# Online Waiting Time Information

## sing Agent-based Modelling to Identify the Potential Effects of LiveLines on he Waiting Times of Attractions in Amsterdam

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In **Engineering and Policy Analysis**

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# Executive Summary

## Context

Managing the crowding and congestion which people cause is becoming increasingly important for cities. A problem related to this are the increasing waiting times of attractions in Amsterdam. For instance, the waiting times for the Van Gogh Museum and the Heineken Experience often exceed one hour. Recently, attention has been paid to the trial of a feature which tries to reduce these waiting times and spread visitors out more between the attractions: LiveLines. The trial ran between April 2017 and June 2017 and displayed the wait times of nine attractions in Amsterdam.

Currently, the trial has been evaluated based on the attitudes of the museums, the reviews of respondents on the LiveLines Web page and the media attention it has gained (Marketing, 2017). However, no knowledge about the effects of the feature on the waiting times has been added to the debate. Hence, a mismatch exists between the initial objective of the feature, namely spreading the visitors more equally between the attractions and reducing wait times, and the method of evaluation used for it.

The purpose of this project was to investigate the effects on the attraction wait times in Amsterdam if visitors use online waiting time information. To fulfil this objective, the following research question was developed:

- ***'What is the effect of online waiting time information on the attraction wait times in Amsterdam?'***

In this project, an agent-based model has been developed to run experiments which led to an answer to this research question.

## Results

The results showed that if a high percentage of users avoid congestion by using LiveLines, the waiting times for attractions are not necessarily reduced. The waiting times for the most popular attractions namely show oscillating behaviour.

The underlying cause is that it takes time from the period when a visitor selects a destination based on the waiting times displayed in LiveLines to the moment when he or she stands in the attraction's queue. If the wait times of an attraction drops below a tipping point, relatively many people decide to go to that attraction. This behaviour creates the oscillations. In short, the problem is the time delay between decision-making and effect emergence.

Adjustments to the system in which a prediction of the waiting times are displayed instead of the current waiting times was expected to reduce this time delay. The results showed that:

- Predictions based on past waiting times leads to a reduction in the amplitude of the oscillations.
- Tailored predictions based on the location of the users and their intentions eliminates oscillations. In this method, LiveLines users send their next attraction choice to the system. Based on the location of the uses and their choices of attractions, the system makes accurate predictions.

## Conclusions

This objective of this research project was to obtain knowledge about the influence of online waiting time information on the attraction wait times in Amsterdam. An agent-based model of the system based on the situation in Amsterdam was developed in Netlogo.

The main scientific contribution of this paper are several refinements on previous related simulation models. These refinements are discussed in the next paragraphs.

First, the behaviour of the agents in related simulation models is either congestion avoiding or congestion disregarding. A congestion-avoiding agent always goes to the attraction with the lowest waiting times. Consequently, the waiting time at this attraction rises quickly, and another attraction becomes the attraction with the shortest waiting time.

By contrast, neither congestion-avoiding nor congestion-disregarding behaviour simplifies the behaviour of the agents in this project's simulation model. In the simulation model of this project, the agents make their decisions by evaluating the wait times of attractions based on their preferences—their preferred attraction choices and their 'maximum willingness to wait' (MWW). Namely, it is assumed that every visitor is congestion avoiding to some extent. However, the threshold of congestion differs per individual and per attraction.

Second, the distances between attractions were not considered in the previous models. Hence, another refinement of this simulation model is its inclusion of travel time between attractions.

Third, the possibility that visitors will wait unit the wait time of an attraction becomes 'acceptable' was not included in the previous models. According to Amsterdam Marketing, if the waiting time is unacceptable to visitors, they are likely wait and simply walk around (Marketing, 2017). This behaviour is included in this project's simulation model.

In conclusion, the findings of these thesis should be considered in the decision-making process on a definite implement of LiveLines. Depending on the objectives of the different actors involved and the expectations about the adoption of LiveLines, several alternatives should be explored for future design of the feature.

# Preface

This thesis has been written to fulfil the graduation requirements of the Engineering and Policy Analysis programme at the Delft University of Technology. I was engaged in researching and writing this thesis from April 2017 until October 2017. The engineering and policy analysis programme teaches students with technical backgrounds how to address complex problems. The programme includes courses on subjects such as economics, statistics, policy analysis and modelling. I especially enjoyed the modelling courses, such as those on discrete event simulation and system dynamics. Therefore, I intended to use a modelling method to analyse a relevant complex problem for my graduation project.

Subsequently, the goal was to find a worthwhile complex problem to analyse. Relatively soon, my attention was drawn to the increased pressure which tourists are creating on the city of Amsterdam, through the constant stream of newspaper articles reporting on this topic.

However, it took quite some time to exactly define a problem suitable to analyse with simulation modelling. After getting in contact with several people from the municipality of Amsterdam to get a better feel for its current challenges, the trial of the LiveLines feature captured my attention.

The trial ran between April 2017 and June 2017 and displayed the wait times of nine museums in Amsterdam. The objective of the feature was to change the behaviour of visitors and, consequently, improve the spreading of visitors between different attractions.

By doing research on how the feature would be evaluated, I found that no quantitative figures were used in the decision-making process regarding the implementation and/or further development of the feature. To support this informed decision-making, I recognised the potential of simulation modelling. Quantitative insights can lead to essential adjustments and make the implementation process easier, and actors are more aware of their interests.

This project has been by far the biggest research project I have ever executed. Some moments have been challenging. However, I would like to thank my supervisors for their excellent guidance during my project. Without their cooperation, I would not have successfully finished my thesis.

Specially, I want to thank Els van Daalen for always being able to set aside time for me if I had any questions, as well as for giving me very concise feedback about my deliverables and trying to connect me with other people if required. I would also like to thank Martijn Warnier for being available if I perceived any modelling problems and for giving me the faith that I would successfully finish my project. Finally, I want to thank my external supervisor, Bas Amelung, for bringing me into contact with agent-based modelling tourism researchers.

In the first place, this thesis is meant for people who are interested in acquiring a better understanding of the potential effects of the online wait time information used among many users in a tourism context. In addition, this thesis may have value for the designers of any tool made to alter the behaviour of visitors by providing congestion information.

*Jeroen Beutler, Amsterdam, 31 October 2017*

# 1. Introduction

## 1.1 Background

The increasing density of people in Amsterdam is attracting significant attention (Daamen, Etta, Gutierrez, Hakvoort, & Nollen, 2016). Currently, 17.3 million visitors visit Amsterdam every year and this number is expected to increase at the current rate of 5% per year (Daamen et al., 2016). This leads to a forecasted 27 million visitors by 2025.

An increase in visitors, increases the pressure on the available attractions (Elliott, 1998).
Besides, residents have changed their recreational behaviour. People from Amsterdam go out more (Daamen et al., 2016). This results in an increased pressure on pubs, restaurants and attractions in the city creating frustration and disapproval among residents and the municipality. Residents frown at the increased waiting and queuing times at attractions and the decrease in attractiveness of the city's parks (Daamen et al., 2016).

In this regard, the municipality of Amsterdam drafted a report, Plan Amsterdam (2016), in which it reacted on challenges related to this phenomenon. The reports drafts guidelines to transform the city towards an innovative and creative city specifically focussing on crowding (Daamen et al., 2016).

Two new features have been released which could tap into the strategic goals of the municipality. One of the features comes from the technology giant; Google. Google updated its so called 'Popular Times' feature with 'real-time information' about the relative popularity of an attraction (Liberatore, 2016). The information is based on the geographic location of Google Maps users.

Amsterdam Marketing, a department of the municipality of Amsterdam also recognises the opportunities of live crowding information. They started a trial using a similar idea as google which they call LiveLines. The trial version of LiveLines feature gave real-time information about the waiting times of 9 museums in Amsterdam and ran between April and June 2017 (Marketing, 2017). The wait times were manually updated by the museums themselves.

The objective of the feature was to change the behaviour of visitors and, consequently, improve the spreading of visitors between different attractions (Daamen et al., 2016). Consequently, leading to shorter waiting times.

Having defined the background of this project, the remainder of this introduction addresses the problem definition of this project (section 1.2). Consequently, the research questions are discussed (section 1.3). Having defined the research direction, the scientific relevance of this direction is discussed (section 1.4). Finally, a reading guide is provided (section 1.5).

## 1.2 Problem Definition

As pointed out in the background section to this paper, the LiveLines feature is expected to contribute to the effective spread of visitors in Amsterdam. In August 2017, Amsterdam Marketing published a report to evaluate the trial of LiveLines (Marketing, 2017).

Amsterdam Marketing is of the belief that the feature should be implemented for two reasons: first, by reason of the significant amount of media attention which the trial attracted, and second, because of the positive reviews of respondents on the LiveLines Web page (Marketing, 2017).

However, the key problem with this reasoning is its lack of consideration of the effects of the initial objective: spreading the number of visitors more equally between attractions (Mulder, 2017).

The importance of this problem is supported by the statement of Amsterdam Marketing that attractions are difficult to convince with regards to implementing the feature because they have limited knowledge about the potential effects of LiveLines on waiting times (Marketing, 2017).

In conclusion, insights into these effects could lead to more effective strategies for further development of the LiveLines feature before implementation. Furthermore, this present study can help to convince critical actors of the feature's potential and ultimately facilitate their collaboration.

In summary, the investigation of the effects of the LiveLines feature is required because a practical need exists. Insight regarding the impact of this feature informs Amsterdam Marketing on how to further develop the feature. Having defined the problem definition

## 1.3 Research Questions

As described in section 1.2, a lack of insight into the potential effects of LiveLines exists. Therefore, the main goal of this project is to obtain quantitative knowledge about the potential effects of LiveLines on the waiting times of attractions in Amsterdam. This will be done by designing a tool that can explore these effects. Additionally, the second main objective of this project is to identify potential additions to LiveLines to successfully implement the LiveLines feature. Based on the research objectives and the problem definition the following research question is formulated:

- ***'What is the effect of online waiting time information on the attraction wait times in Amsterdam?'***

The main research question is subdivided into three sub-questions. The first sub-question serves as a tool to determine how the behaviour of a visitor regarding attraction visiting is affected by using online waiting time information. This question captures the changes in individual behaviour if a visitor is using LiveLines:

1. *'How does waiting time information affect visitors' choice?'*

The behavioural changes of LiveLines is known after having answered the first sub-question. Subsequently, at that stage it is possible to evaluate the effects of adoption of the LiveLines feature. A tool needs to be developed to explore these potential effects. In this project agent-based modelling is used. The following sub-question is formulated:

2. *'What is the effect of LiveLines in its current form on the attraction wait times in Amsterdam?'*

Whereas, the second sub-question investigated the potential effects of LiveLines on the attraction waiting times in Amsterdam, the third sub-question is establishing on the effects of several additions to the LiveLines feature. Subsequently, this leads to the following sub-question:

3. *'What are the effects of several possible additions to LiveLines on the attraction wait times in Amsterdam?'*

## 1.4 Scientific Relevance

Having discussed the practical need and the pursued research questions for assessing the effect of LiveLines on waiting times for museums and other attractions, along with the interest of the involved actors in the LiveLines feature, the following paragraphs will outline the scientific need for research in this field.

In the academic literature, the process of understanding the movement of visitors and its link to their decision-making is called 'tourist movement' (Xia & Zeephongsekul, 2010) (Weimin Zheng, Huang, & Li, 2017). Most previous studies regarding this topic have focussed on the movements of visitors between different destinations (McKercher & Lew, 2008). These studies mainly focussed on aspects that influenced destinations choices. For example, Huybers (2003) identified attributes of destinations and personal characteristics that influence the choice of destinations from prospective tourists from Melbourne, Australia. However, a tourist is likely to visit multiple sites and attractions during a single trip (Ben-Akiva & Lerman, 1985). Hence, the scientific need exists to understand the behaviour of visitors within a specific destination.

Only a few studies have analysed the spatial movement of tourists within destinations (Fennel, 1996) (McKercher & Lew, 2008) (Shoval & Ahas, 2016). Several authors have mentioned that the mapping of tourists' movements within destinations is an underdeveloped field of study (Fennel, 1996) (Weimin Zheng et al., 2017). The former difficulties with acquiring precise location information from tourists have hindered research in intra-attraction movement (McKercher & Lew, 2008).

Nonetheless, with the recent development of internet technology and geographic information technology, tracking and tracing the space-time path of tourists with more precision is possible (Weimin Zheng et al., 2017). The new application of technology, in the form of the LiveLines feature, provides detailed location information and could be used to better understand tourists' activities, and from a governmental policy perspective, it could be used to change tourist behaviour (Weimin Zheng et al., 2017). Understanding tourists' intra-destination movement patterns can be used as a foundation for further empirical studies. This can lead to practical applications for urban planners (McKercher & Lew, 2008). For instance, it can help in deciding what kind of information at what time should be provided to tourists (Weimin Zheng et al., 2017).

The previous paragraphs have discussed the scientific relevance of this project by discussing the limited research of tourism behaviour within destinations. In addition, a scientific need exists to develop a simulation model which represents the system of study. This need exists because the related simulation models which have been developed are not applicable (Kataoka et al., 2004). The developed models in a theme park context are not applicable to this projects' research problem because of several reasons (Kataoka et al., 2004) (W Zheng, Jin, & Ren, 2014).

First, the behaviour of the agents was simplified in these models—An agent could be either congestion avoiding or congestion disregarding. A congestion-avoiding agent always goes to the attraction with the lowest waiting time. Whereas, a congestion disregarding agent goes to it's an attraction of preference. A second reason is that travel time between the attractions was not included in these simulation models (W Zheng et al., 2014).

In summary, two main reasons emphasise the scientific need of this project. First, the underdeveloped research of tourist movement within destinations. Second, the requirement of refinements on previous related models.

## 1.5 Reading Guide

To provide a structured path to the reader, this document is organised in several chapters. In figure 1.1, an overview of this path is shown.
Having defined the problem and research questions in chapter 1, chapter 2 describes the selection of methods used to answer the three sub-questions. Note that the method selection for both sub-question 2 and 3 is described in section 2.2. The underlying reason is that both sub-question 2 and 3 are answered using identical methods.

Chapter 3 incorporates an answer on sub-question 1. In this chapter the behaviour of visitors is analysed using a literature review and results of a questionnaire. The results of this chapter serve as an input to chapter 4.

Chapter 4, 5 and include the steps to answer sub-question 2 and 3, and represent the steps to construct an agent-based simulation model.

Chapter 6 answers sub-question 2. Whereas chapter 7 answers sub-question 3. Chapter 7 discusses the theoretical significance of the findings, the limitations and the practical relevance of the study. This chapter ends with potential applications of the project's results. Subsequently, chapter 8, concludes this thesis and discussed directions for future research. Lastly, this thesis ends with a reflection of important steps of the project.

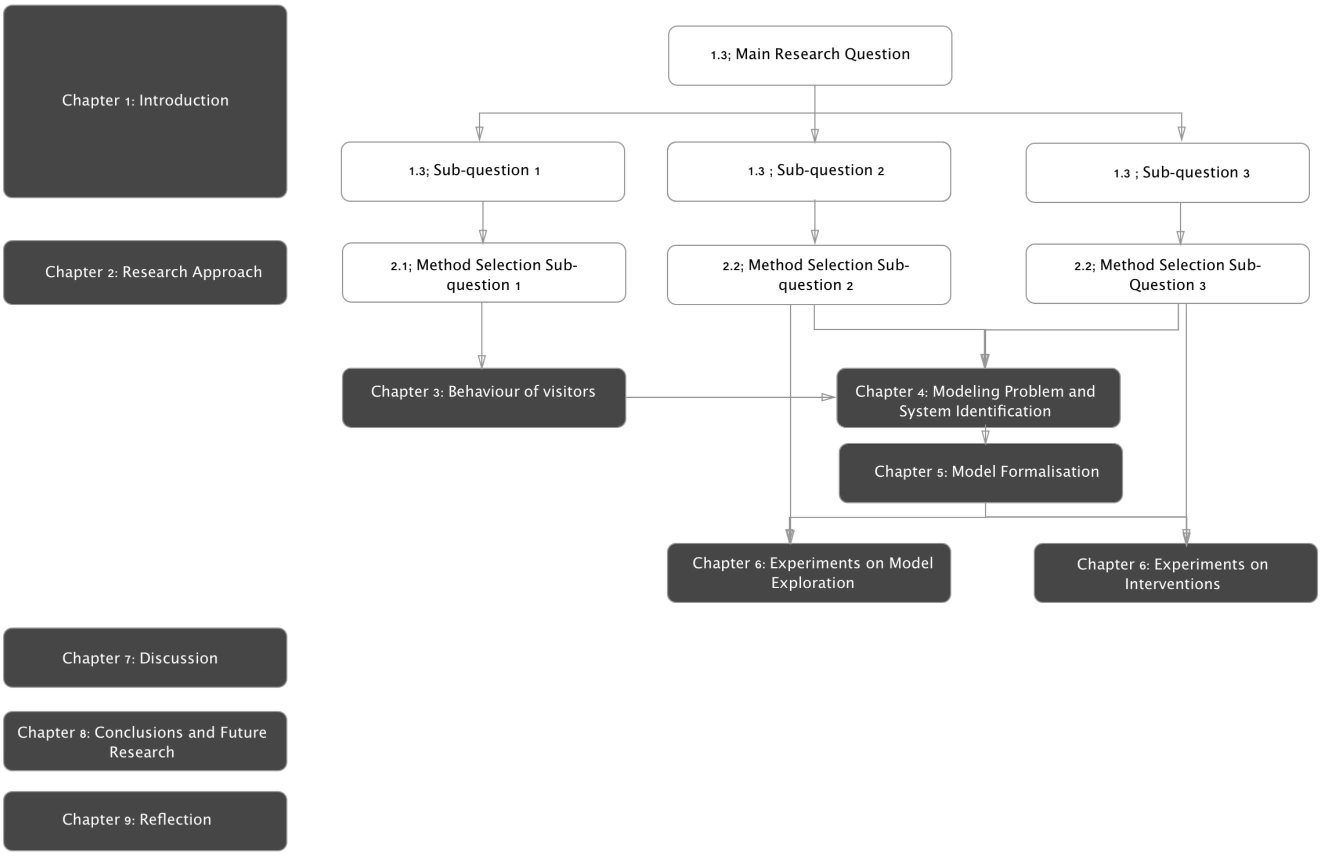


**Figure 1.1; Framework of Thesis**

# 2. Research Approach

This chapter presents a description of the research methods used throughout this thesis. This chapter elaborates on the relevant methods to answer the sub-questions as defined in chapter 1.3. In this chapter, the selected method for answering sub-question 1 is discussed first (section 2.1). This is followed by a discussion of the selected method for answering sub-question 2 and 3 (section 2.2).

## 2.1 Sub-question 1

- ***'How does waiting time information affect visitors' choice?'***

### 2.1.1 Introduction

This question requires a method in which the influence of waiting time on choice of attraction is evaluated. To identify a method which serves this purpose, a detailed understanding of choices is needed. Therefore, it is insightful to get a better feel about choices first.

Whether they realise it or not, people make choices every day. These choices can be insignificant such as the decision on the type of clothes to wear in the morning, or sometimes life changing when deciding on the university to enrol. All choices share that they comprise to a certain extent decision-making. A choice is the selection of an alternative. Before a choice is made these alternatives are evaluated. This evaluation depends on the potential 'advantage' gained by selecting an alternative.

In economic terms, this 'advantage' is called utility, and refers to the total satisfaction received from consuming a good or service (Fishburn, 1970). Choices involve the ordering of alternatives based on their relative utility. This process ultimately results in an optimal choice (Fishburn, 1970). In summary, the utility of the possible alternatives influences the final decision.

This sub-question focusses on visitors' selection between different alternative attractions. Based on the utility theory, the attraction which results in the highest gain of utility will be selected by a visitor. Various aspects could influence this utility gained by visiting an attraction such as, for instance, price, travel time and prior visits. In this sub-question the influence of waiting time on the utility gained is of interest. To investigate this relationship a valuation method has to be used (Choi et al. , 2010).

The utility of public goods, such as attractions, and the effect of waiting times, on this utility can be valued with the aid of non-market valuation methods (Ates, 2014). A variety of non-market valuation methods exist. Before proceeding to examine which of these methods is suitable for answering the sub-question, it is necessary to discuss the underlying theory.

Hence, the next section includes economic utility theory and its applications in tourism research (section 2.1.2) (Kjaer, 2005). Consequently, a non-market valuation method is selected (section 2.1.3 – section 2.1.5). Non-market valuation methods are typically used to determine the utility of public goods such as attractions.

### 2.1.2 Uncertainty in Decision-making

Multiple views on choices based on utility exist. The traditional deterministic approach assumes that an individual chooses the alternative with the highest utility (Mathieson & Wall, 1982) (Timmermans, Fischer, & Nijkamp, 1984).

This approach has been heavily criticised and has led to other theories about decision-making between alternatives for tourists. One of these alternatives is the probabilistic approach. This approach is also based on the previously mentioned utility theory. In this approach, the alternative with the highest utility has the highest probability of being chosen (Starmer, 2000). Thus, this approach takes the uncertainty that the alternative with the highest utility is not always chosen into account.

Mansfeld (1993) argued that an individual's real situation is reflected via a combination of the two methods. The individual's objective when facing a decision is not to maximise his or her utility but to meet a certain expectation (Mansfeld, 1993).

Additionally, destination decision-making typically does not take place in a social vacuum. Social values influence each decision maker (Cheek & Burch, 1976) (Woodrow Mcintosh & Goeldner, 1986). A variety of methods can be used to estimate people's preferences based on utility (Araghi, Lee Park, & Bolling, 2014) (Bierlaire, 1997). These methods consider factors which can be explained but also factors which cannot be explained, such as the influence of social values.

In summary, it has been shown from the previous articles that visitors are not fully rational agents, and thus, their behaviour cannot always be explained. This means that the outcome of every valuation method chosen lacks certainty.

### 2.1.3 Method Selection

Having discussed on the sometimes-irrational decision-making process of visitors and thus the external factors which affect choices in the tourism context and, subsequently, the outcome of every non-market valuation method, the most suitable method for answering the sub-question is determined.

As mentioned in the introduction part of section 2.1, public goods, such as attractions, can be valued with the aid of non-market valuation methods (Ates, 2014).

The most important non-market valuation methods are as follows: travel cost, hedonic pricing, contingent valuation and choice experiments (Kjaer, 2005). These methods are listed in Figure 2.1 (level 3). The methods are classified as revealed preference (RP) methods or stated preference (SP) methods (level 2 of Figure 2.1) (Kjaer, 2005).

To determine which method is appropriate for answering the sub-question, knowing which category (RP or SP) is suitable first (level 2) is necessary.

