Parking Behavioural and Assignment Modelling
Methodology and application for the evaluation of Smart Parking applications

Emmanouil Chaniotakis
Parking Behavioural and Assignment Modelling
Methodology and application for the evaluation of Smart Parking applications

MASTER OF SCIENCE THESIS

For the degree of Master of Science in Transport Infrastructure and Logistics at Delft University of Technology

Emmanouil Chaniotakis

May 3, 2014

Faculty of Civil Engineering, 3ME, TPM · Delft University of Technology
The work in this thesis was supported by TNO. Their cooperation is hereby gratefully acknowledged.
Abstract

This research focuses on the derivation of an assignment model that can be used for the evaluation of Smart Parking ITS applications. Behavioural research is conducted in order to gain understanding of the individuals’ behaviour concerning parking, on three behavioural levels (Strategic, Operational and Tactical), and for two user classes (Familiar and Unfamiliar users). A Parking Decision Process model, which represent the decisions that individuals have to take when parking is suggested. A Stated Preference experiment is conducted –designed using efficient designs– for the investigation of decisions for familiar and unfamiliar users and discrete choice models are derived for familiar users. The outcome of the behavioural research (Parking Decision Process model & MNL Parking Discrete Choice model) is applied in the development of a Parking Assignment Model for simulation on the behavioural levels for both user classes. The components of the Parking Assignment Model are verified and the applicability of the model is examined. Finally, the Parking Assignment Model is applied for the evaluation of the Smart Parking application, developed for the Sensor City project in Assen. The results of the evaluation illustrate the positive impact of the Smart Parking application to the reduction of individuals’ and total travel times.
Extended Summary

Introduction

Parking is creating problems mainly because people have to cruise around to find a vacant parking spot in the urban network. A clear need for applications that can reduce those external effects of parking has arisen, especially the last few years. With parking pricing policies reaching their limits in many European cities, possible improvements could be found in Intelligent Transport Systems (ITS). Such an ITS application (Smart Parking), using reservation for parking has been developed in the context of the Sensor City project, in Assen city, in the Netherlands. However, as the system has not been applied yet in full scale, the benefits are unknown in terms of quantified indicators.

This thesis develops a modelling environment to evaluate Smart Parking applications. For that, the modelling and the comparison of the current situation – Reference scenario – (without the ITS application) and the situation where people are using ITS application – Proposed scenario – is required. This can only be achieved by having a clear indication on how and what people decide given those.

The literature so far does not offer a clear structure of the decision process concerning parking, as most models are add-hoc models. Some suggestions are made (see e.g. Kaplan and Bekhor, 2011) and some models have been developed (behavioural and assignment models) however, there is a lack of structured approaches that could result in a representation of the parking system based on the behavioural characteristics of individuals –especially for the evaluation of Smart Parking applications. Most of the existing behavioural models cannot be directly used in assignment models, because there is no connection to the transport network. Finally, all the related work focuses on familiar users with unfamiliar not to be investigated.

Behavioural Research

The need to define the decision process related to parking and the derivation of models for the parking assignment, based on this process emerged. The parking decision process was
structured on three levels behavioural model. The strategic level contain the decisions to be taken before trip under a habitual pattern. This level, represents the perception of traffic and parking situation pre-trip described by a parking search strategy. The operational level applies when individuals reach the city centre and deal with the dynamics of traffic and parking. The Tactical level applies on traffic interactions such as link choice while cruising or choose a route to drive to a parking destination while on-trip.

For the modelling of the parking decisions, a choice model was constructed based on the assumptions emanating from discrete choice modelling theory. For the derivation of the choice model a survey was conducted. The survey data was collected using a Stated Preference survey. The model derived are able to be applied both on strategic, operational and tactical level. The attributes identified as most important from the literature were the parking price, the walking distance to destination, the travel time to the parking destination, the on-street or off-street parking characterization, parking search time and probability of finding a vacant parking spot. Those were used as a basis for the survey conducted, applying a concept of incorporating the search time in the parking probability. Shortly, it was assumed that individuals decide based on the probability of finding a vacant parking spot upon arrival and after some minutes of searching or waiting.

The survey was divided in three sections: the socio-economic characteristics section, the unfamiliar users section, and the familiar users section which presented scenarios about choosing the most appealing parking destination among two alternatives. The survey design is based on literature of experimental design for the definition of the experimental variables. The process followed for the design of the experiment was a pilot study using efficient design methods for the derivation of a design, which would yield the maximum information possible (under the characteristics of the experiment and the system to be identified).

In the context of the pilot studies two small scale surveys were conducted. The feedback from the respondents and the prior estimators derived was used for a survey of 426 participants. For unfamiliar users, it was derived that 51.1 percent would drive to the destination and then start searching for a vacant parking spot and 34.9 percent would search for information concerning parking and can be treated as familiar with the destination. Finally, 13 percent would start searching from some distance before reaching the destination. Furthermore it was found that 77.6 percent of unfamiliar users would chose to park at an off-street parking destination close to their destination. For the familiar users, the model estimation followed a hypothesis and testing procedure initiating from the MNL model (results are presented in the following table). Several model structure were tested and compared using the goodness of fit metric. All estimators of the models were found to be significant with the parking cost to be the one contributing most to utility followed by the probability after 8 minutes.

**Parking Assignment Model**

The procedure for estimating a choice model took place for the derivation of a parking assignment model to be used in simulation that would represent parking in the context of urban areas for Smart Parking applications. In a more schematic way, Traffic Networks Assignment model are built on the behavioural models combining real-time network (and parking) characteristics with individuals’ preferences. The model derived, intends to represent the decisions included in the decision process model derived during the behavioural research.
The Stochastic User Equilibrium (SUE) assignment was adopted for the representation of the habitual preferences concerning parking on the strategic behavioural level – strategic parking search route. A two levels assignment was developed for representing the parking search route (concentrative parking destinations to be visited) and to encounter for the fact that parking and routing affect each other (travel time to destination is one of the factors affecting parking choices). The first level is the route choice from which the travel times to parking destinations are derived and the second level is the choice of the concentrative parking destination. The travel times are used in the second level of the assignment of the representation of of the parking choices (SUEp) and the parking destinations chosen are used in the first level of the assignment to get accurate travel times.

The main stochastic component of the strategic parking search route is the probability of finding a vacant parking spot (upon arrival and after some minutes). In order to represent this behavioural response and due to the fact that parking is a dynamic process which involves a lot of random variables, an expression that approximates the probability was derived based on a probability simulation model developed. With the input of an arrival process, the distribution of parking durations and the distribution of the maximum wait/cruise time the probability simulation model calculates the probability of finding a vacant parking spot depending on the arrival time and the search time.

The Parking Assignment Model concerning familiar users continues with decisions on the tactical level. This level applies on-trip with individuals to decide to evaluate their strategy in case there is marginal improvement of the newly introduced strategy in comparison to the adopted one – a way of modelling in line with the hybrid route choice modelling principles. Finally, on the operational level the routes taken from one parking destination to another are decided, as well as decision concerning on-street parking on an intersection level. Here, individuals decide the next link to follow, while cruising for parking, based again on the utility function derived.

The model that describes the strategic level is verified with the investigation of some networks. The components of the two other levels are verified in the application of the Parking Assignment Model for the evaluation of the Smart Parking Application.

A modelling approach is introduced for the unfamiliar users, where three user classes are created that are modelled in a different way. The Imperfect Unfamiliar are those who collect information concerning parking before the realization of the trip, hence are modelled as fa-
miliar users. The *Completely Unfamiliar* and the *Searching Unfamiliar* are those, who have no indication concerning the parking situation at the area of the destination. For those, only the route to the destination is decided on the strategic level. When arriving at destination (or close to the destination), the two latter unfamiliar user classes start searching for parking in a random way, or go towards directions indicated by signs that they have seen while driving to the initial destination. In case of a search route that has lead unfamiliar users far away from the initial destinations, a route back to it is again defined.

### Smart Parking application Evaluation

The applicability of the Parking Assignment Model was examined in the context of the *Sensor City* project, for the Smart Parking reservation system developed. The requirements for the implementation of the Parking Assignment Model are presented, and the model is implemented using ITS modeller. Scenarios are derived and evaluated for the city of Assen in the Netherlands, given limitations that exist in ITS modeller. The results suggest verify the Parking Assignment Model and suggest a positive outcome for the use of the Smart Parking reservation system. In the best case the reduction of the average total travel times can reach around 8 percent given 15 percent of unfamiliar users in the reference case and 40 percent of Smart Parkers in the proposed case. The individual travel times are also reduced (Table 1).

**Table 1:** Average Individual Travel Times for the scenarios investigated.

<table>
<thead>
<tr>
<th>Familiar Users</th>
<th>Unfamiliar Users</th>
<th>Smart Parkers</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>AITT (s) Std Dev (s)</td>
<td>AITT (s) Std Dev (s)</td>
</tr>
<tr>
<td>All Familiar</td>
<td>581 294</td>
<td>- -</td>
</tr>
<tr>
<td>Unfamiliar 5%</td>
<td>540 241</td>
<td>1525 1121</td>
</tr>
<tr>
<td>Unfamiliar 15%</td>
<td>519 196</td>
<td>1613 1170</td>
</tr>
<tr>
<td>Smart Parkers 20%</td>
<td>586 288</td>
<td>- -</td>
</tr>
<tr>
<td>Smart Parkers 40%</td>
<td>570 284</td>
<td>- -</td>
</tr>
</tbody>
</table>

Finally, the conclusions and the future work are presented. The future work focuses on the validation of the models presented and the way this can be achieved. Concepts that might be suitable for improving the suggested models are discussed and potential future direction on parking research are discussed.
# Table of Contents

Acknowledgements xvii

I Introduction, Problem Definition & Related Work 1

1 Introduction 3

1.1 Research Motivation ............................................. 3
1.2 Evaluation Approach ............................................. 4
1.3 Smart Parking ................................................ 5
1.4 Problem Definition, Objective & Research Questions .............. 5
1.5 Research Framework ............................................ 6
  1.5.1 Conceptual Design .......................................... 6
  1.5.2 Model Estimation - Verification ............................ 8
  1.5.3 Model Implementation ...................................... 8
  1.5.4 Conclusions ................................................ 8
1.6 Contributions ................................................... 8
1.7 Report Structure ............................................... 9

2 Related work .................................................. 11

2.1 Introduction .................................................. 11
2.2 Problems related to parking and solutions ....................... 12
  2.2.1 Problems related to Parking ............................... 12
  2.2.2 Solutions to Parking Problems ............................ 13
2.3 Modelling of Transportation Systems ........................... 14
  2.3.1 Behavioural Modelling .................................... 15
  2.3.2 Traffic Assignment Models & Simulation .................. 16
2.4 Parking Modelling ............................................ 17

Master of Science Thesis Emmanouil Chaniotakis
## Table of Contents

2.4.1 Categorization and Hierarchy ........................................ 17  
2.4.2 Parking Choice Models .............................................. 18  
2.4.3 Allocation Models .................................................. 21  
2.4.4 Parking Simulation .................................................. 21  
2.5 Data Collection Methods and Parking Data ......................... 22  
2.6 Conclusions .............................................................. 23  

II Parking Behavioural Research ............................................. 25  

3 Theoretical Parking Behaviour ............................................ 27  
3.1 Introduction .............................................................. 27  
3.2 Process model & Choice model Derivation Process ............... 28  
3.3 User Classes ............................................................ 29  
3.4 Parking Behavioural Levels ............................................ 30  
3.5 Behavioural Concept .................................................... 30  
3.6 Parking Decision Process Model ...................................... 31  
3.6.1 Familiar Users ....................................................... 32  
3.6.2 Unfamiliar Users ..................................................... 32  
3.7 Conceptual Experimental Design .................................... 33  
3.7.1 Data Collection Method ........................................... 34  
3.7.2 Familiar Users Section ............................................. 35  
3.8 Expected Experiment Outcome ....................................... 37  
3.9 Conclusions .............................................................. 39  

4 Experiment Design and Model Estimation .............................. 41  
4.1 Introduction .............................................................. 41  
4.2 Notation ................................................................. 42  
4.3 Experiment Design Process .......................................... 44  
4.3.1 Pilot Study ............................................................ 44  
4.3.2 Final Design ........................................................ 46  
4.4 Data Collection & Data Analysis .................................... 48  
4.4.1 Sample Preparation & Stratification ............................ 48  
4.4.2 Socio-demographic Characteristics of the Sample .......... 49  
4.4.3 Unfamiliar Users Characteristics ............................... 50  
4.5 Parking Choice Models Estimation .................................. 51  
4.5.1 Unfamiliar Users ..................................................... 51  
4.5.2 Familiar Users ....................................................... 52  
4.6 Model Verification ...................................................... 58  
4.7 Conclusions - Discussion ............................................. 59

Emmanouil Chaniotakis  
Master of Science Thesis
# Table of Contents

**III Parking Assignment Model: Formulation, Verification & Application**  
61

5 Parking Assignment Model  
5.1 Introduction .............................................................. 63  
5.2 Notation ................................................................ 64  
5.3 Parking Decision Process Summary .............................. 66  
5.4 Conceptual Implementation Procedure .......................... 66  
5.5 Parking Assignment Model for Familiar Users ............... 66  
  5.5.1 Strategic Level ...................................................... 68  
  5.5.2 Tactical Level ...................................................... 74  
  5.5.3 Operational Level .................................................. 75  
5.6 Parking Assignment Model for Unfamiliar Users ......... 76  
  5.6.1 Strategic Level ...................................................... 76  
  5.6.2 Tactical Level ...................................................... 77  
  5.6.3 Operational Level .................................................. 78  
5.7 Parking Probability Model ............................................ 78  
5.8 Conclusions ................................................................. 81

6 Familiar Strategic Level Model Verification ................. 83  
6.1 Introduction ............................................................... 83  
6.2 Model Programming .................................................... 84  
6.3 Verification Process .................................................... 85  
6.4 Initial Parking Destination Preference Model Verification 86  
  6.4.1 Scenario 1: 1 OD, 2 parking destination with same characteristics ... 86  
  6.4.2 Scenario 2: 1 OD, 2 parking destination with different prices ....... 87  
  6.4.3 Scenario 3: The Assen Case: Dynamic, 296 ODs, 11 parking destinations 88  
6.5 Strategic Parking Search Route Verification .................. 91  
  6.5.1 SPSR: Scenario 1: 1 OD, 3 parking destination with same characteristics 91  
  6.5.2 SPSR: Scenario 2: 1 OD, 3 parking destination with different characteristics 92  
  6.5.3 SPSR: Scenario 3: 1 OD, 3 parking destination with different characteristics 93  
6.6 Conclusions ................................................................. 96

7 Parking Assignment Model Application ....................... 99  
7.1 Introduction ............................................................... 99  
7.2 Implementation Requirements ..................................... 100  
7.3 ITS Modeller .............................................................. 101  
  7.3.1 ITS Modeller Limitations ........................................... 102  
7.4 Implementation Modules .............................................. 103  
  7.4.1 Parking Choice Set .................................................. 103  
  7.4.2 Parking Facilities ................................................... 103  
  7.4.3 Familiar Parking Users .............................................. 104
# Table of Contents

7.4.4 Unfamiliar Parking Users ........................................... 105  
7.4.5 Smart Parking Users ................................................ 106  
7.4.6 Other Modules ....................................................... 107  
7.4.7 Programming Details ............................................... 107  
7.5 Sensor City Case ....................................................... 108  
7.5.1 Scenarios ............................................................. 109  
7.5.2 Simulation Results & Interpretation ............................... 110  
7.5.3 Discussion on the results ......................................... 112  
7.6 Conclusions ............................................................. 112  

8 Conclusions, Recommendations & Future work .......................... 113  
8.1 Conclusions ............................................................. 113  
8.2 Recommendations & Future Work .................................... 114  

Bibliography .......................................................................... 117  

A Behavioural Research ......................................................... 125  
A.1 Attributes Examined in the literature ................................ 126  
A.2 Interviews & Panel ....................................................... 127  
A.3 Pilot Study First Round .................................................. 129  
A.4 Pilot Study: Second Round ............................................. 130  

B Parking Assignment Model ................................................... 131  
B.1 Probability Model Simulation .......................................... 132  
B.2 Parking Search Route Verification, Scenario 4 ....................... 136  

Glossary .............................................................................. 137  

Nomenclature ....................................................................... 143  

Emmanouil Chaniotakis Master of Science Thesis
List of Figures

1.1 Components of the evaluation and evaluation approach ........................................ 4
1.2 Smart Parking entities ............................................................................................. 5
1.3 Research Framework ............................................................................................... 7
1.4 Connections of the important research outcomes ...................................................... 10

2.1 Chapter’s components and connections .................................................................. 12
2.2 Hierarchy of Parking Models, (Young et al., 1991) ..................................................... 18
2.3 Joint parking type, parking location and cruising route choice framework (Kaplan and Bekhor, 2011) ........................................................................................................ 20

3.1 Chapter’s components and connections .................................................................. 28
3.2 Derivation Process ................................................................................................... 29
3.3 Parking Behavioural Levels ....................................................................................... 31
3.4 Decision Framework ................................................................................................ 33
3.5 Scenarios questionnaire webpage example ............................................................... 35
3.6 The survey design procedure ................................................................................... 36

4.1 Chapter’s components and connections .................................................................. 42

5.1 Chapter’s components and connections .................................................................. 64
5.2 Implementation Procedure ....................................................................................... 67
5.3 Familiar users modelling framework ......................................................................... 67
5.4 Strategic Parking Search Routes. Each coloured route represents a strategic parking search route that individuals have in mind before trip. ........................................ 68
<table>
<thead>
<tr>
<th>Figure</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>5.5</td>
<td>Assignment parking and route flow chart. Adopted by (Van Nes and Bovy, 2008)</td>
</tr>
<tr>
<td>5.6</td>
<td>Unfamiliar Users modelling framework</td>
</tr>
<tr>
<td>5.7</td>
<td>The two models used for car queues</td>
</tr>
<tr>
<td>5.8</td>
<td>Saturday Shopping, 3000 iterations</td>
</tr>
<tr>
<td>6.1</td>
<td>Chapter’s components and connections</td>
</tr>
<tr>
<td>6.2</td>
<td>MATLAB programming pseudo-code</td>
</tr>
<tr>
<td>6.3</td>
<td>Initial Destination Scenario 1, test network</td>
</tr>
<tr>
<td>6.4</td>
<td>Initial Destination Scenario 2, utility difference over iterations for $\mu = 1$ and $\mu = 40$</td>
</tr>
<tr>
<td>6.5</td>
<td>The Assen network with a focus in the city center. The parking signs represent parking destinations and the blue circles represent OD destinations</td>
</tr>
<tr>
<td>6.6</td>
<td>SPSR Scenario 1: test network</td>
</tr>
<tr>
<td>6.7</td>
<td>SPSR Scenario 2, utilities over iterations for $\mu = 1$ and $\mu = 40$</td>
</tr>
<tr>
<td>6.9</td>
<td>SPSR: Scenario 4, Parking occupancies at the end of each time period</td>
</tr>
<tr>
<td>7.1</td>
<td>Chapter’s components and connections</td>
</tr>
<tr>
<td>7.2</td>
<td>ITS modeller Graphical User Interface (GUI)</td>
</tr>
<tr>
<td>7.3</td>
<td>Modules used in ITS Modeller</td>
</tr>
<tr>
<td>7.4</td>
<td>Off-street parking facility representation</td>
</tr>
<tr>
<td>7.5</td>
<td>Routes followed by a random familiar user in ITS modeller</td>
</tr>
<tr>
<td>7.6</td>
<td>Routes followed by a random unfamiliar user in ITS modeller</td>
</tr>
<tr>
<td>7.7</td>
<td>Parking and rest travel demand for simulation</td>
</tr>
<tr>
<td>7.8</td>
<td>Assen City Centre Parking Destinations locations</td>
</tr>
<tr>
<td>A.1</td>
<td>Decision Process Framework presented</td>
</tr>
<tr>
<td>B.1</td>
<td>Probability Model Simulation Algorithm</td>
</tr>
<tr>
<td>B.2</td>
<td>The morning peak, 2500 iterations</td>
</tr>
<tr>
<td>B.3</td>
<td>Searching for a very long period of time</td>
</tr>
<tr>
<td>B.4</td>
<td>Demand Lower than Capacity, 2500 iterations</td>
</tr>
</tbody>
</table>
# List of Tables

<table>
<thead>
<tr>
<th>Table No.</th>
<th>Description</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Average Individual Travel Times for the scenarios investigated.</td>
<td>vi</td>
</tr>
<tr>
<td>2.1</td>
<td>Parking-related attributes examined in literature</td>
<td>20</td>
</tr>
<tr>
<td>3.1</td>
<td>Parking related attributes examined</td>
<td>34</td>
</tr>
<tr>
<td>4.2</td>
<td>Parking related attributes $1LDes$ Design</td>
<td>45</td>
</tr>
<tr>
<td>4.3</td>
<td>MNL model based on results of the $1LPr$ Design</td>
<td>46</td>
</tr>
<tr>
<td>4.4</td>
<td>Parking related attributes, Final Design</td>
<td>47</td>
</tr>
<tr>
<td>4.5</td>
<td>Fisher Information matrix - $1LPr$ Design</td>
<td>48</td>
</tr>
<tr>
<td>4.6</td>
<td>The Final Design ($FDes$)</td>
<td>48</td>
</tr>
<tr>
<td>4.7</td>
<td>Socio-Demographic Characteristics of the Sample</td>
<td>49</td>
</tr>
<tr>
<td>4.8</td>
<td>CBS Statistics (CBS, 2009)</td>
<td>49</td>
</tr>
<tr>
<td>4.9</td>
<td>Socio-Demographic Characteristics of the Sample</td>
<td>50</td>
</tr>
<tr>
<td>4.10</td>
<td>Multinomial Logit Model</td>
<td>53</td>
</tr>
<tr>
<td>4.11</td>
<td>Average Contribution to the Utility</td>
<td>53</td>
</tr>
<tr>
<td>4.12</td>
<td>Nested Logit Model</td>
<td>54</td>
</tr>
<tr>
<td>4.13</td>
<td>Mixed Logit - Normally Distributed</td>
<td>55</td>
</tr>
<tr>
<td>4.14</td>
<td>Regret Minimization</td>
<td>56</td>
</tr>
<tr>
<td>4.15</td>
<td>Normalized Panel Data Model</td>
<td>57</td>
</tr>
<tr>
<td>4.16</td>
<td>High Income Profile MNL model</td>
<td>58</td>
</tr>
<tr>
<td>4.17</td>
<td>Goodness of fit - MNL model</td>
<td>58</td>
</tr>
<tr>
<td>4.18</td>
<td>Summary of estimated models</td>
<td>60</td>
</tr>
<tr>
<td>Table Number</td>
<td>Description</td>
<td>Page</td>
</tr>
<tr>
<td>-------------</td>
<td>-----------------------------------------------------------------------------</td>
<td>------</td>
</tr>
<tr>
<td>5.2</td>
<td>Saturday shopping, illustrative case simulation</td>
<td>80</td>
</tr>
<tr>
<td>6.1</td>
<td>Initial Destination Scenario 1, parking characteristics</td>
<td>86</td>
</tr>
<tr>
<td>6.2</td>
<td>Initial Destination Scenario 1, link flows</td>
<td>87</td>
</tr>
<tr>
<td>6.3</td>
<td>Initial Destination Scenario 2, parking characteristics</td>
<td>87</td>
</tr>
<tr>
<td>6.4</td>
<td>Initial Destination Scenario 2, parking flows</td>
<td>87</td>
</tr>
<tr>
<td>6.5</td>
<td>PND Off-Street Parking Destination in the Assen city centre</td>
<td>88</td>
</tr>
<tr>
<td>6.6</td>
<td>Initial Destination Scenario 3, First parking destination preferences</td>
<td>90</td>
</tr>
<tr>
<td>6.7</td>
<td>Initial Destination Scenario 3, Probability of finding a vacant parking spot</td>
<td>90</td>
</tr>
<tr>
<td>6.8</td>
<td>Initial Destination Scenario 3, Departures per time periods</td>
<td>90</td>
</tr>
<tr>
<td>6.9</td>
<td>SPSR Scenario 1, parking characteristics</td>
<td>91</td>
</tr>
<tr>
<td>6.10</td>
<td>SPSR Scenario 1, parking search routes nodes, utilities and flows</td>
<td>92</td>
</tr>
<tr>
<td>6.11</td>
<td>SPSR: Scenario 2, parking characteristics</td>
<td>92</td>
</tr>
<tr>
<td>6.12</td>
<td>SPSR Scenario 2, SPSR nodes, utilities, and flows after 300 iterations</td>
<td>92</td>
</tr>
<tr>
<td>6.13</td>
<td>SPSR: Scenario 3, parking characteristics</td>
<td>93</td>
</tr>
<tr>
<td>6.14</td>
<td>SPSR Scenario 3, SPSR nodes, utilities, and flows after 300 iterations</td>
<td>94</td>
</tr>
<tr>
<td>6.15</td>
<td>SPSR: Scenario 4, parking characteristics</td>
<td>95</td>
</tr>
<tr>
<td>6.16</td>
<td>SPSR: Scenario 4, Flows and Utilities of 6 representative Strategic Parking Search Routes</td>
<td>96</td>
</tr>
<tr>
<td>6.17</td>
<td>SPSR: Scenario 4, Parking Occupancies at the end of each time period</td>
<td>96</td>
</tr>
<tr>
<td>7.1</td>
<td>Other Modules used in ITS modeller</td>
<td>107</td>
</tr>
<tr>
<td>7.2</td>
<td>Null ODs defined in ITS modeller</td>
<td>107</td>
</tr>
<tr>
<td>7.3</td>
<td>Programming Classes</td>
<td>108</td>
</tr>
<tr>
<td>7.4</td>
<td>Off-Street Parking Destination in the Assen city centre</td>
<td>109</td>
</tr>
<tr>
<td>7.5</td>
<td>Smart Parking Scenarios</td>
<td>110</td>
</tr>
<tr>
<td>7.6</td>
<td>Average Total Travel Times of investigated scenarios</td>
<td>110</td>
</tr>
<tr>
<td>7.7</td>
<td>ATTT Percentage Change of scenarios investigated</td>
<td>111</td>
</tr>
<tr>
<td>7.8</td>
<td>Average Individual Travel Times for the scenarios investigated</td>
<td>111</td>
</tr>
<tr>
<td>7.9</td>
<td>Average Individual Travel Time during congested period</td>
<td>112</td>
</tr>
<tr>
<td>A.1</td>
<td>The attributes examined in the literature concerning discrete choice modelling for parking</td>
<td>126</td>
</tr>
<tr>
<td>A.2</td>
<td>Fisher Information matrix - $\theta_{Des}$ Design (based on the $\theta_{LP}$ priors)</td>
<td>129</td>
</tr>
<tr>
<td>A.3</td>
<td>Examined Parking related attributes ($\theta_{Des}$ design)</td>
<td>129</td>
</tr>
<tr>
<td>Table</td>
<td>Description</td>
<td>Page</td>
</tr>
<tr>
<td>-------</td>
<td>------------------------------------------------------------------------------</td>
<td>------</td>
</tr>
<tr>
<td>A.4</td>
<td>MNL model based on results of the $0LDes$ design</td>
<td>129</td>
</tr>
<tr>
<td>A.5</td>
<td>Fisher Information matrix - $1LP_r$ Design</td>
<td>130</td>
</tr>
<tr>
<td>A.6</td>
<td>$1LP_r$ Results, 1st &amp; 2nd Sections</td>
<td>130</td>
</tr>
<tr>
<td>B.1</td>
<td>Demand most times lower than capacity - Arrival data</td>
<td>135</td>
</tr>
<tr>
<td>B.2</td>
<td>SPSR:Scenario 4, walking distances to destinations</td>
<td>136</td>
</tr>
</tbody>
</table>
This thesis would not have been possible without the help and support of many. They made it possible for me to accomplish my goals both on a scientific and personal level.

The first person to express my deep appreciation to is Professor Bart van Arem. He was the one who helped me communicate with TNO and set this thesis project, and he was always there to have a discussion whenever I felt like I needed one. I would like to offer my special thanks to Dr. Adam Pel, my daily university supervisor who was always there for me. His positive spirit, his endless ideas on how to make things happen, and his personal support were really important for me. He helped me evolve this work and understand the greater picture. The hours of endless discussions with drawing on the whiteboard were some of the most amazing things I experienced during this thesis! Dr. Riender Happee, my third university supervisor, was always there to help me when I was stuck. In a very practical way, he always had always the solutions I needed!

TNO and its people supported this thesis from the very beginning. I would like to express my deep appreciation to Martijn van Noort and Gerdien Klunder especially. To Martijn van Noort, I am grateful for him being always there to listen my ideas and help me set goals and accomplish them. In all the moments I was lost, Martijn was helped me get get back on track, in the most patient way. Gerdien Klunder was always there to offer her help and discuss all the matters that troubled me.

I would never have been able to work during those months without the support of my family. I am grateful to my parents for supporting me on their own expense without ever questioning my choices. I am grateful to Zoi Tsiatsiana for supporting me to accomplish my goals and fulfil my dreams.

I am deeply grateful to my friends and especially to Chris Bafatakis, George BirPoutsoukis, Haris Efstathiades and Nikos Larisis who were always there to discuss parking. I owe special thanks to George and Chris for the endless nights of discussing aspects of System Identification and Experiment Design and for supporting me whenever I need it. Last but not least, I would like to thank Lara-Brit Zomer for helping me designing a the cover page and Maurits van Hövell for translating the questionnaire in Dutch for me.

Delft, University of Technology
May 3, 2014

Emmanouil Chaniotakis

Master of Science Thesis

Emmanouil Chaniotakis
Part I

Introduction, Problem Definition & Related Work
Chapter 1

Introduction

This section serves as an introduction for the thesis report. It starts by describing the positioning of the thesis in the research context and the contributions. The research questions which are answered throughout this report are derived. A project framework outlines the steps that were followed and the approach that is taken. Finally the report structure is presented.

1.1 Research Motivation

Parking in urban areas is an issue of increasing importance, especially the last few years. There is voluminous literature concerning the problems consequential to the high parking demand, with researchers indicating that the average volume of the total traffic related to parking during peak hours in city centres can reach 30 to 50 percent of the total traffic (Shoup, 2006; Arnott and Inci, 2006). As each trip ends to a parking spot, searching (cruising) for parking is a phenomenon widely met in the urban environment, and it is related to problems in terms of to name but a few: lost time, fuel consumption, traffic flow, safety and emissions (Kaplan and Bekhor, 2011). The main instrument for reducing the impact of parking is the development of parking-related policies. Those balance the demand and supply for parking with the most prominent to be parking pricing (Lam et al., 2006). However, as parking pricing policies reach their limits due to social and political reasons, the need to develop new systems to alleviate the parking impact has become imperative. Lately, Intelligent Transport Systems (ITS), and more specifically Smart Parking applications are being designed and require evaluation before being implemented on a wide scale.

In the literature models describing the parking process are still in their infancy (Young, 2008; Lam et al., 2006). Most of them are ad hoc models developed for a particular application (Young et al., 1991) or only deal with parking under specific -mostly stationary (Lam et al., 2006)- conditions that cannot apply for ITS applications (Mahmassani, 2001a). There are very limited parking simulation models (Gallo et al., 2011; Guo et al., 2013; Benenson et al.,
on mostly a theoretical level, which investigate parking, without taking into account the behavioural characteristics in the assignment process. This leads to the conclusion that there can be an adequate model that would take into account the behavioural characteristics, for modelling Smart Parking applications.

1.2 Evaluation Approach

The evaluation of a Smart Parking application can be achieved by the evaluation of the situation without the application (reference case) and then, the evaluation of the situation –as predicted– with the application (proposed case). The evaluation on a real network and in a wide scale is most times impossible and for that reason models are being developed to represent the decisions and actions taken, in both the reference and the proposed case.

The parking process includes decisions and actions on how individuals cruise for parking, the parking destinations chosen and the routes taken to reach those destinations. The difference between the reference and the proposed case is found on the affect the Smart Parking application has on those decisions and actions. This directly suggests that the model definition of the parking process at the reference case and the effect Smart Parking application has on it are the two modelling modules required for the evaluation of a Smart Parking application (Figure 1.1).

For the reference case, the need for the development of a Parking Assignment Model, on the basis of models that represent the behaviour concerning parking was found to be imperative for two user classes (Familiar and Unfamiliar parking users). This should be accomplished in a way that enables the introduction of the Smart Parking applications effect. The investigation of the decision involved and the modelling of those decisions for assignment purposes implies the conduction of behavioural research.

The starting point of the behavioural research is the investigation of the Parking Decision Process\(^1\), which involves the decisions taken when travellers need to park at an urban environment on defined behavioural levels (pre-trip and on-trip). The decisions should then

---

\(^1\)Parking Decision Process: throughout this thesis, decision process is defined as the series of decisions that individuals face regarding parking. It differs from the definition of Train (2003, page 3) which refers to a single choice
be modelled as an assignment of individuals pre-trip and represents the reactions with the network on-trip. Modelling in various decision levels and for multiple user classes increases the complexity of the Parking Assignment Model. For this reason it is chosen to implement it in a simulation environment.

1.3 Smart Parking

Smart Parking is a parking reservation system that can be described as it consists of mainly three entities: the user, the parking facility agent and the parking management agent (Figure 1.2). The user entity is connected to the system via a device able to communicate (GPRS-3G) and to track position (GPS/GNSS/Galileo). The parking facility entity that provide services (parking spaces) and information to users. The third entity is a control agent that gathers information from the user and the parking entities as well as from various other sources (traffic counts, road sensors) in real time and combines all pieces of information into a suggestion for reserving a specific parking space (Jonkers et al., 2011). The conceptual design of the system informs the driver about the closest - to the destination - available parking spots 15 minutes before arrival to the destination and encourages the driver to reserve a parking spot.

![Figure 1.2: Smart Parking entities](image)

1.4 Problem Definition, Objective & Research Questions

The main problem identified is the lack of a consistent way to model parking for the reference case and for the proposed case. Starting from the motivation of this research, which is the evaluation of the Smart Parking application and given the literature review presented in Chapter 2, a clear need is found to develop a framework that can accommodate the evaluation of Smart Parking applications, based on parking related choice characteristics.

Given the aforementioned need the following objective is formulated:
Introduction

To model adequately parking-related choices in order to represent the parking process, in the reference case in a way that can be used for the evaluation of Smart Parking applications.

