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A digital ecosystem for optimizing service reliability in public transport

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University of Wollongong

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A DIGITAL ECOSYSTEM FOR OPTIMIZING SERVICE RELIABILITY IN PUBLIC TRANSPORT

A Dissertation Submitted in Fulfilment of
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Vu The Tran
B.IT (Hons), M.IT

School of Information Systems and Technology
Faculty of Engineering and Information Science

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CERTIFICATION

I, Vu The Tran, declare that this thesis, submitted in fulfilment of the requirements for the award of Doctor of Philosophy, in the School of Information Systems and Technology, Faculty of Engineering and Information Science, University of Wollongong, is wholly my own work unless otherwise referenced or acknowledged. The document has not been submitted for qualifications at any other academic institution.

(Signature Required)

Vu The Tran
28 July 2014

Dedicated to

My wife Le Thanh

,

My children

,

My Parents and my Family

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List of Abbreviations

AVL Automatic vehicle location

APC Automatic passenger counting

APTS Advanced Public Transportation Systems

ATIS Advanced Traveller Information Systems

CAD Computer aided dispatch

CMDESIM Connected Mobility Digital Ecosystem Simulation

DEA Data Envelopment Analysis

IS Information System

GUI Graphical User Interface

GPS Global Positioning System

TSRD Transit service reliability diagnostic

WAN Wide area network

List of Publications

The following publications are the outcomes during the PhD candidature

0.1 Published Papers

- Vu The Tran, P Eklund, and C Cook. A Digital Ecosystem for Optimizing service Reliability In Public Transport. In *The 16th Pacific Asia Conference On Information Systems (PACIS)*. ACM, 2012
  This publication forms the part of Chapters 1-2.

- Vu The Tran, P Eklund, and C Cook. Toward real-time decision making for bus service reliability. In *Communications and Information Technologies (ISCIT), 2012 International Symposium on*, pages 1098-1103. IEEE, 2012.
  This publication forms the preliminary work of Chapter 4.

- Vu The Tran, P Eklund, and C Cook. Evolutionary simulation for a public transit digital ecosystem: a case study. In *Proceedings of the Fifth International Conference on Management of Emergent Digital EcoSystems*, pages 25-32. ACM, 2013.
  This publication forms the bulk of Chapter 3.

- Vu The Tran, P Eklund, and C Cook. Learning diagnostic diagrams in transport-based data-collection systems. In *Foundations of Intelligent Systems*, pages 560-566. Springer, 2014.
  This publication forms the preliminary work of Chapter 5.

0.2 Papers under Review

- Vu The Tran, P Eklund, and C Cook. Toward real-time multi-criteria decision making for bus service reliability optimization. Submitted to Elsevier journal, revision.
  This publication forms the bulk of Chapter 4.

0.3 Papers under working

- Vu The Tran, P Eklund, and C Cook. A multi-dimensional transit assessment framework in Transport-based Data-collection Systems.
  This publication forms the bulk of Chapter 5.

ABSTRACT

Automatic vehicle location (AVL) and automatic passenger counting (APC) systems can generate a huge quantity and variety of operational, spatial, and temporal data. This potentially allows the discovery of new ways to enhance service quality and transport efficiency by utilizing AVL-APC inputs. There is currently no framework for implementing full service quality improvement cycles from automated data (Boyle 2008) and this motivates our case study. The objective of this research is to apply a digital ecosystem metaphor that extends the use of AVL and APC data for the benefit of transit agencies. The framework concentrates on offering bus service reliability in addition to improving headway, minimizing passenger wait time, and maintaining passenger comfort as well as supporting real-time proactive and reactive scheduling and resource adaptation.

The framework is divided into three components: evolutionary simulation, proactive adaptation, reactive adaptation.

Evolutionary simulation is designed for testing and evaluating traffic planning and management systems using data from technologies such as Automated Vehicle Location (AVL) and automatic passenger counters (APC) and to evaluate their performance at an operational level from the passenger point of view. Evolutionary simulation visualises positive aspects of self-organisation and evolution of a Connected Mobility Digital Ecosystem in a dynamic way, and makes advantages of a Connected Mobility Digital Ecosystem obvious amongst all stakeholders. Evolutionary simulation is used as a foundation framework to implement and test proactive adaptation and reactive adaptation components.

Proactive adaptation makes the system able to anticipate demand and behave optimally and guide bus drivers toward optimal scheduling decisions. Proactive adaptation deals with issues linked to the real-time control of public transit operations to minimize passenger wait time. Issues include: vehicle headway, maintenance of passenger comfort, and lowering the effect of control strategies, employing preventive strategies to forestall bus unreliability and, where unreliability is evident, recovering reliability by using corrective strategies. Proactive adaptation uses a Multi-objective Evolutionary algorithm based dynamic Bayesian networks approach, which provides the ability to reason and predict bus service reliability network as well as to handle multi-criteria decision making to control real-time information.

Reactive adaptation is the ability of the system to utilize and analyse historical data and improve its performance over time. Reactive adaptation evaluates proactive decision making methods to re-plan the strategies, which in turn will improve the real-time control strategies. Reactive adaptation constructs a transit service reliability diagnostic (TSRD) diagram based on a Bayesian network, which has the advantages of an intuitive visual representation with a sound mathematical basis in Bayesian probability. This is implemented to function as our knowledge model to uncover the hidden structure and its relationships that may have an effect on reliability in a transit network and offers insight suggesting approaches for service improvement.

The major contributions of this research are that we have proposed a novel framework which consists of a set of innovative strategies and algorithms for enhancing bus service reliability over their whole lifecycles in transit systems utilizing AVL-APC data.

KEYWORDS: Digital ecosystems, Bayesian network, AI application, knowledge discover, multi-objective optimization, public transit, transit service reliability, transit modeling and simulation, control strategies.

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Chapter 1

Introduction

1.1 Motivation

Automatic vehicle location (AVL) and Automatic passenger counting (APC) systems can handle the collection of a huge quantity and variety of operational, spatial, and temporal data. Traditionally these kinds of data have not been utilized to maximize their full potential in terms of optimizing a transport network. Some AVL systems, designed mainly for real-time applications, fail to capture and/or store data items that might be useful in off-line evaluation. In a real-time mode, AVL and APC data provides operational control and current information to customers and transport managers. In an off-line mode, AVL and APC data can be used to help transit companies analyze performance and enhance operations. Five trends in data use have emerged from the paradigm shift from data poor to data rich, so called "big data". These focus on extreme values; customer-oriented service standards; scheduling, planning for operational control; solutions to roadway congestion; and the discovery of hidden trends [43]. APCs produce an abundant ridership and travel-time database with finer levels of detail compared to fare-based or manual passenger counts, even for agencies with just a few APCs. The increased number of observations provides greater confidence in

decision-making regarding changes in service levels. There is also a need to discover new ways to enhance profitability by using AVL-APC data [18].

However, currently there is no framework allowing the implementation of a full service quality improvement cycle. Problems with successful implementation and operation include guaranteeing that bus assignments are completed, new demands for reports, priority for APC equipment in the maintenance department, and unrealistic expectations regarding turnaround time and data quality [18].

This research proposes a digital ecosystem framework that is generic, and hence can be readily applied to various aspects of bus (and other transport modalities) operational strategies over their whole-of-life-cycles. With data collection from AVL and APC, the framework focuses on providing bus service reliability in terms of improving headway, minimizing passenger wait time, and maintaining passenger comfort as well as supporting real-time proactive and reactive schedule and resource adaptation. Proactive adaptation allows the system to anticipate demand and behave optimally, and reactive adaptation is the ability of the system to assimilate historical data and improve its performance over time. Another result is expected to be control or advise strategies to guide bus drivers toward optimal scheduling decisions.

A simulation will be developed to demonstrate the interaction among buses, passengers and the transit environment. The final purpose and overall objective - is to discover trends that help explain irregularities in operations and suggest new avenues for service improvement.

1.2 Theoretical Basis

“The design-science paradigm seeks to extend the boundaries of human and organizational capabilities by creating new and innovative artefacts” [47] while “The behavioral-science paradigm seeks to develop and verify theories that explain or predict human

or organizational behavior" [47]. The research in the thesis is based design-science research to develop technology-based solutions through creating and evaluating IT artifacts intended to solve important and relevant public transit service problems. The artefacts represented in the research include a software component based on rigorous mathematics.

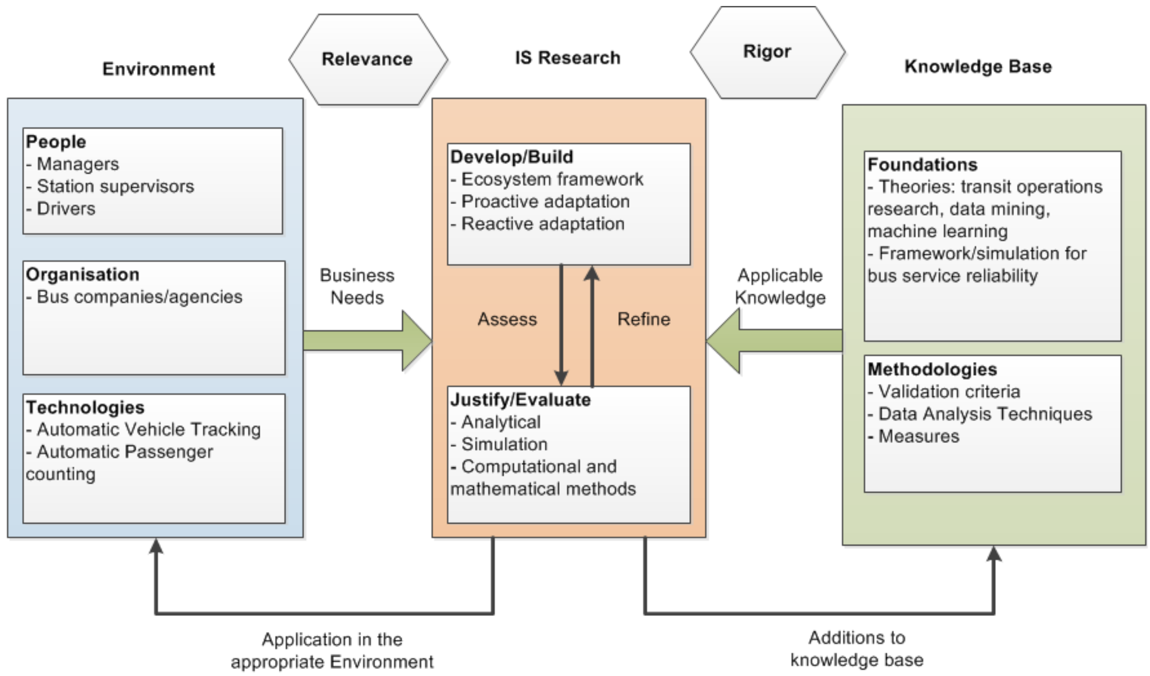

Figure 1.1: Information Systems research methodology applied in the development of an AVL/APC digital ecosystem.

*Original figure from [47]

Figure 1.1 presents our research methodology for understanding, executing, and evaluating the framework. For Information System (IS) research, the environment is composed of people, organizations, and their existing or planned technologies. The organisations are bus agencies and the stakeholders in this research are passengers, managers, station supervisors and drivers. Automatic vehicle tracking and automatic passenger counting technology are employed in bus agencies. "Business needs are assessed and evaluated within the context of organizational strategies, structure, culture,

and existing business processes. They are positioned relative to existing technology infrastructure, applications, communication architectures, and development capabilities. Together these define the business need or "problem" as perceived by the researcher. Framing research activities to address business needs assures research relevance" [47].

The model being developed here addresses research through the building and evaluation of artefacts designed to meet the identified business need. There are three identifiable artefacts produced in this research: evolutionary simulation, proactive adaptation component, and reactive adaptation component. "Research assessment using justify/evaluate activities can result in the identification of weaknesses in the theory or artefact and the need to refine and reassess. The refinement and reassessment process is typically described in future research directions" [47].

"The knowledge base provides the raw materials from and through which IS research is accomplished. The knowledge base is composed of foundations and methodologies" [47]. The foundational theories in this research are transit operations research, data mining and machine learning. "Methodologies provide guidelines used in the justification/evaluation phase" [47]. Validation criteria, data analysis techniques and measures are the methodologies used in the study. "Rigor is achieved by appropriately applying existing foundations and methodologies" [47]. Data analytic, simulation, and computational and mathematical methods are primarily used to evaluate the quality and effectiveness of the artefacts.

1.3 Research Questions

This research challenge is to create computational artefacts that enable public transit agencies to optimize their service reliability through the construction of innovative computer based systems aimed at changing the phenomena that occurs and enhancing the current public transit service. The objective of this research is to obtain know-how

and comprehension that makes it possible for the development and implementation of technology-based solutions to significant public transit service reliability problems.

This research will answer the following questions:

1. What are the factors affecting transit service reliability?
2. How much impact do transit factors have on service reliability?
3. What cost-effective real-time control strategies can be developed to improve service reliability?
4. How can prior knowledge and historical data be used to support real-time decision-making and enhance operational planning?
5. How can the characteristics of a digital ecosystem for the framework be designed and implemented?
6. What are the general features of a transport-based digital ecosystem and how can these be re-used in other jurisdictions?

1.4 Research Model

Figure 1.2 shows the conceptual model for this study. In the real-time mode, a supervisor will receive evaluations of a current scenario which combines previous experience, real-time data including real-time travel demand, transit demand, transit network and assignment data to give optimal proactive adaptation including guidance for drivers leading to optimizing the bus network operations. In the offline mode, historical data is used to study the relationship between factors and to evaluate existing controls and investigate new ones to help to pre-plan the strategies.

Rational decision-making in the context of this research model is determined by "both the relative importance of various goals and the likelihood that, and degree to

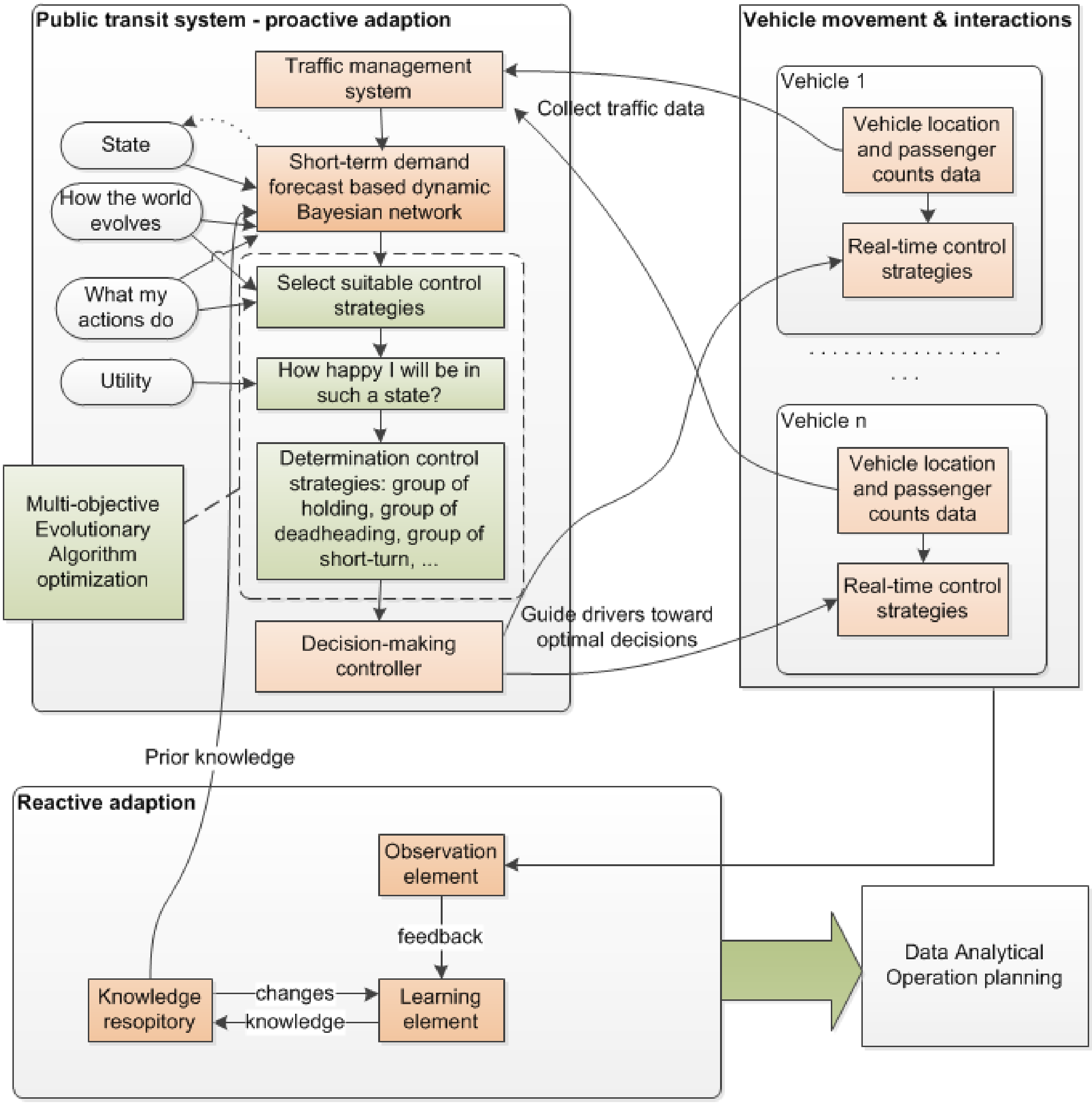

Figure 1.2: Information Systems Research Model for analysis of AVL/APC digital ecosystem.

which, they will be achieved" [89]. Probability provides a method of summarizing the uncertainty that originates from "laziness" and "ignorance". "Laziness" here means there is too much work in listing the complete set of antecedents and consequents required to ensure an exception-less ruleset. The term "ignorance" divides in meaning between theoretical and practical. In theoretical terms "ignorance" here means

there maybe no complete theory so the point at which a complete coverage of rules for the problem domain can never be sufficiently established. In terms of practical "ignorance", even though we know all the rules, we might be uncertain about specific circumstances because not all the necessary deterministic tests have been (or can be) run [89].

1.5 Digital Ecosystem

The digital ecosystem is an approach to guarantee appropriate and timely information accessibility to the public transit community by means of dynamic and amorphous interaction among a multiplicity of small entities to support knowledge sharing, co-creation of knowledge and the advancement of new business models.

The digital ecosystem offers the possibility to adjust dynamically to a changing ecosystem, which enables the system to evolve in line with historical or current trends in system usage, in a self-organizing way. This is the key benefit of using biological approaches in the Digital Ecosystem. In the situation considered in this research the application of a digital ecosystem to optimising a bus service is considered.

1.6 Proposed Methodology

Phase 1 defines the research context through a literature review on relevant topics. Then AVL and APC equipment will be installed on a shuttle bus service in Wollongong, Australia. The simulation environment of the framework will also be developed. Validation criteria will be used to evaluate data modelling from real world data for simulation.

Phase 2 involves developing a proactive adaptation component to help answer Research Questions 1-3 above. The intention is to find strategies to guide drivers towards

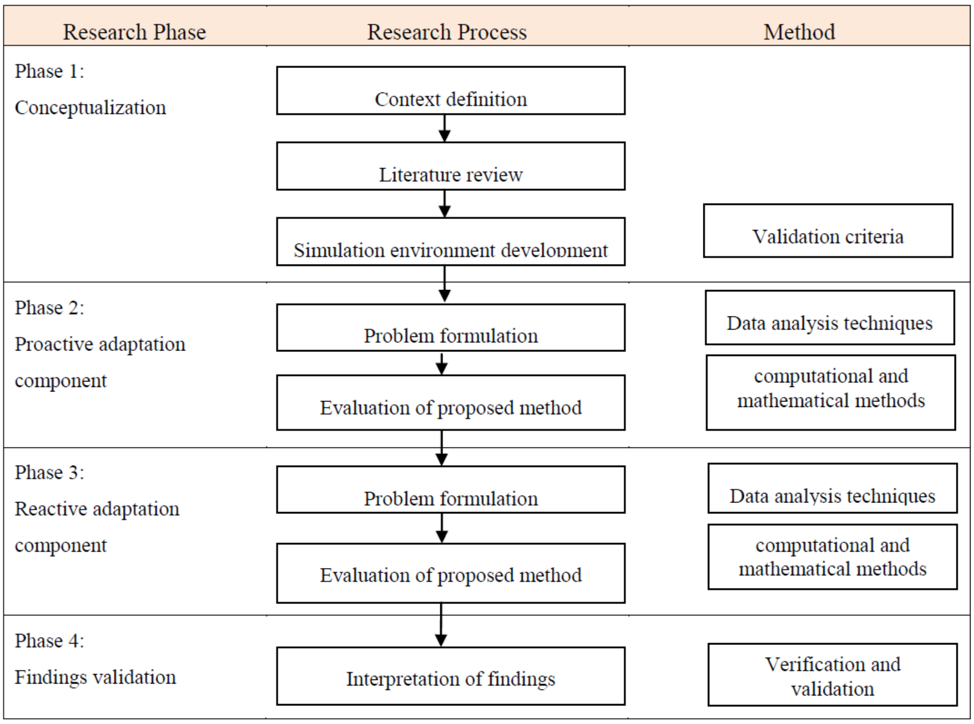

Figure 1.3: Pareto-optimial Passenger wait time and action impact.

optimizing the overall bus network, not strategies solely for an individual bus. This component also is used to study the relationship between factors that affect service reliability, their interactions and interdependencies. Algorithms will be developed to: maintain/restore service reliability for passengers; reduce passenger waiting time; reduce in-vehicle travel time; reduce passenger overcrowding; and for operations, to keep buses on schedule, to maintaining uniform headway, to discover the main causes of unreliability. Data analysis techniques, computational and mathematical methods are used to justify/evaluate the Phase 2 outcomes.

Phase 3 involves developing active adaptation components as part of addressing the Research Questions 1, 2, 4. This phase will evaluate proactive decision making methods to re-plan the strategies, which in turn will improve the real-time control strategies. It will also help to evaluate driving and travel behaviors. There is an interaction between the driver and the system; the driver not only is a user of the system, but

also adjusts to the system itself. The feedback/lessons that drivers receive from their interaction with the system will help them to adjust their behavior. Data analysis techniques, computational and mathematical methods are used to justify/evaluate phase 3 outcomes.

In Phase 4, it is expected that all research questions 1-6 will be answered and findings will be validated.

The utility, quality, and efficacy of each artefact will be rigorously proven via well-executed evaluation methods, which involve the definition of appropriate metrics and gathering and analysis of appropriate data.

1.7 Contribution

This study will contribute towards the body of knowledge in the following ways:

1. The study introduces new approaches for control strategies that can deal with decision making in a multi-criteria environment with uncertainty.

2. An innovative digital ecosystem framework for real-time bus control strategies and operation planning will be developed to better understand the impact and relationship of transit factors, travelers, and drivers and how they affect bus service reliability. This research will develop a framework to implement full service quality improvement cycles.

3. The use of AVL-APC data in the organisation will be extended.

This research also provides clear and practical information to both technical and managerial audiences:

1. For technical audiences: new approaches to decision support using methodologies of machine learning, data mining, and digital ecosystem design will be provided.

2. For managerial audiences: a new framework will be provided that helps managers and planners understand factors that influence service reliability and extend the

capability and cost-effectiveness of transit operations. Transit agencies will be able to provide and analyze service operations, find hidden trends that help explain irregularities in operations and suggest new avenues for improvement. Exploratory analysis also reveals relationships that can lead to better end-of-line identification — end-of-line operations can be both complicated and unpredictable that make trips times and operations at route ends challenging to identify — and to better understanding business needs.

1.8 Thesis Outline

In this section, we present a chapter by chapter overview of the rest of the thesis.

Chapter 2 provides an in-depth discussion on background, existing work and systems that are relevant to our work. In particular, the review focuses on the following three broad areas: (1) Automatic vehicle location (AVL) and automatic passenger counting (APC), (2) Service reliability, and (3) Modeling and Simulation. This chapter carries out a part of the work planned in Phase 1.

Chapter 3 presents an integrated simulation environment, the Connected Mobility Digital Ecosystem Simulation (CmdeSim), designed for testing and evaluating traffic planning and management systems using multi-objective Evolutionary Algorithm optimization and a Bayesian network for bus network prediction. The model developed in CmdeSim is used for simulating different bus scenarios and strategies to identify their strengths and weaknesses for optimizing bus service reliability. CmdeSim is used as a foundation experimental framework for the work in Chapters 4 and 5. This chapter also completes the work planned in Phase 1.

Chapter 4 addresses issues associated with the real-time control of public transit operations to minimize passenger wait time: namely vehicle headway, maintenance of passenger comfort, and reducing the negative impact of control strategies. A Multi-

objective Evolutionary algorithm based on a dynamic Bayesian networks approach is developed to provide the ability to reason and predict bus service reliability network as well as to handle multi-criteria decision making to control real-time information. This chapter implements the proactive component planned in Phase 2.

In Chapter 5, a multi-dimensional transit assessment framework is presented to serve as our knowledge model to analyze automatic data collection. The framework involves a general procedure for constructing a transit service reliability diagnostic (TSRD) diagram based on a Bayesian network. The framework is proposed to automatically build a behavioural model from Automatic Vehicle Location (AVL) and Automatic Passenger Counters (APC) data to discover the variability of transit service attributes and their effects on traveller behaviour. This chapter implements the reactive component planned in Phase 3.

Chapter 6, Conclusions and Future Directions, concludes this thesis and highlights a number of future research directions.

Chapter 2

Background and Literature Review

In this section we review the background, existing literature and implementations that are relevant to this research. In particular, the review focuses on the following four broad areas: (1) Automatic vehicle location (AVL) and automatic passenger counting (APC), (2) Service reliability, (3) Modeling and Simulation, and (4) Digital Ecosystems for transit system;

(1) involves reviews on AVL, APC technologies, the benefits (and pitfalls) associated with various passenger counting technologies. Also, a review of the kinds of decision-making required by bus agencies is encountered. These reviews help frame the business needs as well as identify issues or gaps in implementation using AVL and APC in bus companies/agencies.

(2) includes reviews on the social effects of the problems and effects of service reliability in public transportation. This review will help inform the design and implementation of our algorithms and models. In other words, our solution is supported/informed and strengthened by existing social science-based research about service reliability.

(3) includes reviews on surveys algorithms, techniques and strategies to build models and simulations for bus operational strategies. This will lead to the building of

innovative algorithms and models for our experimental framework and its simulation.

(4) includes reviews on the digital ecosystem metaphor for transit system. This will help to identify the demands for a connected mobility paradigm in transit and to apply digital ecosystem metaphor in transit system.

The remainder of this chapter is organized as follows: history perspective of AVL-APC Systems is presented in Section 2.1; uses of AVL-APC Systems is reported and discussed in Section 2.3; service reliability of public transit systems is presented and discussed in Section 2.4; Section 2.5 reviews models and simulations for transit system; Section 2.6 reviews Digital Ecosystems for transit system, with conclusions presented in Section 2.7.

2.1 AVL-APC Systems: Historical Perspective

2.1.1 AVL System Design

AVL systems incorporate a reliable means of location. In the past, AVL was made for real-time applications including emergency response and computer aided dispatch (CAD), which is generally acquired during a radio system upgrade. More affordable systems purely notify display maps and dispatchers concerning where buses are. More innovative systems monitor buses based on their schedule, which enable one to hence establish schedule deviation and whether or not a bus is off route [42].

Traditional AVL system design has underpinned the real-time process, paying little or no attention to the off-line process. A lot of AVL systems do not capture and store data in a way that is helpful for off-line analysis as they were not designed to do so. The difference between off-line and real-time data is that real-time data is more tolerant of errors. In other words, if errors appear in either the location system or the base map, causing an incorrect bus display, service controllers find out rapidly how to

dismiss/adjust such anomalies. Nevertheless, in a data archive of off-line processes, such errors could become unseen and distort data analyses of running time or schedule deviation [43].

Many agencies purchased AVL mainly for emergency response; that is most reasonably carried out with a straightforward system, which provides no matching to schedule or other operations analysis. Other procurements have required real-time computer-aided dispatch capabilities including schedule matching, but place little focus on off-line analysis capabilities [84] [42]. This issue is because of fracturing inside the transit organization, with AVL procurement generally considered as mainly a radio system upgrade run by the operations control department. Departments that would have taken advantage of off-line analysis either did not recognize the wide ranging positive aspects or were unsuccessful in having an influence on the procurement. “They only ask us to provide the data,” said one AVL vendor; “what they do with it is their business.” Only a few transit agencies have had the know-how in house to transform their AVL data stream into a beneficial database [42].

2.1.2 APC system Design

APC systems incorporate sensors and algorithms that count passengers boarding and alighting. Unlike AVL systems, APC Systems have always been designed for off-line analysis [17] [43]. In the past, APC systems were designed separately from AVL systems and their adoption has been a lot more restricted compared to AVL systems. The sluggish industry for APCs has led to several vendors having gone bankrupt and this has restricted the number of vendors that designed software for APC data analysis. However, that tendency has been changed because of technology innovations that led to transit agencies building up their own APC systems. Transit systems in Seattle, Ottawa, Winnipeg, and Toronto are groundbreaking achievements [43].

APC has not yet seen popular acceptance mainly because of its price and maintenance costs. Where implemented, counters are normally set up on 10 to 15 percent of the fleet. Set up counters on buses are rotated around the system to supply data on every route. Nevertheless, technological advances reviewed in the next section could make passenger counters much more popular [42].

2.2 AVL-APC Systems: Technological Advances

Rapid technological advances since about 1995 offer new AVL and APC systems with more capabilities than older systems. The most effective indicator of what types of systems expecting to see in the future is not the “average” system being used, though the fairly small number of newer systems and older systems with major upgrades [42].

2.2.1 AVL - Technology

AVL built-in Global Positioning System (GPS) receivers locate their whereabouts by triangulation determined by signals obtained from orbiting satellites. Location accuracy of buses is mostly better than 10m, based on the accuracy of clocks in the GPS receivers along with method of correction that are employed. Because GPS needs a line of sight to its satellites, GPS signals can be lost - not only when the buses go underground - but when in the vicinity of tall buildings or other obstructions. Obstructions can additionally reflect GPS signals, causing a phenomena known as multipath that can result in mistaken location estimation [84] [43].

On-board devices that can be integrated with an AVL system consist of APCs, radio control head, odometer (transmission), gyroscope, door sensors, wheelchair lift sensor, farebox, and stop enunciator. Normally, the more devices integrated, the more abundant the data stream, which can support both in matching and in supplying new varieties of information [84] [43].

2.2.2 APC - Technology

In contrast to AVL, APCs have always been built with archived data in mind [17] [43]. APCs employ various technologies for counting passengers such as pressure-sensitive mats, horizontal beams, and overhead infrared sensing [43]. The majority of APC units count passengers using infrared beams. Older units utilized tread mats mounted to vehicle steps. Other transit agencies use video technology, involving multi-object recognition, image segmentation, and feature matching, to count boardings and alightings [18].

APC counting precision is determined by the technology employed, the attention in installing and preserving sensors, and algorithms utilized to transform sensor data into counts. The precision of completed counts also is determined by the efficiency of stop matching, specifying the end of the line and also algorithms employed for screening, parsing, and balancing the data collected [43].

2.3 Uses of AVL-APC Data

A wide-variety of uses for archived AVL-APC data were identified in the literature [63] [13] [54] [12] [97] [100] [43]. One of the richest application areas for archived AVL data involves run-time analysis, including designing scheduled running times and monitoring schedule adherence. Moreover, AVL data can be applied to schedule adherence, headway regularity, and passenger waiting time. Discovering archived AVL-APC data can allow “transit agencies to find hidden trends that help explain irregularities in operations and suggest new avenues for improvement” [43]. A significant move in AVL system development for collecting archived data appeared in the mid-1990s, when Tri-Met with an AVL vendor designed a hybrid AVL-APC system presenting on-board event recording and radio-based communication. However, regardless of what func-

tions a data collection system may have, there is a common demand for archived data analysis. The transit industry is amid a revolutionary shift from a data poor to data rich state. Traditional analysis and decision support tools needed little data, "not because the data has little value, but because traditional management methods had to accommodate a scarcity of data" [43]. Automatic data gathering systems not only do more than meet traditional data needs, but also open up opportunities for new analysis methods that can be used to enhance monitoring, planning, performance, and management [43].

Automatically collected data has two crucial roles in improving the quality process of a transit agency's service, as illustrated in Figure 2.1: one in real time and one off line. In the real-time process, automatically collected data supports operational control by assisting the transit agency with sensing and reacting to deviations from the operational plan, which is a source of real-time information that can be offered to customers via many different kinds of media. In the off-line process, automatically collected data that has been archived drives analyses. It will, in turn, help the transit agency in assessing and improving its operational plan. In the end, having both a good operational plan and good operational control leads to having good operational performance and high passenger satisfaction [43].

There are various studies employing real-time control to improving transit service reliability. Headway and schedule optimization with bus location tracked in real-time is studied by Dessouky et al. [28], Chen and Chen [22], Yu et al. [116], Daganzo and Pilachowski [24] and Bartholdi et al. [10]. They develop self-organising headways and schedules and propose an adaptive control method to adjust bus speed in real-time to cooperate with successive and preceding buses.

With regards to off-line processes, one of the most widely used application areas for archived AVL data is in analysis of running time that involves designing scheduled

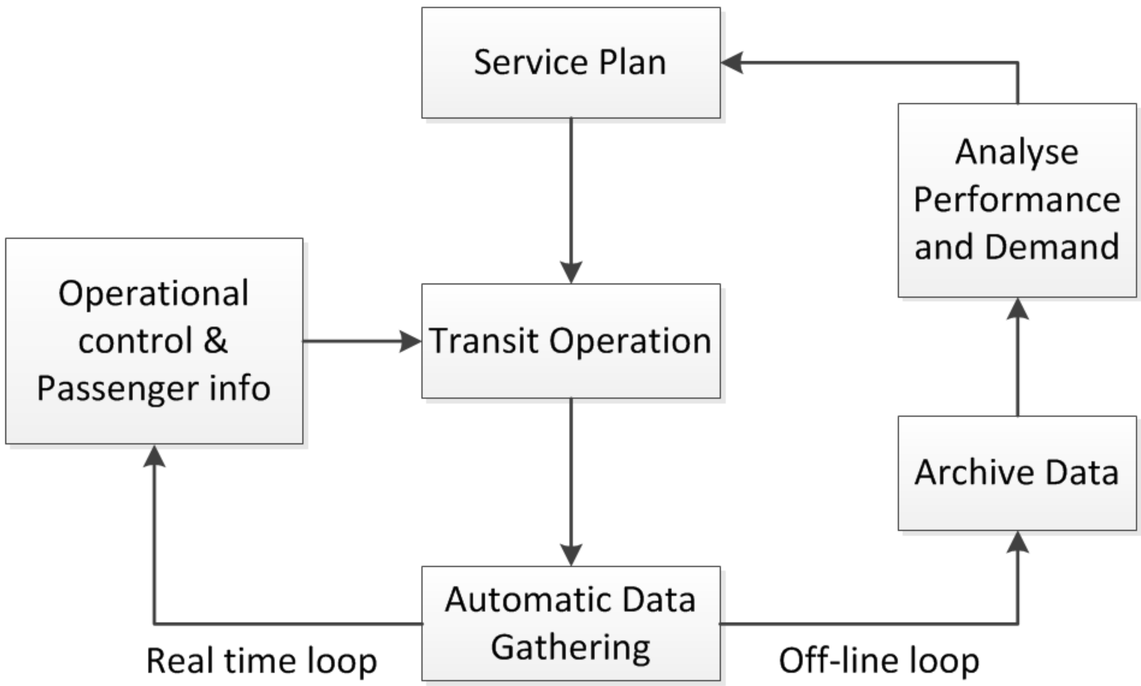

Figure 2.1: Service quality improvement cycle (Source [43]).

running times and monitoring schedule adherence. Conventional scheduling methods use mean observed running times, which can be approximated from small sample sizes. AVL data affords the potential for utilizing extreme values including 85-percentile and 95-percentile running times as being a fundamental input to scheduling. Extreme values are essential to passengers, who worry less about mean schedule deviation than about staying away from extreme deviations [43].

Discovering archived AVL-APC data can allow transit agencies to uncover hidden tendencies that assist in improving operations. To give an example, one agency discovered that an unexpected amount of schedule deviation might be explained by the operator; that is, some operators persistently leave the terminal late or run slow which implies the necessity for much better strategies of operator training and supervision [43].

There are various studies employing off-line analysis to improve transit service re-

liability. Yeh et al. [114], Zak et al. [117] and Agusdinata et al. [3] employed multiple criteria analysis for transport systems performance evaluation. Other studies adopted Data Envelopment Analysis (DEA) to measure the relative performance of production lines. Examples are reported in Boile [14], Nakanishi and Falcocchi [77], Tsamboulas [101], Barnum et al. [9], Sheth et al. [93], Lao and Liu [60], Zhao et al. [119], Hawas et al. [46], Karlaftis and Tsamboulas [51]. Advanced statistical techniques (path analysis, latent variable and structural equation models) also are employed by Joewono and Kubota [49], Stuart et al. [98], Eboli and Mazzulla [33], and Nurul-Habib et al. [44] to measure transit service reliability.

A good example of a sophisticated analysis utilizing a highly detailed AVL data stream is computing and supervising measures of ride smoothness. A smooth ride is undoubtedly crucial to passengers, and AVL data with either very regular observations or accelerometers makes it possible for ride smoothness to be assessed objectively [43].

Up to now, the transit industry has missed a measure of service reliability measured regarding its influence on customers due to the fact traditional measures cannot convey how reliability influences passengers' perceptions [43]. They also lack any mechanism that supports decision making for bus operations on route and at the bus stop simultaneously.

There is a need for higher level analysis concerning tracking trends over time, comparison of routes or periods of time, and so on [43].

2.3.1 Key dimensions in data collections

This section reviews specific data needs for each use in order that people interested in AVL-APC system design can better decide what features are required to aid various analyses. Table 2.1 shows the levels of details available depending on the type of automated systems deployed [42].

Level	**Description**	**Event-Independent Records**	**Event Records**	**Between-Stop Performance Data**
A	AVL without real-time tracking	infrequent (typically 60 to 120 s)		
B	AVL with real-time tracking	infrequent (typically 60 to 120 s)	each time-point	
C	APC or event recorder		each stop	
D	event recorder with between-stop summaries		each stop and between-stop events	recorded events and summaries
E	event recorder / trip recorder	very frequent (every second)	all types	all events, full speed profile

Table 2.1: Levels of spatial and temporal detail for data capture (Source [42]).

Detail level A presents the lowest amount of detail, involving infrequent event-independent location records. Detail level B involves timepoint records. An onboard computer recognises when it gets to the timepoint location. Detail level C includes a record for each and every stop. It is often provided by APC applications and event recorders linked with stop announcement systems, but not usually with AVL. In detail level D, along with stop-level information described in level C, data on each interstop segment is additionally captured. Detail level E consists of near-continuous recording of time, location, and door status every second or every few seconds. This level enables the user to investigate and summarize virtually any measure of performance without needing to identify and configure the system beforehand [42].

Furth et al. [42] also suggests that effective analysis employing archived data from automatic data collection (ADC) systems requires the accessibility of other beneficial data items and databases. The abilities of AVL and APC systems are boosted when other related data items are involved. Potentially valuable data items include: door open and close times, start and stop times, time stamps on passenger entries and exits, off-route events, mechanical and security alarms, communications to and from

the control center, traffic control messages, farebox transactions, and annunciation and destination signs. Related databases include: schedule data, GIs, payroll, farebox, maintenance, weather or special events, and customer satisfaction.

2.3.2 Analysis and Decision Support Tools

Furth et al. [42] also determine a number of analyse and decision support tools employed in current transit practice, and potential functions that would enhance service management and performance, as shown in Table 2.2. The usage code indicates the level of use by agencies with AVL-APC data, where [4] indicates used commonly by agencies with AVL-APC data; [3] indicates used by some agencies with AVL-APC data; [2] indicates used by only a few agencies with AVL-APC data; [1] indicates used experimentally or ad hoc; [0] indicates not used.

Function	**Tool / Analysis [Usage codes]**	**Detail Level Needed**
General service monitoring, including contract compliance	- Missed trips [1] - Schedule adherence [4]	A or B
Targeted Investigations	Trip investigation at gross level (was it there? was it off-route?) [4]	A
	Trip investigation: early, late, overcrowded? [3]	C
	Trip investigation: speed, acceleration [2]	D or E
Scheduling and Monitoring Running Time	Route and segment running time analysis (mean and distribution) [4]	B
	Suggesting running time based on percentiles [3]	B
	Selecting homogeneous running time periods [3]	B
	Suggesting half cycle time based on percentiles [2]	B
	Running time analysis net of holding time [2]	C

	Speed and traffic delay [2]	D
	Unsafe operations monitoring [0]	D or E
	Relating running time to weather, roadway incidents, and special events [1]	B
Schedule Adherence and Connection Protection (service and operational quality)	Percent early, late by timepoint [4]	B or C
	Distribution of schedule deviation at a timepoint [3]	B or C
	Graphical display of schedule deviation distribution along a route [2]	B or C
	Experienced lateness and earliness [1]	C
	Connection protection [1]	C
Headway Analysis (service and operational quality)	Headway deviations (mean and distribution by timepoint) [3]	B or C
	Impact of headway variability on passenger waiting time for random passenger arrivals [1]	C
	Plot successive trajectories (bunching analysis) [2]	C
Demand Analysis	Load profile (mean ons, offs, and load by stop along a route; also passenger-miles) [4]	C
	Load variations [3]	C
	Analysis of trip maximum loads and max load points [1]	C
	Time-dependent demand and load analysis, and suggesting trip start times to achieve load targets [1]	C
	Analyze overload, lift, bicycle, and other events by stop and time [3]	C
	Transfer and linked trip analysis [1]	C
Geographic and Planning Analysis	Geocoding stops and other points of interest [2]	C
	Mapping bus path through shopping centers, new subdivisions, etc. [3]	E
	Comparing measured vs. nominal stop locations [1]	C

	Relate on-off data to demand rates in traffic analysis zones and to geographic database [1]	C
	Relate service quality data to geographic database [1]	B or C
Utilities	Monitoring system failures [4]	A
Other Operations Analysis	Operator performance (schedule adherence, on-time start, running time, headway maintenance) [1]	B or C
	Dwell time analysis [2]	C
	Layover and pull-in / pull-out analysis [0]	B
	Control effectiveness: any service quality monitoring or service analysis, related to control messages	as required for each analysis
	Before / after study - Special event / weather analysis	as required by the type of analysis
Passenger Information Monitoring	Prediction accuracy (match announced stop or predicted arrival time with actual) [1]	C
	Accuracy of route data in destination sign and farebox [0]	A
Payroll	Verify sign-in data [2]	A
	Examine operators duty when theres an overtime claim [2]	A
Maintenance Management	Analyze maintenance incidents [0]	D
	Monitoring vehicle demands [0]	D
	Analyze failure trends [0]	D
Strategic Planning	Trends analysis [2]	as required by the type of analysis

Table 2.2: Decision support tools and analyses and its data needs (Source [42]).

The revision of analyses and decision support tools, potential functions that would enhance service management and performance and detail level of data needed assist in selecting proper analyses and data needed for the study.

2.3.3 System Design and Data Capture Issues

Furth et al. [42] develops findings and guidelines in system design and data capture that are summarized by Cham [109] in Table 2.3.

Issue	**Description**	**Finding and Guidance**
Stop vs. Time-point level detail	Whether data is collected at every stop or only at certain timepoints is a key system design. Time-points level detail is adequate for schedule planning and adherence analysis, while stop level detail is preferred for integration with other data items such as door open/close events.	Stop level detail also has an advantage in that - accuracy and end-of-line issues - wait times, holding time analysis - posted schedules at stop, support for signal priority - better integration with other data systems
Time-at-location vs location-at-time	Time-at-location is usually captured through real-time tracking, while location-at-time is captured by polling vehicles.	The former is preferred because most performance reports refer to arrival and departure times at specific points along the route
Between-stop records	Are full details necessary in general analysis or are summaries sufficient?	Full details are helpful for incident investigation. Summaries are sufficient for speed analysis
Exception data only	Capturing exception data only is useful in real-time operations, but very limiting performance analysis using archived data.	Exception data cannot be used by itself for performance reporting, and must be complemented with other data items.

Central onboard computer with unified location capability and interface	The idea of a 'smart bus' design, where location data is supplied by one central computer. It has integration capabilities, with a single interface and shares its location data with other systems.	Accuracy of location information improves and matching is easier. A single operator interface reduce the error rate in identifiers.
ID verification: real- time vs. off-line	Matching observed and scheduled data is improved with valid sign-in data. Opportunities to maximize valid sign-in data: - Single interface for operator sign-in - Range and validity checks during sign-in - Automatic sign-in, smart-card ID	Real-time ID verification is preferred because remedial action is taken right away and the number of records is reduced. However, post- processing corrections can also be automated to improve data quality.
On-board data recording vs over-the-air transmission	Radio transmission to central computer is needed for real-time operations control. Archiving is done on-board or by central computer during transmission.	Limitation on radio bandwidth restrict the amount of real-time APC data that can be transmitted (on top of the AVL that is already being sent.)
Data from single-purpose system	Use of archived data captured from passenger information systems.	The trend is increasingly towards the supplier offering off-schedule data and reporting capabilities.
Size of equipped fleet	It is customary to equip 100% of the fleet with AVL systems, while only 10% - 15% with APC systems.	Passenger count analysis can be done with only 10% - 15% of the fleet equipped with APC systems (100% equipped fleet if there is a need to report extreme values). For operations data, it is better to equip 100% of the fleet.
Data on control decisions	Supervisors do not usually log any control action decisions in useful archived data files.	Need to capture and code any control actions to flag records and analyse effectiveness.

Location and fare-payment systems	Time-stamping and integration of location records with fare collection data.	Integration can be done in real-time or off-line, and benefits include origin/destination analysis.

Table 2.3: System design and data capture issues (Source [42]) (cited in [109]).

The revision of findings and guidelines in system design and data capture assists to have a proper installation and implementation of AVL-APC system to capture correct data needed for the study.

2.3.4 Assessment of APC Systems

Boyle [18] does a survey on passenger counting technologies to draw out information on automated APC AVL technologies. At the time of the survey, manual data collection was the most typical way of collecting information on ridership. Over the past 10 years, utilization of APCs has grown to be more widespread. The report concentrates on the state of the practice for APC systems in transit agencies.

Level of Satisfaction	**No.**	**%**
Very satisfied	16	40.0
Somewhat satisfied	18	45.0
Somewhat dissatisfied	2	5.0
Very dissatisfied	4	10.0
Total responding	40	100.0

Table 2.4: Agency satisfaction with APC system performance in terms of counting passengers (Source [18]).

In Table 2.4, most respondents are either very satisfied or somewhat satisfied with the performance of their APC system.