As the name suggests, RP is a term used to refer to the observation of preferences. This method requires information about the past choices which individuals made (Kjaer, 2005).

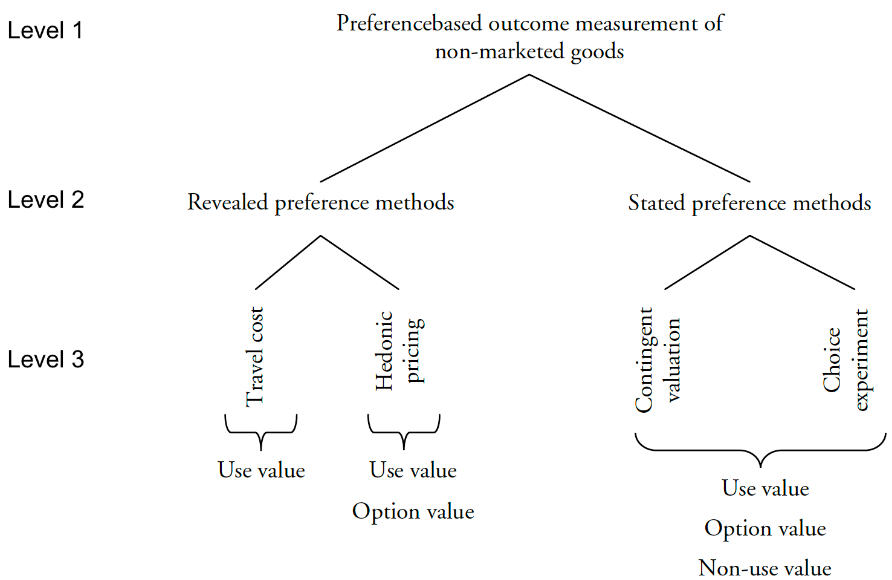


**Figure 2.1; Valuation Methods *(Kjaer, 2005)***

Meanwhile, on the contrary, SP valuation methods rely on the responses of individuals in hypothetical scenarios (questionnaires). The LiveLines feature has been barely used yet; therefore, no analysis of past behaviour can be made. Hence, a SP method needs to be used. The next section describes the synthesis and selection of the two SP methods: choice experiments and contingent valuation methods.

### 2.1.4 (Discrete) Choice Experiments

The purpose of this section is to examine the applicability of choice experiments to answer sub-question 1. Before an answer can be given, understanding the concept of choice experiments is necessary.

The term 'discrete choice' stems from the distinction between continuous and discrete variables to represent a set of alternatives (Bierlaire, 1997). The word 'discrete' means that choosing only one alternative is possible. In a discrete choice situation, a respondent faces a choice among a set of alternatives meeting the following criteria (Bierlaire, 1997):

- The number of alternatives is finite.
- The alternatives are mutually exclusive.
- All alternatives are included.

In a discrete choice experiment questionnaire, the respondent is asked to make multiple choices. Variation across the alternatives in the choice sets is achieved by assigning different levels of utility to these attributes among the distinct questions. An example of a choice experiment survey question is shown in Figure 2.2. Choice experiments are useful for determining the value of different attributes, which are part of an alternative.

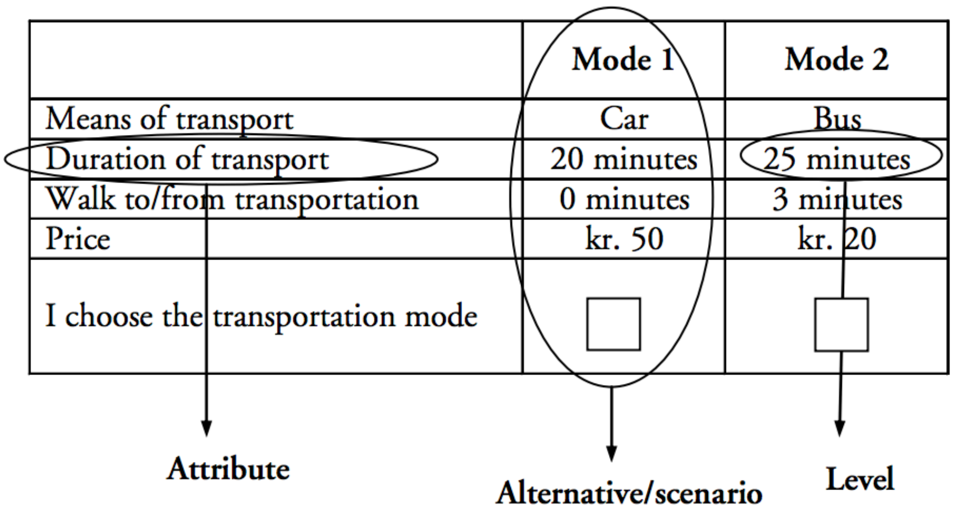


**Figure 2.2; Example of a Discrete Choice Experiment Question *(Kjaer, 2005)***

In tourism research, various studies have used choice experiments to understand decision-making of visitors (Ben-Akiva & Lerman, 1985) (Bierlaire, 1997) (Hearne & Salinas, 2000) (Huybers, 2003). Discrete choice experiments have value when the number of possible choices are limited. For example, in figure 2.2, the respondent can choose between two transport modes. Theoretically, more possible alternatives could have been added to the choice set such as traveling by bicycle, motorcycle or with a taxi. Nonetheless, the number of realistic alternatives remains limited. Therefore, a respondent can relatively easy select its preferred alternative.

If this project would only focus on the choice of attraction of visitors at the beginning of a day, a discrete choice experiments could have been used to investigate the influence of wait times on the preferences of visitors.

However, the system includes a time dimension. Besides, deciding to go to another attraction. A visitor can also decide to wait and go to an attraction at a later stage. The time a visitor could wait in a specific situation is continuous and therefore infinite alternatives exist. Consequently, no discrete choice set could have been constructed to take the time dimension into account.

### 2.1.5 Contingent Valuation Method

The second SP non-market valuation method is the Contingent Valuation methods (CVM). The CVM is used to measure the value of a good or service (Kjaer, 2005). This is done through asking people their 'maximum willingness to pay' (WTP).

In a Contingent Valuation survey a respondent is directly how much they would be willing to pay for a certain service or public good. Contingent Valuation has mainly been used to value the damage which environmental disasters have created. In these situations, the willingness of people cannot be assessed trough investigation of their purchases or their behaviour. The only option is to ask them questions.

The Contingent Valuation Method is based on two core assumptions. First, it assumes that the respondents have well-structured preferences. Second, it assumes that these respondents each have a rational purpose—that the choices they make are to maximise economic utility. In Contingent Valuation, the expression of a utility-maximising respondent is as follows:

$$U(Y, P, S, Q)$$

The utility function describes the maximum amount of utility respondents can derive from their income (Y). Given the price of a market good or service (P) and a non-market good (Q), it also considers other factors, such as demographics (S). In a CV study, the respondents are given a change in the provision of a non-market good or service from its present level: $Q^0$to greater level $Q^1$.

An increase in the provision of the non-market good or service leads to an increase in the amount of money with which a consumer will become indifferent about having that amount of money or the non-market good or service.

$$V(Y, P, Q^0, S) + \varepsilon_0 = V(Y - C, P, Q^1, S) + \varepsilon_1$$

In this formula, 'C' is the maximum monetary compensation an agent is willing to give up for the provision of the non-market good—its maximum WTP.

$$C(Q^0, Q^1, Y, P, S) = WTP < Y$$

In applying the CVM to the influence of waiting times on attraction choices, visitors will have a 'maximum willingness to wait' (MWW) instead of a maximum WTP. The MWW represents the maximum time visitors would wait for a specific attraction. If the waiting time exceeds their MWW, they are not going to that specific attraction and would simply select another alternative.

Meanwhile, the maximum WTP could be limited by available time. Namely, visitors could be less willing to wait long at attractions if they have less available time.

In summary, applying the previously mentioned ideas to the CVM, the MWW of an individual for a specific attraction is restricted by the individual's time left, demographic factors and unobserved factors.

This leads to the following formula:

$$U(LS, T, Q, S)$$

The utility can be derived from the available time an individual has and other demographic factors, such as length of stay, age, gender, etc.

In conclusion, an adjusted Contingent Valuation method is used to investigate how people's choices regarding attractions are influenced by waiting time information. This approach determines the 'maximum willingness to wait' of visitors. In this adjusted 'Contingent Valuation Method, surveys need to be conducted to gather data (Kjaer, 2005). The design of the survey and the analysis of the results are performed in Chapter 3.

## 2.3 Sub-Question 2 and 3:

- ***What could be the potential effects of LiveLines in its current form on the attraction wait times in Amsterdam?'***

- ***What are the potential effects of several additions to LiveLines on the attraction wait times in Amsterdam?'***

In pursuance of finding an appropriate research method to answer these sub-questions the problem which is investigated is classified first. This is discussed in the first part of this chapter (section 2.3.1). The second part includes the selection between various methods which could be used to explore these effects (sections 2.3.1.1 - 2.3.1.4)

### 2.3.1 Complex Adaptive Social Systems

The system which is studied could be classified as a complex adaptive social system (CASS). Before proceeding to examine the similarities between the system investigated for this project and CASS, understanding the concept of CASS is required.

A CASS is composed of interacting and thoughtful agents (Miller & Page, 2007). Their complexity results from the interaction of elements within a system and its environment. This behaviour emerges from nonlinear, spatial-temporal interactions (Chan, 2001). These interactions take place between the elements of the system themselves or between the elements and the environment (Chan, 2001). A CASS is a dynamic system that is able to adapt and evolve with a change in the environment (Chan, 2001).

Because of the different interpretations of CASS's, Chan (2001) developed a framework including four critical attributes. In the subsequent paragraphs, the existence of these attributes in the system of study is discussed.

The first attribute is; 'distributed control' (Chan, 2001). This means no central control mechanism exists which controls the behaviour of the system.
This phenomenon exists in the system of study. The behaviour of the visitors is not determined or controlled by a central actor.

The second attribute is; 'connectivity' (Chan, 2001). As mentioned in the beginning of this part, complexity of CASSs result from, amongst others, the relationship between the agents mutually. Therefore, the decisions of agents are influenced by the decision of other agents.
This attribute is included in the system of study. Namely, if many visitors decide to go to the same museum other visitors may decide not to go because they find the waiting time too long. In addition to that, visitors are not making their decisions in social vacuums. Their decisions are influenced by peers.

The third attribute is; 'sensitive to initial conditions' (Chan, 2001). This means that incremental changes in the initial conditions of variables have a non-linear effect on the outcomes (Chan, 2001). Small changes can have a significant effect on the outcomes.  It is unsure if the system is sensitive to initial conditions, this can be determined after having modelled the problem.

The fourth attribute is; 'emergent order' (Chan, 2001). Emergent behaviour can, for instance, be seen in the flocking behaviour of birds. Research using computer simulations has shown that the flocking behaviour of birds can be modelled using very simple behavioural rules such as, the fact that distance between the birds remains the same. There is no explicit rule to form a flock. However, every time the simulation runs a flock is formed. Therefore, flocking is emergent behaviour. Self-balancing or emergent behaviour like flocking of birds is the result of non-linear feedback between agents.
The tourism system of study, in its current form without LiveLines users, does not include emergent phenomena. No adaptive feedback mechanisms occur. However, when LiveLines would be adopted it is expected that visitors are spread. This can be viewed as emergent behaviour.

According the principles of Chan (2001), the tourism system with LiveLines users can be regarded as a CASS, since the four critical attributes of Chan (2001) are confirmed. This section has demonstrated that the system of study can be viewed as a CASS. What follows, in the next section (2.3.2), is a description of methods to analyse CASS such as the system of study.

#### *2.3.1.1 Simulation Methods*

As discussed above, the tourism system of study can be viewed as a CASS. Exploratory computer-based models can be insightful in studying CASSs (Holland, John, 2006) (Wilensky & Rand, 2015). This section discusses the potential of analysing the system of study with the aid of simulation methods.

Modelling is a method which is used to solve real-world problems. It is used when testing or experimenting in a real environment is either too expensive or simply impossible. Experimentation allows for optimisation prior to implementation (Holland, John, 2006). This can lead to the better performance of the system after it is implemented.

Two major streams exist in modelling: simulation and analytical models (Borschev & Fillopov, 2004). If a dynamic system needs to be investigated, such as a CASS, simulation modelling has often been shown to be more useful (Borschev & Fillopov A., 2004). In simulation modelling, the outputs can be analysed under a variety of inputs (Borschev & Fillopov, 2004). This is particularly important in these type of systems

First the three main simulation methods are discussed to provide a better idea of the commonly used simulation methods and which simulation method suited the research problem best. The following three approaches are most commonly used: system dynamics (SD), discrete event simulation (DES) and agent-based modelling (ABM) (Borschev & Fillopov, 2004). A description of these methods is given in the following sections.

#### *2.3.1.2 System Dynamics*
The first method is System Dynamics (SD). This is a simulation modelling method used to represent complex systems and to gain an understanding of their behaviour over time. It takes into account the complex and nonlinear relationships between the components of a system dynamically (Marshall, Burgos-Liz, Ijzermann, & Crown, 2015).

System dynamics has been used in various fields to understand systems better. It assumes that the behaviour of a system is a consequence of its internal structure rather than being based on external forces. The structure of a system is determined based on feedback loops. The accumulation rates of the feedback loop structure generate the behaviour of the system (Marshall et al., 2015).

From a more technical perspective, SD models include 1) Higher levels of aggregation than other dynamic simulation modelling methods 2) Quantities that change over time and 3) Feedback loops (balancing or reinforcing) (Marshall et al., 2015).

SD models predominantly analyse whole populations rather than individuals. It can be used in policy analysis of social, economic and ecological systems. Especially if these systems are characterized by mutual interaction and feedback structures (Marshall et al., 2015).

#### *2.3.1.3 Discrete Event Simulation*
A second major modelling approach is Discrete Event Simulation (DES). DES is used to analyse processes at an individual level. These individuals are subject to events. These events can be decisions or occurrences (Banks, Carson, Nelson, & Nicol, 1984). DES is mainly used to analyse queueing processes and to analyse the utilisation of resources. The main concepts in DES are events, entities, attributes, queues and resources. (Banks et al., 1984)

#### *2.3.1.4 Agent based Modelling*
The final major simulation method is agent-based modelling. In agent-based modelling a system is modelled consisting of autonomous decision-making agents (Marshall et al., 2015) . Each agent makes decisions based on a set of rules.

The unique characteristics of ABM is its ability to capture emergent phenomena. For instance, congestion, which results from the interaction between individual drivers, is moving in the direction opposite of the cars initially causing a traffic jam (Bonabeu, 2002). Emergent phenomena such as these maybe counter intuitive and hard to predict. Agent-based modelling  is used to predict and understand these phenomena using a 'bottom-up' approach (Bonabeu, 2002).

By contrast, System Dynamics or Discrete Event Simulation models, are using a more 'top-down' approach to map a system or process (Marshall et al., 2015). Agent-based modelling starts with individuals which are described by local rules and their local behaviour. These individuals are called agents (Marshall et al., 2015). Agents interact with each other and live in the same environment and act based on simple behavioural rules. Agents can also hold specific goals and may learn based on past experiences (Wilensky & Rand, 2015). Agent-based modeling has been applied in various scenarios such as movement patterns, urban design and resource management (Marshall et al., 2015).

## 2.4 Selecting the Simulation Model

Having defined the different simulation methods, this section includes a discussion on the method selection on how to analyse the problem in this report. The simulation method selected is agent-based modelling. To understand the selection of this method, the disadvantages of the other methods are discussed first. Subsequently, the advantages of ABM as a method for answering sub-question 2 and 3 are listed.

The first method, SD, would have been less useful for analysing the problem of this thesis due to its inability to handle the heterogeneity of the visitors and the temporal interactions between the visitors. For instance, SD is unable to represent ‘a visitor walking through a city’.

The second method, DES, could technically be used to analyse the problem. The lack of experience with this paradigm prefers the selection of another paradigm. Besides, DES is less flexible in including interactions between agents.

Agent-based modelling (ABM) seems to be the most suitable method in this report for several reasons. First, its use is in line with the findings of several authors who reported that ABM is suitable for analysing CASSs (Hollands, 2008) (Miller & Page, 2007).

Second, ABM can be combined with the geographic information system (GIS) (Chao, Furuta, & Kanno, 2011) (Brown, Riolo, Robinson, North, & Rand, 2003). In this manner, the locations of and distances between the attractions within Amsterdam can be included into the simulation model.

Third, ABM allows for interaction between agents and changing attitudes for behaviours. Even though, this may not be included in the simulation model of study. This allows for flexibility if the model is extended during future research.

Additionally, a scientific need exists for using ABM in a tourism system. In 2016, Johnson et al. published an article about the potential of ABM in tourism research. The article reported on the lack of the integration of ABM in tourism research, even though the characteristics of the tourism system fit the ABM paradigm—the complexity of actors and interconnectedness. In addition, the article provided strategies for increasing the adoption of ABM in tourism research. Using the agent-based method could help with creating awareness of ABM in tourism research.

# 3. Behaviour of Visitors

In this chapter, follows selected approach determined in chapter 2.1. The purpose of this chapter to identify factors which influence the MWW of visitors. The chapter is structured as follows. First, a literature review about the factors influencing the MWW is performed. Consequently, these results are used in the design of a questionnaire. Third, the results of the data analysis are given. Finally, the results are analysed.

## 3.1 Literature Review

The goal of this chapter is to ascertain the effect of waiting times on the attraction choices of visitors. In the academic literature, this field of study is often referred to as 'multi-destination trips' (Glauber, 2012). In the scientific literature, no attempts have been made to analyse the factors which influence the MWW of visitors of attractions or any similar context. More specifically, searching for 'maximum willingness to wait' at *Scopus* showed only articles concerning healthcare.

Some authors have reported on other factors which influence 'multi-destination trip' behaviour (Kozak & Kozak, 2016) (Glauber, 2012). Opperman (1995) found in an empirical analysis that younger tourists visit more destinations during a single trip. Whereas no difference between genders is found (Opperman, 1995).

In addition, two authors published about the influence of one's travel purpose on the visiting of destination choices within destinations (Tideswell & Faulkner, 1993) (Opperman, 1995). Albeit, the they did not quantify these relationships.

Due to the lack of available literature about the factors influencing multi-destination trips, it could be more insightful to zoom out and focus on a wider context and to look at factors which influence the selection of trip destinations. To provide an overview of past research on these factors, the book *Tourist Behaviour: An International Perspective*, published in 2016, is used as a starting point for selecting articles about the influencing factors of the behaviour of visitors (Kozak & Kozak, 2016). This book was selected due to its recent publication date and its review section about the influencing factors regarding travel behaviour.

Several authors have mentioned that demographic factors, such as age, gender, profession, income and group size, influence travel behaviour (Glauber, 2012) (McKercher & Lew, 2008). A higher number of attractions visited is associated with older male tourists with higher levels of education. Income and time budgets have positive but decreasing marginal effects on the number of attractions visited (Glauber, 2012).

In addition, Mckercher (2008) showed that distance from the home country is a discriminating factor in the determination of these demographic factors. In the study, the travel patterns within Hong Kong of visitors originating from five home-country clusters were compared. These clusters were composed of countries which were at similar distances from Hong Kong. The results showed differences in travel patterns between these cohorts. Meanwhile, no significant differences within each of the cohorts were shown. He concluded that travel patterns can be related to demographic factors and countries of origin. Visitors who live in close-by countries are, for instance, more likely to be women and traveling in groups. He also mentioned the importance of prior visitation and the length of stay on the behaviour of visitors. Huybers (2003) furthermore found that distance from the home country influences one's choice of destination and thus one's travel behaviour (Huybers, 2003).

So far, this section has focussed on demographic, measurable factors influencing travel behaviour. The following section focusses on a variety of more intangible aspects influencing travel behaviour.

Fennel (1996) found that informed tourists or specially interested tourists spend more time at attractions. Online information affects younger visitors more than it does older visitors (D, 2009) (Xiang & Gretzel, 2010).

Plog (2002) published a different approach to explaining travel behaviour in 2002. In 2002, Plog introduced the concept of 'venturesomeness' to predict the travel behaviour of visitors. According to his article, 'verturesomemeness' is the main determinant of the types of activities visitors seek (Plog, 2002). Venturers namely visit more attractions which are less similar to the attractions present in their home countries (Plog, 2002).

In summary, based on relevant research articles, one's age, the purpose of one's trip and the distance from one's home country all influence travel behaviour. The findings of this review could suggest that these factors also influence the MWW. These findings were used to design the survey in the next part of the chapter.

## 3.2 Survey Design

The previous section has analysed literature about the factors which could potentially influence the MWW of visitors. The following parts of this chapter focusses on determination of the quantitative influence of various factors on the MWW of visitors. To gain insight in the factors, influencing the MWW, a questionnaire was constructed.

Based on the results of the literature review, the following questions containing demographic information were included. The purpose of these questions was twofold. First, it identified relationships with the dependent variable—MWW. Second, it was used to test the representativeness of the sample—representativeness tests to which extent the sample, the respondents, corresponds with the population.

- What is your age?
- What is your gender?
- What is your country of origin? (to determine distance from home country)
- What is your group size?
- How many times have you been before to Amsterdam?
- What is the length of the current trip?
- Which attractions have you visited during this trip in Amsterdam?

The MWW was determined in the second part of the questionnaire. It was expected that visitors are willing to wait longer for attractions that are preferable. Hence, the respondents were asked to rank the attractions which took part in the LiveLines trial first. These attractions are;

- Rijksmuseum
- Van Gogh museum
- Rembrandt House Museum
- Eye Film museum
- Cobra museum
- Trope museum
- Frans Hals museum
- Heineken Experience
- National Maritime Museum

The respondents were asked to give the maximum time they would be willing to wait for their first, third and finally, their fifth attraction of preference.

In addition to that, the respondents were asked if they had used LiveLines before, how this affected their travel behaviour and how likely they are to use it in the future.

## 3.3 Data gathering

Initially, travel time was expected to influence visitors' MWW. However, during the trial survey, where 10 respondents were asked to answer the questions, it became that travel time didn't influence their MWW. Namely, all the trial respondents gave the same answers under different travel times. Therefore, travel time considerations were excluded from the final format.

The final survey format included 17 questions. To improve the reliability of the results the questions were asked in-person instead of letting the respondents filling in the survey themselves. The average completion time was around 5 minutes. On the 24, 25 and 26$^{th}$ of May 2017, interviews with visitors in 'het Begijnhof' in Amsterdam were held, a total of 100 respondents were gathered.

## 3.4 Analysis

This section provides an overview of the results of the questionnaire and several statistical steps. This section starts with descriptive statistics of the sample. Consequently, the representativeness of the sample is tested by comparing it to the population statistics. Third, the distribution of values of the 'MWW' is tested. Fourth, the relationships between several factors and the MWW are tested. Finally, conclusions are drawn.

