is extracted based on [23], which contains 55 nodes and 192 links (as shown in Figure 4.2).

The length of each link is set as 0.8 km, the capacity of each link is set as 1800 veh/hour. The travel demand between four OD pairs, namely, (1, 10), (5, 45), (13, 42), (40, 55) are considered for analysis. The stochastic demand for each OD pair is assumed to follow a normal distribution, whose mean values are 1300, 1000, 1200, 1100 veh/hour respectively, and the standard deviation values are all set as 50. The sample size for Latin Hypercube sampling is chosen as 10. The value of other parameters are selected based on [65]: for the modal split logit model, $\theta = 10$; for the public transit, $\sigma = 4$ (passenger cars/bus), the frequency of bus service is 15 veh/hour, $\gamma=0.5$; for the BPR function, $\mu=0.15$; $\alpha=4$; the free flow speed of different travel modes are auto $\bar{V}^a=48$ km/h, bus

Algorithm 7: Method of successive averages

Input: Multi-modal transportation network and related parameters

Output: $T_{w,e}^{m*}, d_{w,e}^m, x_{p,e}^m, \forall w \in W, p \in P^{w,m}, m \in M$

Step 0: Initialisation

Road diet plan decision variable y_{ij} is initialised with output of the upper level model;

$d_{w,e}^m = x_{p,e}^m = 0, \forall w \in W, m \in M, p \in P^{w,m};$

Iteration $n = 1;$

Step 1: Link travel cost update

Calculate the travel cost on each link in the multi-modal transportation network with Eqs. 4.1-4.14.

Step 2: Shortest paths identification

Identify the shortest path $p_{s,e}^{w,m}$ for each transportation mode $m \in M$ between OD pair w , $T_{w,e}^{m*} = T_{p_{s,e}^{w,m}}^{w,m}$.

Step 3: All-or-nothing traffic assignment

for each OD pair w do

if $d_{w,e}^a \leq \frac{D_e^w}{1+e^{[\theta(T_{w,e}^{a*}-T_{w,e}^{c*})]+e^{[\theta(T_{w,e}^{a*}-T_{w,e}^{d*})]}}}$ then

$aux(p_{s,e}^{w,a}) = D_e^w;$

$aux(p_e) = 0, \forall p \in P^{w,a} \setminus p_{s,e}^{w,a};$

else

$x_{p_{s,e}^{w,c}} = \frac{D_e^w}{1+e^{[\theta(T_{w,e}^{c*}-T_{w,e}^{a*})]+e^{[\theta(T_{w,e}^{c*}-T_{w,e}^{d*})]}}};$

$x_{p,e}^c = 0, \forall p \in P^{w,c} \setminus p_{s,e}^{w,c};$

$x_{p_{s,e}^{w,d}} = \frac{D_e^w}{1+e^{[\theta(T_{w,e}^{d*}-T_{w,e}^{a*})]+e^{[\theta(T_{w,e}^{d*}-T_{w,e}^{c*})]}}};$

$x_{p,e}^d = 0, \forall p \in P^{w,d} \setminus p_{s,e}^{w,d};$

$aux(p_e) = 0, \forall p \in P^{w,a};$

Step 4: Flow update

The traffic flow between each OD pair w by auto is calculated as

$x_{p,e}^a = \frac{n-1}{n} \cdot x_{p,e}^a + \frac{1}{n} \cdot aux(p_e), p \in P^{w,a};$

$d_{w,e}^m$ is then computed based on Eqs. 4.21, 4.24, and 4.27.

Step 5: Convergence check

If n reaches the maximum number of iterations or

$$\frac{\sum_{w \in W} \sum_{p \in P^{w,a}} (T_{p,e}^a - T_{w,e}^{a*}) \cdot x_{p,e}^a}{\sum_{w \in W} T_{w,e}^{a*} \cdot d_{w,e}^a} + \sum_{w \in W} \left| \frac{d_{w,e}^a - \frac{D_e^w}{1+e^{[\theta \cdot (T_{w,e}^{a*} - T_{w,e}^{c*})]+e^{[\theta \cdot (T_{w,e}^{a*} - T_{w,e}^{d*})]}}}}{D_e^w} \right| +$$

$$\sum_{w \in W} \left| \frac{d_{w,e}^c - \frac{D_e^w}{1+e^{[\theta \cdot (T_{w,e}^{c*} - T_{w,e}^{a*})]+e^{[\theta \cdot (T_{w,e}^{c*} - T_{w,e}^{d*})]}}}}{D_e^w} \right| \leq \epsilon,$$
 the algorithm terminates;

otherwise, $n=n+1$, repeat steps 1-5.

