Complex adaptive systems and the new mobilities paradigm

Author: Daan Kolkman
Supervisor: Dr. Jan Prillwitz

Complex adaptive systems and the new mobilities paradigm

Title: Complex adaptive systems and the new mobilities paradigm
Keywords: Complexity theory, new mobilities paradigm, mode choice, agent-based modelling
Author: Daniël Antony Kolkman
d.a.kolkman@gmail.com
Supervisor: Dr. Jan Prillwitz
Course: GEO4- 3313

Foreword

The process of writing a thesis has been a challenging, inspiring and above all a very fun and instructive experience for me. I learned a lot about how “doing” science can be harsh and demotivating. Especially at times when there seems to be no previous research available or when quantitative analysis just does not give you the results you were hoping for. However, a when these problems are overcome this goes with a sense of achievement and excitement. My thesis project started over a year ago and is now finished. In completing this project I would like to thank Koen Frenken, Melanie Mitchell, Leo Kroon and Evelien van der Hurk for providing me with literature suggestions. Also, I would like to thank Dick Ettema for providing me with literature and discussing transport modeling with me. Subsequently, my thanks go out to Edith Ameraal for providing me with feedback on this thesis. I would not have been able to complete this thesis without the ongoing support of my family, parents, and girlfriend, I would to thank them for that. Moreover, my girlfriend Merel Bontenbal helped me with collecting surveys and I would like to thank her explicitly for helping me with this cumbersome task. Last but certainly not least I would like to express my gratitude to my supervisor Jan Prilwitz. He has allowed me the freedom to set out my own thesis project, but also provided me with help and guidance when I needed it.

Daan Kolkman
Utrecht, May 2012

Summary

The new mobilities paradigm presents a complex and dynamic view of mobility and transportation systems. The paradigm suggests that social science should be practiced through a “mobilities-lens” in which mobility is central to the analysis. Mobility should be central to social science because it is argued to be central to society. Furthermore, the paradigm approaches mobility as a dynamic and unpredictable phenomenon that is hard to capture with quantitative methods. As such, proponents of the paradigm usually employ qualitative methods to study mobility.

The new mobilities paradigm dawns in a context of growing environmental awareness and increasing conviction that something needs to be done in order to curb pollution, unsustainability and climate change. In this context, many policy makers and scientists have called for interventions that aim to reduce car-use and congestion on the one hand and aim to increase the use of active-[1] and public transport modes on the other hand. As of yet, much policy measures have been largely ineffective. Arguably, this ineffectiveness of these interventions is cause for concern; if we cannot exert influence on mobility systems then how can we effect change?

Following from this, mobility is a seemingly unpredictable and hard to influence phenomenon that urgently needs our attention. In order to effect change it is important to better understand the nature of mobility and advance the knowledge on mobility behavior. If it is possible to understand the dynamic nature of mobility, it should be possible to achieve more accurate predictions and develop more effective policy interventions. In this quest for understanding and changing mobility, both quantitative and qualitative methods play their part. Ethnographies provide in depth knowledge, while predictive models can be used to estimate for instance future travel demand.

When the value of both quantitative and qualitative methods is accepted, it follows that the new mobilities paradigm is not equipped for effecting change. The paradigm is explicitly skeptical of traditional quantitative methods since these oversimplify the nature of phenomena and often portray humans as utility maximizers. However, the dawn of computers and the ongoing development of information technology has rapidly increased the possibilities of quantitative methods such as computer modeling. Models can now be designed to include “softer” variables such as attitudes and lifestyles. Moreover, new dynamic modeling techniques have been developed. These new models are able to cope with the complex and dynamic nature of mobility system and can thus be considered a suitable alternative to the traditional quantitative methods that the new mobility paradigm criticizes.

Because the new mobility paradigm is highly skeptical of quantitative methods, the use of dynamic models in new mobility paradigm inspired research arguably requires theoretical backing. Complexity theory provides a starting point for such a theoretical foundation. Both the literature on dynamic models and the literature on the new mobilities paradigm draws from complexity theory; both advocate a view of systems as being unpredictable, dynamic and complex. Seeing as dynamic models and the new mobility paradigm have similar roots, it can be argued that research methods developed in either of the two strands can be used in both areas. This means that dynamic quantitative models can be used in the spirit of the new mobilities paradigm and advance our understanding of mobility as a dynamic and complex system. Vice versa, qualitative accounts can improve the quality of dynamic models.

Agent-based modeling is one of the dynamic modeling techniques used in studies of complex systems. This method is based upon simulating a large number of agents that exert human-like behavior. Arguably, an agent-based simulation approaches the level of sophistication present in

[1] Here, active refers to physically active transport modes such as the bicycle.

society. For instance, agent-based modeling has been used to simulate large urban transport systems with relative accuracy. However, currently no agent-based models use softer factors. These factors are known to increase the quality of traditional quantitative models in transport geography.

This thesis shows that an agent-based model that includes these softer factors can be created. Students' mobility behavior can be simulated in an agent-based model that includes attitudinal and contextual factors such as the attitude towards congestion and weather conditions. These factors arguably contribute to a more realistic and accurate simulation of transport systems. The results of such simulations can in turn be used to predict transport mode demand, but also provide knowledge on the behavior of complex transport systems.

The outcomes of this thesis suggest that dynamic quantitative methods can be used in concurrence to the new mobilities paradigm and in this way advance our knowledge of mobility systems. In addition, complexity theoretic concepts can be used in order to improve our understanding of complex mobility systems. By improving our understanding of these systems, it is arguably possible to intervene more effectively and achieve more sustainable behavior in the long run.

Table of Contents

Foreword ... 5
Summary ... 6
Table of Contents ... 8
Figures ... 9
Tables ... 9
1. Introduction ... 11
2. The new mobilities paradigm and complexity theory ... 17
2.1 The new mobilities paradigm ... 18
2.2 Social science that matters ... 21
2.3 Systems thinking ... 24
2.4 Foundations of complexity theory ... 26
2.5 Complexity theory explored ... 31
2.6 Biological complexity theory ... 36
2.7 Complexity and human geography ... 38
2.8 Complex methodologies ... 47
2.9 Putting it together: Complex mobility systems? ... 50
3. Case study: Transport mode choice amongst students in Utrecht ... 53
3.1 Exploring the application of complexity theory ... 54
3.2 Insights in transport mode choice ... 55
3.3 Agent based modeling and mode choice ... 59
3.4 Methodology ... 61
3.5 Data overview and sample characteristics ... 64
3.6 Data analysis ... 70
3.7 An agent based model for mode choice ... 77
4. Discussion & Conclusion ... 85
5. Literature ... 91
6. Appendices ... 99
Appendix A: Glossary ... 100
Appendix B: Surveys ... 102
Appendix C: DVD ... 110

Figures

Figure 2.5.1:	A plot of function (1) with t_0= 0,25 and r= 3,9	32
Figure 2.5.2:	A Poisson Saturne attractor	33
Figure 2.5.3:	A plot of formula (1) t_0= 0,25 and r= 3,2	33
Figure 2.5.4:	Bifurcation diagram	34
Figure 2.7.1:	Coleman's diagram	39
Figure 2.7.2:	Travel time stability and travel energy stability	45
Figure 3.5.1.1:	Data collection locations	64
Figure 3.5.2.1:	Education of the sample	65
Figure 3.5.4.1:	Household composition of the sample	66
Figure 3.5.6.1:	Primary mode choice	66
Figure 3.5.7.1:	Alternative mode choice	67
Figure 3.7.3.1:	ABM (1) with 1000 identical agents in bad weather	79
Figure 3.7.3.2:	ABM (1) with 1000 identical agents (good weather)	80
Figure 3.7.3.3:	ABM (1) with 1000 identical agents 7 days of not-rainy followed by 7 rainy days	80
Figure 3.7.4.1:	ABM (2) with 1000 identical agents in bad weather	81
Figure 3.7.4.2:	ABM (2) with 1000 identical agents in good weather	81
Figure 3.7.4.3:	ABM (2) with 1000 identical agents in alternating weather	82

Tables

Table 3.2.5:	Determinants of mode choice used in (agent-based) models	60
Table 3.5.4.1:	Questions used to measure attitudes	62
Table 3.5.4.2:	Statements regarding a particular transport mode	63
Table 3.5.12.1:	Attitudes towards travelling	68
Table 3.5.11.1:	Mode characteristics	69
Table 3.6.1.1:	Summary of the factor analysis results (N = 151)	71
Table 3.6.2.1:	Model (1) with demographic and socioeconomic variables	72
Table 3.6.2.2:	Model (2) with attitudinal variables	73
Table 3.6.2.3:	Model (3) with spatial variables	74
Table 3.6.2.4:	Model (4) with tour variables	74
Table 3.6.2.5:	Model (5) including all variables	74
Table 3.6.2.6:	Model (6) including all variables	75
Table 3.6.2.7:	Significant determinants of mode choice	76
Table 3.6.2.6:	Model (7) including all variables	78

1. Introduction

"Geographers have always had a problem in coping with complexity; space complicates to the point where it can easily obscure"

Nigel Thrift (1999)

1.1.1 The need for multidisciplinary science

Recent developments such as globalization, digitalization and climate change make it paramount for scientists to look across to borders of their respective fields. In order to understand and address these phenomena, multi-disciplinary insights are needed. The field of human geography has a long standing tradition in multi-disciplinary research. Human geographers often draw on neighboring disciplines to advance their understanding of spatial phenomena. For example, human geographers have drawn from the literature of economics and sociology. This tendency to venture into different disciplines has made some scientists (Amin and Thrift, 2000; Sui, 2010) to compare geography to a butterfly. They argue that human geography resembles a creature that haphazardly flies through different territories, only occasionally lands on a flower, but never settles down for good. This thesis modestly attempts to uphold this longstanding tradition of multidiciplinarity. More specifically, it explores the merits of complexity theory for application in human geography. As it goes beyond the scope of this thesis to attempt a complete investigation of the tangents and contrasts of these two fields, the focus is on the links between the sub-fields of biologic complexity theory and transport geography.

In short, complexity theory can be defined as the study of complex systems. Complex systems exhibit behavior that cannot be understood by observing their individual parts (Thrift, 1999). Thrift (ibid.) argues that complexity theory should be more central to geographical research. The quote at the beginning of this introduction provides a summary of his thoughts. Thrift (ibid.) suggests that space, the "stuff" we human geographers deal with, tends to make observations and analyses very complicated. At times it can be so complicated that it completely escapes our inquiries. Complexity theory could contribute to our understanding of spatial phenomena. In the context of globalization and climate change, such increased understanding is urgently needed. Several scientists have developed a keen interest in the field of complexity theory. For instance, Castells (2000) and Urry (2007) build on complexity theory in their respective works. They have developed a "complex" view of the world in which dynamic systems, complex networks and flows have the center stage.

Urry (2007) focusses on the analysis of mobility in social science. He suggests that mobility should be central to social science and that phenomena should be studied through a "mobilities lens". These ideas are summarized in what he (ibid.) calls the "new mobilities paradigm". According to Urry and Buscher (2009) this paradigm opens up new avenues for both empirical and theoretical research. Also, the new mobilities paradigm requires new research methods. Such methods are termed "mobile methods" and capture the intricate and complex nature of mobility. These mobile methods are necessary to understand amongst other things increasing car-use and the associated environmental issues (ibid.). Prillwitz and Barr (2009) voice a similar concern and argue that the unsustainable patterns of human mobility should be changed. However, they (ibid.) conclude that attempts to influence travel behavior have so far been ineffective. To rephrase, our current understanding of mobility does not allow for effective policy intervention. By advancing our knowledge of mobility the new mobilities paradigm could contribute to the development of more effective policy measures.