### 3.4.1 Descriptive Statistics

In figure 3.1, the age composition of the sample is shown. Whereas, figure 3.2 shows that 45% of the respondents were males and 55% females.

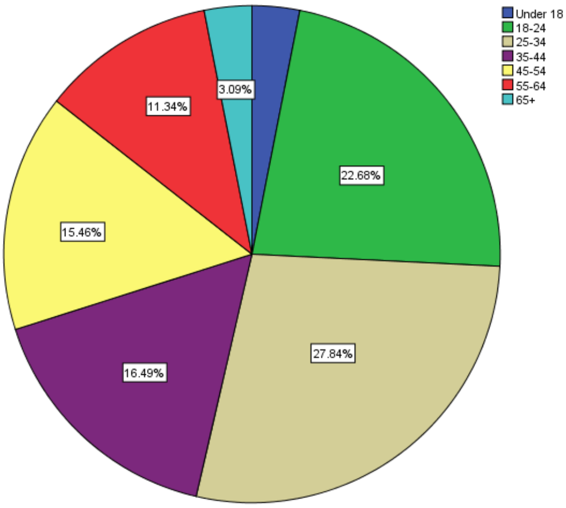


**Figure 3.1; Age Composition of Sample**

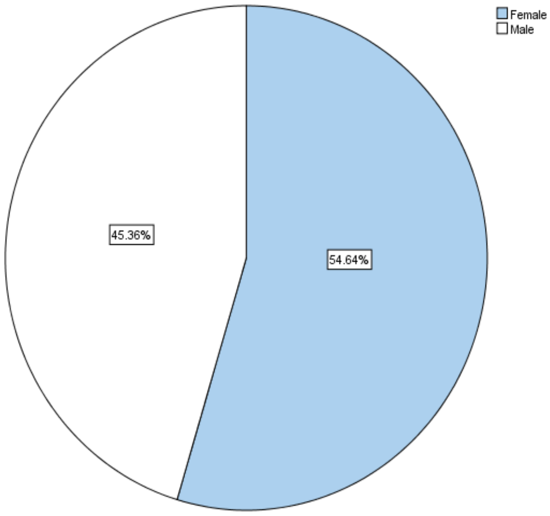


**Figure 3.2; Gender Composition of Sample**

#### 3.4.1.1 Representativeness

The representativeness of the sample is tested by comparing the 'length of stay' and the age distribution of the sample with population data about visitors of Amsterdam. The population data was retrieved from a report published in 2016: *Amsterdam Metropolitan Area: Visitors survey 2016*.

The sample has shown representative for both the 'length of stay' and age distribution. The graphical output of the tests performed in SPSS are provided in Appendix A.2.1 and A.2.2.

#### 3.4.1.2 Maximum Willingness to Wait

On average people are willing to wait 38 minutes for their first choice of attraction. 27 minutes for their third preferred attraction and 19 minutes for their 5$^{th}$ preferred attraction. An overview of these statistics is listed in table 3.1.

| | N | Minimum | Maximum | Mean | Std. Deviation |
|---|---|---|---|---|---|
| First Preference | 97 | 0 | 120 | 38 | 25 |
| Third Preference | 94 | 0 | 90 | 27 | 15 |
| Fifth Preference | 93 | 0 | 60 | 19 | 12 |

**Table 3.1; Descriptive statistics of MWW, (rounded to whole numbers)**

### 3.4.2 Distribution testing of MWW

The 'Maximum Willingness to Wait; serves a role to formalise the behaviour of the visitors in the final simulation model. Therefore, an appropriate probability distribution must be selected to model the uncertainty of the MWW. No distribution had a significant fit with the data. The Poisson distribution was assumed because the MWW is discrete. In figure 3.3, the histogram of the results of the MWW are shown.

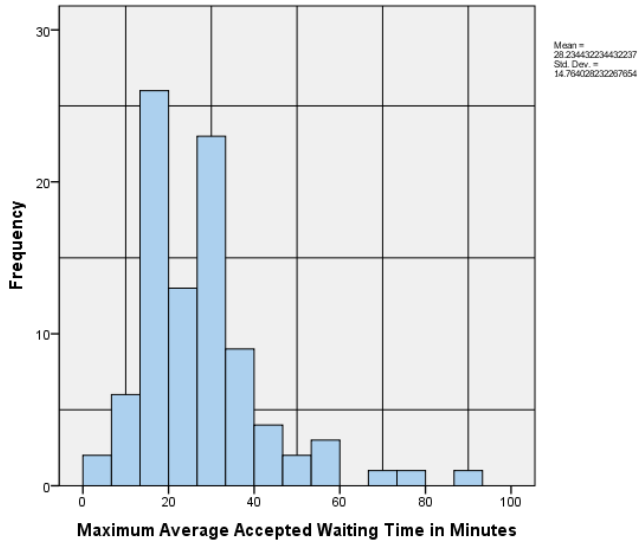


**Figure 3.3; Histogram of all the MWW values together**

### 3.4.3 Bivariate Analysis

Having determined that the sample is representative, the relations between the MWW (dependent variable), and the independent variables, which were recorded with the questionnaire, were tested.

Pearson's correlation

| Independent variable | Pearson Correlation | Sig (2-tailed) | Significant relation (yes/no) |
|---|---|---|---|
| Length of stay | 0.172 | 0.105 | No |
| Age | 0.07 | .950 | No |
| Gender | -0.029 | .789 | No |
| Number of attractions visited | -0.136 | .421 | No |
| Distance home country | -1.46 | 0.155 | No |

**Table 3.2; Pearson correlation test table**

No significant relationship was found between one of the factors and MWW. The SPSS outputs of the bivariate tests are shown in Appendix A.3.

## 3.5 Conclusion

The objective of this chapter was to 'quantify' the behaviour of visitors. These data will determine the behaviour of the visitors in the final simulation model. The initial goal was that the agents in the simulation model had different characteristics such as age, gender and length of stay. Consequently, these characteristics would determine their 'maximum willingness to wait'.

When two or more variables are shown to have a relation with the dependent variable, a regression analysis could have been performed. A regression model serves two functions. First, it explains the factors which influence the dependent variable the most. Furthermore, it can predict the value of the dependent variable based on the values of the independent variables. The lack of correlating variables makes a multiple regression analysis inapplicable. Therefore, no distinction will be made between the 'maximum willingness to wait' for different groups. Consequently, every agent will be given a 'maximum willingness to wait'. The results of the questionnaire are provided in table 3.3

| | 1st choice | 2nd choice | 3rd choice | 4th choice | 5th choice |
|---|---|---|---|---|---|
| Max accepted waiting time | 38 | 33 | 27 | 23 | 19 |

**Table 3.3; Average accepted waiting time for every choice (minutes and rounded to whole numbers)**

# 4. Modelling Problem and System Identification

## 4.1 Structure

As defined in Chapter 2.1, the agent-based modelling paradigm is selected to answer sub-question 2:

- ***'What could be the potential effects of LiveLines in its current form on the attraction wait times in Amsterdam?'***

In addition to that sub-question 3 will be answered with the aid of agent-based modelling:

- ***'What are the potential effects of several additions to LiveLines on the attraction wait times in Amsterdam?***

The approach of Van Dam and Nikolic (2013) described in the book *Agent-Based Modelling of Socio-Technical Systems* is pursued. The process of developing the agent-based model according the principles of Van Dam (2013) is subdivided in four chapters:

- Chapter 4, *Modelling Problem and System Identification*
  Translation of the real-world dynamics into a conceptual model.

- Chapter 5, *Formalisation:*
  Transformation of the model in computer understandable language.

- Chapter 6, *Experimentation on Model Exploration:*
  Investigation of the model in various scenarios. (sub-question 2)

- Chapter 7, *Experimentation on Interventions*:
  Investigation of the model with additions. (sub-question 3)

## 4.2 Problem Formulation and Actor Identification

The first step according to Van Dam et al. (2012) is: Problem Formulation and Actor Identification. Modelling is used when there is a lack of insight in a real-world system, its behaviour or its response to interventions (van Dam, Nikolic, & Lukszo, 2012). Models serve as a tool to improve the dynamics of a system, to explore future scenarios or to find states which should be avoidable. Well-formulated problems generally give better insights. Hence, the first step in building an agent-based model is to formulate the problem the model is trying to solve (van Dam et al., 2012).

According Van Dam (2012) this leads to a series of questions which need to be addressed. These questions define the modelling question, the problem owner, the actors involved and the outcomes of interest. Answers on these questions have been discussed during the 'problem definition' of this thesis. A summary of these answers on these questions are shown below.

**What is the problem? What is the lack of insight which is addressed?**
Currently, there are barely any LiveLines users. The goal of the agent-based model is to get insight into the effect of adoption of the feature on the wait times of attractions.

**Whose Problem is addressed?**
The problem owner is Amsterdam Marketing. This study should lead to a better insight into the system. Insight into the system and future scenarios could give handles to successfully develop the feature.

**What are the outcomes of interest?**
With this study, it is tried to get a better understanding under what conditions the LiveLines feature can operate successfully. Although, successful operation can be measured in a variety of ways, this agent-based model should focus on the waiting time development of the attractions over the day, under different levels of adoption of the LiveLines feature.

**Other actors involved**
The actors which will be included in the modelling effort are: visitors and attractions.

**What is our role?**
With the aid of agent-based simulation, knowledge will be provided to fill the given knowledge gap. In this sense, modelling is a tool that helps to structure the thoughts regarding this problem and to compute results of simple but many interactions (Wilensky & Rand, 2015)

## 4.3 System Identification and Decomposition

Identifying and structuring of the system boundaries is the second step of model construction according Van Dam et al. (2012). Having identified the problem owner and the relevant actors the system identification and decomposition steps requires the modeller to become 'social' to acquire the required information (van Dam et al., 2012). This information can be obtained in various ways—interviews or surveys with relevant actors, a literature review or a combination of these. This information is used to gain insight into the behaviour of the actors involved in the system. The decomposition process starts with an inventory phase, followed by a structuring phase. (van Dam et al., 2012)

**Inventory: System overview**
The first step of decomposing a system includes identifying the physical and the social entities of the system and their relationships (van Dam et al., 2012). This step is the result of consultation with the relevant actors. Information was gathered about the two main actors of the system—visitors and the attractions. Subsequently, the environment in which these actors interact were identified.

*Visitors*
In the problem formulation and actor identification section, the visitors were identified as main agents of the system. Simplification of the behaviour of the visitors was established in chapter 3. The behaviour of the visitors is determined by their MWW, their preferences and the 'type of visitor'

The first characteristic, the MWW, determines the length of the waiting time of an attraction a visitor is willing to wait. The MWW differs per visitor. The averages of the MWW were analysed in chapter 3 and is listed in table 4.1.


**Figure 4.2; Modelling Characteristics of the Visitors**

| | 1st choice | 2nd choice | 3rd choice | 4th choice | 5th choice |
|---|---|---|---|---|---|
| Average max. accepted waiting time (minutes) | 38 | 33 | 27 | 23 | 19 |

**Table 4.1; Maximum willingness to wait – average of sample**

In chapter 3, several distributions were tested on the MWW. None, of these distributions showed to be statistically significant. Nonetheless, a distribution must be chosen in the final simulation model. Netlogo, the simulation software which will be used, includes the following distributions; Uniform, Exponential, Gamma, Normal and Poisson. Because, the wait times in LiveLines are discrete (whole numbers), a Poisson distribution to represent the MWW is chosen.

In addition to that, some other simplifications were made. The second determinant of behaviour, the preferences of visitors includes attractions. A visitor prefers to go to its most preferred attractions. However, in some situations a visitor is going to a less preferred attraction.

Finally, the type of visitor is an important aspect of the behaviour of the visitors. These types of visitors were distinguished in consultation with the founders of LiveLines, Marek Krusel and Nico Mulder, and the evaluation report of the experiment of LiveLines.

The first type are *visitors who not using LiveLines*, their behaviour is not influenced by waiting times.

The second type and third type includes both *visitors using LiveLines*. The difference between the second and third type is that visitors of the second type are willing to wait in the city if the waiting time is not acceptable for them. On the contrary, the third type of visitors will consider other attractions. A systematic description of the behaviour of the different types of visitors is listed chapter 6.

*Attractions*

The second type of agents identified in the problem formulation and actor identification section were the attractions. An interview with the co-founder of the LiveLines feature, Marek Krusel, gave insight into the behaviour and interests of these attractions (in fact the employees).

The attractions update the waiting times in the LiveLines feature. The employees of the attractions make an estimate based on the length of the queue they observe. As part of the trial they were told to update the waiting time at least every half an hour.

Unfortunately, the input data of the feature showed that often the update frequency was significantly lower. Marek Krusel could not describe any underlying factors determining the moment/frequency of time of updating. Hence, no assumptions can be made that determine the moment of updating the waiting times. The characteristics of the attractions are shown in figure 4.3.


**Figure 4.3; Modelling characteristics of Attractions**

*Environment*

The environment of the agent-based model includes an abstract representation of the main roads between the attractions. In addition to that, the waiting times displayed on LiveLines are accessible for all the agents and are therefore part of the environment. An overview of the modelling environment is provided in figure 4.4.


**Figure 4.4; Characteristics of The Modelling Environment**

*Interactions*

The dynamics of an agent-based model is determined by the interactions between its different components (van Dam et al., 2012). In this section the interaction between the visitors, the attractions and the environment is described with the help of figure 4.5

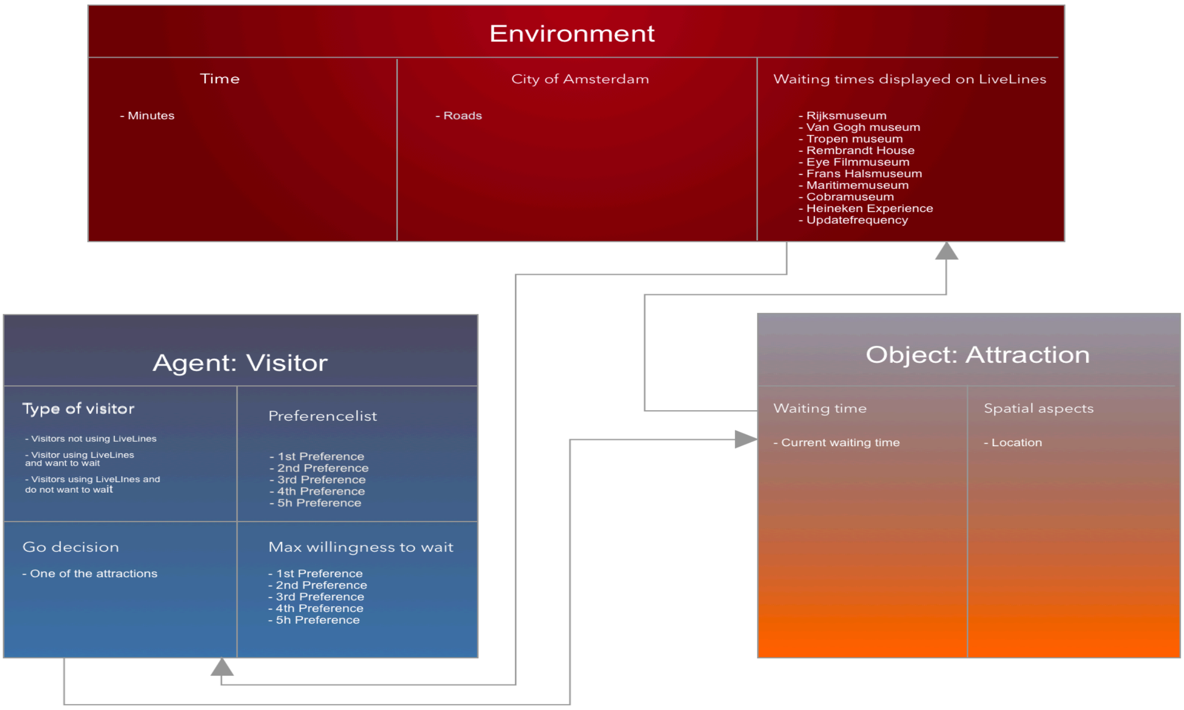


**Figure 4.5; Relationship Diagram Between the Components of the Model**

The decision of attraction choice depends on the waiting times displayed in the LiveLines feature (link between 'Environment' and 'Godecision' of 'Agent: Visitor') and the characteristics of the agent.

This decision influences the waiting time at a specific attraction (link between Go decision and Waiting time of 'Object: Attraction'.

Finally, the waiting time of the attractions determines indirectly the waiting times displayed on the LiveLines feature (Link between waiting time of Object: Attraction and Waiting times displayed on LiveLines of the Environment). The waiting times displayed in LiveLines are namely also based on the moment of updating.

Having, established the and interactions and behaviours of the system's components. It is now time to transform this into computer-understandable language.

# 5. Formalisation

This chapter follows on from the previous chapter, 'System Identification and Decomposition', which outlined the main components of the system—visitors, attractions and the environment. Besides, their characteristics and interactions were established. This chapter executes the next step in the modelling process of van Dam et al. (2012) – 'Concept Formalisation'. During this step, the agents of the system, as well as their behaviours and states are formalised into agent-based ontology. The system as defined into the problem formulation and decomposition step should be transformed into language which is understandable for computers (van Dam et al., 2012). During the phase of concept formalisation, the modeller is forced to explicitly define all the aspects of the model, resulting in a simulation model (van Dam et al., 2012). In this chapter, the model narrative is discussed first. Subsequently, the used modelling assumptions are given.

**Model narrative**

This section focusses on the interactions as defined in section 4.3. This section explains which agent does something at what time and how this affects the system. One agent type actively makes decisions in the model; the visitors. The time step of the model is 2 minutes. The period of interest is one day (9:00 – 18:00).

Furthermore, there are three classifications of behaviour: 'Visitors not using LiveLines', 'Visitors using LiveLines and want to wait for their preferred attraction' and 'Visitors using LiveLines and do not want to wait for their attraction of preference'.

**Visitors not using LiveLines**

1. The agent enters the system.
2. The agent walks directly to its most preferred attraction.
3. The agent gets removed from the system.

**Visitors using the LiveLines feature and want to wait**

1. The agent enters the system.
2. The agent checks if the wait time of its most preferred attraction is lower than its MWW.
3. If the waiting time is 'unacceptable', the agent will walk around until the waiting time becomes 'acceptable'.
4. The agents go to the attraction, if the waiting time is acceptable.
5. The agent removes itself from the system.

**Visitors using LiveLines and do not want to wait**

1. The agent enters the system.
2. The agent checks if the wait time of its most preferred attraction is lower than its MWW.
3. If the waiting time is 'unacceptable', the agent goes to a less preferred attraction with an 'acceptable' waiting time.
4. The agent removes itself from the system.

An action diagram of the visitors is shown in Appendix B.1. In this diagram the executed modelling steps of every tick are shown.

**Objects**

Besides the visitors, the system overview in figure 4.5 which showed several other components of the system; the 9 attractions which took part in the LiveLines experiment. These components are considered as intangible agents – they do not make decisions based on the state of the system. Therefore, they are identified as objects. Each of the museums operates in the same manner— They update their waiting times simultaneously. They process the visitors which arrive at the attractions and they hold a queue. The waiting time at the queue is based on the number of visitors present in the queue.

**Assumptions**

An overview of the most important other assumptions is provided in table 5.1. The assumptions are categorised by either agent, attraction or environment related assumptions.

| *AGENTS* | | |
|---|---|---|
| | 1 | A visitor 'dies' after having visited an attraction and gets replaced by a visitor with new parameter values. |
| | 2 | 1 agent represents 40 visitors. The underlying calculation is found in Appendix B.2.1. |
| | 3 | Visitors spawn at a randomly assigned vertex. |
| | 4 | The visitors walk with the same speed. |
| | 5 | The waiting times of the attractions are updated every 20 minutes. |
| | 6 | Visitors have 5 preferred attractions. |
| | 7 | Visitors have a 'maximum willingness to wait' (MWW). |
| *Attractions* | 8 | All the waiting times are updated simultaneously. |
| | 9 | All the attractions have the same opening and closing times (9:00 – 18:00). |
| *Environment* | 10 | All the waiting times are updated simultaneously. |

**Table 5.1; Modelling Assumptions**

## 5.1 Model Verification

Model verification needs to be performed to check whether the conceptual model is successfully translated into the programme. Verification consists of different types of steps. The steps are executed following the principles of Van Dam et al (2012).

The following steps have been executed:

- ✓ **Recording and tracking agent behaviour**

To verify the model the relevant output variables are selected and monitored. The variables were selected in a way to gain insight into the behaviour of the agent. Numerous times the following process was repeated. An overview of these steps is provided in figure 5.1.

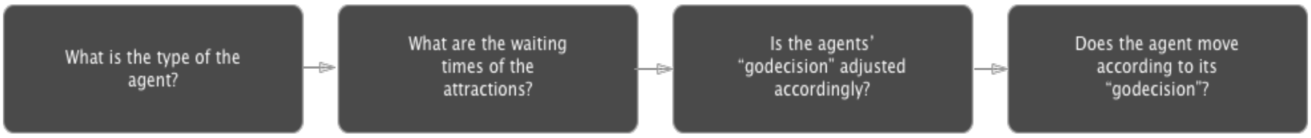


**Figure 5.1; Steps in Recording and tracking agent behaviour**

- ✓ **Minimal model testing**

In this step the model functionalities are tested with 1 agent. In this manner, it is easy to observe if the agents move to the right attraction and get replaced by a random agent. Also, the decision parameters of the agents such as the waiting times were artificially set high. Consequently, part of minimal model testing was to check that a LiveLines using agent is not visiting any attraction.

## 5.2 Model Functionality

Having formalised the agent-based model into Netlogo. This section explains how the formalised model can be used to run simulations. Section 5.2.1 describes the in- and outputs of the user interface. Section 5.2.2 describes the model world.

### 5.2.1 User interface

The setup part includes the following components;

- Buttons to start and stop the simulation.
- Sliders to adjust parameters of the model.

Besides, the user interface includes the *with_prediction*? switch and *adding_visitors switch?*.

- If the with_prediction? switch is turned on, LiveLines displays predicted waiting times.
- If the adding_visitors? Switch is turned on, additional visitors are added to the system after 12:30.

