# Modelling the effects of social networks on activity and travel behaviour



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# Summary

Activity-based models of transport demand are increasingly used by governments, engineering firms and consultants to predict the impact of various design and planning decisions on travel and consequently on noise emissions, energy consumption, accessibility and other performance indicators.

In this context, non-discretionary activities, such as work and school, can be relatively easily explained by the traveller's sociodemographic characteristics and generalised travel costs. However, participation in, and scheduling of, discretionary and joint activities are not so easily predicted. Understanding the social network that lies on top of the spatial network could lead to better prediction of social activity schedules and better forecasts of travel patterns for joint activities.

Existing models of activity-travel behaviour do not consider joint activities in detail, except within households to a limited extent. A recent attempt developed at ETH Zürich to incorporate social networks in a single-day optimisation scheduling model did not model joint activities as such, rather rewarding individuals for scheduling activities at the same location and at the same time as their friends. Realistic social networks were also not incorporated.

The aim of this thesis is to contribute to this rapidly expanding field by developing a simulation of activity and travel behaviour incorporating social processes and joint activities to investigate the effects on activity and travel behaviour over a simulated period of weeks. The model developed is intended as a proof-of-concept.

In order to achieve this aim, an agent-based simulation was designed, implemented in Java, and calibrated and partly verified with real-world data. The model generates activities on a daily basis, including the time of day and duration of the activity. An interaction protocol has been developed to model the activity decision process. Data collected in Eindhoven on social and joint activities and social networks has been used for calibration and verification.

Alongside the model development, several issues are addressed, such as exploring which parameters are useful and their effects, the data required for the validation of agent-based travel behaviour models, and whether the addition of social networks to models of this type makes a difference.

Sensitivity testing was undertaken to explore the effects of parameters, which was applied to increasingly more complex versions of the model (starting from one day of outputs with no interactions between individuals and finishing with full interactions over many days). This showed that the model performed as expected when certain parameters were altered.

Due to the components included in the model, scenarios of interest to policy makers (such as changes in population, land-use changes, and changes in institutional contexts) can be explored. Altering the structure of the input social networks and the interaction protocols showed that these inputs do have a difference on the outputs of the model. As a result, these elements of the model require data collection on the social network structure and the decision processes for each local instantiation. Two more "traditional" transport planning policy scenarios, an increase in free time and an increase in travel cost, showed that the model performs as expected for these scenarios.

It is shown that the use of agent-based modelling is useful in permitting the incorporation of social networks. The social network can have a significant impact on model results and therefore the decisions made by planners and stakeholders. The model can be extended further in several different directions as new theories are developed and data sets are collected.

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# Chapter 1

# Introduction

Recent travel forecasting models have focussed strongly upon the fact that the demand for travel in a spatial network is derived from the activities in which people participate, such as work, school, shopping, sport, leisure, and social events. Non-discretionary activities such as work and school can be partly explained by the traveller's sociodemographic characteristics and generalised travel costs (Hackney and Marchal, 2007). Participation in, and scheduling of, other activities is not as easily predicted.

Participation in social activities is determined by friends and also the groups that one is a member of, i.e., household, workplace/school, sporting groups, voluntary organisations and clubs. These groups form part of an individual's social network. This network is a representation of the people one interacts with, and sometimes also contains an indication of how people are connected and how strongly. People in your network will change over time as you leave jobs, move house etc. and they might also influence where and/or how you travel, by telling you about new locations and travel modes etc.

Understanding the social network that lies on top of the spatial network can lead to better prediction of social activity schedules and therefore better forecasts of travel patterns, in particular for social and leisure activities.

The interest in the area of social activities has evolved from activity-based methods, where the focus is on "*how* individuals select, plan, execute and adapt their activities over time, space and across individuals" (Doherty and Ettema, 2006). This interest covers investigating the formation of social capital and social network geography (Axhausen, 2008), the impact of information and communication technologies (ICT) on leisure activities, in particular the amount of substitution and complementarity and other changes (Mokhtarian et al., 2006), the collection of social network data and activities (Carrasco and Miller, 2009), the generation of social networks (Arentze et al., 2009; Illenberger et al., 2009), and modelling influence (Sunitiyoso and Matsumoto, 2009) and activity generation (Hackney and Axhausen, 2006).

As a result of ICT, the nature of social and leisure activities is changing, and therefore requires more thought and analysis. Mokhtarian et al. (2006) also note that it looks like the demand for discretionary activities will increase in the future. ECMT (European Conference of Ministers of Transport) report 111 states that "in the case of the gainfully employed, the amount of leisure time has considerably increased in the course of time, through shorter daily, weekly and yearly working hours and a shorter working life." (European Conference of Ministers of Transport (ECMT), 2000, p63)

Doherty and Ettema (2006) describe this change in focus as trying to understand what "drives participation in certain activities". They describe three aspects of how networks can influence activity participation:

- our roles in our networks;
- the locations of others in our networks;
- the information contained in the network about activities and locations.

Social activities constitute 25-40% of all trips (based on data from European countries noted in Axhausen (2006)), however are not systematically and consistently considered in activity models. Currently social activities are predicted in an individual manner, with random location choice and only for a single day with no consideration of history. Being able to better predict these activities could lead to improved predictions of activity-travel patterns for urban and transport planners to use when exploring scenarios.

## 1.1 Aim and scope

The aim of this thesis is to develop an agent-based simulation model of activity and travel behaviour incorporating social processes and joint activities.

An agent-based simulation is a computational model of individuals interacting within an environment. The model will then be used to investigate the effect of social processes on activity and travel behaviour, and will be a proof-of-concept that is extensible. A point of difference to many existing transport models is that activities will be modelled over many days, so that activity history can be taken into account.

The model focuses on the activity and travel generation that emerges from the network: predicting the participants in, frequencies of, and locations of social activities. This project is mainly interested in day-to-day/short-term social activities that do have a travel component. While the model is empirically realistic, the focus is not on the replication of a given environment.

This approach is very different to existing models of travel demand, which tend to use statistical approaches on activity-travel data collections and also tend to focus on one aspect of demand, e.g., the group size, the time of day, the activity duration etc. The model developed in this thesis covers a larger range of issues, however a trade-off is that they are covered in restricted detail. This is in part due to complexity, and in part due to a lack of data or specific theory for the transport domain. We are aware of data collection and analysis efforts regarding several aspects of the model which are currently underway. Once those results are established, this model could be extended. As the effects of different aspects can be explored together, the model can cater for a wider range of scenarios and policies of interest to planners. An advantage of agent-based modelling is that behaviour can more closely model the real world and the model is more flexible when new or different behaviours are identified.

In the long-term, the processes developed can be used in large-scale simulation models of travel demand, in particular assisting in the formulation of daily activity patterns.

## 1.2 Research questions

This thesis makes two major contributions: how these sorts of models can be built (taking into account the expectations and theories of both the transport modelling community and the agent-based modelling/simulation community), and whether the inclusion of social networks into transport models makes a significant difference to the model outcomes.

The following questions will be covered in this thesis:

- How can social behaviours be modelled in the context of travel behaviour?
- How can these models be calibrated and validated?
- Can the separate effects of parameters be identified?
- Does the incorporation of social networks have an effect on the model outcomes in the context of activity-travel modelling?
- How can the concepts behind this model be incorporated into existing models?

## 1.3 Overview

In chapter 2, an overview of transport modelling is presented, focussing on activities, activity-based models and joint activity models.

However, the focus of this thesis is joint activities outside households, therefore chapter 3 describes social network models and data collection efforts for social activities.

Following on from existing work, the conceptual model is described in chapter 4. This casts a broader net across many aspects that are relevant to a model of social activities and makes connections with research in other domains. This chapter also describes the overall modelling process, from problem definition through to experimentation, that will form the backbone of the following chapters.

In chapter 5, the conceptual model is refined and a design and implementation is demonstrated. This chapter is based around a basic software engineering process and shows how these sorts of models can be developed.

Methods for validation are discussed in chapter 6. Although this is a theoretical chapter, it provides background for the remainder of the thesis and discusses some of the issues behind the validation of transport and agent-based models. As we will see in chapter 4, validation is an ongoing part of the process and should not be left to the end, however it is placed here to provide some continuity with the final chapters.

Chapter 7 describes the data used and the calibration process. The generation of the input social networks is discussed, along with a demonstration of model verification, in particular looking at the internal consistency and a model walkthrough.

The outcomes of a sensitivity analysis are reported in chapter 8. This provides an indication of the effects of changing different parameters. In order to investigate the performance of the model, the model is tested in several steps with increasing complexity, beginning with one day and no interactions between agents, then expanding to many days, and then adding in interactions.

An illustration of the model is described in chapter 9, in order to demonstrate the effect of changing the social networks and decision processes. The effects of changing the interaction protocol (how people decide to participate in an activity with someone else) and the input network (how people are connected to each other in the population) are explored, as well as two scenarios of current interest to transport planners (an increase in free time and an increase in travel cost).

Chapter 10 brings the thesis to a conclusion with suggestions for future work. In particular, ongoing research regarding several aspects of the model is discussed, as well as recommendations for how the outcomes of this model can be disseminated into existing models.

# Part I

# Background

# Chapter 2

# The activity-travel aspect

Modelling plays a key role in transport and urban planning. It is rare to be able to experiment with changes to the transportation and urban framework of a city in-situ[1]. As a result, being able to create an artificial representation to explore potential effects of changes can be of great assistance to planners, stakeholders, and decision makers.

This chapter describes how transport modelling has developed from early trip-based models to activity-based models, which are currently being used in practice. The notion of an activity is defined and current activity-based models are reviewed. These models can be divided into different categories, depending on the approach used. Finally, models which focus on joint activities in households are described.

## 2.1 The planning process

With respect to transport planning, modelling forms part of a larger decision-making process. According to Ortúzar and Willumsen (2001, p25):

> Transport planning models on their own do not solve transport problems. To be useful they must be utilised with a decision process adapted to the chosen decision-making style.

The process consists of the steps outlined in figure 2.1. Firstly, the problem must be defined, which is specified as a "mismatch between expectations

[1] Some smaller changes can be trialled, such as temporary barriers in a residential area, or the timetable changes (trialling a every-10-minutes departure rather than a set timetable) undertaken by Nederlandse Spoorwegen (Dutch Railways) in 2010.

and perceived reality". Data is collected about the present state, and the model is constructed. The process then splits in two: on one hand a set of potential solutions or schemes must be generated, usually with assistance from stakeholders, and then the planning variables must also be forecast, e.g., the expected population growth in the area, changes in car ownership.

The model is then tested in two ways: by testing different scenarios to confirm that the model is reasonable, and by testing solutions to estimate how well the model performs. Finally, the solutions are evaluated, a recommendation is made, and the preferred solution is implemented.

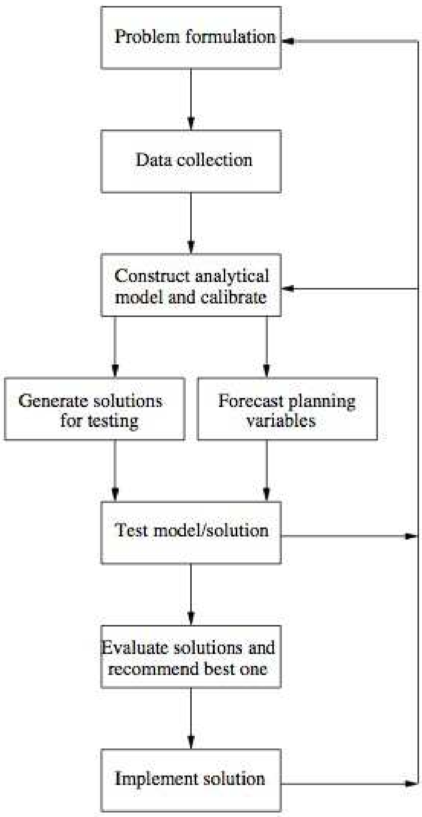



Figure 2.1: The planning process.

This process is reasonably simple, as noted by Ortúzar and Willumsen (2001), and is useful for smaller transportation problems which are "well-defined and constrained". However, most transportation problems tend not to be simple. In those cases, a monitoring step can be added and continuous planning can be implemented, where the model is frequently updated with new data and behaviours.

## 2.2 Transport modelling

An established approach for transport modelling is the "four-step" model (McNally, 2002), which was developed in the 1950s for looking at travel behaviour at an aggregate level. The area to be modelled consists of zones, which can be based on defined zones, such as postcodes or local government areas, or custom defined by the modeller. The model contains the following steps:

- trip generation, in which the origin and destination zones of trips are calculated, taking into account trip purposes and sociodemographics;
- trip distribution, which determines trips made between two zones;
- mode choice, in which the mode of travel (e.g., car, public transport, etc.) is determined for each trip;
- route assignment, which allocates trips to a particular route.

A strength of the four step model is the logical process (Banister, 2002), however, many aspects of the model have been criticised. According to Banister (2002), the process is too rigid and the model is more concerned with reducing travel time instead of other travel measurements. It cannot take into account individual choice (Golledge and Gärling, 2004) and cannot represent "the decisions that consumers make when confronted with alternative choices" (Domencich and McFadden, 1975). Although it was created to be simple, it fails to recognise that transport is complex (Boyce, 2002).

In the early years of the 2000s, the four-step model was still being described as state-of-the-art as it was seen to be the only approach available (McNally, 2002). However, research into disaggregate modelling started becoming popular in the 1980s, especially with the development of more powerful computing technology and increased confidence in computational models (Ortúzar and Willumsen, 1994).

## 2.3 Activities

Another drawback of the four-step model is that it is based on trips, rather than activities (McNally, 2002), which is contradictory to current belief about travel behaviour.

Axhausen (2008) states that an activity is “a continuous interaction with the physical environment, a service or person, within the same socio-spatial environment, which is of importance to the person.”

Activities are generated due to “physiological, psychological and economical needs” (Wen and Koppelman, 2000). The different activities are commonly categorised as subsistence (work-related), maintenance (keeping the household running), and leisure. Leisure activities are difficult to define: for example, what may be considered maintenance for one person could be leisure for another (Mokhtarian et al., 2006). However, these categories are inherently individualistic, whereas we are concerned with social activities. Following Arentze and Timmermans, we define social activities to be those activities that involve commitments to meet other persons at certain locations and times. Furthermore, these commitments may impose constraints upon the times and locations of other activities (Arentze and Timmermans, 2008).

There exist two schools of thought on activity generation for travel behaviour purposes. The first is that activities stem from desires, as proposed by Chapin (1974) who considered the propensity to participate in an activity along with the available opportunities. The other approach is that the activity set is constrained in various ways. Hiägerstrand’s (Hägerstrand, 1970) constraints included capability (need to sleep and eat), coupling (need to coordinate with other people or comply with opening hours of institutions), and authority (need to conform to societal laws and customs) constraints. The former, more needs-based school is relevant for our work; in particular Chapin (1974) noted that discretionary activities are generated more by choice than by constraints. More specific theories of determining duration and frequency are reviewed by Arentze and Timmermans (2000).

## 2.4 Activity-based models

Activity-based models "aim at predicting which activities are conducted where, when, for how long, with whom, the transport modes involved and ideally also the implied route decisions." (Arentze and Timmermans, 2000)

This is different to the traditional trip-based models that focus on single trips, rather than trip chains. It also emphasises why the travel is being undertaken. Certain activity-based models also model the choice process, as opposed to choice models where only the outcome is modelled.

Hägerstrand (1970) is often cited in articles on activity-based approaches as one of the first to recognise that the focus should be more on people rather than locations. In the late 1980s, Kitamura (1988) discussed the current state of activity-based analysis and looks at the contribution to the science of travel behaviour and as a planning tool. Algers et al. (2005) presented a more recent analysis of models focussing on their use in urban transport analysis. They claim that four step models are better for evaluating construction of new infrastructure rather than for managing existing demand. They also claim that activity-based models are not a well-defined family of models. Some systems use utility maximisation, some focus on scheduling fixed/flexible activities, modelled by logic rules or decision tables, and some predict how patterns will change in response to policy.

Several articles (Axhausen, 2000; Jovicic, 2001; Kitamura, 1988; McNally, 2000; Wang, 1998) list elements of the activity-based approach. Some lists overlap with others, however the main points are:

- The key element is that travel is derived from activity participation.
- Activities are influenced, planned, and executed in coordination with one's household and social networks.
- The focus is on sequences of activities rather than single trips or single activities.
- There are various constraints on activities.

Several models of activity-based travel demand modelling have been created and fall into several categories according to Timmermans et al. (2002b).

### 2.4.1 Constraint-based models

Models can be based on constraints, where all possible activity sequences are generated and then checked for feasibility. Some of the attributes that are checked for include whether there is enough time between activities, whether activities can start after the start time and end before closing time, and that the activity sequence is not violated (e.g., leaving work before work starts). Choice or preferences are not taken into account.

As a result of the lack of choice modelling, a drawback of these models is that if the space-time environment is changed, the modelled behaviour does not change in a reasonable manner, leading to unrealistic results.

### 2.4.2 Choice models

Another type of models are those based on utility maximisation and other choice heuristics. Choice and constraint models can be combined. Activity-based models currently in development use several linked choice models, either in a nested (e.g., Bowman and Ben-Akiva) or sequential (e.g., CEMDAP, FAMOS) fashion.

Travel demand is the result of decisions made by an individual (Bierlaire, 1998), therefore choice models appeared to be a suitable approach. These decisions could be about activity, destination, departure time, mode and itinerary. The "unit" is still single trips, like the trip-based models.

The elements of choice models are:

- the decision maker;
- the alternative options to choose from;
- the attributes of each alternative;
- the decision rules.

The decision maker represents individual entities whose decision making behaviour is being modelled. The entities could be either an individual person or a household. Attributes of the decision maker that will affect the decision outcome need to be included in the model. For transport models, these include income, car ownership, etc.

In a choice model, each decision maker has a discrete set of alternatives to choose from. This is usually a reduced set of the universal set of alternatives, as the decision maker may not be aware of all the alternatives that exist in the environment.

Each alternative in the choice model has attributes associated with it. As with the attributes of the decision maker, information is required on the properties that are likely to influence the decision maker.

The decision rule determines the calculations used to choose an unique alternative (Ben-Akiva and Lerman, 1985). This could be based on a dominance calculation, where the alternative that is better than all others based on its attributes is chosen, however there may not be a single alternative that satisfies this criteria. Another method is satisfaction, where the attributes of the chosen alternative exceed a certain threshold. A common rule makes use of utility theory, where the "value" of a particular alternative is calculated and the most "valuable" alternative is chosen. The actual utility value is unimportant, rather how it compares to the utilities of the other alternatives.

The utility can be calculated using different models. All models are based on a combination of a deterministic part and a stochastic part. The deterministic part is calculated from the attributes of both the decision maker and the alternative. The stochastic part allows for unobserved factors. The stochastic terms are either uniformly distributed, normally distributed (probit) or IID Gumbel distributed (logit). Logit models are most commonly used as linear models are not useful at extreme values and probit models lack a closed analytical form.

The simplest model is a binary choice model with two alternatives to choose between, which can then be generalised to a multinomial choice model, usually a multinomial logit model. This model can only be used if the alternatives are independent (the Independence from Irrelevant Alternatives property). This property is defined as follows: "the ratio of the probabilities of any two alternatives is independent from the choice set" (Bierlaire, 1998).

An often-cited example of this is the red/blue bus paradox: imagine a traveller has two mode choices – a car and a red bus – and both are equally attractive and have a probability of 0.5. If another option is added to the choice set, then if the alternatives are independent, then the probabilities become 0.33 for each option. However, if this new option is a blue bus, that is, identical to the red bus except for the colour (which, for our rational traveller, does not affect their preferences) and therefore the probability for the car should remain 0.5 and the probabilities of the two buses should sum to 0.5. If alternatives are correlated, then a nested logit model is used, in which correlated alternatives are grouped together.

The current state-of-the-art choice model is the mixed logit model. This improves on the logit model by permitting "random taste variation, unrestricted substitution patterns, and correlation in unobserved factors over time" (Train, 2009).

The main drawback to the choice model approach to transport models is that the processes that result from policy or societal changes cannot be fully represented in a choice model. The relationship between activities across a day is also not an important consideration (Doherty and Ettema, 2006). (Marchal and Nagel, 2005) claim that the use of utility models for large transport models is infeasible, as the number of choices is too great. They also note that the actual decision process is not modelled, just the outcome.

An example of a choice model is CEMDAP (Comprehensive Econometric Micro-Simulator for Daily Activity-Travel Patterns) This is a continuous-time activity-travel modelling system, consisting of a suite of econometric models (Pinjari et al., 2007). It is developed by the Center for Transportation Research (CTR) at the University of Texas at Austin. The system is implemented in Visual C++ using a PostgreSQL database backend.

There are two parts to the system. Generation-allocation models handle the decision-making process and determines the activities to be undertaken and their constraints. Scheduling models determine how activities are scheduled to form activity-travel patterns. It also uses space-time constraints in pattern choices and claims to be applicable at any spatial/temporal resolution.

FAMOS (Florida Activity Mobility Simulator) is another activity-based system used for forecasting and policy analysis (Pendyala et al., 2004). It was developed for the Florida Department of Transportation at University of South Florida. It takes advantage of the data already collected for four step models and therefore the data requirements include zonal socio-economic data, zonal network level-of-service data and household travel survey data.

The output of the model is a series of activity-travel records for all people, that can then be aggregated spatially and temporally. Activity-travel patterns are simulated at an individual level. The system consists of two modules: the Household Attributes Generator System, which generates the household/individual attributes and their fixed activities agenda, and the Prism-Constrained Activity Travel Simulator, which determines the individual schedules.

Cirillo and Axhausen (2010) used a six-week diary to create a multi-day mixed multinomial model of activity choice and timing. They found that the sociodemographic variables were not as dominant as the history. Although this approach was promising, there were issues with the history and also some of the activities, in particular shopping tours on the weekend.

### 2.4.3 Computational process models

Computation process models are essentially rule-based systems. The model contains a series of rules that can be triggered to (re)schedule activities. They are seen to be more realistic than pure utility-based models as the particular rules can be fired in particular contexts.

ALBATROSS is a multiagent rule-based model that attempts to predict travel demand by predicting activity schedule choice. The schedule is based on the activity agenda, cognitive environment, and available modes and land-use patterns (Arentze et al., 2000). The decision rules in ALBATROSS are derived from empirical data. The model is based around households.

### 2.4.4 Microsimulation

Instead of looking for the theory behind the data, microsimulations use probability distributions from the data to simulate activity patterns at an individual level. As a result it is considered to be more data-driven.

TRANSIMS (TMIP, 2011) is one of the better known applications of microsimulation of transport. It simulates the movement of people and individuals second-by-second in a regional area (it has been tested in Dallas, Texas and Portland, Oregon). The network is made up of a grid with cells of 7.5m: vehicles can be single cell or multiple cell (for example, in the case of buses).

The four components of the model make use of local surveys and other data sources. The population synthesiser uses census data to generate households and their locations. Activity and demographic surveys are used to create an individual activity plan for each individual. Route plans are then generated from the activity plans, and finally the traffic simulator generates the actual traffic.

The final outputs can be analysed by looking at individuals or aggregate results, both spatially (e.g., for a link) and temporally (e.g., for a specific time period). Although the model does not take into account detailed driver behaviour or detailed intersection processes, it is useful for analysing congestion, fuel usage, emissions and safety in more detail than previous models.

### 2.4.5 More recent approaches

Moving forward from Timmermans et al. (2002b) are two newer approaches to modelling activities. For example, newer versions of TRANSIMS are more agent-based, in that "the travelers are maintained as individual entities with individual attributes, and make individual decisions based on these attributes" (Balmer, 2007).

Another modelling toolkit, developed parallel to TRANSIMS is MATSIM (matsim.org, 2007). MATSIM consists of a database with the input data for a scenario, a data preparation tool, an agent initialisation module, results analysis, and a module to handle the demand optimisation process. Each agent is given an activity schedule or plan, including locations and routes. Each plan is evaluated, plans are randomly modified, and plans are deleted if better plans are found (Hackney, 2009). MATSIM has been used for large-scale simulations of Switzerland, among other applications.

Both TRANSIMS and MATSIM are open source, meaning that modules can be added and changes can be made by researchers and users outside the core development/research groups.

These toolkits are used for modelling activity-based demand in general. More detailed agent-based models, in particular those dealing with some form of social behaviour, will be covered in chapter 3.

An approach currently being explored for generating discretionary activities is based on needs. Activities both satisfy and generate needs and needs grow over time (Arentze and Timmermans, 2009). Maslow's hierarchy of needs has been proposed as a starting point (Miller, 2005), however it is difficult to collect data for model validation. A separate set of needs was proposed by Arentze and Timmermans (2006) which could be identified through empirical research.

More recently, Nijland et al. (2010) undertook a combination of face-to-face interviews and internet questionnaires to identify six basic needs: social contact, physical exercise, relaxation, fresh air/outdoors, new experiences, and entertainment. A further survey including an activity diary showed that these needs were intuitively related to activity choice, e.g., those with high social contact needs were more likely to visit friends and cafés.

## 2.5 Joint-activity modelling

Activity-based travel demand modelling has centred around individual plans and scheduling, however the presence of joint activities can influence individual plans (Gliebe and Koppelman, 2002). As a result of this, research into joint scheduling within households has grown in importance.

The types of interactions and influences can be categorised as (Timmermans and Zhang, 2009; Zhang and Daly, 2009):

- joint trip-making and activity participation, such as travelling together to work/school or going out for dinner;
- influence from other family members, which could also include task allocation, such as one person undertaking shopping for the whole household;
- household resource allocation, such as sharing a car;
- time allocation.

Kitamura (1988) pointed out that the household structure "significantly influences" individual patterns, but whether this structure was useful for prediction was unclear. Bowman and Ben-Akiva (1997) summarise the research regarding how households affect activity demand:

- "households influence activity decisions;
- the effects differ by household type, size, member relationships, ages and genders;
- children, in particular, impose significant demands and constraints on others in the household."

However, these appear to be more about influence on individual decisions and not specifically about joint decisions or activities. For example, I may go shopping more often if I need to purchase groceries for a four-person household instead of a two-person household, but I could undertake that activity alone and schedule that by myself. As noted by Zhang and Daly (2009):

> In the context of transportation policies, ignoring such interpersonal interactions could overestimate the effects of policies and might lead to inappropriate investments. However, the dominating travel behaviour models have mainly built upon individual decision-making theories, which assume that an individual can decide his/her behaviour based on his/her own preference.(Zhang and Daly, 2009)

Activity-travel schedules need to be synchronised in time and space. This is a more complicated task than it may seem. As Gliebe and Koppelman (2002) recognise, sometimes household members may stay longer or arrive earlier at a particular location.

In addition to these analytical studies, several models of joint activity participation have been developed over the years. Examples include Scott and Kanaroglou (2002) who developed a trivariate ordered probit model, Meka et al. (2002) who adopted the structural equations approach, Srinivasan and Bhat (2006) who used a combination of different models and Angrainni et al. (2010) who applied decision trees.

Rindt et al. (2003) reports on the development of a simulation kernel for agent-based activity microsimulation based on the re-characterisation of human activity as interaction between autonomous entities. They started from the idea that “human activity is the negotiated interaction of socially and physically situated individuals and settings” and as a result their kernel assumes that behaviour is adaptive. People, groups and resources (such as buildings) were represented as agents and used a variant of the contract net protocol to organise activities. The framework described was flexible and did not impose many restrictions on negotiations, but was not a complete model in itself.

## 2.6 Discussion

Activity-based modelling has taken the field from looking at only *where* and *when*, with the four-step model, to *what* with the development of activity-based models. These latter models are reaching a level of maturity and are being used outside academia by planners to assist in decision making.

Transport models have evolved in the past fifty years, starting from aggregate models and moving to more disaggregate models looking at the reasons for travel and focussing on activities. Several activity-based models, such as ALBATROSS, CEMDAP, FAMOS, and Ben-Akiva and Bowman-style nested-logit models, are being used outside academia. Microsimulation models permit the simulation of large populations. However, most models are still single-day models, meaning the effects of history cannot be realistically seen.

The disadvantage of pure choice and constraint modelling is that they may not cater well with a change in policy, the environment or activity choice set. This is an important consideration for planners. The development and addition of agent-based techniques to these models permits individual decision-making to be undertaken and therefore the effects can be explored by planners.

However, most research has continued the individual focus from trip-based models, which means that interpersonal relationships cannot be realistically modelled. We know that not all trips and activities are undertaken alone, and hence a level of precision is missing. In order to counteract this, some studies have looked at joint activities. All these studies took into account the heads of households only. Obviously, the problem of joint activity-participation involving people outside the household is equally important for improving transport demand models.

# Chapter 3

# The social aspect

Transport modellers have recognised the need for models to reflect real-world activities better by including activities involving more than one person. Within household activities have been studied, however many activities are undertaken in groups which are not connected by living at the same residence.

Social networks are a technique for describing how individuals are connected to each other, be it in terms of friendship, offering help, sharing knowledge etc. The approach is based on network analysis, which has been used for several domains (such as technological networks (e.g., the Internet) or biological networks (e.g., food webs)), but it has been recognised that social networks differ in their structure (Newman and Park, 2003).

This chapter begins with a discussion of the theory behind social activities, before defining social networks. Modelling social networks, focussing on those incorporating a spatial component, is discussed. Following this, we return to transport applications by reviewing current research in the area of social networks and transport, in particular looking at the collection of data, the generation of networks, and modelling approaches.

## 3.1 Why do we interact and participate in social activities?

Much of the literature appears to accept the need for human interaction as a given, not dissimilar to the acceptance of travel as a derived demand. But why do we want to interact with other people?

Maslow (1943) developed a theory of motivation based around a hierarchy of needs. At the very bottom level are the physiological needs, such as sleep, maternal behaviour, and food. These are considered to be the basic needs for a human.

In the second level, safety, lies a preference for the familiar and a "safe, orderly, predictable, organized world". This encompasses a routine, a stable job, and access to insurance (e.g., health, disability, old age) to help with unforeseen circumstances.

Once the physiological and safety needs have been fulfilled, humans will then look for love, affection and belongingness:

> He will hunger for affectionate relations with people in general, namely, for a place in his group, and he will strive with great intensity to achieve this goal.(Maslow, 1943, p381)

Once one has a group of friends, the next step is to develop self-esteem:

> These are, first, the desire for strength, for achievement, for adequacy, for confidence in the face of the world, and for independence and freedom. Secondly, we have what we may call the desire for reputation or prestige (defining it as respect or esteem from other people), recognition, attention, importance or appreciation.(Maslow, 1943, pp381-382)

Given these needs, it appears that regular interaction with others for different purposes is a technique for meeting this need. For example, a way of achieving respect and esteem from others is by sharing information, or becoming a "powerful" node in one of your networks.

This is a step further from previous transport models that have focussed on the more basic needs, such as sleep and eating/grocery shopping (which can be roughly classed as physiological needs by Maslow) and attending work and school (which can be classed as safety needs by Maslow).

## 3.2 Social networks

Social networks are defined by a set of nodes and links connecting the nodes. Many applications have been investigated, ranging from networks found in biology to which researchers are working together (Strogatz, 2001). From our point of view, the nodes are people, located in space, who are connected to other people. Both the nodes and links can have attributes. For example, a person node could contain age, gender, and other sociodemographic information, while the link between two people could contain when they met, when they last saw each other, and the nature of their connection (e.g., friends, family, work colleagues etc.).

There are two ways of looking at social networks. Global properties of a network can be measured using a whole or complete network, where all of the nodes and links in the study area are known. For transport applications, however, it is not possible to survey an entire town and find out who knows who in order to create a complete network. As a result, egocentric or personal networks are more useful for open systems. These focus on a single person (an ego) and their links to other people (known as alters) (Carrington et al., 2005). The individuals can be sampled from a larger population and links between alters can also be investigated.