1.1.2 Advancing the understanding of complexity in human geography

Urry and Buscher's (2010) illustrate their call for new mobile methods, they elaborate that the new mobilities paradigm employs notions of meaning, complexity and dynamism. These concepts can hardly be captured by existing research methods that focus on linearity and equilibriums. Since the ideas of dynamism and complexity originate from the natural sciences (Urry, 2007), it should arguably be rewarding to extend our scope towards these fields of science in order to acquire suitable methods. However, an earlier attempt to connect quantum physics with human geography (Peterman, 1994) was quickly and relentlessly shot down by several critics (see Chapell, 1995; Campbell, 1995). These critics state that quantum theory engages in the study of objects in a micro-context and is therefore not applicable in any analysis of living beings. While physics might seem the obvious choice for acquiring mobile methods, the field provides no means of connection to the discipline of human geography.

Other feedback to "Quantum Geography" suggests that the life sciences might be a more appropriate starting point for advancing complexity research in social science (Courtney and Hardwick, 1995). Within the field of biology several sub-disciplines are potentially suitable for this purpose. For instance Zimmerer (1994, p. 109) states: " (..) new ecology focuses on disequilibria, instability and complex systems in the human built and natural environment". It build on recent insights from physics but has adapted these insights to work with living beings. Zimmerer (1994) argues that the complementarity of human ecology with human geography has been touched upon, but has never been studied extensively. Scoones (1999) explicitly states that social science in general could benefit from building upon conceptions of complexity theory in the life sciences. While such links between biology and human geography might seem farfetched, the idea itself is certainly not new. Almost a hundred years ago Park et al (1925) leant heavily on ecological concepts and metaphors to explain the organization of cities.

However, human geography has arguably developed quickly over the past century, so one could question the validity of combining insights from these fields. . In response to the lack of attention in geography to the 150th anniversary of the publication of "The Origin of Species" Castree (2009) wrote an essay concerning the relationship between the two fields. He argues that Darwin's work was concerned with geographic topics and that Darwin is the only world-famous thinker next to Marx which geographers have good reason to discuss. However Castree also indicates that the link between geography and Darwinism has all but disappeared after the Second World War. Castree's commentary sparked a sharp debate among several geographers (Kearns, 2009; Summerfield, 2010; Driver, 2010; Finnegan, 2010) discussing the link between geography and biology. In response to the debate Sui (2010) states that "geography and biology have been intellectually more connected than each discipline is willing to admit".

Since the use of complexity theory in social science is still highly debated (Rai and Schaffer, 2001), it could be rewarding to look into the suggested linkages between human geography and biologic conceptions of complexity theory. The outcomes of this research could be used in evaluating the prospects of the application of complexity theory in human geography. Furthermore, such research could contribute towards tackling the "problem" of complexity in neighboring fields such as economics and sociology. In relation to transport geography and the new mobilities paradigm, insights from biologic complexity theory could contribute to the development of mobile methods. In addition, exploration of the link between biology and geography could inspire new studies that built on insights from both fields, but do not explicitly address complexity theory.

An example of such human geography and biology inspired research is the work of Kolbl and Helbing (2003). They show that travel time consistency can be explained by the energy consumption of the human body. The article thus deals with the dynamic system of mobility and manages to explain it quantitatively by employing ecological causality. In other words, an evolutionary selection variable - energy preservation- is used to explain travel behavior, which is the focus of many geographical accounts. Kolbl and Heling's (ibid.) article has been received with skepticism by geographers Mokhatarian and Chen (2004). They point out that the findings conflict with statistical observations such as the overall rise in average automobile travel time and more congestion. This is opposed to Kolbl and Helbing's (2003) view that congestion leads to higher human energy consumption - due to physical stress - and a drop in automobile use. The execution of biology and human geography inspired is thus by no means straightforward.

Another human geography and biology inspired research by Changizi (2009) suggests that transport systems are similar to synaptic connections. He suggests that scaling laws might be similar for these different systems operating under similar pressures. Subsequently he goes on to explain the similarities of synaptic connections in the brain and highway networks in cities in theory and presents empirical evidence of this similarity. He concludes by suggesting that these two systems might actually be instances of a more general class of network. One cannot help seeing the resemblance between this article and the work of Park et al (1925). Changizi (2009) also suggests that the brain and the city have much in common, just as Park et al (1925) described the city as resembling an organism.

1.1.3 Research questions and aim

To summarize, it can be argued that current human geographical research is grounded in biological thinking, but human geographers have moved away from biology after the Second World War (Sui, 2010). However, recent insights on dynamic systems have sparked a renewed interest in physics and biology amongst human geographers. Looking into biologic complexity theory potentially offers tools to improve our understanding of dynamic systems in society. It has been illustrated that some scholars have already found ways to combine the fields, but much difficulties are still to be overcome. This master thesis will explore the relation between biology and human geography by evaluating the theoretical tangents of biologic complexity and the new mobilities paradigm. In addition, this thesis explores how insights from biologic complexity can contribute to the development of mobile methods:

"To what extent do transport geography and subfields from biology relate to each other in terms of complex systems and how can insights from biologic complexity theory be used in improving the applicability of the new mobilities paradigm?"

This main question will be explored by providing the answers to the sub-questions bellow:

I. What is the new mobilities paradigm and what are its merits and criticisms?
II. To what extent can social science be applied in society and how does research help progress in it?
III. What is complexity theory, what is its genealogy and which concepts are employed in it?
IV. What are the unique features of biological complexity theory?
V. To what extent do concepts from (biological) complexity relate to existing literature in human geography?
VI. What methodologies can be employed in complexity inspired research?
VII. To what extent can biological complexity contribute to the applicability of the new mobilities paradigm in society and research?
VIII. What factors are known to influence mode choice?
IX. What factors influence the mode choice of students?
X. To what extent can mode choice behavior be explained by an agent based model?

It has been mentioned (p. 7) that recent work in transport geography has indicated problems with the predictability of transport systems. Common scapegoats go by the name of non-linearity and dynamic change. In the present era environmental issues and the scarcity of fossil fuels however call for policy intervention. However, successful policy intervention relies on successful prediction, which has proven to be problematic. On the basis of a shared history the biologic conceptualization of complexity is supposed to be more suited for applications within human geography. Still, to understand biologic complexity one must have a firm understanding of complexity theory in general.

The aim of this master thesis is twofold. First it aims to contribute to the development of the new mobilities paradigm and possibly advance its applicability in empirical research and policy-formulation. Secondly, this will be done by exploring the field of complexity theory and attempting to translate its contents to a geographical perspective. These two goals come together in the theoretical section of this thesis. In the empirical section an example of complexity theory inspired human geographical research will be executed. This empirical research aims to show if the field of complexity can live up to the high expectations set by Thrift (1999) and others.

1.1.4 Structure

Chapter 2.1 investigates the new mobilities paradigm and discusses its merits and criticisms. Following this, chapter 2.2 delves deeper into the applicability of social science in general. Systems theory is introduced as a potential solution to this in chapter 2.3. Chapter 2.4 introduces the reader to complexity theory's philosophical underpinnings and in chapter 2.5 the main concepts of the theory are set out. Chapter 2.6 builds on this and introduces biological complexity to the reader. Subsequently, the possible advantages of complexity theory for human geography are explored in chapter 2.7. Then chapter 2.8 elaborates on some complex methodologies and in chapter 2.9 the implications of complexity theory for the new mobilities paradigm are discussed. In the empirical section the mobility behavior of students will be analyzed by using a multinomial logistic model and an agent based model. Each chapter provides a partial answer to one of the sub-questions.

2. The new mobilities paradigm and complexity theory

2.1 The new mobilities paradigm

In his book "Mobilities" Urry (2007) sets out the new mobilities paradigm. Here, he proposes a "mobility turn" in social sciences. It is argued that there are multiple kinds of movement which social science has inadequately examined and that recent technological innovations have necessitated the development of a new paradigm. Urry (ibid.) summarizes the shortcomings of previous studies as follows: (i) there has been neglect of movement and communication and the forms in which they are economically, politically and socially organized. (ii) There has been a minimization of the significance of these forms of movement in respect to social institutions. (iii) Social science has focused upon the patterns in which humans directly interact, ignoring the material infrastructure that facilitate them (Ibid. p.19).

2.1.1 Foundations of a new paradigm

Urry (p. 42) explains that his paradigm builds on an eclectic range of theories, including amongst others: complexity theory, nomadism, sedentarism, fluidity and moving materials. The most significant ones are discussed here. To start, Urry (2007) employs complexity theory. As stated in the introduction (p.9) complexity theory moves away from reductionism by considering systems as a whole. In the natural sciences complexity theory explains the behavior of gasses not by looking at the single atom, but at the entire system of atoms that compose the gas. Furthermore, complexity theory deals with time-dependent systems, such as chain reactions in nuclear fission. Complex systems are considered to be dynamic and develop over time. Over long periods of time these systems can be relatively stable, until reaching a tipping point after which changes occur rapidly. Related and well known concepts that were developed in complexity theory are the *butterfly-effect* and *path-dependency*. Complexity theory will be discussed in more detail in subsequent chapters (2.4;2.5;2.6).

By representing mobility as a complex system, Urry moves away from the static notion of place adopted in sedentarism. In effect, the theories of fluidity and nomadism are more suitable to Urry's framework. These theories focus on the flows and movements between places, instead of considering the places in themselves. From the spatial turn in the social sciences he takes the idea that spaces are comprised of various materials and environments; the meaning of objects and places can change over time and varies depending on the context in which they are used. Furthermore, he borrows the concept of hybrid geographies, in which humans and non-humans that enable on another to move across networks, for example the driver-car.

In addition, Urry draws upon migration studies to show that face-to-face interaction remains important, despite major innovations in communication technology. Members of diasporas still meet each other intermittently to underline and reaffirm their relationships. In the same context, Urry argues that the place where meetings take place gives meaning to the nature of a relationship. For instance, meeting a potential client in a bar gives of different signal opposed to meeting him or her in your executive office. From Kaufman (2000) Urry draws the idea of *motility*. *Motility* is the way in which an individual employs his or her mobility potential for different activities. Urry (2007) goes on to argue that people are not necessarily more mobile because they have the means to do so. Urry's calls his own conception of potential mobility "network capital".

2.1.2 The new mobilities paradigm explained

The new mobilities paradigm promotes thinking through a mobilities lens, effectively establishing a new social science that is post-disciplinary (ibid., p. 7). Urry argues that no social relationship is ever fixed in space. Instead, interaction is based on intermittent presence and absence and dependent on different forms of travel and communication. There are five interdependent mobilities employed in maintaining relationships: (i) corporeal travel, for work, leisure, et cetera (ii) physical movement of objects (iii) imaginative travel through images of peoples and places (iv) virtual travel (v) communicative travel through person to person messages. Moreover, social life is not independent from nature and objects; humans and non-humans interact in different ways, enabling or constraining each other's *network capital*. These relations between humans and non-humans is dynamic; it is adaptive and changes of time. Finally, these relations involve feelings and emotions and are therefore subjective.

The variety of mobility systems is more diverse in an affluent society. The larger the range of mobility systems, the more complex the intersection between these systems become. Mobility systems move people, objects and information at different speeds. Because the wealthiest people have the greatest access to means of mobility, inequalities are produced. As technology becomes more advanced, mobility systems become more reliant on expert knowledge. While a mobility system might be "ready-to-hand" or easy to use, in the event of a breakdown only experts can fix and reinstate the system. Finally, as mobility systems become more advanced, people leave more traces in digital systems, which can cause privacy problems.

As stated, mobility systems linger over time and are path-dependent. Some mobility systems, like air travel, are spatially fixed and new systems have to find their place in this competitive environment. Because of this rigidity mobility systems can be subject to "lock-in"; a situation in which innovations do not occur. Because mobility systems can span across the globe, they pose a challenge to the sovereignty of the nation state. Government power focusses on territory and subjects, but mobility systems enable these subjects to be foot-loose and make them harder to monitor. In summary, Urry (ibid., p. 52) states that the new mobilities paradigm examines how social relations necessitate the movement of people, objects, information and images across distance.

