Optimization and scheduling for a large-scale urban transportation system involving human factors

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SINGAPORE

**Optimization and Scheduling for a Large-Scale
Urban Transportation System Involving Human
Factors**

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School of Electrical & Electronic Engineering

2020

Optimization and Scheduling for a Large-Scale Urban Transportation System Involving Human Factors

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School of Electrical & Electronic Engineering

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

2020

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.

February 28, 2020

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Date

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Yi Zhang

Supervisor Declaration Statement

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.

February 28, 2020

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Date

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Prof. Rong Su

Authorship Attribution Statement

This thesis contains materials from 2 papers published in the following peer-reviewed journals in which I am listed as the first author.

Materials of Chapter 2 appear in Yi Zhang, Kaizhou Gao, Yicheng Zhang, and Rong Su. "Traffic Light Scheduling for Pedestrian-Vehicle Mixed-Flow Networks." *IEEE Transactions on Intelligent Transportation Systems*, vol. 20, no. 4 (2018): 1468-1483.

The contributions of the co-authors are as follows:

- Prof Su suggested the initial direction, provided guidance and edited the manuscript drafts.
- I developed the pedestrian model, discussed the model with Dr Gao Kaizhou and Dr. Zhang Yicheng.
- I integrated my pedestrian model with the vehicle model formulated by Dr. Zhang Yicheng.
- Dr Gao Kaizhou developed the evolutionary algorithm and I implemented the algorithm.
- I wrote the code and ran the simulation to test the efficiency of the model.
- I prepared the manuscript drafts. The manuscript was revised by Dr Gao Kaizhou and Dr. Zhang Yicheng.

Materials of Chapter 2 appear in Yi Zhang, Yicheng Zhang, and Rong Su. "Pedestrian-Safety-Aware Traffic Light Control Strategy for Urban Traffic Congestion Alleviation." *IEEE Transactions on Intelligent Transportation Systems* (2019).

The contributions of the co-authors are as follows:

- Prof Su suggested the initial direction, provided guidance and edited the manuscript drafts.

- I formulated the model, discussed the model with Dr. Zhang Yicheng.
- I developed the evolutionary algorithm with repairing mechanism (EARM) to solve the proposed model.
- I wrote the code and ran the simulation to test the efficiency of the model.
- I prepared the manuscript drafts. The manuscript was revised by Dr. Zhang Yicheng.

Chapter 4 describes a new model, which has neither been published in peer-reviewed journals nor been accepted by any conferences.

The contributions of the co-authors are as follows:

- Prof Su suggested the initial direction, provided guidance and edited the manuscript drafts.
- I developed the model, discussed the model with Dr. Zhang Yicheng.
- I wrote the code and ran the simulation to test the efficiency of the model.

February 28, 2020

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Date

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Yi Zhang

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Summary

Many urban areas are facing heavy traffic congestions, pollutions, noises and traffic fatalities. Limited financial resources and physical space cannot support continuous infrastructures expansion, which calls for other alternative solutions to address the above problems. Traffic signal control, as one of the most essential strategies to tackle this challenge, has been applied and studied over the past several decades. However, existing traffic signals generally focus on optimality of vehicle flows, but the pedestrian delay is seldom considered. Also, many adaptive traffic signal strategies focus on increasing the traffic efficiency, which may unintentionally affect the safety of the system. According to Traffic Police accident statistics, the proportion of the pedestrian fatal accidents on signalized crosswalks is 22%. Besides the traffic light control, public transportation, another effective solution to address the urban issues due to its larger ridership and sustainability on economic efficiency, environmental protection and social equity, has also been studied for several decades. Especially for Singapore, a densely-populated small city-country with a 648 km^2 main island and a total population of 5.6 million. Clearly, developing an efficient public transport system is definitely indispensable in order to solve serious traffic issues with a limited land supply and exploding transport demands.

Therefore, this thesis focuses on solving the above issues by designing adaptive traffic signal controllers for both vehicles and pedestrians and developing optimal dispatching and operating strategies for public transport systems. The thesis includes three technical chapters: The first technical chapter develops a model to provide traffic light scheduling for pedestrian-vehicle mixed-flow networks, where a macroscopic pedestrian “hopping” model at an intersection is formulated, which is capable of reflecting the changing capacity during one time interval resulted from the crosswalk length and pedestrian relatively lower speed. By considering drivers’ psychological response to traffic signal states, a network-based vehicle flow model is adopted. Both pedestrian performance and vehicle performance are integrated together via the weighted sum method, which could be translated into monetary values for economic considerations or delay costs for efficiency evaluation. By connecting with the commercial simulator, Vissim, experiment studies are carried out to illustrate the usefulness of our proposed solution. The second part of the thesis investigates the potential impact of the pedestrian movement to the vehicle traffic networks when pedestrian safety is considered in the system. Considering

the high-incidence rate of pedestrian violations during Flashing GREEN (FG), an additional Dynamic All RED (DAR) phase is introduced at the end of each FG period, whose duration is adaptively adjusted according to the number of non-compliant pedestrians. With computational complexity being a concern for our model, an evolutionary algorithm with repairing mechanism (EARM), is proposed to solve our problem. Thirdly, we address the bus dispatching system from the tactical and operational level, with the aim to minimize passenger delay and bus vacancy by scheduling corresponding vehicles. Meanwhile, we take the stop-skipping control strategies into account and allow the bus-platoon dispatching to guarantee an efficient bus service. Also, passengers' perceived delay is firstly formulated by a nonlinear function, which describes the dissatisfaction of the passengers who have not boarded after their expected bus arrival time. Moreover, we compare our method with the traditional fixed schedule and the optimized non-platoon schedule, and the simulation results illustrate the efficiency of our method.

Overall, the thesis proposes three major problems faced by the researchers and policy makers in the intelligent transportation field. The suggested guidelines and methods can assist in developing a comprehensive and sustainable urban transport system in order to provide citizens a smarter, safer and more interactive transportation experience.

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List of Abbreviations

SCOOT	Split, Cycle and Offset Optimizing Technique
TRANSYT	TRAffic Network StudY Tool
SCATS	Sydney Coordinated Traffic Adaptive System
DS	Degree of Saturation
TUC	Traffic-responsive Urban Control
NN	Neural network
FL	Fuzzy Logic
CTM	Cell Transmission Model
LWR	Lighthill-Whitham-Richards model
CA	Cellular Automata
SF	Social Force model
PCM	Pedestrian Crossing Model
MPC	Model Predictive Control
FG	Flashing Green
SG	Steady Green
DAR	Dynamic All Red
EARM	Evolutionary Algorithm with Repairing Mechanism
EPP	Exclusive Pedestrian Phase
TWC	Two-Way Crossing
MILP	Mixed Integer Linear Programming
HS	Harmony Search algorithm
GA	Genetic Algorithm
EA	Evolutionary Algorithm
TCT	Traffic Conflict Technique
HCM	Highway Capacity Manual
HSM	Highway Safety Manual
V2X	Vehicle to Everything
APC	Automatic Passenger Counter systems
FS	Frequency Setting
BTD	Bus Timetable Design
VSP	Vehicle Scheduling Problem
DSP	Driver Scheduling Problem

Chapter 1

Introduction

Summary - In this chapter, we first present the importance and necessity to develop a sustainable pedestrian/transit-oriented transport system, which is captured by three different problems, from efficiency-based traffic signal control, pedestrian safety concern to urban transit schedule, and these three problems will be elaborately discussed in the following chapters of the thesis. Next, the structure of the thesis is arranged in the final subchapter.

1.1 Motivation and Objectives of the Research

At the early 21st century, the rapid growth of the population facilitates the urban sprawl and results in a series of problems, such as traffic congestions, pollution, noises and traffic fatalities. However, the number of automobiles is still continually increasing, which has surpassed the existing capacity. Blindly expanding facilities to satisfy the automobile demands is unsustainable due to limited resources and high costs. Therefore, it is indispensable to develop an eco-friendly sustainable transport with high efficiency of utilizing the existing traffic network.

Although many transformational products have been developed and used on the road, such as autonomous vehicles and drones, their applications have not been massively implemented due to its potential security concerns [1]. From the perspective of existing traffic facilities, many researchers have proposed the concept of the pedestrian/transit-oriented transport, which is designed for the human body instead of the car body [2]: "cities with very high walking, cycling and transit mode share (i.e., 75% or more) typically have high density, mixed use urban centres at or above 100-200 people per hectare and are supported by a transportation strategy that prioritizes pedestrians first, then cyclists followed by transit users." [3]

Walking, as a primary mode of transportation, can not only be environmental

friendly but also improve physical fitness. However, many city guidelines focus on smoothing vehicle traffic, without taking walkability into account[4]. Walking is a basic, eco-friendly and affordable transport, therefore, improving walkability can help to achieve social equity and reduce traffic congestions, pollution emissions and energy consumption. A good walkability also has strong potential economic benefit, such as increasing employment, tax revenue and property values [4]. Although complete walking trips only occupies 22% of the whole trips, walking is also included in 70% of other trips [5]. However, walking is often undervalued since it is difficult to be measured and evaluated, also, policy makers normally take it for granted [6]. The quality of the urban facilities has a strong influence on people's decisions to select walking or driving. Also, walking is a typical access to public transport, thereby the increase of the pedestrian walking safety and pleasantness will lead to the increase of the use of public transport [7].

On the other hand, the public bus system, a typical ride-sharing transport, serves a variety of access needs throughout the city-center area to the suburban area. Compared with other transit modes, infrastructure investments for bus transport can be substantially lower. Many public transports, such as subway and metro, are struggling with the unprofitable situation, however, the public bus system can quickly achieve profitability and operate without a financial subsidy [8][9][10]. According to the report [11], the public bus system, operated in TransMilenio of Bogotá, Columbia from 2000, is a typical intelligent bus system which includes the dedicated bus lane, advanced control system, smart fare collection system and reasonable ticket price. A series of good results have been achieved, such as high passenger satisfaction, low gas emission, large capacity and profitable operation. Proper bus planning and operation can attract more passengers, namely, encourage commuters to select public buses rather than the private automobiles as their travel mode, which leads to the reduced utilization of the private cars with low occupancy and the alleviation of the traffic congestion and air pollution accordingly [12].

In view of this, the thesis focuses on achieving a sustainable pedestrian/transit-oriented transport system by providing strategies to enhance existing system performance, where three problems are formulated and analyzed. These three problems mainly discuss the combined vehicle-pedestrian efficiency, pedestrian safety and multi-bus dispatching considering passengers' perceived delay, respectively, which are all developed via the macroscopic traffic flow model, where the first two parts focus on the traffic signal control and the last part is for the bus schedule design. The specific motivation and objectives for each part are extensively illustrated in the following three subchapters.

1.1.1 Urban Traffic Signal Control for Large Scale Network

In view of the increasing traffic congestion in urban road networks, tremendous efforts have been made to tackle this challenge via many different measures over the past several decades, and the urban traffic signal control is one of the most essential strategies among all these measures. Traffic signal control has experienced the changes from fixed-time strategies [13][14][15][16] to traffic-responsive strategies, from isolated intersection control [13][14] to coordinated intersection control [17][18][19], from model-free control [18][19] to model-based control [20][21][22][23][24] and learning-based control [25][26][27].

Fixed-time strategies are derived off-line with an open-loop control structure, and the signal setting is determined by calculating the optimal signals based on the average historical data. Since the settings of fixed-time strategies are not based on real-time data, its drawbacks soon become obvious when the traffic flow is stochastic, therefore, traffic-responsive strategies are developed to avoid the disadvantages once the equipments such as roadside communication units, cameras and loop detectors for real-time control system are installed. Corresponding Typical works are Split, Cycle and Offset Optimizing Technique (SCOOT), store-and-forward based approaches and model-based optimization methods. SCOOT is regarded as the traffic-responsive version of TRAFFIC Network Study Tool (TRANSYT) and was first developed by Hunt and Robertson [28], which run repeatedly in real time to investigate the change of cycle time, offsets and splits at individual intersections. However, SCOOT lacks of adaptability to random or non-typical incident occurrences. The store-and-forward model is a simplified traffic flow model, which was first developed by Gazis and Potts [22]. Unfortunately, the model is too simple and fails to capture the dynamics of the traffic flow, meanwhile, requires a larger control input interval, which restricts the frequency of real-time decision making. Model-based traffic-responsive strategies have also been released, and many of them are developed based on cell-based models and follow the receding horizon approach. Cell Transmission Model (CTM)[29][30], as one typical cell-based model, has been adopted in many model-based strategies due to its accuracy in reproducing congestion phenomena and the propagation of traffic waves [31][32][33]. Although the introduction of the receding horizon mechanism in the model-based strategies can incorporate future predictions and avoid myopic determination, it can also increase the computational burden if the scale and the prediction horizon of the problem are very large.

Besides the intersection-based signal control strategies, region-based perimeter control methods have also been studied to reduce congestions by controlling the incoming flows or outgoing flows of each region [34][35][36]. Both the theoretical analysis [37][38] and the field experiment [35] have been conducted to prove the existence of the macroscopic fundamental diagram (MFD) describing the relationship of space-mean flow, density and speed on a large urban area. Also, if the link densities of the studied region have low variance, namely, the network is

homogeneously distributed, then the corresponding MFD is well-defined, in other words, the flows with low dispersion for the same densities [39]. Moreover, the shape of the MFD is not very sensitive to the demand patterns. Based on the two above properties, the design of the perimeter control strategy to alleviate the region congestion becomes possible. The optimal control policy for a single MFD system is derived by Daganzo in [38]. After that, multi-region perimeter control strategies have been proposed, either considering system stability [40], adopting model-predictive control approach [39], other types of controls [35][36] or modifying the system dynamic [41].

In the current literature most attentions are paid on vehicles, this is reasonable when the pedestrian volume is low. However, in the downtown areas where a large number of pedestrians interfere with vehicular traffic, optimizing traffic signals only for vehicles may create more conflicts between both traffic participants and potentially reduce the economic interest [4], since pedestrians in CBD areas are usually potential customers of nearby shopping malls. Moreover, most of the studies only incorporate concerns for pedestrians by adding constraints such as minimum green time or pedestrian clearance time [42][43]. Pedestrian delay is not equally considered like vehicles. Based on the limited studies on this issue, multi-objective approaches have been proposed, mainly based on either simulation-based or mathematical programming methods.

In simulation-based studies, a simple hypothetical network with fixed-time non-coordinated signal cycles is analyzed for the effects of signal cycle timings on the delay caused by both vehicles and pedestrians [44]. Various multi-attribute weighting criteria are applied to traffic delays in order to examine cost trade-offs between pedestrians and vehicles [45]. Considering mathematical programming approaches, both pedestrian crosswalk layouts and traffic signal optimization for pedestrians are studied. A model which estimates pedestrian delays at a two-stage crosswalk is developed in an analytical form [46]. Optimization of traffic signals for both vehicles and pedestrians in an isolated intersection is formulated as a quadratic programming problem considering one-stage or two-stage crosswalks [47]. Optimal pedestrian signal timings are integrated into the corresponding optimization models either as one part of an objective function or as constraints, see [42] and [43]. An optimization model, which selects pedestrian phase patterns between the normal Two-Way Crossing (TWC) and the Exclusive Pedestrian Phase (EPP) with the trade-off between safety and efficiency factors in an isolated intersection, is proposed in [48] and [49]. Meta-heuristic algorithms are applied to solve traffic signal optimization problems for both pedestrians and vehicles [50][51]. In these studies, the same characteristics can be summarized as: 1. Most studies focus on one isolated intersection; 2. The majority of the analyses are based on deterministic queuing model; 3. Vehicle and pedestrian delay models are nonconvex; 4. The optimized signal setting can only be calculated based on historical data and cannot adaptively adjusted according to the traffic demand.

Based on the discussion above, there are two major problems requiring to be addressed:

- Pedestrians' efficiency is seldom mentioned in the coordinated traffic signal control strategies.
- The increase of the problem scale leads to the increase of the computational complexity.

Therefore, the objectives of the Chapter 2 are listed as follows:

- Pedestrian flows are modeled and considered in the cost function. Specifically, we establish a macroscopic pedestrian “hopping” model at an intersection, whose flow dynamic is capable of reflecting the changing capacity during one time interval resulted from the crosswalk length and pedestrian relatively lower speed. By integrating a network-based vehicle flow model, a traffic light scheduling problem for a mixed-flow network is proposed. Sum of the pedestrian delay cost and the vehicle delay cost by applying different weights on both sides formulates the final objective, which generates traffic signal setting from the trade-off between pedestrians and vehicles.
- The trade-off between the model accuracy and the algorithm complexity leads to the selection of CTM in our problem. Since our approach is a model-based optimization method for traffic signal scheduling within a large traffic network, and we need to not only describe the traffic movements but also control the traffic light. More elaborated models may not contribute much on system control, instead it would make our computational complexity even higher. In view of this, we select the CTM because it not only belongs to the category of the macroscopic model which largely reduces the computational time, but also can reproduce congestion phenomena and the propagation of jams which guarantees a certain degree of system accuracy. Moreover, besides the utilize of the Mixed Integer Linear Programming (MILP) to solve the problem after all logic constraints are translated into the corresponding linear constraints, the evolutionary algorithm is also adopted to solve the problem efficiently.

1.1.2 Pedestrian Safety under Signalized Intersection

According to National Highway Traffic Safety Administration [52], roughly 25 to 40 percent of traffic fatalities is pedestrian deaths in urban areas. Therefore, many countermeasures have been proposed to improve pedestrian safety and mobility.

A better walking environment with proper road design can significantly improve the pedestrian mobility and reduce exposures between vehicles and pedestrians.

Many underpasses or overpasses have been developed in order to segregate the vehicle flow from the pedestrian flow. However, the construction of the underpass or overpass requires the support of the topography, which may cost \$500,000 - \$4 million depending on site characteristics [53]. Also, pedestrians will not use them if they can cross on the ground near the location. Road width is another crucial factor that influence the pedestrian safety. Many studies found that wide roads normally accompany with the increase of the fatal crashes [54][55][56]. Since the wide road somehow leads to the high speed of the vehicle, namely, drivers seem to behave aggressively on widen roads, which accordingly exacerbates the possibility of the crashes. On the other hand, a wide road stands for a long crosswalk from a pedestrian perspective, which reduces their non-compliance rate due to the high chance of failure on successful crossing. Therefore, the utilize of the traffic median, whose original purpose is to improve pedestrian safety by shortening cross distance, may reversely facilitates their risk-taking behaviors [57]. Also, many traffic-calming measures, such as curb extension, speed humps, street trees and etc, have been implemented in the roadway to reduce speed of motor vehicles and improve visibility for drivers and pedestrians. Collision frequencies decline significantly after the traffic calming measures are installed [58][59]. Moreover, traffic signals also largely decrease the traffic crashes especially in high volume links and intersections. Many researchers found that pedestrian safety can be significantly improved via the pedestrian signalization by conducting before-and-after experiments [60][61]. Although the improvements are determined by the specific characteristics such as location, road design, road user behaviors and signal settings, pedestrian injuries and fatalities are reduced by installing traffic signals when compared with crossings without pedestrian signals [62].

To better provide safer environment for pedestrians, the pedestrian self-organized phenomena is also analysed. Self-organization is defined as the spontaneous organization caused by non-linear interactions between many objects or subjects without any planned or organized intervention. There are four typical self-organized phenomena: Stop-and-Go waves, herding, Faster-is-Slower effect and lane formulation. Stop-and-Go waves [63] refer to a temporarily interrupted, longitudinally unstable flows which appears in unidirectional flow when density increases. Herding [64] describes pedestrians all follow each other instead of choosing the optimal path, and this phenomenon frequently occurs during stressful evacuation situations [65][66]. Faster-is-Slower effect [67] describes a phenomenon that the density in the queue is increasing gradually when the front of the queue is stopped, due to the impatience of pedestrians, accordingly, the successor try to follow up and so forth, producing a wavelike propagation of the gap to the end of the queue. Lane formulation generally appears in counterflows (bidirectional flows), pedestrians with different forward directions automatically separate with each other and form lanes of uniform walking direction [68]. The fundamental diagrams for pedestrian flows are also investigated: the unidirectional pedestrian flow, passing a narrow corridor to form an oversaturated bottleneck upstream, is analysed in [69][70]. The bidirectional flows are also conducted either from

the theoretical analysis [71][72] or the field experiment [67][73]. Bidirectional experiments carried out by Helbing observed that counterflows are significantly more efficient than unidirectional flows [67]. This phenomenon is studied by Lam in detail at congested-flow (at-capacity) situation [73], and they found that the total effective capacity of bidirectional flows reaches the maximum at balanced flow ratio, and then drops symmetrically according to the deviation of the flow ratio from that balanced value.

Although pedestrian safety has gained increasing attention from local governments and organizations, the majority of the adaptive traffic signal control strategies are still primarily built for smoothing vehicle flows [27][24][33], while pedestrian safety is rarely taken into account in the adaptive traffic signal design. Even if the pedestrian safety is modeled as one of the performance indexes, the signal control still concerns isolated intersection rather than coordinated intersections [48][49]. This may be partially due to the uncontinuity of pedestrian flows in different intersections, in contrast to vehicle flows in an urban network. However, with the common adoption of GPS-enabled mobile devices for pedestrian applications, the establishment of pedestrian networks become possible by mobile users' volunteered data collections [74]. The current routes of navigation services are based on road networks and do not include off-road walking paths [75]. Once pedestrian network databases are publicly available like those for road networks, the study on traffic signal control of pedestrian networks will be an indispensable part of the overall traffic network control.

Also, pedestrian crashes still exist even though the traffic signal is installed at intersections or mid blocks. According to Traffic Police accident statistics [76], the proportion of the pedestrian fatal accidents on signalized crosswalks is 22%. More than 30% of the total pedestrian fatalities can be attributed to the illegal crossing behavior, which is affected by many factors, such as age and sex, waiting times, traffic volume and speed, social psychology and road layout (road width, presence of the median refuge) [77].

According to the discussion above, two major problems can be summarized as follows:

- Adaptive traffic signal control normally takes vehicle's efficiency into account, without paying much attention on pedestrian's safety.
- The relationship between efficiency and safety is not elaborately analysed in the literature.

Therefore, the objectives of the Chapter 3 are listed as follows:

- A mathematical model for pedestrian crossing on a signalized intersection is formulated, whose arrival flow and leaving flow of each waiting zone,

which incorporate the pedestrian average non-compliance rate, are separately described in order to make the model more realistic, then an additional DAR phase is introduced at the end of each Flashing GREEN period, whose duration is adaptively adjusted according to the number of non-compliant pedestrians via pedestrian crossing time model [78]. By integrating with the vehicle network model based on CTM, a pedestrian-safety-aware traffic light control strategy is developed with the aim to reduce both traffic congestions and pedestrian-crossing risks.

- The constrained method, which utilizes the preferred evaluation object as cost objective while the others are treated in constraints, is adopted to quantify performance trade-off, where vehicle efficiency is regarded as our objective and the pedestrian crossing safety is modeled in our constraints. By using this way, the impacts of pedestrian safety on a vehicle network can be evaluated, which is important for transportation professionals to make proper decisions on phase pattern selection.

1.1.3 Urban Transit Schedule

Due to the larger ridership and sustainability on economic efficiency, environmental justice and social equity, public transportation has been studied for many years [79], however, the design of the public transport system involves many complicated problems. One of the most troublesome issues is the origin-destination passenger demand, which varies significantly along the route at different stops and different periods. Therefore, the expected fixed bus schedule cannot provide efficient services for such fluctuated demand patterns. In order to make a good trade-off between a reliable and sustainable bus service and a proper bus operational cost, many operating strategies have been proposed in the past several decades [80].

One of the essential methods satisfying the stochastic demand is to select a proper schedule interval for the operating bus line, which can be classified as the bus frequency setting problem. The frequency setting problem has been studied from analytic model, data collection approach to optimization-based mathematical model. Based on the assumption that the capacity of the vehicles is sufficiently large to accommodate all waiting passengers, Newell presents that the frequency is approximately proportional to the square root of the arrival rate of passengers by deriving the analytic model [81]. Two point check methods via daily and hourly maximum passenger load points and two ride check methods via the original and the adjusted load profiles are discussed and compared according to the collected data by Ceder [82][83]. Moreover, many mathematical optimization models are developed, with the aim to either minimize the passenger waiting time or the operational cost [84][85][86][87]. Besides adjusting schedule interval by proposing bus frequency problems, adaptive bus size control has been proposed to help improve the bus operation service. Oldfield and Bly propose a mathematical model

to study the relationship between the operating cost and the optimal bus size, and they found that the increase of the bus size can also increase the operational cost [88]. The deficit function is used to determine the minimum number of buses required to satisfy the pre-arranged timetable [89]. Also, Sun et al. propose an optimization model by dispatching buses with hybrid sizes and uneven headway, in order to minimize both passenger waiting cost and bus operational cost [90].

Due to the stochastic enroute traffic and the fluctuated passenger demand, the phenomenon such as vehicle bunching may still exist no matter how well the bus schedule is planned in advance. Therefore, real-time control strategies are required for a bus operation system. One of the efficient control strategies is the stop-skipping strategy. Eberlein et al. [91] propose a mathematical model involving holding strategy and stop-skipping strategy in order to minimize the passenger waiting time. The results indicate that the cost reduction by combined control involving both holding and stop-skipping strategies is approximately 37%, which is larger than any of the single strategy. The stop-skipping strategy is also adopted in [92], where the two different skipping policies are discussed. An optimization model based on holding strategy and stop-skipping strategy for a corridor with multiple bus lines is developed in [93]. Based on the real-time headway information, the bus holding time is adaptively adjusted in order to eliminate bus bunching [94]. To evaluate different transit control strategies, [95] compares eight scenarios in two different approaches from three dimensions: bus capacities, service frequencies and load profiles. Also, a hybrid dynamic model of a single bus line is presented with a dual objective of regularizing spacings and improving bus service speed [96]. To further improve the bus operation efficiency, many bus signal priority strategies have also been proposed [97][98][99]. The second policy allows the alighting process occurring in the skipped segment while the first does not. The method is developed by solving a nonlinear integer programming problem under the assumption that vehicle capacity is large enough to serve all the waiting passengers. A nonlinear programming model adopting stop-skipping strategy is proposed for a single transit bus route, with consideration of both bus volume dynamic and stop volume dynamic [100], however, its prediction horizon is just equal to the bus number and the boarding limit constraint is not considered in the model.

According to the discussion above, two major gaps can be summarized as follows:

- Previous studies usually investigated the stop-skipping strategy, hybrid bus schedule and bus frequency problems separately. Also, many studies do not consider bus capacities in bus volume dynamics.
- Normally the passenger waiting time is modeled as the cost objective, without considering passenger's perceived delay, which is more proper to characterize waiting passengers' anxiety.

Therefore, the objectives of the Chapter 4 are listed as follows:

- A mixed logical dynamic model of a ring-route bus line with a stop-skipping strategy is firstly developed with consideration of the stop demand dynamics and the bus demand dynamics. The bus depot in our model is allowed to dispatch a single bus or a bus platoon for each trip, which can provide different bus capacity sizes for each trip. Also, the dispatched bus platoon can be separated at the stop if the waiting passenger demands are not large, which make our method more flexible and data-driven. With the aim to minimize the passenger waiting time and the bus vacancy, a MILP model is developed after translation of the mixed logical constraints. Considering the computational complexity of the MILP formulation, modified Genetic Algorithm (GA), one of the famous evolutionary algorithms, is also applied to solve the problem.
- Besides the normal passenger waiting time, passengers' perceived delay time is also formulated in the model. Passengers who arrive between trips k and $k + 1$, we assume these passengers' expected boarding time is $k + 1$, and their dissatisfaction will be incurred due to longer waiting time if they cannot board at trip $k + 1$. This dissatisfaction is formulated by a nonlinear function, which describes the dissatisfaction of the passengers who have not boarded after their expected bus arrival time.

1.2 Main Contributions of the Thesis

The major contributions of this PhD thesis are listed as follows:

- **An adaptive traffic signal control for urban network efficiency**
A macroscopic traffic flow model for a pedestrian-vehicle mixed-flow network is formulated, with the aim to minimize the total network cost for both pedestrians and vehicles. The pedestrian volume dynamics in each junction is determined by the source corner volume, the capacity of each crosswalk affected by the associated traffic signal setting and the remaining space the destination corner. The formulation of the vehicle traffic network is extended from the CTM, which is combined with the pedestrian network to form a holistic mixed-flow network. Using the integrated model and translating the logic constraints into corresponding linear constraints, an adaptive traffic signal control strategy is proposed where MILP problems are solved in a receding horizon mechanism. To overcome the high complexity involved in the large scale traffic network in MILP formulation, a meta-heuristic Harmony Search (HS) algorithm is adopted to solve the problem in real time.
- **An adaptive traffic signal control for pedestrian crossing safety**
A traffic signal strategy considering the total vehicle delay and the pedestrian safety in the entire network is formulated. The extended pedestrian flow model incorporates the characteristics of pedestrian non-compliance

behaviors, in which pedestrian dynamics are updated by the pedestrian incoming flow from nearby areas, pedestrian arrival flow from crosswalks and pedestrian leaving flow to crosswalks. By combining the network-based vehicle macroscopic model, a traffic signal scheduling problem is formulated with the aim to alleviate the vehicle delay meanwhile increase the pedestrian safety. Considering the high complexity of the model, two evolutionary algorithms (GA and HS) with the repairing mechanism are developed to solve the problem, where the repairing mechanism addresses the issues that the interactions between the signal setting and the pedestrian volume update.

- **A platoon-based bus schedule design incorporating stop-skipping strategy**

A platoon-based bus dispatching strategy with the bus stop-skipping strategy is proposed for a ring road bus transport system. Both a single bus and a bus platoon are allowed to be dispatched for each trip from the depot, in other words, our method dispatches buses with variable sizes. Also, the dispatched buses in each trip can skip several stops as long as the objective is minimized, and the objective is captured as the passenger delay time and the bus vacancy in order to meet the interests from the demand side and the supply side. Both the variable bus size and the stop-skipping strategy makes our model more flexible and adaptive to meet the passenger demand. Meanwhile, we formulate the passengers' perceived delay time as a nonlinear function, which captures the passengers' dissatisfaction due to their elongated wait. Both MILP and GA are adopted to solve the problem in order to make the trade-off between the result quality and the computational time.

1.3 Structure of the Thesis

The thesis elaborately describes three problems directly related to the pedestrian/transit-oriented transport system, considering pedestrian-vehicle efficiency, pedestrian safety and transit efficient dispatching involving pedestrians' dissatisfaction captured by their perceived delay time, respectively. Three major parts are all linked by the involvement of people in terms of pedestrians or passengers, and describe the impacts of people to different aspects of a transport system, which could lead to an eventual integration of all these factors into one single intelligent system, addressing both safety and performance simultaneously. The structure graph of the whole thesis is drawn in Fig. 1.1, and the contents of three major chapters are illustrated as follows:

Chapter 2 Efficiency-based Traffic Signal Control for Pedestrian-Vehicle Mixed-Flow Networks

The content of this chapter is published in [101]. This chapter firstly gives an overview on urban traffic flow modelling for both pedestrians and vehicles, then

Figure 1.1: The structure graph of the thesis

existing traffic signal control strategies are also summarized. By extending the traditional CTM, an adaptive traffic signal strategy for a pedestrian-vehicle mixed-flow urban traffic network is proposed. Using the mathematical transformation technique, the original problem is converted into a MILP problem and solved via the commercial solver, e.g., GUROBI. Furthermore, to improve the computational time, HS, one evolutionary algorithm, is adopted to solve the problem in real time.