Social network analysis methods for complete networks are well-developed, however egocentric networks require some adaptation. These methods help describe the properties of the network and expose patterns, allowing comparison between networks. Hanneman and Riddle (2005) define several popular methods: for example, the centrality (or power) of a node can be measured by counting the number of connections (or the degree) of a node.

## 3.3 Collecting data for egocentric networks

In order to investigate real-life social networks, data must be collected. The main methods for gathering information for an egocentric network are name generators and name interpreters.

Name generators are used to identify the alters of the ego. Subjects are asked to provide the names of their contacts. They may be provided with some guidance on the alters sought after, such as your family, your neighbours, your colleagues, people you are close to, or people you interact with frequently. Spatial or temporal restrictions may also be placed on the alters required. In some case, subjects may be given a list and asked who they know (possibly in a closed-network situation) or they may just be asked to freely name people (Carrington et al., 2005).

Name interpreters are used to obtain information about alters and their relationship to the subject and to other alters. This provides most of the data for describing the network (Carrington et al., 2005).

Another approach is the use of a contact diary to record the names and details of people interacted with, as well as details of the interaction if required. Fu (2005) illustrates two extreme approaches to collecting data about daily interactions. The first consists of a single question:

> On an average, about how many people do you have contact with in a typical day, including all those who you say hello, chat, talk or discuss matters with, whether you do it face-to-face, by telephone, by mail, or on the internet and whether you personally know the person or not? Please give your estimate and select one from the following categories that best matches your estimate: (1) 0-4 persons; (2) 5-9 persons; (3) 10-19 persons; (4) 20-49 persons; (5) 50-99 persons; (6) over 100 persons.

This approach is easy to administer, however only provides an estimate of daily contact.

The second approach involved three people keeping a detailed contact diary, in which the following was recorded for every interaction:

- demographics/socio-economic status of every contact
- contact characteristics: form, content, duration
- location
- audience
- who initiated the contact
- whether ego expected the contact
- whether it was pleasant/meaningful
- relationship between ego/contact, how long known, how frequently in contact, how close/important contact is

This approach collected a lot of useful data, but is extremely time-consuming on the participant's part. It is not stated why there were only three participants, however the length of the study (3-4 months) may have been a factor. The participants spent more than 30 minutes every day completing the diaries, and at completion the diaries contained 2685 unique individuals, 1320 of which were acquaintances, and 8001 interactions.

Kadushin (2005) states the use of publicly-available data to collect data for networks may not be ethical, as people may be named as part of a network who don't know and/or haven't consented to being named. Analysis of public data to reveal underlying patterns is not entirely permissible either. Privacy is a also a major concern for dedicated surveys as names need to be collected in order to construct the network, however names are not necessary for egocentric data collection.

## 3.4 Social network modelling

Social simulation is an active field, which developed as an experimental method for testing theories in social sciences. These models revolve around the interactions between social entities. In this section, we look at social network models, and in particular those which incorporate some spatial context.

As Newman (2002) recognised, research has been slow in understanding the actual workings of networked systems and the focus has been on structural form and analysis. As a result, there are many methods for generating (e.g., the small world model (Watts and Strogatz, 1998) and the scale-free network (Barabasi and Albert, 1999)) and measurements for comparing static, complete (and not necessarily social) networks (e.g., Hanneman and Riddle (2005)). However, it has been recognised that social networks have certain properties, in particular with respect to the similarity between people, their spatial proximity, the overall clustering coefficient (i.e., how tightly-knit the network is) and the variation in size of personal networks (e.g., how many friends do people have; also known as the degree). Progress has been made with incorporating spatial considerations into network generation (Barthélemy, 2003; Hamill and Gilbert, 2009; Wong et al., 2006). These models claim to model social networks more accurately than previously proposed models that do not consider distance between network nodes. Hamill and Gilbert (2009) presented a model known as social circles, where two people are connected depending on the distance between them. This distance could be social (e.g., based on whether two people are similar in terms of age, gender, occupation, religion, or shared values etc.) or spatial.

Hackney and Axhausen (2006) claim that social networks can be generated using behavioural tendencies from sociology, including homophily, bridging social capital (where people are similar in one way but different in another), and putting limits on the number of relationships. The latter property is one of the principles used by Jin et al. (2001) in their investigation into growing networks. Other principles included increased chances of meeting another person if you and them have a mutual friend, and decaying tie strengths decay over time.

In their review of homophily, McPherson et al. (2001) define homophily as the "principle that contact between similar people occurs at a higher rate than among dissimilar people". Some of the attributes that are used as similarity measures include gender, age, education, occupation, social class, behaviour, attitudes, abilities, beliefs, and aspirations.

Distance is also a key factor in the maintenance of relationships. McPherson et al. (2001) claim that the most basic source of homophily is space as we "are more likely to have contact with those who are closer to us in geographic distance than those who are distant." Wong et al. (2006) concur, although they specifically state it is a baseline homophily.

## 3.5 Modelling social interactions in transportation

We now turn to the opposite approach of adding social context to existing spatial models. As a example, one of the first urban planning models was Schelling's model of segregation, in which individuals were modelled in a cellular automata environment and changed their location in order to satisfy their needs for living among similar people. There is both a spatial and social component to this model. Edmonds (2003) extended this model to include a social network, which individuals used to align themselves with their friends.

As this research area is still developing, most of the work undertaken deals with the early steps of modelling: collection of real-world data, the generation of input populations, and the development of toy models.

### 3.5.1 Data collection

As part of the Connected Lives study, Carrasco and Miller (2009) collected data on individuals' personal networks and interactions and used multi-level modelling to look for influences on frequencies of activities. The results showed that the number of components (i.e., subgroups), density, and degree of centrality of the personal network influences the frequency of social interactions, and are a better indication of frequency than the size of the network or isolates. Younger people tend to have a higher frequency of activities, as well as egos and alters with similar ages. The latter is an example of homophily, which is based on the idea that individuals interact with others who are similar to them (McPherson et al., 2001). Homophilies can be separated into two groups: those based on status, both ascribed (e.g., age, gender, etc.) and acquired (e.g., occupation, religion, etc.), and those based on values, such as attitudes and beliefs.

A data set was collected in 2008 in the Eindhoven region (van den Berg et al., 2008). The idea behind this data collection was to examine the relationship between the built environment, ICT use, and social networks and travel. As such, the survey asked questions about all social interactions over a two day period, including those via phone, email and SMS, but excluding those with a household member or about work-related issues. A follow-up survey elicited more details about individual's social networks. Respondents were asked to name people who they felt very close to and people they felt somewhat close to. Name interpreters were then used to obtain details regarding the relationship of the alter to the ego, the distance between the ego's and alter's residences, and the frequency of contact using different media (van den Berg et al., 2009).

Kowald et al. (2009) used a snowball survey in Switzerland, in which respondents provide details of the members of their social network, and those members are then approached to complete the survey, which leads to an expanding connected network. The first part of the survey collects the ego's characteristics (including a mobility biography), a name generator (focussing on leisure contacts and people of high emotional importance), details of the alters names, and a sociogram to collect cliques. An activity diary for eight days collects data on activities, including "the location/destination, joining persons and the planning background".

Carrasco (2009) describes a new data collection in Chile in 2008. The survey focuses on four different urban areas with high/low income and high/low access to services and transport facilities in order to be able to compare the effect of the socio-urban context. Information about emotionally close and/or frequently contacted alters was collected, as well as “their frequency and duration of face-to-face and virtual (ICTs) interactions”. The survey collects ”ego-alter frequencies of interaction” so as to get a wide range of activities over a longer period of time, and gets an idea of regular/irregular activities. A two-day activity diary is also collected, and asks about ”four of the most usual social activities” as well as the last time they occurred.

Kowald et al. (2009) noted that the response burden with these sorts of surveys can be high, as a lot of details are being collected, in particular personal details about friends. They note that a level of trust needs to be established with respondents, by providing incentives and an explanation of how the data will be used. van den Berg et al. (2008) noted that their personal approach, in which potential participants were approached in person, not via email or postcard, also worked well.

### 3.5.2 Network generation

Given the data collected for activity-travel modelling purposes, at least two network generation algorithms have been developed. Illenberger et al. (2009) presented a model based on spatial distance, while Arentze et al. (2009) developed an algorithm based on spatial and social distance. The latter can also be extended to include the influence of common friends, following the theory that if person 1 is friends with person 2 and person 3, then persons 2 and 3 have a good chance of also being friends.

### 3.5.3 Modelling

Research into integrating the effects of social networks and interactions with activity patterns is very recent; as Axhausen (2006) notes, “transport research, but also sociological research has in the past not looked at the link between social networks, locational choices and travel”. Currently, no model thoroughly incorporates all three concepts – selection, influence, and activity generation – we have identified in the introduction to this thesis. Most models focus on one or two concepts and in most cases at a very basic level. For example, initial social networks usually follow a generic random graph model, which is not realistic. However, most of these models are described as preliminary or proof-of-concept.

We have chosen to discuss only agent-based models here, however some research has also been undertaken into integrating social networks and influence into choice models. Dugundji and Gulyas (2005) developed a model in which each agent's choice is influenced by numbers of neighbours/socio-economic peers making each choice. They state that as discrete choice theory is based on individual choice, the challenge is to include interdependence in decision maker's choices. They found that the heterogeneity in the model (individual characteristics, individual attributes or choice alternatives, alternative availability) generated different dynamics and therefore cannot be ignored. Paez et al. (2008) describes a multinomial discrete choice approach for investigating decision making in social situations, in particular residential choice, and found that the degree distribution in the social network affected both the macro- and micro-level outcomes, whereas the clustering coefficient had no effect. It was noted by Dugundji et al. (2011) that these approaches require further development, including developing the social network formation and dynamics and improved integration with both social network analysis and agent-based modelling fields.

Social activities have not been fully incorporated in activity-based travel models (Arentze and Timmermans, 2008). These activities, however, place constraints on other non-social activities, which signals their importance in activity scheduling.

Sunitiyoso et al. (2006) have investigated mostly influence, by exploring the spread of soft (or psychological) policy measures, such as environmental awareness and encouraging car-sharing, and in particular the influence of a minority influence group. The model also included meeting and communicating with other agents. Their experiments showed that diffusion did occur and that club membership was more effective at spreading information than neighbours. Sunitiyoso and Matsumoto (2009) also investigated the spreading of mode choice behaviour. The model has two layers: a traveller model that models the decision making process, and a transport model that models the transport system and provides generalised costs as feedback. Agents have a parameter representing their belief of how their actions influence others and how others influence them. They can change their mode using two rules: those using the payoff rule find the neighbour with the best payoff from the last round and changes to their behaviour, and the conformists change their behaviour to match the majority of their neighbours.

Hackney and Axhausen (Hackney, 2005; Hackney and Axhausen, 2006) also developed a simple model looking at how activities are generated. The agents are located on a grid and are provided with an amount of travel budget. At each time step each agent decides which of its neighbours (those that can be reached within budget) it would like to visit in order to increase its social status. All trips are home-based, so the agent needs to have enough budget for a return trip. The social status indicator is (normalised) betweenness centrality: the number of shortest paths that pass through the agent. As expected, those with better access to others had the higher social statuses at the end of the simulation.

Hackney and Marchal (2009), building on previous work, developed a microsimulation which incorporated a social network on top of a daily activity scheduler. The individuals in the system exchange information with each other, either about locations or about friends. Currently the system does not include collaborative scheduling.

Focussing on both influence and selection, the model created by Marchal and Nagel investigates where "individuals perform activities such as shopping and leisure" (Marchal and Nagel, 2005). Agents in the model have limited information about the environment and are connected to several other agents through a social network. Agents are provided with plans and travel around a network carrying out activities individually. Links with other agents are created or reinforced when agents travel to the same location and decay over time if a meeting has not occurred for a while. Each agent has some knowledge of the area around their homes and workplaces, as well as two buffers of "useful" locations and not so useful locations. Every timestep each agent randomly selects a cell that they are aware of and informs their friends of this cell. The friends evaluate the cell and if the inclusion of that cell into their travel plans leads to an improvement, then the cell is added into their useful buffer of cells. If not, then it randomly replaces a not-so-useful cell in their memory. This leads to some cooperative behaviour as the agents are storing and possibly sharing information that is not useful for themselves.

The essence of this model has been used as a basis for a recent extension for MATSim (matsim.org, 2007) that allows for the inclusion of social network data into a large-scale model (Hackney and Marchal, 2007). In this model, individuals make visits to locations, alter the strength and existence of ties, exchange information with each other, and modify their plans by updating the location of secondary activities during each run. At the moment, the selection and influence strategies are simple, but more realistic behaviours could be incorporated. Agents repeat the same day, updating their plans after each day, until equilibrium is reached.

With respect to simulation properties of existing models, both Marchal and Nagel (2005) and Hackney and Marchal (2007) report on the computational aspects of their models and make estimates of the computational complexity. Comments are also made on the usefulness and practicality of exploring social aspects and their effects (Ettema et al., 2007; Hackney and Axhausen, 2006). Collection of more data will be required and it may be that simulations with more data input and more detail do not provide an improvement in forecasting. As a large amount of travel is now for social/leisure purposes, it seems reasonable that we attempt to understand the reasons behind it. Ideally, the enhancements will lead to a better understanding of activity scheduling processes (Ettema et al., 2007).

## 3.6 Discussion

Participation in social activities can be shown to be based on human needs. However, previous transport models have understandably concentrated on the more basic physiological and safety needs ahead of belongingness needs, following Maslow's categorisation.

Having said that, the research field of social networks can be used to assist in analysing and understanding the interactions that can and do occur in a population. Small populations can be represented as a complete network, in that all population members and links are included, which can then be analysed with standard social network analysis methods to look for patterns and similarities with other networks.

In some cases, such as for transport models of cities, it is infeasible to collect a complete social network containing all city inhabitants and visitors as nodes and their interactions as links. Therefore egocentric networks must be used, and some adaptation of the network analysis methods may be needed.

Network data can be collected in several ways, however care must be taken with the privacy of the alters named by respondents and the response burden placed on respondents. This has implications for the quantity and quality of data collected, and therefore the quality and usefulness of the models developed using this data.

Several models of generic friendship selection and influence have been proposed. These have formed a basis for existing models in the transport field. However, these latter models have focussed on only one of selection, influence or activity generation, meaning they are limited in their application. In the following chapters, we move into the model development phase and demonstrate how flexible and extensible social activity-travel models can be developed.

# Part II

# Model development

# Chapter 4

# Conceptual model

The creation of a transport model (at the implementation level) follows an expanding set of processes. In chapter 2, the planning process was described, which works through from defining the transportation problem, collecting data, constructing a model, generating solutions and future values of input variables, testing the model, making a final recommendation for a solution and the implementation thereof. Suffice to say, this process is not the focus of this thesis, as we are not solving a transportation problem as such. This thesis is more concerned with improving the outcomes and recommendations from a model by incorporating social networks, reviewed in chapter 3. However, the planning process needs to be kept in mind throughout the model development process, as it provides an idea of how the model will be used in practice.

Zooming in on the model construction step, it is possible to define a process for the development of a generic model. This has some overlap with the testing and experimentation phases of the planning process.

This chapter starts the modelling process portion of this thesis. Firstly, the overall modelling process is described. The conceptual model is then dissected in more detail, looking at the model units, the types of links between two people, network dynamics, interactions, activities, and how relationships can be maintained.

## 4.1 The modelling process

Figure 4.1 gives an overview of a possible modelling process, adapted from Law and Kelton (2000). Like the planning process, it begins with a problem definition and collection of data. However, in this case, the collection of information or potential theories is also included. The validation of the conceptual model is defined by Sargent (2005) as "determining that (1) the theories and assumptions underlying the conceptual model are correct and (2) the model's representation of the problem entity and the model's structure, logic, and mathematical and causal relationships are "reasonable" for the intended purpose of the model." The model is then implemented and verified, validation and experimentation are carried out, and the results are reported.

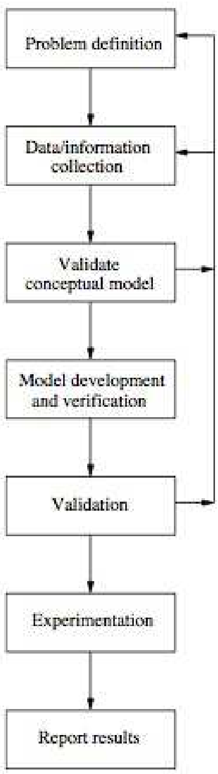



Figure 4.1: The modelling process as described by Law and Kelton (2000).

Keep in mind that the process in figure 4.1 was developed with discrete-event simulation in mind, and is more industrial than research-oriented. However, like the planning process, it provides an overview of what is expected from a simulation study. The remainder of this thesis will work through the steps of conceptual model, model development, validation, and experimentation.

This chapter describes the conceptual model. It provides a broad overview over how travel and activities can be influenced by social networks; not all of it will be implemented in the final model, however is included so as to provide directions for future work.

Note that other sources, such as Banks (1998), move the conceptual model validation step to after the model development. Although this step should be considered early in the model development process, in this thesis the validation of the conceptual model will be discussed in chapter 6 alongside the other validation steps.

## 4.2 The conceptual model

The conceptual model contains descriptions of the subsystems and their interaction, any assumptions, and information about the data that is available (Law and Kelton, 2000).

In this chapter, the following subsystems will be described:

- Model units: the main elements in the model;
- Typology of links/relationships: the types of links between people and their nature, i.e., how they are initially determined;
- Dynamics: how the network changes over time (selection) and how people are influenced in the model (influence);
- Interactions: how people interact with each other on an instantaneous level, i.e., sending invitations and sharing info;
- Activities: how people participate in more substantial activities;
- Relationships: techniques for maintaining relationships.

As this is a broader view of the model, data does not exist or is in preliminary stages of collection for some of the subsystems. The available data will be described in chapter 7.

## 4.3 Model units

There are two main layers to the model: the transport layer and the social layer. The transport layer contains a representation of the environment, i.e., locations and the travel options between them (see section 4.3.4 for more details). The social layer contains information about social connections (section 4.3.2).

The main units in the model will be individuals (section 4.3.1) and links (section 4.3.3). Groups (section 4.3.6) are also an important part of the model.

### 4.3.1 Individuals

The people in the system are modelled as individual entities. Each individual:

1. has a home location and a possible work/school location, and knows about a number of locations in their environment;
2. knows a certain number of other people, or acquaintances;
3. interacts with and responds to others;
4. moves around the environment, both in the short-term and long-term;
5. maintains an agenda, consisting of activities with properties such as location and start time;
6. is interested in creating and maintaining relationships, by interacting and engaging in activities with others.

Individuals are situated in, and move about, an environment. They also update their beliefs and attributes, based on their experiences in the environment and also interacting with others.

Each individual will have their own viewpoint of the two layers: an egocentric network containing their contacts, and a set of locations they are familiar with. These will change over time, and both layer viewpoints will influence the other, by discovering new locations and meeting new people, and learning about and utilising new locations from one's contacts.

Each person will also have their own opinions on the attributes of locations, and these can change over time, possibly due to influence from others.

They will also have their own expectations of travel time (split by mode) between locations. This will be initialised from the global network, but will be altered slightly for each person for variability.

Each person has an agenda, which lists their activities for a given day. It is envisaged that a portion of the day will be blocked out for work/school activities and physiological requirements, and the leftover can be used for social activities. The scheduling process will not be overly complex, as that is not the point of this version of the model, however this can be altered in future versions.

Network capital is also relevant, although we do not incorporate all of these concepts. Larsen et al. (2005) define network capital as the various networking tools used by individuals, specifically:

- movement competencies: walk, carry baggage, read timetables, use mobiles etc.
- location-free information and contact points: websites, diaries etc.
- communication devices, so that arrangements can be made or altered, in particular whilst in transit
- appropriate, safe, and secure meeting places
- physical/financial access: email, internet, phone, car, fuel, planes, buses etc.
- time/money/resources for the above, in particular to cover the need for a change of plan due to system failure

Network tools are relational: if one individual has email, then it is worthless unless their friends also use email. However, the higher network capital a person has, the more connected and less isolated they are likely to be.

### 4.3.2 Social network

As covered in chapter 3, Scott (1991) defines social networks of consisting of relations (or links) and attributes (or properties). Attributes are the attitudes, opinions and behaviours as properties of agents and groups. Relational data are the connections, ties, and contacts between the agents. In our network, the individuals are the agents with attributes, who are connected to each other.

This network can be dynamic in the sense that the properties of the individuals and the properties (and possibly presence) of links change over time.

### 4.3.3 Links

Granovetter (1973) states that the link strength is "a (probably linear) combination of the amount of time, the emotional intensity, the intimacy (mutual confiding), and the reciprocal services which characterize the tie".

Individuals are linked to each other. Each of these pairs is represented by a connection containing information (properties) about their relationship.

Individuals interact with each other, with the frequencies/purposes etc. dependent on the attributes of the connection (e.g., the type, strength of connection).

During these interactions, people may influence each other in some way. The main type of influence we are interested in is sharing information about the environment. Influence such as sharing network tools (for example, working through the Technology Adoption Lifecycle (innovators, early adopters, early/late majority, laggards)) is too long-term for our model.

The type of our links cover all the types listed in Borgatti et al. (2009): similarity (group membership), social relations (family, friend, or other role), interactions (talked to/helped etc.), and flows (information).

The properties of the links may be directed/asymmetric or symmetric. The properties can also change over time, and the links themselves may appear or disappear (possibly reappearing) over time.

### 4.3.4 Environment

The environment will be a simulated environment, that may be a representation of a real-world environment. Different locations need to be defined and possibly their attractiveness and/or their usefulness to the different groups, e.g., membership "headquarters".

The environment can either be grid- (cells with locations on particular cells) or vector-based (streets linking locations). This depends upon how detailed movement is to be modelled and also the requirements of the model.

For this version, a vector-based representation is used, as the environment is not uniform and we are not interested in small-scale movement, but rather larger-scale movement within and between cities.

Within the environment there are locations of interest. People travel to these locations for activities. These locations require some data about, for example, opening times. Individuals will store their own quality attributes for locations they are aware of.

### 4.3.5 Households

Individuals are members of a household, which consists of a small group of people living together. It does not function in the same way as a group, therefore it should be distinct. Individuals in the same household may share mobility (e.g., cars) and ICT tools (e.g., computers).

Some activities may be organised by one person on behalf of a partner or family, therefore the roles people play in a household (e.g., partner, child) also need to be defined.

### 4.3.6 Groups

A group is a number of people who are connected in some formal way, such as working together or participating in reasonably formal activities together as members of a club.

When people belong to a group, they are connected to all other members. If they leave the group, then the group connection is lost. It may be that they still stay in contact with some people from the group, but this relationship will be of a different type.

Group properties, such as membership requirements and common meeting places, need to be defined. For example, there is the notion of casual groups, i.e., a group of people who go to the pub together. For more formal groups, a prospective member could request to join a group or be invited. Group formation is described further in section 4.5.4.

## 4.4 Typology of relationship/links

Reasons for creating links include:

1. Birth and marriage/partnership (family)

2. A job, a new residence, a new school for a child, etc.

3. Becoming a member of a group such as family, work, union/club, etc.: automatically linked to everyone in the group, may not extend past the membership period

4. Chance meetings may become connections: “the probability of an incidental interaction between two persons is a function of the probability that the two persons meet and the probability that either one of the two initiates a social interaction when they meet. The first probability is a function of the degree of overlap of the activities in space and time and the nature of the activities. The second probability is a function of the current size of the person’s social and information needs” (Arentze and Timmermans, 2006)

For this model, we are looking at short-term time periods only (i.e., a few months), so we are not planning to model these events explicitly. If required, these longer-term changes could be approximated with adding and deleting links in the social network. However, this information is useful for defining relationship categories as shown in table 4.1. Depending on the category, the link can be determined from data (i.e., household member data), link types (e.g., family), common group membership, or from the environment (e.g., two people with residences on the same street are neighbours).

| Social category | Always present? | Decision/source |
|---|---|---|
| Household | Yes | Data |
| Relatives | Yes | Links |
| Work/school | No | Membership |
| Union/clubs | No | Membership |
| Friends | Yes | Links |
| Neighbourhood | Yes | Environment |

Table 4.1: Suggested relationship categories.

## 4.5 Dynamics

In chapter 3, we defined social networks as a set of nodes and links connecting the nodes. However, the set of links is not constant forever: we meet new people and lose contact with people over time. The investigation of networks over time, or longitudinally, is known as social network dynamics. The formation of personal networks and groups, as well as selection and influence between people, are of interest.

### 4.5.1 Selection

Connections need to be created and destroyed over time. Connections are made based on some form of utility or payoff – there should be a benefit to forming a connection. There are several theories on how connections can be created:

- Higher chance of becoming friends with people with more friends
- Meeting people at the same location (i.e., by chance, at work, joining a club etc.)
- There is an upper limit of one's number of friendships (Jin et al., 2001; Roberts et al., 2009) or aims to have a certain number of friends (Zeggelink, 1997)
- There is a higher chance of meeting another person if you and them have a mutual friend (Burt, 2000; Jin et al., 2001)
- Higher chance of meeting "similar" people (Burt, 2000; McPherson et al., 2001; Zeggelink, 1994)

The factors we are interested in then are homophily/similarity, physical distance, and common friends. These factors can be used with minor adjustments for each social category. Strengths of ties are also symmetric/reciprocal, however for groups this is debatable.

As an example, Arentze and Timmermans (2008) described a similarity equation for use in determining the maximum potential of needs satisfaction, i.e., the more similar the person the more likely that the interaction will satisfy needs.

$$Q_{kij} = \prod_{R}(1 - (\frac{x_s^i - x_s^j}{r_s})^{\lambda_{sk}}) \prod_{\neg R}(1 - (\epsilon_{sl(i)l(j)})^{\lambda_{sk}}) \tag{4.1}$$

where

- $R$ is the set of continuous variables
- $\neg R$ is the set of categorical variables
- $x_s$ is a value for a particular variable $s$ and $r_s$ is the range
- $\lambda_{sk}$ are weights
- $\epsilon$ is the difference between two levels

Zhang et al. (2008) put forward a model architecture based on groups (social connections), neighbourhoods (spatial connections), and networks (both social and spatial connections). In that model, however, the neighbourhood network changes as a person moves around the environment. In our model, it will be related to the person's home location.

Reasons for dissolving ties are that interests, values and opinions are not shared and that maintenance costs may be too high (e.g., distance) (van de Bunt et al., 1999).

The main method for modelling the destruction of connections is to have the strength decay over time (Burt, 2000; Jin et al., 2001; Marchal and Nagel, 2005). If the two individuals do not meet again, the strength should eventually decay to 0. If they do meet, then the strength is reset to 1. Unfortunately we have no specific longitudinal data to test this on, however some estimates exist for other data sets (for example, for a financial organisation described in Burt (2000)).

### 4.5.2 Personal networks

In terms of a limit on the number of acquaintances in a personal network, Roberts et al. (2009) consider networks to have layers. The innermost layer is support (around five individuals who provide advice and help in times of need), the middle layer sympathy (around 12-15 individuals whom the ego is in contact with at least monthly), and the outer active (individuals whom the ego has contacted in the past two years and/or feels like they have a personal relationship with). The authors were interested in whether the inner two layers could explain the variation in the active layer. Two types of constraints were discussed: cognitive (e.g., can only maintain so many relationships simultaneously) and time budgeting (e.g., it takes time to build/maintain a relationship). Using a questionnaire, it was found that there was an upper limit of 24 alters for the support and sympathy layers, and 136-150 for the entire personal network. These findings are important for incorporating dynamic personal networks, as the network size cannot increase indefinitely.

### 4.5.3 Influence

Influence is the effect on the character or behaviour of something or someone. We are interested in observing the influences that arise from interactions between people.

Modelling spread can be divided into two different objectives: where the property being spread is undesirable and needs to be controlled or eradicated (epidemics etc.), and where the property being spread is desirable and should be spread quickly (rumours, new innovations etc.) (Boccaletti et al., 2006)

Valente (1995) covers a range of different aspects of diffusion models. He reviews both positional (influenced by neighbours only) and structural (influenced by the wider network) models. Threshold models are also described, where a certain number of neighbours or the groups must activate before a particular individual does. Two such models are described by Kempe et al. (2003). The Linear Threshold Model starts with a random number of "activated" nodes and each node has a threshold. Once the sum of their neighbours' influences is above the threshold, the node is activated. The Independent Cascade Model also starts with a random number of activated nodes, however each node gets a once-only chance to activate its neighbour nodes with probability $p$. Kempe et al. (2003) then explores which nodes to target for maximum influence, which leans more towards affecting change rather than observation.

On the other hand, Eubank et al. (2004) present a method for generating the network for determining the spread of disease. They use TRIPS to generate people's travel activity for a day. From that data, a bipartite graph linking people and locations is created and an indication of colocations and possibilities for spread is found.

The influence of mobility tools can also be explored, i.e., if so many of your friends have phones, you will eventually get one too. Mode choice has also been explored by Sunitiyoso and Matsumoto (2009), as mentioned in chapter 3. In their model, the agents used both payoff (where the individual changes their behaviour to the behaviour of the neighbour with the highest payoff) and conformist (in which the individual changes their behaviour to that of the majority of their neighbours) to model behaviour change. Other concepts that could be "influenced" from person to person are locations (e.g., knowledge of new locations and attributes thereof) and mobility, for example of modes (e.g., someone could recommend the bus between A and B).

### 4.5.4 Group formation

The operation of formal, existing groups is not that well studied. Most work focusses on identifying clusters of similar people, which could signify an informal group. However, Backstrom et al. (2006) looked at people joining a blogging site and also "joining" an academic community (in this case, a conference or a journal). They also noted that similar work was lacking.

The three concepts identified by Backstrom et al. (2006) were membership, growth and change. Membership was found to be influenced by the number of friends already in the group, therefore incomplete triads (i.e., where person A is linked to persons B and C, but person B and C are not linked) were of interest. However, if there were a lot of closed triads inside the group already, then group growth was likely to be minimal.

Some earlier work by McPherson et al. (1992) also found something similar. The member/non-member ties are critical, as they can produce new members, as well as take members away from the group. Their group concepts included variation, selection, and retention.

Zhang et al. (2008) measure group membership as individuals having a similar strategy to a group, so it is along the lines of clustering. If the strategy of the individual falls out of line with the group, then they are deemed to have left. In their simulation, individuals, once in a group, are assigned a rank that determines how influential and influenced they are by the group.

These theories do not apply as much to workplaces, where you may or may not know anyone before joining. For our model, workplace membership can be determined automatically from the individual's workplace as defined in the input. Community groups can use a combination of the above techniques: people could invite others to join and people could align themselves with groups they feel an affinity with.

## 4.6 Interactions

Individuals interact with each other. They can make appointments with each other, share information about locations and plans, and possibly influence each other's thresholds for certain actions.

There are different methods of interaction:

- in person (synchronous);
- phone (synchronous);
- email (usually asynchronous);
- mail (asynchronous);
- SMS (either, but usually asynchronous);
- IM (either, but usually synchronous).

There is also a difference in nature of these methods. For example, by calling a landline, you are calling a location, whereas by calling a mobile, you are calling the person irrespective of location (Kwan, 2007).

Interaction purposes can include informal chatting, information exchange, joint activity, or making an appointment. These purposes are independent of the specific activity purposes generally used in models, such as shopping, social, leisure etc.

## 4.7 Activities

We differentiate between activities and interactions. Activities run for substantial periods of time and are usually undertaken in a group. Extended or pre-arranged phone or IM conversations could be seen as activities, but as face-to-face encounters are more common, we intend to focus on face-to-face activities.