2.1.3 The development of mobile methods

Urry (p. 39) argues that the new mobilities paradigm necessitates new ways of studying mobilities. This is consequence of considering social phenomena through a *mobilities lens* that focusses on dynamism. In the book "Mobile Methods" Buscher, Urry and Witchger (2011) explore a variety of methods that qualify as *mobile methods*. Buscher et al (p.13) argue that mobility-oriented science should:

(i) Highlight how life is woven together by mobility practices
(ii) Study how mobility affects life as a whole
(iii) Consider the way spatial practices become embedded in space and vice versa

Moreover, it is argued that the survey and interview are outdated research methods (ibid., p.14) and that *mobile methods* are intrinsically experimental (ibid., p.120). The *mobile methods* that Buscher et al (ibid.) present are mostly ethnographic. The studies' methodologies range from participative observation to the shadowing of research subjects. Finally, the authors argue that *mobile methods* can be the catalyst in driving public experiments with mobility systems. Such public experiments are the only way of testing how proposed policy measures hold up in a real world setting; public experiments maximize complexity. This is opposed to the scientific experiment in which factors are isolated and complexity is reduced in order to discover causalities between variables

Buscher et al (ibid., p. 15) are sceptical of recent developments in information technology. These developments allow for tracking people's movement by large corporations. They (Buscher et al, 2011) point towards the dangers of this "Panopticon"[2] for privacy and democracy. Regardless of these dangers, Buscher et al (ibid.) suggest that quantitative methods cannot fully capture the

[2] The concept of the panopticon is to allow an observer to observe all inmates of an institution without them being able to tell whether or not they are being watched. It was first used by the philosopher Jeremy Bentham (1791)

fleeting and subjective nature of mobilities (ibid., p.15). While the book adopts a critical stance towards quantitative research, it does not shun them completely. Buscher et al introduce the idea of *qualculation*; this involves a combination of powerful quantitative methods with qualitative judgement. By quantifying data, scientists can acquire new sensitivities or ideas that they are unable to acquire by merely using their own senses. For instance, humans are unable to observe the movement of millions of cars from the sky, but a system consisting of satellites and automobile navigation systems can. Such data can be studied to observe patterns, behaviors and practices in a fashion resembling ethnography.

The discussion of quantitative methods is continued in a chapter written by Watts and Lyons (2010). In this chapter it is argued that small improvements in the experience of individual journey can manifest themselves as economic benefits on an aggregative level. Watts and Lyons are skeptical of the current economic models of passengers because they fail to consider what happens while people are on the move; passengers are essentially considered inactive while being mobile. The authors (ibid.) oppose this and argue that models should consider the productive activities that passengers engage in while traveling. Furthermore, Buscher et al (ibid.) argue that quantitative studies based upon number crunching generally do not provide much information about human behavior regarding mobility. The case is again made for a combination of calculation and qualitative judgment: *qualculation*.

This chapter answers the first sub question: *“What is the new mobilities paradigm and what are its merits and criticisms?”* To summarize, the paradigm sees mobilities as interdependent dynamic systems of humans, objects and information which change over time. The new mobilities paradigm argues that the study of mobility has so far mostly been ignored or been integrated into different fields. Urry argues that instead, mobility should be central to our analysis of the social and economic organization of society. As such, the merits of the paradigm lay in that it puts mobility at the center of social science and treats it as a dynamic phenomenon. In addition, the new mobilities paradigm provides a way of thinking about power-structures, feelings and emotions in mobility. Current *mobile methods* allow for context rich descriptions of peoples’ experiences with mobility systems. Furthermore, the idea of *qualculation* offers a foundation for the analysis of quantitative data gathered by information systems. The findings of *mobile method* studies could be used to set up public experiments. However, it is unclear to what extent current *mobile methods* provide adequate basis and support for such public experiments. Arguably, the bias towards qualitative research methods in the new mobilities paradigm does not provide the “solid” evidence that convinces policy makers to cooperate with public experiments. As such, the paradigm could be criticized for ignoring the potential application of new findings.

As was argued in the introduction there is a need for new ways of thinking about mobility to address large contemporary issues such as climate change. It can be said that the intricacies of mobility system are difficult to capture and understand, let alone to influence. The new mobilities paradigm is a transport geographical way of thinking about mobility systems that does capture complexity and dynamism. In the next chapter the link between social science and policy formation and intervention will be explored in order to investigate how the applicability of dynamic theories such as the new mobilities paradigm can be improved.

2.2 Social science that matters

The new mobilities paradigm offers scientists a new approach to advance their understanding of mobility systems. A more advanced understanding of mobility systems can in turn contribute to policy formation and eventually towards the development of more sustainable mobility systems. This chapter explores how the social sciences are currently conducted and aims to identify how researchers can both contribute to theory and improve daily life. Since policy measures aiming to change contemporary mobility systems have been largely ineffective (Goodwin, 2003), it is important to identify how change can be effected. This chapter looks into the ways that the social sciences can achieve changes in society. Since the last chapter concluded that the new mobilities paradigm is skeptical of quantitative methods, this chapter features an overview of the quantitative versus qualitative debate.

2.2.1 The science wars

In "Making social science matter" Flyvbjerg (2001) states that the "science wars" are still very relevant. The science wars started with the publication of a hoax article by the physicist Alan Sokal (1996). This article was a feigned review of the implications of recent developments in physics for the cultural sciences. The debate erupted when Sokal himself unveiled that his article was a fake; sparking strong reactions from the camps of the natural- and social sciences in equal measure. Central to the science wars is the idea that much of social science produces so called "So what-results" (Flyvberg, p. 132). This term is used to refer to research outcomes in the social sciences that have no implications for anyone; if the results of such research were to be falsified, no one would care or notice.

The idea that much of social research concerns itself with subjects that do not have much value outside of academia raises a very fundamental issue. If social research has such limited implications, then what is its contribution to the advancement of knowledge? In response, Flyvbjerg argues that the social sciences should stop trying to imitate the natural sciences and stop striving for explanatory or predictive theory. Because just as the social sciences do not contribute much to predictive theory, the natural sciences have not contributed much to reflexive analysis which involves values and meanings. Social sciences have a strong basis to contribute to the political, economic and cultural development because of their sensitivity to context. In other words, social sciences can provide a mirror to society.

2.2.2 Social sciences and society

Flyvbjerg (2001) argues that the social sciences have to adopt a more practical research structure if they are to matter again. This research structure is referred to as "phronesis". Studies based on the concept of phronesis attempt to transcend the analytic level and involve subjective judgments by the researcher. In a general sense, phronesis is a way of doing research in which the scientist is highly involved with his subject and tries to alter the status quo. In effect, the researcher focusses on existing power-structures, social order and conflicts and tries to uncover and influence these patterns. Doing so involves some measure of subjective judgment on the part of the researcher to decide what way the balance should be tipped. Flyvbjerg (ibid.) argues that especially in democratic societies change is effected by turning the public opinion on the ones in charge. By uncovering social injustice the scientist can influence the direction in which society develops.

Byrne (1998) also touches upon the nature of the social sciences. He argues that there is an inherent difference between the natural- and social sciences. This difference concerns the availability of data. Whereas in the natural sciences there is often an abundance of data on a single event, in the social sciences there is an abundance of different events with little data. Byrne does not share Flyvbjerg's view that scientists should become involved in the public debate. Instead, he argues that social scientists should study the trajectory of society and attempt to illustrate what possible futures lay ahead. Once these potential paths are identified by analysis, the social scientist should present his findings and rely on the “collective agency of the free citizens” (ibid., p.167) to work towards to most preferable alternative.

While Byrne (ibid.) depicts the prediction of the trajectory of society as a possibility, Johnson (2010) is skeptical of such predictions. He argues that policy formation always requires prediction, but suggests that traditional methods of prediction, such as quantitative scenario analysis, are not sufficient for analyzing the future state social systems. Johnson (ibid.) makes the point that while social systems might behave with regularity of a long period of time, they can also experience periods of radical change such as is the case in revolutions. This view is shared by Mitchel (2009) who also states that traditional “predict-and-act” models are unable to cope with the uncertainties evident in reality. Scenario analyses quantify future benefits and costs for a set of policy options. The different scenarios then get assigned different probabilities and policy makers are relied upon to decide upon the most favorable scenario. However, this presents an illusion of certainty to policymakers as social systems are all but predictable. In view of this high level of uncertainty in social systems, some scientists have called for social science to abandon its scientific aspirations and instead focus upon achieving political change (Latour, 2010). Others, like Geyer and Rihani (2010) argue that intervention in social systems is possible with the appropriate philosophy. To be successful, policymakers and scientists must accept the limited predictability of social systems. Top-down management and command and control from the center are fundamentally misconceived (ibid.).

To increase the grasp on social systems one might argue for further advancing our knowledge of the state of those systems. That way, it might be possible to successfully predict the trajectory of society. However, Mitchel (2009) argues that this strategy is ineffective since while we gather more knowledge on the present state of a system the opportunity to intervene passes. Rather than seeking to eliminate uncertainty, we should highlight it and then find ways to manage it. One example of this is employing robust strategies. These are strategies that might not be the best option available, but provide satisfactory outcomes in a wide range of future scenarios. Once a decision is made, this does not mean that policymakers should follow that path mindlessly. Instead, as new information comes in they should redirect funds and effort into the most promising avenues. If we ignore the uncertainty in predictions about the natural and social world it might appear to policymakers that science fails. In the long run this might undermine the image of science and make policymakers ignore it altogether (Mitchel, 2009).

2.2.3 An interplay between quantitative and qualitative methods

As opposed to Flyvbjerg (2001), Johnson (2010) and Mitchel (2009) argue that the social- and natural sciences will move more towards each other in the long run. The natural sciences can provide the basis for analyzing and quantifying systems with high uncertainties and those uncertainties can be explained and understood by qualitative social science. Furthermore, social scientists are experienced in employing rhetoric, which is of importance in convincing policy makers of adopting a more flexible and adaptive style. By combining the strength of these two fields social scientists can use the real world as their laboratory for conducting experiments that matter both to science and society. Johnson and Mitchel’s view seems to be aligned with that of Urry (2011) that also stresses the importance of public experiments.

The take-home point from this chapter is as follows. Social sciences are inherently different from natural sciences, but both have their merits. In addition, policy makers should be convinced about the uncertainty of social systems and adopt a more flexible stance. While there are major differences between the natural and social sciences this does not mean that they cannot complement each other. By using quantitative models from natural sciences and qualitative insights from social sciences, policy formation can be improved and social sciences can “matter” again.

On the one hand, quantitative research can be unable to inspire policy if the results are presented with little rhetoric. On the other hand qualitative research can be unconvincing in the face of policymakers because of the problem of such studies with external reliability (Bryman, 2008). Arguably, an approach that includes both quantitative backing and a qualitative judgment has the best odds of convincing policymakers in the long run. To refer to chapter 2.1, economic models might inspire much policy at present, but fail to capture some very important aspects of mobility. On the other hand ethnographic research provides valuable insights into human behavior, but fails to deliver a firm foundation to inspire policy formation or public experimentation.

This chapter answers the second sub question: "To what extent can social science be applied in society and how does the application of social science instigate progress? To improve the applicability of the social science, social scientists should think about how their research can contributes to society. For the research practice, this involves adding not only recommendations for future research and providing policy recommendations but also possibly adopting a stance on how the current situation can be improved. In addition, there is a need for suitable theories, methods and models which allow for the prediction of systems with a high degree of uncertainty. This involves both quantitative modeling and gaining context sensitive information by qualitative methods. To inspire policy formation cooperation between proponents of quantitative research methods and proponents of qualitative research methods is paramount.

As was illustrated in chapter 2.1 most currently explored mobile methods are qualitative methods. This chapter argues in favor of combining quantitative and qualitative methods to inspire change. Since policy measures for mobility systems have largely been ineffective in the past, the new mobilities paradigm could benefit from quantitative methods that have similar theoretical foundations. This chapter also suggests that the social sciences and natural sciences are expected to move closer together in the future. This provides an additional ground for looking towards the natural sciences in order to enhance the understanding and application of complexity in social sciences such as human geography. The next chapter introduces systems thinking as a viable alternative to traditional approaches that are unable to deal with high levels of uncertainty. Alternative dynamic models associated with systems thinking could provide the basis for quantitative mobile methods.