This leads the following main research question:

*What choice model and assignment model enables to adequately simulate the parking choice behavior of familiar and unfamiliar drivers, and allows to evaluate the impact of a Smart Parking application in an urban setting?*

The research question to be answered introduces a wide spectrum of sub questions:

1. Which are the problems caused by parking and which are the solutions proposed?
2. What is the state of the art in parking modelling?
3. Which are the decisions involved in the parking process?
4. Which are the characteristics that shape individuals decisions concerning parking?
5. How can an experiment on parking behaviour be adequately designed?
6. How can individuals' choices concerning parking be modelled?
7. What assignment model can be used adequately to represent parking choice behaviour?
8. How can the Smart Parking application be evaluated?
9. What are the effects of the Smart Parking application?

1.5 Research Framework

In order to proceed with the research in a systematic way, a framework was developed (Figure 1.3). It is divided into five sections, starting with the Problem Definition and going to the Conceptual Design, the Model Estimation & Verification, the Model Implementation and ends with the Conclusions. In the next sub-sections, the several project framework components are presented apart from the problem definition presented in Section 1.4.

1.5.1 Conceptual Design

The conceptual design is going to be based on the results of the literature review (Chapter 2), and the research questions (Chapter 1). There are two main components: the theoretical parking behavioural models (Chapter 3) and the conceptual parking assignment.

Starting from the behavioural research, the conceptual design requires the definition of the *behavioural process* related to parking, the *behavioural-decision levels*, the *user classes*. The choice of the decisions to be represented as well as the *attributes* which shape those decisions are parts of the conceptual design. The conceptualization includes also the *conceptual experiment design* which refers to the way the experiment is going to be conducted and the expected model outcome expressed in hypotheses that are going to be used to test for different models’ *structures*. On the Conceptual Assignment Framework the definition of the approach on how different decisions and decision levels are modelled is required as well as the mathematical formulation (Chapter 5).
Objectives (Ch. 1)
Create a modelling framework that could represent the parking process in the reference and proposed case of ITS applications

Research Question (Ch. 1)
What would be an appropriate model framework for the reference case capable of being used for the evaluation of ITS applications?

Figure 1.3: Research Framework
1.5.2 Model Estimation - Verification

The conceptual design of the behavioural research leads to the actual experiment design and the experiment (Chapter 4). The hypothesis of the conceptual design are tested and a verification of the model is intended. For the Assignment Framework the required verification is takes place based on the results of the model estimation (Chapter 6).

1.5.3 Model Implementation

In this part, the Parking modelling Assignment Framework is applied for the smart parking application in the context of the Sensor City project. Scenarios are derived for the Smart Parking application and the actual results are presented and interpreted (Chapter 7).

1.5.4 Conclusions

Finally, given the behavioural research and the Parking Assignment Models, conclusions are presented (Chapter 8) with a discussion on the way the framework is developed and implemented as well as the shortfalls that might exist. The future work is also included.

1.6 Contributions

This thesis contributions lay on both theoretical, methodological and practical level:

1. Theoretical & Methodological Contributions:

   (a) *Synthesis of common practices on parking modelling and data collection.* In Chapter 2 a review of the models on parking is presented with a focus on choice models and Parking Assignment Models. Shortfalls of the models are identified. The data collection methods are presented with a focus on efficient designs for Stated Preference experiments.

   (b) *Parking Decision Process model.* The parking process is analysed qualitatively on a behavioural context (Chapter 3). The decisions involved are investigated for familiar and unfamiliar users and are structured on the tree behavioural levels (Strategic, Tactical and Operational).

   (c) *Parking Choice Models.* A Stated Preference experiment is conducted on the basis of the Parking Decision Process model for the investigation of the parking-related behaviour (Chapter 4). A newly introduced set of choice attributes is proposed to be used for the representation of the parking decisions. Several model structures are tested based on hypotheses starting from the simple MNL model structure with the Panel Data for Mixed Logit to be the most satisfactory model.

   (d) *Parking Assignment Model.* A dynamic Parking Assignment model is conceptually designed, formulated and –partially– implemented to represent the parking process on the basis of the Parking Decision Process model and by using the MNL Parking Choice model (Chapter 5). The model is verified to some extend in test networks.
and an application (Chapter 6 & Chapter 7) and the applicability of the model is explored (Chapter 7).

(e) Future Work. Potential future research directions are identified contributing indirectly to the growing body of research and literature on this topic. Propositions are made on both the behavioural and assignment work conducted. They aim on improving the proposed models and on ways of further validation of it.

2. Practical Contributions:

(a) Efficient Design of SP Experiment. The efficient design are investigated and applied for the behavioural research allowing for the evaluation of the usage of Efficient Designs. A 3 level pilot study is conducted showing the potential of such designs to increase the amount of information that can be acquired by using efficient designs.

(b) Smart Parking application evaluation. The evaluation of the Smart Parking application proposed in the context of the Sensor city takes place based on the Parking Assignment Model formulated. Scenarios based on different percentages of unfamiliar users and different penetration rates of the Smart Parking application are developed, simulated and interpreted. The results suggest the proof of the concept by indicating reductions of total and individuals’ travel times.

1.7 Report Structure

This report is divided in three main parts followed by the conclusions and the future work.

Part I. Introduction, Problem Definition and Related Work
The first part serves as an introduction of the study (Chapter 1) with a literature review on related scientific subjects to introduce to the basic concepts required for understanding this thesis (Chapter 2). In the Introduction the research question, the research framework and the research approach are presented. In the literature review, subjects such as the problems caused by parking, the way transport systems are modelled with emphasis on parking and the data collection methods are explored.

Part II: Parking Behavioural Research
The second part of the report refers to the behavioural research conducted concerning parking. In the beginning the conceptual behavioural model is presented (Chapter 3) with the definition of behavioural levels, user classes, the main concept and the conceptual experimental design. The conceptual design leads to the actual experiment design, the survey conducted and the estimation of a model (Chapter 4).

Part III. Parking Assignment Model: Formulation Verification and Application
The third part guides the reader through the Parking Assignment Model for simulation based on the principles of the behavioural research. It starts with the presentation of the conceptual Parking Assignment Model (Chapter 5) where the main idea is presented followed with the models formulations. A verification of some important components is presented in Chapter 6. Further verification is provided by the actual application
of the Parking Assignment Model for the evaluation of the smart parking application (Chapter 7). The implementation requirements, the way it was implemented and the results are presented and discussed.

Conclusions - Future Work
Finally, the conclusions of this research are presented with a short discussion in Chapter 8 where also the future work is described.

In the chapter of this thesis research components are presented, all aiming to the derivation of the Parking Assignment Model. For a better navigability in this report, diagrams are presented in every chapter with the important components highlighted. The highlighted components are those used throughout this report. The key research components that are going to be derived in the chapters of this thesis and the connections between them are presented in Figure 1.4.

Figure 1.4: Connections of the important research outcomes
Chapter 2

Related work

This chapter goes through the basics of the literature concerning parking. The problems related to parking and the solution streams are presented. The modelling of transport systems is introduced with a focus on the behavioural modelling and the traffic assignment models. The way parking is modelled is presented as well as an introduction to data collection methods.

2.1 Introduction

One of the first papers for parking indicated that parking-related problems are the result of people wanting to park exactly outside the door of their destination (Behrendt, 1940). The increase of transportation demand changed the problem towards the difficulty of finding a vacant parking spot at all. Searching for a parking spot became a reality and solutions were proposed oriented towards increasing supply by building (usually) off-street parking. As this approach was found to create problems, the solutions were then oriented towards managing demand with policies or information applications.

The need to find solutions to the parking related problems arose the need for representing parking choices and derive models that would represent the parking dynamics. Starting from the very basics, a model is a “simplified representation of a part of reality ” used to investigate a part of the real world and what will happen in case of changing something (Bovy et al., 2006). In the beginning models were very simple. However, managing demand requires more detailed characteristics of demand, yet representing the way individuals behave in relation to parking, more sophisticated models arose.

The main reason for modelling parking is to test applications or policies which would be disturbing and costly in real life. As transportation is closely interrelated to human behaviour a rather big part of transport modelling is the representation of the discrete decisions taken by decision makers. Data is required in order to derive models with data collection methods to be of increased importance.
This chapter answers to the following research questions on what the literature suggests in those fields:

1. Which are the problems caused by parking and which are the solutions proposed?
2. What is the state of the art in parking modelling?
3. Which are the decisions involved in the parking process?
4. Which are the characteristics that shape individuals decisions concerning parking?

In this part, the related work on the problems caused by parking on the parking modelling and data collection are presented. The related work on the components is used in the following chapters as presented in Figure 2.1. In the beginning, the problem space and the solution space are explored 2.2.1. A short review of the way the transport system is modelled is presented (Section 2.3). Then the modelling of parking is explored starting with the hierarchization of parking models and the models already proposed 2.4. Finally the Data Collection Methods are shortly explored (Section 2.5).

2.2 Problems related to parking and solutions

2.2.1 Problems related to Parking

Parking is a transport component causing high externalities such as congestion, space occupation, reduced safety and others (Feitelson and Rotem, 2004). There is extensive literature in which the problem is addressed and suggested solutions are provided. Chronologically, the literature started by addressing the parking problem a few years after the mass production of cars. Aspects such as the occupancy of public or private space for parking aesthetics, safety and vulnerable users mobility are some of the issues examined for parking (Smith, 1947; Ricker, 1948; Swanson, 1989; McCoy et al., 1990; Arnold and Gibbons, 1996; Akbari et al.,
2.2 Problems related to parking and solutions

2003; Feitelson and Rotem, 2004; Shoup, 2006; Davis et al., 2010a) and are briefly presented here.

To begin with, the occupancy of public or private space for parking is addressed by several researchers (Davis et al., 2010a; Feitelson and Rotem, 2004; Arnold and Gibbons, 1996). It seems that parking occupies space especially in city centres. Akbari et al. (2003), as an example, found that for Sacramento parking can reach 57 per cent of commercial areas. The surface can be thought as closed areas that cannot be used for other uses –e.g. as recreation– affecting the urban development (Feitelson and Rotem, 2004).

On the traffic side, there are strong indications of the effect parking has on increasing congestion, and causing delays. Shoup (2006) conducted a wide research on cruising for parking and indicated a straightforward example: In a city with 470 parking spaces and a turnover rate of 17 (cars/day/parking space) around 8000 cars are cruising every day. Taking into account that the average cruising time is 3.3 minutes in this area, the time spent on cruising is 440 hours per day. Shoup (2006) also found that the average cruising for parking time in the USA ranges between 3.3 to 14 minutes and that the average share of traffic cruising for parking was close to 30 percent of the total traffic. Although the preceding issues are met, to this extent, mainly in the USA, they are not far removed from Europe. There is, however, only little literature, to the best of our knowledge, on the parking issues in Europe and even fewer is updated. Bonsall and Palmer (2004) presented a review indicating that in Frankfurt, in 1994, parking traffic was about 40 percent of the average total travel time of journeys, and in London between 30 to 40 percent. In the Netherlands there is a much lower car dependency in urban environments, and the pricing for parking is at the appropriate level (van Ommeren et al., 2012). Recently, van Ommeren et al. (2012) conducted a research on cruising in the Netherlands for the effects of age, sex, income activity, number of passenger and others. It was found that the average time of cruising is about 36s per trip with 30 per cent of the total trips to cruise. Although the evaluation of the impact of cruising for parking to traffic might vary from city to city, it is confirmed by many researchers (Mouskos et al., 2000; Arnott et al., 2005; Arnott and Inci, 2006) with the logic behind its importance to be simple: cars which stay into the network, cruising in circles, interfere with traffic.

To conclude, the increase of demand for motorised transportation parking has become an important issue requiring attention. Problems are identified to an extent, however, yet not solved.

2.2.2 Solutions to Parking Problems

The two basic solutions streams to reduce parking externalities are policies – with emphasis to pricing policies– and information systems. Due to the immediate effect that parking pricing has, it was the one to be mainly analysed in the literature (Gillen, 1978; Arnott and Rowse, 1999; Arnott and Inci, 2006; Davis et al., 2010a,b).

The main subjects examined, concerning pricing, were elasticities price sensitivity and reaction to pricing policies (Ottosson et al., 2013; Mei et al., 2010; Caicedo, 2012; Jansson, 2010; Calthrop and Proost, 2006; Anderson and de Palma, 2004; Hensher and King, 2001). However, parking pricing has boundaries and raises matters of equity, rights and spillover effects. Other policies that are generally implemented deal with the creation of parking zones in city centres with well defined users for each class.
The main form of information systems for parking is the Parking Guidance & Information systems (PGI). PGI systems have been developed and implemented in several cities, providing information via Variable-Message Signs (VMS), and directing drivers to parking lots with available parking spaces. Several systems structures have been proposed however, PGI systems have issues such as changing occupancy (multiple-cars-chasing-single-space), phenomena that are not yet overcome (Wang and He, 2011). Several studies are conducted on this subject drawing the conclusion that the systems were not responding to travellers needs (Thompson and Bonsall, 1997a). Generally, people were not aware of the system, and there is a clear indication that familiar with the system users do not change their behaviour. Waterson et al. (2001) conducted a simulation study on the effectiveness of PGIs and found out that the actual magnitude of the benefits for such a system is low. The reduction of the total travel time for all drivers in the network was found to be in the range of 0.1 to 1 per cent. The reason that PGIs do not appreciate a high acceptance is the shortfalls that cannot be easily overcome as asserted by Geng and Cassandras (2012). Starting with the location of the VMS, and the relative traffic there might be a high possibility not to find a vacant parking spot at the place directed to, even if indicated so. In other words, motorists might consider the system unreliable. Furthermore, PGIs can create more undistributed congestion caused by the traffic moving to the indicated available parking spots using the links indicated by traffic signs.

With technological evolution and especially ITS, new solutions are deployed to reduce the effect of cruising for parking (Caicedo, 2009, 2010; Rodier and Shaheen, 2010; Banerjee and Al-Qaheri, 2011; Geng and Cassandras, 2012). A new generation of ITS technologies for parking is evolving under the name Intelligent Parking Services (IPS), incorporating personalized cooperative systems and using reservation of parking space. IPS systems work by monitoring the location and the destination of the driver, in order to provide personalized information by, for example, finding and reserving a parking spot, give routing advice, and generally simplifying the procedure of parking (Geng and Cassandras, 2012; Jonkers et al., 2011; Teodorović and Lučić, 2006). The results were found to be rather promising with Geng and Cassandras (2012) indicating that, for the simulation of the Smart parking application for a part Boston university, the travel times of the users were reduced to half under heavy traffic with the inclusion of on-street parking. Thompson and Bonsall (1997b) presented a case using IPS where the total reduction of travel times in the network was of 22 percent and in the inner city of 49 percent.

### 2.3 Modelling of Transportation Systems

The transport system can be defined as “a set of elements and interactions between them that produce demand for travel and the provision of transportation services to satisfy this demand” (Cascetta, 2009). The representation of this system is approached by modelling the components of the system that seem to have a clear influence to the outcome. In the context of evaluating an ITS application the two main components to be explored are the modelling of the behavioural characteristics using mainly discrete choice models and the traffic assignment modelling.
2.3 Modelling of Transportation Systems

2.3.1 Behavioural Modelling

Starting with the behavioural modelling, Train (2003) asserted that the goal of discrete choice models is to understand and represent the behavioural process that lead to individuals decisions, as well as a mathematical formulation which can represent those decisions. These models represent the choice of an alternative among different alternatives (Louviere et al., 2000). The main concept is that individuals assess the available alternatives and make decisions based on their needs and environmental factors. The researcher observes attributes of the alternatives and attributes of individuals which, combined in a set of functions, represent the decision taken (Train, 2003). Due to the complexity of decision makers’ behaviour, the mathematical description of decisions cannot represent all the attributes of all individuals in a deterministic way. For this reason, probability is used to take into account stochasticity of decisions (Train, 2003). There are several mathematical models (model structures) used with one of the most widely used for the description of individuals’ decisions to be the Random Utility Maximization (RUM) (Cascetta, 2009). This section focuses on the presentation of mainly the RUM family models. Furthermore, some other model structures are also described in short, due to the probable relation to the behavioural model derived in this research.

Random Utility Maximization

Random Utility Maximization decision theory includes models that assume that the decision makers try to maximize their utility (gain or profit) or minimize their disutility from the several alternatives offered (Train, 2003). The utility of decision maker \( i \) of the \( n \) alternative is \( U_{in} \) and in the utility maximization concept the decision maker will choose alternative \( i \) over alternative \( j \) if and only if \( U_{in} > U_{ij}, \forall n \neq j \). The utility can be described by the attributes related to alternative and attributes related to the decision maker (let \( x_{in}, \forall n \) be a set of alternative specific attributes and \( d_i, \forall i \) be a set of the decision maker specific attributes). As a consequence, the utility is a function of those two sets of attributes \( (U_{in} \approx V(x_{in}, d_i)) \).

However, in order to describe the attributes not taken into account by the researcher, the formulation of utility function includes an error term, leading to the denotion of the utility function as \( U_{in} = V_{in} + \epsilon_{in} \) where \( \epsilon_{in} \) describes the difference between the “real” utility \( (U_{ini}) \) and the “observed” utility \( (V_{in}) \). As the \( \epsilon_{in} \) is unknown and given some characteristics that the researcher define or assume the probability to choose alternative \( n \) over \( j \) can be calculated (Louviere et al., 2000).

The difference in the observed utility of two alternatives must be just larger than the difference of the unobserved utility for the two alternatives to describe the decision taken (Equation 2.1). It is rather clear that in discrete choice modelling, the important factor is the difference in the utilities of two alternatives and not the absolute utilities.

\[
(V_{nj} - V_{jq}) > (\epsilon_{jq} - \epsilon_{nj}) \quad (2.1)
\]

The previous mentioned, are only valid under the very basic assumption that the alternatives are mutually exclusive and that the decision maker selects the alternative that maximizes the utility out of the available choice set (Cascetta, 2009; Train, 2003; Louviere et al., 2000).

There are several models structures that are widely used and are based on this theory. The most simple is the Multinomial Logit model (MNL). MNL is based on the assumption that
the random residuals $\epsilon_{in}$ are independently and identically distributed (i.i.d.) as Gumbel random variables. The probability of choosing alternative $n$ among available alternatives $(1, 2, ..., m \in C)$ where $C$ is the set of the available alternatives is given by Equation 2.2.

$$P_n = \frac{e^{\mu V_n}}{\sum_{n=1}^{m} e^{\mu V_n}}$$ (2.2)

Other model structures, such as Nested Logit models (NL), Generalized Extreme Values (GEV) models, Probit models and Mixed Logit models are derived in an effort to overcome the i.d.d. assumption imposed in the MNL model structure.

**Other Decision Theories**

Apart from the widely used Random Utility Maximization other concept arose due to the incapability of the former to address alternative ways of taking decisions. Prospect theory is one of the most widely used for describing the differentiation of the way people value gains, losses risks and opportunities (Kahneman and Tversky, 1979). Another concept that is lately introduced is the regret minimization concept based on the notion that users do not decide in order to maximize the utility obtained but in order to minimize the regret (Chorus, 2010).

### 2.3.2 Traffic Assignment Models & Simulation

An important component of the representation of the Transport System is the Traffic Assignment modelling which assign individuals to routes (Bovy et al., 2006). Assignment models are described in three levels: macroscopic, mesoscopic and macroscopic. The most common assignments on a macroscopic level are the so-called steady-state assignments, which assign traveller without taking into account the dynamic character of traffic. There are also dynamic models that can represent traffic both on a macroscopic, mesoscopic and microscopic level. On a microscopic level, the models that are used are simulation-based focusing on small study areas. Mesoscopic models are a combination of macroscopic and microscopic models given the representation needs.

Concerning macroscopic steady state models, there are several algorithms proposed in the literature in order to assign travellers in an aggregated way. The most common are the All or Nothing assignment (AoN), the Deterministic User Equilibrium assignment (DUE) and the Stochastic User Equilibrium assignment. The AoN assignment does not take into account congestion and assigns all travellers to the routes which offer the highest utility. DUE are based on the assumption that users have a perfect knowledge of the network which leads to an equilibrium as travellers choose in such a way that no traveller can increase the obtained utility (or decrease the obtained disutility). This is known as the Wardrop’s principle (Van Nes and Bovy, 2008). The SUE is an extension of the DUE assuming that travellers have imperfect information of the network. Due to the wide use of those algorithms, details on the way they are implemented is not presented but can be found in (Cascetta, 2009, chapter 5). The output of those models consists of aggregated travel times and travel costs, as well as aggregated link flows. Steady state models (or aggregated models) are capable of being used for long term planning horizons applications.
With the development of ITS applications, the representation of traffic and its propagation as well as the dynamics of traffic are required to be represented in order to evaluate the magnitude of the impact of such a system. This detailed representation is not possible with the macroscopic models (Mahmassani, 2001a) and for that reason simulation is employed. In a simulation environment, car following models, gap acceptance models and lane changing models are used in order to represent the behaviour of individuals while driving (Barcelo et al., 2005).

2.4 Parking Modelling

There are several types of parking-related models with different purposes, such as design of a parking facility, optimization of parking entrances, or representation of interactions between users and parking.

The simplest and very common way of including parking in transport model is to include the costs of parking in the generalized cost function of travel and use it in the well known 4 step transport model (Young et al., 1991). This kind of models does takes into account the parking as a transport component, but it fails to represent the real dynamics of parking. Generally, it does not give any indication for most of the aspects of parking choices except for the mode choice (if it is included) and the route choice.

In this section a review of the models concerning the representation of interactions between users and parking is intended, with focus on choice models and assignment models. In order to structure the presentation, the several parking model categorizations found in the literature are presented in such a way that could be helpful for understanding the positioning of the models discussed later.

2.4.1 Categorization and Hierarchy

After several decades of parking research, literature offers studies and overviews which categorizes and hierarchies the parking modelling procedure (Feeney, 1989; Young et al., 1991; Martens and Benenson, 2008; Van der Waerden, 2012). To begin with, Martens and Benenson (2008) indicate that parking is categorized in spatially implicit and spatially explicit parking models. In general spatially implicit models are static and focus on travellers parking destination choices while spatially explicit (simulation) models focus on parking search processes and choices on a more disaggregated level.

Young and Taylor (1991) hierarchies models based on their scale of the examination area (Figure 2.2). Starting from microscopic and moving to macroscopic, 4 levels can be distinguished: The parking lot level, the parking zone level, the sub-region level and the urban level. Those models communicate using a model that represent the connections between different levels (Young, 2008).

Another important distinction by Young et al. (1991); Young (2008) is the categorization of models based on their objective. Generally, the parking models are distinguished in Parking Design models, Parking Allocation models, Parking Search models, Parking Choice models and Parking Interaction models. Parking design models are used to design parking, calculate capacities, dimensions and generally understand the performance of the parking system.
Parking allocation models are introduced to assign parkers to the parking stock. Parking search models are used to investigate the search process travellers undergo while parking choice models are used for the measurement of travellers reactions to parking supply. Finally, parking interaction models are used for the investigation of the response - interaction of people to new policies and applications and are a combination of the parking choice models and the parking allocation models.

In this research, there is mainly a focus on Parking Choice Models and Parking Allocation models. For that purpose, those are the models presented in the following sections.

### 2.4.2 Parking Choice Models

The decisions that are related to parking can be approached from two angles: either by incorporating parking decision as a component of choices related to transport, or studying the decisions that are related explicitly to parking. Generally the following decisions were considered as directly related to parking by most researchers (e.g. Lam et al., 2006; Kaplan and Bekhor, 2011; Young et al., 1991).

- the decision to travel or not
- the destination choice
- the mode choice
- the route choice
- the parking location choice
2.4 Parking Modelling

- the parking type model

Those decisions are studied in direct connection to parking or by including parking in transport-related models. In the next sections, parking modelling as found in the literature is analysed given the different angles of approach.

Parking as a component of transport choice models

Young et al. (1991) present researches on the inclusion of parking attributes in the mode choice process. It is asserted that only a few investigate parking impact on the mode choice explicitly with research to be focusing on the impact of parking fees, search time and excess (walking to a destination) time to the mode choice. In the following years the investigation of the impact of attributes affecting the change of parking location and/or mode change was a subject researched by many researchers (Hess, 2001; Tsamboulas, 2001; Gillen, 1977; Cervero, 2002; Willson and Shoup, 1990).

Finally, in a more holistic approach, Polak et al. (1991) suggested a structure of decisions for City Center travellers in which parking is involved, trying to incorporate both behavioural and assignment research streams. It starts with the decision to go to a specific city centre or choose another one, continues with mode choice and ends with the parking destination choice.

Parking as a choice

Parking as a choice can be defined by two major choices: the parking type (on-street or off-street) and the parking location which is a representation of several sub choices and trip and parking attributes. The main question that those model ask is “where do travellers park?”.

Initially, studies described parking at a more aggregated spatial level and more specifically they were investigating the attributes which shape people’s preferences on choosing the desired –among alternatives– parking destination (Gillen, 1978; Goot, 1982; Polak et al., 1991; Hunt and Teply, 1993; Brandley et al., 1993; Lambe, 1996). Furthermore, there were some studies, which combined parking choices with other characteristics such as trip purpose (Van der Waerden and Oppwal, 1995) model choice (Coppola, 2004) and traffic flow (Carrese et al., 1996). Most of the abovementioned models are formulated under discrete choice model structures. The main attributes that are found in the literature are presented in Table 2.1, with a complete list of the parking related choice models attributes to be presented in Appendix A.

A framework which combined models proposed in the above mentioned studies on a more microscopic level was proposed by Van der Waerden et al. (2003) to model the behaviour, in a parking lot. Two main parking attributes were chosen to be studied. The first was the status of parking space examined in relation to the adjacent parking spaces, and the second was the location of the ticket machine, entrance and exit point. A nested model was proposed for two levels of decisions: First, on a parking spot level and second the choice of parking space within the parking strip.

There is some literature on the combination of the micro behaviour with the macro behaviour usually using modelling on layers. Kaplan and Bekhor (2011) presented a choice framework (Figure 2.3) which investigates the choices of parking type, parking location, and search for
Table 2.1: Parking-related attributes examined in literature

<table>
<thead>
<tr>
<th>Attributes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Parking Cost</td>
</tr>
<tr>
<td>Walking Time</td>
</tr>
<tr>
<td>Access Time</td>
</tr>
<tr>
<td>Parking Search/waiting time</td>
</tr>
<tr>
<td>Duration</td>
</tr>
<tr>
<td>Gender</td>
</tr>
<tr>
<td>Safety / Condition of parking</td>
</tr>
<tr>
<td>Age</td>
</tr>
<tr>
<td>Illegal Parking Fine</td>
</tr>
<tr>
<td>Trip Purpose</td>
</tr>
<tr>
<td>Value of time/ Income</td>
</tr>
<tr>
<td>PGI usage (familiar/unfamiliar)</td>
</tr>
<tr>
<td>Occupation</td>
</tr>
<tr>
<td>Public Transport Interaction</td>
</tr>
</tbody>
</table>

Parking. The validity of this framework has not been yet proven. In the same context, Van der Waerden (2012) presented Pamela, a group of discrete choice models that were used to simulate parking-related behaviour.

Figure 2.3: Joint parking type, parking location and cruising route choice framework (Kaplan and Bekhor, 2011)
2.4.3 Allocation Models

As described by Young (2008), the parking allocation models could fall in one of the following categories: Optimization models, Constraint models, Gravity models and Traffic Assignment models.

Optimization models are used for the measurement of the efficiencies of parking such as parking locations and parking size (Schneider et al., 1976; Oppenlander and Dawson, 1988; Owen and Daskin, 1998; Farhan and Murray, 2008). Parking constraints model allocate travellers based on distance, price and other characteristics to an accepted parking (not optimal) location. The gravity models are used to define the parking destination (generally origin constrained) based on entropy-maximizing gravity models (Bates, 1972).

Finally, assignment models assign travellers for route and parking. Thompson and Richardson (1998) presented a simulation “parking search model” in which individuals search for parking space and accept or reject the vacant parking spots based on a disutility function as well as a function to represent the likelihood to select a particular turning movement. It was shown that parking behaviour can be described by a search process with some modifications (Thompson and Richardson, 1998).

On a more disaggregated level limited research have focused on the parking search process. Young and Taylor (1991) refers to PARKSIM as a model that describes the parking search in a car park. It represents the parking manoeuvres vehicles’ interactions and the search process itself based on the travel time to the parking space and the walk time to the destination (Van der Waerden et al., 2003).

Lately there are assignment models (Lam et al., 2006; Gallo et al., 2011) which try to capture the dynamics of parking in the context of assignment. Lam et al. (2006) introduces a User Equilibrium which encounters for the departure time, parking destination and parking duration. A BPR-like function is used as a cost function and the model encounters for multiple user classes and car parks. On the other hand Gallo et al. (2011) derives a parking assignment for simulation based on a three layer assignment for simulating parking choices on a trip layer, a cruising layer and a walking layer.

In the last few years, there is also a trend towards agent-based models. PARKAGENT, is a spatially explicit model which simulates the behaviour of drivers in the microscopic search process. Drivers search for vacant parking spots starting from their destination and expanding their area and the acceptable distance from the destination while time passes. If drivers exceed a specific time then they choose to go to an off-street parking location (Benenson et al., 2008). It is important to state that PARKAGENT is designed to describe the search process for free residential parking and in the context of Israeli cities.

2.4.4 Parking Simulation

Young and Weng (2005) presented a review of the models used in order to simulate parking. Starting from the very basics models for speed, acceleration and braking are required to be representing the trip behaviour but also the parking related behaviour on those matters. Car following models are required and generally are generally used in the same way as in traffic. Furthermore, lane changing gap acceptance and overtaking models are very important in the
modelling of the parking procedure. Finally especially for on-street parking the intersection behaviour and the parking-unparking procedure are required to be modelled in an explicit way.

2.5 Data Collection Methods and Parking Data

One of the most important components of behavioural modelling is the data on which the model is estimated and the way to obtain it. The literature on this subject is rather extended, with Revealed Choice and Stated Choice (or Revealed and Stated Preference) research to be the most common methods. The concept is to investigate what are the factors which shape people’s choices regarding parking in order to be able to predict the actual choice of individuals. Train (2003) asserts that revealed preference data is related to “people’s actual choices in real-world” while SP presents “hypothetical choice situations”. For both types of data collection, a long debate was taking place about the ability—and to what extent—they can reproduce the actual people’s behaviour and be used to draw conclusions for further planning (Audirac, 1999; Hensher, 1994) but their usability has long overcome this debate.

SP methods receives criticism due to their reference to a non-experienced and as a consequence possibly not well defined by the researcher situation (Audirac, 1999). On the other hand, there is the advantage that researchers control the situation presented including subjects that they want to be analysed (Van den Berg et al., 2012; Louviere et al., 2000). With all the advantages and disadvantages the SP method is widely used in transport research (Hensher, 1994). For the SP methods the reference literature is considered to be the (Louviere et al., 2000). Research focuses lately on the determination of the methods to make data collection more efficient and better represent reality (Street et al., 2005; Bliemer et al., 2009; Rose et al., 2008).

The design of a survey has also received attention by many researchers (e.g. Gunn et al., 1992; Carson et al., 1994; Louviere et al., 2000; Rose et al., 2008; Bliemer et al., 2009). The main streams were based on Design of Experiments (DoE) used in other sciences starting with factorial designs (Full and Fractional) and later with the so called efficient designs. Generally, designs are governed by the definitions of manipulated variables which are mainly referred to as “factors” and manipulated values which are referred as “attributes” (Louviere et al., 2000). As described by Louviere et al. (2000) “A designed experiment is therefore a way of manipulating attributes and their levels to permit rigorous testing of certain hypotheses of interest”.

Factorial Designs are designs combine and test attribute levels (Antony, 2003a). Full factorial designs test all combinations of attribute levels with the number of experiments required to be the product of the number of levels for all factors with the number of choice situation to be given by Equation 2.3. For example in case of 5 factors of 3 levels for each the full factorial design would require $3 \times 3 \times 3 \times 3 \times 3 = 243$ experiments required. In case of a questionnaire this means that 243 questions have to be asked for the investigation of all interactions of the factors involved. As it is rather obvious most times this is not possible. For that reason fractional factorial designs and efficient designs emerged to reduce the number of experiments required (Antony, 2003b; Rose and Bliemer, 2008). The most common fractional factorial design is the orthogonal design where the main criteria to be satisfied is the independence.
of the parameters and the level balance (e.g. Louviere et al., 2000). Based on coding for orthogonal designs it should be satisfied that the sum of the inner product of any column (choice situation) is zero (equation 2.4).

\[ S = \prod_{j=1}^{J} \prod_{k=1}^{K_j} l_{jk} \]  \hspace{1cm} (2.3)

\[ \sum_{s=1}^{S} x_{j_1,k_1,s_1} \times x_{j_2,k_2,s_2} = 0 \]  \hspace{1cm} (2.4)

On the other hand efficient designs have a different concept. The idea is that by having some prior information on the results of the design it is possible to create a design that would increase the information obtained (Rose et al., 2008). Based on the inverse of the Fisher Information Matrix (named as Asymptotic Variance Covariance Matrix – AVC matrix) the standard errors of a design can be calculated if the parameters are known. Of course as this is the purpose of a survey the prior values of the parameters are used.

The measure of information contained in the data is intuitively related to the information matrix. The asymptotic normality of the parameters has been exploited in the past and especially, the fact that the covariance matrix can be asymptotically approximated by the (scaled) inverse of the information matrix. Under these conditions, very common measures which have been used to qualify the identified model make use of the covariance matrix \( P_\theta \):

- \( \min_{x \in X_{id}} \det(P_\theta) \) (D-optimality)
- \( \min_{x \in X_{id}} \text{Tr}(P_\theta) \) (A-optimality)
- \( \min_{x \in X_{id}} \text{Tr}(WP_\theta) \) (L-optimality)
- \( \min_{x \in X_{id}} \lambda_{\text{max}}(P_\theta) \) (E-optimality)

Concerning parking, there are both Revealed Choice researches (Gillen, 1978; Goot, 1982; Hunt and Teply, 1993), Stated Choice researches (Axhausen and Polak, 1991; Van der Waerden and Oppwall, 1995; Bonsall and Palmer, 2004) and combined (Brandley et al., 1993; Tsamboulas, 2001). The available studies can be categorized based on the trip purpose (commuting, shopping, business), the attributes investigated and the method of acquiring the data (Revealed Choice and Stated Choice) (Van der Waerden, 2012).

## 2.6 Conclusions

The literature review had a twofold character. First of all, subjects that can be required for the understanding of this study are examined, and a review of the available studies on parking is presented. Second of all, the literature review revealed areas that have not been investigated and require attention, especially in the case of modelling ITS applications.
• No indication of unfamiliar users- Most models assume the full knowledge of the network by users.