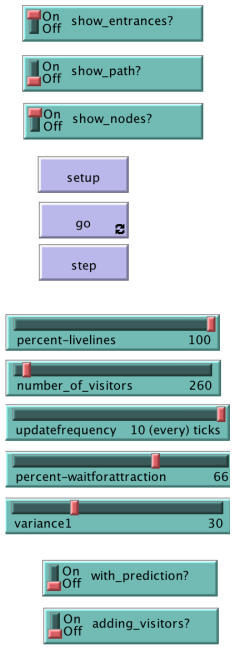


**Figure 5.2; Netlogo User Interface of the Model**

### 5.2.2 The model world

The model world visualises the current state of the model. It contains animations which are updated every tick. The model world is mainly useful to understand the underlying processes and for verifying and validating the model. The starting location of the visitors is random (on one of the vertices). Their colour indicates if they are using the LiveLines feature;

- The red colour resembles visitors which do not use LiveLines
- The green colour resembles visitors which use LiveLines

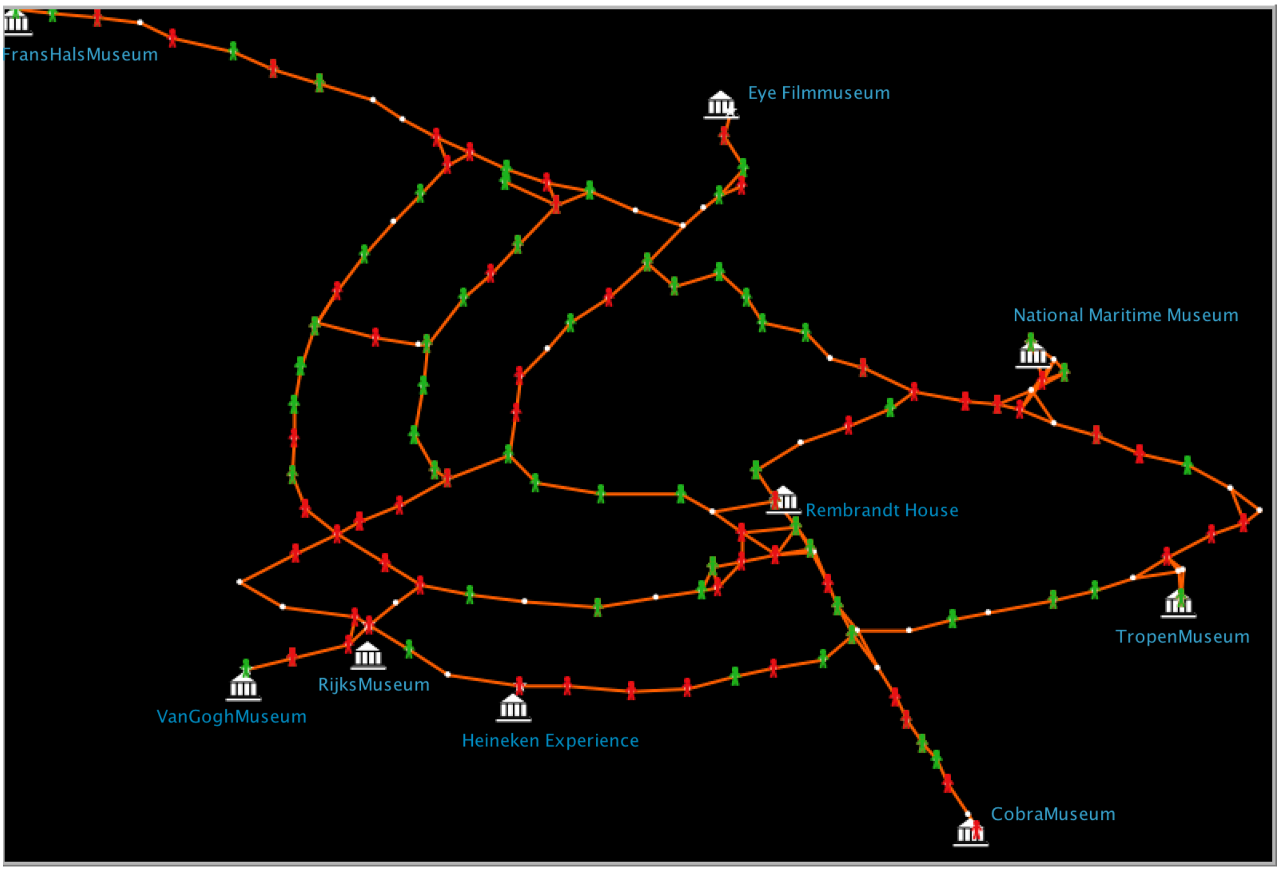


**Figure 5.3; Model World in Netlogo**

### Output

An illustration of the output windows of the simulation is shown in figure 5.4. Graphs of the waiting times of the different attractions are listed in that figure. In figure 5.4, the monitors and graphs are shown for demonstration purposes. The horizontal x-axis are the ticks of the simulation. Recall, that one tick corresponds with 2 minutes. On the y-axis, the waiting time in minutes is given.

The monitors above the graphs give information about the waiting time at this specific tick.

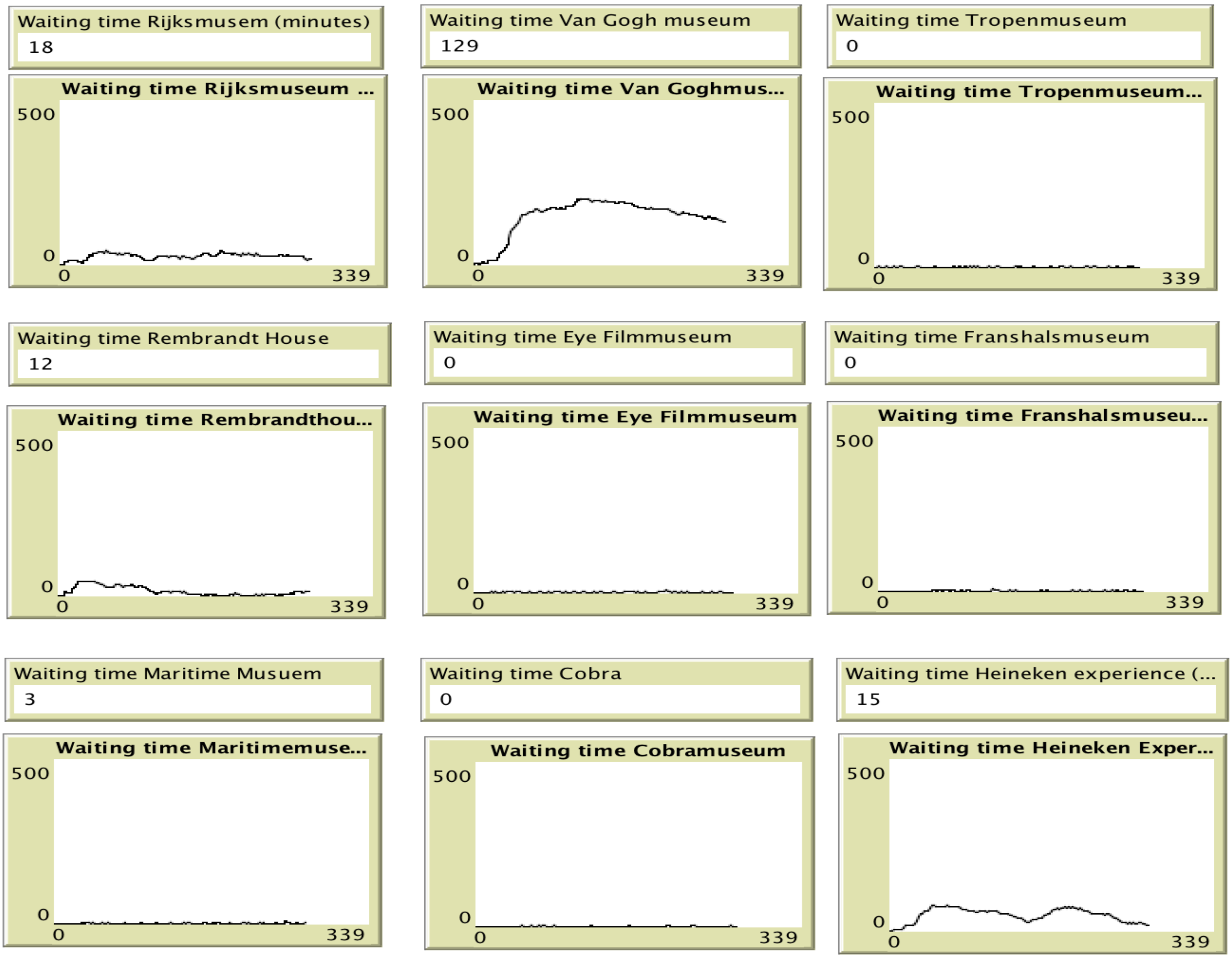


**Figure 5.4; Illustration of Output Windows in the Netlogo Interface**

Having formalised the conceptual model in Netlogo, it is now time to explore the behaviour of the model under different circumstances in the following chapter.

# 6. Experiments on Model Exploration

At this point, the model is a computer tool which transforms the input into the predefined key performance indicators (KPIs). To explore all the dynamics the model can generate, the model should be investigated in different settings. The KPIs of the system are the waiting times of the attractions over the course of the day. This chapter starts with the experiment choices. This section is followed by the behavioural results of the system.

The following sub-question (2) is answered in this chapter:

'***What could be the potential effects of LiveLines in its current form on the attraction wait times in Amsterdam?***'

This chapter starts with a reasoning behind the executed experiments (section 6.1). Subsequently, the results of the experiments are discussed distinctively (section 6.2 - 6.4). Lastly, sub-conclusions are given (section 6.5).

## 6.1 Approach

To identify the range of potential effects LiveLines can have in its current form, displaying the current wait times, several experiments were executed. In Table 6.1, the experiments are shown.

To identify the basic behaviour of the developed simulation model Experiment 1 and 2 were executed. Experiment 1 provides the reference scenario of the simulation model. Whereas, Experiment 2 identifies the effects of LiveLines on the waiting times of attractions.

The last two experiments of this chapter evaluate the sensitivity of the model. In experiment 3, the sensitivity of the model to a sudden increase in visitors was evaluated. Meanwhile, Experiment 4 evaluates the sensitivity of the 'maximum willingness to wait'. The purpose of this experiment is to evaluate if another distribution of the MWW affects the model behaviour. The distribution of the MWW, gathered with the questionnaire, does namely not have a significant fit with the assumed Poisson distribution. For example, if another distribution leads to significantly different simulation results, increased uncertainty in simulation model exists.

| Experiment type | Experiment number | Name | Runs | KPI's |
|---|---|---|---|---|
| Reference scenario | 1 | Reference scenario | 100 | Waiting times museum 1,2 and 3 |
| | 2 | Adoption of LiveLines | 100 | Waiting times museum 1,2 and 3 |
| Uncertainty | 3 | Effect of increase in visitors with LiveLines | 15 | Waiting times museum 1,2 and 3 |
| | 4 | Effect of different MWW with LiveLines | 100 | Waiting times museum 1,2 and 3 |

**Table 6.1; Overview of the experiments**

## 6.2 Experiment 1: The Reference Scenario

As explained in section 6.1, the first experiment comprises the reference scenario. The purpose behind the reference scenario is to be able to judge the efficacy of the interventions, and should closely reflect the real-world system behaviour. The setup conditions of the reference scenario are set to mimic the wait times of the attractions of Amsterdam. These wait times are based on the dataset provided by Amsterdam Marketing, and contains the input data of the LiveLines trial.

LiveLines only indirectly influences the wait times of attractions with short waiting times. The wait times are influenced indirectly because the wait times are affected by visitors who are going to less preferred attractions, attractions with generally shorter waiting times, if the waiting time of their preferred attractions is too long. Therefore, the wait times of the following attractions, with waiting times generally under 5 minutes, are not the key performance indicators of the system:

- Rembrandt House
- Eye Film Museum
- Frans Hals Museum
- National Maritime Museum
- Cobra Museum
- Tropen Museum

The average wait times of the three other attractions, the Van Gogh museum, Rijksmuseum and the Heineken Experience, were used to generate comparable attractions in terms of waiting times over the course of the day.

The first day of Easter, the 16th of April, was selected as the reference day because of two reasons. First, the attractions updated their waiting times frequently on the 16th of April. Secondly, the impact of the LiveLines feature on busy days such as these are of interest. The wait times of the Van Gogh museum (figure 6.1), The Rijksmuseum (figure 6.2) and the Heineken Experience (figure 6.3) on the 16th or 15th of April are shown below.

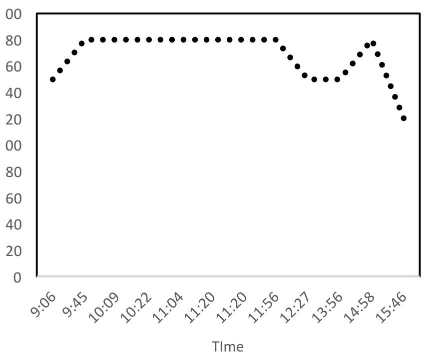


**Figure 6.1; Wait Times Van Gogh on 16th April**

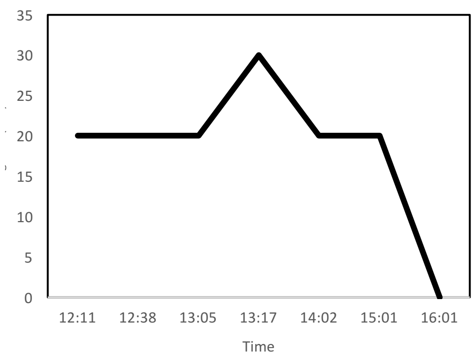


**Figure 6.2; Wait Times Rijksmuseum 16th of April**

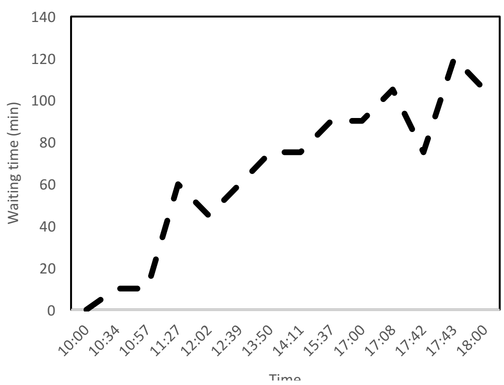


**Figure 6.3; Waiting Times Heineken Experience 15th of April**

The model parameters were set to mimic the behaviour of the waiting times of the attractions on the 15th and 16th of April. The values of the general setup variables are provided in table 6.2.

| Model Setup | |
|---|---|
| Initial Number of Agents | 260 |
| Percentage using LiveLines | 0 |
| Update frequency | 10 ticks (every) |
| Runs | 100 |

**Table 6.2; Model Setup of the Reference Scenario (Experiment 1)**

### 6.2.1 Results

In this section the simulation results of the average of 100 simulation runs are provided. The behaviour of the waiting times of the three attractions are shown in figure 6.4.

The real system wait times were compared with the outcomes of the simulation runs. The waiting times of the Heineken experience continually increase according the dataset of Amsterdam Marking. Whereas, in the same dataset the wait times decrease to 0 minutes at the Rijksmuseum. The simulation model does not exactly reflect the behaviour of the real system. Therefore, from now on, the names of the attractions in the scenarios shall be unlabelled.

The advantage of this is that the effect of policies can be easier identified, since the wait times develop more constantly over the course of the day. The disadvantage is its difficultness to make statements about the quantitative effects of LiveLines.

. The following indicators assess the performance of the unlabelled system:

- *Waiting time Attraction 1:* The waiting time of an attractions where sometimes the waiting time exceeds the MWW and sometimes not.

- *Waiting time Attraction 2:* The waiting time of a busy attraction, where the waiting time does exceed the MWW with a large difference.

- *Waiting time Attraction 3:* The waiting time of an attraction where the waiting time exceeds the MWW with a small difference.

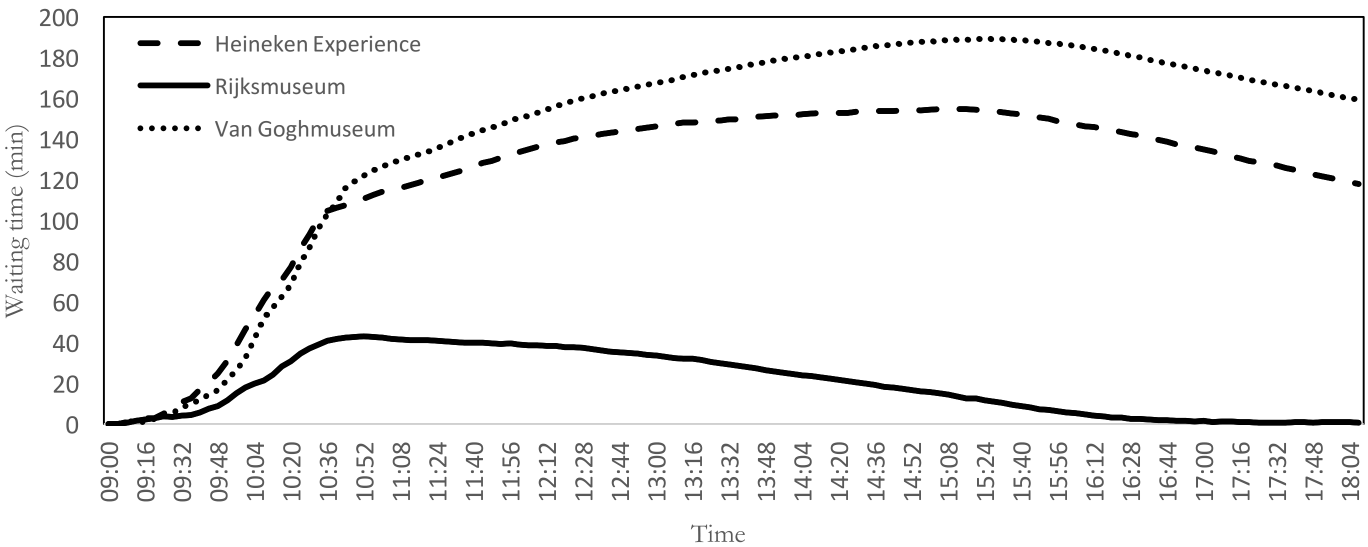


**Figure 6.4; Output of the Reference Scenario (Experiment 1)**

The experiment was executed with both 15 and 100 simulation runs. The reliability of the results increase if the number of runs increases – The number of runs negatively correlates with the confidence interval. However, the downside for a high number of runs is the computational complexity of the simulation and the complexity of the data analysis.

Hence, to determine the reliability of the results, the results of both 15 and 100 simulation runs are provided in table 6.3. Attraction 1 has large confidence intervals. The underlying reason is that the confidence intervals is relative to the attractions wait times.

Smaller confidence interval means more reliable results. The results of the simulation are more accurate when confidence intervals are small.

| attraction | Average 95% Confidence interval (15 runs) | Average 95% Confidence interval (100 runs) |
|---|---|---|
| Attraction 1 | ± 40% | ± *19.5 %* |
| Attraction 2 | ± 7,5 % | ±3.4 % |
| Attraction 3 | ± 9.6 % | ± 3.7 |

**Table 6.3; Confidence intervals of Attraction 1, 2 and 3 (Experiment 1)**

The exact distribution of the error terms over time of both 15 and 100 simulations are shown in Appendix B.3.1.

## 6.3 Experiment 2: Adoption of LiveLines

During this experiment, the effects of adoption of the LiveLines feature on the wait times will be investigated. The simulation setup is comparable with Experiment 1, apart from the percentage of LiveLines users. The percentage of users is adjusted every 100 runs. The model setup of Experiment 2 is shown in table 6.4.

The table should be interpreted as follows. The percentage of LiveLines users is comprised of 11 different percentages. Therefore, in total: 1 * 11 * 1 * 100 = 1100 simulation runs were executed.

| Model setup | |
|---|---|
| Initial Number of Visitors | 260 |
| Percentage using LiveLines | 0, 10, 20, 30, 40, 50, 60, 70, 80, 90, 100 |
| Update frequency | 10 ticks (every) |
| Runs | 100 |

**Table 6.4; Model Setup of Experiment 2**

### 6.3.1 Results

In figure 6.5, the wait times of Attraction 1 over the course of the day under different percentages of LiveLines users is shown. To understand the dynamics of the results a description of the behaviour of the model is given in the subsequent sections.

No significant differences between the different adoption percentages until approximately 10:30 are observed—the differences lie within the predetermined 95% confidence interval of $\pm$19,5%.

Another observation is that higher percentages of LiveLines users creates oscillating behaviour in the behaviour of the wait time over the course of the day – around 15:00 these differences are the greatest. The confidence intervals (95%) are too large to state that the difference in wait times, between for instance 10% users and 0% users, is significantly different. Nonetheless, the claim that oscillations occur can be concluded, because in almost every case 10% of more users lead to more visible oscillations – lower waiting times around 12:20 and higher waiting times around 15:00.

The underlying reason for these oscillations is that Attraction 1 is generally less preferred by visitors than Attraction 2 or 3. This means that for many visitors Attraction 1 is their second or third option. Consequently, visitors using LiveLines, go to their second or third preference of attraction—in this case Attraction 1. This leads to more popularity and thus higher waiting times of less popular attractions—In this case Attraction 1.

In addition to that, oscillations are observed, because the wait times exceed the MWW of the $2^{nd}$ and $3^{rd}$ option of people at some stage— 'The MWW' is namely on average 33 and 27 minutes for the second and third option respectively resulting in a decrease of wait times. Of course, part this decrease is also due to the general decrease of waiting times in the reference scenario.

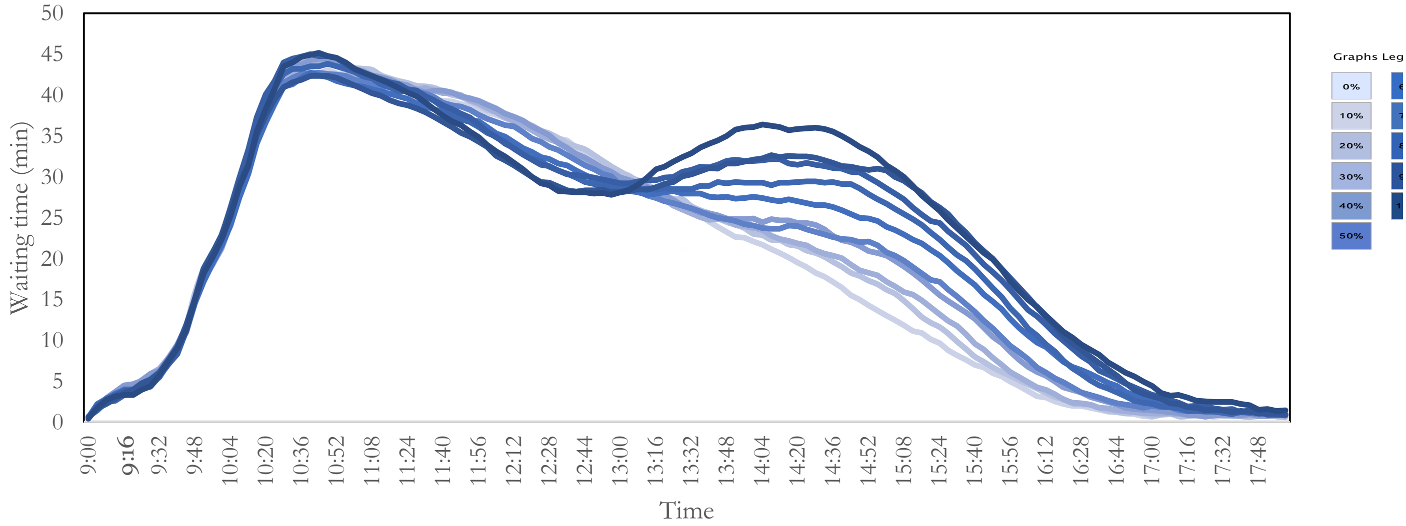


**Figure 6.5: Attraction 1 (Experiment 2)**

Having determined the effects on the wat times of a less popular attraction, Attraction 1, the effects on the more popular Attraction 2 and 9 are analysed in the subsequent part. In figure 6.6 and 6.7 the results of the adoption of LiveLines on the waiting times of Attraction 2 and Attraction 3 are shown.