Chapter 3 Pedestrian-Safety-Aware Traffic Signal Control for Urban Traffic Congestion Alleviation

The content of this chapter is accepted in [102]. A literature review on urban traffic safety is introduced firstly in the chapter, which involves the severity of the pedestrian safety, pedestrian crossing at mid-block roads and intersections, factors influencing pedestrian compliance and signal strategies to improve safety at intersections. After that, we develop a mathematical model addressing the pedestrian-vehicle conflicts by presenting a traffic signal control strategy for urban traffic networks that aims to minimize vehicle traveling delays (increase efficiency) as well as pedestrian crossing risks (increase safety). An additional DAR phase is introduced at the end of each pedestrian Flashing GREEN period, whose duration is adaptively adjusted in order to provide sufficient crossing time for non-compliant pedestrians. The evolutionary algorithm with repairing mechanism is proposed to

solve the problem.

Chapter 4 A Dynamic Optimization Model for Bus Schedule Design

An overview on urban transit scheduling is firstly presented in this chapter, which includes the strategic planning, tactical planning, the operational planning and the real-time control of the urban transit system. In the second part, a platoon-based bus dispatching strategy with the bus stop-skipping strategy for a ring road bus transport system is formulated. With the aim to minimize both the passenger delay time and the operating bus vacancy, a MILP formulation is developed and solved by the commercial solver GUROBI. Also, the concept of the passengers' perceived waiting time is firstly proposed by a nonlinear function, a GA is adopted to solve the problem with a nonlinear cost in real time.

Chapter 2

Efficiency-based Traffic Signal Control for Pedestrian-Vehicle Mixed-Flow Networks

Summary - In this chapter, we first give an overview of urban traffic flow modelling for both pedestrians and vehicles and existing traffic signal control strategies. First, we introduce multiple traffic models based on their levels of details, especially describe the macroscopic modelling, since it is extensively used in our problem formulation. Next, several existing urban traffic signal control strategies are proposed, also, their advantages and disadvantages are compared. In the second part, we present an adaptive traffic signal strategy for a pedestrian-vehicle mixed-flow urban traffic network. We firstly propose a novel mathematical model of pedestrians crossing a junction. By combining a link-based vehicle network model, a traffic light scheduling problem is formulated with the aim to strike a good balance between pedestrians' needs and vehicle drivers' needs. The problem is firstly converted into a Mixed-Integer Linear Programming (MILP) problem via a novel transformation procedure, which is solvable by several existing solvers, e.g., GUROBI. Then a meta-heuristic method called Harmony Search algorithm (HS) is also adopted to reduce the computational complexity in MILP. Numerical simulation results are provided to illustrate the effectiveness of our real-time traffic light scheduling strategy for pedestrians and vehicles, and the potential impact of the pedestrian movement to the vehicle traffic flows.

2.1 Literature Review

This section introduces the background of traffic flow modelling and the review of traffic control methods. For the traffic flow modelling, we provide the classification

and the main concepts of existing models for both vehicles and pedestrians. Next, we briefly give the review of traffic light control strategies from the fixed methods to the adaptive methods.

2.1.1 Urban Traffic Flow Modelling

2.1.1.1 Vehicle flow modelling

Traffic flow modelling can be classified into three categories according to the level of details. Firstly, a traffic system can be described by a microscopic model, namely, the space-time of the systems' entities, e.g., drivers or vehicles, and their interactions are described at a high level of detail, where each individual will have its own function to represent corresponding dynamics when facing different external effects. Secondly, mesoscopic models specify the behavior of each small group of traffic entities. Thirdly, macroscopic models describe traffic in an aggregate manner. The concepts of flow, density and velocity are adopted in the model. Due to the fewer number of parameters, macroscopic models are easier to be calibrated and validated [103]. As for microscopic and mesoscopic models, they are more suitable for off-line traffic simulation analysis. The macroscopic models, which is the category that our models belong to, will be elaborately described in this subchapter.

Macroscopic traffic models capture traffic systems from the level of aggregate variables, accordingly, they are suitable to be applied on real-time control problems. Generally, the aggregate variables are the density ρ , the average speed v and the flow q . The analogy between vehicle flows and continuous fluids or gases leads to the inheritance of the conservation law [104] to a macroscopic traffic system, which is captured as:

$$\frac{\partial \rho(x, t)}{\partial t} + \frac{\partial q(x, t)}{\partial x} = 0 \quad (2.1)$$

where x and t are road location and time, respectively, equation (2.1) indicates that the increase in variation of flow at space is equal to the decrease in variation of density at time if no entering or leaving traffic occurs, in other words, the number of vehicles in cell x increases according to the balance of inflow at the boundaries x and $x + dx$ of the cell. The righthand of the equation (2.1), 0, can be replaced by traffic generation rate $g(x, t)$ in freeway, and $g(x, t)$ is the vehicles arrival rate at an on-ramp or the vehicle leaving rate at an off-ramp. Another formulation is also commonly applied to many macroscopic models:

$$q(x, t) = \rho(x, t)v(x, t) \quad (2.2)$$

However, equations (2.1) and (2.2) are not enough to describe the traffic dynamics since the number of unknown variables is larger than the number of equations. Therefore, extra equations to characterize the relationship of three unknown

variables should be considered in order to obtain a complete description of the traffic system. For this reason, many fundamental diagrams are developed by field experiments, which is a diagram capturing the relationship between traffic flow and traffic density or the relationship between the average speed and traffic density. When density is small, namely, there are few cars driving on the road, accordingly, their speed is high but the flow is lower due to the limited car numbers, then more vehicles drive into the road, which leads to the increase of the density and flow. As the density increases, the critical congested situation could occur when density is large than the critical density, more severe congestion will appear if density is still increasing. Based on the fundamental diagram, many models have been developed to capture this relationship, e.g., Lighthill-Whitham-Richards (LWR) model [105], payne model [106], CTM [29][30]. The LWR model is a continuous model and an expected velocity equation described by a function of the density is adopted to capture the traffic system, and payne model chooses a higher-order equation to describe the dynamics of the average speed, both models are not efficient for real-time control on a large-scale network. However, CTM is the discrete-time model and its fundamental diagram is simplified as a trapezoid-shape function, accordingly, it is feasible to apply CTM on model-based traffic control.

CTM can be not only used on freeway to describe continuous traffic flow but also used on urban roads to describe the stop-and-go traffic flow controlled by traffic lights, then a set of control strategies adopting model-based optimization methods, are proposed to operate an efficient traffic network, which will be clearly explained in the next section. Without deriving relationship from the fundamental diagram, store-and-forward model [23] is presented by simplifying the urban interrupted flow as the corresponding continuous average flow, in order to provide convenience to traffic signal settings under traditional framework, which includes the concept of splits, cycles and offsets. Due to the simplification of the model, store-and-forward model is particularly useful for the saturated traffic network and has a low computational complexity.

2.1.1.2 Pedestrian flow modelling

Modelling on pedestrians typically focus on the off-line simulation analysis [107], thereby many pedestrian models belong to the microscopic level, which is evaluated according to three criteria: Firstly, the ability to reproduce the motions during crowd movements, e.g., entering and exiting a bottleneck. Next, the ability to capture self-organization phenomena. Finally, the computational cost and applicability of the model. In the following content, Cellular Automata (CA), Social Force model (SF) and CTM are discussed.

The CA model describes pedestrian movements by jumping a grid of cells in a discrete manner, which is firstly applied on modelling pedestrian flows in the 1990s by Blue and Adler [108], who present the discrete pedestrian dynamics on

partitioned cells based on a set of rules. The decision of forwarding to the next cell depends on the other pedestrians, infrastructure and the destination. In order to model the self-organized phenomena and collective effects in pedestrian movements, Schadschneider et. al. [109][110][111] introduce the concept of dynamic and static floor field in CA to modify the transition probabilities to neighboring cells. The dynamic floor field reflects the dynamic interaction between nearby pedestrians, and the static floor field corresponds to the constant properties of the surroundings.

The SF model [112] is firstly developed by Dirk Helbing, it describes the movements of each pedestrian in a continuous space and time, which are influenced by a driving force vector pointing to the destination and counterforces from other pedestrians and barriers. By introducing clogging effects when pushy behavior appears in pedestrian crowds for emergency, the desired speed is corrected in driving force formulation [113]. Considering the sight range of the pedestrians, the repulsive interaction force is also modified to more accurately describe the pedestrian movement [114]. Then Helbing discusses a set of self-organized phenomena and the influence of obstacles in escape exit by adopting social force model [67]. After that, an elliptical repellent force field is proposed and calibrated by extracting the camera video data [115].

A few finite applications of CTM on pedestrian flows have been proposed. Asano et al. [116] extend the vehicle CTM to describe pedestrian multi-directional propagation, but they only propose the concept of a converting function without conducting validation and giving the specific form of the converting function, which can substitute the multi-directional densities for an equivalent unidirectional density based on the standard CTMs flow transmission rules. Then a pedestrian evacuation model based on the CTM is proposed [117], which also does not validate against real data. A macroscopic loading model [118] in public walking areas is specified by adopting the approach of Asano et al. [116] and the theory of continuum model [119].

The above discussed models are all very complicated, which make their implementation on real-time urban traffic control impossible. However, our problem in Chapter 2.2 is a macroscopic model-based optimization problem for traffic signal scheduling within a large traffic network, and we need to not only describe the pedestrian movements but also control the traffic light. More elaborated model may not contribute much on system control, instead it would make our computational complexity even higher. In view of this, with consideration of the common regulation applied in some network-based evacuation models [120] (extend cell-based macroscopic vehicle flow to pedestrian side), our pedestrian model is developed by extending the basic principle of vehicle traffic signal optimization problem via CTM on pedestrian movements, also, considering the unique pedestrians characteristics, construct the capacity function to describe the pedestrian flows elaborately.

2.1.2 Overview of Existing Traffic Light Control Strategies

Traffic signal may not necessarily be installed in intersections with few traffic volumes, however, its value will be soon realized once the traffic flows become significant. In highly congested urban roads, properly adjusting traffic signals to minimize total delay time for road users is becoming increasingly important. According to the different characteristics, control strategies deployed on traffic road can be classified into two categories with four different types: fixed time strategies and traffic responsive strategies, isolated strategies and coordinated strategies. Fixed-time strategies are derived off-line by calculating the optimal signal settings based on the average historical data. Traffic-responsive strategies are derived online by calculating the optimal signal settings based on real-time data. Isolated strategies refer to single intersections while coordinated strategies consider a whole network [121].

At the early 20th century, fixed-time control was firstly applied on the intersections [13]. Many studies focus on isolated intersections, e.g., stage-based strategies, which determine the optimal splits and cycle time. Besides isolated intersections, researchers also pay attention on several connected two-way arterial, then the concept of MAXBAND was firstly developed by Little [18][19]. MAXBAND methods try to maximize the bandwidth to let vehicles drive at a free-flow speed without meeting any of RED lights, but the obtained bandwidth could hardly guarantee the sufficiency to allow the amount of traffic to pass through the system. Then TRANSYT [17] was developed under the class of network-based fixed-time traffic signal control. TRANSYT is a model-based off-line optimization problem and can automatically determine signal settings according to the known network conditions. Its traffic model describes both signalized intersections and non-signalized intersections, whose flow dynamics take platoon dispersion into account based on average historical data. The smoothing factor obtained from observed data is applied on the outflow of a link to capture the inflow of the next connected link, and the optimization objective is chosen with any weighted sum between the journey time and the number of stops. Also, a 'hill climbing' approach is adopted to solve the optimization problem.

Although fixed-time strategies have a better performance in the decrease of government or company expenditure, their drawbacks soon become apparent when meeting with stochastic traffic volume profiles, the ever-changing construction of urban infrastructure facilities, inenarrable human response and other random incidents. Fixed-time approaches are open-loop and cannot adjust signal settings to satisfy the changed traffic demands. Therefore, Traffic-responsive strategies are emerged to make up for this deficiency.

It is the application of the real-time measurements (loop detectors, video cameras, etc.) that the implementation of traffic-responsive control strategies becomes a possibility. Before developing fully-responsive control strategies based on

optimization, several semi-responsive strategies are firstly implemented in many systems, which select fixed-time plans according to measured flows or vary the GREEN durations at important junctions. After that, a fully-responsive urban traffic control system is proposed by Robertson et.al. [28], which has been named SCOOT. SCOOT is the traffic-responsive version of TRANSYT and it uses traffic information measured from the upstream links, unlike outgoing flows in TRANSYT obtained from average historical data, prediction of queues in SCOOT is developed on the real-time measurements, so different cyclic flow profiles can be obtained on the basis of current traffic situation, which is more accurate compared with the fixed historical flow profile in TRANSYT. Optimizers for cycle length, offset and split are used to minimize number of stops and delays through synchronization of the entire network. Unfortunately, SCOOT suffers from lacking adaptability to random or non-typical incident occurrences.

Instead of considering a traffic model, SCATS (Sydney Coordinated Traffic Adaptive System) is a control system which can dynamically choose the pre-determined signal plans by adjusting offsets and splits according to the current traffic situations [122]. There are several levels of the system structure of the SCATS: The information obtained from loop detectors, which is located in front of the stop-line, is sent to the local intersection computer, then several local computers are used to optimize cycle time, splits and offsets before the optimal signal is transmitted to the regional computer, which contains several local computers partitioned into the same subsystem. The regional computers are connected to a central computer monitoring the entire system. SCATS try to allocate GREEN times in order to provide an equal DS (degree of saturation) of all approaches. The major priority is given to the critical intersection, and other neighboring intersections are adjusted accordingly. Traffic signals in a subsystem will have the same cycle length and are updated at the end of every cycle. Although the performance of SCATS is superior, cost on purchasing and maintaining the hardware facilities related to the entire system is a significant expense.

Several fully-responsive model-based control strategies based on optimization are proposed. Typical works are store-and-forward based approaches, OPAC [123], PRODYN [124], CRONOS [20] and RHODES [21]. Store-and-forward model, firstly developed by Gazis and Potts [22], describes a model by simplifying the stop-and-go flow into a continuous flow, which is adopted on network-wide Traffic-responsive Urban Control (TUC) via linear multivariable feedback regulator [125]. The TUC strategy is subsequently extended to allow real-time cycle, offset control and public transport priority [126]. After that, an open-loop constrained linear quadratic optimal control problem and an open-loop constrained nonlinear optimal control problem are formulated, which refine the model by taking a limited vehicle demand at the upstream link and limited remaining space at the downstream link into account [23][24]. Nevertheless, simplification of the flow model requires the control input interval be equal to or larger than the cycle length, which restricts the frequency of real-time decision making. Similarly, OPAC [123], PRODYN [124],

CRONOS [20], RHODES[21], also solve a dynamic optimization problem in real time based on a simple traffic flow model. The performance of model-based optimization methods relies on traffic flow models and the receding horizon procedure. The more accurate the model is, the better the control performance will be, however, the computational complexity will go higher as well, which can be partially mitigated by existing meta-heuristic algorithms.

CTM-based vehicle flow models have been studied in the literature. Hong K. Lo extends the CTM from freeway to urban traffic network by formulating the problem as a MILP problem [31][32], while the traditional signal framework is still adopted and the cycle time is fixed in the model. Then a S^* model, also formulated as a MILP problem, is proposed via Model Predictive Control (MPC) in a discrete manner [33], and the model considers the growth process of queue length and allows for different cycle times in different intersections. But this strategy usually struggles with the prohibitively high computational complexity for large traffic networks. Fortunately, many meta-heuristic algorithms are adopted to solve the urban traffic optimization problem [50][48][49][127][128][129]. Among all these meta-heuristics, the harmony search (HS) algorithm considers each component variable in a vector independently and generates new vectors from all the existing vectors, which can achieve a good trade-off between diversification and intensification by tuning its stochastic operators [130][131]. For this reason, the HS algorithm is also adopted in our traffic signal scheduling problem, which will be illustrated later.

The artificial intelligence methods have also been applied on adaptive traffic signal control. Signal controllers using reinforcement learning approaches are developed via the network-wide multi-agent coordination and the relationship between actions, states and environment [26][27]. Although no prespecified traffic model is required, the exponential growth of the state-action space with the increase of the agents may fail to efficiently solve the problem. Neural Network (NN) is another technique that has been employed for signal controllers. A fuzzy NN system is formulated via the Simultaneous Perturbation Stochastic Approximation (SPSA) algorithm to update the weight online [25]. Chao et al. propose an intelligent traffic light control strategy based on extension neural network theory for isolated intersection [132]. However, NN-based methods need to consider appropriate number of layers and neurons, also, they are not easily adjustable when new traffic situation occurs. Moreover, Fuzzy Logic (FL) is adopted in traffic signal control to mimic human thinking or experts' knowledge when the mathematical model is very difficult to formulate [133][134]. The CA mechanism with particle swarm optimization method is proposed to solve traffic light scheduling problem [135]. Also, a CA-based multi-intersection model representing the evolution of the traffic network is developed to reduce the traffic pressure [136].

Traffic signal control for pedestrian networks are seldom mentioned in the literature, which could be partially due to the uncontinuity of pedestrian flows in different intersections, in contrast to vehicle flows in an urban network. However, with the

common adoption of GPS-enabled mobile devices for pedestrian applications, the establishment of pedestrian networks become possible by mobile users' volunteered data collections [74]. The current routes of navigation services are based on road networks and do not include off-road walking paths [75]. Once pedestrian network databases are publicly available like those for road networks, the study on traffic signal control of pedestrian networks will be an indispensable part of the overall traffic network control.

Although there are many studies on vehicle traffic light control, inevitable issues in urban traffic control, such as coordinating network-based pedestrian and vehicle flows, have not been adequately addressed. Hence, this study proposes a quantitative criterion for selecting suitable phase patterns for an entire network based on current mixed traffic demands to efficiently make a trade-off between pedestrians and vehicles. Specifically, we firstly establish a macroscopic pedestrian "hopping" model at an intersection, which describes flow dynamics via logic constraints and is capable of reflecting the changing capacity during one time interval resulted from the crosswalk length and pedestrian relatively lower speed. By considering drivers' psychological response to traffic signal states, a network-based vehicle flow model is adopted. Both pedestrian performance and vehicle performance are integrated together via a weighted sum method, which could be translated into monetary values for economic considerations or delay costs for efficiency evaluation. Simulation-based experiment studies are carried out to illustrate the usefulness of our proposed solution.

2.2 Formulation of the Traffic Light Scheduling for Pedestrian-Vehicle Mixed-Flow Networks

This section first give the representation of the network, then elaborately provides the formulation of our problem of traffic light scheduling for pedestrian-vehicle mixed-flow networks.

2.2.1 Network Representation

An urban traffic network consists of a set of road links $L \in \mathcal{L}$ and intersections $J \in \mathcal{J}$. Our proposed mixed-flow network consists of a vehicle network and pedestrian crossing in each intersection. Note that developing a complete pedestrian network with consideration of different route infrastructures, e.g, footpath, arcade and crosswalk, is not a straight-forward task, so we only consider a Pedestrian Crossing Model (PCM) around the intersection, which could be indirectly connected to PCMs in other intersections by vehicle flow network, and we assume that there are

To simplify our presentation, we make the following assumptions: 1.The pedestrian demands and diversion ratios (α and β) in one specific corner are known, where $\alpha + \beta = 1$. 2.The departure ratio γ , which denotes the ratio of leaving pedestrians in each corner, is known. 3.The network boundary demands for entrance and exit are known. 4.The link turning ratios of the network are known.

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2.2.2 Problem Description and Model Formulation

To better describe the network model, the parameters and decision variables used in our optimization model are summarized in Table 2.1. And if the variables described below are attached with J on the upper right position, it means that these parameters are associated with intersection J .

2.2.2.1 Constraints for pedestrian volume dynamics

Let i ($i \in \mathcal{W}$) be the index of corners in the anticlockwise direction at an intersection as shown in Fig. 2.1, namely, $i = \{1, 2, 3, 4\}$, and j_h (j_v) is the index of adjacent corners that provide pedestrian flows in horizontal (vertical) directions, then j_h and j_v follow the rule below: $j_h = \begin{cases} i+1 & i \in \{1, 3\} \\ i-1 & i \in \{2, 4\} \end{cases}$ $j_v = \begin{cases} j_h+2 & i \in \{1, 2\} \\ j_h-2 & i \in \{3, 4\} \end{cases}$ The sources of pedestrians at corner i are classified into three types: (1) pedestrians from its adjacent corner j_h , (2) from its adjacent corner j_v and (3) pedestrians from other places who have not crossed the road at this intersection and have just entered the shaded corner i waiting to cross. Similarly, the outputs of pedestrians at corner i are also classified into three types: (1) pedestrians who want to go to corner j_h , (2) who want to go to corner j_v and (3) those who have already crossed, reached their destination and do not want to cross anymore, and the third component of outputs is part of the first two components of sources which is specified by the departure ratio $\gamma_i(k)$. The incoming flow from each adjacent corner can be divided into two groups: group I regards corner i as their destination corner, and they will leave the crossing system as they reach the corner, while group II regards corner i as their transfer corner, and they still need to wait to make a second crossing via the other crosswalk. $\gamma_i(k)$ describes the proportion between the number of pedestrians in group I and the number of pedestrians who just arrive the corner i (the sum of group I and group II) during time interval k . The properties above can be captured by the following equations:

$$(\forall k \in \mathbb{N})(\forall i \in \mathcal{W})$$

$$P_i(k+1) = P_i(k) + \Delta(d_i^p(k) - s_i^p(k)) \quad (2.3a)$$

$$d_i^p(k)\Delta = I_i(k) + \sum_{(j,i) \in \cup_{J \in \mathcal{J}} \mathcal{F}_p^J} f_{ji}^p(k) \quad (2.3b)$$

$$s_i^p(k)\Delta = \sum_{(i,j) \in \cup_{J \in \mathcal{J}} \mathcal{F}_p^J} f_{ij}^p(k) + \left\lfloor \gamma_i(k) \sum_{(j,i) \in \cup_{J \in \mathcal{J}} \mathcal{F}_p^J} f_{ji}^p(k) \right\rfloor \quad (2.3c)$$

where $\lfloor \cdot \rfloor$ is the largest integer not greater than the input argument. The above equations are the extended conservation law for the waiting pedestrians at signalized intersections. Although the relationship shown above is deterministic, it tries to

Table 2.1: Notations for model variables

Parameter	Definition
Δ	Duration of each time interval.
i, j	The index of waiting zones (corners) in the anticlockwise direction at an intersection as shown in Fig. 2.1, or the index of one specific road link.
$\mathcal{L}$	A set of links.
$\mathcal{J}$	A set of intersections.
J	One specific intersection, $J \in \mathcal{J}$.
$\mathcal{L}^J$	The set of links connected with intersection J .
Ω_p^J	A set of phases which control pedestrian flows in intersection J .
Ω_v^J	A set of phases which control vehicle flows in intersection J .
Ω^J	A set of phases in intersection J , $\Omega^J = \Omega_p^J \cup \Omega_v^J$.
o	One specific phase, $o \in \Omega^J$.
$\theta_o(k)$	Traffic light state in associated phase o during time interval k , $\theta_o(k) = 0$ and $\theta_o(k) = 1$ denote the RED and GREEN traffic lights, respectively.
$f_{ij}^p(k)$	The number of pedestrians going from corner i to corner j during time interval k , $i \in \mathcal{W}$, $j \in \mathcal{W}$.
$f_{ij}^v(k)$	The number of vehicles driving from link i to link j during time interval k .
$P_i(k)$	The number of pedestrians waiting to cross the street in corner i at time instant k .
$\hat{P}_o(k)$	The capacity of the crosswalk associated with phase o during time interval k .
$\hat{P}_i$	The maximum volume of corner i .
$C_i(k)$	The number of vehicles in link i at time instant k .
$\hat{C}_i$	The maximum volume of link i .
$s_i^p(k)$	The pedestrian outgoing rate of corner i in each time interval k .
$s_j^v(k)$	The vehicle outgoing rate of link j in time interval k .
$d_i^p(k)$	The pedestrian incoming rate of corner i in each time interval k .
$d_j^v(k)$	The vehicle incoming rate of link j in time interval k .
$I_i(k)$	The number of incoming pedestrians of corner i without using crosswalk during time interval k , $I_i(k)$ is part of $d_i^p(k)$.
$\eta_{ij}(k)$	The pedestrian diversion ratio from corner i to corner j at time instant k , $\eta \in \mathcal{H} = \{\alpha, \beta\}$, where α is the horizontal diversion ratio from corner i to corner j_h , β is the vertical diversion ratio from corner i to corner j_v .
$\gamma_i(k)$	Pedestrians departure ratio at corner i at time instant k , which is applied on the incoming flow of corner i , aiming at those who have already used crosswalk and reached destination.
$\lambda_{ij}(k)$	Turning ratio of vehicles in link i towards link j during time interval k , $\sum_{j \in \mathcal{L}: (i,j) \in \cup_{J \in \mathcal{J}} \mathcal{F}_v^J} \lambda_{ij}(k) = 1$.
H_p	Prediction horizon, $H_p = N\Delta$, where N is the prediction steps.

reflect the average effect of the real system with the stochastic nature, and the similar approach can also be found in many model-based optimization method [39][96].

2.2.2.2 Constraints for pedestrian crossing flow

Unlike roadways where vehicle flows connected by links, the topology structure of the pedestrian waiting zones around the intersection are four isolated areas connected by crosswalks, and the crosswalk cannot be neglected in pedestrian modelling since the relatively lower speed of the pedestrians. Additionally, the essence of our adaptive control strategy is a real-time signal timing optimization algorithm, the traditional concepts of cycle time, splits and offsets, which are inherent in existing signal optimization methods, will not appear in our adaptive algorithm. Instead, the optimal policy, a set of GREEN and RED sub-sequences with various lengths, is calculated for the entire prediction horizon in order to minimize our cost function, but only implemented the head section without degrading the performance of the optimization procedure. The optimized switching times of the GREEN-RED sequences are based on our pedestrian flow model, and we must guarantee that pedestrians on crosswalks should all be cleared at the end of each GREEN sub-sequence, and each GREEN sub-sequence is composed of several continuous GREEN time intervals. In view of the two problems illustrated above, the concept of the hopping, which satisfy both the topology structure of the pedestrian waiting zones and the clearance mechanism at the end of each GREEN sub-sequence, will be clearly discussed in the following content.

The empirical model proposed by Virkler et al. [143] conducted 304 observations for two-way crossings to investigate the crossing time of pedestrian platoons, and they found that both the platoon size and the size of the opposing platoon will not affect the crossing time for the front of the platoon, while the crossing time for the rear of a platoon is affected by the size of the primary platoon but not significantly affected by the opposing platoon size. Moreover, the crossing time for pedestrian platoons, which is also recorded in HCM 2010 [78], was found after several regression analyses:

$$T = \begin{cases} I + \frac{L}{S_p} + 0.27N_{ped}, & \text{if } W \leq 3m \\ I + \frac{L}{S_p} + 0.81\frac{N_{ped}}{W}, & \text{if } W > 3m \end{cases} \quad (2.4)$$

where T is the total crossing time (s), I is the start-up time (s) and usually is 3.2s, L is the length of crosswalk (m), W is the width of crosswalk (m), S_p is the average walking speed (m/s), and N_{ped} is the size of the pedestrian platoon. The equation (2.4) indicates that the minimum time for N_{ped} pedestrians successfully reaching the other curb under a certain length and width of the crosswalk. We can slightly

change the form of the equation (2.4):

$$N_{ped} = \begin{cases} \left\lfloor \frac{T-I-\frac{L}{S_p}}{0.27} \right\rfloor, & \text{if } W \leq 3m \\ \left\lfloor \frac{(T-I-\frac{L}{S_p})W}{0.81} \right\rfloor, & \text{if } W > 3m \end{cases} \quad (2.5)$$

The equation (2.5) indicates that if the length and width of the crosswalk is L and W , and the allowable passing time is T , the number of pedestrians successfully finish crossing can be up to N_{ped} . Owing to the discrete characteristics of our model, we can set the crossing time T as integer times of the sampling interval period Δ : we use $N_{ped,n\Delta}$ to represent N_{ped} if $T = n\Delta$, which describes the capacity for successfully crossing pedestrians when the length of time is $n\Delta$. Then the difference between $N_{ped,(n+1)\Delta}$ and $N_{ped,n\Delta}$ can be obtained as $\frac{\Delta}{0.27}$ if $W \leq 3m$ or $\frac{\Delta W}{0.81}$ if $W > 3m$, which is actually the capacity for successfully crossing pedestrians at the last sampling period Δ of time duration $(n+1)\Delta$, and this value is larger than $N_{ped,\Delta}$, which is the capacity at the first sampling period Δ of time duration $(n+1)\Delta$, and this is due to the pedestrians' characteristics (I and S_p) and crosswalk structures (W and L). Therefore, corresponding capacity for pedestrian successfully finish crossing during each time interval Δ can be obtained by equation (2.5) according to the state of the traffic light.

1. If $W \leq 3m$,

$$\hat{P}_o(k) = \begin{cases} \left\lfloor \frac{\Delta-I-\frac{L}{S_p}}{0.27} \right\rfloor, & \text{if } (k=1) \vee (\theta_o(k-1)=0) \\ \left\lfloor \frac{\Delta}{0.27} \right\rfloor, & \text{if } \theta_o(k-1)=1 \end{cases} \quad (2.6)$$

2. If $W > 3m$,

$$\hat{P}_o(k) = \begin{cases} \left\lfloor \frac{(\Delta-I-\frac{L}{S_p})W}{0.81} \right\rfloor, & \text{if } (k=1) \vee (\theta_o(k-1)=0) \\ \left\lfloor \frac{\Delta W}{0.81} \right\rfloor, & \text{if } \theta_o(k-1)=1 \end{cases} \quad (2.7)$$

The equation (2.6) and (2.7) illustrate that the capacity for successfully crossing pedestrians in current GREEN time interval depends on the previous time interval: if the previous time interval is RED, then the capacity is a small value, otherwise, the capacity is a large value. At the beginning of each simulation, we assume the previous signal state is RED, so the capacity is a small value when $k = 1$. The reason why capacity during one time interval Δ changes is the start-up time I and

the time spending on crosswalk $\frac{L}{S_p}$ appeared in equations (2.4)-(2.7). When the previous traffic signal state is RED, namely, $\theta_o(k-1) = 0$, there are no pedestrians on the crosswalk at the start of current GREEN time interval ($\theta_o(k) = 1$), however, when the previous traffic signal state is GREEN ($\theta_o(k-1) = 1$), pedestrians are walking on the crosswalk at the start of current GREEN time interval if there are sufficient demand on the waiting zone, accordingly, the capacity for the latter must be larger than the former. In other word, we can regard the changing of capacities due to the changing states of the traffic light, namely, traffic light states could also influence the flow dynamics, which means our system follows not only a time-driven paradigm but also an event-driven paradigm (traffic light states). And we model this influence from events into equations (2.6) and (2.7).

The specific hopping flow can be described as:

$$f_{ij}^p(k) = \min_{o \in \Omega_p^J: (i,j) \in h_p^J(o)} \{\hat{P}_o(k), \lfloor P_i(k)\eta_{ij}(k) \rfloor, \hat{P}_j - P_j(k)\} \quad (2.8)$$

The equation above indicate that the outgoing hopping flow is determined by the capacity $\hat{P}_o(k)$ of current time interval, the demand in corner i at time instant k , $P_i(k)\eta_{ij}(k)$, and the remaining space of the waiting zone j , $\hat{P}_j - P_j(k)$. Because our signal scheduling is an on-line optimization strategy, the optimized signal setting can be obtained in advance, so the Flashing GREEN can be activated several seconds (time for one person to cross the road successfully) before the switching time from GREEN to RED. And we do not consider pedestrian non-compliance behavior in this chapter, namely, we assume that pedestrians in waiting zones will all stop to cross once the traffic light turns Flashing GREEN. In real situations, pedestrians may speed up and cross the road during the Flashing GREEN period, then the actual arrival pedestrians in other curb may be larger than our assessment. This requires to consider the relationship among pedestrian compliance rate, pedestrian volume and remaining Flashing GREEN time, which is discussed in next chapter.