• Most of the research on parking choices is outdated (see Appendix A).

• There is room for examination of additional attributes in choice models.

• The main stream of research is on a macroscopic level for mode choice and destination choice and not on a microscopic level giving little space for understanding the impact of parking to traffic.

• There is little understanding on how people behave in relative changes for the network characteristics.

Starting from unfamiliar users it is believed that parking is a transport component for which there is a chance of having imperfect or not having at all information about the situation at the destination’s area. For that reason it is intended to explore the way people behave when unfamiliar with an area to visit. Furthermore, as the urban environment changes in a quite fast way there is a need for data which would be updated.

On the attributes that are investigated in the literature, a rather important gap was found on the way users behave with relation to the parking availability (probability of finding a vacant parking spot), while it seems to be a very important parameter when it comes to choosing a parking destination.

On the assignment for parking, most models presented use a BPR- like function in order to describe the interaction with traffic. This fail to respond to the fact that individuals would visit a parking destination even if there is low a chance to find a vacant parking spot upon arrival, but there is high chance of finding a parking spot just after a few minutes of waiting.
Part II

Parking Behavioural Research
Chapter 3

Theoretical Parking Behaviour

In this section the proposed theoretical model, describing how people behave when they want to park is presented. The behavioural levels for parking are defined and the necessary user groups for which the behavioural research is intended are described. The decision process model and the survey experiment that took place is conceptually designed.

3.1 Introduction

The understanding of the decisions taken in the parking process, and how individuals decide upon them are crucial for the representation of the parking process. The definition of the parking decision process model and the discrete choice models help towards this direction, with the investigation of the attributes which shape those decisions and the way individuals evaluate the available alternatives to be required. In order to fulfil those requirements there is a need to explicitly define and analyse the parking system (users, network), and the decisions behavioural levels. The behavioural research is going to be used as the basis for the parking assignment modelling framework.

The decisions are explored on a decision process level starting with pre-trip decisions and moving towards the decisions taken while individuals interact with traffic (on-trip). In order to have a clear structure of the decision process it is chosen to categorize decisions on a three-layer behavioural model. Different users of the network imply the definition of users classes.

Towards this understanding, and for the estimation of the discrete choice model a Stated Preference experiment is conducted. The reasoning for conducting an experiment lays on two main reasons. First of all, parking regulations in the urban environment have changed since the latest experiments affecting the behaviour concerning parking. Second of all, it was believed that the attributes widely used in the literature, partially represent parking choices and that there might be a set of attributes which would describe the choice in a more representative way.
The focus of this research –on the impact of a new system to the existing traffic– implies the consideration of trips only made by car. A probable increase of traffic caused by the usage of the new system is not taken into account. The investigation of parking involves the definition of the strategy that people select when choosing for parking on a pre-trip level and the interaction with traffic when reaching the destination area (on-trip) for a defined network with fixed number of trips and fixed departure times concerning shopping.

This chapter presents the theoretical behavioural research, where parking decision process and other required components are presented (Figure 3.1) answering to the following research questions:

3. Which are the decisions involved in the parking process?
4. Which are the characteristics that shape individuals decisions concerning parking?
5. How can an experiment on parking behaviour be adequately designed?
6. How can individuals’ choices concerning parking be modelled?

It starts by presenting the process followed for deriving the parking decision process model and the choice model (Section 3.2). User Classes and the Behavioural Levels are defined in Section 3.3 and Section 3.4 respectively. The behavioural concept is presented (Section 3.5), followed by the Decision Process Framework (Section 3.6). Finally, the Conceptual Experiment Design follows (Section 3.7), the Expected Outcome of the experiment (Section 3.8) and conclusions (Section 3.9) are presented.

![Figure 3.1: Chapter’s components and connections](image-url)

### 3.2 Process model & Choice model Derivation Process

The derivation of a Parking Decision Process model including the conceptual design of the choice models incorporated and the conceptual experiment design are conducted based on a
systematic process presented in (Figure 3.2). The need for a choice model that would accommodate the representation of some parking-related decisions, taking into account the interaction with the transport system was used as a guideline. The starting point of this process is the available literature on parking modelling. The models used to represent parking behaviour, the user classes for which behaviour was modelled, and the data collection methods were investigated (presented in Chapter 2). Furthermore, the modelled attributes were identified and categorized based on their frequency of appearance.

The process for the derivation of a conceptual decision process flow model includes interviews of 5 individuals and a panel of 4 students. The interview structure, the questions asked and the participants characteristics are presented in the Appendix A. Based on the results of the interviews the panel and the input of the thesis supervisors the decision process model was derived.

The decision process model was used as the starting point for the definition of the conceptual choice model and as a consequence of the components of the experiment. The definition of the experiment’s components and its process is referred to as experiment design.

3.3 User Classes

Before continuing with any decision process specification, there is a need to investigate the users (also referred to as travellers or individuals) of the system and try to aggregate them into groups (users’ classes) characterized by the same decisions process. The results of interview, the nature of the motivation system and the conclusions of the literature study lead to distinction of two user’s classes. The travellers which are familiar with the parking situation at the destination and those who are unfamiliar with that situation.

In is clearly evidenced in the literature, that transport research usually focuses on travellers who are assumed to have knowledge of the system (see Bovy et al., 2006). This cannot always be the case – especially for parking. Travellers might be unfamiliar with the parking situation at areas of the cities they even dwell. It is logical that in case someone is unfamiliar with the parking situation cannot be treated as part of a group which assumes full knowledge. Unfamiliar users take different decisions, or even considers different levels of alternatives characteristics. However, there is nothing preventing unfamiliar users from becoming familiar, by acquiring knowledge of the transport system.
Both the familiar travellers and the unfamiliar travellers are segmented in groups based on the trip purpose and the duration of parking. This research focuses on the investigation of the parking habits in the context of shopping and for a duration of 2-3 hours. Further segmentation or generalization is unfortunately rather impossible in the context of this study mainly due to data collection issues described later (Section 3.7). Any generalization made is meant to be for these particular user groups.

In conclusion, the definition of the users’ classes aims towards the direction of a consistent definition of all the components of the parking system investigated. The distinction presented in this section continues to apply throughout this thesis with all models derived to apply only for familiar or unfamiliar users.

### 3.4 Parking Behavioural Levels

Parking behaviour is analysed on three behavioural levels, with respect to the undergoing behavioural process of individuals: Strategic, Tactical and Operational. Those three levels apply for both the familiar and the unfamiliar users however, different decisions are involved in each user class.

In this research, the **strategic** level incorporates the strategy individuals’ devise before trip, in order to park. The **tactical** level deals with the interaction between the individuals and the traffic and parking dynamics. This level includes decisions to proceed from one parking destination to another one, given the strategy mentioned above. Furthermore, this layer contains decisions which are related to the change of the initial strategy after interacting with the transport system. Finally, the **operational** level is related to link choice when cruising, or route choice decisions while it is intended to travel from one parking destinations to another.

The definition of the behavioural levels indicate an order of decision to be followed (e.g. the strategic level defines the decisions on the tactical level). In this case, the strategic level is the first to appear in the decision process determining the decisions on the operational level. The tactical level defines the decisions of the operational level. Apart from the decision flow from the tactical to the operation level, decisions on the operational level might lead back to the tactical level, given the interaction of the individual with the transport system. On the other hand the strategic level is based on the perception of individuals concerning the parking system and take place before trip.

In conclusion, the behavioural levels are going to be used throughout this report in order to define in a more consistent way which decisions are taken and when this takes occurs. A more thorough analysis of the behavioural levels for each user class is provided in the following section. The decisions that are involved in the parking process are presented, and the decision process framework is derived.

### 3.5 Behavioural Concept

The interviews and the panel conducted showed that there is a distinct pattern of behaviour among familiar and unfamiliar users. For that reason the description of every model is based on that pattern.
Familiar  The discussion during the panel study and interviews illustrated an existence of a habitual pattern of people when choosing parking. The traffic situation at the destination as well as the state of the parking destinations available was found to be crucial in the decision process. However, it was also observed that people expect a certain amount of delay (cruising) when they want to park. In other words, people would visit a parking destination if they would expect to find a vacant parking spot in a “short” period of time but would not wait or search if this period becomes “long”. This train of thought led to the following behavioural concept:

*Individuals choose a parking destination based on their preferences concerning price of the parking destination, distance of the parking destination from destination, travel time to the parking destination’s location, parking type as well as the probability of finding a vacant parking spot upon arrival and/or after a certain amount of time.*

In order to make this concept clear two illustrative examples of different parking situations are presented:

**Example 3.1.** Imagine going to a city centre during the morning peak for shopping. It is well known that the turnover rate due to commuters is low during this period of time. If there is not a vacant parking spot at a parking destination when arriving, it is highly unlikely to find a vacant parking spot after cruising for some minutes.

**Example 3.2.** Imagine going to a city centre, for shopping, on a Saturday afternoon, where the turnover rate is high. There is a high probability of parking after a short period of time if individuals cruise or wait at a parking destination, the latter described by a high turnover rate.

Unfamiliar Users  Unfamiliar users have not been investigated to the best of the author’s knowledge, indicating the need to cater for this user class in the experimental design. The idea is that there is a strategy on acquiring information for parking and that generally people would randomly search for parking.

### 3.6 Parking Decision Process Model

There is a twofold reasoning behind the illustration of the decision process concerning parking: to set the guidelines based on which the survey experiment is designed, and to guide
the parking assignment framework models derivation. More specifically, the decision process framework was employed to describe the decisions taken while choosing a parking destination (Figure 3.4). As already mentioned it is a corollary of the literature review, individual interviews and panel interviews.

The random traveller (decision maker) who wants to travel to a city centre, by car can be described by a set of attributes describing the traveller (e.g. age, income, gender, age, area of living, network familiarity) and a set of preferences for the attributes which can characterize the parking alternatives. As described above, the main differentiation in the behavioural process is found based on familiarity with the parking situation at the destination.

From the already described clusters of attributes there is a decision on a parking search strategy. If travellers find an available parking spot at the destination they park and they are out of the system. However, if there is no vacant parking spot at the initial destination, they either continue searching or re-evaluating the alternatives each group have in mind.

In conclusion, it is important to be noted that, it is impossible to completely represent each and every single decision and to investigate all the options on the same level in the context of this research. Those two deficiencies prompt for the assumptions which will be explicitly stated when necessary in the remainder of the report.

3.6.1 Familiar Users

If a traveller is familiar with the system, there are various important factors that affect their decisions. Based on personal characteristics, trip characteristics and of course parking characteristics the decisions of route choice and parking destination can described by a habitual pattern on the strategic level – before the initialization of the trip. The general idea is that by assigning utilities to each alternative familiar travellers choose both route and destination in a process which maximizes utilities (or minimizes disutilities) for both choices. The strategy realised is structured as a \textit{strategic parking search route}.

As already mentioned above, there is a case that the situation at the destination is not as expected. This can either been realized by arriving at the destination and finding out that the parking location is full, by being informed by PGIs before arriving at destination or by just interpreting the traffic situation while driving. In this case and on an operational level they have to choose to follow their initially planned strategy or change it. In case of the continuing following the strategy they have to decide again on what to do. Finally in case of searching for on-street parking (on a tactical level) travellers define their search route in the parking destination area.

3.6.2 Unfamiliar Users

Although unfamiliar travellers generally search for informations (Maps/navigation devices) before making a trip, there might by a different approach when deciding for parking on the strategic level. Speed of searching, rationality of decisions and choices are rather influenced by the unfamiliarity effect. However, it is believed that people who search for information can be treated as familiar users as they have altered their parking destination based on the information gathered.
It is important to state that although there is no knowledge of the parking situation in a city not visited before there is a general preference (based on interviews) on the parking type (on-street and off-street) which is based on previous experiences, individual preferences and trip attributes. Furthermore, there is a strategy on the start of the searching process which was either arrive at destination and then start searching or start searching before arriving using the blocks or the street numbers to define the distance from destination. On an operational level, in case of first arriving at the destination and afterwards search for parking unfamiliar travellers choose to pick a direction to search in case of not coming across any parking destination while driving to their destination which is influenced by the information received by PGI systems. Finally on the tactical level unfamiliar travellers choose their search route.

3.7 Conceptual Experimental Design

The lack of a behavioural model that can incorporate the required behavioural characteristics lead to the design of a survey based on the decision framework presented above. It was decided to design a web-based Stated Preference survey consisting of 3 sections: Personal Characteristics Section, Unfamiliar Parking User Section and Familiar Parking User Section.

The first section (Personal Characteristics) was decided to consist of seven (7) questions for the age, the income, the gender, the educational level and the area of living (Postcode). In this part of the survey there are two threshold for the continuation of the survey: the possession of a driver’s license and the frequency of driving by car at a city centre. In case an interviewee do not pass one of those two “frontier questions” (No driver’s licence and/or frequency of driving to a city centre less than once per month) he or she is not allowed to continue.

The second part is about the behaviour of unfamiliar users. It is rather important to state that unfamiliarity is not only encountered as if people do not know anything about the places they visit but also as they rather have a vague perception of the situation to be faced upon arrival. This is rather normal as people do know for example that most Dutch cities do not offer free parking and that especially in dense urban areas it is rather expensive. On this assumption
(that users have a perception of the situation to face upon arrival) this part is formulated. First the acquirement of information process (parking strategy) is investigated. Secondly the preference between on-street and off-street parking is investigated in an unfamiliar urban environment. Furthermore two questions are asked for the reaction in case of waiting and the maximum waiting time before going to another parking destination.

The third part of this survey involves the investigation of the decisions concerning familiar users. This part is designed as a Stated Preference survey for two alternatives with varying attributes (characteristics of parking) in the scenarios created. The design process of this part of the survey is presented in the following section. In general 12 questions are asked which are produced based on an efficient design from priors from the literature and a pilot study. The attributes that were generally investigated during the experiment design are presented in 3.1. This attribute set is derived mainly from attributes investigated in the literature by other researchers enriched based on Decision Process Model and the need to develop a discrete choice model able to be used in an assignment context. For this reason, apart from the well investigated attributes (Appendix A), the probability of finding a parking spot after some minutes is introduced, as a way to describe the search time in a probabilistic way. Those attributes were introduced in the conceptual experiment design and changed during the pilot study (for the final design see Section 4.3.2)

Table 3.1: Parking related attributes examined

<table>
<thead>
<tr>
<th>Attributes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price</td>
</tr>
<tr>
<td>Distance from Destination</td>
</tr>
<tr>
<td>Travel time</td>
</tr>
<tr>
<td>Parking Type</td>
</tr>
<tr>
<td>Probability upon arrival</td>
</tr>
<tr>
<td>Probability after 4 minutes</td>
</tr>
<tr>
<td>Probability after 8 minutes</td>
</tr>
</tbody>
</table>

3.7.1 Data Collection Method

As already mentioned, one of the goals of this behavioural research is to have a representative sample of the Netherlands. The only way to achieve that, given the limited resources available, was via a web-based survey. This by itself can be considered as representative, as the Netherlands has a very high percentage of internet penetration with 94 percent of individuals to access the internet at least once a week (Eurostat, 2009).

For that reason an account on the TU Delft server was set up and the LimeSurvey\(^1\) Platform was installed and modified to meet the standards required on appearance and functionality. An example a questionnaire structure is presented in the Figure 3.5.

\(^1\)LimeSurvey is an open-source platform available at [www.limesurvey.org/](http://www.limesurvey.org/) for creating and distributing surveys. It requires a L.A.M.P. account with a configured SQL-Database and PHP.
In order to receive in a rather small period of time the results of the survey and avoid issues regarding the representative character of the sample (given the Dutch population) a company was employed (Respondenten Database\textsuperscript{2}) to distribute the questionnaires.

### 3.7.2 Familiar Users Section

**Stated Preference Design Properties**

One of the most important aspect of an experiment design is the reliability of the collected data. Lately, there is a discussion on the correlation of the complexity\textsuperscript{3} of the Stated Preference research to the choice process. As it was evidenced by Hensher (2006); Caussade et al. (2005a) largest dimensions of a stated preference (in terms mainly of the number of attributes) can result in a biased model estimation. As parking choice is a rather complex decision process with many factors it was decided to use methodologies for the experimental design that would result in an acceptable number of questions and the smallest possible number of examined attributes (as well as attribute levels). As such, it was decided to be tested on efficient designs and orthogonal designs and decide which could yield more information.

\textsuperscript{2}Respondenten Database (http://www.respondentendatabase.nl/) is a company in the Netherlands that has a database of people are paid to participate in surveys

\textsuperscript{3}As defined by (Hensher, 2006)
with the lowest “complexity cost”. Finally, in order to have a representative sample of the Dutch population the required number of questionnaires was set to be 400 responses. This sample size is in line with the estimated required sample by (Krejcie and Morgan, 1970) which indicates that for a population of Netherlands and a degree of accuracy of 0.05 the representative sample size is around 384 respondents.

The idea of the conceptual experimental design is to define a process that would guide the experimental design process away from possible complications that would risk the outcome of the survey. For that reason the experimental design was planned to follow a process with a two rounds pilot study based on efficient designs. The process defined goes through the design of a first survey to be used for the definition of an initial set of priors. Then the design of a second survey to be used for the definition of the priors for the final design (Figure 3.6).

![Diagram](image)

**Figure 3.6: The survey design procedure**

**Attributes’ values**

For the attribute values, it was chosen to follow, where possible the principle of the extreme values on the attribute specification. Starting with the price, the general idea is that especially for shopping parking is most times paid. The average hourly fee at a Dutch city centre is €1.55 for on-street parking and €1.52 for off-street parking (van Ommeren et al., 2012). For Assen the price is €1.71 per hour (Gemmente Assen, 2013). On the other side the price in Rotterdam or other major Dutch city is around €3 with Amsterdam to be the most expensive (around €5) (van Ommeren et al., 2012). Another factor which determines the choice of this particular values is the way pricing is implemented in the Netherlands. Generally parking pricing is governed by large zones of paid parking offering free parking in rather distant locations to be chosen. For that reason, there is little fluctuation in the parking price which is not overshadowed by other dominant characteristics.

The choice of the distance from the parking destination to the actual destination is based on the largest and the minimum distance from a destination. The smallest distance is around 100 and the largest distance 500- 700, decided based on the maximum catchment area used for public transport.

The travel time from home to parking destination is chosen in the same context for a typical Dutch city. It is done in a way that those travel times would be realistic enough to use the car as a means of transport for shopping.

Concerning the parking type, in this study it is considered to be an attribute under examination in an effort to capture the effects of the characteristics that are not examined and are
perceived as different by travellers.

Finally the probability chosen is based on real life characteristics. As described later in the Parkability model (Section 5.7), the probability of finding a vacant parking spot is a variable which is affected by a rather large amount of factors (arrival time and search time from a travellers perspective and parking capacity, arrival rate to the parking destination, parking duration of other travellers, on-street or off-street). It is however important to present some extreme cases to decision makers to understand the way they behave based on that probability function.

3.8 Expected Experiment Outcome

Personal Information
The collection of the personal characteristics takes place for mainly two reasons. First of all, in order to examine the representative character of the sample against the population. Of course it is not possible to take into account all the socio-demographic attributes yet, it should at least include the characteristics that generally are important for the examined behaviour. In this case the survey data collection is designed in a way to reduce the possibility of having a non representative sample. Second of all, it is rather common in models resulting from behavioural research surveys to include socio-demographic as part of the model structure due to their significance.

Unfamiliar Users
As there is little information on how unfamiliar individuals behave when it comes to parking, and given the limited number of questions allowed in order to capture behavioural characteristics in both familiar and unfamiliar users an introduction in this user’s class behaviour is intended. The questions would serve as a basis to model the assignment of unfamiliar users. The main two hypothesis are:

Hypothesis 3.1. The decision process for an unfamiliar user does not include pre-trip preparations concerning parking.

Hypothesis 3.2. Unfamiliar users decide upon a specific parking type before the realization of the trip.

Finally, a hypothesis is made on the existence of patterns of behaviour for specific socio-demographic characteristics concerning the choice of an unfamiliar parking strategy and the parking type:

Hypothesis 3.3. Socio-Demographic characteristics yield significant estimators regarding the parking strategy and the choice of parking type by unfamiliar users.

The testing of hypotheses is presented in Section 4.5.

Familiar Users
The familiar user section concept is to get enough information in order to derive a discrete choice model. The basic model that can be derived is the Multinomial Logit Model based on the concept of Random Utility Maximization with the (representative) utility $V_{i,opd}$ for the
random individual $i$ travelling from the random origin $o$ to the random destination $d$ for the random parking destination $p$ to be:

$$V_{i,o,p,d} = \beta_p + \beta_1 \cdot C_p + \beta_2 \cdot T_{o,p} + \beta_3 \cdot W_{p,d} + \beta_4 \cdot O_p + \beta_5 \cdot P_{q1,p} + \sum_{0}^{a} \beta_{(u+a)} \cdot P_{q_u,p}$$  \hspace{1cm} (3.1)

Where:

- $\beta$s: Attribute Estimators
- $C_p$: Parking price of parking destination $p$
- $T_{o,p}$: Travel time from origin $o$ to parking destination $p$
- $W_{p,d}$: Walking distance from parking destination $p$ to destination $d$
- $O_p$: Dummy variable for on-street (0) or off-street (1)
- $P_{q1,p}$: Probability of finding a vacant parking spot at parking destination $p$ upon arrival
- $q_a$: Number of minutes after arrival examined
- $P_{q_u,p}$: Probability of finding a vacant parking spot at parking destination $p$ after $q$ minutes

This is based on the following hypothesis:

**Hypothesis 3.4.** Parking for shopping, given a specific parking duration is determined by five significant classes of characteristics: the price, the travel time from home to the parking destination, the walking distance from the parking destination to the individuals’ destination (i.e. shopping centre), the parking type, the probability of finding a vacant parking spot upon arrival and the probability of finding a vacant parking spot after a period of time.

The betas ($\beta$) are the parameters (or estimators) of the MNL model to be estimated with $\beta_p$ being the Alternative Specific Constant (ASC) for parking alternative $p$. For this research it was chosen to use generic estimators and non-labelled alternatives.

MNL however is not the only model structure that could apply. The attribute examined as well as the character of parking give an impression of the alternative model structure that might apply. For this reason, hypotheses are formulated in order to derive a more representative model for the choice of a parking destination. The concepts that are going to be tested are presented as hypotheses and briefly analysed.

Starting from the fact MNL model fails to capture heterogeneity in taste and taking into consideration that there is a high possibility that people would value differently the different attributes describing parking, the decision to test a mixed logit was taken. Another modelling approach that might be appealing for the representation of behaviour regarding choosing a parking destination is the Random Regret Minimization approach, which basic notion is that people would minimize the regret when choosing between parking alternatives. Panel data and profiles also seem appealing for this behavioural research.

Finally, Prospect theory seem to be very appealing for the particular attributed describing the parking choice especially for one reason: The probability after 8 minutes can be perceived as a risk given the fact that travellers expect to park in a period of time and depending on the results of the survey this is probably lower than 8 minutes. Although mentioned for matters
of consistency, prospect theory is not investigated due to implementation problems. The idea of implementation is presented in the future work chapter.

Based on the above-mentioned hypotheses are formulated:

**Hypothesis 3.5.** The attributes chosen to represent the utility and experiment design can result in an estimated Multinomial Logit (MNL) model which can describe the parking choice.

**Hypothesis 3.6.** Nested Logit (NL) can improve the estimated parameters.

**Hypothesis 3.7.** Heterogeneity in taste concerning the choice of the parking destination apply suggesting for a mixed logit (MMNL) modelling approach.

**Hypothesis 3.8.** The choice of parking destination can be better described by the Random Regret Minimization model structure approach.

**Hypothesis 3.9.** The choice of parking destination can be better described by the Prospect Decision Theory model structure approach.

**Hypothesis 3.10.** Panel Data can improve the performance of the model.

**Hypothesis 3.11.** Estimation of profiles can reduce the probable heterogeneity of the estimated model.

The hypotheses presented in this section are tested in Section 4.5 with conclusions on which is the most appropriate model structure.

### 3.9 Conclusions

In this chapter theoretical insights concerning the parking process were presented. Some preliminary steps towards this direction, such as the definition of the user classes as well as the segmentation of decisions in behavioural levels are introduced. The preliminary steps revealed, in a way, the behavioural concept and the behavioural components to be investigated in an experiment and how those decisions are structured in a Decision Process model.

Both for familiar and unfamiliar users the main concept is that there are decisions revealing a strategy on approaching parking as well as operational and tactical characteristics that can be represented. Familiar users indicate a habitual pattern by developing parking search routes and unfamiliar users indicate preferences on their planning concerning parking.

Based on the Decision Process framework the conceptual experiment design was derived in such a way that it would result in the acquisition of more information about the estimators of the attributes examined. The attribute levels are conceptually defined and hypotheses are made concerning the expected outcome of the experiment. Finally the concept of the data collection process is described.
Chapter 4

Experiment Design and Model Estimation

In this section the experiment design process and the results of the research study conducted on 424 individuals in the Netherlands are presented. In the beginning the experimental design process is analysed. Afterwards, the sample is examination on its available characteristics for being representative for the population and the sample preparation and stratification is presented. Finally the behavioural models estimated are presented.

4.1 Introduction

The design of a survey and the analysis of the acquired information are both very important components of behavioural research. As the system describing the behavioural responses of individuals is complex, its identification and the investigation of the experimental designs were rather limited to some basic concepts of efficient designs.

The literature suggests that the most usual design for Stated Preference research is the orthogonal design. However, as it is indicated by Rose et al. (2008) even in case there is only an indication of the priors\(^1\), designing a survey with efficient design techniques yields more information. This information can be described by the Fisher Information Matrix\(^2\) with the highest information to result in lower variance described by the Cramer Rao Inequality\(^3\) (given that some conditions on the estimators properties are met). The experiment design process does not take into account the application (which in this case is the prediction) with the

---

\(^1\)Priors are prior estimators of the unknown vector of true parameters \(\theta\) that is tried to estimate

\(^2\)The Fisher Information Matrix is a way of measuring the information contained in a random variable, for an unknown parameter \(\theta\) (see Ljung, 2010).

\(^3\)The Cramer Rao inequality states that there can be no (unbiased) estimator \(\theta\) that can have a lower variance than the inverse of the Fisher Information Matrix (see Ljung, 2010).
goal to be the identification (and estimation) of a model that would describe the choice in a realistic way.

The analysis of the outcome of the survey is based on the well-known discrete choice behavioural models, using hypothesis formulated in the previous chapter. The evaluation of the hypothesis tests are based on the adjusted $\rho$ as suggested in the literature (Chorus, 2010).

This chapter answers the following research questions:

5. How can an experiment on parking behaviour be adequately designed?

6. How can individuals’ choices concerning parking be modelled?

This chapter presents the Experimental Design Process and the Estimation of Discrete Choice models (Figure 4.1), components well connected to the previous chapter and used in the derivation of the Parking Assignment Model. It starts with the introduction of the experiment design process (Section 4.3), leading to the final design used for the Stated Preference research conducted (Section 4.3.2). The sample is stratified 4.4.1 and the obtained data is analysed, using descriptive statistics (Section 4.4.2). The hypothesis concerning the model structure are tested for unfamiliar and familiar users (Section 4.4.3 and 4.5) and conclusions made 4.7.

### 4.2 Notation

For clarification reasons the notation for this chapter is introduced and is going to be as follows:

Emmanouil Chaniotakis                         Master of Science Thesis
4.2 Notation

Indices:

- \(d\): Destination
- \(k\): Parking Spot
- \(n\): Individual
- \(o\): Origin
- \(p\): Parking Destination

Parameters, Variables & Expressions:

- \(0LDes\): The efficient design produced using the \(0LP\) estimators
- \(0LP\): The vector of prior estimators from the literature
- \(1LDes\): The efficient design produced using the \(1LP\) estimators
- \(1LP\): The vector of prior estimators from the first round of the pilot study
- \(2LP\): The vector of prior estimators from the second round of the pilot study
- \(ASC1\): Alternative Specific Constant for alternative 1
- \(ASC2\): Alternative Specific Constant for alternative 2
- \(FDes\): The final design, produced using the \(2LP\) estimators
- \(-2[\mathcal{L}(0) - \mathcal{L}(\hat{\beta})]\): Likelihood ratio test
- \(C_p\): the hourly parking price of parking destination \(p\) (expressed in \(\text{€/h}\))
- \(\Lambda\): Inter-arrival Time random variable
- \(\mathcal{L}(\hat{\beta})\): Final log-likelihood
- \(\mathcal{L}(0)\): Initial (null) log-likelihood
- \(O_p\): Dummy variable for on-street (0) or off-street (1)
- \(Pr_p^q\): probability of finding a vacant parking spot at parking destination \(p\) within \(q\) minutes of waiting/searching
- \(Pr_p^{0}\): probability of finding a vacant parking spot at parking destination \(p\) upon arrival
- \(q\): number of minutes after arrival examined
- \(\hat{\rho}^2\): Adjusted likelihood ratio index
- \(t\): Time instance
- \(T_{o,p}\): the travel time from origin \(o\) to parking destination \(p\) (expressed in minutes)
- \(W_{p,d}\): the walking distance from parking destination \(p\) to destination \(d\) (expressed in meters)
- \(\hat{\beta}\): the estimated values of the model parameters (estimators)
- \(\beta_1\): Price attribute estimator
- \(\beta_2\): Walking Distance attribute estimator
- \(\beta_3\): Travel Time attribute estimator
- \(\beta_4\): Parking Type (on-street or off-street) attribute estimator
- \(\beta_5\): Probability upon arrival attribute estimator
- \(\beta_6\): Probability after 4 minutes attribute estimator
- \(\beta_7\): Probability after 8 minutes attribute estimator
- \(\theta_0\): The vector of true value of the estimators
- \(\rho^2\): Likelihood ratio index

---

\(^4\)For definitions see Train (2003)
4.3 Experiment Design Process

The experimental design process for the familiar section (as conceptually designed in the previous chapter - Section 3.7) was initially implemented from data from the literature and compared to the orthogonal design. The comparison was made on the D-error estimator (the determinant of Variance Covariance Matrix). As expected, the orthogonal design was found to be ineffective with many scenarios to be governed by dominating alternatives. As such, the first round of the pilot study was introduced to have a clearer indication of the estimators. Afterwards, the design process continued with the derivation of the second round’s design and was completed with the final design. All the experiment designs were produced using Ngene. The model structure chosen to use for the designs was the MNL model.

4.3.1 Pilot Study

The pilot studies were held among student of TU Delft (first round) and employees of TU Delft and TNO (second round). Both were accompanied with feedback that was used to evaluate the complexity of the questionnaire and for content-wise improvements.

**Pilot Study: First Round**

The first round’s design was created based on a combination of the available priors from literature ($0LPr$). The priors were based on the researchers of Van der Waerden (2012); Axhausen and Polak (1991). The Fisher information matrix and the attributes and the attribute-levels used are presented in Table A.2 and A.3 respectively of Appendix A.

In this design there were some dominant alternatives in some scenarios and the information that could be acquired was not the maximum (the design was sub-optimal) mainly due to the combination of the two studies. However this design could again accommodate more information than an orthogonal design (which yielded a higher number of dominant scenarios) and it was chosen to be implemented in the first round of the pilot study with a small sample.

After acquiring the answers from 11 respondents an MNL model was estimated using BIOGEME based on their responses for the second round of the pilot study. This model is presented in the Table A.4 of Appendix A. Feedback was also provided with most respondents indicating that the survey was rather demanding and large. The MNL model estimators (Table A.4) form the $1LPr$ estimators’ set to be used in the design of the experiment, for the second round of the pilot study. It has to be stated, that the results of this model (based on the $0LPr$) can be considered as biased. The reason this stands is due to the fact that the model represent a very small and behaviourally specific sample of international students who live in the Netherlands, having a drivers license and occasionally using a car. However, it is believed that it provides a better representation of the estimators of the model and that the values of the estimators are closer to the vector of true values ($\theta_0$). This is believed due to the fact that the $0LPr$ were normalized estimators’ values of attributes which were similar to the attributes investigated.
Pilot Study: Second Round

The second round of the pilot study is based on the \( 0LDes \) design, from the \( 0LPp \) priors. Some changes were implemented in the design, based on the information and the feedback acquired from the first round. The walking distance from destination was increased to 700 meters, as it was found that 500 meters was not considered to be much different in individuals’ perception from the 100 meters (during discussions after filling out the questionnaire most respondents indicated that it does not make a difference to have to walk 500 or 100 meters). Furthermore, the travel time from home was changed towards more realistic car travel times, as in the Netherlands it is more common to cycle for such travel times. The values used in the design of the \( 1LDes \) are presented in the Table 4.2.

### Table 4.2: Parking related attributes \( 1LDes \) Design

<table>
<thead>
<tr>
<th>Attributes</th>
<th>Levels</th>
<th>Level Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price</td>
<td>2</td>
<td>€1.5 / €2.5</td>
</tr>
<tr>
<td>Distance from Destination</td>
<td>2</td>
<td>100 meters / 700 meters</td>
</tr>
<tr>
<td>Travel time</td>
<td>2</td>
<td>16 min / 24 min</td>
</tr>
<tr>
<td>Parking Type</td>
<td>2</td>
<td>On-Street / Off-Street</td>
</tr>
<tr>
<td>Probability upon arrival</td>
<td>2</td>
<td>10% , 40%</td>
</tr>
<tr>
<td>Probability after 4 minutes</td>
<td>2</td>
<td>30%, 70%</td>
</tr>
<tr>
<td>Probability after 8 minutes</td>
<td>2</td>
<td>60%, 100%</td>
</tr>
</tbody>
</table>

The Fisher information matrix of this design is presented in Table A.5 of Appendix A. In comparison to the Fisher information matrix produced by the \( 0LDes \) design, it is rather obvious that the information that can be acquired is higher. Furthermore this design was produced without any dominant scenarios and with a D-error of 0.10. This round’s questionnaires was distributed in a different and a bit more diverse sample within the employees of the Delft University of Technology and TNO. It was filled out by 35 respondents. It was accompanied by feedback from the participants. The statistics of those respondents are presented in Table A.6 of Appendix A.

An MNL model that was estimated, using **BIOGEME** and is presented in Table 4.3. On the estimators side (\( \beta_1 \) for price, \( \beta_2 \) for walking distance, \( \beta_3 \) for access time, \( \beta_4 \) for on-street or off-street, \( \beta_5 \) for probability upon arrival, \( \beta_6 \) for probability after 4 minutes, \( \beta_7 \) for probability after 8 minutes) the results seem to be as expected, with \( \beta_1 \), \( \beta_2 \) and \( \beta_3 \) to be negative and \( \beta_4 \), \( \beta_5 \), \( \beta_6 \) and \( \beta_7 \) to be positive.