A similar initial peak as in Attraction 1 is observed in the waiting times of both Attractions 2 and 3. In addition to that, in Attraction 2 and 3, increased percentages of LiveLines users create higher amplitudes in the oscillations of the waiting times.

The underlying reason for this behaviour is that when the wait times of a preferred attraction of a LiveLines user exceeds the MWW of its corresponding choice, 2/3 of the visitors walk around and wait until the waiting time becomes 'acceptable'. This leads to simultaneous decisions when waiting times become 'acceptable'. This creates the oscillations.

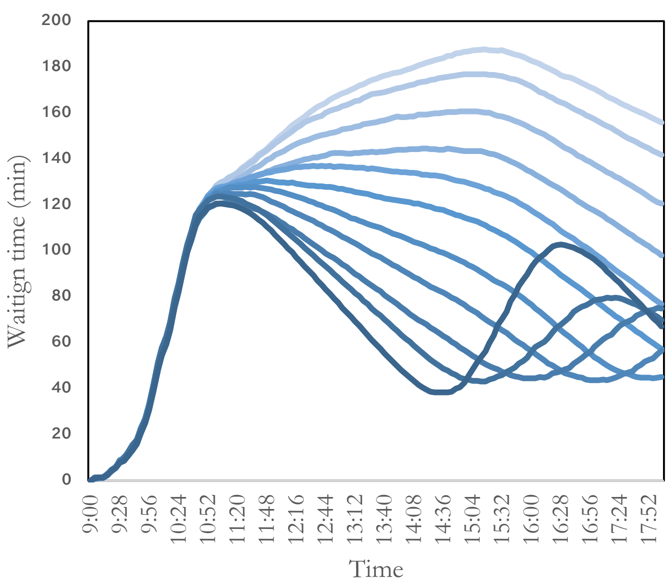


**Figure 6.6; Attraction 2 (Experiment 2)**

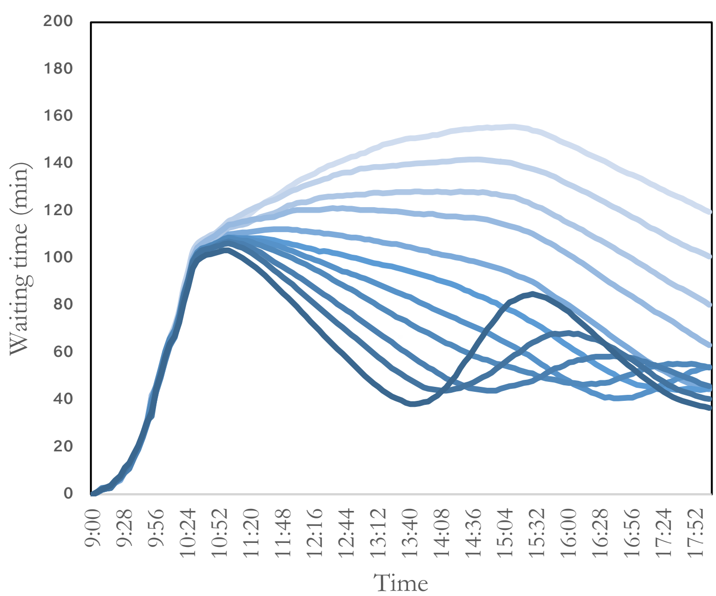


**Figure 6.7; Attraction 3 (Experiment 2)**

The difference between Attraction 2 and Attraction 3 is the length of both period and amplitude of the oscillations. This difference exists because the waiting times for Attraction 3 drop quicker below the MWW. The oscillations occur earlier at Attraction 3. Therefore, the effects can be observed more clearly. The underlying reason is that the wait times get acceptable for the LiveLines users at an earlier stage.

## 6.4 Experiment 3: Effect of Sudden Increase of Visitors

During this experiment, the effect of adding 20 visitors every two minutes (every tick) to the system (after 12:30) is explored. The model setup is shown in table 6.5

Model setup

| | |
|---|---|
| Number of Visitors | 260 |
| Number of visitors added to the system after 12:30 | 20 (per tick) |
| Percentage using LiveLines | 30, 70, 100 |
| Update Frequency | 10 ticks (every) |
| Runs | 15 |

**Table 6.5; Model Setup Experiment 3**

### 6.4.1 Results

With 30% of LiveLines users the waiting times of all the attractions keep increasing. This is because 70% is not using LiveLines and is, therefore, congestion disregarding.
In figure 6.8, the scenario of 70% LiveLines users is shown. The waiting times of Attraction 2 and 3 continue to increase. The underlying reason is that 30% of the visitors are not using LiveLines and will still go to the attractions. This is also the reason that waiting time after peak of Attraction 1 at 14:00 decrease slowly.

With 100% LiveLines users (figure 6.9) oscillations occur. However, the amplitudes of the oscillations are higher than without the sudden increase of visitors. The straight line of Attraction 1 after 15:48 is probably because of the period of the oscillations was beyond the time frame of the simulation.

This explanation seems likely because there is no reason that these oscillations would occur at Attraction 2 or 3 but not at attraction 1.

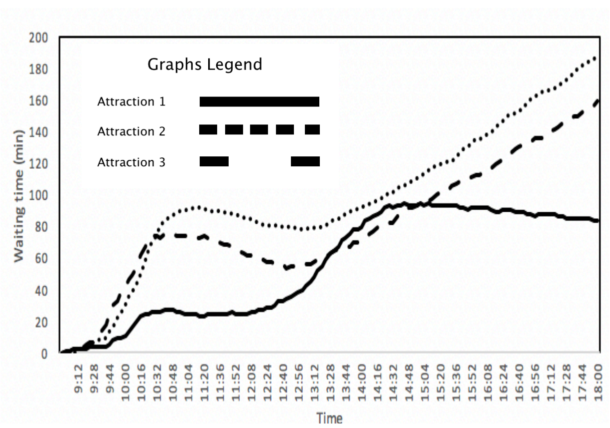


**Figure 6.8; Attraction 1,2.3: (70% adoption) (experiment 3)**

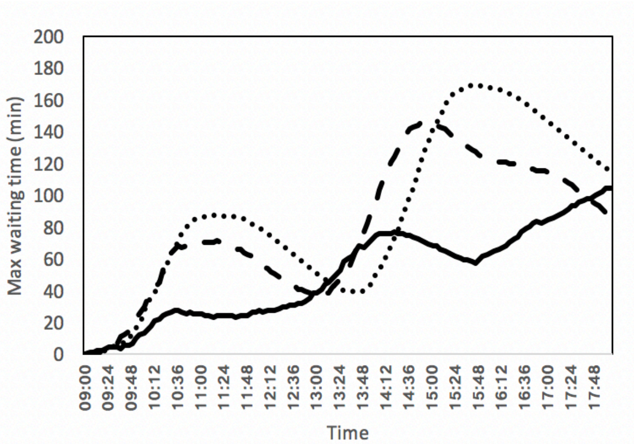


**Figure 6.9; Attraction 1,2.3: (100% adoption) (Experiment 3)**

## 6.5 Experiment 4: Sensitivity of MWW

In the following experiment, the effect of another probability distribution of the MWW was tested because of uncertainty in the distribution of the MWW. Instead of a Poisson distribution a Normal distribution with various variance levels was used as the MWW parameter of the agents. The normal distribution was chosen because this distribution allows to change the variance. The simulation setup is provided in table 6.6. The test was run with 100% adoption of LiveLines to have only agents in the system whose decisions are affected by changes in the variance.

| Model setup | |
|---|---|
| Number of Visitors | 260 |
| Percentage using LiveLines | 100 |
| Variance max willingness to wait | 5, 15, 30 |
| Update frequency | 10 ticks (every) |
| Runs | 15 |

**Table 6.6; Model Setup Experiment 4**

### 6.5.1 Results

No influence of the MWW on the KPI's could be observed. As an example, the graphs of Attraction 2 are shown. No difference is observed between the scenarios. The same results are observed on the waiting times of Attraction 1 and 3. In Appendix B.3.2 the graphs of Attraction 1 and 3 are shown.

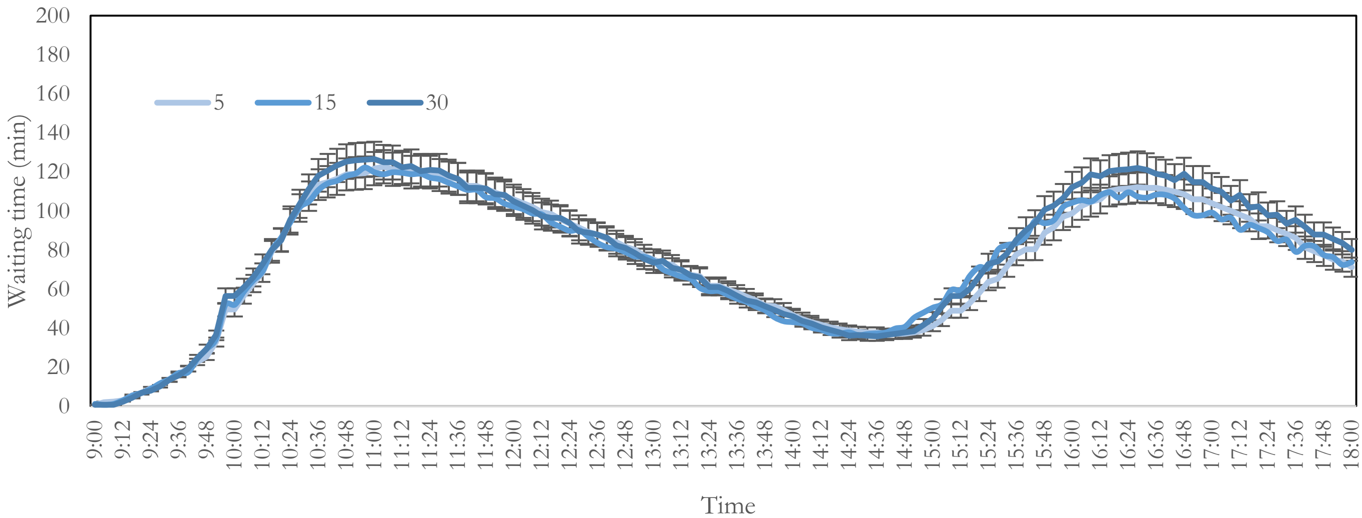


**Figure 6.10; Attraction 2 Including Confidence Intervals (Experiment 4)**

## 6.6 Sub-conclusions

The research question of this chapter was s as follows:

***"What could be the potential effects of LiveLines in its current form on the attraction wait times in Amsterdam?'***

The results of experiment 2 showed that if more agents avoid congestion by using LiveLines, the waiting times for the entire system will not necessarily reduced. The wait times for the popular attractions show oscillating behaviour. The underlying cause is the period of time for visitors to select a destination based on the waiting times displayed in LiveLines to the moment when they stand in the attraction's queue. In short, the problem is the time delay between decision-making and effect emergence.

# 7. Experiments on Interventions

This chapter answers the following sub-question:

- ***'What are the effects of several possible additions to LiveLines on the attraction wait times in Amsterdam?'***

This chapter starts with an explanation of the chosen experiments to answer this sub-question.

## 7.1 Approach

First, in experiment 5, the effect of adjusting the update frequency of LiveLines is investigated. Currently, the waiting times in LiveLines are updated every 40 minutes. This experiment investigates the effects of increasing this update frequency to see whether shorter intervals between the updates influence the waiting times. This experiment also serves as a tool to evaluate if an automatic queue system would be effective—With an automatic queue system the waiting times of the attractions are updated continuously.

Experiments 6 and 7 two methods which could potentially reduce the time-delay problem and, thus, reduce the oscillations are investigated.

In experiment 6, the effect of a prediction in the LiveLines feature was evaluated. In this experiment, a prediction of the waiting times in the near future was displayed instead of the 'current' waiting times. The prediction was based on recent changes in the waiting times. For example, if the waiting time of an attraction increased with five minutes in the last 20 minutes, the predicted waiting times in 20 minutes will be five minutes longer than the current waiting time.

Whereas, in experiment 7, the effect of a prediction method based on the intentions of other visitors is investigated— in this method the visitors send their next attraction to visit to the system. Subsequently, in this experiment, LiveLines displays tailored waiting time information depending on the location of the user.

An overview of the executed experiments is shown below (Table 7.1). Every experiment was analysed first with 15 runs. If the number of simulation runs was too low to draw conclusions, the number of runs was increased to 100.

| | | | | |
|---|---|---|---|---|
| Interventions | *5* | Effect of higher update frequency | 15 | Waiting times museum 1,2 and 3 |
| | 6 | Prediction on past values | 100 | Waiting times museum 1,2 and 3 |
| | 7 | Personalised Prediction | 15 | Waiting times museum 1, 2 and 3 |

**Table 7.1 Overview of the experiments**

## 7.2 Experiment 5: Increasing the Update Frequency

Currently, in the real system, the attractions are told to update their waiting times at least once every half an hour. In this scenario, the effects of frequency of updates are explored under different percentage of LiveLines users in the system. The following setup was used to explore the waiting time developments of Attraction 1, 2 and 3

| Model setup | |
|---|---|
| | 260 |
| Percentage using LiveLines | 100 |
| Update frequency | 1, 4, 7, 10 ticks (every) |
| Runs | 15 |

**Table 7.2: Model Setup Experiment 5**

### 7.2.1 Results

No significant differences are observed between Attraction 1 and 2 and 3 when the update frequency was changed (Appendix B.3.3). As an example, in figure 7.1 the effects of update frequency on the waiting time development on Attraction 2 are shown.

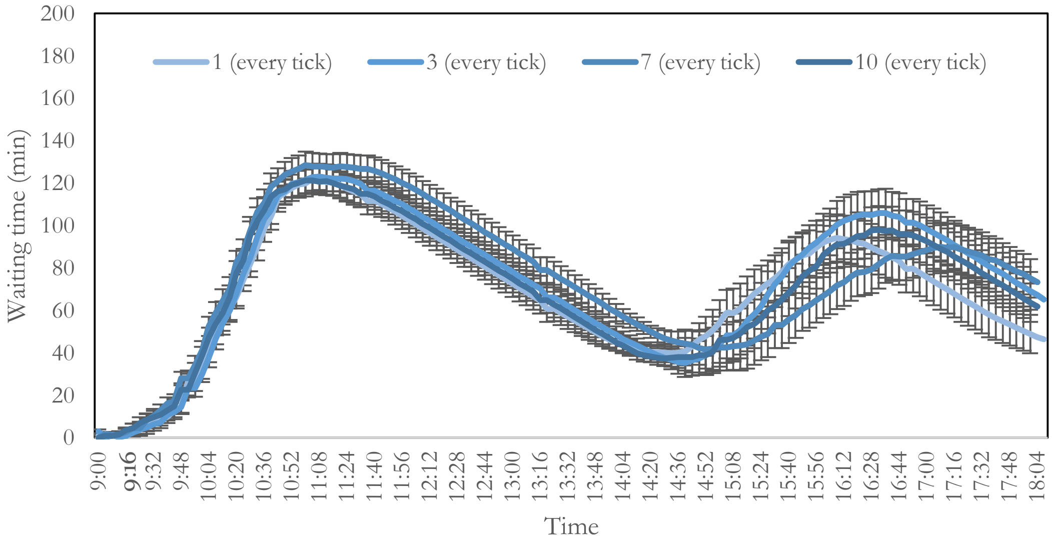


**Figure 7.1; Attraction 2 (Experiment 5)**

## 7.3 Experiment 6: Prediction Based on Past Values of Wait Times

During this experiment, the displayed times in LiveLines will not be the actual waiting times but the predicted waiting times.

The predicted waiting times is based on the change in waiting times during the last 20 minutes. The predicted waiting time is the waiting time expected after 20 minutes (10 ticks). The time frame of 20 minutes is set because it takes on average 20 minutes to go from a random location within the city towards an attraction.

| Model setup | |
|---|---|
| Number of Visitors | 260 |
| Percentage using LiveLines | 0, 10, 20, 30, 40, 50, 60, 70, 80, 90, 100 |
| With prediction? | on |
| Update frequency | 10 ticks (every) |
| Runs | 100 |

**Table 7.3; Model Setup Experiment 6**

### 7.3.1 Results

In this section the results of the waiting time developments are discussed. The graphs of the museums without prediction are compared with the graphs of the museums when prediction is displayed in LiveLines. In all the museums, the amplitude of the oscillations decreases. The underlying reason is that visitors using LiveLines get noticed earlier if the waiting times become too long for them.

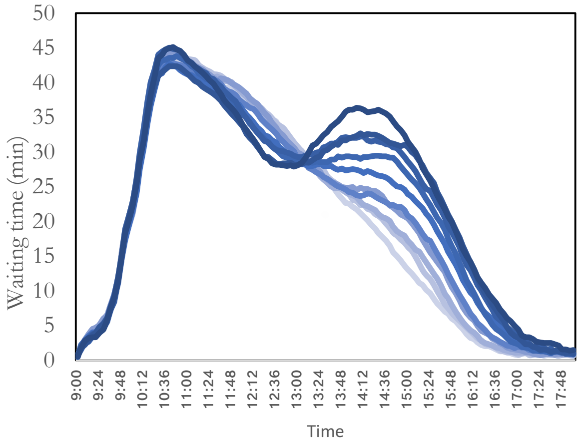


**Figure 7.2; Attraction 1 (Experiment 2)**

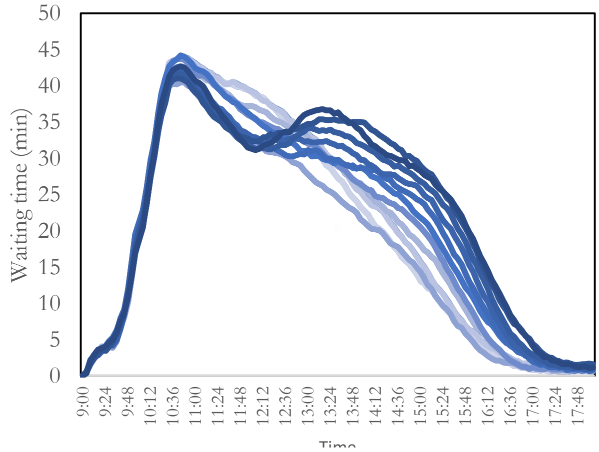


**Figure 7.3; Attraction 1 (Experiment 6)**

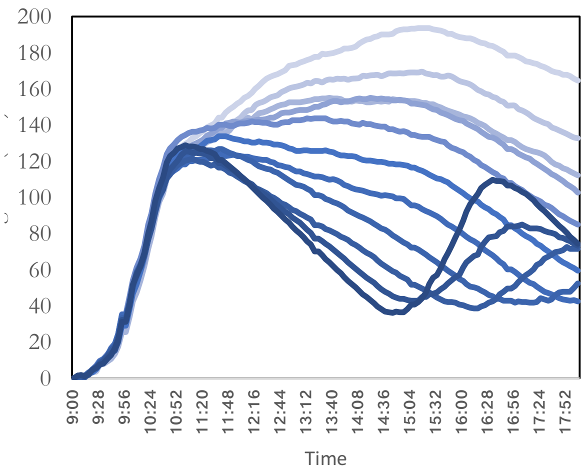


**Figure 7.4; Museum 2 (Experiment 2)**

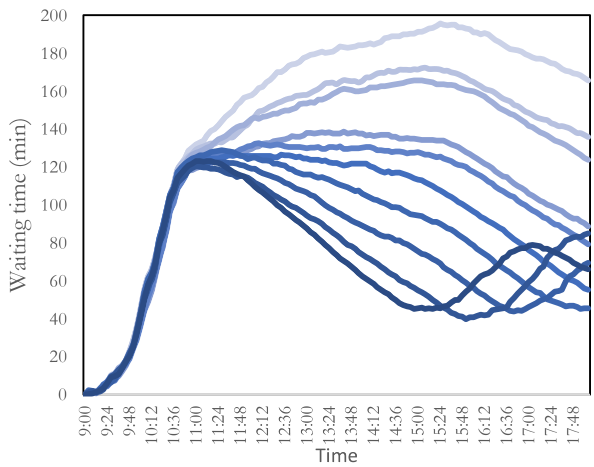


**Figure 7.5; Museum 2 (Experiment 6)**

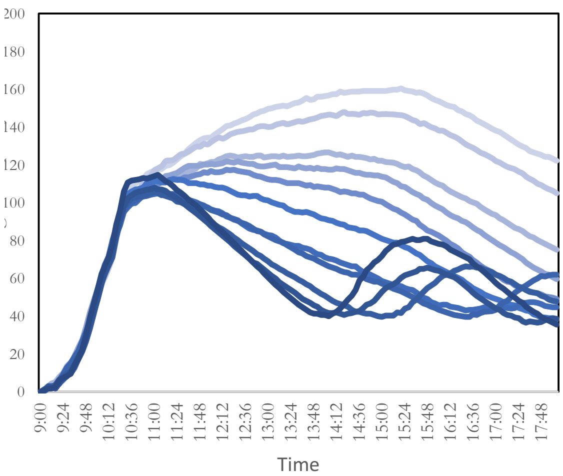


**Figure 7.6; Attraction 3 (Experiment 2)**

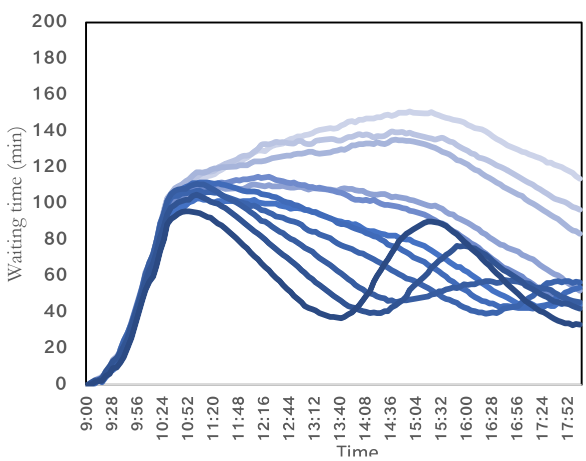


**Figure 7.7; Attraction 3 (Experiment 6)**

## 7.4 Experiment 7: Prediction Based on Intentions of Other Visitors

During this experiment the displayed waiting times in LiveLines are personalised. The waiting times are based on the distance between the user and the attractions and the intentions of other users.