2.2.2.3 Constraints for link dynamics and vehicle flow dynamics

According to the conservation of vehicles, the dynamic of each link follows the rule:

$$(\forall k \in \mathbb{N}) C_j(k+1) = C_j(k) + \Delta(d_j^v(k) - s_j^v(k)) \quad (2.9)$$

$$f_{ij}^v(k) = \min\{\lfloor \lambda_{ij}(k)C_i(k) \rfloor, \hat{C}_j - C_j(k), \lfloor l_{ij}(k)v_i^*d^*n\Delta \rfloor\} \quad (2.10)$$

Incoming flow $d_j^v(k)$ and outgoing flow $s_j^v(k)$ can be captured by the following equations:

$$d_j^v(k)\Delta = \sum_{j \in \mathcal{L}: (i,j) \in \cup_{J \in \mathcal{J}} \mathcal{F}_v^J} f_{ij}^v(k) \quad (2.11a)$$

$$s_j^v(k)\Delta = \sum_{j \in \mathcal{L}: (j,i) \in \cup_{J \in \mathcal{J}} \mathcal{F}_v^J} f_{ji}^v(k) \quad (2.11b)$$

The flow dynamics constraint described in Condition (2.10) indicate that the outgoing flow $f_{ij}^v(k)$ is determined by the current upstream volume $\lambda_{ij}(k)C_i(k)$ of link i , the downstream remaining space $\hat{C}_j - C_j(k)$, and the capacity from link i to link j in one time interval, which is captured by the critical speed v^* , critical density d^* , time interval Δ , lane number n and the speed category $l_{ij}(k)$. We construct the outflow $f_{ij}^v(k)$ within each time interval as a nonlinear mixed logical switching function over the upstream link's density, the downstream link's density and capacity, and the drivers' psychological behavior respond to the past continuous state of traffic lights.

The intention of the psychological response is that drivers are more likely to keep a high speed $v_{ij}(k)$ if the phase o has been active for the past r intervals and the downstream link has sufficient space to receive the flow. Thus the corresponding speed is $v_{ij}(k) = l_{ij}(k)v^*$, where the speed category $l_{ij}(k)$ can be approximated by a set of discrete speed levels: $l_{ij}^0 \geq \dots \geq l_{ij}^r > 0$ as follows:

$$l_{ij}(k) = \sum_{m=0}^r \delta_{ij}^m(k) l_{ij}^m \quad (2.12a)$$

$$\sum_{m=0}^r \delta_{ij}^m(k) l_{ij}^m - \theta_o(k) = 0 \quad (2.12b)$$

$$(\forall q \in [0, r-1]) \quad (1 - \theta_o(k-q-1)) \prod_{m=0}^q \theta_o(k-m) = 1 \Leftrightarrow \delta_{ij}^{r-q}(k) = 1 \quad (2.12c)$$

$$\prod_{m=0}^r \theta_o(k-m) = 1 \Leftrightarrow \delta_{ij}^0(k) = 1 \quad (2.12d)$$

$$(\forall m \in [0, r]) \quad \delta_{ij}^m(k) \in \{0, 1\} \quad (2.12e)$$

Condition (2.12b) indicates that all $\delta_{ij}^m(k) = 0$ if the traffic light of phase o is RED, then from Condition (2.12a), $l_{ij}(k) = 0$. If the traffic light of stage o is GREEN, then $l_{ij}(k)$ can only choose one speed level l_{ij}^m determined by the following Conditions (2.12c)-(2.12d), which indicate that the actual speed can be obtained when looking back the number of consecutive green light intervals from current interval k . The larger the number of consecutive green light intervals, the higher the speed category. We also conducted road tests on this part, which preliminarily validate our proposed flow dynamics model, and the relevant contents are shown in [144], which are based on Singapore transportation systems.

2.2.2.4 Constraints for conflict flows between pedestrians and vehicles

The conflict happens when GREEN traffic light is assigned for both pedestrian flows and turning vehicle flows. Some literatures are conducted to investigate the pedestrian delay caused by vehicular platoon [145][146]. As our traffic signal scheduling problem is developed by a discrete-time macroscopic model-based optimization approach, we can only restrict the successfully passing flow during each time interval. Also, considering probability analysis and gap acceptance, which is at the category of microscopic simulation model, will make our network-based optimization problem far more complex. Additionally, in road traffic rules [147]: “The driver of every vehicle approaching a pedestrian crossing shall, unless he can see that there is no pedestrian thereon, proceed at such speed as will enable him to stop his vehicle before reaching the crossing.”

In view of this, the priority rule is constructed to deal with the conflict between pedestrian flows and vehicle turning flows. During each time interval, only if the pedestrians are all cleared so that the corresponding vehicle flow can pass the conflict area. We use h_{pv}^J to denote association of each pedestrian flow to relevant conflict vehicle flows. $h_{pv}^J : \mathcal{F}_p^J \rightarrow \mathcal{F}_v^J$.

$$\begin{aligned} &(\forall o \in \Omega^J, (i, j)^p \in h_p^J(o), (i, j)^v \in h_v^J(o), f_{ij}^v(k) \in h_{pv}^J(f_{ij}^p(k))), \\ &\theta_o(k) = 1 \wedge f_{ij}^p(k) \neq 0 \Rightarrow f_{ij}^v(k) = 0 \end{aligned} \quad (2.13)$$

Equation (2.13) indicates that once the traffic signal phase o is chosen, namely, its traffic signal state $\theta_o(k) = 1$, and if the pedestrian flow $f_{ij}^p(k)$ is not cleared, then corresponding conflict vehicle flow $f_{ij}^v(k)$ must be zero.

2.2.2.5 Constraints for adaptive signal setting

In any time interval k , only one phase for an intersection J could be active, which can be described as follows:

$$\sum_{o \in \Omega^J} \theta_o(k) = 1 \quad (2.14a)$$

$$(\forall o \in \Omega^J) \theta_o(k) = 0 \Rightarrow (\forall (i, j) \in h_{p/v}^J(o)) f_{ij}(k) = 0 \quad (2.14b)$$

$$(\forall o \in \Omega^J)(\forall k \in \mathbb{N}) \theta_o(k) \in \{0, 1\} \quad (2.14c)$$

where $\mathbb{N}$ denotes the set of natural numbers, $h_{p/v}^J(o)$ means $h_p^J(o)$ or $h_v^J(o)$. Equation (2.14a) indicates that only one phase is GREEN and the others are all RED for one specific intersection J at time interval k . Equation (2.14b) illustrates that all associated flows with stage o are zero if the stage traffic light is RED. Also, $f_{ij}(k)$ can be pedestrian flows or vehicle flows, which is determined by the phase setting.

2.2.2.6 Optimal objective function for our mixed-flow network model

The general purposes for traffic signal control on a congested network are to maximize the total system throughput, to reduce travel time for all travelers or to minimize the queue length of entire network. In our study, we constantly select the optimal phase patterns for different intersections in order to maximize the total system throughput. In another way, our goal is to minimize all travelers remaining in the system during a time window. By multiplying time interval Δ , cost functions which capture the total delay time for pedestrians and vehicles in the entire network within N time intervals can be formulated as follows, respectively:

$$V_D = \sum_{J \in \mathcal{J}} \sum_{k=1}^N \sum_{i \in \mathcal{L}^J} [C_i(k) - \sum_{i \in \mathcal{L}^J: (i,j) \in \cup_{J \in \mathcal{J}} \mathcal{F}_v^J} f_{ij}^v(k)] \Delta \quad (2.15a)$$

$$P_D = \sum_{J \in \mathcal{J}} \sum_{k=1}^N \sum_{i \in \mathcal{W}^J} [P_i^J(k) - \sum_{i \in \mathcal{W}^J: (i,j) \in \cup_{J \in \mathcal{J}} \mathcal{F}_p^J} f_{ij}^p(k)] \Delta \quad (2.15b)$$

Note that since vehicles and pedestrians are two different type of traffic demands, simply sum them together as our cost function does not satisfy the measurement standard for two different objects. Accordingly, we provide different weights on both sides as our efficiency performance index.

$$\begin{aligned} U_D = & \sum_{J \in \mathcal{J}} [C_v^J (\sum_{k=1}^N \sum_{i \in \mathcal{L}^J} [C_i(k) - \sum_{i \in \mathcal{L}^J: (i,j) \in \cup_{J \in \mathcal{J}} \mathcal{F}_v^J} f_{ij}^v(k)] \Delta) \\ & + C_p^J (\sum_{k=1}^N \sum_{i \in \mathcal{W}^J} [P_i^J(k) - \sum_{i \in \mathcal{W}^J: (i,j) \in \cup_{J \in \mathcal{J}} \mathcal{F}_p^J} f_{ij}^p(k)] \Delta)] \end{aligned} \quad (2.16)$$

where C_v^J and C_p^J are weight coefficients for vehicles and pedestrians at intersection J , respectively. We could give different meaning on weight coefficients, such as monetary value for economic considerations or delay costs for efficiency evaluation. The quantity of C_v^J and C_p^J could reflect the priority level among different intersections, also, the priority level between pedestrians and vehicles in one specific intersection. For those vital intersections with large traffic volumes, higher weights should be allocated, while in some shopping areas, pedestrian connectivity largely determines the job effective density, which has a strong relationship with the economic productivity [148][149], we should provide higher C_p^J rather than C_v^J for those intersections.

2.3 Solution Algorithms

2.3.1 A MILP Formulation for Network Total Delay

So far we have derived our pedestrian-vehicle mixed-flow optimization problem as a linear cost function (2.16) with its associated constraints which depict priority rules (2.13), traffic light compatibility (2.14a)-(2.14c), pedestrian volume dynamics (2.3a)-(2.3c), capacity limitation (2.6) or (2.7), pedestrian hopping flow constraint (2.8), vehicle volume dynamics (2.9), vehicle flow constraints (2.10) and (2.11), and vehicle speed level constraints (2.12). Conversion of vehicle mixed-logical constraints is omitted here, which has formally established in [150]. Among all the remaining constraints, (2.13), (2.14b), (2.3), (2.6), (2.7) and (2.8) can be converted into mixed integer linear constraints. Equations (2.3) can be rewritten as:

$$P_i(k+1) - P_i(k) + \sum_{(i,j) \in \cup_{J \in \mathcal{J}} \mathcal{F}_p^J} f_{ij}^p(k) \leq I_i(k) + (1 - \gamma_i(k)) \sum_{(j,i) \in \cup_{J \in \mathcal{J}} \mathcal{F}_p^J} f_{ji}^p(k) \quad (2.17a)$$

$$P_i(k+1) - P_i(k) + \sum_{(i,j) \in \cup_{J \in \mathcal{J}} \mathcal{F}_p^J} f_{ij}^p(k) - \epsilon \geq I_i(k) + (1 - \gamma_i(k)) \sum_{(j,i) \in \cup_{J \in \mathcal{J}} \mathcal{F}_p^J} f_{ji}^p(k) - 1 \quad (2.17b)$$

Proposition 2.1 *Replacing Equation (2.3) with Inequalities (2.17) in the model leads to the same solution.*

Equation (2.6) and (2.7) can be translated into the following constraints by introducing binary variable δ_o :

$$\delta_o = 1 \iff k = 1 \quad (2.18a)$$

Then the logic relationship above can be rewritten as:

$$M_1(\delta_o - 1) \leq k - 1 \leq M_1(1 - \delta_o) \quad (2.19a)$$

$$\hat{P}_o(k) - n(\Delta - I - \frac{L}{S_p}) \leq M_1(1 - \delta_o) \quad (2.19b)$$

$$- \hat{P}_o(k) + n(\Delta - I - \frac{L}{S_p}) - 1 \leq M_1(1 - \delta_o) - \epsilon \quad (2.19c)$$

$$\hat{P}_o(k) - n(\Delta - I - \frac{L}{S_p}) \leq M_1\theta_o(k - 1) \quad (2.19d)$$

$$- \hat{P}_o(k) + n(\Delta - I - \frac{L}{S_p}) - 1 \leq M_1\theta_o(k - 1) - \epsilon \quad (2.19e)$$

$$\hat{P}_o(k) - n\Delta \leq M_1(1 - \theta_o(k - 1)) \quad (2.19f)$$

$$- \hat{P}_o(k) + n\Delta - 1 \leq M_1(1 - \theta_o(k - 1)) - \epsilon \quad (2.19g)$$

where $n = \frac{1}{0.27}$ if crosswalk width W is smaller and equal to 3m, otherwise, $n = \frac{W}{0.81}$. M_1 is a sufficiently big integer, e.g., $M_1 \geq \max_k(H_p, \pm(\hat{P}_o(k) - n(\Delta - I - \frac{L}{S_p})), \pm(\hat{P}_o(k) - n\Delta))$, and ϵ is sufficiently small.

Proposition 2.2 *Replacing Equation (2.6) or (2.7) with Inequalities (2.19) in the model leads to the same solution.*

Equation (2.8) can be translated into the following constraints by introducing binary variables $\rho_o^1(k)$, $\rho_o^2(k)$ and $\rho_o^3(k)$:

$$\rho_o^1(k) = 1 \iff P_i(k)\eta_{ij}(k) \leq \hat{P}_o(k) \quad (2.20a)$$

$$\rho_o^2(k) = 1 \iff P_i(k)\eta_{ij}(k) \leq \hat{P}_j - P_j(k) \quad (2.20b)$$

$$\rho_o^3(k) = 1 \iff \hat{P}_o(k) \leq \hat{P}_j - P_j(k) \quad (2.20c)$$

Then the above logic relationship can be rewritten as:

$$P_i(k)\eta_{ij}(k) - \hat{P}_o(k) \leq M_2(1 - \rho_o^1(k)) \quad (2.21a)$$

$$P_i(k)\eta_{ij}(k) - \hat{P}_o(k) \geq \epsilon + (-\epsilon - M_2)\rho_o^1(k) \quad (2.21b)$$

$$P_i(k)\eta_{ij}(k) - (\hat{P}_j - P_j(k)) \leq M_2(1 - \rho_o^2(k)) \quad (2.21c)$$

$$P_i(k)\eta_{ij}(k) - (\hat{P}_j - P_j(k)) \geq \epsilon + (-\epsilon - M_2)\rho_o^2(k) \quad (2.21d)$$

$$\hat{P}_o(k) - (\hat{P}_j - P_j(k)) \leq M_2(1 - \rho_o^3(k)) \quad (2.21e)$$

$$\hat{P}_o(k) - (\hat{P}_j - P_j(k)) \geq \epsilon + (-\epsilon - M_2)\rho_o^3(k) \quad (2.21f)$$

With the relationship developed above, we can restrict our flow as follows:

$$\rho_o^1(k) = 1 \wedge \rho_o^2(k) = 1 \iff f_{ij}^p(k) = P_i(k)\eta_{ij}(k) \quad (2.22a)$$

$$\rho_o^1(k) = 0 \wedge \rho_o^3(k) = 1 \iff f_{ij}^p(k) = \hat{P}_o(k) \quad (2.22b)$$

$$\rho_o^2(k) = 0 \wedge \rho_o^3(k) = 0 \iff f_{ij}^p(k) = \hat{P}_j - P_j(k) \quad (2.22c)$$

Then the above logic relationship can be rewritten as:

$$f_{ij}^p(k) - P_i(k)\eta_{ij}(k) \leq M_2(1 - \rho_o^1(k)) + M_2(1 - \rho_o^2(k)) \quad (2.23a)$$

$$- f_{ij}^p(k) + P_i(k)\eta_{ij}(k) \leq M_2(1 - \rho_o^1(k)) + M_2(1 - \rho_o^2(k)) \quad (2.23b)$$

$$f_{ij}^p(k) - \hat{P}_o(k) \leq M_2\rho_o^1(k) + M_2(1 - \rho_o^3(k)) \quad (2.23c)$$

$$- f_{ij}^p(k) + \hat{P}_o(k) \leq M_2\rho_o^1(k) + M_2(1 - \rho_o^3(k)) \quad (2.23d)$$

$$f_{ij}^p(k) - (\hat{P}_j - P_j(k)) \leq M_2\rho_o^2(k) + M_2\rho_o^3(k) \quad (2.23e)$$

$$- f_{ij}^p(k) + (\hat{P}_j - P_j(k)) \leq M_2\rho_o^2(k) + M_2\rho_o^3(k) \quad (2.23f)$$

where M_2 is a sufficiently big integer, e.g., $M_2 \geq \max_k(\pm(f_{ij}^p(k) - P_i(k)\eta_{ij}(k)), \pm(f_{ij}^p(k) - \hat{P}_o(k)), \pm(f_{ij}^p(k) - (\hat{P}_j - P_j(k))), \pm(P_i(k)\eta_{ij}(k) - \hat{P}_o(k)), \pm(P_i(k)\eta_{ij}(k) - (\hat{P}_j - P_j(k))), \pm(\hat{P}_o(k) - (\hat{P}_j - P_j(k))))$, and ϵ is sufficiently small.

Proposition 2.3 *Replacing Equation (2.8) with Inequalities (2.21) and (2.23) in the model leads to the same solution.*

Equation (2.13) can be translated into the following constraints by introducing binary variable $\delta_{ij}(k)$:

$$f_{ij}^p(k) \leq M_3\delta_{ij}(k) \quad (2.24a)$$

$$f_{ij}^v(k) \leq M_3(1 - \theta_o(k)) + M_3(1 - \delta_{ij}(k)) \quad (2.24b)$$

where M_3 chosen to be sufficiently big, e.g., $M_3 \geq \max_k(f_{ij}^p(k), f_{ij}^v(k))$.

Proposition 2.4 *Replacing Equation (2.13) with Inequality (2.24) in the model leads to the same solution.*

Let M_4 chosen to be sufficiently big, e.g., $M_4 \geq \max_k(f_{ij}(k))$, then equation (2.14b) can be translated into the following form:

$$(\forall o \in \Omega^J, \forall (i, j) \in h_{p/v}^J(o)) f_{ij}(k) \leq M_4\theta_o(k) \quad (2.25)$$

Proposition 2.5 *Replacing Equations (2.14b) with Inequality (2.25) in the model leads to the same solution.*

Finally, we can solve our traffic scheduling problem as a mixed integer linear programming problem: the objective function is equation (2.16) with phase constraints (2.14a) and (2.25), priority constraint (2.24), pedestrian constraints (2.17), (2.19), (2.21) and (2.23), and vehicle linear constraints in [150]. Then our problem can be solved by existing commercial solvers, e.g. GUROBI. In order to further improve the computational efficiency, we also consider an evolution algorithm - Harmony Search Algorithm.

2.3.2 Discrete Harmony Search Algorithm for Network Total Delay

Considering the NP-hardness of our MILP problem, many meta-heuristic optimization approaches have been developed in order to overcome the

computational deficiencies of mathematical techniques. Although the final result may not be the global optima, a good signal setting (near optimum) in real time is more urgently needed rather than the best solution with costly time.

The HS algorithm, mimicking the musical performance process to reach a perfect state of harmony, is one of meta-heuristic algorithms [151]. In the HS, three parameters play the major roles in obtaining the best 'harmony': Harmony Memory Size (HMS), Harmony Memory Considering Rate ($HMCR$) and Pitch Adjustment Rate (PAR). HMS defines the number of existed solution vectors in the Harmony Memory (HM), $HMCR$ is the rate of selecting the values from the HM and PAR sets the adjustment rate of the pitch from the HM . In discrete HS algorithm, the solution X_i is the i^{th} solution in the HM , and it is a n dimensional vector $X_i = \{X_i(1), X_i(2), \dots, X_i(n)\}$, which consists of n decision variables of the optimization problem.

Step 1 - Initialization

The element $X_i(k)$ of each harmony vector X_i in the HM can be generated as follows:

$$\begin{aligned} X_i(k) &= LB(k) + (UB(k) - LB(k)) * rand(), \\ \forall k &= 1, 2, \dots, n \quad \text{and} \quad \forall i = 1, 2, \dots, HMS \end{aligned} \quad (2.26)$$

where $LB(k)$ and $UB(k)$ are the lower bound and upper bound of the decision variable $X_i(k)$, respectively, and $rand()$ randomly generates value between 0 and 1.

Step 2 - Improvisation

The new harmony vector X_{new} is created by setting the HS parameters: $HMCR$, PAR and random selection. Firstly, if a random value $rand()$ in the range of $[0, 1]$ is less than $HMCR$, the decision variable $X_{new}(k)$ is randomly selected from any value in the HM , otherwise, $X_{new}(k)$ is generated according to the upper and lower bounds of the decision variable $X_i(k)$. After improvisation, the pitch adjustment with a probability of PAR is applied to the new harmony vector if this vector is selected from the current HM . The whole process is illustrated in Algorithm 1: BW is the bandwidth, which is defined to find possible neighborhood solutions, and $i \in \{1, 2, \dots, HMS\}$, $X_i(k)$ is randomly selected from HM .

Step 3 - Update and Stopping condition

After determining the objective function values in HM , the harmony vector which give the worst objective function value is removed from the HM . Next step is to check the termination criterion, e.g, the number of NI , once the predetermined criterion is met, the searching process is terminated, otherwise, go back to Step 2.

A four-phase pattern is discussed in case study 2.4.1, which is shown in Fig. 2.3. The specific process to obtain the optimal solution is illustrated in Algorithm 2.

Algorithm 1 Generating new harmony vector

If ($rand1() < HMCR$)

$$X_{new}(k) = X_i(k) \quad (2.27)$$

 If ($rand2() < PAR$)

$$X_{new}(k) = X_{new}(k) \pm rand() \times BW \quad (2.28)$$

 End

Else

$$X_{new}(k) = LB(k) + (UB(k) - LB(k)) \times rand() \quad (2.29)$$

End

Algorithm 2 The whole process to obtain the optimal solution

Set HMS and NI (the number of iterations).

Initialize harmony vectors with group size HMS : HM_1 .

For $i=1$ to NI

 Generate new harmony vectors with group size HMS : HM_2 .

 For $j=1$ to HMS

 Select two harmonies: $H_{1,j}$ and $H_{2,j}$ from HM_1 and HM_2 , respectively.

 Compare two harmonies: $H_{1,j}$ and $H_{2,j}$.

 If $H_{2,j}$ is better than $H_{1,j}$

 Replace $H_{1,j}$ by $H_{2,j}$ in HM_1 .

 End

 End

 Set BestSignal = $H_{1,1}$.

 For $j=2$ to HMS

 Compare two harmonies: BestSignal and $H_{1,j}$.

 If $H_{1,j}$ is better than BestSignal.

 Allocate $H_{1,j}$ to BestSignal.

 End

 End

End

2.4 Numerical Examples for Model Evaluation

2.4.1 Case Study - Pedestrian-Vehicle Mixed-Flow Network under Bidirectional Four-Phase Framework

In this case study we consider a pedestrian-vehicle mixed-flow network shown in Fig. 2.2. To illustrate the efficiency of our proposed model, we choose a four-phase signal setting in our simulation to investigate the interaction between pedestrians and vehicles, which is shown in Fig. 2.3. The network has n_h horizontal links per column and n_v vertical links per row, and the total number of intersections is $n_J = n_h n_v$. In the following tests, we apply our strategy on the network which has links and intersections all in the same topology, and the layout of each intersection follows the intersection connected by Jln Bahar Road and Jurong West Avenue in Singapore, which has four lanes at each arm and change to five lanes when approaching intersection (two lanes extend to three lanes when vehicle flows enter the intersection), and crosswalks with 15m-length and 3m-width. Parameters used in the case study are listed in Table 2.2. The pedestrian average speed and start-up time are taken from [143]. The critical vehicle speed and density are chosen below in order to meet the base saturation flow rate, 1900 veh/hour/lane [78]. The vehicle cost and pedestrian cost are all provided with the same importance in our case study, which could be modified in our future work once specific background is involved.

Figure 2.2: Layout of the traffic network and the intersection

2.4.1.1 Computational efficiency

In order to see the computational efficiency of our proposed model, we test our strategy with various network sizes and prediction horizons. After translating into a mixed integer linear programming problem, our urban traffic signal scheduling problem can be solved by an optimization solver. In our experiment, GUROBI [152] is used in MATLAB to solve the problem on a PC with an Intel(R) Xeon(R) CPU E5-2680 v3 @2.50GHz and RAM 64GB.

Figure 2.3: A four-phase pattern

Table 2.2: Parameters used in case study

Parameters	Descriptions	Associated Values
Δ	sampling period	20s
S_p	pedestrian average speed	1.2m/s
L	crosswalk length	15m
W	crosswalk width	3m
I	start-up time	3.2s
$\hat{C}_i$	maximum volume of link i	100
$\hat{P}_i$	maximum volume of corner i	150
l_{ij}^0	higher speed level	1.0
l_{ij}^1	lower speed level	0.7
v^*	critical vehicle speed	25 km/h
k^*	critical vehicle density	75 veh/lane/km
n	lane number near the intersection	3
L	link length	250m
C_v^J	vehicle cost	\$1
C_p^J	pedestrian cost	\$1

The Table 2.3 illustrates the potential complexity involved in solving this problem, which lists the total number of decision variables N_x and the total number of constraints N_{cons} with prediction steps $N = 5$ and $N = 10$ (prediction horizon $H_p = N\Delta$) under different network sizes. Clearly, we need to solve a large mixed integer linear programming problem for a large urban traffic network, so some efficient computational algorithms need to be considered.

By setting the total initial vehicle volume and pedestrian volume at 360 and 1440 with large vehicle turning ratio, we apply our mixed integer linear programming to the network with different sizes and different time horizons to check how fast the scheduling problem can be solved, and we tested cases of $n_v = n_h = 3, 4, 5, 6, 7, 8, 9, 10$ and $H_p = 20, 40, 60, 80$ seconds, respectively. Table 2.4 depicts the processing time of the proposed model associated with Table 2.3. The dash line in Table 2.4 means that MATLAB fails to run GUROBI due

Table 2.3: Numbers of decision variables and constraints

$n_v = n_h$	N=5		N=10	
	N_x	N_{cons}	N_x	N_{cons}
3	3834	8001	7584	15936
4	6784	14272	13424	28432
5	10570	22345	20920	44520
6	15192	32220	30072	64200
7	20650	43897	40880	87472
8	26944	57376	53344	114336
9	34074	72657	67464	144792
10	42040	89740	83240	179240

to memory insufficiency. In Table 2.4, we can see that GUROBI can solve the 10×10 junctions with a 20-second prediction horizon in only 0.3253 second, which is equivalent to solving a mixed integer linear programming problem with 9080 integer and binary decision variables and 18460 constraints. This is definitely workable in practical real-time scheduling environment, because only 1.6265% ($0.3253/20$) of the time is used for computation. However, when the network and prediction horizon become larger, the probability of successfully solving the scheduling problem in real time becomes lower. For example, a 8×8 network with a 60-second prediction horizon needs 1889.5 second to obtain a (near-)optimal signal profile, which has already reached approximately 95 times of the sampling period 20 second, so the computational challenge requires more efficient algorithms.

Table 2.4: Processing time of proposed model + MILP

$n_v = n_h$	$H_p = 20s$	$H_p = 40s$	$H_p = 60s$	$H_p = 80s$
3	0.0419	0.2813	1.9318	7.2363
4	0.0625	0.6971	70.852	184.8
5	0.0998	3.0202	100.48	269.1
6	0.1197	8.0069	166.13	-
7	0.1774	10.836	541.99	-
8	0.2069	10.638	1889.5	-
9	0.2679	14.545	-	-
10	0.3253	19.802	-	-

To cope with this challenge, a discrete harmony search algorithm discussed in Chapter 2.3.2 is used to solve the problem. The population size (Harmony Memory Size) is 30, the iteration times for each trial are 1000, and the trial times to obtain each near-optimal result are 30. Parameters $HMCR$ and PAR are set as 0.95 and 0.5, respectively. The sizes of the traffic grids are from 3×3 to 10×10 , and the prediction horizons are 20 seconds, 40 seconds and 60 seconds, respectively.

The comparison results between MILP and HS are shown in Table 2.5. By applying the optimal traffic signal settings obtained from MILP to the entire network, the actual delay times J^* are listed in the table, and the computed delay times J by applying near-optimal signals from HS are also listed in the table. Additionally,

we can see that the difference degree $\frac{J-J^*}{J^*}$ between delay times obtained from two different algorithms is very small. Although the gap between J and J^* become larger when both network size and prediction horizon increase, the difference degree is still below 25% for a 10×10 network with a 40-second prediction horizon. Certainly, the outcome quality will gradually decrease with the growth of the network size and prediction horizon. However, the computational times, refer to the second column of Table 2.5, significantly drop when applying HS algorithm, especially for the large traffic network with longer prediction horizon. For example, a 8×8 traffic system with 60s prediction horizon require 1889.5s in Table 2.4 to obtain the optimal solution by MILP. However, with the same scale setting, the HS algorithm only needs 6.7988s to get a solution, which has a 23.31% gap from the optimal solution. The above descriptions indicate that HS can provide a significant increase of efficiency meanwhile ensuring an acceptable degree of performance degradation.

Table 2.5: A comparison between computed and actual time delay for HS with MILP

Instance	$H_p = 20s$			
$n_v = n_h$	Processing Time	J	J^*	$\frac{J-J^*}{J^*}$
3	0.2985	1080	1080	0.00%
4	0.5286	1920	1920	0.00%
5	0.8220	3069	3000	2.30%
6	1.2154	4564	4320	5.65%
7	1.6712	6341	5880	7.84%
8	2.1723	8455	7680	10.09%
9	2.6715	10974	9720	12.90%
10	3.3102	13702	12000	14.18%
Instance	$H_p = 40s$			
$n_v = n_h$	Processing Time	J	J^*	$\frac{J-J^*}{J^*}$
3	0.6227	2418	2418	0.00%
4	1.1089	4197	3968	5.77%
5	1.7265	6775	6190	9.45%
6	2.4857	10092	8904	13.34%
7	3.3928	14125	12110	16.64%
8	4.4222	18826	15808	19.09%
9	5.6131	24357	19998	21.80%
10	6.9434	30387	24680	23.12%
Instance	$H_p = 60s$			
$n_v = n_h$	Processing Time	J	J^*	$\frac{J-J^*}{J^*}$
3	0.9517	3565	3540	0.71%
4	1.6864	6766	6272	7.88%
5	2.6245	11112	9780	13.62%
6	3.7874	16566	14064	17.79%
7	5.2253	23041	19124	20.48%
8	6.7988	30794	24972	23.31%
9	8.6450	39561	-	-%
10	10.684	49546	-	-%

2.4.1.2 Phase analysis with different traffic inputs

We consider a 3×3 traffic network and a total of 9 intersections are involved in the system. Since traffic volumes and its associated turning ratios are the major parameters which influence the optimal phase patterns of our proposed model, we conduct our simulation under various traffic volume inputs with different vehicle turning ratios. In our phase setting, only ϕ_2 and ϕ_4 allow all vehicle turning flows to pass, so we calculate the proportion of ϕ_2 and ϕ_4 among total four phase patterns to see how traffic inputs influence the optimal phase selection, which could further validate our model.

According to the traffic inputs described in Table 2.6, 18 cases are summarized and listed in Table 2.7. Table 2.8 indicates the proportion of ϕ_2 and ϕ_4 in optimized solutions from *Case 1* to *Case 9* with various traffic demands input and small vehicle turning ratios. Similarly, Table 2.9 shows the proportion of ϕ_2 and ϕ_4 in optimized solutions from *Case 10* to *Case 18* with various traffic demands input and large vehicle turning ratios.