FIGURE 4.2: Example network

$\bar{V}^b = 25$ km/h, bicycle on link without road diet $\bar{V}_1^c = 8$ km/h, bicycle on link with road diet $\bar{V}_2^c = 12$ km/h. The minimum average speed of auto mode $\bar{v}^l$ is set as 40 km/h. It is assumed that the capacity of link is reduced by $\zeta = 25\%$ on each link with road diet. The BLOS scores for links are all set as four. The construction cost constraint is represented by the limitation on maximum the number of bike-way links allowed to be constructed, which is set as 20.

The convergence process of the solution algorithm is shown in Figure 4.3, and the computation time is 41.22 minutes on a personal computer with Intel Core i5 CPU 2.3 GHz, 8 GB RAM and MacOS 10.14. The result shows that a total of 16 links (i.e., (1,2), (2,3), (5,6), (6,7), (9,10), (7,17), (13,14), (14,24), (17,27), (24,33), (27,36), (33,42), (36,45), (40,41), (41,49), (54,55)) are selected for the optimal road diet plan, under which the expectation of the share of automobile commuters under stochastic demand is minimised while the share of commuters using bicycle or bike-and-ride as the mode of transportation is maximised. Under the optimal road diet NDP derived, the interests of automobile users have also been catered for with the speed constraint.

Table 4.2 shows the proportions of commuters with different modes of transportation between each OD pair before and after the implementation of road diet plan, as well as the percentage change. With the implementation of the optimal road diet plan, the overall share of automobile commuters is reduced by

FIGURE 4.3: Convergence process

7.08%, while the share of bicyclists and bike-and-ride users is increased by 2.43% and 4.65% respectively. We should also note that the final road diet plan needs to be consistent with other socio-economic and institutional factors which are necessary to be considered, like the citizen's will, maintenance cost, construction rules, etc.

TABLE 4.2: Mode share with/without road diet plan

Road diet	OD pair	Auto	Bike	Bike-and-ride
Before implementation	(1, 10)	0.9702	0.0010	0.0288
	(5, 45)	0.8358	0.0060	0.1582
	(13, 42)	0.7698	0.0285	0.2022
	(40, 55)	0.9945	0.0021	0.0034
	Total	0.8872	0.0094	0.1034
After implementation	(1, 10)	0.9219	0.0034	0.0747
	(5, 45)	0.7608	0.0380	0.2012
	(13, 42)	0.6647	0.0917	0.2452
	(40, 55)	0.9868	0.0044	0.0088
	Total	0.8164	0.0337	0.1499

4.4.2 The effect of maximum bike-way links constraint

The maximum number of bike-way links allowed to be constructed is utilised as a substitute for monetary budget constraint in this paper. In this section, the effect of the maximum bike-way links constraint is investigated with sensitivity analysis, whose results are shown in Table 4.3.

TABLE 4.3: Impact of maximum bike-way links constraint (monetary budget)

Max no. of bike-way links allowed to be constructed	Mode share		
	Auto	Bike	Bike-and-ride
0	0.8872	0.0094	0.1034
1	0.8840	0.0094	0.1066
2	0.8795	0.0097	0.1108
3	0.8791	0.0101	0.1108
4	0.8787	0.0110	0.1102
5	0.8727	0.0111	0.1162
6	0.8718	0.0122	0.1159
7	0.8695	0.0148	0.1157
8	0.8666	0.0186	0.1148
9	0.8655	0.0196	0.1148
10	0.8616	0.0248	0.1136
11	0.8601	0.0268	0.1131
12	0.8418	0.0315	0.1267
13	0.8298	0.0332	0.137
14	0.8267	0.0332	0.1401
15	0.8222	0.0335	0.1444
16	0.8164	0.0337	0.1499
17	0.8164	0.0337	0.1499
18	0.8164	0.0337	0.1499
19	0.8164	0.0337	0.1499
20	0.8164	0.0337	0.1499

As the maximum number of bike-way links allowed to be constructed increases from 1 to 16, the expectation of the share of automobile users under stochastic demand continues to decrease, while the share of bike and bike-and-ride users continues to increase respectively. The results illustrate a trade-off between the monetary budget constraint and the objective to discourage the use of automobiles. It is also observed from Table 4.3 that as the maximum number of bike-way links constraint value is above 16, the constraint has no further effect

on the mode share. In this case, additional bike lanes cannot further improve the travel time of bicyclists and bike-and-ride users between the OD pairs under the demand level considered, hence the mode share remain unchanged.