For example, if a user is 20 minutes away from Attraction 1, the feature displays the expected waiting time of Attraction 1 in 20 minutes. As explained earlier, the system bases its prediction on the intentions of other users. When a user decides to go to an attraction, the visitor always informs the system about its next destination. In this manner, the system knows when the users will arrive and can generate personalised predictions. In figure 7.7, a schematic overview of the process is given.

In level 1 of figure 7.7, the process of a visitor who just made its choice of attraction is shown. While making a reservation, the smartphone of the visitor sends its current location and choice of reservation towards the server. Based on this information, the server increases the waiting time in the future for that specific attraction.
In level 2, the process of a visitor who is still considering to which attraction it wants to go is shown. LiveLines is displaying the expected waiting time at the estimated time of arrival. The expected waiting time is projected until maximally 100 minutes in the future —This is the maximum travel time between the vertices and attractions.

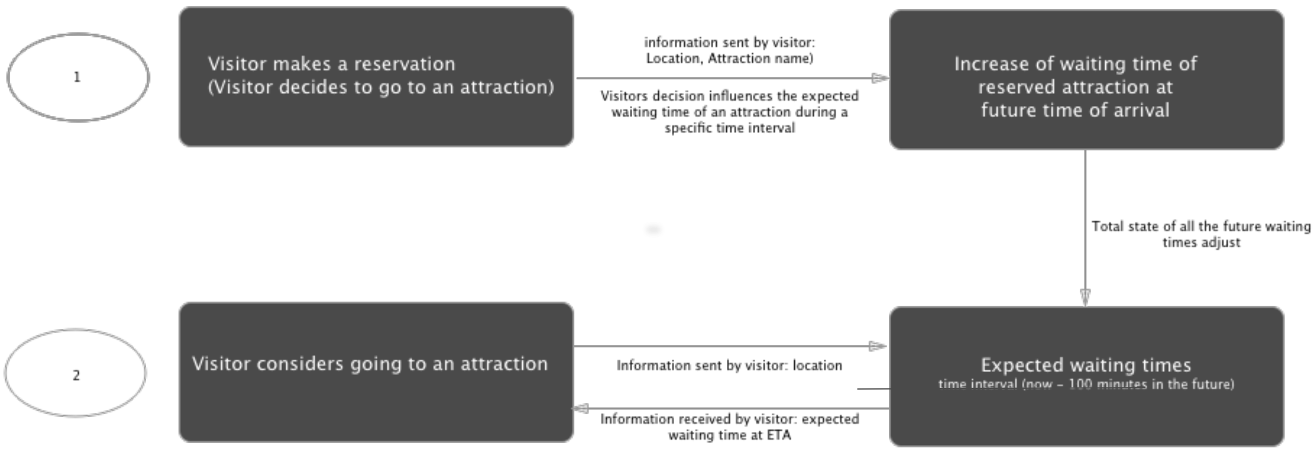


**Figure 7.7; Schematic Overview of Process in Experiment 7**

| Model setup | |
|---|---|
| Number of Visitors | 260 |
| Percentage using LiveLines | 30 70 100 |
| With prediction? | on |
| Runs | 100 |

**Table 7.4; Setup of Experiment 7**

### 7.4.1 Results

For all percentages of LiveLines adoption (30% ,70% and 100%) the total number of visitors in the system remained around 30.000. This means in every scenario, approximately the same number of museum visits take place.

No significant differences in waiting times are observed between 30, 70 and 100 percent of LiveLines users at Attraction 1 (Appendix B.3.4). In figure 7.8, the results of the simulation runs at Attraction 2 are visualised.

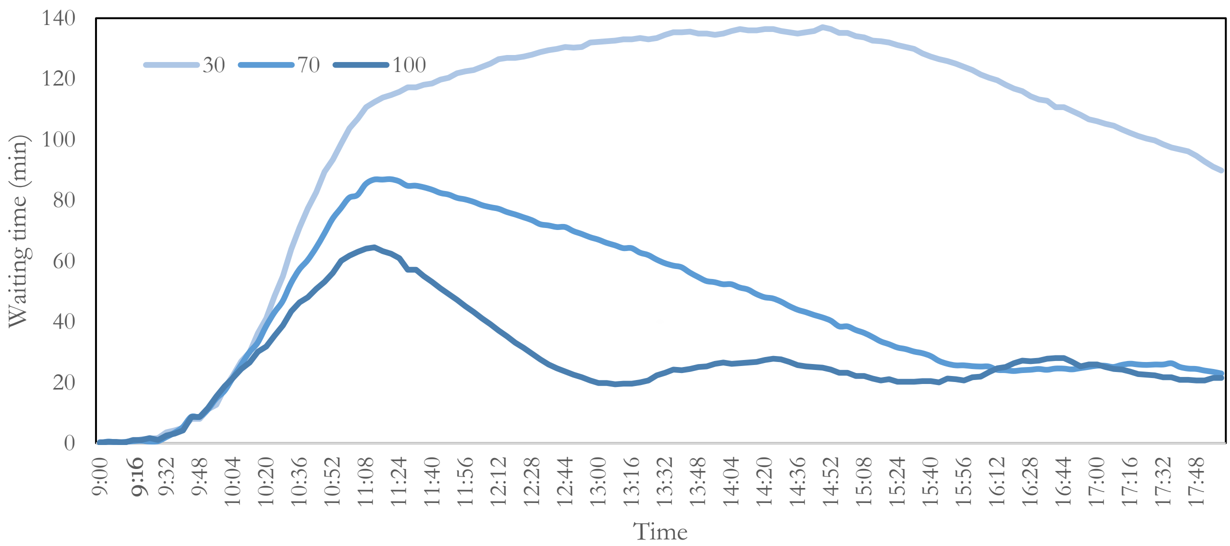


**Figure 7.8; Attraction 2 (Experiment 7)**

In figure 7.8 and 7.9, an initial peak takes occurs in all the scenarios around 11:00. The underlying reason is that the probability of visitors making decisions at the same time in the beginning is high—the initial number of visitors are generated spread over the first 13 ticks. Consequently, relatively, a great number of visitors then make their decisions in the beginning on the same information.

A significant decrease under 70% and 100% users is shown between 11:00 and 13:00. Under 70% of users the speed of decrease in waiting times after the peak at 11:00 occurs more gradually. This underlying reasons is that, in this situation, 30% of the visitors are not taking the waiting times into account, and do not take long waiting times into account.

For both 70% users and 100% of users, the waiting times after 16:30, remain around the same value (25 minutes). This is unexpected, since a higher percentage of users is expected to result in lower waiting times. An explanation for this phenomenon is that the LiveLines users 'compensate' for the non-users. Consequently, this means that the queues of the popular attractions are mainly composed of non LiveLines users.

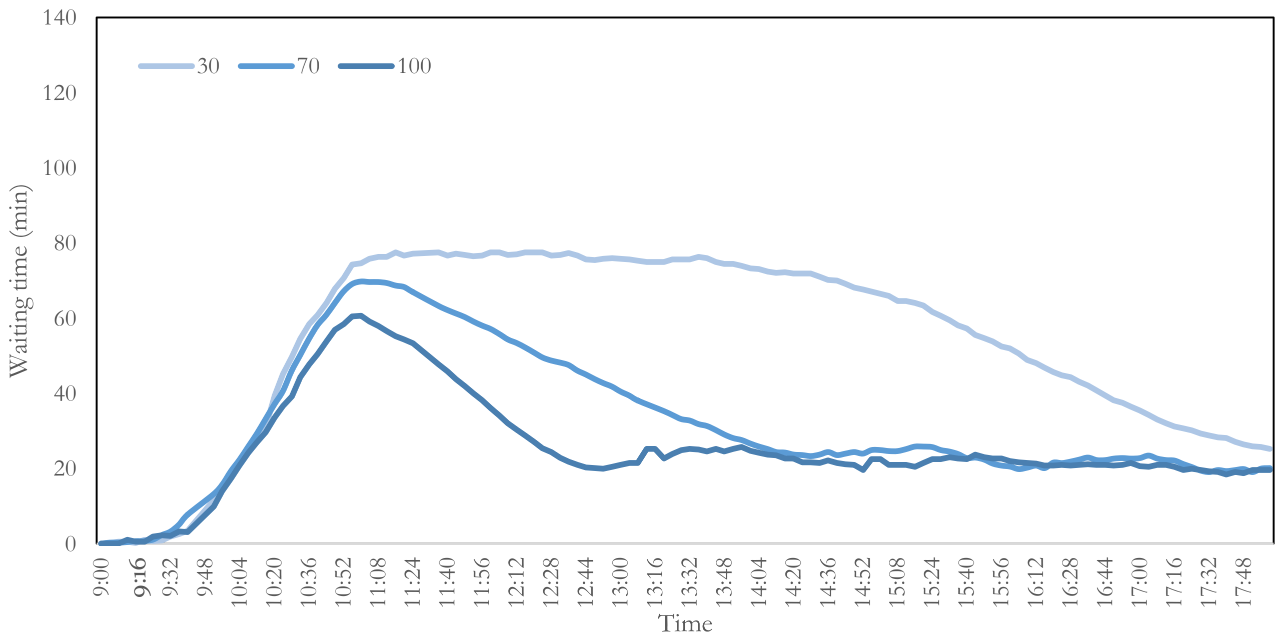


**Figure 7.9: Attraction 3 (Experiment 7)**

In figure 7.9, the results of experiment 7 on Attraction 3 are provided. Comparable effects to Attraction 2 are observed. The main difference is that the 'equilibrium' state with 70% and 100% users is reached earlier (14:00) than at museum 2 (16:00). The underlying reason is that the initial peak is less high in the beginning because Attraction 3 is less popular than Attraction 2. Hence, the 'equilibrium state' is reached at an earlier stage. In both attractions, the oscillations are non-existent. Minor oscillations are observed at Attraction 2 and Attraction 3, but these oscillations lie within the predetermined confidence intervals.

## 7.5 Sub-Conclusion

This chapter tried to give an answer on the following sub-question:

- ‘*What are the potential effects of several additions to LiveLines on the attraction wait times in Amsterdam*?’

The effect of increasing the update frequency does not have a significant effect on the attraction wait times. Hence, for instance, the addition to LiveLines such as automatic queues proved not to be effective.

Adjustments to the system which predict future waiting times can reduce the time delay between decision-making and effect emergence. Two methods of prediction were investigated.

In experiment 6, this prediction was based on past waiting times. This led to a decrease in the amplitude of the oscillations. The problem is that when an agent performs an action based on a past state, a gap between the agents’ estimate and future state remains.

Finally, in experiment 7, a coordination system was proposed that estimates the future state of the waiting times based on the intentions of users. The results showed that the time delay problem was solved. No significant oscillations in the waiting times were observed.

# 7. Discussion

The purpose of this project was to evaluate if waiting time information is effective in the spreading of visitors more equally between attractions.

The findings of this project suggest that LiveLines in its current form is not effective in the spreading of visitors; having too many people use LiveLines creates oscillating behaviour in the attraction wait times.

The results of the project indicated that displaying predictions of the waiting times instead of the current waiting times influences these oscillations. The effects of two different prediction techniques were investigated. Prediction based on recent changes in waiting times reduced the amplitude of the oscillations. Meanwhile, prediction based on the intentions of users was effective in eliminating the oscillating behaviour.

This chapter will first elaborate on the scientific relevance of these findings by comparing the previously mentioned findings with the scientific literature:

- Finding 1: High percentage of LiveLines users led to oscillations in the behaviour of wait times of popular attractions.
- Finding 2: Congestion can be reduced if the Intentions of Users are known

Consequently, in the third part of this chapter, the limitations of this project are discussed. This is followed by a discussion of the implications and considerations for the future development of LiveLines. Finally, the potential of applying the findings to other areas is discussed.

## 7.1 Related Work

In this section, the two major findings are compared with the relevant scientific literature.

### 7.1.1 Main Finding 1: High percentage of LiveLines users led to oscillations in the wait times behaviour of popular attractions.

The results of the experiments showed that oscillations in the waiting times occur if wait time information was provided to high percentages of visitors. In scientific literature, this is considered as the time-delay problem.

This problem has been observed in a similar context by Zheng et al. (2014) and Kataoka (2004).

The simulation model of Zheng et al. et al. (20014) represents a theme park including nine attractions and three entrances. Whereas, the simulation model of Kataoke (2004) includes 6 attractions. In these models, every agent visits multiple attractions, and the agents receive congestion information on their mobile device. Those, who receive this message move to a less congested location. When too many visitors would use this information, oscillations in the waiting times have been observed.

In both models of Zheng et al. (2014) and Kataoka (2004) simplifications were made. Refinements to address these simplifications were made in this project.

First, the behaviour of the agents in the model of Kataoka (2004) is either congestion avoiding or congestion disregarding. A congestion-avoiding agent always goes to the attraction with the lowest waiting times. Consequently, the waiting time at that attraction rises quickly, and another attraction becomes the attraction with the shortest waiting time (Kataoka et al., 2004) .

By contrast, the behaviour of the agents in the simulation model of Kataoka (2004) and this project is that the agents' behaviour is not simplified by either congestion-avoiding nor congestion-disregarding behaviour. In the simulation model, the agents make their decisions by evaluating the wait times of attractions based on their preferences – preferred choices of attraction and their 'maximum willingness to wait'. Namely, it is assumed that every visitor is to some extent congestion avoiding. However, the threshold of congestion differs per individual and differs per attraction.

Second, the distance between the attractions were not considered in the model of Zheng (2014) previous models. In the models of Zheng (2014) it was assumed that there is no travel time between the attractions. This does not reflect to the real world. Hence, another refinement of this simulation model is that travel time between the attractions exists.

Third, the possibility for visitors to wait was not included in the models of Zheng et al. (2014) and in Kataoka (2004). According to Amsterdam Marketing, if the waiting time is unacceptable to visitors, they are likely wait and simply walk around (Marketing, 2017). This behaviour is included in this project's simulation model.

In conclusion, the results of the simulation model of this project, which included extensions on previous related simulation models also observes oscillations when high percentages of agents are using wait time information.

### 7.1.2 Main Finding 2: Congestion can be reduced if the Intentions of Users are known

The previous finding confirms that the time-delay problem still exists after having made refinements to a previous simulation model. Previous research on how to reduce this time-delay has been focussing on developing algorithms that reduces the congestion and oscillations. These types of algorithms dynamically coordinate the behaviour of the vising behaviour of agents.

These types of algorithms are used in various areas. The main objective of this is to increase the efficiency of individual users and of the entire system simultaneously. Previous research has focussed on algorithms, which include the generation of adjusted recommendations to users based on the intentions and preferences of other users (Cheng, Chen, Horng, & Wang, 2013) (Li, Zhou, & Hua, 2012). In summary, these algorithms give users strategic recommendations to increase the overall performance of a system. Social coordination systems are used in various areas:

- Road traffic

In the road traffic context, social coordination is expected to reduce traffic congestion and thus to shorten each driver's trip time. This is achieved by coordinating users' driving plans per their destinations and road constraints.

- Supply Chain

Social coordination is useful for increasing the efficiency of the supply chain by adapting in a real-time manner to changing environment.

These algorithms have showed to reduce congestion and the time-delay problem in these areas. The algorithm proposed in this simulation model also showed to reduce this time-delay problem – The results showed that no oscillations occur at the proposed attractions.

However, the proposed system of this project does not make recommendations. Because each agent possesses the parameter: 'maximum willingness to wait', the agents could make decisions themselves. Thus, the system regulates itself without needing to give the users recommendations. In contrast to previous research on developing these types of algorithms (Li et al., 2012) (Li, Wu, Zhu, & Hu, 2009),

## 7.2 Limitations of the Study

In the following sections, the limitations are discussed which are expected to have the greatest potential impact on the quality of the findings. These limitations will be discussed in order of the steps taken during this project (Chapter 3: Behaviour of Visitors, Chapter 4: Modelling Problem and System Identification, Chapter 5: Formalisation).

**7.2.1 Behaviour of Visitors**

As stated, a preference method was used to determine the 'maximum willingness to wait' of visitors. The extent of the discrepancy between the stated behaviour in the questionnaire and the actual behaviour of visitors is unknown. Hence, this method lacks certainty.

A second aspect which could have influenced the results is that the location of the survey was at two spots: het Begijnhof and 't Spui. The sample proved to be representative for length of stay and age composition. However, it could have been that the sample was not representative for socioeconomic background. These types of questions were not included in the questionnaire.

**7.2.2 Modelling problem and system identification**

In the modelling problem and system identification phase, simplifications in the environment were made, which could have influenced the results.

In Amsterdam, at some attractions, it is possible to reserve tickets at specific time slots. For instance, at the Van Gogh Museum, these tickets provide access to a priority queue. Meanwhile, at the Anne Frank House, these tickets are mandatory before 15:30. These museums' specific policies were not included in this project.

Additionally, only attractions in Amsterdam which were included in the LiveLines trial were included in the project. Conceivably, when LiveLines is adopted in large numbers, additional visitors will shift from the attractions not using LiveLines to the attractions using LiveLines due to increased exposure.

**7.2.3 Formalisation**

In the formalisation phase, an important assumption was made. During this phase, it was determined that agents 'die' after having visited an attraction. The agents are replaced with 'random' agents. The main problem with this assumption is that some of the initial parameters of the agents give them a greater probability of visiting an attraction. Consequently, the agents with these parameters are replaced with agents with randomly assigned parameters. Hence, this assumption creates a shift in some of the population's average parameter values.

Generally, visitors who consider other attractions are replaced more quickly. Consequently, at the end of the simulation, more visitors who are willing to wait exist in the simulation model. This could have had effects on the amplitude of the oscillations. This issue could have been resolved by copying the parameter values of the agent who dies into the new agent. However, this approach was not followed because it lacked the stochastic input of the parameters.

In addition, visitors who are replaced cannot 'learn' or adapt their behaviour. In the real world, visitors generally stay a couple of days in Amsterdam. During this trip, they visit multiple attractions. Experiencing long or short queues could influence their behaviour towards using online waiting time information or their MWW. The number of attractions and lengths of stay did not influence the results.

Another limitation during the formalisation phase of the project was that the model was not comprehensively validated. Model validation is a process which determines whether the programming implementation of the conceptual model is correct (van Dam et al., 2012). In this project the model has only be validated by expert opinion. In the future research section of the subsequent chapter, some other methods for validating the model are discussed.

## 7.3 Application of Findings in Congestion Context

In this part, the potential of the application of the findings in other applications is discussed.

The findings of this project could also have implications when we zoom out and focus on the current challenges of Amsterdam regarding crowding. The findings of this project could aid in the crowd management challenges in Amsterdam.

In 2015, researchers of Delft University of Technology and Amsterdam Metropolitan Solutions released a feature called 'Social Glass' (Seijlhouwer, 2015). The tool makes uses of social data to determine crowding information. It includes algorithms which recognise the locations of users. For example, if many people are currently posting tweets at the dam square, the system can identify that the Dam Square is currently busy.

During Sail 2016, an event in Amsterdam with over 3 million visitors, the tool has been used for crowd management. Busy areas were identified with Social Glass. If areas were identified as 'busy' people were guided with the aid of police officers and information matrices to other parts of the city.

While having proved their purpose during an event, these data could also be used to relieve pressure on the busy parts of cities during a general day in the future, according to the founders (Seijlhouwer, 2015). For example, if individuals consider park A and park B to go to and finds online that Park A is more crowded than park B, they would be likely to go to park B. Additionally, when Park A is currently very crowded they could decide to go to Park A at a later stage. The findings of this project could have implications for these design considerations.

The first major finding discussed in this chapter, oscillating behaviour when congestion information is offered, could be applied to this context. Namely, it is expected that when this feature is offered to people directly, giving the current crowding information of locations within the city, it will not be effective because oscillations in crowding would occur.

Hence, the findings of the proposed design solution suggest that it is required to estimate future crowding levels based on the intentions of users to prevent oscillations in crowding. Hence, the efforts of the researchers should also focus on algorithms which identify intentions in social data. In this manner, oscillations in the crowding levels could be prevented.

In conclusion, the findings of this project can have its value in other applications, specially in situations in which people currently have the possibility to go choose between different locations and can go somewhere at a later stage.

## 7.3 Implementation

Besides the effects on the wait times various other principles must be considered. In this section, some of these issues are discussed. First, the preliminary interests and objectives of the most important actors are analysed. Second, some options to influence the behaviour of visitors are discussed. Finally, recommendations for Amsterdam Marketing are given.

### 7.3.1 Involved Actors

The research problem does not only include technical aspects but is also characterised by a variety of actors with different interests and objectives. The power, interests, perceptions and resources of the involved actors need to be considered to increase the likelihood of successful implementation. Therefore, an overview of the actors regarding the issue is given. Based on expert opinion, an interview with the founders of LiveLines, the following actors and their interests were determined.

- **Municipality of Amsterdam**

A few years ago, the objective of the Municipality of Amsterdam was to attract more tourists to Amsterdam. Recently this attitude has changes. The number of visitors is creating too much pressure on the city of Amsterdam. Therefore, the main objective of the municipality is now to remain an attractive city for the citizens of Amsterdam.

- **Citizens**

Whereas, a variety of attitudes exists towards crowding among citizens. It seems that the general tendency is that the city centre of Amsterdam is becoming too crowded. This is supported by the research report of Plan Amsterdam (Daamen et al., 2016).

The attitude of citizens towards the long waiting times of some attractions is unknown. Citizens could perceive the long waiting times as a symptom of the increased crowding within the city and do not experience these waiting times themselves. Citizens are namely expected to know already better at which moments the waiting times are shorter. In addition to that, they have more flexibility to visit an attraction at another time.

- **Popular Attractions**

According the founders of LiveLines, the popular attractions such as the Rijksmuseum and the Van Gogh Museum did not directly have an interest in the LiveLines feature. They were willing to participate because they felt they should do something back to the city after having benefited from the increased number of visitors in Amsterdam.
Besides, it is important to note that the Municipality of Amsterdam cannot oblige the attractions to participate in the LiveLines project.