Table 2.6: Traffic volumes and vehicle turning ratios

Volume in System	Total Vehicles	Total Pedestrians	
Lower Traffic Volume	360	540	
Modest Traffic Volume	540	720	
Higher Traffic Volume	1080	1440	
Vehicle Flow Ratio in System	Turn left, Go straight, Turn right		
Small Turning Ratio	0.2	0.6	0.2
Large Turning Ratio	0.4	0.2	0.4

Table 2.7: Traffic volumes in different cases

Case No.	Total Vehicles	Total Pedestrians	Vehicle Flow Ratios
<i>Case 1</i>	360	540	0.2 0.6 0.2
<i>Case 2</i>	360	720	0.2 0.6 0.2
<i>Case 3</i>	360	1440	0.2 0.6 0.2
<i>Case 4</i>	540	540	0.2 0.6 0.2
<i>Case 5</i>	540	720	0.2 0.6 0.2
<i>Case 6</i>	540	1440	0.2 0.6 0.2
<i>Case 7</i>	1080	540	0.2 0.6 0.2
<i>Case 8</i>	1080	720	0.2 0.6 0.2
<i>Case 9</i>	1080	1440	0.2 0.6 0.2
<i>Case 10</i>	360	540	0.4 0.2 0.4
<i>Case 11</i>	360	720	0.4 0.2 0.4
<i>Case 12</i>	360	1440	0.4 0.2 0.4
<i>Case 13</i>	540	540	0.4 0.2 0.4
<i>Case 14</i>	540	720	0.4 0.2 0.4
<i>Case 15</i>	540	1440	0.4 0.2 0.4
<i>Case 16</i>	1080	540	0.4 0.2 0.4
<i>Case 17</i>	1080	720	0.4 0.2 0.4
<i>Case 18</i>	1080	1440	0.4 0.2 0.4

In order to clearly understand and visualize the meaning behind the data, we draw the graph shown in Fig. 2.4 via data in Tables 2.8 and 2.9. Dotted lines correspond

to Table 2.8 while solid lines correspond to Table 2.9, and the nodes shown in graph are the specific data listed in both Tables. Each line illustrates that the proportion of ϕ_2 and ϕ_4 reveal a downward trend with the increase of the pedestrian volume, this definitely conforms to the reality, when the pedestrian volume is increasing, phases which give the right way to pedestrians should certainly be increased to adapt to current demands, which accordingly leads to the decreasing of the other phases, in our case, are ϕ_2 and ϕ_4 . For *Case 1* to *Case 9*, dotted GREEN line (*Case 7* & *8* & *9*) is hovering above the dotted RED line (*Case 4* & *5* & *6*), which is also larger than the dotted BLUE line (*Case 1* & *2* & *3*), this is because the impacts from pedestrian side are dissipated by increasing vehicle volumes when the same pedestrian input is applied. For example, in the first-column nodes in dotted lines with lowest pedestrian volumes: three nodes have the same pedestrian volume 540, since the vehicle volumes are gradually increasing from 360 to 1080, the pedestrians' influence is accordingly decreasing, which results in the reduction of ϕ_1 and ϕ_3 , oppositely, an increased proportion of ϕ_2 and ϕ_4 . Similarly, this phenomenon could also be found in solid lines from *Case 10* to *Case 18* in Fig. 2.4. The reason solid lines are locating above the dotted lines is that the latter 9 cases all have larger vehicle turning ratios while the former 9 cases have relatively smaller vehicle turning ratios.

The data, shown in Tables 2.8 and 2.9, and the figure, shown in Fig. 2.4, all indicate that our proposed approach will change the signal setting strategy according to the traffic demands.

Table 2.8: The proportion of ϕ_2 and ϕ_4 in optimized phase patterns with small turning ratio

Proportion Value	Lower Pedestrian Volume	Modest Pedestrian Volume	Higher Pedestrian Volume
Lower Vehicle Volume	0.1056	0.0722	0.0000
Modest Vehicle Volume	0.1389	0.1222	0.0778
Higher Vehicle Volume	0.2000	0.1833	0.1333

Table 2.9: The proportion of ϕ_2 and ϕ_4 in optimized phase patterns with large turning ratio

Proportion Value	Lower Pedestrian Volume	Modest Pedestrian Volume	Higher Pedestrian Volume
Lower Vehicle Volume	0.3167	0.2056	0.1000
Modest Vehicle Volume	0.4167	0.3333	0.2389
Higher Vehicle Volume	0.5889	0.4444	0.3500

Figure 2.4: ϕ_2 and ϕ_4 proportions according to pedestrian volume

2.4.1.3 Delay comparison under different control strategies

To show the effectiveness of our proposed strategy, we utilize the commercial software Vissim to compare the traffic delay time between our method and the other two methods, which are developed from the deterministic queuing model. Vissim is a microscopic multi-modal traffic flow simulation software, which is an ideal tool to simulate traffic patterns, and Viswalk is one of its internal package used to simulate pedestrian flows. The first method (**M1**) proposed in [48] considers the conflict delay between pedestrians and turning vehicles. The second method (**M2**) proposed in [50] adopts the pedestrian delay function from Virkler's model [153]. Both **M1** and **M2** determine the optimal fixed-time traffic signal setting for pedestrians and vehicles via weighted-sum approach and all focus on a single intersection based on average historical flows. In order to compare with our network-based method, the connected average vehicle flows and pedestrian flows for each intersection are first extracted from the simulator - Vissim, then the optimal traffic signals are calculated for each intersection individually. The 3×3 traffic network built in Vissim and the layout of each intersection are shown in Fig. 2.5a and Fig. 2.5c, respectively. The communication of our method and the simulator is shown in Fig. 2.5b, where an on-line signal control is implemented.

We test three different methods via Vissim under the same OD pairs and the same random seed, which guarantee simulation runs with identical input files. After one-hour (3600s) simulation, the average delay for pedestrians and vehicles in each time interval Δ are extracted from the network performance results of Evaluation Menu in Vissim. Fig. 2.6 shows the average delay results for both pedestrians and vehicles under three different methods: The blue lines, green lines and red lines indicate the average delay cost by applying our methods, **M1** and **M2** with the increase of the simulation time, respectively. At the initial of the simulation, the delay is very lower since the quantity of both traffic participants in system are lower,

Figure 2.5: Integration of Matlab and Simulator and layout of the traffic network

which also leads to free-flow speed for vehicles. With the increase of the time, more and more vehicles and pedestrians are involving in the system, average delay during each time interval finally increased to a certain value and oscillate around this value. Clearly, our method outperforms both **M1** and **M2**, and the delay in **M1** or **M2** declines by approximately 35% if our method is applied.

We also test the pedestrian delay and vehicle delay separately under different objectives, namely, when equation (2.15a) is regarded as the performance index, the average delay for vehicles and pedestrians are drawn in Fig. 2.7 and Fig. 2.8 with red color, respectively. Also, when equation (2.16) is regarded as the performance index, the average delay for vehicles and pedestrians are drawn in Fig. 2.7 and Fig. 2.8 with blue color, respectively. Obviously, lower vehicle delay is obtained when only optimize vehicles, which is realized at the expense of pedestrians. However, this phenomenon can be alleviated when both participants are considered in the objective function.

Figure 2.6: Comparison of average delay cost for both pedestrians and vehicles under three different strategies

Figure 2.7: Average vehicle delay under two different performance objectives

2.4.2 Case Study - Weight Investigation on a Simplified Traffic Network Profile

In the case study 2.4.1, the performance weights allocated to pedestrians and vehicles are all known. If the weighted sum approach is adopted on traffic signal optimization between pedestrians and vehicles. However, an effective metric for pedestrians and vehicles haven't been determined, namely, the value of C_p and C_v , our strategy illustrated below could solve this problem from another perspective. If a complete library about the performance of pedestrians and vehicles when various weights on both sides are applied is developed, then with the performance we hope to reach, we can allocate corresponding weights to pedestrians and vehicles by checking the

Figure 2.8: Average pedestrian delay under two different performance objectives

library. The simulation below only considers the performance graph when weight on pedestrian side is changed, namely, our goal in this part is to see how the vehicle cost will be affected if we assign different priorities to the pedestrian side.

Note that this bidirectional four-phase framework involves large computational complexity and weight investigation needs to obtain the optimal result every time when the weight is changed, so we consider a traffic network with only two phases to simplify our problem but could also extend the basic findings to more realistic systems. Similar to the parameter setting in the first case study, the simplified traffic network only has traffic flows moving from the left to the right horizontally and from the top to the bottom vertically, accordingly, each junction only has two phases shown in Fig. 2.9. In order to reflect the more real effects from the pedestrian side to the entire integrated network, GUROBI [152] is also used in MATLAB to obtain the optimal solution.

In order to quantify the effects from pedestrians to vehicles in an range no matter how many traffic demands are involved, we slightly change the form of our cost function to keep both in the same magnitude. The approach we use to scale down objective functions is given as follow:

$$P_D^{trans} = \frac{P_D}{|P_D^{max}|} \quad (2.30)$$

$$V_D^{trans} = \frac{V_D}{|V_D^{max}|} \quad (2.31)$$

where P_D and V_D are our original pedestrian cost function (2.15a) and vehicle cost function (2.15b), respectively, and P_D^{max} and V_D^{max} are the absolute maximum of P_D and V_D respectively, which can be obtained by changing the direction of the objective functions (2.15) from min to max and calculate the optimal result. This approach

can effectively make the magnitudes of two different-scale problems comparable. Obtaining P_D^{max} and V_D^{max} is regarded as the input of our later simulation, and it only needs to be calculated once for each network size, so the computational time on calculating P_D^{max} and V_D^{max} is not our concern. Finally, the new cost function becomes $U_D = V_D^{trans} + mP_D^{trans}$.

The entire process is illustrated in Fig. 2.10. Before initializing the loop, we firstly calculate the optimal signals $\theta_{ped}(k)$ only contains the pedestrian network, which means our cost function is only P_D , and constraints (2.9), (2.10), (2.11), (2.12) and (2.13) are not involved in our optimization. Then at first step of the whole flow chart, the weight m on the pedestrian side is initialized as 0, the optimal signal result $\theta(k)$ is calculated only for the vehicle network. Next, the weight m is updated by adding one, then the optimal signal result $\theta_{new}(k)$ is obtained for the current objective function. At the third step, we compare the value of $\theta(k)$ and $\theta_{new}(k)$, and we will record the value of m as the turning weight if $\theta(k)$ and $\theta_{new}(k)$ are different, on the contrary, we compare $\theta(k)$ with $\theta_{ped}(k)$, and the comparison process is terminated if they are same, otherwise, we update m and calculate the optimal solution again. Also, $\theta(k)$, $\theta_{new}(k)$ and $\theta_{ped}(k)$ all represent traffic signal states for the entire network in the entire prediction horizon. After many trials on the increment of m , value 1 is chosen since a smaller increment could last long before the termination while larger increment may lead to information shortage. We test networks from 3 by 3 to 10 by 10 with 40s prediction horizon in our simulation. Table 2.10 and Table 2.11 show the state of the vehicle traffic light in 3×3 and 4×4 networks, respectively, 0 means the traffic light is RED and the corresponding horizontal flow is blocked, and 1 means the traffic light is GREEN and the corresponding vertical flow is blocked. The weights that we give in two Tables below are all the turning points, which are the values we recorded in Fig. 2.10, and these weights are exactly associated with the change of one or several vehicle traffic lights.

Figure 2.9: A simplified integrated urban traffic network

In order to better summarize our primary findings, we give the succeeding texts below:

1. The states of vehicle traffic signals for the integrated model are exactly the

Figure 2.10: The flow chart of obtaining turning weight points

same as the pure vehicle traffic model when the weight applying on the pedestrian side is 0.

2. With the increase of the weight value, the vehicle signal states begin to change, as shown in Table 2.10 and 2.11 (the specific change signals are highlighted). Finally, the transform process is finished and all the vehicle signal states are exactly the same as the pedestrian traffic signal states when only optimize a pedestrian model, after that, no matter how heavy the weight is, the vehicle signal states will not change at all.
3. The total vehicle delay presents a comprehensively rising trend as a whole, although vehicle delays may decrease at some turning weight points, e.g., vehicle delay ratio curve descend a bit when weight (x-axis) is near 20 for network 8 by 8, as shown in Fig. 2.12b. The total vehicle delay eventually becomes stabilized after completely converted to a pure pedestrian signal, meanwhile the total pedestrian delay drifts steadily downward until the minimum pedestrian delay is reached. Also, all changes are in step form, which is shown in Fig. 2.11 and Fig. 2.12.

Table 2.10: Pedestrian impact on vehicle side for network 3×3

Turning Weight m	0	2	3	4	5	8
First Time Interval	0 1 0	0 0 1	0 0 1	0 0 1	0 0 1	0 0 1
	1 0 1	1 1 0	1 1 1	1 1 1	1 1 1	0 1 1
	0 1 0	1 0 1	1 0 1	1 0 1	1 0 1	1 0 1
Second Time Interval	1 0 1	1 0 0	0 0 0	0 0 1	0 0 1	0 0 1
	0 1 0	0 1 1	0 1 1	0 1 1	1 1 1	0 1 1
	1 0 1	1 1 0	1 1 1	1 0 1	1 0 1	1 0 1

Choosing a suitable weight is very difficult in order to balance both vehicles and pedestrians, especially when involving a large network and a long time horizon. Our findings give a way to quantitatively illustrate how pedestrians affect the vehicle

Table 2.11: Pedestrian impact on vehicle side for network 4×4

Turning Weight m	0	2	3	5	6
First Time Interval	0 1 0 1	1 1 0 1	0 0 0 0	0 0 0 0	0 0 0 0
	1 0 1 0	1 0 1 0	0 0 0 1	0 0 0 1	0 0 0 0
	0 1 0 1	0 0 0 1	0 0 0 1	0 0 0 1	0 0 0 1
	1 0 1 0	0 0 1 0	0 0 1 1	0 0 0 1	0 0 0 1
Second Time Interval	1 0 1 0	0 1 0 0	0 0 0 0	0 0 0 0	0 0 0 0
	0 1 0 1	1 1 0 1	0 0 0 0	0 0 0 0	0 0 0 0
	1 0 1 0	1 0 1 0	0 0 1 1	0 0 1 1	0 0 1 1
	0 1 0 1	0 0 0 1	0 0 0 1	0 0 0 1	0 0 0 1
Turning Weight m	11	14	30		
First Time Interval	0 0 0 0	0 1 0 0	0 1 0 0		
	0 0 0 0	0 0 0 0	0 0 0 0		
	0 0 0 1	0 0 0 1	1 0 0 1		
	0 0 1 1	0 0 1 1	0 0 1 1		
Second Time Interval	0 0 0 0	0 1 0 0	0 1 0 0		
	0 0 0 0	0 0 0 0	0 0 0 0		
	0 0 1 1	0 0 1 1	1 0 1 1		
	0 0 1 1	0 0 1 1	0 0 1 1		

network, which is expressed as a piecewise constant function. In our integrated mixed-flow model, the originally separated pedestrian network is now connected due to its coupling with the vehicle network, and a small change in the vehicle network could bring a significant impact on the whole system. In other words, the vehicle network has a much larger influence on the total vehicle network delay than the pedestrian network. For this reason, we need to put a larger weight value on the pedestrian side in order to match the influence of the vehicle network. For example, in Table 2.11, the weight on the vehicle part is always 1 and the vehicle traffic signal begins to change until the weight on the pedestrian side is equal to 2, which means as long as the weight of the pedestrian side is between 0 and 2, its impact on the total traffic network delay cannot be obviously felt. The piecewise constant function of the vehicle network delay with respect to the weight values assigned to the pedestrian side shown in Fig. 2.11 and Fig. 2.12 clearly illustrates this fact.

2.5 Concluding Remarks

In this chapter, an overview on the urban traffic modelling and existing traffic signal control approaches are provided. First, vehicle models are partitioned into three categories: the microscopic model, the mesoscopic model and the macroscopic model, where the CTM, which belongs to the macroscopic model, is adopted and extended in our modelling in second part, due to its ability to

Figure 2.11: The change of delay-ratio curve under different weight of traffic composition from network 3×3 to network 6×6

completely describe traffic dynamics under different traffic density environments. Second, the signal control approaches are provided from the fixed-time strategy to the adaptive model-based strategy. The fixed-time strategies and the logic-based traffic-responsive strategies control the signals based on the historical or current measured traffic data, however, the model-based strategies can predict the traffic behavior of the network, therefore, we optimize traffic signals based on model-based strategies for a pedestrian-vehicle mixed-flow network.

In the second part, we have proposed a traffic light scheduling problem aiming to minimize the total network cost for both pedestrians and vehicles. The pedestrian volume dynamics in each junction captures the characteristics of the conventional two-way crossing of the crosswalk topology, and the pedestrian flow dynamics is described by the source corner volume and the capacity of each crosswalk

Figure 2.12: The change of delay-ratio curve under different weight of traffic composition from network 7×7 to network 10×10

determined by the associated traffic signal setting. Then a vehicle traffic network is introduced by considering driver's psychological response, which is combined with the pedestrian network to form a holistic traffic network. To overcome the high computational complexity involved in real-time traffic light scheduling, a meta-heuristic HS algorithm is adopted. Our case studies show that HS algorithm can provide a significant increase of computational efficiency with tolerable reduction of performance, also, the proposed traffic signal scheduling strategy can effectively reduce traffic cost and change the traffic signal settings according to the demand input. Moreover, by comparing with two existing methods, the average delay graph highlights the effectiveness of our method. In addition, our simulation indicates that the influence of pedestrians on the total vehicle delay can be captured by a piecewise constant function, suggesting that the performance of the vehicle network may not always be sensitive to pedestrian volume changes

in the pedestrian network, which could be exploited to lower the computational complexity incurred in real-time traffic light scheduling problems. Although assumptions such as prior knowledge of the arrival flow rates of pedestrians are required for our theory, this can be solved by many existing technologies. They will be relaxed in our future works, and relevant model identification algorithms will be developed to estimate those rates.

Chapter 3

Pedestrian-Safety-Aware Traffic Signal Control for Urban Traffic Congestion Alleviation

Summary - In this chapter, a literature review on urban traffic safety is given in the first subchapter, where the severity of the pedestrian safety, pedestrian crossing at mid-block roads and intersections, factors influencing pedestrian compliance and signal strategies to improve safety at intersections are all elaborately discussed. The pedestrian non-compliance rate, as an important factor related to pedestrian-vehicle crashes, are influenced by many factors, such as age and sex, waiting times, traffic volume and speed, social psychology and road layout. Accordingly, many strategies have been proposed to improve pedestrian safety. After that, the model explained in the second part seeks to address the pedestrian-vehicle conflicts by presenting a traffic signal control strategy for urban traffic networks that aims to minimize vehicle traveling delay (increase efficiency) as well as pedestrian crossing risk (increase safety). First, a macroscopic model for pedestrian-vehicle mixed-flow networks is proposed. Considering the high-incidence rate of pedestrian violations during Flashing GREEN (FG), an additional Dynamic All RED (DAR) phase is introduced at the end of each FG period, whose duration is adaptively adjusted according to the number of non-compliant pedestrians. With computational complexity being a concern for our model, an evolutionary algorithm with repairing mechanism (EARM), is proposed to solve our problem. Case studies are provided to illustrate the potential impact of the pedestrian movement to the vehicle traffic networks when pedestrian safety is considered in the system, as well as the efficacy of our traffic light control strategy for pedestrians and vehicles on risk reduction.

3.1 Literature Review on Urban Traffic Safety

With the increase of the automobile transportation, vulnerable road users, pedestrians and bicyclists, are becoming increasingly susceptible to traffic crashes. Most victims were pedestrians in these crashes, which mainly occurred in developing countries due to its constant urbanization and rapid growth of private cars [154]. Also, approximately 70% of pedestrian deaths took place in urban cities rather than rural areas [155], however, the proportion of pedestrian deaths in traffic crashes at rural areas is over 2.3 times larger than that of urban areas due to higher vehicles speeds in the suburb [156]. There are many factors affecting the pedestrian safety, which can be summarized as driver personal characteristics (driver gender, age, licensing and etc), pedestrian characteristics (pedestrian gender, age, volume and etc), vehicle factors (Vehicle malfunction, high volume, vehicle speed and etc), demographic/social/policy factors (land use & zoning, populations, laws, climate change and etc) and roadway designs (intersection geometry, roadway lighting, urban planning and etc) [157].

The traffic-related pedestrian crashes can be mainly classified as the following categories: intersection crashes (17.3%), turning-vehicle crashes (9.8%), mid-block crashes (26.5%) [158]. The intersection crashes include intersection dash and other types of crashes, such as drivers'/pedestrians' violation or misjudged gap. Similarly, the mid-block crashes consist of mid-block dash (driver's view is not blocked while pedestrian is running), mid-block dart out (driver's view is blocked) and other types. To avoid the above crashes and improve the pedestrian safety, many countermeasures have been proposed to reduce pedestrian injuries and fatalities. Traffic light control, as one of the effective strategies, has been broadly implemented in many cities successfully. Many researchers have conducted before-and-after experiments to test the efficiency of the signal strategy and found that pedestrian safety can be significantly improved by the pedestrian signalization [60][61]. Although the improvements are determined by the specific characteristics such as location, road design, road user behaviors and signal settings, pedestrian injuries and fatalities are reduced by installing traffic signals when compared with crossings without pedestrian signals [62].

Most pedestrian behavior-related research via signal control strategies is designed for mid-block crossing, and there are four types of pedestrian signals for mid-block crossing: Zebra crossing, Pelican crossing, Puffin crossing and Toucan crossing [159]. Zebra crossing allow pedestrians automatically having right of way. Drivers should pay attention to pedestrians who stand at the curb preparing to cross and pedestrians who already walk on the crosswalk, and are only allowed to move if all pedestrians are cleared and reach the other side of the curb. Zebra crossings normally have two sets of flashing amber beacons located at each curb of the road, which is used to remind drivers upstream that there is a sidewalk ahead. Pelican crossing is activated by pressing a button on a pillar located at each curb of the

road. Then the light shown for vehicles changes to red in few seconds or minutes depending on the specific setting. The light for pedestrians changes to green, amber and finally red according to the timer set for the internal controller. Some Pelican crossings have the pedestrian signal installed with a countdown timer to show how much time left to safely cross the road. Puffin crossing is similar to the Pelican crossing, and the difference is the use of the sensors which are installed along the crosswalk. If no pedestrians are detected on the road during the amber period previously mentioned in Pelican, the traffic signal will directly change to green to allow vehicle crossing, thereby saving time for drivers. Toucan crossings work in the same way as puffin crossings, detecting potential crossing users by sensors. The main difference is that Toucan crossings consider both pedestrians and bicyclists. Based on the layout of the crosswalk, whether a median refuge is considered in the middle of the road, signalized mid-block crossing can also be classified as one-stage crossings and two-stage crossings. Due to the introduction of the median refuge, two sets of traffic lights are implemented in each half of the road, which accordingly leads to a two-stage signal setting.

Safety-based adaptive traffic signal control is not widely used at intersections, whereas efficiency, as a basic metric to quantify performance of the traffic system at intersection, has been studied extensively for several decades. However, by-products of blindly pursuing efficiency, in particular, the increased possibility of having traffic accidents, are definitely worthy of attention at signalized intersections. According to Traffic Police accident statistics [76], the proportion of the pedestrian fatal accidents on signalized crosswalks is 22%. More than 30% of the total pedestrian fatalities can be attributed to the illegal crossing behaviors. Therefore, it is essential to understand the factors affecting pedestrian's non-compliance behaviors.

Before introducing the possible influencing factors, the components of pedestrian signals are firstly explained. The pedestrian signal at intersection is generally composed of three phases: steady green, flashing green (amber) and red phases. Steady green phase is used to let pedestrians cross the road, and its duration is normally determined by the pedestrian volume. The flashing green is used to clear pedestrians, thereby avoid collisions between pedestrians on the crosswalk in the current phase and the non-compatible vehicles in the subsequent phase. Also, the red phase is designed to release vehicle flows in an antagonistic direction. Accordingly, the pedestrian categories can be classified as compliers and non-compliers based on their behaviors [77]. Compliers are pedestrians who legally cross the road when the traffic light is steady green while the non-compliers are pedestrians who start to enter the crosswalk when the traffic light is either flashing green or red. The factors that affect pedestrian compliance with traffic signals can be summarized as the following several elements: age and sex, waiting times, traffic volume and speed, social psychology and road layout (road width, presence of the median refuge) [77]. Bernhoft and Carstensen [160] found that the older road users find it dangerous to cross a road without a pavement, and prefer signalized intersections.

Also, the younger pedestrians are more likely to violate the traffic signals than older pedestrians [161]. Sex difference is another factor affecting the pedestrian compliance rate: Both Yagil et al. [162] and Papadimitriou et al. [163] found that female pedestrians behave more safely compared with male pedestrians by conducting questionnaire-based personal interviews. A number of literatures also conclude that the longer pedestrians have to wait, the greater the likelihood of the occurrence of the illegal crossing [77][164][165]. Moreover, a high traffic volume will lead to the increase of the tendency to wait for the green signal, lack of traffic, on the other hand, increase the tendency to cross during the flashing green or red phase [162]. And the non-compliance rates will increase if there is a median refuge, since the appearance of the median refuge relatively narrows the street width [57]. Many studies have also been carried out from the psychology-based perspective. The Theory of Planned Behaviour (TPB) have been applied to predict the pedestrian road crossing intentions [166][167][168]. The behaviour intention results from three major considerations in TPB: behaviour belief, which considers the extent of the individual's attitude towards the behaviour which leads to positive or negative outcomes, normative belief, which describes the perceived social pressure to perform or not perform the behaviour, and control belief, which is the individual's attitude about the presence of factors that may facilitate or hinder performance of the behaviour. On the other hand, the pedestrians' risk behaviour is predicted by evaluating the self-balance between the acceptable risk degree and the perceived risk degree [169]. The limited information that pedestrians can master leads to the gap between the perceived risk degree and the actual risk degree [170]. Also, the psychological time is more significant when the human is deeply unhappy [171], and the psychological time is non-linearly increasing after a certain threshold [165][171]. Based on both the balance model and waiting-time threshold model, [169] analyses the pedestrians' unsafe crossing behavior.

Besides the above mentioned factors, the setting of the signal phases also influence the pedestrian's compliance rate, where Two-Way Crossing phase (TWC) and Exclusive Pedestrian Phase (EPP) are two typical phases which have been compared in many literatures. The TWC allows pedestrian crossing concurrently with the adjacent through-vehicle movements. Whereas the EPP, which allows pedestrian cross in all directions when all vehicle flows are stopped, has been used in many cities in order to increase the convenience of pedestrian crossing. The EPP potentially increases the safety as long as vehicles and pedestrians comply with the signals, since the conflicts between pedestrian flows and vehicle turning flows are eliminated [172]. However, the EPP also increases delays for both traffic participants owing to the increased cycle length resulting from the additional pedestrian phase and the decreased green ratio for vehicles and pedestrians [173]. The increased delay time also leads to the increased pedestrian non-compliance rate, which inversely reduces the expected safety benefits by avoiding the conflicts between pedestrian flows and vehicle turning flows. Although the EPP increases the pedestrian delay because of the longer cycle time, it reduces the travel distance of those diagonal-crossing pedestrians [174]. Moreover, the EPP is more significant

when large pedestrian volumes and large vehicle turning flows are involved in the system [175][176].

In order to improve the pedestrian safety, it is necessary to design traffic signals by taking the pedestrian's behavior into account, meanwhile, balance the vehicle delay so that both efficiency and safety can be met. The "Smart Mobility 2030" [177] has been proposed by Singapore Land Transport Authority with the aim to build a more comprehensive and sustainable intelligent transportation ecosystem. To realize such a sustainable, assistive, interactive and informative transportation system, multi-objective way of thinking is inevitable in decision making by considering the interest of multi-modal transportation participants. Efficiency and safety among multi-objective indexes are two crucial aspects respectively described in Highway Capacity Manual (HCM) [78] and Highway Safety Manual (HSM) [178], which thereby adopted as evaluations in our optimization problem by taking both vehicles and pedestrians into account.

Traditional efficiency-based traffic control strategies include fixed-time control, traffic-responsive control and artificial-intelligence control, which has already been elaborately discussed in Chapter 2.1.2. While in the category of the safety, field studies, simulation-based studies and mathematical model are all sought to investigate the impacts of signal settings on road safety. In the field studies, by comparing the coordinated traffic system and the isolated traffic system, Moore and Lowrie found that a 20-percent improvement was obtained in terms of the total number of accidents occurring within coordinated signal systems [179]; Wong et al. investigate the possible contributory factors to traffic injury crashes at 262 signalized intersections, and the results indicate that the incidence of severe crashes are attributed to many factors, such as tram stops, number of pedestrian streams, road environment, traffic composition, lane width, and curvature [180]; Studies conducted by Guo et al. [181] and Midenet et al. [182] also found that the coordination of signals has positive impacts on intersection safety; The relationship between the traffic conflicts and the traffic accidents is also analyzed in [183]. Meanwhile, many microsimulation models are widely available to provide for researchers to evaluate surrogate measures of safety: Klunder et al. assess road safety via the Multi-Agent Real-time Simulator (MARS) by comparing the new infrastructure and the traffic system beforehand [184]; A micro-level behavioral method for estimating crash potential at signalized and non-signalized intersections is proposed in [185]; Stevanovic et al. combine the microsimulation software Vissim, Vissim-based Genetic Algorithm for Optimization of Signal Timings (VISGAOST) and the Surrogate Safety Assessment Model (SSAM) to generate a Pareto set between traffic conflicts and vehicle throughputs [186]. Unlike efficiency modeled as performance index on traffic operations, the safety issue does not receive much attention in mathematical model-based signal strategies. Ma et al. propose an optimization model, which selects pedestrian phase patterns between the normal TWC and the EPP with the trade-off between safety and efficiency factors in an isolated intersection, by using the weighted-sum method [49] and the

Pareto set [48].

In view of the insufficient studies about the efficiency and safety optimization on signal strategies via mathematical model, we developed our model to fill the gap. Generally, there are three major methods to quantify performance trade-off: Weighted-sum method sums several different objects together after multiplying different weights on associated objects to formulate a single-objective function; Pareto-optimal set is generated by finding a group of non-dominated solutions; Constraint method utilizes the preferred evaluation object as cost objective while the others are treated in constraints. In our study, we select the constraint method, in which vehicle efficiency is regarded as our objective and the pedestrian crossing safety is modeled in our constraints. To the best of our knowledge, most existing literatures on signal optimization strategies via constraint methods only reflect the pedestrian safety at each signal phase whose duration is no less than the fixed pedestrian clearance period, see [42] and [187]. Meanwhile, the pedestrian non-compliant behaviors which may lead to a longer clearance period are not considered in their models. However, we adjust the phase duration according to the number of illegal-crossing pedestrians in order to ensure their safe crossing. The reason why we utilize a constraint method but not the other two is that the impacts of pedestrian safety on vehicle network can be evaluated via this method, which is also important for transportation professionals to make proper decisions on phase pattern selection.