Urry (2004) lists reasons for being somewhere as:

- legal, economic, and familial obligations, either specific (bride to groom) or generic (funeral)
- social obligations: "essential for developing extended relations of trust"

- time obligations: to be with specific “significant others”
- object obligations: to see something, sign contract
- obligations to place: “need to sense a place”
- event obligations: “need to experience a particular ‘live’ event”

Of these, our interest is in social, time, place, and event obligations.

Tinsley and Eldredge (1995) looked into the psychological benefits of leisure participation, and categorised a list of activities based on people’s perceptions of which needs the activities satisfied. The eleven groups they found in a clustering analysis of a large leisure activity data set are:

- agency: vigorous physical activity
- novelty: physical, new things
- belongingness: receive attention, coordinate
- service: assist/influence
- sensual enjoyment: intellectual, with others
- cognitive stimulation: intellectual, solitary
- self-expression: self-improvement
- creativity: more challenging self-improvement
- competition: no obligation
- vicarious competition: watching sport
- relaxation: routine, no challenge
- residual: left over activities that don’t fit elsewhere

This is a useful classification for thinking about why people participate in activities. It also ties in with the needs-based theory proposed by Arentze and Timmermans (2009). This is a new framework for activity-based modelling which takes into account individual needs. Activities both satisfy and induce needs.

### 4.7.1 Activity properties

Activities can be thought of in different ways.

There can be many different sorts of activity *nature*: to visit someone at home, someone comes to visit your home, or a group outing to another location.

Several activity *purposes* are possible (possibly following Urry's list): to meet up with someone, to visit a place, to visit an event, or to spend time with someone.

The *group* with which the activity is shared is also important. This refers back to section 4.4.

In terms of the activity details and trips associated with the activity, there are several attributes: date/time, duration, location, mode of transport for both parties etc. During the interaction, these properties could be fixed or open for negotiation. For example, an invitation could be issued, where the time and location of the activity cannot be altered, such as attending a concert. Invitees could suggest other invitees however.

The properties in the context of this model are discussed further in section 7.2.1.

### 4.7.2 Scheduling

The scheduling in the model can be simple, as we are more interested in the interaction and dynamics. However, it is useful to take opportunity costs into consideration when scheduling.

The opportunity cost for a particular resource, such as time and money, is the next highest valued alternative use of that resource. For example, this could be a different activity, or possibly doing nothing.

## 4.8 Relationships

van de Bunt et al. (1999) describes a friendship "lifecycle" as moving from unknown, to neutral, then to either friendly or troubled. From friendly the relationship can also become friend and possibly best friend.

Ideally, we should have some concept of history in each relationship. The notion of credit is helpful, to determine who should compromise when in a disagreement situation. Ettema et al. (2007) describe this for two people $g$ and $h$ as:

> ... each time $h$ satisfies personal needs of $g$ the existing credit $h$ has regarding $g$ increases with the amount of needs of $g$ satisfied. ... Perhaps more importantly, this logic also implies that receiving help decreases one's credit: receiving help from $g$ decreases $h$'s credit with the amount of need satisfaction of $h$ (by the help).

So for each help activity between two people, their credit with regard to each other is increased (for the helper) or decreased (for the helpee) by the amount of need satisfaction of the helpee (so therefore equal and opposite – if $g$'s credit wrt $h$ is x, then $h$'s credit wrt $g$ is -x). This could be represented by two personal variables or a single link variable, however we assume the notion of power (also discussed in Ettema et al. (2007)) means that the credit will not be equal and opposite, so the latter idea will be invalid.

This is also discussed in Schröter et al. (2005). They describe a conceptual model in which agents exchange objects. Credit can be based on experiences, relations, or debts; the latter is proposed for their model. Credit is also assumed to be symmetric.

Another notion that could be useful is that of trust networks. This is of interest to social network researchers, especially in explicit online networks such as LinkedIn. The ratings can be used to determine how trusted a new contact is. However, a requirement for the developed algorithms is that everyone has rated their contacts in some way, and those ratings can be used to generate a trust rating between two unconnected people. In some cases, the fact that a link exists is an indication of trust. This sort of reputation ranking is more useful in one-shot networks, rather then in networks with repeated interactions.

Reciprocity, which underlies the idea of credit, is more relevant. Nowak and Sigmund (2005) state:

> Direct reciprocity is captured in the principle: "You scratch my back, and I'll scratch your's".

However, more interest is shown towards indirect reciprocity, where the giver of something does not necessarily expect something back from the recipient, but from anyone. This ties in with the trust network theory and is more suited to a business-like environment with few repeated interactions between pairs.

Another idea presented by Ettema et al. (2007) is the notion of power. This is defined by Cook (1977) as:

> In any exchange relation Ax;By, the power of A over B ($P_{AB}$) is the ability of A to decrease the ratio x/y (where A and B represent the actors, and x and y the resources involved in the exchange and x/y the exchange ratio.)

For a model of activity generation and scheduling, this implies that some sort of time is being exchanged.

## 4.9 Discussion

Taking into account the type of model we want to build and the existing literature, a conceptual model for a model of activity-travel behaviour incorporating social networks has been presented. The model units, relationship types, potential dynamics and interactions, and types of activities have been identified.

It is clear that there are many possible aspects that can be included in a model of this type. The personal network can be formed in many ways, including family members, club colleagues, and work/school colleagues. Households can share tools, such as cars and computers, which places constraints on activities. The relationships between people can also be defined in great detail in terms of whether one has more influence or power or whether one "owes" the other.

As in previous transport models, it is wise to narrow these aspects down in order to build a model that is implementable and understandable. Afterwards, more aspects can be added or alternative models constructed.

As a result, we will ignore dynamic networks and large group activities for the time being. These aspects are currently being researched by others and can be incorporated at a later stage. We will also concentrate on face-to-face activities, i.e., where people need to be in the same location at the same time. However, keeping in mind that the other functionalities might be added in the near future is useful knowledge for the design phase.

A key element of the conceptual model is the interaction or exchange involved in scheduling activities. This implies that we require a modelling approach that can handle communication and interaction between individuals. Another key point is the multiple day structure of the model, requiring that history and time need to be tracked. If I did something for you, then next time you do something for me. How long has it been since I saw a certain person? In the next chapter, we describe a design and implementation that can cater for these elements.

# Chapter 5

# Model design and implementation

Once a conceptual model is in place, the design process can begin. This step involves ensuring that the requirements and the "imaginary" model that has been specified can be developed in a way that it is maintainable and can be checked against the specification as a form of guarantee.

Given our assumption that history plays a strong role in planning social activities, and the nature of joint activities requiring some form of interaction between individuals, this makes it difficult to use pure mathematical and statistical models. Agent-based modelling, in which individuals are modelled to interact with each other and their environment, is slowly becoming more popular in transport and land-use modelling, as it permits individual behaviours to be modelled with less abstraction and more flexibility.

Klügl (2009) notes that agent-based simulation differs to agent-based software engineering (AOSE), which focusses on the specification and development of more open systems. Some of the concepts from AOSE can still be used, especially in the absence of a fully-usable meta-model for agent-based simulation.

As a strict definition of agent-based modelling is non-existent, we begin with our position on agent-based modelling and how it is appropriate for the model we want to build. We then describe several methods for designing agent-oriented systems and the design process we have chosen. The design of the agents and the interactions between them is explained in detail. The implementation is then outlined. The chapter follows the software engineering process, as shown in figure 5.1, by covering design, implementation, and testing but omitting the requirements and maintenance phases. The requirements of the model were covered in the conceptual design, however it is noted that some aspects, such as dynamic networks and large group activities, are not included in this version of the model to permit easier investigation of the influence of basic social networks on individuals.

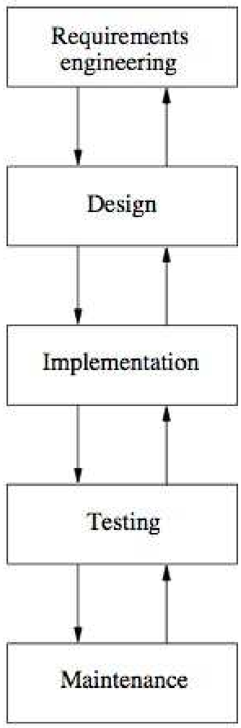



Figure 5.1: A basic software engineering process: the waterfall.

## 5.1 Agent-based modelling

The individuals will be represented as agents. A definition of an intelligent agent is the following from Padgham and Winikoff (2004, p3): "An Intelligent Agent is a piece of software that is

- Situated - exists in an environment

- Autonomous - independent, not controlled externally
- Reactive - responds (in a timely manner!) to changes in its environment
- Proactive - persistently pursues goals
- Flexible - has multiple ways of achieving goals
- Robust - recovers from failure
- Social - interacts with other agents"

Given the range of definitions of agents and agent-based modelling, a thesis should announce its stance. In the early 2000s, several definitions were available, ranging from Davidsson (2000)'s "simulated entities modelled and implemented in terms of agents" to Edmonds (2000)'s "attempt to model a multi actor system with a multi agent system". Some ignored the real world, while some implied that no simplification occurred.

Recently, and from a spatial point of view, Batty (2008) offered "systems composed of individuals who act purposely in making locational/spatial decisions". Although this is suitable for our domain, no mention is made of whether the decisions are made individually or jointly.

Gilbert (2008) defines agent-based modelling as:

> Formally, agent-based modelling is a *computational* method that enables a researcher to create, analyze, and *experiment* with *models* composed of *agents* that interact within an *environment*. (Gilbert, 2008)

This is sufficiently broad, even mentioning the steps involved, and, unlike the other definitions, includes interactions. This definition will be assumed for the remainder of this thesis.

However, agent-based modelling is a relatively new approach for transport and land-use models. Sanford Bernhardt (2007) notes that common applications of agent-based modelling in transport are traffic and pedestrian simulations and demand modelling. The former tend to be undertaken at a microscopic level, while the latter can be more strategic.

In this field, individual models are traditionally based on microsimulation methods. For models with a strong focus on the spatial element, cellular automata are often used. For example, if a planner would like to know the effect of a particular seating configuration in a pedestrianised street, then a cell-based environment (where particular cells can be blocked out to represent seating) will be more informative than a link-based environment. As the International Microsimulation Association (2010) notes, these approaches exist in pure forms as well as combined forms:

> In a pure [cellular automata] all entities are spatially located within a grid of cells, and all entities have only one attribute (alive or dead), with behaviours deterministically dependent upon the state of neighbouring cells. In a pure [agent-based model] the emphasis is on the interaction between individuals, with the main attribute of each individual being their operating characteristics (behavioural rules), which evolve stochastically over time in response to the success or failure of interactions with other individuals. In a pure [microsimulation] transition probabilities lack evolutionary and spatial dimensions. As microsimulation models add more behavioural and spatial interaction between individual units, as CAs add a growing range of individual attributes and start to incorporate aspatial behaviours, and as ABMs add both space and fiscal/demographic characteristics to their agents, the three approaches move towards a common ground. (International Microsimulation Association, 2010)

In our model, we require the attributes generally found in microsimulations, as well as the interactions between individuals, which are not neighbourhood-based as in cellular automata. As a result, our model falls in the space between microsimulation and agent-based modelling.

### 5.1.1 Appropriateness

Agent-based modelling is frequently used for applications where the behaviour and intentions of heterogeneous individuals and interaction between individuals is required. As presented in chapter 2, transport models have evolved from aggregate models to individual-based models that focus on behaviour. The latter appears to fit with the agent paradigm.

Both Bonabeau (2002) and Macal and North (2006) present sets of system attributes that are ideal for selecting agent-based modelling for that system, including amongst others:

- agents have dynamic relationships with other agents;
- relationships form and dissolve;
- agents have a spatial component to their behaviours and interactions;
- the topology of the interactions is heterogeneous and complex.

Our system consists of different people, their relationships and interactions with each other, and their movement around the transport system. The topology is not homogeneous and clusters may form. Therefore agent-based modelling appears to be appropriate for our model, due to the complex relationships and interactions between individuals and the individuals' situatedness in an urban environment.

### 5.1.2 Types of models

Having decided on an agent-based approach, we still need to determine what sort of model we are building.

Gilbert (2004) discusses several dimensions of simulation models. These are listed in table 5.1 with notes on our stance.

Gilbert (2008) goes into more detail with respect to the detail of the model:

- Abstract: basic social processes are modelled
- Middle-range: characteristic social processes, but results can be generalised
- Facsimile: exact reproduction of target phenomena

Many agent-based models fall into the abstract category, as they start out as an exploration of a theory and/or the evolution of simple rules, usually without real-word data. Ours is more of a middle-range model, as we are not targetting a specific system, however are incorporating theoretical concepts and data from a real-world scenario.

| Dimension | Description | Our model |
|---|---|---|
| Abstract vs Descriptive | How detailed the model is with respect to the units modelled. | We are building a descriptive model, as we are attempting to realistically describe human behaviour. |
| Artificial vs Realistic | Whether we are modelling real social problems or not. | Our model is realistic. |
| Positive vs Normative | Also known as explanatory vs predictive. | Aiming for normative (i.e., being able to be used for policy recommendations) but more positive (i.e., aiding understanding) in its current form. |
| Spatial vs Network | Whether the action takes place in a spatial setting, or in a networked environment where space is not taken into account. | Our model sits in the middle, as we want to incorporate networks into what is currently a spatial model. |
| Complex vs Simple agents | The cognitive abilities of the agents. This could range from simple rule-based agents to those using cognitive architectures. | Again, we are in the middle, as the utility set-up is not complex, however we want some more detail at the individual level. The simplest of agents are really only useful for overall aggregate prediction. |

Table 5.1: The dimensions of our model.

## 5.2 Design

Several design methodologies have been developed for agent-oriented applications. Many elements are similar across methodologies. Most methodologies are developed for the engineering of "physical" (problem-solving or decision-making) applications, which are characterised by open dynamic environments, heterogenous participants and common goals. An example is the control of a manufacturing system, where a software agent could replace a human controlling a machine, or an open auction system, where agents make offers on behalf of a human.

The Gaia methodology (Wooldridge, 2000) is divided into analysis (the identification of roles, specifying interactions between agents) and design (defining agents, services, and acquaintances). This was noted to be insufficient for open systems, and was soon extended by Juan et al. (2002) (as ROADMAP) for this purpose. One of the shortcomings of Gaia for modelling purposes is the lack of separate environment model: this information can be found in the role definitions (Juan et al., 2002).

ROADMAP kept the analysis and design phases of Gaia, but added more models to the analysis phase. Analysis now consists of use-case, environment, knowledge, role, protocol and interaction models.

Gaia purposely did not include a requirements phase, assuming it was independent of the analysis and design. However, ROADMAP does include specific requirements models. Another methodology, Prometheus (Padgham and Winikoff, 2004), which was developed for a particular architecture of agents, provides some useful generic requirements models, such as system goals and scenarios.

The previous methodologies impose some form of process. INGENIAS (Pavón and Gómez-Sanz, 2003) does not, however it provides views of the world, including models of agents, interactions, tasks/goals, organisations, and the environment.

Some of the traditional AOSE methodologies have properties that make them more suitable for MABS, for example, an emphasis on cooperation and emergence. Bernon et al. (2005a) describe ADELFE, which was developed for adaptive multi-agent systems. The agents are considered to be cooperative, and the emphasis is on how local interactions lead to a global system. However, these methodologies still lack or have limited components for culture, social-cognitive reasoning, values and norms, which are required for fully-fledged MABS.

An effort has been made to create a compilation of several meta-models currently in use that can be used as a reference point to achieve some form of standardisation and maturity (Bernon et al., 2005b). The common models were found to be agent (as defined in section 5.1), role ("an abstraction of a portion of a social behaviour of an agent"), tasks ("a (set of) activity(ies) that generates some effects"), and communication (based on messages and following a protocol). Other important elements were environment, organisation and social structure, cooperation, mental attitudes, and services.

Taking into account the different methodologies, we now move into the detailed design phase of the process. The key elements we will discuss include the system goals, environment, acquaintances and social structure, roles, and services and tasks. The internals of the agents are specified, including which roles they play in the system, the services that they offer, and the tasks they undertake. The acquaintances between the different agents are also defined.

### 5.2.1 System goals

The goals of the agents in the system are derived from the social needs of humans. These include interacting with, and gaining the respect and esteem of others. The system goals are therefore:

- establishing and maintaining (longterm) relationships with other people;
- sharing experiences with other people, in the form of joint activity participation, possibly within a group/club setting;
- sharing (giving and gaining) information with other people;
- learning individually about their local environment.

Levels of achievement are measured individually, e.g., everyone will have some level of satisfaction. If they are not satisfied with their current situation, then they will try to change it. The same applies to how involved people will be in the community: it is dependent upon their needs.

### 5.2.2 Environment

The environment has a link- or graph-based representation. The links contain the distance between nodes. The nodes exist at a point in two-dimensional space, and most (if not all) nodes contain a location, which is a facility where (joint) activities can be undertaken. There is also the potential ability to store available travel modes and associated travel times for links.

There are several different types of location, and each type has a set of attributes. The major distinction is between a private residence (home) and a public location (out of home). As an example, the latter will have restricted opening hours. Categories of public locations include restaurants/cafés, cultural locations (e.g., museums, theatres), green space, and sport centres/gyms.

### 5.2.3 Acquaintances and social structures

The population is divided into two groups: core and non-core. The individuals in the core partition are located in the study area, i.e., output will be generated for these individuals. However, not all of the acquaintances of the core individuals live in the study area, but they still need to be present in the model. They form the non-core population, who do not start interactions, but do respond to them.

Each person has a set of acquaintances, which is defined by their social network. Each social link between two people stores information that is specific to that link: how long it has been since they last saw each other and a similarity measure, which follows from the notion of homophily. Links are undirected, meaning that friendships are mutual. Social links can also contain the type of the relationship (e.g., family, work, friend).

The key concepts in a measure of similarity would be distance between the two and the type of relationship. Age and gender could also be used, as well as the time the pair have known each other and the relationship type.

The social structure of our model is similar to the CASE model proposed by Zhang et al. (2008), however a difference is that our neighbourhood is static.

Our acquaintance selection model is based on the similarity between two people, the geographic distance between them, and their friends in common. When considering proposing or participating in an activity, the agent's time availability, the opportunity costs, and the time since they last saw the other agent are taken into account. Other concepts, such as the social credit balance between the two agents and their satisfaction from their previous encounter could also be included in future versions of the model.

### 5.2.4 Roles

Role models are used to define the roles present in the system, along with their permissions and responsibilities. In this model, individuals play roles only within interactions. Each activity has a *host*, who is responsible for starting a conversation and making a final decision, and one or more *respondents*, who are invited to participate in an event by a host.

### 5.2.5 Services and tasks

The main task of an individual is to meet its goals discussed in section 5.2.1. They will do this by initiating and participating in discussions about activities, as well as participating in the activity itself. Utility maximisation is used to determine the preferred activity choices.

The key service is the evaluation of activities, which incorporates a number of subservices: deciding who to invite for an activity, evaluating proposals, undertaking activities, updating properties, and keeping a schedule. The individuals in our model each have an agenda, and will interact and negotiate with others to schedule social activities, in particular negotiating about participants, time, and location. After participating in an activity, individuals update their state depending on their satisfaction with the activity.

Individuals will also meet new people as a result of activity participation, so another important service is the maintenance of a personal network. Just as their activities are influenced by their social network, their network is influenced by their activity participation.

As people participate in or discuss activities, they may visit or learn about new locations. The individuals will also keep track of the locations they are familiar with. They may share them with others, which is a form of influence.

## 5.3 Implementation

Many packages for creating agent-based models currently exist. Some are based on particular agent types and some are more flexible, in that the modeller is allowed more freedom to create their own behaviours whilst taking advantage of a general framework handling time management and other aspects of the simulation. Many models are implemented without the assistance of a modelling package (i.e., implemented directly in Java or C#) as “many ABS tools and platforms make limiting assumptions regarding the way that entities are modelled” (Davidsson et al., 2007).

NetLogo is a multi-agent programmable modelling environment[1]. Due

[1] http://ccl.northwestern.edu/netlogo/

to its simplistic language, it has gained much popularity amongst non-programmers and social scientists. The environment consists of agents, which can be turtles (individuals or units), patches (cells in the environment), links (connections between turtles), and the observer (which oversees all happenings in the world). Code can be written in NetLogo's own language to update turtles, patches and links. Although it is reasonably rich, caters for social and spatial elements, is well documented, and is easy to learn, the functionality is limited and as a result would be more suited to an abstract model.

Repast (Repast Organization for Architecture and Development, 2008) is an open-source agent-modelling toolkit. Models can be developed in Python, Java or C#. A new version of the Repast toolkit, Simphony, was released in November 2007. This release contains integration with R, a statistical computing environment, and other programs, as well as a point-and-click interface for model building, and the flexibility to create custom behaviours in either Java or Groovy, a dynamic, script-like language that compiles to Java bytecode. Visualisation tools are also included. Repast projects consists of a number of agents with a catalogue of actions which are scheduled for moments in time. The agents are located in space, which could be a network or a grid.

Crooks (2007) provides a good overview of using an older version of Repast for geospatial simulation. While Repast has advantages in the non-content-specific parts of the simulation (e.g., providing a graphical user interface (GUI) for users to interact with the model, providing graphing and visualisation tools, permitting import and export of certain file formats), there are also disadvantages in the overhead of having to learn the particular programming tool/language, it is difficult to reuse models (especially those developed by someone else), and the required functionality may not be present.

Although it is functionally richer than NetLogo, the high learning overhead and lack of a local user community (at the time of development) was a strong argument against using Repast. It was also unclear how to run the different actions required in a timestep. The deciding factor was that Repast had no built-in communication facility, meaning that we would have to develop our own communication module in any case.

From the transport world, MATSim was an option, however was too large-scale and focussed more on trip generation and routing than what we required. UrbanSim[2] was similar:

> UrbanSim was designed based on a micro-simulation approach to modeling household choices of residential location, business location choices, and real estate development and prices, and the use of a dynamic, annual simulation of the evolution of cities over time. (Borning et al., 2007)

Both these models are based more on the microsimulation side of the scale, which could also limit our ability to incorporate more agent-oriented behaviour.

As a result, the implementation was undertaken in Java. Python was used for prototyping and to get an idea of how the model would operate, however the runtime performance was reasonably slow.

In terms of "helper" applications, R, an open-source statistical programming environment[3], is useful for output analysis, and the JUNG library (Java Universal Network/Graph Framework[4], provides a lot of support for networks, including structures, algorithms for analysis, and visualisation.

We now describe the model in detail, from the individual units to the whole, concentrating on the agents, the interactions, and the overall model.

### 5.3.1 Agent

Utility-based agents are used as this allows the agents to evaluate the outcomes of participating in different activities. This has advantages and disadvantages: from the point of view of the agent community, utility functions are difficult to develop and tend to oversimplify the real-world processes (Wooldridge, 2009), however as the aim is to create a model of a sample population for a city, i.e., thousands of agents, the agent model needs to be simple in order to be scalable. We will return to the agent architecture at the end of this section after describing the utility function.

As mentioned in chapter 2, utility-based models are often used in the transport community, therefore to be consistent with other travel demand models a utility-based approach is required. However, transport models

[2] http://www.urbansim.org/
[3] http://www.r-project.org/
[4] http://jung.sourceforge.net/

incorporating multiple days and activity history are few in number. The most notable is Aurora (Joh et al., 2001), which assumed that the utility functions are S-shaped. That is, monotonically increasing, meaning that the need increases as time passes from the previous day the activity was undertaken, and with a small gain at the beginning and end. Extending from this work, Nijland et al. (2011) showed that an S-shaped function can be used for certain activities, amongst them social visits.

A utility function (Equation 5.1) has been developed to take into account the required issues – the host of the activity ($i$), type ($a$) of the activity, location ($l$), day ($d$), time ($y$), the other person involved ($j$), duration ($r$), whether it is a work day or not ($w_{id}$), the work status of the host ($w_i$) –, essentially, what, where, when and who. On top of this, whether it is a work day or not ($w_{id}$) and the work status of the host ($w_i$) are also taken into account.

The utility function is as follows:

$$
\begin{aligned}
U_i(a,l,d,y,j) &> r \times u^*(d, w_i, w_{id}) && (5.1)\\
U_i(a,l,d,y,j) &= V_i^{ady} + V_i^{al} + V_i^{j} - cost(l) + \epsilon_i^{st} && (5.2)\\
V_i^{ady} &= f_t(\alpha_i^{ady}, d - t_i^a) + \epsilon_i^a + \epsilon_i^y && (5.3)\\
V_i^{al} &= f_t(\alpha_i^{al'}, d - t_i^l) + \epsilon_i^l && (5.4)\\
V_i^{j} &= f_t(s_{ij}, d - t_i^j) + \epsilon_i^j && (5.5)\\
f_t(x,t) &= (\frac{2}{1+e^{-xt}}) - 1 && (5.6)\\
s_{ij} &= Q_g + Q_a && (5.7)\\
cost_{(l)} &= a + b \times ln(tt_{i(l)}) && (5.8)
\end{aligned}
$$

Activities can have a type ($a$), chosen from sharing experiences, sharing information, informal chatting, visiting each other, and other. The different types can be used to determine who is suitable for a given activity. Activities also have a location ($l$) with a type (home or out-of-home), which determine the duration of the activity ($r$).

The threshold for the function ($u^*$) is based on duration and whether the individual is working on the proposed day or not (Equation 5.1).

The components of the utility function $U_i$ consider when an individual last undertook an activity (Equation 5.3), visited a location (Equation 5.4), or saw someone (Equation 5.5). These values ($t^l$, $t^a$, $t^j$) are combined with the date of the proposed activity $d$ to find the last time the particular event happened. The utility increases over time (Equation 5.6), so that an activity/location/person that an individual hasn't seen/visited for a while is more attractive than one seen/visited the previous day. The time of day ($y$) is used only as a constraint, e.g., if an activity has already been scheduled or if the individual is working.

The preferences for an activity with a particular type, day, and time ($\alpha_i^{ady}$) and for a particular location ($\alpha_i^l$) are also inputs to the model. In this instance of the model, we consider preferences to be unidimensional as a simplification. It could be that preferences are dependent on the composition of the group, for example, in terms of gender, cultural background, size of the group etc.

For each pair of individuals $i$ and $j$, a similarity measure ($s_{ij}$) was calculated (Equation 5.7, taking into account age ($Q_a$) and gender ($Q_g$). The travel time to the location ($tt_i$) is also taken into account (Equation 5.8), based on the individual perception of the environment and distance, which contributes to a travel cost ($cost_{(l)}$). All travel is assumed to start and end at the individuals' home location.

The errors ($\epsilon$) are normally distributed and are drawn at initialisation.

As a simplification, the relationship type is not currently used. This can be easily added in the future, however more investigation is required into the nature of activities between people with particular relationships.

This function forms part of the agent as a whole; the architecture is shown in figure 5.2. The agent has percepts (e.g., invites) and actions (e.g., update own properties, participate in an activity). Percepts are processed, potential actions are generated and evaluated, and an action occurs. The agent also has a database containing information about their schedule, travel and activity history, the social and spatial networks, and their preferences. The utility function at this stage is the same for all agents and is known to all agents.

### 5.3.2 Interaction

Interactions between agents are an important component of agent-based applications. The individuals in our model each have an agenda, and interact and negotiate with others to schedule social activities, in particular negoti-

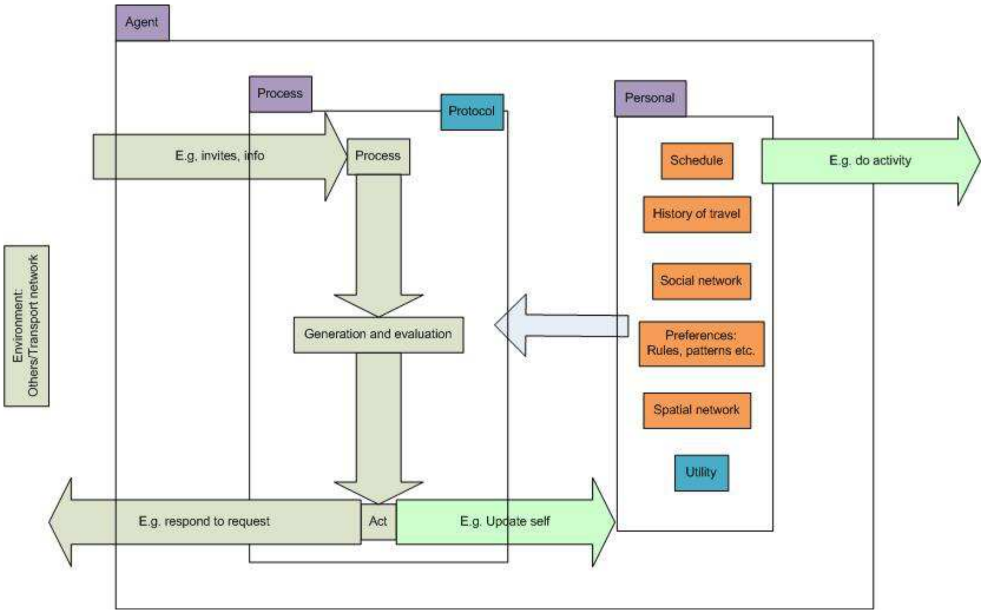



Figure 5.2: The architecture of the agent.

ating about the nature of the activity, participants, time, and location.

This means that current methods of modelling decision processes in an individual manner will need to be revised to take into account that many decisions are made jointly. In some cases, joint activity decision making within households has been investigated, however existing models do not capture the actual mechanisms behind the decision making. Moreover, these models focus on interactions within households and have not considered personal social networks at large.

However, according to Mokhtarian et al. (2006), there are two triggers for beginning an interaction:

> “When one goes to a ball game with friends, is the activity social, or entertainment? The answer probably affects the activity choice process, including the choice set of perceived alternatives: if the primary motivation is social, one may first decide to get together with friends, and then choose an activity around which to organize the gathering, whereas if the primary motivation is entertainment, one may first decide to attend the ball game and then see who else is able to join.” (Mokhtarian et al., 2006)

Therefore, both activities and acquaintances need to be evaluated to see whether there is a need to be satisfied. In chapter 9, we explore different protocols that cover both these cases, however for the remainder of this chapter we discuss the protocol used as the base case, which is based on choosing the person first.

Agent interactions have several components: the negotiation set (the possible proposals), a protocol, strategies, and a rule to determine that the interaction is complete (Wooldridge, 2002). Note that this is more encompassing than the choice model components described in chapter 2. The alternatives and their attributes fall into the negotiation set. The interaction makes no mention of the decision maker, however their preferences could fall into strategies, along with the decision rules.

For the negotiation set, we have developed a list of activity patterns, including the activity purpose and location, as well as an indication of which acquaintances are likely to be involved and when (e.g., interacting socially with work colleagues is likely to be during the week, whereas visiting family is mostly a weekend activity).

As mentioned earlier, Rindt et al. (2003) reports on the development of a simulation kernel for agent-based activity microsimulation, in which agents used a variant of the contract net protocol (Davis and Smith, 1981) to organise activities. While the contract net protocol makes sense for task allocation, it is not as suitable for activity generation and scheduling. Activities do not necessarily have to be carried out once proposed: they can be withdrawn or cancelled. Even when an activity has been generated, it is not a case of allocating it to one person: it might be that two or more people would be good companions for an activity. Unlike the dispatch centre example, there is no requirement for the global optimisation of travel costs. As a result, it does not appear to be a good starting point for developing our negotiation protocol.