Table 2.5 shows the main positive aspects of APC for the agencies from the survey. The major benefits involved accessibility to data at a much finer level of detail followed

Benefit	**No.**	%
Finer level of detail (stop/segment/ trip)	14	36.8
quality of data	11	28.9
Running time data to adjust schedules	10	26.3
Better basis for decision making	6	15.8
quantity of data	6	15.8
Timeliness of data	5	13.2
Total responding	38	100.0

Table 2.5: Primary benefits of APCs (Source [18]).

by enhancement of quality of the data and the accessibility to running time data for schedule adjustments.

Problem	**No.**	%
None/usual start-up issues	10	25.6
Reports/reporting software	5	12.8
Data processing and analysis	4	10.3
Data validation	4	10.3
Hardware problems	4	10.3
Total responding	39	100.0

Table 2.6: Problems encountered with the APC system (Source [18]).

Table 2.6 summarizes issues with the APC system. The most often reported problems included reporting, data processing, data validation, and hardware.

Improvement	**No.**	%
Contract and procurement	8	25.0
Additional APCs	7	20.6
Approach	7	20.6
Testing	4	11.8
Hardware	3	9.4
Training	2	5.6
Total responding	32	100.0

Table 2.7: Improvement to the APC process (Source [18]).

Respondents were questioned, "If you could go back in time and change only one aspect in the process of purchasing, installing, and using your APC system and associated methodology, what would you change?" Table 2.7 represents the results.

Improvements in contract and procurement were most regularly mentioned with 25% as they facilitated stricter contractual requirements, and buying an entire system via a single vendor, avoiding purchase via a consortium, and adjustments to internal procedures. Additional APCs and variations in approach also were mentioned highly with 20.6% with respondents being more informed about hardware and software choices. Testing, different alternatives of hardware, and improved training were also ranked by more than one respondent.

Effects	**No.**	**%**
Positive		
Improved communications between departments	7	20.6
Greater value placed on ridership data	7	20.6
Better data leading to improved decision-making ability	5	14.7
Greater responsiveness to public/others	3	8.8
Ability to provide data to end users	3	8.8
Negative		
Difficulty with bus assignments	7	20.6
Constant/increased demands for new or reformatted reports	5	14.7
APC maintenance has low priority	4	11.8
Unrealistic expectations re: turnaround time and data quality (i.e., not perfect)	4	11.8
Total responding	34	100.0

Table 2.8: Effects of interaction among multiple APC users (Source [18]).

Deployment of APCs inevitably includes multiple departments inside the transit agency. Table 2.8 shows the results of the effects of APC use on the transit agency. The most beneficial aspects of APC implementation included improved communication among departments, greater value placed on ridership data, improved decision-making ability, greater responsiveness, and the ability to provide the needed data to end users. Other positive effects were related to external agencies and reaction of management to more beneficial reporting.

The most regularly pointed out negative aspects of successful implementation and

operation involved problems/difficulties with bus assignments, new needs for reports, priority for APC equipment in the maintenance department, and unrealistic expectations in terms of turn-around time and data quality. Amongst other negative effects were worries from operators and the union, including data accuracy and dealing with missing data, disappointment regarding start-up problems, APC system weakness to communications problems, insufficient commitment from all departments in terms of maintenance of the data collection and training.

2.4 Service Reliability

Bus service unreliability influences passengers adversely simply because it forces passengers to wait longer. Especially, on high frequency routes, headway uniformity is essential to passengers due to the effect on waiting time and overcrowding. Overcrowding is vital to passengers for their comfort - and to operations as it can certainly delay boarding and alighting. The number of passengers can also be significant in planning as it would be a measurement of transport network performance [43].

Reliability involves both on-time performance and the uniformity of headways. Irregular headways cause irregular passenger loadings, with a late transit vehicle serving not merely its normal passengers but also passengers that have come early for the following vehicle. Eventually, the vehicle drops further and further behind schedule and many more passengers are adversely affected. On the other hand, vehicles following can have less than normal passenger loads and may have a tendency to run in advance of schedule. The "bunching" phenomenon is frustrating both to passengers of the bunched buses and to passengers awaiting for other buses who watch numerous buses for another route arrive while they lose time waiting for their particular bus [56].

Passengers badly suffer from the effects of unreliability including additional waiting time, late or early arrival at destinations and missed connections, which raises their

stress and irritation [11]. Reliability has also been recognized as essential in identifying the transport mode choice [103]. Hence, unreliability in public transport can deter existing and potential passengers [66].

Unreliability, in addition, impacts a passenger's total trip time. For instance, if persons feel a transit vehicle may leave early, they might come sooner to make sure not to miss a bus or train. Likewise, if passengers are not assured of coming to their destination punctually, they might select an earlier departure, though this would frequently means arriving much sooner than desired [56].

For the bus companies, unreliability produces associated costs caused by a decline in passenger miles and decline in fleet usage. They also threaten revenue as a result of decline in passenger numbers. Reliability benefits operating companies, firstly by enhancing their internal performance and minimizing operating costs, and secondly to profit from increased patronage because of service enhancements [66].

The concept of reliability is of importance not merely for public transport users, but for the bus operators [66]. The transit industry is currently missing a measure of service reliability and its effect on customers because conventional measures do not show how much reliability has impacted passengers' perceptions. [43].

2.4.1 Factors Affecting Reliability

Many factors cause bus unreliability: day-to-day and within-day variance in traffic flow and traffic jam levels result in delays and make bus journey times unpredictable, extreme passenger demand leads to lengthier dwell time at bus stops; buses do not invariably operate on schedule, or appear in bunches; operators have inadequate extra capacity to deal with service breakdowns [66].

Typically, the factors impacting on bus reliability could be classified into the following groups:

Factor	Description
Traffic conditions	(for on-street, mixed-traffic operations), including traffic congestion, traffic signal delays, parking maneuvers, incidents, etc.;
Road construction or track maintenance	create delays and may force a detour from the normal route;
Vehicle and maintenance quality	influences the probability that a vehicle will break down while in service;
Vehicle and staff availability	reflecting whether there are sufficient vehicles available to operate the scheduled trips (some vehicles will be undergoing maintenance and others may be out-of-service for various reasons) and whether sufficient operators are available on a given day to operate those vehicles;
Transit preferential treatments	such as exclusive bus lanes or conditional traffic signal priority that operates only when a bus is behind schedule, that at least partially offset traffic effects on transit operations;
Schedule achievability	reflecting whether the route can be operated under usual traffic conditions and passenger loads, with sufficient layover time provided for operators and sufficient recovery time to allow most trips to depart on time even when they arrived at the end of the route late;
Evenness of passenger demand	both between successive vehicles and from day to day for a given vehicle and run;
Differences in operator driving skills	route familiarity, and adherence to the schedule particularly in terms of early ("hot") running;
Wheelchair lift and ramp usage	including the frequency of deployment and the amount of time required to secure wheelchairs;
Route length and the number of stops	increase a vehicles exposure to events that may delay it delays occurring earlier along a route result in longer overall trip times than similar delays occurring later along a route;
Operations control strategies	used to react to reliability problems as they develop, thus minimizing the impact of the problems.

Table 2.9: Factors affecting reliability (Source [18]).

The revision of factors affecting service reliability assists to implement traffic factors of the simulation and study reliability factors for testing control strategies for the study.

2.4.2 Reliability Measures

Service quality could be assessed by taking into consideration customer perceptions and expectations, or by a selection of simple disaggregate performance measures which can be employed for measuring the capability of the transit agency to provide services that satisfy customer expectations [71]. A transit performance measure is categorized as a quantitative or qualitative factor used to assess a certain aspect of a transit [56]. Figure 2.2 describe service quality loops from a customer and a provider view.

There are various approaches to measure service reliability in public transit. Nathanail [78], Tyrinopoulos and Antoniou [104], Eboli and Mazzulla [32] employed an approach based on the transit users' perception or satisfaction. The different aspects of the transit service are rated by the users through a satisfaction survey. The most common aspects of transit service are the reliability, frequency, capacity, fare, cleanliness, comfort, security, staff, information, and the ticketing system. Lao and Liu [60] used another approach, employing different efficient variables to the transit system demand and operation involving ridership, travel time, travel distance, frequency, service duration, revenue, manpower, cost, accident data, fuel consumption and emission to calculate the performance indicators. Sheth et al. [93] and Abreha [2] applied a third approach, which included the consolidation of the first two approaches: users' opinions and efficiency indicators.

Table 2.10 shows categories of service quality measures. The Transportation Research Board, through the Transit Cooperative Research Program, Washington, D.C.

developed interesting research about service quality measures, summarized in some reports in which the different transit service aspects are widely and fully described [71] [90] [56].

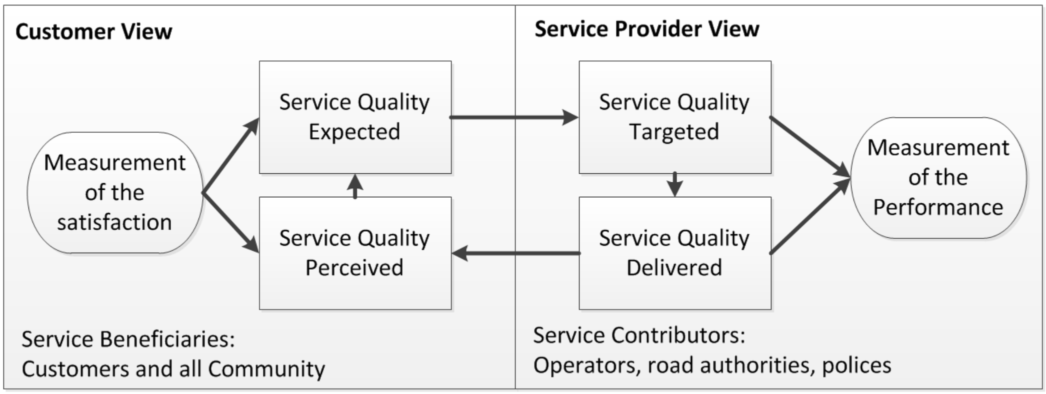

Figure 2.2: Quality loop model [90].

Class	**Description**		**Determinants**
Availability	Basic coverage of the service by geography, time, mode	Network	Distance to stops/stations; need for transfers; area covered
		Timetable	Operating hours; frequency
Accessibility	Interface with other transportation modes and physical access to transportation services	External interface	Pedestrians; cyclists; taxi users; private car users
		Internal interface	Entrances/exits to stops/stations; internal movement at stops/stations; access to vehicles; internal movement in vehicles
		Ticketing	Home ticketing; ticketing within system; ticketing at other locations
Information	Availability of information pertinent to the planning and execution of a journey or a pattern of journeys	General information	Availability; accessibility; time; customer care; comfort; security; environment
		Travel information in normal conditions	Street directions; stop identity; vehicle direction; route; time; fare; type of ticket
		Travel information in abnormal conditions	Current network status; suggested alternative; refund/redress; suggestions and complaints; lost property
Time	Time used for planning and executing a journey or a pattern of journeys	Length of travel time	-
		Punctuality	-

		Reliability	-
Customer Care	Elements needed to make the journey easier and more pleasant, typically through human presence	Commitment	-
		Customer interface	Inquiries; complaints; redress; suggestions
		Staff	Availability; attitude; skills; appearance
		Physical assistance	At service disruptions; toward mobility- impaired; toward inexperienced customers; movement of luggage, etc.; persons with strollers
		Ticketing options	Exchangeability; flexibility; concessionary tariffs (discounts); through ticketing; payment options
Comfort	Physical comfort obtained through the design of or use of installations and vehicles or through ambient conditions	Ambient conditions	Air quality and temperature; weather protection; cleanliness; brightness; congestion; noise; intrusive activity
		Facilities	Seating and personal space; toilets/washing; luggage and other objects; communication; refreshments; commercial services; entertainment
		Ergonomics	Ease of movement; furniture design
		Ride comfort	Starting/stopping; during travel
Security	Actual degree of safety from crime or accidents and the feeling of security resulting from that and other psychological factors	Safety from crime	Staff/police presence; lighting; visible monitoring; layout; identified help points
		Safety from accidents	Presence/visibility of supports; avoidance/visibility of hazards; active safeguarding by staff

		Perception of security	Conspicuousness of safety measures; mastery of network; press relations
Environmental Impact	Effects on the environment resulting from public transportation	Pollution	Emissions; noise; visual pollution; vibration; dust and dirt; odor; waste
		Natural resources	Energy; space
		Infrastructure	Effect of vibrations; wear on road, etc.; capacity demand; disruption

Table 2.10: Description of attributes (Source [90]).

The revision of categories of service quality measures assists to understand and implement transit assessment framework for our research.

Table 2.11 indicates some recommended measures of service reliability, which take into account time-of-day and day-to-day variability, and also accounts for interrelationships between various measures [109].

Measure	**Description**
Distributions of travel time (total travel, in-vehicle, wait times).	1. Mean. 2. Coefficient of variation (for skewed distributions, standard deviation should exclude extreme values). 3. Percent of observations 'N' minutes greater than the mean value.
Schedule adherence, measured at any point along the route.	1. Average deviation from schedule 2. Coefficient of variation (from average deviation, not schedules) 3. Percent of arrivals N minutes later than average deviation from schedule
Distribution of headways	1. Mean. 2. Coefficient of variation. 3. Percent of headways: **a.** Greater than X percent of average or scheduled headways, where $X \geqslant 1$ **b.** Lower than Y percent of average or scheduled, where $Y \leqslant 1$

Seat Availability	1. Passenger loads (demand and capacity)

Table 2.11: Recommended measures of service reliability
(Source Abkowitz et al. (cited in [109])).

The revision of distributions of travel time, schedule adherence, measured at any point along the route, distribution of headways, and seat availability to assess their pros and cons in explaining service reliability. It helps to understand interactions and effects of service attributes.

2.4.3 Improvements to Reliability

As shown in Figure 2.3 improving service reliability can be achieved in two ways. First, enhancements at the operational level, and possibilities at the strategic and tactical level. The most typical approach to enhance reliability is to make corrections at the operational level. These adjustments can be carried out to the operations in real time or to the operations conditions [106].

The primary actor in real time adjustments is the driver. The drivers are assigned a schedule and are influenced by their behavior and the environment. Crucial to obtaining a high reliability is leaving on time at the terminal. The driver has critical impact on this; alongside the departure discipline, their driving style is also an essential aspect. To obtain a level of high reliability consistent driving styles are essential. To modify operations in this manner, training and feedback are crucial. In terms of real time adaptation, both driver and dispatcher can adapt operations to accomplish a greater operational performance [106].

In addition to improving real time operations, there are other ways to increase quality of service. By enhancing the conditions for the operations, quality of services

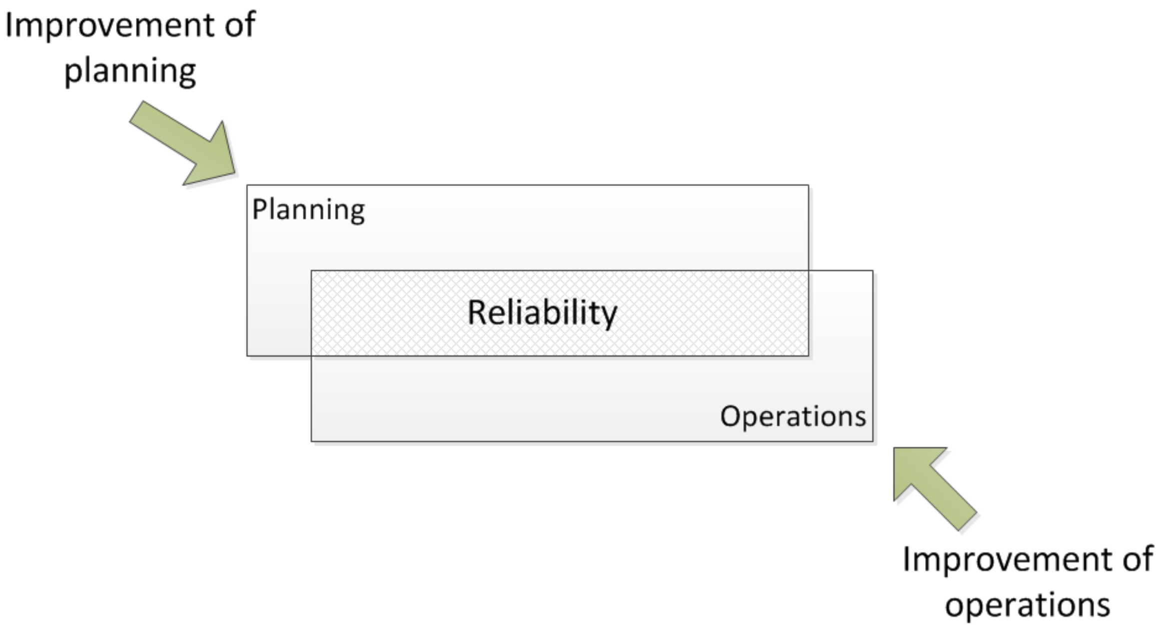

Figure 2.3: Service Reliability Role Planning Operations (source [106]).

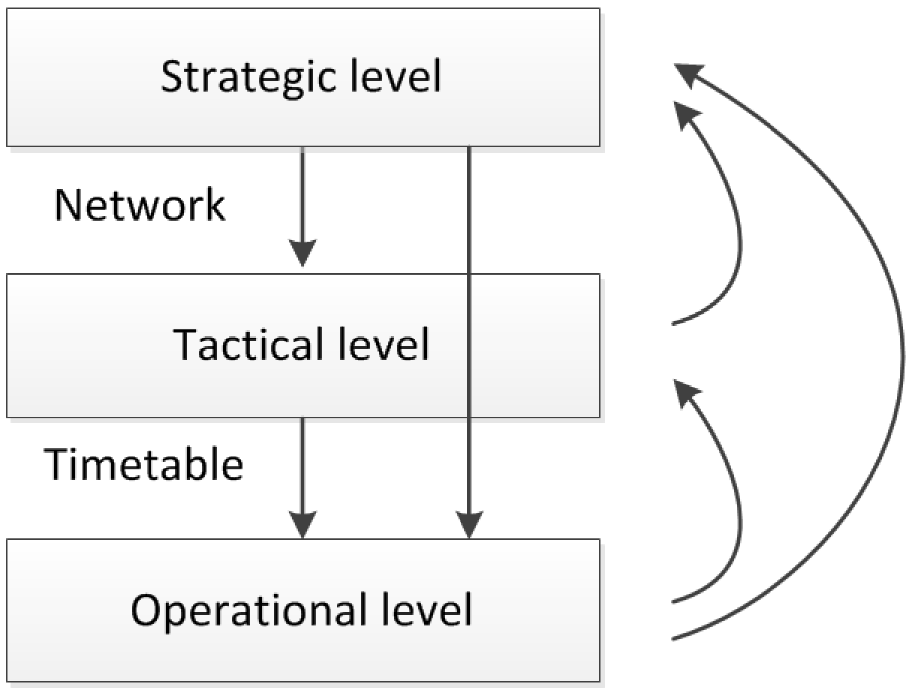

Figure 2.4: Planning Stages of Public Transport Services (source [106]).

can improve as well. Figure 2.4 demonstrates the planning stages of public transport. At the strategic level the network is created, which is utilized for the following phases, including the timetable design and the operational level. At the tactical level, the indicative frequencies are expanded to a detailed timetable utilized by both travelers and then for the planning of the crew and the fleet. The final level is the operational level, in which level of service is assessed by a numerous quality indicators. Through the use of feedback loops to the upper level, these indicators are utilized to enhance quality of the plans [106].

The strategies to enhance reliability are as follows: 1) Priority strategies, where transit vehicles are given special treatment to lower the impact of external factors. 2) Control strategies, which include direct handling of active service operations. 3) Operational strategies, that involve adjustments to route, schedule and resource allocation. Strategies are also grouped into two other categories: a) Preventive strategies, targeted at lowering the likelihood of reliability problems generating. b) Corrective or restorative strategies, provided to avoiding further distribution of problems and reestablishing normal operations. Strategies are shown in Table 2.12 [109].

Applying holding control strategies is addressed by Fu & Yang [41], Zhao et al. [118], Zolfaghari et al. [120], Teng and Yang [99] , Lo and Chang [68] and Xuan et al. [113] for minimizing the waiting time of passengers and reducing passenger travel time. Eberlein et al. [31] employed real-time deadheading strategies to assist the transport system to determine dispatch times, vehicles to deadhead, and stations to skip to enhance service quality in highly irregular headways, while Delle Site and Filippi [26] employed short-turn strategies to evaluate the trade-offs between user and operator costs with weights attached to each.

Previous studies of bus control strategies do not provide methods that have the ability to handle uncertainty in transit operations arising from within the transit en-

Strategies	Preventive	Corrective
Priority		
Exclusive Lanes	X	
Signal Priority	X	X
Control		
Holding		X
Passing/Overtaking		X
Turnback		X
Skip stops		X
Speed Modifications	X	X
Operational		
Reserve vehicle and drivers	X	X
Schedule adjustments	X	X
Express service	X	
Improve vehicle access (fare collection, boarding and alighting)	X	

Table 2.12: Strategies to improve service reliability (Source Abkowitz et al. ([109])).

vironment and via the randomness of passenger arrivals. They also lack a mechanism that provides multiple control strategies (preventive control, holding, expressing, short-turning, deadheading) which are integrated in the same decision making mechanism.

2.5 Modeling and Simulation

Models/simulations for transit operations have been studied for many years. Chen and Chen [20] propose the stochastic simulation method to analyse the route-level transit service reliability for high frequency bus route services. The method describes the process of bus services, headway variation, and average passenger waiting time under different passenger demand and running time fluctuations. A model for optimizing bus route headway has been developed by Yu et al. [115] for a given network configuration and demand matrix. This aims to find an acceptable balance between passenger and operator costs to maximize service quality and reduce operational costs. Zolfaghari, Azizi, and Jaber [120] have developed a mathematical model for a holding control

strategy based on real-time data of bus position to minimize the waiting time of passengers at all stops on the route.

A lot of the previous research into the factors influencing bus reliability pays attention to the problem determining a suitable operations control strategy. This problem is caused by the complicated interactions that induce unreliability. Generally simulation models are developed to find how the factors of unreliability interact and to analyze various implementations of operations control strategies [110]. Designing and developing traffic simulation is addressed by Krajzewicz [59], Morgan [72], Nguyen [82], Balmer et al. [8], Papageorgiou et al. [87], and Mehta [70] to represent bus operations at various levels of detail. A primary variation in bus route simulation models is whether or not the traffic representation is symbolized explicitly or implicitly [110].

2.5.1 Explicit Traffic Representation

Symbolizing transit operations in a microscopic traffic model is extremely beneficial in evaluating lane and signal priority operations control strategies, as demonstrated by Khan and Hoeschen [53], Morgan [72], and Chandrasekar et al. [19], amongst others using industrial modeling packages [110].

Beside numerous industrial traffic simulation packages available that explicitly represent transit such as VISSIM, MITSIM, and CORSIM, several other researchers have built up simulation models from scratch that do not count on traffic data but include the traffic impact implicitly via the travel time distributions. Development of a model from scratch with full use of the source code permits the user to adjust the model to new operations control strategies and inputs more readily [110].

2.5.2 Implicit Traffic Representation

According Milkovits [110], before the popular implementation of onboard automatic data collection systems, early models were designed and built up with data from surveys Senevirante [92] or radio signposts Andersson et al. [4]. Bus route simulation models dependant on onboard collected data vary from fairly simple Monte Carlo simulation models carried out in Excel [86] and [37] to highly detailed models carried out in MATLAB Moses [73].

The Monte Carlo simulation models carried out by Fattouche [37] and Pangilinan et al. [86] have limited application emphasis and demand the assumption that successive transit trips are independent. Pangilinan et al. [86], on the other hand, considered more aspects of the route and did not make any assumption of independence between successive trips. Hence, the model designed in this research might be employed to high frequency routes with more confidence to test operations control strategies [110].

Senevirante [92] also built up a Monte Carlo simulation model at the stop level of detail so applying the model to a new route could possibly be very labor-intensive because travel time and passenger demand for each segment and stop have to be estimated. The simulation model was designed at the key stop level of detail to make simpler the configuration simpler. The simulator schedule was set up by trips and blocks to assist any headway and running time modifications [110].

Moses [73] developed a micro-simulation bus model utilizing AVL/APC data, using MATLAB at the stop level of detail. However, Moses was not able to validate the model with regards to route travel time and headway variation. The failure to validate was caused by the inadequate representation of operator behavior, dwell times, and route specific attributes. The model, which is developed at the key stop level of detail, enables to get more information about dwell time to be incorporated at the stops where dwell time has a substantial effect on running time. The operator behavior is

symbolized utilizing agent based modeling techniques [110].

2.5.3 Evaluating and Comparing Simulation Modeling Packages

Starting in the 1990s, numerous studies were carried out to examine various traffic simulation packages and their capability to effectively simulate various test networks and transportation system configurations. A comprehensive review of simulation models was carried out by the Institute for Transport Studies at the University of Leeds (ITS, 2000). The study compared the features of more than 50 simulation packages [50].

Reference	**Packages Compared**	**Key Findings**
Middelton and Cooner, 1999	CORSIM (FRESIM component), FREQ and INTEGRATION	Models were used to simulate congested freeway conditions. All models performed relatively well for uncontested conditions. They were all, however, inconsistent in their ability to accurately model congested conditions.
Bloomberg and Dale, 2000	CORSIM and VISSIM	Models compared for congested arterials. Found models produced consistent results among them. Also cited that both equally user friendly with respect to initial coding. Paper stressed need to understand how models work and compute performance measures.
Boxill and Yu, 2000	CORSIM, INTERGRATION, AIMSUN and PARAMICS	Models were evaluated on their ability to simulate ITS. Study concluded that AIMSUN and PARAMICS have significant potential for modeling ITS but require more calibration and validation for the U.S. CORSIM and INTERGRATION were concluded to be the most probable for ITS applications due to familiarity and extensive calibration/validation.

Barrios et al., 2001	CORSIM, VISSIM, PARAMICS and SimTraffic	Packages were evaluated based on their graphical presentation (animation) capabilities. In particular, the selected package was to be used to simulate bus operations. A review of transit-related and visualization capabilities of each model is presented. Ultimately, VISSIM was selected due to its 3-D capabilities.
Trueblood, 2001	CORSIM and SimTraffic	Results showed little difference between models for arterials with low to moderate traffic. Paper stressed importance of user familiarity with models and need to properly validate.
Choa et al., 2002	CORSIM, , PARAMICS and VISSIM	Ability of models to accurately simulate a freeway interchange is compared. Study concluded that CORSIM was the easiest to code. Cited link-based routing in CORSIM and POARAMICS as a source of potential inaccuracy in modeling closely spaced intersections. VISSIM uses route-based routing that eliminates problems associated with link- based. Ability of CORSIM to compute control delay for individual approaches was cited as an advantage. Artificial barrier between surface streets and freeways in CORSIM cited a source of inaccuracies. PARAMICS and VISSIM were determined to more closely reflect actual conditions. 3-D capabilities of PARAMAICS and VISSIM cited as an advantage.
Demmers et al., 2002	CORSIM and SimTraffic	Model results compared for congested arterial conditions. Models produced different results for the same arterial.

Kaskeo, 2002	VISSIM, CORSIM and SimTraffic	Simulations were conducted and compared for three facility types: freeways, interchanges, and arterials with coordinated signals. Stated that CORSIM was the most mature and widely used package. Study found that VISSIM was most powerful and versatile (e.g., roundabout, LRT, and pedestrian capabilities). Study found VISSIM the least user friendly and cited additional effort and post-processing to make use of outputs. SimTraffic was found to be the most straightforward to use.
Tian et al., 2002	CORSIM , SimTraffic and VISSIM	Signalized arterials were studied. Results indicate that outputs varied with link length and speed range in addition to volume levels. In general outputs varied more as volume approached capacity. CORSIM displayed less overall variability than SimTraffic.
Bloomberg et al., 2003	CORSIM, INTEGRATION, MITSIMLab, PARAMICS, VISSIM and WATSIM	All six models were applied to signalized intersections and freeways. Study concluded that all models performed reasonably well and were fairly consistent. The study underscored the need for thorough and consistent calibration in simulations modeling.

Table 2.13: Summary of previous traffic simulation comparisons (Source [50]).

Traffic simulation packages utilize basic traffic flow, speed, and density relationships in order for estimation of network capacity and system performance. There are two main kinds of simulation models, micro-simulation and macro-simulation. Micro-simulation models include specific car-following, vehicle performance, and lane changing algorithms to model individual vehicle behavior. Macro-simulation models, however, concentrate not on individual vehicles in the traffic stream but rather take

into account traffic as an aggregative flow using continuum equations. These macroscopic models generally demand less data input and less complicated coding efforts but offered corresponding lower levels of output detail [50].

Although a wide variety of simulation models have been developed and implemented, a simulation environment that provides all the functionality needed for testing and evaluating all scenarios of public transit systems is still not available.

2.6 Digital Ecosystem for Transit System

2.6.1 Need for a Connected Mobility Paradigm in Transit

Study on Advanced Traveller Information Systems (ATIS) signify that travellers make smarter travelling decisions when they are kept informed. In the dynamic setting of urban public transport systems, yet, the capability to be well informed is not enough, travellers demand ability to timely access and quickly evaluate the information based on their own mobility. Regrettably, most public transport ATIS are not adapted or customised to satisfy individual needs [61].

Interactive maps, route planners, and real-time service alerts are becoming vital parts of public transport systems. Even so, these systems obviously lack a capability to dynamically target information to the individual needs [111]. Most online transit tools, for instance, have yet to integrate an awareness of travellers' preferences or mobility-related needs. Personalisation provides a prosperous possibility to match information to the suitable individual traveler and minimizes the demand for manually seeking related transit notifications [62].

Transit offers mobility to people who cannot or prefer not to drive, which includes accessibility to jobs, education and medical services [5]. Transit lowers congestion, gasoline consumption and the nation's carbon foot-print [25] [91]. Still, from a cus-

tomer point of view, a mobility option is only a choice if it is fast, comfortable and reliable [88]. Transit agencies constantly work to enhance transit travel time and on-time performance, such efforts, however, generally appear at a considerable cost [107]. One affordable way to overcome unreliability from the user point of view is to offer connected mobility paradigm via real-time and timely transit information. Real-time and timely information can support riders to feel more in control of their trip, which includes rider waiting time and perception of safety.

Katrin Dziekan [30] has also done substantial work with rider responses to real-time and timely arrival information via at-stop displays. The study shows that real-time arrival displays boost feelings of security, minimize uncertainty, improve ease-of-use, adapt travel behavior and enhance customer satisfaction. Most importantly, the capability to know when the next vehicle is arriving gives travelers' perception of wait time in accordance with the true time spent waiting.

Previous studies are still missing a Connected Mobility Paradigm that provides real-time and timely information to travellers by means of dynamic and amorphous interaction among a multiplicity of transit entities.

2.6.2 Digital Ecosystem Paradigm

"Digital business ecosystems are designed to evolve under the pressure of economic forces and to adapt to local conditions. Adaptation and evolution are partly achieved by embedding specifically designed evolutionary mechanisms into their architecture and their structure, and partly through the participation of local stakeholders in the process of their development. In other words, digital ecosystems assume that the dynamic and self-organising properties can only go so far; technology is also constructed through the continuous formalisation of the knowledge and the processes that the socio-economic and cultural systems to which it is coupled express. When the tech-

nology, being constructed, becomes the medium that facilitates the formalisation and distribution of the knowledge from which the same technology emerged, the pace of transformation from the material to the knowledge economy accelerates, justifying the characterisation of ICT as a catalyst for growth” [75].

Cutting down the limitations to distributed cooperative work and shared knowledge production enables the synchronising of dynamic social and communication networks over ever quicker time scales, driving the ecosystem metaphor to a distributed cognitive system and a collective intelligence. The capability to engage in the modelling of knowledge and in technology production drives a better sense of controlling the ways of socio-economic advancement, resulting in an increasingly active and creative involvement of smaller actors in social and economic operations, with corresponding better autonomy and empowerment [75].

In the digital ecosystem paradigm, the shared knowledge, common models, and training modules are viewed as a kind of human capital accrued, formalised, and inlayed inside the digital ecosystems. The sharing of ideas enables the cooperative growth of applications, but additionally constructing of appropriate behaviours and a shared perception of reality, developing a standard identity and assisting participation at a “community” level [29].

Return to transit systems, resources and provision transport can be configured based on the known whereabout of passengers and vehicles is a specific example of the generic digital ecosystem paradigm which can be applied in smart buildings, hospitals, freight networks/logistics for energy grids and traffic networks.

Thinking holistically about optimising the overall behaviour of the transport network from distributed sensor input - the digital ecosystem metaphor applies nicely here - and the solution to a particular transport optimisation problem in the free bus network using intelligent systems technology. Passenger satisfaction is the objective

function to normalise across the transport network and this requires some coordinated system-wide response to reach that convergent state. It realises a coordinated intelligent distributed system based on geographically dispersed sensor input.

The digital ecosystem is an approach to ensure suitable and timely information accessibility to the public transit community by means of dynamic and amorphous interaction among a multiplicity of transit entities to offer the opportunity to adapt dynamically to changes of transit environment, allowing the system to evolve in accordance with historical or current trends in transit system usage, in a self-organizing way.

2.7 Conclusion

In this chapter we presented a comprehensive overview of AVL, APC technologies in Sections 2.1 and 2.2; the benefits (and pitfalls) associated with various passenger counting technologies in Sections 2.3, 2.3.1, 2.3.2, 2.3.3, and 2.3.4; the social effects of the problems and effects of service reliability in public transportation in Sections 2.4, 2.4.1, 2.4.2, and 2.4.3; algorithms, techniques and strategies to build models and simulations for bus operational strategies in Sections 2.5, 2.5.1, 2.5.2, and 2.5.3; digital ecosystem related issues in transit in Sections 2.6.1 and 2.6.2. This overview provided an understanding of the business need and help to identify issues or gaps that will be addressed in the thesis:

1. Sections 2.1 and 2.2 assist to decide which AVL-APC technologies and procedures are appropriate for the study and help to setup proper environment for the study. Sections 2.6.2 and 2.6.1 shows the needs for a connected mobility paradigm in transit. Digital ecosystem metaphor is selected as connected mobility paradigm in building the Wollongong Shuttle bus system. In Sections 2.5, 2.5.1, 2.5.2, and 2.5.3, the literature review of simulation models

identifies that although a wide variety of simulation models have been developed and implemented, a simulation environment that provides all the functionality needed for testing and evaluating all scenarios of public transit systems is still not available. This is the motivation to develop Evolutionary Simulation model in Chapter 3.

2. Sections 2.3.1, 2.3.2, 2.3.3, and 2.3.4 review analyses and decision support tools, detail level of data needed and findings and guidelines in system design and data capture. These support in capturing needed data and designing a proper decision functions in Chapter 4. In Sections 2.4.3, the literature review of AVL-APC real time control strategies identifies that previous studies do not provide methods that have the ability to handle uncertainty in transit operations arising from within the transit environment and via the randomness of passenger arrivals. There is an unfilled need for a mechanism that provides multiple control strategies (preventive control, holding, expressing, short-turning, deadheading) which are integrated in the same decision making mechanism. They also lack any mechanism that supports decision making for bus operations on route and at the bus stop simultaneously in Section 2.3. These issues will be addressed in Chapter 4.

3. Sections 2.4.1 and 2.4.2 review factors affecting reliability and current reliability measures. These help to build a effective assessment framework in Chapter 5. In Section 2.3, the literature review of AVL-APC off-line analysis identifies that previous research evaluating transit service reliability using AVL systems focused on quantifying the advantages of AVL systems in increasing reliability; they did not make an effort to take into account factors behind a decline in reliability along problematic routes. This issue will be addressed in Chapter 5.

Chapter 3

Evolutionary Simulation for a Public Transit Digital Ecosystem

This chapter presents an integrated simulation environment called the Connected Mobility Digital Ecosystem Simulation (CmdeSim) designed for testing and evaluating traffic planning and management systems using multi-objective Evolutionary Algorithm optimization and Bayesian network used for bus arrival prediction in a transport network. CmdeSim represents traffic data flows in a local bus network and is used to predict bus service reliability. A graphical user interface (GUI) allows visualization of the simulation: including animation of vehicle movements on a map route. Simulation is an important element for assessing the performance of alternative real-world designs and is a much cheaper alternative to operational testing. It thereby allows the analysis of the robustness of a design in a much shorter time frame. CmdeSim, which is a simulation based evaluation, is an off-line tool for testing system designs before their operational implementation and for studying complex interactions among the various components of a public transit system. The developed model in CmdeSim is used for the simulation of different bus scenarios and strategies to identify their strengths and weaknesses for optimizing bus service reliability. CmdeSim describes

firstly how a public transit system is composed and this can sequently help understand which are the most important factors and actors that should be included in the Digital Ecosystem for Public Transit Operations in order to make the system a self-sustaining, convergent transport ecosystem.

3.1 Introduction

The objective of this research is to develop a tool that can be used to evaluate the benefits of Advanced Public Transportation Systems (APTS): Intelligent Transportation Systems applied to public transit. The objective of APTS is in turn to change the way transit services are provided to customers and the way customers use the service. Automated vehicle location (AVL) and Automated passenger counters (APC) are examples of these types of APTS. CmdeSim is a simulation able to represent the behaviors of buses traveling along their routes, including simulating passenger demand. It also allows the demonstration of these technologies to assist bus transit service providers make decisions by implementing intelligent transportation technologies. CmdeSim further allows testing and evaluation of the effects and impacts of various designs and strategies on the transportation network. It models bus transit services at the system, route segment and bus stop level in order to fully capture bus transit operations dynamics. In so doing, it permits the testing different scenarios for the public transit system.

Various traffic simulation programs exist that are able to represent bus operations at various levels of detail. Krajzewicz [59] developed an online traffic simulation for the city of Dublin using the iTransIT ITS framework to describe possible evaluation scenarios. Morgan [72] implemented a tool, based on MITSIMLab (a microscopic traffic simulation laboratory) that may be used to simulate APTS and to evaluate the performance at an operational level of dynamic traffic management strategies.

Nguyen [82] developed a flexible traffic model that is used for simulating different traffic scenarios to identify the optimal signal control policy in several traffic scenarios. Balmer et al. [8] presented a micro-simulation – part of the research project MATSim – focused on the computational performance of different parts of the transport network. Papageorgiou et al. [87] showed a microscopic simulation model developed and utilized for transportation planning applied for the Strovolos Avenue (in Nicosia, Cyprus) traffic network. Mehta [70] developed a simulation based real-time system with traffic prediction and guidance generation.

Although a wide variety of simulation models have been developed and implemented, a simulation environment that provides all the functionality needed to test and evaluate all scenarios of public transit systems is still not available. This chapter presents an integrated simulation environment that addresses a particular need. CmdeSim is a computer-based modeling environment that is used as a research tool to study different control strategies to predict and maintain bus service reliability using multi-objective Evolutionary Algorithm optimization and a Bayesian network for bus network prediction. The simulation is also used to visualize the growth of the existing public transit systems during the process of building a Connected Mobility Digital Ecosystem [35]. The main contribution of this chapter lies in the development of the laboratory environment for evaluating operations and the application of control strategies to study the factors influencing network reliability. A simulation model also provides visual elements to allow its user to visualize variability of movement, passenger demand and other factors influencing bus operations. The environment is intended to make use of the data automatically collected from bus systems.

The remainder of the chapter is organized as follows. Sections 3.2 and 3.3 represent the CmdeSim architecture and the role of the evolutionary simulation in the context of a Connected Mobility Digital Ecosystem. The simulation methodology is discussed in

Section 3.4 and the simulation component is presented in Section 3.5. The formulation of transit behavior is discussed in Section 3.6. Case study and validation of the model is reported and discussed in Sections 3.7 and 3.8. Finally, conclusions are presented in Section 3.9.

3.2 Surveillance system

The University of Wollongong (UOW) is a public university located in the coastal city of Wollongong, 80 km south of Sydney, Australia. As the UOW campus community has grown, accessing the physical campus has become increasingly difficult by car, the main problem being the shortage of parking. To ameliorate this, the University has provided two free shuttle bus service routes (UniShuttle) connecting the campus, the local railway station and parts of the city. There is also a free CityShuttle bus service, provided by the State Government of New South Wales, which covers transport over most of the rest of the city. The free bus services are well patronised by both University and general community. The buses are free so there is no ticketing system.

Transportation modeling systems are always concerned with capturing the varied interactions between drivers, vehicles, and the infrastructure. In the case of free public transport, a key technological challenge is the capture of actual passenger trips to find where passengers get on and off the transport at different locations and at what times. For free buses, current practice allows the driver to tally the number of passenger who enter the bus but the driver has no tally of passengers who exit, so counting passengers on provides one input to the overall information system.

Figure 3.1 describes the architecture for the implementation of APTS in a free passenger transport network. It is an example of one type of transit surveillance system. AVL and APC capture and generate different level data. CmdeSim simulates the performance of the communications and location technologies by representing the

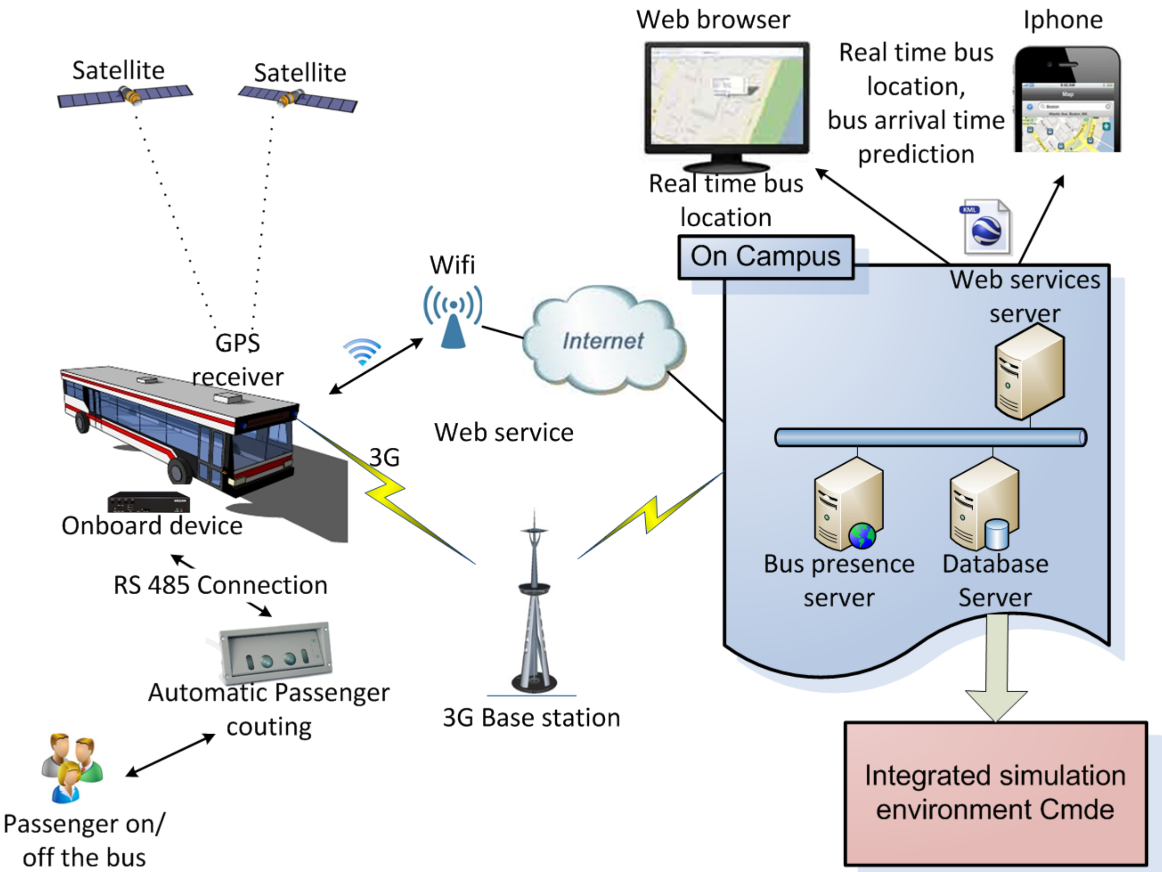

Figure 3.1: Advanced Public Transportation System Architecture for Wollongong, Australia.

availability of public transit data when and where it is available in the real world.

The APTS system consists of three major components: (1) an onboard AVL – installed on the vehicle and an APC unit installed on the door and connected to AVL via an RS485 port. GPS technology is used to collect vehicle location information; on-board APC systems are used to collect passenger load information, and a web service is used to transmit this information back to the server; (2) a bus presence server – responsible for receiving data from web service, processing and storing it to a database server; (3) and a web server, which provides services to end users and matches data to map and data for management level data warehousing. The surveil-

lance system provides complete information on the network's state and communicates with CmdeSim via a mysql database. CmdeSim is connect to the database server to show the movement of the bus along the route.

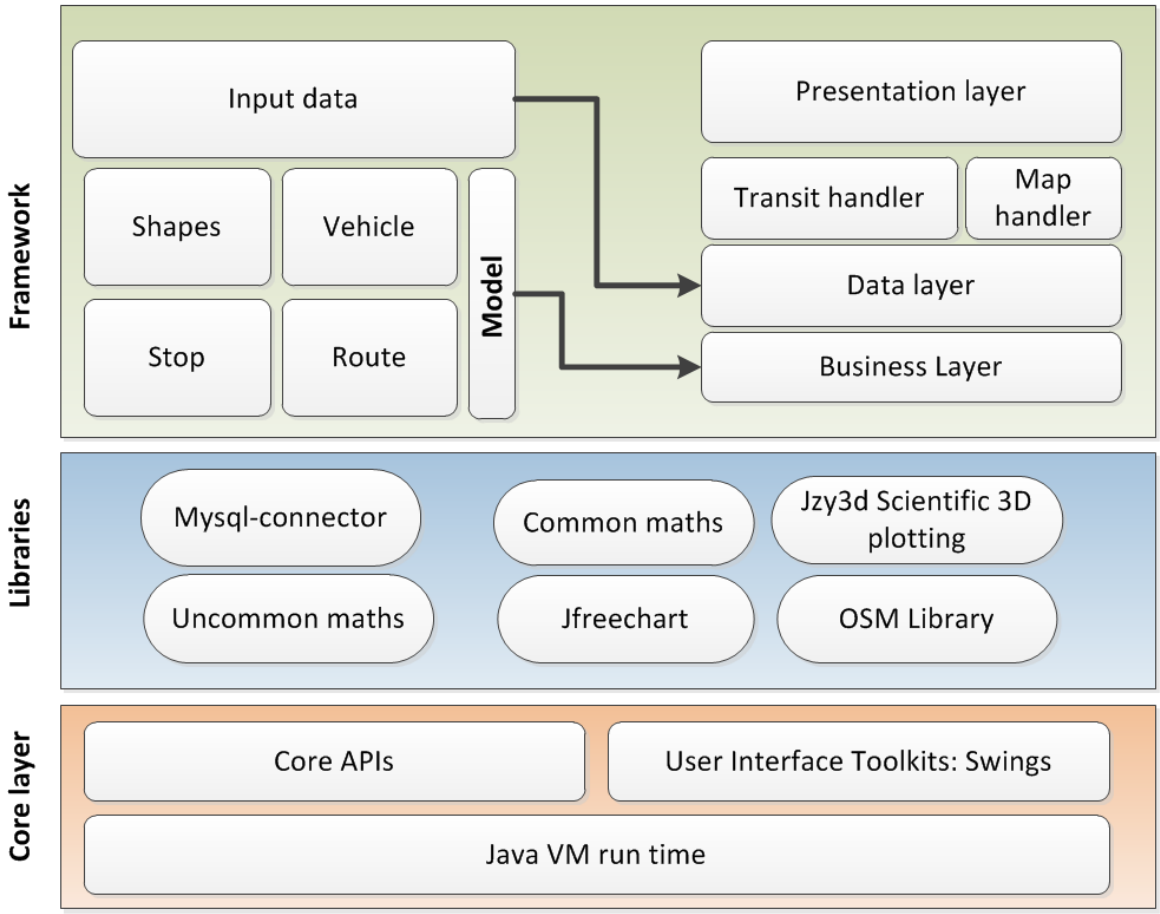

Figure 3.2: Software architecture of the Connected Mobility Digital Ecosystem Simulation (CmdeSim).