2.3 Systems thinking

"All is flux, nothing stays still"
– Heraclitus

(Strokes, 2000)

The previous chapter explored an approach to how science can contribute to policy formation. It shows that social scientists do not have methods that can quantify systems with high degrees of uncertainty. Such methods are available in the natural sciences and more specifically in complexity theory. To understand complexity theory it is important to first introduce systems thinking.

2.3.1 The history of systems science

Some authors (Wolfram 2002; Bertalanffy, 1972) argue that the history of system sciences dates back as far as the dawn of European philosophy. However, a complete overview of systems science is not the aim of this thesis so here the discussion starts with the scientific revolution in the 17th century. This revolution is significant because it entailed the replacement of metaphysical-descriptive methods by mathematical-positivistic one; the idea of a cosmos governed by goals was replaced by the description of events in terms of causality and mathematical laws. The positivistic world-view is returned to later, for now it is enough to understand that it refers to the reduction of phenomena into small parts that relate to each other in mechanic fashion.

This mechanic world view got strengthened by Isaac Newton's law of gravity. According to Ryan (2008) this major breakthrough caused a cascade. Through the formulation of his laws Newton united terrestrial and celestial dynamics. Since the heavens and earth seemed to be governed by the same laws it became probable that mathematics could also explain life on earth. This view influenced 19th century science as it was believed that the whole world could be explained in this deterministic and mechanic way. Social scientists applied the same paradigmatic views to explain the incredible shifts taking place in late 19th century; because of the industrial revolution society changed faster than ever before. Social scientists were looking for ways to study society as mechanic system governed by laws, without reducing it to the individual behavior of people (Castellani and Haffert, 2009). In this context it is important to mention the work of Darwin, who looked at evolution as a system of natural selection (Mitchel, 2009).

Despite its initial widespread popularity the systems tradition was in large measure dead by the first half of the 20th century (Castellani and Haffert, 2009). This happened because social scientists were beginning to see the limits of the mechanistic systems approach. For instance, it provides no means to explain random events; if the world behaves in a mechanistic fashion then how can one explain eccentric inventions like the nylon stocking (Wolfram, 2002). Furthermore, the continued development of the ideas of Darwin led to the belief that phenomena in the biological and social world were not reducible into elementary parts (Castellani and Haffert, 2009).

2.3.2 The inception of complexity

A resurgence of systems science took place in the second part of the 20th century. Scientists built upon the work of Poincare, who discovered instability in physical systems (Mitchel, 2009) and Lorenz, who discovered that small variations in the initial input could result in very large differences in the output of mathematical models (Johnson, 2010). Geyer and Rihani (2010) argue that such discoveries did not disprove the existing law-dominated paradigm, but rather showed that not every phenomenon was orderly, predictable and subject to law-like rules. Some systems conform to the classical framework, but others do not.

Still, these discoveries had wide implications as they show that even physical systems are not always predictable by linear superposition. Superposition means that if input A leads to result X and input B leads to result Y then input A and B combined would lead to X and Y. Instead, this relation can also be non-linear, meaning that input A+B would result in Z. A different result than adding up the results of A and B separately. Furthermore, it was argued that causality itself could be non-linear. This means that the relation between variables is not always straightforward and predictable, but subject to context-influences and changes over time (Geyer and Rihani, 2010).

It should be noted that the use of computers played a crucial role in the resurgence of systems thinking. With the help of powerful computers mathematicians are now able to solve the non-linear equations that had previously been impossible to calculate (Capra, 2005). These non-linear systems are not only used to explain for instance the expansion of gasses, but are also related to the basic properties of living systems by Prigogine (1980). This study of systems that involve non-linear relations is referred to as complexity theory.

2.3.3 Networks or systems?

Recently, the study of networks has become widespread; Castells (2000) for example shows how modern society is dominated by networks. Barabasi (2002) argues that networks are everywhere and that a network-based paradigm allows for new viewpoints to study a wide variety of subjects. He coins the term “complex social networks” to refer to society. It is important to note here that the concepts of network and system seem to be highly related and are used interchangeably throughout the literature. Barabasi (2002) suggests that networks are in fact a way of thinking about complex systems:

> “Networks are by their very nature the fabric of most complex systems, and nodes and links deeply infuse all strategies aimed at approaching our interlocked universe.”

In considering the literature used for this thesis, it seems that the term “networks” is employed more frequently to refer to phenomena that include humans or are of human making. The term “systems” is more frequently used in regard to non-living systems and to refer to systems which include organisms other than humans. However, it is the view of the present author that the word “system” is used more frequently in publications on biological complexity and for this thesis it is the most appropriate choice.

This chapter showed how systems theory was developed to cope with the changes in society but was initially abandoned for its inability to cope with random phenomena and phenomena irreducible to small parts. Breakthroughs in the natural sciences, where non-linear systems were initially discovered, led to the development of new quantitative techniques which can cope with randomness and complex systems. The next chapter will delve deeper into philosophical background of complexity theory to provide the reader with more understanding of its underlying train of thought.

2.4 Foundations of complexity theory

"Linearity is a reductionist dream and nonlinearity can be a reductionist's nightmare"
- Melanie Mitchel

Mitchel (2009)

The previous chapter introduced systems thinking as way of approaching phenomena. This chapter looks into the philosophical foundations of complexity theory. A firm understanding of these foundations is necessary to understand what sets complexity theory apart from other theories. This chapter starts with a discussion of the epistemological and ontological roots of complexity theory and positions complexity theory in relation to positivism, post-modernism and critical realism. From this point on, all concepts that are introduced are highlighted and listed in appendix A for reference.

2.4.1 Defining complexity theory

Complexity theory is notoriously hard to define (Nowotny, 2005), but the following quote by Thrift (1999, p. 33) provides the reader with some basic understanding: "The study of the behavior of macroscopic collections of interacting units that are endowed with the potential to evolve in time. Their interactions lead to coherent collective phenomena, so-called emergent properties that can be classified only at higher levels than those of individual units." To put it differently, complexity is concerned with the change in and of interrelatedness in the range of components that constitute a system.

While this definition might cause more confusion that it does supply clarity, for the moment it is important to remember that complexity theory finds its origins in the natural sciences where it was developed in relation to thermodynamics. There it explained the behavior of atoms in systems of gases. Complexity is also useful in the social sciences because it helps us to understand systems that consist of many individual parts and are marked by high level of interrelatedness. In layman's terms complexity might be best described as: "everything relating to everything and changing without apparent order." These are the first two aspects of complexity theory; ***(i) interaction*** and ***(ii) connectivity***.

Complexity theory argues that some phenomena that cannot be captured by traditional paradigms. Such phenomena exert complex behavior, which means amongst other things that they are non-linear and dynamic. Complexity is thus an aspect of a phenomenon and can be conceptualized in several ways. Complex systems, complex networks and complex adaptive systems are all ways of conceptualizing the same kind of phenomena. All these conceptualizations have their merits and shortcomings and are intended for the study of different complex phenomena. The differences between these conceptualizations will become clear in subsequent chapters (2.6 and 2.7).

2.4.2 What complexity is not

At this point it is important to distinguish complexity from complication to avoid confusion. As indicated before, complexity theory studies phenomena which cannot be understood as the sum of their parts. Complex systems feature feedback loops and non-linear interactions between the parts; if one were to deconstruct such a system he or she would obscure the interaction effect. Complicated systems can be understood by the sum of their parts, they are complicated because of a large amount of parts, not because of the nature of interactions between those parts (McGlade and Garnsey, 2006).

Castellani and Hafferty (2009) argue that another important distinction should be made between chaos theory and complexity theory. In some literature these two theoretical strands are taken for the same kind of science, but is not the case; most complex systems do not exert chaotic behavior. Chaos does occur in complex system but it is not a generally observed trait. Furthermore, it should be noted that chaos does not equal complete randomness, but rather an orderly disorder with the absence of hierarchical structures that produces outcomes (Urry, 2005).

Since there is a lot of discussion on the nature of complexity theory, it is important to discuss its philosophical foundations. This can be illustrated by juxtaposing some authors on the subject. Capra (2005) for instance argues that complexity is a mathematical theory and should not be confused with a complete scientific paradigm. Mitchel (2009) on the other hand states that complexity has far reaching implications for both philosophy and scientific theory. Whether or not complexity is a complete paradigm, the ongoing discussion on the nature of it requires that we develop a deeper understanding of complexity as a theory (Nowotny, 2005). To achieve this, different scientific philosophical movements will be summarized and after that be related to complexity.

2.4.3 Positivism

Positivism is a set of approaches that seeks to apply principles from the natural sciences to social phenomena (Aitken and Valentine, 2006). The Positivistic method is concerned with the establishing of models which have predictive power (Byrne, 1998). Towards this goal it employs the concepts of verification and falsification. Verification concerns itself with the formulation of theory by means of deductive reasoning; by using empiric data hypotheses are tested and confirmed. Falsification is used to undermine theory by trying to identify cases of exception in which a theory does not hold. In the system of logic-positivism a theory holds as long as it cannot be falsified (Aitken and Valentine, 2006).

Positivism adheres to an epistemology in which our knowledge is a reflection of a reality which is objective and accessible to all. In other words, theories that are based on empirical data represent reality in an unbiased way. It stresses the importance of concepts with causal relations. Its methodology is built around the formal experiment in which it is attempted to uncover causal relations by changing one variable and keeping the rest stable (Aitken and Valentine, 2006). Positivism looks for universal order and an objective reality, based upon theories and formulas (de Pater, 2005). An example of positivist thinking is economical modeling which is based upon rationality and utility functions (Wilson,2008).

Positivism is criticized (de Pater, 2005; Byrne, 1998) for being reductionist in the sense that it argues that everything is reducible to simple equations and causal relations. However it is still widely agreed that the quantitative methods of positivism are robust and scientifically sound. In geography positivism can be related to the quantitative revolution during the 1960’s when geography switched from begin descriptive to explanatory. Despite its positivism remains strong in human geography and a large number of geographers still attempt to the find laws through quantitative methods. Breakthroughs in computer sciences have allowed for the continued -and arguably improved- application of positivist methodology (Aitken and Valentine 2006).

2.4.4 Post-modernism

As opposed to positivism, post-modernism dissociates itself from the search for overarching principles or *metanarratives* (Aitken and Valentine 2006). It also challenges the view that human actors are rational in their behavior, instead post-modernists argue that behavior is influenced by experiences, attitudes and beliefs. Post-modernist accounts are reflexive and stress the importance of power-relations (de Pater, 2005). Subsequently, post-modernism argues that knowledge is a social construct. Facts and science are not objective but matters of interpretation and faith. They argue that the world is inherently complicated, confusing and contradictory and cannot be explained by means of equations and causal relations (Aitken and Valentine, 2006).

Post-modern scientists stress the fragmented nature of reality (de Pater, 2005). Post-modernists are therefore highly suspicious of research that implies that there is an objective reality or that there can be objective knowledge. Furthermore, the movement rejects notions of duality between agency and structure. Instead, they argue that society is marked by a high level of interconnectivity and chaos. In their research post-modernists usually employ qualitative methods because they believe that quantitative methods are too reductionist. They argue that methods like ethnography can provide a detailed look into the motivations behind behavior and how research subjects experience the world (Bryman, 2008).

Post-modernism has been criticized because it can lead to nihilism. Nihilism leads to the conclusion that no objective reality, instead reality is what different people take it to be. Therefore, it is impossible to come to descriptions of this reality which are objective. From this it follows that science can never advance its knowledge since all accounts and views are equally true (de Pater, 2005). In human geography, post-modernism has been increasingly popular and this is most evident in ethnographic accounts which focus on interpretations of phenomena and peoples experiences in interaction with the world (Aitken and Valentine, 2006).