The protocols we use are based on those developed by Wainer et al. (2007) for agreeing on a meeting time. As these protocols are concerned with only one issue (time), elements from multi-issue negotiation need to be incorporated. Fatima et al. (2006) explains three methods for dealing with issues in multi-issue negotiation: all issues are discussed together (package deal), issues are discussed separately and independently of each other (simultaneous), or issues are discussed one after the other (sequential). Although it has been shown that proposing complete deals at each step is computationally more complex, it has advantages such as Pareto optimality (Fatima et al., 2006). In our model, it is too difficult to decide issues independently (for example, the activity may determine the time and location or vice versa) and also determine in which order they should be discussed (should we decide on the activity first? or who we want to see? or when we are free?), therefore we use the package deal method.

Two individuals are involved in each interaction: a host, who starts the interaction and makes the final decision, and a respondent. The host begins by creating a list of people and a default activity (visiting at home, evening, minimum duration). The host evaluates this same activity option but with different people, and the person who forms part of the activity with the highest utility that exceeds the threshold is selected as the respondent. If no options exceed the threshold, the host does not start an interaction.

The protocol proceeds as follows:

1. Host proposes an activity.

2. The respondent then creates a list of the possible day/time combinations and sends them to the host.

3. The host collates the day/times and creates a list of the *intersection* of the suggestions.

4. The respondent determines what type of locations are appropriate from the patterns provided. They then look up which locations they know of that match those location types.

5. The host collates the locations and creates a list of the *union* of the suggestions.

6. The host then creates a list of possible activities, taking into account when agents are available and the locations they have suggested. The list is returned to the respondent.

7. The respondent evaluates this list using a utility function and returns the list with their preferences.

8. Using the Borda ranking method, the host determines the chosen option and notifies the respondent, who adds the activity to their schedule. The host also adds the activity to their schedule.

Torroni (2002) describes a process for determining termination of dialogues, however he focusses on open dialogues, whereas our dialogue is predetermined. One useful technique is to create a state transition diagram and show that the dialogue proceeds towards final states.

Looking at the properties proposed by Jennings et al. (2001):

- guaranteed success (agreement will be reached): yes, or an agreement to disagree
- maximises social welfare
- Pareto efficient (no other outcome that will make someone happier without reducing someone else's happiness): depends on the ranking algorithm used
- individual rationality (best interests to play by the rules)
- stability (e.g., Nash equilibrium)
- simplicity
- distribution (no single point of failure)

Quenum et al. (2006) proposes the following:

- Liveness: "For every role of a protocol, events will always occur and fire some transition until the concerned role enters a terminal state."
- Safety: messages are received and handled by one or more roles; each action is triggered by an unambiguous set of events
- Termination of each role

The protocol satisfies a number of basic properties, such as termination, liveness, and safety. The protocol contains no loops and is completed in a constant number of rounds. All messages are sent from one role to another (either from host to respondent or vice versa) and the messages are unambiguous regarding the next step. Both roles proceed towards termination states, either when an activity has been scheduled, when a respondent cannot suggest any suitable days or does not approve of the activities suggested, or all parties cannot agree on options to negotiate about.

We further assume that interactions and activities are undertaken between two agents, who are connected to each other in the social network. This means that the social and location networks do not change (as new connections are not being made), therefore the centrality calculations do not change. However, the protocol can be used for larger groups of people.

### 5.3.3 Model overview

Finally, we turn to the model as a whole. The model consists of seven modules: input, simulation, environment, population, schedule, output, and util. Within the population module, a communication module is located. The package structure and the flow of control is shown in figure 5.3.

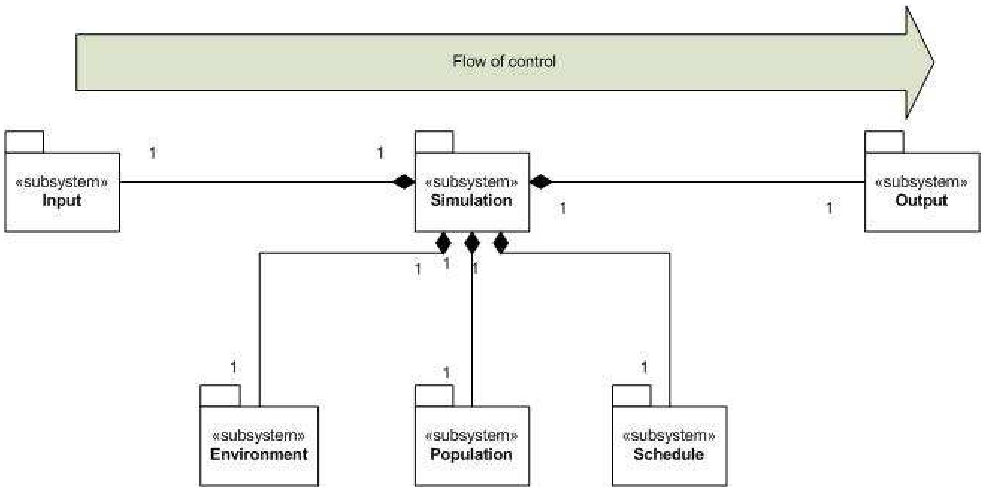



Figure 5.3: An overview of the packages.

#### Input

Several input files are required for the model to run:

- The synthesis file simply lists the names of all the input files for a particular scenario.
- The similarity file contains the values for $\lambda_a$ and $\lambda_g$.
- The alpha location file contains the values for $\alpha_l$.
- The alpha day/time file contains the values for $\alpha_{dy}$.

- The duration file contains the durations for each location type.
- The threshold file contains the threshold values for each work day and type.
- The error file contains the error values.
- The travel file contains the travel cost values.
- The beta file contains the values of the beta parameters.
- The node file contains a list of postcodes with x- and y-coordinates.
- The link file contains a list of node IDs signifying a link between two nodes.
- The location file contains a list of locations, including their name, type, node location, and opening hours. A second file with the same format provides the list of home locations.
- The people file contains a list of individuals and their socio-demographic values. Although several values are included, only age, gender, and work status are actively used. Two files of this type are input: one containing the core population and one containing the non-core population.
- The alts file contains a list of the links between two people.
- The "my locations" file contains a list of the locations each individual knows of at the beginning of a run.

These files are produced in CSV format for ease of generation. At this current stage, it is easier to separate the different elements of a scenario into different files for the extensive sensitivity testing, meaning only a small file has to be changed for each run. However in the future it will be easier to generate a larger file, most probably in XML format, with all the details for a particular scenario. The detailed column lists are provided in appendix A.

**Simulation**

The simulation runs as follows:

1. Initialise:
   (a) Read parameters from file
   (b) Initialise environment
   (c) Initialise population and social network
2. For each day:
   (a) For each person:
      i. Determine if they want to start an interaction on that day
      ii. If so, start interaction
      iii. If interaction completes successfully, possibly schedule activity
   (b) For each time of day
      i. Find activities to execute in the global schedule
      ii. For each activity:
         A. Each participant updates self: visited location today, undertaken activity today, travel
         B. Each link updates self: last seen today, travel
3. Print outputs

The order of execution of the people in step 2(a) is randomised.

**Environment**

The global network shall be stored as a network, with location details for some of the nodes.

The level of detail of the environment is intended to be at city level, i.e., it should contain main streets and locations for a particular city, as well as include links to neighbouring towns to take into account day trips. Each link will have a distance and possibly certain modes associated with it. Each mode will have an associated cost per kilometre, which will be used to calculate travel costs, and an indication of speed per kilometre plus an error term, which will be used to calculate the length of trips.

The locations will contain some properties that are global to the system, such as opening times and name. Individuals will have a separate object which stores their personal information about a location that they know about, such as the distance from their home, their preferred mode, and their error value for that location. Preferences and quality attributes can also be included here in future development iterations.

### Population

The population module stores the agents, the social network and the communication module. Figure 5.4 shows an overview of the Population module. The population is divided into core and non-core individuals, who are connected by links (shown as arrows).

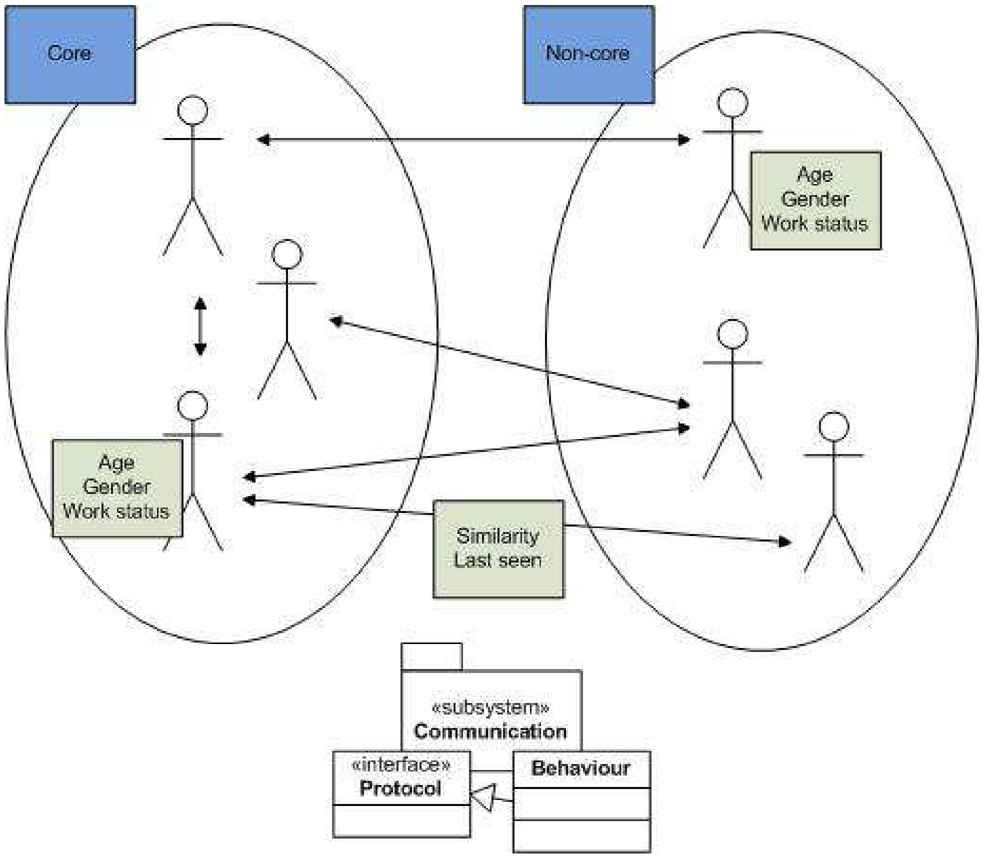



Figure 5.4: The architecture of the social network and interactions.

The population and social network objects are initialised from input files. These files contain details for each individual and alter. Individual attributes, such as age, gender and work status, are stored within each individual.

A social network stores all the relationships between modelled individuals. Attributes that are common to both individuals, such as when they last saw each other and their similarity, are stored in this network. Like with locations, individuals also keep a record of their alters with personal information, such as error values.

In this version of the model, the social network is not dynamic, meaning that links between people do not change over time.

### Communication

The population subsystem also handles the communication between agents. Each agent has a message queue, which they process in a first-in, first-out manner.

Messages have a sender and a receiver. In this implementation they are one-to-one only, however one-to-many messages are possible. Each message belongs to a conversation, which has a unique ID. When a message is sent, it is placed in the queue of the receiving agent.

One conversation will be executed at a time to avoid time clashes. Within each simulation time step $t$, there will be an interaction $n$, which consists of steps $S$. At each step $s$, the agents in the conversation will check their message queues. This may not be 100% realistic (as in reality two conversations with completely distinct groups of people can occur at once), however it is feasible to imagine that one would not have two conversations at once. There is no concept of real time or deadlines.

An interaction protocol consists of a Protocol object, which specifies the possible messages, and a Behaviour object, which specifies the behaviours on receipt of messages. At this stage, all individuals have the same behaviour, however this can be altered in future versions. Another future extension is the inclusion of influence between people, such as sharing information about good locations (e.g., the café on the main street is good) and transport options (e.g., parking at the local shopping centre is limited).

### Schedule

The schedule stores the activities for each person, as well as all the activities in the system.

Each day is divided into four parts: morning, afternoon, evening and night. No activities take place at night. Initial prototypes ignored time altogether, however dividing the day into hours is too detailed.

An assumption was made that people working full time would be occupied during both the morning and afternoon, and those working part time would be occupied during one (or both) of these time periods. This hard constraint was relaxed after calibration, as it is not entirely certain that someone working full time would work 9 to 5. Each person is designated as being in full- or part-time work or not working at all from the input files.

### Output

At this stage, five outputs files are produced:

- The personal output file contains data relating to each individual, such as their sociodemograpic details, values for the $\beta$ parameters, the total number of activities as well as by type and location, their social network measurements (centrality and clustering), and how many locations they know of.

- The pair output file contains data relating to each link or pair of individuals, such as their ages and genders, their similarity value, the distance between their two home locations, the total amount of activities undertaken together and the amount of travel undertaken by each for those joint activities.

- The conversation output file contains details for each conversation, including the host agent, the number of messages exchanged, and the outcome of the conversation.

- The schedule output file contains a list of each activity undertaken by each individual, including details of the activity itself (day, time, location, type), the distance from home, and the times since the location and location type were visited, the activity type was undertaken, and the participant was last seen.

- The activity output file contains details for each activity, including the day, day type, time, time type, duration, type, location, location type, host, and participants.

These files are produced in CSV format for ease of analysis in R and Excel. The detailed column lists are provided in appendix A.

**Util**

The util module contains objects that do not fit anywhere else, such as sorting objects.

## 5.4 Testing

The code was tested using unit tests. This involves testing the individual code components, such as objects and methods, by providing input and ensuring that the unit works as expected on its own. In Java, this can be undertaken with JUnit[5].

For example, the input objects were tested using a sample input file. The resulting object, which should contain the same parameters as in the input file, was then examined to ensure that this indeed was the case.

However, testing becomes more complicated when the agent behaviour needs to be tested. This is covered in the next chapter.

## 5.5 Discussion

In this chapter, a design has been presented for the conceptual model. Although there is no specific mature design methodology for agent-based models, AOSE methodologies can be used to design and describe the system.

In order to summarise the agentness of the model, we refer to Gilbert (2008)'s classification of agent-based models: perception, performance, policy, and memory.

- Perception: the individuals can detect incoming requests and has some knowledge of the sender;
- Performance: the individuals are capable of evaluating requests;
- Policy: the individuals attempt to select activities that suit them, by using an utility function to evaluate activities;

[5] http://www.junit.org/.

- Memory: the individuals are aware of the environment and also how long ago it is that they saw someone, visited a location, undertook a particular activity and so on.

As mentioned in chapter 2, decision making in transport models has been predominantly individual. With the addition of an interaction protocol, a feature of agent-based models, it is possible to model interpersonal influences. The proposed protocol is not wholly cooperative, in that there is one agent (the host) who "runs" the negotiation and makes the final decision, however it is clear that the preferences of the participants are taken into account when making the final decision.

Given our assumption that history plays a strong role in planning social activities, and the nature of joint activities requiring some form of interaction between individuals, agent-based modelling is an appropriate methodology.

One area of agent-based modelling that has not been explored thoroughly is validation. However, in order for a model to be used in the real world, calibration and validation is necessary, and is expected from a model of a transport system. Our next step is to demonstrate how this model can be verified, calibrated and validated.

# Part III

# Validation and experimentation

# Chapter 6

# Validation

Models of travel demand are becoming more disaggregate and behaviour-driven. As a result, agent-based modelling is gaining popularity and has been used for, amongst other applications, modelling pedestrian behaviour (Haklay et al., 2001) and route choice behaviour (Bush, 2001; matsim.org, 2007). This shift from single-facet aggregate models to multi-faceted disaggregate models involves a substantial increase in complexity, which in turn has major implications for the estimation and validation of these models. The problem of estimation and validation of multi-agent models tends to be more complicated. A model such as Feathers (Bellemans et al., 2010), for example, assumes that individuals have context-dependent aspiration levels and learn.

The aim of validation is to describe what the model is capable of doing, and then the user can determine whether it is suitable for its purpose (Amblard et al., 2007). Empirical validation has traditionally been dominant in transport modelling, where model outputs are compared to data collected from real systems. However, these statistical techniques are not always applicable to agent-based models due to lack of data and possible chaotic/non-linear behaviour in the system (Klügl, 2008). Despite this, several methodologies have been proposed, which include a combination of face and empirical validation tests. The processes within the model are also inspected as well as the model outputs.

This chapter focusses on the theory behind verification, calibration and validation that is useful for agent-based models of travel behaviour and social networks. Verification is discussed only briefly, and as calibration is the focus of the following chapter, this chapter is mainly concerned with validation. Firstly, the different terms are defined, following by a review of validation in agent-based modelling and activity-travel modelling. Secondly, a suggested validation process is presented, which then forms the backbone for the following chapters.

## 6.1 Definition of terms

> Modellers often plunge into the difficulty of setting up a set of rules and building a model. Yet the process of validation requires a clear view of what the model is attempting to explain and for what purpose. What are the key facts that the model needs to explain and how well must it do it? (Ormerod and Rosewell, 2006)

Validation is an important part of the modelling process and cannot be ignored until after the model has been developed. It differs from model verification in that verification is about checking that the model has been built correctly following a specification, whereas validation deals with whether the right model has been built.

There is a difference between calibration and estimation following Ortúzar and Willumsen (1994). Calibration is the selection of parameters with non-null values to optimise a goodness-of-fit measure, which is a function of the observed data. Estimation is determining which values make the observed data more likely, and therefore which parameters are necessary.

Crooks et al. (2008) defines validation as the extent of the goodness of fit to data collected from the real world. Calibration is where the model is "fine-tuned" to a particular context, which involves determining the parameter values.

Gilbert (2004) explains that validation is often considered to be only about comparing outputs to observed data at the expense of being able to use the model to increase understanding of a system or, as is generally seen in the transport field, to experiment with policy changes. This latter criterion is just as important. Validation is not concerned with showing whether the model is useful, but how (Louie and Carley, 2008).

Carley (1996) states that "the level of validation chosen depends on the model's purpose", therefore the purpose of the model will often lead to the amount of validation possible. From the other point of view, the data available could also determine the possible validity.

## 6.2 Validation issues and concepts in agent-based modelling

Agent-based models "consist of a system of agents and the relationships between them" (Bonabeau, 2002). The agents perceive their environment and other agents, make decisions following some rules, and act, possibly changing the environment in the process. Agents can also evolve over time, learning about their past experiences. Modelling at such a low level is sometimes more natural than attempting to, for example, create flow equations.

These components mean that the model can become very complex very quickly and as a result, validation of agent-based models is not a simple task. Making small changes at the micro-level, for example to the decision rules or interactions between agents, could produce very different results at the aggregate level. As a result, it becomes necessary to validate at both the macro/aggregate and micro/disaggregate level and both are difficult, if not impossible (Gilbert, 2004). Batty et al. (2004) note that as we move to richer and more detailed model structures, that they cannot be wholly validated.

Klügl (2008) lists several problems with agent-based models that may hinder validation:

- it is not as easy to collect descriptive values at the individual level for comparison to data as it is at the aggregate level;
- nor is it easy to collect the real-world data for comparison at the individual level;
- methods for validating the dynamics of an agent-based model are underdeveloped;
- models may exhibit chaotic behaviour as a result of feedback and nonlinearity in the system, which is difficult to validate;
- the time and other resources required to obtain the necessary model outputs should not be underestimated; and

| Types of validity | Behavioral v. | Structural v. | Both |
|---|---|---|---|
| Face v. | illustration | Understanding | training |
| Statistical v. | regression-like forecast | Prediction | what-if forecast |
| Both | more reliable forecast | more reliable prediction | strategic advice |

Table 6.1: Relation between type of validity and simulation objective (Klügl, 2008)

- too many parameters used with an automated optimising calibration should be able to fit the data in some way, so it is not possible to reject the model.

### 6.2.1 Types of validation

Troitzsch (2004) defines three types of validity following Zeigler:

- replicative: matches data already collected;
- predictive: matches data before they are collected;
- structural: matches data and the processes of the real system.

This was further elaborated by Klügl (2008), who proposed the following categories in two dimensions:

- the approach: face (human-observable tests) vs. empirical (statistical tests);
- the observed element: behavioural (studying the input and output of the model; encompasses replicative and predictive validity) vs. structural (the relations and reasoning in the model)

Returning to the idea of how a model is useful, she notes that both informal and formal validation techniques are required, and that different tests are needed for different purposes (see Table 1).

### 6.2.2 Validation processes

Klügl (2008) describes a process for validating agent-based models, beginning with face validation, in particular animations, assessing output, and tracking single agents. Once this is satisfactory, sensitivity analysis should be undertaken. Parameters should then be calibrated, and after this stage, statistical validation can be completed. In the final step, all data should be used to thoroughly test the model.

Barlas (1996) presents process validation, which is focussed on structural validity. There are several types of tests described:

- direct structure tests: the structure of the model is compared with knowledge about the real system structure. Tests include comparing with information gathered from the system being modelled (qualitative and quantitative) and from theory, comparing equations with knowledge, and extreme value testing on individual equations with a comparison with the real world.

- structure-oriented behaviour tests: the structure is indirectly tested by looking at behaviour. Tests include extreme condition testing (is the real world also sensitive to the same parameters?), relationships between variables (phases), and modified testing (if a real system can be modified in some way and data collected, does the model change in the same way?).

- behaviour pattern tests: moving on from the structure, are the outputs sensible? In particular, patterns (periods, frequencies, trends etc.) are more important than replicating data points. This can be done statistically (means, variances etc.) or visually.

Both processes comply with Gilbert's recommendation to validate at several levels.

## 6.3 Validation of activity-based models

Activity-based models differ from previous transport modelling approaches by "modelling relationships between individuals, households, and cities" (Buliung and Kanaroglou, 2007), which is not dissimilar to our definition of an agent-based model. Instead of only modelling the trips or trip-chains (tours), the activities of individuals are modelled and the travel derived from the activity-chain. This implies that a disaggregate approach is required in order to model individual behaviour and the associated spatial and temporal constraints.

Several models have been developed and are at various levels of maturity. The structure of models varies: some are based on utility maximisation and optimisation of daily schedules (e.g., PCATS), while some are rule-based (e.g., ALBATROSS).

These models are built for predictive purposes. In comparison to earlier transport modelling approaches, activity-based models are considered to be more behavioural and are therefore more transferable to different regions (Pendyala et al., 2004), however the focus has been on predictive validity and empirical comparison to data. Kurth et al. (2006) recognise that the separate components of an activity-based model (e.g., tour-level mode choice, tour-level mode choice, tour-level time-of-day choice, trip-level time-of-day choice) require testing. Sensitivity is also considered as important, however is more of a reasonableness test. Two overall sensitivity tests have been proposed in Kurth et al. (2006): comparing temporal outputs to a calibrated four-step model, and policy-oriented tests. Kurth et al. (2006) propose changes to the spatial environment only (e.g., different development densities, urban spread), whereas (Pendyala and Bhat, 2006) also mention that socio-demographic changes and pricing policies should be explored.

Buliung and Kanaroglou (2007) state that validation of activity-travel models is usually aggregate and consists of residual analyses. They point out that PCATS takes an average result over several runs and compares predicted and observed means for several activity-travel indicators, which is an accepted practice for validation of agent-based models.

Pendyala et al. (2004) used data from the 1999 Southeast Florida Household Travel Survey to validate the PCATS model. They presented mean comparisons of model outputs and observed data for the following variables:

- average daily trip rates (worker, student, other);
- average daily fixed and flexible activities (worker, student, other);
- first home departure time and final home arrival time (worker, student, other);

- modal split (single occupancy vehicle (SOV), HOV driver, HOV passenger, transit, other) to fixed and flexible activities.

Pinjari et al. (2007) describe the validation techniques used for CEMDAP, an activity-based model based on discrete choice. Activity diaries containing information about the type of activity, location, start time, end time, and transport mode were used. The measurements used were percentage shares (for discrete choices) and distributions (for continuous choices). Pattern-, tour- and trip-level characteristics are investigated. Comparison with the four-step model is also undertaken.

A type of sensitivity analysis was also carried out, in that several scenarios were tested: an increase in in-vehicle travel time, increase in costs, and increase in population. The outputs discussed (at pattern level) were the number of worker tours and stops, work start and end times, trip chaining, and average daily duration of activities.

The first round of validation for ALBATROSS used data from an activity-travel survey carried out in the Rotterdam region in 1997. The data included, for each activity, the purpose, the start and end time, the location, the mode used and travel time, and if others were involved in the activity. The outputs of the model that were compared were the mode for work, activity with whom, activity duration, start time, trip-chaining, and activity locations.

The re-estimation of ALBATROSS looks at the model components separately. At the tree-level, goodness-of-fit, chi-square (discrete) and F-stat (continuous) tests are undertaken. Predicted activity-travel patterns are compared with observed using string alignment techniques at the disaggregate level. At the aggregate level, several model outputs, such as number of work/secondary fixed/flexible activities, tours, activities in tour mode, activity type, mode of first link, activity duration, travel party, trip chaining, distance, and work duration are compared to observed data using chi-square/frequency differences and t-test/mean differences.

The calibration and validation of TRANSIMS for a small corridor network in an urban area was demonstrated in Park and Kwak (2011). The outputs to be evaluated were the travel times for two road sections and the vehicle count. A Latin Hypercube Design sampling approach was used to generate 200 parameter sets for testing, which were each run with five different seeds. The “best” set was chosen and is evaluated for stochastic variance. Finally, an alternative origin-destination matrix is used to test if the parameters perform adequately with unseen data.

This brief summary of validation attempts of activity-based model shows that although the model are more complex than trip and tour-based models, the principles of validation have not fundamentally changed. The reason is that the activity-based models described in this section restrict themselves to modelling variables based on observed data. They do not include more abstract behavioural concepts or principles and they are not dynamic and except for ALBATROSS, they are founded on full behavioural outcomes as opposed to an assumed underlying process that leads to emerging aggregate patterns. In that sense, validation of the majority of activity-based model implies a test of goodness-of-fit, and not a validation of the underlying behavioural process. However, the latest generation of dynamic activity-based models focus on social networks, aspiration, dynamic choice sets and similar concepts. For the reasons discussed, existing validation protocols may not be sufficient and not be applicable to these kinds of models.

## 6.4 Related verification/validation work

Looking back at the existing models of social and travel behaviour reviewed in chapter 3, very few have described how their model was verified or validated. As shown in Hackney and Marchal (2009), sensitivity analysis can be undertaken. Four types of inputs were varied: the starting social network (none, a random graph, and a random graph with addition and deletion of links), social interactions (none or sharing one location with a friend per time step), utility function, and replanning (varying proportions of changing route, changing activity time, changing locations based on agent knowledge or the whole environment). The outputs described in detail are:

- the number of people travelling at a particular time of day;
- the degree distribution of the social network; and
- the distance between home locations of connected pairs.

They also collect overall values for average trip distances, average trip duration, and the number of clusters and components in the social network. This shows an overlap between the outputs generated for activity-travel and transport models and social network models. By generating aggregate characteristics of social networks about which data are available as part of a sensitivity analysis, the changes induced by changing parameters can be checked to see if they are consistent with behavioural assumptions, which can be derived from theory, statistical analyses or even qualitative research.

## 6.5 Process

In case of complex agent-based model, process validation is arguably just as critical as outcome validation and sensitivity analysis. The following set of approaches may be used for that purpose.

### 6.5.1 Conceptual model validation

Recall from chapter 4 that the validation of the conceptual model is defined as "determining that (1) the theories and assumptions underlying the conceptual model are correct and (2) the model's representation of the problem entity and the model's structure, logic, and mathematical and causal relationships are "reasonable" for the intended purpose of the model" (Sargent, 2005).

This can be undertaken in the form of formal reviews by colleagues and stakeholders, and, in academic circles, informal feedback from other researchers. Tracing through the model specification on paper is also useful.

### 6.5.2 Direct structure tests

Structural validity is required if we want to say anything about the explanatory nature of the model, as output-only validity is only useful for prediction. We should be looking for "agent reasoning" and "causal relationships between variables" (Klügl, 2008).

If the structure of the model more closely reflects the real system, then if the real system changes then the model should be able to adapt. McNally (2000) noted a limitation of the four-step model in that it had "inadequate specification of interrelationships between travel and activity participation and scheduling" and therefore could not handle changes in, e.g., work hours, peak hours.

The equations and processes can be checked against the literature (theoretical structure). The equations can also be checked individually to ensure they perform as intended. For example, does the utility function capture time-of-day preferences? Processes, such as interaction protocols developed to make agreements, can also be tested individually. Again, in simple models, the behaviour of the model can be proven analytically. However, in complex model, emerging patterns and system response cannot be analytically derived. This is the very reason that in the agent-based research community often numerical simulation is used not only to illustrate the workings of the model, but also to examine alternative trajectories.

### 6.5.3 Face validation

The three techniques advised for face validation by Klügl (2008) are inspecting animations of the model, looking at the output of the model, and looking through the eyes of one agent in the model (immersion). (Gilbert, 2004) notes that face validity may be the only option available to micro-level validation in the absence of data on how individuals make decisions.

We can observe the dynamics of the social network over time, looking at the links created and deleted. However, social network dynamics are difficult to validate as the data collected is only a snapshot and also the time range of our model is too short-term to require explicit modelling of events that could change a social network such as marriage, children, and commencing a new job or at a new university.

The best approach for the social network is to check that it looks like a social network based on the theory regarding social network properties. As an example, Hamill and Gilbert (2009) mention properties such as low whole network density, personal networks with limited size and different sizes, fat-tailed distribution of connectivity, assortativity on degree (i.e., many links connect to others with many links), high clustering/homophily, communities, and short path lengths.

Another possibility is to use the methods described in the exponential random graph (e.g., Robins et al. (2007)) and dynamic network literature (e.g., Snijders et al. (2010)). This uses statistical methods to look for patterns in networks, such as the number of triads in the network, in order to compare to real-world networks. However, both of these may need to be adapted to work with personal or non-complete networks.

We are interested in the change and correlation in location knowledge and whether this is affected in some way, however we have no data regarding this. Theory on influence and rumour-spreading can be used to check if the information exchange is reasonable.

### 6.5.4 Structure-oriented behaviour

The main technique used in structure-oriented behavioural testing is sensitivity analysis, by which we want to determine the effects of different parameter values and inputs. It can be undertaken before calibration, in order to determine if any parameters are insignificant enough to be removed, or afterwards, in order to explore the effects of policy changes.

A first step is to test the seed variability by varying the seeds. A number of runs will be undertaken (around 50) with the same parameters. This will work best with the outputs that provide a single value for a run, such as total/average activities and total/average travel.

Sensitivity analysis can take the form of either altering parameters given a "base scenario" (i.e., changing single inputs) or providing different scenarios (e.g., increase in car ownership). For our model, different parameters, such as thresholds for utility functions and input matrices, can be altered to see the effects. Extreme values or bounds are also of interest.

Kleijnen (1995) notes that Design of Experiments, in which the inputs to the experiment (or in this case, model) are methodically varied and the outputs investigated, is commonly used for sensitivity testing, but often in an inferior manner: only one parameter is changed at a time. Ideally interactions between parameters are also required, however this is time-consuming. We are looking for the influences of parameters on outputs, for example in the form of elasticity coefficients (e.g., a change of x% is observed for a particular output when an input is changed by y%) (Chattoe et al., 2000).

The latter option of changing scenarios can also be used. As with other transport models, the environment can be altered. For models that include a social network component, the initial network can also be altered, along with the strategies for individuals in terms of decision making.

### 6.5.5 Behavioural pattern tests

For this stage, we are looking to match patterns found in the observed data. This is a form of statistical analysis as defined by Klügl (2008).