4.4.3 The effect of average auto speed constraint

The conversion of existing road space into bike lanes can negatively affect the auto users, as the road space in most metropolitan areas is usually not sufficient [106]. A constraint on the expectation of the minimum average speed of automobiles is introduced in Eq. 4.17 in order to ensure the benefits of automobile users under the implementation of road diet plan. This section analyses the effect of average auto speed constraint on the expectation of average speed of automobiles and the share of automobile users, as displayed in Figure 4.4.

FIGURE 4.4: The effect of auto speed constraint

The figure depicts that when the minimum required auto speed is less than 46.2 km/h, the auto share remains constant under the multi-modal user equilibrium condition with the implementation of the same optimal road diet plan. In other

words, the average auto speed constraint has no limitation on the derivation of the optimal road diet plan. Then, as the minimum required auto speed increases, the average speed of automobiles and the share of automobile users increases accordingly, as the travel time by automobile decreases. The optimal road diet plan derived changes at this stage to satisfy the average auto speed constraint. When the minimum required auto speed is greater than 46.9 km/h, the constraint can only be satisfied under the current demand level without any road diet plan implementation. The blue dotted line in Figure 4.4 represents the share of automobile users when no road diet plan is implemented.

4.4.4 The effects of demand levels

This section discusses the effects of demand levels on mode share. The demand level varies from 0.5 to 2.5 times of the demand level considered in the test instance section. Figure 4.5 shows the variation in the expectation of average speed of automobiles, and displays together with the expectation of the reduction of automobile share after the implementation of the optimal road diet plan under different demand levels.

The figure shows that as the demand level increases, the average speed of automobiles decreases which can be explained by the congestion effect caused by the implementation of road diet plan. It is also observed that the reduction of automobile share becomes more obvious as the demand level increases. This can be explained by the fact that the travel time by automobile increases due to congestion, and more commuters are willing to switch to bicycle or bike-and-ride under the multi-modal user equilibrium condition. When the demand level is set as three times the demand of the test instance, the minimum average speed constraint for automobiles which is set as 40 km/h cannot be satisfied, even if no road diet plan is implemented, hence higher demand levels are not included in the sensitivity analysis. Generally, the figure also illustrates a trade-off between the benefits of automobile users (average speed of automobiles) and the objective to move toward sustainable transportation modes (reduction of automobile share) under road diet implementation.

FIGURE 4.5: The effects of demand levels

4.4.5 Stochastic demand v.s. deterministic demand

In practice, the uncertainty in road network exists as a result of demand fluctuation. In this paper, we assume that the demands between OD pairs are stochastic, which are independent and follow specific known probability distribution. The stochastic demand scenarios are generated based on Latin hypercube sampling method. Figure 4.6 illustrates the effects of ten different demand scenarios generated with Latin hypercube sampling method and the overall stochastic demand scenario on auto share when speed constraint is set as 46.2km/h.

Under different demand levels, different optimal road diet plans can be generated. Road diet plan $D1$ - $D10$ are generated based on the ten deterministic demand scenarios respectively, and road diet plan S is generated under the overall stochastic demand. For this particular test instance, road diet plans S , $D1$, $D2$, $D4$ – $D7$ and $D9$ are the same. Figure 4.6 shows that the stochastic road diet plan S always gives the lowest auto share compared to other plans, under the ten deterministic demand scenarios and the stochastic demand scenario. It is also

FIGURE 4.6: Stochastic demand v.s. deterministic demand

observed that stochastic road diet plan S does not satisfy the speed constraint under demand scenario 3, 8 and 10. This can be explained by the fact that the speed constraint considered in this paper is the expectation of the average speed over all demand scenarios under stochastic demand distribution. As shown in the rightmost column in Figure 4.6, the road diet plan S is the optimal plan under stochastic demand distribution where all constraints are satisfied, which captures the uncertainty in transportation demand. Otherwise, the road diet plans ($D3$, $D8$, and $D10$) computed with deterministic approach which ignores the uncertain demand effect can be sub-optimal in handling stochastic demand.

4.5 Conclusions

With the growth of the economy and car ownership in urban areas, the application of road diet plan for converting motorised lane space to bike-way is able to promote more sustainable transportation system. Bike-and-ride system where bicycle for the first-mile and/or last-mile integrates with public transport has

been promoted in many countries, which extend the speed and reach of bicycle. In this paper, we formulate a road diet network design problem with bike-and-ride as an alternative mode of transportation to automobiles under stochastic demand. The interests of various types road users have been catered for in a congested multi-modal transportation network.