CmdeSim is implemented in Java and has an integrated graphical user interface (GUI) for the visualization the simulation process, an important tool for the verification of input data and its presentation as simulation output. The GUI provides animation of the vehicle movements, and a graphical display of traffic data and map route. CmdeSim has a modular structure, which makes it suitable for adding new functionality.

Figure 3.2 depicts the software the architecture of CmdeSim . JfreeChart[1] and Jzy3d - Scientific 3D[2] plotting are Java libraries for building the 2D and 3D chart of the output of simulation. Uncommon maths and common maths are Java classes that are used for computation. The OpenStreetMap (OSM) library[3] includes base classes for drawing maps.

The outputs generated by CmdeSim are variously vehicle-level data, stop-level data, and segment-level data. CmdeSim also generates measures of effectiveness that are used to evaluate alternative control strategies, the performance of buses along their routes, and the passenger experience during the simulation.

3.2.1 In-vehicle computer

The shuttle buses are installed with VTC 2100 as in-vehicle computer and an AVL unit.

The VTC 2100, shown in Figures 3.3 and 3.4, is an economic version of vehicle personal computer with high performace for use in transportation applications. The VTC 2100 system is designed in a compact form factor, yet maintaining the industrial requirements for high availability, wide operation temperature range, and vibration protection. The design also follows the in-vehicle industrial standard, eMark. More features needed for in-vehicle operations, for instance power ignition delay control, low-power protection, SMBus connection and capture module, etc., are included from other NEXCOM's in-vehicle computer products. The GPS is an built-in function of VTC 2100. With expansion capabilities, e.g 3.5G, Bluetooth, etc., the unit can be added to cover varieties of application requirements. Dual VGA display connections make the VTC 2100 an ideal selection for in-vehicle signage platforms as well.

[1]http://www.jfree.org/jfreechart/
[2]http://www.jzy3d.org
[3]http://www.openstreetmap.org

Figure 3.3: Onboard PC Front View (Source [81]).

Figure 3.4: Onboard PC Rear View (Source [81]).

3.2.2 APC Unit

A "brandname" PCN-1001, shown in Figure 3.5, is installed on the Shuttle buses as APC unit and connected to VTC 2100.

The PCN-1001 is a compact and autonomous device-based of non-contact stereoscopic vision technology. It has been designed to count passengers alighting and boarding the doorways of buses and trains. It is also used to count people as they enter or leave buildings or any other area with restricted access.

Figure 3.6 shows the installation of PCN-1001. The stereoscopic cameras capture images of the area below the device (Detection Area); the inclusion of high luminosity infrared LED emitters enables this to be accomplished even in complete darkness. The PCN-1001 must be installed so that the front panel is positioned horizontal to the floor. To achieve this, the angle between the front panel and the enclosure can be

adjusted from 0 to 20 (or by using an extender up to 45, the extender also increases the protection of the rear side). Thanks to these characteristics the PCN-1001 can be mounted in a variety of locations, even on non-horizontal surfaces.

The PCN-1001 analyses objects passing within the detection area, considering height, shape and direction. After identifying if an object is a person entering or leaving, the incoming or outgoing values are stored accordingly, together with time and date information. This information can be made immediately available via RS485 or downloaded at a later date for analysis.

The PCN-1001 can be stand-alone or connected together with a vehicle server (the Control Unit) that can pre-process, store and upload information from the all vehicle passenger counters.

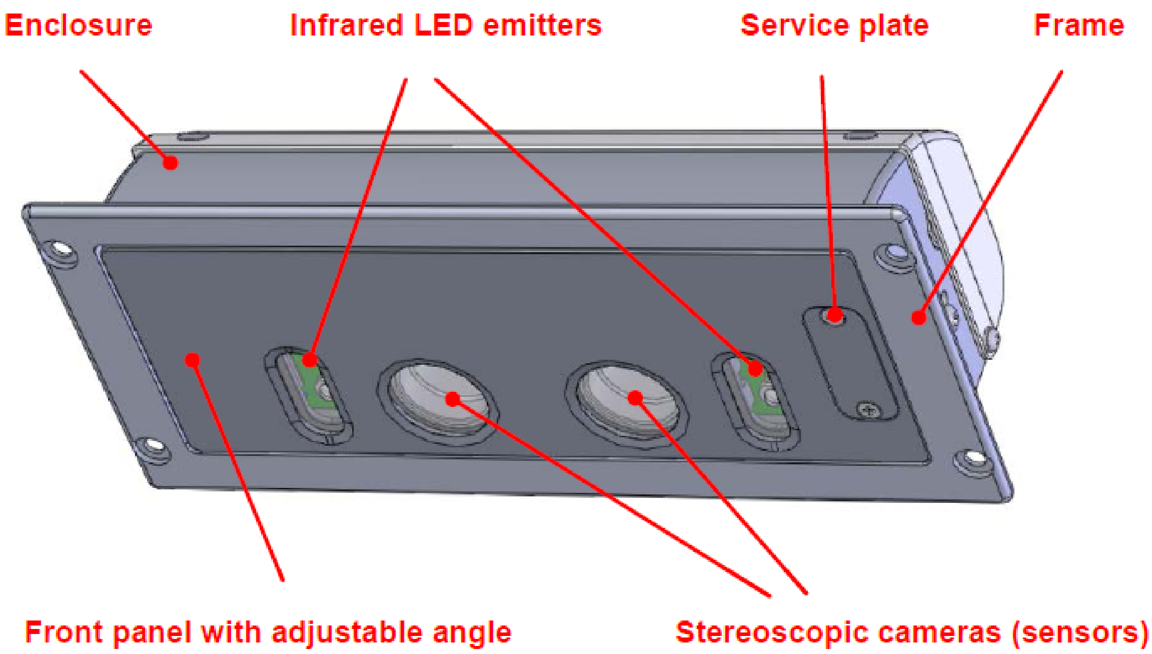

Figure 3.5: Pcn1001 Front side (Source [105]).

The typical installation height of the PCN-1001 should be made with the following conditions:

- keeping the PCN-1001 in the middle of the doorway;
- keeping the front panel parallel to the floor.

Additionally, distance "G" between the front panel perpendicular axis and the door should be large enough to prevent the inclusion of the upper area of the door frame. Usually G should be less than 50 cm.

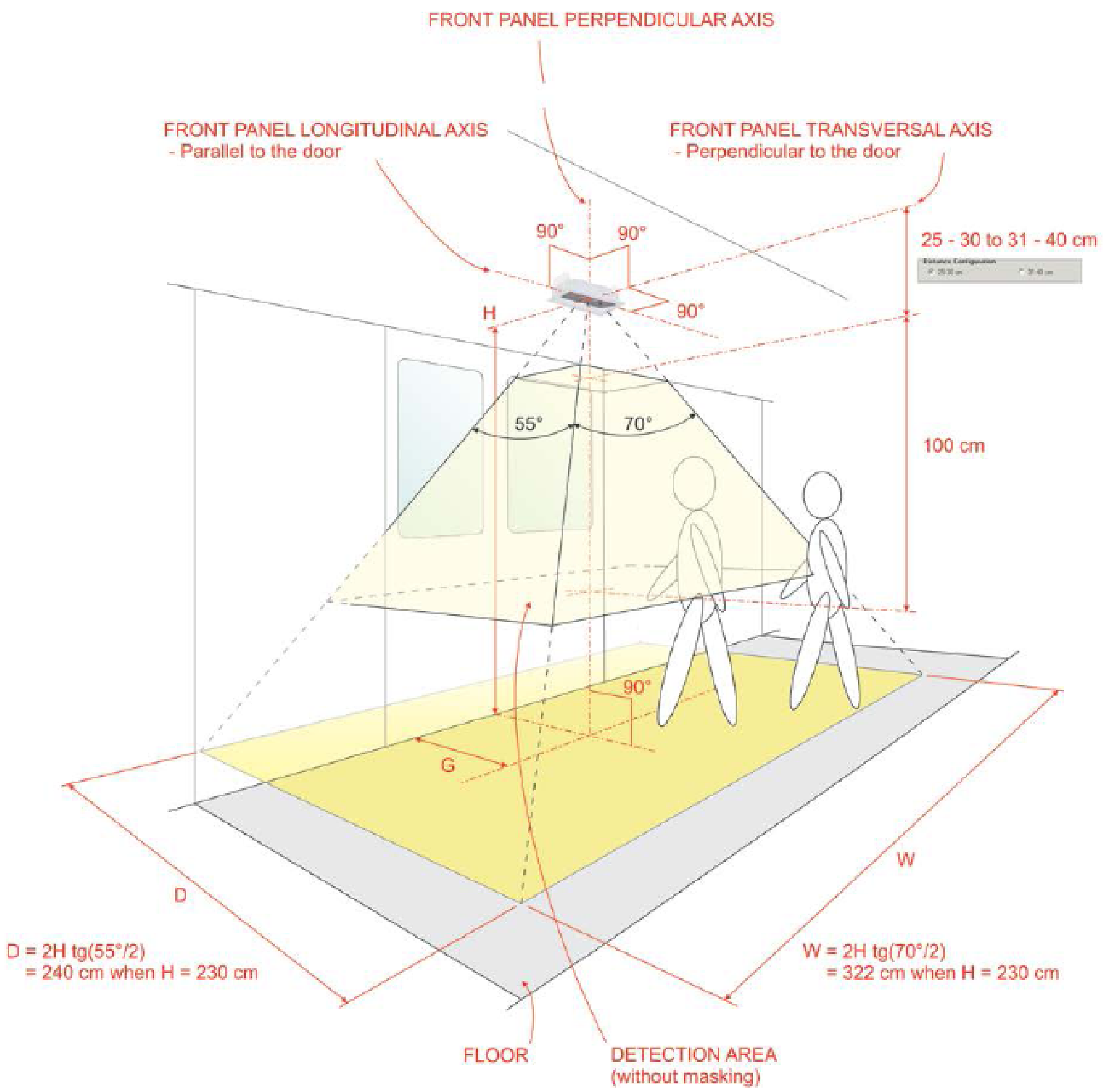

Figure 3.6: The "brandname" PCN1001 Installlation (Source [105]).

3.3 Evolutionary Simulator in the context of a Digital Ecosystem

A Digital Ecosystem is defined as an open, flexible, domain-clustered demand driven approach, with properties of self-organisation and scalability [15]. In other words, a Digital Ecosystem is the technical infrastructure "that transports, finds and connects services and information over Internet links enabling networked transactions and the distribution of all the digital 'objects' present within the infrastructure" [74]. Key to the idea is "an isomorphic model between biological behavior and the behavior of the software, based on theoretical computer science implications and leading to an evolutionary, self-organizing and self-optimizing environment" [74]. Digital ecosystems are inspired by properties of natural ecosystems.

Just like natural ecosystems, digital ecosystems are capable of evolving; they should be self-aware and self-organising. As describing in [35], our public transit system is highly self-aware as it knows where every single bus is and each bus's passenger counts are known in real-time via the AVL and APC systems. The passenger interacts with the system using their smartphone. The passenger and bus interactions within the public transit environment fosters and supports interaction, where the system can be self-sustaining and self-balancing due to evolving patterns of usage. The digital ecosystem is an approach to ensure relevant and timely content availability to the public transit community through dynamic and amorphous interaction among a multiplicity of small entities to support knowledge sharing, co-creation of knowledge and the development of new business models.

Figure 3.7 depicts the Connected Mobility Digital Ecosystem and the role of the CmdeSim simulation in the system. The CmdeSim Evolutionary Simulation allows the system to evolve according to historical or current trends in system usage. Overall

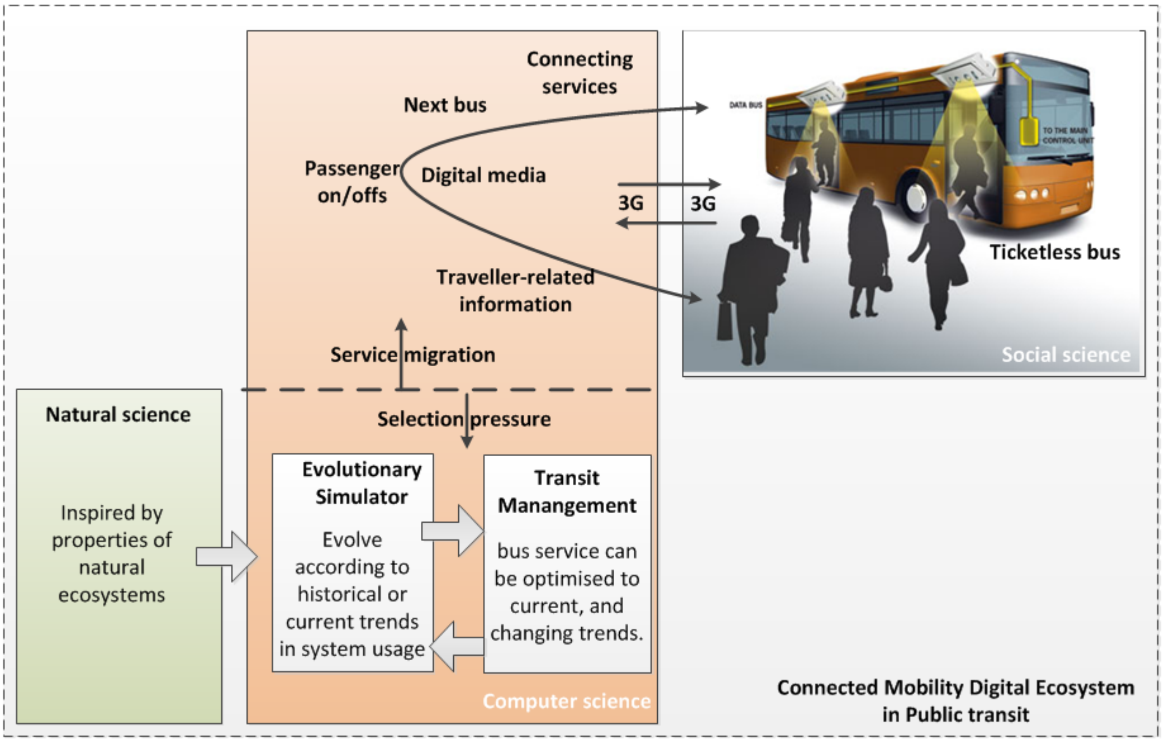

Figure 3.7: A Connected Mobility Digital Ecosystem.

the circular bus service can be optimised to current, and changing trends. In other words, the simulation can be understood as an instrument for visualizing an ongoing process and as a tool to validate different hypotheses to improve service reliability.

The opportunity to adapt dynamically to a changing ecosystem in a self-organizing way is the major advantage of utilizing biological approaches in the Digital Ecosystem. Therefore Evolutionary algorithms and Bayesian networks are sympathetic optimisation techniques for simulation. It is hard to predict how a real-world ecosystem will evolve, but utilising a simulator makes it possible to isolate key parameters influencing the evolution of a digital ecosystem.

3.4 Simulation methodology

Simulation provides a powerful methodology to evaluate public transit with opportunities to develop models that represent actual systems or systems under development. In this way, modifications to the system or process improvements can be tested. This permits the study of the effects of variation upon system inputs and changes in system conditions and structures upon system behaviors.

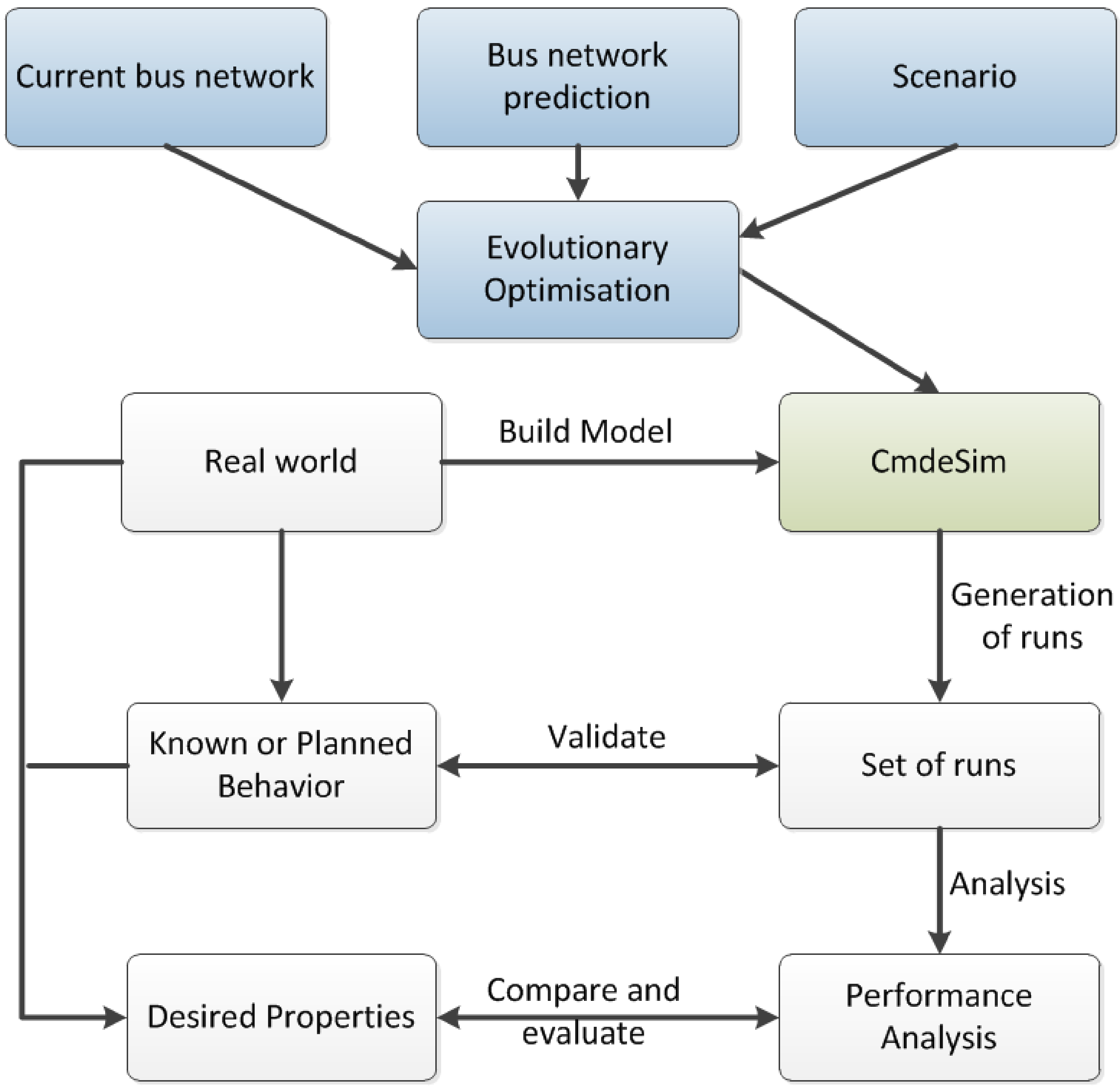

Figure 3.8: Simulation methodology.

"All models are wrong, some models are useful" [16] and *"any simulation model is only as good as the input data"* [1] are popular credos to bear in mind when using simulation methods. A simulation model must be developed to fit with a specific purpose. Figure 3.8 depicts the simulation methodology of CmdeSim. The simulation model developed in this chapter is designed to study bus service reliability factors and real-time operation control strategies on the bus reliability in terms of minimising passenger wait time, alleviating passenger crowding and even headway control with optimisation via multi-objective Evolutionary Algorithm optimization and Bayesian network for bus network prediction. The simulation also provides a mechanism to allow the prediction of the reliability state of the network. The simulation model captures different levels of data so that it has sufficient detailed data to represent and study the operation of the model.

3.5 Simulation component

CmdeSim includes a GUI for visualization of the simulation input and output. Origin destination flows in the entire network and stops are graphically displayed and vehicle movements animated. The simulation allows loading of different scenarios, provides a navigate and zoom map network, and a pause and resume a simulation run option.

The simulation starts with the loading of simulation parameters: OSM map, network presentation file, passenger demand and the scenario definition. The simulation process is described as follows:

- read vehicles, schedule, and fleet assignment from input file and assign vehicles to the route;
- passenger data is generated for each bus stop per time period;
- advance vehicle positions, update their speeds and pickup passengers;

- update GUI display;

- update the simulation time clock and move to next iteration.

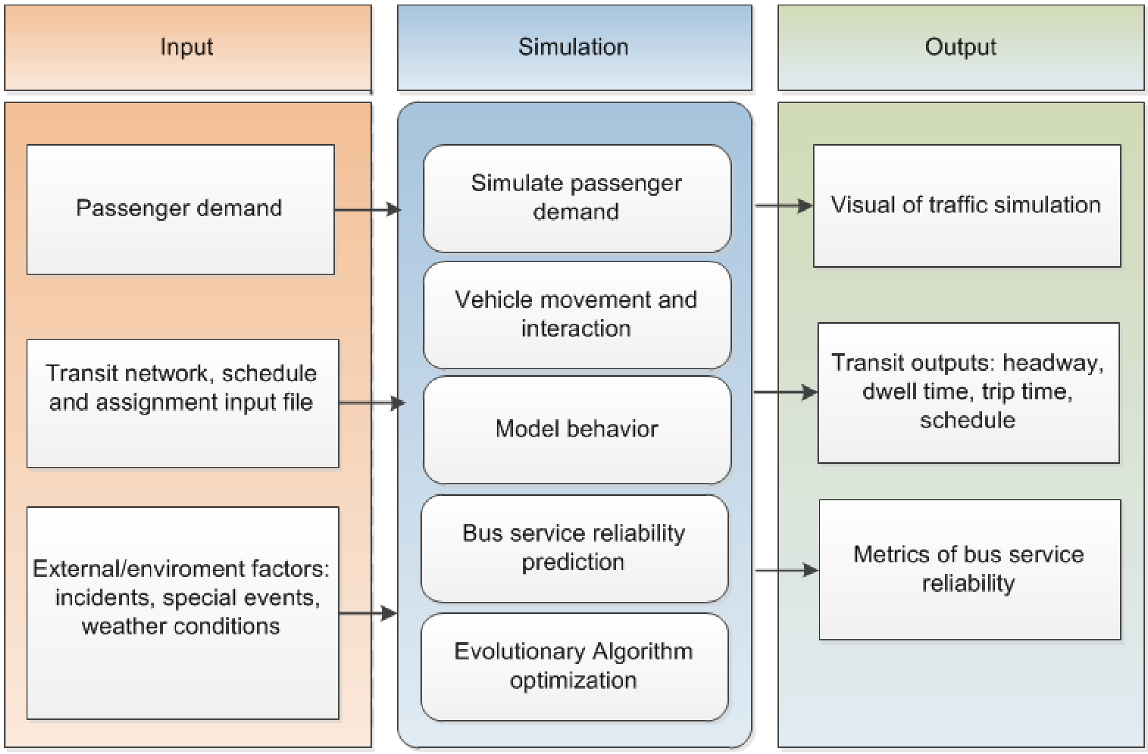

Figure 3.9: Simulation component.

Figure 3.9 represents different components of the simulation. The next section provides details of the each component.

3.5.1 Simulation Inputs

3.5.1.1 Transit Network

The road network is essential as it represents the available infrastructure of the environment, and models the paths of public transport in several ways.

The transit network can be created using a graphical editor shown in Figure 3.10. The network database in XML format includes links, or paths, in the network that

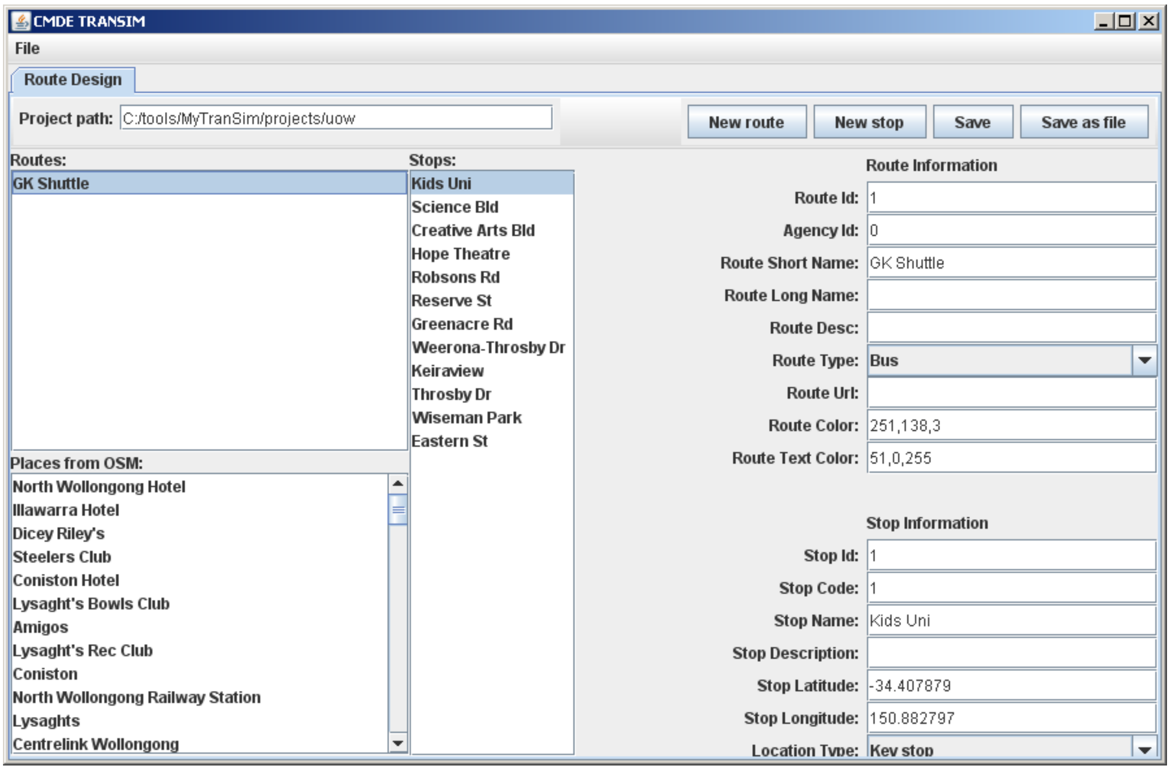

Figure 3.10: Network Editor.

makes up bus routes and the designs and locations of bus stops along those routes. The definition of the transit network file in CmdeSim is important as it affects the interaction of the transit service, buses in a fleet to be assigned, the passengers and the surrounding bus transit environment.

CmdeSim represents a transit network using OSM maps and XML network.xml that is able to represent road segments and route segments. CmdeSim shows the detail transit network that can be used to simulate various ranges of bus transit operations and strategies. Passenger boarding, alighting, waiting time and crowding phenomena can be all simulated.

Figure 3.11 illustrates the way a bus route is defined in the transit network input file network.xml. The file can define the entire bus route from terminal to terminal, or simulate just a portion of a route. When the transit network file is read, route data

objects are created and loaded on the OSM map. The transit network file is described as a collections of routes represented as a list of routes. Each route has a unique ID number and has associated with it a list of shapes (longitude and latitude) that make up its paths and a list of bus stops along their paths. Attribute direction in the route tag is use to define the bus heading.

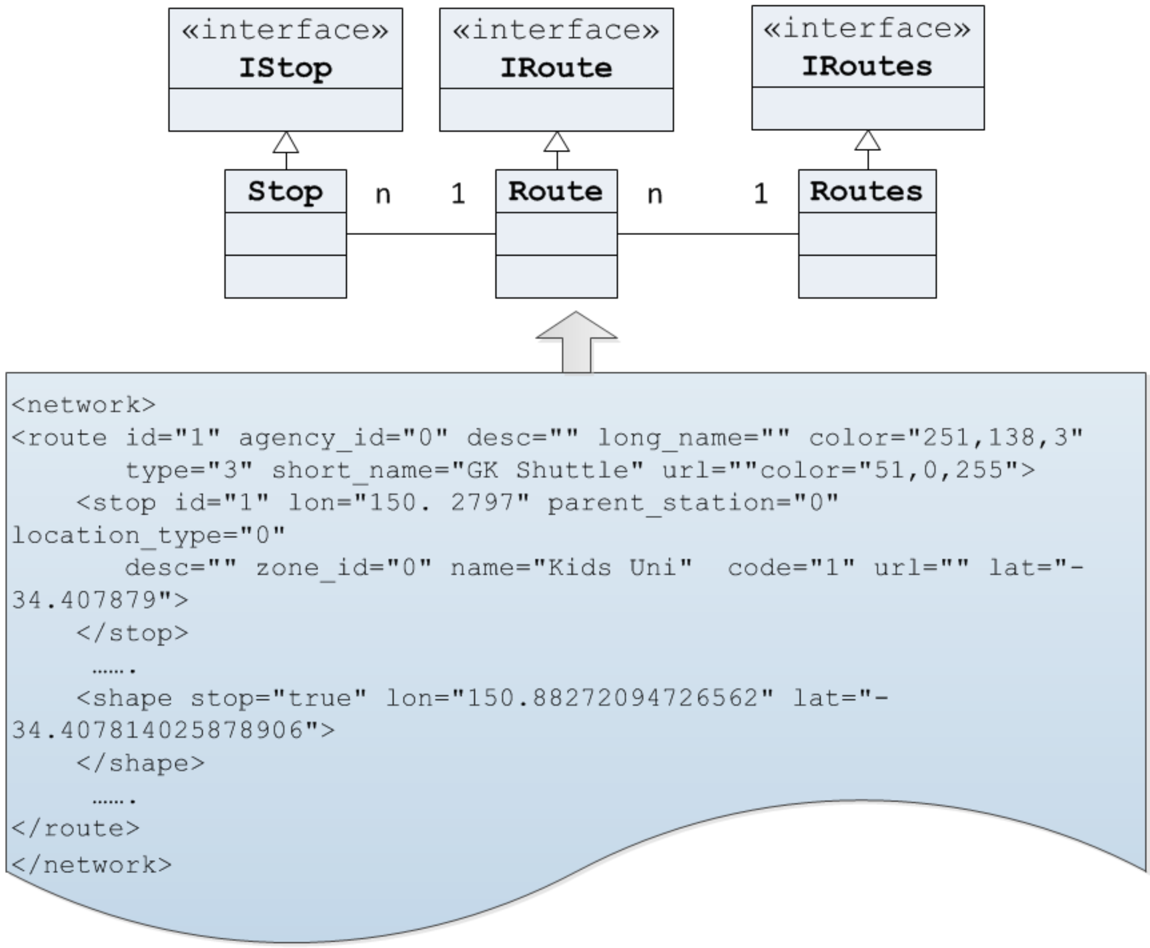

Figure 3.11: Transit network data model.

3.5.1.2 Schedule Design

Figure 3.12 illustrates the way a schedule definition file is defined in the schedule.xml and its object mapping. The schedule definition file describes individual trips on a

route that a bus might travel. When the schedule definition file is read, trip data objects are created. Each trip object has a unique ID number, is assigned to only one route, and is given a series of scheduled arrival times at the bus stops along that route. Since some bus routes in the network are frequently visited — and without specified arrival times — a trip may have no arrival times.

The scheduled arrival times are likewise optional. Thus, the user may define frequent bus services that have no specified arrival times, but rather a design headway, the ideal time/distance between buses. The value of the design headway is specified in the fleet assignment file as an attribute of the transit parameters. The sequence of arrival times in the schedule file should correspond to the sequence of stops on the route.

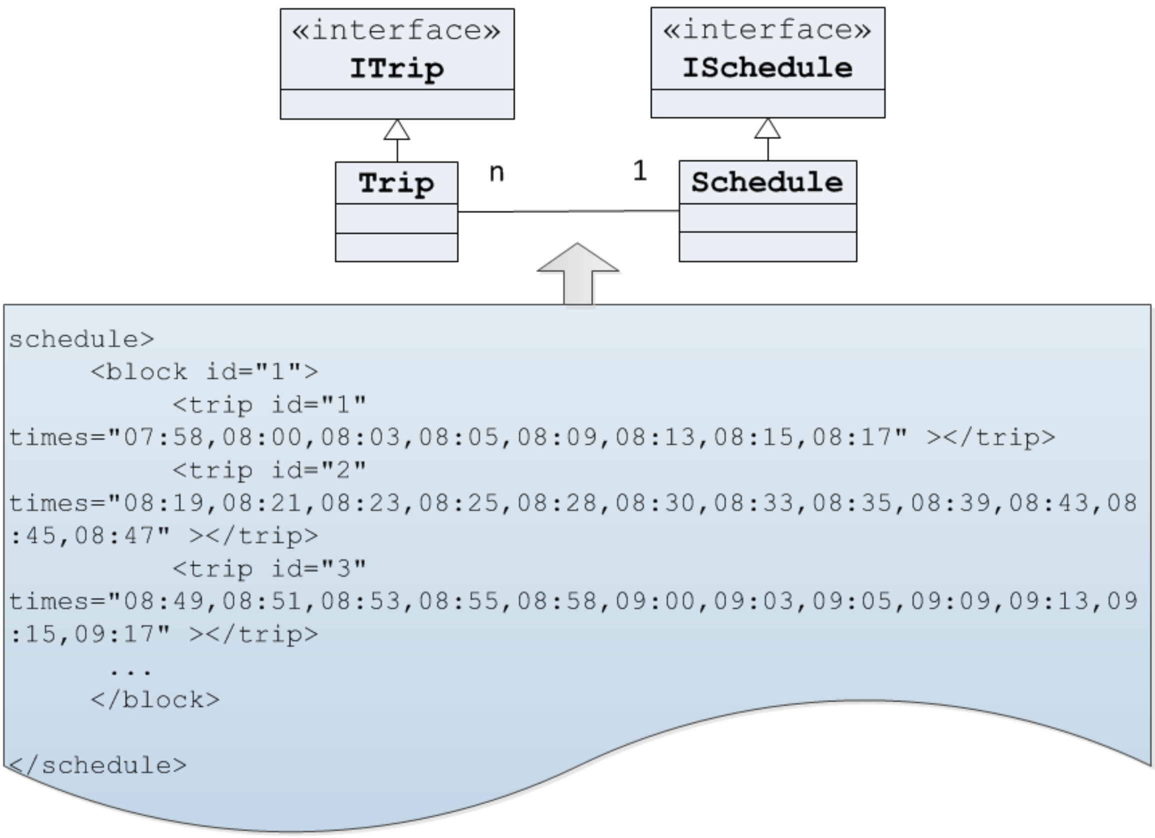

Figure 3.12: Schedule data model.

The schedule file also defines blocks, which are a series of trips to which a single bus may be assigned. Each block has a unique ID and a list of trip IDs that correspond to the sequence of trips to which the bus is assigned. The end time of one trip must be the start time of the next trip in the run.

3.5.1.3 Fleet assignment

Figure 3.13 illustrates the way the fleet assignment file is defined in the plan.xml and its object mapping. The fleet assignment file defines the run to which each bus in the fleet is assigned and the start time at which the bus enters the transport network. When the bus assignment file is read, bus assignment data objects are created. The route ID is the constant link between the vehicle and its assignment. The bus assignment object stores route ID, vehicle ID, bus driver, the run to which it is assigned, and a number of variables that track the vehicle's progress with respect to its assignment, such as the current trip, the next scheduled arrival time, passenger load, and schedule deviation at the last stop. A bus that is assigned a given trip knows its path through the network because each trip is assigned a unique route ID to which it corresponds.

The bus assignment file defines a run and the start time in the simulation at which the bus enters the network and begins serving the trips in the run.

3.5.1.4 Passenger Demand

Passenger demand is an important component in modeling bus transit operations because passenger behavior is a primary influence on bus dwell time, which is the time a bus remains at stops to serve passenger boarding and alighting. It is important to understand the nature of passenger activity to simulate this idea accurately. Passenger demand is represented as a boarding for the entire route and considered to be random – as it may vary by time of day (and day of the week) – and is a variable at the route and stop levels. It also has temporal variability as it might be affected by external

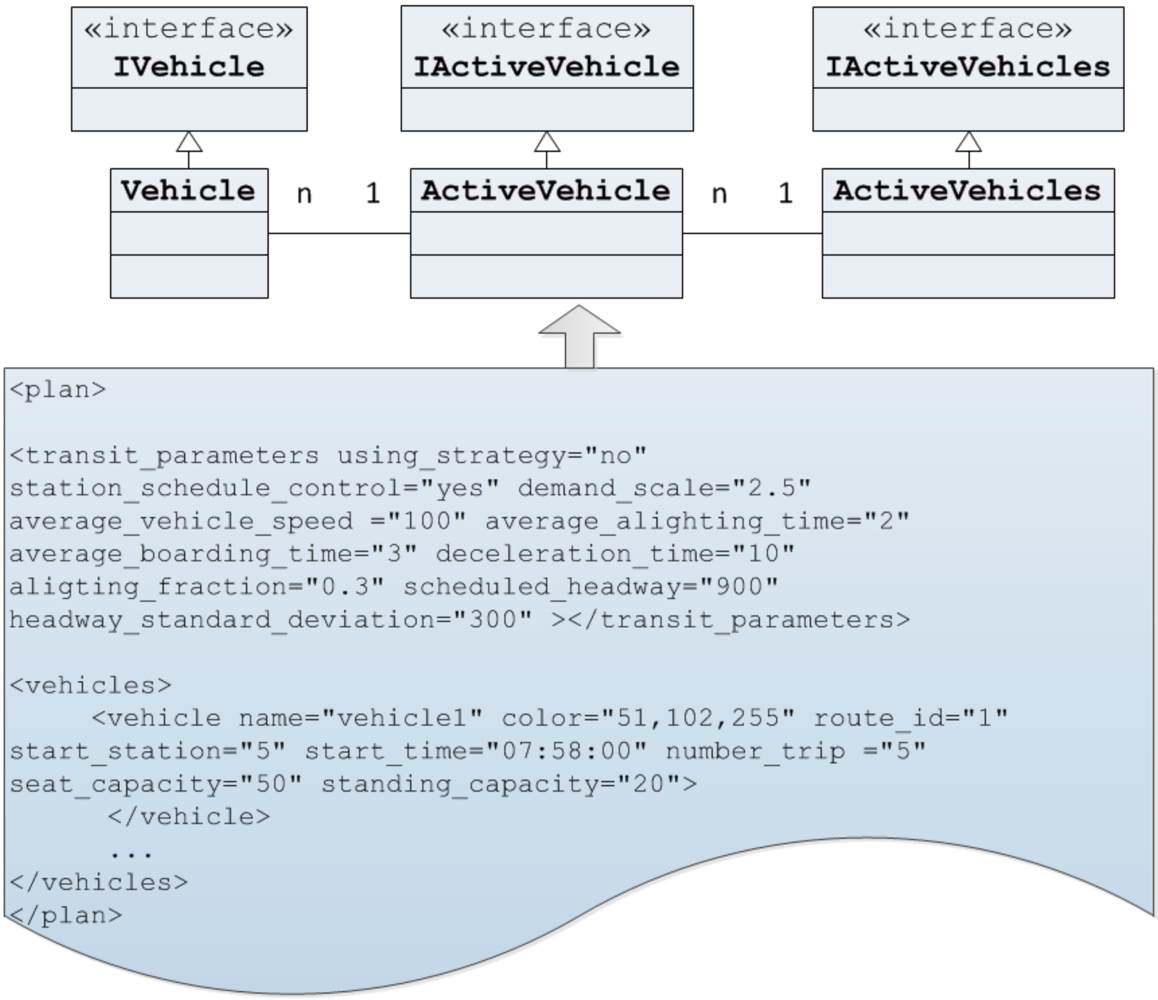

Figure 3.13: Fleet assignment data model.

factors such as festivals, sporting and other special events.

Passenger demand on a bus route is calculated across time and by location from historical data as described in Figure 3.14. Passenger arrival rate is modelled as follows:

- calculate the distribution of passenger boarding for a week and weekdays per bus stop;
- calculate passenger boarding for 15 minute time period per day and bus stop;
- calculate passenger boarding rate per minute at each stop.

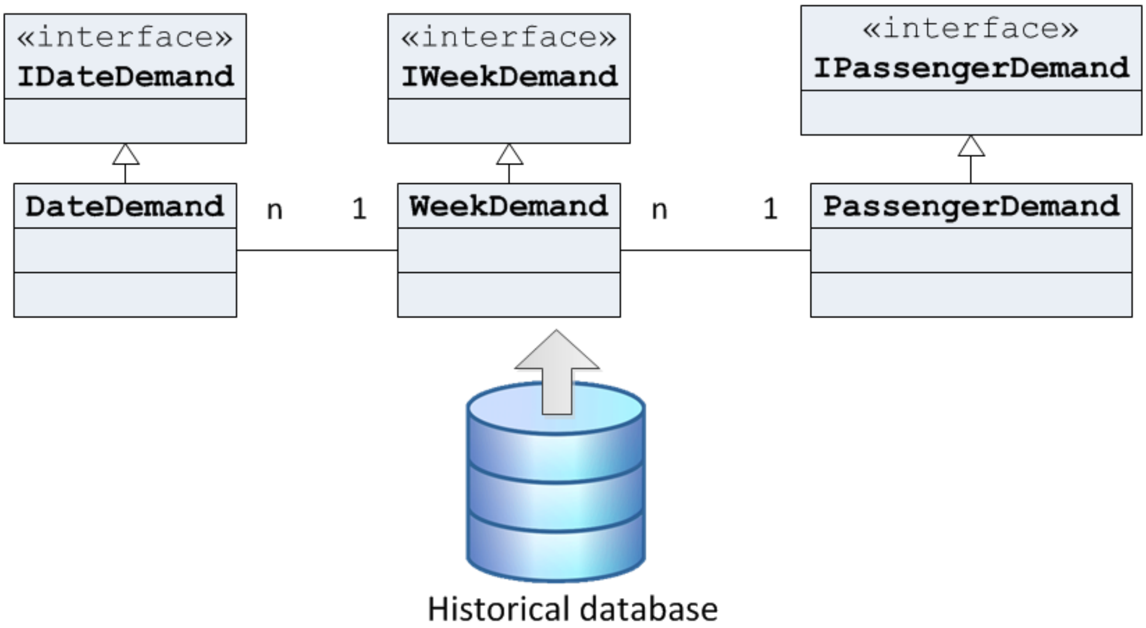

Figure 3.14: Travel demand.

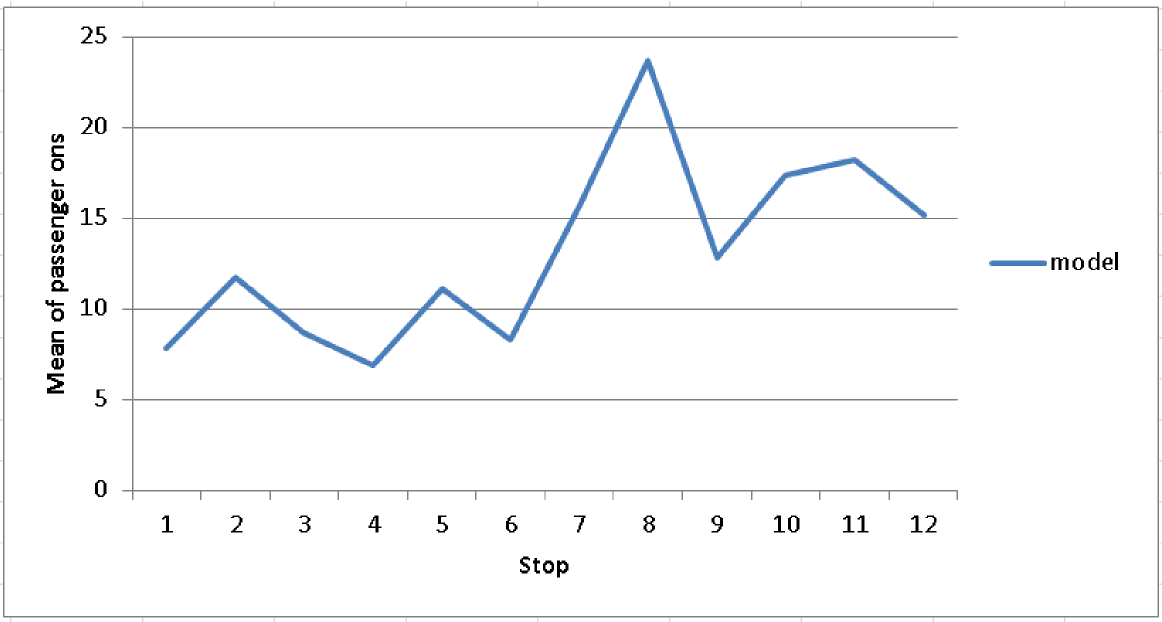

Figure 3.15: Mean passenger ons.

Figures 3.15 and 3.16 represent mean of number passenger boarding and alighting that are generated from the simulation.