#### Calibration

Calibration involves finding the parameter values that produce appropriate outputs. One method of doing this is to create a model population based on the surveyed population and taking a two-day sample from the model of their behaviour. The modelled aggregate behaviour can then be measured against the actual aggregate behaviour. We will need to use statistical measures that are parameter-sensitive.

Traditional forms of calibration used in transport modelling (e.g., log-likelihood) may not be as appropriate for agent-based models because of the non-linearity in the system and the need to investigate several levels of complexity. In addition to this, Fagiolo et al. (2006) note that the structural content of agent-based models, particularly in the context of economic modelling, require a different approach to analysis, and therefore a different approach to empirical validation.

One approach to calibration can be undertaken with various samples (train-and-test). A possibility is to use the technique of k-fold cross validation, where k is generally 10 (Kohavi, 1995). The dataset is split into ten parts, and then trained on nine parts and tested on the remaining part. This is repeated ten times.

#### Patterns

For the two-day sample, we can also match against frequencies of activities on particular days. A possible list of outputs could include:

- number of activities (per person, per location, per day of week)
- frequency/interval of activities (per person, per location, per type)
- distribution of activity group sizes/types of groups
- amount of travel
- social network properties: network density, size of personal networks, clustering, path lengths

An indication of frequencies for particular activities could be useful in place of a detailed activity diary. In this manner, the activity generation for locations types could be validated, however the distances travelled could be modelled incorrectly.

**External validation**

In order to test the model more thoroughly on previously unseen data, a general activity data set can be used, especially if it contains group size and the type of group (e.g., household, non-household).

## 6.6 Discussion

Transport modellers are building models that are more concerned with modelling individual and dynamic behaviours than previously. This necessitates a shift in the modelling approach to individual- and agent-based models, which has implications for estimation and validation, due to both the complexity of the model and the data available.

This chapter has investigated validation methods for agent-based models in the activity-travel context, in particular focussing on models incorporating joint social activities. The principles of validation are similar for traditional, agent-based, and transport-specific simulations, however the vocabulary differs slightly.

A suggested validation process was presented. Although our process is tailored to our model, the steps may be appropriate for other individual-based activity-travel models. It covers several different validation techniques which will provide more insight into the usefulness and appropriateness of the model. Readers will note that many elements of the approaches are not very different from validation of simple non-agent-based models. However, as only particular empirical validation is possible the approach also includes some non-conventional elements.

As also noted by Gilbert, it is important to validate agent-based models at different levels, both individual level and aggregate level. However, this may be difficult, especially at the disaggregate level either because no data are available or because the model uses abstract behavioural concepts. In our case, we have data from the real world at an individual level, but we do not have information about how people made a particular decision to meet with a certain group of people or undertake a particular activity, nor do we have information about individuals long-term plans. Different data collections are necessary to provide adequate data for validation of both the activities and social processes. On the other hand, the fact that agent-based models tend to generate emerging aggregate patterns from individual behavioural principles as opposed to using aggregate input offers validation potential.

In general, the type and amount of validation required depends on the aims of the model, the model setup, the data available, and the level of confidence/validation/accuracy desired, which should be determined before model development begins. In the following chapters, the data available is discussed along with calibration and a demonstration of some of the validation techniques mentioned.

# Chapter 7

# Data and calibration

A model that is intended to be applied to the real world requires some sort of estimation or calibration as part of the validation process.

Most models in transport are data-driven, meaning that a lot of data is to be collected for testing and demonstrating that the model is working as expected and that only items and attributes for which data can be collected are included in the model. However, this means calibration limits and influences the model development (Windrum et al., 2007). Working with data that is not as specific means the model is not tied to a particular data collection tool or questionnaire and could be more easily adapted.

In this chapter, the data available for our model is explained, and the generation of input networks is demonstrated. The calibration process is discussed, along with a demonstration of model verification, in particular looking at the internal consistency and a model walkthrough.

## 7.1 Data

Various datasets were used in determining parameters and expected outputs for the model. As mentioned, the model is not data-driven. This means it is more theoretically valid than empirically valid, but is also not tied to one particular data collection.

### 7.1.1 Social interactions

For the social interactions, a data set was used that was collected in 2008 in the Eindhoven region (van den Berg et al., 2008). The idea behind this data collection was to examine the relationship between the built environment, ICT use, and social networks and travel. As such, the survey asked questions about all social interactions over a two day period, including those via phone, email and SMS, but excluding those with a household member or about work-related issues.

747 respondents completed the initial activity diary-style survey, which contained three parts:

- an interaction diary, asking about the purpose of the interaction, the location, the start and end time, whether it was prearranged, routine, or coincidental;
- details about each person interacted with, such as age, gender, the type of relationship, and how far they live from each other; and
- details about the respondent, such as age, gender, work status, and their use of travel modes and ICT tools.

For our purposes, the whole survey could not be used, as we were interested in face-to-face activities only. The data was filtered to include only those living in the Eindhoven area (postcodes 5600 AA - 5659 ZZ), only those interactions with people of a certain social category (see section 7.2.1 for details), and interactions that were prearranged or routine. This left 521 valid respondents who undertook 530 valid activities (with 4732 valid alters).

This dataset provided the output targets or expected values. The alpha parameters (the preferences for an activity with a particular type, day, and time ($\alpha_i^{ady}$) and for a particular location ($\alpha_i^l$)) were initially set based on data collected from this survey, but were adjusted to reflect the outputs.

The categories in the data were reassigned as shown in tables 7.1 and 7.2. Note we originally had categories for shop and cafe, however due to the low number of activities at these locations in the data, those activities were transferred to the "other" category. These categories still exist in the model implementation.

### 7.1.2 Activity types

As a starting point for developing a classification of activity types, existing classifications were investigated. Most had a specific purpose in mind, and

| Code | English description | Our category |
|---|---|---|
| 1 | doing an activity together | experience |
| 2 | visit someone | visiting |
| 3 | receive a visit | visiting |
| 4 | talking | chatting |
| 5 | quick question | info |
| 6 | make an appointment | info |
| 7 | give information/advice | info |
| 8 | receive information/advice | info |
| 9 | discussion | info |
| 10 | other | other |

Table 7.1: The activity type recoding.

| Code | English description | Our category |
|---|---|---|
| 1 | home | home |
| 2 | someone else's home | home |
| 3 | work | other |
| 4 | school | other |
| 5 | shop | shop/other |
| 6 | cafe/restaurant | cafe/other |
| 7 | on the way | other |
| 8 | other | other |

Table 7.2: The location type recoding.

only considered a subset of the activities we are interested in (sometimes along with other activities outside our scope). We needed to consider a combination of these lists.

Kemperman and Timmermans (2008) provided a list of social/leisure activities for looking at the connection between activity participation and urban environment. Their list was the starting point for our list, as it included social visits (hosting friends, relatives), time-out activities, community/club activities, cultural activities (cinema, museum, concert), visiting restaurant/cafe, disco, recreational activities outside and inside and touring. They also differentiated between in-home and out-of-home activities. However, this list is not focussed on joint activities and omits some of the activities we are interested in.

Tinsley and Eldredge (1995) created a clustering of leisure activities based on which psychological needs they satisfied. This is useful as it goes back to why people do activities in the first place. Their clustering has been used as a check to ensure no cluster is completely ignored in our classification.

Mokhtarian et al. (2006) were interested in the effect of ICT on activities. They found it difficult to categorise activities, however looked at a time/location dependent/independent split. Activities that are location-independent could possibly be replaced by an activity using ICT, whereas location-dependent activities are less likely to be replaced.

Ettema et al. (2007) suggested a purpose that is not covered by the other literature: help and support. These are activities that “involve a physical activity implying that a person spends time for the benefit of someone else.” (Ettema et al., 2007).

Bhat and Lockwood (2004) looked at physically active and passive modes and activities. This is an interesting distinction not picked up by others, and is another way of looking at activities.

From these classifications it is clear that there are many ways of looking at activities. Some rely more on locational attributes, i.e., where the activity is taking place, to determine the type, while others rely more on the purpose or needs fulfilled by the activity. The former is easier to deduce from existing data collections, whilst the latter requires respondents to consider and communicate why they are undertaking a particular activity. In moving on from a solely “where” approach, the purpose of the activity will become important. Having said that, it adds more complexity to the data collection and more recall of whether an activity was undertaken for, e.g., social or experiential purposes.

In this project, both location and activity types were used, in order to provide flexibility with classification. However, the counts for some combinations differed greatly (e.g., visiting activities tended to take place at home locations, experience activities at out-of-home locations). This means that a combined activity-location type could reduce the number of parameter values needed in the model.

### 7.1.3 Social networks

Arentze et al. (2009) developed an algorithm using the data from van den

Berg et al. (2008) to synthesise social networks. This was based on three components: the similarity between two people, the distance between them, and the amount of common friends they share. The initial illustration did not include the third component.

This algorithm was coded in Python and used to generate a large social network based on a population synthesised from Dutch MON data. In order to test our model with smaller populations, a subset of the network was extracted. This process is described further in section 7.2.1.

The illustration only made use of certain relationship types, as shown in table 7.3. As a result, our data also only used these relationship types.

| Code | English description | Included? |
|---:|---|---|
| 1 | Partner | No |
| 2 | Father/mother | No |
| 3 | Child | No |
| 4 | Brother/sister | No |
| 5 | Other relative | No |
| 6 | Household member | No |
| 7 | Neighbourhood member | Yes |
| 8 | Colleague | Yes |
| 9 | Fellow student | Yes |
| 10 | Union member | Yes |
| 11 | Other friend | Yes |
| 12 | Other acquaintance | Yes |
| 13 | Other | No |

Table 7.3: The relationship type categories included in our analysis.

### 7.1.4 Durations

Our utility function calls for durations of activities. These were implemented in a discrete manner, so that each activity type had a minimum, mean, and maximum duration. However, the AMADEUS data (Timmermans et al., 2002a), which was used, aligned more with our proposed location types rather than our activity types. Therefore the duration values are associated with location types, rather than activity types.

### 7.1.5 Intervals

In the social interaction data collection (van den Berg et al., 2008), some idea of how often activities were undertaken was provided for certain activities, such as visiting friends, going to the cinema, and going out to eat. However, apart from visiting friends, which occurred around every 13 days on average, the other activities had averages of more than 100 days, which was outside the time scale of our model.

Data on intervals between activities was collected as part of a project on needs-based modelling (Nijland et al., 2009). One of the surveys administered asked, for a list of 37 activities, how long ago each activity had been undertaken (in the past six months), and if it was planned for the future, and if so, for when.

The data set consisted of 290 respondents in the Eindhoven region. Looking at the intervals for certain activities provided an indication of the intervals between them. Visiting activities averaged around 12 days, which corresponded to the social interaction survey.

In the end, these values were used to provide a rough indication for the beta values. As with durations, however, the data were skewed more towards our concept of locations, rather than our activity types, as the data did not distinguish between individual and group activities.

### 7.1.6 Locations in Eindhoven

The data on locations in Eindhoven was collected, again, for another project on how people move around a city[1]. In this case, a list of cafes, restaurants, sports centres, museums, and other public locations was collated. For our purposes, locations outside the Eindhoven area were removed. Due to the lack of interest in eating out from the social interaction data, the restaurants were also reduced to 25% of the original list.

## 7.2 Synthesis of input networks

Three different types of networks – realistic, with both distance and similarity weighting, random with distance weighting, and purely random – are

[1] I am grateful to Anastasia Moiseeva and other members of the Urban Planning Group at TU Eindhoven for collating this data.

generated to be used for model testing, along with a base case in which there is no persistent network. Before they are used as model inputs, however, the three types of networks will be evaluated for their appropriateness as a representation of a social network.

The populations used were taken from a synthesised population based on MON data. This synthesised population consisted of 218,203 individuals in 136,753 households. For each person, the data contains their age, gender, work status, and whether they have a driver's licence. For each household, the data contains the postcode, the household composition, the age of the youngest child, and the number of cars and bicycles in the household.

Note that the population is divided into two: those who we are evaluating, based in Eindhoven (the core population), and those who are friends with someone in that group, not necessarily based in Eindhoven (the non-core population).

For all experimentation, the core population was kept constant. However, the different methods used for deriving the social networks meant that the non-core population differed.

### 7.2.1 Realistic

Given the data collected for activity-travel modelling purposes, at least two network generation algorithms have been developed. Illenberger et al. (2009) presented a model based on spatial distance, while Arentze et al. (2009) developed an algorithm based on spatial and social distance. The latter can also be extended to include the influence of common friends, following the theory that if person 1 is friends with person 2 and person 3, then persons 2 and 3 have a good chance of also being friends.

The algorithm developed by Arentze et al. (2009) was used for the input network for this model, as it made use of relevant data for our case study, in particular homophily. Given the following utility function:

$$
\begin{aligned}
U_{ij} &= V_{ijk}^{Q} + V_{ijk}^{D} + V_{ijk}^{C} + \epsilon_{ij} && (7.1)\\
V_{ijk}^{Q} &= \sum_{s} \beta_{ks} Q_s(X_{is}, X_{js}) && (7.2)\\
V_{ijk}^{D} &= \delta_k \ln D(L_i, L_j) && (7.3)\\
V_{ijk}^{C} &= \chi_k C(N_i, N_j) && (7.4)
\end{aligned}
$$

we estimate the probability of a link between person $i$ and person $j$ to be

$$P(i \leftrightarrow j) = \frac{exp(V_{ij} - max(\mu_i, \mu_j))}{1 + exp(V_{ij} - max(\mu_i, \mu_j))} \tag{7.5}$$

where $V^Q_{ijk}$, $V^D_{ijk}$, and $V^C_{ijk}$ are the utilities for similarity, distance, and common friends respectively, $k$ is a social category, $s$ is an attribute, $X_{ps}$ is the value person $p$ has for attribute $s$, $Q_s$ is a measure of similarity for attribute $s$, $L$ is the base location of a person, $D$ is the distance between two locations, $N$ is the existing personal social networks of a person, $\mu_p$ is the threshold value for person $p$, and $\beta_{ks}$, $\delta_k$ and $\chi_k$ are weights. In the estimation, $k$ and $V^C_{ijk}$ were ignored, leaving only similarity (on age and gender attributes) and distance components.

Based on the estimation procedure, $\delta$ = -1.606, $\beta_{age}$ = 0.888, $\beta_{gender}$ = 0.713, threshold base value = 6.835, threshold effect (male) = 0.512, threshold effect (age<40) = 0.177, threshold effect (60<age<70) = -0.608, and threshold effect (age>70) = -0.228. The distance between two people is divided into seven buckets (0-1km, 1-5km, 5-15km, 15-30km, 30-60km, 60-100km, 100+km) and $D(L_i, L_j)$ is set to be a middle point of the associated range (1km, 3km, 10km, 22.5km, 45km, 80km, 140km). The similarity was calculated as $Q_{gender}$ = 1 if the genders of $i$ and $j$ are the same, and 0 otherwise. Age similarity was calculated as $4 - n$, where $n$ is the difference in levels between the ages of $i$ and $j$. In order to achieve a reasonable average number of friends, a threshold scale factor is used, which is dependent on the size of the synthetic population.

The procedure was coded in Python and proceeded as follows:

1. The individuals in the household sample file are read in along with their attributes. Those living in Eindhoven are marked as being in the core population.

2. Each individual $i$ is assigned a threshold $\mu_i$ based on their sociodemographic attributes, the threshold base value and the threshold effects. For example, a male in their 70s has a threshold of 6.835 + 0.512 - 0.228 = 7.128.

3. For each potential pair $i$ and $j$:

(a) The maximum threshold, $max(\mu_i, \mu_j)\times$ the threshold scale factor, the similarity, $\sum_s \beta_s Q_s(X_{is}, X_{js})$, and the distance between the two people, $\delta \ln D(L_i, L_j)$, are calculated.

(b) The probability of a connection is calculated, using Equation 7.5.

(c) A random number is drawn and is used to determine whether a connection is made or not.

Once this is calculated for the entire sample population, smaller samples of different core population sizes are extracted.

Two alterations were made to the parameters:

- In order to achieve the correct number of links, the threshold requires factoring. For this scenario, the factor was 1.17.
- As the distance distribution was quite different to the data when $\delta$ = -1.606, it was also altered to create a better distribution. The $\delta$ parameter used in this scenarion was -1.35.

The average network size was 12.5 and the average distance between alters was 21.69km.

### 7.2.2 Random, but distance weighted

This is identical to the realistic network, however the probability of links occurring is based on distance only. Similarity is not taken into account. The threshold is chosen so that the average network size is similar to the realistic network.

The utility equation was based on the actual distance, which was log-transformed and multiplied by -1.4. The threshold was 4.8.

For this network, the average network size was 12.8 and the average distance between alters was 24.36km.

### 7.2.3 Random

The random network is persistent over the duration of the model run. These are created by taking a population and an "'equivalent" realistic network, and taking the average number of connections in the realistic network as a target. Based on the population size $n$ and the target average degree $d_{av}$, a uniform probability is calculated ($d_{av}$ / $(n-1)$) and Monte Carlo simulation is used to determine whether each link exists or not.

As there is sometimes overlap in the networks, the network size was a little lower than expected. The average network size was 12.0 and the average distance between alters was 95.98km.

### 7.2.4 Random choice

In the random choice "network", there is no persistence between model steps and is therefore not a network as such. At each step in the model, 12 people are chosen from the entire population. This corresponds roughly with our calculation that people have 12 alters on average.

The non-core population consisted of 10% of the total synthesised population, or around 21522 people.

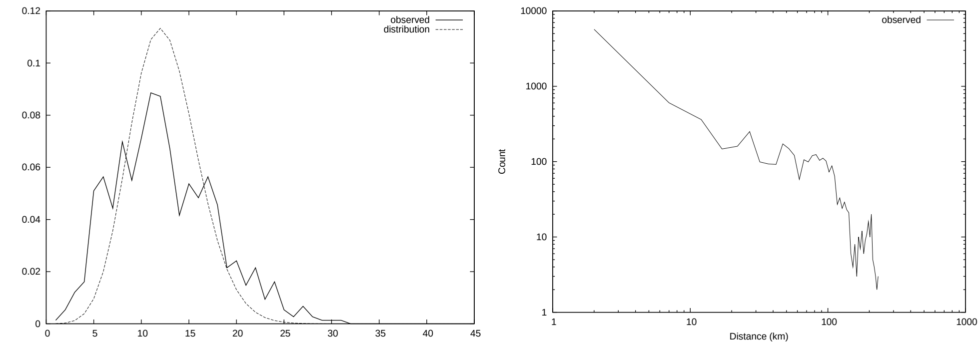
### 7.2.5 Evaluation and comparison

As mentioned in chapter 3, there are many metrics for social networks. Hamill and Gilbert (2009) points out that social networks tend to have the following attributes:

- low whole network density
- limit to the size of personal networks
- differences in size of personal networks
- fat-tailed distribution of connectivity (more power-law like)
- assortativity on degree (many links connect to others with many links)
- high clustering/homophily
- communities
- short path lengths between alters

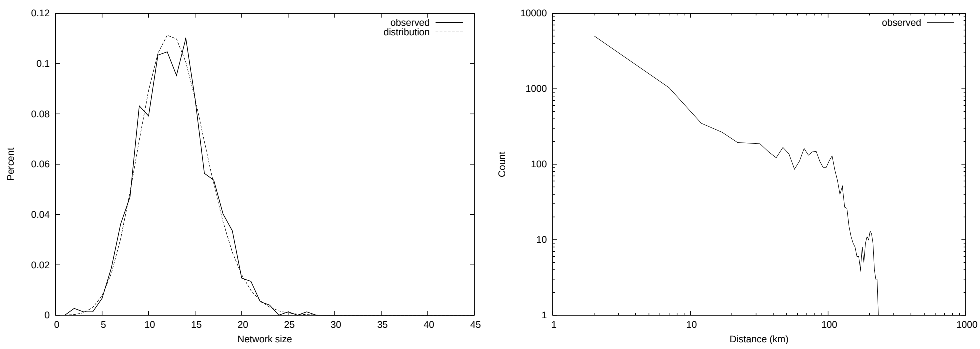
The additional properties in comparison to Wong et al. (2006) are variation in network sizes and assortativity.

Looking at the sizes of personal networks and the distances between individuals, we can see that the realistic networks (figure 7.1) generated are suitable. Compared to the distance-weighted network (figure 7.2), the distribution of the network sizes looks like a social network with the " fat tails" and flat peak, whereas the distance weighted network tends to follow the distribution. Comparing the distribution of distances in the model, plotted on a log scale, the networks with a distance weight have a power-law distribution, whereas the random network (figure 7.3) does not.




(a) Network size (b) Distance distribution

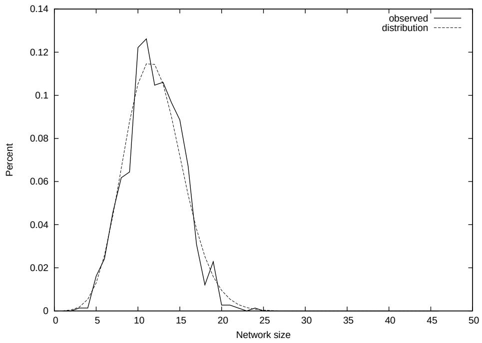
Figure 7.1: Properties of the realistic network.



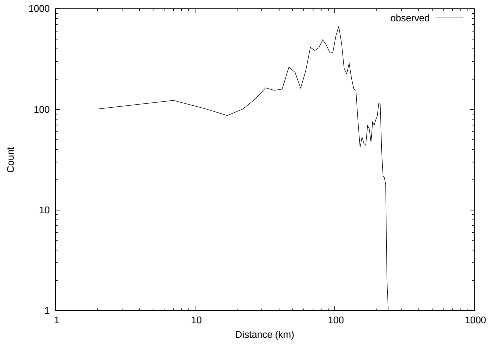

(a) Network size (b) Distance distribution

Figure 7.2: Properties of the distance-weighted network.

Therefore, we are satisfied that the generated realistic network is representative of a social network in terms of personal networks and personal distances. While the distance-weighted network suffices in terms of distances, the sizes of the personal networks do not reflect what is expected of




(a) Network size




(b) Distance distribution

Figure 7.3: Properties of the random network.

a social network.

## 7.3 Calibration

Calibration of agent-based models is slightly more difficult than usual for two reasons: dealing with parameter structures and avoiding the tuning trap (Klügl, 2008).

For our model, the calibration was undertaken manually. Expected values from the social visit dataset were collected by expanding the data from two days to a full week. The model was then run for a week, following a warmup period, and the model outputs compared to the expected outputs as a chi-square test, sum of squared differences and percentage differences. This was undertaken in an aggregate manner for activities by day, work status, work day, gender, age, location type and activity type. In addition to this, location type, activity type, and day were disaggregated by age and gender.

As an example, the expected values for day (and disaggregated by day) were extracted in the following manner:

1. The data is filtered as described in section 2.1 and a crosstab of day vs. age is extracted. (table 7.4)

2. The number of people who responded for each day of the week is tallied, as well as the number of people in each age category, and a

crosstab of the number of people by age and day. (table 7.5)

3. The number of activities is divided by the number of people per day (table 7.6), and per age and day (table 7.7). Per age is the sum of the daily averages for the week (table 7.8; note this is the sum of the columns in table 7.7). In some cases this will need to be divided by 2 (the number of days in the sample) and multiplied by 7 to get to seven days.

| Day/Age | 1 | 2 | 3 | 4 | 5 | Total |
|---|---|---|---|---|---|---|
| 1 | 27 | 39 | 11 | 8 | 0 | 85 |
| 2 | 20 | 40 | 24 | 10 | 1 | 95 |
| 3 | 30 | 43 | 13 | 8 | 2 | 96 |
| 4 | 24 | 62 | 9 | 2 | 2 | 99 |
| 5 | 23 | 40 | 8 | 4 | 0 | 75 |
| 6 | 18 | 16 | 6 | 2 | 1 | 43 |
| 7 | 11 | 13 | 7 | 1 | 0 | 32 |
| Total | 153 | 253 | 78 | 35 | 6 | 525 |

Table 7.4: The number of valid activities by day and age.

| Day/Age | 1 | 2 | 3 | 4 | 5 | Total |
|---|---|---|---|---|---|---|
| 1 | 35 | 57 | 26 | 11 | 4 | 133 |
| 2 | 41 | 54 | 31 | 22 | 4 | 152 |
| 3 | 57 | 64 | 27 | 20 | 5 | 173 |
| 4 | 48 | 76 | 24 | 10 | 5 | 163 |
| 5 | 38 | 65 | 21 | 11 | 2 | 137 |
| 6 | 40 | 79 | 24 | 11 | 5 | 159 |
| 7 | 35 | 63 | 17 | 7 | 3 | 125 |
| Total | 294 | 458 | 170 | 92 | 28 | 1042 |

Table 7.5: The number of survey respondents by day and age.

### 7.3.1 Increasing population size

In order to quickly find a parameter set, the model was run with a population of 198 individuals. It is therefore important to test whether the parameters are also suitable for larger populations.

| Day | Activities |
|---|---|
| 1 | 0.639 |
| 2 | 0.625 |
| 3 | 0.555 |
| 4 | 0.607 |
| 5 | 0.547 |
| 6 | 0.270 |
| 7 | 0.256 |

Table 7.6: The number of activities per person per day.

| Day/Age | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| 1 | 0.771 | 0.684 | 0.423 | 0.727 | 0 |
| 2 | 0.488 | 0.741 | 0.774 | 0.455 | 0.25 |
| 3 | 0.526 | 0.672 | 0.481 | 0.4 | 0.4 |
| 4 | 0.5 | 0.816 | 0.375 | 0.2 | 0.4 |
| 5 | 0.605 | 0.615 | 0.381 | 0.364 | 0 |
| 6 | 0.45 | 0.203 | 0.25 | 0.182 | 0.2 |
| 7 | 0.314 | 0.206 | 0.412 | 0.143 | 0 |

Table 7.7: The number of activities per person per age per day.

Three larger populations were created, of 497, 745, and 994 people. In order to match the data, the thresholds needed to be increased slightly. The magnitude of the increase appeared to be dependent on the number of links and the size of the entire population. The percentage of double edges – that is, the edges that appear twice in the model due to person $i$ having an alter $j$ who is also in the core population, and therefore person $j$ also has a link to person $i$ – was calculated as $(\#edges - popsize)/\#edges$, and the factor was taken to be the difference in the value between the base case (in the case, the network with a core population of 198) and the network in question. Table 7.9 shows the threshold factors for each network.

This calculation does not give an identical result to the network used for calibration, but provides reasonable output. Table 7.10 shows whether there is a difference between the modelled and expected outputs for each network as chi-square values (with p-values in parentheses) for time, workdays, locations, types, and weekday/weekend outputs.

From these results, it is clear that it is difficult to calibrate for all aspects.

| Age | Activities |
|---|---|
| 1 | 3.655 |
| 2 | 3.937 |
| 3 | 3.096 |
| 4 | 2.470 |
| 5 | 1.25 |

Table 7.8: The number of activities per person per age.

| Core size | Edges | Population size | % double edges | Threshold factor |
|---|---|---|---|---|
| 198 | 2504 | 2467 | 0.0148 | 1.0000 |
| 497 | 6258 | 5958 | 0.0479 | 1.0332 |
| 745 | 9293 | 8627 | 0.0717 | 1.0569 |
| 994 | 12675 | 11431 | 0.0981 | 1.0834 |

Table 7.9: The threshold factors for each network.

The day of the week, in particular, fluctuates wildly between network sizes, and an abstraction to weekend/weekdays or workdays is recommended. As shown in table 7.11, the percentage difference between the modelled and expected outputs for weekday and weekend activities are more stable and fall within 12%. Weekend activities are slightly overpredicted, whilst weekday activities are underpredicted.

### 7.3.2 Increasing run duration

The calibration was undertaken with a warmup of 28 days. In this section, the effects of extending the warmup time (in increments of 7 days) is presented. This test was underaken with core population sizes of 198 and 745.

In both cases, the overall number of activities is stable (table 7.12) and is within 3% of the expected value.

Although the smaller population shows minimal change in terms of the percentage difference to the expected number of activities of particular types or on particular days, there are changes when the larger population is used. In terms of the activity location types, the out-of-home activities increase significantly from -0.23% difference with a 28 day warmup to 9.64% with a

| Core size | Workdays | Weekday | Time | Location | Type |
|---|---|---|---|---|---|
| 198 | 0.269 (0.87) | 18.78 (0.005) | 0.096 (0.95) | 0.064 (0.80) | 0.500 (0.97) |
| 497 | 0.656 (0.72) | 0.926 (0.34) | 2.266 (0.32) | 0.851 (0.36) | 2.543 (0.64) |
| 745 | 0.409 (0.82) | 1.830 (0.18) | 4.021 (0.13) | 3.332 (0.07) | 9.184 (0.06) |
| 994 | 0.571 (0.75) | 99.11 (0.0001) | 6.505 (0.04) | 6.141 (0.013) | 16.844 (0.002) |

Table 7.10: Chi-square results for calibration of network size.

| Core size | Weekdays | Weekends |
|---|---|---|
| 198 | -4.21 | 11.83 |
| 495 | -5.56 | 3.87 |
| 745 | -5.03 | 5.67 |
| 994 | -5.99 | 5.47 |

Table 7.11: Percentage differences between modelled and expected outputs for weekday/weekend activities per network size.

56 day warmup. A similar effect occurs with information activities (7.34% to 23.96%) and weekend activities (5.67% to 12.47%). Checking the change in proportion of activities shows a small increase for out-of-home activities (55.3% to 58.6%) and a greater increase for information activities (31.8% to 35.3%). As weekday activities are more numerous than weekend activities, the proportion change is negligible (16.5% to 16.9%).

This could be due to the larger parameter value assigned to information activities outside the home, which is 1.4 times greater than the other location parameter values. It could also be an effect of the interval parameter values, which were set very coarsely. It shows that while a reasonable parameter set can be found by adjusting parameter values, there are extra effects on the substitution of activities that also need to be checked. We are also making an assumption that the weeks are similar; having a longer-term data set would assist in being able to calibrate longer periods of time.

## 7.4 Initial verification and validation

In this section, two tests are described. The first, internal consistency, is a form of structured-oriented testing and verification: does the model perform adequately with respect to variation? The second involves a walkthrough

| Core size | Expected | 28 days | 35 days | 42 days | 49 days | 56 days |
|---|---|---|---|---|---|---|
| 198 | 693.05 | 680.6 | 678.03 | 687.9 | 685.4 | 687.17 |
| 745 | 2607.69 | 2518.57 | 2525.43 | 2559.07 | 2561.47 | 2614.8 |

Table 7.12: Total activity counts for varying warmup periods.

and is a form of face validation using immersion: by following one agent, are the results acceptable?

The same sample input network that was used for the calibration was used. All activity history is set to -7 (i.e., a week previously), so agents last saw everyone, did all activities, and visited all out-of-home locations 7 days previously.

### 7.4.1 Seeds/internal consistency

An initial verification test is to look at the internal consistency of the model. One way of carrying this out is sometimes referred to as "internal validation" and involves running the model with different seeds to look at the stochastic variability over many runs. Sargent (2005) states that a lack of consistency could be an indication of a questionable model.

The test works best with single aggregate values from the model, such as the total number of activities or the total amount of travel. In our case, we focus on the number of activities generated in the model.

For 60 runs, the running mean and standard deviation is calculated for all runs up to that point. The standard deviation is divided by the overall mean to find the coeffiecient of variance.

The distribution of the number of activities is reasonably normally distributed with mean 2523.6 and standard deviation 46.23 (using a Kolmgorov-Smirnov test and comparing with a random normal distribution of 60 data points with the afore-mentioned mean and standard deviation). For both the mean (figure 7.4) and the coefficient of variance (figure 7.5), the model appears to reach a stable state after 30 runs. The coefficient of variance levels out at around 2%. This could vary if the error values were altered. However, the variability is not excessive and does not indicate further issues with the model.