2.4.5 Critical realism

Unlike the post-modernist accounts, critical realists do believe in an objective reality. This reality exists separately from our interpretations of it, this does not mean that interpretations are not important, but simply that the world is always there (Aitken and Valentine 2006). Critical realists subscribe to the idea that science is just one way of knowing the world, other accounts like fictional books also describe reality but do so in a different way. Some accounts of the world will be better than others, depending on how accurate they can approach or describe this reality. Critical realism strives to identify the processes which are at work in society. Some of these processes might not be apparent or empirically observable. These processes can be accepted because even while they themselves are not observable, their effects are (Bryman, 2008).

Critical realism accepts that the concepts it uses to understand reality are likely to be temporary. This follows from the idea that the world is separate from our knowledge of it; there are always different ways to describe it. However, since we are not able to control reality to the point where we can make everything happen, we should be able to separate more true ideas from less true ones. Moreover, since we are not omnipotent in our influence on reality there must continue to exist ways of improving our knowledge of it. Critical realism is thus concerned with the outcomes of interventions and improving the effectiveness of these interventions (Bryne,1 998).

In a sense, critical realism tries to steer between the extremes posed by positivism (reductionism) and post-modernism (nihilism/relativism). Believes are not separated in categories of true and untrue and our knowledge of the world is not absolute. On the other hand the notion of all knowledge or accounts of reality being equally true is rejected (Aitken and Valentine 2006). So critical realists assert that there is a real world, separate from our interpretation of it. A somewhat extreme and blunt example might clarify here: In ancient Greece people used to think that the anger of the god Jupiter was responsible for lightning, in contemporary times we have discovered that lighting is actually an atmospheric discharge of electricity. In the sense of post-modernism this would mean that reality has changed since our conception of lighting has changed, in the sense of critical realism this would mean that through our efforts we have learned more about the real nature of lightning. In geography critical realism is employed in economic geography and uses both quantitative as well as qualitative research methods.

2.4.6 Complexity

Complexity theory is an attempt to understand social reality by employing methods which approach this reality as a system. The essence of this approach is the belief that something is lost when a system is reduced to the sum of its parts (Byrne, 1998). This is the third aspect of complexity which will be referred to as (***iii) non-compressibility.*** In dealing with the complex nature of reality both quantitative as qualitative studies have their proponents (Bryman, 2008). It is important to note in this context that while some of complexity theory's methods might be quantitative this does not mean that these methods are necessarily positivist (Byrne, 1998).

Complexity is not beyond our understanding; it requires new ways of understanding (Mitchel, 2009). So while some of its research methods might be quantitative it tries to do away with the positivist criticism of reductionism by looking at the system as a whole, not as a sum of its parts which can be described by laws. Furthermore, complexity theory also dissociates itself from the metanarratives which are deemed to be impossible by post-modernist accounts. Complexity theory does note that very different social phenomena might be instances of the same type of system. So while a set of overarching rules for prediction is impossible, different systems might behave in similar ways (Byrne, 1998).

Complexity theory does not equal postmodernism. In the literature of the latter movement much has been said about the limits of modern science; how science is just one way of knowing the world and has no authority over other forms of knowledge. Complexity theory can only be called postmodern in the sense that it is beyond modernism. In other words, it is an effort to go beyond the linear and static and instead look at the non-linear, dynamic, and evolving. Because this changes the ways of doing science complexity scientists are forced to ask the same questions as post-modernists (Castellani and Hafferty, 2009). Furthermore, it is important to restate that even complexity does not equal chaos. Complex phenomena might be hard to predict, but are not impossible to fathom. It is thus not necessary to descend into the scientific pessimism of abandoning rational, objective knowledge like the postmodernists (Byrne, 1998).

As opposed to post-modernists, complexity scientists still believe in mathematics, albeit in a new more computational, qualitative and nonlinear way (Capra, 2005). They believe in rigorous empirical study although they know that complete description of anything is impossible, both because of the limits of the knower and the methods used (Castellani and Hafferty, 2009). However, one should realize that complexity theory is by no mean driven by physics envy; this should be clear from the anti-reductionist character of the movement (Byrne, 1998). A complexity theoretic approach recognizes the limits of predictability and knowledge (Geyer and Rihani, 2010). Furthermore, as is indicated above, complexity theorists use to both quantitative and qualitative methods.

Another important observation is that complexity theory does subscribe to the critical realist view of a reality which is objective and knowable through empirical study. This means that both qualitative post-modernist ethnographic accounts and quantitative positivist accounts can contribute to our understanding of reality. Byrne (1998) argues that realism provides the best ontological foundation for complexity. By advancing this understanding social scientists can provide accounts of possible trajectories for complex systems and figure out ways to steer development into a certain direction. This point is also made by Mitchel (2009) who states that positivism can be useful in many cases, but fails just as many times as it succeeds. She goes on to illustrate that some complex systems can be reduced to simple laws. A striking example is that of our solar system as explained by a few equations by hands of Copernicus. Systems such as the climate however do not fit in a reductionist approach and require a more sophisticated handling. The usage of complexity theory should thus be based on the nature of the phenomenon, the thing the research is aiming to explain and the context-sensitivity of the system.

Geyer and Rihani (2010) argue that in essence complexity theory does not disprove of either post-modernism or positivist tendencies. They state that complexity acts more like a bridge between the two frameworks for reconciling these opposing positions. Basically the orderly and disorderly frameworks are equally flawed. Both assume that humanity and its relationship to nature are inherently orderly or disorderly when in reality they are both. In effect, complexity theory provides a strong basis for social research that strives to improve everyday life, as discussed in chapter 2.2. Also, complexity theory is very relevant in relation to the new mobilities paradigm because it provides ways of understanding systems which are inherently unstable and unpredictable. Complexity theory might offer the new mobilities paradigm a way of quantitatively researching mobility that does justice to the complex nature of the phenomenon. In the next chapter the contents of complexity theory will be presented in detail.

2.5 Complexity theory explored

The previous chapter discussed the philosophical underpinnings of complexity theory. It concluded that complexity theory fits within the critical realist tradition. Furthermore, it illustrated three aspects of complex systems: *connectivity*, *interaction* and *non-compressibility*. In the current chapter other aspects of complexity theory will be explored.

2.5.1 A structured approach for analyzing complexity theory

Complexity is not a well-defined subject and opinions about the field constitutes differ from person to person (Mitchel, 2009A). The goal of the overview provided in this chapter is to introduce the reader to some of the vocabulary employed in the literature. It is not the intention to develop or distill a coherent theory of complexity; such a task would be well beyond the scope of this thesis. In referring to complexity theory this thesis refers to the whole field of complexity theories and does not point at one particular theory. Also, it is important to stress that there exist many different sets of concepts in these complexity theories. The concepts introduced here do by no means form a complete account, nor should the exclusion of certain concepts be regarded as a rejection of their validity. Nevertheless, the concepts introduced in this chapter are central to the field of complexity and should provide the reader with an adequate feel of what the field constitutes. This chapter deals with complexity as used in physics and mathematics. As was mentioned in chapter 1 the link between these fields and geography is problematic to say the least. However, to develop a firm understanding of complexity it is important that the reader understands its jargon.

Some of the concepts related to complexity theory are rather abstract and could hard to fathom; therefore it might provide clarity to employ examples. The formula bellow serves the purpose of illustrating the different concepts by plotting them in a graph. For instance, it will be shown that minor changes in the parameters and variables of the formula will result in widely different plots. The function employed describes population growth and was first introduced for its chaos exerting behavior by May (1976).

$$t_{n+1} = rt_n(1 - t_n)$$

The formula has the following variables:

- t_n is a number between zero and one, and represents the ratio of existing population to the maximum possible population at year n, and hence t_0 represents the initial ratio of population to maximum population (at year 0)
- r is a positive number, and represents a combined rate for reproduction and starvation
  In other words; if the population ratio drops population decreases, if the population ratio rises the population increases. An increase could be associated with natural population growth through reproduction and a decrease would indicate starvation due to overcrowding.

2.5.2 Complexity theoretic concepts

A central aspect of complexity theory is that it regards systems as open or **(iv) dissipative**. This idea stems from the second law of thermodynamics. This law states that physical systems have the tendency to increase their disorder over time. In order to maintain any kind of stability or organization, energy has to be fed into the system externally. Systems are open in the sense that they interact with other systems. For example, planet earth needs the sun to maintain its temperature. There is thus connectivity and interaction between earth and the sun. The idea of *dissipation* thus relates to the fact that complex systems interact with their environment in order to maintain their stability.

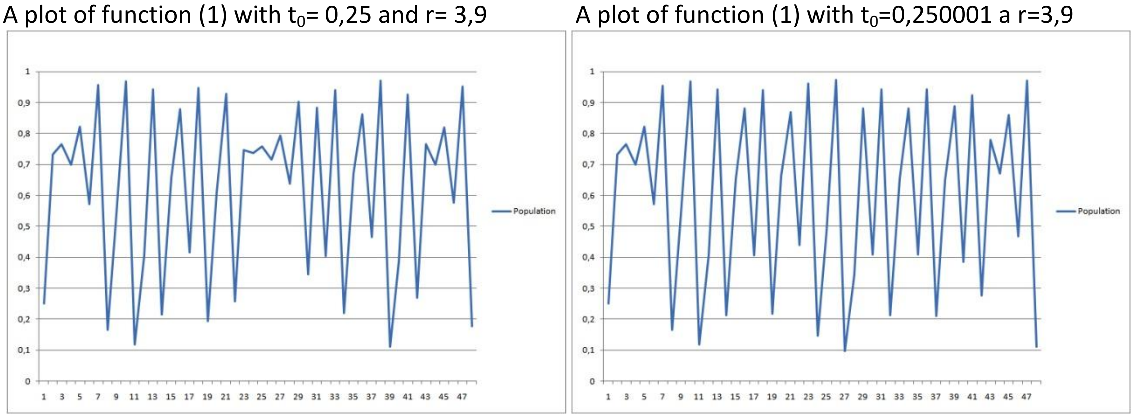
From the above it follows that complex systems are in a ***(v) far-from-equilibrium state.*** Imagine that the sun would somehow cease to function; the earth would cool down and enter a state in which no life is possible. This new state can be thought of as equilibrium, in which nothing changes. Luckily, our solar system is not in equilibrium but constantly exchanges energy with the sun, so maintaining a climate suitable for live. Non-interaction is thus equal to equilibrium. Complex systems have a high level of interaction and are thus far from an equilibrium state (Geyer and Rihani, 2010).

Complex systems thus need to exchange energy with other systems in order to maintain their stability (Geyer and Rihani, 2010). Urry (2005) agrees with this and adds that it is exactly this lack of tendency towards equilibriums which makes complex systems so hard to predict; they are on the edge of total chaos. Non-complex systems are found at equilibrium states, for example a single marble lying at the bottom of a bowl or a jet engine on which stability and predictability we depend for air-travel (Geyer and Rihani, 2010). While these systems can be sophisticated, they do not depend on interaction with other systems to maintain their stability. This makes these regular systems more predictable.

The earlier notions of *connectivity* and *interaction* are not essentially unique to complex systems. One could argue that a complicated system like the jet-engine also has these features. It is however the nature of these two concepts which makes them unique to complexity. As pointed at in the systems science section (Chapter 2.3), **(*vi) non-linearity*** plays an important role. In complex systems the patterns of *connectivity* and *interaction* are inherently instable. As opposed to the jet engine in which kerosene is injected and always produces thrust, complex systems are highly sensitive to their initial conditions. This attribute of complex systems is referred to as **(*vii) sensitivity to initial conditions***.

Figure 2.5.1 illustrates the implications of *sensitivity to initial conditions* using formula (1). At first sight both graphs might resemble one another, but closer inspection reveals that their trajectories are very different. While both plots have a short overture followed by a sequence of several peaks and valleys these general characteristic are the only thing they share. The small change in the initial value of t (t_0= 0,25 $\rightarrow$ t_0 = 0,250001) makes a difference for the trajectory of the population ratio. This example shows how complexity exerts itself even in simple functions. From this, one can imagine that a similar change in more complicated functions could be even more dramatic.