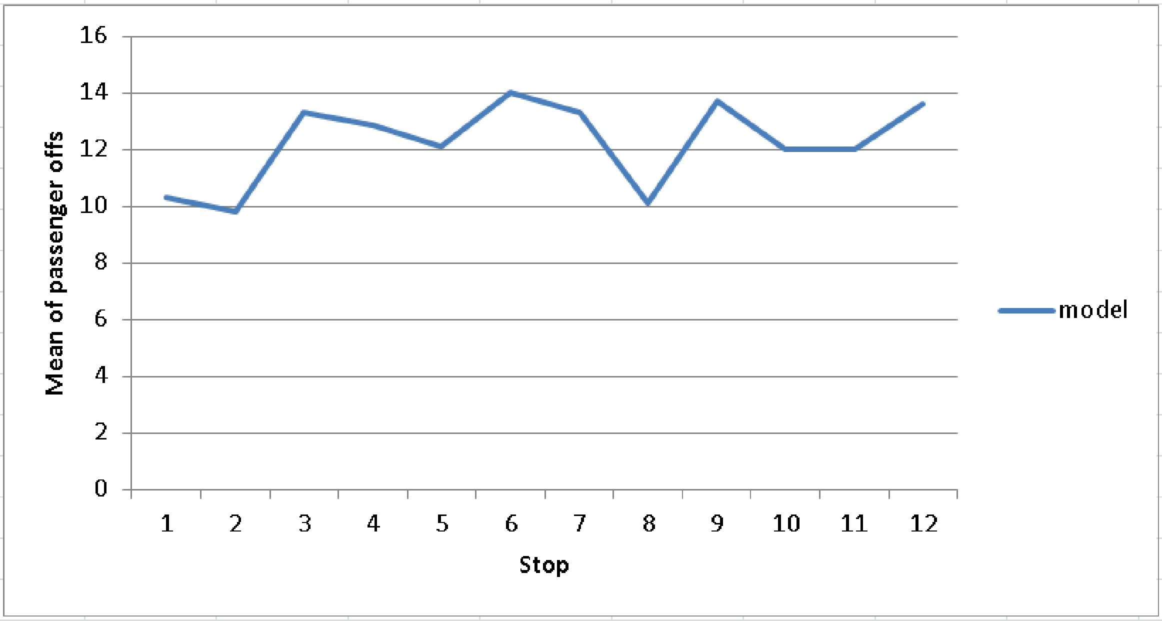

Figure 3.16: Mean passenger off.

3.5.2 Simulation Outputs

The output of the CmdeSim provides visualisation of transit operations and metrics of bus service reliability, which are analyzed using output data files that are produced during simulation runs.

Figure 3.17 shows various analysis outputs that allows evaluation of the efficiency of the simulation. These metrics are used to evaluate the effect of control strategies on travel and in-vehicle times, to measure stop-level bus reliability with (and without) employing control strategies, to present space-time headway adherence before and after applying control strategies, and to show the trade-off between control strategies.

3.6 Model Behavior Formulation

It is important to understand the nature of vehicle activity in order to model bus behavior showing when and how frequently buses arrive at specific locations along

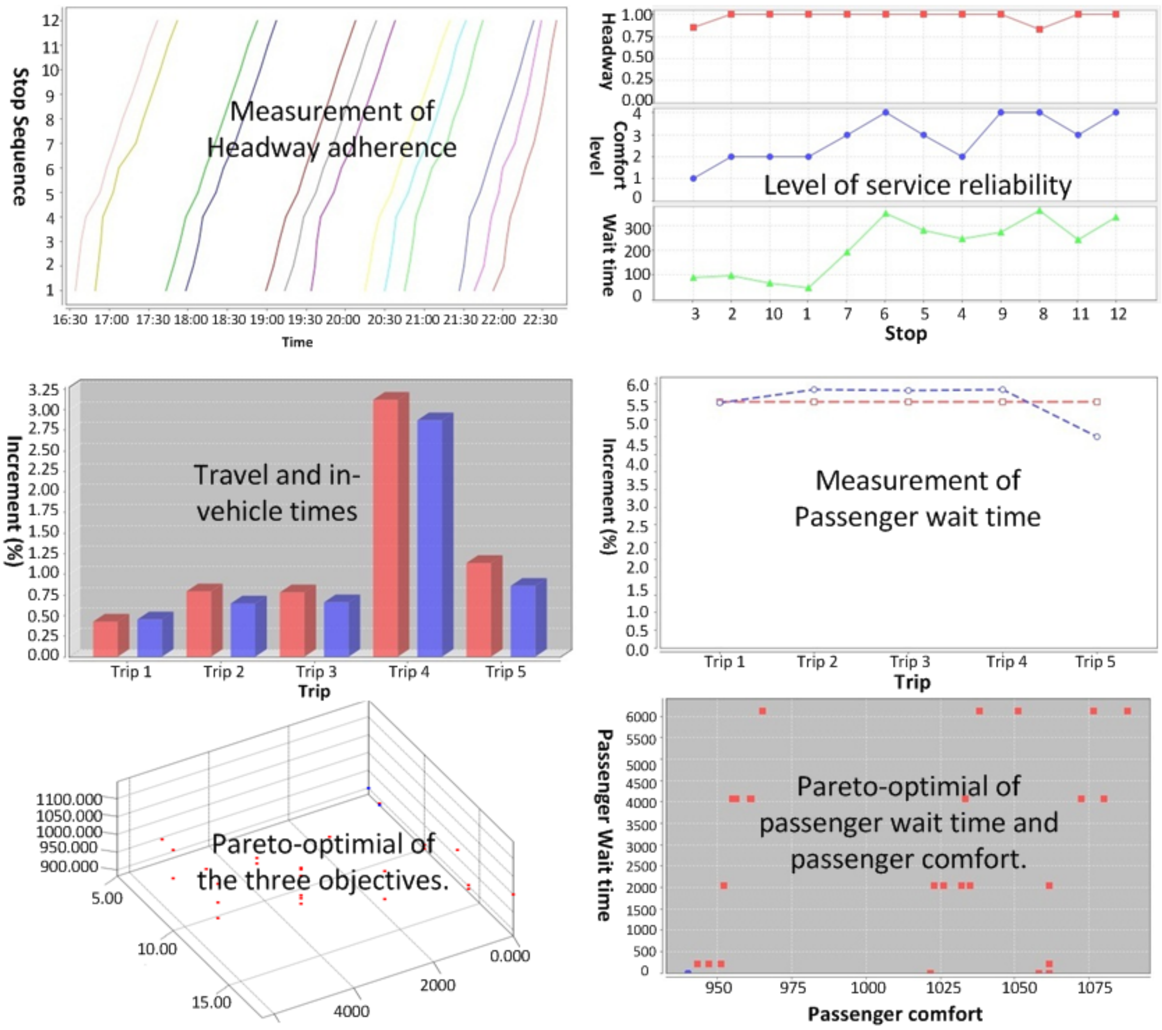

Figure 3.17: Measure of Efficiency.

the route: not only as a function of the schedule, but including effects of various random disturbances. Figure 3.18 shows interaction of various components of the transit system. Vehicle movements between bus stops refer to bus operator driving behaviors that control the vehicles from one stop to the next, after it has pulled out of a stop and before it has begun to pull into the next stop.

The headway $\mathcal{H}_{i,k}$ depends on the previous headways, running time differences and

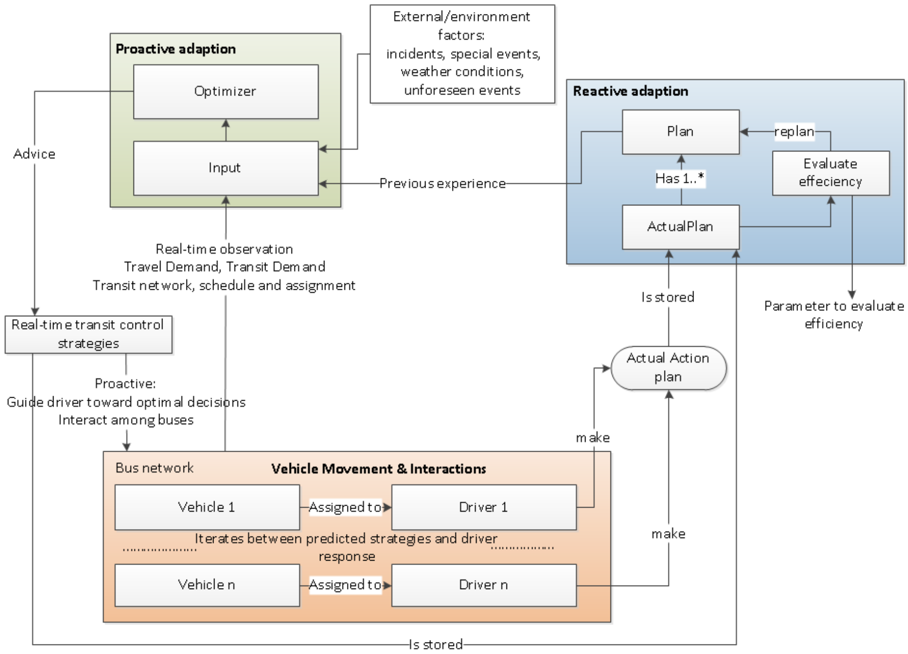

Figure 3.18: Simulation flow.

dwelling differences.

$$\mathcal{H}_{i,k} = \mathcal{H}_{i,k-1} + \Delta\mathcal{R}_{i,k} + \Delta\mathcal{D}_{i,k} \tag{3.1}$$

$\Delta R_{i,k}$ is the difference in running time between bus i and its predecessor $i-1$ when they arrive at stop k and $\Delta\mathcal{D}_{i,k}$ is the difference in dwell time between bus i and its predecessor $i-1$ when they dwell at stop k.

$$\Delta\mathcal{R}_{i,k} = \mathcal{R}_{i,k} - \mathcal{R}_{i-1,k} \tag{3.2}$$

$$\Delta\mathcal{D}_{i,k} = \mathcal{D}_{i,k} - \mathcal{D}_{i-1,k} \tag{3.3}$$

Bus behavior at stops has mostly to do with dwell time, which is time to open and close doors, and the time it takes to serve passengers on and off the bus. It is assumed

that boarding and alighting cannot occur simultaneously. The dwell time is as follows:

$$\mathcal{D}_{i,k} = \alpha \mathcal{A}_{i,k} + \beta \mathcal{B}_{i,k} \tag{3.4}$$

where $\mathcal{A}_{i,k}$ is number of passengers alighting vehicle i at stop k, $\mathcal{B}_{i,k}$ is number of passengers boarding vehicle i at stop k, α is average alighting time for each passenger, and β is average boarding time for each passenger. The number of passengers alighting and boarding is calculated by the following equations:

$$\mathcal{A}_{i,k} = \rho_k \mathcal{L}_{i,k} \tag{3.5}$$

$$\mathcal{B}_{i,k} = \lambda_k \mathcal{H}_{i,k} \tag{3.6}$$

where ρ_k is passenger alighting fraction of the on-board passenger at stop k, λ_k is passenger arrival rate (number of persons per minute) at stop k, and $\mathcal{L}_{i,k}$ is number of on-board passengers of vehicle i when it departs stop k.

3.7 Case Study: Wollongong

A case study of bus operations on the Gwynneville-Keiraville bus route, represented in Figure 3.19, in the central region of the regional city of Wollongong, Australia – whose population is approximately 300,000 – is used to demonstrate and test the simulator.

An Advanced Public Transportation System, which is a part of the Connected Mobility Digital Ecosystem project [34], is implemented with the objective of enhancing public transit services. AVL and APC are installed for buses on the UniShuttle service as part of the project.

The shuttle bus network is small enough that it was possible to collect complete

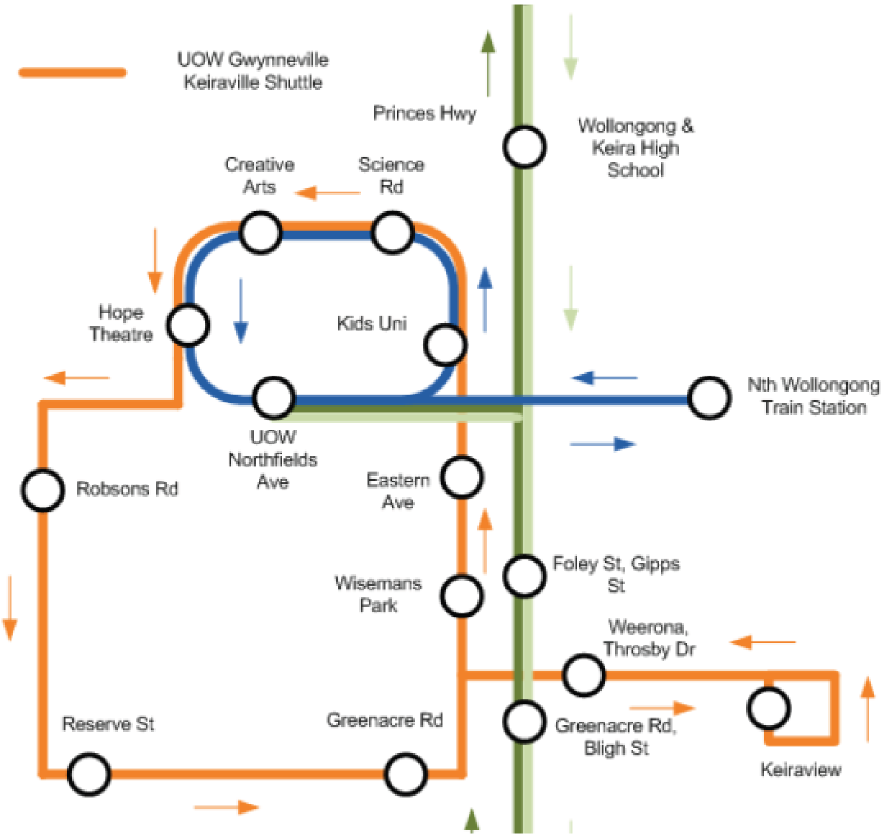

Figure 3.19: Gwynneville-Keiraville route.

data about the vehicle and passenger movements without the instrumenting and data requirements being over-whelming. Still there is a large amounts of data being collected. Even though there are only 7 buses there are still gigabytes of data being collected and stored.

3.8 Verification and Validation

Verification and validation of any simulation model are important to ensure confidence that the obtained simulation results are accurate and meaningful. CmdeSim ensures that all factors affecting the simulated bus operations are captured and stored to log data for verification and validation. The following verification techniques are used:

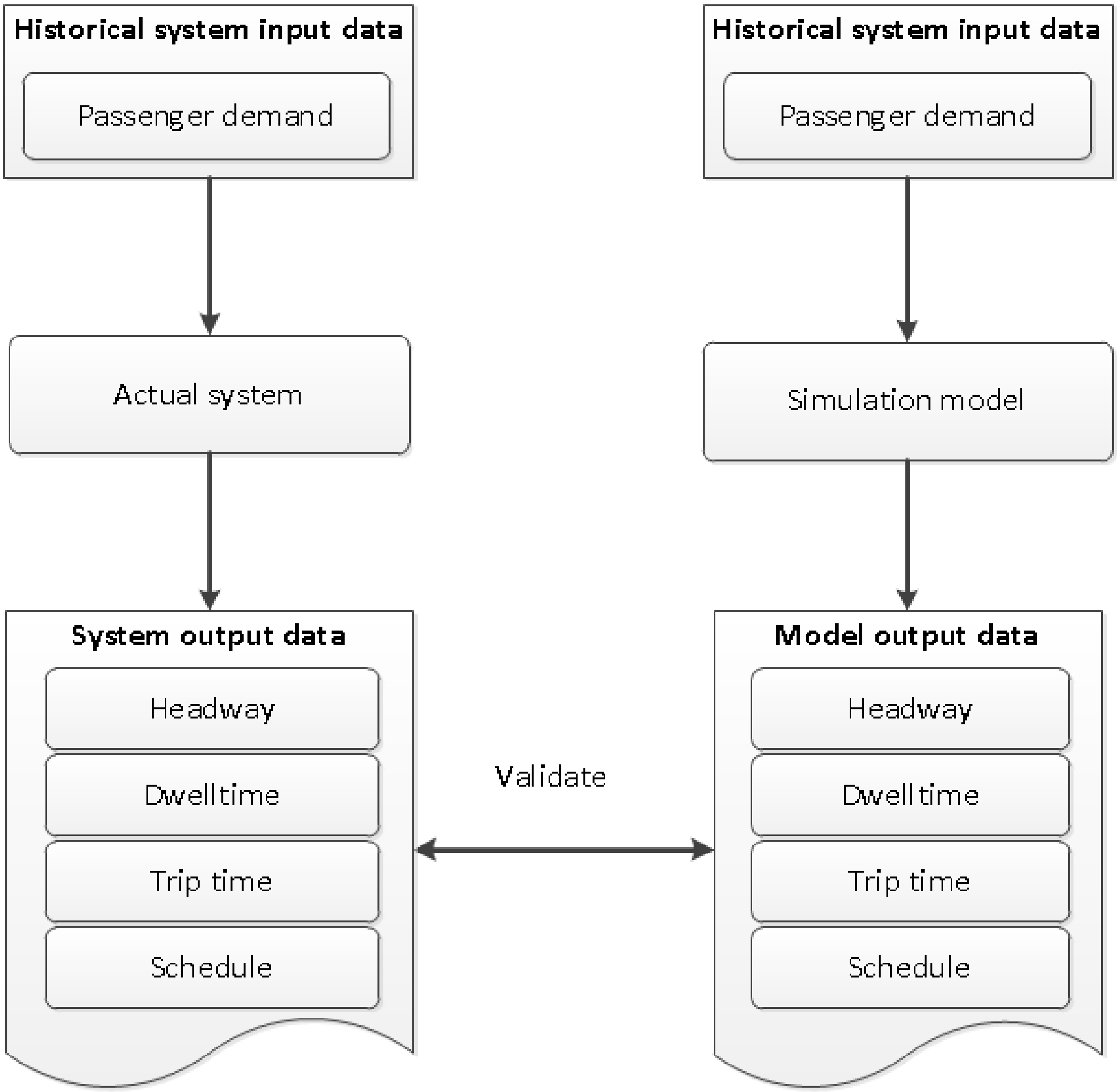

Figure 3.20: Simulation Validation.

Visual Inspection: GUI helps to confirm that the route layout configurations are correct. Vehicle behavior near or at a stop can be checked and verified by visual interaction.

Code verification: To confirm that implementation of passenger demand, terminal and bus behavior are calculated and programmed accurately.

Once an initial model is constructed it should be validated to ensure it adequately represents the system and underlying processes under investigation. One useful test is to choose a model state variable with a known pattern of variation over some time period. The model is then run to see if it accurately generates the reference behavior. If the simulated behavior and the observed behavior of the system correspond well, it can be concluded that the simulation reasonably represents the system behavior. The values of metrics of measured performance will be the baseline performance against which any new operations control strategy will be subsequently compared. It is important to run comparisons of simulated data that represent an aspect of the real world to test differences between the observed data and the model output.

Figures 3.20 shows an inspection approach for comparing the outputs from the real-world system with the simulation outputs by running the simulation model with historical system input data (passenger demand) and compare the system and model output data (headway, dwell time, trip time, and schedule adherence). In other words, the system and the model experience the same observations from the input data, which results in model and system outputs being positively correlated. Tables 3.2, 3.3, 3.4, and 3.5 show results of output data validation for headway adherence, dwell time, trip time and schedule adherence.

	Passenger On				Passenger Off				Passenger Load				Dwell Time (min)			
Stop	**mean**	**stdev**	**min**	**max**	**mean**	**stdev**	**min**	**max**	**mean**	**stdev**	**min**	**max**	**mean**	**stdev**	**min**	**max**
1	7.8	7.38	0	25	10.3	4.93	2	17	41.2	22.47	6	83	0.9	0.47	0.24	1.89
2	11.7	6.31	2	22	9.8	5.79	0	16	47.6	20.82	16	76	1.08	0.41	0.54	1.6
3	8.7	8.18	0	20	13.3	4.86	5	21	49.9	22.43	18	85	1.05	0.5	0.44	1.77
4	6.89	4.79	0	14	12.89	5.67	0	18	44.67	20.42	8	70	0.95	0.38	0.37	1.47
5	11.1	8.85	2	32	12.1	2.97	6	17	52.4	20.31	25	91	1.13	0.48	0.57	2.14
6	8.3	5.28	0	17	14	3.98	8	21	50.6	13.5	25	69	1.05	0.3	0.54	1.37
7	15.7	5.44	9	23	13.3	5.23	6	21	63.7	15.21	40	91	1.4	0.31	0.95	1.92
8	23.67	17.74	4	65	10.12	5.04	1	17	72.12	31.32	33	135	1.69	0.81	0.7	3.45
9	12.8	8.15	0	25	13.7	3.72	8	19	58.6	22.95	19	95	1.27	0.5	0.44	2.05
10	17.4	9.32	2	28	12	3.53	6	17	64.1	20.25	29	88	1.44	0.48	0.6	2
11	18.23	10.47	9	38	12	5.13	4	20	66	26.25	34	104	1.48	0.6	0.85	2.47
12	15.2	7.92	4	32	13.6	4.95	6	21	63.6	19.59	29	91	1.38	0.43	0.69	2.14

Table 3.1: Passenger activity analysis table.

	Schedule headway		**Model**		**Comparison**	
Stop	**mean**	**stdev**	**mean**	**stdev**	**mean diff**	**stdev diff**
1	15	5	14.99	2.75	-0.01	-2.25
2	15	5	15	2.86	0	-2.14
3	15	5	14.81	4.2	-0.19	-0.8
4	15	5	16.93	5.79	1.93	0.79
5	15	5	14.94	3.24	-0.06	-1.76
6	15	5	15.1	3.33	0.1	-1.67
7	15	5	15.15	3.27	0.15	-1.73
8	15	5	14.85	3.29	-0.15	-.1.71
9	15	5	14.97	3.94	-0.03	-1.06
10	15	5	14.97	3.54	-0.03	-1.46
11	15	5	16.52	7.44	1.52	2.44
12	15	5	14.62	4.97	-0.38	-0.03

Table 3.2: Headway comparison table: simulation model vs real-world.

	Real Dwell time		**Model**		**Comparison**	
Stop	**mean**	**stdev**	**mean**	**stdev**	**mean diff**	**stdev diff**
1	0.42	1.6	0.9	0.47	0.48	-1.13
2	0.52	1.88	1.08	0.41	0.56	-1.47
3	0.2	0.9	1.05	0.5	0.85	-0.4
4	0.66	2.6	0.95	0.38	0.29	-2.22
5	0.32	1.16	1.13	0.48	0.81	-1.18
6	0.35	1.23	1.05	0.3	0.7	-0.93
7	0.37	1.31	1.4	0.31	1.03	-1
8	0.39	1.34	1.69	0.81	1.3	-0.53
9	0.25	1	1.27	0.5	1.02	-0.5
10	0.23	0.98	1.44	0.48	1.21	-0.5
11	0.2	0.9	1.48	0.6	1.28	-0.3
12	0.2	0.88	1.38	0.43	1.18	-0.45

Table 3.3: Validation of Dwell time table: simulation model vs real-world.

The summary and statistics in Table 3.2 show that the headway adherence is not statistically significantly different from the real world observations. Headways are calculated for each trip at each time point based on the arrival (or departure) of the previous (or next) bus at the same time point. The simulation accurately reproduced the headway adherence with the passenger demand condition similar to that observed in the real world. The model reproduces the mean scheduled headway of 15 minutes. The validation of the headway variance indicates that the simulation model pays a

	Obs	**Mean**	**Stdev**	**Max**	**Min**
Real world	85	25.9	2.48	34.87	21.75
Model	85	26.08	4.94	30.15	17.5
Observed difference = 0.18					
Standard Deviation of Difference = 0.5995					

Table 3.4: Validation of Trip time table: simulation model vs real-world.

	Obs	**Mean**	**Stdev**	**Max**	**Min**
Real world	735	1.63	1.11	4.95	0.02
Model	571	2.38	1.34	4.87	0.02
Observed difference = 0.75					
Standard Deviation of Difference = 0.0694					

Table 3.5: Validation of Schedule variance table: simulation model vs real-world.

proper weight to each factor impacting on bus service reliability because the variance of the headway is determined by the activity of all inputs to the route including trip times, and passenger demand. Headway variance is a effective way of measuring route performance of the model simply because short and long headways both affect the variance of the headway.

Table 3.1 represents passenger activities that are generated from the simulation. The summary and statistics in Table 3.3 show that the dwell time is not statistically significantly different from the real world observations. Behavior at and near stops involves all behaviors where a bus operator participates in order to pull into a stop, serve passengers, and reenter the traffic stream. The majority of simulating behavior at and near stops focused on dwell time, or the period of time when a bus is stopped at a bus stop to serve passengers. Dwell time is the sum of time spent stopped with the doors closed, the time spent to open and close the doors, and the time when the doors are open for passengers to board and alight. Dwell time of the model at stops is calculated depends on passenger activity and the stop location (passenger alighting and boarding at each stop location). It is important to model passenger demand properly as it is a main impact on the dwell time and is essential to assess the influence on service variability. The simulation reproduced the dwell time with the

GK Shuttle - Free UOW Gwynneville-Keiraville bus service

Weekday Service - during session and exams periods* - indicative times only

	Eastern Entrance - Kids Uni	Science Bld	Creative Arts Bld	Hope Theatre	Robson's Rd	Reserve St	Green-acre Rd	Weerona-Throsby Dr	Keiraview	Throsby Dr	Wiseman Park	Eastern St	Kids Uni
AM					7:58	8:00	8:03	8:05	8:09	8:13	8:15	8:17	8:19
					8:13	8:15	8:18	8:20	8:24	8:28	8:30	8:32	8:34
	8:19	8:21	8:23	8:25	8:28	8:30	8:33	8:35	8:39	8:43	8:45	8:47	8:49
	8:34	8:36	8:38	8:40	8:43	8:45	8:48	8:50	8:54	8:58	9:00	9:02	9:04
	8:49	8:51	8:53	8:55	8:58	9:00	9:03	9:05	9:09	9:13	9:15	9:17	9:19
	9:04	9:06	9:08	9:10	9:13	9:15	9:18	9:20	9:24	9:28	9:30	9:32	9:34
	9:19	9:21	9:23	9:25	9:28	9:30	9:33	9:35	9:39	9:43	9:45	9:47	9:49
	9:34	9:36	9:38	9:40	9:43	9:45	9:48	9:50	9:54	9:58	10:00	10:02	10:04
	9:49	9:51	9:53	9:55	9:58	10:00	10:03	10:05	10:09	10:13	10:15	10:17	10:19
PM	4:34	4:36	4:38	4:40	4:43	4:45	4:48	4:50	4:54	4:58	5:00	5:02	5:04
	4:49	4:51	4:53	4:55	4:58	5:00	5:03	5:05	5:09	5:13	5:15	5:17	5:19
	5:04	5:06	5:08	5:10	5:13	5:15	5:18	5:20	5:24	5:28	5:30	5:32	5:34
	5:19	5:21	5:23	5:25	5:28	5:30	5:33	5:35	5:39	5:43	5:45	5:47	5:49
	5:34	5:36	5:38	5:40	5:43	5:45	5:48	5:50	5:54	5:58	6:00	6:02	6:04
	5:49	5:51	5:53	5:55	5:58	6:00	6:03	6:05	6:09	6:13	6:15	6:17	6:19
	6:04	6:06	6:08	6:10	6:13	6:15	6:18	6:20	6:24	6:28	6:30	6:32	6:34
	6:19	6:21	6:23	6:25	6:28	6:30	6:33	6:35	6:39	6:43	6:45	6:47	6:49
	6:34	6:36	6:38	6:40	6:43	6:45	6:48	6:50	6:54	6:58	7:00	7:02	7:04
	7:04	7:06	7:08	7:10	7:13	7:15	7:18	7:20	7:24	7:28	7:30	7:32	7:34
	7:34	7:36	7:38	7:40	7:43	7:45	7:48	7:50	7:54	7:58	8:00	8:02	8:04
	8:04	8:06	8:08	8:10	8:13	8:15	8:18	8:20	8:24	8:28	8:30	8:32	8:34
	8:34	8:36	8:38	8:40	8:43	8:45	8:48	8:50	8:54	8:58	9:00	9:02	9:04
	9:04	9:06	9:08	9:10	9:13	9:15	9:18	9:20	9:24	9:28	9:30	9:32	9:34
	9:34	9:36	9:38	9:40	9:43	9:45	9:48	9:50	9:54	9:58	10:00	10:02	10:04
	10:04	10:06	10:08	10:10	10:13	10:15	10:18	10:20	10:24	10:28	10:30	10:32	**

Figure 3.21: Real world schedule.

passenger demand condition similar to that observed in the real world. The validation of the dwell time variance indicates that behavior at and near stops are simulated properly.

The summary and statistics in Table 3.4 show that the trip time is not statistically significantly different from the real world observations. Running time for a trip is the difference in observed arrival or departure time between any two time points on the route. Variability in running times is certain. This variability can be a result of randomness in traffic conditions, and passenger loads. If running times are insufficient, the majority of the buses will have a poor on-time performance. The simulation reproduced the trip time with the passenger demand condition similar to that observed

in the real world. The validation of the trip time variance indicates that the simulation model pays a proper weight to simulate uncertainty in transit operations.

The summary and statistics in Table 3.5 show that the schedule adherence is not statistically significantly different from the real world observations. Figure 3.21 represents real world scheduled departure time. Schedule deviations, which is actual departure time minus scheduled departure time, is calculated for each trip at each time point on the route. A schedule deviation might propagate, with the vehicle dropping further from schedule, resulting in further service deterioration. When actual running times are under scheduled, buses are likely to run early. Passengers who time arriving at stops based on schedules will be left waiting for a bus that has already left, and will have to wait considerably longer than expected. The simulation reproduced the schedule adherence with the passenger demand condition similar to that observed in the real world. The validation of the schedule variance indicates that operations of schedule adherence are simulated properly.

3.9 Conclusion

The purpose of this chapter is to describe a methodology and a tool that can be used to simulate public transit with real-time bus operations using data from technologies such as Automated Vehicle Location (AVL) and automatic passenger counters (APC) and to evaluate their performance at an operational level from the passenger point of view. Such a tool is useful to researchers and public transport service providers alike. Beside the possibility of the tool being used for visualising positive aspects of self-organisation and evolution of a Connected Mobility Digital Ecosystem in a dynamic way, the simulation is also an interesting instrument for training and communication and shows the potential of making benefits of Connected Mobility Digital Ecosystem visible amongst all stakeholders. In order to fully capture bus transit operations, the

simulation models bus transit services at the system, route segment and bus stop levels. Verification and validation techniques are used to make sure that the results are accurate and meaningful.

Chapter 4

Toward real-time multi-criteria decision making for bus service reliability optimization

This chapter addresses issues associated with the real-time control of public transit operations to minimize passenger wait time: namely vehicle headway, maintenance of passenger comfort, and reducing the impact of control strategies. The randomness of passenger arrivals at bus stops and external factors (such as traffic congestion and bad weather) in high frequency transit operations often cause irregular headway that can result in decreased service reliability. The approach proposed in this chapter, which has the capability of handling the uncertainty of transit operations based on Multi-objective evolutionary algorithm using a dynamic Bayesian network, applies preventive strategies to forestall bus unreliability and, where unreliability is evident, restore reliability using corrective strategies. This approach also provides a mechanism to reason about current states, to predict future states of the transit network, and to handle multi-criteria decision making. A real bus route operating in Wollongong, Australia together with its passenger load data are used in the simulation analysis to

verify and evaluate the proposed approach.

4.1 Introduction

Measuring and reducing unreliability in a bus service is the focus of this chapter. Unreliability affects passengers because it causes them to wait longer. Particularly on high frequency bus routes headway regularity is important to passengers because of its impact on waiting time and overcrowding. Overcrowding is key to passengers because it impacts their comfort in a direct way and headway irregularity compounds operations because it slows boarding and alighting.

Passenger numbers are also important in transport planning because this measures network efficiency. For transit services with short headways, passengers can be assumed to arrive (more or less) randomly, namely independently of the schedule. Headway variability causes passengers to perceive that a service is unreliable, especially when "bunching" of buses occurs (clustering of the buses within a short distance of one another). The transit industry has (so far) lacked a measure of service reliability in terms of its impact on customers because traditional metrics do not express how much reliability impacts on passengers' perceptions. In this chapter, service reliability is measured based on passenger wait time, comfort and bus headway [43].

In order to minimize unreliability, it is important to identify its possible causes in bus operations. Prevention strategies focus on reducing the variability of vehicle running and dwelling times, while corrective strategies focus on reducing negative impacts to passengers. Passenger costs, operation costs and implementation feasibility are used to evaluate corrective strategies. The most common corrective strategies are reviewed in this section: namely "holding", "expressing", "short-turning" and "deadheading" [109].

Corrective strategies, using headway and schedule optimization with bus location

tracked in real-time is addressed by Dessouky et al. [28], Chen and Chen [22], Yu et al. [116], Daganzo and Pilachowski [24] and Bartholdi et al. [10]. These approaches develop real-time corrective strategies by coordinating buses along their route. Recently, Bartholdi et al. [10] presented a method of coordinating buses for self-organising headways and schedules: schedule and target headway is abandoned in this method. Yu et al. [116] introduces a model for optimizing bus route headway representing a balance between passenger and operator costs. Daganzo and Pilachowski [24] propose an adaptive control method to adjust bus speed in real-time to cooperate with successive and preceding buses. Chen and Chen [22] include a simulation model for predicting unreliability and advising a suitable running time to prevent headway irregularity.

"Holding" is the control strategy of delaying a bus at some point in the network for a fixed amount of time. It aims to rectify a bus-running-early event or to prevent buses from forming short headways, namely bunching. Holding can be schedule-based to ensure on-time performance, or headway-based to maintain even distance/time between consecutive buses [109].

Designing and implementing holding strategies is addressed by Fu & Yang [41], Zhao et al. [118], Zolfaghari et al. [120], Teng and Yang [99] , Lo and Chang [68] and Xuan et al. [113]. These researchers consider methodologies for minimizing the waiting time of passengers and reducing passenger travel time by applying holding control strategies. A distributed control approach based on multi-agent negotiation is presented where stop and bus agents communicate with others in real-time to achieve dynamic coordination of bus dispatching at various stops. A comparison between the negotiation algorithm, on-schedule and even-headway strategies is made in [118]. Zolfaghari et al. [120] proposes a mathematical model with real-time data of the bus position. In earlier work, Lo and Chang [68] focus on applying fuzzy control in the transfer model using real-time information obtained from intelligent transportation

systems. Xuan et al. [113] develop dynamic holding strategies, which use a virtual schedule at the control points. Near-optimal solutions can be achieved using this approach.

Among the corrective strategies, "expressing", "short-turning" and "deadheading" all involve station skipping but using varying strategies. "Expressing" involves sending a bus to a stop further downstream and skipping (not servicing) some, or all, intermediate stops. The objective of this strategy may be either to increase the headway between buses (separating bunched buses) or to close a service gap further downstream, both in an attempt to balance headways and improve service past the end of the express segment [109]. "Short-turning" involves directing a bus to end its current trip before it reaches the terminus and in so doing service the route in the other direction. This strategy is employed to return a late bus to schedule, or when an extra service is needed in the opposite direction, either due to higher passenger demand or gaps in service [109]. "Deadheading" involves pulling a bus from service and running it empty for a segment of the route [109].

Work on station skipping strategies to minimize total average passenger cost to the system by Eberlein et al. [31] proposed a real-time deadheading approach, which helps the transport system decide dispatch times, vehicles to deadhead, and stations to skip to improve service quality in highly irregular headways. In the approach of Delle Site and Filippi [26] to short-turn strategies, the trade-offs between user and operator costs with weights attached to each is provided as an objective function.

There are a number of studies on measurement for the evaluation of transit service reliability. Chen and Chen [21] measure the route-level transit service reliability for high frequency bus route services. Xumei et al. [23] analyze service reliability based on route-based punctuality, a deviation index based on stops, and an evenness index based on stops. Eboli and Mazzulla [32] propose performance measures for both passenger

perceptions and the transit agency. Lin and Ruan [64] propose a time-point (stop) level probability-based headway regularity metric to measure bus service reliability.

Extensive work on multi-objective optimization is addressed by Atashkari et al. [7], Atashkari et al. [6], Liu et al. [65], Jamali et al. [48], Singh et al. [94], Neema and Ohgai. [80]. These provide methodologies for solving multi-objective optimization in various decision support systems. Atashkari et al. [7] propose a multi-objective genetic algorithm with Pareto approach to optimize the thermodynamic cycle. Kaveh and Laknejadi [52] present hybrid methods which combine a particle swarm method with a charge system search. However, multi-objective optimization approaches based on dynamic Bayesian networks have not previously been applied to transport service reliability.

Previous studies do not provide methods that have the ability to handle uncertainty in transit operations arising from within the transit environment and via the randomness of passenger arrivals. They also lack any mechanism that supports decision making for bus operations on route and at the bus stop simultaneously. This chapter focuses on an approach for real-time multi-criteria decision-making based on dynamic Bayesian networks. These have the ability to handle uncertainty, reason about current states, and predict future states in cooperation with multi-objective optimization at each time slice in order to find appropriate strategies that maintain bus service reliability. The bus service reliability in our work takes into account passenger wait time, headway adherence, in-vehicle time, and passenger comfort, which are combined via Pareto comparisons in the fitness assignment processes.

The remainder of this chapter is organized as follows: our proposed methodology for real-time decision making is presented in Section 4.2; simulation and results are reported and discussed in Section 4.3, with conclusions presented in Section 4.4.

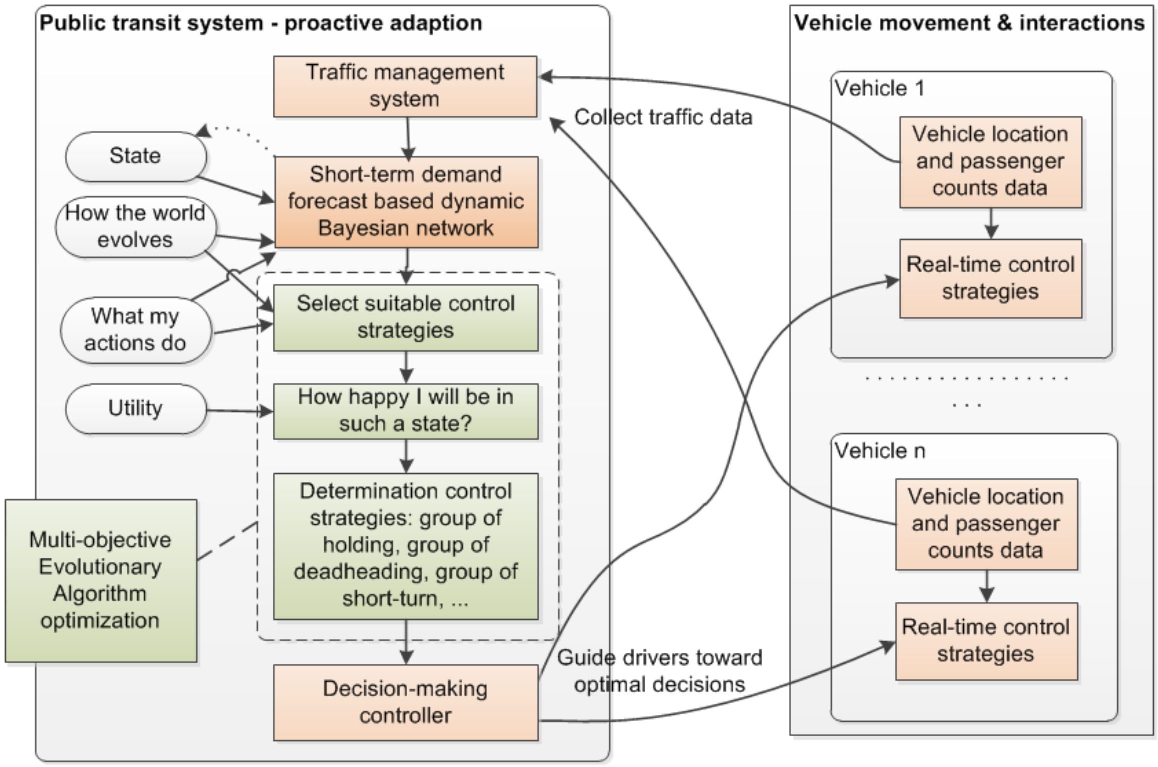

Figure 4.1: Contextual Model for bus operation control.

4.2 Proposed methodology

Figure 4.1 shows the proposed model for controlling bus operations. In the real-time mode, a supervisor will receive evaluations of a current scenario including real-time travel demand, transit demand, bus network and assignment data. This is then used to give optimal proactive adaptation, including guidance for drivers leading to the goal of optimizing the bus network operations. The intention is to find strategies to guide drivers towards optimizing the overall bus network, not strategies solely for optimizing individual bus usage.

Real-time passenger demand and bus operation data are assumed to be collected from automatic passenger counting (APC) and automatic vehicle location (AVL) systems. Figure 4.2 shows the system architecture used to collect AVL-APC data. The

AVL and APC devices record on-board events and 3G-based communication is also installed on the bus. In this way, useful data such as bus position and passenger on/off events are transmitted in real-time back to a central server via a secure connection.

AVL along with APC systems can handle the collection of a huge quantity and variety of operational, spatial, and temporal data. Traditionally these kinds of data have not been utilized to maximize their full potential in terms of optimizing a transport network [43]. APCs produce abundant patron and travel time databases with a finer level of detail compared to fare-based or manual passenger counts, even for agencies with just a few APCs. The increased number of observations provides greater confidence in decision-making regarding changes in service levels. There is also a need to discover new ways to enhance profits by utilizing AVL-APC data [18].

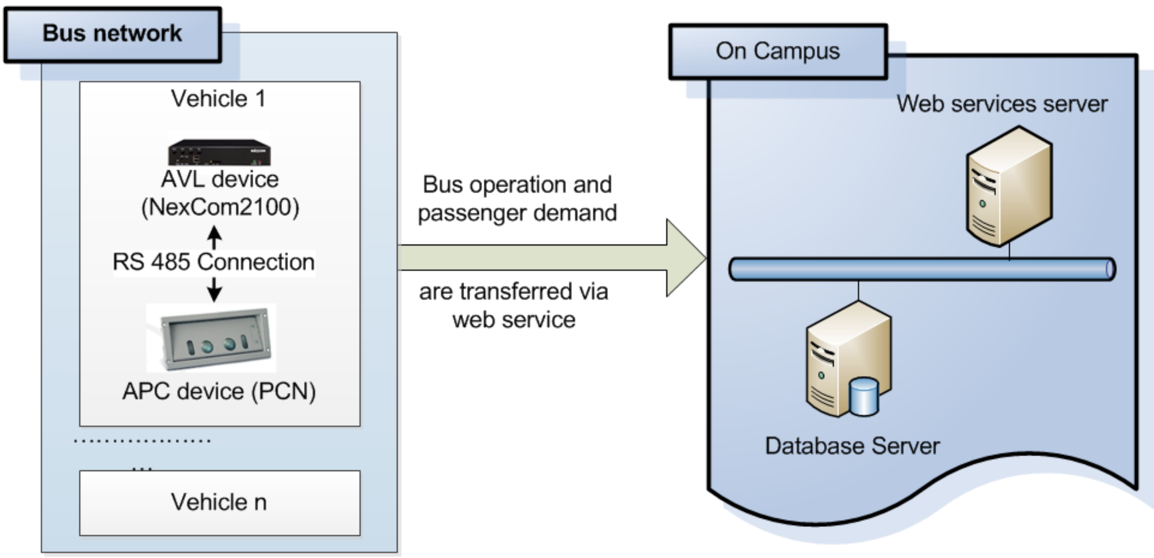

Figure 4.2: Architecture of the Conected Mobility Digital Transport Ecosystem.

There are two main mechanisms in our control methodology: (1) state reasoning and demand prediction model, (2) multi-criteria decision making.

1. provides a mechanism that allows reasoning about current states and prediction about future states of bus operation based on a dynamic Bayesian network. This

provides adequate information for (2) to make in-time and appropriate decision making.

2. provides a mechanism that allows suitable rational decision making for bus drivers on the route, namely preventive strategies, and at the bus stop, namely corrective strategies.

The approach presented here differs from existing bus control approaches in the following ways:

- it provides the ability to handle the uncertainty of transit operations that arises from within the transit environment and via the randomness of passenger arrivals;
- it supports decision-making on the route and at a station or stop;
- it provides multiple control strategies (preventive control, holding, expressing, short-turning, deadheading) integrated in the same decision making mechanism;
- it has multiple objective functions: headway adherence, passenger wait time, in-vehicle time, passenger comfort – all combined via Pareto comparisons in the fitness assignment processes.

The details of these two mechanisms are described in the following two sub sections.

4.2.1 State reasoning and demand prediction model

Rational decision-making in the context of this chapter depends on "both the relative importance of various goals and the likelihood that, and degree to which, they will be achieved" [89]. Probability offers a means of summarizing the uncertainty that originates from "laziness" and "ignorance". "Laziness" here means there is too much

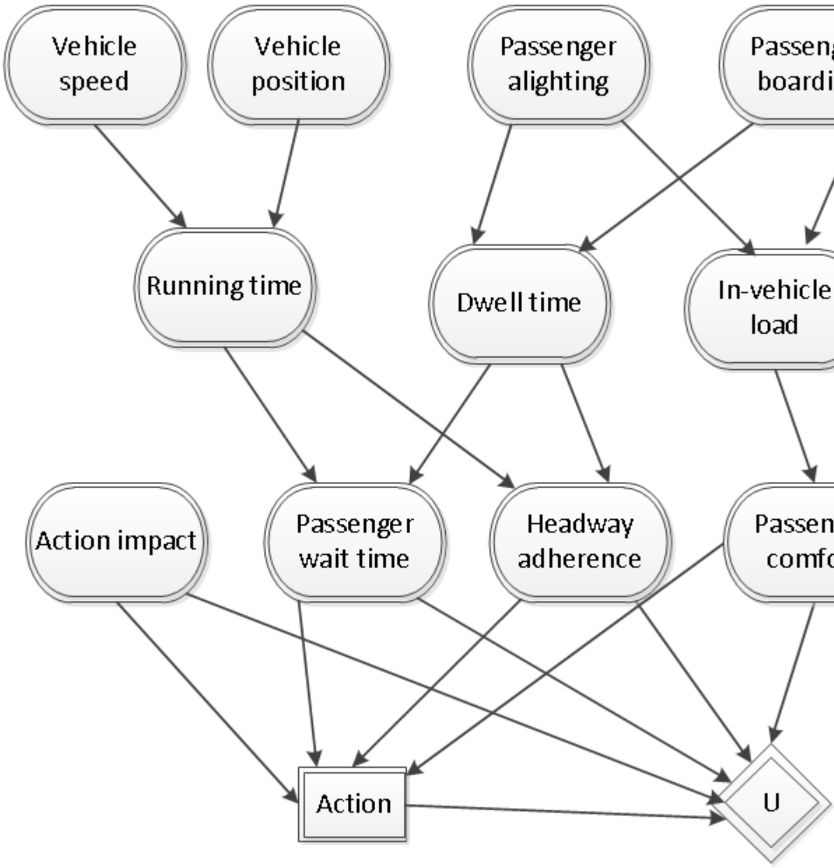

Figure 4.3: The state of the bus network at a given point in time.

work in listing the complete set of antecedents and consequents needed to ensure an exception-less ruleset. The term “ignorance” splits in meaning between theoretical and practical. In theoretical terms “ignorance” means there maybe no complete theory so the point at which a complete coverage of rules for the problem domain can never be adequately determined. In terms of practical “ignorance”, even though all the rules are known, there is uncertainty about specific circumstances because not all the necessary deterministic tests have been (or can be) run [89]. Decision-making Bayesian networks have the ability to handle these types of uncertainty.