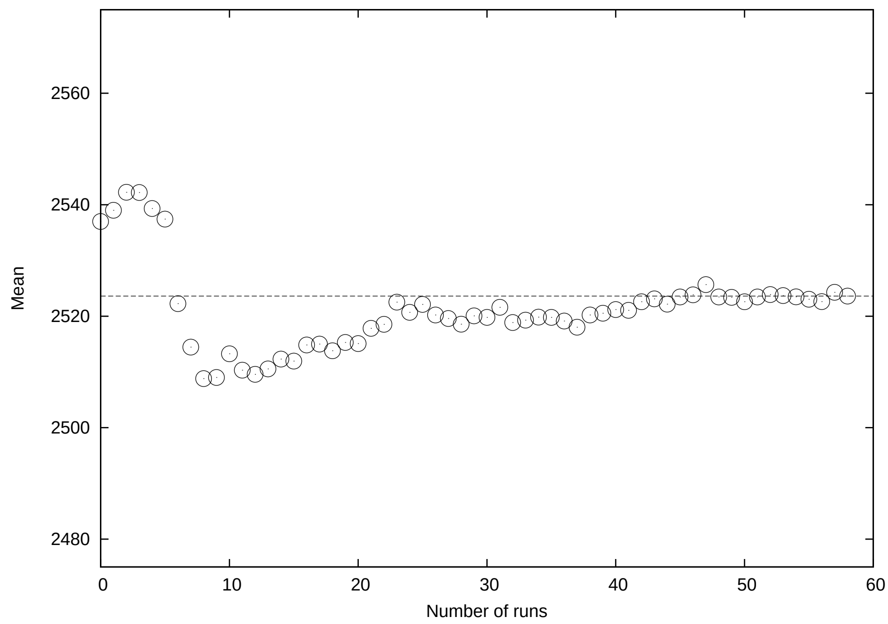



Figure 7.4: Mean of total activities across runs.

### 7.4.2 Individual walkthrough

A method proposed by Klügl (2008) was looking at the agents individually to see if they are performing as expected. This can be complicated, as we are dealing with schedules which cannot be easily aggregated. On a pattern basis (e.g., every N days the individual visits a certain location), it is possible, but on a point basis (e.g., using one seed the individual stays at home on Monday, but with another seed they visit a friend, and so on for many runs) it is difficult. In this section, we will make use of the outputs from a single run with a single seed for a single person over a 10 week period. Note that the same population was used as for the calibration, however only the outcomes for one person were extracted.

The person under investigation is female, aged under 35, does not work, and has 11 acquaintances in the network. These acquaintances are spread out in the Netherlands as shown in figure 7.6, however most are local to the Eindhoven area. This person was chosen as their network size was typical of the individuals in the model.

From the locations visited by this individual over 10 weeks (figure 7.7), we can see that they are not traversing their entire spatial network. It is

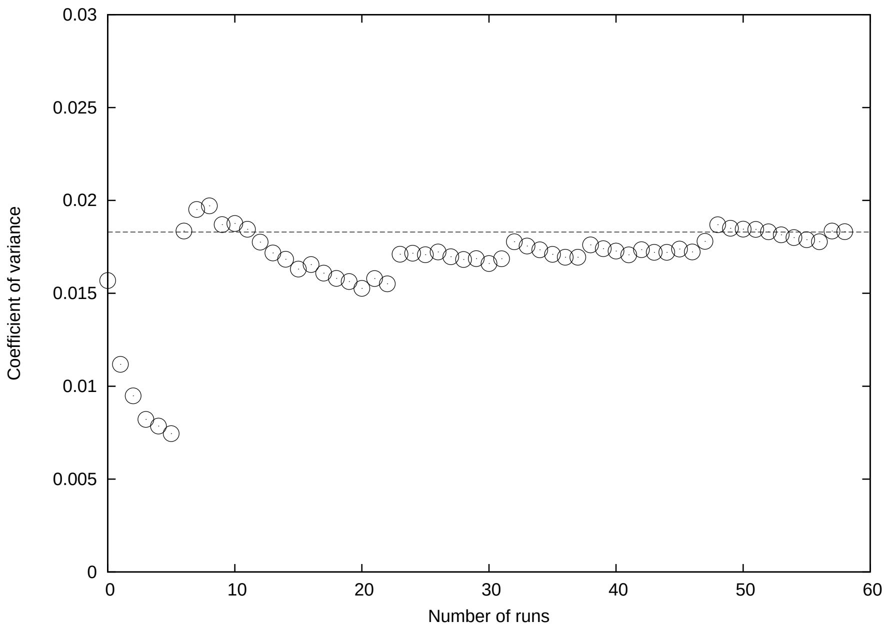



Figure 7.5: Coefficient of variance for total activities across runs.

reasonable to expect that people will not see all their friends in their friends' home locations in a 10-week period.

A sample week for the same individual, shown in table 7.13, shows variety in both the activity type (visiting, information, experience, chatting) and location type (home, other). We also see some evidence of activities occurring on the same day. As this was seen in the data, it seems plausible, especially as activities of all durations were included in the calibration dataset, so it could be that these are shorter activities. Updating the influence of time pressure during the process of scheduling for a day, instead of once at the start of the day, could assist.

For this run, the two people whom the individual saw the most are two friends with the highest similarity. These two individuals were also seen reasonably regularly: one every 9.7 days (with a range of 6 to 13 days) and the other every 6.2 days (with a range of 4 to 8 days). Another acquaintance who lived close by but did not have the highest similarity was seen every 7.4 days (4 to 11 day range). It appears that the model can generate reasonably "regular" activities, however this might not be realistic. More longer term data would be required regarding the actual activities and participants to compare the ranges.


Figure 7.6: An individual's social network

## 7.5 Discussion

The chapter has described the data used and the calibration process for the model. Several different data sets were required to obtain all the data required for creating a realistic scenario for illustration.

Several social networks were generated for experimentation. Although the simplest method is to use a random network, the realistic network based on actual data aligned more with the accepted properties of a social network.

The main problem with not having one single data collection or access to a set of coherent data collections, like the FEATHERS project (Bellemans et al., 2010), is trying to find the relevant data across several disparate sets which use different activity and other concept types. The duration data is not just for joint activities, nor is the interval data. As a result, these parameters were estimated and modelled very coarsely.

In terms of missing data, more detail is required for the interaction and decision making process. This could be undertaken in the form of a stated preference survey.

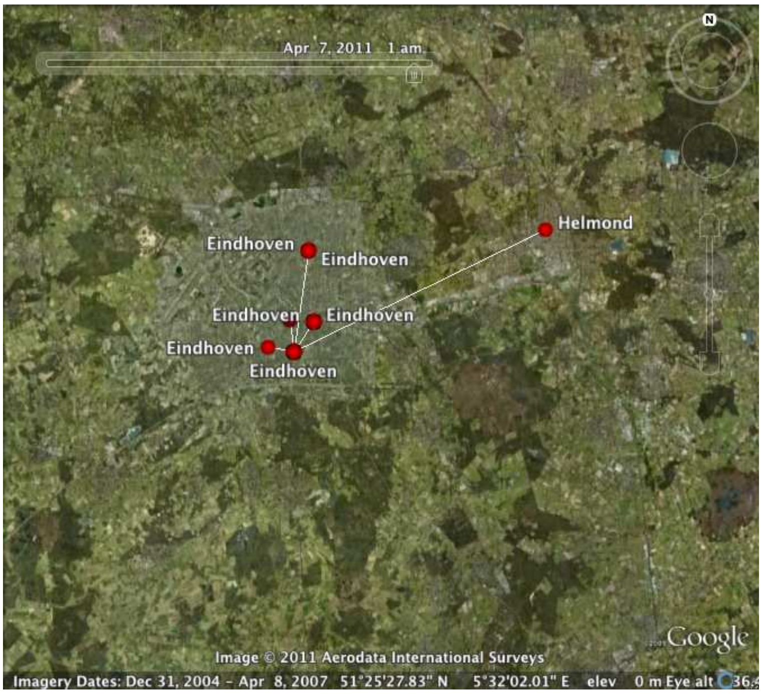



Figure 7.7: The locations to which an individual travels.

The calibration process was difficult and time-consuming. An alternative approach to fully manual calibration could be to generate sets of parameters and search for some sort of "optimal" set. Given the amount of parameters that could be set for this model, this is also difficult, and the approach is better suited to models with fewer parameters and a smaller range of possible values. Calibrating a multi-day model with only two days of sample data is also fraught with difficulties, as it is assumed those two days are representative. A longer-term data set would be preferable for future work in calibration.

The long-term stability was also explored, as well as the individual behaviour. Both showed that the model performs as expected. The variability is low, and shows that around 30 seeds are required before the model reaches a steady state. The immersion experiment showed that agents are able to generate activities with a variety of people at a variety of locations, however more long-term data is required for full validation.

However, as a reasonably suitable set of parameter values has been found, we can now experiment with the outcomes of the model.

| Day | Morning | Afternoon | Evening |
|---|---|---|---|
| Mon | | | visit@home |
| Tue | | | |
| Wed | | | |
| Thu | | | |
| Fri | info@other | | chat@other |
| Sat | exp@home | info@other | |
| Sun | | | |

Table 7.13: An individual's schedule for a week (activity type @ location type).

# Chapter 8

# Sensitivity analysis

A sensitivity analysis is undertaken to determine the effects of different parameter values and inputs. It can be undertaken before or after calibration.

In this chapter, we add complexity step-by-step to the model setup and analyse the behaviour of the model. This demonstrates how the model works at more detailed level, and provides examples of how a model's operation can be shown for validation purposes. The process covers both direct structure testing and structure-oriented testing.

A series of sensitivity tests are carried out, varying a range of parameters and exploring the effects. The model process is altered between each step, beginning with one day and no interactions between agents, expanding to many days, and then adding in interactions. At each step, the variation of the outputs is demonstrated by varying the input parameters. It is expected that the aggregate outputs will increase if certain parameters are increased (e.g., by increasing the attractiveness of undertaking activities at home) and will decrease for other parameters (e.g., increasing the threshold parameters should lead to fewer activities being undertaken).

## 8.1 Setup

The same sample input network that was used for the calibration was used. All activity history is set to -7 (i.e., a week previously), so agents last saw everyone, did all activities, and visited all out-of-home locations 7 days previously. Home locations were visited on day 0. Each configuration was run with ten seeds.

The results were analysed in a number of ways:

- By visually inspecting results;
- By using correlation tests (Pearson) on the total number of activities or the proportion of activities (where different activities or locations were involved) compared to the parameter inputs, providing a correlation value denoted as r;
- By using Fisher's r-to-z transformation to compare correlations;
- By using Kolmgorov-Smirnov tests to investigate the difference between distributions, providing a measurement denoted as D;
- By using chi-square tests to see if the total number of activities differs with respect to the parameter, both for each type separately and by combining the types that the parameter doesn't affect;
- By calculating the importance of parameters, following (Hamby, 1994). The equation used is:

  $$I = \frac{s_X^2}{s_Y^2} \tag{8.1}$$

  where $s_X^2$ is the variance of the parameter outputs and $s_Y^2$ is the variance of the parameter inputs. This enables the effect of the size of the change in the parameter to be seen.

The values of the parameters are shown in table 8.1. Those marked with an asterisk are averages across all the values of that parameter that match the fixed value. For example, the given value for the threshold parameter ($f_{wd}$) is an average across the three parameters that apply to full-time workers.

| Parameter | Base value | Other values |
|---|---|---|
| $\lambda_{gender}$ (gender) | 0.713 | 0.357, 0.535, 0.891, 1.070, 1.426 |
| $\lambda_{age}$ (age) | 0.888 | 0.444, 0.666, 1.110, 1.332, 1.776 |
| $f_{wd}(fulltime, \forall d)$ (thresf)* | 2.047 | 1.126, 1.433, 1.740, 2.354, 2.661 |
| $\alpha^{l}_{\forall a,other}$ (home)* | 5.482 | 4.385, 4.934, 6.030, 6.578, 7.1260 |
| $\alpha^{l}_{chatting,\forall l'}$ (lchat)* | 5.902 | 4.722, 5.312, 6.492, 7.083, 7.673 |
| $\alpha^{d}_{\forall a,monday,\forall y}$ (mon)* | 2.361 | 1.652, 2.007, 2.715, 3.069, 3.423 |
| $\alpha^{d}_{\forall a,\forall d,afternoon}$ (midday)* | 3.591 | 2.514, 3.052, 4.130, 4.668, 5.207 |
| $\alpha^{d}_{chatting,\forall d,\forall y}$ (dchat)* | 2.889 | 2.023, 2.456, 3.323, 3.756, 4.190 |
| $\beta^{p}_{0}$ (betap) | 0.025 | 0.01, 0.04, 0.055, 0.07, 0.085 |
| $\beta^{l}_{other}$ (betal) | 0.025 | 0.01, 0.02,0.03, 0.04, 0.05 |
| $\beta^{a}_{visiting}$ (betaa) | 0.045 | 0.015, 0.025, 0.035, 0.055, 0.065 |
| $\alpha^{tt}$ (travel) | -0.5 | 0.0, -0.25, -0.75, -1.25, -1.75 |

Table 8.1: Parameter values used in the sensitivity testing.

## 8.2 Individual, one day

The idea behind this step is to test the sensitivity of the utility function for one day with no interactions. This means that each individual will select their ideal activity *without* collaborating with others. It is a form of structure testing, in that only the utility function is being tested.

In order to clearly see the outcomes of the utility function, no simulation warmup is used, so the results presented are for day 1 of the simulation.

The expectation is that different parameters affect the different properties of activities being carried out in the following ways:

1. An increase in parameter values should lead to an increase in activities, except for increasing the threshold and travel cost which should lead to a decrease;

2. Changing $\lambda_{gender}$ and $\lambda_{age}$ should affect the similarity of people chosen for activities;

3. Increasing $\alpha^{l}_{\forall a,other}$ should increase the number/proportion of activities carried out out-of-home;

4. Increasing $\alpha^{l}_{chatting,\forall l'}$ should increase the number/proportion of activity of type "chatting";

5. Increasing $\alpha^{d}_{\forall a,\forall d,afternoon}$ should increase the number/proportion of activities carried out in the afternoon;

6. Increasing $\alpha^{d}_{chatting,\forall d,\forall y}$ should increase the number/proportion of activity of type "chatting";

7. Increasing $\alpha^{tt}$ should decrease the amount of travel undertaken.

Table 8.2 shows the correlation between the different values of the parameters and the total number of activities. All parameters have a significant relationship. As expected, the threshold has an inverse relationship. The most important parameters, as seen in the third column, are threshold, age, and the day of the week, which means that these parameters have the largest impact on the outputs.

In terms of activities disaggregated by age and gender, adjusting age or gender values leads to a change in the activities undertaken with someone of

| | Parameter | p | Importance |
|---|---|---|---|
| $\lambda_{age}$ | 0.96 | 0.00 | 3478.26 |
| $\alpha^{d}_{chatting,\forall d,\forall y}$ | 0.29 | 0.03 | 41.71 |
| $\alpha^{l}_{\forall a,other}$ | 0.86 | 0.00 | 94.31 |
| $\alpha^{l}_{chatting,\forall l'}$ | 0.26 | 0.04 | 22.94 |
| $\alpha^{d}_{\forall a,\forall d,afternoon}$ | 0.96 | 0.00 | 271.26 |
| $\alpha^{d}_{\forall a,monday,\forall y}$ | 0.97 | 0.00 | 1908.42 |
| $\lambda_{gender}$ | 0.71 | 0.00 | 374.50 |
| $f_{wd}(fulltime, \forall d)$ | -0.99 | 0.00 | 26849.47 |
| $\alpha^{tt}$ | -0.77 | 0.00 | 1847.20 |

Table 8.2: Correlations for total activities (individual, one day).

the same age or gender. The number of activities between people with the same age (keeping in mind that age is represented on a scale of 1 to 5) has a correlation of 0.876 ($p < 0.00001$) with an increase in the age parameter. A similar effect can be seen between the gender value and the number of activities between people of the same gender ($r = 0.652$, $p < 0.00001$).

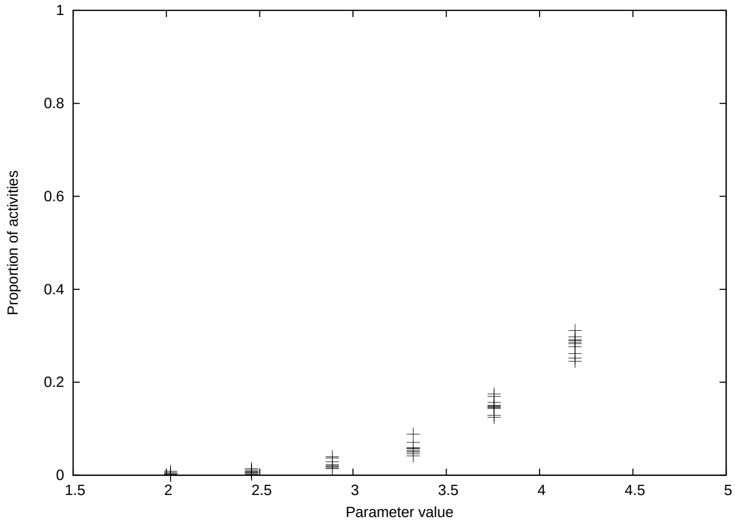
Looking at the types of activities, both chatting parameters (set via day and via location) have a strong effect on the number and proportion of chatting activities. Via location, the chi-square result of each parameter value vs chatting/non-chatting activities returns a value of 315.66 ($df = 5$, $p < 0.00001$), and via day, 266.02 ($df = 5$, $p < 0.00001$). Figure 8.1 shows that the type of activities is sensitive to small changes in the parameter.

In terms of home/out-of-home activities, a strong relationship can be seen from the home parameter. The chi-square result is 34.9 ($df = 5$, $p < 0.00001$). Figure 8.2 shows that this parameters does influence the proportion of out-of-home activities.

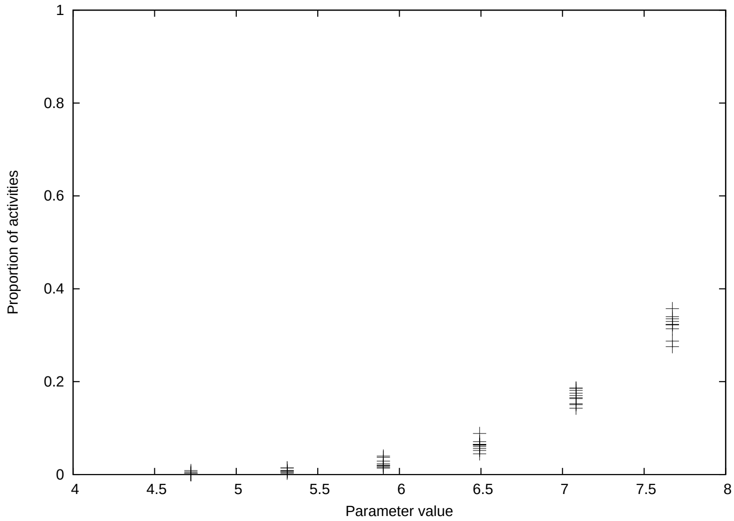
The time of day that is chosen for activities is affected by adjusting the parameter regarding time. It is clear from figure 8.3 that this is a strong relationship.

Finally, the average distance that individuals travel is affected by changing the cost of travel. The correlation between the cost and travel per person is -0.694 ($p < 0.00001$).

From these results, it can be seen that the utility function performs reasonably for one day. All hypotheses are supported. This, however, is not the most realistic test, especially as some activity types and location types are dominant due to their high parameter values. More variation is expected when many days are introduced, where the frequency of activities will come into play and a simulation warmup is also used.




(a) Activity type




(b) Location type

Figure 8.1: The effects of changing type parameters on the proportion of chatting activities.

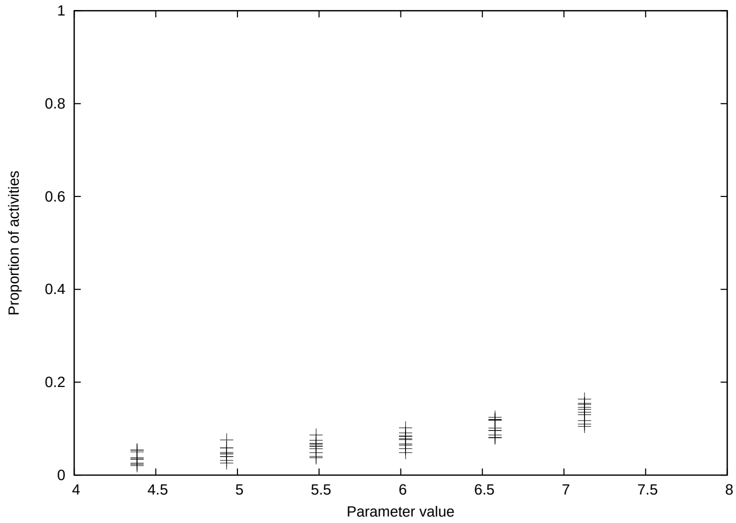



Figure 8.2: The effects of changing location parameters on the proportion of out-of-home activities.

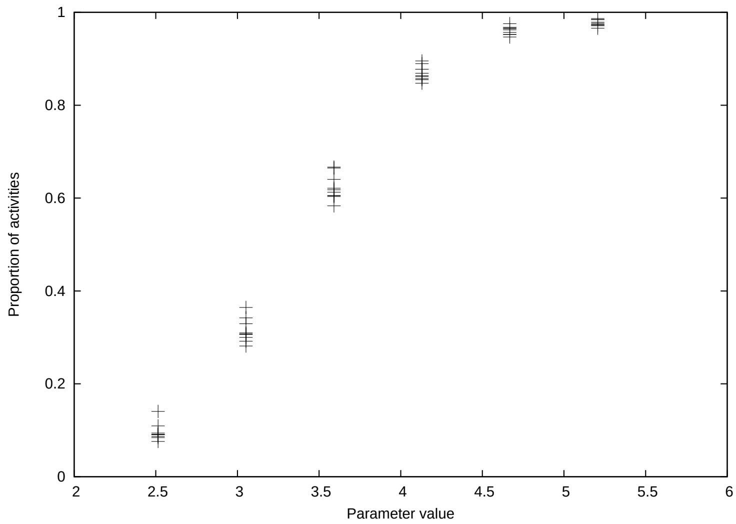



Figure 8.3: The effects of changing time parameters on the proportion of afternoon activities.

## 8.3 Individual, many days

In this case, the individuals in the model select activities over a number of days, again with no collaboration with others. As this is closer to the intended functionality of the model, in that the model will run for more than one day, this is moving more towards the structure-oriented testing component of process validation. The same hypotheses in the previous section are tested, along with some additions:

- Increasing $\alpha^{d}_{\forall a,monday,\forall y}$ should increase the number/proportion of activities carried out on a Monday;
- Changing $\beta^{p}$ should affect how often people are seen;
- Changing $\beta^{l}_{other}$ should affect how often home locations are seen;
- Changing $\beta^{a}_{visiting}$ should affect how often visiting activities are undertaken.

Table 8.3 shows the correlation between the different values of the parameters and the total number of activities. All parameters have a significant relationship, except for altering the gender value and the activity type part of the location parameter: note that these parameters resulted in lower correlations than the other parameters in the one-day scenario. As expected, the threshold has an inverse relationship. The most important parameters are now the beta parameters, as they are reasonably small and therefore small alterations to their values have a large effect on the results. The reduction in influence of the age and gender parameters corresponds to the findings in Cirillo and Axhausen (2010), where socio-demographic variables were found to not be as dominant as expected for multi-day models.

The number of activities between people with the same age (keeping in mind that age is represented on a scale of 1 to 5) has a correlation of 0.672 ($p < 0.00001$) with an increase in the age parameter. A similar effect can be seen between the gender value and the number of activities between people of the same gender ($r = 0.376$, $p < 0.005$). These relationships are weaker than for the one-day case.

For chatting via location, the chi-square result of each parameter value vs chatting/non-chatting activities returns a value of 10.55 ($df = 5$, $p = 0.06$), and via day, 45.53 ($df = 5$, $p < 0.00001$). This signifies a weakening

| | Parameter | p | Importance |
|---|---|---|---|
| $\lambda_{age}$ | 0.82 | 0.00 | 8306.74 |
| $\alpha^{d}_{chatting,\forall d,\forall y}$ | 0.78 | 0.00 | 6272.11 |
| $\alpha^{l}_{\forall a,other}$ | 0.96 | 0.00 | 7623.24 |
| $\alpha^{l}_{chatting,\forall l'}$ | -0.18 | 0.17 | 514.25 |
| $\alpha^{d}_{\forall a,\forall d,afternoon}$ | 0.90 | 0.00 | 5260.18 |
| $\alpha^{d}_{\forall a,monday,\forall y}$ | 0.69 | 0.00 | 2821.68 |
| $\lambda_{gender}$ | 0.23 | 0.07 | 3147.45 |
| $f_{wd}(fulltime, \forall d)$ | -0.99 | 0.00 | 338555.14 |
| $\alpha^{tt}$ | -0.96 | 0.00 | 135615.23 |
| $\beta^{a}_{visiting}$ | 0.92 | 0.00 | 13076604.76 |
| $\beta^{l}_{other}$ | 0.99 | 0.00 | 380437634.29 |
| $\beta^{p}_{0}$ | 0.92 | 0.00 | 7246804.66 |

Table 8.3: Correlations for parameters and activities (individual, many days).

in the influence once the model is analysed over multiple days, which is to be expected as the agents will experience more varied activities over many days then when compared with just one day of outputs.

In terms of home/out-of-home activities, a strong relationship can be seen from the home parameter. The chi-square result is 43.8 (df = 5, $p < 0.00001$). This is similar to the one-day case.

As in the previous scenario, the time parameter affects the time of day of activities. It is clear from figure 8.4 that increasing the afternoon parameters leads to more activities taking place in the afternoon.

Finally, the average distance that individuals travel is affected by changing the cost of travel. The correlation between the cost and travel per person is -0.946 ($p < 0.00001$). This is stronger, due to the repetition involved.

A new addition in this case is the ability to look at a day of the week and also the days between activities. Firstly, increasing the day of the week parameter for Monday leads to more activities on Monday as expected. The chi-square result for activities taking place on a Monday vs. activities on other days is 100.43 ($p = 0$). There is no obvious day for which Monday is substituting.

The interval or days between activities is influenced by the beta parameters. Figure 8.5 shows the effect of each parameter on the intervals: for people, for visiting activities, and for activities out-of-home. Note that the

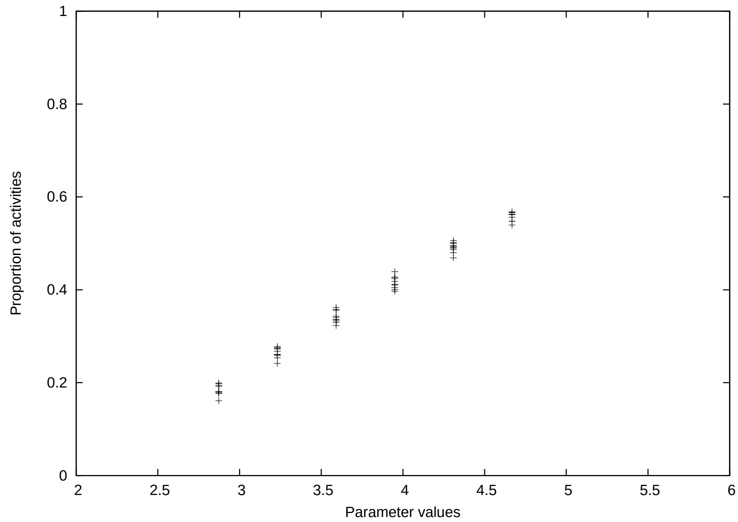
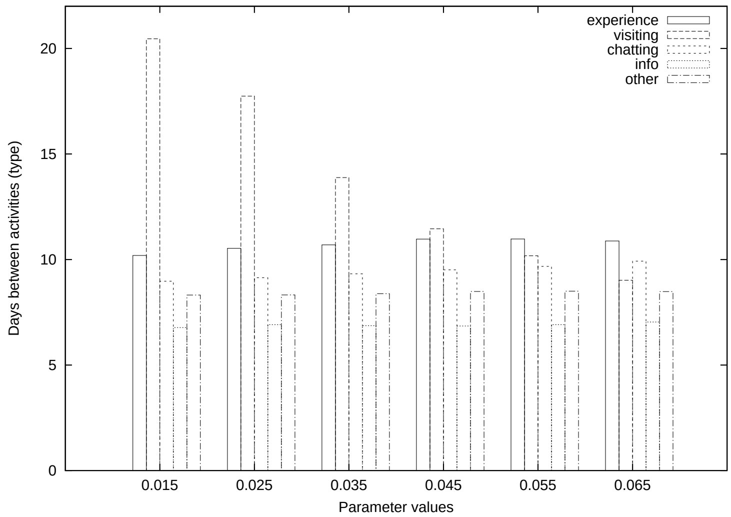



Figure 8.4: The effects of changing time parameters on the proportion of afternoon activities.

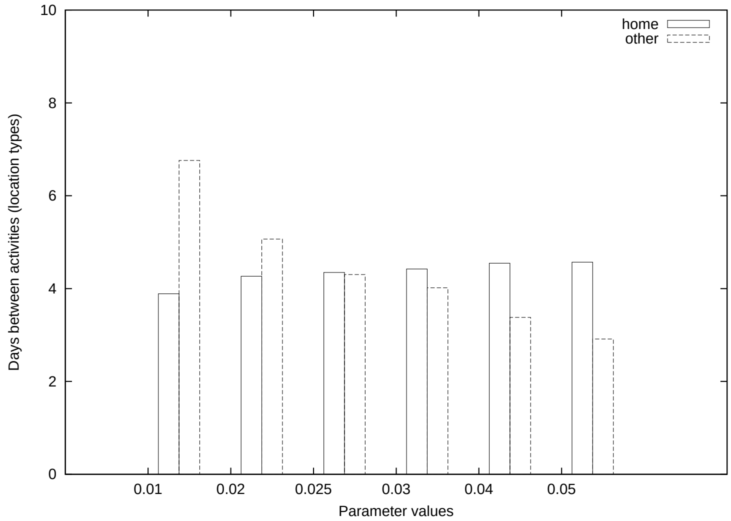
timing between seeing alters is not linear, but appears to have a peak.

We can now also investigate the performance of the utility for a single individual. The change in calculated utilities for individual $b$, when individual $a$ visiting individual $b$ at $b$'s home in the evening, is also shown. As shown in figure 8.6, the various components of the equation form patterns, which sum to the overall utility. Note that all components do not have to be at their peak for the activity to exceed the threshold. In this case, $a$ visits $b$ at home on day 38.

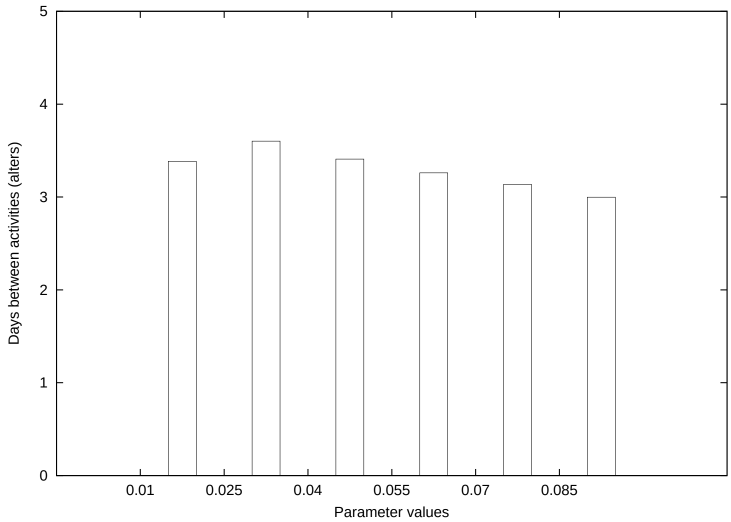
With some minor exceptions, most of the hypotheses proposed were supported. As this is a stepping stone to the final version of the model, the exceptions should be noted, however are not cause for concern at this stage.