The main contributions of the chapter are listed as follows. Firstly, we formulate a mathematical model for pedestrian crossing on a signalized intersection, whose arrival flow and leaving flow of each waiting zone are separately described in order to make the model more realistic, then the duration of DAR is obtained according to the number of illegal-crossing pedestrians via pedestrian crossing time model [78]. By integrating with the vehicle network model based on CTM [29][30], a pedestrian-safety-aware traffic light control strategy is developed with the aim to reduce both traffic congestions and pedestrian-crossing risks. Secondly, both the GA and the HS with the repairing mechanism are proposed in order to meet the requirement of the real-time signal switching. Thirdly, efficiency on vehicle side is evaluated by comparing the traditional adaptive signal strategy with our proposed method. Based on the traffic conflict technique [188], one method used to evaluate the road risk, the safety cost under two strategies is also illustrated. Moreover, we establish quantitative standards for selecting signal strategies between the efficiency and safety in an economic evaluation framework.

3.2 Formulation of the Pedestrian-Safety-Aware Traffic Light Control Strategy

Since our signal setting is developed from the pedestrian perspective, basic terminology about pedestrian signals is firstly overviewed before presenting our model. The pedestrian phase is composed of the discharge time and the clearance time. The discharge time, Steady GREEN (SG) for pedestrian signal indication, is used to release pedestrians to leave the curb, which is normally determined by the pedestrian queue. For our model, the discharge time for pedestrians is also GREEN for associated compatible vehicle flows in the same phase, so the duration of SG is dominated by the vehicle demand. The clearance time, Flashing GREEN (FG) for pedestrian signal indication, is designed to avoid collisions between pedestrians on the crosswalk in current phase and the non-compatible vehicles in subsequent phase, which is normally determined by the pedestrian average speed and the crosswalk length. Besides the fixed FG, we also consider additional clearance time in our model, called Dynamic All RED (DAR) in this chapter, in order to let those illegal-crossing pedestrians safely reach the other curb.

3.2.1 Notations

Several types of parameters and control variables are summarized in Table 3.1 and Table 3.2 in order to clearly describe the model. The geometrical parameters specify the layout of an intersection or network, as shown in Fig. 3.1a and Fig. 3.1b. The signal parameters are used to describe the signal constraints in Chapter 3.2.2.1. The traffic parameters illustrate the vehicle and pedestrian flows and associated volumes in our model. We highlighted here that $f_{ij}^{p,a}(k)$ is the pedestrian arrival flow from corner i to corner j via crosswalk, and $I_i(k)$ is the pedestrian incoming flow from nearby areas without using crosswalks. The control variables are updated according to the constraints in Chapter 3.2.2.1.

Our traffic network is defined as a collection of road links $L \in \mathcal{L}$ and intersections $J \in \mathcal{J}$. Pedestrian crossing flows are only restricted in an intersection, a complete pedestrian network with consideration of various types of route infrastructures are beyond the scope of this chapter and not considered in our model. Each pedestrian crossing network consists of four waiting zones, shades corners in Fig. 3.1b. There are two major inputs in our model. One part of the inputs are from the historical data while the others are from the on-line system feedback. The two probability distributions described in the subsequent model, as shown in Fig. 3.4 and Fig. 3.5, are collected from the historical data. While the pedestrian volumes, diversion ratios (α and β) and departure ratio (γ) in one specific corner are the known inputs from on-line feedback, also, vehicle incoming flows from boundary of the network and the link turning ratios are collected in real time. These online inputs can be realized

Figure 3.1: Layout of traffic network and phase pattern at each junction

by many existing approaches, e.g., human detection and direction estimation via cameras [137], V2X wireless communication [139], data mining from surrounding buildings [142] and traffic flow prediction models [141].

3.2.2 Pedestrian Safety Analysis

The pedestrian traffic signal in Singapore typically starts with 5s of SG and changes to 20s of FG. In general, the duration of FG is obtained based on the pedestrians' average crossing time which is determined by the average speed whose value is set as 1.2 m/s [189]. In other words, FG is used to clear pedestrians who are on the crosswalk, and pedestrians are not suggested to enter into crosswalks if FG occurs. However, a significant number of pedestrians still choose to cross during FG, which leads to higher risks to encounter traffic conflicts or accidents.

In order to address such issue, an extra duration is allocated at the end of each FG. Fig. 3.1c and Fig. 3.1d illustrate two simplified phases used in this chapter. Based on Fig. 3.1c and Fig. 3.1d, the phase composition is drawn in Fig. 3.2 from both pedestrians' perspective and vehicles' perspective. Clearly, there are

Table 3.1: Notations and Definitions

Geometry parameters	
i, j	The index of the road link, as shown in Fig.3.1a, or the index of waiting zones (corners) in the anticlockwise direction at an intersection, as shown in Fig. 3.1b.
$\mathcal{L}$	A set of links.
$\mathcal{J}$	A set of intersections, $J \in \mathcal{J}$.
$\mathcal{W}^J$	Four waiting zones in intersection J .
$\mathcal{F}_p^J (\mathcal{F}_v^J)$	The set of pedestrian (vehicle) streams in intersection J , $\mathcal{F}_p^J \in \mathcal{W}^J \times \mathcal{W}^J$ ($\mathcal{F}_v^J \in \mathcal{L} \times \mathcal{L}$).
Signal parameters	
Ω_p^J	A set of phases which control pedestrian flows in intersection J .
Ω_v^J	A set of phases which control vehicle flows in intersection J .
Ω^J	A set of phases in J , $\Omega^J = \Omega_p^J \cup \Omega_v^J$.
o	One specific phase, $o \in \Omega^J$.
$h_p^J (h_v^J)$	The association of each phase to relevant compatible streams, $h_p^J : \Omega_p^J \rightarrow 2^{\mathcal{F}_p^J}$ ($h_v^J : \Omega_v^J \rightarrow 2^{\mathcal{F}_v^J}$)
$\tau_i^J(k)$	The necessity to add DAR after FG during current phase regarding to corner i at the intersection J .
$CT_o^{i,J}(k)$	DAR period for corner i of the intersection J .
$CT_o^J(k)$	Final DAR period for the intersection J .
Δ	Duration of each time interval, set as 5s in the case study.
H_p	Prediction horizon (time window), $H_p = N\Delta$, where N is the number of the prediction steps.
Traffic parameters	
PV_{ij}	The percentage of illegal-crossing pedestrians at corner i with the destination corner j
$f_{ij}^{p,d}(k)$	The number of pedestrians leaving from corner i to corner j via crosswalk during time interval k , $i \in \mathcal{W}$, $j \in \mathcal{W}$. The flow is shown as the orange arrow in Fig. 3.1b.
$f_{ij}^{p,a}(k)$	The number of pedestrians arriving from corner i to corner j via crosswalk during time interval k , $i \in \mathcal{W}$, $j \in \mathcal{W}$. The flow is shown as the green arrow in Fig. 3.1b.
$f_{ij}^v(k)$	The number of vehicles driving from link i to link j during k .
$P_i(k)$	The number of pedestrians waiting to cross the street in corner i at k .
Cap_i	The leaving capacity of the source corner i .
$\hat{P}_o(k)$	The capacity of the arrival flow with phase o during k .
$\hat{P}_i$	The maximum volume of corner i .
$C_i(k)$	The number of vehicles in link i at k .
$\hat{C}_i$	The maximum volume of link i .
$I_i(k)$	The number of incoming pedestrians of corner i without using crosswalk during k .
$\eta_{ij}(k)$	The pedestrian diversion ratio from corner i to corner j at k , $\eta \in \mathcal{H} = \{\alpha, \beta\}$, where α is the horizontal diversion ratio from corner i to corner j , β is the vertical diversion ratio from corner i to corner j .
$\gamma_i(k)$	Pedestrians departure ratio at corner i at k , which is applied on the incoming flow of corner i , aiming at those who have already used crosswalk and reached destination.
$\lambda_{ij}(k)$	Turning ratio of vehicles in link i towards link j during k .

Table 3.2: Control Variables

$\theta_o(k)$	Traffic light state associated with phase o at k , $\theta_o(k) = 0$ and $\theta_o(k) = 1$ denote the RED and GREEN traffic lights for both vehicle flows and pedestrian flows under the same phase o , respectively.
$\delta(k)$	The indicator of the second Flashing GREEN. $\delta(k) = 1$ indicates that there is one phase under the last time interval of FG at k .
$l_o(k)$	The parameter to represent the DAR state associated with stage o at k . $l_o(k) = 1$ represents that phase o is during DAR period at k , and the duration of DAR is determined by the number of non-compliant pedestrians, which will be explained in Chapter 3.2.2.2.

three components for each phase from pedestrians' perspective: SG, FG and DAR. Instead of applying the fixed-time strategy, the duration of SG is adaptively adjusted and determined by the vehicle demands. Then a fixed two time intervals of FG is followed behind. Finally, DAR is applied to provide more time for crosswalk clearance. During DAR, both vehicle flows and pedestrian flows in all directions are stopped, only provided for pedestrians who are already on the crosswalk.

Figure 3.2: An example of traffic light change for phase 1

3.2.2.1 Adaptive traffic signal setting

In order to implement the above signal strategy, auxiliary parameters, $\theta_o(k)$, $\delta(k)$ and $l_o(k)$, are required. The specific definitions can be found in Table 3.2. $\theta_o(k)$, $\delta(k)$ and $l_o(k)$ are all binary variables. Fig. 3.3 is drawn to illustrate one possible example of the above descriptions for both phases 1 and 2. According to the example shown in the Fig. 3.3, a set of rules are developed in order to satisfy the relationship between these binary variables.

Rule I: The relationship between the DAR indicator and the traffic signal states -

Figure 3.3: An example of state sequences for signal settings

I

$$(\forall k \in \mathbb{N}) \sum_{o \in \Omega^J} l_o(k) = 0 \Rightarrow \sum_{o \in \Omega^J} \theta_o(k) = 1 \quad (3.1)$$

Equation (3.1) illustrates that only one active phase o for an intersection J exists at k as long as DAR does not occur.

Rule II: The relationship between the DAR indicator and the traffic signal states - II

$$(\forall k \in \mathbb{N}) l_o(k) = 1 \Rightarrow \sum_{o \in \Omega^J} \theta_o(k) = 0 \quad (3.2)$$

Equation (3.2) describes that traffic lights for all directions must be RED if DAR for any phase o occurs.

Rule III: The consistency of the traffic signal states

$$(\forall k', k'' \in \mathbb{N}) (k' + 3 \leq k'') (\forall k \in [k' + 1, k'' - 1])$$

$$\delta(k') = 1 \wedge \delta(k'') = 1 \wedge \sum_{i=k'+1}^{k''-1} \delta(i) = 0 \wedge l_o(k) = 0 \Rightarrow \theta_o(k) = \theta_o(k+1) \quad (3.3)$$

where the symbol " $\wedge$ " indicates the logic operation "AND". $\delta(k') = 1 \wedge \delta(k'') = 1 \wedge \sum_{i=k'+1}^{k''-1} \delta(i) = 0$ indicates that two adjacent last FGs belong to different phases occur at k' and k'' , respectively, namely, $k' = 5$ and $k'' = 10$ shown in Fig. 3.3. Since at least one time interval of SG and two time intervals of FG are considered for each phase, we have the condition $k' + 3 \leq k''$. Accordingly, equation (3.3) guarantees that multiple time intervals of SG and FG will have the same state if they control a group of compatible traffic flows, e.g., $\theta_1(1) = \theta_1(2) = \theta_1(3) = \theta_1(4) = \theta_1(5) = 1$ while $\theta_1(8) = \theta_1(9) = \theta_1(10) = 0$ in Fig. 3.3.

Rule IV: The switch of the traffic signal states

$$\begin{aligned}
 & (\forall k', k'' \in \mathbb{N})(k' + 3 \leq k'') \\
 & \delta(k') = 1 \wedge \delta(k'') = 1 \wedge \sum_{i=k'+1}^{k''-1} \delta(i) = 0 \Rightarrow \theta_o(k') + \theta_o(k'') = 1
 \end{aligned} \tag{3.4}$$

Equation (3.4) indicates that if phase o is GREEN for current several time intervals, then the next followed GREEN sequence must occur in other phases, e.g., $\theta_1(5) + \theta_1(10) = 1$ in Fig. 3.3.

3.2.2.2 Dynamic all RED duration constraints

The process to determine the duration of DAR depends on two steps: 1. The number of illegal-crossing pedestrians at the start of FG, which determines the necessity to involve DAR after FG. For simplicity, we do not consider the non-compliant behaviors from incoming pedestrians during the FG, due to the limited time duration which leads to the limited violation volume. If no violated intention is found, FG is used to let pedestrians already on the crosswalk finish crossing, otherwise, DAR is required since FG is not enough for those illegal-crossing pedestrians to safely arrive the other curb. 2. The transition instant to the other phase is determined, by adding the averaged crossing time after the last moment that all illegal-crossing pedestrians leave the source corner.

There are many reasons affecting the pedestrian crossing behaviors, e.g., personal characteristics (age, gender, safety awareness), traffic conditions (pedestrian flow rate, group size, vehicle traffic volume, red signal time) and trip purpose [190]. From an aggregate perspective, the number of illegal-crossing pedestrians at current moment is hard to obtain due to the stochastic nature and the nonlinear characteristics. However, because of the daily-repeated travel demand and traffic supply, meaningful traffic patterns can be found through the massive accumulated traffic historical data collected from advanced sensors [191]. Therefore, we can adopt the expectation of the percentage of the illegal-crossing pedestrians (the ratio between the number of illegal-crossing pedestrians and the number of total pedestrian volumes) to determine the DAR period. Fig. 3.4 shows several possible probability distributions for the percentage of the illegal-crossing pedestrians PV_{ij} , which is drawn in order to visually describe the equation (3.5), and the specific distribution relies on the extracted traffic dataset at corresponding intersections, which could be influenced by many factors, e.g., the structure design of the road and the amount of pedestrians.

According to Fig. 3.4, the corresponding expectation, namely, the average

Figure 3.4: The probability distribution of the percentage illegal-crossing pedestrians from corner i to corner j

percentage of the illegal-crossing pedestrians can be formulated as:

$$E(PV_{ij}) = \sum_{PV_{ij}} PV_{ij} h_{ij}(PV_{ij}) \quad (3.5)$$

Then the state of $\tau_i^J(k)$ can be determined according to the number of the violated pedestrians:

$$(\forall i \in \mathcal{W}^J) E(PV_{ij}) P_i(k) \eta_{ij}(k) > 0 \wedge \delta(k+1) = 1 \Rightarrow \tau_i^J(k) = 1 \quad (3.6)$$

Where $E(PV_{ij}) P_i(k) \eta_{ij}(k)$ represents the average number of illegal-crossing pedestrians from corner i to corner j . Equation (3.6) indicates that DAR in intersection J will be considered in current phase as long as the "violated intention" of any corner in intersection J is found.

After $\tau_i^J(k)$ is determined, the duration of DAR is influenced by the clearing process of those illegal-crossing pedestrians, whose discharge distribution could also be extracted from the accumulated historical data. The number of non-compliant pedestrians who just leave the corner decreases with the lapse of the FG due to the increased risk. Considering the limited capacity of the crosswalk, the non-compliant pedestrians at the end of SG may not all leave the corner at the first time interval of FG if the volume of illegal-crossing pedestrians is quite large. Then it is straightforward to conclude that they will be released gradually, and this clearing process can be modeled as a queue with a random leaving flow process, which will be decreasing with the lapse of the FG. According to the volume of the violated pedestrians, a corresponding leaving distribution graph, Fig. 3.5, is

drawn, which shows possible examples for the leaving distribution of the total illegal-crossing pedestrians according to time. The x-axis and y-axis are the time passed after the start of FG and the percentage of the violated pedestrians who start crossing during current time interval Δ , respectively. q denotes the start of FG, namely, $\delta(q + 1) = 1$. Based on the averaged non-compliant pedestrians,

Figure 3.5: The probability distribution for the clearing process of the illegal-crossing pedestrians from corner i to corner j

corresponding leaving distribution is selected:

$$P_{r-1} < E(PV_{ij})P_i(k)\eta_{ij}(k) \leq P_r \Rightarrow g_{ij}(k) = g_{ij}^r(k) \quad (3.7)$$

Accordingly, the duration of DAR is formulated as the following equations:

$$\tau_i^J(k) = 0 \Rightarrow CT_o^{i,J}(k) = 0 \quad (3.8a)$$

$$\tau_i^J(k) = 1 \Rightarrow CT_o^{i,J}(k) = G_{ij}^{-1}(100\%)\Delta + \frac{L}{S_p} - (q-1)\Delta - 2\Delta \quad (3.8b)$$

$$CT_o^J(k) = \max\{CT_o^{1,J}(k), CT_o^{2,J}(k), CT_o^{3,J}(k), CT_o^{4,J}(k)\} \quad (3.8c)$$

$$(r-1)\Delta \leq \max\{CT_o^J(k), 0\} \leq r\Delta \Rightarrow \sum_{i=2}^{r+1} l_o(k+i) = r \quad (3.8d)$$

where L is the length of crosswalk (m), S_p is the average walking speed (m/s), $G_{ij}(k)$ is the cumulative function of the distribution $g_{ij}(k)$, and G_{ij}^{-1} is the reverse function of G_{ij} . Equation (3.8a) indicates DAR for corner i is not considered if no violated intension is found. $G_{ij}^{-1}(100\%)\Delta$ is the time that all illegal-crossing pedestrians just leave the source corner and enter into the crosswalk, by adding the averaged crossing time ($\frac{L}{S_p}$) and subtracting the time duration before FG ($(q-1)\Delta$) and the duration of FG (2Δ), equation (3.8b) indicates the duration of DAR for corner i . Final DAR for the intersection J is determined when the maximum of the $CT_o^{i,J}(k)$ is selected,

as shown in equation (3.8c). r is an integer to specify the number of intervals for DAR. Equation (3.8d) shows how $l_o(k)$ is specified by r .

3.2.2.3 Pedestrian departure flow constraints

Assume that crosswalks have sufficient capacity to accommodate pedestrian flows, pedestrian departure flows can be described as the following equations:

$$(\forall o \in \Omega_p^J, (i, j) \in h_p^J(o)) :$$

$$\theta_o(k) = 0 \wedge l_o(k) = 0 \Rightarrow f_{ij}^{p,d}(k) = 0 \quad (3.9a)$$

$$\theta_o(k) = 1 \wedge \delta(k) = 0 \wedge \delta(k+1) = 0 \Rightarrow f_{ij}^{p,d}(k) = \min\{P_i(k)\eta_{ij}(k), Cap_i\} \quad (3.9b)$$

$$\theta_o(k) = 1 \wedge \delta(k+1) = 1 \Rightarrow f_{ij}^{p,d}(k) = g_{ij}(k)E(PV_{ij})P_i(k)\eta_{ij}(k) \quad (3.9c)$$

$$\theta_o(k) = 1 \wedge \delta(k) = 1 \Rightarrow f_{ij}^{p,d}(k) = g_{ij}(k)E(PV_{ij})P_i(k-1)\eta_{ij}(k-1) \quad (3.9d)$$

$$(\forall n, m \in \mathbb{N}^+) \quad l_o(m-1) = 0 \wedge \sum_{n=m}^k l_o(n) = k - m + 1 \Rightarrow$$

$$f_{ij}^{p,d}(k) = g_{ij}(k)E(PV_{ij})P_i(m-2)\eta_{ij}(m-2) \quad (3.9e)$$

Equation (3.9a) indicates that pedestrians are not allowed to cross if traffic light is RED. Equation (3.9b) illustrates that the pedestrian leaving flow is restricted by the demand $P_i(k)\eta_{ij}(k)$ and the leaving capacity Cap_i if the traffic light is under SG. Equation (3.9c) indicates that the pedestrian leaving flow from corner i to corner j during first time interval of FG is obtained by the multiplication of three components: the leaving function $g_{ij}(k)$, the averaged percentage of illegal-crossing pedestrians at corner i with the destination corner j $E(PV_{ij})$ and the pedestrian volumes at corner i with the destination corner j $P_i(k)\eta_{ij}(k)$, namely, $g_{ij}(k)E(PV_{ij})P_i(k)\eta_{ij}(k)$. Similarly, we can obtain the crossing flow for second time interval of FG and DAR period, as shown in equations (3.9d) and (3.9e), respectively.

3.2.2.4 Pedestrian arrival flow constraints

The pedestrian arrival flow from crosswalks is restricted by its corresponding leaving flow from the source corner and the arrival capacity $\hat{P}_o(k)$, which is explained in Chapter 3.2.2.5. The pedestrian arrival flow constraints can be described as the following equations:

$$(\forall o \in \Omega_p^J, (i, j) \in h_p^J(o)) :$$

$$\begin{aligned}
 (\forall m \in \mathbb{N}^+) \quad & \theta_o(m) = 0 \wedge \sum_{n=m+1}^k \theta_o(n) = k - m \wedge \theta_o(k) = 1 \\
 \Rightarrow f_{ij}^{p,a}(k) = & \min\{f_{ij}^{p,d}(k) + \sum_{n=m+1}^{k-1} (f_{ij}^{p,d}(n) - f_{ij}^{p,a}(n)), \hat{P}_o(k), \hat{P}_j - P_j(k)\} \quad (3.10a)
 \end{aligned}$$

$$\begin{aligned}
 (\forall m, q \in \mathbb{N}^+) \quad & \theta_o(m) = 0 \wedge \sum_{n=m+1}^q \theta_o(n) = q - m \wedge l_o(q) = 0 \wedge \sum_{n=q+1}^k l_o(n) = k - q \\
 \Rightarrow f_{ij}^{p,a}(k) = & \min\{f_{ij}^{p,d}(k) + \sum_{n=m+1}^{k-1} (f_{ij}^{p,d}(n) - f_{ij}^{p,a}(n)), \hat{P}_o(k), \hat{P}_j - P_j(k)\} \quad (3.10b)
 \end{aligned}$$

Equation (3.10a) corresponds to equations (3.9b), (3.9c) and (3.9d), and equation (3.10b) corresponds to (3.9e). Equation (3.10a) indicates that both the leaving flow of current SG time interval or FG time interval at k and all accumulated leaving flows from past several time intervals which have not arrived the curb can contribute to the arrival flow $f_{ij}^{p,a}(k)$, which is also constrained by the arrival capacity $\hat{P}_o(k)$ and the remaining space in corner j . $\hat{P}_o(k)$ is the maximum number of pedestrians successfully crossing the road during k , which is influenced by the previous traffic signal state, and is elaborately explained in Chapter 3.2.2.5. Equation (3.10b) illustrates that the arrival flow from the crosswalk during the DAR period is also bounded by the leaving flow at k plus the accumulated unarrived flow on the crosswalk, the arrival capacity and the remaining space of the destination corner.

3.2.2.5 Pedestrian arrival capacity constraints

The crossing time for pedestrian platoons, which is recorded in HCM 2010 [78], was found after several regression analyses:

$$CT = \begin{cases} I + \frac{L}{S_p} + 0.27N_{ped}, & \text{if } W \leq 3m \\ I + \frac{L}{S_p} + 0.81\frac{N_{ped}}{W}, & \text{otherwise} \end{cases} \quad (3.11)$$

where CT is the total crossing time (s), I is the reaction time (s), L is the length of crosswalk (m), W is the width of crosswalk (m), S_p is the average walking speed (m/s), and N_{ped} is the size of the pedestrian platoon. By changing the form of equation (3.11) and adding the traffic signal states, we can obtain the following relationship:

$$\tilde{P}_o(k) = \begin{cases} \left\lfloor \frac{\Delta - I - \frac{L}{S_p}}{\tau S} \right\rfloor, & \text{if } (k = 1) \vee (\theta_o(k - 1) = 0) \\ \left\lfloor \frac{\Delta}{\tau S} \right\rfloor, & \text{if } \theta_o(k - 1) = 1 \end{cases} \quad (3.12a)$$

$$\hat{P}_o(k) = \max\{\tilde{P}_o(k), 0\} \quad (3.12b)$$

where $\mathcal{TS}$ is determined by the topology structure of the crosswalk: $\mathcal{TS} = 0.27$ when the crosswalk width $w \leq 3m$, otherwise, $\mathcal{TS} = \frac{0.81}{w}$. We omit the mathematical derivation process to obtain equation (3.12a), which is elaborately explained in Chapter 2.2 and our previous paper [192][101]. The motivation behind is that the capacity for successfully crossing pedestrians in current k depends on its previous time interval $k - 1$: if the traffic signal state of phase o at $k - 1$ is RED, then the arrival capacity is a small value, otherwise, the arrival capacity is a large value. The reason leading to the changing capacity in the same time duration is because the startup time I and the crossing time $\frac{L}{S_p}$: when $\theta_o(k - 1) = 0$, there are no pedestrians on the crosswalk at the start of k , while pedestrians may walk on the crosswalk if previous traffic signal is GREEN ($\theta_o(k - 1) = 1$), which leads to higher capacity for the latter case. Due to the small time interval Δ chosen for our model, whose value may be less than the sum of the startup time I and the crossing time $\frac{L}{S_p}$, which could lead to a negative capacity value in equation (3.12a), therefore, equation (3.12b) is utilized to avoid such phenomenon.

3.2.2.6 Pedestrian volume dynamics

Volume update in corner i ($i \in \mathcal{W}^J$) is illustrated as follows:

$$P_i(k + 1) = P_i(k) + I_i(k) - \sum_{(i,j) \in \cup_{J \in \mathcal{J}} \mathcal{F}^J} f_{ij}^{p,d}(k) + (1 - \gamma_i(k)) \sum_{(j,i) \in \cup_{J \in \mathcal{J}} \mathcal{F}^J} f_{ji}^{p,a}(k) \quad (3.13)$$

Volume dynamic in corner i is restricted by the incoming flow from nearby areas $I_i(k)$, the leaving flows from corner i to other adjacent corners $\sum_{(i,j) \in \cup_{J \in \mathcal{J}} \mathcal{F}^J} f_{ij}^{p,d}(k)$ and the arrival flows from crosswalks $\sum_{(j,i) \in \cup_{J \in \mathcal{J}} \mathcal{F}^J} f_{ji}^{p,a}(k)$. However, only part of the arrival flows will stay in corner i and contribute to the volume update at next interval since these part of pedestrians regards corner i as their transfer station, and they need to make a second crossing to reach their final destination. While the other part of arrival flows will directly leave the waiting zone, which is captured by the departure ratio $\gamma_i(k)$, so they are required to be deleted from the system.

3.2.3 Vehicle Traffic Analysis

The vehicle model is the same as the previous vehicle model in Chapter 2.2, and also has been elaborately explained in [43][101]. To ensure the integrity of the model in this chapter, the formulations of the vehicle flows are briefly illustrated below.

3.2.3.1 Vehicle volume dynamics

According to the CTM [29][30], the link dynamic is restricted by the incoming flows and outgoing flows, for each link $j \in \mathcal{L}$, we have the following relationship:

$$(\forall k \in \mathbb{N}) C_j(k+1) = C_j(k) + \sum_{j \in \mathcal{L}: (i,j) \in \cup_{J \in \mathcal{J}} \mathcal{F}_v^J} f_{ij}^v(k) - \sum_{j \in \mathcal{L}: (j,i) \in \cup_{J \in \mathcal{J}} \mathcal{F}_v^J} f_{ji}^v(k) \quad (3.14)$$

where $\sum_{j \in \mathcal{L}: (i,j) \in \cup_{J \in \mathcal{J}} \mathcal{F}_v^J} f_{ij}^v(k)$ is the total number of arriving vehicles to link j during time interval k , and $\sum_{j \in \mathcal{L}: (j,i) \in \cup_{J \in \mathcal{J}} \mathcal{F}_v^J} f_{ji}^v(k)$ is the total number of leaving vehicles from link j during time interval k .

3.2.3.2 Vehicle flow constraint

The flow dynamics constraint described below indicates that the outgoing flow $f_{ij}^v(k)$ is determined by the current upstream volume $\lambda_{ij}(k)C_i(k)$ of link i , the downstream remaining space $\hat{C}_j - C_j(k)$, and the capacity from link i to link j in one time interval, which is influenced by the aggregate traffic variables (critical speed v^* and critical density d^*), and the speed category $l_{ij}(k)$.

$$f_{ij}^v(k) = \min\{\lfloor \lambda_{ij}(k)C_i(k) \rfloor, \hat{C}_j - C_j(k), \lfloor l_{ij}(k)v_i^*d^*n\Delta \rfloor\} \quad (3.15)$$

$$(\forall o \in \Omega_v^J, (i,j) \in h_v^J(o)) \quad \theta_o(k) = 0 \Rightarrow f_{ij}^v(k) = 0 \quad (3.16)$$

where n is the lane number. $v_i^*d^*n\Delta$ illustrates the capacity to release the vehicles during k , in order to reflect the drivers' psychological behavior respond to the past continuous state of traffic lights, one more parameter, $l_{ij}(k)$, is considered in our model, which is captured by traffic signal states in past $r+1$ time intervals. The intention of the psychological response is that drivers are more likely to keep a high speed $v_{ij}(k)$ if the phase o has been active for the past r intervals and the downstream link has sufficient space to receive the flow. Road tests to validate this part has also been conducted, which is elaborately illustrated in [144]. Equation (3.16) indicates that the vehicle flow is stopped as long as its associated phase o is RED.

3.2.3.3 Cost function

The optimal phase pattern is selected to minimize the vehicle volume left in the entire network within a certain time window, by multiplying time interval Δ , the

total vehicle delay time can be estimated as follows:

$$V_D = \sum_{J \in \mathcal{J}} \sum_{k=1}^N \sum_{i \in \mathcal{L}^J} [C_i(k) - \sum_{i \in \mathcal{L}^J: (i,j) \in \cup_{J \in \mathcal{J}} \mathcal{F}_v^J} f_{ij}^v(k)] \Delta \quad (3.17)$$

3.3 Solution Algorithm

The proposed optimization model is complex, involving many mixed logic constraints, and the scale of the problem increases dramatically with the number of intersections and window sizes rising. Therefore, it is tedious to change all above constraints into mixed-integer linear constraints, and is time-consuming to find the global optimal signal settings by traditional mixed integer linear programming. Besides that, constraints (3.3), (3.4) and (3.8d), which involve decision variables in time steps, make their translation into equivalent linear constraints troublesome. In view of this, we adopt the evolutionary algorithm (EA) to solve our problem via its internal heuristic. Typical evolutionary algorithms may randomly generate variables for each individual, e.g., the variable array shown in Fig. 3.3, and directly apply the results to the objective function (fitness function) in order to obtain corresponding cost. However, in our problem, infeasible individuals could be generated if constraints (3.1), (3.2), (3.3) and (3.4) are not satisfied. Also, the length of DAR is adaptively adjusted according to the number of the illegal-crossing pedestrians. Therefore, repairing process is required after the initialization of each individual and every time when the length of each DAR is determined. The entire steps of the Evolutionary Algorithm with Repairing Mechanism (EARM) is illustrated in Algorithm 3 and Fig. 3.6.

In step 1, the populations for θ_o , δ , l_o are initialized, and each individual is called the chromosome and the harmony in GA and HS algorithm, respectively. In step 2, the initialized signal populations are transferred into the repairing function, in which the duration of each DAR is determined based on the number of illegal-crossing pedestrians at the end of SG. After the confirmation of the DAR, signal states θ_o and δ after time slots of the determined DAR are re-initialized in order to satisfy the constraints (3.1)-(3.4), and finally the revised populations $RepPop_0$ are created in step 2. In step 3 the vehicle cost for the modified signals (θ_o , δ , l_o) of the initial population is calculated. Next, a loop starts in step 4: Function **GenNewIndiv** determines the new individual inherited from previous initialized population or generated from the new random function according to the update parameters ($UpPara$) of the GA and the HS; Similarly, function **RepairPed** is provided to repair the infeasible individuals, and the fitness value is calculated from the function **FitFuncVeh**; After that, function **IndivSelect** chooses the signals with better fitness from two populations. The above process repeats until step 5. In step 5, the EARM algorithm stops when the stop criterion (NI) is met. Meanwhile,

the best result is obtained after the iterative process. In order to clearly illustrate the whole process, several important functions are illustrated below.