Figure 4.3 presents a Decision-making Bayesian network, which maintains a belief state that represents which states of the bus network are currently possible and the

causal relations between variables of the network at any point in time based on real observation. The bus network can update its belief state. There are three types of nodes used in Figure 4.3:

- chance nodes (ovals) represent random continuous variables. The set of variables is: $\mathcal{X}_\Gamma = \{$speed $\mathcal{V}_i$, position $\mathcal{X}_i$, number of passengers alighting $\mathcal{A}_{i,k}$, number of passengers boarding $\mathcal{B}_{i,k}$, running time $\mathcal{R}_{i,k}$, dwell time $\mathcal{D}_{i,k}$, in-vehicle load $\mathcal{L}_{i,k}$, headway adherence $\mathcal{H}_{adherence}$, passenger wait time $\mathcal{T}_{wait}$, action impact $\mathcal{T}_{impact}$, passenger comfort $\xi_{comfort}\}$. Speed and position influence running time. Passenger boarding and alighting influences dwell time and in-vehicle load. Running time and dwell time influence passenger wait time and headway adherence. Passenger comfort is influenced by in-vehicle load. Each chance node has associated with it a distribution that is indexed by the state of its parent nodes. The bus network can express uncertainty about dwell time, running time, in-vehicle load, headway adherence, and passenger wait time.

- Decision nodes (rectangles) represent points where the decision-maker has a choice of actions. A decision variable, e.g. *Action*, with states $\mathcal{X}_D = \{$no action, preventive control $px_{i,k}$, holding $hx_{i,k}$, expressing $ex_{i,k}$, short-turning $sx_{i,k}$, deadheading $dx_{i,k}$ $\}$. Preventive control is the route control while the other controls are station controls. The choice of action influences the utility that will result.

- Utility nodes (diamonds) represent utility functions. The utility node has as parents variables of headway adherence, passenger wait time, action impact, passenger comfort and action, describing the outcomes that directly affect utility. The utility node represents the expected utility associated with each action.

However, the structure of the network in Figure 4.3 is a static model. In other words, the network only allows reasoning and decision making about the current state

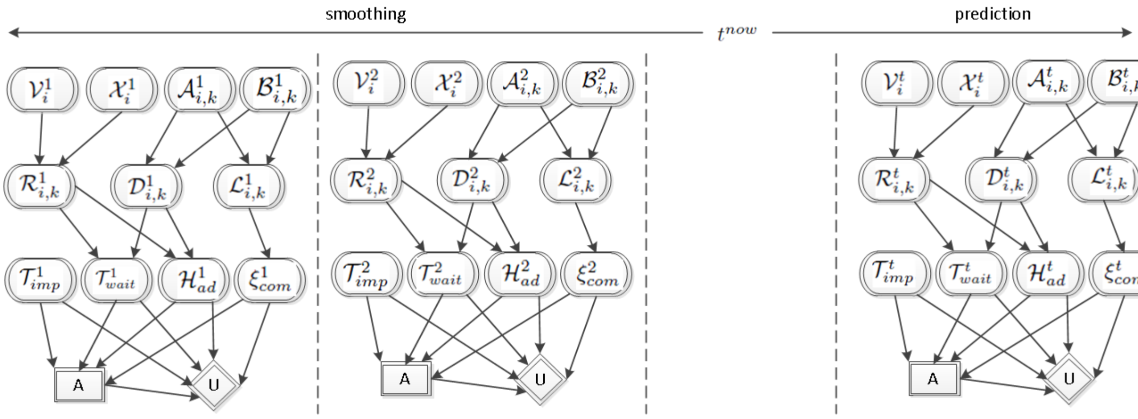

Figure 4.4: Bus network time slices.

of the bus network so it cannot reason about the state of the bus network at previous and future points in time. In order to monitor the state of the system over a specific period of time, a dynamic Bayesian network model [89][57] is proposed. Figure 4.4 shows a dynamic Bayesian network model with t time slices for a bus network based on the static network in Figure 4.3. Each time step models the state of the bus network at a specific point in time; the dashed lines present the separation of the model into time slices. In Figure 4.4, smoothing is the process of querying about the state of the bus network at a previous time step from the current time, while filtering is the process of querying and predicting the state of the system from the current time to future steps. The conditional probability distributions $P(\mathcal{V}_i^t|\mathcal{V}_i^{t-1})$, $P(\mathcal{X}_i^t|\mathcal{X}_i^{t-1})$, $P(\mathcal{A}_i^t|\mathcal{A}_i^{t-1})$, $P(\mathcal{B}_i^t|\mathcal{B}_i^{t-1})$ $P(\mathcal{R}_{i,k}^t|\mathcal{R}_{i,k}^{t-1})$, $P(\mathcal{D}_{i,k}^t|\mathcal{D}_{i,k}^{t-1})$ and $P(\mathcal{L}_{i,k}^t|\mathcal{L}_{i,k}^{t-1})$ are the relevant transition probability distributions. The state of the bus network at the current point in time will impact the state of the system in the future and be impacted by the state of the system in the past. The development of the bus network is specified by links between variables in different time-slices. In this chapter, the interval between slices is assumed to be fixed. For monitoring bus network states, a practical interval is 5 minutes.

In the next section a multi-criteria decision making approach is considered to im-

prove headway, minimize passenger wait time, maintain passenger comfort, and reduce the impact of control strategies. This is achieved by applying preventive and corrective control strategies complemented by a state reasoning and demand prediction model.

4.2.2 Multi-criteria decision making

4.2.2.1 Objective functions

Decision making for bus operations to provide service reliability in this chapter is driven by a set f of four objective functions ($f = f_1, f_2, f_3, f_4$). These functions are combined via Pareto comparisons in the fitness assignment processes.

a) f_1 **– Passenger wait time** One of the most important aspects of service reliability in bus operations is to minimize passenger wait time at bus stops. The first objective function f_1 returns the total time that passengers wait for buses across all bus stops on the route. The optimum of f_1 is zero. f_1 is calculated by the following equation:

$$f_1 = \mathcal{T}_{wait} = \sum_{i=1}^{n}\sum_{k=1}^{m}(\frac{\lambda_k(\widetilde{\mathcal{AD}}_{i,k} - \mathcal{AD}_{i-1,k})^2}{2} + \mathcal{P}_{i,k}(\widetilde{\mathcal{AD}}_{i,k} - \mathcal{AD}_{i-1,k})) \quad (4.1)$$

The first part of the equation takes into account passengers who arrive randomly at stop k since the last bus departed stop k. The second part involves passengers who are left behind at stop k because the bus is full.

b) f_2 **– Headway adherence** The second objective function minimizes headway fluctuation. The function f_2 returns the number of fluctuations from the scheduled

headway. The optimum of f_2 is zero. f_2 is calculated by the following equation:

$$f_2 = \mathcal{H}_{adherence} = \sum_{i=1}^{n}\sum_{k=1}^{m}(\widetilde{\mathcal{H}}_{i,k} - \mathcal{SH})^2 \tag{4.2}$$

c) f_3 – **Passenger comfort** The third objective function is used as a measure of how content passengers are when on the bus. The function f_3 returns the ratio of the number of passengers on the vehicle to seated and standing capacity of the vehicle. The optimum of f_3 is level 1. From the passengers' view point, the crowding experiences are categorised as follows [43]:

Table 4.1: Passenger comfort.

Passenger comfort	**Level of service**
Can sit next to unoccupied seat	1
Can choose seat	2
Seated	3
Standing but not crowded	4
Full	5
Borderline of crowded and overcrowded	6

f_3 is calculated by the following equation:

$$f_3 = \xi_{comfort} = \sum_{i=1}^{n}\sum_{k=1}^{m}\frac{\widetilde{\mathcal{L}}_{i,k}}{\mathcal{L}_{max}} \tag{4.3}$$

d) f_4 – **Impact of control strategies** The fourth objective function minimizes impact of applying control strategies. f_4 returns the extra wait time of passengers when applying control strategies. The optimum f_4 is zero. f_4 is calculated by

the following equation:

$$f_4 = \mathcal{T}_{impact} = \sum_{i=1}^{n}\sum_{k=1}^{m} \widetilde{\mathcal{L}}_{i,k} \times hx_{i,k} + (ex_{i,k} + dx_{i,k} + sx_{i,k}) \times \widetilde{\mathcal{H}}_{i,k} \times \widetilde{\mathcal{PD}}_{i,k} \quad (4.4)$$

4.2.2.2 Multi-objective optimization

Handling multi-objective problems, namely multi-criteria optimization, can be described as a process of finding the vector of decision variables $\vec{x}^* = (x_1^*, x_2^*, ..., x_n^*)$, where n is number of buses and $x_i^* \in \{hx, ex, dx, sx, px\}$ is the control strategy applying for bus i at decision time, which minimizes the vector function,

$$min\vec{f}(\vec{x}) = (w_1 \times f_1(\vec{x}) + w_2 \times f_2(\vec{x}), f_3(\vec{x}), f_4(\vec{x})) \quad (4.5)$$

where $\vec{x} = (x_1, x_2, ..., x_n) \in \Omega \in R^n$ is called the decision variable, the set Ω is called the feasible region and n is the number of objectives.

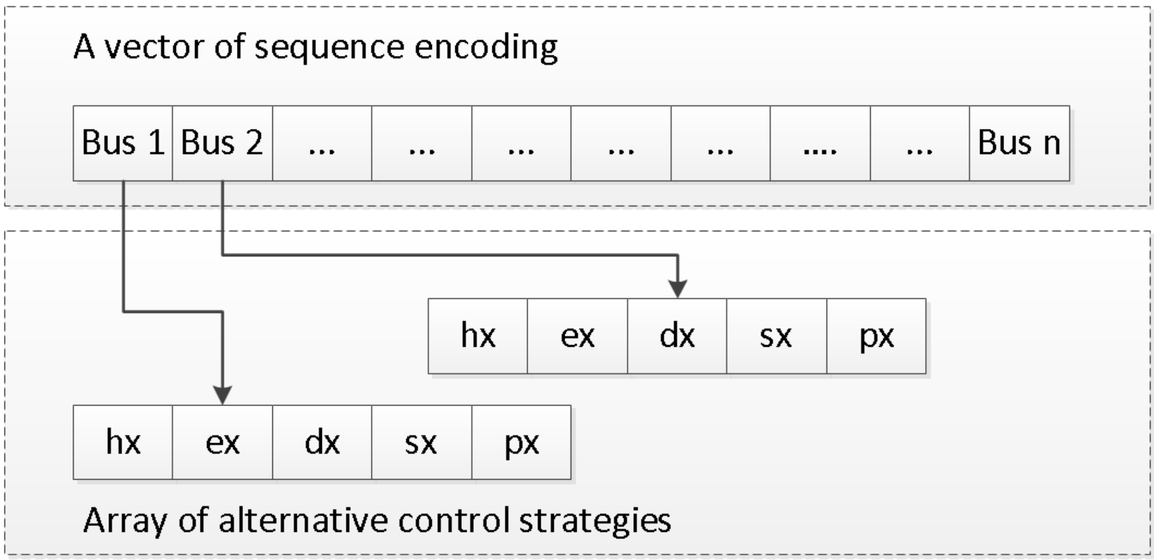

Figure 4.5: Control sequence encoding.

Figure 4.5 depicts control sequence encoding of n buses. Each bus selects a control from the list. The solution will balance the optimization of an individual bus and the whole bus network. The details of the algorithm are as follows:

$$
\begin{aligned}
Minimize\ \ & = \textstyle\sum_{i=1}^{n}\sum_{k=1}^{m}(w_1 \times (\frac{\lambda_k(\widetilde{\mathcal{AD}}_{i,k}-\mathcal{AD}_{i-1,k})^2}{2} \\
& = \quad +\mathcal{P}_{i,k}(\widetilde{\mathcal{AD}}_{i,k} - \mathcal{AD}_{i-1,k})) \\
& = \quad +w_2 \times ((\widetilde{\mathcal{H}}_{i,k} - \mathcal{SH})^2) \\
Minimize\ \ & \textstyle\sum_{i=1}^{n}\sum_{k=1}^{m}\frac{\widetilde{\mathcal{L}}_{i,k}}{\mathcal{L}_{max}} \\
Minimize\ \ & \textstyle\sum_{i=1}^{n}\sum_{k=1}^{m}\widetilde{\mathcal{L}}_{i,k} \times hx_{i,k} \\
& \quad +(ex_{i,k} + dx_{i,k} + sx_{i,k}) \times \widetilde{\mathcal{H}}_{i,k} \times \widetilde{\mathcal{PD}}_{i,k}
\end{aligned}
$$

that satisfies the constraints

$$0 \leqslant \mathcal{L}_{i,k} \leqslant \mathcal{L}_{max}\ \forall\ i,k \in (I,K) \tag{4.7}$$

$$\mathcal{L}_{i,k} \leqslant \mathcal{PD}_{i,k}\ \forall\ i,k \in (I,K) \tag{4.8}$$

$$
\begin{aligned}
\widetilde{\mathcal{L}}_{i,k} \leqslant \mathcal{L}_{i,k-1} + (ex_{i,k} + dx_{i,k} + sx_{i,k})(\widetilde{\mathcal{A}}_{i,k} \\
- \widetilde{\mathcal{B}}_{i,k})\ \forall\ i,k \in (I,K)
\end{aligned} \tag{4.9}
$$

$$
\begin{aligned}
\widetilde{\mathcal{AD}}_{i,k} \leqslant t^{now} + \widetilde{\mathcal{R}}_{i,k}(1 + px_{i,k}) \\
+ hx_{i,k}\ \forall\ i,k \in (I,K)
\end{aligned} \tag{4.10}
$$

$$\widetilde{\mathcal{AD}}_{i,k} \geqslant \mathcal{AA}_{i,k} + \mathcal{D}_{i,k} \ \forall \ i,k \in (I,K) \tag{4.11}$$

$$0 \leqslant \mathcal{P}_{i_k} \leqslant \mathcal{PD}_{i,k} - \mathcal{L}_{max} \ \forall \ i,k \in (I,K) \tag{4.12}$$

$$\widetilde{\mathcal{H}}_{i,k} \leqslant \mathcal{H}_{i,k-1} + \Delta\widetilde{\mathcal{R}}_{i,k} + \Delta\widetilde{\mathcal{D}}_{i,k} \tag{4.13}$$

$$\Delta\widetilde{\mathcal{R}}_{i,k} = \widetilde{\mathcal{R}}_{i,k}(1 + px_{i,k}) - \mathcal{R}_{i-1,k} \ \forall \ i,k \in (I,K) \tag{4.14}$$

$$\Delta\widetilde{\mathcal{D}}_{i,k} = \widetilde{\mathcal{D}}_{i,k} + hx_{i,k} - \mathcal{D}_{i-1,k} \ \forall \ i,k \in (I,K) \tag{4.15}$$

$$\widetilde{\mathcal{D}}_{i,k} = \alpha\widetilde{\mathcal{A}}_{i,k} + \beta\widetilde{\mathcal{B}}_{i,k} \ \forall \ i,k \in (I,K) \tag{4.16}$$

$$\widetilde{\mathcal{AD}}_{i,k} - \mathcal{AD}_{i-1,k} < SH \tag{4.17}$$

$$0 \leqslant hx_{i,k} \leqslant \mathcal{HT}_{max} \ \forall \ i,k \in (I,K) \tag{4.18}$$

$$\widetilde{\mathcal{AA}}_{i,k} - \mathcal{AD}_{i-1,k} > SH \tag{4.19}$$

$$dx_{i,k} - dx_{i,k+1} < 0 \ \forall \ i,k \in (I,K) \tag{4.20}$$

$$ex_{i,k} - ex_{i,k+1} < 0 \; \forall \; i,k \in (I,K) \tag{4.21}$$

$$\sum_{k=1}^{m} dx_{i,k} < m/2 \; \forall \; i,k \in (I,K) \tag{4.22}$$

$$\sum_{k=1}^{m} ex_{i,k} < m/2 \; \forall \; i,k \in (I,K) \tag{4.23}$$

$$ex_{i,k}, dx_{i,k}, sx_{i,k} \in \{0,1\} \; \forall \; i,k \in (I,K) \tag{4.24}$$

$$0 \leqslant w_1, w_2 \leqslant 1 \tag{4.25}$$

Figure 4.6 presents a time space representation of a bus operation. If service unreliability is predicted, the optimization algorithms will advise the decision making for buses at selected bus stops to restore the reliability. Constraints (4.7)-(4.9) represent the number passengers on board when the bus departs the stop. Constraints (4.10) and (4.11) represent departure time of bus i at stop k. Constraint (4.12) represents passenger demand and those left at a bus stop. Constraints (4.13)-(4.16) restrict headway and dwell time. The headway $\mathcal{H}_{i,k}$ depends on the previous headways, running time differences and dwelling differences. $\Delta R_{i,k}$ is the difference in running time between bus i and its predecessor $i-1$ when they arrive at stop k and $\Delta D_{i,k}$ is the difference in dwell time between bus i and its predecessor $i-1$ when they dwell at stop k. (4.17) and (4.18) restrict holding time strategy. Constraints (4.19)-(4.23) restrict skipping strategies. Inequality (4.19) is the deadhead and expressing feasible constraint. Constraints (4.20) and (4.21) ensure that the skipped stops in the deadhead/expressing strategy are consecutive. Constraints (4.22) and (4.23) restrict deadhead/expressing

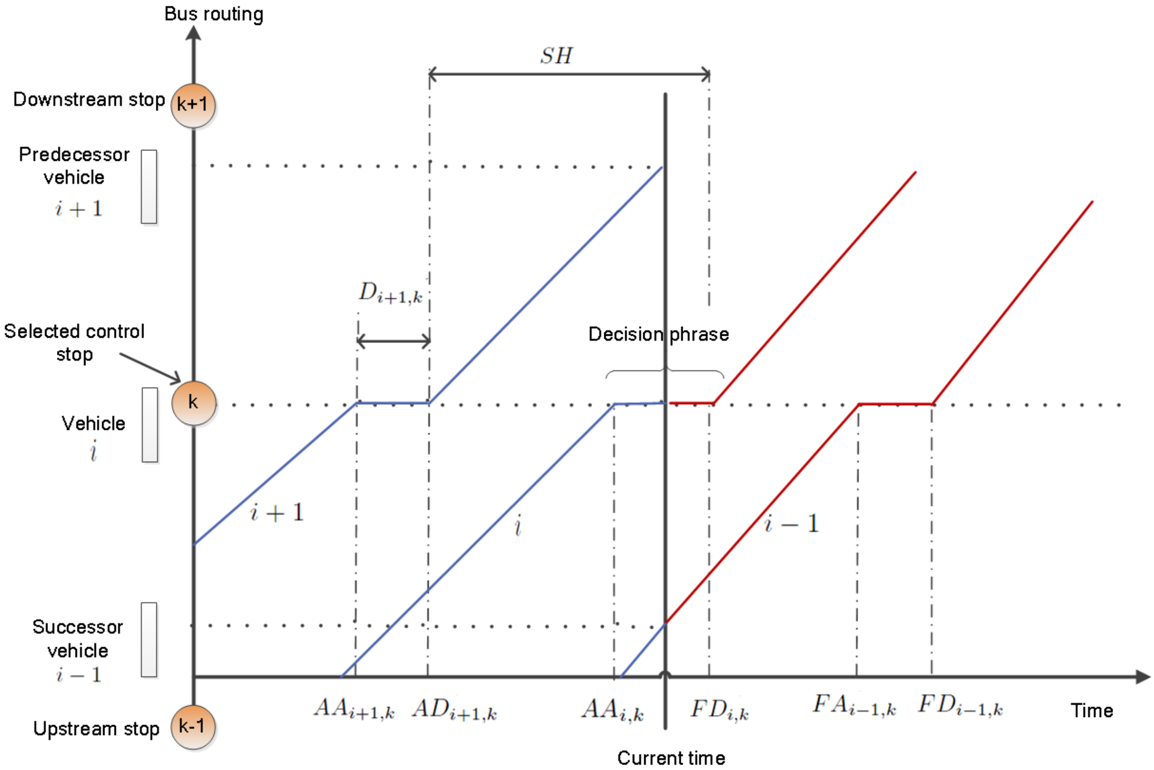

Figure 4.6: Time and journey-based diagrammatic view of bus operations.

to a single direction. Constraints (4.24)-(4.25) impose boundary and initial conditions.

In this chapter, objective functions f_1 and f_2 are considered to be optimizeable simultaneously. This can mean that improvement of one can lead to an improvement of the other. f_1 and f_2 use a weighted-sum approach, which is an approach for solving multi-objective optimization problems; each objective f_i is multiplied with a weight w_i representing its importance and then summed into a single objective function. f_4 is considered to be in conflict with f_1 and f_2 while f_3 is independent so it does not influence any other objective function. With the objectives to be optimized being in conflict with each other, it is difficult to find a single optimal solution for this type of problem; instead a set of trade-off solutions that represent the best possible compromise among the completing objectives is proposed. Pareto comparisons in the fitness assignment processes are used to handle the multi-objective optimization

problem in this chapter. It "defines the frontier of solutions that can be reached by trading-off conflicting objectives in an optimal manner" [108].

In the definition of Pareto dominance, a vector $\vec{u} = (u_1, u_2, ..., u_m)$ is said to dominate $\vec{v} = (v_1, v_2, ..., v_m)$ (denoted by $\vec{u} \prec \vec{v}$), if $\vec{u}$ is partially less than $\vec{v}, u_i v_i, \forall\ i \in \{1...m\}$ and there exists $i \in \{1...m\}$ such that $u_i < v_i$.

A feasible solution $\vec{x}$ is said to be non-dominated with respect to the set Ω, if there does not exist another $\vec{x'} \in \Omega$ such that $\vec{f}(\vec{x'}) \prec \vec{f}(\vec{x})$.

A multi-Objective Evolutionary Algorithm (MOEA) is proposed for handling multi-objective problems in this chapter. Deterministic algorithms are most often used if a clear relationship exists between the characteristics of the possible solutions. If the relation between a solution candidate and its "fitness" are not so obvious, as in the case of transit operation, probabilistic algorithms come into play. Details of MOEA implementation are explained in the next section.

4.2.2.3 MOEA Optimization

Evolutionary algorithms (EAs) are population based stochastic optimization heuristics inspired by evolution theory such as mutation, crossover, natural selection, and survival of the fittest in order to refine a set of solution candidates iteratively [108]. An EA starts with a random initial population. Then the fitness of each individual is determined by evaluating the objective function. After the best individuals are selected, new individuals for the next generation are created. The new individuals are generated by altering the individuals through random mutation and by mixing the decision variables of multiple parents through crossover. Then the generational cycle repeats until some convergence criterion is fulfilled or a fixed number of generations has evolved.

Figure 4.7 depicts the whole process of multi-criteria decision making. Station reasoning and demand prediction model provides information about current and predicted

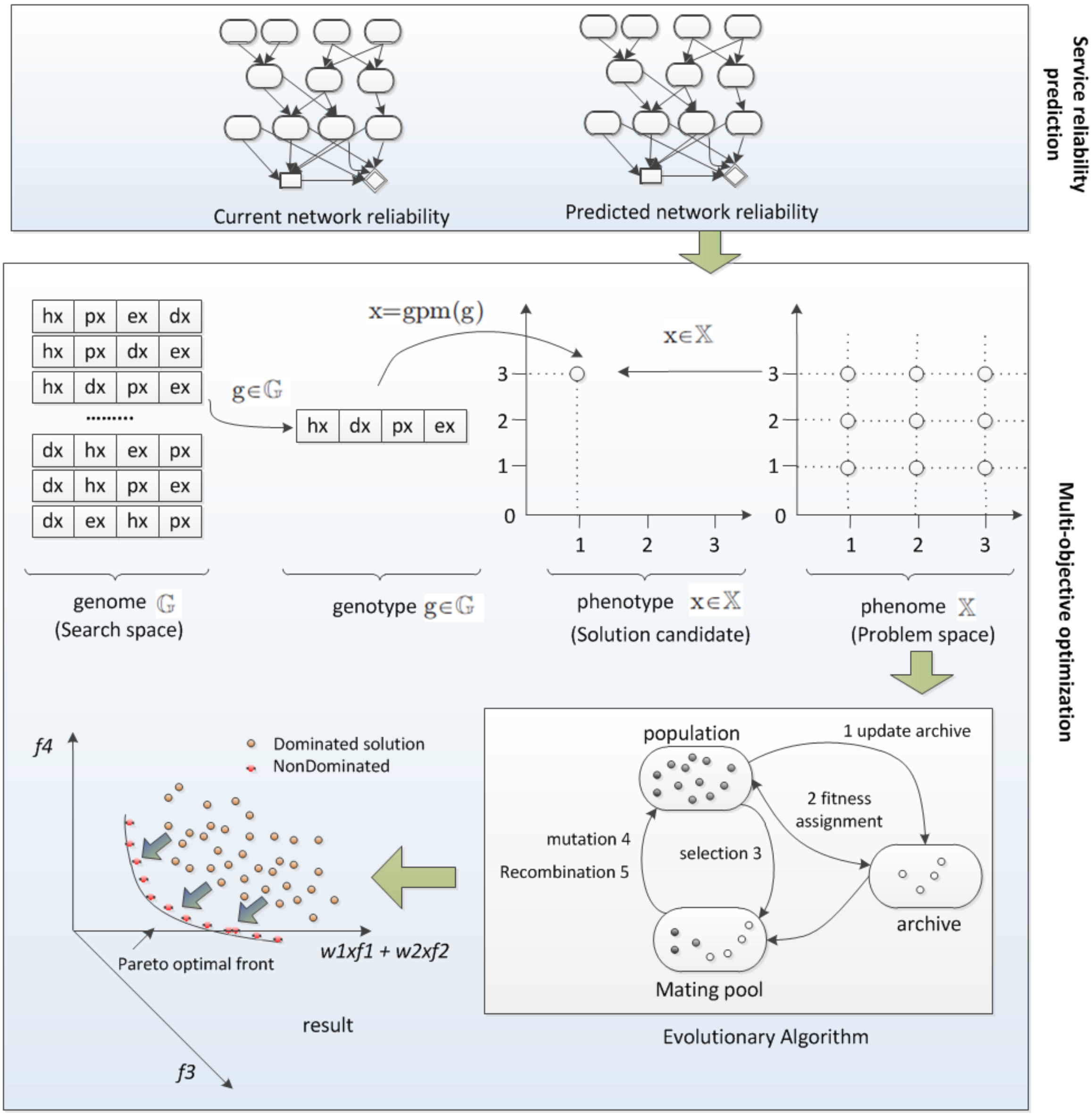

Figure 4.7: The process of multi-criteria decision making.

bus service reliability, which are used to decide whether multi-objective optimization process should be run. The multi-objective optimization process represents the relation of search space (genome), a problem in search space (genotype), solution candidate (phenotype) and problem spaces (phenome). Genotype-phenotype mapping should at least map one genotype to each element of the problem space. Pareto-optimal front

set, which contains the best solution candidates, is returned at the end of evolutionary algorithm. The details of the Evolutionary Algorithm [108] are as follows.

Algorithm 1: Optimisation of control strategies

---

input : *pop*: the population of individual p, which is the vector of future control sequence strategy
input : *arc*: the archive is the set of best individuals found so far
input : *popSize*: the population size
input : *arcSize*: the archive size
input : *mate*: the mating pool
input : f^*: the fitness function resulting from the fitness assigning process
output: X^*: return the set of best solution candidates discovered

begin
    $t \longleftarrow 0$
    $arc \longleftarrow \emptyset$
    pop $\longleftarrow$ *initPop(popSize)*
    while $\neg$*stopCriteria* **do**
        arc $\longleftarrow$ *updateOptimalSet(arc,pop)*
        arc $\longleftarrow$ *truncateOptimalSet(arc, arcSize)*
        $f^* \longleftarrow$ *assignFitness(pop,arc)*
        mate $\longleftarrow$ *select(pop,arc,* f^**, popSize)*
        $t \longleftarrow t + 1$
        pop $\longleftarrow$ *reproducePop(mate)*
    return *getOptimalSet*(*pop* $\bigcup$ *arc*)

---

1. In the first iteration $t = 0$, archive *arc* is assigned with the empty set and the function *initPop(popSize)* produces an initial, randomized population consisting of *popSize* individuals.

2. The function *stopCriterion()* checks whether the algorithm should terminate or continue evolving.

3. The archive *arc* is updated with the function *updateOptimalSet* which inserts new, unprevailing elements from the population into it and also removes individuals from the *arc* which are superseded by those new optima.

4. If the optimal set becomes too large *truncateOptimalSet* reduces it to a proper size, and clustering techniques are employed to maintain the population diversity.

5. The algorithm assigns a scalar fitness $f^*(p.x)$ to each individual p by comparing its vector of objective values $\vec{f}(p.x)$ to other individuals in the population *pop*. The function f^* is built by a fitness assignment process *assignFitness*, employing the Pareto ranking method. It first chooses the individuals that are beaten by no one, namely the non-dominated set of individuals and assigns a scalar fitness value to them. It then checks the rest of the population *pop* and chooses those which are not beaten by the remaining individuals and assigns them a slightly worse fitness value and so on. This process repeats until all solution candidates received one scalar fitness.

6. The function *select* chooses *popSize* interesting individuals from the population *pop* and places them into the mating pool *mate*.

7. The function *reproducePop* then employs mutation and/or recombination techniques to generate a new population inside the mating pool.

8. The function *getOptimalSet* is used to extract all the non-prevailed individuals p from the final population and to return the best solution candidates $X^* = (\vec{x}_1^*, \vec{x}_2^*, ..., \vec{x}_k^*)$. A control sequence $\vec{x_l}^* = (x_1^*, x_2^*, ..., x_n^*)$, where $l \in \{1...k\}$, $i \in \{1...n\}$ and $x_i^* \in \{hx, ex, dx, sx, px\}$, is selected from the pseudo-optimal Pareto front and applied to the bus system.

4.3 Simulation and results

4.3.1 Simulation

A case study of bus operations on the Gwynneville-Keiraville bus route in the regional city of Wollongong, Australia (population 300,000) is used to demonstrate and test the simulator. The simulator deals with a single time period, namely the peak period from 16:34 to 22:32 on weekdays.

4.3.1.1 Route Characteristics

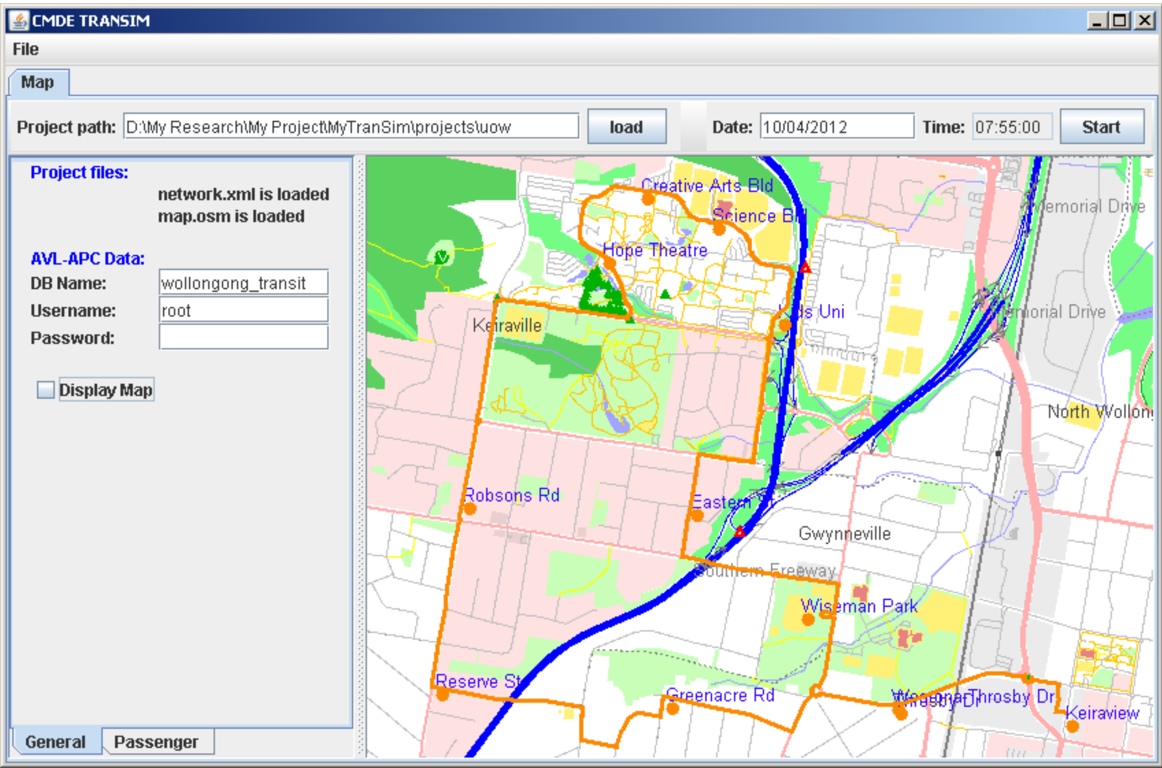

Figure 4.8: The programmed Simulation environment.

During the evening peak, the route runs from the Eastern Entrance of the University of Wollongong and makes 11 stops on its circular route around various parts of central and inner suburban Wollongong before returning to begin its route again.

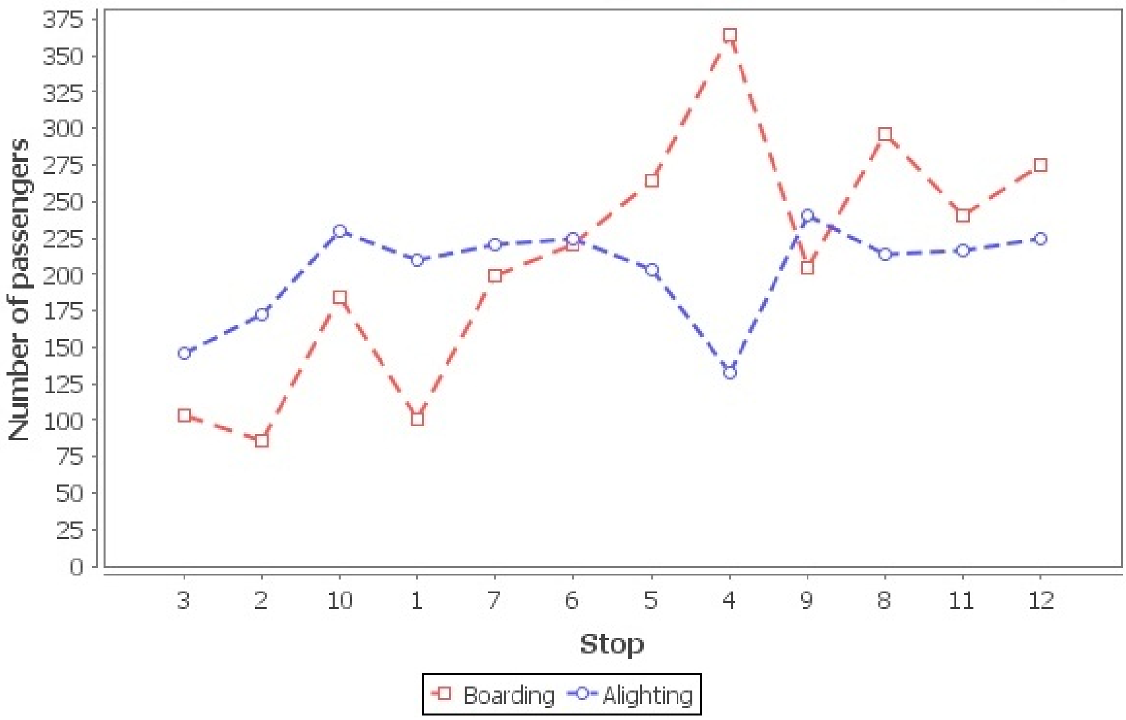

Figure 4.9: Passenger boarding and alighting at each bus stop.

The total route is about 8 kms. The scheduled headway is 15 minutes ($SH = 15$). There are 3 buses running in the evening peak with start times: 16:34pm, 16:49pm, and 19:34pm. The capacity of a bus is assumed to be 70 – including passengers both seated and standing. The simulation involves generating random variables from known probability distributions of variables such as running times and passenger arrival rates. Passenger arrivals to the system are assumed to be distributed according to a Poisson random variable with known mean. Figure 4.8 shows the simulation environment, which has been developed in Java.

4.3.1.2 Passenger demand

The parameters representing passenger demand at each time point are statistically drawn from historical data from the period February 28 to September 16, 2011. Figure 4.9 shows number of passenger boarding and alighting per stop for a day. The boarding,

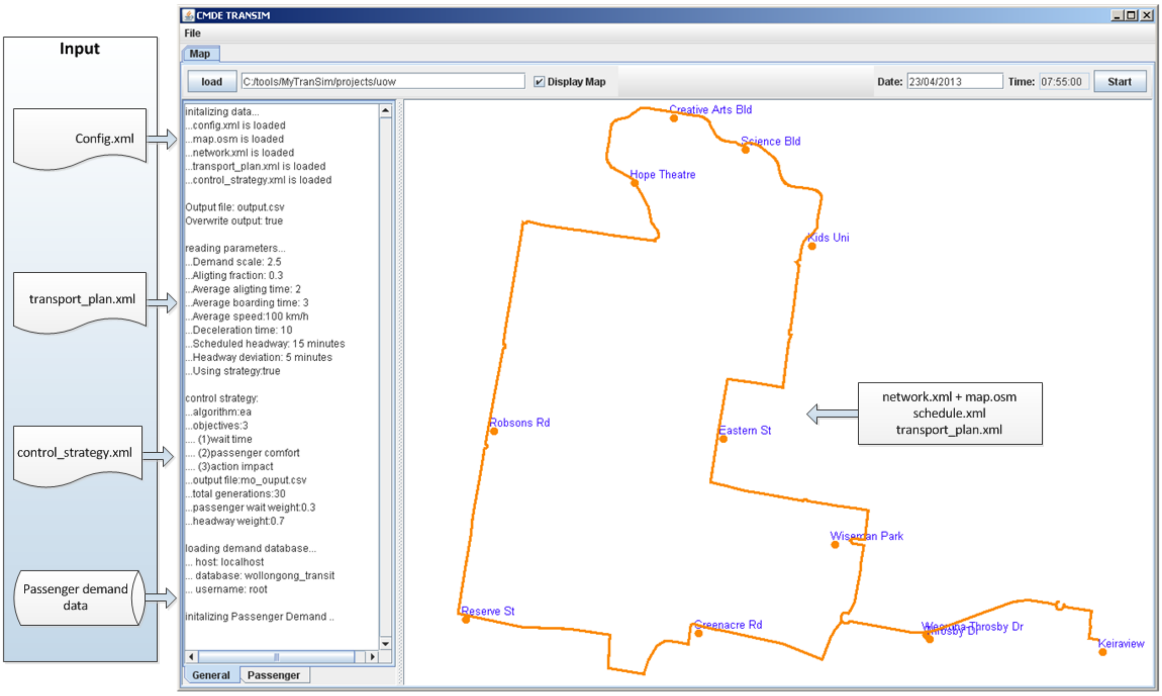

Figure 4.10: Experiment settings.

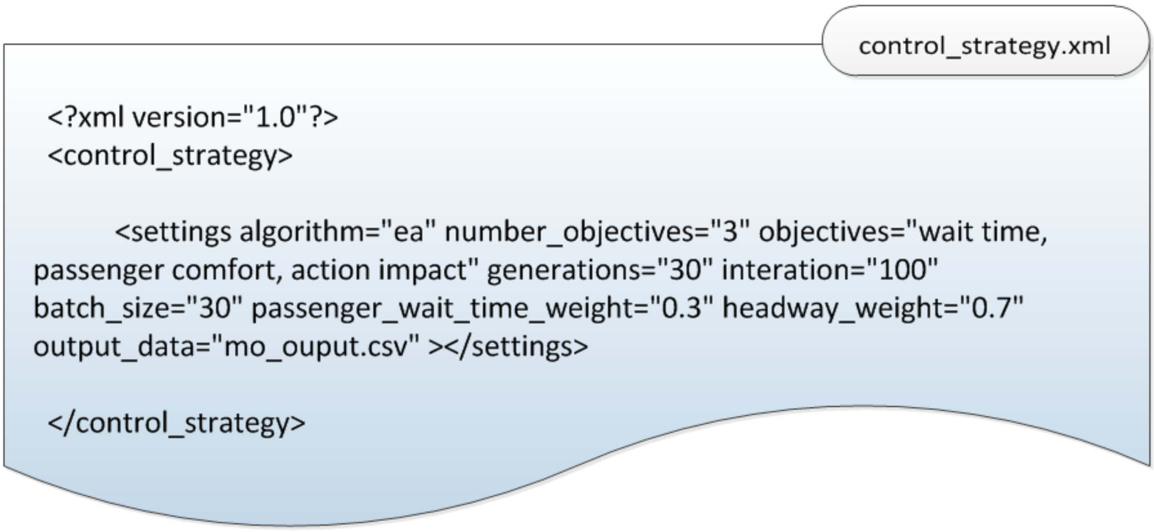

Figure 4.11: Control strategy file.

the alighting time per passenger and passenger alighting fraction are assumed to be 5 seconds, 5 seconds and 0.3 respectively, which means $\alpha = 5$, $\beta = 5$, $\rho_k = 0.3$.

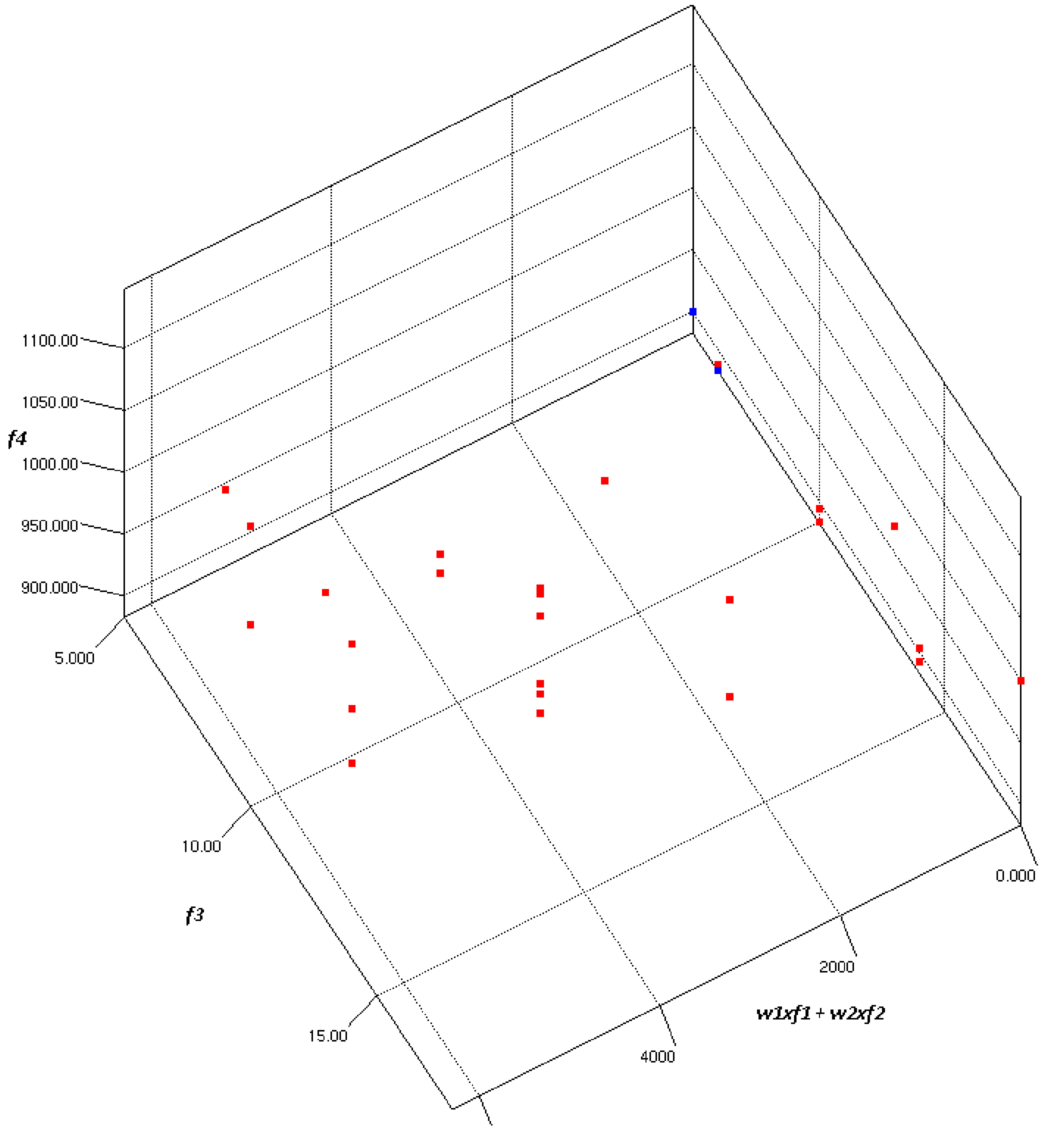

Figure 4.12: Pareto-optimial of the three objectives.

Passenger arrival rate is modelled as follows:

- calculate the distribution of passenger boarding for a week and weekdays per bus stop;
- calculate passenger boarding for 15 minute time period per day and bus stop;
- calculate passenger boarding rate per minute at each stop.

4.3.1.3 Experiment settings

Figure 4.10 represents the experimental settings for the simulation. The simulation loads transit parameters from configuration files: osm map, network presentation file, passenger demand and control strategy definition. The simulation process starts with reading and loading vehicles, schedule and fleet assignment file, and assigns vehicles to the route. Passenger data is then generated for each bus stop per time period, the simulator advances vehicle positions, updates their speeds and pickup number of passengers.

Figure 4.11 represents the control strategy file that defines parameters for multi-objective evolutionary algorithm optimization.