(a) Activity type




(b) Location type




(c) Alters

Figure 8.5: The effects of changing type parameters on the interval or days between activities.

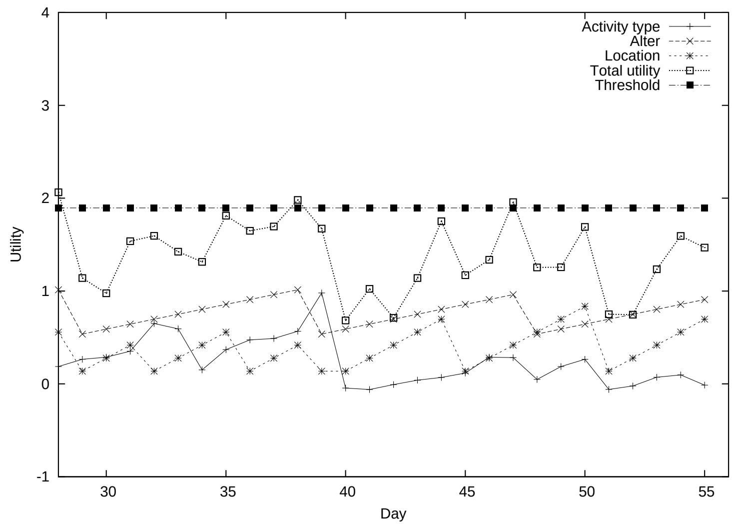



Figure 8.6: Utilities over time between two individuals.

## 8.4 Interactions, many days

For the final step in this sensitivity run, interactions are incorporated into the model. The same hypotheses are explored as for the previous section.

Table 8.4 shows the correlation between the different values of the parameters and the total number of activities. All parameters have a significant relationship. As expected, the threshold has an inverse relationship. The most important parameters are still the beta parameters, followed by threshold and age.

| | Parameter | p | Importance |
|---|---|---|---|
| $\lambda_{age}$ | 1.00 | 0.00 | 952947.02 |
| $\alpha^{d}_{chatting,\forall d,\forall y}$ | 0.46 | 0.00 | 10870.24 |
| $\alpha^{l}_{\forall a,other}$ | 0.79 | 0.00 | 7055.61 |
| $\alpha^{l}_{chatting,\forall l'}$ | 0.37 | 0.00 | 2416.51 |
| $\alpha^{d}_{\forall a,\forall d,afternoon}$ | -0.27 | 0.04 | 6468.60 |
| $\alpha^{d}_{\forall a,monday,\forall y}$ | 0.39 | 0.00 | 9798.94 |
| $\lambda_{gender}$ | 0.88 | 0.00 | 54884.18 |
| $f_{wd}(fulltime, \forall d)$ | -0.98 | 0.00 | 980835.44 |
| $\alpha^{tt}$ | -0.96 | 0.00 | 70494.35 |
| $\beta^{a}_{visiting}$ | 0.75 | 0.00 | 16256399.05 |
| $\beta^{l}_{other}$ | 0.98 | 0.00 | 247265397.55 |
| $\beta^{p}_{0}$ | 1.00 | 0.00 | 1023987631.32 |

Table 8.4: Correlations for parameters and activities.

The number of activities between people with the same age (keeping in mind that age is represented on a scale of 1 to 5) has a correlation of 0.992 ($p < 0.00001$) with an increase in the age parameter. A similar effect can be seen between the gender value and the number of activities between people of the same gender ($r = 0.955$, $p < 0.000001$). These relationships are stronger than for the cases without interactions, and there is noticeably less variance in the outputs.

For chatting via day, the chi-square result of each parameter value vs chatting/non-chatting activities returns a value of 146.7 ($df = 5$, $p < 0.00001$), and for via day, 128.89 ($df = 5$, $p < 0.00001$).

In terms of home/out-of-home activities, a strong relationship can be seen from the home parameter. The chi-square result is 41.52 ($df = 5$, $p < 0.00001$). This is similar to the previous cases.

As in the previous scenarios, the time parameter affects the time of day of activities. It is clear from figure 8.7 that increasing the afternoon parameters leads to more activities taking place in the afternoon. Note that the proportion is decreasing as more complexity is being added to the model.

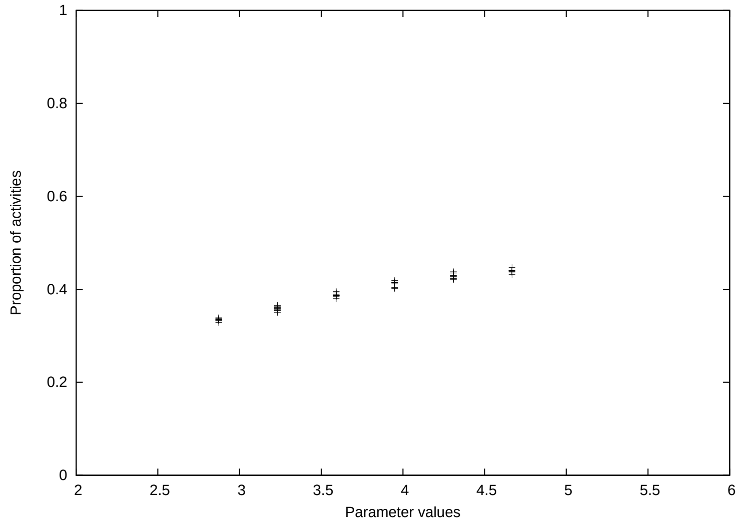


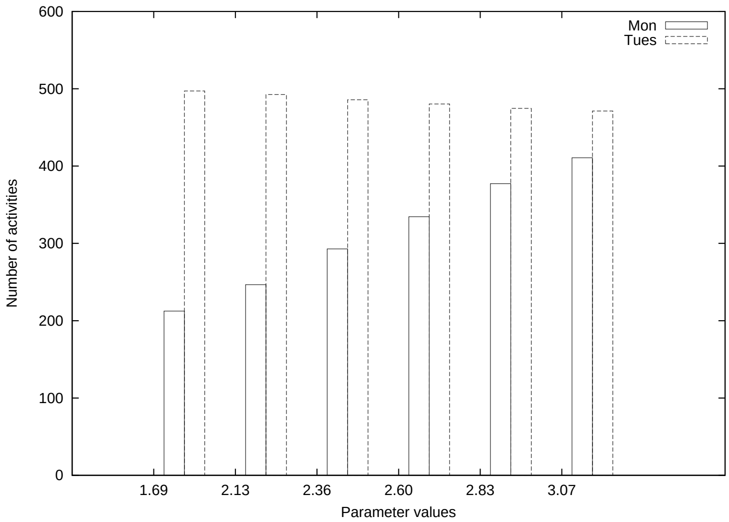

Figure 8.7: The effects of changing time parameters on the proportion of afternoon activities.

Finally, the average distance that individuals travel is affected by changing the cost of travel. The correlation between the cost and travel per person is -0.953 ($p < 0.00001$). This is stronger, due to the repetition involved.

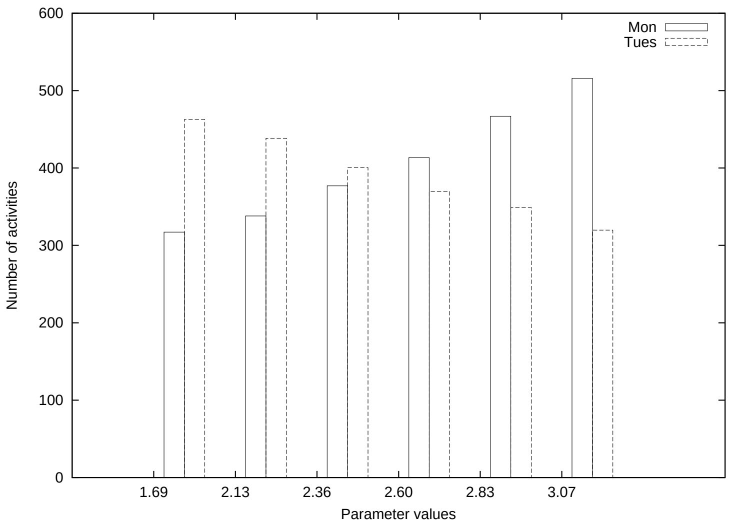
Increasing the day of the week parameter for Monday leads to more activities on Monday as expected. The chi-square result for activities taking place on a Monday vs. activities on other days is 79.81 ($df = 5$, $p < 0.00001$). In this case, it is more obvious that many activities are being brought forward from Tuesday (figure 8.8): the gradient of the line for Tuesday is five times steeper than for the case with no interactions.

The effects of the beta parameters are similar to the previous case.

At the final step in the overall analysis, the hypotheses are all supported.




(a) No interactions




(b) Interactions

Figure 8.8: The effects of changing day parameters.

## 8.5 Discussion

The aim of the preceding tests was to explore the behaviour of the model under simple changes to inputs, i.e., varying a parameter. The model was tested at three different levels: for one day only with no interactions, for many days with no interactions, and for many days with interactions.

Stepping from a simpler model to a more complex model permits any differences due to the number of days and the incorporation of interactions to be seen. Being able to test the utility function for one day (a form of direct structure testing) is useful to determine that it is performing correctly. Once this is satisfactory, we can proceed to structure-oriented testing, where the "full model" (many days with interactions) is tested.

After inspecting the utility function, it can be seen that it performs reasonably well in sensitivity testing. The parameters appear to affect the outcomes in the expected manner, which means that it should be possible to estimate the model on data.

Sensitivity testing with parameters alone is important for understanding the model output. In the next chapter, we explore the effects of changing the model processes and consider several policy scenarios.

# Chapter 9

# Illustration

In terms of model development, testing the details of the model by exploring the effects of parameters is an important step. In the previous chapters, we have seen how the parameters can be estimated and the effects of changing the parameters.

However, for planners and other end-users, the interest lies more in exploring inputs that are more realistic, such as differing city layouts or changes to the population. As mentioned in the literature review (chapter 2), one aim of transport models is to explore the effects of various policies or changes to the environment or population. These could be direct, such as the addition or removal of a road or public transport line, or indirect, such as a shift in population demographics or habits. The latter could also include experimenting with changes in population structures and decision-making.

In this chapter, we focus on the effects of alternative decision processes and scenarios. The effects of changing the interaction protocol (how people decide to participate in an activity with someone else) and the input network (how people are connected to each other in the population) are explored, as well as two scenarios of current interest to transport planners (an increase in free time and an increase in travel cost). The outcomes are discussed in terms of the effect on *where*, *who*, and *what* people are doing. In all cases, the input parameters estimated in calibration are used unless otherwise noted. It is worth noting that the model described is not replicating a given environment, therefore the values of parameters and inputs are not based on evidence and are only examples of how parameters can be changed.

## 9.1 Differing interaction protocols

In this section, we investigate the effects of different protocols to see if there is a difference in the outcomes of the model. If decisions are made differently, we can expect to see differences in who is seen, where people are travelling, and what activities people are undertaking. The outcomes of a data collection could be used to determine how people make decisions, therefore this is an input to the model that the planner could expect to change.

In an ideal world, the model should be fully recalibrated for each protocol, however as the calibration process used was reasonably basic (that is, point-based rather than pattern-based), redoing the process will simply serve to find a reasonable set of numbers which is not necessarily realistic. Without a specific data collection, we are not in a position to say which protocol is more realistic. However, if the model performs the same with the same inputs and different protocols, then we can assume that the protocol is insignificant and that further investigation regarding decision making is unnecessary. Some minor calibration was undertaken so that model generated approximately the same number of activities for each protocol, so that the disaggregate activity types could be more easily compared.

### 9.1.1 Protocols

Three protocols were selected for exploration. In this section, the base case is the enumeration protocol.

#### Enumeration

Enumeration is not a traditional protocol as such, however is a representation of what currently happens in models. Each person in the core population evaluates all possible activities for all of their friends, that is, each combination of activity type, location, and friend is generated and evaluated. If both friends determine that a particular activity exceeds their thresholds, then that activity is added to the shortlist. The activity with the maximum joint utility across all friends is chosen.

#### Negotiation, selecting person first

This is the protocol used in chapter 8 and described in section 5.3.2.

#### Negotiation, selecting activity first

In this variation on the previous protocol, the first step is to choose an activity, using a random person from the host's list of friends as a default. Once the activity is chosen, then the host offers it to the friend who gives the host the best utility for the activity. If that friend declines, the host offers the activity to the next-best friend and so on, until someone accepts or everyone declines.

### 9.1.2 Setup

The same sample input network that was used for the calibration was used. All activity history is set to -7 (i.e., a week previously), so the agents last saw everyone, did all activities, and visited all out-of-home locations 7 days previously. Home locations were visited on day 0. Each protocol was run with 30 seeds, with a warmup of 28 days, followed by 28 days for which results were collected. We also assume that all agents use the same protocol and strategy for the duration of the model run.

Some minor calibration was undertaken in terms of the total number of activities generated. The thresholds for each scenario are adjusted so that the total number of activities are the same as for the base protocol case (9267.93 activities). As a result, the thresholds for the enumeration protocol are multiplied by 2.24, which results in 9242.33 activities, and for the activity-first protocol by 1.98, which results in 9251.13 activities. The distribution of activities for both pairs of individuals and individuals alone are not dissimilar.

### 9.1.3 Outcomes

In terms of *who* is seen, there is a difference in how many *unique* people are seen during the simulation period. In the enumeration protocol, 9.13 people are seen on average, compared to 9.71 in the person-first protocol and 9.62 in the activity-first protocol (both significantly different to the enumeration protocol with $p < 0.02$ using a t-test). This could be because of the higher threshold employed in the enumeration case.

The type of people seen also differs. In all cases, there is a relationship between the similarity of two people and how many activities they engage in together. However, the strength of the relationship is stronger for the person-first protocol ($r = 0.245$, $p < 0.00001$) than for the activity-first ($r = 0.173$, $p < 0.00001$) and the enumeration protocols ($r = 0.177$, $p < 0.00001$). Although these relationships are weak, we are interested in the comparison between scenarios: a comparison of the correlations shows that the similarity correlation for the person-first protocol is significantly different ($p < 0.0001$). As this protocol puts the emphasis on the person chosen for the activity, it is understandable that the similarity has a larger effect.

Moving towards *where* people are travelling, the distance between the home locations of two individuals has an effect on the number of activities undertaken together. Keep in mind that in the social network, distance plays a part in the selection of friends, so there is already some preference for those people who live close to the ego. In the enumeration case, there is no relationship between the distance between two agents and the number of activities they participate in together. This could be because all activities and person combinations are evaluated, and therefore have more chance each day of being selected, whereas in the other protocols, the host proposes only their preferred locations. In the two negotiation protocols, there is a weak negative relationship as expected (person-first $r = -0.052$, activity-first $r = -0.054$, $p < 0.0001$).

The locations being visited are also affected by the protocol used. Firstly, the unique number of locations visited by each individual differs, especially in the enumeration protocol (4.88 locations) in comparison with the person-first (5.23 locations) and activity-first (5.36 locations) protocols (both significantly different to the enumeration protocol with $p < 0.0001$). Again, this is possibly a by-product of an increased threshold, meaning less attractive locations are cut off. As in the number of unique people seen, there is no difference between the two negotiation protocols. The postcodes visited also differ slightly across protocols ($\chi = 308.8$, $df = 58$, $p < 0.00001$). Table 9.1 shows that the distribution across suburbs is very minor.

Following the *who* and *where* of activities, *what* is also of interest. The different types of activities generated in each protocol is shown in table 9.2. There is a significant difference ($\chi = 115.9$, $df = 8$, $p < 0.00001$).

There is a more marked difference in the location types of activities ($\chi$

| | Enumerate | Person | Activity |
|---|---|---|---|
| Centrum | 3417.83 | 3166.37 | 3790.83 |
| Gestel | 1772.27 | 1731.37 | 1743.77 |
| Stratum | 1190.13 | 1131.33 | 1225.73 |
| Woensel-Zuid | 529.80 | 621.60 | 446.97 |
| Woensel-Noord | 1581.80 | 1636.03 | 1381.70 |
| Tongelre | 442.63 | 499.07 | 363.50 |
| Strijp | 316.67 | 303.50 | 289.83 |

Table 9.1: Total number of activities in each suburb.

| | Enumerate | Person | Activity |
|---|---|---|---|
| Experience | 1793.00 | 1421.40 | 1627.93 |
| Visiting | 1012.53 | 1170.60 | 1036.53 |
| Chatting | 2247.93 | 1968.63 | 2108.20 |
| Info | 2404.93 | 3046.17 | 2705.60 |
| Other | 1783.93 | 1661.13 | 1772.87 |

Table 9.2: Total number of activities for each type.

= 791.4, df = 2, $p < 0.00001$). From table 9.3, it can be seen that the out-of-home locations are dominant in all cases, however they are visited more frequently in the activity-first and enumeration protocols. The people-first protocol appears to give home activities more precedence.

| | Enumerate | Person | Activity |
|---|---|---|---|
| Home | 2211.13 | 4030.57 | 3199.20 |
| Other | 7031.20 | 5237.37 | 6051.93 |

Table 9.3: Total number of activities for each location type.

Finally, from a computational viewpoint, the model runs much quicker with the negotiation protocols (person-first 36.13s, activity-first 43.5s) than with the enumeration protocol (470.75s)[1]. As expected, being able to eliminate possibilities reduces the run time.

[1]These tests were undertaken with 10 runs, of which the two outliers were discarded, and the remainder averaged. The computer used was an Intel Core2 Duo 3GHz with 2Gb of RAM.

### 9.1.4 Discussion

The interactions between agents at the micro level are expected to affect the overall model behaviour at the macro level. If the individual decision making does not have any effect on the overall behaviour, then it can be safely disregarded. In this scenario, the outcomes of three protocols (enumerate, people-first, activity-first) were presented.

The interaction protocol is not as significant as expected for *where* (post-codes, suburbs, number of unique locations) and *who* (similarity, distance, number of unique people seen), however the type of activities is affected. This could be a result of the default setting in the person-first protocol, which uses a home activity as the base case.

Being able to limit the number of activities considered affects the run time. Exploring how choice sets are constrained, depending on the relationship and prior activities, would mean that the protocol can be refined to perform in a reasonable manner.

Naturally, only three protocols and strategies were explored, all based on theory rather than data, and the model was not recalibrated between runs. More attention to these details could lead to more significant results; for example, people can have different strategies in general, and could also change strategies over time. However, the differences demonstrated show that this is an important part of the model and that further work is required in understanding how people make decisions about joint activities.

## 9.2 Differing network structures

Although the network is an input, it is more complex than a parameter value. In some cases, the model process needs to be altered to accommodate the network in question. Again, this is an aspect that a planner could expect to change in light of the results of a data collection: it could be that people's social networks are formed differently in different populations.

When the network is altered, we would expect to see a change in the type of people seen. Depending on the location of friends, a difference in where people are travelling is also expected.

### 9.2.1 Network structures

For our situation, a useful parallel for comparing networks can be found in Axelrod et al. (2002). Although it covers a different sort of cooperation (the agents play the Prisoner's Dilemma Game and adapt their strategy based on their more successful neighbours), the setup and results are interesting. One network is temporary, that is, non-persistent – the neighbours change every timestep. The other two networks are persistent: one uses immediate spatial neighbours, while the other uses a random network. The results showed that there was little difference in the model outcomes between the persistent networks, meaning that finding a realistic network in this case was unnecessary, however there was a difference between no network and a network.

In this section, four different network structures were used, which were originally described in section 7.2. The network with no persistence is considered to be the base case.

#### No persistent network

In this "network", there is no persistence between model steps. At each step in the model, 12 people are chosen from the entire population. This corresponds roughly with our calculation that people have 12 alters on average. This is considered the base case, as existing transport models do not explicitly include a network.

Agent-based models tend to have some sort of neighbour structure, so non-persistency can be problematic. In the case of no persistent network, we assume that all people were last seen 15 days previously, which is the average from the realistic network. This means that the similarity component of the utility function can be retained and no adjustment of the threshold is necessary.

**Random**

This network is persistent and contains links that are created randomly between people.

**Random, but distance weighted**

This network is identical to the realistic network, however the probability of links occurring is based on distance only. Similarity is not taken into account.

**Realistic**

This network is also persistent and contains links that are based on both the distance between agents and their similarity. The creation of the realistic network was described in detail in section 7.2.1, using the algorithm developed by Arentze et al. (2009).

### 9.2.2 Setup

The same sample input network that was used for the calibration was used. All activity history is set to -7 (i.e., a week previously), so the agents last saw everyone, did all activities, and visited all out-of-home locations 7 days previously. Home locations were visited on day 0. Each protocol was run with 30 seeds, with a warmup of 28 days, followed by 70 days or 10 weeks for which results were collected.

### 9.2.3 Outcomes

Beginning with *who*, the similarity of people seen differs for each network. The relationship between the similarity and the number of activities undertaken ranges from 0.033 ($p < 0.00001$) for no network, to 0.458 and 0.471 (both $p < 0.00001$) for the random and random distance networks, to 0.237 ($p < 0.00001$) for the realistic network. As the two random networks contain little or no similarity, it appears that people are preferring those with more similarity.

Looking in more detail, a distinction can also be seen in the number of activities undertaken with people of the same age and gender. There is a difference across networks for age (table 9.4; $\chi$ = 5276.77, df = 3, p $<$ 0.00001). The realistic network shows more similarity on age, while the other networks do not. This could also be because the realistic network is weighted in the favour of similarity, therefore more activities are going to be undertaken with similar people. The same occurs for gender (table 9.5; $\chi$ = 2286.68, df = 3, p $<$ 0.00001).

| | non | random | random-dist | real |
|---:|---:|---:|---:|---:|
| Different age | 12693.00 | 13849.87 | 14384.23 | 8915.70 |
| Same age | 10137.67 | 6775.30 | 7324.10 | 14864.57 |

Table 9.4: The number of activities with people the same age or not for each network.

| | non | random | random-dist | real |
|---:|---:|---:|---:|---:|
| Different gender | 8465.33 | 9019.47 | 9374.70 | 5890.10 |
| Same gender | 14365.33 | 11605.70 | 12333.63 | 17890.17 |

Table 9.5: The number of activities with people the same gender or not for each network.

Figure 9.1 shows that the no-network scenario means a lot more distinct people are seen. For the persistent networks, more people are seen when the network has more weight. This could be because the egocentric networks already contain more similar or more attractive people. In the realistic network, most people see all of their friends at least once – the average ratio of friends seen to network size is 0.978 – whereas this does not occur for the random networks (ratios between 0.87-0.90).

Looking at *where* activities take place and the location of alters (that is, where activities could potentially take place), there are differences in where people are (potentially) travelling. Figure 9.2 shows an example of one person's travel-space in different networks. The two random networks show a much larger spread of locations than when the network is distance-weighted.

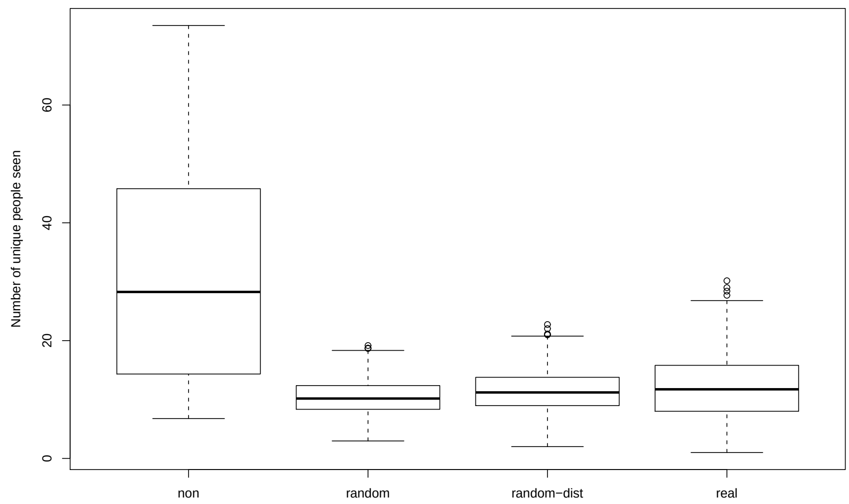



Figure 9.1: The number of unique people seen for each network.

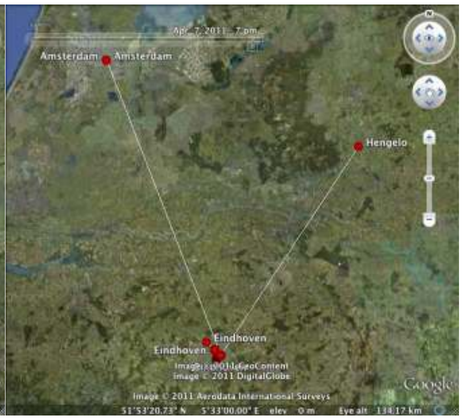
Figure 9.3 shows that those in the networks that are distance-weighted in some way visit more locations. In particular, they visit more friends at the friend's home.

The amount of activities between friends over different distances is also strikingly different. Figure 9.4 shows that when the network is distance-weighted, more interactions take place between friends living closer to each other, whereas the random networks generate more activities between friends who live more than 60 kilometres apart. This is unrealistic, as it is expected that friends who live further away would be seen much less.

An interesting way of looking at the complexity in the system is by calculating the entropy of the interactions with participants in different postcodes. If the entropy is lower, then that means the uncertainty is lower, and therefore there is less variation in the postcodes visited. The entropy was calculated by taking the frequencies of activities with alters in each postcode for every individual. The frequencies were then changed to proportions, and the entropy equation $-\sum_{pc \in PC} p \times ln(p)$ was used, where $p$ is the proportion for a particular postcode $pc$, summing over the set of all postcodes $PC$. The entropies for individuals were then averaged across the entire population.

Measuring the entropy of one person's interactions, by looking at the


(a) No network




(b) Random network


(c) Distance-weighted network


(d) Realistic network

Figure 9.2: Travels in different networks for an agent.

postcodes of where the participants in activities live, we see that the realistic network returns 2.178, the distance-weighted network 2.230, the random network 2.332, and no network 6.291. This shows that using a network with some sort of weighting ensures less variability in the people chosen to interact with, as expected.

Finally, looking at *what* activities people are doing, we can see that the type of activities (figure 9.5; $\chi = 354.55$, df $= 12$, $p < 0.00001$) and the location types of activities (figure 9.6; $\chi = 559.70$, df $= 3$, $p < 0.00001$) are also affected by the network. The activity type is reasonably ordered, in that informational/chatting activities dominate in all network scenarios, but location type is not as clear cut.

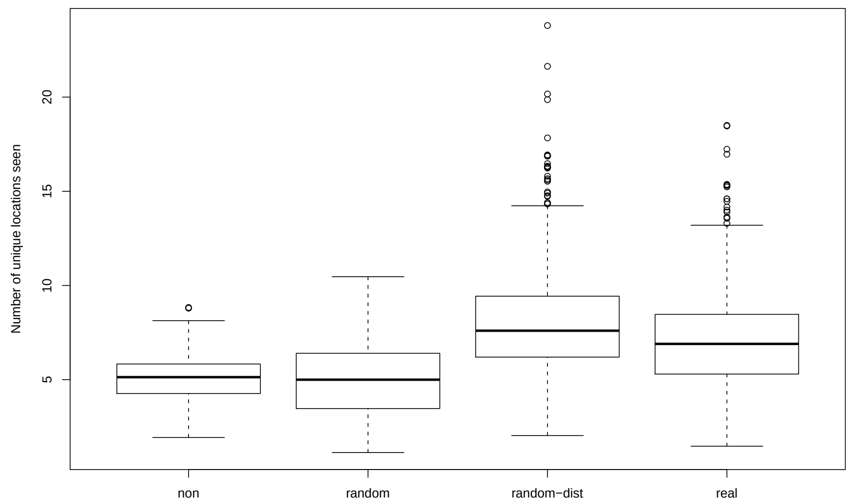



Figure 9.3: Number of unique locations visited for each network.

### 9.2.4 Discussion

As in Axelrod et al. (2002), there is a difference between no network and a network of some description. The entropy measurements demonstrate that a scenario with no persistent network is extremely random in terms of location.

However, a random network only reduces the amount of locational variation – for example, the number of activities between far-away friends is still comparable to having no persistent network.

For comparison with varying protocols, we see more variation in the people seen and the locations visited with different input networks. The type and number of people undertaking activities are clearly influenced by the network. The effect is expected, as the model was designed with this constraint. However, this means that the discovery of a representative network is necessary in order to generate realistic results.

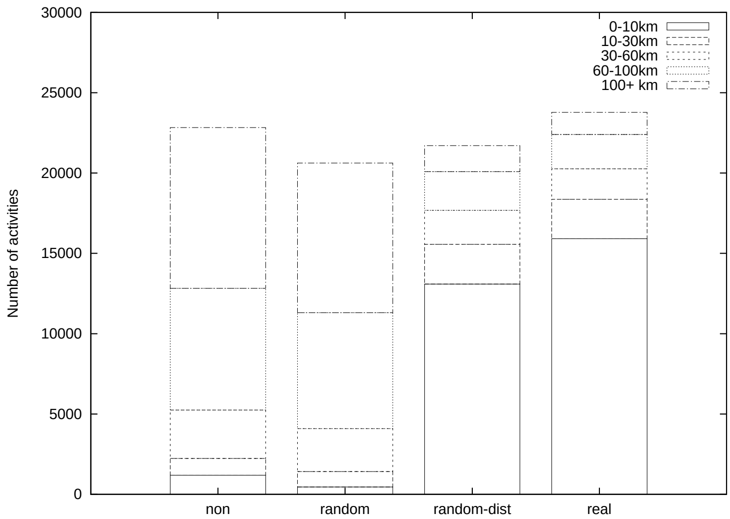



Figure 9.4: Activities between friends based on distance between houses.

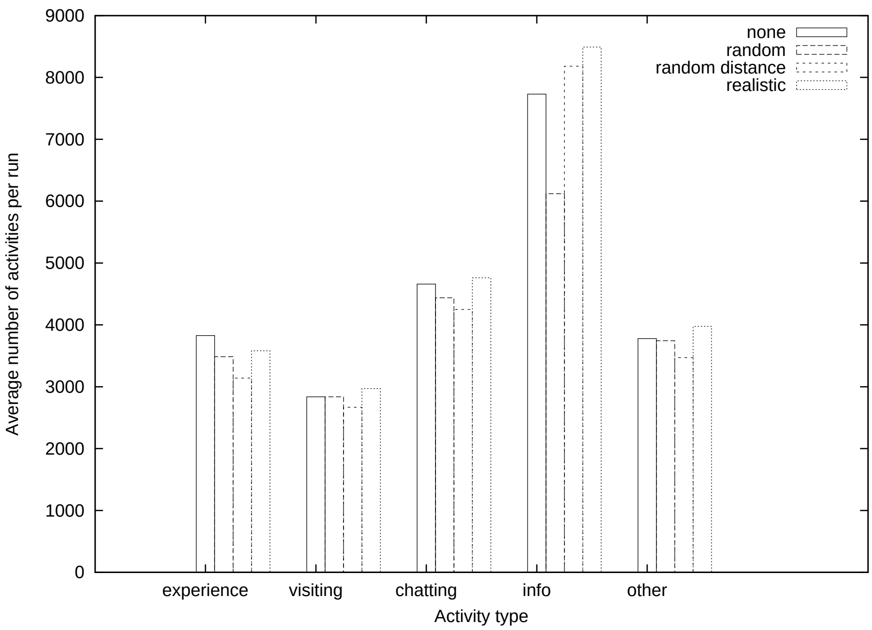



Figure 9.5: Activity type counts for each network.