Algorithm 3 Evolutionary Algorithm with Repairing Mechanism (EARM)

AHS (InputData, InputDataPed, InputDataVeh, $PopSize$, $UpPara$, NI)

Input: InputData - Network size, Prediction horizon; InputDataPed - Pedestrian incoming flows; InputDataVeh - Vehicle incoming flows; $PopSize$ - Population size; $UpPara$ - Update parameters; NI - Number of iterations

Output: BestResult - The best signal schedule for our problem

1 $Pop_0 \leftarrow \mathbf{Init}(\text{InputData}, PopSize)$ for all intersections

(Pop_0 includes $PopSize$ of θ_o , δ , l_o)

2 $RepPop_0 \leftarrow \mathbf{RepairPed}(\text{InputData}, \text{InputDataPed}, Pop_0)$

(The repairing process occurs when pedestrian dynamic is considered)

3 $Fit_0 \leftarrow \mathbf{FitFuncVeh}(\text{InputData}, \text{InputDataVeh}, RepPop_0)$

(Vehicle delay cost is calculated based on the determined traffic signals)

4 **For** $i=1$ to NI

4.1 $NewPop_i \leftarrow \mathbf{GenNewIndiv}(\text{InputData}, PopSize, UpPara)$

4.2 $NewRepPop_i \leftarrow$
 $\mathbf{RepairPed}(\text{InputData}, \text{InputDataPed}, NewPop_i)$

4.3 $Fit_i \leftarrow$
 $\mathbf{FitFuncVeh}(\text{InputData}, \text{InputDataVeh}, NewRepPop_i)$

4.4 $Fit_0 \leftarrow \mathbf{IndivSelect}(Fit_i, Fit_0)$

End For

5 **Return** BestResult $\leftarrow Fit_0$

Figure 3.6: The whole process for the proposed algorithm

3.3.1 Population Initialization

Based on the value of the individual δ , the traffic signal array θ_o is developed while the DAR array l_o is created during the repairing process. The entire initialization is described in Algorithm 4. In step 1, δ is firstly developed via the function **GenLastGREEN**, which specifies whether $\delta_J(k) = 1$ or 0 based on the following rule: : 1. The space of two adjacent "1" must larger than or equal to two time intervals, since at least one time interval for SG and one time interval for the first FG must be reserved between two adjacent "Last FG". 2. The first two time intervals cannot be assign "1" for δ , since the first state of the signal array θ_o must be SG for one phase, namely, RED for the other phase. In the initial stage, all the l_o arrays are set as 0, which make the constraint (3.1) feasible but will also be modified in the next repairing function. After the determination of the array δ , both the position of each "Last FG" and the total number of "Last FG" on the array δ are recorded in step 2. In step 3, the state of the traffic signal array θ_o is determined according to the following rules: 1. The states of θ_o between two adjacent "Last FG" must be the same, namely, constraint (3.3) is satisfied. 2. The states of θ_o before one "Last FG" should be opposite with the states after this "Last FG", namely, constraint (3.4) is satisfied.

Algorithm 4 Initialization of Individuals

Init (InputData, *PopSize*)

Input: InputData: $J \in \mathcal{J} = \{1, \dots, m\}$ - Index of intersections, $k \in \mathcal{K} = \{1, \dots, N\}$ - Window size; *PopSize* - Population size;

Output: $\{\theta_o, \delta, l_o\}_J$ - Initial assigned signals

For all *PopSize*

1 *Intersection_J* $J \in \mathcal{J}$

1.1 $\delta_J \leftarrow \text{GenLastGREEN}(J, \text{WindowSize})$

1.2 $l_{o,J} \leftarrow 0$

2 **For all** $k \in \mathcal{K}$

2.1 $\text{Index}(\text{Num})_J \leftarrow k$ **If** $\delta_J(k)$ is 1

2.2 $\text{Num}_J \leftarrow \text{Num}_J + 1$ **If** $\delta_J(k)$ is 1

End For

3 **For all** $m \in \text{Num}_J$

3.1 **For** $k \in \{\text{Index}(m)_J + 1, \text{Index}(m + 1)_J\}$

3.1.1 $\theta_o(k)_J \leftarrow 1 - \theta_o(\text{Index}(m)_J)$

End For

End For

End For

Return SigResults $\text{Pop}_J \leftarrow \{\theta_o, \delta, l_o\}_J$

3.3.2 Repairing Infeasible Individuals

In order to satisfy the equations (3.1)-(3.4), the newly generated l_o based on harmonies δ and θ_o leads to the adjustment of harmonies δ and θ_o , which conversely affect the value of l_o . Fig. 3.6 clearly shows the whole process, the repairing mechanism involves both the signal-setting transform and the pedestrian volume update. When signal state is SG, equations (3.9b) and (3.10a) are used for pedestrian volume update. When signals state is FG, equations (3.9c) (3.9d) and (3.10a) are used for volume update, which is followed by the determination of the DAR duration. If violation intention is found, DAR required to be added. The duration of DAR is calculated via equations (3.8), which leads to the change of the signal arrays (δ, θ_o, l_o) in next several time intervals. Namely, $l_o(k)$ is set as 1 in time intervals which are used to characterize the DAR, meanwhile, $\theta_o(k)$ is set as 0 based on equation (3.2) in corresponding time intervals. After that, in the IRA stage shown in Fig. 3.6, signal states $\theta_o(k)$ and $\delta(k)$ after the determined DAR are required to be re-initialized, namely, the left orange part shown in the Fig. 3.6, since $\theta_o(k)$ during DAR time slots is modified as 0, which disrupts the original order and may not satisfy the relationship (3.3) and (3.4). Then the above process continues until the signal states in entire time window are visited, which means all change to purple, as shown in Fig. 3.6.

3.3.3 Generating New Populations

We adopt the GA with the roulette mechanism and a single-point crossover, and the roulette method is one of the parent selection methods, which aim to determine the chromosomes that will be allowed to generate offspring. The main steps are illustrated in Algorithm 5: Firstly, parents are selected via function **ParentSelection**. Then if randomly generated value $rand1()$ in the range of $[0, 1]$ is larger than the Mutation Probability ($MutProb$), mutation will be processed according to step 2.1, otherwise, crossover will be considered if $rand2()$ is smaller than the Crossover Probability ($CroProb$). Finally, function **AdjProperIndiv** is applied to adjust the infeasible individuals of δ and generate associated θ_o and l_o .

In the HS, Harmony Memory Considering Rate ($HMCR$) and Pitch Adjustment Rate (PAR) are the parameters used to produce the new harmonies. According to Algorithm 6, when randomly generated value $rand1()$ in the range of $[0, 1]$ is less than the $HMCR$, new harmonies are selected from current existing population, and if $rand1() < HMCR$ meanwhile $rand2() < PAR$, a small change is applied on the existing harmonies. BW is the bandwidth, which is defined to find possible neighborhood solutions. However, if randomly generated value is large than or equal to the $HMCR$, new harmonies are generated by function **Init**. Similarly, function **AdjProperIndiv** is applied to adjust the infeasible individuals of δ and generate associated θ_o and l_o .

Algorithm 5 Generate New Chromosomes

GenNewIndiv (InputData, PopSize, Pop)**Input:** InputData: $J \in \mathcal{J} = \{1, \dots, m\}$ - Index of intersections, $k \in \mathcal{K} = \{1, \dots, N\}$ - Window size;
PopSize - Population size;Pop - Signal results: $\{\theta_o, \delta, l_o\}$;**Output:** $\{\theta_o, \delta, l_o\}$ - Newly generated signals $\delta_{Parent} \leftarrow \mathbf{ParentSelection}(\delta)$ **For all** PopSize1 **If** rand1() < MutProb1.1 **If** rand2() < CroProb1.1.1 **For all** $J \in \mathcal{J}, k \in \mathcal{K}$ 1.1.1.1 $\delta(k)_J^{New} \leftarrow \mathbf{crossover}(\delta_{Parent, J})$ **End For**1.2 **Else**1.2.1 **For all** $J \in \mathcal{J}, k \in \mathcal{K}$ 1.2.1.1 $\delta(k)_J^{New} \leftarrow \delta_{Parent}(k)_J$ **End For****End If**2 **Else**2.1 **For all** $J \in \mathcal{J}, k \in \mathcal{K}$ 2.1.1 $\delta(k)_J^{New} \leftarrow \mathbf{Mutate}(\delta_{Parent, J})$ **End For****End If****End For** $\{\theta_o, \delta, l_o\} \leftarrow \mathbf{AdjProperIndiv}(\delta)$ **Return** NewSigResults NewPop $\leftarrow \{\theta_o, \delta, l_o\}$

Algorithm 6 Generate New Harmonies

GenNewIndiv (InputData, PopSize, Pop)

Input: InputData: $J \in \mathcal{J} = \{1, \dots, m\}$ - Index of intersections, $k \in \mathcal{K} = \{1, \dots, N\}$ - Window size;

PopSize - Population size;

 Pop - Signal results: $\{\theta_o, \delta, l_o\}$;

Output: $\{\theta_o, \delta, l_o\}$ - Newly generated signals

For all PopSize

 1 **If** rand1() < HMCR

 1.1 **For all** $J \in \mathcal{J}, k \in \mathcal{K}$

 1.1.1 $\delta(k)_J^{New} \leftarrow \delta(k)_J$
End For

 1.2 **If** rand2() < PAR

 1.2.1 **For all** $J \in \mathcal{J}, k \in \mathcal{K}$

 1.2.1.1 $\delta(k)_J^{New} \leftarrow \delta(k)_J + BW * rand()$
End For
End If

 2 **Else**

 2.1 **For all** $J \in \mathcal{J}, k \in \mathcal{K}$

 2.1.1 NewInputData $\leftarrow (k_{new} \in \{1, \dots, N\}, J)$

 2.1.2 **Init**(NewInputData, 1)

End For
End If
End For
 $\{\theta_o, \delta, l_o\} \leftarrow \text{AdjProperIndiv}(\delta)$
Return NewSigResults NewPop $\leftarrow \{\theta_o, \delta, l_o\}$

3.4 Numerical Examples

The purpose of this chapter is to demonstrate the impacts for selecting this pedestrian-safety-aware traffic signal pattern on both safety and efficiency of entire network before expanding to multidirectional vehicle flows, so we choose a two-phase signal setting in our simulation, as shown in Fig. 3.1c and Fig. 3.1d, to investigate the interaction between pedestrians and vehicles. Model validation and comparison can be conducted by connecting our proposed method with the commercial simulator, e.g., Vissim, Viswalk, and we have been communicating with the Vissim developer PTV Inc. to see whether it is possible to improve Viswalk to facilitate simulation of illegal behaviors, which shall be considered in our future work. In the following case studies, the applicability of the proposed model and the effectiveness and impacts of the resulting signal timing are demonstrated. The Manhattan-shape network, as shown in Fig. 3.7, is used in our case studies with n_h horizontal links per column and n_v vertical links per row, and the total number of intersections is $n_J = n_h n_v$. Firstly, experimental comparisons between the performance of the genetic algorithm and the harmony search algorithm are conducted. In order to evaluate the impacts of our proposed strategy on urban network, we compare the proposed strategy with our previous adaptive traffic signal strategy on both delay cost and safety cost. Our previous adaptive traffic signal strategy does not include dynamic all red durations, and a specific model is presented in our arXiv document [144], where the objective is the same as our proposed cost (3.17), also, the volume dynamic constraint and the flow constraints are the same as our proposed constraints (3.14) and (3.15),(3.16), only the phase constraints are different with (3.1)-(3.4). The reasons why we compare the proposed method with our previous adaptive signal strategy are: 1. We have made comparisons between our adaptive signal strategy with a SCATS-like signal control algorithm and the latest fixed-time algorithm in [193], and the outcomes indicate that our adaptive signal strategy outperforms the other two methods. Thus, by comparing with our previous strategy in [193], we will know the ultimate sacrifice of efficiency when pedestrian safety is considered in the model. 2. The mainstream traffic light control strategies rarely consider pedestrians in their models, and in cases where pedestrians are modelled, the efficiency is usually the predominant concern rather than the safety of pedestrians and network-wise efficiency considered in our framework. So we can hardly find any mainstream traffic signal control strategy for a fair comparison with our method, as their control objectives are not aligned well. 3. Our model requires the simulator to simulate the pedestrians' illegal-crossing behavior. Commercial simulator like Vissim cannot easily describe the pedestrian illegal crossing. Putting other mainstream techniques into our case studies will create significant simulation obstacles, whereas including our adaptive strategy is relatively easier, as we can directly update the signal control code to take the pedestrian illegal behaviors into account. We assume intersections and links in the network have the same topology. Maximum of 3 time intervals of DAR is considered in our case studies. Parameters used in the following case studies

Figure 3.7: Layout of the pedestrian-vehicle mixed-flow network

are listed in Table 3.3. Due to the significant non-compliant behavior occurring during FG [189], the averaged percentage of non-compliant pedestrians $E(PV_{ij})$ is set as 0.8 in our simulation, which could be modified in our future work once specific background and real dataset are involved. The leaving capacity Cap_i is used to formulate the associated probability distribution for the clearing process of the illegal-crossing pedestrians, as shown in Fig. 3.5. The pedestrian average speed is slightly higher than the normal speed 1.2m/s, which is because pedestrians are usually walking faster during FG and is taken from [189]. The critical vehicle speed and density are chosen below in order to meet the base saturation flow rate, 1900 veh/lane/hour [78]. The pedestrian incoming flows are randomly generated with its associated averaged value from 200 ped/m/hour to 1800 ped/m/hour. Similarly, the vehicle incoming flows are also randomly obtained with its associated averaged value from 200 veh/lane/hour to 1800 veh/lane/hour.

3.4.1 Computational Efficiency

Sixteen cases with various network sizes and time windows are generated. Both GA and HS are coded in C++ and run on a PC with an Intel(R) Core(TM) CPU i7-3770 v3 @3.40GHz and RAM 8GB. We tested cases of $n_v = n_h = 3, 5, 7, 10$ and $H_p = 15, 30, 60, 100$ seconds, respectively. The population size and the iteration number of both algorithms are set as 50 and 1000, respectively. To make a fair comparison between two algorithms, all experiments are conducted with 30 replications. For the GA algorithm, the mutation probability and the crossover probability are set as 0.25 and 0.5 [50]. For the HS algorithm, parameters $HMCR$ and PAR are set as

Table 3.3: Parameters used in case study

Parameters	Descriptions	Associated Values
Δ	sampling period	5s
$E(PV_{ij})$	the expectation of non-compliant ratio	0.8
S_p	pedestrian average speed	1.87m/s
L	crosswalk length	7m
W	crosswalk width	3m
I	start-up time	1s
$\hat{C}_i$	maximum volume of link i	100
$\hat{P}_i$	maximum volume of corner i	150
Cap_i	The leaving capacity of corner i	30
v^*	critical vehicle speed	25 km/h
k^*	critical vehicle density	75 veh/lane/km
n	lane number	1

0.95 and 0.5, respectively [194].

Tables 3.4 and 3.5 depict the computational time and the vehicle delay of the proposed model associated with GA algorithm and HS algorithm, respectively. Clearly, the computational time increases as the size of the network and the time window increase. And the computational time is larger than the model described in Chapter 2.2, this is because each occurrence of DAR will launch a new signal update for subsequent time intervals. Also, the GA has higher computational time for finding the minimum delay time compared with the HS, which is mainly resulting from the additional time cost on "Parent Selection".

In Tables 3.4 and 3.5, the minimum (Min.), average (Ave.), and maximum (Max.) values of the vehicle delay within 30 repeats have been reported. The search mechanism of EA algorithms includes exploration and exploitation. For our proposed problem, the HS method performs better than the GA when the size of the time window is small. However, with the increase of the time window, the GA method outperforms the HS eventually. This indicates that HS could exploit the search space better for the small cases while the GA is relatively successful on jumping from the local minimum when the search space is large. Moreover, the convergence rate of both GA and HS is compared in Fig. 3.8, in which networks 3×3 and 10×10 with prediction horizons 30s and 100s are drawn, respectively. The red line corresponds to the HS, while the blue line corresponds to the GA. When the prediction horizon is small, the HS converges faster compared with the GA. However, GA outperforms HS when the prediction horizon is large.

3.4.2 Delay Evaluation

To investigate the impact of the proposed method when pedestrian safety is involved in entire network, we consider a 3×3 network with 9 intersections and 1 min prediction horizon, and compare the traffic delay time between the proposed strategy

Table 3.4: Computational time and vehicle delay of proposed model + GA

Instance		Genetic Algorithm			
Network Size	H_p (s)	Computational Time (s)	Opt		
			Min	Avg	Max
3×3	15	2.91	23	23.27	24
	30	3.40	147	161.57	174
	60	4.54	572	657.10	710
	100	6.35	1322	1647.60	1806
5×5	15	3.65	31	34.83	39
	30	4.91	264	287.83	303
	60	7.41	1256	1292.23	1329
	100	10.92	3554	3684.17	3782
7×7	15	4.55	36	43.60	50
	30	6.36	371	397.83	412
	60	11.02	1811	1859.07	1899
	100	17.33	5676	5833.53	5924
10×10	15	6.57	65	72.83	80
	30	10.12	539	574.43	593
	60	18.30	2612	2669.77	2722
	100	28.68	8109	8234.93	8344

Table 3.5: Computational time and vehicle delay of proposed model + HS

Instance		Harmony Search Algorithm			
Network Size	H_p (s)	Computational Time (s)	Opt		
			Min	Avg	Max
3×3	15	2.91	23	23.13	24
	30	3.44	124	140.63	158
	60	4.64	604	664.43	719
	100	6.26	1387	1741.67	1848
5×5	15	3.58	30	34.20	40
	30	4.77	251	263.53	275
	60	6.83	1200	1317.67	1382
	100	10.24	3663	3812.43	3912
7×7	15	4.34	38	43.10	48
	30	6.11	351	367.70	388
	60	10.45	1863	1919.60	1977
	100	16.50	5852	5994.37	6134
10×10	15	6.09	63	70.87	76
	30	9.87	493	525.60	553
	60	17.50	2665	2759.77	2820
	100	27.68	8223	8431.43	8623

(a) Network 3×3 with window size 30s (b) Network 3×3 with window size 100s (c) Network 10×10 with window size 30s (d) Network 10×10 with window size 100s

Figure 3.8: Convergence patterns for GA and HS

and the traditional strategy without DAR. Fig. 3.9a shows the impacts of pedestrian volume and vehicle volume on the vehicle delay of two different signal strategies. We calculate several data points and draw corresponding surfaces to fit the data points, where the red surface and the green surface in Fig. 3.9a are the total vehicle delay corresponds to the proposed signal strategy in this chapter and our previous traditional adaptive signal strategy without DAR, respectively. As the volumes of pedestrian and vehicle increase, the total vehicle delay increases under both signal strategies. Also, the cost of our proposed strategy always increases faster than the traditional one due to the additional DAR intervals considered in our model. Besides that, the vehicle delay will increase with the increase of the pedestrian flow under a fixed vehicle flow input, and this is because the rising pedestrian volume potentially increases the number of non-compliant pedestrians, and accordingly induces the increase of the DAR duration, which in turn increase the vehicle delay. However, the

vehicle delay is still dominated by the vehicle flow, which performs as a significant delay increase under a fixed pedestrian flow input as the vehicle flow increases. When both pedestrian and vehicle flow are small, the green surface is above the red surface but the green data points are actually less than the red one, this is because two surfaces intersect at the lower input in order to fit all data points reasonably. In order to clearly show the gap variation between two strategies, we also draw the

(a) The total vehicle delay in two signal strategies under various traffic compositions

(b) The delay difference between two signal strategies under various traffic compositions

Figure 3.9: The total vehicle delay and its delay difference between two signal strategies

contour lines in Fig. 3.9b, which indicates the delay difference between two strategies under various traffic compositions. Obviously, the difference becomes larger with

the increase of the pedestrian and vehicle flows. Moreover, the slope of the contour lines indicate that the vehicle flow has more impact on the vehicle delay, specifically, the color zone is cold-toned when the pedestrian flow is 1800 ped/h and the vehicle flow is 600 veh/h, however, the color zone becomes warm-toned when the vehicle flow is 1800 veh/h and the pedestrian flow is 600 ped/h, which is consistent with the Fig. 3.9a.

3.4.3 Risk Evaluation

Although the additional DAR duration leads to the increase of the vehicle delay, the potential risk is largely decreased. In order to show the efficiency of our method on risk control, we record the number of crossing pedestrians $f_{ij}^{p,a}(k)$ at the last time interval of current phase in entire traffic network. Although we model $f_{ij}^{p,a}(k)$ at the last time interval of current phase as the successful crossing pedestrian flows, its value can still somehow reflect the potential risk colliding with the conflicting vehicle flow in next followed phase. Fig. 3.10c shows the averaged number of crossing pedestrians at the last time interval of current phase with the increase of the pedestrian flow under various vehicle flows and signal strategies, when the averaged percentage of violated pedestrians is set as 0.8. The solid lines correspond to the traditional signal strategy without DAR while the dotted lines correspond to the proposed strategy.

Clearly, for solid lines, there are higher pedestrian volumes arriving the destination corner just before the phase switch time, and these quantities grow gradually as the pedestrian flow goes up. Conversely, the amount of crossing pedestrians in our proposed method is much smaller but also does not present a steady increase as the pedestrian flow increases, which results from the appearance of the additional DAR. When the traditional signal strategy is applied, the ideal case is that all illegal-crossing pedestrians will finish crossing during the fixed FG. The increased pedestrian volume potentially induces the increased non-compliant pedestrian volume, which definitely increase the non-compliant pedestrian flow at the last FG. Unlike the fixed FG in traditional signal control, the crossing time is adjusted according to the amount of the non-compliant pedestrians in our proposed method: The number of time intervals for DAR will gradually increase as the pedestrian volume rises, which leads to the violated behaviors close to the phase switch time do not always increase as the pedestrian flow goes up. Their change depends on both the non-compliant pedestrian volume and the DAR duration.

Besides the averaged percentage of violated pedestrians considered as 0.8 in Fig. 3.10c, we also draw the graphs when the averaged percentages are 0.2 and 0.5 in Fig. 3.10a and Fig. 3.10b, respectively. The same range of y-axis is applied on three subfigures in order to clearly make the comparison. Obviously, when the violation rate is 0.2, the gap between the signal strategy with and without DAR is small,

however, with the increase of the violation rate, the gap of two strategies becomes increasingly large. This indicates that the necessity to add DAR after each phase in order to guarantee the safety of the pedestrians, especially when pedestrians around the intersection behave aggressively. In order to quantitatively evaluate traffic safety under two different methods, the Traffic Conflict Technique (TCT) is adopted to give a clear specification on safety analysis. The collection of sufficient accident statistics depends on the accident history of past several years, and the collisions seldom occurs compared with traffic conflicts. Also, the traffic conditions can change significantly during years [195][196]. Limited historical accident data impose restrictions on the accidents-based traffic safety analysis. Moreover, the number of accidents can be expected to change with the pedestrian-vehicle exposure [197]. Therefore, many accidents-based methods are gradually surrogated by TCT, which uses the relation between exposure and risk to evaluate safety performance. Based on TCT, the definition of the exposure proposed by Nilsson [198] is used in our case study: "Exposure is equal to the square-root of the product of the number of pedestrians per hour and the number of motor-vehicles per hour that may get involved in a conflict with the pedestrians". In our case study, the potential exposure is the pedestrian flow at the last time interval of current phase and the vehicle flow at the beginning of the next followed phase. According to Garden [188], the relationship between the probability of an accident PA_{ij} and the exposure is illustrated in the following equation:

$$PA_{ij} = EA * P_{tune} * \sqrt{f_{ij}^p * (f_{mn}^v + f_{nm}^v)} \quad (3.18a)$$

$$R_{ij} = C_A * PA_{ij} \quad (3.18b)$$

where f_{ij}^p is the averaged pedestrian flow from corner i to corner j at the last time interval of current phase, with the unit of ped/hour, f_{mn}^v and f_{nm}^v are the averaged vehicle flows from link m to link n and from link n to link m at the first time interval of the next followed phase, respectively, with the unit of veh/hour. P_{tune} is the parameter to transform the number of exposures to the number of accident. EA is the correction parameter. Both P_{tune} and EA are determined by the specific road environment, and are set to 0.286 and 0.01 in our case study, respectively, which are taken from the literature [49][188]. PA_{ij} is the potential traffic accident from corner i to corner j , by multiplying the monetary cost per accident, C_A , the safety cost R_{ij} from corner i to j is obtained accordingly. The value of C_A is adopted from Swedish National Road Administration [188], \$65000. Then the total risk cost for the entire network is added together for each traffic composition, and the Fig. 3.11a is drawn to show the risk cost under different traffic compositions. In Fig. 3.11a, the red surface and the green surface are the risk cost corresponds to our proposed signal strategy and the traditional adaptive signal strategy, respectively. With the increase of the pedestrian flow and the vehicle flow, the risk cost gradually increases under both signal strategies. Under the lower pedestrian flow and vehicle flow, the cost of our method is lower than but close to that of traditional method. As the vehicle flow and pedestrian flow increase, the cost of traditional method increases

faster than that of ours and eventually leads to a large gap between two methods. The contour graph shown in Fig. 3.11b further indicates that the risk cost gap between two methods becomes increasingly larger as the pedestrian and vehicle flow increase.

3.4.4 Trade-off between Efficiency and Safety

After comparing two methods on delay and risk evaluation, a more interesting problem whether delay or risk should be paid more attention is emerging. In order to compare both properties in a fair standard, an economic framework is discussed below. By applying traditional signal strategy without DAR, an one hour window size is considered to optimize signal settings. Next, the generated vehicle delay is multiplied by its associated monetary cost per hour, \$6, which is also adopted from Swedish National Road Administration [188]. While the safety effect is still assessed by the relationship between the pedestrian-vehicle exposures and traffic accident mentioned in Chapter 3.4.3, where the exposures are the square root of the product of the averaged number of pedestrians per hour at the last time interval of current phase and the averaged number of conflicting vehicles per hour at the first time interval of next followed phase in entire window size.

The risk cost and the delay cost are drawn in Fig. 3.12 with two different perspectives. Clearly, both costs increase as the pedestrian flow and the vehicle flow increase. Both surfaces are the outcomes after fitting the data points. The red one and the green one correspond to the delay cost and the risk cost, respectively. The slope of two surfaces indicate that the delay cost is determined by the vehicle flow (the vehicle delay is only affected by the vehicle volume input when signal strategy without DAR is applied), and the risk cost increases with both traffic participants but is dominated by the pedestrian flow. Additionally, the cost of risk outperforms that of delay when both traffic demands are lower. However, as the vehicle and pedestrian flows increase, the risk cost eventually exceeds the delay cost. This reveals the application domain of different traffic signal strategies: When both traffic demands are low, the traditional adaptive signal strategy can be kept to maximize the efficiency and maintain the original safety policy. However, the safety level is definitely required to be strengthened when both traffic demands are higher, which leads to consideration of adopting our proposed strategy or applying other countermeasures.

3.5 Concluding Remarks

In this chapter, we firstly give an overview on urban traffic safety considering the severity of the pedestrian safety, pedestrian crossing at mid-block roads and

intersections, factors influencing pedestrian compliance and signal strategies to improve safety at intersections. Due to the exponential increase of the vehicles and urban sprawl in many countries, pedestrian injuries and fatalities are increasing rapidly per year. Traffic signal control, as an essential strategy to reduce traffic crashes, has been studied for decades. However, conflicts and crashes between pedestrians and vehicles are still existing due to pedestrian's non-compliance behavior, which is influenced by many factors, such as age, sex, waiting times, traffic volume and speed, social psychology and road layout. In order to reduce pedestrian non-compliance rate, many strategies have been proposed with the goal to improve pedestrian safety.

In the second part, we presented a traffic signal strategy considering the total vehicle delay and the pedestrian safety in the entire network. The pedestrian volume dynamics are updated by three different pedestrian flows: pedestrian incoming flow from nearby areas, pedestrian arrival flow from crosswalks and pedestrian leaving flow to crosswalks. Two different capacities are considered to describe pedestrian flows: The pedestrian leaving flow is determined by the source corner volume and the leaving capacity of each crosswalk which leads to the phenomenon that non-compliant pedestrians are gradually released from the source corner, while the pedestrian arrival flow is restricted by the pedestrian leaving flow and the receiving capacity of each crosswalk determined by the associated traffic signal setting. By combining a link-based vehicle network model, a traffic signal scheduling problem is formulated with the aim to alleviate the vehicle delay and increase the pedestrian safety. Moreover, the signal setting and the reasonable time to release the illegal-crossing pedestrians are optimized simultaneously. To overcome the high computational complexity involved in traditional mixed-integer linear program, two evolutionary algorithms (GA and HS) with the repairing mechanism are developed. The results of the case study reveal that the network-wise vehicle delay will increase as the pedestrian volume increases but is still dominated by the vehicle volume, and our method can provide a significant decrease of traffic safety cost but is realized at the expense of the vehicle delay. Along this way, an economic-based evaluation standard to analyze the trade-off between pedestrian safety and vehicle delay are studied in our work in order to assist decision makers to better select signal phase patterns. However, the pedestrian non-compliant behavior and the computational complexity involved in our proposed method should be extended in our future work.

(a) The averaged percentage of violated pedestrians is 0.2

(b) The averaged percentage of violated pedestrians is 0.5

Figure 3.10: The sensitivity analysis of the averaged number of non-compliant pedestrians at last time interval of current phase

(c) The averaged percentage of violated pedestrians is 0.8

Figure 3.10: The sensitivity analysis of the averaged number of non-compliant pedestrians at last time interval of current phase

(a) The total risk cost in two signal strategies under various traffic compositions

(b) The risk cost difference between two signal strategies under various traffic compositions

Figure 3.11: The total risk cost and its risk difference between two signal strategies

(a) First perspective

(b) Second perspective

Figure 3.12: The monetary cost of vehicle delay and potential accident of traditional signal strategy under various traffic compositions

Chapter 4

Multi-Bus Scheduling for Minimal Passenger Perceived Waiting Time

Summary - In this chapter, an overview of urban transit scheduling is firstly presented. The planning strategies and the real-time control strategies are elaborately discussed in the review part. For an urban transit system, its planning process can be characterized at different levels: the strategic level, tactical level and operational level, which involve many different problems, such as the transit network design problem, frequency setting problem, bus timetable design problem and, etc. Due to the stochastic nature of traffic flows and passenger demands, real-time control strategies are also implemented to provide better services for transit users. After that, a platoon-based bus dispatching strategy with the bus stop-skipping strategy for a ring road bus transport system is formulated in the second part. Both GA and MILP are developed to solve the problem, in which the passenger delay time and the operating bus vacancy are minimized subject to the volume dynamic constraints on both buses and stops. Comparison between MILP and GA on the computational time and result quality is conducted to show the efficiency of our method. The concept of the passengers perceived waiting time is also proposed, which is illustrated by a nonlinear function. Due to the nonlinear cost in the objective function, the GA is adopted to solve the problem in order to minimize the passenger perceived delay time and the operating bus vacancy. Also, performance of our method and the traditional bus schedule strategy is discussed in the case study, which indicates the potential of the platoon dispatching in mitigating the passengers perceived delay.