4.3.2 Results and analysis

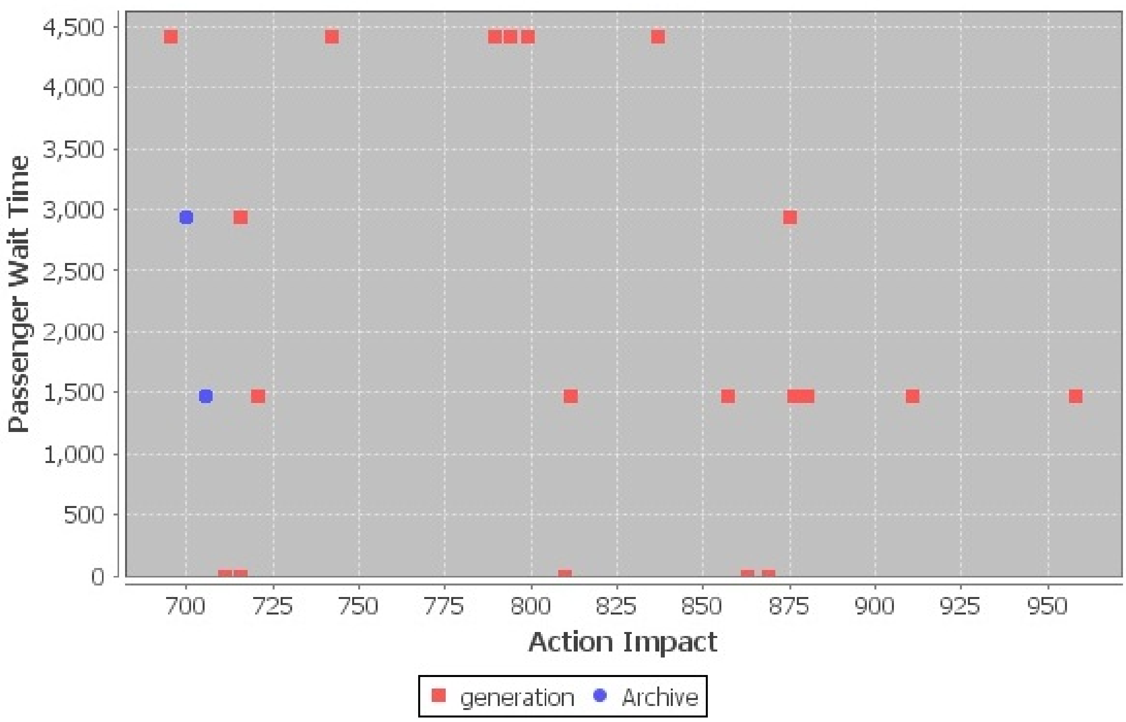

Figure 4.13: Pareto-optimial of passenger wait time and action impact.

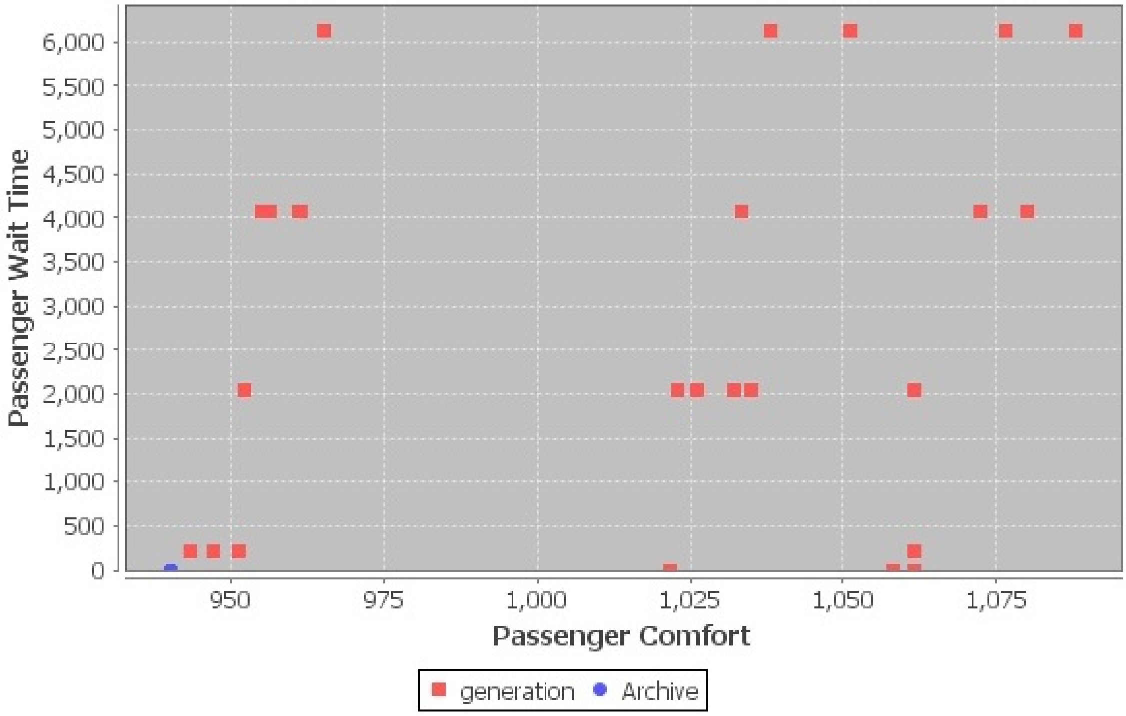

Figure 4.14: Pareto-optimial of passenger wait time and passenger comfort.

The non-dominated solutions of the three objectives: f_1, f_2, f_3 obtained from 100 iterations are shown in Figure 4.12 by blue-colored points. Figure 4.13 shows the trade-off between passenger wait time and action impact. Figure 4.14 shows the trade-off between passenger wait time and passenger comfort. Square points represent evolutionary algorithm solutions, circle points represent the pseudo-optimal Pareto front. All results presented in Figures 4.12, 4.13, and 4.14 are obtained by optimizing the three objectives and then plotted in 3D graph and 2D graphical form. These figures provide evidence that the model developed in this study is successfully able to generate the Pareto front for a multi-objective bus service problem. The algorithm is not only able to find the true (or approximate) Pareto optimal front, but also maintain a good distribution of solutions.

After generating a Pareto optimal configuration with the set of good solutions, several key performance indicators are calculated for each solution. Decision makers

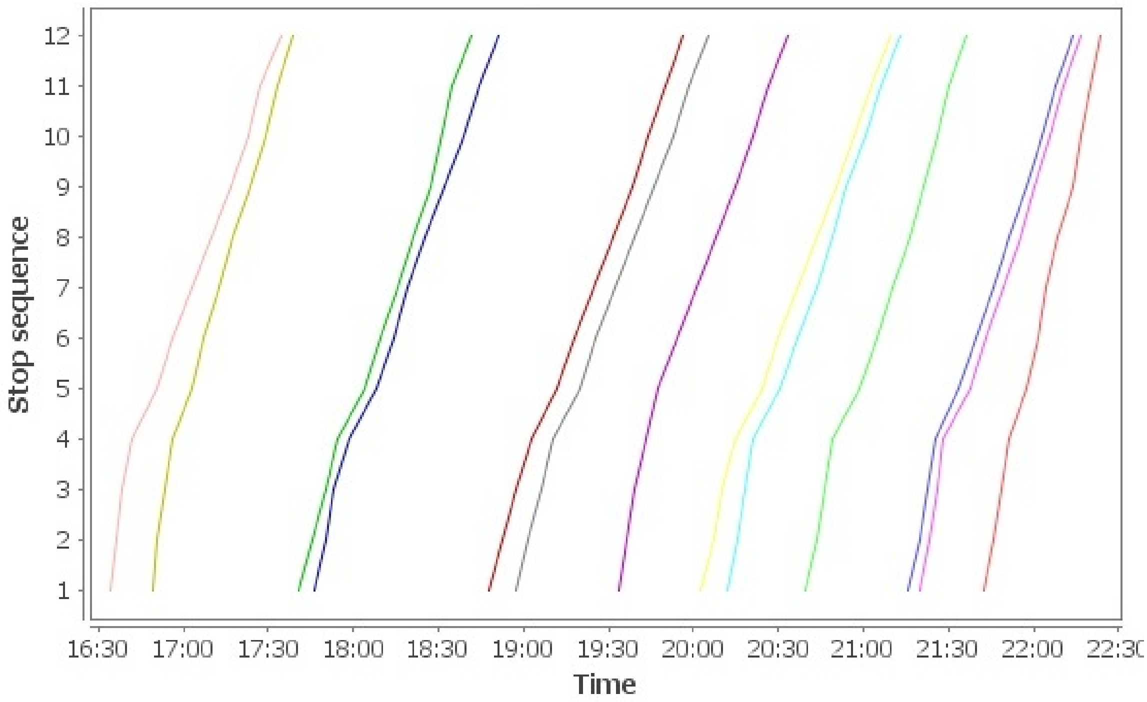

Figure 4.15: Headway adherence without control.

can also choose any non-dominated solution from an experimental run based on their preference weight vectors.

Performance parameters used in this chapter are used to address transit service reliability from the perspective of passengers. Passenger throughput based weight is proposed to aggregate reliability from the stop level to route level. Route-based reliability reflects the reliability performance of a bus operation at the route level, which can be used to assess the reliability of a specific route. On the other hand, stop-based reliability focuses on reliability at the stop level, which can be used to assess the reliability of a specific stop, route, or transit network.

For short-headway services, the variability of headways is the main route-based measure for evaluating transit reliability. An effective control strategy improves service reliability by reducing headway variability, which in turn results in shorter passenger waiting times. Figures 4.15 and 4.16 present space-time headway adherence before

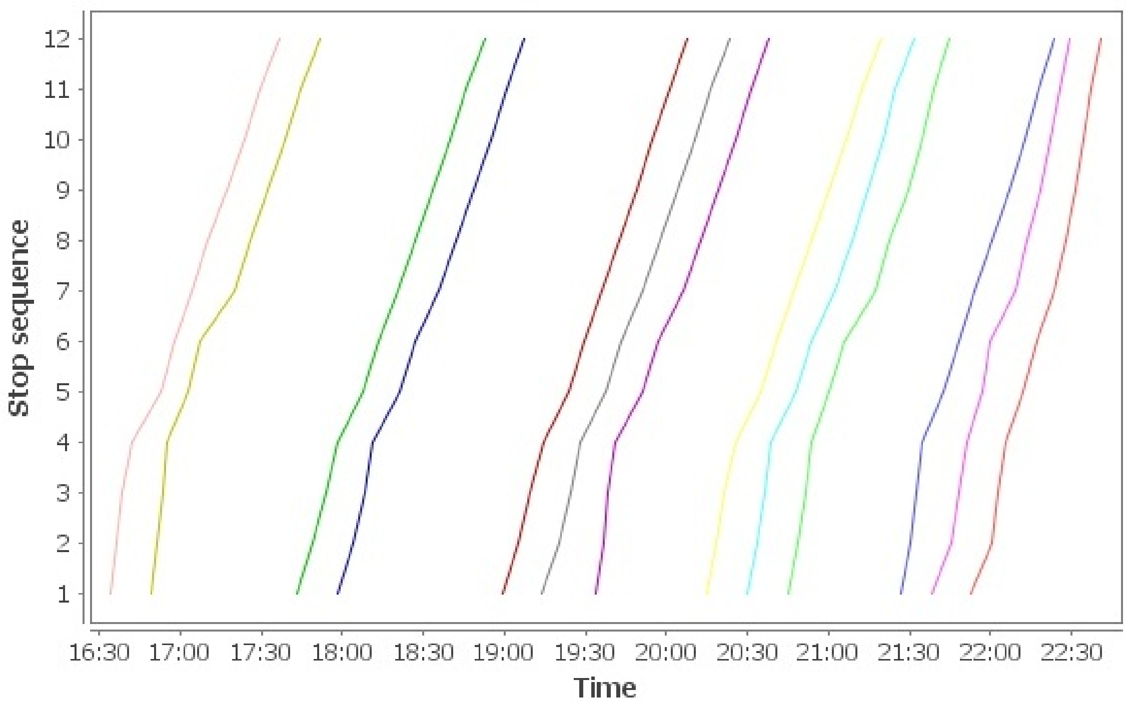

Figure 4.16: Headway adherence with control.

and after applying control strategies for the peak hour (16:30 – 23:00). There is more bunching in Figure 4.15 while Figure 4.16 shows more even headway.

Another performance route-based measure is passenger wait time. Figure 4.17 shows passenger wait time compared with expected wait time. The equations for passenger wait and expected wait time used in Figure 4.17 are as follows:

$$W = \frac{(\sum_{i=1}^{n}\sum_{k=1}^{m}(\frac{AD_{i,k}-AD_{i+1,k}}{2} + \frac{\varepsilon}{2(AD_{i,k}-AD_{i+1,k})}))}{K} \tag{4.26}$$

$$E[W] = \frac{SH}{2} + \frac{\varepsilon}{2SH} \tag{4.27}$$

where K is the number of runs in a trip. The results of passenger wait time analysis indicates that with the holding control strategy, the level of passenger wait time is kept to expected levels.

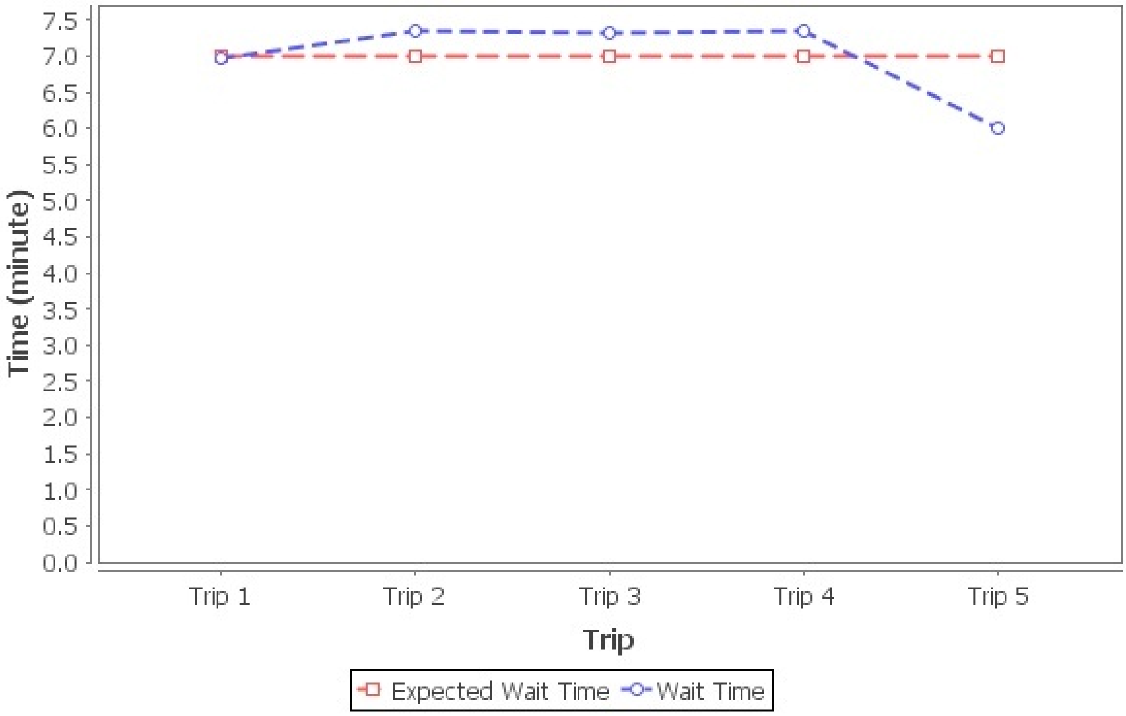

Figure 4.17: Passenger wait time.

Bus reliability at the stop level is considered from a passenger's point of view, which can be used to enhance reliability from a passenger's perspective. Line charts in Figure 4.19 and 4.18 are used to measure stop-level bus reliability with (and without) employing control strategies. Equations are used to calculate the service reliability of headway $\mathcal{SR}_h$, passenger wait time $\mathcal{SR}_w$ and passenger comfort $\mathcal{SR}_c$ are as follows:

$$\mathcal{SR}_h = \sum_{i=1}^{n} \sum_{k=1}^{m} P\{\frac{\mathcal{H}_{i,k} - \mathcal{H}_0}{\mathcal{H}_0} \leqslant r\} \tag{4.28}$$

$$\mathcal{SR}_w = \sum_{i=1}^{n} \sum_{k=1}^{m} (\mathcal{B}_{i,k} + \mathcal{P}_{i,k})(\mathcal{AD}_{i,k} - \mathcal{AD}_{i-1,k}) \tag{4.29}$$

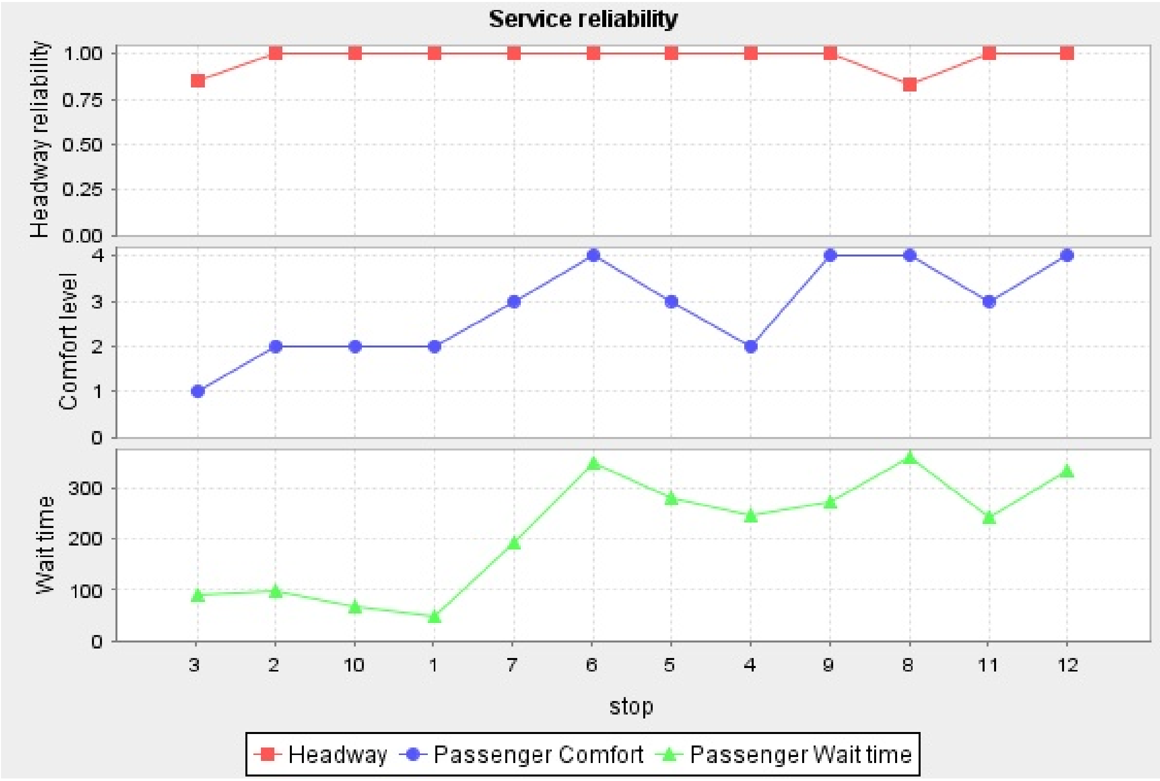

Figure 4.18: Service reliability with control.

$$\mathcal{SR}_c = \begin{cases} \sum_{k=1}^{m} \frac{\sum_{i=1}^{n} \frac{\mathcal{L}_{seated}}{\mathcal{L}_{i,k}}}{n} & \text{if } \mathcal{L}_{seated} >= \mathcal{L}_{i,k} \\ \sum_{k=1}^{m} \frac{\sum_{i=1}^{n} \frac{\mathcal{L}_{standing}}{\mathcal{L}_{i,k} - \mathcal{L}_{seated}}}{n} & \text{if } \mathcal{L}_{seated} < \mathcal{L}_{i,k} \end{cases} \tag{4.30}$$

The results in Figure 4.19 and 4.18 indicate that there was low service reliability for the bus transit network before applying the control strategies. Applying control strategies helps to dramatically improve service reliability.

Figure 4.20 shows the effect of control strategies on travel and in-vehicle times, which are calculated by the following equations:

$$\mathcal{TT} = (1.0 - \frac{\sum_{i=1}^{n} \sum_{k=1}^{m} (FD_{i,k} - AD_{i+1,k})}{\sum_{i=1}^{n} \sum_{k=1}^{m} (AD_{i,k} - AD_{i+1,k})}) \times 100 \tag{4.31}$$

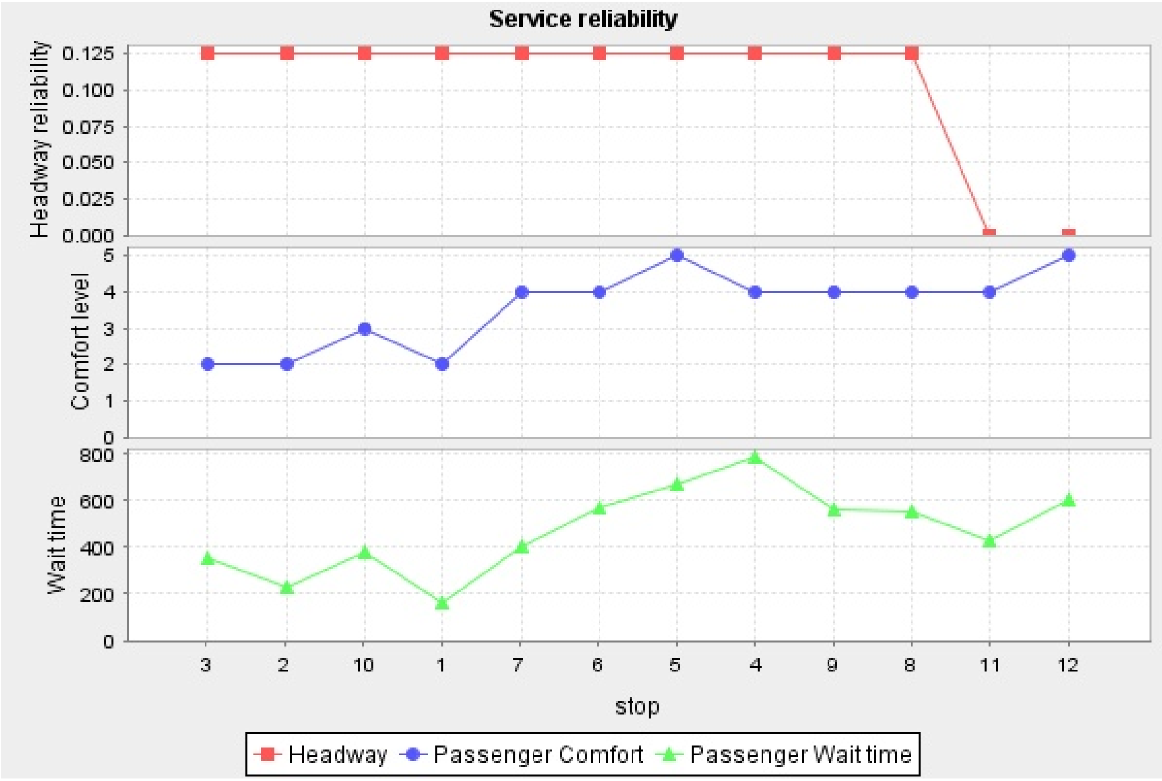

Figure 4.19: Service reliability without control.

$$\mathcal{VT} = (1.0 - \frac{\sum_{i=1}^{n}\sum_{k=1}^{m}(FD_{i,k} - AD_{i+1,k}) \times L_{i,k}}{\sum_{i=1}^{n}\sum_{k=1}^{m}(AD_{i,k} - AD_{i+1,k}) \times L_{i,k}}) \times 100 \tag{4.32}$$

Control strategies may cause delays to on-board passengers and longer travel times that may result in higher fleet costs. However, improved regularity of headways can reduce the in-vehicle time of the passengers at the subsequent stops. In addition, passenger waiting time at bus stops can in practice be considered more important than passenger in-vehicle waiting time.

4.4 Conclusion

Aiming at enhancing transit service reliability from passenger's point of view, this chapter uses headway adherence, passenger wait time and passenger comfort to mea-

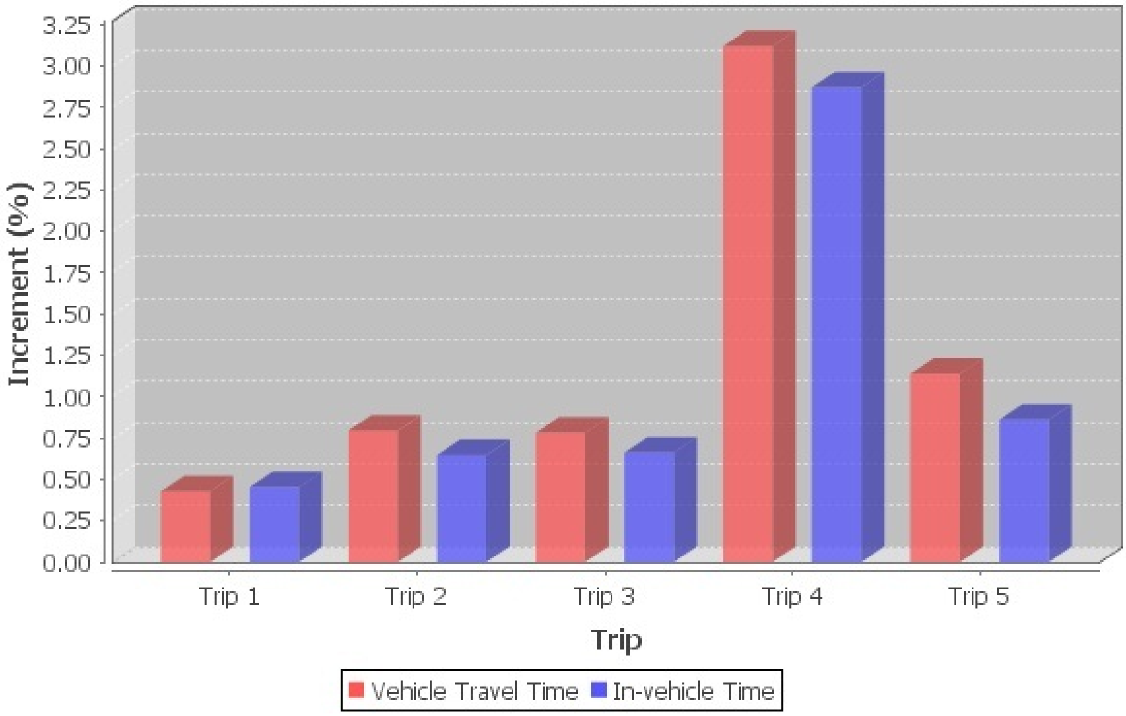

Figure 4.20: Travel and in-vehicle times.

sure service reliability of a high frequency bus route. In recent years, many studies have focused on developing real-time control strategies for transport networks. However, none of the available methods are adequately robust for dynamic multi-criteria decision-making under environmental uncertainty nor do they fully support corrective and preventive control strategies. Regarding corrective strategies, this chapter focuses on multi-criteria decision making that involves the selection of the best actions from a set of alternatives, each of which is evaluated against multiple, and often conflicting, criteria. Holding, expressing, short-turning and deadheading corrective control strategies are used in this chapter. Our approach also deals with minimizing passenger overcrowding, which is considered among the major issues in modern public transport management.

The Multi-objective Evolutionary algorithm based dynamic Bayesian networks approach provides the ability to reason and predict bus service reliability network as well

as to handle multi-criteria decision making to control real-time information. It is able to handle uncertainty which, when presented through variables based on probability and its dynamic choosing action, yields the highest expected utility. Another advantage of this approach is that it considers headway adherence, running time, dwell time and decision-making as continuous values. The effect is that the algorithm is more flexible in decision-making compared to existing transit control methods.

A simulation-based evaluation enables us to verify the efficiency of this approach. The simulation examined performance and level-of-service by capturing the interactions between transit operations and passenger demand. Pareto-optimal analysis is used to measure efficiency of a multi-objective evolutionary algorithm. Route and stop level analysis for transit service reliability improves passenger decision-making processes and enhances daily route service management by the transit agents.

Chapter 5

A multi-dimensional transit assessment framework in Transport-based Data-collection Systems

Understanding the relationships that influence reliability in a transit network provides insight about approaches for service improvement. In this chapter, a multi-dimensional transit assessment framework is presented with adequate flexibility to measure efficiency of public transit service, and to demonstrate the use of the framework through case studies. The framework involves constructing a transit service reliability diagnostic (TSRD) diagram based on a Bayesian network, which is proposed to automatically build a behavioural model from Automatic Vehicle Location (AVL) and Automatic Passenger Counters (APC) data to discover the variability of transit service attributes and their effects on traveller behaviour. A TSRD diagram allows us to describe and analyse factors affecting public transport by combining domain knowledge with statistical data, thus enabling a public transport network that incorporates service reliability

and theoretical knowledge into the process of knowledge discovery. The framework assists in evaluating proactive decision making methods to re-plan the strategies, which in turn will improve the real-time control strategies. It will also help to evaluate driving and travel behavior. There is an interaction between the driver and the system; the driver not only is a user of the system, but also a part of the system itself. The feedback/lessons that they have received from their interaction with the system help them to adjust their driving behavior.

5.1 Introduction

> *"The transit industry is in the midst of a revolution from being data poor to data rich. Traditional analysis and decision support tools required little data, not because data has little value, but because traditional management methods had to accommodate a scarcity of data" [43].*

The measurement of transit performance has been, and will continue to be, an essential concern for allocating resources among competitive transit agencies. Performance measurement is essential for evaluating management performance of the transit service with regards to community expectations, for examining management problems relating to service costs, and as a supervising tool for enhancing service reliability [45].

With the introduction of technologies such as Automatic Vehicle Location (AVL) and Automatic Passenger Counters (APC), large quantities of data are increasingly becoming available and it is important to investigate to how this data can be used to improve transport service reliability. The growth of public transport databases necessitates new approaches to help characterize reliability and improve service planning and operations control.

Several researchers have employed multiple criteria analysis for transport systems performance evaluation. Yeh et al. [114] applied a fuzzy multi-criteria analysis tech-

nique to assess overall performance of an urban public transport system. Zak et al. [117] utilized a multiple criteria analysis method with graphical facilities to evaluate the transit vehicle assignment problem. Agusdinata et al. [3] employed exploratory modeling to deal with the uncertainty in intelligent speed adaptation policy in urban transportation networks.

Data Envelopment Analysis (DEA), a non-parametric method introduced by Farrell [36], which used a linear programming technique, were also employed by Boile [14], Nakanishi and Falcocchi [77], Tsamboulas [101], Barnum et al. [9], Sheth et al. [93], Lao and Liu [60], Zhao et al. [119], Hawas et al. [46], Karlaftis and Tsamboulas [51] to measure the relative performance of production lines. The shortcoming of DEA is that statistical analysis and hypothesis testing are not possible because of the non-parametric nature of DEA.

Other studies adopted more advanced statistical techniques, like path analysis, latent variable and structural equation models. Some examples are reported in Joewono and Kubota [49], Stuart et al. [98], Eboli and Mazzulla [33], and Nurul-Habib et al. [44].

To be specific, Joewono and Kubota [49] employed the path analysis and binomial regression approaches to uncover the relationship among variables and to study the predictive power of several variables on overall satisfaction. In Stuart et al. [98], and in Eboli and Mazzulla [33] structural equation models were formulated as a way to investigate the impact of the relationship between global customer satisfaction and transit service quality aspects. Through this kind of model the strength of the relationships could be quantified and in comparison with the another with regards to both direct and indirect effects. Nurul-Habib et al. [44] model coupled with latent variable models for catching unobserved latent variables in investigating causes of using transit systems as expressed as a function of peoples perception and attitude towards transit service

quality and attributes. The model can be used to connect the relationship between the reason behind selecting public transport instead of other modes of transportation and variables defining the perception or attitude towards transit service. The shortcoming of the path analysis technique is that if the models are determined by correlations between variables in a given data set, path analysis cannot show causality or the direction of causal effects.

Among knowledge discovery techniques, Bayesian networks, a characterisation of probabilistic knowledge by a graphical diagram, provides a comprehensive method of representing relationships and influences among nodes. Bayesian networks are now a fundamental technique in pattern recognition and classification [58][79][83].

A variety of studies induce Bayesian networks from data. Oniśko et al. [85] showed how Bayesian network parameters from small data sets and Noisy-OR gates can be used to reduce the data requirements in learning conditional probabilities. Nadkarni et al. [76] described a procedure for constructing Bayesian networks from expert domain knowledge using causal mapping. Tungkasthan et al. [102] proposed a practical framework for automating the construction of a diagnostic Bayesian network from WWW data sources. In that work, a SMILE (Structural Modeling, Interface, and Learning Engine) Web-based interface allows one to perform Bayesian network diagnosis through the Web. Song et al. [95] presented a Bayesian network approach to assessing risks of service failures in a clinical setting based on the dependence relationships among individual service failures. Liu et al. [67] constructed the Bayesian network structure from dependencies implied in multiple relational schemas based on acyclic database theory and its relationships with probabilistic networks, the network can be constructed using the independence information implied in the relational schemas instead of mining the instances.

As can be seen from any study of the literature including those above, a wide variety of studies have used Bayesian networks as a knowledge discovery mechanism; however employing Bayesian networks to analyze service reliability using data derived from AVL and APC in public transport is novel. To date, the transit industry has lacked a measure of service reliability measured in terms of its impact on customers because traditional measures cannot express how reliability impacts on passengers' perceptions [43]. Also, previous research evaluating transit service reliability using AVL systems focused on quantifying the advantages of AVL systems in increasing reliability [96] [55]; those studies did not make an effort to fully grasp factors behind decline in reliability along problematic routes.

This chapter therefore focuses on building an assessment framework with adequate flexibility to discover and evaluate performance of a transit network, and to demonstrate the use of the framework via case studies. Transit knowledge presentation of the framework constructed from data from AVL-APC is presented via a transit service reliability diagnostic (TSRD) diagram based on a Bayesian network. A TSRD diagram has the ability to represent cause-effect relationships between transit factors and expresses how each factor will impact on others. The multi-dimension framework can perform in three ways: (i) as a guide for reasoning the causes of service unreliability (evidential reasoning, causal reasoning, and intercausal reasoning); (ii) as an offline analysis tool to improve service quality (filtering, and smoothing) and; (iii) as a learning component for real-time decision making. The main contribution of the framework is to take a new approach to realizing the problem of service reliability that enables transit planners to recognize the influence of transit factors on a route's overall performance, to develop specific strategies to enhance service reliability.

The remainder of the chapter is organized as follows. The proposed methodology for constructing the TSRD diagram is presented in Section 5.2. The experimental

results are reported and discussed in Section 5.3.

5.2 Proposed Methodology

Transit service providers have to measure the performance of their service to find out how effective the service is. Performance assessment is required to record the present demand tendencies, peaks of operation, existing stakeholders problems, and unexpected service needs. These measures can be utilized for supervising, assessing economic efficiency, communicating the organizations achievements and challenges, establishing service standards and observing community positive aspects [90].

The research methodology followed in this study is shown in Figure 5.1. Utilizing actual AVL-APC data and different transit factors identified in the literature, the learning algorithm is implemented to discover relationships between different variables. After validating the network performance and precision, the capability of information propagation is used to evaluate possible changes within the network with capturing transit service, the operating conditions, and the user characteristics and needs. Given all the above, it is expected that the framework can be generalized.

There are three major mechanisms in our methodology: (1) data collection, (2) transit knowledge representation, (3) analysis and interpretation:

1. AVL and APC are installed for buses on the UniShuttle service in the city of Wollongong to collect transit data. AVL-APC data is transmitted and collected via Web service back to server;

2. transit knowledge representation constructed from the above AVL-APC data is presented via a transit service reliability diagnostic (TSRD) diagram based on a Bayesian network;

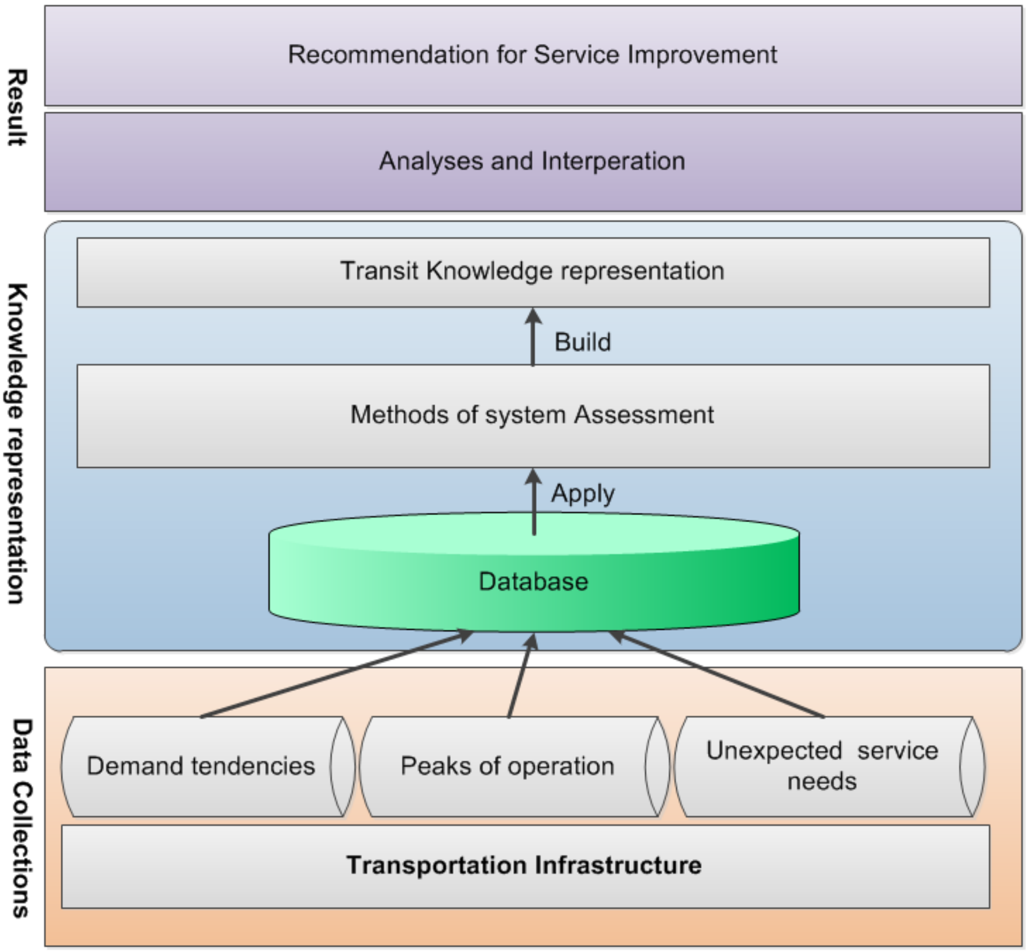

Figure 5.1: Research Methodology.

3. analysis and interpretation of the constructed transit knowledge representation is used to demonstrate the use of the framework to give recommendations for service improvement.

The approach presented here differs from existing transit assessment framework approaches in the following ways:

- it provides the ability to use the framework for offline analysis and enhance of

real-time control strategies;

- it allows the automatic building of a transit behavioural model from AVL-APC data to study service reliablity;

- it provides the ability to assess an existing transit system and also a potential new transit systems;

- it provides the versatility in the selection of criteria indicators and methods, which allow select appropriate analysis approaches in line with the objectives and resources.

Details of each mechanisms are described in the following sub sections.

5.2.1 Data Collections

A case study of bus operations on the Gwynneville-Keiraville bus route of the UniShuttle service is used to demonstrate and test the proposed method. During the evening peak, the route runs from the Eastern Entrance of the University of Wollongong and makes 11 stops on its circular route around various parts of central and inner suburban Wollongong before returning to begin its route again. The total route is about 8 kms.

Figure 5.2 shows summary statistics collected from AVL and APC. The bus location data is updated to the server every 10 seconds for all the buses that are running at any one time. As at the end of July 2012 there were a total of 1,844,964 vehicle (bus) location events stored in a MySQL database on our servers. The average monthly number of vehicle events captured is 132,000. Passenger counts are stored in the onboard computer in the bus for real-time display passenger ons and offs and are synchronised to the server every 5 seconds. In total there are an average of 4,630 passenger events per month captured.

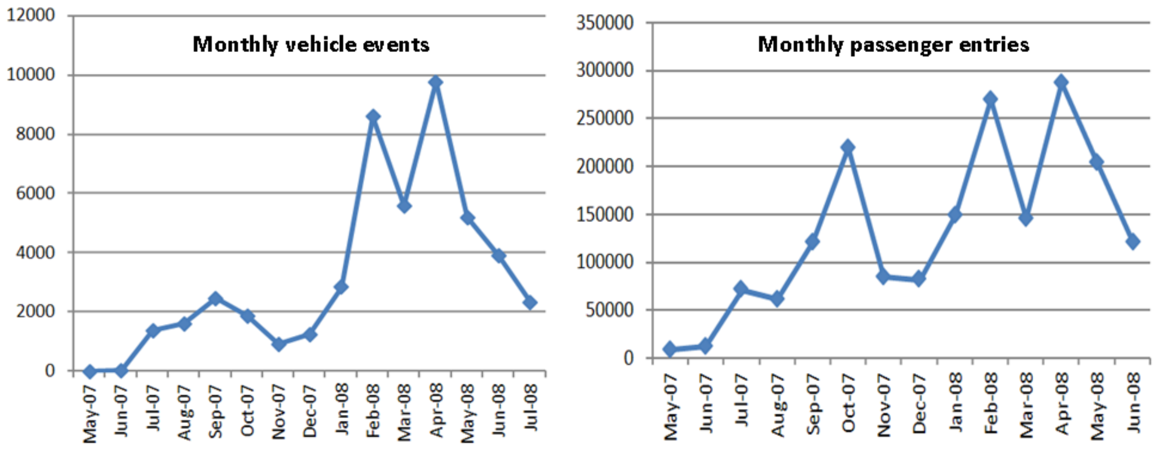

Figure 5.2: Monthly vehicle and passenger events

5.2.2 Transit knowledge presentation

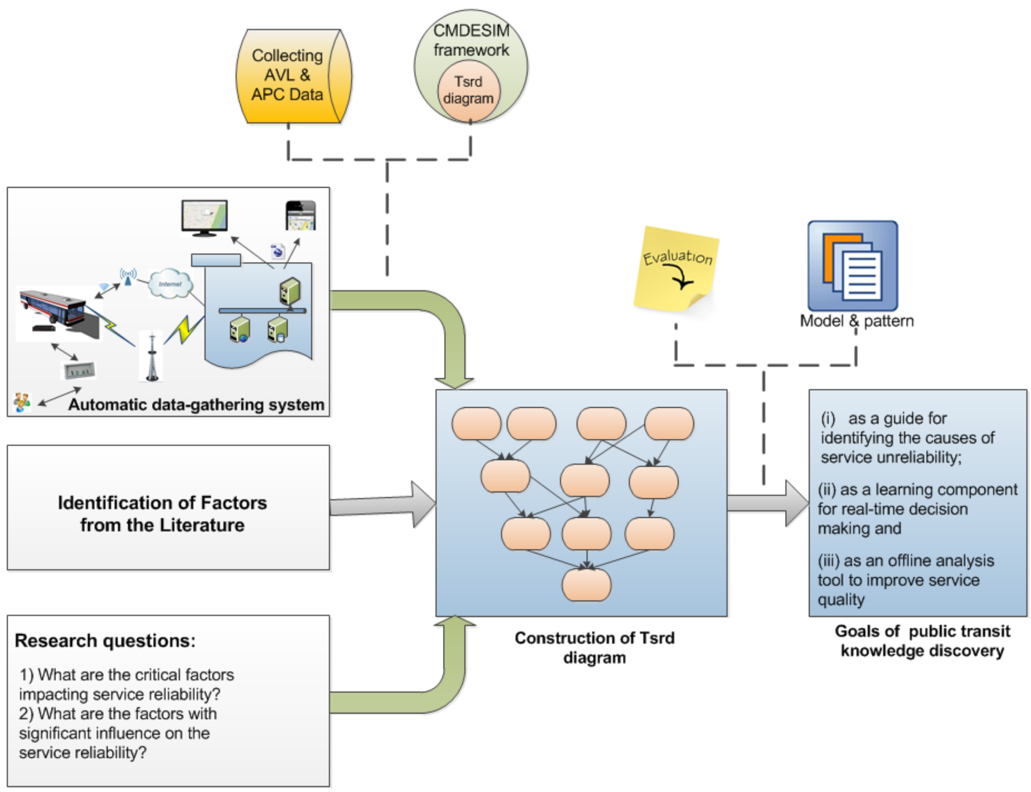

Figure 5.3: Architecture of service reliability discovery.

Figure 5.3 shows the architecture of the discovery process from AVL and APC data. Transit knowledge representation of the framework is presented via a TSRD diagram based on a Bayesian network – a prediction-oriented method – and is built as part of Connected Mobility Digital Ecosystem Simulation (CMDESIM) to provide a better understanding of what causes problems in the transit system, prevent these problems through better service planning and operations management, and develop strategies to correct them once they present.

Service reliability in a public transport network can be considered as the variability of service attributes and its effects on passenger behavior. Service unreliability mainly comes from uncertainty in transit operations that arises from within the transport environment and via the randomness of passenger arrivals. Deriving cause-effect relationships from data is important to discover causes of unreliability.

A TSRD diagram can help characterise the transit network and discover causes of service unreliability as its ability to encode directional relations represent cause-effect relationships. This representation is achieved via a network $\mathcal{N}(\mathcal{G}, \Theta)$, where $\mathcal{G} =< \mathcal{U}, \mathcal{E} >$ is a directed acyclic graph, $\mathcal{U}$ is a set of nodes expressed as $\mathcal{U}\{u_1, u_2, ..., u_n\}$, $\mathcal{E}$ is a set of arcs, and Θ represents a set of conditional probability distributions. The nodes represent the variables and the links between each node pair represent the causal relationships between the variables.

A TSRD diagram based on a Bayesian network, which allows relationship mining affords identification of local interactions within one process, where the value of one variable directly depends upon a small number of other variables [40]. It also enables one to identify factors that directly influence service reliability, as well as to investigate the propagation of information throughout the entire network.

Constructing a TSRD diagram consists of four steps:

1. preparation of transit discovery data set;

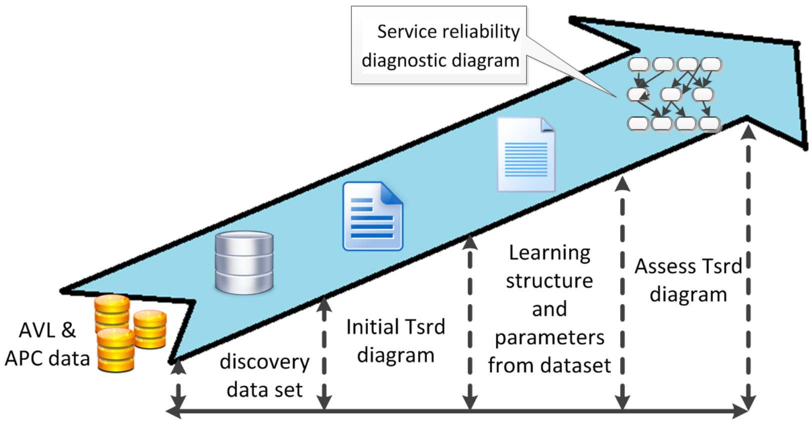

Figure 5.4: Process of constructing TSRD diagram.

2. determining an initial TSRD diagram;

3. learn structure and parameters of the TSRD diagram from the training set;

4. assess/test the TSRD diagram.