- **Unpopular Attractions**

The unpopular attractions, attractions with generally short wait times, perceive LiveLines as a possible marketing tool. The hope that the LiveLines Web Page visitors are more likely to go to their attraction

- **Visitors**

Visitors prefer short wait times (Avi-Itzhak & Levy, 2004). In this manner, they can visit more itineraries and experience more of aspects of the city of Amsterdam.

Based on the overview of the interests of the actors, it seems that the popular attractions are of critical interests, since they are essential for successful implementation and their current attitude towards LiveLines seems not very positive.

### 7.3.3 Influencing

Governments are increasingly adopting behavioural science techniques for changing individuals' behaviour to meet policy objectives (Berartzi, Behshears, Milkman, & Sunstein, 2017). These interventions alter people's decision-making without coercion. A key feature of influencing is its attempt to adjust the behaviour of individuals without forbidding other options. Influencing could be used to improve the desired behaviour of the system. Biases in the evaluation of alternatives were derived from the book 'The Psychology of Judgment and Decision Making' by Plous (1993). Three applications of influencing are discussed in the subsequent paragraphs.

#### *7.3.3.1. Adding a Story to the Waiting Times*

The type of influencing discussed in this section does not clearly use a human bias. Amsterdam Marketing noticed that the different attractions had their own opinions about presenting the information. For instance, generally less popular attractions did not want to convey that they were very unpopular. Hence, for instance, the following message was given:

*Current waiting time: 0 minutes: 'It's a good moment to go*

By contrast, some popular attractions did not want to convey that their waiting times were commonly very long. Hence, for instance, the following message was displayed for these attractions:

*Current waiting time: 120 minutes: 'It's now a popular time.'*

#### *7.3.3.2 Presenting Alternatives*

A possibility to adjust the behaviour of visitors makes use of the anchoring or rank preference bias (Plous, 1993). First, the anchoring bias could be used to influence the decision-making of users (Plous, 1993). Anchoring is the using of irrelevant information to evaluate a piece of information (Gilovich, Griffin, & Kahneman, 2002). Translated to the LiveLines architecture, this could lead to displaying an attraction with a very low waiting time first, followed by an attraction with a higher waiting time. Consequently, the user evaluates the second attraction with the higher waiting time more negatively. This could lead to a lower likelihood of the visitor's going to that attraction. In this manner, the behaviour of visitors can be influenced.
Second, the rank preference bias could be used to influence the behaviour of users. (Plous, 1993). The theory behind the rank preference bias is that alternatives which presented earlier have greater probability to be chosen.

#### *7.3.3.3 Displaying Incorrect Information*

To adjust the behaviour of tourists, false waiting times could be displayed in LiveLines. For instance, to prevent an initial peak during the beginning of the day, the waiting times of popular museums could be set to a level at which some visitors decide not to go. In conclusion, there are various opportunities in the design of the LiveLines system to adjust the performance of the system. In the recommendations section (7.4), the role of these opportunities in the implementation process are discussed.

## 7.4 Recommendations

The different interests of the actors, and the goals of the municipality, which are not totally clear, make it difficult to make any recommendations for a definite implement. Therefore, the following recommendations are based on the next steps in the process which need to be pursued.

**1, Deeper understanding of the actors' objectives**

- A deeper understanding of the municipality's objectives is required. Does it want to reduce the lengths of the queue even when this leads to more crowding in the city?

- Become informed on the attractions' perceptions of the ideal waiting time development over the course of a day. This information can then be used in the simulation model to adjust the preferred alternative to. This can help to convince actors to participate. In addition, biases could be used to adjust the behaviour of visitors. These behavioural changes could also be included in the simulation model.

**2. Making a prediction of the development of users**

Based on the results of the previous step, the desired or expected number of users can be determined.

- If the desired or expected number of users is low, LiveLines in its current form can be effective.

- If the desired or expected number of users is high, another design of LiveLines should be implemented.

**3. Choosing appropriate design based on the expected users and actors' objectives**

If the expected number of users is high, the following design options should be considered. Then, a system is recommended which captures the intentions of visitors. The following methods could serve this purpose:

- A system as proposed in this project, which provides personalised wait times based on the distance of a LiveLines user from an attraction. With this method, the intentions of the visitors must be known to make these predictions. This method is fair only if everybody uses it.

- Whereas this system has not been investigated in this project, it, too, incentivises users to mention to which attraction they are going by making an additional queue for them. The effectiveness of this method should be investigated with simulation modelling first.

# 8. Conclusions and Future Research

In this chapter, the conclusions and directions for future research are discussed. The conclusion section is structured as follows. First, the sub-questions are answered in order. Subsequently, the final research question is answered.

## 8.1 Answering the Sub-Questions

### 8.1.1 How does waiting time affect visitors' choice?

Several non-market valuation methods were considered to capture the behavioural changes of visitors regarding attraction choice when they would be using waiting time information. The Contingent Valuation method was chosen.

The Contingent Valuation method established that every visitor has an 'maximum willingness to wait' (MWW). The value of this MWW influences a visitor's attraction choice. For example, if a visitor's MWW is 30 minutes, and if the waiting time displayed in LiveLines is 40 minutes, the visitor is expected not to go to that attraction.

Subsequently, the aim was to identify factors influencing this MWW. However, no correlating variables were found. Therefore, no distinction will be made between the MWW for different groups. Consequently, every agent is given a MWW. The averages of this MWW are provided in Table 8.1.

| | *1st choice* | *2nd choice* | *3rd choice* | *4th choice* | *5th choice* |
|---|---|---|---|---|---|
| *Max accepted waiting time* | 38 | 33 | 27 | 23 | 19 |

**Table 8.1. Average accepted waiting time for every choice (minutes and rounded to whole numbers)**

### 8.1.2 *What is the effect of LiveLines in its current form on the attraction wait times in Amsterdam?'*

An agent-based simulation model was developed to answer sub-question 2. The results of the experiments showed that if more agents avoid congestion by using LiveLines, the waiting times for the entire system will not necessarily be reduced. The wait times for the popular attractions show oscillating behaviour over the course of the day.

The underlying cause is the period between when a visitor selects a destination based on the waiting times displayed in LiveLines to the moment when he or she stands in the attraction's queue. In short, the problem is the time delay between decision-making and effect emergence.

### 8.1.3 What are the potential effects of several additions to LiveLines on the attraction wait times in Amsterdam?

The objective of this sub-question was to identify additions or policies which can reduce the time delay and thus the oscillation behaviour of the popular attractions.

First, the effect of increasing the update frequency of the wait times by the attractions was investigated. If proved to be effective, this could, for instance, lead to an automatic queue system. Currently, the attractions update their wait times every 30 to 40 minutes. The effect of increasing the update frequency does not have a significant effect on the attraction wait times. Hence, for instance, the addition of automatic queues to LiveLines would not be very effective.

Two adjustments to the system which predict future waiting times could reduce the time delay between decision-making and effect emergence. Two methods of prediction were investigated.

Prediction based on past waiting times leads to a decrease in the amplitude of the oscillations. The problem is that when an agent performs an action according to a past state, a gap between the agent's estimate and the future state remains.

In the final experiment, an algorithm was developed that estimated the future state of the waiting times based on the intentions of users. The results showed that the time delay problem was solved. No significant oscillations in the waiting times were observed.

## 8.2 Answering the Main Research Question

### 8.2.1 'What are the potential effects of online waiting time information on the attraction wait times in Amsterdam?'

The objective of this thesis research was to obtain knowledge about the influence of online waiting time information on the attraction wait times in Amsterdam. An agent-based model of the system including visitors, attractions and the environment based on the situation in Amsterdam was developed in Netlogo.

The results of the simulation model showed that LiveLines reduces wait times if a small percentage of visitors use it. However, the simulation model also showed that LiveLines in its current form proved not to be effective when the percentage of users was large; oscillations in the wait times occurred.

The oscillating behaviour of popular attraction wait times was observed in cities if a higher percentage of visitors used online waiting time information. The percentage of LiveLines users and the amplitude of these oscillations are positively correlated.

Two interventions for minimising these oscillations were investigated. The first method, prediction based on past values, reduced the amplitude. However, the oscillations still existed with this method. Meanwhile, the second method of prediction, personalised prediction based on the decisions of other users, eliminated the oscillations.

#### *8.2.1 Scientific Contribution*

The main scientific contribution of this paper is a refinement of previous simulation models regarding wait time information for attractions. This project makes several contributions to the existing simulation models.

First, the behaviour of the agents in the previous related simulation models is either congestion avoiding or congestion disregarding. A refinement of this project's simulation model, the agents make their decisions by evaluating the wait times of attractions based on their preferences – preferred choices of attraction and their 'maximum willingness to wait'. Namely, it is assumed that every visitor is to some extent congestion avoiding. However, the threshold of congestion differs per individual and differs per attraction.

Second, a refinement of the simulation model of this project is that distances between attractions are included.

Third, the visitors in Amsterdam are frequently expected to wait until the waiting time of an attraction becomes acceptable—If the waiting time is unacceptable for visitors, they are likely to wait and walk around. This refinement was made based on the expert opinion Amsterdam Marketing, and has been included in the project's simulation model.

#### *8.2.2 Societal Contribution*

The value for the problem owner is that this project makes the Amsterdam Marketing aware that LiveLines in its current form will not be effective with high percentages of users. Depending on the objectives of the involved actors and the adoption expectations of LiveLines, suitable alternatives should be considered for future design.

## 8.3 Future Research

In this section, several directions for future research are discussed. First, two potential validation methods are discussed. Second, two possible model extensions are examined.

### 8.3.1 Future Research on Validation of the Model

First, a revealed preference (RP) method could be used to verify the simulation model. The behaviour of two visitor groups could be compared by using Global Position System trackers: a group which is not using LiveLines and a group which is using LiveLines. The MWW of the LiveLines user group should be known beforehand. In this way, it can be investigated if the LiveLines visitors act according their MWW.

Second, expert opinion could be used to verify the simulation model (van Dam et al., 2012). A discussion could be organised with the relevant attractions, behavioural scientists and tourism researchers to assess the accurateness of the conceptualisation of this project's simulation model.

### 8.3.2 Future Research on Model Extension

First, the current the agent-based model can be extended by adding museum-specific policies to the model. Several museums, such as the Rijksmuseum and the Van Gogh Museum, offer the opportunity to buy tickets in advance. These additional queues could be added to the simulation model. The number of tickets for each timeslot is limited. A future model could focus on the effects of increasing the number of tickets for each timeslot and thereby decreasing the number of tickets for the regular queues. The effects on an individual level, the wait times of the specific attractions, and the system's performance could lead to new insights.

Second, the current simulation model could be extended by adding additional priority queues to the attractions for LiveLines users. In this manner, visitors are incentivised to use LiveLines. The people who inserted their next attraction to visit in LiveLines are given access to an extra queue. Insight into the effects of this policy could lead to new insight on how to further develop the feature.

# 9. Personal Reflection

In this chapter, I will reflect on the major steps of this research project and on the relevance of the topic and its fit with the engineering and policy analysis programme.

### 9.1 Research Proposal

Personally, I think that defining the direction of my dissertations was the most challenging by far. Whereas, I knew from the start I wanted to analyse a problem related to tourism in Amsterdam with a modelling method, it was difficult to define a clear problem definition suitable for analysis. It took me about two months to formulate my exact direction for my thesis project. I had to reformulate my thesis topic two times, this was somehow frustrating.

### 9.1 Modelling Process

The modelling effort took me quite some time. In the beginning, I tried to model the problem in Anylogic. I wanted to use this software this due to the animation capabilities of this software. The foundation of Anylogic is JAVA. I experienced that because I did not have any prior experience with JAVA, it would have been too time consuming to learn JAVA while modelling. In addition to that, nobody at TU Delft had experience with Anylogic, so if I perceived any modelling problems nobody could help.

Subsequently, I decided together with my second supervisor, Martijn Warnier, to model the problem in Netlogo. This process was relatively easy. I wrote many lines of code. I am sure that a more experienced modeller would need fewer lines of code. Martijn gave me several tips on how to reduce the lines of code. However, I felt that, for my own understanding, it was easier for me to maintain my current method of coding.

### 9.2 Results

I am satisfied with the results of the experiments. Initially, most people would think that if more people would use LiveLines, the better it would be for the wait times of attractions. However, the simulation results showed that more users are not necessarily better.

Probably the greatest feat of this research is its current relevance. Crowd control and the management of visitor flows is becoming increasingly important. For example, the municipality of Amsterdam founded Amsterdam Metropolitan Solutions – an organisation which focusses on these crowding challenges.

### 9.3 Fit with Study Programme

The link between the project and the engineering and policy analysis programme could have been strengthened if a more thorough actor analysis was executed. A quick scan revealed that some actors have conflicting objectives. A method within the Engineering and Policy Analysis programme such as cognitive mapping could have been used to obtain more insight in the perceptions of the involved actors.

However, overall I am satisfied with the project's fit with the engineering and policy analysis programme. This project used a system perspective to decompose the problem through the identification of the main actors, which determined the performance of the system. Second, to explore the potential effects of LiveLines in its current form, simulation modelling was used.

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# Appendix A

## A.1 Statistical Steps

In this section (A.1) the statistical steps which were required to perform to analyse the data are described. First, the cleaning of the Data File is described in part (A.1.1). This cleaning includes, for instance, deletion of missing responses.
Subsequently, in part (A.1.1), data file additions are discussed. Sometimes the form of the data should be adjusted to have a successful statistical analysis.

### A.1.1 Data File Cleaning

The following steps were executed during the data file cleaning:

- Deleting of Missing Responses—Three responses were deleted due too many missing answers.
- Changes in Country Names—Incorrect spelling was corrected. For instance, Holland was changes to the Netherlands.

### A.1.2 Data File Additions

To perform a statistical analysis new variables were introduced. The following variables have been added to the dataset. It is important to mention that this is an iterative process, since results in SPSS sometimes needed changes in the data file. Therefore, a distinction is made between additions mad before the SPSS analysis and after:

- An additional variable was created which consist of the distance of the country of origin to –Amsterdam

- A variable was created summing the number of attractions which had been visited.

## A.2 SPSS Output Windows of Representativeness

In this part, the results of the statistical tests are given. Testing for representativeness is needed to determine whether a sample is representative of the population it is drawn from.

### A.2.1 Representativeness for Length of Stay

In this section the representativeness for the *length of stay* of visitors is tested. The report mentions that on average visitors stay 3.8 nights in Amsterdam (*Amsterdam Metropolitan Area ; Vistors Survey 2016*, 2016) The means of were compared using a one sample t-test. The following hypothesis is formulated:

*H0: The sample is representative regarding to length of stay*
*H1: The sample is not representative regarding length of stay*

| *T* | *df* | *Sig. (2-tailed)* | *Mean difference* | *95% Confidence Interval of the Difference (Lower / Upper)* |
|---|---|---|---|---|
| *0.837* | 96 | .405 | 0.138 | -.19 / .47 |

**Table: A.1 Results of test with test value 3.94**

A significance value of 0.405 (2-tailed) was found. This value is higher than 0.05 and the 0-hypothesis can therefore not be rejected. Therefore, the difference between the sample and the population is not statistically different. In summary, it is assumed that the data is representative for *length of stay*.

### A.2.2 Representativeness for Age Distribution

Secondly, the representativeness of the data has been tested for the age distribution. Data of age distribution of tourists was gathered from the Amsterdam Marketing report (*Amsterdam Metropolitan Area ; Vistors Survey 2016*, 2016). The measured values were compared with a chi-square test.

| *Age group* | *Observed N* | *Expected N* | *Residual* |
|---|---|---|---|
| *<20* | 9 | 10.7 | -1.7 |
| *21-30* | 35 | 31.0 | 4.0 |
| *31-40* | 20 | 17.5 | 2.5 |
| *41-50* | 13 | 14.5 | -1.5 |
| *51-60* | 15 | 11.6 | 3.4 |
| *>60* | 5 | 11.6 | -6.6 |
| *Total* | 97 | | |

**Table A.2: Comparing observed Age distribution with the data of the visitors**

| *Chi-Square* | *6.059[a]* |
|---|---|
| *df* | 5 |
| *Asymp. Sig.* | .301 |

**Table A.3: Results of The Chi-square Test**

No significant difference between the sample and the population is found. The chi-square value is higher than 0.05. Therefore, the sample is assumed to be representative for the age distribution.

## A.3 SPSS Output Windows of Bivariate Tests

In this section a detailed overview of the output of the bivariate tests are given. As mentioned in the report the following relationships were tested (table A.4)

*Pearson's correlation*

| *Independent variable* | Pearson Correlation | Sig (2-tailed) | Significant relation (yes/no) |
|---|---|---|---|
| *Length of stay* | 0.172 | 0.105 | No |
| *Age* | 0.07 | .950 | No |
| *Gender* | -0.029 | .789 | No |
| *Number of attractions visited* | -0.136 | .421 | No |
| *Distance home country* | -1.46 | 0.155 | No |

**Table A.4 Pearson Correlation Table (not rounded)**

In the subsequent sections (A.3.1 - A.3.5) the SPSS output windows of the correlation tests which investigate the correlation of different variables with the 'maximum willingness to wait' are provided.

### A.3.1 Pearson correlation: Length of Stay

| | | ***LENGTH OF STAY*** | **AVERAGE_ACCEPTED WAITING TIME** |
|---|---|---|---|
| **LENGTH OF STAY** | Pearson Correlation | 1 | .172 |
| | Sig. (2-tailed) | | .105 |
| | N | 95 | 90 |
| **AVERAGE_ACCEPTED WAITING TIME** | Pearson Correlation | .172 | 1 |
| | Sig. (2-tailed) | .105 | |
| | N | 90 | 90 |

**Table A.5: SPSS Pearson correlation output between length of stay and accepted waiting time**

### A.3.2 Pearson Correlation: Age

| | | *Average Accepted Waiting time* | *Age* |
|---|---|---|---|
| *Average Accepted Waiting time* | Pearson Correlation | 1 | .007 |
| | Sig. (2-tailed) | | .950 |
| | N | 90 | 90 |
| *Age* | Pearson Correlation | .007 | 1 |
| | Sig. (2-tailed) | .950 | |
| | N | 90 | 95 |

**Table A.6: Pearson correlation between Age and average accepted waiting time**

### A.3.3 Pearson Correlation: Gender

| | | Average Accepted waiting time | Gender |
|---|---|---|---|
| Average Accepted Waiting time | Pearson Correlation | 1 | -.029 |
| | Sig. (2-tailed) | | .789 |
| | N | 90 | 90 |
| Gender_Dummy | Pearson Correlation | -.029 | 1 |
| | Sig. (2-tailed) | .789 | |
| | N | 90 | 95 |

**Table A.7; Pearson Correlation table gender and max. average accepted waiting time**

### A.3.4 Pearson Correlation: Number of attractions visited

| | | Attractions per day | Average_AcceptedWaitingtime |
|---|---|---|---|
| Attractions per day | Pearson Correlation | 1 | -.136 |
| | Sig. (2-tailed) | | .421 |
| | N | 87 | 90 |
| Average_AcceptedWaitingtime | Pearson Correlation | -.136 | 1 |
| | Sig. (2-tailed) | .421 | |
| | N | 87 | 90 |

**Table A.8 Pearson correlation table: Attractions per day and Average accepted waiting time**

### A.3.5 Pearson Correlation: Distance from Home Country

| | | Attractions per day | Distance from home country |
|---|---|---|---|
| Distance from home country | Pearson Correlation | 1 | -1.46 |
| | Sig. (2-tailed) | | .155 |
| | N | 88 | 90 |

**Table A.9 Pearson correlation table: Attractions per day and Average accepted waiting time**

## A.4 Fitting a Distribution to MWW

This section provides the SPSS output windows of the tests to check whether a poisson distribution could be fitted to the 'maximum willingness to wait'. The waiting times are displayed discrete character of the Poisson distribution

The results of the test are listed in table A.10. All, the three variables, have a significance value of < 0.05. Therefore, a Poisson distribution could not be assumed.

| | N | Minimum | Maximum | Mean | Std. Deviation |
|---|---|---|---|---|---|
| First Preference | 97 | 0 | 120 | 37.80 | 24.564 |
| Third Preference | 94 | 0 | 90 | 27.34 | 15.129 |
| Fifth Preference | 93 | 0 | 60 | 19.34 | 12.192 |

**Table A.10; MWW values**

| | | First Preference | Third Preference | Fifth Preference |
|---|---|---|---|---|
| N | | 97 | 94 | 93 |
| Poisson Parameter[a,b] | Mean | 37.80 | 27.34 | 19.34 |
| Most Extreme Differences | Absolute | .576 | .335 | .344 |
| | Positive | .576 | .335 | .344 |
| | Negative | -.216 | -.212 | -.243 |
| Kolmogorov-Smirnov Z | | 5.672 | 3.245 | 3.321 |
| Asymp. Sig. (2-tailed) | | .000 | .000 | .000 |

**Table A.11; Output of Kolmogorov-Smirnov test**

### A.4.1 MWW Graphs

In figure A.1 - A.4, a graphical overview is given of the 'maximum willingness to wait' collected in the questionnaire.