Figure 2.5.1:
A plot of function (1) with t_0= 0,25 and r= 3,9 — A plot of function (1) with t_0=0,250001 a r=3,9



Eventually, a complex system will settle down in a certain pattern. This relatively stable pattern is called an **(iix) attractor**; it is the pattern towards a system evolve.s Once a system reaches the attractor it will continue to follow it even when slightly disturbed. As it moves around the attractor a complex system frequently returns to roughly the same state but never the exact same one (Mackenzie, 2005). In the left plot of figure 2.5.1 the pattern displayed for 3 > t < 22 can be seen as an attractor. This pattern is repeated in a similar fashion multiple times. Loosely formulated the attractor can be seen as the trajectory of any given system which is resistant to slight perturbations.

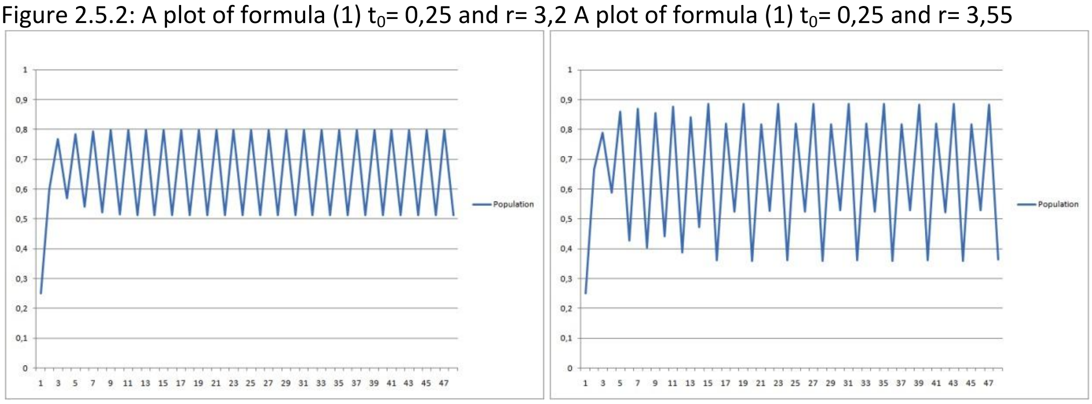
The *attractor* describes the long term behavior of a system (Geyer and Rihani, 2010) and shows a certain kind of stable patterns (Capra, 2005). An attractor state is a set around which complex systems revolve over time. When one solves a non-linear equation that forms an attractor the result is not an equation but a visual shape. This shape is an attractor and can have one to several dimensions that represent the different variables needed to describe the system. So with every variable added, the system gets an additional dimension (Mackenzie, 2005). An example of such an attractor can be seen in figure 2.5.1.

Figure 2.5.1: A Poisson Saturne attractor (Desprez, 2007)

The space formed by these different dimensions is called ***(ix) phase space***. This is the space of all possible states of the system. As a system changes through time it is possible to trace a path through the phase space (Capra, 2005). Harrison et al (2006) define it somewhat differently: ”Phase space captures all the possible spaces in which a spatio-temporal system might exist in theoretical terms. Phase space, then, contains not just what happens but what might happen under different circumstances. It’s the space of the possible”.

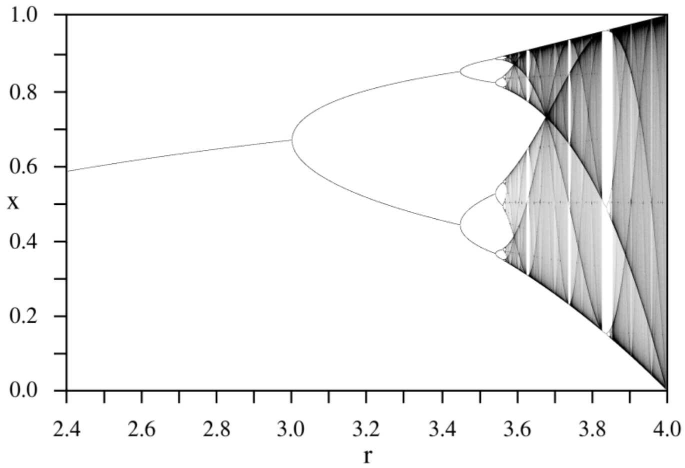
The previous paragraphs show that complex systems exert a great deal of stability over time and follow the same attractor; it was mentioned that an attractor state can resist perturbations. However, there are cases in which minor increases in variables can lead to large changes in the system. When a variable exerts a minute change over increments of time, there comes a point when the summed change of all these increments tips over the attractor to a different state (Urry, 2005). Such tipping points are referred to as ***(x) bifurcation points*** (Byrne,1998). An example might help here, see figure 2.52.

Figure 2.5.2: A plot of formula (1) t_0= 0,25 and r= 3,2 A plot of formula (1) t_0= 0,25 and r= 3,55



So change in complex systems occurs by small changes in its conditions. These small changes can eventually have a major influence on the behavior of the system. The critical values needed to tip a complex system are referred to as **(xi) Feigenbaum constants**, named after the scientist Mitchell Feigenbam (Mackenzie, 2005). The constants refer to the distance between bifurcation points in complex systems; the Feigenbaum constant is the limiting ratio of the distance between subsequent bifurcation points[3]. Figure 2.5.3 shows a bifurcation diagram for a logistic map, such as is the function introduced earlier.

Figure 2.5.3 : Bifurcation diagram (Springerimages, 2011)



As the r value increases a complex system moves from stability to oscillation between 2, 4, 6, etc. values and eventually ends up in a state of chaos at which the system does not behave according to any pattern. In Figure 2.5.2 it can be seen how, in correspondence to the bifurcation diagram, function (1) moves from an oscillation between 2 to an oscillation between 4 points. This illustrates the sensitivity to initial conditions which was referred to earlier. A small change in the initial reproduction rate leads to a whole different plot of the function (1). In other words the small change leads to the function settling down in a different attractor. The attractor in this case being the oscillation between 2 or 4 points.

The fore-last important aspect of complexity is that they are ***(xii) ubiquitous.*** Urry (2005) states that complexity theory could break down the barriers between the natural and social sciences, the reason for this is that complexity is *ubiquitous* (Mitchel, 2009). It is omnipresent in the sense that what is true of natural systems is true for social systems, the latter might however be harder to study. The idea is that complex systems all work in similar ways, it is not that they are the same. Byrne (1999) argues that this is true for ecological systems and cities; they are not the same, but operate in similar ways.

It is important here to emphasize that the complexity of physical systems is assumed to be less than that of respectively biological- and social systems (Mitchel, 2009A). Latour (2010) argues that complexity theorists no longer make any distinction between the natural and the social realm. They approach everything as being a similar system; from ants to scientific paradigms or economic markets. There is an overarching advantage in this since when everything is a kind of system there is no longer a clear divide between the natural and social sciences. For the first time widely different data might look as familiar to physicists and to sociologists. The next chapter (2.6) will discuss this further.

[3] The Feigenbaum constant is expressed mathematically as δ = 4.669201609102990671853203(Wolfram, 2001)

Related to the aspect of *ubiquity* is ***(xiii) self-similarity.*** While the concept of *ubiquity* explains that complex systems exist in a wide variety and in differing setting, *self-similarity* refers to the fact that complex systems often look the same at different scales. An well put example is given by Mitchel (2009A): “If you look at a small section of the coastline it does not have exactly the same shape as the entire coastline but is visually similar in many ways. “ This similarity across scales is often associated with fractals. Because patterns repeat themselves on many different scales such systems are sometimes even called scale-free systems. Such scale-free systems abide by regularities called power law distributions and are resilient to perturbations. Scale free systems have been observed in the internet, highway systems, but also in bacteria (Barabasi, 2002). In chapter 2.7 the notion of self-similarity will be discussed further.

The past three chapters (2.3, 2.4 and 2.5) have introduced the reader to complexity theory and its origins. Based upon these three chapters, the third sub research question can be answered. *“What is complexity theory, what is its genealogy and what concepts are part of this theory?”* Complexity theory consists of a set of theories that try to conceptualize and represent the workings of complex systems. Complex systems are phenomena that have large amounts of interacting parts and are marked by non-linear behavior. The many interactions within a complex system give rise to a high degree of unpredictability. Complexity theory stems from the natural sciences and has roots in systems theory. As a result of technical innovations in the second part of the 20th century it became possible to study complex systems. From this point in time, complexity theory developed rapidly and spread into different scientific disciplines. There is no consensus on the jargon of complexity theory but several central concepts have been introduced and be reviewed in Appendix A.

In the next chapter biological complexity is explored. The chapters sows biological complexity comes closer to the complex nature of social systems than the purely physical form of the complexity. As argued in the introduction, biological systems are more complex than physical systems and thus biology is a more logical starting point for a discussion of complexity in social phenomena and human geography.

2.6 Biological complexity theory

The previous chapter introduced overarching concepts of complexity theory to provide a basic understanding of what complexity is. As argued the complexity of social systems differs from complexity of physical systems. This chapter provides more insight into the nature of biological complexity, which is used as the backbone for the rest of this thesis.

2.6.1 Degrees of complexity

One could argue that social systems are not very different from natural systems because of human agency. This issue has been debated by Strathern and Baldwin (2006) who illustrate that our inability to predict social complex systems in our everyday decisions diminishes any differences between the natural and social world. Geyer and Rihiani (2010) contest this and argue that human consciousness, agency and our ability to change our environment make social complexity different from physical complexity. For example, while natural gases cannot make choices about their behavior animals do have this ability. Moreover, by evolution the behavior of organisms changes in order to improve their competitiveness and increase the odds of their survival. Subsequently, while all gasses are prone to the same set of rules every biological habitat has unique characteristics. In contrast to natural gasses, organisms have the ability to change their behavior in accordance to their environment. Consequentially, biological complex systems are commonly referred to as complex adaptive systems. Here the word "adaptive" could be taken to refer to the ability of organisms to act purposefully.

2.6.2 Concepts of biologic complexity theory

The first biologic complexity concept is ***(i) emergence***, this concept is related to the concept of *non-compressibility* introduced in the previous chapter. Capra (2005) argues that biologic, living systems continually recreate themselves by interaction of their parts. Emergence in this context is the spontaneous occurrence of order by this interaction. Emergent properties are the phenomena which are the result of interaction between the parts of the system; the things that are lost when one would deconstruct the system. Because of the non-linearity existent in complex systems, *emergence* is hard to predict (Thrift, 1999).

A second concept relates rather directly to the work of Darwin and is about the evolution of complex systems. Complex biological systems have the tendency to develop themselves in the direction of ***(ii) good enough strategies***. Evolution does not lead to the optimal solution; there is no endpoint to the process. Instead, evolution results in several strategies that are good enough for an organism to survive (Geyer and Rihani, 2010). If evolution did have an optimal strategy then there would have evolved only one organism, clearly this is not the case.Another concept taken from evolution is that of ***(iii) frozen accidents.*** In evolution changes made in the past of a species become an integral part of it from that point on. Geyer and Rihani (2010) offer the example of the carbon based nature of organisms. Once life had developed in this direction, all following organisms followed this path. Frozen accidents thus lead to historically stable properties or regularities which become impossible to change once they have been adopted.

The fourth concept unique to biological complex systems is that of ***(iv) redundancy***. Redundancy of biological complex systems for example occurs in the DNA. Because of the vital role DNA plays in the procreation of all organism it is believed that it evolved a redundant structure. This means if one of the pair of genes would fail, the copy of that gene would still be able to provide the organism with the information needed to grow, for example, arms. *Redundancy* in biologic systems is thus a failsafe mechanism to ensure the organisms' survival (Mitchel, 2009). Another example could be the fact that human beings have two kidneys and can live perfectly fine with just one. Related to the concept of *redundancy* is that of ***(v) robustness.*** *Robustness* also provides a kind of failsafe mechanisms to organisms, but works in a different way. Instead of having copies it has been proven that in the case of brain damage healthy parts of the brain have the ability to assume the function that the damaged area used to play. This means that biologic complex systems have the ability to resist damage or system failure by having other parts step in and provide the same function (Mitchel, 2009). Barabasi (2002) supports this statement, arguing that ecosystems are able to retain their basic functions even under large internal reproduction error rates.