On the estimators significance, some tests were run with alternative specific constants (ASC) and without, resulting in insignificant ASCs. Apart from the MNL model, the results of the pilot survey were tested against the MMNL model (mixed logit) in order to test for heterogeneity in the population. It was found that the variances of the parameters were not significant and that the MNL model performed better than the MMNL.

It has to be stated, that it is rather unsafe to draw conclusions based on this model due to the low number of participants and the fact that the sample is not representative of the (Dutch) population. This model is only useful towards the direction of a more efficient design for the final survey. The results for the \( 1LPp \) design were only used for the actual survey of 400
 respondents fitting the demographic characteristics of the Netherlands in order to investigate the parking behaviour based on the attributes already presented.

The feedback that accompanied the survey was constructive towards the direction of a better design. Most of the feedback was on the questionnaire being time-consuming and rather difficult due to the high number of attributes. This resulted (as described) in participants eliminating some attributes and making decisions based on those considered as the most important. This stands in line with what Hensher (2006); Caussade et al. (2005b) assert about SP complexity, where there seems to be a tendency to have an increased likelihood of biased parameters in case of a wider range of attributes. The final design was shaped given the feedback and the priors of the second round of the experimental process.

### 4.3.2 Final Design

For matters of consistency the final design is presented including all the questions and the way it was implemented.

**Personal Information**  In this part, changes were made concerning the formulation of the phrases used. The personal characteristics investigated are:

- Age
- Gender
- Income
- Education Level
- Postcode

---

**Table 4.3: MNL model based on results of the $1LP_r$ Design**

<table>
<thead>
<tr>
<th>Parameter number</th>
<th>Description</th>
<th>Coeff. estimate</th>
<th>Asympt. std. error</th>
<th>t-stat</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>$\beta_1$ (Price)</td>
<td>-0.550</td>
<td>0.115</td>
<td>-4.80</td>
<td>0.00</td>
</tr>
<tr>
<td>2</td>
<td>$\beta_2$ (Walking Dist)</td>
<td>-0.00135</td>
<td>0.000185</td>
<td>-7.32</td>
<td>0.00</td>
</tr>
<tr>
<td>3</td>
<td>$\beta_3$ (Travel Time)</td>
<td>-0.0729</td>
<td>0.0160</td>
<td>-4.55</td>
<td>0.00</td>
</tr>
<tr>
<td>4</td>
<td>$\beta_4$ (Parking Type)</td>
<td>0.470</td>
<td>0.0964</td>
<td>4.88</td>
<td>0.00</td>
</tr>
<tr>
<td>5</td>
<td>$\beta_5$ (Pr. Arrival)</td>
<td>1.73</td>
<td>0.511</td>
<td>3.39</td>
<td>0.00</td>
</tr>
<tr>
<td>6</td>
<td>$\beta_7$ (Pr. 8 min)</td>
<td>1.07</td>
<td>0.417</td>
<td>2.56</td>
<td>0.01</td>
</tr>
</tbody>
</table>
• Possession of drivers license
• Frequency of shopping at the city centre

**Unfamiliar Users**  This part was restructured and reformulated, to appeal more on the behaviour of travellers based on feedback received. The issues investigated are:

• Parking Search Strategy (Plan route before trip, Arrive and search, search before reaching destination)
• Parking Type Preferences (On-Street, Off-Street)
• Reaction after 4 minutes of search or wait
• Maximum searching time before going to an alternative of other parking type

**Familiar Users**  The design for the final version of the Familiar Users part was based on the priors derived by the 2nd round of the pilot study ($2LPr$) with some important modifications. The feedback resulted in the elimination of the attribute describing the probability of finding a vacant parking spot after 4 minutes, in an effort to make the questionnaire less complex.

**Table 4.4:** Parking related attributes, Final Design

<table>
<thead>
<tr>
<th>Attributes</th>
<th>Levels</th>
<th>Level Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Parking Type</td>
<td>2</td>
<td>On-Street / Off-Street</td>
</tr>
<tr>
<td>Price</td>
<td>2</td>
<td>€1.25 / €2.5</td>
</tr>
<tr>
<td>Distance from Destination</td>
<td>2</td>
<td>100 meters / 700 meters</td>
</tr>
<tr>
<td>Travel time</td>
<td>2</td>
<td>16 min / 24 min</td>
</tr>
<tr>
<td>Probability upon arrival</td>
<td>3</td>
<td>10%, 40%, 70%</td>
</tr>
<tr>
<td>Probability after 8 minutes</td>
<td>3</td>
<td>40%, 70%, 100%</td>
</tr>
</tbody>
</table>

The 1st level of the price attribute was also changed from 1.5 to 1.25 to introduce a wider price range. Due to the large number of questions required, it was decided to divide the scenarios’ in two blocks, in order to reduce the number of the scenarios per respondent and increase the size of the design. 24 questions were blocked in two blocks (12 scenarios per respondent). The final design’s attributes and levels are presented in Table 4.4.

The final design ($FDes$) was produced using Ngene. Again, combinations of factors were tested using as a benchmark the D-error (as the priors of the model were fixed, the level values in the range of the level values used for the model calculation resulted in different models). It was found that a design of 3 levels (given the number of attributes and the number of choice situations) would have better results in acquiring the most information. The Fisher information matrix is presented in Table 4.5 and the final design, in Table 4.6. To conclude, the questionnaire was translated into Dutch.
### 4.4 Data Collection & Data Analysis

#### 4.4.1 Sample Preparation & Stratification

The final questionnaire was distributed by a private company with a goal of getting 400 respondents in total constituting a representative sample of the Dutch population. Two questionnaires were distributed (due to blocks). The total number of responses was 474 (208 and 266), giving a fair margin for sample stratification. From the 474 responses 426 were fully completed (89.9 percent).

---

**Table 4.5:** Fisher Information matrix - 1LPr Design

<table>
<thead>
<tr>
<th>Prior</th>
<th>b1</th>
<th>b2</th>
<th>b3</th>
<th>b4</th>
<th>b5</th>
<th>b7</th>
</tr>
</thead>
<tbody>
<tr>
<td>b1</td>
<td>8.082256</td>
<td>-276.819</td>
<td>-8.51605</td>
<td>0.401154</td>
<td>0.881225</td>
<td>0.73299</td>
</tr>
<tr>
<td>b2</td>
<td>-276.819</td>
<td>1862152</td>
<td>-2401.33</td>
<td>667.3109</td>
<td>470.6781</td>
<td>504.5564</td>
</tr>
<tr>
<td>b3</td>
<td>-8.51605</td>
<td>-2401.33</td>
<td>331.0492</td>
<td>2.840189</td>
<td>4.391558</td>
<td>3.123128</td>
</tr>
<tr>
<td>b4</td>
<td>0.401154</td>
<td>667.3109</td>
<td>2.840189</td>
<td>5.172644</td>
<td>-0.36803</td>
<td>-0.14773</td>
</tr>
<tr>
<td>b5</td>
<td>0.881225</td>
<td>470.6781</td>
<td>4.391558</td>
<td>-0.36803</td>
<td>1.231664</td>
<td>-0.01488</td>
</tr>
<tr>
<td>b7</td>
<td>0.73299</td>
<td>504.5564</td>
<td>3.123128</td>
<td>-0.14773</td>
<td>-0.01488</td>
<td>1.554122</td>
</tr>
</tbody>
</table>

**Table 4.6:** The Final Design (FDes)

<table>
<thead>
<tr>
<th>Choice</th>
<th>C1</th>
<th>W1,d</th>
<th>T0,1</th>
<th>O1</th>
<th>Pr10</th>
<th>Pr1s</th>
<th>C2</th>
<th>W2,d</th>
<th>T0,2</th>
<th>O2</th>
<th>Pr20</th>
<th>Pr2s</th>
<th>Block</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1.25</td>
<td>100</td>
<td>24</td>
<td>1</td>
<td>0.1</td>
<td>0.4</td>
<td>2.5</td>
<td>700</td>
<td>16</td>
<td>0</td>
<td>0.7</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>2</td>
<td>1.25</td>
<td>100</td>
<td>24</td>
<td>0</td>
<td>0.1</td>
<td>0.4</td>
<td>2.5</td>
<td>700</td>
<td>16</td>
<td>1</td>
<td>0.4</td>
<td>0.4</td>
<td>1</td>
</tr>
<tr>
<td>3</td>
<td>2.5</td>
<td>100</td>
<td>16</td>
<td>1</td>
<td>0.1</td>
<td>1</td>
<td>1.25</td>
<td>700</td>
<td>24</td>
<td>0</td>
<td>0.7</td>
<td>0.7</td>
<td>2</td>
</tr>
<tr>
<td>4</td>
<td>2.5</td>
<td>100</td>
<td>24</td>
<td>0</td>
<td>0.7</td>
<td>0.7</td>
<td>1.25</td>
<td>700</td>
<td>16</td>
<td>1</td>
<td>0.1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>5</td>
<td>1.25</td>
<td>700</td>
<td>24</td>
<td>1</td>
<td>0.1</td>
<td>1</td>
<td>2.5</td>
<td>100</td>
<td>16</td>
<td>0</td>
<td>0.7</td>
<td>0.7</td>
<td>2</td>
</tr>
<tr>
<td>6</td>
<td>1.25</td>
<td>700</td>
<td>24</td>
<td>0</td>
<td>0.4</td>
<td>0.4</td>
<td>2.5</td>
<td>100</td>
<td>16</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>7</td>
<td>1.25</td>
<td>700</td>
<td>24</td>
<td>0</td>
<td>0.7</td>
<td>1</td>
<td>2.5</td>
<td>100</td>
<td>16</td>
<td>1</td>
<td>0.1</td>
<td>0.4</td>
<td>2</td>
</tr>
<tr>
<td>8</td>
<td>2.5</td>
<td>700</td>
<td>24</td>
<td>1</td>
<td>0.7</td>
<td>1</td>
<td>1.25</td>
<td>100</td>
<td>16</td>
<td>0</td>
<td>0.1</td>
<td>0.4</td>
<td>1</td>
</tr>
<tr>
<td>9</td>
<td>1.25</td>
<td>700</td>
<td>16</td>
<td>0</td>
<td>0.1</td>
<td>1</td>
<td>2.5</td>
<td>100</td>
<td>24</td>
<td>1</td>
<td>0.4</td>
<td>0.4</td>
<td>1</td>
</tr>
<tr>
<td>10</td>
<td>1.25</td>
<td>700</td>
<td>16</td>
<td>0</td>
<td>0.7</td>
<td>0.7</td>
<td>2.5</td>
<td>100</td>
<td>24</td>
<td>1</td>
<td>0.1</td>
<td>0.4</td>
<td>1</td>
</tr>
<tr>
<td>11</td>
<td>2.5</td>
<td>700</td>
<td>16</td>
<td>1</td>
<td>0.4</td>
<td>0.4</td>
<td>1.25</td>
<td>100</td>
<td>24</td>
<td>0</td>
<td>0.1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>12</td>
<td>1.25</td>
<td>700</td>
<td>16</td>
<td>1</td>
<td>0.1</td>
<td>1</td>
<td>2.5</td>
<td>100</td>
<td>16</td>
<td>1</td>
<td>0.4</td>
<td>0.4</td>
<td>1</td>
</tr>
<tr>
<td>13</td>
<td>2.5</td>
<td>100</td>
<td>16</td>
<td>0</td>
<td>0.1</td>
<td>1</td>
<td>1.25</td>
<td>700</td>
<td>24</td>
<td>1</td>
<td>0.4</td>
<td>0.4</td>
<td>1</td>
</tr>
<tr>
<td>14</td>
<td>1.25</td>
<td>700</td>
<td>16</td>
<td>0</td>
<td>0.1</td>
<td>1</td>
<td>2.5</td>
<td>100</td>
<td>24</td>
<td>0</td>
<td>0.7</td>
<td>0.7</td>
<td>1</td>
</tr>
<tr>
<td>15</td>
<td>2.5</td>
<td>700</td>
<td>16</td>
<td>0</td>
<td>0.7</td>
<td>1</td>
<td>1.25</td>
<td>100</td>
<td>24</td>
<td>1</td>
<td>0.1</td>
<td>0.4</td>
<td>2</td>
</tr>
<tr>
<td>16</td>
<td>2.5</td>
<td>100</td>
<td>24</td>
<td>0</td>
<td>0.1</td>
<td>1</td>
<td>1.25</td>
<td>700</td>
<td>16</td>
<td>1</td>
<td>0.4</td>
<td>0.4</td>
<td>2</td>
</tr>
<tr>
<td>17</td>
<td>1.25</td>
<td>100</td>
<td>16</td>
<td>0</td>
<td>0.1</td>
<td>0.4</td>
<td>2.5</td>
<td>700</td>
<td>24</td>
<td>1</td>
<td>0.7</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>18</td>
<td>2.5</td>
<td>700</td>
<td>24</td>
<td>0</td>
<td>0.7</td>
<td>1</td>
<td>1.25</td>
<td>100</td>
<td>16</td>
<td>1</td>
<td>0.1</td>
<td>0.4</td>
<td>2</td>
</tr>
<tr>
<td>19</td>
<td>1.25</td>
<td>100</td>
<td>24</td>
<td>0</td>
<td>0.1</td>
<td>0.7</td>
<td>2.5</td>
<td>700</td>
<td>16</td>
<td>1</td>
<td>0.1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>20</td>
<td>1.25</td>
<td>100</td>
<td>16</td>
<td>0</td>
<td>0.4</td>
<td>0.4</td>
<td>2.5</td>
<td>700</td>
<td>24</td>
<td>1</td>
<td>0.1</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>21</td>
<td>1.25</td>
<td>700</td>
<td>16</td>
<td>0</td>
<td>0.1</td>
<td>0.4</td>
<td>2.5</td>
<td>100</td>
<td>24</td>
<td>1</td>
<td>0.7</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>22</td>
<td>2.5</td>
<td>100</td>
<td>16</td>
<td>0</td>
<td>0.1</td>
<td>0.4</td>
<td>1.25</td>
<td>700</td>
<td>24</td>
<td>1</td>
<td>0.7</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>23</td>
<td>1.25</td>
<td>100</td>
<td>24</td>
<td>1</td>
<td>0.1</td>
<td>1</td>
<td>2.5</td>
<td>700</td>
<td>16</td>
<td>0</td>
<td>0.4</td>
<td>0.4</td>
<td>2</td>
</tr>
<tr>
<td>24</td>
<td>1.25</td>
<td>700</td>
<td>24</td>
<td>0</td>
<td>0.4</td>
<td>0.4</td>
<td>2.5</td>
<td>100</td>
<td>16</td>
<td>1</td>
<td>0.1</td>
<td>1</td>
<td>2</td>
</tr>
</tbody>
</table>
The average completion time was 5.7 minutes. Due to the fact that the data collection scheme was under payment, it was chosen to further eliminate responses which followed a pattern of random responses, given the time taken to process the information and by comparing it to the average. The average time taken to answer one question in the Familiar Users section was 16 second. In that context, the responses which were found to have an average completion time of under 5 seconds were eliminated. After the stratification of the sample—by the elimination of the uncompleted questionnaires and those who followed a pattern of random answers—the number of completed responses was reduced to 397.

### 4.4.2 Socio-demographic Characteristics of the Sample

Table 4.7 summarises the Personal Characteristics section and the Unfamiliar Users section. For the comparison with data concerning the population of the Netherlands the values which refer to the Dutch population are presented in Table 4.8.

<table>
<thead>
<tr>
<th>Table 4.7: Socio-Demographic Characteristics of the Sample</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Used participations</strong>        397, (83.8% of total)</td>
</tr>
<tr>
<td><strong>Average age</strong>        45.64</td>
</tr>
<tr>
<td><strong>Age- standard deviation</strong>       14.9</td>
</tr>
<tr>
<td><strong>Age - Classes</strong>      5 [18-19), 147 [20-40), 192 [40-65), 53 [65-80)</td>
</tr>
<tr>
<td><strong>Age -Classes (Perc)</strong>      1.3% [18-19), 37.0% [20-40), 48.4% [40-65), 13.4% [65-80)</td>
</tr>
<tr>
<td><strong>Number of female</strong>      215 (54.2% of completed)</td>
</tr>
<tr>
<td><strong>Highest level of education</strong>    29 P.S, 202 H.S, 137 H.E, 27 MSc, 2 Ph.D.</td>
</tr>
<tr>
<td><strong>Highest level of education (Perc.)</strong>  7.3% P.S., 50.9% H.S., 34.5% H.E, 6.8% M.Sc, 0.5% Ph.D.</td>
</tr>
<tr>
<td><strong>Income</strong>   71 A, 95 B, 113 C, 63 D, 20 E, 35 F</td>
</tr>
<tr>
<td><strong>Income (Perc)</strong>   17.9% A, 23.9% B, 28.5% C, 15.9% D, 5.0% E, 8.8% F</td>
</tr>
<tr>
<td><strong>Shopping using car</strong>   0 a, 44 b, 108 c, 46 d, 179 e, 20 f</td>
</tr>
<tr>
<td><strong>Shopping using car (Perc)</strong>   0.0% a, 11.1% b, 27.2% c, 11.6% d, 45.1% e, 5.0% f</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Table 4.8: CBS Statistics (CBS, 2009)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Percentage of female</strong>   50.5%</td>
</tr>
<tr>
<td><strong>Age -Classes (Perc)</strong>   35.5% [20-40), 49.0% [40-65), 15.4% [65-80)</td>
</tr>
<tr>
<td><strong>Highest level of education (Perc.)</strong>  5.4% P.S., 55.1% H.S, 32.2% H.E, 6.5% M.Sc, 0.6% Ph.D.</td>
</tr>
</tbody>
</table>

Master of Science Thesis

Emmanouil Chaniotakis
Where:
- A : €5000 - €15000
- B : €15000 - €25000
- C : €25000 - €35000
- D : €35000 - €45000
- E : €45000 - €55000
- F : > €55000

Where:
- e : Weekly
- f : Every day

PS : Primary School
HS : High School
HE : Higher Education
M.Sc : Master’s Degree
Ph.D : Doctoral Degree

Although it is always difficult to encounter for representativeness of a sample, it seems from the available statistics from CBS (Table 4.8) that the sample can be considered as such. More specifically the sample can be considered well distributed for the female percentage, age and highest level of education. The comparison was not able for the income and the shopping habits due to difficulties in acquiring this data.

4.4.3 Unfamiliar Users Characteristics

For this user class, descriptive statistics were derived indicating some interesting patterns (Table 4.9). The investigated characteristics refer to the parking search strategy, the preferred parking type the reaction of parkers after 4 minutes of searching (or waiting) and the maximum time of searching (or waiting). It has to be noted that the order of the questions was as presented in Table 4.9. Individuals who chose for off-street at the parking type preference question, only faced the questions concerning off-street reaction after 5 minutes and for the maximum search time, and those who chose for on-street only faced the questions for on-street parking.

**Table 4.9: Socio-Demographic Characteristics of the Sample**

<table>
<thead>
<tr>
<th>Unfamiliar Strategy</th>
<th>199 A1, 145 A2, 53 A3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unfamiliar Strategy (Perc)</td>
<td>50.1% A1, 36.6% A2, 13.4% A3</td>
</tr>
<tr>
<td>Preference for off-street</td>
<td>312, (78.6%)</td>
</tr>
<tr>
<td>Reaction after 5 minutes (on-street)</td>
<td>60 B1, 25 B2</td>
</tr>
<tr>
<td>Reaction after 5 minutes (on-street) - Perc</td>
<td>70.6% B1, 29.4% B2</td>
</tr>
<tr>
<td>Reaction after 5 minutes (off-street)</td>
<td>77 C1, 189 C2, 46 C3</td>
</tr>
<tr>
<td>Reaction after 5 minutes (off-street) - Perc</td>
<td>24.7% C1, 60.6% C2, 14.7% C3</td>
</tr>
<tr>
<td>Max searching time - on-street (av.)</td>
<td>12.9 minutes (Std Deviation: 8.4)</td>
</tr>
<tr>
<td>Max waiting time - off-street (av.)</td>
<td>8.4 minutes (Std Deviation: 4.7)</td>
</tr>
</tbody>
</table>
Where:

A1 : Plan route and start searching for parking after arriving to destination
A2 : Plan route and parking destination before trip
A3 : Plan route and start searching for parking some distance before destination
B1 : Continue searching for a vacant on-street parking destination
B2 : Go to the closest off-street parking destination
C1 : Go directly to the closest off-street parking destination
C2 : Go to the closest off-street parking destination while searching for on-street parking
C3 : Start searching for off-street parking

The unfamiliar strategy refers to how individuals behave, when they want to drive to a city centre they are not familiar with. As it is evidenced, 63.5 per cent of individuals interviewed do not search for parking information before trip and just drive to their destination. The majority of the individuals would just start looking for parking after reaching their destination. Based on this outcome it is suggested that **Hypothesis 3.1** can be retained.

A rather impressive outcome from the survey is the fact that almost 78.6 per cent prefer searching for off-street parking location when being unfamiliar with the area, indicating a clear preference for off-street parking facilities. Based on this outcome, **Hypothesis 3.2** can be retained.

Concerning the reaction to waiting, most individuals with a preference for on-street parking destinations would continue searching for on-street. The individuals who prefer off-street parking destination are less determinant concerning the parking type, choosing to drive to another parking destination and search in the meanwhile for on-street vacant parking spots.

Finally, the maximum search time for off-street parking destinations is lower than the maximum search time for on-street parking destination. A rather important observation concerning the maximum searching (waiting) time is the fact that the values of the final questionnaire (with a more diverse sample) are higher than the values from the second round of the pilot study participants of which are considered to have a higher than average value of time.

### 4.5 Parking Choice Models Estimation

On of the reasons for the realization of the behavioural research is the derivation of models that would be able to represent individual’s choices concerning parking. For that reason both for familiar and unfamiliar users it was attempted to derive choice models.

#### 4.5.1 Unfamiliar Users

For unfamiliar users a hypothesis is formulated (Hypothesis 3.3) for the significant affect of the socio-demographic characteristics of individuals in the choices concerning the parking strategy and the preferred parking type. A utility function was formulated and tested:

Let $s_{od}$ be the alternative strategy of the random unfamiliar individual $u$ and $V_{u,s_{od}}$ be representative utility of the alternative strategy $s_{od}$. The utility is:
\[ V_{u,s_{opd}} = ASC_{s_{opd}} + b_1 \cdot Age + b_2 \cdot Gender + b_3 \cdot Educ + b_4 \cdot Income + b_5 \cdot Shopping \quad (4.1) \]

Let \( s_p \) be the strategic choice on parking type of the random unfamiliar user \( u \) and \( V_{u,s_p} \) be representative utility of the alternative strategic parking type choice \( s_p \). The utility is:

\[ V_{u,s_p} = ASC_{s_p} + b_1 \cdot Age + b_2 \cdot Gender + b_3 \cdot Educ + b_4 \cdot Income + b_5 \cdot Shopping \quad (4.2) \]

The utilities \( V_{u,s_{opd}}, V_{u,s_p} \) were tested using BIOGEME starting from an alternative specific constant and adding the socio-demographic attributes. However none of the attributes were found to be significant leading to the rejection of Hypothesis 3.3. This lead to the conclusion that the choice of unfamiliar users concerning the strategy was not able to be modelled under the principles of discrete choice modelling. The descriptive statistics presented in section 4.4.3 are going to be used as such, in the modelling procedure presented in 5.6.

### 4.5.2 Familiar Users

The expected outcome of this survey concerning familiar users (Section 3.8) involved data to be used for the derivation of a choice model. This involves the test of the hypotheses formulated (Hypothesis 3.5 to 3.11) for the model structure. The hypotheses tests take place in the following sections. The exploration of the different model structures aim to provide a better understanding on the behaviour of individuals. This is achieved by finding which are the behavioural concepts (e.g. heterogeneity in taste) that fit better to people’s stated preferences.

#### Multinomial Logit

Starting with the simple MNL, the estimation procedure included the usage of alternative specific constants as well the inclusion of demographics. Neither the ASC nor the inclusion of demographics improve the model derived and presented in Table 4.10 with the utility to be described by Equation 4.3. The methodology for estimating the estimators is not going to be presented as it is very well covered in the literature (see Louviere et al., 2000; Train, 2003).

\[ V_{i,opd} = \beta_1 \cdot C_p + \beta_2 \cdot T_{o,p} + \beta_3 \cdot W_{p,d} + \beta_4 \cdot O_p + \beta_5 \cdot P_{p}^0 + \beta_7 \cdot P_{p}^8 \quad (4.3) \]

Concerning the estimation, it was found that the model behave as expected. The most important estimator that contributes most to the utility is (as expected) the price \( C_p \) followed by the probability of finding a vacant parking spot after 8 minutes (\( P_{p}^8 \)). The contribution is presented in the Table 4.11 for the average level of attributes. The contributions to the utility were again as expected given the available literature on parking and the feedback received from the pilot studies except for the probability after 8 minutes which was not found to be investigated. All estimators were found to be significant and the signs were as expected: Price (\( C_p \)), Walking Distance (\( W_{p,d} \)) and Travel Time (\( T_{o,p} \)) were found to be negative while
Table 4.10: Multinomial Logit Model

<table>
<thead>
<tr>
<th>Parameter number</th>
<th>Description</th>
<th>Coeff. estimate</th>
<th>Asympt. std. error</th>
<th>t-stat</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>$\beta_1$ (Price)</td>
<td>-0.735</td>
<td>0.0322</td>
<td>-22.85</td>
<td>0.00</td>
</tr>
<tr>
<td>2</td>
<td>$\beta_2$ (Walking Dist)</td>
<td>-0.000580</td>
<td>6.60e-005</td>
<td>-8.78</td>
<td>0.00</td>
</tr>
<tr>
<td>3</td>
<td>$\beta_3$ (Travel Time)</td>
<td>-0.0110</td>
<td>0.00451</td>
<td>-2.44</td>
<td>0.01</td>
</tr>
<tr>
<td>4</td>
<td>$\beta_4$ (Parking Type)</td>
<td>0.119</td>
<td>0.0346</td>
<td>3.43</td>
<td>0.00</td>
</tr>
<tr>
<td>5</td>
<td>$\beta_5$ (Pr, Arrival)</td>
<td>0.569</td>
<td>0.0831</td>
<td>6.84</td>
<td>0.00</td>
</tr>
<tr>
<td>6</td>
<td>$\beta_7$ (Pr, 8 min)</td>
<td>1.18</td>
<td>0.0710</td>
<td>16.54</td>
<td>0.00</td>
</tr>
</tbody>
</table>

Diagnostic: Convergence reached...
Final gradient norm: $+8.162e-003$

FinalTable 4.11: Average Contribution to the Utility

<table>
<thead>
<tr>
<th>Estimator</th>
<th>Estimators Values</th>
<th>Average Level</th>
<th>Contribution</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta_1$ (Price)</td>
<td>-0.735</td>
<td>1.875</td>
<td>1.378125</td>
</tr>
<tr>
<td>$\beta_2$ (Walking Dist)</td>
<td>-0.000580</td>
<td>400</td>
<td>0.232</td>
</tr>
<tr>
<td>$\beta_3$ (Travel Time)</td>
<td>-0.0110</td>
<td>20</td>
<td>0.22</td>
</tr>
<tr>
<td>$\beta_4$ (Parking Type)</td>
<td>0.119</td>
<td>0.5</td>
<td>0.0595</td>
</tr>
<tr>
<td>$\beta_5$ (Pr, Arrival)</td>
<td>0.569</td>
<td>0.4</td>
<td>0.2276</td>
</tr>
<tr>
<td>$\beta_7$ (Pr, 8 min)</td>
<td>1.18</td>
<td>0.7</td>
<td>0.826</td>
</tr>
</tbody>
</table>

off-street parking type, probability upon arrival ($Pr_0^p$) and probability after 8 minutes ($Pr_8^p$) were found to be positive.

The results for the Multinomial Logit model suggest that Hypothesis 3.4 should be retained. As initially hypothesised the attributes were all found to be significant. Furthermore, Hypothesis 3.5 should be retained as it seems that MNL is capable of representing parking decisions. This of-course does not mean that other models structures could not outperform the MNL model derive, but it suggest that it is a model that fit the outcome of the survey in an acceptable manner.

Nested logit

Hunt and Teply (1993) found that parking decisions can be modelled using Nested Logit with one of the nests to be used to be the parking type. For this reason the creation of

---

The contribution is estimated as the quotient of the estimator value and the average attribute level.
Experiment Design and Model Estimation

one level with two groups took place (On-Street, Off-Street) and the model was tested using BIOGEME.

The diagnostics of the estimated Nested Logit are presented in Table 4.12. As clearly indicated the nesting given the parking type does not hold as a model that estimated better the data. Furthermore, it is indicated that the region of trust is too small. Given the above-mentioned the hypothesis of improved estimation using Nested Logit (Hypothesis 3.6) is rejected.

Table 4.12: Nested Logit Model

<table>
<thead>
<tr>
<th>Model</th>
<th>Nested Logit</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \mathcal{L}(0) )</td>
<td>-3293.835</td>
</tr>
<tr>
<td>( \mathcal{L}(c) )</td>
<td>-3291.889</td>
</tr>
<tr>
<td>( \mathcal{L}(\hat{\beta}) )</td>
<td>-2912.326</td>
</tr>
<tr>
<td>(-2[\mathcal{L}(0) - \mathcal{L}(\hat{\beta})])</td>
<td>763.019</td>
</tr>
<tr>
<td>( \rho^2 )</td>
<td>0.116</td>
</tr>
<tr>
<td>( \bar{\rho}^2 )</td>
<td>0.114</td>
</tr>
<tr>
<td>Final gradient norm</td>
<td>+9.626e-02</td>
</tr>
<tr>
<td>Diagnostic</td>
<td>Radius of the trust region is too small</td>
</tr>
</tbody>
</table>

Mixed Logit

Mixed logit was developed in order to overcome the constraint imposed by MNL for the random residual \( \epsilon_{ni} \) to be independently and identically distributed as Gambel type two random variables (Section 2.3.1). Mixed Logits on the other hand allow the random residual to get any distribution my having a part of which the residual is iid extreme value and another that contains the heteroskedasticity (Train, 2003), encountering for heterogeneity in taste.

For this particular application the estimators were set to be both normally and uniformly distributed. The procedure of starting from one parameter and adding the rest of them was also followed here. The model yielding the highest \( \bar{\rho}^2 \) was the one that the estimator \( \beta_5 \) is normally distributed while the rest estimators are fixed. This utility to be presented in Equation 4.4.

In Table 4.13 the estimated model of normally distributed estimator is presented. The uniformly distributed estimated model resulted in slightly lower final likelihood \( \mathcal{L}(\hat{\beta}) = -2908.913 \).

\[
V_{i,\text{opd}} = \beta_1 \cdot C_p + \beta_2 \cdot T_{o,p} + \beta_3 \cdot W_{p,d} + \beta_4 \cdot O_p + B_5 \sim N(E[B_5], \sigma_5) \cdot P_{t_p}^0 + \beta_7 \cdot P_{r_p}^8
\] (4.4)

As it is evidenced by the final log likelihood \( \mathcal{L}(\hat{\beta}) = -2908.913 \), the Mixed logit model structure is performing slightly better than the MNL model structure \( \mathcal{L}(\hat{\beta}) = -2912.326 \). However the difference is rather small which is the case also for the \( \bar{\rho}^2 \).

In conclusion, it is important to mention that, although the significance of the difference between the likelihoods has to be tested using the Akaike Likelihood ratio index (Ben-Akiva and
Table 4.13: Mixed Logit - Normally Distributed

<table>
<thead>
<tr>
<th>Parameter number</th>
<th>Description</th>
<th>Coeff. estimate</th>
<th>Asympt. std. error</th>
<th>t-stat</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>$\beta_1$ (Price)</td>
<td>-0.910</td>
<td>0.0926</td>
<td>-9.83</td>
<td>0.00</td>
</tr>
<tr>
<td>2</td>
<td>$\beta_2$ (Walking Dist.)</td>
<td>-0.000726</td>
<td>0.000108</td>
<td>-6.74</td>
<td>0.00</td>
</tr>
<tr>
<td>3</td>
<td>$\beta_3$ (Travel Time)</td>
<td>-0.0141</td>
<td>0.00561</td>
<td>-2.52</td>
<td>0.01</td>
</tr>
<tr>
<td>4</td>
<td>$\beta_4$ (Parking Type)</td>
<td>0.161</td>
<td>0.0468</td>
<td>3.44</td>
<td>0.00</td>
</tr>
<tr>
<td>5</td>
<td>$\beta_5$ (Pr. Arrival)</td>
<td>0.734</td>
<td>0.132</td>
<td>5.57</td>
<td>0.00</td>
</tr>
<tr>
<td>6</td>
<td>$\sigma_5$ (Std. Dev.)</td>
<td>2.38</td>
<td>0.721</td>
<td>3.31</td>
<td>0.00</td>
</tr>
<tr>
<td>7</td>
<td>$\beta_7$ (Pr. 8 min)</td>
<td>1.43</td>
<td>0.151</td>
<td>9.51</td>
<td>0.00</td>
</tr>
</tbody>
</table>

Swait, 1986) there is a difference between the likelihoods. This allow to retain Hypothesis 3.7.