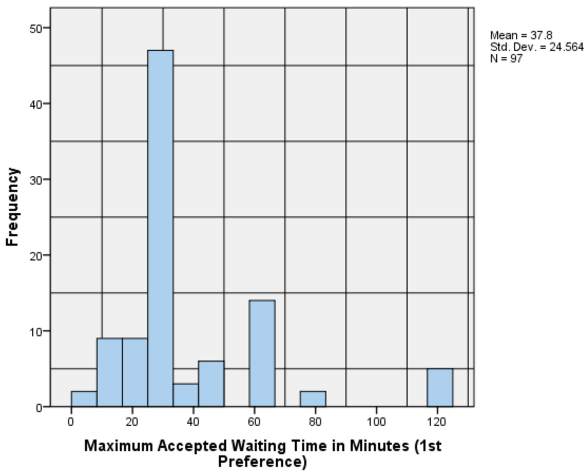


**Figure A.1; MWW (1st preference)**

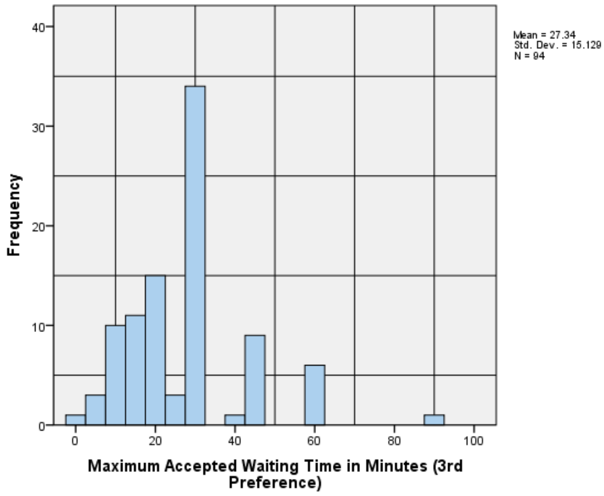


**Figure A.2; MWW (3rd Preference)**

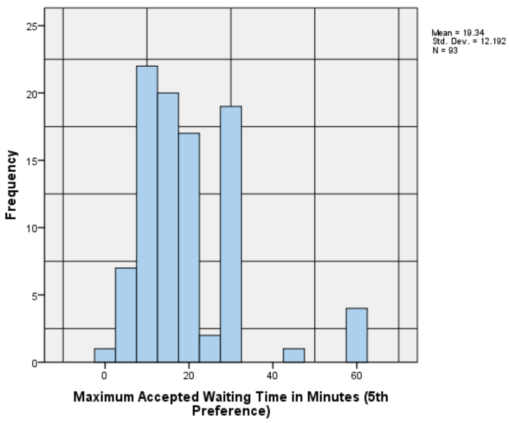


**Figure A.3; MWW (5th preference)**

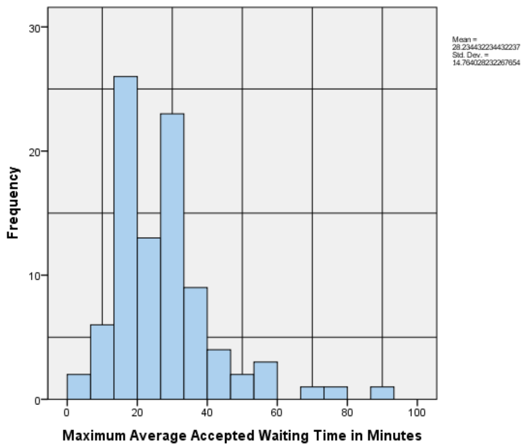


**Figure A.4; MWW (cumulative)**

# Appendix B

## B.1 Action Diagram of the Visitors

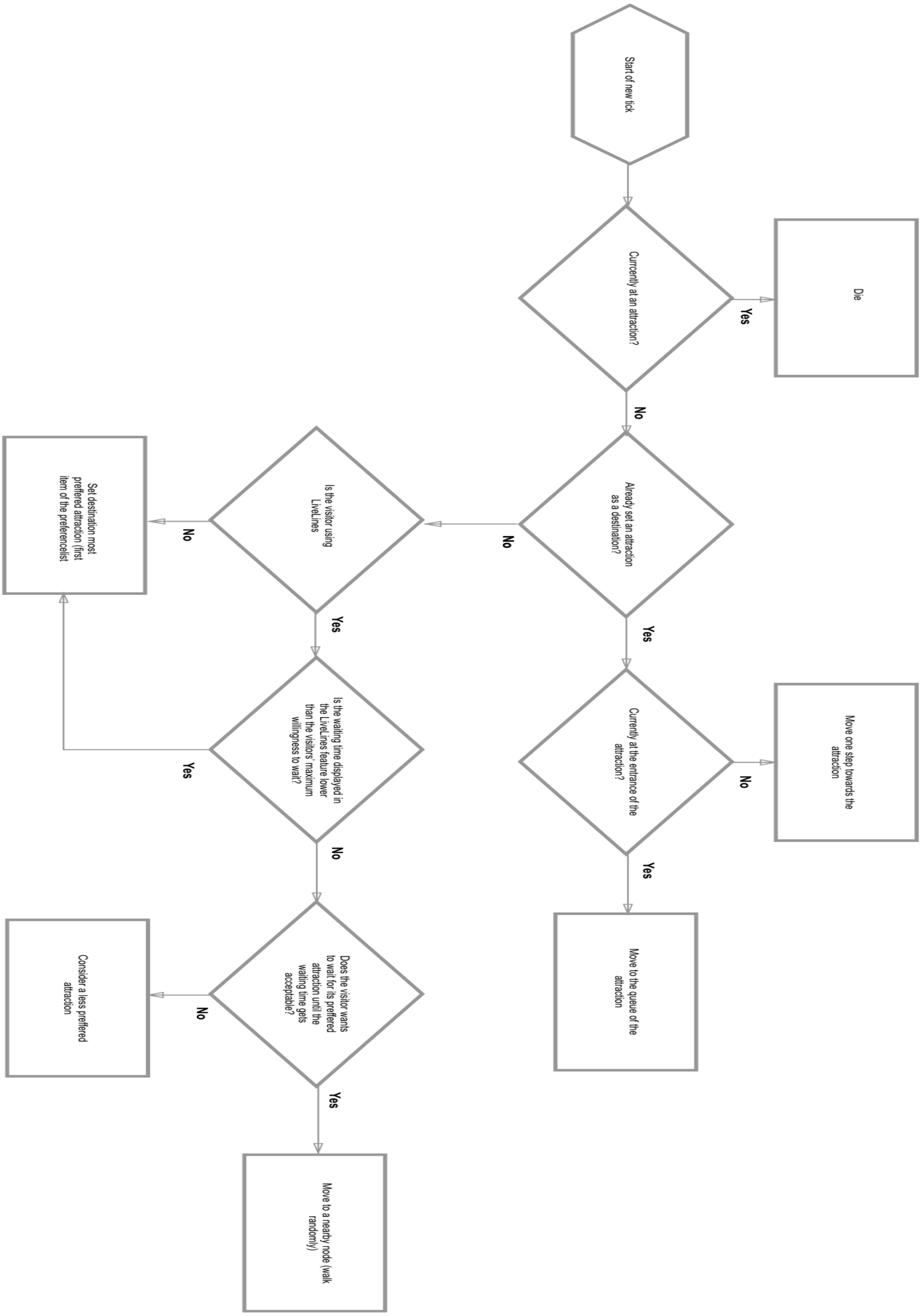


**Figure B.1; Action Diagram of Visitors**

## B.2 Model Setup

### B.2.1 Agent representation

The average daily visitors of the following attractions in Amsterdam which took part in the trial of LiveLines are known:

Rijksmuseum:  +- 6000 visitors/day
Van Gogh museum: +- 5800 visitors/day
Eye Filmmuseum +-  2000 visitors/day
Maritime Museum +- 1000 visitors/day
Heineken experience +- 1500 visitors/day

(Parool, 2016)

In total: 16300 visitors per day
No numbers were found about the following museums;

Frans Hals museum
Cobra Museum
Rembrandt House
Tropen museum

Since days of interest is a very busy day, 30.000 visitors are assumed during a day in the Easter weekend.

During a run (day) in the simulation model, between 700-900 visitors enter the system.  30.000 / 800 = around 40 visitors. Therefore, 1 agent represents 40 visitors.

## B.3 Additional Graphs

### B.3.1 Experiment 1: Reference Scenario Including Confidence Intervals

In the following figures the confidence interval development is shown for 15 and 100 runs respectively.

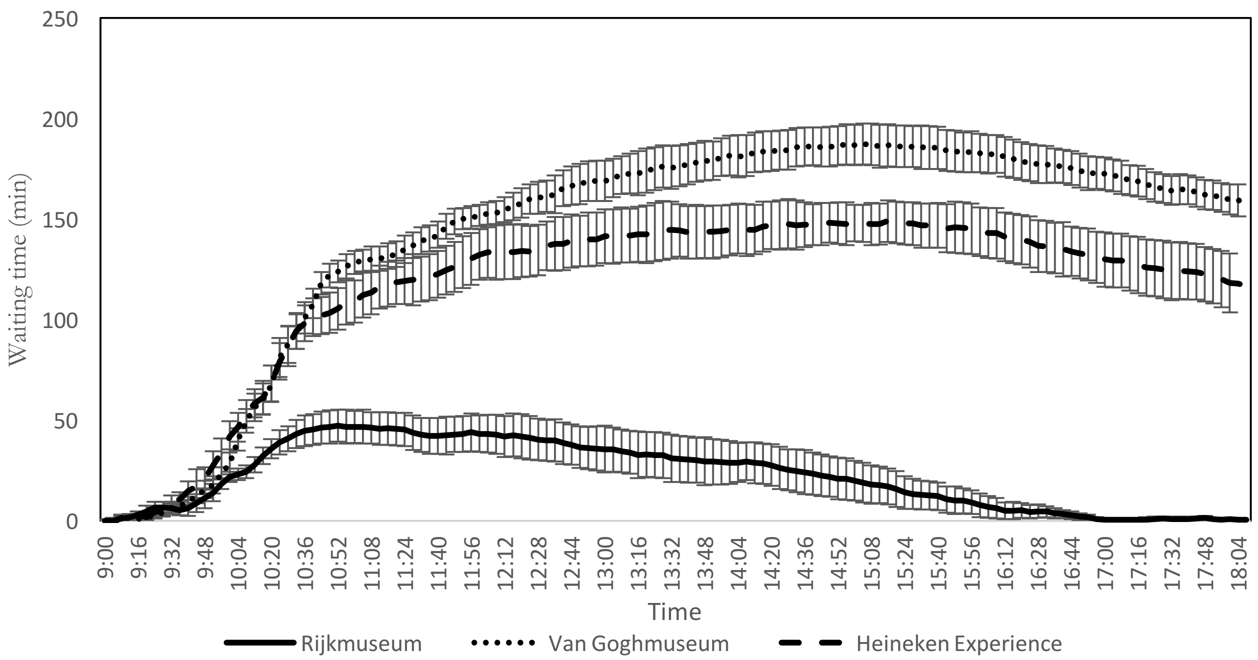


**Figure B.2; Reference Scenario including confidence interval (15 runs) (Experiment 1)**

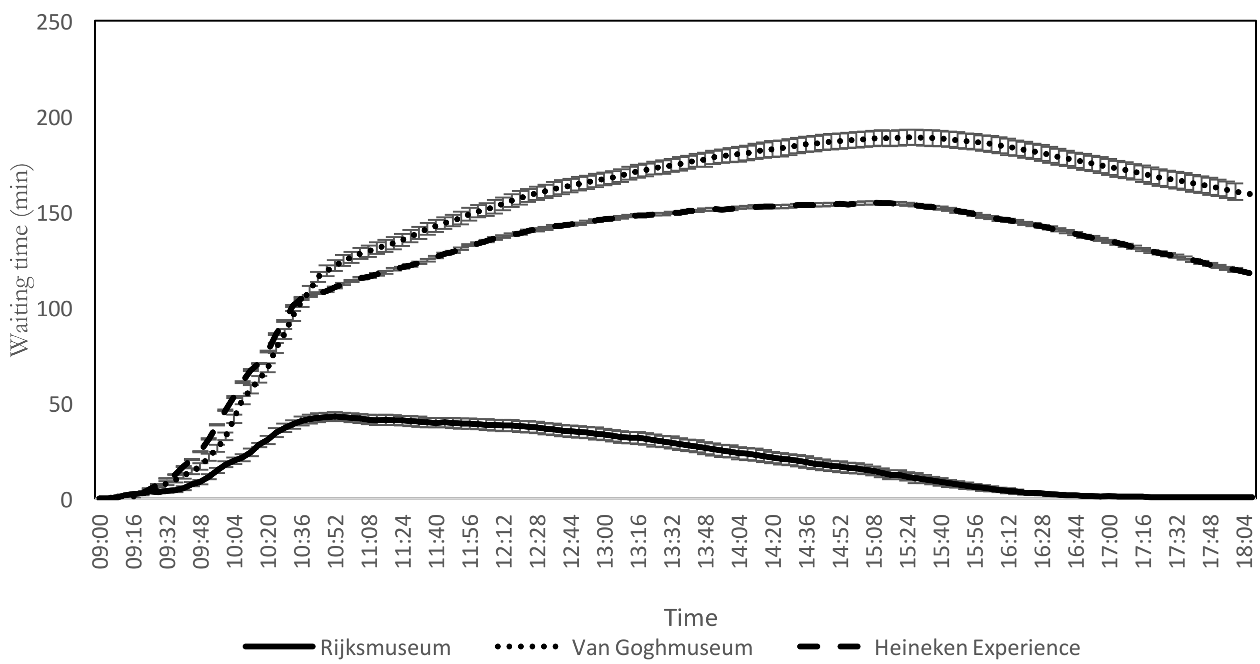


**Figure B.3; Reference Scenario Including confidence interval (100 runs) (Experiment 1)**

### B.3.2 Experiment 4: Graphs

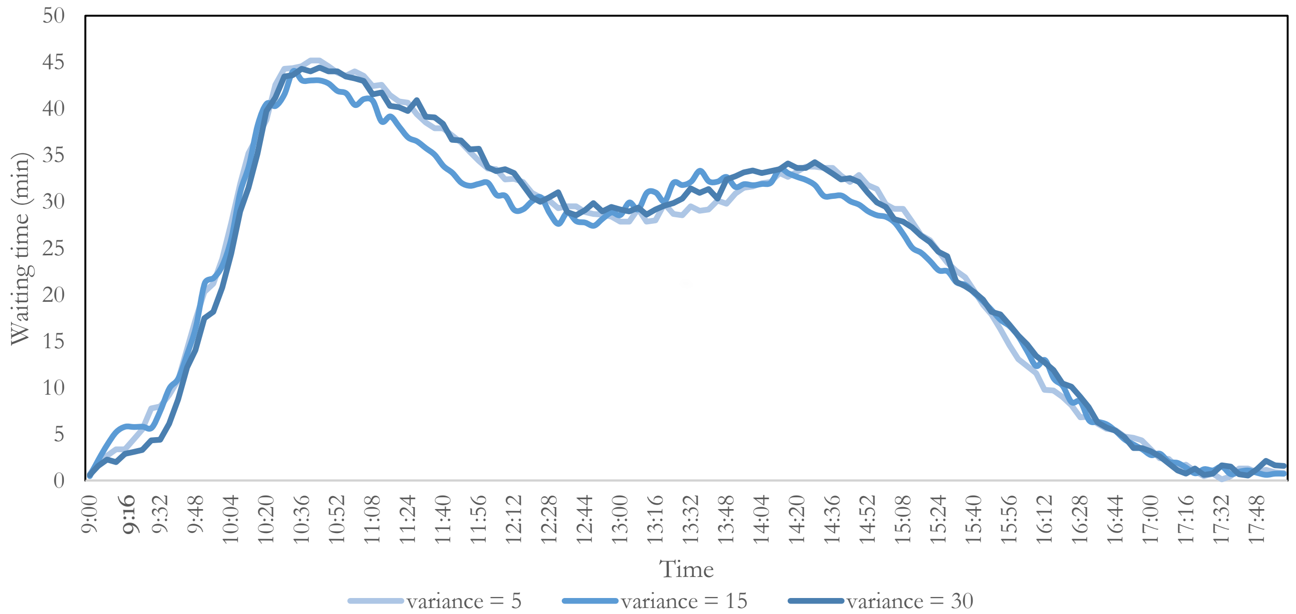


**Figure B.4; Attraction 1 (Experiment 4)**

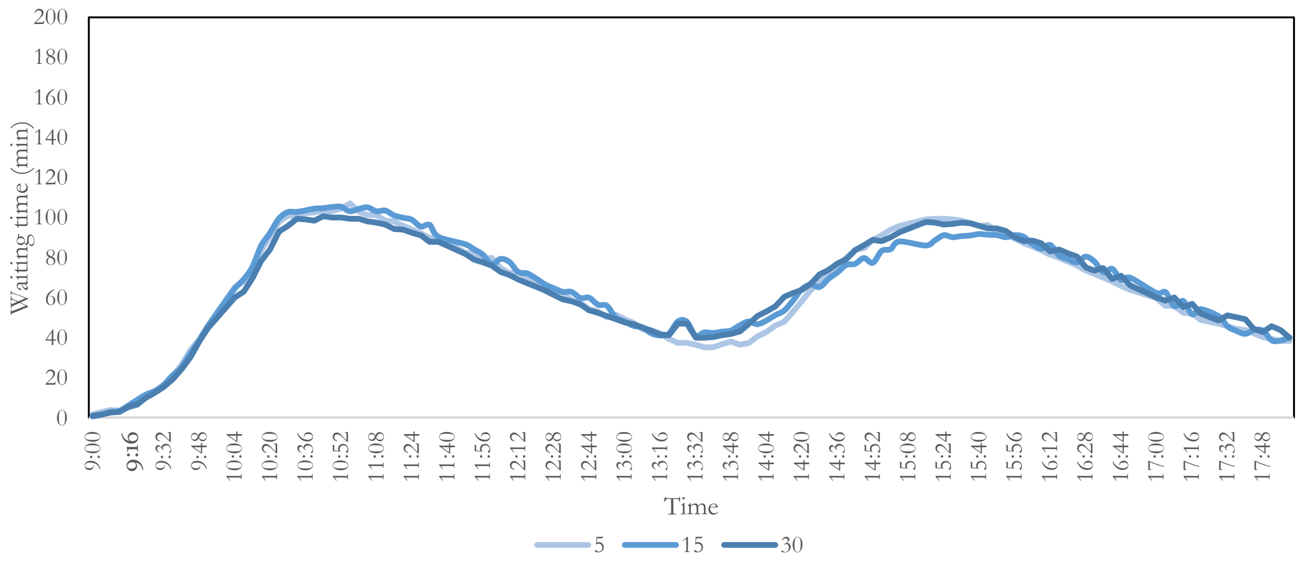


**Figure B.5 Attraction 3 (Experiment 4)**

### B.3.3 Experiment 5: Graph

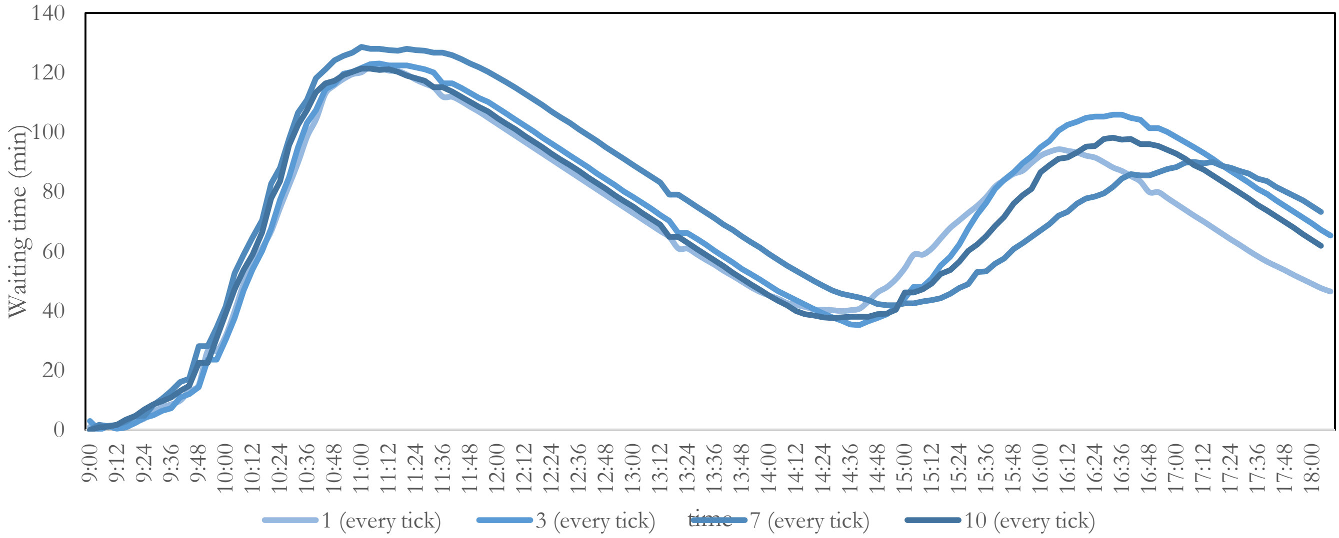


**Figure B.6; Museum 2 (Experiment 5)**

### B.3.4 Experiment 7: Graph

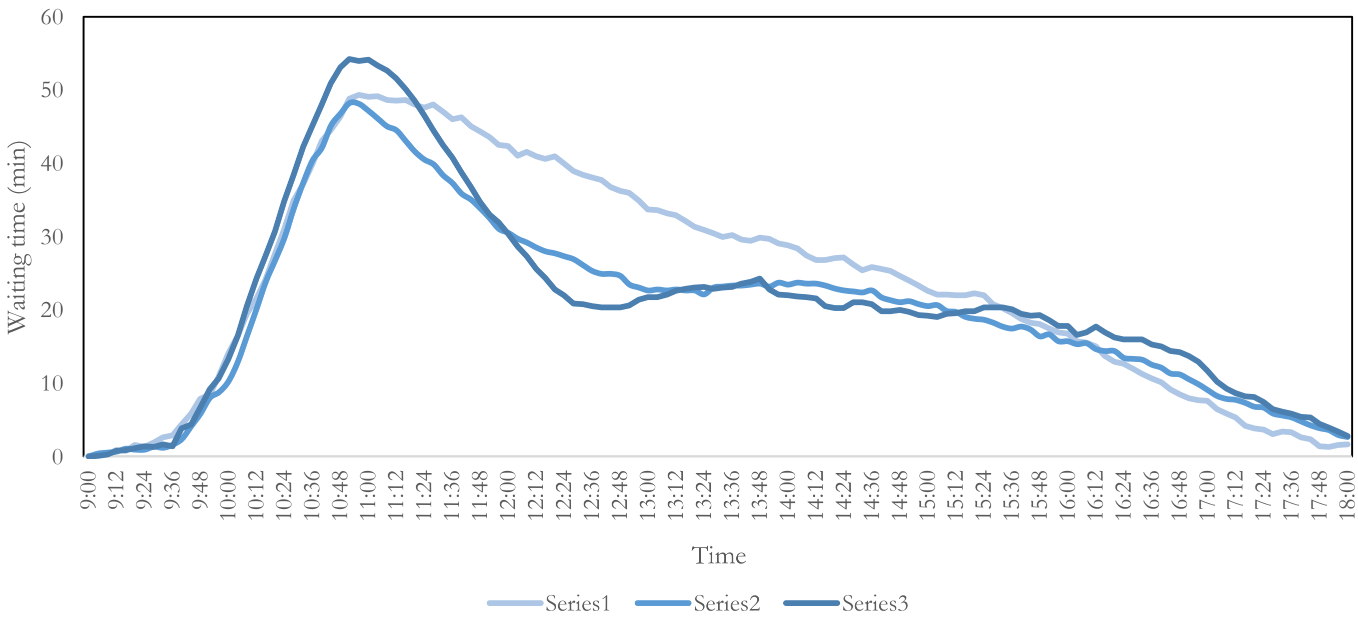


**Figure B.7; Attraction 1 (Experiment 7)**

# Appendix C

Dataset description.

- A total of 4635 waiting times were entered
- The maximum waiting time entered is 180 minutes

| attraction | Number of observations (in total 3 months) |
|---|---|
| Rijksmuseum | 42 |
| Van Gogh | 985 |
| Heineken Experience | 200 |

**Table C.1; Dataset Description**