While complex adaptive systems have built in mechanisms which allow them to resist changes this does not mean they are unsusceptible to every perturbation. Because of the nature of such systems some disturbances might cause a total collapse. Suppose that a very important part of a system is affected, *robustness* or *redundancy* might then allow for other parts of the systems to take on the load of the succumbed part. The stress on these remaining parts now increases, making it more likely for those parts to fail as well. If this happens it could cause a system-wide overload as more and more parts of the system fail causing a domino effect. This effect can be referred to as ***(vi) cascading system failure*** (Mitchel, 2009A). Barabasi (2002) states that this has been observed in electricity networks, the internet, ecosystems and the economy, concluding that all complex systems have their Achilles heel.

The seventh biological complexity concept that introduced is that of the ***(vii) fitness landscape.*** This is the biological equivalent of the phase space introduced in the previous section. The fitness landscape relates to the idea of *good enough strategies*. Because there are multiple strategies that are suited for a specific environment, there are multiple successful organisms. All these organisms represent peaks in the fitness landscape in the sense that they are adapted to their own specific niche (Byrne, 1998). These peaks in the landscape can be considered the equivalent of the attractor introduced earlier as they form the current trajectory of the system of evolution. Examples of this are the long neck of the giraffe that makes it very suited for eating leafs from tall trees and the speed of the cheetah that makes it able to hunt antelopes. These widely differing strategies are both successful in the same fitness landscape. Barabasi (2002) suggests that the *fitness landscape* itself is the biologic exponent of *phase space* introduced in chapter 2.5.

However, the *fitness landscape* itself is also subject to change over time. One can imagine that in an evolutionary setting the trees would evolve to become even taller to prevent the giraffe from getting to their leaves. There exists an interaction between the environment and the system which drives innovations in both. Furthermore, one could argue that competition between different species also drives this kind of evolutionary arms race. For instance, the relation between herbivores and omnivores is one of ongoing competition as both try to outperform the other. In the literature this phenomena is referred to as ***(viii)* co-evolution.** Co-evolution is not always predatory of nature but can also occur as cooperation between species (Kallis & Norgaard, 2009).

The current chapter argued that biological complexity is different and usually more complex than complexity in physical systems. This makes it possible to answer the fourth subquestion: *"What are the unique features of biological complexity theory?"* The biological conceptualization of complexity theory differs from "mainstream" complexity by highlighting the adaptive nature of complex systems. This adaptation means that parts of the system have the ability to change their role or strategy within the system. This could be seen as the influence of evolutionary dynamics on complexity theory. Organisms in complex systems have the ability to adapt to their circumstances. This aspect contributes to the unpredictability of such systems. In Appendix A, all concepts of biological complexity theory introduced in this chapter are listed for reference.In the next chapter the notions of complexity that have been introduced in chapter 2.5 and 2.6 will be related to the literature in the field of human geography.

2.7 Complexity and human geography

"I invoke the first law of geography: everything is related to everything else, but near things are more related than distant things."
- Waldo Tobler
(Tobler, 1970)

The previous chapters (2.4, 2.5, 2.6) presented the gist of complexity theory. Many concepts were introduced to help the reader to achieve a firm understanding of complex systems and how they can be conceptualized. Chapter 2.6 argued that biological complexity theory offers the most tangents with human geography and should thus be given preference over other strands of complexity theory. The current chapter explores notions of complexity theory in relation to human geographical literature; in addition, it explicitly states some of the tangents that the previous chapters hinted at.

To start the discussion of complexity in human geography consider the quote above. After reading the previous chapters, one should immediately see the similarity between the quote and earlier definitions of complexity. What is interesting about the quote is that it was written before the resurgence in systems science (see chapter 2.2). Furthermore, the idea that everything is related to everything is referred to as "the first law of geography"; this underpins the idea that complexity theory lies at the heart of geography. In dealing with spatial phenomena, geographers have essentially dealt with complexity since the inception of the field.

Chapter 2.4 argued that complex systems are inherently hard to predict, especially when looking into the distant future. Andersson (2008) argues that when dealing with urban systems human control declines with every increasing scale of time and space studied. This means that our ability to predict spatial systems is very limited in the long run and is marked by a high degree of uncertainty. This view of systems is arguably related to the one advocated in the literature on complexity theory as shown in the previous chapters (2.3 – 2.6). The relation between the disciplines of human geography and complexity theory is however not as one-sided as one might believe. Many of the main themes of complexity science are actually geographical by definition (Torrens, 2010). For instance, the behavior of natural gases has a spatial aspect and in Darwin's theory of evolution geography plays an important role (See introduction).

Sullivan (2003) argues that many concepts from complexity theory are indeed useful in combination with longstanding ideas in geography. In human geography, complexity has been studied in relation to air travel (Brockman et al, 2006) and creative industries (Comunian, 2010). Brockman et al (2006) reveal that there are common underlying principles that govern the growth of international transport systems. In addition, they show that these systems follow a power-law distribution and are resilient to random perturbations. However, when nodes were removed according to their rank-size the systems soon disintegrated into several smaller systems. The gist of the article lies in that it shows where the vulnerabilities of these systems are. Comunian (2010) uses complexity theory to conceptualize the dynamics of the creative sector in urban economies. He concludes that complexity is of added value and calls for more complexity theory inspired research. However, he adds that choosing the right research methodology is problem for studies using complexity theory. This difficulty will be discussed further in chapter 2.9.

Complexity theory is also used within evolutionary economic geography. Within this discipline, regional economic development is considered a dynamic process. Evolutionary economic geographers use complexity theoretic concepts such as *co-evolution*, *path-dependency* and *the fitness landscape* in order to understand the formation of clusters (Martin en Sunley, 2006) and processes of innovation (Pajunen en Maunla, 2008; Frenken, 2006). Pajunen and Maunla (2008) suggest that the main strength of complexity inspired research lies in the fact that it sheds light on dynamic processes. However, they (ibid.) also suggest that such complexity inspired research itself is very complicated. More specifically, Pajunen and Maunla (2008) argue that it is very hard to empirically prove the existence of *co-evolution*.

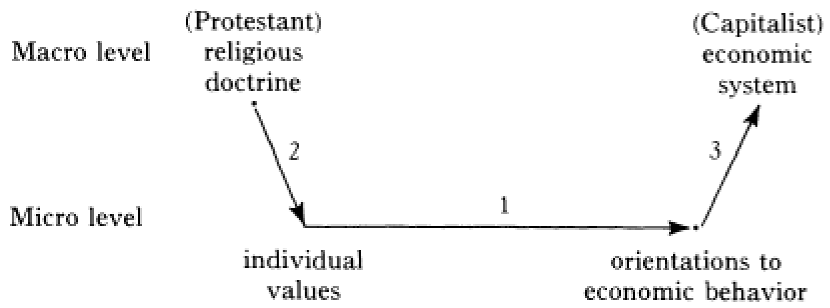
It is important to stress again that this transfer of complexity theory into the social sciences is still in its infancy (Chettiparamb, 2006). Consequently, any account of it will be subject to heavy debate. Capra (2002) argues that living systems find themselves near the edge of chaos which is also typical for the behavior of gases. In his book, the point is made that being *far-from-equilibrium* allows organisms to adapt to changes in their environment more efficiently. The fact that complexity is found to be central to all living systems arguably makes the step from biology to the social sciences an small one. Urry (2005) suggests that a complexity turn in the social sciences is already taking place. It is important to understand here that complexity cannot be confined to either social or natural processes; it occurs equally in both, although in different ways.

For human geography, complexity theory can form a link between the physical environment and the social processes that take place there (Harrison et al, 2006). The relation between the social and the natural is said to be central to human geography. This dialectic is also central to complexity theory (Ratter, 2006). Since the relation between the natural and social world is central to much of geography, complexity theory can play an important part in the future development of the spatial sciences (Torrens, 2010). Much has been said about the importance of (biologic) complexity theory to human geography and vice versa without providing explicit examples of how the two fields can relate. The purpose of paragraphs 2.7.1 – 2.7.4 is to offer such examples. Paragraphs 2.7.1, 2.7.2 and 2.7.3 compare complexity with existing theories within human geography. Paragraph 2.7.4 relates concepts from complexity theory with concepts from transport geography.

2.7.1 Structuration theory complexity

In an article about social theory and structuration, Coleman (1986) sets out what he calls “the micro-to-macro problem”. This relates to the process through which individual behaviors become collective patterns. Coleman argues that to explain macro phenomena social scientists move down to the micro level to elucidate changes at the individual level and then try to move back up to the macro level (see figure 2.7.1). The example used by Coleman is taken from Weber (1905) and is about the influence of the religious doctrine on the economic system. Weber argues that the Protestant doctrine had an influence on the individual values of people which in turn influenced their economic behavior. Coleman argues that Weber fails to illustrate how these behaviors combine to form the capitalistic economic system. So a major problem so far has been the link from micro to macro; scientists are unable to explain how individual behavior leads to changes in society as a whole. Complexity theory would argue that this link could be explained by *emergence*. This means that individuals interact with one another and that this process leads to an attractor state or the observed macro behavior (Mitchel, 2009A). The number 3 link in figure 2.7.1 can thus be explained through the process of *emergence*. Furthermore, the hardened complexity scientist would argue that since these processes are emergent, it makes no sense to try to understand them on the micro level.

Figure 2.7.1: Coleman’s diagram (Coleman, 1986)



2.7.2 Contextuality, relational space and Lefebvre's trialectics

As suggested in earlier paragraphs of this chapter, the idea that behavior is partly dependent on the local environment is important to geography. This idea is commonly referred to in geography as contextuality and stands for idea that all knowledge is situated and that the individual and context are entangled: there is a rejection of dualism of structure. Ratter (2010) argues that both contemporary geography and complexity are highly context sensitive. For example, geography values locality and historical contingency and complexity underlines the importance of frozen accidents and path dependency. Following this, one could argue that the methodologies employed in complexity theory research are also highly suited for application in human geographic research. These ideas are supported by Schwanen and Kwam (2009). They argue that recent developments in complexity theory have made it possible for the complexities of urban and social systems and people's everyday life to be taken into account.

Inherent to the contextuality of knowledge is the rejection of dualism, which can also be found in complexity theory. Complex systems are composed not of micro- and macro-variables but include a wide range of different variables. More importantly, complexity theory makes no distinction between structure and agent; both have equal agency. Subsequently, complexity theory is context sensitive in the sense that it recognizes that systems can have different forms in different circumstances. Also the idea that systems are *dissipative* relates to contextuality. The advantage of complexity theory for contemporary human geography might lie in the fact that it argues that even though complex systems can be different, they also share some characteristics. This is an important observation since it allows for the comparison of different complex systems.

In addition, complexity theory presents a move away from Euclidian conceptions of space and suggests that phenomena should be understood through the interaction of their separate parts. This is an idea that seems to resonate within the human geographic literature on absolute, relative and relational space ('O Sullivan. 2006). In terms of the concepts introduced in this thesis, one can argue that the *attractor* and the *fitness landscape* illustrate the relational nature of complexity theory. The former is a graphic portrayal of the relation between several variables within *phase space*, which constitutes all the possible states of a system. The latter shows how evolutionary fitness is subject to interactions through co-evolution and thus occurs in an ever-changing relational landscape.

A further similarity is expressed explicitly by Byrne (1999). Byrne argues that that large parts of Lefebvre's work could have been drawn straight from the domain of complexity theory. This statement is backed by Portugali et al (2006), who argues that Lefebvre's ideas on the production of space are essentially equal to complexity theory's notion of *dissipation* and *inter-connectivity*. Both approaches argue that space is not an objective entity but an outcome of the historically specific socio-spatial relations. In other words, complex systems need to be reproduced in order to maintain themselves in the long run. Lefebvre explains this process through his trialectics, whereas complexity theory argues that this an inherent aspect of a complex system. Furthermore, the idea that systems are ever-changing and transforming seems to be close to the concept of *far-from-equilibrium* in complexity theory (Portugali et al, 2006).