Since data from AVL and APC sources are heterogeneous and uncertain, the initial step combines data from various sources and tables into one dataset which can then be used in the discovery process. The second step is the construction of an initial TSRD diagram, which is based on cause-effect relationships to draw links between transit variables. The initial TSRD diagram reveals the qualitative relationships between variables in public transit systems. Next, the structure of the initial TSRD diagram and the parameters of variables need to be learned from the dataset. Learning the structure, causal relations, and parameters of variables – which reveal the quantitative relationships between variables – from the dataset is important for a comprehensible and extensible TSRD diagram. The final step is the assessment of the candidate TSRD diagram.

5.2.2.1 Preparation of transit discovery dataset

a) Understanding the problem context: It is essential to obtain an obvious comprehension of the problem context. The problem being addressed is normally clarified and refined during the knowledge engineering process. Answers to the questions below provide a list of known and unknown variables that offer a beneficial starting point for discovery dataset preparation and structure building [58]:

Q: "What do you want to reason about?"

Q: "What don't you know?"

Q: "What information do you have?"

Q: "What do you know?"

"A very common impulse, when something is known about the problem, is to want to put it in the model. But including everything known, just because it is known, simply adds complexity to the model without adding any value (and in fact often reduces value). Instead, the knowledge engineer must focus on the question to limit the number of variables in the model, at least in the beginning, in order to keep the knowledge engineering task tractable. The key is to determine which are the most important variables" [58].

Understanding the problem context of building transit assessment framework assists to develop a proper dataset for discovery process. Return to transit service reliability problem in terms of variable identification, the main interest of transit service reliability diagnosis is to identify the unreliability causes from which the passenger is suffered. The dataset built from the raw database in next the section needs to focus on this purpose.

b) Processing Discovery Dataset: In this step, the generation of improved data for the knowledge discovery process is undertaken. From the original public

transit data set variables relevant for the study are considered and selected. The raw AVL and APC data is represented in Tables 5.1, 5.2 and 5.3.

Table 5.1: Sample of bus stop data.

StopName	**Longitude**	**Latitude**	**SegmentID**	**StopNumber**
Kids Uni (Stop A)	150.882797	-34.407879	1	1
Science (Stop B)	150.880234	-34.404812	12	2
Creative Arts (Stop C)	150.877472	-34.403828	18	3

Table 5.2: Sample of vehicle (bus) location data.

BusID	**Longitude**	**Latitude**	**Timestamp**	**Speed**	**SegmentID**
01	150.891352112	-34.405434377	10/21/2011 6:56:31 PM	6.56	1
01	150.891358482	-34.405373922	10/21/2011 6:56:20 PM	23.40	12
01	150.89143029	-34.405431443	10/21/2011 6:55:48 PM	7.14	8

Table 5.3: Sample of passenger counts data.

BusID	**Longitude**	**Latitude**	**Timestamp**	**Counts**	**On/Off**
01	150.891352112	-34.405434377	10/21/2011 6:56:31 PM	3	1
01	150.891352112	-34.405434377	10/21/2011 6:56:32 PM	4	1
01	150.891352112	-34.405434377	10/21/2011 6:55:33 PM	5	0
01	150.891352112	-34.405434377	10/21/2011 6:56:34 PM	2	0

The raw data needs to be normalized by combining, matching and processing data from the three tables above to expose the variables required for the analysis; this involves extraction and transformation of the attributes. This process is usually very project-specific and the variables may vary, depending on how the TSRD diagram is to be used. In this case, all data is integrated into one dataset including all of the attributes and their possible states that will be considered for the study of service reliability. Table 5.4 represents all combined attributes that are used.

c) **Discretizing variables:** Though it may be possible to develop TSRD diagram with the continuous variables, most effective approach is to discretize them.

Table 5.4: Description of attributes.

No.	**Variables**	**Possible states**
1	vehicle Speed $\mathcal{V}$	{Slow, Normal, Fast}
2	vehicle position $\mathcal{X}$	{OnSchedule, OffSchedule}
3	running time $\mathcal{R}$	{OnTime, LessThan5MinLate, MajorLate}
4	passenger alighting $\mathcal{A}$	{Low, Normal, High}
5	passenger boarding $\mathcal{B}$	{Low, Normal, High}
6	dwell time $\mathcal{D}$	{Negligible, Major, Minor}
7	in-vehicle load $\mathcal{L}$	{Normal, Excessive, Unaccepted}
8	passenger wait time $\mathcal{T}_{wait}$	{Negligible, Major, Minor}
9	headway adherence $\mathcal{H}_{adherence}$	{Negligible, Major, Minor}
10	passenger comfort $\xi_{comfort}$	{Good, Accepted, Unaccepted}
11	service reliability $\mathcal{SR}$	{Yes, No}

This means that they are transformed into multinomial variables where each value determines a different subrange of the original range of continuous values. The optimal discretization may differ based on the situation. The third column of Table 5.4 shows a possible discretization when modeling the service reliability problem.

This is also the step in which to define the goals and understanding of what should be done with the TSRD diagram.

5.2.2.2 Determining an initial TSRD diagram

Question: "What causes headway irregularity?"

Answer: "Passengers alighting or boarding and the bus waiting for passengers running to catch the bus"

Modeling: Draw arcs from those nodes to the *Headway adherence* node.

After deciding what variables and states to model, an initial TSRD diagram $\mathcal{N}^0$ is constructed by causal influence and considering conditional independence by drawing causal links among nodes following the kind of question and answering example given above.

Determining the initial TSRD diagram can be described as a process of drawing an edge from X to Y if and only if X is a direct cause of Y relative to V, where V is a set of random variables, and X, Y ∈V.

To properly characterize the dependence and independence relations among a set of variables of the transit service reliability domain, it is important to have directed links from causes to effects. In other words, if X is a direct cause of Y, directed link from X to Y is added. If done the other way around with link Y to X, this will result in faulty statements of dependence and independence and, faulty inference.

To establish the causal relationships, it is helpful to ask direct questions about dependence between variables. Once identified, arcs are added from those causal variables to the affected variable. Probabilities on the edges are obtained by subjective estimates. Figure 5.6 depicts the TSRD diagram $\mathcal{N}^0$ by combining knowledge of bus operations in Figure 5.5 and asking these cause-effect questions. The main interest of service reliability diagnosis is identifying the causes of unreliability. The context variables in this case are the background information about passengers alighting, passengers boarding, bus position and speed.

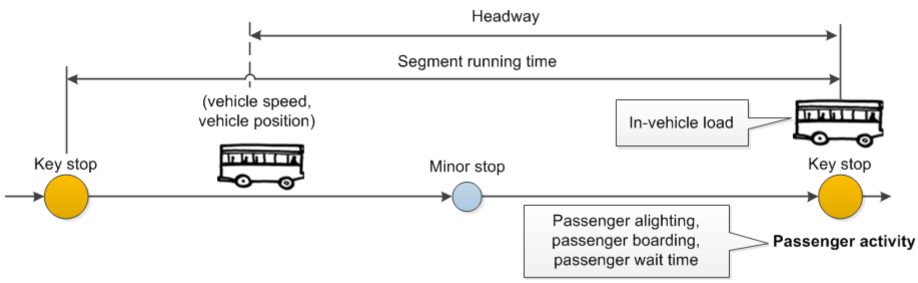

Figure 5.5: Bus model.

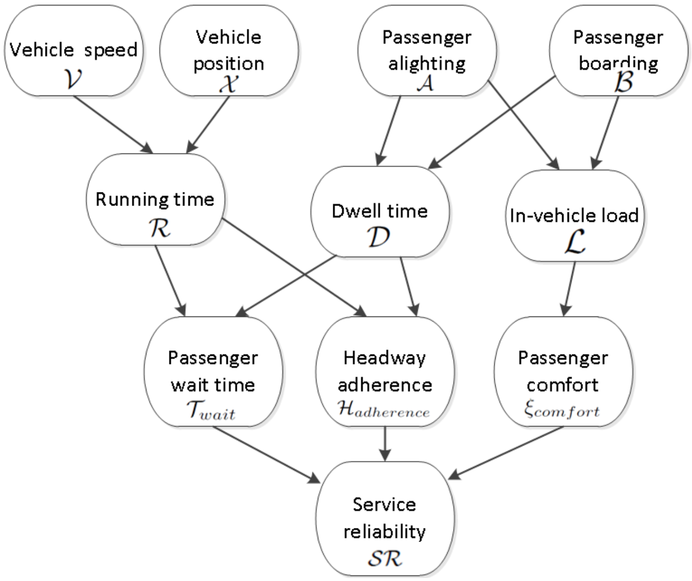

Figure 5.6: Initial TSRD Diagram.

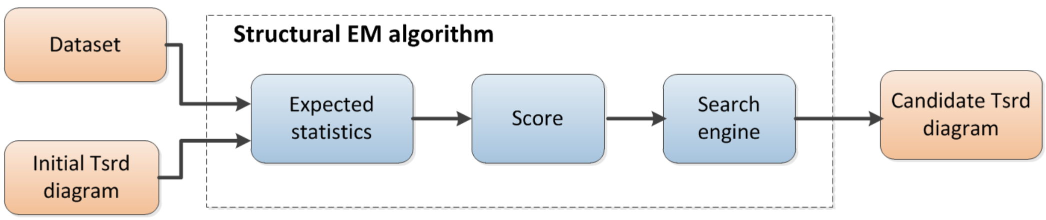

Figure 5.7: Structure Learning architecture.

5.2.2.3 Learning structure and parameters from the data set

The initial TSRD diagram alone is not usually good enough because there is often not sufficient causal knowledge to establish the structure of the network model. Learning the structure, causal relations and parameters from a data set is essential for refining and conditioning the TSRD diagram.

Structure learning is an optimisation problem whose goal is to obtain the best graph that represents the conditional independence relationships in the data. There are three main types of methods used for solving this problem: (i) constrained-based, where conditional independence tests are used on identifying relationship constraints,

(ii) score and search, where a score is employed to evaluate the fitness of the model, and a search method enables discovering the search space of acyclic directed graphs, and (iii) hybrid, which are a combination of the previous two [69] [79].

Figure 5.7 describes the process of applying the learning algorithm. The applied structural Expectation Maximization (EM) algorithm, which is a score and search method, requires an initial TSRD diagram $\mathcal{N}^0$ and a dataset $\mathcal{D}$ as a starting point for iteration. Learning the probabilities of attributes of the TSRD diagram from data is a form of unsupervised learning. The objective here is to deduce a network that best describes the probability distribution over the training data $\mathcal{D}$.

The structural EM algorithm is an extension to the standard Expectation Maximisation algorithm [27] and is described in [38] and [39]. The algorithm performs a search in the joint space of structure and parameters. At each step, it can either find better parameters from the current structure, or select a new structure. The function Q is the expected score, given by:

Algorithm 2: Learning structure and parameters from dataset

input : $\mathcal{D} = \{x^1, ..., x^n\}$: a data set
input : $\mathcal{N}^0 = (\mathcal{G}', \Theta^0)$: an initial network
output: $\mathcal{N}^* = (\mathcal{G}^*, \Theta^*)$: return the candidate network

begin
  Loop for n= 1,2,... until convergence **begin**
    Find a model $\mathcal{G}^{n+1}$ that maximises $Q(\mathcal{G}, \Theta : \mathcal{G}^n, \Theta^n)$
    Let $\Theta^{n+1} = Q(\mathcal{G}^{n+1}, \Theta : \mathcal{G}^n, \Theta^n)$
  return $\mathcal{N}^*$

$$Q(\mathcal{G}, \Theta : \mathcal{G}^*, \Theta^*) = E[\log P(O, h : \mathcal{G}, \Theta) - \text{Penalty}(\mathcal{G}, \Theta)] \tag{5.1}$$

where O are the observed variables, h are the values of the hidden variables, and the penalty depends on the dimensionality of $\mathcal{G}$. The procedure converges to a *local* maxima.

5.2.2.4 Assess structure and parameters

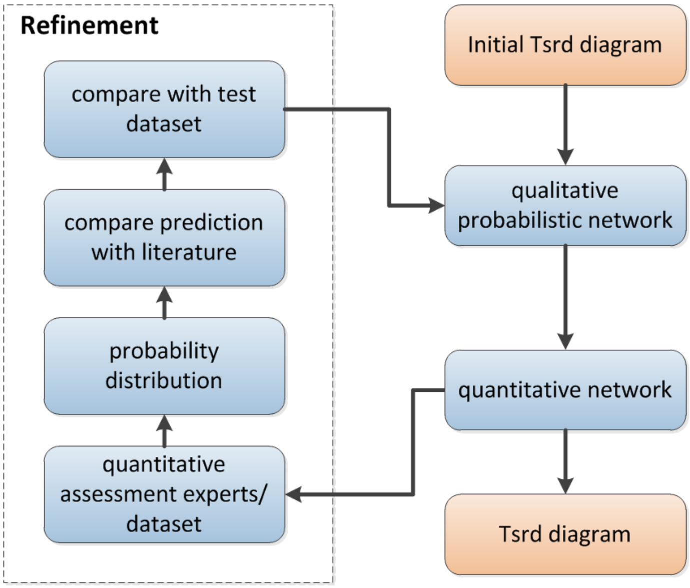

Figure 5.8: Evaluation & validation.

Figure 5.8 shows the evaluation and validation process. It is crucial that the structure and parameters of the model are validated. The structure evaluation can reveal that an important variable has been overlooked, or if irrelevant nodes have been included, node values that are not appropriate. Validation is a means to confirm that the model is an accurate representation of the domain. The evaluation and validation in this case concerns comparing the behaviour of a network.

5.3 Results and discussion

Figures 5.9 and 5.10 represent experimental results of transit service reliability diagnostic (TSRD) diagram before and after learning from the dataset in the case study. In Figure 5.9, after learning, the topology is changed, with two new arcs added. The new connections are from VehiclePosition node to In-vehicleLoad node and from Dwell-Time node to PassengerWaitTime node. After the validation step, the final diagram

is showed in Figure 5.10, and the conditional probability tables (CPTs) annotate the nodes. These represent how much reliability exists in the current transit network

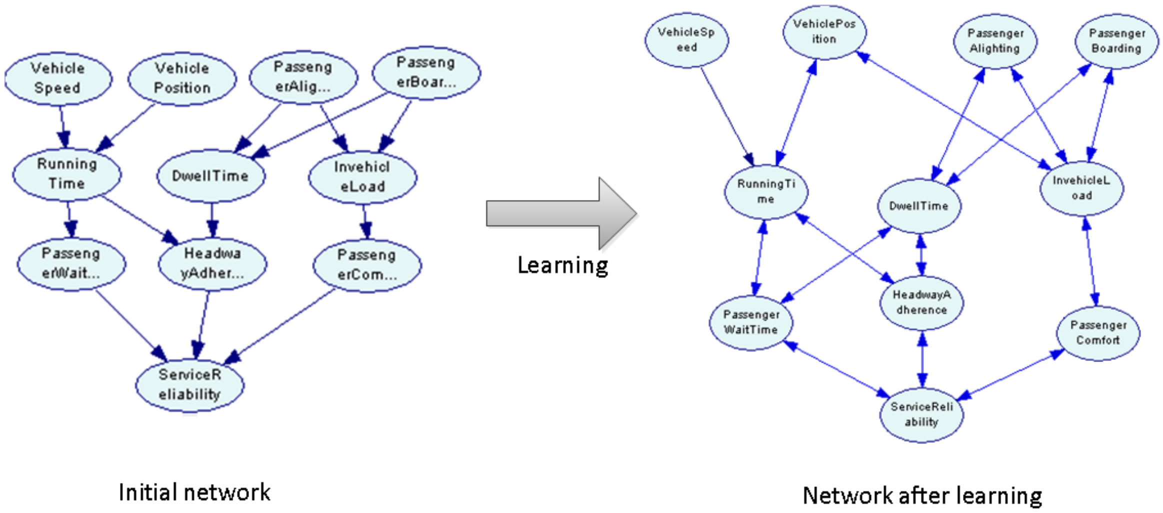

Figure 5.9: Result of learning process.

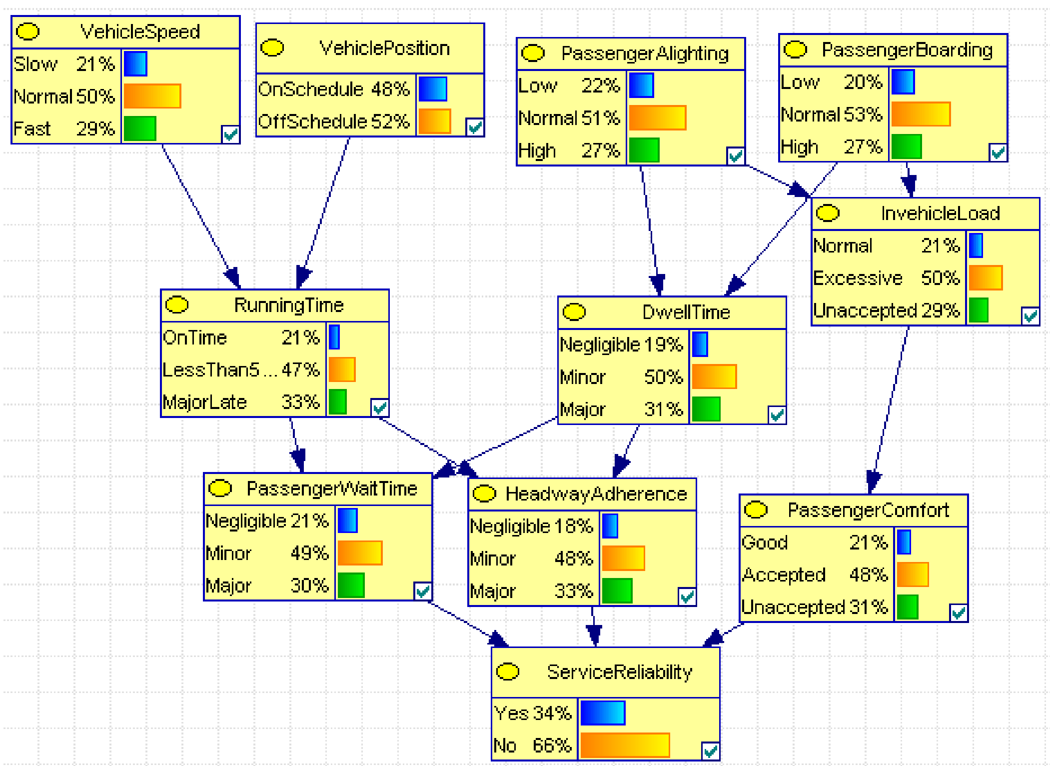

Figure 5.10: The final TSRD diagram: after learning.

data. Each row in a CPT contains the conditional probability of each node value for a conditioning case.

The diagrams are divided into direct and indirect indicators of service reliability. Direct indicators are: PassengerWaitTime, PassengerComfort and HeadwayAdherence. Indirect indicators are: RunningTime, DwellTime and In-vehicleLoad. The data comes from evidence nodes (VehicleSpeed, VehiclePosition, PassengerAlighting, and PassengerBoarding) which in turn changes the outcome of indirect and direct indicators.

The next sections show three ways of using TSRD diagram : (i) reasoning the causes of service unreliability; (ii) Offline analysis tool; (iii) and learning component for real-time decision making.

5.3.1 Reasoning the causes of service unreliability

Based on these results, measures to reduce service unreliability should balance PassengerWaitTime, PassengerComfort and HeadwayAdherence as the service unreliability is similarly impacted (posterior probability) by each of these three indicators. Figure 5.11 shows the posterior probability table of DwellTime impacted by PassengerAlighting and PassengerBoarding.

Transport management would be advised to better control these figures so that service reliability is improved. Of the indirect factors, DwellTime has the greatest posterior probability 0.81 (minor and major), as these factors affect PassengerWaitTime and HeadwayAdherence. The posterior probability for In-vehicleLoad and RunningTime is

PassengerAlighting	Low			Normal			High		
PassengerBoarding	Low	Normal	High	Low	Normal	High	Low	Normal	High
Negligible	0.21702128	0.19821429	0.14603175	0.22616822	0.14626866	0.18985507	0.26296296	0.21986755	0.19130435
Minor	0.45744681	0.53125	0.51587302	0.55607477	0.51679104	0.5326087	0.36111111	0.43377483	0.5
Major	0.32553191	0.27053571	0.33809524	0.21775701	0.3369403	0.27753623	0.37592593	0.34635762	0.30869565

Figure 5.11: Dwell Time Posterior Probability.

0.79. These probabilities are high enough to indicate that transportation management should pay more attention to scheduling and planning to improve running time and reduce passenger load. In some ways this is an obvious recommendation: namely that service reliability is improved by more buses and fewer passengers.

TSRD diagram is used to compute new probabilities when new information is acquired and to find a high probability joint assignment to some subset of indicators. Reasoning the causes of service unreliability presents via three reasoning patterns: evidential reasoning, causal reasoning and intercausal reasoning.

5.3.1.1 Evidential reasoning

Evidential reasoning is to reason from effects to causes (from bottom to up). It can be seen that RunningTime indicator and DwellTime indicator have a common effect:

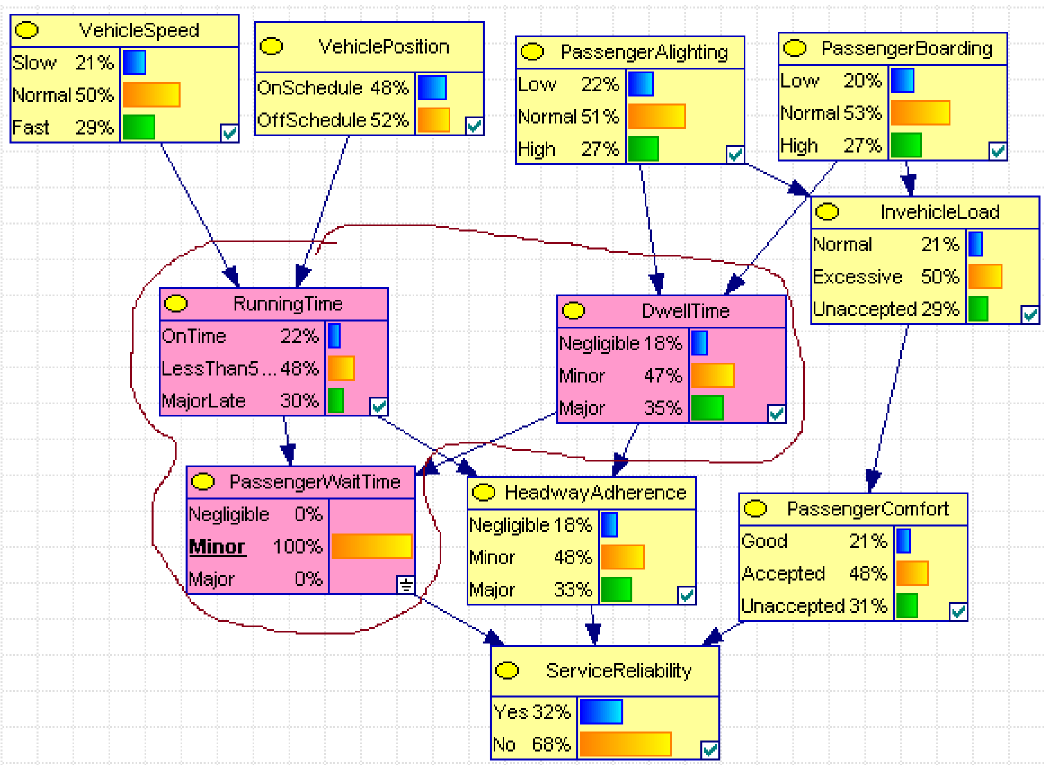

Figure 5.12: TSRD diagram: evidential reasoning.

PassengerWaitTime indicator. In Figure 5.12, we have added the evidence where PassengerWaitTime indicator takes Minor value. It can be seen that DwellTime indicator increases its Major value to 0.35, and decreases Minor value to 0.47 and Negligible value to 0.18. Another indicator to be taken into account is RunningTime indicator, which values go from 0.21 to 25.6 in OnTime state, from 0.47 to 0.48 in LessThan5Minutes state and 0.33 to 0.30 in MajorLate state. The instantiation of a common effect results in a dependency between its causes simply because each cause clarifies a way the appearance of the effect.

5.3.1.2 Causal reasoning

Causal reasoning is to reason from causes to effects (from top to bottom) of various factors. It can be seen that DwellTime indicator and In-vehicleLoad indicator have a

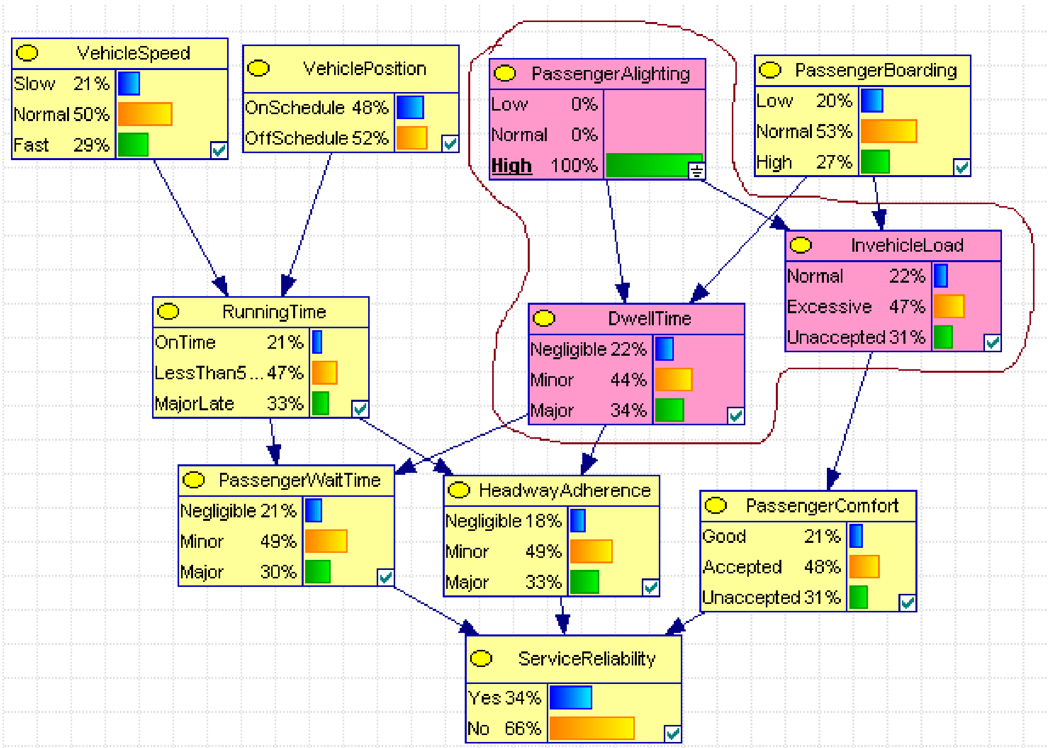

Figure 5.13: TSRD diagram: causal reasoning.

common cause: PassengerAligting indicator; which has causal links into both DwellTime and In-vehicleLoad indicators. Hence, DwellTime and In-vehicleLoad indicators have a dependency between them through this common cause. In Figure 5.13, it can be seen that when PassengerAligting indicator is instantiated to high value, then DwellTime indicator has Major state going from 0.31 to 0.34, and Minor state changing from 0.50 to 0.44; In-vehicleLoad indicator varies from 0.21 to 0.22 in Normal state, from 0.50 to 0.47 in Excessive state and from 0.29 to 0.31 in Unaccepted state. DwellTime indicator shows more influence when PassengerAligting indicator is instantiated to high value.

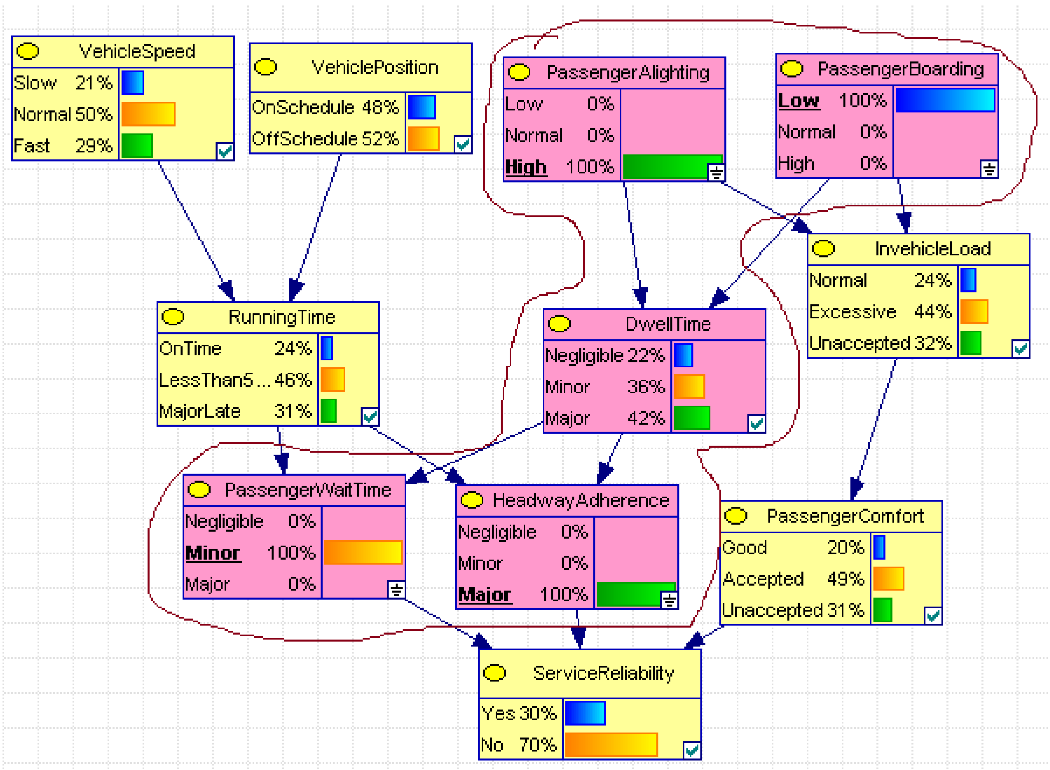

Figure 5.14: TSRD diagram: Intercausal reasoning.

5.3.1.3 Intercausal reasoning

Intercausal reasoning is to reason when different causes of the same effect can interact. In Figure 5.14 the variation on DwellTime indicator are mostly interested in studying. Trying to find the most likely assignment to DwellTime indicator is to compute $P(DwellTime = Major|e)$. In Figure 5.14, the most likely assignment to DwellTime indicator when PassengerAlighting indicator is instantiated to high, PassengerBoarding indicator is instantiated to low, PassengerWaitTime indicator is instantiated to Minor and HeadwayAherence is instantiated to Major.

5.3.2 Offline analysis tool

In the offline mode, historical data is used to study the impacts, namely the relationship between factors and to evaluate proactive decision/control decision to re-plan the strategies.
The use of TSRD diagram in offline analysis represents two aspects: Filtering and Smoothing.

Filtering: Filtering using a TSRD diagram is used to compute the belief state of the posterior distribution of transit service reliability over the most recent state, given all the observations (evidence) of the public transit factors made so far. In other words, its purpose is to compute $P(\mathcal{U}_{t+1}|e_{1:t+1})$, where $\mathcal{U}_t = \{\mathcal{D}_t,\ \mathcal{L}_t,\ \mathcal{R}_t,\ \mathcal{T}_{waitt},\ \mathcal{H}_{adherencet},\ \xi_{comfort_t},\ \mathcal{SR}_t\}$ denotes the set of unobservable state variables at time t, $\mathcal{E}_t = \{\mathcal{V}_t,\ \mathcal{X}_t,\ \mathcal{A}_t,\ \mathcal{B}_t\}$ denotes the set of observable evidence variables e_t and $P(e_{1:t+1})$ denotes the likelihood of the evidence sequence.

Filtering is used for state estimation of the transit network so that rational decisions can be made for real-time decision making component. To demonstrate use of filtering of TSRD diagram, an example of computing the prediction for the probability of service

reliability from time = 0 to time = 2 is illustrated as follows: At the beginning of bus schedule $t = 0$, there are no new observations yet, only prior belief of past service reliability $P(SR_0)$. In the next 5 minutes (assuming time slicing is 5 minute intervals) $t = 1$, new observations $\mathcal{V}_1$, $\mathcal{X}_1$, $\mathcal{A}_1$, $\mathcal{B}_1$ available. At time $t = 2$, there are more new observations $\mathcal{V}_2$, $\mathcal{X}_2$, $\mathcal{A}_2$, $\mathcal{B}_2$. Prediction of service reliability from $t = 0$ to $t = 2$ is as follows:

$$\begin{aligned} P(\mathcal{SR}_2|\mathcal{V}_1, \mathcal{X}_1, \mathcal{A}_1, \mathcal{B}_1, \mathcal{V}_2, \mathcal{X}_2, \mathcal{A}_2, \mathcal{B}_2) &= P(\mathcal{SR}_2|\mathcal{T}_{wait2}, \mathcal{H}_{adherence2}, \xi_{comfort_2}) \\ &\times P(\mathcal{T}_{wait2}|\mathcal{R}_2, \mathcal{D}_2) \times P(\mathcal{H}_{adherence2}|\mathcal{R}_2, \mathcal{D}_2) \\ &\times P(\xi_{comfort_2}|\mathcal{L}_2) \times P(\mathcal{R}_2|\mathcal{V}_1, \mathcal{X}_1, \mathcal{V}_2, \mathcal{X}_2) \\ &\times P(\mathcal{D}_2|\mathcal{A}_1, \mathcal{B}_1, \mathcal{A}_2, \mathcal{B}_2) \times P(\mathcal{L}_2|\mathcal{A}_1, \mathcal{B}_1, \mathcal{A}_2, \mathcal{B}_2) \end{aligned} \tag{5.2}$$

Smoothing Smoothing using a TSRD diagram is carried out to compute the posterior distribution over a past state, given all the observations (evidence) of the public transit factors made to date. In other words, it is to compute $P(\mathcal{U}_k|e_{1:t})$, where $0 \leqslant k < t$.

Smoothing is used to refine the past estimation of TSRD diagram. To demonstrate use of smoothing of TSRD diagram, an example of computing the past estimation for the probability of service reliability at time $k = 1$, given the observations at times $t = 1$

and $t = 2$, is calculated as follows:

$$\begin{aligned} P(\mathcal{SR}_1|\mathcal{V}_1, \mathcal{X}_1, \mathcal{A}_1, \mathcal{B}_1, \mathcal{V}_2, \mathcal{X}_2, \mathcal{A}_2, \mathcal{B}_2) &= P(\mathcal{SR}_1|\mathcal{T}_{wait1}, \mathcal{H}_{adherence1}, \xi_{comfort_1}) \\ &\times P(\mathcal{T}_{wait1}|\mathcal{R}_1, \mathcal{D}_1) \times P(\mathcal{H}_{adherence1}|\mathcal{R}_1, \mathcal{D}_1) \\ &\times P(\xi_{comfort_1}|\mathcal{L}_1) \times P(\mathcal{R}_1|\mathcal{V}_1, \mathcal{X}_1, \mathcal{V}_2, \mathcal{X}_2) \\ &\times P(\mathcal{D}_1|\mathcal{A}_1, \mathcal{B}_1, \mathcal{A}_2, \mathcal{B}_2) \times P(\mathcal{L}_1|\mathcal{A}_1, \mathcal{B}_1, \mathcal{A}_2, \mathcal{B}_2) \end{aligned} \tag{5.3}$$

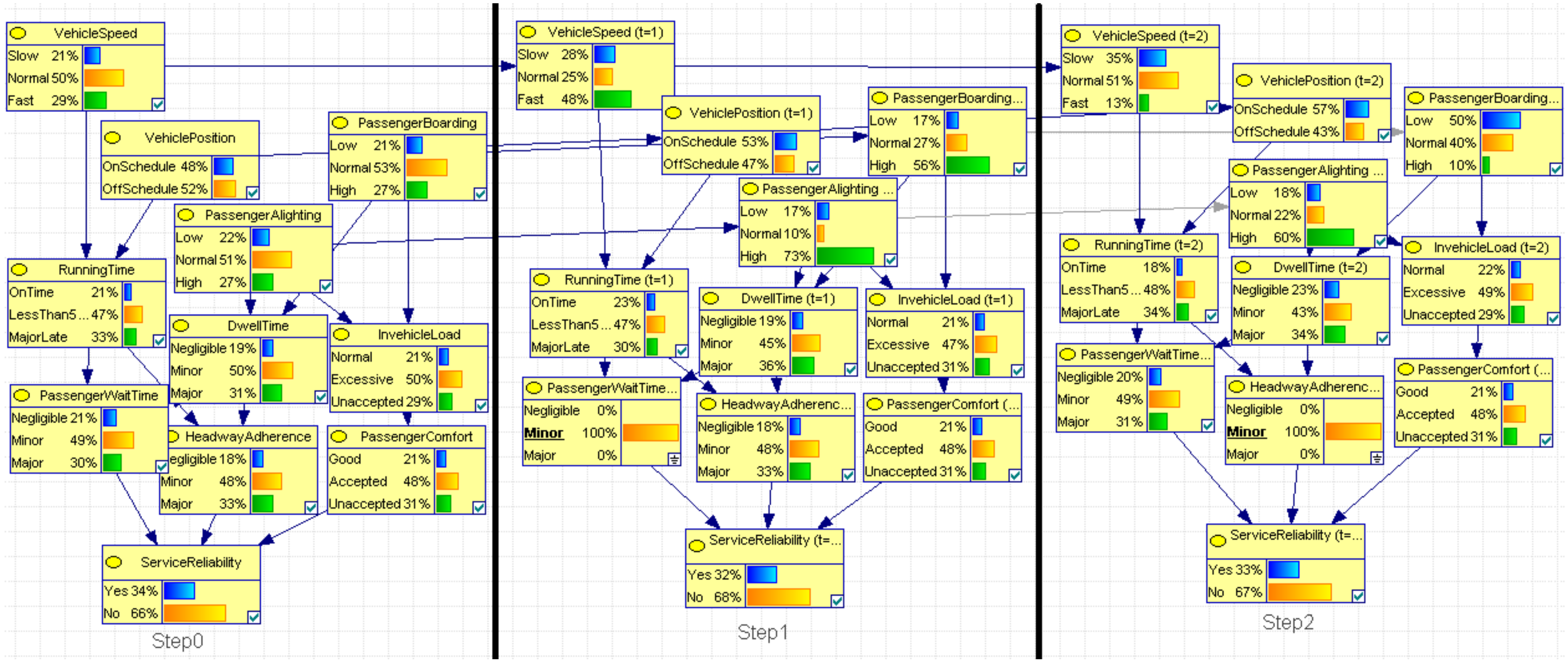

Figure 5.15: Dynamic network model with 3 time slices.

Figure 5.15 shows a result of dynamic network model, monitoring the state of the system with 3 time slices for a bus network. Each time step models the state of the bus network at a specific point in time; the lines present the separation of the model into time slices.

5.3.3 Learning component for real-time decision making

As shown in Figure 5.16, knowledge representation of the assessment framework is used as prior knowledge of real-time control strategies. Learning enables the transit systems functioning in initially unfamiliar environments and to become more competent than its preliminary knowledge.

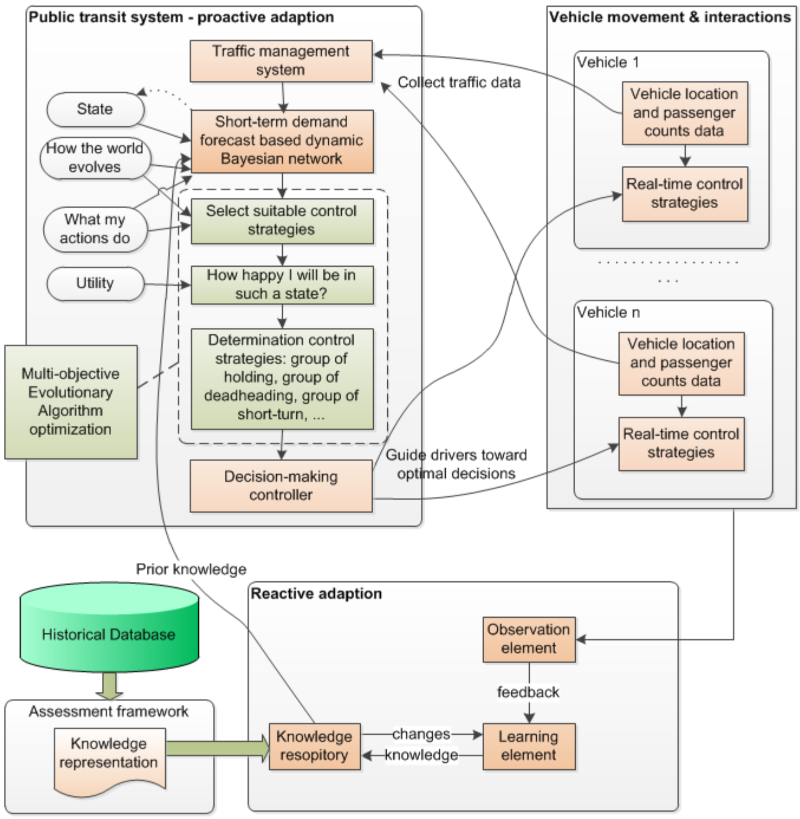

Figure 5.16: Learning Component.

Learning element is responsible for making enhancements, and the knowledge

repository. The learning element utilizes feedback from the observation element on how the transit system is doing and decides how the knowledge repository should be revised to perform better in the future. It will help to evaluate driving and travel behavior. There is an interaction between the driver and the system; the driver not only is a user of the system, but also a part of the system itself. The feedback/lessons that they have received from their interaction with the system will help them to adjust their behavior.

Observation of the results of its actions can permit the bus to learn "What my actions do.". The buses goes out on the road and drives use knowledge repository. The observation element observes the world and passes information along to the learning element. From this experience, the learning element is able to formulate a rule saying this was a bad or good action, and the knowledge repository is modified by installation of the new rule.

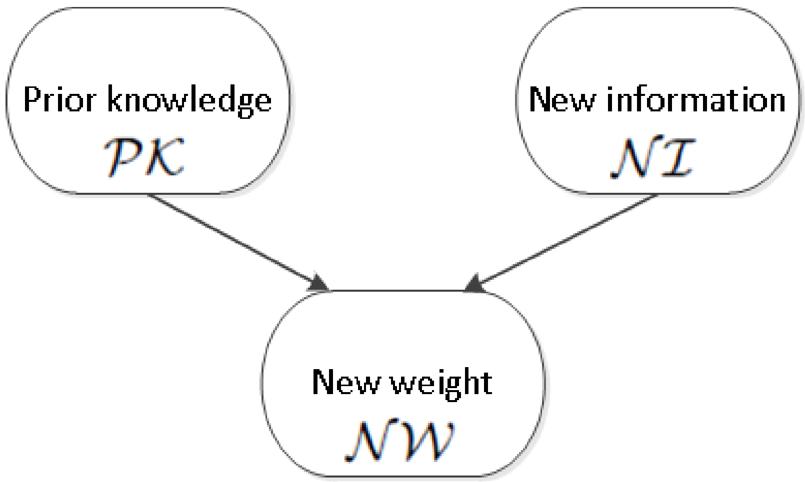

Figure 5.17: Role of prior knowledge in learning.

Figure 5.17 shows the role of prior knowledge in the learning process, which supports decision makers. Equation in [112] is used to calculate the relationship of prior

knowledge $\mathcal{PK}$, new information $\mathcal{NI}$ and new knowledge weight $\mathcal{NW}$ as follows:

$$g(\mathcal{NW}|\mathcal{PK},\mathcal{NW}) = \frac{\pi(\mathcal{NW}) \times P(\mathcal{PK},\mathcal{NI}|\mathcal{NW})}{\pi(\mathcal{NW})} \tag{5.4}$$

This Equation means that once new evidence of $\mathcal{NI}$ node in the network is obtained, the new estimation of $\mathcal{NW}$ node in the network can be updated using the new information. The weight $\mathcal{NW}$ is viewed as the result of the joint influence of new information and prior information. Any change in the new information or prior information can lead to the change of the weights.

With the increasing complexity of decision, decision makers often have to consider the current and past information of each alternative. The use of prior knowledge in learning results in a picture of cumulative learning simply where learning process boost learning ability as they obtain more knowledge.

5.4 Conclusion

Modern transport data-collection systems provide rich sources of information which can potentially do a lot more than meet traditional reporting needs. They generate larger and richer data streams from AVL and APCs that can be mined. Modern scheduling and customer service monitoring is oriented around extreme values (outrider events) rather than traditional mean values. This is mainly because of the large sample sizes produced by automatic data collection and so attention focuses on unusual events rather than the routine.

As these kinds of information are characterized as heterogeneous and uncertain, the multi-dimension framework presented in this chapter is to serve as our knowledge model to analyze automatic data collection. The TSRD diagram of the framework has the advantages of an intuitive visual representation with a sound mathematical

basis in Bayesian probability and provides an effective approach for analysis of the public transit system to reveal the hidden structure and its relationships, and more importantly, its rules. The framework can be used in three ways: (i) as a guide for reasoning the causes of service unreliability (evidential reasoning, causal reasoning, and intercausal reasoning); (ii) as an offline analysis tool to improve service quality (filtering, and smoothing) and; (iii) as a learning component for real-time decision making. A case study is used to evaluate and demonstrate the use of the multi-dimension framework.

Chapter 6

Conclusions

This chapter summarises the main components of the proposed framework for applying a digital ecosystem metaphor that extends the use of AVL and APC data for the benefit of transit agencies, the major findings of the application of the framework on the Gwynneville-Keiraville bus route in the central region of the regional city of Wollongong, and future extensions and research.

Section 6.1 briefly describes components of the proposed framework. The results of the case study of bus operations on the Gwynneville-Keiraville bus route in the central region of the regional city of Wollongong are presented in Section 6.2. Finally, Section 6.3 suggests extensions to the proposed framework and areas of future research.

6.1 Research summary

This research suggests a digital ecosystem framework that is generic, and therefore could be conveniently employed to various aspects of bus (along with other transport modalities) operational strategies over their whole-of-life-cycles. With data collection from AVL and APC, the framework targets on offering bus service reliability with regards to improving headway, minimizing passenger wait time, and maintaining passenger comfort along with supporting real-time proactive, reactive schedule and resource adaptation.

The presented framework consists of three components: 1) Evolutionary simulation; 2) Proactive adaptation; and 3) Reactive adaptation. The simulation is built up to demonstrate the interaction between buses, passengers in the transit environment. Proactive adaptation makes it possible for the system to foresee demand to be able to respond optimally, and reactive adaptation is the functionality of the system to assimilate historical data and reinforce its performance over time. The contribution of the research is the combined contribution of each design artefact.