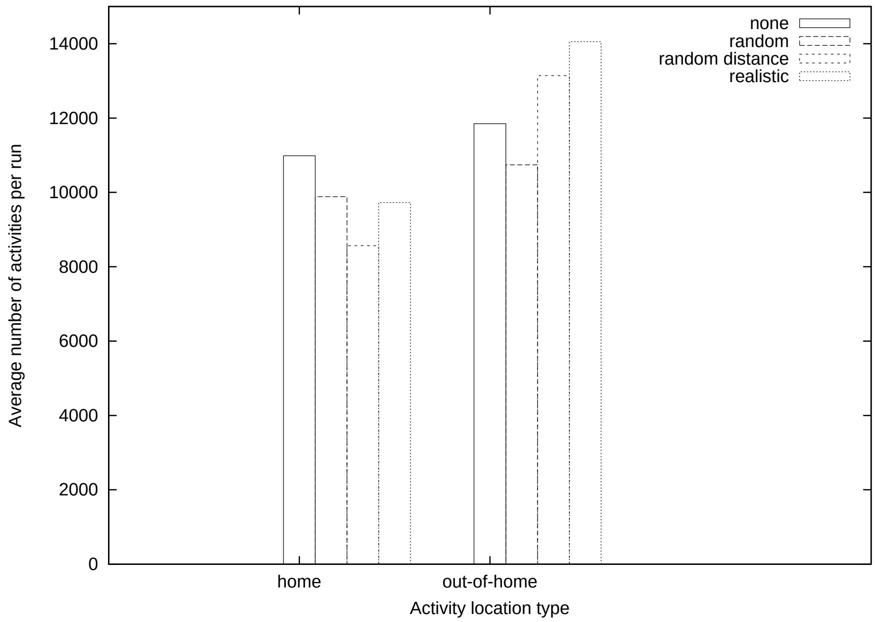



Figure 9.6: Location type counts for each network.

## 9.3 Policy demonstration

As mentioned in the literature review (chapter 2), one aim of transport models is to explore the effects of various policies or changes to the environment or population. These could be direct, such as the addition or removal of a road or public transport line, or indirect, such as a shift in population demographics or habits.

In this section, two scenarios are described. The first is an increase in leisure time, which is reasonably indirect – the government cannot enforce more leisure time. However, as alluded to in the motivation of this thesis, this is an area of interest to policy makers. For this scenario, we expect to see an increase in activities, and possibly differences in the location and types of activities.

The second is more direct: an increase in travel cost, which has been and will remain an important factor in transport modelling. The main expectation in this scenario is that travel will be reduced, meaning fewer activities are conducted.

In both cases, only one parameter is altered, meaning it resembles sensitivity analysis. However, only one alternative value is explored, and the values are examples only and are not based on a real-world value. In addition, the outcomes of the model are discussed more in the light of a policy exploration.

### 9.3.1 Setup

The same sample input network that was used for the calibration was used. All activity history is set to -7 (i.e., a week previously), so all agents last saw everyone, did all activities, and visited all out-of-home locations 7 days previously. Home locations were visited on day 0. Each protocol was run with 30 seeds, with a warmup of 28 days, followed by 70 days or 10 weeks for which results were collected.

The increase in leisure time is represented by multiplying the threshold values by 0.8, meaning individuals have more time to undertake activities.

The increase in variable travel costs is represented by increasing the travel cost from 0.5 to 1.5, meaning that travel is considered more expensive.

### 9.3.2 Outcomes: time use

There was a marked increase in activities (from 23780.27 to 31301.87), which already meets expectations. In terms of the activity type and location type, the increase was evenly spread across all types.

In terms of similarity, those friends who were less similar were seen more when individuals had more free time, however the difference to the base case was not significant ($\chi$ = 8.5127, df = 9, p = 0.4834). Looking at friends with the same age and gender also showed no significant difference between cases. The distance between friends also made no difference to how often they were seen.

Due to the increased number of activities, the amount of travel per person increased and the distribution of travel per person was significantly different (D = 0.1839, p < 0.00001, see figure 9.7). The average number of locations visited also rose from 7.10 in the base scenario to 8.28 in the increased time scenario, showing that people have more time for exploring.

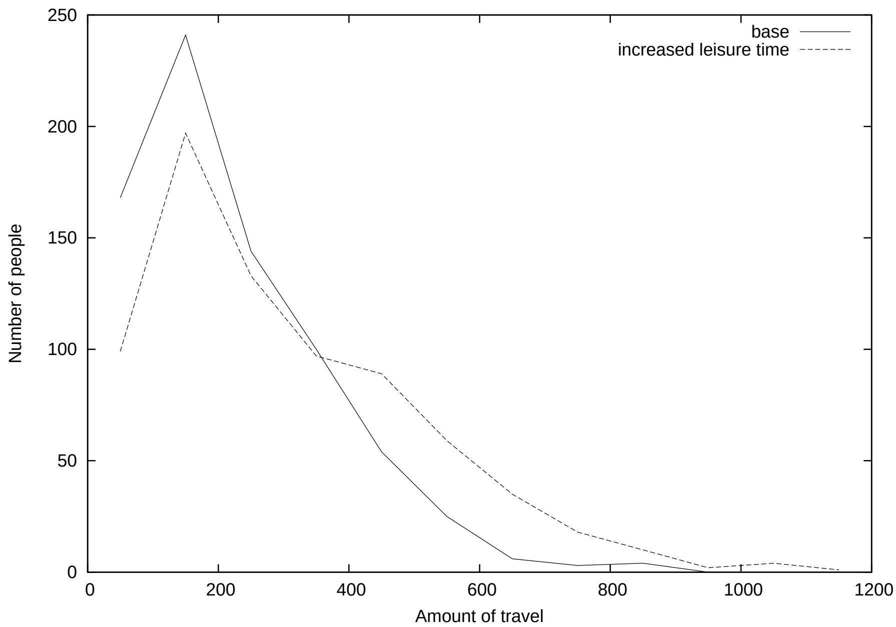



Figure 9.7: Amount of travel per person with more leisure time.

### 9.3.3 Outcomes: travel cost increase

As expected, the number of activities drops when the travel cost is increased (from 23780.27 to 20674.53).

Another noticeable difference is in the location of activities, which swings strongly to favour home-based activities (from 40.9% to 56.6%; see figure 9.8). The types of activities also changes, as more visiting activities take place (figure 9.9).

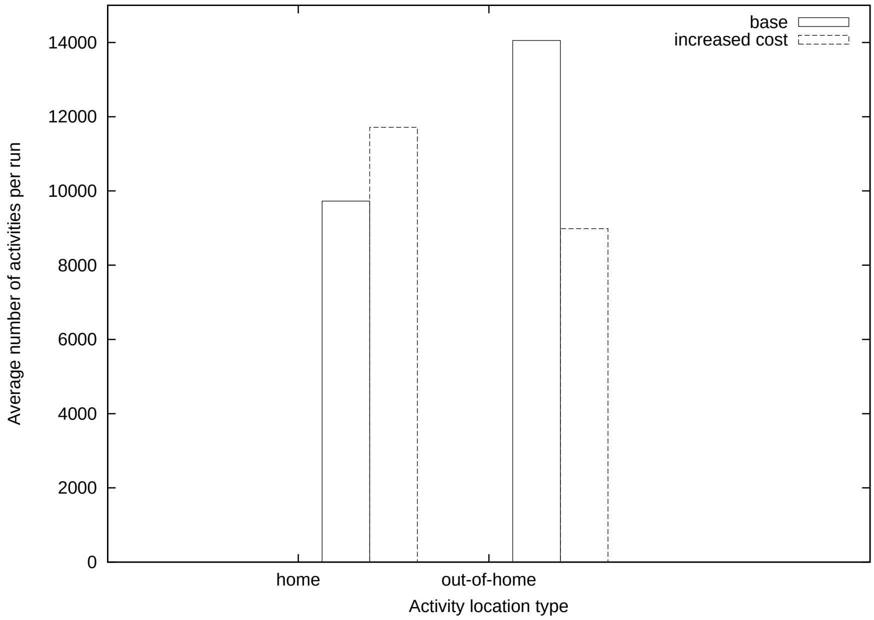



Figure 9.8: Location type counts for increased travel cost.

As in the time usage scenario, no difference is seen based on similarity: the decrease in activities is constant across all friends. The same applies for the distance between friends. However, there is a small difference in the size of the correlations: the correlation between similarity and the number of activities increases from 0.237 to 0.269 ($df = 8625$, $p < 0.05$). For distance, the correlation with the number of activities becomes slightly stronger (from -0.054 to -0.087, $df = 8625$, $p < 0.05$). This means there is a preference towards more similar and spatially closer friends when travel costs increase.

In terms of travel, there is a noticeable reduction. The average travel per person decreases from 219.49 to 186.02 and the average travel per activity per person decreases from 6.06 to 5.77. Figure 9.10 shows that people travel

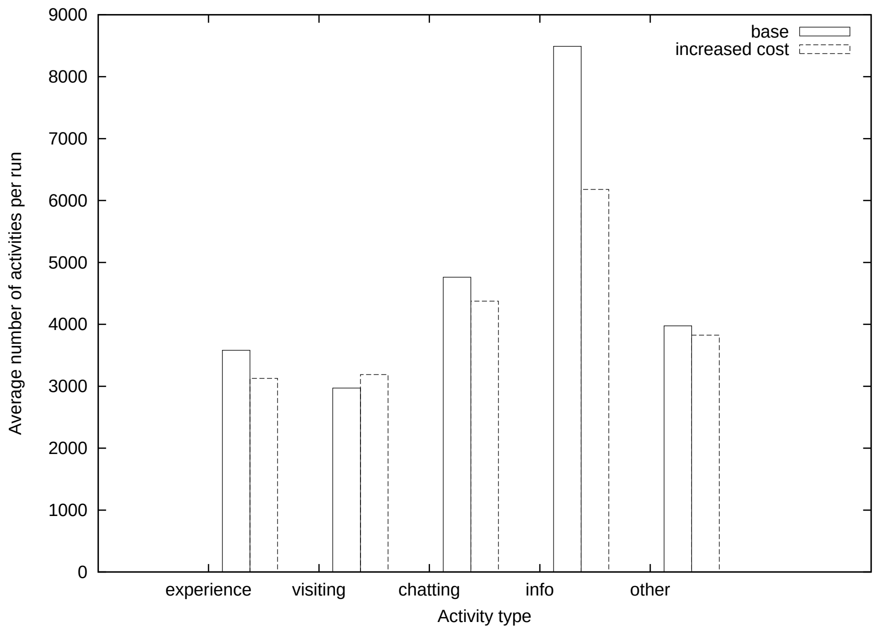



Figure 9.9: Activity type counts for increased travel cost.

less once travel costs are increased and, again, the distribution of travel per person is significantly different (D = 0.1463, $p < 0.00001$).

### 9.3.4 Discussion

The aim of this section was to explore scenarios that are directly of interest to transport planners and policy makers. Some interesting effects arose from the scenario explorations.

The similarity in the personal networks had little effect in both scenarios. Friends were equally less (in the case of increased travel cost) or more (in the case of more leisure time) seen regardless of their similarity. In the increased leisure time scenario, the increase in activities was reasonably well-spread across people and activity types. It is difficult to say whether this is representative of the entire population or not – some people might spend more time on one particular activity or person, and others might spread the time around more evenly – therefore more disaggregate analysis may be required.

As expected, the increased travel cost scenario showed a decrease in travel and also an increase in home-based activities. The latter also means

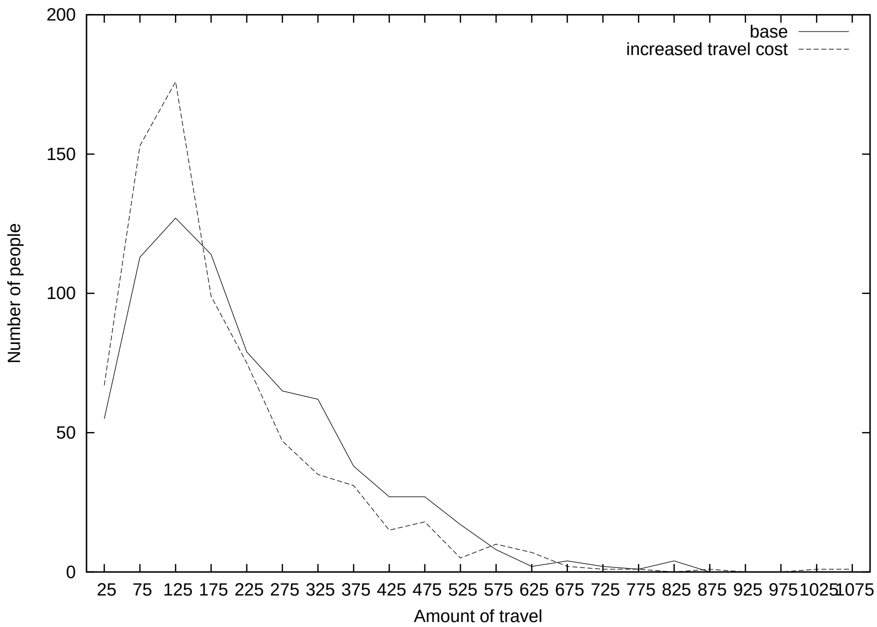



Figure 9.10: Amount of travel per person with increased travel cost.

there is a change in the type of activities being undertaken: visiting activities, which are more likely to take place at home, increase while all other types decrease.

The effects noted are not unsurprising, and it appears that the model performs reasonably for these policy scenarios. Dynamic networks would possibly lead to more effect. It would be expected that networks would become larger or smaller with the different time and cost constraints. This applies to both the social and spatial networks, as far-away locations could decrease or increase depending on the scenario.

# Chapter 10

# Conclusions and future work

This thesis has presented an agent-based simulation model of activity and travel behaviour incorporating social processes and joint activities, which has then been used to investigate the effect on activity and travel behaviour. A conceptual model was developed, from which a prototype model was designed and implemented. Experimentation in the form of sensitivity tests, input variation, and scenario testing demonstrated how the model worked.

Although the model was not tied to a particular data set, the model was set up for the city of Eindhoven in the Netherlands and used data on social networks and activities in that area to estimate parameters.

This chapter will discuss the questions raised in the introduction, as well as collating ideas for future directions.

## 10.1 Summary

Participation in and scheduling of social and joint activities is not as easily predicted as non-discretionary activities such as work and school. It appears that demand for discretionary activities will increase in the future and that ICT is already having an influence on when and where activities are undertaken.

Understanding the social network that lies on top of the spatial network could lead to better prediction of social activity schedules and therefore better forecasts of travel patterns, in particular for social and leisure activities.

Activity-based travel demand modelling has centred around individual plans and scheduling, and, using definitions from Maslow's hierarchy of needs, on the more basic physiological and safety needs ahead of belongingness needs. Participation in social activities can be shown to be based on human needs, and the presence of joint activities can influence individual plans. Previous research has focussed on joint activities within households, however this omits activities undertaken with people outside the household. Several projects have been undertaken on data collection, input network generation, and the effects of friend selection or friend influence on activity generation.

In designing such a model, many concepts are relevant: the units in the model, the relationships and interactions between individuals, the dynamics of the social network, and the types of activities generated by the model. These elements are frequently studied separately, however all could have an influence on how people travel.

Agent-based modelling and simulation permits the simulation of the behaviour of individuals and their interactions. Many methodologies for designing agent-based systems have been proposed that can be adapted for the design of simulations. The model designed allows us to specify attributes and behaviours at the individual level, as well as an egocentric network for each individual. The interaction protocol (i.e., how individuals suggest and come to an agreement on an activity) can also be specified.

However, the additional detail inherent in an agent-based model means that validation needs to be closely investigated. Both the transport modelling community and the agent community have reasonably mature processes for validation. A process is suggested that incorporates process validation, starting with exploring the structure of the model and then proceeding to behaviour.

Many data sources were used, based in the Eindhoven area, for the calibration of the model. This gives an idea of the amount of data required and the potential difficulty in creating a coherent dataset. The calibration process was based on point replication. Verification and walkthrough tests were also carried out to check that the model provided sensible outputs.

Sensitivity testing was undertaken to explore the effects of parameters, which was applied to increasingly more complex versions of the model (starting from one day of outputs with no interactions between individuals and finishing with full interactions over many days). This showed that the model performed as expected when certain parameters were altered.

Finally, several examples of policy scenarios were demonstrated. Altering the structure of the input social networks and the interaction protocols showed that these inputs do have a difference on the outputs of the model. As a result, these elements of the model require data collection on the social network structure and the decision processes for each local instantiation. Two more "traditional" transport planning policy scenarios, an increase in free time and an increase in travel cost, showed that the model performs as expected for these scenarios.

## 10.2 How can we model and validate social behaviours?

The advantage of using an agent-based simulation model is the flexibility in the individual settings and the inherent sociality. Using existing theory from agent-based negotiation, it could be shown how agents can reach an agreement, so the process is also modelled, not just the outcome.

A mix of different validation approaches is required, such as the face validation vs. empirical validation and behavioural vs. structural validation proposed by Klügl (2008), in order to explore the different facets of the model.

Calibration and validation was shown to be difficult, in particular in light of the expected standards/approaches from the transport community. One drawback is the integration of aggregate data: if N activities of one type are needed and M of another type, then the parameter values are not immediately obvious. Much experimentation is needed to find parameter values that approach the required output.

Although this thesis has not provided concrete solutions to the validation issue, we hope that it will generate further discussion. In the activity-demand context, it may be that a shift in expectations is required, from both end-users and modellers, regarding what can be validated and how. Future work involves testing and refining the process on our model, and providing a set of recommendations/lessons learned for similar models.

## 10.3 Can the separate effects of parameters be identified?

Using sensitivity analysis, the effects of changing input parameters on the results can be seen. As expected, by increasing the value of preferences for different types, locations, days and times of activities, the overall number of activities with those types increases. In the case of increasing threshold values, the overall number of activities decreases. This shows that it should be possible to estimate the model on data.

## 10.4 Do social networks make a difference?

In running the model with several different social network configurations, it can be seen that the social network does have an effect on the model outputs when compared to using a non-persistent network. In particular, the locations and people visited differ significantly. This shows that a realistic social network is required as input in order to obtain useful outputs for policy makers.

On top of this, it can also be seen that the decision processes within the network also make a difference and require further investigation.

As a cautionary note, even though the input networks and decision processes showed differences with this model initialised with data in Eindhoven, it may not be the case with other models or models based in different locations. However, it would be wise to add similar tests to the verification/validation suite for these sorts of models in order to be sure of the effects.

## 10.5 How can it be integrated?

An abstract or middle-range model is a good place to start with the modelling of processes, however this model is not immediately of use to planners outside academia. Integration with existing mature models or further development is required before it can be of practical use.

With TRANSIMS, the model development started with a prototype for one area (Dallas/Fort Worth) and was then expanded and generalised (Lawson (2006) describes the experimental history of TRANSIMS up to the mid

2000s). This process is long-term and involves a large number of people-hours in designing, developing, testing, and refining the model, as well as access to and/or collection of relevant data. Lawson (2006) notes that the use of open-source software and collaboration with universities and research groups are beneficial for increasing the maturity of models.

A promising approach is to use an iterative layered system, in that the social activities model is linked to an existing activity-travel model and the model process iterates between the two layers: the social network updates based on the activity plans and the activity plans are generated based on the social network, not dissimilar to the work of Hackney (Hackney, 2009). Alternatively, the social model could be used as a way of searching for parameters and choice sets that could be inputs to the activity-travel model.

Several researchers are working on the development of layered multi-agent systems (Dignum and Dignum, 2010), in which layers can be used for different levels of detail. In our case, the negotiation component could form one layer, which then informs the activity scheduling layer, which then flows into the travel scheduling layer.

## 10.6 Where to from here?

This thesis had two overall contributions: how these sorts of models can be built (taking into account the expectations and theories of both the transport modelling community and the agent-based modelling/simulation community), and whether the inclusion of social networks into transport models makes a difference. It has been shown that the use of agent-based modelling is useful in permitting the incorporation of social networks and that this incorporation can affect the outcomes of the model. However, there are still strands of this work that require further exploration. Several of these, such as the incorporation of group activities and the more detailed incorporation of network capital concepts, have already been discussed in the conceptual model outlined in chapter 4.

The first matter to consider for future work is the collection of data. A range of data is needed, from more aggregate data on group size and composition and types of activities to more specific data on how decisions are made. This notion of "levels" of data has been recognised by projects such as FEATHERS (Bellemans et al., 2010). Data on decision making could be collected by asking people how they came to a decision after the fact (for example, Clark and Doherty (2008) asked people which issues (start time, end time, type, location, and people involved) of a particular activity were fixed before the activity took place) or by setting up an experiment and observing people making hypothetical decisions. This is commonly used in models based on exchange, such as asking people how they would share an amount of money.

Another issue with transport models is scope: how detailed does the model need to be? The exploration of social activities within a city requires a detailed representation of the environment, however, as we have seen, people undertake activities outside their home city. As people move about more, their networks will cover a reasonable distance. In a country like the Netherlands, then a nation-wide model is feasible, and as people often commute from one side of the country to the other, their networks are widely spread.

Time is also an important scope consideration for transport models. The temporal difference between organising daily activities and network changes requires further investigation. Sharmeen et al. (2010) are currently undertaking a long-term survey of how social networks change over time and the effect on travel patterns. Once these results are available, the networks in the model presented in this thesis can be made dynamic.

An aspect not thoroughly explored in existing transport models is that of culture. Different societies operate in different ways regarding social activities (as the author has discovered firsthand). For example, it is common for some societies to plan activities well ahead of time, while other societies are more informal. This means that the decision making strategies developed in one cultural context may not be transferable to another. In terms of more detailed decision making, the concept of credit and power introduced by Ettema et al. (2007) have been the focus of preliminary models by Ma et al. (2011) and Ronald et al. (2010) respectively.

Software tools that incorporate cultures and norms are being developed (e.g., MASQ (Tranier, 2007)). Once these reach maturity, they will be useful to explore the social network dynamics and possibly generated activities. On top of this, Hamill (2010) also noted that better "building blocks" are needed for building agent-based models with social networks. This work is outside the scope of this thesis, however these research strands will be of use in the future.

To conclude, there are some immediate threads that can be picked up. Further experimentation with the form of utility function can be undertaken, in particular in light of the data already collected in Eindhoven. Group size can be incorporated. The detail of the spatial environment can be increased and possibly linked to a GIS file format for easy import. On top of this, the model could be attached for a travel model so that the agents can get feedback on different modes and travel options. Environment exploration and preferences (such as those developed in Han et al. (2009)) can be included.

The model presented in this thesis is an initial step in incorporating social networks into multi-day activity-demand models. The literature identifies this as an important step. This thesis has shown that the social network can have a significant impact on model results and therefore the decisions made by planners and stakeholders. There are many possible directions in which this model can be taken. The next step will be determining which is the priority.

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# Appendix A

# Module overview

This chapter lists the classes developed for the model described in this thesis. The reader is directed to chapter 5 for a more detailed explanation of how the model works.

## A.1 sasim.main

### Main

The main class for the simulation. Processes command line, creates a simulation object, runs simulation, and creates output.

### Simulation

Contains the population, environment, runtimes, and the global schedule.

## A.2 sasim.input

### Synthesis.java

Handles the reading in of files and initialising the simulation components.

The main input file needs file names in the following order:

sim, alpha location, alph day time, duration, threshold, beta, error, nodes, links, locations, home locations, core, non core, alts, mylocs

### ISimilarityReader.java, SimilarityReader.java

An interface for the similarity parameters and an instance to read files and calculate similarity.

The file format is:

```
lambda_age, lambda_gender
age levels
gender levels
```

### AlphaLocationReader2.java, AlphaLocationReader.java

Objects for reading in and storing of $\alpha_l$ parameters. AlphaLocationReader reads only one value for each combination, AlphaLocationReader2 uses sociodemographic variables.

The file format is:

```
<header>
activity, location, constant, values*
...
```

### AlphaDayTimeReader.java, AlphaDayTimeReader2.java

Objects for reading in and storing of $\alpha_{ady}$ parameters. AlphaDayTimeReader reads only one value for each combination, AlphaDayTimeReader2 uses sociodemographic variables.

The file format is:

```
<header>
activity, day, time, constant, values*
...
```

### DurationReader.java

Reads in duration data from a file.

The file format is:

```
location, duration_values*
...
```

### ThresholdReader.java

Reads in threshold values and stores them.

The file format is:

```
work status, work type, value
...
```

### BetaReader.java, TextBetaReader.java

An abstract class for a beta parameter and a concrete class with a read method.

The file format is:

```
<header>
type, type number, constant, values*
...
```

### EnvironmentReader.java, TextEnvReader.java

An abstract class for environments and an object that reads two files (postcodes and links).

The postcode file format is:

```
postcode, x, y
...
```

The link file format is:

```
end1, end2, distance
...
```

### LocationReader.java, TextLocationReader.java

An abstract class that reads two files of locations (home and non-home).

The file format is:

```
id, type,detailed type,name, postcode,opening_hours*
...
```

The opening hours are 14 values long: open and close for seven days of the week.

### PeopleReader.java, TextPeopleReader.java

An abstract class for reading the population in and an instance thereof. This takes two files: core and non-core people.

The file format is:

```
id, postcode, child, car,work, age, licence, gender
...
```

### AltReader.java, TextAltReader.java

An abstract class for reading the links in and an instance thereof.

The file format is:

```
i,j, type,last seen, strength, known since
...
```

### MyLocsReader.java, TextMyLocsReader.java

An abstract class for reading personal location knowledge and an instance thereof.

The file format is:

```
person id, location id, last seen
...
```

### TravelReader.java

A class for reading travel cost parameters: a constant (which is also a constant for the entire equation) and a factor.

The file format is:

```
constant, factor
```

## A.3 sasim.environment

### LocationType.java

An enum of the location types used in the model: HOME, SHOP, HORECA, OTHER.

### IEnvironment.java

Interface for an environment.

### Postcode.java

Contains details for a postcode, such as x and y coordinates.

### EnvLink.java

Contains information about an link between two postcodes.

### NetworkEnvironment.java

Implementation of an environment using a network representation of postcodes and links with a separate list of locations.

### Location.java

Contains details for a location, such as the id, postcode, location type, location name, and opening hours.

## A.4 sasim.activity

### ActivityType.java

An enum of the activity types used in the model: EXPERIENCE, VISITING, CHATTING, INFO, OTHER.

### WorkType.java

An enum of the work types used in the model: NONE, PART, FULL.

### TimeType.java

An enum of the time types used in the model: MORNING, AFTERNOON, EVENING, NIGHT. Also contains methods to determine the relevant category for a time, and the start and end times of a category.

### DurationType.java

An enum of the duration types used in the model.

### Day.java

An enum of the day types in the model. Also contains a method to convert a day number to a day of the week.

### Schedule.java

The schedule for a Person.

### GlobalSchedule.java

The schedule for the whole simulation.

### Activity.java

Contains details for an activity: id, day, time, duration, type, location, host, participants. Also contains methods to execute the activity by updating personal and link attributes.

### ActivityOption.java, ActivityOptionNoNetwork.java

Contains details about an activity and its utility to a particular person. The no network variant does not include the Uj component of the utility function, instead replacing it with a constant.

## A.5 sasim.population

### Person.java

Contains details about a person, such as their attributes (age, gender, children, car ownership, licence, work status, home location), parameter values, behaviour, the number of activities they have undertaken, the time since they last undertok particular activities, a message queue, a personal schedule, a list of alters, and the list of locations visited and people seen.

### ISocialNetwork.java

An interface for the social network. Declares amongst others methods for addling links, returning all pairs, and retrieving details about pair relationships.

### Population.java

Contains details about the population, in particular a list of all people, a list of non-core individuals, and a list of core individuals. Also stores the GlobalSchedule, the objects containing parameter values, a list of conversations, and the social network.

### PersonLink.java

Contains details about a link that are shared, namely similarity, last seen, and location similarity.

### SocialNetwork.java

A representation of a social network.

### Alt.java

Contains personal details for an alter, namely error.

### MyLocation.java

Contains personal details for a location, namely error, last seen, distance and travel cost.

## A.6 sasim.population.communication

### Conversation.java

Contains details about a conversation.

### ConversationStatus.java

An enum of conversation statuses: SUCCESS, FAIL, TIME, PERSONAL, PREFS.

### Message.java

Contains information about a message between two agents: conversation id, message type, message value, sender.

### MessageQueue.java

A queue of messages. Extends LinkedList at the moment, but could be customised if necessary.

### IProtocol.java

Base interface for a protocol.

## A.7 sasim.output

### ActivityOut.java

Writes output for each activity in CSV format.

Writes id, day, day type, time, time type, duration, type, location, loc type, host, and participants of each activity.

### ConversationOut.java

Writes output for each conversation.

Writes id, host, number of messages exchanges, and the error code.

### PairsOut.java

Writes output for each link.

Writes id1, id2, activities, similarity, distance between home locations, lastSeen, strength, knownSince, travel1, travel2, work1, work2, age1, age2, gender1, gender2, locSim0, and locSimN.

locSim0 is the location similarity at the beginning of the simulation, locSimN at the end.

### PersonalOut.java

Writes output for each person in CSV format.

Writes id, age, child, gender, car, driver, work, betaA, betaL, betaP, number of activities, activities per type, activities per location, amount of travel, work type per day, activities per day, activities per worktype, centrality, clustering, unique locations visited, locations known at beginning, locations known at end.

### ScheduleOut.java

Writes output for the schedule for each person in CSV format.

Writes id, day, time, act, location, activity type, location type, activity time since, location type time since, location time since, distance, participant, participant time since

## A.8 sasim.util

### ActivityOptionComparator.java, ActivityOptionNoNetworkComparator.java

Compares two ActivityOption(NoNetwork)s and orders by decreasing utility.

### Errors.java

Reads and stores error variables.

### BetaParameter.java

Stores a beta parameter.

### ActivityComparator.java

Compares two Activities and orders by increasing id.

# Curriculum Vitae

Nicole Ronald was born in Melbourne, Australia. In 2002, she completed a combined degree at the University of Melbourne, graduating with a Bachelor of Science, majoring in computer science, and a Bachelor of Engineering (Civil) with Honours.

During her undergraduate study, Nicole undertook work experience with various transport consultancies and research groups in the Melbourne area. After graduating, she worked at Sinclair Knight Merz as a graduate transport modeller, working on projects for the public sector. In 2005, she moved to the academic sector, undertaking a variety of technical and administrative tasks in her role as Casual Teaching Manager for the Department of Computer Science and Software Engineering at the University of Melbourne.

Nicole returned to the University of Melbourne in 2003 to begin a masters by research, where she was attached to the AgentLab in the Department of Computer Science and Software Engineering. She graduated in 2006 with a thesis entitled "Agent-based approaches to pedestrian modelling". Whilst there, she served as both president and secretary for the Computer Science and Software Engineering Postgraduate Group. She also tutored and supervised bachelor students.

In 2007, Nicole joined the Design and Decision Support Systems group in the Department of Architecture, Building, and Planning, Eindhoven University of Technology, Netherlands. During her candidature, she was a committee member for PromoVE and PhD Network Bouwkunde, and supervised later-year bachelor students.

Her research interests include agent-based modelling and model development, in particular how models can be used by planners and engineers in decision processes.