The problem is formulated as a mixed integer non-linear bi-level optimisation model: the upper level aims to minimise the share of commuters using automobiles; the lower level aims to assign traffic flow under multi-modal user equilibrium (MUE) condition. To solve the road diet optimisation model, firstly, the set of feasible paths are generated based on the depth first search algorithm. A path-flow penalty-based branch-and-bound algorithm is used to determine the optimal road diet plan, and the method of successive averages (MSA) is utilised for multi-modal path flow assignment. A numerical example is applied to demonstrate the performance of the model formulation.

Some policy implications are summarised as below: (1) increasing the budget for bike-way constructions may not always improve the modal share; (2) the modal share of automobile increases when the minimum required speed for auto increases above a certain value; (3) a higher demand level encourages a larger population to shift to bike-and-ride or cycling; (4) stochastic road diet design performs better than deterministic road diet design in consideration of demand fluctuation.

The model can be easily adapted to road networks with existing bike lanes by modifying the constraints and parameters. Before the implementation of road diet plan, if there already exists bike-way link (i, j) between two nodes, additional constraints $y_{ij} = 0$ can be introduced by the decision makers when applying the model in this paper. Moreover, the percentage reduction in capacity on roadway link with road diet ζ can also be modified for the construction of different types of bike lanes, such as dedicated cycle lanes and shared paths. However, there is a limitation as this paper ignores the congestion effect on bike lanes, which could be considered in future research systematically. For further research, the bike share system and public transport planning can also

be taken into consideration. Different objective functions in the upper level of the model, for example, to minimise the total system travel time, to minimise the expectation of the share of kilometers traveled by auto, can also be applied to analyse the effect of different objective functions on the optimal road diet plan, such that the results can be more convincing.

Chapter 5

Conclusions & future work

5.1 Thesis conclusions

Cycling is a sustainable mode of transportation, providing economic, environmental and social benefits. This study aims to investigate the bikeability and bike-way network design problem systematically, in order to promote cycling as an alternative mode of transportation to automobiles and have a better understanding of cycling. The results from bikeability in the first part of this thesis can provide implications and guidance based on bicyclists comfort perception to bike-way network design problem in the second part of the thesis, such that the infrastructure designed is attractive to bicyclists. Please also note that the final bike-way network construction plan need to be consistent with other socio-economic and institutional considerations, such as citizen's will, maintenance cost, construction rules, etc. The main findings are summarised as follows:

(1) Cycling comfort evaluation with Instrumented Probe Bicycle

Chapter 2 derives a Cycling Comfort Index (CCI) to measure the cycling comfort level on various types of cycling facilities. An Instrumented Probe Bicycle (IPB), equipped with a video camera and a set of sensors is used for data collection in Singapore. Convolutional neural network (CNN) is applied for automatic video processing. The extreme gradient boosting (XGBoost) algorithm is applied to derive CCI based on cycle track characteristics and survey participants' ratings.

(2) Multi-objective bike-way network design problem with space-time accessibility constraint

Chapter 3 formulates a multi-objective integer linear programming model to determine the spatial layout of bike-way networks and bike-way link types. The objectives considered in the model include to maximise the accessibility, minimise the number of intersections, maximise bicycle level of service, and minimise total construction cost, with monetary budget and space-time constraint. Augmented ϵ -constraint method (AUGMECON) is applied as the solution algorithm. Two numerical examples are utilised to demonstrate the feasibility of model and effectiveness of solution algorithm.

(3) Road diet network design with bike-and-ride in a multi-modal network under stochastic demand

Chapter 4 formulates a road diet network design problem in a multi-modal transportation network with bike-and-ride commuters, automobiles and bicyclists under stochastic demand level. The problem is formulated as a mixed integer non-linear bi-level optimisation model, where the upper level aims to minimise the share of automobiles and the lower level conducts multi-modal traffic assignment. A path-flow penalty-based branch-and-bound algorithm is utilised to derive the optimal road diet plan in the upper level, and the method of successive averages is applied for multi-modal traffic assignment in the lower level. To test the feasibility of model and effectiveness of solution algorithm, numerical example is applied.

5.2 Future direction

There are several problems that need further research: (1) The congestion effect on bike lanes can be investigated systematically in further studies, such that the user equilibrium problem of bicyclists can be better addressed. (2) Public transit network design problem and bike-share system design problem can be integrated with bike-way network design problem such that the model formulation is more

realistic. (3) The route choice of bicyclist is not only affected by the cycling comfort level, but also the safety level. Future research may further address the safety problem of bicyclists.

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