**Random Regret Minimization Theory**

The random regret minimization theory –as already discussed in Section 3.8– is based on the fact that people would try to minimize their regret of choosing one alternative over the other. This means that individuals would actually try to minimize the chance that another alternative would have a higher utility than the one chosen (Chorus, 2012). The regret minimization formulation is presented:

Let $p_1, p_2$ be the two parking alternatives examined. The regret associated with alternative $p_1$ ($RR_{p_1}$) is presented in Equation 4.5 (Chorus, 2012).

$$RR_{p_1} = \ln(1 + \exp[\beta_1 \cdot (C_{p_2} - C_{p_1})]) + \ln(1 + \exp[\beta_2 \cdot (W_{p_2} - W_{p_1})]) + \ln(1 + \exp[\beta_3 \cdot (T_{p_2} - T_{p_1})]) + \ln(1 + \exp[\beta_4 \cdot (O_{p_2} - O_{p_1})]) + \ln(1 + \exp[\beta_5 \cdot (P_{p_2}^{8} - P_{p_1}^{8})])$$

In the same manner the utility is derived for the second alternative. The model structure was implemented in **BIOGEME** and the results are presented in Table 4.14.
### Table 4.14: Regret Minimization

<table>
<thead>
<tr>
<th>Model</th>
<th>Random Regret Minimization</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\mathcal{L}(0)$</td>
<td>-3293.835</td>
</tr>
<tr>
<td>$\mathcal{L}(\hat{c})$</td>
<td>-3291.889</td>
</tr>
<tr>
<td>$\mathcal{L}(\hat{\beta})$</td>
<td>-2912.326</td>
</tr>
<tr>
<td>$-2[\mathcal{L}(0) - \mathcal{L}(\hat{\beta})]$</td>
<td>763.019</td>
</tr>
<tr>
<td>$\rho^2$</td>
<td>0.116</td>
</tr>
<tr>
<td>$\bar{\rho}^2$</td>
<td>0.114</td>
</tr>
<tr>
<td>Final gradient norm</td>
<td>+8.162e-003</td>
</tr>
<tr>
<td>Diagnostic</td>
<td>Convergence reached...</td>
</tr>
<tr>
<td>Iteration</td>
<td>11</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Parameter number</th>
<th>Description</th>
<th>Coeff. estimate</th>
<th>Asympt. std. error</th>
<th>t-stat</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>$\beta_1$ (Price)</td>
<td>-0.735</td>
<td>0.0322</td>
<td>-22.85</td>
<td>0.00</td>
</tr>
<tr>
<td>2</td>
<td>$\beta_2$ (Walking Dist)</td>
<td>-0.000580</td>
<td>6.60e-005</td>
<td>-8.78</td>
<td>0.00</td>
</tr>
<tr>
<td>3</td>
<td>$\beta_3$ (Travel Time)</td>
<td>-0.0110</td>
<td>0.00451</td>
<td>-2.44</td>
<td>0.01</td>
</tr>
<tr>
<td>4</td>
<td>$\beta_4$ (Parking Type)</td>
<td>0.119</td>
<td>0.0346</td>
<td>3.43</td>
<td>0.00</td>
</tr>
<tr>
<td>5</td>
<td>$\beta_5$ (Pr. Arrival)</td>
<td>0.569</td>
<td>0.0831</td>
<td>6.84</td>
<td>0.00</td>
</tr>
<tr>
<td>6</td>
<td>$\beta_7$ (Pr. 8 min)</td>
<td>1.18</td>
<td>0.0710</td>
<td>16.54</td>
<td>0.00</td>
</tr>
</tbody>
</table>

The log likelihood ($\mathcal{L}(\hat{\beta}) = -2912.326$) is exactly the same as of the MNL model, as happens with the $\rho^2$ leading to the conclusion that the Random Regret Minimization model structure does not lead towards the direction of a better representation. Thus, **Hypothesis 3.8** is rejected.

### Panel Data

Most model assumes that responses are independent of each other, which is not the case when dealing with Stated Preference data consisting of multiple choice situations. In this case, each respondent had to respond to twelve (12) choice situations, making the assumption of independent responses rather naive. Panel Data models is introduced as a solution to the correlation of answers of respondents due to the multiple answers given in Stated Preference (Daly and Hess, 2010).

As it is suggested by Walker (2001) a model with Panel data is estimated and then normalized. Here the normalized estimation is presented. The parameter used as Alternative Specific Constant was the Parking Type ($O_p$).

As it is clearly indicated there is a rather high improvement using the panel data estimation. The Final Log-Likelihood of the estimators ($\mathcal{L}(\hat{\beta}) = -2829.736$) is lower that the final likelihood derived by all the models tested (e.g. MNL $\mathcal{L}(\hat{\beta}) = -2912.326$) and the $\bar{\rho}^2$ is higher (Panel Data: 0.139, MNL: 0.114). The estimators of the Panel data are as expected with the signs to be normal and the Alternative Specific Constant to have quite some variation.
4.5 Parking Choice Models Estimation

Table 4.15: Normalized Panel Data Model

<table>
<thead>
<tr>
<th>Model</th>
<th>Mixed Logit for panel data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Halton draws</td>
<td>4000</td>
</tr>
<tr>
<td>$\mathcal{L}(0)$</td>
<td>-3293.835</td>
</tr>
<tr>
<td>$\mathcal{L}(c)$</td>
<td>-3291.889</td>
</tr>
<tr>
<td>$\mathcal{L}(\hat{\beta})$</td>
<td>-2829.736</td>
</tr>
<tr>
<td>$-2[\mathcal{L}(0) - \mathcal{L}(\hat{\beta})]$</td>
<td>928.200</td>
</tr>
<tr>
<td>$\rho^2$</td>
<td>0.141</td>
</tr>
<tr>
<td>$\bar{\rho}^2$</td>
<td>0.139</td>
</tr>
<tr>
<td>Final gradient norm</td>
<td>+3.707e-03</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Parameter number</th>
<th>Description</th>
<th>Coeff. estimate</th>
<th>Asympt. std. error</th>
<th>t-stat</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>$ASC_{off}$</td>
<td>0.132</td>
<td>0.0535</td>
<td>2.46</td>
<td>0.01</td>
</tr>
<tr>
<td>2</td>
<td>$\sigma_{off}$ Std. Dev.</td>
<td>0.789</td>
<td>0.0842</td>
<td>9.38</td>
<td>0.00</td>
</tr>
<tr>
<td>3</td>
<td>$\beta_1$ (Price)</td>
<td>-0.821</td>
<td>0.0499</td>
<td>-16.45</td>
<td>0.00</td>
</tr>
<tr>
<td>4</td>
<td>$\beta_2$ (Walking Dist)</td>
<td>-0.000624</td>
<td>9.04e-05</td>
<td>-6.90</td>
<td>0.00</td>
</tr>
<tr>
<td>5</td>
<td>$\beta_3$ (Travel Time)</td>
<td>-0.0129</td>
<td>0.00556</td>
<td>-2.33</td>
<td>0.02</td>
</tr>
<tr>
<td>6</td>
<td>$\beta_5$ (Pr. Arrival)</td>
<td>0.652</td>
<td>0.0986</td>
<td>6.61</td>
<td>0.00</td>
</tr>
<tr>
<td>7</td>
<td>$\beta_6$ (Pr. 8 min)</td>
<td>1.31</td>
<td>0.102</td>
<td>12.82</td>
<td>0.00</td>
</tr>
</tbody>
</table>

Profiles

In this section an illustrative example on the potential of using profiles to describe the familiar users is presented. Normally, the formulation of hypothesis and testing and the usage of factor analysis to derive the profiles would be suggested, however the derivation of such a model structure is beyond the scope of this thesis only one case is presented.

For this illustrative example, only participants with income higher than €45000 are examined. The expected outcome is a lower importance of price and a higher importance of probabilities due to higher value of time. The fact that the mixed logit did not indicate a strong existence of heterogeneity in taste indicates a low improvement if existing in the estimated profiles (if any).

For the “Rich” profile investigated, the values of the estimators are as expected, with the probability of finding a vacant parking spot to be more important as well as the walking distance and the travel time.

It is important to state that with only this illustrative example it is not possible either to reject or retain the null hypothesis that profiles could provide a better module for modelling the behaviour concerning parking-related choices. Further investigation is required towards this direction.
Table 4.16: High Income Profile MNL model

<table>
<thead>
<tr>
<th>Parameter number</th>
<th>Description</th>
<th>Coeff. estimate</th>
<th>Asympt. std. error</th>
<th>t-stat</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>$\beta_1$ (Price)</td>
<td>-0.735</td>
<td>0.0892</td>
<td>-8.24</td>
<td>0.00</td>
</tr>
<tr>
<td>2</td>
<td>$\beta_2$ (Walking Dist)</td>
<td>-0.000713</td>
<td>0.000177</td>
<td>-4.02</td>
<td>0.00</td>
</tr>
<tr>
<td>3</td>
<td>$\beta_3$ (Travel Time)</td>
<td>-0.0240</td>
<td>0.0120</td>
<td>-2.00</td>
<td>0.05</td>
</tr>
<tr>
<td>4</td>
<td>$\beta_4$ (Parking Type)</td>
<td>0.109</td>
<td>0.0925</td>
<td>1.18</td>
<td>0.24</td>
</tr>
<tr>
<td>5</td>
<td>$\beta_5$ (Pr Arrival)</td>
<td>0.749</td>
<td>0.227</td>
<td>3.30</td>
<td>0.00</td>
</tr>
<tr>
<td>6</td>
<td>$\beta_7$ (Pr 8 min)</td>
<td>1.52</td>
<td>0.199</td>
<td>7.64</td>
<td>0.00</td>
</tr>
</tbody>
</table>

4.6 Model Verification

Model verification is a tedious task in general. Although the models derived seem to behave as expected (with the costs to be negative and the utilities to be positive) and the estimation process did not resulted in general in little radius of fit or other negative diagnostics. Although the goodness of fit is presented for all models and is described by the likelihood ratio index (see Train, 2003, section 3.8), it was intended to further explore it, by comparing the predicted percentage of choosing one alternative to the actual percentage of people choosing the same alternative. It is important to keep in mind that as Train (2003) clearly indicates, this metric for the goodness of fit should not used due to the fact that it “misses the point of probabilities”. In this case, a random choice situation was chosen, the utilities and the probabilities were calculated and compared to the actual choices of individuals. The resulted percentages are presented in Table 4.17 indicating a rather high goodness of fit.

Table 4.17: Goodness of fit - MNL model

<table>
<thead>
<tr>
<th>Alternative</th>
<th>Actual Percent</th>
<th>Predicted Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alternative 1</td>
<td>42.5%</td>
<td>48.4%</td>
</tr>
<tr>
<td>Alternative 2</td>
<td>57.5%</td>
<td>51.6%</td>
</tr>
</tbody>
</table>

It is important to mention at this point that a proper verification and to an extend validation would require further investigation. One of the ways this could be possibly done is by collecting...
again data and comparing the choice of individuals to the one initially derived. Another way would require the assignment of individuals given a network structure and the actual recording of the chosen parking destinations. Both approaches were found to be too costly to implement.

The first approach would require a new experiment which was not possible to take place in the context of a thesis. However, the pilot studies indicate—without verifying or validating—that for two more small but yet different samples the estimators derived behave in the same manner (same signs and same magnitude). For the second approach the validation would first of all require the derivation of assignment models (see Chapters 5 and Chapter 6) and the actual measurement of people driving to each parking destination and which of them actually park at that specific parking destination. This is again very difficult to implement due to the difficulty in recording the actual choices concerning parking. More information concerning this method of validation is presented in Chapter 6.

4.7 Conclusions - Discussion

In this chapter the outcome of the behavioural experiment was presented. Starting from the experiment design, the process followed resulted in an efficient design, with the information to be acquired to be higher that the one derived using orthogonal design. Of course, the design used cannot by any means be characterized as optimal except for the usage of resulted information to estimate models. This happens due to the fact that the model structure is one of the factors which determine the resulted design. Of course due to the nature of the experiment it is impossible to investigate different model structures using optimal (or efficient) designs for each of them.

By implementing the design of the experiment, 474 responses were recorded of which due to lack of completeness and patterns of randomness in the responses 397 were used. Descriptive statistics were derived for the personal characteristics of the sample and were compared to the characteristics of the population showing same patterns and allowing to be assumed as representative of the population.

For unfamiliar users the hypothesis formulated in the previous chapter were investigated and the behavioural characteristics were analysed, without the usage of Discrete Choice modelling. In general a rather informative perspective on a user class which has received little attention was provided. The descriptive statistics presented are going to be used for the definition of unfamiliar user classes and the assignment of unfamiliar users.

The resulted data concerning familiar users was investigated to an extend and some models structures were tested based on hypotheses initially derived in the Chapter 3. In table 4.18 the estimators and the metrics are presented. The model with the best goodness of fit was the normalized panel data model with the basis to be the Multinomial Logit.

The verification of the Multinomial Logit was presented indicating that model structure with better goodness of fit can be considered verified as well.
Table 4.18: Summary of estimated models

<table>
<thead>
<tr>
<th></th>
<th>MNL</th>
<th>Nested Logit</th>
<th>Mixed Logit</th>
<th>Regret Min</th>
<th>Normalized Panel</th>
<th>Rich Profile</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta_1$</td>
<td>-0.735</td>
<td>-0.91</td>
<td>-0.735</td>
<td>-0.821</td>
<td>-0.735</td>
<td></td>
</tr>
<tr>
<td>$\beta_2$</td>
<td>-0.00058</td>
<td>-0.00073</td>
<td>-0.00058</td>
<td>-0.00062</td>
<td>-0.00071</td>
<td></td>
</tr>
<tr>
<td>$\beta_3$</td>
<td>-0.01</td>
<td>-0.0141</td>
<td>-0.01</td>
<td>-0.00129</td>
<td>-0.024</td>
<td></td>
</tr>
<tr>
<td>$\beta_4$</td>
<td>0.119</td>
<td>0.161</td>
<td>0.119</td>
<td>0.132</td>
<td>0.109</td>
<td></td>
</tr>
<tr>
<td>$\beta_5$</td>
<td>0.569</td>
<td>0.734</td>
<td>0.569</td>
<td>0.652</td>
<td>0.749</td>
<td></td>
</tr>
<tr>
<td>$\beta_T$</td>
<td>1.18</td>
<td>1.43</td>
<td>1.18</td>
<td>1.31</td>
<td>1.52</td>
<td></td>
</tr>
<tr>
<td>$\sigma_b$</td>
<td>2.38</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.789</td>
</tr>
<tr>
<td>$\sigma_{eff}$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.789</td>
</tr>
<tr>
<td>$\bar{p}^2$</td>
<td>0.114</td>
<td>0.114</td>
<td>0.115</td>
<td>0.114</td>
<td>0.139</td>
<td>0.113</td>
</tr>
</tbody>
</table>
Part III

Parking Assignment Model: Formulation, Verification & Application
5.1 Introduction

This chapter presents the Assignment Model for familiar and Unfamiliar users, on all behavioural levels. For each user class and behavioural level, the conceptual model is presented, followed by its formulation—when applicable. The Assignment Model is strongly connected to the Behavioural Research conducted and presented as it is used in the Assignment Model for prediction of individuals' behaviour. The Parking Decision Process is used as reference for the modelling of the decisions and the discrete choice model is used to represent the way choices are made.

The discrete choice model on which the assignment models are practised is the Multinomial Logit model, derived in Section 4.5.2. The introduction of a more sophisticated model can take place rather easily although a simple model structure would allow for direct analysis of the results and verification.

The parking assignment model takes into account both traffic interactions, and parking interactions. In a sense, it could be described as a Dynamic Traffic Model with Parking, however, for consistency with the terminology used in parking modelling it is referred to as Parking Assignment Model.

In this chapter the following research question is answered:

7. What assignment model can be used adequately to represent parking choice behaviour?
The findings of this chapter are going to be used in the evaluation of the Smart Parking application at Chapter 7. The components presented are to some extend verified in the application and in Chapter 6. The research components and their connections are presented in Figure 5.1.

This chapter is structured as follows:

First the notation is presented in Section 5.2. The Parking Decision Process model is summarised (Section 5.3) for consistency in the presentation and then the Parking Assignment Model is presented for familiar and unfamiliar users in Section 5.5 and Section 5.6 respectively. A model to represent the probability of finding a vacant parking spot is introduced in Section 5.7 and finally the conclusions are presented 5.8.

5.2 Notation

For clarification reasons the notation for this chapter is introduced in alphabetical order and is going to be as follows:

Indices:

- \( a \): Number of iteration
- \( d \): Destination
- \( i \): Individual
- \( m \): User Class (In the user-class of familiar/unfamiliar users )
- \( o \): Origin
- \( \pi \): Parking Destination

Parameters, Variables & Expressions:

- \( A_\pi(x) \): Number of arrivals during \( x \)
- \( B(N,L) \): Transport network
5.2 Notation

- \( C_\pi \) : The hourly parking price of parking destination \( \pi \)
  (expressed in €/h)
- \( D \) : Set of destinations
- \( D_\pi(x) \) : Number of departures during \( x \)
- \( E_{\pi,od}^m \) : Parking Demand for parking destination \( \pi \)
  from \((o,d)\)
- \( E_\pi \) : Total parking demand for parking destination \( \pi \)
- \( F_{o,od}^m \) : Travel demand for the random OD pair \( o,d \)
- \( f_{S_\omega}^p \) : Travel Demand for parking search route \( S_\omega \)
- \( G \) : Duality Gap
- \( K_\pi \) : Capacity of parking destination \( \pi \)
- \( L \) : Set of directed links
- \( l \) : Random link
- \( M \) : Set of User Classes
- \( N \) : Set of nodes
- \( n_{dec} \) : Decision Node
- \( O \) : Set of origins
- \( O_\pi \) : Dummy variable for on-street (0) or off-street (1)
- \( OD \) : Set of Origin Destination Pairs
- \( P_{qs}^p \) : Probability of finding a vacant parking spot
  at parking destination \( p \) after \( q \) minutes
- \( P^0_\pi \) : Probability of finding a vacant parking spot
  at parking destination \( p \) upon arrival
- \( Q(t_i) \) : Number of vehicles waiting/searching for
  parking at the moment of arrival of individual \( i \)
- \( r_{o,d} \) : Route from node \( o \) to node \( d \)
- \( R_{o,od} \) : Choice-set of routes from node \( o \) to node \( d \)
- \( S_\Omega \) : Choice set of parking search route for
  a random \((o,d)\)
- \( S_\omega \) : Random Parking search route
- \( S_\omega(\pi) \) : Parking Destination in a parking search route
- \( T_{o,d} \) : Average travel time from node \( o \) to node \( d \) (in minutes)
- \( U_{o,\pi,d}^m \) : Utility parking destination \( p \) when travelling
  from \( a \) and for the initial destination \( d \) for user-class \( m \).
- \( W_{o,d}^m \) : Walking Distance from node \( o \) to node \( d \)
- \( \beta_{1}^m \) : Price attribute estimator for user class \( m \)
- \( \beta_{2}^m \) : Walking Distance attribute estimator for user class \( m \)
- \( \beta_{3}^m \) : Travel Time attribute estimator for user class \( m \)
- \( \beta_{4}^m \) : Parking Type (on-street or off-street) attribute estimator
  for user class \( m \)
- \( \beta_{5}^m \) : Probability upon arrival attribute estimator for user class \( m \)
- \( \beta_{6}^m \) : Probability after 4 minutes attribute estimator for user class \( m \)
- \( \beta_{7}^m \) : Probability after 8 minutes attribute estimator for user class \( m \)
- \( \Gamma \) : Improvement Threshold
- \( \lambda_0 \) : Maximum searching time
- \( \Pi \) : Set of Parking Destinations
Penalty (large value)
Waiting time of individual i (minutes)

5.3 Parking Decision Process Summary

Before starting with the presentation of the parking assignment modelling framework and its components, a review of the Parking Decision Process and the components is presented. As it is described in Section 3.4, parking can be described on three behavioural levels: the strategic the tactical level and the operational level. The parking decision process framework is defined for two user classes: the familiar user-class and the unfamiliar user-class (Section 3.3).

Unfamiliar users have a strategy on searching or not information pre-trip as well as for the desired parking type. The operational level applies after reaching the destination (or when close to it) where a search direction is chosen. Afterwards, the route towards the direction chosen is defined on the tactical level and, in case of on-street parking the link on intersection level.

5.4 Conceptual Implementation Procedure

The Parking Assignment Model is proposed to be implemented in a simulation environment. The reasons are mainly practical but also methodological.

On the practical side, the implementation of the components of the Parking Assignment Model, in a macroscopic Dynamic Stochastic User Equilibrium assignment, for both familiar and unfamiliar users and on all behavioural described is a tedious work that was considered to be out of the scope of this thesis. On the methodological side, it is generally acknowledged in the literature (see Section 2.3.2) that the exploration of ITS application and their impact magnitude is not captured by steady-state models, due to the dynamic character of traffic information and in this case of parking occupancies, departures and arrivals. This is widely evidenced in the verification of the familiar strategic level presented in Section 6.4.3, where the time interval of 15 minutes do not provide for understanding on re-routings that might take place.

Here, the Parking Assignment model is developed in order to be implemented in two phases: Pre-trip and On-trip. The pre-trip phase represents the strategic level of the parking decision process and it is developed for being the input of the simulation. The on-trip phase is completely developed for being implemented in a simulation environment.

5.5 Parking Assignment Model for Familiar Users

In this section, a detailed description on how the familiar users are modelled is intended for the three behavioural levels. Modelling familiar users is in-line with the decisions presented in the familiar section of the Parking Decision Process model (Section 3.6). In short, Familiar users device a parking search strategy on the strategic level (pre-trip). While on-trip, this...
strategy might be revised given information received (operational level). On the tactical level, routes from parking destination to parking destination are derived, as well as off-street parking choices on an intersection level. This process is represented in an assignment modelling context in Figure 5.3. For matters of clarification, the concept and the formulation is presented in this section.

![Figure 5.2: Implementation Procedure](image)

![Figure 5.3: Familiar users modelling framework](image)
5.5.1 Strategic Level

Familiar users are assumed to follow a **habitual pattern** when it comes to parking. This assumption is supported by the behavioural research and more specifically, by the interviews conducted. The habitual pattern includes the devise of a strategy (**pre-trip**) consisting of visits to sequential parking destinations until a vacant parking spot is found (Figure 5.4). The basic assumption that shape familiar users assignment on a strategic level is:

**Assumption 5.1.** Familiar individuals plan a search route that passes from 3 sequential parking destination pre-trip. This route is referred to as **strategic parking search route** (**SPSR**).

![Figure 5.4: Strategic Parking Search Routes. Each coloured route represents a strategic parking search route that individuals have in mind before trip.](image)

Familiar users are assumed to have knowledge of the system which falls among the definition of equilibrium assignments (see Cascetta, 2009, chapter 5). The general idea of equilibrium assignments is that travellers have information of the system in question and try to minimize the travel costs (or maximize the obtained utilities). This can be described as an equilibrium in which the utility of each traveller cannot be increased (Deterministic User Equilibrium). Another expression of the famous Wardrop’s principle assumes individuals having imperfect information, but still acting in a way that would maximize the obtained utility leading to a partial equilibrium, where the perceived utilities cannot be increased (SUE). The same concept is **assumed** to apply for parking choice in a network structure:
Assumption 5.2. Familiar parking users can be represented –in an assignment context– by a Stochastic User Equilibrium for parking with the stochastic terms to be the travel time to the parking destination and the probability of finding a vacant parking spot.

In this study, the probability of finding a vacant parking spot at a parking destination is related to the number of travellers who would prefer to park at this parking destination. Furthermore, in the strategic parking search route assignment model the chance of acquiring the utility of a parking destination is directly related to the probability of finding a vacant parking spot at the destination with the exception of the travel time spent on going from one parking destination to another (which cannot be avoided in order to find out if there is an available parking spot). The main difference from the approaches already suggested ((see Lam et al., 2006; Gallo et al., 2011)) is the fact that those studies use a BPR-like empirical function as the stochastic term.

Conceptually, the Parking Search Route assignment is a two level equilibrium assignment. The first level is Stochastic User Equilibrium assignment for the estimation of travel times ($SUE_r$) and the second is a Stochastic User Equilibrium assignment for the estimation of the parking search route flows ($SUE_p$). The decomposition of the assignment on two levels lays on the fact that both equilibrium levels have travel time as a common attribute. Travel time is related to the route flows, which is the output of the parking assignment. The Parking Search Route assignment is presented in Figure 5.5. The outcome of the strategic level for familiar users required to simulate parking are the search routes (with a route to be a set of links) and the route flows.

**Figure 5.5:** Assignment parking and route flow chart. Adopted by (Van Nes and Bovy, 2008)

Due to the fact that the $SUE_r$ is rather common and well documented (for reference see Bovy et al., 2006; Cascetta, 2009) only some elements of this level will be discussed with the main focus to be given to the second part of the assignment ($SUE_p$). $SUE_p$ is defined as a stochastic user equilibrium assignment where no individual can increase his/her perceived
obtained utility. The stochasticity is entailed in the probability of finding a vacant parking spot upon arrival and after 8 minutes.

**Strategic Parking Search Route Formulation**

The presentation of the formulation goes as follows:

Definitions are provided which apply for both levels of the assignment. Then the formulation of the second level \( \text{SUE}_P \) is presented assuming steady travel times. Finally, the algorithm of the complete Parking Route Assignment is presented.

Let \( B(N, L) \) denote a transport network with \( N \) to be a set of nodes and \( L \) to be a set of directed links. Let \( O \subseteq N \) be a set of origins and \( D \subseteq N \) be a set of destinations, which are the centroids of the zones defining of the Origin Destination pairs. The random origin destination pair is denoted as \((o, d)\in OD\) where \( OD \) is a set of all the Origin Destination pairs. Also let \( \Pi \subseteq N \) be a set of all the parking destinations represented in the transport network \( B \) by a single central node.

For a random pair of nodes \((o, d), \forall o, d \in N\), let \( R_{o,d} \) be a set of routes\(^1\) from \( o \) to \( d \) with \( r_{o,d} \in R_{o,d} \) to be a random route from \( o \) to \( d \).

For ease of notation the parenthesis used in the notation of a pair of nodes is dropped.

The travel time from the random origin node \( o \) to the random destination node \( d \) given a certain route is estimated in the \( \text{SUE}_r \) assignment and is a function of the free-flow travel time and the congestion of the \( l \in r \) (BPR-function). \( T_{o,d} \) is defined as the average travel time from \( o \) to \( d \) derived by the SUE given all routes \( r_{o,d} \in R \). Furthermore, \( W_{o,d} \) is defined as the walking distance from \( o \) to \( d \).

The behavioural research on parking concluded that for a random pair \( o, d \) and a user class \( m, (m = 1, 2, ..., M) \) of familiar users, the utility of a random parking destination \( \pi \in \Pi \) can be defined:

\[
U^m_{o,\pi,d} = \beta^m_1 \cdot C_{\pi} + \beta^m_2 \cdot W_{\pi,d} + \beta^m_3 \cdot T_{o,\pi} + \beta^m_4 \cdot O_{\pi} + \beta^m_5 \cdot P^0_{\pi} + \beta^m_7 \cdot P_{8,\pi}(5.1)
\]

For ease of notation we denote utility as follows:

\[
U^m_{\pi} = \beta^m_3 \cdot T_{o,\pi} + \bar{U}_{\pi} = \bar{T}_{o,\pi} + \bar{U}_{\pi} \tag{5.2}
\]

where \( \bar{T}_{o,\pi} = \beta^m_2 \cdot T_{o,\pi} \) and \( \bar{U}_{S_{\pi}(\pi)} = \beta^m_1 \cdot C_{\pi} + \beta^m_3 \cdot W_{\pi,d} + \beta^m_4 \cdot O_{\pi} + \beta^m_6 \cdot P^0_{\pi} + \beta^m_8 \cdot P_{8,\pi} \).

The probabilities of the random parking destination \( \pi \) \((Pr^0_{\pi}, Pr^8_{\pi}(t_a))\) can be extracted from Equation 5.14.

Each parking destination is characterised by probabilities of finding a vacant parking spot at the destination. From the behavioural research, it was indicated that people would wait an amount of time \((\lambda^{O_{\pi}})\), where \( O_{\pi} \) is the parking type. Consequently, individuals would go to a different parking destination in case of not finding a vacant parking spot.

---

\(^1\)Route is a set of directed links connecting in a direct way two nodes
Let $S_{o,d}^ω$ be a vector representing a choice set\(^2\) of strategic parking search routes for the random Origin Destination pair $(o, d)$ with $S_{o,d}^ω, \in S_{o,d}^ω, \omega = 1, 2, ..., \Omega$ be a vector of sequential parking destinations with $S_{o,d}^ω(\pi), \pi = 1, 2, ..., \Pi$ to denote the parking destinations of the sequence.

As individuals would maximize again the utility of each parking search route, a new function $U_S^{o,d}$, representing the parking search route utility of $Z$ random consecutive parking destinations $S_ω(\zeta) \in \Pi, \zeta = 1, ..., Z$ is defined.

For the sake of an explanatory example, let $S_ω$ be a random strategy with $1, 2, 3$ to be the sequential parking destinations in $S_ω$. For ease of notation the $o, d$ is dropped. The utility of the $S_ω$ sequence is given:

\[
U_{S_ω}^m = \bar{T}_{o,S_ω(1)} + P_{S_ω(1)}^\lambda O^ω \cdot \bar{U}_{S_ω(1)} + \\
+ (1 - P_{S_ω(1)}^\lambda O^ω) \cdot \bar{T}_{S_ω(1),S_ω(2)} + (1 - P_{S_ω(1)}^\lambda O^ω) \cdot P_{S_ω(2)}^\lambda \cdot \bar{U}_{S_ω(2)} + \\
+ (1 - P_{S_ω(1)}^\lambda O^ω) \cdot (1 - P_{S_ω(2)}^\lambda O^ω) \cdot \bar{T}_{S_ω(2),S_ω(3)} + (1 - P_{S_ω(1)}^\lambda O^ω) \cdot (1 - P_{S_ω(2)}^\lambda O^ω) \cdot P_{S_ω(3)}^\lambda \cdot \bar{U}_{S_ω(3)} + \\
+ (1 - P_{S_ω(1)}^\lambda O^ω) \cdot (1 - P_{S_ω(2)}^\lambda O^ω) \cdot (1 - P_{S_ω(3)}^\lambda O^ω) \cdot \psi
\]  

(5.3)

The explanation of the previous equation is rather simple. Each line is referring to a parking destination of the $S_ω$ strategy except for the last line which will be explained later. The general idea is that each individual using this strategy “obtains the part of the utility” for driving to the parking destination and there is a probability that the rest of the parking utility would be obtained if and only if the individual parks at that location. In other words, as described in Section 5.5, the probability of finding a vacant parking spot is defining the probability of obtaining the utility for the parking destination visited.

For ease of notation the $\lambda O^ω$ is dropped.

Given Equation 5.3 the utility of a parking search route is defined:

\[
U_{S_ω}^m = \bar{T}_{o,S_ω(1)} + P_{S_ω(1)} \cdot \bar{U}_{S_ω(1)} + \\
+ \sum_{i=1}^{\bar{S}_ω} \prod_{j=1}^{i-1} (1 - P_{S_ω(j)}) \cdot \left[ \bar{T}_{S_ω(i-1),S_ω(i)} + P_{S_ω(i)} \cdot \bar{U}_{S_ω(i)} \right] + \\
+ \prod_{k=1}^{\bar{S}_ω} (1 - P_{S_ω(k)}) \cdot \psi
\]  

(5.4)

Where $\psi$ represents a penalty of large negative value. Usage of $\psi$ is suggested in order represent the urge of travellers parking after 3 parking destinations. It is interpreted as a threshold that travellers should have find a vacant parking destination even-though they might first travel to destination that have high generalized utility but low probability.

\(^2\)The choice set derivation is not in-depth covered in this thesis. A suitable, yet not tested, choice set derivation methodology that might apply is presented by Swait (2001)
Let $F_{m(o,d)}$ be the travel demand of the random OD pair $(o,d)$ for user class $m$, $S_\omega^m$ the vector of Parking Search Route for $(o,d)$, user class $m$ and $f_{S_\omega}^m$ be the travel demand of the random strategic parking search route $S_\omega$ ($f_{S_\omega}^m = \text{MNL}^m(U_{S_\omega(o,d)}|S_\Omega, F_{(o,d)}, \forall S_\omega \in S_\Omega)$).

It holds by definition of the MNL, yet important to mention, that $f_{S_1}^m + f_{S_2}^m + ... + f_{S_\Omega}^m = F_{m(o,d)}$.

The number of individuals driving to each parking destination for the random OD pair $(o,d)$ is:

$$E_{m(o,d)} = \sum_{\omega=1}^{\omega=\Omega} \left( \delta_{\pi, S_\omega(i)} \cdot F_{m(o,d)} + \sum_{i=2}^{i=|S_\Omega|} \prod_{j=1}^{j=i-1} \left( 1 - P_{S_\omega(j)} \right) \cdot P_{S_\omega(i)} \cdot f_{S_\omega}^m \cdot \delta_{\pi, S_\omega(i)} \right) \cdot f_{S_\omega}^m $$ (5.5)

where:

$$\delta_{\pi, S_\omega(i)} = \begin{cases} 1, & \text{if } \pi \in S_\omega(i) \\ 0, & \text{if } \pi \notin S_\omega(i) \end{cases} \quad \text{(5.6)}$$

The total number of individuals visiting a parking destination $\pi$ given all the OD pairs is:

$$E_{\pi} = \sum_{m=1}^{m=M} \sum_{o,d=1}^{o,d=OD} E_{m(o,d)} \quad \text{(5.7)}$$

The Method of Successive Averages is used for flow averaging on the parking flow level. Let $a$ be the current iteration and, for ease of notation, let $e_{\pi}^a$ be the flow of the random parking $\pi$ at iteration $a$.

$$e_{\pi}^a = e_{\pi}^{a-1} + (e_{\pi}^a + f_{\pi}^{a-1}) / a \quad \text{(5.8)}$$

Given the total number of individuals arriving at a parking destination the probabilities are calculated using the equation 5.14.

Here the convergence criteria used is based on duality gap presented in Equation 5.9.

$$G = \sum_{m=1}^{m=M} \sum_{\omega=1}^{\omega=\Omega} \left( U_{m(o,d)} \cdot f_{S_\omega}^m \right) - \sum_{m=1}^{m=M} \sum_{o=1}^{o=OD} \sum_{d=1}^{d=D} \left( U_{m(o,d), \text{min}} \cdot f_{S_\omega}^m \right) \cdot \frac{f_{S_\omega}^m}{m=1} \sum_{o=1}^{o=OD} \sum_{d=1}^{d=D} \cdot F_{(o,d)} \cdot U_{m(o,d), \text{max}} \quad \text{(5.9)}$$

where $U_{S_\omega, \text{max}}$ is the maximum utility that can be obtained from a strategic parking search route for a particular OD for a particular user class.
As it is a Stochastic User Equilibrium assignment the duality gap is not expected to reach 0. However in case it does not converge properly, yet stabilize it is suggested to use the parking search route flow comparison as a convergence criterion.

The algorithm:

**Step 1** The strategic parking search route flows $E_{x,o,d}^m, \forall p \in P$, are set to 0, the probabilities $(P_{x,p}, P_{x,p}^8, \forall p \in P)$ are set to 1.

**Step 2** The utilities of all the strategic parking search routes $U_{oabcd}^R, \forall abc \in R$ are calculated.

**Step 3** The flow percentage of all strategic parking search routes $P_{oabcd}^m, \forall OD, m$ is calculated using the logit model.