4.1 Literature Review on Urban Transit Scheduling

Urban sprawl prevents a well-planned urban development. Many urban areas are suffering from serious traffic congestions, pollution, noise and traffic fatalities. Public transportation, as a solution to address the above issues, has been studied for several decades due to its larger ridership and sustainability on economic efficiency, environmental protection and social equity [79]. However, public transport systems often lack a good trade-off between the waiting passengers from the demand side and the operation cost from the public administration. Limited operating buses and relatively high fares can largely decrease the risk for government deficits and promise the fastest payback of the investment on the physical infrastructure, however, it will make the public transit, a system which tries to benefit all citizens, unaffordable, which deviates from its original purpose. Therefore, most public transport systems depend on the subsidies provided from the local government.

Besides the concern from the economic inputs and outputs, the public transport systems also struggle to provide a high level of service in order to meet the requirements from the highly stochastic time-dependent demand patterns. Even if the daily commuters' traveling patterns can be explored, one-time events, such as the population evacuation after the large concert, the road traffic accident and weather changes, could make the implement of the effective bus operation complicated and cumbersome. Fortunately, with the development of the new technologies, many advanced bus transport systems have been designed, in which the bus dispatching system is combined with the intelligent transportation system [199]. With the help of these advanced equipments, such as GPS, V2X and Automatic Passenger Counter systems (APC), a large amount of data can be collected to better serve the bus operation, which also leads to the realization of a real-time bus dispatching system [200][201].

There are three planning layers in the public transportation system: strategic planning, tactical planning and operational planning [202]. Strategic planning refers to the transit network design, which determines the bus line, bus stop location and types of buses. Tactical planning aims at improving the level of public service and reducing the operational cost. The specific problems are related to the Bus Frequency Setting (FS) [87] and Bus Timetable Design (BTD) [203][204][90]. The bus frequency setting determines the number of dispatched buses per unit time based on the passenger demands at this time period. While the bus time table design defines the specific departure times of buses for all stops along the bus lines, which is usually determined after the bus frequency setting. Operational planning refers to the short-term decision, which includes Vehicle Scheduling Problem (VSP) [203][90] and Driver Scheduling Problem (DSP) [205]. Vehicle scheduling problems try to assign the vehicles to associated bus operating trips, with the aim to minimize the

operation cost. Driver scheduling problems determine drivers-trips assignment for entire scheduled trips such that the drivers' costs are minimized. Besides the three planning strategies mentioned above, transport systems are still facing challenges from the uncertainty of many factors, such as the en-route traffic, stop demands and weather conditions. In order to solve these issues, real-time control strategies are applied in the bus operation system to provide a better user experience. Control strategies in the bus operation system can be divided into two categories: station control and inter-station control. Station control includes holding strategies (hold vehicles in some stations) [206] and stop-skipping strategies (let vehicles skip some stations) [80], while inter-station control considers decisions taken between stops, e.g., bus speed control [207][96] and traffic signal priority [208]. As discussed before, the public transport system is very complicated, and computationally demanding to find an integrated solution by exploiting the aforementioned three planning stages simultaneously. Therefore, a separate approach is implemented to solve the public transport problems, in which the outcome of the previous planning stage is taken as inputs for the current stage.

In the Chapter 4.2, we address the bus dispatching system from the tactical and operational level, with the aim to design transit timetable and dispatch corresponding vehicles. Meanwhile, we take the stop-skipping control strategies into account to guarantee an efficient bus service. Therefore, literatures related to FS, BTD and station control strategies are elaborately discussed in the following content.

Proper frequencies for a bus transport system not only attract more passengers to increase revenue but also control the operational cost in a reasonable range. Several methods have been proposed in the literature. Newell presents that the frequency is approximately proportional to the square root of the arrival rate of passengers by deriving the analytic model, however, his deduction is based on the assumption that the capacity of the vehicles is sufficiently large to serve all waiting passengers [81]. Another approach is based on the data collection proposed by Ceder [82][83], in which two point check methods via daily and hourly maximum passenger load points and two ride check methods via the original and the adjusted load profiles are discussed and compared: The point check methods should be applied when a relatively flat data profile is provided, otherwise, the ride check methods are more appropriate. Besides that, many mathematical optimization models are also developed, with the aim to either minimize the passenger waiting time or the operational cost. Han and Wilson [85] propose the frequency setting problem in conjunction with the transit route selection, in which the passenger waiting time and the bus crowdedness level are minimized subject to the constraints such as fleet size and loading feasibility, and the bus frequency, as the solution of the external layer of the optimization model, is obtained from the passenger flow determined by solving a trip assignment model in the inner layer with known origin-destination pairs. Also, Furth and Wilson [84] propose another model to maximize the net social benefit under the constraints such as fleet size, total subsidy and levels of

vehicle loading. After that, the two previous works are extended and formulated as a nonlinear programming problem by Verbas and Mahmassani [86]: The bus patterns, consisting of subsets of stops of the normal bus line, are firstly introduced as the decision variables in the model in order to either minimize the net cost or maximize the ridership and the waiting time. The passenger flow, used to characterize the waiting time and derived from the trip assignment in [85], is replaced by the relationship between elasticity of ridership and the headways in [84], and this relationship is used in [86] to represent the associated saved waiting time without taking the trip assignment model into account. Later, the proposed nonlinear programming problem is extended and implemented on a large urban network in order to investigate the impact of the heterogeneity of the ridership elasticity [87].

Bus timetable problems specify the departure and arrival times of each bus trip along the bus stops in the transit network. Ceder [83] constructs the bus timetable by passenger load data: Based on the determined bus frequency [82], the bus departure times are calculated according to the evenly spaced headways. However, the even-headway timetable cannot guarantee the homogeneous distribution of the passenger loading volumes on each bus due to the stochastic nature of the passenger demands, which leads to the development of the even-load timetable. Besides developing timetables satisfying demand patterns from the collected data, Ceder and Tal [209] also create a timetable for a transit network in order to maximize the bus synchronization, in which a MILP problem is developed and is solved by a heuristic algorithm in the polynomial time. Note that the road uncertainty may lead to the randomness of the bus travel time, Wu et al. [210] propose a stochastic integer programming model by introducing the slack time into timetables in order to minimize the randomness of the bus travel time, thereby mitigate passenger waiting time for the entire transit network. A genetic algorithm with local search is adopted to solve the problem due to the computational complexity. As mentioned earlier, public transport systems face two challenges: one from the public users and the other from the public administration. How to make bus services more effective to attract more passengers and simultaneously guarantee an economical operation to increase the revenue is also studied in some multi-objective problems. Hassold and Ceder [211] propose a bi-objective optimization model to create bus timetable with the aim to minimize both the passenger waiting time and the empty seats penalty. Based on the costs of each path generated by the demand pattern, the optimal route composed of a set of paths including the start and the end depots is calculated by solving a multi-objective shortest path problem. Although many methods have been proposed to design proper bus frequencies and timetables, the bus operation still cannot guarantee a better service due to the highly stochastic demand patterns and complicated enroute environments. Therefore, other operational strategies, e.g., short turning and deadheading, are proposed in order to address the above issue. Short turning method operates some bus trips serving only part of the route with heavy demands. A schedule coordination between the full-length trip and the short turning trip is proposed [212], in which the location of turnback points, the vehicle sizes, trip headways are all involved in order to minimize the fleet size. The

deadheading refers to an empty trip between two terminals in order to transfer the buses from a terminal with low demands to a terminal with high demands, thereby solving the issue that some terminals run out of buses during peak hours. Ceder [213] uses the concept of the deficit function, which characterizes the net number of trips departing from the terminal, to minimize the fleet size by dispatching buses with deadheading trips. More recently, a method which integrates both the short-turning strategy and deadheading strategy is proposed, with the goal to minimize the waiting cost and the operation cost by satisfying a demand profile [214].

Regardless of how well a transit system is scheduled, phenomena such as vehicle bunching may still exist due to the stochastic enroute traffic and the fluctuated passenger demands. Therefore, real-time control strategies are essential for bus operation systems. The most common methods for station control are holding strategies and stop-skipping strategies. Abkowitz and Lepofsky [215] implement a headway-based control strategy, which holds buses only in one specified stop to a fixed threshold, on two different routes in order to maintain the evenly-spaced headway. The final results found that the method performs well in one of the route while performing badly in the other route, which may be resulted from the limited data collection and complex road traffic for the second route. Eberlein et al. [91] propose the mathematical model involving a holding strategy and a stop-skipping strategy in order to minimize the passenger waiting time. The real data for Massachusetts Bay Transportation Authority (MBTA) Green Line in Boston is adopted to test the model and the results indicate that the cost reduction by combined control involving both holding and stop-skipping strategies is approximately 37%, which is larger than any of the single strategy. Later the similar model with only the holding strategy is elaborately explained in [216] with more rigorous proofs and detailed simulations on bus trajectories and headway variations. The stop-skipping strategy is also adopted in [92], where the two different skipping policies are discussed. The second policy allows the alighting process occurring in the skipped segment while the first does not. The method is developed by solving a nonlinear integer programming problem under the assumption that vehicle capacity is large enough to accommodate the passenger volume. Numerical results indicate that the second policy is more appropriate for the distribution pattern of downtown-oriented passengers, however, this is not founded for the reverse direction. In order to meet the constantly changing passenger demands along the route, a real-time optimization model adopting stop-skipping strategies is proposed with the assumption that vehicle overtake phenomenon never happens in the entire prediction horizon [80]. Also, bus type selection and scheduling interval setting are considered in the timetable optimization, which involve the bus volume dynamics with the waiting passenger demands known as the inputs [90].

Although the uncertainty exists in urban roads which leads to many studies on the transit reliability, advanced bus systems have been implemented around the world with the improvement and adoption of the high-tech sensors [199]. Buses

operate on dedicated bus lanes, with GPS enabled route controllers and digital video cameras to collect real-time information, which leads to significantly decreasing uncertainties in these intelligent transport systems. Therefore, the model in the following subchapter concentrates on the efficiency improvement, by developing the timetable and applying the stop-skipping strategy with the aim to meet passengers travel demand meanwhile reducing the bus operation cost. Specifically, a mixed logical dynamic model of a ring-route bus line is firstly developed with consideration of the stop demand dynamics and the bus demand dynamics. Since the uncertainty is not considered in this paper, the headway between buses dispatched in adjacent trips will be kept in the entire operation. Accordingly, only the timetable in the depot is required to be determined. The bus depot in our model dispatches a single bus or a bus platoon for each trip. Also, the boarding control is applied at each stop. Passengers' perceived delay is firstly formulated by a nonlinear function, which describes the dissatisfaction of the passengers who haven't boarded after their expected bus arrival time. With the aim to minimize the passenger waiting time and the bus vacancy, a MILP model is derived after proper transformation of the mixed logical constraints. Considering the computational complexity of the MILP formulation, modified GA is applied to solve the problem. The case studies indicate that GA can significantly reduce computational time without reducing too much result quality. Moreover, we compare our method with the traditional fixed schedule and the optimized non-platoon schedule, and the simulation results illustrate the efficiency of our method.

4.2 Formulation of the Bus Scheduling Problem

4.2.1 Bus Line Topology

The road network for bus lines is defined as a directed graph $\mathcal{G} = \{\mathcal{S}, \mathcal{L}\}$, where $\mathcal{S}$ is the set of stops along the bus route with any stop $i \in \mathcal{S}$, and $\mathcal{L}$ is the link between two adjacent stops. Let $\mathcal{B}$ be the set of buses, for each bus b , we have $b \in \mathcal{B}$. Bus route in this chapter is defined as a ring road, which means buses start from the depot and finally arrive at the same depot, as shown in Fig. 4.1. Also, either a single bus or multiple buses are allowed to be dispatched from the depot. If a group of buses is released from the depot simultaneously, we call this group of buses a bus platoon, i.e., they are in the same trip. Constant headway Δ is applied for adjacent trip determination instants. The bus platoon dispatched from the depot may disperse and aggregate according to the following principles: 1. If a bus stops at stop i , then the other buses behind this bus in the same platoon will also need to stop at stop i . 2. If there are passengers with destination j on the bus b , then bus b must stop at stop j . Note that the ring road is regarded as the bus route, buses released before will eventually arrive back to the depot, and thereby can be re-dispatched from the depot if the total planning horizon hasn't

Figure 4.1: A ring-route bus line

been reached. Accordingly, the bus return horizon is determined in this chapter by the distance of the ring road in order to illustrate whether the previously dispatched bus can be reused again from the depot. A bus dispatch pattern is described by three characteristics: bus dispatch trip, bus return horizon and bus stop-skipping strategy. The bus dispatch trip denotes the trip that the dispatched bus belongs to. Since we consider a ring route as a bus line, the bus return horizon means the travel time that the dispatched bus finishes a round trip. And bus stop-skipping strategy allows the dispatched bus either stop or skip any stations along the bus line.

Major assumptions for our optimization model are illustrated below:

- Although buses dispatched at trip k may stop at stop i and buses dispatched at trip $k + 1$ may ignore stop i , bus overtake phenomenon is not considered in this chapter. In other words, the dwell time spent in each stop is assumed to be small and can be neglected compared with the headway Δ .
- The proposed strategy is assumed to be applied on an intelligent bus system, where dedicated bus lane, traffic signal priority and V2X communication system are all implemented, and this system can largely reduce the interactions between the private cars and the on-road buses, which significantly decreases the enroute traffic uncertainty. Therefore, uncertainty occurred in the link is not considered in our model, which leads to the assumption that the headway is kept in entire operation time once the buses are dispatched from the depot. In other words, the headway regularization is not the concern of this chapter.

In order to better describe the bus dispatching model, the parameters and decision variables used in our optimization model are summarized in Table 4.1.

Table 4.1: Notations for model variables

Parameter	Definition
i, j	The index of the stop.
b	The index of the bus.
k	The index of the trip.
Δ	Headway between trip k and trip $k + 1$.
T_{return}	A round-travel time, travel time that the dispatched bus finishes the bus line.
$\mathcal{S}$	The stops set.
$\mathcal{B}$	The buses set.
N	Planning horizon.
C_b	The capacity of bus b .
$P_{i,j}(k)$	The number of passengers waiting at stop i with destination stop j when buses of trip k are coming.
$V_{b,i,j}(k)$	The number of passengers on bus b with destination stop j when bus b of trip k reaches stop i .
$B_{b,i,j}(k)$	The number of boarding passengers of bus b of trip k at stop i with destination stop j .
$A_{b,i}(k)$	The number of alighting passengers of bus b of trip k at stop i .
$f_{i,j}(k)$	The number of newly coming passengers at stop i with destination stop j between trips k and $k + 1$.
$x_b(k)$	Bus dispatch indicator. A binary variable. Whether bus b is dispatched at the trip k . $= 1$ if bus b is dispatched at k . $= 0$ if bus b is idle at k .
$Q_{b,i}(k)$	Bus stop indicator. A binary variable. Whether bus b of trip k will stop at stop i . $= 1$ if bus b stops at stop i . $= 0$ if bus b skips stop i .

4.2.2 Problem Description and Model Formulation

4.2.2.1 Volume dynamics in stops

The dynamic of the volume at stop i with destination stop j , $P_{i,j}(k)$, can be updated as follows:

$$P_{i,j}(k+1) = P_{i,j}(k) + f_{i,j}(k) - \sum_{b \in \mathcal{B}} B_{b,i,j}(k) \quad (4.1)$$

where $P_{i,j}(k)$ is the passenger volume at stop i with destination stop j when buses of trip k are coming, $f_{i,j}(k)$ is the incoming passengers at stop i with destination stop j between trips k and $k + 1$, and $B_{b,i,j}(k)$ is the number of boarding passengers of bus b of trip k at stop i with destination stop j . Equation (4.1) describes that the number of passengers at stop i with destination stop j is determined by the incoming passengers $f_{i,j}(k)$ and the sum of the all boarding passengers $\sum_{b \in \mathcal{B}} B_{b,i,j}(k)$.

4.2.2.2 Volume dynamics on buses

Volume dynamics on buses is updated according to the bus stop, which can be illustrated as follows:

$$\sum_{j \in \mathcal{S}} V_{b,i+1,j}(k) = \sum_{j \in \mathcal{S}} V_{b,i,j}(k) + \sum_{j \in \mathcal{S}} B_{b,i,j}(k) - A_{b,i}(k) \quad (4.2)$$

where $V_{b,i,j}(k)$ is the number of passengers on bus b with destination stop j when bus b of trip k just reaches stop i , and $A_{b,i}(k)$ is the number of alighting passengers of bus b of trip k at stop i . Equation (4.2) indicates that the passenger volume of bus b when it reaches stop $i + 1$ is equal to the passenger volume of bus b when it reaches stop i plus the boarding flow $\sum_{j \in \mathcal{S}} B_{b,i,j}(k)$, and minus the alighting flow $A_{b,i}(k)$.

4.2.2.3 Boarding flow constraints

Since bus stop-skipping strategy is adopted in this model, we use binary variable $Q_{b,i}(k)$ to denote whether bus b of trip k will stop at stop i or not. If $Q_{b,i}(k) = 1$, bus b of trip k will stop at stop i , otherwise, it will skip the stop i .

$$B_{b,i,j}(k) \leq Q_{b,i}(k)M \quad (4.3a)$$

$$\sum_{j \in \mathcal{S}} B_{b,i,j}(k) \leq C_b - \sum_{j \in \mathcal{S}} V_{b,i,j}(k) \quad (4.3b)$$

$$\sum_{b \in \mathcal{B}} B_{b,i,j}(k) \leq P_{i,j}(k) \quad (4.3c)$$

where M is a very large value, and C_b is the capacity of the bus b . Equations (4.3a) indicates that the boarding flow is restricted by the bus stop indicator $Q_{b,i}(k)$, namely, passengers can board on bus b at stop i only if bus b stops at stop i . Equation (4.3b) indicates that the total passenger boarding flow cannot exceed the remaining space of the bus b . Also, equation (4.3c) describes that the total passenger boarding flow at stop i with destination stop j cannot exceed the number of waiting passengers at stop i with destination stop j .

4.2.2.4 Alighting flow constraints

Equation (4.4) illustrates that passenger alighting flow of bus b of trip k at stop j cannot exceed the volume on bus b with the destination stop j . Since we only consider a single bus line in this model, the alighting passengers, who may reach their destination or prepare to make a transfer, will not be described in this chapter

and shall be studied in our future work.

$$A_{b,j}(k) \leq \sum_{q \in \mathcal{S}} V_{b,q,j}(k) \quad (4.4)$$

4.2.2.5 Bus reschedule gap

Due to the assumption that the bus route forms a ring road, the previous dispatched buses can be re-dispatched once come back to the depot. Since the road uncertainty is not considered in this chapter, we assume that all buses will spend the same time finishing one round-trip, and T^{return} represents the round-trip time of the route.

$$(\forall b \in \mathcal{B}) \quad x_b(k) = 1 \Rightarrow \sum_{i=1}^{\lfloor \frac{T^{return}}{\Delta} \rfloor} x_b(k+i) = 0 \quad (4.5)$$

where $x_b(k)$ is a binary variable, which is used to indicate that whether bus b is dispatched at trip k , and $\lfloor \cdot \rfloor$ is the largest integer not greater than the input argument. $x_b(k) = 1$ means bus b is dispatched at k , otherwise, it is idle in the depot. The above equation indicates that bus b cannot be re-dispatched unless it has finished the round trip.

4.2.2.6 Stop criterion

The dispatched bus platoon may bring more bus vacancy if the bus platoon stops at one station which does not have so many passengers, thus, the stop of entire bus platoon will waste the source. In order to provide a high level of the bus service meanwhile guarantee a better trade-off between the supply and the demand, we allow the bus platoon can be separated when it approaches the bus station: If any bus of the bus platoon stop at the stop, then buses driving behind in the same platoon will also need to stop, which can be captured as follows:

$$\begin{aligned} &(\forall b', b \in \mathcal{B})(\forall j \in \mathcal{S}) \\ &b < b' \wedge Q_{b,j}(k) = 1 \wedge x_{b'}(k) = 1 \Rightarrow Q_{b',j}(k) = 1 \end{aligned} \quad (4.6)$$

Equation (4.6) indicates that if bus b is in front of bus b' and bus b of trip k stops at stop j , also, bus b' is dispatched at trip k , then bus b' must stop at stop j .

Moreover, if there exist demands with destination j on bus b , then bus b must stop at stop j .

$$\begin{aligned} &(\forall b \in \mathcal{B})(\forall i, j \in \mathcal{S}) \\ &V_{b,i,j}(k) \neq 0 \Rightarrow Q_{b,j}(k) = 1 \end{aligned} \quad (4.7)$$

4.2.2.7 Bus dispatching constraints

Bus stop indicator $Q_{b,i}(k)$, boarding flow parameter $B_{b,i,j}(k)$, alighting flow parameter $A_{b,i}(k)$ and bus volume parameter $V_{b,i,j}(k)$ are all determined by the dispatched parameter $x_b(k)$, namely, only if the bus b is dispatched at trip k , the mentioned parameters belong to trip k could be active in the model, which can be described as follows:

$$(\forall b \in \mathcal{B})(\forall i, j \in \mathcal{S})$$

$$x_b(k) = 0 \Rightarrow Q_{b,i}(k) = 0 \quad (4.8a)$$

$$x_b(k) = 0 \Rightarrow B_{b,i,j}(k) = 0 \quad (4.8b)$$

$$x_b(k) = 0 \Rightarrow A_{b,i}(k) = 0 \quad (4.8c)$$

$$x_b(k) = 0 \Rightarrow V_{b,i,j}(k) = 0 \quad (4.8d)$$

Equation (4.8a) indicates that bus b can be applied stop-skipping strategy only if the bus b is dispatched. Similarly, boarding flow $B_{b,i,j}(k)$, alighting flow $A_{b,i}(k)$ and bus volume $V_{b,i,j}(k)$ must be 0 if bus b is not dispatched in trip k , as shown in equations (4.8b), (4.8c) and (4.8d).

4.2.2.8 Objectives for the entire ring road

We consider three different performance indexes in our model: Passengers' total delay, passengers' perceived delay and total bus vacancy.

Passengers' total delay

We try to minimize the passenger queue waiting at each station, by multiplying the headway Δ , the estimated passenger's total delay through all stations and entire planning horizons is captured by the following equation:

$$J_{td} = \sum_{i,j \in \mathcal{S}} \sum_{k=1}^N P_{i,j}(k) \Delta \quad (4.9)$$

where N is the prediction step, and the prediction horizon $H_p = N\Delta$.

Passengers' perceived delay

Time can be measured both subjectively and objectively [217][171]. Many researchers focus on minimizing the actual passenger delay, but neglects the impact of passengers psychological perception. Time reflected on the clock is the actual

time from the objective perspective, while time can also be perceived based on users feelings [218][219][220]. The perceptions of waiting time have a significant influence on the user experience, and thereby affecting passengers transport mode selections [221][222]. To enhance the public transit's popularity, the passengers' perceived delay is modelled as follows:

For passengers who arrive between trips k and $k + 1$, we assume these passengers' expected boarding time is $k + 1$, and their dissatisfaction will be incurred due to longer waiting time if they cannot board at trip $k + 1$. This dissatisfaction, called perceived delay in the chapter, is captured by the following nonlinear function:

$$D(i, j, k + 1, m) = \max\{f_{i,j}(k) - \max[\sum_{b \in \mathcal{B}} \sum_{l=k+1}^m B_{b,i,j}(l) - (P_{i,j}(k) - \sum_{b \in \mathcal{B}} B_{b,i,j}(k)), 0], 0\} \theta(m - (k + 1)) \quad (4.10)$$

Equation (4.10) describes the perceived delay for passengers who arrive between trips k and $k+1$ at stop i with destination stop j but still have not boarded on buses of trip m . The term $\max[\sum_{b \in \mathcal{B}} \sum_{l=k+1}^m B_{b,i,j}(l) - (P_{i,j}(k) - \sum_{b \in \mathcal{B}} B_{b,i,j}(k)), 0]$ represents the number of boarding passengers at stop i with destination stop j from trip $k + 1$ to trip m , which is contributed by the incoming flow after trip k (those who arrive before trip k have already been removed in the term, namely, $P_{i,j}(k) - \sum_{b \in \mathcal{B}} B_{b,i,j}(k)$). Also, the term $\max\{f_{i,j}(k) - \max[\sum_{b \in \mathcal{B}} \sum_{l=k+1}^m B_{b,i,j}(l) - (P_{i,j}(k) - \sum_{b \in \mathcal{B}} B_{b,i,j}(k)), 0], 0\}$ captures the number of remaining passengers after trip m with destination stop j at stop i and these passengers arrive stop i during trip interval k . The term $\theta(m - (k + 1))$ is a nonlinear function of its arguments, such as exponential function, and $\theta(m - (k + 1))$ indicates the perceived time elapse from the expected arrival time $k + 1$.

Based on the above description, the total passengers' perceived delay through all stations and entire planning horizons is described as follows:

$$J_{pd} = \sum_{i,j \in \mathcal{S}} \sum_{k=1}^{N-1} \sum_{m=k+1}^N D(i, j, k + 1, m) \quad (4.11)$$

Total bus vacancy

We also try to minimize the empty seats of each bus from bus operator's perspective in order to improve bus utilization, which is captured as follows:

$$J_{bv} = \sum_{b \in \mathcal{B}} \sum_{k=1}^N \sum_{i \in \mathcal{S}} (C_b - \sum_{j \in \mathcal{S}} V_{b,i,j}(k)) \quad (4.12)$$

Optimal objective function for the dynamic bus model

We consider two different objectives, the first one tries to minimize passengers' total estimated delay and the remaining seats in each bus, the objective is illustrated as follows:

$$Cost_1 = C_{td}J_{td} + C_{bv}J_{bv} \quad (4.13)$$

where C_{td} and C_{bv} are the weight coefficients for passengers' total delay and bus vacancy, respectively. The above equation is a linear function, which could be solved via both MILP and Evolutionary Algorithms (EA), while the second cost can only be solved by the EA due to its nonlinear function of passengers' perceived delay:

$$Cost_2 = C_{pd}J_{pd} + C_{bv}J_{bv} \quad (4.14)$$

where C_{pd} is the weight coefficient for passengers perceived delay.

4.3 Solution Algorithms

So far the bus scheduling problem has been derived as a mixed logical dynamic model, which involves a linear cost function (4.13) and a nonlinear cost function (4.14) with mixed logic constraints, e.g., stop criterion constraints (4.6) and (4.7), bus dispatching constraints (4.8), bus reschedule constraints (4.5), and linear constraints, e.g., stop volume dynamics (4.1), bus volume dynamics (4.2), boarding flow constraints (4.3) and alighting flow constraints (4.4). In the simulation of this chapter, we firstly consider the linear case by using both MILP and GA to solve the problem and comparing the difference of the computational time and the result quality, while the nonlinear case is solved by GA and is compared with other dispatching strategy.

In this subchapter, we firstly translate the above logic constraints into mixed integer linear constraints, then solve a MILP problem via commercial solver, GUROBI [152], in order to find the global optimal solution. The specific conversion process can be found in the following Chapter 4.3.1. With computational complexity being a concern for our model, the genetic algorithm, one of the famous evolutionary algorithms, is also adopted to solve our problem via its internal heuristic, which is discussed in Chapter 4.3.2.

4.3.1 A MILP Formulation for Bus Scheduling Model

The logic constraints mentioned above involve stop criterion constraints (4.6) and (4.7), bus dispatching constraints (4.8) and bus reschedule constraints (4.5). The first stop criterion constraint (4.6) can be translated into the following constraints

by introducing the auxiliary variable $\delta_{bb'}(k)$:

$$b < b' \Leftrightarrow \delta_{bb'}(k) = 1 \quad (4.15)$$

Then the logic relationship above can be rewritten as:

$$b - b' \leq -\epsilon + M_1(1 - \delta_{bb'}(k)) \quad (4.16a)$$

$$b' - b \leq M\delta_{bb'}(k) \quad (4.16b)$$

$$Q_{b',j}(k) - 1 \leq M_1(1 - \delta_{bb'}(k)) + M_1(1 - Q_{b,j}(k)) + M_1(1 - x_{b'}(k)) \quad (4.16c)$$

$$1 - Q_{b',j}(k) \leq M_1(1 - \delta_{bb'}(k)) + M_1(1 - Q_{b,j}(k)) + M_1(1 - x_{b'}(k)) \quad (4.16d)$$

where ϵ is sufficiently small and M_1 is a sufficiently big integer, e.g., $M_1 \geq \max(\pm(b - b'))$.

Proposition 4.1 *Replacing Equation (4.6) with Inequalities (4.16) in the model leads to the same solution.*

Similarly, the second stop criterion constraint (4.7) can be converted into the following inequalities by introducing binary variable $\rho_{b,i,j}(k)$:

$$V_{b,i,j}(k) \neq 0 \Leftrightarrow \rho_{b,i,j}(k) = 1 \quad (4.17)$$

Then the logic relationship above can be rewritten as:

$$V_{b,i,j}(k) \leq M_2\rho_{b,i,j}(k) \quad (4.18a)$$

$$V_{b,i,j}(k) \geq \epsilon - M_2(1 - \rho_{b,i,j}(k)) \quad (4.18b)$$

$$1 - Q_{b,j}(k) \leq M_2(1 - \rho_{b,i,j}(k)) \quad (4.18c)$$

where ϵ is sufficiently small and M_2 is a sufficiently big integer, e.g., $M_2 \geq \max_k(V_{b,i,j}(k))$.

Proposition 4.2 *Replacing Equation (4.7) with Inequalities (4.18) in the model leads to the same solution.*

Let M_3 chosen to be sufficiently big, e.g., $M_3 \geq \max_k(Q_{b,i}(k), B_{b,i,j}(k), A_{b,i}(k), V_{b,i,j}(k))$, then equation (4.8) can be translated into the following form:

$$Q_{b,i}(k) \leq M_3x_b(k) \quad (4.19a)$$

$$B_{b,i,j}(k) \leq M_3x_b(k) \quad (4.19b)$$

$$A_{b,i}(k) \leq M_3x_b(k) \quad (4.19c)$$

$$V_{b,i,j}(k) \leq M_3x_b(k) \quad (4.19d)$$

Proposition 4.3 *Replacing Equation (4.8) with Inequalities (4.19) in the model leads to the same solution.*

Also, let M_4 chosen to be sufficiently big, e.g., $M_4 \geq \max_k (\sum_{i=1}^{\lfloor \frac{T^{return}}{\Delta} \rfloor} x_b(k+i))$, then equation (4.8) can be translated into the following form:

$$\sum_{i=1}^{\lfloor \frac{T^{return}}{\Delta} \rfloor} x_b(k+i) \leq M_4 x_b(k) \quad (4.20)$$

Proposition 4.4 *Replacing Equation (4.5) with Inequalities (4.20) in the model leads to the same solution.*

Finally, we can translate our bus scheduling problem as a MILP problem: the objective function is equation (4.13) with stop criterion constraints (4.16) and (4.18), bus dispatching constraints (4.19), bus reschedule constraints (4.20), stop volume dynamics (4.1), bus volume dynamics (4.2), boarding flow constraints (4.3) and alighting flow constraints (4.4). Then our problem can be solved by existing commercial solvers, e.g. GUROBI. In order to further improve the computational efficiency, we also consider one of the evolution algorithms - GA.