The main contribution of Evolutionary simulation component lies in the development of the laboratory environment as a foundation framework for evaluating operations and applying control strategies to study the factors influencing network reliability. A simulation model also supplies visual elements permitting its user to visualize variability of movement, passenger demand and other factors having an influence on bus operations. The environment is intended to make use of the data automatically collected from bus systems. Such a tool is useful to researchers and public transport service providers alike.

The main contribution of the Proactive component is to develop and implement a component capable of dealing with uncertainty that comes from within the transit environment and through the randomness of passenger arrivals, reason about current states, and predict future states along with multi-objective optimization at each time slice in order to find appropriate strategies that preserve bus service reliability. Bus service reliability in our work takes into account passenger wait time, headway adherence, in-vehicle time, and passenger comfort, which are combined via Pareto comparisons in the fitness assignment processes. It supports decision-making on the route and at a station or stop and provides multiple control strategies (preventive control, holding, expressing, short-turning, deadheading) which are integrated in the same decision making mechanism.

The main contribution of the Reactive component is to develop an assessment framework to uncover and evaluate the performance of the transit network. Transit knowledge of the framework constructed from data from AVL-APC, which is heterogeneous and uncertain, is presented via a transit service reliability diagnostic (TSRD) diagram based on a Bayesian network, offering an efficient approach for the investigation of the public transit system to expose the hidden structure and its relationships. A TSRD diagram is able to symbolize cause-effect relationships among transit factors and expresses how each factor will influence others. A TSRD diagram can be utilized in three ways: (i) as a guide for reasoning the causes of service unreliability (evidential reasoning, causal reasoning, and intercausal reasoning); (ii) as an offline analysis tool to improve service quality (filtering, and smoothing) and; (iii) as a learning component for real-time decision making.

6.2 Major findings

This section summaries the findings of the research through building and implementing three artefacts.

With regards to the Evolutionary simulation component, the results show that it simulates the transit environment accurately. GUI of the simulation aids verify that the route layout configurations are correct, implementation of passenger demand, terminal and bus behavior vehicle behavior near or at a stop are computed and developed accurately. Model validation of the simulation model results were validated by a comparison to the observed headway, dwell time, trip time, and schedule adherence on route Gwynneville-Keiraville. Test statistics in Section 3.8 show that they are not statistically significantly different from the real world observations. Passenger demand, arrival and departure behavior, and dwelltime are modeled to vary around the observed value to simulate the influence of each factor on service reliability.

With Regards to the Proactive adaptation component, the results is shown in Section 4.3.2, the control strategy boosts service reliability by lowering headway variability, which in turn leads to shorter passenger waiting times. There is more vehicle bunching in headway adherence without control while headway adherence with control shows more even headway via space-time headway adherence measurement. Fewer bunched buses aid bus service and passenger loads in better allocated along the route due to the fact buses following a larger gap are more likely to be heavily loaded as they pick up all passengers who may have arrived since the previous bus. Bus reliability at the stop level is considered from a passengers point of view, which can then be used to enhance reliability from a passengers perspective. Stop-based reliability measurement is also used to measure stop-based reliability. The results show that there was low service reliability for the bus transit network prior to applying the control strategies. Applying control strategies assists dramatically strengthen service reliability.

Control strategies might result in delays to on-board passengers and longer travel times that could cause higher fleet costs. Nevertheless, improved uniformity of headways is effective in reducing the in-vehicle time of the passengers at the subsequent stops. Furthermore, passenger waiting time at bus stops can in practice be regarded more significant than passenger in-vehicle waiting time.

With Regards to the Reactive adaptation component, the results is shown in Section 5.3, after learning from the dataset, the topology of the knowledge representation of the assessment framework is changed, the new connections are added from VehiclePosition node to InvehicleLoad node and from DwellTime node to PassengerWaitTime node. After the validation step, the casual connection from VehiclePosition node to InvehicleLoad node is eliminated as the expert judgement is that it is inappropriate. Knowledge representation presented via final TSRD diagram, are divided into Direct indicators: passenger wait time, passenger comfort and headway adherence and in-

direct indicators are: running time, dwell time and in-vehicle load. The data arises from evidence nodes (vehicle speed, vehicle position, passenger alighting, passenger boarding) which in turn changes the outcome of indirect and direct indicators.

According to our results, measures to lower service unreliability should balance passenger wait time, passenger comfort and headway adherence as service unreliability is similarly influenced (posterior probability) by each of these three indicators. The result is also used to study the impacts, namely the relationship between factors and to evaluate proactive decision/control decision to re-plan the strategies. Moreover, it is used as prior knowledge of real-time control strategies. Learning enables the transit systems functioning in initially unfamiliar environments and to become more competent than its preliminary knowledge.

6.3 Future research

The case study application of the framework for optimizing service reliability revealed a number of areas for future extensions.

6.3.1 Development of model

The model needs to be developed to further discover the interrelationship among factors behind service unreliability as the complexities of reasons behind service unreliability were not fully examined.

6.3.2 Adaption to other public transit systems

This simulator design enables the model to be extended to simulate other control strategies via configurable inputs and be able to adapt to any other high-frequency bus route with the same assumptions.

Appendix A

A.1 Notation list

The following variables and parameters are used in the proposed formulations:

n: number of vehicles

m: number of bus stops

i: index of vehicles, i = 1,..., n

k: index of stops, k = 1,..., m

I: set of buses operating on the route $I = \{1, 2, 3, ..., n\}$

K: set of station on the route $K = \{1, 2, 3..., m\}$

$\mathcal{A}_{i,k}$: number of passengers alighting vehicle i at stop k

$\widetilde{\mathcal{A}}_{i,k}$: forecast/estimate number of passengers alighting vehicle i at stop k

$\mathcal{B}_{i,k}$: number of passengers boarding vehicle i at stop k

$\widetilde{\mathcal{B}}_{i,k}$: forecast/estimate number of passengers boarding vehicle i at stop k

$\mathcal{L}_{i,k}$: number of on-board passengers of vehicle i when it departs stop k

$\widetilde{\mathcal{L}}_{i,k}$: forecast/estimate number of on-board passengers of vehicle i when it departs stop k

$\mathcal{P}_{i_k}$: Number of passengers left behind by bus i at stop k

$\mathcal{PD}_{i,k}$: number of passengers waiting for bus i at stop k

$\widetilde{\mathcal{PD}}_{i,k}$: forecast/estimate number of passengers waiting for bus i at stop k

$\mathcal{D}_{i,k}$: dwell time for vehicle i serving the passengers boarding and alighting at stop k

$\widetilde{\mathcal{D}}_{i,k}$: forecast/estimate dwell time for vehicle i serving the passengers boarding and alighting at stop k

α: average alighting time for each passenger

β: average boarding time for each passenger

λ_k: passenger arrival rate (number of persons per minute) at stop k

ρ_k: passenger alighting fraction of the on-board passenger at stop k

$\mathcal{H}_{i,k}$: leading headway of vehicle i departing from stop k

$\widetilde{\mathcal{H}}_{i,k}$: forecast/estimate leading headway of vehicle i departing from stop k

$\mathcal{R}_{i,k}$: running time of vehicle i from stop $k-1$ to stop k, including time spent accelerating from stop $k-1$ and decelerating to stop k

$\widetilde{\mathcal{R}}_{i,k}$: forecast/estimate running time of vehicle i from stop $k-1$ to stop k, including time spent accelerating from stop $k-1$ and decelerating to stop k

$\mathcal{V}_i$: speed of vehicle i

$\mathcal{X}_i$: position of vehicle i

$\mathcal{L}_{max}$: maximum passenger capacity of vehicle

$\mathcal{L}_{seated}$: maximum passenger seated capacity of vehicle

$\mathcal{L}_{standing}$: maximum passenger standing capacity of vehicle

$\mathcal{SH}$: scheduled headway

$\mathcal{HT}$: holding time

ε: standard headway deviation

$\mathcal{AA}_{i,k}$: actual arrival time of vehicle i at stop k

$\widetilde{\mathcal{AA}}_{i,k}$: forecast/estimate arrival time of vehicle i at stop k from stop $k-1$

$\mathcal{AD}_{i,k}$: actual departure time of vehicle i at stop k

$\widetilde{\mathcal{AD}}_{i,k}$: forecast/estimate departure time of vehicle i at stop k from stop $k-1$

$\mathcal{T}_{wait}$: passenger waiting for the vehicle at stop

$\mathcal{T}_{impact}$: passenger waiting on the vehicle

$\mathcal{H}_{adherence}$: headway adherence of the bus

$\xi_{comfort}$: passenger comfort

$\mathcal{D}$: main dataset

$\mathcal{B}$: a Bayesian Network

$\mathcal{X}, \mathcal{Y}, \mathcal{Z}$: one dimensional variable

x, y, z: value of corresponding variables $\mathcal{X}, \mathcal{Y}, \mathcal{Z}$

n: number of variables

$\mathcal{G}$: directed acyclic graph of a Bayesian Network

$\mathcal{U}$: universe, set of variables (nodes in the domain $U_1, ..., U_n$)

$\mathcal{E}$: set of edges of a Bayesian Network

Appendix B

B.1 Data Collection System: PCN-1001 Programming

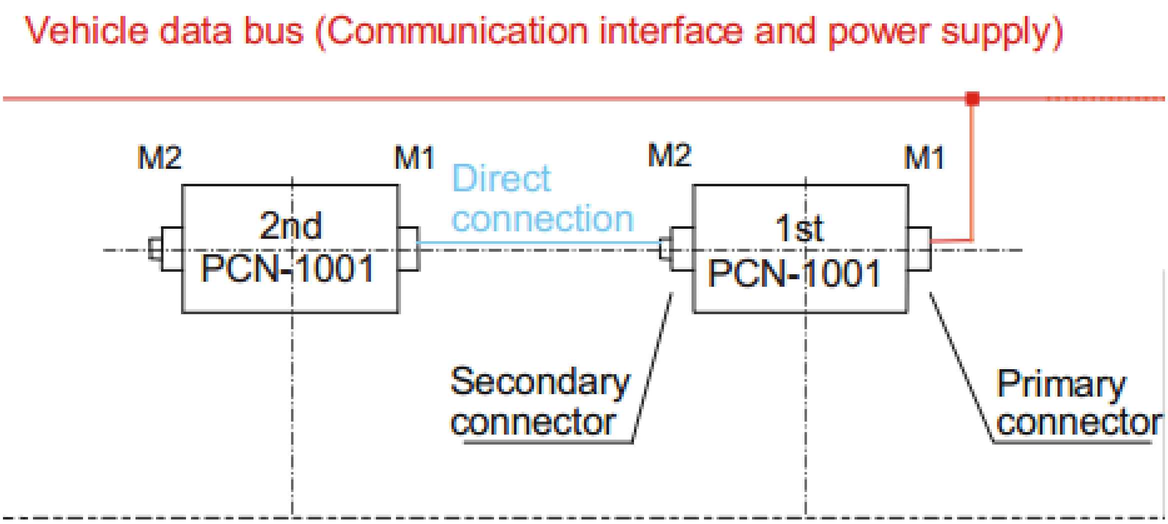

Figure B.1: PCN Network Configuration (Source [105]).

The Data Collection System collects the counter parameters of various PCN-1001 systems installed into a bus. These data will be stored in onboard computer VTC 2100 and synced back to Server constantly.

By employing the RS485 port built in PCN-1001, it is able to to create a network

of PCN-1001 systems managed by a Central Unit via the data bus of the vehicle as shown in Figure B.1. The Central Unit is the "Master" device. The PCN-1001 devices are "Slaves", each one with a different network address.

B.1.1 RS485 port set-up

Command	Description	Values
serial_id	Sets the PCN-1001 address in the RS485 network.	Between 0 and 254
serial_br	Sets the port baud rate	0x7 = 300 bits/sec 0x8 = 600 bits/sec 0x9 = 1200 bits/sec 0xb = 2400 bits/sec 0xc = 4800 bits/sec 0xd = 9600 bits/sec 0xe = 19200 bits/sec 0xf = 38400 bits/sec 0x1001 = 57600 bits/sec 0x1002 = 115200 bits/sec 0x1003 = 230400 bits/sec 0x1004 = 460800 bits/sec 0x1007 = 921600 kbits/sec
serial_db	Sets the data byte size	0x20 = 7 bits 0x30 = 8 bits
serial_pr	Sets the parity	0 = none 0x100 = even 0x300 = odd
serial_sb	Sets the number of stop bits	0 = one bit 0x40 = two bits

Figure B.2: Configuration of RS485 Port(Source [105]).

Table B.2 shows commands to configure the RS485 port on the PCN-1001. Before starting communications, it is crucial to verify that the RS485 port configuration (Baud Rate, Data Bits, Parity and Stop Bits) is correct.

B.1.2 The SNP protocol

Table B.3 show the message format of SNP Protocal. The packet format includes the addresses of both the sender and recipient and the number of packets to be sent with the current packet number. Bit stuffing is not used because, once the length of data

Name	Length (bytes)	Contents
PreAmble	5	5 times 0xFF, to be sent prior to the initial character in order to give time for change of transmission direction
StartCharacter	1	SOH = 0x01
Source	1	Address of sender
Destination	1	Address of recipient
TotalPacketNumber	1	Total number of packets
PacketNumber	1	Number of this packet First packet has number 1
DataLength	2	States the length of the data field LSB (Least Significant Byte) is to be sent first
Data	0 to MAX_DATA_LENGTH	Each byte can contain 0 to 0xFF
CRC16	2	CRC16 (x16 x15 x2 x0) check sum calculated from Source to Data (both fields included) with an initial value of -1. LSB is to be sent first
Postamble	1	0xFF.

Figure B.3: SNP Protocol: Message Format(Source [105]).

field is stated, all values can be sent in the data field. The length of the data field can be maximum $MAX\_DATA\_LENGTH = 1024$ bytes.

There is only one master on the bus, all others are slaves. When the master has sent a message to a slave, slave replies with an answered message. A slave cannot send anything to a master without being requested. It is able to send requests to all slaves at a time (broadcast).

B.1.3 Broadcast Message

Each message between "Master" and "Slave" is formed in the following format:

Source	Destination	TotalPacketNumber	PacketNumber	DataLength

Figure B.4: SNP Protocol: Broadcast Message (Source [105]).

where:

Source: Address of the device transmitting the message

Destination: Address of the target device

TotalPacketNumber: Quantity of Packets to be sent

PacketNumber: The number of the current packet being sent

DataLength: Length of the data in thisPacket [0x01 to 0xFE or MAX (255)]

B.1.4 Data Field

All the commands exchanged between the Master and the Slave units have to be encapsulated in the SNP transmission.

Name	Length (bytes)	Contents
Command	0-256 bytes	Command
String terminator	1	0
Value 1	1,2,4	First parameter
Value 2	1,2,4	Second parameter
....	1,2,4	....

Figure B.5: SNP Protocol: Data Field (Source [105]).

The string, the string terminator and some parameters form all the commands. Each parameter can be a number or a string. The message is included in the data field of the SNP protocol. This field can have a maximum length contained in the MAX_DATA_LENGTH.

Appendix C

C.1 CmdeSim Simulation: Software Design

This appendix describes CmdeSim Simulation in terms of software design. Figure C.1 shows the organisation of CmdeSim source code and the relationship of nine main packages of the source code is shown in Figure C.2. These main packages are:

- uow.cmde.transim.util package, which implements utilities libraries for other packages;
- uow.cmde.transim.view package, which implements view layer for the simulation;
- uow.cmde.transim.osmmap package, which implements map component for the simulation;
- uow.cmde.transim.transit.model package, which implements core model objects of the transit operations;
- uow.cmde.transim.transit.demandmodel package, which implements model for passenger demand;
- uow.cmde.transim.historydata package, which simulates passenger demand from database;

- uow.cmde.transim.offline.tools package, which implements offline analysis tools;
- uow.cmde.transim.multiobjective package, which implements real time control strategies;
- uow.cmde.transim.transit.outputanalysis package, which implements analysis of control strategies.

Figure C.3 shows the relationship of classes of model objects in transit operations, which includes modelling stop object, route object, shape object, and vehicle object. These classes provide information for controller and view layer.

Figure C.4 shows the relationship of classes of transit operations, which includes drawing street maps, routes and vehicles, simulating passenger demand for each stop by time and day, and operations at stop(passenger boarding and alighting).

Figure C.5 shows the relationship of classes of real time optimization, which includes short-term prediction, multi-objective evolutionary algorithm, and control strategy.

Figure C.6 shows the relationship of classes of offline analysis, which includes constructing Tsrd diagram from database, and generating metrics to evaluate the effect of control strategies.

Figure C.7 shows the sequence diagram of transit operations, which includes sequence operations from simulating transit entities to performing stop operations.

Figure C.8 shows the sequence diagram of real time optimization, which includes sequence operations from forecasting transit service reliability to applying optimization algorithm to control transit operations.

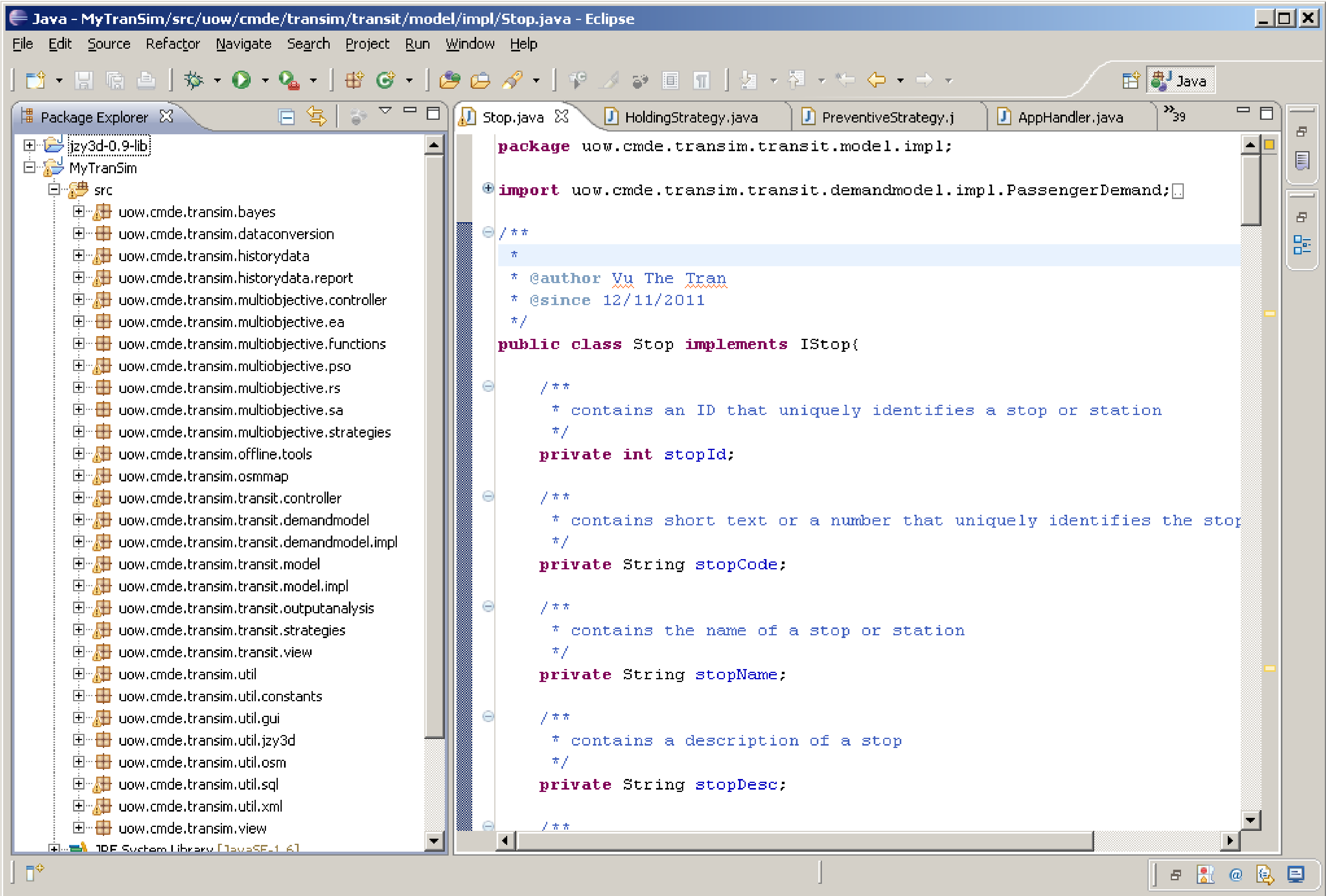

Figure C.1: Code in Eclipse.

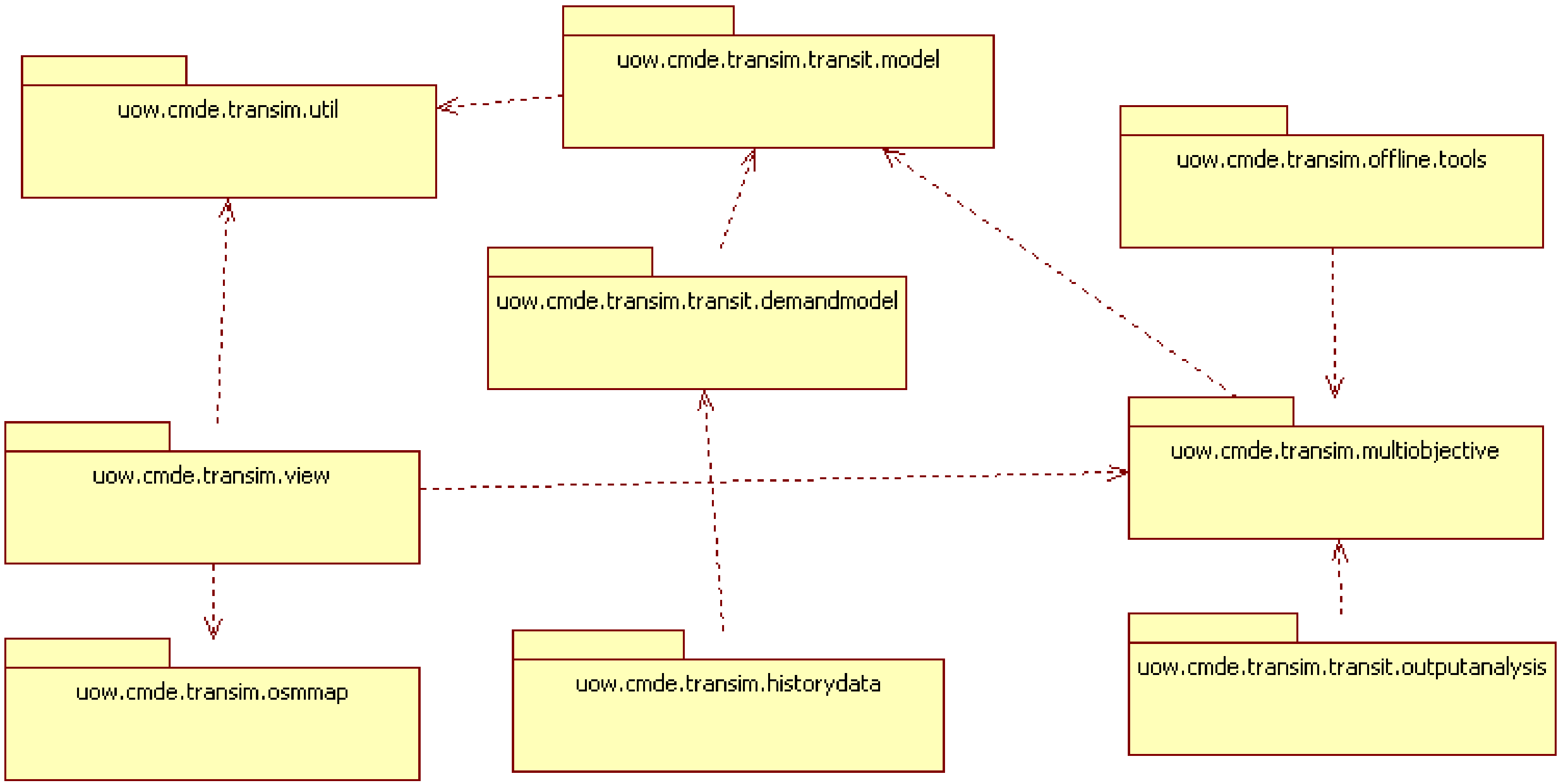

Figure C.2: Package Diagram.

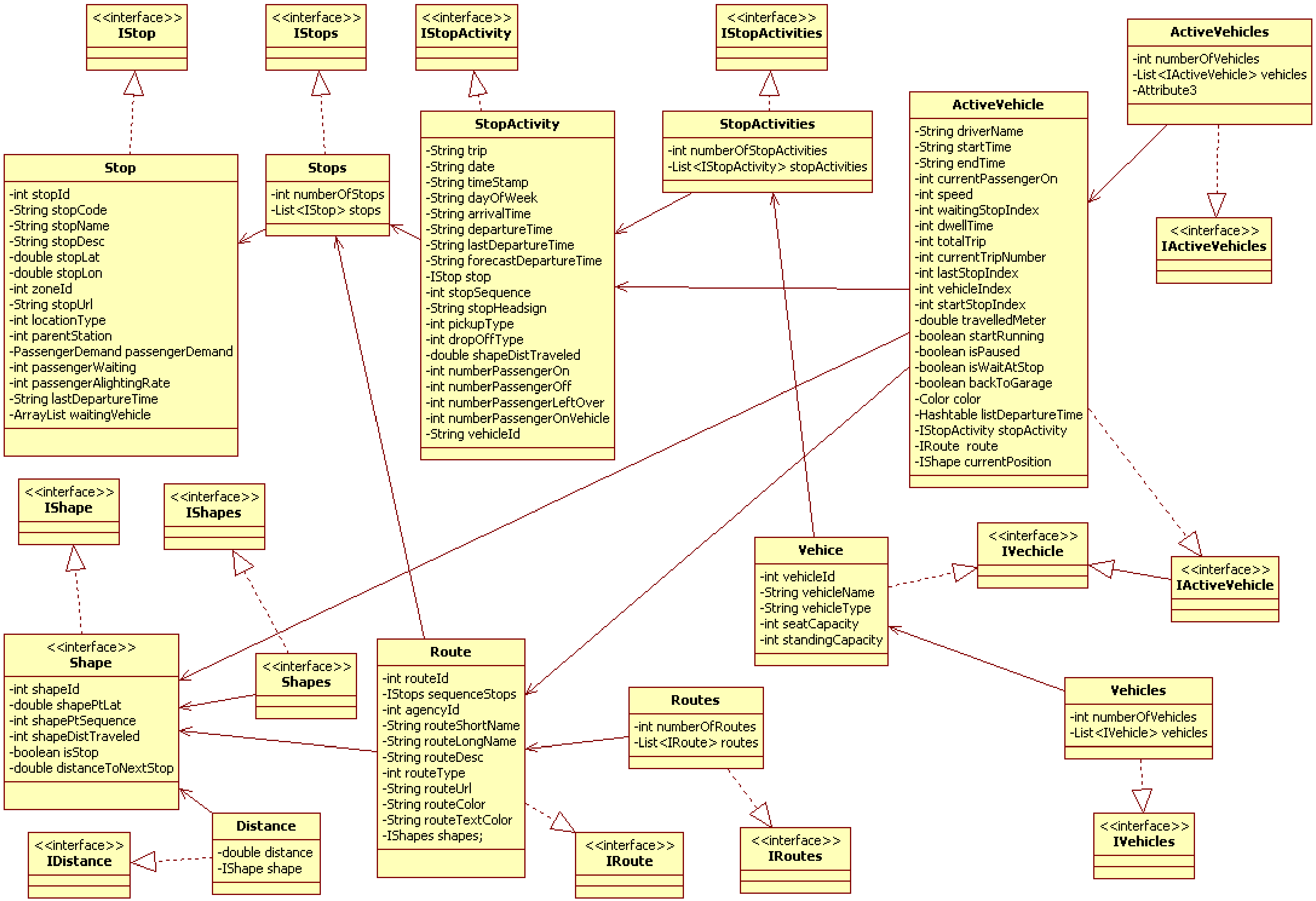

Figure C.3: Class Diagram: model objects.

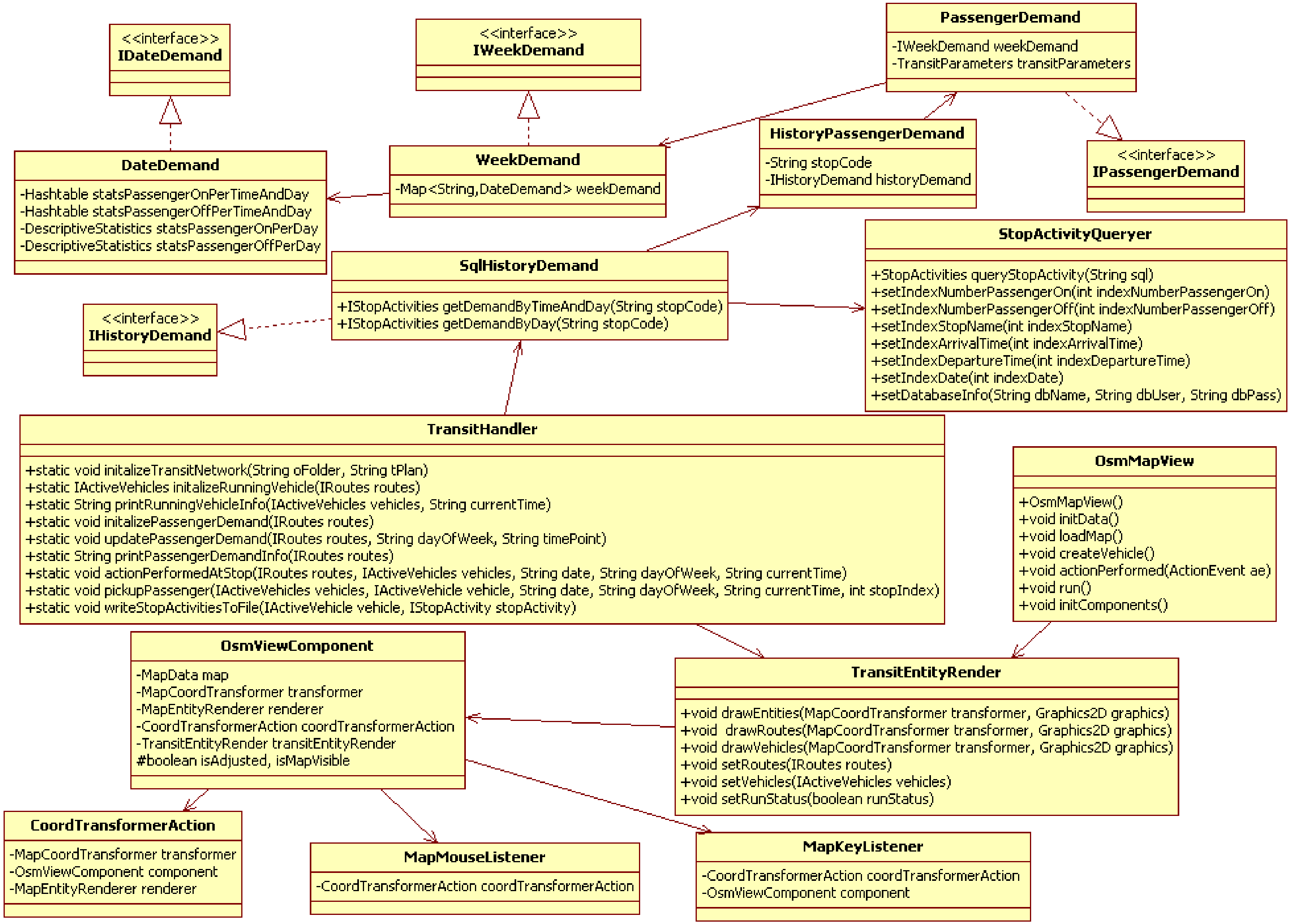

Figure C.4: Class Diagram: transit operations.

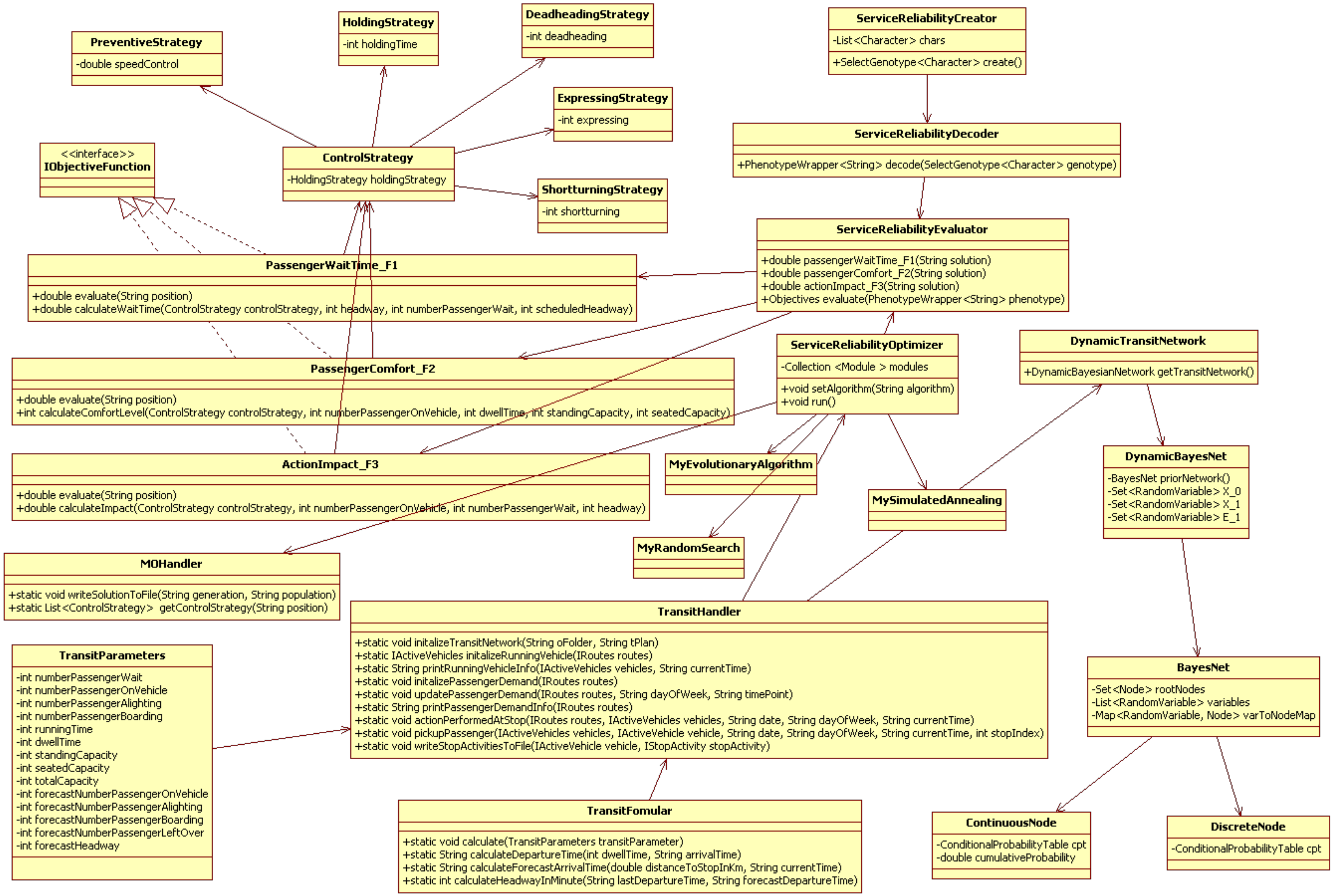

Figure C.5: Class Diagram: real time optimization.

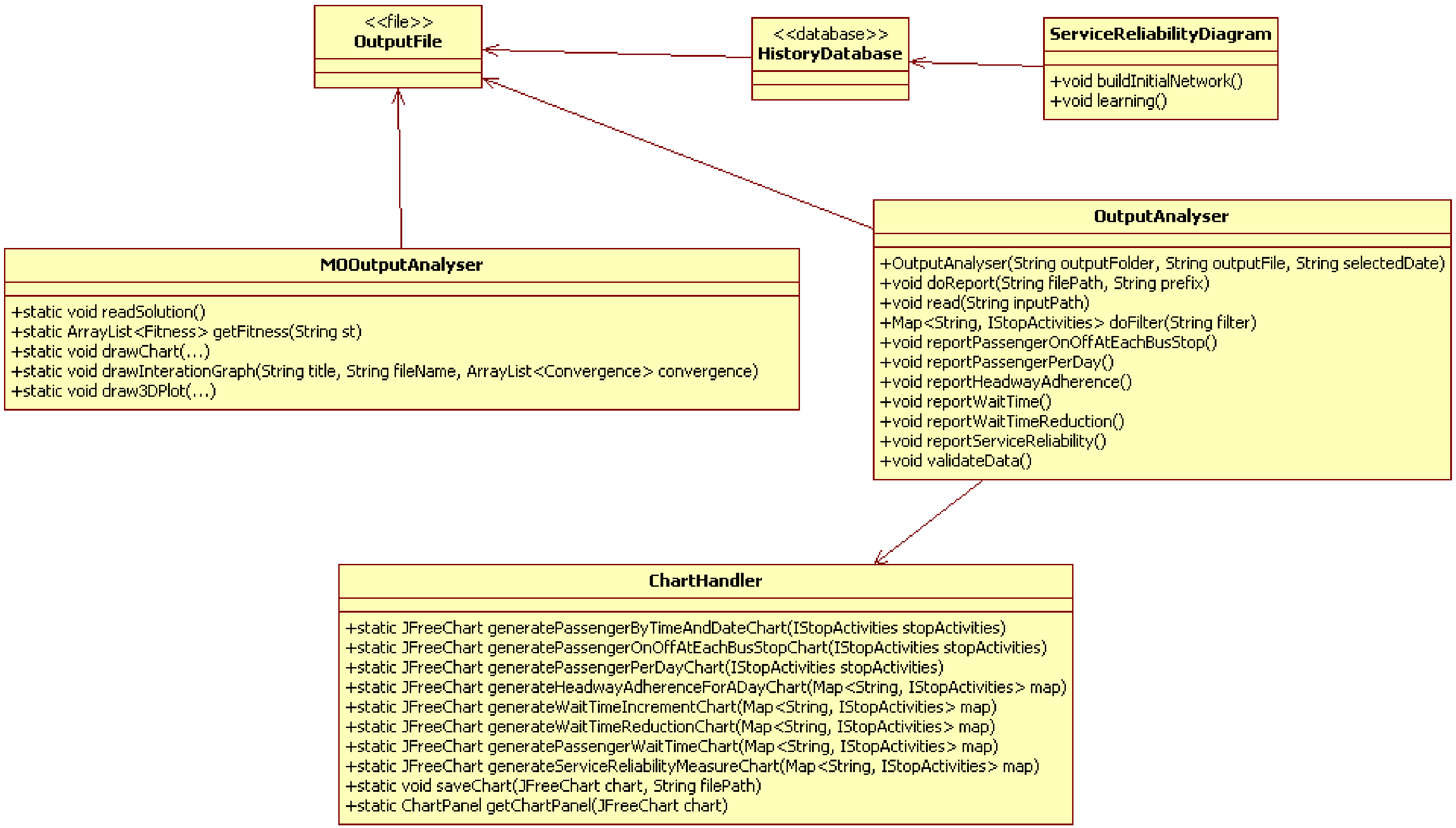

Figure C.6: Class Diagram: offline analysis.

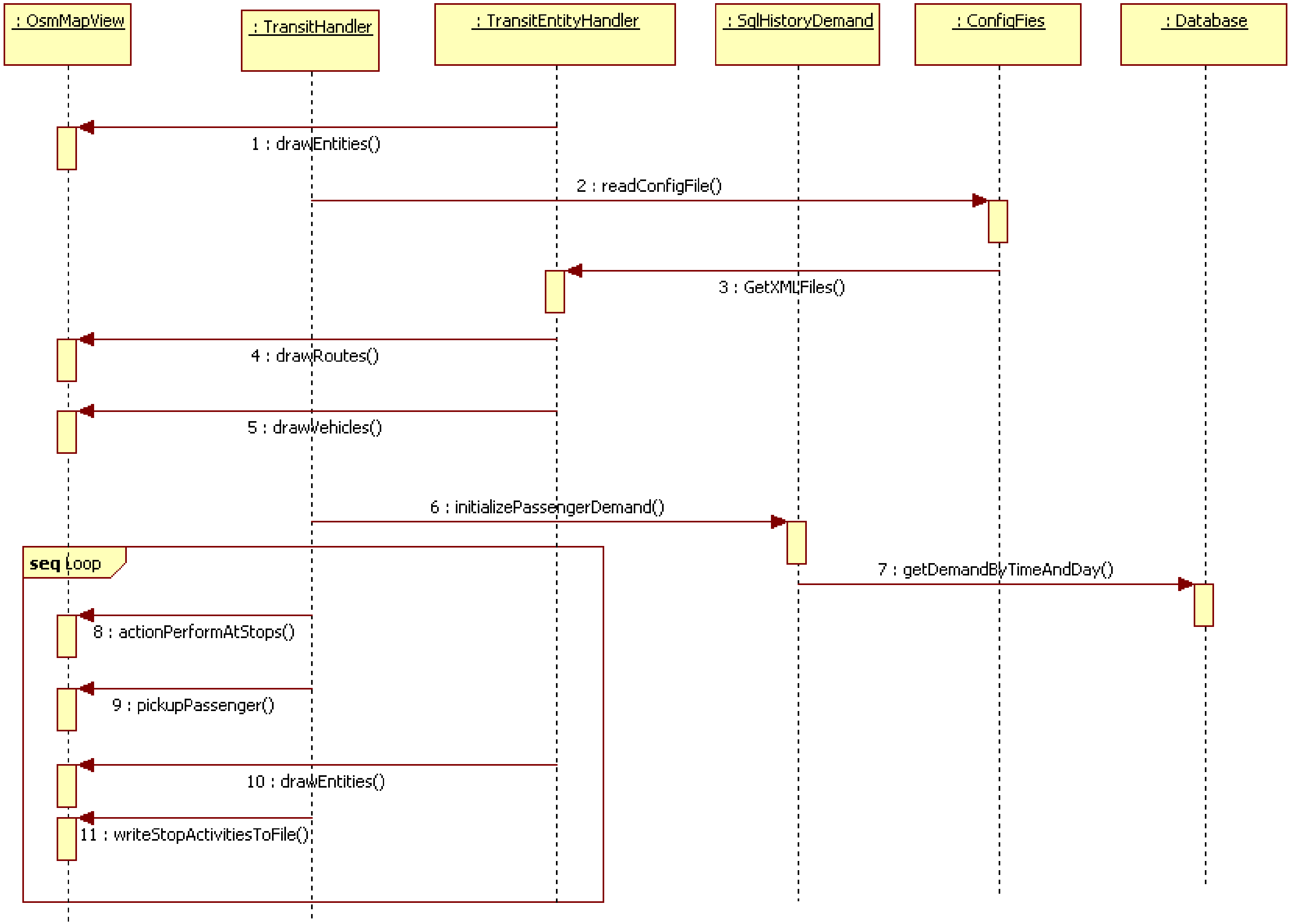

Figure C.7: Sequence Diagram: transit operations.

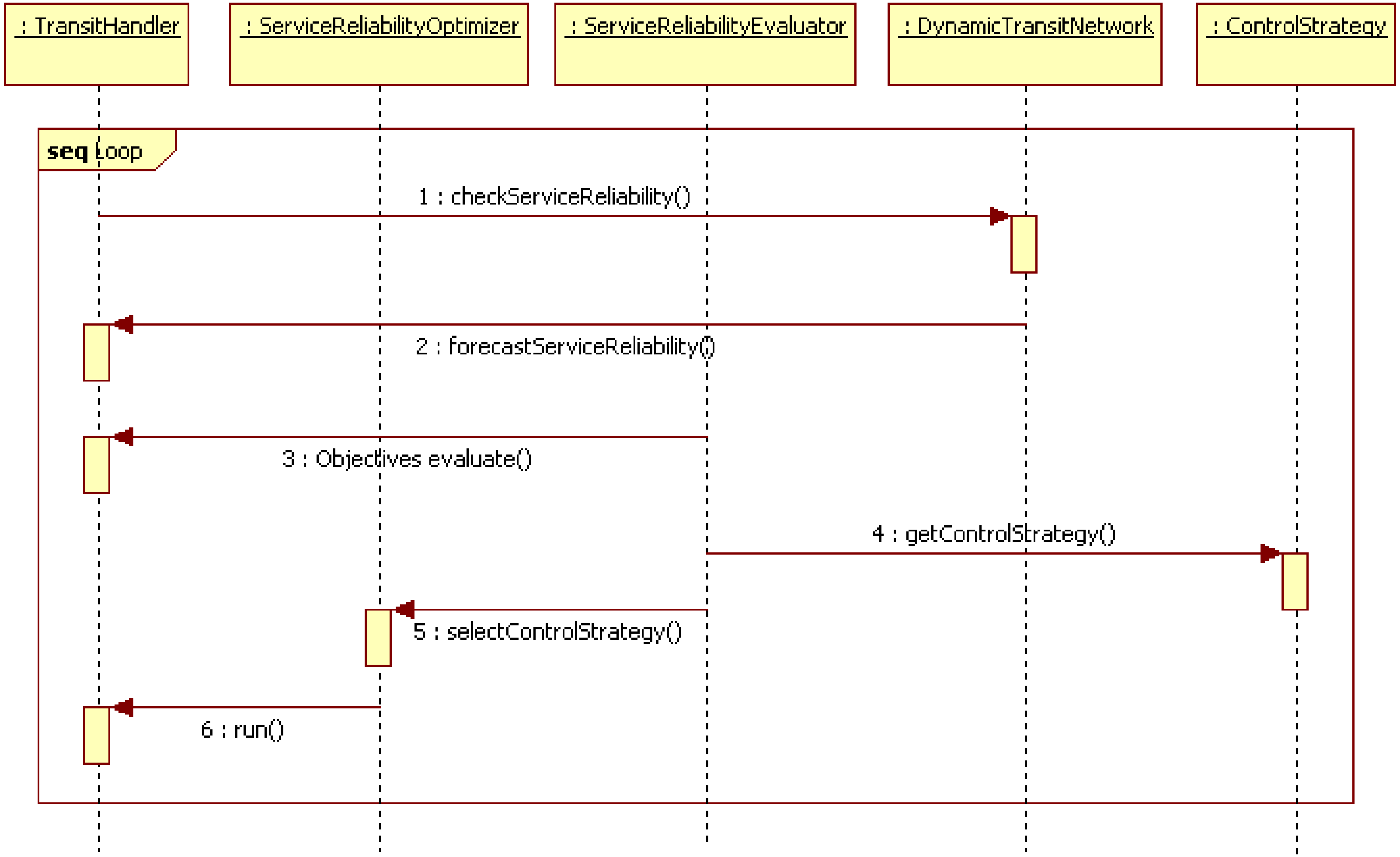

Figure C.8: Sequence Diagram: real time optimization.

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