**Step 4** The total number of individuals driving to each parking destination is calculated.

**Step 5** The probabilities are estimated.

**Step 6** If the number of iterations is 2 or more, MSA for the strategic parking search route flows apply.

**Step 7** The convergence criteria is checked. If not reached go to Step 2.

At this point, all the components required are presented. The convergence of the strategic parking search route assignment is presented in Equation 5.9.

The algorithm for the combined assignments is presented:

**Step 1** The $S$ set of all possible permutations is derived.

**Step 2** The travel times for all $S_{\omega} \in S$ components is estimated based on the $SUEr$ with the travel flows to be driving from their initial origin $o$ to their initial destination $d^3$.

**Step 3** The strategic parking search route flows are estimated based on the $SUEr$.

**Step 4** The travel times are estimated for all routes based on flows derived by the $SUEr$.

**Step 5** The strategic parking search route flows are estimated based on the $SUEr$.

**Step 6** MSA apply on the parking search route flows.

**Step 7** The convergence criteria is checked. If not reached go to Step 4.

This assignment can be easily used in a dynamic context. The two variables of dynamic character are the probabilities of finding a vacant parking spot and the travel times. The travel times can be derived dynamically using one dynamic traffic assignment (e.g INDY (see Bliemer, 2007)). On the probability the model that approximates probability (presented in Section 5.7) is by definition dynamic (Equation 5.14).

For a macroscopic assignment, the derivation of a SPSR assignment would be enough to measure the actual travel times on the network using the probabilities of finding a vacant parking spot in order to derive the travel times and the loads of the network’s links. However, on a microscopic assignment more in depth definition of the two other behavioural levels is required.

---

3The estimation is achieved by assigning 0 individuals as input flow $\forall PR$
5.5.2 Tactical Level

The tactical level includes the interaction with other individuals on-trip. Individuals interacting with others, might result in a change of strategy, in the same manner as a route might have changed, due to congestion of the links initially thought to offer lower travel costs (higher utility) (Ben-Akiva et al., 1991). It is in-line with the literature on en-trip route choice models and hybrid route choice models where the route is evaluated respectively at every intersection or given some minimum improvement (Pel, 2011) and the bounded rationality concept that is also implemented in DYNASMART (Mahmassani, 2001b) where the route is evaluated at specific points.

Here, travellers re-evaluate their initial strategy based on changes concerning the perceived travel times or the perceived probability of finding a vacant parking spot which is described again in the context of utility maximization. In the utility derived for the SPSR (Equation 5.4 in Section 5.5.1), the only stochastic terms are the travel time and the probability of finding a vacant parking spot allowing the use of the utility for the description of changes. The decision of individual to re-evaluate the alternative strategy is based on a comparison of the expected situation and the experienced situation given an improvement margin. The expected situation is defined as the utility perceived by individuals before trip, while the experienced situation is defined as the utility perceived by travellers, given information received on-trip.

It is chosen to apply this particular behavioural level in certain nodes of the network where individuals would decide to change their strategy (Strategy Evaluation). Those points are named decision nodes and are located at the boundaries of the centre area (entrance decision node), when receiving information from PGIs (PGI decision node) and in case of arrival at a parking destination which is full (P.D. decision node).

Strategy Evaluation Formulation

The formulation of the tactical level requires the investigation of some important characteristics that are found to be out of the scope of this thesis. Some examples are:

1. Where are the decision points located?
2. What is the “safety threshold” difference of utilities that would make individuals change routes?
3. How is the situation perceived by individuals?

Answering those questions would require the realization of a series of experiments. For this reason the formulation of the tactical level is presented only for the sake of completeness in a generic form and not is not further analysed.

Let $n_D$ be a random decision node and $l$ be the random link on which the random individuals $i$ is positioned, described by an origin node $n_{ol}$ and a destination node $n_{ld}$. Let $n_{dec}$ be a dummy variable that described whether $i$ is approaching a decision node:

$$n_{dec} = \begin{cases} 
0, & \forall n_D \neq n_{ld} \\
1, & \forall n_D = n_{ld} 
\end{cases}$$  \hspace{1cm} (5.10)
Let $E[U_i]$ be the expected value of the utility of the initially planned parking search route for individual $i$ and $U_i$ be the experienced utility. The choice to evaluate the initially planned parking search strategy $E_{U_iN}$ is given by the following:

$$V_i = \begin{cases} n_D \cdot 1, & U_i / E[U_i] < \Gamma \\ n_D \cdot 0, & U_i / E[U_i] > \Gamma \end{cases} \quad (5.11)$$

where $\Gamma$ is the improvement threshold.

The choice of an alternative parking search strategy is the same as presented in Section 5.5.1 updated by the acquired information and by the perceived values of components of the utility function and only in case $V_i = 1$.

### 5.5.3 Operational Level

The operational level, as described initially, involves decisions concerning routes and search directions in case of on-street parking, on-trip. Routes are derived by minimizing the travel time between one parking destination and another given congestion. In a sense it is assumed that individuals evaluate their options based on the perceived travel times (taking into account congestion).

The search process when referring to on-street parking is described as a decision at each intersection given again the utility maximization decision theory. For example, when a familiar individual stops at an intersection he/she has to peak a link to follow in order to find parking. If he/she believes that the at link ahead there is higher probability of finding a vacant parking spot, while all the other characteristics are perceived to be the same, he/she would choose to follow the link with higher probability.

The utility based context allow for travellers to re-visit links that have been already visited before based on the distance from the destination the fact that a vehicle cannot stop while cruising for parking and given the fact that probabilities are updated based on departure of vehicles. This is in line with the myopic run-and-tumble search process presented by (Kaplan and Bekhor, 2011).

### On-Street Search Process Formulation

In this subsection the formulation for the on-street parking search is presented. Let $n_\delta$ be an intersection node and $l$ be the random link on which the random individuals $i$ is positioned, described by an origin node $n^l_o$ and a destination node $n^l_d$. Let $n_{dec}$ be a dummy variable that described whether $i$ is approaching an intersection node:

$$n_{dec} = \begin{cases} 0, & \forall n^l_d \neq n_\delta \\ 1, & \forall n^l_d = n_\delta \end{cases} \quad (5.12)$$

Now let $l^h$, $\forall n^l_d = n_{dec}$ be the random intersecting link where $h = 1, 2, ..., H$ with $L_H$ to be the vector with all intersecting links. Also let $U_{lh}$ be the utility of $l^h$. The probability of choosing one of the intersecting links is:
\[ P_{th} = n_{dec} \sum_{h=1}^{H} e^{U_{th}} \] 

(5.13)

5.6 Parking Assignment Model for Unfamiliar Users

The unfamiliar users were treated in a rather different way compared to familiar users due to their lack of information concerning the parking situation. Given this special attribute, unfamiliar users are modelled under a random adaptive context presented in the following sections. The general idea on how unfamiliar users are modelled is presented in Figure 5.6.

5.6.1 Strategic Level

It is accepted that unfamiliar users have a strategy, concerning parking with people either becoming familiar users (with imperfect information of the system) and drive directly towards the parking destinations chosen (36.6% - Imperfect Unfamiliar), or arrive at destination first and then start searching (50.1% - Completely Unfamiliar), or start searching before arriving at the destination (13.4% - Searching Unfamiliar) – see Section 4.4.3. Furthermore, travellers would mostly search for off-street parking destinations (78.6%). As it can be directly understood the strategic level of decisions contain a route towards the parking destination or
5.6 Parking Assignment Model for Unfamiliar Users

the actual destination (which due to unfamiliarity is assumed to be the shortest route) and the parking type.

While the Completely Unfamiliar and the Searching Unfamiliar only select the parking type on the strategic level, Imperfect Unfamiliar search for parking information before trip. It is assumed that individuals search information concerning the attributes that would be important for them and are included in the utility with the exception of the probability components. It is assumed Imperfect Unfamiliar individuals derive a choice set with their preferred parking destinations and create a search route given the utilities estimated by the individual. The assumptions made are summarized in the following:

Assumption 5.3. Unfamiliar users who search for information pre-trip are assumed to be treated as familiar users assigning utilities to parking search routes constituting a choice of parking search routes to consider. Finally, a parking search route similar to what familiar users follow is selected.

5.6.2 Tactical Level

It is important to mention at this point that data collected concerning unfamiliar users was informative enough only for getting some preliminary insight in some aspects of the decisions involved. As already mentioned this happened due to the limited number of questions that could be accommodated.

The procedure of parking search for unfamiliar users is structured in different ways according to the strategy chosen to follow and the parking type chosen.

Completely Unfamiliar
Individuals arrive at the destination and, while on-route, collect information concerning parking. If they see any parking destination or any sign indicating one or more parking destination they choose to drive to their destination and then re-route to the parking destination perceived to be the closest to their destination.

If individuals do not see any sign or parking destination they are assumed to pick a random direction (namely: north, south, west, east) and drive towards it look around for parking given their initial preference. If they have drive up to a distance away from their destination they peak a different route towards back to the destination completing one search cycle. This is followed until they find a parking destination or a sign containing information concerning parking. In case the chosen parking destination is full search is continued as described above.

The distance away from the destination people choose to re-route back depends on the network’s structure and the size of the city centre.

Searching Unfamiliar
This user class is modelled in the same way as the Completely Unfamiliar with the exception that it is assumed they know where the destination is and they do not drive to it. They simply arrive at the area of the destination and search in the same manner as Completely Unfamiliar users do with the difference that they do not arrive at the destination but just at the area defined as closed to destination.

Imperfect Unfamiliar
The tactical level for this user class is modelled in the same way as the tactical level for familiar users with the information acquired at parking decision points (PGIs, Parking Destinations).
5.6.3 Operational Level

On the operational level concerning unfamiliar users it is assumed that the Completely Unfamiliar and Searching Unfamiliar individuals pick randomly their (unfamiliar) parking search route given the direction selected on the tactical level. In case of straying far away from the destination without finding a vacant parking spot, they are assumed to pick a different route back to the initial destination. The choice of the route is done on a random way by excluding route that have been used before and, in case there is non left to be excluded, picking a same route. This is again in line with the myopic search and tumble behaviour described by Kaplan and Bekhor (2011). In case of on-street parking they randomly select a link at intersections.

It is very important to mention, that some features of this modelling framework, concerning unfamiliar users, apply in limited networks as there are usually signs at central spots, which intend to guide visitors to parking destinations. The reason for presenting such a rather extended representation lies on the need to provide a simulation environment, where even the worst case scenario can be handled by a model that can completely represent the unfamiliar user class.

5.7 Parking Probability Model

In the conceptual behavioural design, it was introduced that a set of attributes to be investigated refer to the probabilities of finding a vacant parking spot (either upon arrival or after some minutes). The problem that directly arises is how probability is defined and how it is connected to characteristics of the parking destinations that can be observed. The goal in other words is to “translate” the probability of finding a vacant parking spot to measurable parking-related characteristics.

The probability of finding a vacant parking spot is related to the following parking-related characteristics:

1. The capacity of the parking destination
2. The number of occupied parking spots
3. The number of arriving vehicles
4. The number of departures

The characteristics should be included in an mathematical expression that represents the probability. This is a rather tedious task because the above mentioned characteristics are random variables with some being interdependent (e.g. arrivals and departures). Although several attempts were made to try to describe the probability in an analytic way (such as: renewal process, Markov Chains, steady state solutions) the results were not satisfactory, due to assumptions’ violations.

For that reason it was decided to create a event-based simulation that would be allow for the definition of a model to approximate the probability encountered by individuals. The input of the simulation is a variable arrival process, the distribution of the duration of parking, a distribution of the maximum search times and the parking destination capacity.

Emmanouil Chaniotakis
Master of Science Thesis
The simulation is repeated several times and the output is the probabilities of finding a vacant parking spot upon arrival and after some minutes by counting the number of parked vehicles given their arrival time and dividing them by the total number of vehicles searching for parking at that time.

The general concept is that its driver arrives at a specific parking location and if there is a vacant parking spot he/she parks immediately and a parking duration (and as a consequence a departure time) is assigned to him/her. If there is no vacant parking spot upon arrival the driver enters a queue which works either on the First In First Out (FIFO) principle (Figure 5.7a) for off-street parking (for which people are not allowed to enter if it is full) or on a random base for on-street parking (Figure 5.7b). The algorithm of the simulation and 3 examples are presented in the Appendix B.

(a) FIFO model

(b) Equal Probabilities

Figure 5.7: The two models used for car queues

An example is presented in order to investigate the workability of the model:

Example 5.1. Saturday shopping:

An interesting case is presented for Saturday shopping day when people park for a rather small period of time (around 150 minutes). Due to the low duration there a high turnover rate as different vehicles park and several times in a day at a parking location. Such an illustrative case, was simulated with the arrival rate presented in Table 5.2 (Poisson Process) and for a parking destination with capacity of 250 parking spot, with variable duration of parking and variable variation of of the parking duration (again extreme value distributed). The maximum search time was assumed to be 10 minutes.

For having a more realistic parking demand in this illustrative example, the parking occupancies were recorded (from 10:00 to 14:00 - 20 minutes intervals) for three concentrative Saturdays in the centre of Delft using the website of the Delft municipality. Those parking occupancies were used to derive the arrival rates assuming that during an recording interval there were either only arrivals or only departures.

As it is presented in 5.8 the probabilities change based on the time of arrival and as well based on the search time an individual is willing to search for parking. In the beginning of
Table 5.2: Saturday shopping, illustrative case simulation

<table>
<thead>
<tr>
<th>Arrival Rates (veh/h)</th>
<th>Duration of Parking (min)</th>
</tr>
</thead>
<tbody>
<tr>
<td>90</td>
<td>150</td>
</tr>
<tr>
<td>108</td>
<td>150</td>
</tr>
<tr>
<td>108</td>
<td>150</td>
</tr>
<tr>
<td>138</td>
<td>150</td>
</tr>
<tr>
<td>120</td>
<td>150</td>
</tr>
<tr>
<td>108</td>
<td>150</td>
</tr>
<tr>
<td>90</td>
<td>150</td>
</tr>
<tr>
<td>48</td>
<td>120</td>
</tr>
<tr>
<td>24</td>
<td>60</td>
</tr>
<tr>
<td>6</td>
<td>20</td>
</tr>
</tbody>
</table>

The examined period the probability is 1 as every vehicle arriving can park. Afterwards the probability drop with the increased number of arrivals to increase again if travellers wait, as there are many departures (around 200 to 300 minutes).

Figure 5.8: Saturday Shopping, 3000 iterations

The definition of a model that would describe the probabilities of finding a vacant parking...
spot comes into the field of model identification and as mentioned before out of the scope of this study. However an expression is derived that was tested against the results of the simulations that took place and was found to approximate those probabilities.

Let $i$ be the random individual arriving at moment $t_i$ at the parking destination $\pi$ willing to wait $x_i$ minutes. On the parking characteristics, let $K_\pi$ be the capacity of parking destination $\pi$, $P_\pi(t_i - dt)$ be the number of parked vehicles just the moment before the arrival of individual $i$, $D_\pi(x)$ be the number of departures during $x$, $A_\pi(x)$ be the number of arrivals during $x$ and $Q(t_i)$ be the number of vehicles waiting/searching for parking at the moment of arrival of individual $i$.

The probability of finding a vacant parking spot is defined:

$$P = \begin{cases} K - E[P_\pi(t_i - dt)] + E[D_\pi(x_i)] , & K - E[P_\pi(t_i - dt)] + E[D_\pi(x_i)] \leq E[A_\pi(x_i)] + E[Q(t_i)] \\ \frac{K - E[P_\pi(t_i - dt)] + E[D_\pi(x_i)]}{E[A_\pi(x_i)] + E[Q(t_i)]} , & K - E[P_\pi(t_i - dt)] + E[D_\pi(x_i)] > E[A_\pi(x_i)] + E[Q(t_i)] \end{cases}$$

with $E[\cdot]$, denoting the expected value.

5.8 Conclusions

In this chapter the parking assignment models were presented and formulated. The general concept is based on the decision process model and the choice model derived in the behavioural research (Chapters 3 and 4).

For familiar users a parking search route assignment was formulated that describes the habitual pattern of individuals concerning parking pre-trip. The modelling of the additional level –for simulation– is presented and generically formulated in short details and depth due to lack of several behavioural characteristics. The reason of that lies on the lack of results on the behavioural characteristics for specific components of those levels and time limitations.

For unfamiliar users, the general concept under which they can be modelled is presented. The model is based on a random decisions on direction choice and route choice reasoned on the fact that unfamiliar users do not have information on where the parking destinations are located. Of course, information is acquired from signs or by driving by parking destinations and unfamiliar users drive towards that direction.
6.1 Introduction

The special character of the Strategic Parking Search Route model (SPSR) for familiar users requires the verification of the concept in some situations that would prove that it does work as expected. The other components of the Parking Assignment Model are verified and discussed, in the context of the application presented in Chapter 7. As described in Section 5.5.1 the strategic parking search route is a two level stochastic user equilibrium assignment. In the first level ($SUE_1$), the travel times to the parking destinations are calculated. Those are used in the second level of the assignment ($SUE_2$) to define the flows to the parking destinations. The assignment iterates until the travel times and the flows to the parking destination settle.

Due to the rather high complexity of the model it is chosen to go through a series of tests starting from rather simple situations and going towards more complex situation. Furthermore, it is chosen to start by testing the model for only the initial destination (initial destination preference model) and then apply the strategic parking search route.

For the initial parking destination preferences model, 3 scenarios are tested. Two of low complexity and one for the city of Assen which is actually implemented as the input for the Smart Parking Application evaluation. On the SPSR 4 scenarios are tested with the first 3 to be for simple network with different parking characteristics. The fourth scenario is a simplified version of the Assen network tested for initial parking destination preferences model.

This chapter answers partially the following research question in terms of the model verification:

7. What assignment model can be used adequately to represent parking choice behaviour?

This chapter is structured as follows: First the way the model was programmed is presented in Section 6.2 followed by the verification process (Section 6.3). The verification of the initial
destination is presented in Section 6.4 for 3 simple scenarios. The Strategic Parking Search Route verification is presented in Section 6.5 for 4 scenarios.

This chapters’ components are highly connected to the previous chapter and the following. The verification process is meant to serve as a feedback loop to evaluate the strategic level of the Parking Assignment Model for familiar users. Furthermore, the third scenario examined serves as the input for the simulation in the evaluation of the Smart Parking Application. The research components and their connections to previous and later chapters are presented in Figure 5.1.

6.2 Model Programming

The general concept is that the Parking Search Route Model –describing a habitual pattern– would be used as an input for simulation. The model was coded in MATLAB with the input to be in Extensible Markup Language (XML file) for the Road Network (will be referred to as Network) and transport demand (will be referred to as OD pairs). The output of the code is the parking search routes in a way that can be the input of a simulation program.

The pseudo-code of the program created for the verification of the algorithm is presented in Figure 6.2. In the beginning, the simulation files and the parking characteristics are inserted as input. All the strings are transformed to integers, and tables are created. With all the required components to be in a proper form, the route derivation procedure takes place for the ODs inserted and for some null ODs in order to have a more realistic representation of the travel times to parking destinations. The route derivation outcome is an assignment map, for each time period, which is used for the SUEr for all ODs, for all periods. The output of the SUEr (travel times) is used as an input of the SUEp assignment which outcome is the parking search routes and their demand. Those are again used in the SUEr assignment in order to derive more accurate travel times given the demand of the parking search routes. This takes place iteratively until it converges, given the duality gap (or flow differences between iterations) described in the previous chapter.

Emmanouil Chaniotakis

Master of Science Thesis
6.3 Verification Process

The verification process goes through a series of tests for the verification of the programming and modelling components of the parking search route assignment. The modules to read XML files and derive routes as well as the $SUEr$ assignment were initially tested\(^1\). Afterwards, the $SUEp$ component is examined, for both the initial destination preference and the strategic parking search route. In general, the complexity increases with the scenarios examined with the last scenario for the Initial Parking Destination Preference and the SPSR model to be implemented in a dynamic context for the Assen Network.

\(^1\)The results of those tests were considered to be out of the context of this thesis and are not presented
6.4 Initial Parking Destination Preference Model Verification

6.4.1 Scenario 1: 1 OD, 2 parking destination with same characteristics

The first scenario to be tested is a very simple network presented in Figure 6.3. The network consists of 5 nodes, one OD pair (1,4) with a demand of 3000 and two parking destinations located at nodes 3 and 5 which share the same parking characteristics (price, capacity, distance from destination, travel time from origin) –presented in Table 6.1. There are two route to the initial destination ($R_1 = (1, 2, 3, 4), R_2 = (1, 2, 5, 4)$).

For the route cost calculation a BPR-function function is used ($T_l = f_{fl} + 0.15(f_l/L_l)^4$) where $T_l$ is the travel time for the random link $l$, $f_{fl}$ is the free flow travel time of link $l$, $f_l$ is the flow on link $l$ and $L_l$ is the capacity $l$. For the parking assignment the Equation 5.1 was used as presented in Equation 6.1. The scale parameter ($\mu$) of the Logit Assignment is set to 1.

The period of examination is assumed to be one hour (steady-state solution).

$$U^m_{o,p,d}(t_a) = -0.735 \cdot C_p - 0.00058 \cdot W_{p,d} - 0.011 \cdot T_{o,p} + 0.119 \cdot O_p +$$
$$+0.569 \cdot Pr^0_p(t_a) + 1.18 \cdot Pr^5_p(t_a)$$  \hspace{1cm} (6.1)$$

As expected, the parking algorithm converges in two iterations for the parking assignment and two iterations for the total assignment. The link flows and parking flows are presented in the Table 6.1. The parking occupancies are –as expected– 1500 for each parking destination.

```
<table>
<thead>
<tr>
<th>Parking Destination Node</th>
<th>Price</th>
<th>Parking Type</th>
<th>Capacity</th>
<th>Travel Time</th>
<th>Walking Distance</th>
</tr>
</thead>
<tbody>
<tr>
<td>3</td>
<td>€2</td>
<td>Off-Street</td>
<td>1500</td>
<td>≈ 20 min</td>
<td>483 m</td>
</tr>
<tr>
<td>5</td>
<td>€2</td>
<td>Off-Street</td>
<td>1500</td>
<td>≈ 20 min</td>
<td>483 m</td>
</tr>
</tbody>
</table>
```

This very simple example illustrates the basic fact that the algorithm is capable of producing the expected results in the case of only examining the initial parking destination. It is directly
6.4 Initial Parking Destination Preference Model Verification

Table 6.2: Initial Destination Scenario 1, link flows

<table>
<thead>
<tr>
<th>Link Flows</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1-2</td>
<td>3000</td>
</tr>
<tr>
<td>2-3</td>
<td>1500</td>
</tr>
<tr>
<td>2-5</td>
<td>1500</td>
</tr>
<tr>
<td>3-4</td>
<td></td>
</tr>
<tr>
<td>5-4</td>
<td></td>
</tr>
</tbody>
</table>

understandable that such a habitual pattern, in the case of routes and a parking destinations with exactly the same characteristics would result in an equilibrium with same number of individuals driving to every parking destination.

6.4.2 Scenario 2: 1 OD, 2 parking destination with different prices

Another interesting scenario for the initial parking destination is tested. The network is the same as the one presented in Figure 6.3 with parking destinations of different prices. The parking characteristics are presented in Table 6.3. The travel demand for the OD pair (1,4) is set to be 400. In this scenario two tests take place. One with the scale parameter ($\mu$) to be set to 1 and one to be set to 30—a very high number approximating a DUE assignment.

Table 6.3: Initial Destination Scenario 2, parking characteristics

<table>
<thead>
<tr>
<th>PDN$^2$</th>
<th>Price</th>
<th>Parking Type</th>
<th>Capacity</th>
<th>Travel Time</th>
<th>Walking Distance</th>
</tr>
</thead>
<tbody>
<tr>
<td>3</td>
<td>€2.3</td>
<td>Off-Street</td>
<td>200</td>
<td>$\approx$ 20 min</td>
<td>400 m</td>
</tr>
<tr>
<td>5</td>
<td>€3</td>
<td>Off-Street</td>
<td>200</td>
<td>$\approx$ 20 min</td>
<td>400 m</td>
</tr>
</tbody>
</table>

The flows of the two tests are presented in Table 6.4 indicating a clear difference of the flows between the two assignments. This is of course logical as the $\mu = 40$ is in a way making the algorithm more aggressive towards the percentage of individuals choosing an alternative, pointing to another direction of that of the $\mu = 1$ which is representing the choice of individuals based on the Stated Preference research results.

Table 6.4: Initial Destination Scenario 2, parking flows

<table>
<thead>
<tr>
<th>$\mu = 1$</th>
<th>$\mu = 40$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Parking 1 (3)</td>
<td>227</td>
</tr>
<tr>
<td>Parking 2 (5)</td>
<td>173</td>
</tr>
</tbody>
</table>

The results are in line with what expected for the initial destination model. The parking which receives the highest flow is the one with the lowest price, yet there are still individuals driving to the more expensive parking destination. The break-even point, where the utilities are (almost) equal is when more individuals travel to the cheaper parking destination and the probability of finding a vacant parking spot is around 71 percent.

$^2$Parking Destination Node - The node where the parking is represented

Master of Science Thesis
Emmanouil Chaniotakis
It is rather obvious that the convergence of the algorithm for the $\mu = 1$ case (Figure 6.4a) would require a higher margin in the duality gap in comparison to the case of $\mu_1$ set to 40 (Figure 6.4b). This is the case due to the fact that the assignment model is based on the choice model derived.

6.4.3 Scenario 3: The Assen Case: Dynamic, 296 ODs, 11 parking destinations

The network of Assen was used for the final evaluation of the initial destination assignment model. The network is presented in Figure 6.5. It consists of 296 parking-related OD pairs distributed in 8 periods of 15 minutes. In this scenario only the traffic related to parking is examined. The significant characteristics of this scenario are that first of all it is dynamic for many OD pairs and that it takes into account departures based on hourly parking duration. The total demand for parking is 4006 vehicles.

In the Assen city centre there are 11 parking destination with various capacities and prices. The prices examined and the capacity of each parking destination are presented in Table 6.5. The total capacity of all parking destinations is 3256 vehicles. As it is clear the capacity is lower than the absolute demand, yet by taking into account the departures that will take place all individuals have the opportunity to park after some delay.

<table>
<thead>
<tr>
<th></th>
<th>3</th>
<th>4</th>
<th>7</th>
<th>8</th>
<th>23</th>
<th>9</th>
<th>10</th>
<th>13</th>
<th>14</th>
<th>15</th>
<th>22</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price</td>
<td>2.0</td>
<td>2.0</td>
<td>1.7</td>
<td>1.7</td>
<td>1.7</td>
<td>1.7</td>
<td>1.7</td>
<td>1.7</td>
<td>1.7</td>
<td>1.7</td>
<td>0</td>
</tr>
<tr>
<td>Capacity</td>
<td>240</td>
<td>190</td>
<td>85</td>
<td>175</td>
<td>230</td>
<td>500</td>
<td>270</td>
<td>166</td>
<td>190</td>
<td>610</td>
<td>600</td>
</tr>
</tbody>
</table>

It is important to mention at this point that the purpose of this model is to define where individuals will drive first when heading towards their destination. Where they actually park is not examined. The reason that this model is tested is because it is used as an input for the simulation in the application which is presented and explained in Chapter 7. In order to have
6.4 Initial Parking Destination Preference Model Verification

Figure 6.5: The Assen network with a focus in the city center. The parking signs represent parking destinations and the blue circles represent OD destinations.

some realism in where those travellers actually park and the actual occupancies of parking destinations the individuals who do not find a parking spot are uniformly distributed to the parking destinations with available capacity at the end of each period.

On the results the model behaves as expected. Focus is given on the flows associated with parking and not travel times. In Table 6.6 the individuals travelling to each parking destination (Parking Flows) are presented. The results suggest that around 25 percent would travel to one parking destination (the free parking destination) with the rest of the parking flows to be rather evenly distributed with the lower to be identified at the parking destinations with higher price and the destinations with rather low capacity (which reduces the probability). The walking time also plays an important role in the derived utilities. The parking destinations closer to destinations receive relatively more traffic than others (e.g. PDN 7).

In order to get a better understanding of what the results suggest the probabilities and the departures for each period are presented in Table 6.7 and Table 6.8. It is rather obvious that due to the fact that departures are incorporated in the probabilities the probabilities are rather high given the sample time of the periods. In case of smaller examination periods it is expected to have more periods with lower probabilities.

In conclusion for this scenario, it can be accepted that the model behaves in a comprehensive manner although in such a large scenario it might be difficult to interpret sometimes the results due to the multivariate utility and the large variations on the parking destination characteristics. The period width used (15 min) is believed to be rather large and incapable of representing the dynamics with regards to parking departures and arrivals. It is believed that the Strategic Parking Search route is more capable of representing and analysing indi-
individuals choices concerning parking as it does take into account the search process that people undertake when searching for parking. The presentation of this scenario intends to show the capabilities of the mode and its behaviour. Furthermore it is used as an input in the simulation for the evaluation of the Smart Parking Application presented in Chapter 7.

Emmanouil Chaniotakis  
Master of Science Thesis
6.5 Strategic Parking Search Route Verification

6.5.1 SPSR: Scenario 1: 1 OD, 3 parking destination with same characteristics

This scenario presents a first verification of the strategic parking search route. The network, presented in Figure 6.6 consists of 6 nodes, with one OD pair (1,6) with a demand of 300 vehicles. There are 3 parking destination (3,4,5) and all share the same characteristics presented in Table 6.9. It is clear from the geometry that the minimum distance between parking destinations is 400 with only the distance between parking destination at node 3 and parking destination at node 5 to have a distance of 800 meters.

![Figure 6.6: SPSR Scenario 1: test network](image)

**Table 6.9: SPSR Scenario 1, parking characteristics**

<table>
<thead>
<tr>
<th>Parking Destination</th>
<th>Price</th>
<th>Parking Type</th>
<th>Capacity</th>
<th>Travel Time</th>
<th>Walking Distance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Parking 1 (3)</td>
<td>€2</td>
<td>Off-Street</td>
<td>100</td>
<td>≈ 20 min</td>
<td>400 m</td>
</tr>
<tr>
<td>Parking 2 (4)</td>
<td>€2</td>
<td>Off-Street</td>
<td>100</td>
<td>≈ 21 min</td>
<td>400 m</td>
</tr>
<tr>
<td>Parking 2 (5)</td>
<td>€2</td>
<td>Off-Street</td>
<td>100</td>
<td>≈ 20 min</td>
<td>400 m</td>
</tr>
</tbody>
</table>

The number of possible permutations $z$ (and as a consequence the number of possible parking search routes per route) is given by Equations 6.2 which in this case (with 3 parking destinations) results to 6 possible parking search routes for the OD modelled. The utility expressed in Equation 5.4 was used with the estimators of the MNL model presented also in Equation 6.1.

$$z = \frac{P!}{(P - 3)!}$$

(6.2)

The resulted parking search routes with their utilities (probabilities are set to 1) and the resulted flows are presented in table 6.10. As of course expected the parking route flows for all the SPSRs have the same flow of 50 individuals. The algorithm converged with one iteration as all the SPSRs share the same cost.

Master of Science Thesis Emmanouil Chaniotakis
### Table 6.10: SPSR Scenario 1, parking search routes nodes, utilities and flows

<table>
<thead>
<tr>
<th>First</th>
<th>Second</th>
<th>Third</th>
<th>Utility</th>
<th>Flows</th>
</tr>
</thead>
<tbody>
<tr>
<td>3</td>
<td>4</td>
<td>5</td>
<td>-0.12</td>
<td>50.1</td>
</tr>
<tr>
<td>3</td>
<td>5</td>
<td>4</td>
<td>-0.12</td>
<td>50.1</td>
</tr>
<tr>
<td>4</td>
<td>3</td>
<td>5</td>
<td>-0.13</td>
<td>49.9</td>
</tr>
<tr>
<td>4</td>
<td>5</td>
<td>3</td>
<td>-0.13</td>
<td>49.9</td>
</tr>
<tr>
<td>5</td>
<td>3</td>
<td>4</td>
<td>-0.12</td>
<td>50.0</td>
</tr>
<tr>
<td>5</td>
<td>4</td>
<td>3</td>
<td>-0.12</td>
<td>50.0</td>
</tr>
</tbody>
</table>

### 6.5.2 SPSR: Scenario 2: 1 OD, 3 parking destination with different characteristics

This scenario goes one step further on the verification of the strategic parking search route. Parking destinations with different characteristics are introduced and examined for the network presented in Figure 6.6 with a demand of 300 vehicles. There are again 3 parking destinations with characteristics presented in Table 6.11.

#### Table 6.11: SPSR: Scenario 2, parking characteristics

<table>
<thead>
<tr>
<th>Parking Destination</th>
<th>Price</th>
<th>Parking Type</th>
<th>Capacity</th>
<th>Travel Time</th>
<th>Walking Distance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Parking 1 (3)</td>
<td>€3</td>
<td>Off-Street</td>
<td>150</td>
<td>≈ 20 min</td>
<td>400 m</td>
</tr>
<tr>
<td>Parking 2 (4)</td>
<td>€2</td>
<td>Off-Street</td>
<td>50</td>
<td>≈ 21 min</td>
<td>400 m</td>
</tr>
<tr>
<td>Parking 3 (5)</td>
<td>€2</td>
<td>Off-Street</td>
<td>100</td>
<td>≈ 20 min</td>
<td>400 m</td>
</tr>
</tbody>
</table>

Again in this scenario the convergence was tested using two different scale parameter (\( \mu = 1 \) & \( \mu = 10 \)). For both tests the results are presented in the Table 6.12. The results seem to be logical. Less travellers choose the parking search routes which is the most expensive (Parking Destination Node (PDN) 3) and most travellers choose to go to the parking destination which is less expensive and has the second largest capacity (PDN 4). This behaviour is of course more obvious in the case of \( \mu = 40 \), where only 3 vehicles would choose to take the parking search route with the first destination to be parking destination at node 3. It is also illustrated that in the case where the scale factor is set to 40 the flows the utilities get closer to the lowest value (-0.76).

#### Table 6.12: SPSR Scenario 2, SPSR nodes, utilities, and flows after 300 iterations

<table>
<thead>
<tr>
<th>SPSR Nodes</th>
<th>( \mu = 1 )</th>
<th>( \mu = 40 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>First</td>
<td>Second</td>
<td>Third</td>
</tr>
<tr>
<td>5</td>
<td>4</td>
<td>3</td>
</tr>
<tr>
<td>5</td>
<td>3</td>
<td>4</td>
</tr>
<tr>
<td>4</td>
<td>5</td>
<td>3</td>
</tr>
<tr>
<td>4</td>
<td>3</td>
<td>5</td>
</tr>
<tr>
<td>3</td>
<td>5</td>
<td>4</td>
</tr>
<tr>
<td>3</td>
<td>4</td>
<td>5</td>
</tr>
</tbody>
</table>

Again it is obvious that the convergence of the algorithm for the \( \mu = 1 \) case (Figure 6.7a)
would require a higher margin in the duality gap in comparison to the case of the scale factor set to 40 (Figure 6.7b). This is the case due to the fact that the assignment model is based on the choice model derived.