4.3.2 Genetic Algorithm for Bus Scheduling Model

Note that the complexity of the proposed MILP problem is NP-hard, we adopt the GA to solve our problem. GA has been successfully demonstrated on many bus scheduling problems, in which both good quality solutions and reasonable computational time are satisfied [223]. We adopt the GA with the elitist parent selection and a single-point crossover, and the specific process of entire GA method is captured in Fig. 4.2. Firstly, each chromosome of the whole population is randomly generated in the initialization step. Then the generated chromosomes are transferred into the fitness function with the aim to evaluate the performance of each chromosome. After that, the parents, chromosomes with better performance, are selected to generate offsprings in the next step. After the offsprings are evaluated by the fitness function, chromosomes with better performance is kept in the next cycle and those with the worst objective function value is removed from the population. Then the above process continuous until the termination criterion is met. In the following part, the scheme to generate feasible decision variables that satisfy the discussed constraints will be elaborately explained. There are two types of decision variables existing in the proposed model: Firstly, the binary variables $x_b(k)$ and

Figure 4.2: The flow diagram of the GA

$Q_{b,i}(k)$. Secondly, due to the existence of the inequalities (4.3) and (4.4), the integer variables $B_{b,i,j}(k)$ and $A_{b,i}(k)$ also become the decision variables in the GA.

The initialization of the binary variables is described in Algorithm 7. In step 1, the dispatch indicator $x_b(k)$ is randomly initialized, and the function **rand()** is used to randomly generate integer 0 or 1. In order to satisfy the constraint (4.5), step 1.2 is added to guarantee the bus re-dispatch pattern. After the bus dispatch indicator is generated, the bus stop indicator $Q_{b,i}(k)$ is initialized in step 2. In step 3, the state of the bus stop indicator needs to be modified according to the rule: if the front bus stops at stop i , then the buses behind in the same trip should also stop. The bus volume dynamics described in equation (4.2) can be rewritten as follows without taking the alighting flow $A_{b,i}(k)$ into account as long as the stop j is after stop $i + 1$, namely, $j > i + 1$.

$$V_{b,i+1,j}(k) = V_{b,i,j}(k) + B_{b,i,j}(k) \quad (4.21)$$

Under this simplification of the bus volume dynamics, we only need to consider the initialization of the boarding flow variables $B_{b,i,j}(k)$, then the stop j of $V_{b,i,j}(k)$ in constraint (4.3b) is the stop after the stop i , while the stop j of $V_{b,i,j}(k)$ in cost function (4.12) is the stop at stop i or after the stop i .

The initialization of the boarding flow variables $B_{b,i,j}(k)$ is decoded by a random real fraction number η according to the number of stopped buses at each stop (the

Algorithm 7 Initialization of Binary Individuals**Init** (InputData, PopSize)**Input:** InputData: $b \in \mathcal{B} = \{1, \dots, n\}$ - Index of buses, $i \in \mathcal{S} = \{1, \dots, m\}$ - Index of stops, $k \in \mathcal{K} = \{1, \dots, N\}$ - Window size; PopSize - Population size;**Output:** $\{x_b(k), Q_{b,i}(k)\}$ - Initial dispatched indicators, initial stop indicators**For all** PopSize1 **For all** $k \in \mathcal{K}$, **For all** $b \in \mathcal{B}$ 1.1 $x_b(k) \leftarrow \text{rand}()$ 1.2 **For all** $k' \in \mathcal{K} \wedge k' < k$ 1.2.1 $x_b(k) \leftarrow 0$ **If** $x_b(k')$ is 1 **and** $k < k' + T^{\text{return}}$ **End For****End For**2 **For all** $k \in \mathcal{K}$, **For all** $b \in \mathcal{B}$, **For all** $i \in \mathcal{S}$ 2.1 $Q_{b,i}(k) \leftarrow 0$ **If** $x_b(k)$ is 02.2 $Q_{b,i}(k) \leftarrow \text{rand}()$ **If** $x_b(k)$ is 1**End For**3 **For all** $k \in \mathcal{K}$, **For all** $b \in \mathcal{B}$, **For all** $i \in \mathcal{S}$ 3.1 **For all** $r \in \mathcal{B}$ **and** $r < b$ 3.1.1 $Q_{b,i}(k) \leftarrow 1$ **If** $x_b(k)$ is 1 **and** $Q_{r,i}(k)$ is 1**End For****End For****End For****Return** Results Pop $\leftarrow \{x_b(k), Q_{b,i}(k)\}$

outcome of the Algorithm 7). The following equations describe the situation that N buses ($b_1, b_2, \dots, b_m, \dots, b_N$) of trip k stop at stop i :

$$B_{b_1,i,j}^{\text{demand}}(k) = \lfloor P_{i,j}(k) \eta_1 \rfloor \quad (4.22a)$$

$$B_{b_m,i,j}^{\text{demand}}(k) = \lfloor P_{i,j}(k) \prod_{p=1}^{p=m-1} (1 - \eta_p) \eta_m \rfloor \quad (4.22b)$$

$$B_{b_N,i,j}^{\text{demand}}(k) = \lfloor P_{i,j}(k) \prod_{p=1}^{p=N} (1 - \eta_p) \rfloor \quad (4.22c)$$

where $\eta_1, \dots, \eta_m, \dots, \eta_N$ are all randomly generated real values between 0 and 1, and $\lfloor \cdot \rfloor$ is the largest integer not greater than the input argument.

The number of possible destination stops for passengers waiting at stop i is listed as $i + 1, i + 2, \dots, N_s, 1$ if i is not the terminal stop ($i > 1$) or $i + 1, i + 2, \dots, N_s$ if i is the first stop, where N_s is the total number of stops on the ring route. We use $g_1, g_2, \dots, g_m, \dots, g_N$ to denote the possible destination stops of stop i . Accordingly,

the boarding flows determined by bus vacancy for bus b are captured as follows:

$$B_{b,i,g_1}^{bus}(k) = \lfloor (C_b - \sum_{j \in \mathcal{S}} V_{b,i,j}(k)) \eta'_1 \rfloor \quad (4.23a)$$

$$B_{b,i,g_m}^{bus}(k) = \lfloor (C_b - \sum_{j \in \mathcal{S}} V_{b,i,j}(k)) \prod_{p=1}^{p=m-1} (1 - \eta'_p) \eta'_m \rfloor \quad (4.23b)$$

$$B_{b,i,g_N}^{bus}(k) = \lfloor (C_b - \sum_{j \in \mathcal{S}} V_{b,i,j}(k)) \prod_{p=1}^{p=N} (1 - \eta'_p) \rfloor \quad (4.23c)$$

where $\eta'_1, \dots, \eta'_m, \dots, \eta'_N$ are also randomly generated real values between 0 and 1. The final boarding flow for bus b_m with destination stop g_m is the minimum of the above equations, which can be illustrated as follows:

$$B_{b_m,i,g_m}(k) = \min(B_{b_m,i,g_m}^{demand}(k), B_{b_m,i,g_m}^{bus}(k)) \quad (4.24)$$

The high-tech of the intelligent transportation system [199] provides the possible practical implementation to control the boarding flow. This could be realized via the communication between the arrival bus and the waiting passengers. The arrival bus will send a message to relevant passengers in the front queue at the bus station to notify them enter into the designated boarding area. Once buses reach the station, only passengers who are waiting at the designated area are allowed to board the bus. By doing so, the bus operator can effectively control the number of passengers boarding a bus in the platoon, and leave necessary capacity to passengers in the downstream stations to avoid the situation where the bus is fully boarded at the upstream several stations with no space for passengers at subsequent stations, thereby cause a high perceived delay time in subsequent stations.

4.4 Numerical Examples

In this part, we firstly test our strategy with various bus stops and prediction horizons in order to see the computational efficiency of our proposed model under two different algorithms. Then the comparison between our proposed strategy, the traditional fixed schedule strategy and the optimized non-platoon strategy is conducted with respect to different passenger demands. The bus line in the case study is a circle line, as shown in Fig. 4.1. The headway between two adjacent trips is $\Delta = 10\text{min}$. The capacity of each bus is 200 (This could be possible if a double-decker bus is considered). There are N_s bus stops on the bus line, and N_b buses in the depot, H_p is the prediction horizon with $H_p = N\Delta$.

4.4.1 Computational Complexity

The bus scheduling problem is firstly solved by an existing optimization solver, GUROBI, after translating into a MILP problem. In the experiment, GUROBI is used in MATLAB to solve the problem on a PC with an Intel(R) Core(TM) i7-4770 CPU @3.40GHz and RAM 8GB. Then the GA is also adopted to compare with the MILP method. The Table 4.2 indicates the initial setting for *Case* 1 to *Case* 16 with different bus stops N_s , prediction horizons H_p and return horizons T^{return} . Table

Table 4.2: Initial settings for different cases

	N_b	N_s	H_p	T^{return}
case 1	3	10	5 Δ	4 Δ
case 2	3	15	5 Δ	6 Δ
case 3	3	20	5 Δ	8 Δ
case 4	3	25	5 Δ	10 Δ
case 5	3	10	6 Δ	4 Δ
case 6	3	15	6 Δ	6 Δ
case 7	3	20	6 Δ	8 Δ
case 8	3	25	6 Δ	10 Δ
case 9	3	10	7 Δ	4 Δ
case 10	3	15	7 Δ	6 Δ
case 11	3	20	7 Δ	8 Δ
case 12	3	25	7 Δ	10 Δ
case 13	3	10	8 Δ	4 Δ
case 14	3	15	8 Δ	6 Δ
case 15	3	20	8 Δ	8 Δ
case 16	3	25	8 Δ	10 Δ

4.3 and Table 4.4 depict the processing time and the entire cost for *Case* 1 to *Case* 8 and *Case* 9 to *Case* 16 under two different algorithms, respectively. The total passenger waiting time and the bus vacancy are also listed in the table. In Table 4.3, we can see that GUROBI can solve a bus line with 10 bus stops and one-hour prediction horizon (*Case* 5) in only 2.7869 seconds, which is equivalent to solving a MILP problem with 2916 integer and binary decision variables and 7665 constraints, thereby, the real-time scheduling is definitely workable since only 0.46% (2.7869 s/10 min) of the time is used for computation. However, with the increase of the bus stops and prediction horizons, the computational time increases exponentially, which leads to the reduction of the probability of the real-time scheduling. Specifically, a bus line with 25 bus stops and a 80 min prediction horizon (*Case* 16) needs 804.41 seconds to obtain the final result, which has already exceeded the headway more than 200 seconds, and this definitely cannot be applied on a rolling horizon mechanism, so more efficient algorithms are required to overcome the computational challenge. To cope with this challenge, the GA discussed in Chapter 4.3.2 is adopted

to solve the problem. The population size is 50 and the iteration times are 1000. Crossover rate and mutation rate are set as 0.5. The actual costs are J^* listed in Tables 4.3 and 4.4 by applying MILP on the entire bus line, and the computed costs J by applying near-optimal scheduling from GA are also listed in the Tables 4.3 and 4.4. It is obvious to see that GA requires more time to find a good solution compared with MILP when the problem scale is small, however, the computational advantages of the GA gradually emerge with the increase of the problem scale. As mentioned before, a bus line with 25 bus stops and a 80 min prediction horizon (*Case 16*) requires 804.41 seconds in MILP to obtain the optimal result, now only needs 43.677 seconds in GA to get a result, which is also in a good quality, since only 8.657% gap is found from the optimal result. All the other cases in Tables 4.3 and 4.4 also indicate that the difference degree is below 15%, which illustrates that GA can provide a significant increase of efficiency meanwhile ensuring an acceptable degree of performance degradation.

Moreover, the averaged passenger delays are also provided for the MILP method, as our model is a discrete-time model, and the delay of each passenger can only be multiple times of the trip interval Δ , which leads to the results that the estimated delay could be larger than the real delay. But the estimated values of the average passenger delay are also worthy to be studied, as shown in Tables 4.3 and 4.4, the averaged delays which already surpass 20 minutes may require the adjustment of the bus dispatching intervals, which belongs to another public bus tactical problem - bus frequency settings, and shall be studied in our future work.

4.4.2 Cost Comparison between Our Method and Other Methods for the Linear Objective

We now consider a bus line with 10 bus stops and 5 buses in the depot. The prediction horizon is 80 min and the round-trip time is 40 min. We test our model with the linear objective (4.13) in several different passenger volumes to see the corresponding delay cost. The total incoming passenger flows of all stops and all trips range from 8000 passengers to 16000 passengers, increasing at an interval of 1600 passengers. The incoming passenger flows between two adjacent trips are randomly generated. The performance of our proposed strategy, the fixed-dispatch strategy and the non-platoon optimized strategy is compared in Fig. 4.3. In fixed-dispatch strategy, only one bus is allowed to be dispatched for each trip and each bus will stop at every stop along the bus line. And the non-platoon strategy includes bus stop-skipping strategy but only allows one bus to be dispatched at each trip. Both the non-platoon strategy and our proposed strategy are obtained from MILP. Fig. 4.3a shows the total cost of three strategies according to the passenger incoming flows. The red line, the blue line and the green line are under our proposed strategy, the non-platoon strategy and the fixed strategy, respectively. The total costs under three strategies all become increasingly large with the increase of the

(a) Total Cost

(b) Passenger delay

Figure 4.3: Performance comparison between our strategy and fixed schedule strategy

(c) Bus vacancy

Figure 4.3: Performance comparison between our strategy and fixed schedule strategy

passenger incoming volumes. Clearly, our method outperforms the other two, and the non-platoon optimized strategy is superior to the fixed strategy. Besides the total cost, the passenger waiting time and the bus vacancy are also drawn in Fig. 4.3b and Fig. 4.3c, respectively. Similar to the total cost, our strategy leads to lower passenger waiting time compared with the fixed strategy and the non-platoon strategy.

In Fig. 4.3c, the bus vacancy of the fixed strategy decreases according to the increase of the passenger volume. The reason is that the number of bus trips is fixed in a 80 min prediction horizon, and the fixed strategy only allows one bus to be dispatched at each trip, then the bus vacancy definitely should decrease as the average boarding passengers become increasingly large. However, since our method and non-platoon method allows the stop-skipping strategy, which leads to the phenomenon that the bus vacancy may increase even the passenger volume increases, this is also shown in Fig. 4.3c. When the total passenger volume is 16000, the bus vacancy for red line increases compared with its value when the total passenger volume is 14400. The gap is not very clear since the difference between two values is very small, which can be clearly reflected in Fig. 4.4c. Although the bus vacancy under our proposed method fluctuates as the increase of the passenger volume, its value is still the smallest among all methods.

The three graphs also show the advantages of the platoon dispatching when compared with non-platoon strategy. Since platoon dispatching brings more flexibility in the bus operation, especially when the passenger volumes are distributed asymmetrically in time and space. Additionally, the platoon dispatching is not the same as the bus bunching. Since the latter is observed due to the traffic uncertainty occurred on the road, and the vacancy that the bunching buses bring do not match the passenger demands at the stop. However, the platoon dispatching is driven by the passenger demands, and we do not consider road uncertainty in this thesis. Therefore, the bus platoon can serve more passengers if there are large amount of people waiting at the stop, which is an impossible task for one single bus to accomplish in one time.

4.4.3 Cost Comparison between Our Method and Other Methods for the Nonlinear Objective

Besides the estimated total passenger delay in (4.13), we now test our model with nonlinear cost (4.14) and compare with the other two different strategies: non-platoon strategy and fixed strategy. We use quadratic form $(m - (k + 1))^2$ in the case study to represent the nonlinear relationship $\theta(m - (k + 1))$ in function (4.10). Similarly, a bus line with 10 bus stops and 5 buses is considered in the case study. The prediction horizon is 80 min and the round-trip time is 40 min, and the total incoming passenger flows of all stops and all trips range from 11200

passengers to 19200 passengers, increasing at an interval of 1600 passengers. The results of the non-platoon strategy and our proposed strategy are obtained by GA. Fig. 4.4 illustrates the performance of three strategies under the nonlinear objective (4.14).

Fig. 4.4a, 4.4b and 4.4c depict the total cost, passenger waiting delay and bus vacancy of three strategies, respectively. Also, the green line, the red line and the blue line are under our proposed strategy, the non-platoon strategy and the fixed strategy, respectively. Clearly, our strategy outperforms the other two in both total costs and passenger perceived delay. Also, due to the nonlinear increase of the passengers' anxiety, the advantages of our method on passengers' perceived waiting time is becoming more and more obvious as the passenger volume increases, which is clearly shown in Fig. 4.4b. Although the fixed strategy is worse than our proposed strategy and non-platoon strategy on total cost and passenger perceived delay, its bus vacancy is largely reduced, however, the bus vacancy for the proposed method and the non-platoon method fluctuates as the demand increases. The reason has been mentioned in Chapter 4.4.2, which is due to the stop-skipping strategy applied in these two methods. Besides that, the boarding flow of fixed strategy is determined only by the demand and the bus vacancy, passengers in the station will all board the bus if there are sufficient remaining space in the bus. However, the boarding flow is decision variables in our method and non-platoon method, and only part of the waiting passengers could successfully board the bus which still has space to accommodate passengers but directly leave the current station and drive to the downstream one. This is because we want to keep necessary space for passengers at subsequent stations to avoid their longer wait, which could also leads to the high bus vacancy results in Fig. 4.4c. However, this could be tuned via the weights applied on each element of the objective once the specific background is involved, which could be studied in our future work.

4.5 Concluding Remarks

In this chapter, we provide an overview for the urban transit system. Due to the complexity of the urban transit system, problems existing in the system are divided into subproblems and are solved sequentially, which takes the results of the previous subproblem as the inputs of the current subproblem. Also, since we address the bus dispatching system from the tactical and operational level with the consideration of the stop-skipping control strategies, literatures related to FS, BTD and station control strategies are elaborately discussed in the literature review.

In the second part, a platoon-based bus dispatching strategy with the bus stop-skipping strategy is firstly proposed for a ring road bus transport system. Either a single bus or a bus platoon is allowed to be dispatched from the depot. Also, the bus platoon can be separated at the stop if there are no huge lines of

(a) Total Cost

(b) Passenger delay

Figure 4.4: Performance comparison between our strategy and the non-platoon strategy

(c) Bus vacancy

Figure 4.4: Performance comparison between our strategy and the non-platoon strategy

people waiting at the stop, which makes our strategy more flexible and adaptive to meet the passenger demand. Meanwhile, we formulate the passengers' perceived delay time as a nonlinear function, which captures the passengers' dissatisfaction due to their elongated wait. Our objective considers both the passenger waiting time and the bus vacancy in order to meet the interests from the demand side and the supply side. After translating several mixed logical constraints, a MILP model is developed to formulate the problem. In facing the computational challenge, we adopt the GA, one of the evolutionary algorithms, to help to solve our problem in real time. Simulation results indicate that GA can provide a significant increase of efficiency meanwhile ensuring an acceptable degree of performance degradation. Additionally, we compare our method with the traditional fixed dispatching strategy and optimized non-platoon strategy. The results illustrate that the performance of our method outperforms the other two, which indicates that platoon dispatching brings flexibility in bus operation and achieve better balance between the supply and the demand.

Table 4.3: A comparison between computed and actual time delay for MLP with GA - case 1 to case 8

Operation setting	MLP					GA					$\frac{J-J^*}{J^*}$
	Computational Time	Total Cost J^*	Total Passenger Delay (* Δ min)	Bus Vacancy	Average Passenger Delay(min)	Computational Time	Total Cost J	Total Passenger Delay (* Δ min)	Bus Vacancy		
case 1	2.1568	30596	7326	23270	13.537	12.571	33207	8145	25062	8.534%	
case 2	22.523	46001	8865	37136	15.048	16.640	50363	10113	40250	9.482%	
case 3	93.081	60462	11296	49166	17.146	22.346	67690	13849	53841	11.95%	
case 4	256.51	76444	14998	61446	20.356	34.128	86378	18234	68144	12.99%	
case 5	2.7869	37499	10889	26610	17.175	17.251	42170	12507	29663	12.46%	
case 6	55.224	58563	12459	46104	18.409	20.329	62376	13921	48455	6.511%	
case 7	180.00	76703	15633	61070	20.936	29.111	84299	18185	66114	9.903%	
case 8	350.76	94649	18417	76232	23.018	36.922	105323	21821	83502	11.28%	

Table 4.4: A comparison between computed and actual time delay for MILP with GA - case 9 to case 16

Operation setting	MILP					GA				$\frac{J-J^*}{J^*}$
	Computational Time	Total Cost J^*	Total Passenger Delay (* Δ min)	Bus Vacancy	Average Passenger Delay(min)	Computational Time	Total Cost J	Total Passenger Delay (* Δ min)	Bus Vacancy	
case 9	6.1880	45015	12894	32121	17.584	17.968	49949	15412	34537	10.96%
case 10	47.315	67268	17424	49844	22.422	23.198	74335	18525	55810	10.51%
case 11	296.24	93304	19956	73348	23.942	33.219	100964	23517	77447	8.210%
case 12	513.54	115115	23810	91305	26.651	42.542	126856	28842	98014	10.20%
case 13	12.323	54578	16174	38404	19.633	19.105	59423	18627	40796	8.877%
case 14	50.948	79684	23105	56579	26.813	24.879	88078	24675	63403	10.53%
case 15	317.63	110386	24990	85396	27.107	33.739	118347	29379	88968	7.212%
case 16	804.41	136252	29820	106432	30.048	43.677	148048	35823	112225	8.657%

Chapter 5

Conclusions and Future Work

Summary - In this thesis, we have provided strategies from a pedestrian/transit-oriented perspective: we have designed adaptive traffic signal control strategies by developing macroscopic mixed-flow models in order to either reduce delay time for pedestrians and vehicles or improve pedestrian crossing safety for urban traffic network. Furthermore, we have also presented a multi-bus dispatching strategy with the aim to minimize passenger delay from the demand side and bus vacancy from the supply side. This chapter concludes this thesis by summarizing the main contributions and suggesting directions for future research.

5.1 Summary of Contributions

The major contributions presented in this dissertation can be summarized as follows:

- **Develop macroscopic pedestrian crossing model integrating the impacts of traffic light**

In Chapter 2, the proposed pedestrian volume dynamics in each junction captures the characteristics of the conventional two-way crossing of the crosswalk topology, and the pedestrian crossing flow model is based on CTM, and is determined by the source corner volume, the capacity of each crosswalk and the remaining space of the destination corner, where the capacity is changed according to the states of the traffic signal. Our traffic signal setting follows a discrete-time manner, when the previous traffic signal state is RED, namely, there are no pedestrians on the crosswalk at the start of the current GREEN time interval, however, when the previous traffic signal state is GREEN, pedestrians are walking on the crosswalk at the start of the current GREEN time interval if there are sufficient demands on the waiting zone, accordingly, the capacity for the latter must be larger than the

former. In other words, we can regard the changing of capacities due to the changing states of the traffic light.

- **Develop a macroscopic pedestrian crossing model considering pedestrian non-compliance behaviors**

The pedestrian non-compliance behavior is not considered in the model proposed in Chapter 2. In order to capture this characteristic, the pedestrian crossing flow is separated as the leaving flow and the arrival flow, as shown in Fig. 3.1b in Chapter 3. The pedestrian leaving flow is determined by the source corner volume and the leaving capacity of each crosswalk which leads to the phenomenon that non-compliant pedestrians are gradually released from the source corner, while the pedestrian arrival flow is restricted by the pedestrian leaving flow and the receiving capacity of each crosswalk determined by the associated traffic signal setting, which is the same as the capacity described in pedestrian crossing flows in Chapter 2. In order to capture the pedestrian leaving flow during the FG period, the average pedestrian non-compliance rate is studied and learnt from the historical data. The number of illegal-crossing pedestrians at each time interval is hard to obtain due to the stochastic nature and the nonlinear characteristics. However, due to the daily-repeated travel demand and traffic supply, meaningful traffic patterns can be found through the massive accumulated traffic historical data, thereby the expectation of the pedestrian non-compliance rate can be obtained accordingly.

- **Design traffic signal control strategy for pedestrian-vehicle mixed-flow networks to reduce traffic congestion**

In the current literature, most researchers pay attention on vehicles, neglecting the interest of pedestrians in the downtown areas. Optimizing traffic signals only for vehicles is not fair for pedestrians, and may create more conflicts between vehicles and pedestrians. Moreover, in the literature modelling pedestrian delay, the majority of the analyses are based on isolated intersections and design traffic signals via deterministic queuing models. Therefore, we develop our traffic signal scheduling strategy for pedestrian-vehicle mixed-flow networks to fill the gap. Specifically, by developing the pedestrian crossing model and integrating with the vehicle flow model extended from CTM, a traffic signal scheduling strategy for both pedestrians and vehicles is proposed with the aim to strike a good balance between pedestrians' needs and vehicle drivers' needs.

- **Design traffic signal control strategies in order to alleviate the vehicle traveling delays as well as pedestrian crossing risks**

Conflicts between pedestrians and vehicles are one of the common safety issues at signalized intersections. Pedestrian FG, a time interval for pedestrians on crosswalks to safely finish crossing before the next phase occurs, may fail to clear the crosswalk in the allotted time, due to the significant pedestrian non-compliant behavior. In this manner, probability

of pedestrian-vehicle exposures increase when non-compatible vehicle flows are released at the next immediate phase. Therefore, we propose a traffic signal control strategy for urban traffic network that aims to minimize vehicle traveling delay (increase efficiency) as well as pedestrian crossing risk (increase safety) by introducing an additional phase DAR after each FG period. The duration of DAR is adaptively adjusted according to the number of non-compliant pedestrians. Simulation has been carried out to illustrate the potential impact of the pedestrian movement to the vehicle traffic networks when pedestrian safety is considered in the system, as well as the efficacy of our traffic light control strategy for pedestrians and vehicles on risk reduction.

- **Integrate hybrid bus size (platoon dispatching) and stop-skipping strategy for urban transit schedule**

In order to improve the public transit service, the bus dispatching with variant sizes and stop-skipping strategy are combined together to minimize the passenger delay time and the operating bus vacancy. Both a single bus and a bus platoon are allowed to be dispatched from the depot. Also, the bus platoon can be separated at the stop if there are no huge lines of people waiting at the stop, which makes our strategy more flexible and adaptive to meet the passenger demand. Meanwhile, we formulate the passengers' perceived delay time as a nonlinear function, which captures the passengers' dissatisfaction due to their elongated wait.

5.2 Recommendations for Future Works

This part discusses problems that have not been addressed and can be studied in future research.

5.2.1 Macroscopic Flow Modelling and Traffic Signal Control

- **Prediction of the vehicle turning rates and pedestrian non-compliance rate using real data**

The vehicle turning rates (λ) and pedestrian diversion rates (α and β) in Chapter 2 and pedestrian non-compliance rate (PV) in Chapter 3 are the inputs of the corresponding optimization models. In current studies, we assume they are known in advance. While in the real traffic environment, they are required to be learned from the real historical data, which can be collected by using the integration of technologies, such as human detection and direction estimation of pedestrians via nearby cameras, V2X wireless

communication, traffic flow prediction models and data analysis from nearby buildings. The prediction of these input data jumps into the model identification field, which may utilize machine learning techniques.

- **Modelling the vehicle turning flow and the pedestrian crossing flow in conflict area**

In the current model, the vehicle turning flow can pass the conflict area as long as the pedestrian flow is cleared. Since the CTM is adopted and extended to develop the corresponding pedestrian flow and vehicle flow, the capacity of the vehicle turning flow in CTM should drop due to the block of the pedestrians, similarly, the pedestrian flow should also be influenced by the vehicle turning flow. Therefore, a more elaborated model is required to be designed in order to accurately reflect their interactions.

- **The impacts of pedestrian bidirectional flows**

The impacts of pedestrian bidirectional flows, a typical form of the pedestrian flow on the crosswalk, can be considered in the future model. According to [224], lane formulation, as one of self-organized phenomena, generally appears in a bidirectional flow: pedestrians with different forward directions automatically separate with each other and form lanes of uniform walking directions. This phenomenon maximizes the average walking speed and minimizes the encounter chances between oppositely moving pedestrians [63], which shall be modeled in our future work.

- **Efficiency and safety evaluation of different phase patterns for urban traffic networks**

Models developed in Chapters 2 and 3 only use the normal TWC phase as case studies to discuss the efficiency and safety of the traffic network, respectively. Other phases, such as EPP, could also be tested, thereby providing suggestions to transportation professionals on phase pattern selections.

- **Considering the modelling of the heterogeneous layout of the traffic network**

Currently, we only model the signalized intersection and the pedestrian crosswalk, however, the traffic network is heterogeneous, involving many different types of facilities, such as non-signalized intersections, roundabouts, overpass, underpass, median refuge and etc. These facilities could be considered in the future research, and the comparison between different facilities are also very interesting to be explored, e.g., evaluation of the impacts of the overpass and underpass at the intersection when compared with crosswalks.

5.2.2 Bus Dispatching Modelling and Transit Operation Strategy

- **Modelling the specific loading time at each stop**

The bus loading time is mainly determined by the boarding flow and the alighting flow. The current bus model focuses on the bus dispatching and the efficiency improvement, without taking the loading time at each stop into account, and assume the bus dwell time at each stop can be neglected compared with the enroute traveling time. However, in order to accurately reflect the real system, the loading process is required to be added in our next study.

- **Considering holding strategy and bus speed control in order to maintain the headway**

Besides the efficiency study of dispatching buses to meet the stochastic passenger demands, transit reliability is also important in public transportation systems. The stop-skipping strategy is adopted in the current model, while other strategies, such as the holding strategy and bus speed control, could also be designed to maintain the headway thereby avoiding the phenomenon like bus bunching.

- **Modelling multi-line bus dispatching to maximize the number of bus synchronizations**

The current bus dispatching model only focuses on a single ring road, without considering the multiple bus lines commonly existing in the real public transport system. The synchronization of different bus lines can provide convenience for transfer passengers, which is also worthwhile to explore.

5.2.3 Optimization Algorithms for Large-scale Networks

- **Distributed MILP**

Traffic flow model in Chapter 2 and bus schedule model in Chapter 4 all involve many decision variables and constraints. After translating into the MILP problem, the model become even more complicated. Conceivably, the increase of the problem scale and the prediction horizon will definitely increase the computational complexity, which leads to the infeasibility of the centralized MILP solver. Therefore, in order to solve the problem in real time, distributed MILP techniques can be adopted by decomposing the problem into several subproblems and solving each subproblem individually.

- **Using mathematical programming techniques to solve the nonlinear cost after linearization**

The passenger perceived delay, as part of the objective in Chapter 4, is modeled as a nonlinear function, and we solve the optimization problem directly by

adopting the evolutionary algorithm, which cannot guarantee the optimality of the final results. Another solution is to linearize the cost and solve the problem using MILP to obtain the optimal results under the approximated linearized cost, and algorithm efficiency can be explored by comparing the above two methods.

5.2.4 Additional Directions for Future Work

- **Extending the current optimization-based macroscopic modelling approach to other large-scale networks**

Many large-scale systems have the flow-based characteristics, such as air traffic management, pedestrian evacuation, logistic systems and smart grids, we can extend the macroscopic modeling approach from the current urban traffic field to these network-based systems.

- **Developing pedestrian simulation models under different facilities**

We have modeled the pedestrian crossing at the intersection crosswalk, which is presented as a bidirectional flow. Generally, multi-directional pedestrian flows exist in many public walking areas. Also, pedestrian flows present different self-organized phenomena under different walking environments. In order to reduce the computational time, macroscopic modelling approaches can also be utilized to develop pedestrian simulation models and reproduce pedestrian's self-organization, such as lane formulation, Stop-and-Go waves and herding.

Author's Publications

Journal Papers:

1. **Y. Zhang**, Y. Zhang, and R. Su, "Pedestrian-Safety-Aware Traffic Light Control Strategy for Urban Traffic Congestion Alleviation," *IEEE Transactions on Intelligent Transportation Systems*, 2019.
2. **Y. Zhang**, K. Gao, Y. Zhang, and R. Su, "Traffic light scheduling for pedestrian-vehicle mixed-flow networks," *IEEE Transactions on Intelligent Transportation Systems*, vol. 20, no. 4, pp. 1468-1483, 2018.
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