![Graph](image)

**Figure 6.7:** SPSR Scenario 2, utilities over iterations for \( \mu = 1 \) and \( \mu = 40 \)

### 6.5.3 SPSR: Scenario 3: 1 OD, 3 parking destination with different characteristics

Another final scenario is presented based on the network presented in Figure 6.6 with again a demand of 300 vehicles. The differences comparing to the previous scenarios are the prices and capacities of the parking destinations examined (Table 6.13). The price is different for all three parking destinations, with one parking destination to be free. It is important to mention that the discrete choice model used was not estimated for so low price values, however it is assumed for the sake of this scenario that it is applicable. In this example again two cases were examined with different scale factors (\( \mu = 1 \& \mu = 40 \)).

**Table 6.13:** SPSR: Scenario 3, parking characteristics

<table>
<thead>
<tr>
<th>Parking Destination</th>
<th>Price</th>
<th>Parking Type</th>
<th>Capacity</th>
<th>Travel Time</th>
<th>Walking Distance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Parking 1 (3)</td>
<td>€3</td>
<td>Off-Street</td>
<td>100</td>
<td>( \approx 20 ) min</td>
<td>400 m</td>
</tr>
<tr>
<td>Parking 2 (4)</td>
<td>€2</td>
<td>Off-Street</td>
<td>100</td>
<td>( \approx 21 ) min</td>
<td>400 m</td>
</tr>
<tr>
<td>Parking 3 (5)</td>
<td>€0</td>
<td>Off-Street</td>
<td>100</td>
<td>( \approx 20 ) min</td>
<td>400 m</td>
</tr>
</tbody>
</table>

The results are presented in Table 6.14. It is rather obvious that the SPSR model behaves as expected. A large percentage of travellers prefer to visit first the free parking destination. In the case of the scale factor being set to 40 it is clearly evidenced that travellers would prefer only the parking search route where the parking price is increasing with the first parking destination to be free (node 5) and the last to be the most expensive (node 3).
Table 6.14: SPSR Scenario 3, SPSR nodes, utilities, and flows after 300 iterations

<table>
<thead>
<tr>
<th>SPSR Nodes</th>
<th>$\mu = 1$</th>
<th>$\mu = 40$</th>
</tr>
</thead>
<tbody>
<tr>
<td>First</td>
<td>Second</td>
<td>Third</td>
</tr>
<tr>
<td>5 4 3</td>
<td>0.64 94</td>
<td>0.19 300</td>
</tr>
<tr>
<td>5 3 4</td>
<td>0.48 80</td>
<td>-0.01 0</td>
</tr>
<tr>
<td>4 5 3</td>
<td>-0.16 42</td>
<td>-0.29 0</td>
</tr>
<tr>
<td>4 3 5</td>
<td>-0.20 41</td>
<td>-0.38 0</td>
</tr>
<tr>
<td>3 5 4</td>
<td>-0.86 21</td>
<td>-0.86 0</td>
</tr>
<tr>
<td>3 4 5</td>
<td>-0.86 21</td>
<td>-0.86 0</td>
</tr>
</tbody>
</table>

SPSR: Scenario 4: Dynamic, 7 ODs, 6 periods, 6 Parking Destinations with different characteristics

The network of the Assen city was used in order to test the Strategic Parking Assignment in a dynamic basis with multiple ODs and parking destinations (Figure 6.8a). For computational and presentation-related reasons, the traffic demand was reduced using broader zones. The travel demand used in this scenario is illustrative, without reflecting the real traffic demand of the Assen city. The examined time period is 1 hour and 30 minutes in 6 (15 minutes) periods. The number of ODs examined are 7 per time period and the total traffic demand is 3378. The demand distribution is presented in Figure 6.8b.

(a) SPSR Scenario 4: Assen city test network

(b) SPSR Scenario 4: Demand over time examined

It was chosen to include 6 off-street parking destinations with illustrative capacity again for computational and presentation-related reasons. The total capacity of all the parking destinations is 3256. All parking destinations have the same price, with the exception of the parking destination located at node 22 which is free. The parking have share approximately the same travel time from same origins and the walking distance from the destinations in the city centre are presented in Table B.2 of Appendix B.

---

3A simple example can illustrate the computational intensity of more parking destinations: 11 off-street parking destinations allow for 990 possible strategic parking search route per OD while 6 parking destinations
The potential number of parking search route (per OD pair) with 6 parking destinations is 120. It has to be stated that by no means individuals would ever consider all of the possible parking search routes. The definition of dynamic choice sets is required, yet out of the context of this research. It is important to note that the of parking is set to be 2 hours which means that there will be no departures during the examined period. It is rather clear that 122 are expected to follow a parking search route but not to find any available parking spot as the parking destination are all be full at the end of period 7.

Furthermore, the probability $P^{\lambda_{O}}$ in the utility function (Equation 5.4) used in this example is the probability of finding a vacant parking spot upon arrival, as no departures are expected and individuals are assumed to abandon a parking destination immediately after visiting and finding out that there is no available parking spot.

On the results, the assignment behaves as expected with the most used strategic parking search routes to be those who were passing from the free parking destination (PDN 22) and going to the closest ones in the first periods until the parking occupancy reaches the capacity for PDN 22. The individuals driving to other parking destinations are the result of the stochasticity incorporated in the $SUep$.

More specifically, from the first to the third period the assignment converges in 2 iterations due to the fact that the vehicles driving to each parking destination do not reach capacity and the probability of finding a vacant parking spot does not drop. In the fourth, fifth and sixth period the number of individuals parking at the first parking destination drops and the more iterations are required for the situation to stabilize (40-80 iterations).

The estimated utilities of 6 strategic parking search routes for one OD pair in all six periods are presented in Table 6.16. It is clearly evidenced that in the first 3 periods (0-15 min, 15-30 min, 30-45 min) the parking search route which first destination is the free parking destination (PDN 22) is the one with the highest utility (this apply for all strategic parking search routes which have the first parking destination be the free parking destination). This changes gradually in the fourth (45-60 min) fifth (60-75 min) and sixth (75-90 min) period where the probability of finding a vacant parking spot drops. In the forth period (45-60 min) the utility has dropped, yet it is still rather high when compared to the rest utilities. This become even more obvious in the fifth and sixth period. There the utility has dropped beyond other utilities. One think that is remarkable is the effect that the large number introduced in Equation 5.4—which represents the utility of finding a vacant parking spot. When individuals

---

Table 6.15: SPSR: Scenario 4, parking characteristics

<table>
<thead>
<tr>
<th>P. D. Node</th>
<th>Price</th>
<th>Parking Type</th>
<th>Capacity</th>
</tr>
</thead>
<tbody>
<tr>
<td>9</td>
<td>€1.7</td>
<td>Off-Street</td>
<td>740</td>
</tr>
<tr>
<td>10</td>
<td>€1.7</td>
<td>Off-Street</td>
<td>460</td>
</tr>
<tr>
<td>13</td>
<td>€1.7</td>
<td>Off-Street</td>
<td>251</td>
</tr>
<tr>
<td>14</td>
<td>€1.7</td>
<td>Off-Street</td>
<td>365</td>
</tr>
<tr>
<td>15</td>
<td>€1.7</td>
<td>Off-Street</td>
<td>840</td>
</tr>
<tr>
<td>22</td>
<td>€0</td>
<td>Off-Street</td>
<td>600</td>
</tr>
</tbody>
</table>
do not park, even after three sequential parking destinations, the utility of this route is set to the high number.

Table 6.16: SPSR: Scenario 4, Flows and Utilities of 6 representative Strategic Parking Search Routes

<table>
<thead>
<tr>
<th></th>
<th>0-15 min</th>
<th>15-30 min</th>
<th>30-45 min</th>
<th>45-60 min</th>
<th>60-75 min</th>
<th>75-90 min</th>
</tr>
</thead>
<tbody>
<tr>
<td>SPSR</td>
<td>Fl</td>
<td>Util</td>
<td>Fl</td>
<td>Util</td>
<td>Fl</td>
<td>Util</td>
</tr>
<tr>
<td>22</td>
<td>14</td>
<td>15</td>
<td>2</td>
<td>0.80</td>
<td>2</td>
<td>0.80</td>
</tr>
<tr>
<td>14</td>
<td>22</td>
<td>10</td>
<td>1</td>
<td>-0.06</td>
<td>1</td>
<td>-0.06</td>
</tr>
<tr>
<td>15</td>
<td>10</td>
<td>9</td>
<td>1</td>
<td>-0.06</td>
<td>1</td>
<td>-0.06</td>
</tr>
<tr>
<td>10</td>
<td>15</td>
<td>22</td>
<td>1</td>
<td>-0.01</td>
<td>1</td>
<td>0.01</td>
</tr>
<tr>
<td>13</td>
<td>22</td>
<td>14</td>
<td>0</td>
<td>-0.09</td>
<td>1</td>
<td>-0.09</td>
</tr>
<tr>
<td>9</td>
<td>13</td>
<td>22</td>
<td>1</td>
<td>-0.04</td>
<td>1</td>
<td>-0.04</td>
</tr>
</tbody>
</table>

On the flows side, it is rather obvious that the flow of each strategic parking search route is proportional to the actual utility (keep in mind that those are rounded numbers). In the cases where the utility is very low the number of individuals driving to each parking destination are 0 with the most prominent case to be the last period in which the most routes are not followed with route (15-10-9) to be the most followed.

The parking occupancies for the periods examined are presented in Table 6.17 and Figure 6.9. The actual number of vehicles parking at the destination is rather representative of what was expected and in line with the representative utilities of the parking search routes presented in Table 6.16.

Table 6.17: SPSR: Scenario 4, Parking Occupancies at the end of each time period

<table>
<thead>
<tr>
<th></th>
<th>9</th>
<th>10</th>
<th>13</th>
<th>14</th>
<th>15</th>
<th>22</th>
</tr>
</thead>
<tbody>
<tr>
<td>0-15 min</td>
<td>28</td>
<td>29</td>
<td>28</td>
<td>29</td>
<td>30</td>
<td>104</td>
</tr>
<tr>
<td>15-30 min</td>
<td>41</td>
<td>42</td>
<td>43</td>
<td>43</td>
<td>42</td>
<td>161</td>
</tr>
<tr>
<td>30-45 min</td>
<td>71</td>
<td>71</td>
<td>69</td>
<td>70</td>
<td>71</td>
<td>237</td>
</tr>
<tr>
<td>45 - 60 min</td>
<td>143</td>
<td>151</td>
<td>111</td>
<td>143</td>
<td>145</td>
<td>98</td>
</tr>
<tr>
<td>60 - 75 min</td>
<td>266</td>
<td>167</td>
<td>0</td>
<td>79</td>
<td>279</td>
<td>0</td>
</tr>
<tr>
<td>75-90 min</td>
<td>191</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>274</td>
<td>0</td>
</tr>
</tbody>
</table>

6.6 Conclusions

This chapter presented the verification process of the Strategic Parking Search Route assignment. The process followed included the implementation of the SPSR for very simple cases starting from the examination of only the initial destination. Some focus was given on the sensitivity of the SPSR to different prices and capacities and also to the different results that yield with a Logit scale factor ($\mu$) of 1 and a large scale factor (40) that is closer to DUE assignment. Finally the SPSR was implemented dynamically in the Assen’s city network using illustrative demand and parking destinations’ characteristics. The representative outcome presented illustrated the way the model behaves. In general the model was found to behave
as expected in all cases with the illustrative examples to give a rather clear picture on the stochasticity involved in decisions and the way that this is incorporated in the SPSR model.

In the initial parking destination preference model for the city of Assen it is important to mention that there is a clear indication of the model not being capable of capturing the dynamics of parking decisions, occupancies departures and probabilities given the large period intervals. The parking search route one the other hand is capable of representing to some extend this dynamics due to the fact that it encounters for multiple destinations, yet a smaller period interval is considered to be again important.
In this section the implementation of the parking assignment is presented. The requirements for the implementation are introduced as well as the actual implementation, with all the components involved, in ITS modeller. Finally the Sensor City case study is presented and the results are analysed.

7.1 Introduction

The Parking Assignment Model is –as described in Chapter 5– a package of modelling modules capable of simulating parking in an urban environment, for the representation of the existing situation (reference case) and for representing Smart Parking Applications as scenario cases. The suitability for evaluating Smart Parking applications lies on the behavioural representation of the perception on the probability of finding a vacant parking spot, which is the basis of parking-related ITS applications. The strategic level of the parking assignment model have been verified in Chapter 6 ensuring only partially the applicability of the Parking Assignment Model. In this chapter the rest of the components are verified and the applicability of the model is evaluated based on an implementation in the context of the Sensor City project for the Smart Parking application.

The implementation in a simulation environment have some requirements that should be met. In this study, the Parking Assignment Model is implemented in ITS modeller, a (Java-programmed) modelling environment, developed by TNO to simulate Intelligent Transport Systems (ITS). The reasoning for using ITS modeller and the limitations that lead to a partial implementation of the Parking Assignment Model are presented.

The evaluation of the Smart Parking application took place the city network of Assen for 5 scenarios developed. It is important to state that due to network limitations and limitations of the ITS modeller (see Section 7.3.1), the implementation takes into account only off-street parking and for an illustrative traffic demand that does not correspond to the realistic travel
demand of the city. The scenarios developed are based on illustrative values of unfamiliar users and smart parkers.

This chapter answers to the following research questions:

7. **What assignment model can be used adequately to represent parking choice behaviour?**
8. **How can the Smart Parking application be evaluated?**
9. **What are the effects of the Smart Parking application?**

This is the chapter where all the components presented in the previous chapters of the report converge and are being applied to some extend in the case study for the Smart Parking Application of the Sensor City. The connections between the thesis components are presented in Figure 7.1.

The chapter is structured as follows: First the implementation requirements of the Parking Assignment Model are presented (Section 7.2), followed by a presentation of the ITS modeller and its limitations (Section 7.3), as well as the implementation modules that were programmed in ITS modeller (Section 7.4). Finally the Sensor City case is presented including the simulation results and the results interpretation (Section 7.5) followed by conclusions regarding the implementation and the results (Section 7.6).

### 7.2 Implementation Requirements

For the simulation of parking, there are several basic requirements that should be met. The primary requirements for the implementation of simulation of parking have been described in detail by Young and Weng (2005) and have been briefly presented in Section 2.4.4. However, in order to fully implement the Parking Assignment Model (Section 5) some further requirements are important to be met.

As it has been clear parking is modelled in 3 behavioural levels. The strategic (pre-trip) the operation and the tactical. On the strategic level the parking search route for each individual
is defined. On the operational level the “re-evaluation” takes place, while the tactical level includes the route choice and the search directions. The 3 levels shape the requirements for simulation:

**Parking Search Route:** The simulation is required to be able to include routes with multiple *visit points*.

**Information transfer:** The simulation is required to be able to include some type of infrastructure that can transfer information to individual actors such as Message Signs.

**Decision Points:** The simulation should have points where the parking search route strategy should be re-evaluated based on the input from the network.

**Route Derivation en-route:** During the simulation routes must be able to be derived.

**Intersection direction choice:** A decision should be able to be taken every time a vehicle is reaching an intersection while searching for on-street parking.

**Ability to represent Parking Facilities** On-street and off-street parking facilities should be modelled, in such a way that would make it possible to replicate the on-street parking procedure and the parking manoeuvring.

Given those requirements, it was chosen to use the ITS modeller as the simulation tool due to the fact that it qualified for most of the modules required for the implementation of the Parking Assignment Model.

### 7.3 ITS Modeller

ITS modeller is a simulation tool, developed by TNO that would be able to cater the needs of simulating ITS applications (Figure 7.2). The major advantage of ITS modeller is that first of all it is designed in such a way that the programming of ITS applications can be done in a very robust way, with pre-defined modules to be offered. The fact that it is written in Java, an object-oriented programming language allows for modular programming with ITS modeller to offer many modules that can be used to model most ITS cases. A complete presentation of ITS modeller is not intended for this thesis however it is important to mention in this section the components that were used to make the parking modelling possible.

As most advanced Java programs ITS Modeller has a “core” that it is intended not to be modified and provides an *interface* that gives the opportunity to access the core of ITS Modeller in a safe way. The modules used focused on the modelling of actors behaviour (individuals) and the modelling of the infrastructure (Figure 7.3). The modules used and the programming are further presented in the following sections of this chapter for each specific case. As ITS Modeller is an advanced simulation tool it includes several vehicle, vehicle acceleration, driving, lane choice, and car following models that can be modified according to the application.
ITS Modeller Limitations

ITS Modeller is a tool currently under development by TNO and as a consequence there are some limitations on the functionalities of the tool that are presented and shortly analysed in the next few paragraphs. Those limitations are the main reason behind the investigation of the Smart Parking application, on a rather illustrative form.

**Free Flow Cost Function:** The first limitation of ITS Modeller is that it does not take congestion into account while calculating route costs (free flow travel time as route cost) in a logit route choice model. Several corrective actions were taken in order to account for congestion, such as decreasing the scaling parameter of the Logit Model ($\mu$), increasing the speed of the highways for the route cost estimation. Although those results improved the assignment the results were not realistic in comparison to real traffic data.

**Intersection Braking Model Flaw:** The second limitation of the ITS modeller is the fact that there is a flaw with the intersection braking model that could not be detected and fixed during this thesis. For this reason the intersection braking model was not used.
Origin - Destination Pair Generation: The Origin Destination pairs in ITS Modeller serve as a very basic input which is not modifiable. New OD pairs cannot be added and the number of actors cannot be changed during simulation. This is rather important in case of parking, where individuals who parked have to depart. For this reason the individuals departing trips are not represented.

Route Generation: ITS Modeller requires predefined routes for each Origin- Destination pair. This does not allow for individual actors to change their route while being in the network and for example change direction unless there is a pre-defined route that includes the link on which the traveller is on. This made rather impossible the modelling of on-street parking search which requires the definition of a direction at each intersection. Furthermore a Smart Routing Application that would take into account congestion would require an unrealistic route choice set for total simulation time.

On-Street Parking Facilities: ITS Modeller does not include any form of parking infrastructure. For on-street parking it would be rather difficult and time consuming to implement from scratch a scheme such as the one described in the modelling requirements in the context of a thesis. Furthermore the Smart Parking System under examination is only used for off-street parking destination. For this reason on-street parking was not included.

Link Flows: The link flows on links are not available during the simulation, imposing the usage of corrective tools to measure the number of vehicles driving towards a parking destination.

7.4 Implementation Modules

The modelling of both, the reference and the Smart Parking application cases require a number of modules to be implemented in ITS modeller. Those modules constitute the basis for the simulation. In this section, the developed and implemented modules are presented for the parking facilities, the familiar users, the unfamiliar users and the Smart Parking Users (Smart Parkers). There are also other modules regarding the modelling of vehicles' movements and interaction with each other that were not developed, yet used. Those are also summarised in this section. Finally, some useful details on how those modules were programmed are presented.

7.4.1 Parking Choice Set

The size of the Assen city and the fact that there are 11 parking destinations lead to the decision to use one universal choice set including all 11 parking destinations for all parking users. In this context, all travellers heading to the city centre looking for parking, can visit all the 11 parking destination.

7.4.2 Parking Facilities

The parking facilities in ITS Modeller are represented in a very simple way using a traffic light, a traffic counter and a Message Sign (Figure 7.4). When a vehicle passes the traffic
counter the load of the Parking facility is increased. The parking facility is programmed as a controller (Parking Controller) that controls the traffic light and the message sign while it collects information at every time-step from the traffic counter. The message sign transfers an information object from the controller to the actors. The traffic light turns red if the parking facility is full.

![Figure 7.4: Off-street parking facility representation](image)

Due to the fact that as described before familiar users are assumed to have information for the system’s state and Smart Parkers receive information from the system for multiple parking destinations the introduction of a “Back Office” controller which plays the role of the parking management entity is programmed. The Back-Office Controller collects information from the Parking Controllers and make it accessible to the familiar users via the Message Sign.

Finally, the departures of vehicles from any parking facility are events based on the arrival time of each vehicle to the parking facility and a random variable representing the duration of parking. When a departure is taking place the load of the parking facility is reduced and in case the traffic light was red it becomes again green.

### 7.4.3 Familiar Parking Users

The familiar users are programmed to be in line with the Parking Modelling Framework given the ITS modeller limitations described above. To begin with, in ITS modeller it is not possible to predefine routes with specific passing points that could serve as the parking destinations included in a parking search route. For this reason only the choice of the first parking destination is governed by the habitual pattern describing choices.

The process starts by pre-defined Origin Destination pairs, representing the first parking destination to be visited, given the actual destination, in the context of the behaviour on the strategic level. The simplified version of the strategic parking search route model (initial parking destination preference) is used due to mainly time limitation. When vehicles reach a parking destination that is full, they get information from the PGIs (tactical level) and they choose the next parking destination under the scheme of the Logit RUM-based behavioural model derived (see Chapter 4). The same process is followed until all familiar users find a parking destination. An example of the way a random familiar individual would react is presented in the Figure 7.5. The driver has chosen (pre-trip) to visit the parking destination closer to his/her destination (Parking Route). When arriving there, he/she finds out that
it is full and decides to drive to another parking destination (Parking to Parking Route 1). However the second parking to visit is also full so he/she decides to drive to a third parking destination (Parking to Parking Route 2). It is important to mention here that the unfamiliar users were assumed of not being aware of the existence of the other user classes –when applicable. In other words, familiar users decide, without taking into account the parking-related decisions of the Smart Parkers or the Unfamiliar users of the system.

![Figure 7.5: Routes followed by a random familiar user in ITS modeller](image)

### 7.4.4 Unfamiliar Parking Users

As described in the behavioural research, the majority of the unfamiliar users choose to visit the initial destination, while others either get close to the initial destination and park or search for parking before trip. In this implementation unfamiliar users were directed to drive towards the initial destination. While driving, travellers are searching for a parking destination and if they find a parking destination they “store the location” and continue driving until they reach their destination. After they visit their destination they visit the stored location to park. In case travellers do not find a parking destination and they reach the destination, they choose a direction (north, south, west, east) and then follow a random predefined route towards this direction. During this route they again search for parking until they reach a point at the network which is located around 500 meters from the initial destination (applicable for the city of Assen). If they have reached this point they take a random predefined route back to their initial destination, while again searching for parking until they find a vacant parking spot. An example of a random unfamiliar user is presented in Figure 7.6. The predefined
routes are produced based on a K-shortest path penalty algorithm, used in ITS modeller, with a high number of iterations (30). The driver drives to the initial destination without finding any parking on this route. Then he/she chooses to take a route to south, and when reaching a point where it is distant to the initial destination and he/she decides to go back.

![Routes followed by a random unfamiliar user in ITS modeller](image)

**Figure 7.6:** Routes followed by a random unfamiliar user in ITS modeller

It is important to mention at this point that the unfamiliar users module was only used for one destination in the city centre for users originating from several origins.

### 7.4.5 Smart Parking Users

The implementation of the smart parking users was based on the Smart Parking application developed for the Sensor City. Individuals receive information about the parking destinations via an application for a Smart phone replicated by a Message Sign that is controlled from the Back-Office controller containing information for all parking destinations at the area to be visited. Individuals decide to reserve a parking spot at a parking destination. At this point it is **assumed** that all drivers using the reservation system comply with the reserved parking spot. The choice of one of proposed parking destinations is modelled using the Logit RUM-based behavioural model derived (see Chapter 4), only for parking destinations which have available parking spots at the moment of the reservation. Given a chosen parking destination, the reservation procedure takes place by informing the Back-Office controller and the Parking controller involved to reserve the parking spot (which essentially means to increase the load of the parking destination by the parking controller). Individuals who get a reserved parking
spot follow the shortest route to the destination. In case there is no available parking spot at any destination the same procedure is followed until a parking reservation is made.

### 7.4.6 Other Modules

For the simulation of parking some modelling modules that ITS modeller has were used. The modules are presented in Table 7.1. As all those modules has been applied in several studies further details are not presented. Finally, the route choice set generation algorithm is a K-shortest path penalty algorithm and the route choice is based on the Logit route choice.

#### Table 7.1: Other Modules used in ITS modeller

<table>
<thead>
<tr>
<th>Module</th>
</tr>
</thead>
<tbody>
<tr>
<td>Free driving model</td>
</tr>
<tr>
<td>Car following model</td>
</tr>
<tr>
<td>Adjacent lane speed adaptation model</td>
</tr>
<tr>
<td>End of lane model</td>
</tr>
<tr>
<td>Anticipatory behaviour model</td>
</tr>
<tr>
<td>Gap searching model</td>
</tr>
<tr>
<td>Speed limit model</td>
</tr>
<tr>
<td>Traffic-light braking model</td>
</tr>
<tr>
<td>Vehicle acceleration model</td>
</tr>
<tr>
<td>Right lane model</td>
</tr>
<tr>
<td>Left lane change model</td>
</tr>
<tr>
<td>Free - flow route cost model</td>
</tr>
</tbody>
</table>

Apart from the Origin Destination pairs for the users, in ITS modeller, it is important to define OD pairs (*null ODs*) for re-routing. For that reason the following null OD pairs are created (Table 7.2):

#### Table 7.2: Null ODs defined in ITS modeller

<table>
<thead>
<tr>
<th>OD Pairs</th>
</tr>
</thead>
<tbody>
<tr>
<td>From parking destinations to parking destinations</td>
</tr>
<tr>
<td>From all origins to all parking destinations</td>
</tr>
<tr>
<td>From unfamiliar distant points to unfamiliar destination</td>
</tr>
</tbody>
</table>

### 7.4.7 Programming Details

A Java Package was created in an external Java Archive (jar) file containing 10 classes (Table 7.3). In general, the controllers control the infrastructure and set the information (Serializable type of class) actors receive using the AdviceSupplier classes. The actors receive the information and use the RouteSupplier to define a new route. Each class is attributed with several *methods* required to perform the required actions. In general travel times, walking distances, probabilities of finding vacant parking spots and utilities are calculated. Furthermore, parking states, location of message signs, destination choice and route choice are defined by methods.
### Table 7.3: Programming Classes

<table>
<thead>
<tr>
<th>Class Name</th>
<th>Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>BackOffice</td>
<td>Controller</td>
</tr>
<tr>
<td>SmartInfo</td>
<td>Serializable</td>
</tr>
<tr>
<td>ParkingController</td>
<td>Controller</td>
</tr>
<tr>
<td>PChInfo</td>
<td>Serializable</td>
</tr>
<tr>
<td>ParkingRouteCosts</td>
<td>RouteCostSupplier</td>
</tr>
<tr>
<td>PrisAdviceSupplier</td>
<td>AdviceSupplier</td>
</tr>
<tr>
<td>PrisRouteSupplier</td>
<td>RouteSupplier</td>
</tr>
<tr>
<td>SmartParkerAdvice</td>
<td>AdviceSupplier</td>
</tr>
<tr>
<td>UnfamiliarAdviceSupplier</td>
<td>AdviceSupplier</td>
</tr>
<tr>
<td>UnfamiliarInfo</td>
<td>Serializable</td>
</tr>
</tbody>
</table>

#### 7.5 Sensor City Case

The network of the Assen City (Drenthe province) is used, for the test of the Parking Assignment Model. Due to complications with the given travel demand for parking at the city centre and the fact that in ITS modeller the route costs do not include congestion in the calculation of the route costs, the travel demand used is an illustrative demand that does not generally correspond to the realistic travel demand. However, as this test is mainly for illustrating the capabilities of the model the travel demand is not of major importance. A total number of 15502 individuals on average constitute the travel demand for 2 hours of simulation, with different user classes for parking users and normal users of the network. Parking users only visit the city centre of the city of Assen with the other to be assigned to destinations out from the city centre where parking is not examined. The parking users visiting the city centre are in total 4006 and the rest of traffic is 11496 individuals distributed as shown in Figure 7.7.

![Travel demand](image1)

**Figure 7.7:** Parking and rest travel demand for simulation

The city centre of Assen has 11 parking destinations (Figure 7.8) with a total parking capacity of 3256 including a Park & Ride facility and a 600 parking spot free car park. The parking
demand as presented in 7.7b is higher in total with comparison to the parking capacity. However, the actual capacity in two hours of a parking destination depends as well to the departures. In this context, the demand was distributed in such a way that there would be a small period of time when there would be very limited availability of parking spots.

![Figure 7.8: Assen City Centre Parking Destinations locations](image)

**Table 7.4: Off-Street Parking Destination in the Assen city centre**

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price</td>
<td>2.0</td>
<td>2.0</td>
<td>1.7</td>
<td>1.7</td>
<td>1.7</td>
<td>1.7</td>
<td>1.7</td>
<td>1.7</td>
<td>1.7</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>Capacity</td>
<td>240</td>
<td>190</td>
<td>85</td>
<td>175</td>
<td>230</td>
<td>500</td>
<td>270</td>
<td>166</td>
<td>190</td>
<td>610</td>
<td>600</td>
</tr>
</tbody>
</table>

**7.5.1 Scenarios**

The scenarios developed to be tested are considered to be illustrative scenarios. The demand is expressed with percentages of unfamiliar users, familiar users and smart parking users. The scenarios are presented in the Table 7.5.

For each scenario, the pre-trip familiar strategic model was implemented for the initial destination preference. Familiar users were assumed to have partial information of the other user classes which was implemented by changing the capacity of the parking destinations.
Table 7.5: Smart Parking Scenarios

<table>
<thead>
<tr>
<th>Scenario Name</th>
<th>Familiar Users</th>
<th>Unfamiliar Users</th>
<th>Smart Parkers</th>
</tr>
</thead>
<tbody>
<tr>
<td>AllFamiliar</td>
<td>100%</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Unfamiliar5</td>
<td>95%</td>
<td>5%</td>
<td>-</td>
</tr>
<tr>
<td>Unfamiliar15</td>
<td>85%</td>
<td>15%</td>
<td>-</td>
</tr>
<tr>
<td>Smart20</td>
<td>80%</td>
<td>-</td>
<td>20%</td>
</tr>
<tr>
<td>Smart40</td>
<td>60%</td>
<td>-</td>
<td>40%</td>
</tr>
</tbody>
</table>

in relation to the percentage of Smart Parkers and Unfamiliar users. Each scenario evaluation included 10 simulations with different random seeds. The simulation time for almost all scenarios was around 1 hour and 45 minutes and multiple computers were used.

7.5.2 Simulation Results & Interpretation

The representation of the scenarios are evaluated solely on travel times. This is a consequence of problems related to the route choice diagnostics that were not able to be solved in this thesis time plan. This would allow for results on the average number of parking visits and analysis on the distance from the actual destination.

The Average Total Travel Times (ATTT) of the scenarios investigated are presented in Table 7.6. All the scenarios investigated have small difference when it comes to the ATTT indicating that the modules implemented are behaving in a rather appropriate manner. As expected, the scenario with the highest ATTT is the *Unfamiliar15* scenario where due to the unfamiliarity many time is spend in order to find parking destinations. It is rather clear that the Smart Parking application to be tested improves the parking situation in both the *Smart20* scenario and especially in the *Smart40* scenario.

Table 7.6: Average Total Travel Times of investigated scenarios

<table>
<thead>
<tr>
<th>Scenarios</th>
<th>ATTT (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>AllFamiliar</td>
<td>8498104</td>
</tr>
<tr>
<td>Unfamiliar5</td>
<td>8680841</td>
</tr>
<tr>
<td>Unfamiliar15</td>
<td>9086461</td>
</tr>
<tr>
<td>Smart20</td>
<td>8473091</td>
</tr>
<tr>
<td>Smart40</td>
<td>8376374</td>
</tr>
</tbody>
</table>

In Table 7.7 the change percentages concerning the ATTT is presented with each column to represent the increase or decrease percentage of travel time give the column scenario basis. As presented, the smart parking scenarios always contribute towards a reduction of total travel times. The largest reduction of travel times (7.8 %) is found when comparing the *Unfamiliar15* scenario to the *Smart40* scenario. The lowest reduction is found when comparing the *AllFamiliar* scenario to the *Smart20* scenario. This is rather logical as by definition the *AllFamiliar* scenario includes a habitual pattern of user who have full knowledge of the system and try to increase the utility which takes into account the probability of finding a vacant parking spot. Towards a better allocation of travellers, the city of Assen offer parking with almost the same price (with the exception of parking destination 11 which is free - Table 7.4).
Table 7.7: ATTT Percentage Change of scenarios investigated

<table>
<thead>
<tr>
<th></th>
<th>AllFamiliar</th>
<th>Unfamiliar5</th>
<th>Unfamiliar15</th>
<th>Smart20</th>
<th>Smart40</th>
</tr>
</thead>
<tbody>
<tr>
<td>AllFamiliar</td>
<td>-</td>
<td>-2.1%</td>
<td>-6.5%</td>
<td>0.3%</td>
<td>1.5%</td>
</tr>
<tr>
<td>Unfamiliar5</td>
<td>2.2%</td>
<td>-</td>
<td>-4.5%</td>
<td>2.5%</td>
<td>3.6%</td>
</tr>
<tr>
<td>Unfamiliar15</td>
<td>6.9%</td>
<td>4.7%</td>
<td>-</td>
<td>7.2%</td>
<td>8.5%</td>
</tr>
<tr>
<td>Smart20</td>
<td>-0.3%</td>
<td>-2.4%</td>
<td>-6.8%</td>
<td>-</td>
<td>1.2%</td>
</tr>
<tr>
<td>Smart40</td>
<td>-1.4%</td>
<td>-3.5%</td>
<td>-7.8%</td>
<td>-1.1%</td>
<td>-</td>
</tr>
</tbody>
</table>

On a more disaggregated analysis of the results, the Average Individual Travel Times (AITT) for trips directed to the city centre (and as a consequence end to a parking destination) are presented in the Table 7.8 for each user class. The travel times are as expected with the Smart Parkers to experience the lowest individual travel times. The travel times of the unfamiliar users are increased due to the fact that no PGI systems or signs are implemented.

Table 7.8: Average Individual Travel Times for the scenarios investigated

<table>
<thead>
<tr>
<th></th>
<th>Familiar Users</th>
<th>Unfamiliar Users</th>
<th>Smart Parkers</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>AITT (s)</td>
<td>Std Dev (s)</td>
<td>AITT (s)</td>
</tr>
<tr>
<td>AllFamiliar</td>
<td>581</td>
<td>294</td>
<td>-</td>
</tr>
<tr>
<td>Unfamiliar5</td>
<td>540</td>
<td>241</td>
<td>1525</td>
</tr>
<tr>
<td>Unfamiliar15</td>
<td>519</td>
<td>196</td>
<td>1613</td>
</tr>
<tr>
<td>Smart20</td>
<td>586</td>
<td>288</td>
<td>-</td>
</tr>
<tr>
<td>Smart40</td>
<td>570</td>
<td>284</td>
<td>-</td>
</tr>
</tbody>
</table>

In general, the AITT are considered to be of the same magnitude, for all user classes in the scenarios. In a more detailed analysis, for familiar users the average travel time is around 9.3 minutes with a standard deviation of 4.3 minutes. The lowest AITT is experienced in the Unfamiliar15 scenario. This occurs due to the fact that unfamiliar users only visit specific parking destination and cannot find some parking destinations which are, as a consequence, visited by less individuals.

Unfamiliar users generally experience –comparatively– rather high individual travel times (around 26.2 minutes) due to the fact that as described, there are no parking signs indicating directions. It is worth noting that the standard deviation is also rather high (around 19 minutes). This is again, the result of the fact that there are no signs indicating directions in the network and unfamiliar travellers have to follow predefined routes until they find a parking destination where there are vacant parking spots.

The individual travel times were also examined during a period of high parking demand (60 min to 84 min) and the results are presented in Table 7.9. As it clearly shown, there is an increase in the travel times of all user classes –compared to the individual travel times for the total simulation time– apart from the Smart Parkers which have a pattern of same travel times in all cases.

Finally, the results concerning the smart parkers are in line with the findings of (Geng and Cassandras, 2012). Smart parkers experience in general lower travel times (around 8.4 minutes) than any other user class, due to the elimination of re-routings.
Table 7.9: Average Individual Travel Time during congested period

<table>
<thead>
<tr>
<th></th>
<th>Familiar Users</th>
<th></th>
<th>Unfamiliar Users</th>
<th></th>
<th>Smart Parkers</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>AITT Std Dev</td>
<td>AITT Std Dev</td>
<td>AITT Std Dev</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AllFamiliar</td>
<td>623 348</td>
<td>-</td>
<td>-</td>
<td></td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Unfamiliar5</td>
<td>622 296</td>
<td>2431</td>
<td>943</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Unfamiliar15</td>
<td>565 231</td>
<td>2339</td>
<td>1107</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Smart20</td>
<td>703 364</td>
<td>-</td>
<td>-</td>
<td>499</td>
<td>185</td>
<td></td>
</tr>
<tr>
<td>Smart40</td>
<td>684 324</td>
<td>-</td>
<td>-</td>
<td>504</td>
<td>188</td>
<td></td>
</tr>
</tbody>
</table>

7.5.3 Discussion on the results

The smart parking application was tested in the context of the Parking Assignment Model. The implementation using the ITS modeller had some limitations, which only allowed for partially (unfamiliar & familiar users). The deficiencies discussed impose the further investigation for the evaluation of the smart parking applications.

However, it is important to mention that the results first of all verify, to the implementation extend, the Parking Assignment Model. It seems that the model is capable of representing the parking choices. On the travel times that are estimated, the effect of parking is obvious with the users to re-route to other parking destination in order to find a vacant parking spot. This directly suggest that parking should be taken into account when representing the traffic situation in an urban setting.

On the results concerning Smart Parking it is shown that it can contribute to lower travel times. The smart parking application is both cases used, yield for lower travel times – especially in the case of high usage and in a congested setting. In both smart parking scenarios tested, the smart parkers experience the lowest travel times. It is important to mention that this implementation only encountered for the smart parking application without taking into account smart routing which combined in the conceptual design of the Sensor City project. The inclusion of the smart routing application is believed to further reduce the travel times.

7.6 Conclusions

In this chapter the implementation of the parking assignment framework was presented. The requirements for implementing the parking assignment modelling framework in a simulation context are also included. Furthermore, the actual implementation is presented using ITS modeller for the smart parking reservation system of the Sensor city project. which is evaluated under scenarios developed. The results of the scenarios developed and simulated are presented and interpreted under the limitations of ITS modeller. The results generally suggest that the framework produces rather realistic results, taking into account the illustrative demand and by comparing an expected situation with the results. It is believed that the results suggest the contribution of the smart parking application to the reduction of the travel times however it is strongly recommended to evaluate further cases with a newer version of ITS modeller in which the problems above mentioned would be overcome.
8.1 Conclusions

This thesis presented the development of a simulation-based parking assignment model for the evaluation of Smart Parking applications.

Behavioural research was conducted, proposing a decision process model, that describes the choice for two user classes (familiar and unfamiliar parking users), on three behavioural levels (strategic, tactical and operations). A survey was conducted with 397 complete/stratified responses for the investigation of those decisions and several model structures were examined to derive the model that can best represent parking choices. The attribute set used in the experiment was based on those found in the literature, yet different, by combining the probability of finding a vacant parking spot and the search time, into the newly introduced attribute of the probability after some minutes of searching/waiting. All attributes investigated were found to be significant in the model structures examined, supporting this inclusion.

The two probabilities investigated (upon arrival and after some minutes of searching) allow for the connection of the parking system with the choice of individuals as they were defined using parking related stochastic characteristics such as the arrival rate and duration. For that reason, a novel probability model based on simulation is introduced to approximate the true probability experienced by individuals.

The parking decision process model and the MNL parking choice model are used for the parking assignment model concerning familiar users. The decisions are represented in all behavioural models and the modelling methodology is suggested. This methodology differs to the methodologies presented in the literature, as it is solely based on the utility function of the MNL model. A habitual pattern is assumed on the strategic level, and a novel parking search route consisting of sequential parking destinations to be visited is suggested. On the tactical level, the re-evaluation of the strategy is introduced, for the first time for parking, given an improvement margin. Finally, on the operational level, decisions concerning routes
and on-street search decisions are included. The verification of the novel strategic search route show a realistic approach, in line with the theory related to them. A second user class, the unfamiliar users are introduced for the first time in parking modelling. They were modelled to have a diverse behaviour with some to search for information, and some drive to the destination and then start searching on the strategic level. On the tactical level for those without information concerning parking, a search process was defined in a random pattern of choosing direction and a random search, assumed to represent the lack of information.

The assignment framework was introduced in ITS modeller by coding the components for the evaluation of the Smart Parking reservation system developed in the Sensor City project and scenarios were investigated. The application of the framework shows the potential of using the Parking Assignment Model. It is found that it can be implemented in a simulation environment and is capable of representing the situation in a realistic way. On the other hand, is is found that the results for the scenarios developed indicate that the reservation system can improve the traffic conditions and offer lower travel times for its users.

Both the reference cases and the scenario cases are found to yield realistic results concerning travel times and parking choices. Even the case of unfamiliar users (who were found to have increased travel time) seems to be realistic, taking into account the lack of parking related signs in the implementation. The improvements of average travel times (both total and individual-based) were found to be of rather small magnitude, which is expected, as it is in line with the magnitude of many ITS applications.

8.2 Recommendations & Future Work

In general, it is believed that the parking assignment framework is capable of evaluating parking related ITS applications and that the results of the implementation on the Smart Parking application are promising. In this section, recommendations are made in three directions (Behavioural Research, Assignment Framework, Implementation & Smart Parking case). Those recommendations are considered as further steps for improving the components of this thesis with a strong focus on the further development of the parking assignment modelling framework for ITS applications.

**Behavioural Research:** In the behavioural research, the suggestions mainly lay on the experimental design, the examination of other model structures validation and the investigation of unfamiliar users. Starting with the experimental design, it is important to mention that it was attempted to collect information for a rather large number of decisions and two user classes. This was done due to the limited resources available. It is suggested to limit the scope of future experiments, on this subject and conduct more specialised experiments with focus on components of the decision process and its development.

On the model structures, one strongly suggested to be further investigated is prospect theory. The probability of finding a vacant parking spot after some minutes can be perceived as a risk by individuals. A possible suggestion what was attempted to be investigated in this research (not possible due to software problems) would be to use as a reference point the probability of finding a vacant parking spot after 8 minutes set to one (1). Any variation
from that would be perceived as a risk of not acquiring a parking spot. Furthermore, it is suggested to further investigate the derivation of profiles.

On the validation, it is suggested to conduct further experiments for validating the results of the choice models, as well as the decision process itself. This can be done in two ways. The first would be to conducting more independent experiments and compare the estimators of those models. This would help also towards a larger sample which would be more likely to be representative of the population and the vector of estimators to be closer to the vector of real values. The second way of validating the choice model would be the actual record of the parking choices in a network environment. This again requires an experiment by using devices that can track the location of individuals. Finally, it is important to state that unfamiliar users choices are explored up to a certain depth that it is found to be sufficient in the context of this thesis. Experiments are suggested with a focus on this user class, as it seems that they can affect greatly traffic.

**Parking Assignment Modelling Framework:** The modelling framework presented is developed to a certain point that can be used to describe parking in a reference case scenario and a suggested case scenario with a focus on ITS. The main issue that directly arises is the validation of that framework. To some extend a verification is presented, and the results of the application seem to be realistic; however, it is required to further work on validation especially for the reference case. Towards this direction, the implementation of the framework in full scale is required for a network where the actual travel time and the parking interactions are measurable. The result of the simulation should be compared to the realistic model in order to investigate, to evaluate the predictability of the framework.

Familiar users are assumed to have full knowledge of the all the characteristics. It is believed that fuzzy logic can be appropriate for the modelling of the perceived probabilities (upon arrival and after some minutes). In this context, it is suggested to derive membership functions for the probabilities and model the choice using them. Furthermore, it is recommended to investigate the usage of other models structure in the modelling framework.

On a more general note, it is suggested that the components regarding the re-evaluation of the strategy the on-street parking search process as well as the unfamiliar tactical and operational should be further developed with representative values to be defined for all the required variables (improvement margin, distance from initial destination etcetera).

**Implementation & Smart Parking Case** The implementation of the parking assignment modelling framework took place for evaluating the applicability of the model, verifying the simulation components and evaluating the Smart Parking application. The recommendations mainly focus on the full scale implementation of the model as well as the specific case of smart parking. Starting from the implementation, it is recommended to fully implement all the behavioural levels in order to investigate also, how the strategic parking search route model, the re-evaluation model and the on-street search model behave in a simulation environment. In order to accomplish this, the requirements described in Chapter 7 should be met. The implementation should include also some modules to store parking related and route choice related data that were not implemented due to time limitations. Given this data, more detailed analysis on the behaviour of the models can be achieved what would essentially result to a better verification of the model.
On the Smart Parking application, there is much room for improvement concerning the realism of the evaluation components. Initially, the limitations of ITS modellers should be completely overcome, and a realistic traffic demand should be defined. In the case of those being implemented, the evaluation of more scenarios in the context of sensitivity analysis is proposed. More realism could be added by conducting a Stated Preference experiment on the acceptance and compliance rate of such application. The results can be used in the scenarios’ derivation process. Finally, it is important to investigate further the case of the unfamiliar users as it seems that those are the ones who would potentially use a smart parking reservation system.


Emmanouil Chaniotakis Master of Science Thesis


Master of Science Thesis

Emmanouil Chaniotakis


Appendix A

Behavioural Research
## A.1 Attributes Examined in the literature

Table A.1: The attributes examined in the literature concerning discrete choice modelling for parking

<table>
<thead>
<tr>
<th></th>
<th>P cost</th>
<th>Walking</th>
<th>Access</th>
<th>Search</th>
<th>Duration</th>
<th>Type</th>
<th>Age</th>
<th>Ill. fine</th>
<th>Purpose</th>
<th>Income</th>
<th>PGI usage</th>
<th>Occupancy</th>
<th>Probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td></td>
<td>x</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td></td>
<td>x</td>
<td></td>
<td>x</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>x</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>x</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td></td>
<td></td>
<td>x</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td></td>
<td>x</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td></td>
<td>x</td>
<td></td>
<td></td>
<td>x</td>
<td></td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td></td>
<td>x</td>
</tr>
<tr>
<td>9</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td></td>
<td>x</td>
<td></td>
<td></td>
<td>x</td>
<td></td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td></td>
<td>x</td>
<td></td>
<td></td>
<td>x</td>
<td></td>
<td></td>
</tr>
<tr>
<td>11</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td></td>
<td>x</td>
<td></td>
<td></td>
<td>x</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

where:

1. Gillen (1978)  
7. Thompson and Richardson (1998)  
10. Ruisong et al. (2009)  
11. Van der Waerden (2012)
A.2 Interviews & Panel

Informal interviews took place with 5 students as well as a panel of 4 students which where asked the following questions:

- Which are the most important parking related characteristics you take into account when parking?
- You want to park in Delft, What do you do?
- How do you approach parking when being unfamiliar of the parking situation at a city centre?

In interviews, after the short discussion an extended –yet simplified– version of the parking decision process presented in Figure A.1 was presented to the interviewees and asked if it is in line with the decision process they would follow.

The same process was followed and the same questions were asked to the panel of students. In this context discussion was allowed and stimulated for the understanding of the decision process undertaken.

In the first question the answers were mainly: Price and distance from destination. Two individuals indicated the chance of finding a vacant parking spot.

The second question gave information of how people behave and that they have a pattern they follow. Most people said that given the location, they chose to visit some places summarizing the concept in the following expression: “If I do not find a vacant parking spot there, I go there”.

In the third question the answers were a bit diverse. One indicated that he searches information before trip while most said that they reach their destinations and search randomly around.
Figure A.1: Decision Process Framework presented
A.3 Pilot Study First Round

Table A.2: Fisher Information matrix - 0LDes Design (based on the 0LPr priors)

<table>
<thead>
<tr>
<th>Prior</th>
<th>$\beta_1$</th>
<th>$\beta_2$</th>
<th>$\beta_3$</th>
<th>$\beta_4$</th>
<th>$\beta_5$</th>
<th>$\beta_6$</th>
<th>$\beta_7$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta_1$</td>
<td>3.189033</td>
<td>-125.862</td>
<td>0.572742</td>
<td>-0.2476</td>
<td>-0.00399</td>
<td>0.054507</td>
<td>0.046</td>
</tr>
<tr>
<td>$\beta_2$</td>
<td>-125.862</td>
<td>94595.07</td>
<td>-1418.93</td>
<td>124.3795</td>
<td>-21.385</td>
<td>-72.765</td>
<td>-72.765</td>
</tr>
<tr>
<td>$\beta_3$</td>
<td>0.572742</td>
<td>-1418.93</td>
<td>29.17504</td>
<td>-0.5505</td>
<td>0.132362</td>
<td>0.565399</td>
<td>0.565399</td>
</tr>
<tr>
<td>$\beta_4$</td>
<td>-0.2476</td>
<td>124.3795</td>
<td>-0.5505</td>
<td>3.189033</td>
<td>-0.07872</td>
<td>-0.0477</td>
<td>-0.0388</td>
</tr>
<tr>
<td>$\beta_5$</td>
<td>-0.00399</td>
<td>-21.385</td>
<td>0.132362</td>
<td>-0.07872</td>
<td>0.137759</td>
<td>0.137522</td>
<td>0.080258</td>
</tr>
<tr>
<td>$\beta_6$</td>
<td>0.054507</td>
<td>-72.765</td>
<td>0.565399</td>
<td>-0.0477</td>
<td>0.137522</td>
<td>0.375164</td>
<td>0.219608</td>
</tr>
<tr>
<td>$\beta_7$</td>
<td>0.046</td>
<td>-72.765</td>
<td>0.565399</td>
<td>-0.0388</td>
<td>0.080258</td>
<td>0.219608</td>
<td>0.293147</td>
</tr>
</tbody>
</table>

Table A.3: Examined Parking related attributes (0LDes design)

<table>
<thead>
<tr>
<th>Attributes</th>
<th>Levels</th>
<th>Level Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price</td>
<td>2</td>
<td>€1.5 / €2.5</td>
</tr>
<tr>
<td>Distance from Destination</td>
<td>2</td>
<td>100 meters / 500 meters</td>
</tr>
<tr>
<td>Travel time</td>
<td>2</td>
<td>6 min / 12 min</td>
</tr>
<tr>
<td>Parking Type</td>
<td>2</td>
<td>On-Street / Off-Street</td>
</tr>
<tr>
<td>Probability upon arrival</td>
<td>2</td>
<td>10% , 40%</td>
</tr>
<tr>
<td>Probability after 4 minutes</td>
<td>2</td>
<td>30% , 70%</td>
</tr>
<tr>
<td>Probability after 8 minutes</td>
<td>2</td>
<td>60% , 100%</td>
</tr>
</tbody>
</table>

Table A.4: MNL model based on results of the 0LDes design

<table>
<thead>
<tr>
<th>Parameter number</th>
<th>Description</th>
<th>Coeff. estimate</th>
<th>Asympt. std. error</th>
<th>t-stat</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>ASC2</td>
<td>-0.00102</td>
<td>0.320</td>
<td>-0.00</td>
<td>1.00</td>
</tr>
<tr>
<td>2</td>
<td>$\beta_1$ (Price)</td>
<td>-1.05</td>
<td>0.288</td>
<td>-3.63</td>
<td>0.00</td>
</tr>
<tr>
<td>3</td>
<td>$\beta_2$ (Walking Dist)</td>
<td>0.000198</td>
<td>0.00290</td>
<td>0.07</td>
<td>0.95</td>
</tr>
<tr>
<td>4</td>
<td>$\beta_3$ (Travel Time)</td>
<td>-0.120</td>
<td>0.118</td>
<td>-1.02</td>
<td>0.31</td>
</tr>
<tr>
<td>5</td>
<td>$\beta_4$ (Parking Type)</td>
<td>-0.306</td>
<td>0.214</td>
<td>-1.43</td>
<td>0.15</td>
</tr>
<tr>
<td>6</td>
<td>$\beta_5$ (Pr arrival)</td>
<td>-0.664</td>
<td>1.25</td>
<td>-0.53</td>
<td>0.60</td>
</tr>
<tr>
<td>7</td>
<td>$\beta_6$ (Pr 4 min)</td>
<td>2.56</td>
<td>0.899</td>
<td>2.84</td>
<td>0.00</td>
</tr>
<tr>
<td>8</td>
<td>$\beta_7$ (Pr 8 min)</td>
<td>1.10</td>
<td>1.03</td>
<td>1.06</td>
<td>0.29</td>
</tr>
</tbody>
</table>
A.4 Pilot Study: Second Round

Table A.5: Fisher Information Matrix - $1LP_r$ Design

<table>
<thead>
<tr>
<th>Prior</th>
<th>$\beta_1$</th>
<th>$\beta_2$</th>
<th>$\beta_3$</th>
<th>$\beta_4$</th>
<th>$\beta_5$</th>
<th>$\beta_6$</th>
<th>$\beta_7$</th>
</tr>
</thead>
<tbody>
<tr>
<td>b1</td>
<td>3.525623</td>
<td>-258.985</td>
<td>-10.7156</td>
<td>-0.00633</td>
<td>0.073982</td>
<td>0.440436</td>
<td>0.285536</td>
</tr>
<tr>
<td>b2</td>
<td>-258.985</td>
<td>1269224</td>
<td>-604.751</td>
<td>-92.6581</td>
<td>30.55953</td>
<td>44.68388</td>
<td>54.2208</td>
</tr>
<tr>
<td>b3</td>
<td>-10.7156</td>
<td>-604.751</td>
<td>225.6399</td>
<td>-3.46417</td>
<td>1.362394</td>
<td>3.472271</td>
<td>2.238255</td>
</tr>
<tr>
<td>b4</td>
<td>-0.00633</td>
<td>-92.6581</td>
<td>-3.46417</td>
<td>3.525623</td>
<td>0.085139</td>
<td>0.114409</td>
<td>0.107337</td>
</tr>
<tr>
<td>b5</td>
<td>0.073982</td>
<td>30.55953</td>
<td>1.362394</td>
<td>0.085139</td>
<td>0.17176</td>
<td>0.144904</td>
<td>0.067904</td>
</tr>
<tr>
<td>b6</td>
<td>0.440436</td>
<td>44.68388</td>
<td>3.472271</td>
<td>0.114409</td>
<td>0.144904</td>
<td>0.372534</td>
<td>0.168001</td>
</tr>
<tr>
<td>b7</td>
<td>0.285536</td>
<td>54.2208</td>
<td>2.238255</td>
<td>0.107337</td>
<td>0.067904</td>
<td>0.168001</td>
<td>0.247421</td>
</tr>
</tbody>
</table>

Table A.6: $1LP_r$ Results, 1st & 2nd Sections

<table>
<thead>
<tr>
<th>Completed participations</th>
<th>35, (70% of total)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average age</td>
<td>31.3</td>
</tr>
<tr>
<td>Age- standard deviation</td>
<td>7.9</td>
</tr>
<tr>
<td>Number of female</td>
<td>7 (20.0% of completed)</td>
</tr>
<tr>
<td>Highest level of education</td>
<td>9 H.S. , 14 H.E . , 9 MSc , 2 Ph.D.</td>
</tr>
<tr>
<td>Highest level of education (Perc.)</td>
<td>25.7% H.S. , 40.0% H.E , 25.7% M.Sc , 5.7% Ph.D.</td>
</tr>
<tr>
<td>Income</td>
<td>7 A, 3 B, 6 C, 5 D, 7 E, 7 F</td>
</tr>
<tr>
<td>Income (Perc)</td>
<td>20.0% A, 8.6% B, 17.1% C, 14.3% D, 20.0% E, 20.0% F</td>
</tr>
<tr>
<td>Shopping using car</td>
<td>9 a, 9 b, 6 c, 2 d, 8 e, 1 f</td>
</tr>
<tr>
<td>Shopping using car (Perc)</td>
<td>20.0% a, 8.6% b, 17.1% c, 14.3% d, 20.0% e, 20.0% f</td>
</tr>
<tr>
<td>Unfamiliar Strategy</td>
<td>13 A1, 18 A2, 4 A3</td>
</tr>
<tr>
<td>Unfamiliar Strategy (Perc)</td>
<td>37.1% A1, 51.4% A2, 11.4% A3</td>
</tr>
<tr>
<td>Preference for off-street</td>
<td>27, (77.1%)</td>
</tr>
<tr>
<td>Max searching time - on-street (av.)</td>
<td>11.1 minutes (Std Deviation: 7.2)</td>
</tr>
<tr>
<td>Max waiting time - off-street (av.)</td>
<td>4.6 minutes (Std Deviation: 3.5)</td>
</tr>
</tbody>
</table>

Where:

- **A**: €5000 - €15000
- **B**: €15000 - €25000
- **C**: €25000 - €35000
- **D**: €35000 - €45000
- **E**: €45000 - €55000
- **F**: > €55000
- **a**: Once per year
- **b**: Once per 6 months
- **c**: Once per month
- **d**: 3 times per month
- **e**: Weekly
- **f**: Every day
- **H.S.**: High School
- **H.E.**: Higher Education
- **M.Sc**: Master’s Degree
- **Ph.D**: Doctoral Degree
- **A1**: Plan route, search upon arrival
- **A2**: Plan route and parking
- **A3**: Search before arrival (planned route)
Appendix B

Parking Assignment Model
B.1 Probability Model Simulation

Simulation Algorithm

Figure B.1: Probability Model Simulation Algorithm
Probability Model Examples

Example B.1. Commuters Morning Arrival Process:

The first and probably the easiest case is the morning commuters parking process. It can be assumed that commuters do not interfere with residents and any other user group as for example the residents have already depart earlier to arrive at the required period of time to their destination. In this context all the other components of the parking system are constant and the probability of finding a vacant parking spot is only based on the arrival process and from a user perspective only on the arrival time.

The probability of finding a vacant parking spot is given by the equation giving the probability in a Poisson Process:

\[ Pr[V|t, w_j] = Pr[P(t) \leq V|t, w_j] = \sum_{j=1}^{V} Pr[P(t) = j] \]  

(B.1)

where \( V \) is the number of vacant parking spots at the start of the period under examination. It is important to note that it does not make any difference to wait in order to find a vacant parking spot as in this case there are no departures involved in the model described.

In the same context the simulation gives the same results. The following figure (Figure B.2) shows the probability of finding a vacant parking spot in a morning peak for a parking destination of 250 vacant parking spot, with an average arrival rate of 120 vehicles per hour (following a Poisson process). As it is illustrated there is no change in the probability of
finding a vacant parking spot even after waiting/searching 30 minutes which is a rather extreme condition as indicated by van Ommeren et al. (2012). This is reasonable due to the fact that commuters mainly park for a long period of time (4 to 8 hours).

**Example B.2. Maximum searching/waiting time:**

An interesting example which has been investigated is the probability of finding a vacant parking spot even if the traveller has to wait for a very long period of time. Of course this situation is unrealistic however it is interesting to find out how the simulation model behaves. The situation presented is for a parking destination of 150 parking spots with an arrival rate of 180 vehicles per hour for a period of 150 minutes (2 hours and 30 minutes). Each traveller has a duration of parking extreme value distributed with a mean of 2 hours and a variance of 20 minutes. As it is illustrated (Figure B.3) if a particular traveller arrives after a particular time there is low probability of finding a vacant parking spot.

![Probability of finding a vacant parking spot](image)

**Figure B.3:** Searching for a very long period of time

The travellers who arrive early is definite that they will find a vacant parking spot upon arrival. On the other hand this probability is very low as time progresses due to the fact that there is a very big queue of cars expecting to park at some point. Even in case there is an arrival there is always a very long queue of which the traveller in question immediately becomes a member of.

**Example B.3. Demand Lower than Capacity:**

Another case which is sometimes met is the case where the capacity is higher than the demand at almost any moment. Such cases are rather rare during peak hours but can be the case...
for off-peak hours. Given variable arrival rates for different time periods (presented in the following table) the probability is always very close to one (1),

<table>
<thead>
<tr>
<th>Arrival Rate (veh/h)</th>
<th>Arrival Duration (h)</th>
</tr>
</thead>
<tbody>
<tr>
<td>90</td>
<td>1</td>
</tr>
<tr>
<td>90</td>
<td>2</td>
</tr>
<tr>
<td>150</td>
<td>1</td>
</tr>
<tr>
<td>138</td>
<td>1</td>
</tr>
<tr>
<td>90</td>
<td>1</td>
</tr>
<tr>
<td>108</td>
<td>1</td>
</tr>
</tbody>
</table>

Based on the arrivals presented in Table B.1, a duration of parking to be extreme valued distributed with a mean of 120 minutes (2 hours) and a variance of 20 minutes and a capacity of 200 vehicles the following probability surface arises (Figure B.4). Its meaning is that for all the study period there is a very high probability to find at least one vacant parking spot upon arrival or after a few minutes of waiting.

![Probability of finding a vacant parking spot](image)

**Figure B.4:** Demand Lower than Capacity, 2500 iterations
### B.2 Parking Search Route Verification, Scenario 4

In the following table the walking distance from the destinations to the parking destinations examined are presented.

<table>
<thead>
<tr>
<th>Destinations</th>
<th>PDN 9</th>
<th>PDN 10</th>
<th>PDN 13</th>
<th>PDN 14</th>
<th>PDN 15</th>
<th>PDN 22</th>
</tr>
</thead>
<tbody>
<tr>
<td>2297</td>
<td>846.5</td>
<td>932.4</td>
<td>1212</td>
<td>1192</td>
<td>1166</td>
<td>1322</td>
</tr>
<tr>
<td>2475</td>
<td>812</td>
<td>775.3</td>
<td>454.2</td>
<td>451.5</td>
<td>428</td>
<td>558.7</td>
</tr>
<tr>
<td>2530</td>
<td>1011</td>
<td>1095</td>
<td>1374</td>
<td>1353</td>
<td>1327</td>
<td>1252</td>
</tr>
<tr>
<td>3264</td>
<td>254.1</td>
<td>217</td>
<td>447</td>
<td>426.4</td>
<td>400.4</td>
<td>982</td>
</tr>
<tr>
<td>3762</td>
<td>394.6</td>
<td>342.7</td>
<td>822.5</td>
<td>801.9</td>
<td>775.9</td>
<td>1173</td>
</tr>
<tr>
<td>4050</td>
<td>1009</td>
<td>1038</td>
<td>954.3</td>
<td>925.6</td>
<td>902</td>
<td>292.1</td>
</tr>
<tr>
<td>6006</td>
<td>780.8</td>
<td>809.8</td>
<td>814.9</td>
<td>789.8</td>
<td>766.3</td>
<td>772.2</td>
</tr>
</tbody>
</table>

**Table B.2**: SPSR:Scenario 4, walking distances to destinations
Glossary

**A**

Alternative Specific Constant  A constant in utility that captures the average effect of the unobserved utility factors (Train, 2003, Chap. 1).

Alternative  One of the available options individuals have to choose upon in a choice situation.

Attribute  A observed factor which shape individuals decisions concerning alternatives (it is sometimes referred to as source of utility) (Train, 2003, Chap. 1).

Attribute level  The values of attributes examined in a Stated Preference survey.

**B**

Behavioural Levels  The levels on which decisions are structured (Strategic, Tactical and Operational).

Behavioural Research  The investigation of individuals’ behaviour.

**C**

Choice Model  See Discrete Choice Model.

Choice Set  A set of alternatives individuals have to choose from for a specific choice situation (Train, 2003, Chap. 1).

Choice situation  A situation when individuals have to decide between alternatives.

Complexity of SP  The amount of information that respondents have to process when responding in a Stated Preference experiment (Hensher, 2006).

Cramer Rao Inequality  The proof that for unbiased estimation the lowest variances and covariances that can be achieved are the values of the inverse information matrix.

Cruise for parking  The process of searching for parking in an urban environment.

**D**

Master of Science Thesis  Emmanouil Chaniotakis
<table>
<thead>
<tr>
<th><strong>Glossary</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Data Collection</strong></td>
</tr>
<tr>
<td><strong>Decision Node</strong></td>
</tr>
<tr>
<td><strong>Descriptive Statistics</strong></td>
</tr>
<tr>
<td><strong>Design of Experiment</strong></td>
</tr>
<tr>
<td><strong>Destination</strong></td>
</tr>
<tr>
<td><strong>Discrete choice model</strong></td>
</tr>
<tr>
<td><strong>Disutility</strong></td>
</tr>
<tr>
<td><strong>Duality Gap</strong></td>
</tr>
<tr>
<td><strong>Estimator</strong></td>
</tr>
<tr>
<td><strong>Experiment Design</strong></td>
</tr>
<tr>
<td><strong>Externalities</strong></td>
</tr>
<tr>
<td><strong>Familiar</strong></td>
</tr>
<tr>
<td><strong>Fisher Information Matrix</strong></td>
</tr>
<tr>
<td><strong>Generic estimators</strong></td>
</tr>
<tr>
<td><strong>Heterogeneity in Taste</strong></td>
</tr>
<tr>
<td><strong>Individuals</strong></td>
</tr>
<tr>
<td><strong>Interviews</strong></td>
</tr>
<tr>
<td><strong>Labeled alternatives</strong></td>
</tr>
<tr>
<td>Term</td>
</tr>
<tr>
<td>-------------------------</td>
</tr>
<tr>
<td>Link</td>
</tr>
<tr>
<td>Model</td>
</tr>
<tr>
<td>Model Structure</td>
</tr>
<tr>
<td>Node</td>
</tr>
<tr>
<td>Off-Street</td>
</tr>
<tr>
<td>On-Street</td>
</tr>
<tr>
<td>On-Trip</td>
</tr>
<tr>
<td>Orthogonal Experiment</td>
</tr>
<tr>
<td>Panel</td>
</tr>
<tr>
<td>Panel Data</td>
</tr>
<tr>
<td>Parking Assignment</td>
</tr>
<tr>
<td>Parking Assignment Modelling Framework</td>
</tr>
<tr>
<td>Parking Capacity</td>
</tr>
<tr>
<td>Parking Decision Process</td>
</tr>
<tr>
<td>Parking Destination</td>
</tr>
<tr>
<td>Parking Pricing</td>
</tr>
<tr>
<td>Parking Process</td>
</tr>
<tr>
<td>Parking Spot</td>
</tr>
</tbody>
</table>
Parking Type  The type of a parking destination (On-Street or Off-Street)

Pilot Study  A preliminary study of small scale to identify possible problems in an experiment

Pre-Trip  Before the actual realization of the trip

Priors  A set of prior estimators of the factors which shape individuals decisions used for the definition of a more efficient experiment design

Prospect Theory  A decision theory in which the losses risks and gains are valued differently (Kahneman and Tversky, 1979)

Random Utility Maximization  A decision theory in which individuals try to maximize the utility from their choices between different alternatives

Regret Minimization  A decision theory based on the notion that when people make decisions try to minimize the regret of choosing one alternative over the other (Chorus, 2010).

Representative Sample  A subset of the population that reflects the members of the entire population

Route  A set of links that represents the connection of two nodes in a network (Merriam Webster Dictionary).

Smart Parking  Applications for parking which are based on ITS applications

Stated Preference  A form of experiment in which respondents state their choice in mainly hypothetical situations.

Steady-state  A model that does not take into account time.

Strategic Parking Search Route  A route including sequential parking destinations that individuals device before trip

travellers  Individuals, users

Unfamiliar  A user who is assumed to have no information of the characteristics of the parking destination in the area visited

User Class  A class of users who share common behavioural characteristics allowing to model as one group

Users  Individuals, travellers

Utility  The representation of the individuals’ satisfaction/usefulness experienced by taking a decision
| Validation | The process of ensuring that a model has the accuracy required to be used in the application that it is designed to be used (e.g. prediction) |
| Verification | The process of ensuring that a model is implemented in a correct way and that it can behave in an expected way |
Nomenclature

AITT  Average Individual Travel Time
AoN   All or Nothing
ASC   Alternative Specific Constant
ATTT  Average Total Travel Time
DoE   Design of Experiment
DUE   Deterministic User Equilibrium
GEV   Generalized Extreme Values models
IPS   Intelligent parking system
ITS   Intelligent Transport System
MMNL  Mixed Logit Model
MNL   Multinomial Logit model
NL    Nested Logit
PD    Parking Destination
PDN   Parking Destination Node
PGIs  Parking Guidance & Information Systems
PAM   Parking Assignment Model
RP    Revealed Preference
RUM   Random Utility Maximization
SP    Stated Preference
SP    Smart Parking
SUE   Stochastic User Equilibrium
SUEp  Stochastic User Equilibrium on a parking level
SUEr  Stochastic User Equilibrium on a route level
VMS   Variable Message Sign