There are also differences between Lefebvre's work and complexity theory. The biggest contrast between the two approaches lies in the fact that complexity theory does not offer an explanation of meaning and more specifically place. In Lefebvre, place is argued to be produced through the interaction of spatial practices, representations of space and spaces of representation (Leary, 2009). Through these interactions meaning is attributed to places. Meaning is however not stable and subject to change over time. In complexity theory there is no mention of meaning in relation to the interconnectivity of the parts of a system.

2.7.3 Actor-network theory

To follow up on the previous paragraphs, complexity theory does not deal with meaning explicitly. Within the social sciences, actor-network theory (ANT) is a train of thought that arguably deals with meaning through a relational view of space (Murdoch, 2006). When relating ANT to complexity theory one stumbles upon both explicit and implicit similarities between the two views. Doing justice to the extensive writings on ANT requires many pages and exceeds the purpose of the present thesis.[4] For the current purpose, it is enough to list some important aspects of the approach.

Murdoch (1998) describes that ANT examines how actors are incorporated into chains and networks, indicating how discrete spaces become relationally linked, and showing how relations constitute and compose differing phenomena. Another definition (Bosco, 2005) describes Actor-network theory as an attempt to understand the complex and elusive nature of society. Initially, ANT concerned itself with the study of the construction of scientific knowledge. Over the past few decades however, the approach has been used to study a wide variety of subjects. ANT is about tracing the connections that exist among a variety of actors and understanding the world through the interactions between these entities. Moreover, ANT attributes agency to both human as non-human actors, referring to these as actants. ANT focuses on how phenomena are performed, or in other words, acted out. ANT is more than a research methodology and much has been written on the unfortunate naming of the theory.[5] Latour (2006) suggests that a more appropriate name for the theory might have been "actant-rhyzome ontology". This arguably refers to the philosophical implications of ANT; it is theory of being and existence.

Thrift (1999) argues that many metaphors from complexity theory have spilled over to actor-network theory. It is no surprise then that the two theories have things in common. However, before listing these similarities it is important to point at the major differences between the two approaches. A first difference is that although ANT does not explicitly denounce quantitative methods one can argue that it is more inclined towards qualitative methods. Latour (2005, p 41) for instance, mentions that ethnography allows for members of society to define themselves and this is deemed to be "crucial" in doing research. Contrarily, chapter 2.4 showed that complexity theory allows leeway for both quantitative as qualitative methods.

A second contrast lies on a philosophical level. Smith and Jenks (2006) argue that ANT is not at all well equipped to deal with notions of complexity. They state that ANT does not do justice to the intricate nature of complexity and criticize ANT's post-modernistic roots. As was shown in chapter 2.4 complexity theory adheres to the ontology of critical realism. Although the foundations of complexity theory and ANT are heavily debated, regardless of one's allegiance, ANT arguably allows more room for relativism and constructionism than complexity theory does. Next to these two major differences, smaller differences could probably be found when considering complexity theory and ANT in more detail. However, since the purpose of this chapter is to "place" complexity in human geographic theory, more attention will be given to the similarities.

The first similarity is that both ANT and complexity study complex systems. As stated in the above paragraphs, understanding complex systems is one of the aims of actor-network theory and in complexity theory the study of complex systems is the core activity as well. As an example of this one could point at the studies of the World Wide Web that both fields have engaged in.[6] Also, both ANT and complexity theory fundamentally stress the importance of *interaction*. In ANT the importance is

[4] For more information on Actor-network theory see, amongst others (Bosco, 2006), Latour (2005) and Law & Hassard (1999)

[5] For more information on the issue of naming ANT see: Law & Hassard(1999) and Latour (2005)

[6] For ANT, see Danowski and Park (2009), for complexity theory, see Tredinnick (2009)

stressed of multiple actors combining agency and in complexity non-linear effects are considered. In addition both complexity theory and ANT stress the importance of uncertainty present in systems. Latour (2005) makes this very explicit in his book, mentioning it in the title of several chapters (p. 27, p. 43, p. 63, p. 87, p. 121).

Secondly, both ANT and complexity theory can be said to have abandoned traditional views of aggregation and reductionism. Neither theory believes that every phenomenon can be understood by looking at the macro-scale. Instead, complexity theory was shown (chapter 2.7) to adhere to *emergence*. In turn, ANT believes that connections or ties are more important than aggregates because it is through these ties that behavior and meaning are performed. Both strands argue that by looking at the aggregate macro-scale scientists miss many of the intricacies of the phenomenon under study.

Another striking resemblance might be found in the roots of ANT. In his book "Reassembling the social" Latour (2005 p.14) states that Tarde is one of the inspirational sources of ANT. Latour quotes Tarde (1895) saying:

"But this means that everything is a society and that all things are societies. (..) And it is quite remarkable that science, by a logical sequence of its earlier movements, tends to strangely generalize the notion of society. It speaks of cellular societies, why not of atomic societies? Not to mention societies of stars, solar systems. All of the sciences seem fated to become branches of sociology".

The peculiar thing about the quote is that Tarde seems to be suggesting that the word "society" refers to phenomena that feature a high level of *interconnectivity*. Following this, he argues that sociology is actually present at the micro-atomic to the interstellar level and thus should be of major influence there. If Latour's interpretation of Tarde is correct than it shows a strong resemblance to the notion of *ubiquity* voiced by complexity theory. This point is made more explicit by Latour (ibid. p. 65) when he argues that "social" equals association. Association could be compared to *interconnectivity* in complexity theory.

A fourth similarity is that ANT views systems as entities that have to be performed. Latour argues that as soon as humans would stop making and remaking groups, they would stop to exist. This seems to be similar to the idea of complexity theory that a system which is in equilibrium is essentially dead. Both strands seem to adhere to the idea that systems need to be reproduced in order to maintain their viability. This becomes clearer in the following quote taken from Latour (2005, p 70):

"If sociologists had the privilege to watch more carefully baboons repairing their constantly decaying social structure, they would have witnessed what incredible cost has been paid when the job is to maintain, for instance, social dominance with no thing at all, just social skills"

Here it is argued that if social structure is not reproduced it will stop to exist. Furthermore it is stated that an incredible cost is paid for the maintenance of these structures. This further specification looks very much like the contents of the second law of thermodynamics (see chapter 2.4). The law states that complex systems are *dissipative*. This means that in these systems disorder is bound to increase over time. To combat this, energy has to be put back into the system very much like the baboons have to invest in their social order.

Fifthly, ANT mentions that systems are performative. In other words, connections between parts of the system have to be maintained and renewed constantly. During these interactions however, sometimes the link between parts changes somewhat. So while systems seem to be stable over time, their meaning is constantly being altered and restructured. This is similar to the notion of the attractor in complexity theory which illustrates how a complex system follows a line of variables but never touches upon the same set twice.

From this follows a sixth similarity: both ANT and complexity theory seem to have abandoned a one hundred percent linear view of the world. In complexity theory this is made very explicit through the notion of non-linear interactions and through the ideas of *robustness* and *redundancy* causality is less predictable. In ANT this also seems to be followed as Latour (2005) argues that systems are reconstructed endlessly and that the same interaction will not over time lead to the same outcome. ANT suggests that ideas or meanings can be mediated through interaction. Furthermore both ANT and complexity argue that links themselves are subject to change over time.

Seventhly, both ANT and Complexity theory try to develop a vocabulary that describes features that are present in reality, but abstain from meta-language. Meta-language can be described as using the same concept to describe different situations. In other words, meta-language is an attempt to fit phenomena within an existing vocabulary instead of considering them ad-hoc. Both ANT and complexity theory argue that similar effects such as "translation" or "*emergence*" take differing forms according to the situation and these differences are very important to understand the subject under study.

Eighthly, both ANT and complexity theory (see chapter 2.1 and 2.4) argue that many fields of science might be at play within the same phenomenon. It is not that one phenomenon has several aspects such as an economic, physical and social one. Instead all these aspects interact between each other. This is perhaps best illustrated by the following quote from Latour (ibid., p 78):

> “One cannot call oneself a social scientist and pursue only some links [social links] and stop as soon as there is some physical relation interspersed in between the others”

Both ANT and complexity theory advocate an integration of multiple fields to more adequately understand intricate phenomena.

The ninth similarity is that both ANT and complexity theory see the structure of complex systems as inherently unstable. In ANT this means that sudden breakdowns can cause silent intermediaries to become full blown mediators (ibid., p 57) . This means that parts of a system that a first did not influence its operations can suddenly become of crucial importance. This is also present in complexity theory in the idea of *cascading failure*. In such a failure the breakdown of one part of the system suddenly makes another part of it crucial to its operations. Then, depending on the strength of that part the whole system stands or fails.

Related is the idea that some parts of a system can be more important than others. ANT here suggests a “topological focus”, stating that not everything is connected to everything. Instead, different actants are related to one another to different degrees (ibid., 2005). In complexity theory this idea is present for example in the idea of power-laws. These laws show that in scale-free systems there always exist parts which are of more importance than others. Both fields thus adhere to a heterogenic view of the parts or nodes.

Furthermore, both in complexity theory as in ANT non-human objects are supposed to be of importance. In complexity theory this is illustrated through the concepts of *co-evolution* and the *fitness landscape* which show how many factors influence the success of organisms in a competitive environment. In ANT it is stressed that objects play an important role in sustaining systems because they can change the meaning of a performed action. For example, waving a flag is totally different than waving a gun.

To conclude the comparison, one can say that complexity theory and actor-network theory share many characteristics. Arguably, complexity theory is better equipped to deal with quantitative research and ANT has more tools for qualitative research. Both however study the same phenomenon and have similar ideas about the workings of complex systems. In relation to the subject of this thesis both approaches seem to be of great importance in improving our understanding of mobilities. Complexity theory seems to have some overlap with the already commonly used framework of ANT. However, the quantitative edge of complexity theory might serve to persuade policymakers of adapting the public experiments introduced in chapter 2.1. This chapter has shown that complexity theory can be made to work with existing human geographic theories. In seeing this overlap and considering the quantitative strength of complexity theory, human geographers could certainly benefit from it.

2.7.4 Transport geographic constructs and complexity theory

The first concept of complexity that can be used in transport geography is that of *path dependence.* The current modal split of transport modes could be seen as *path dependent*; the breakthrough of technologies like the automobile and the airplane are suitable examples of this. Once these modes were introduced, many countries adapted their infrastructure to accommodate them. The technological innovations that led to these new modes can be seen as *frozen accidents* that resulted in a certain modal split. This is because the transport modes require a great deal of infrastructure and support systems and are thus resilient to change. Switching to new mode of transport requires a lot of work and will only occur if the new mode has a higher peak in the fitness landscape than the existing transport modes.

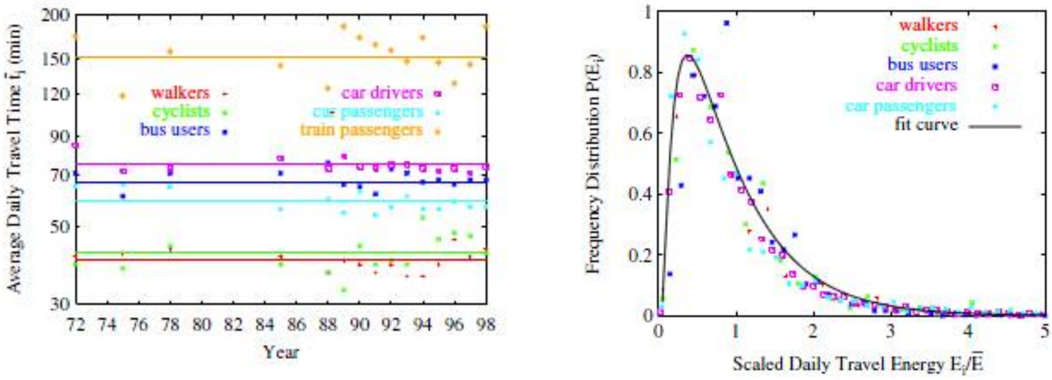
The persistence of patterns of mobility could be explained in terms of complexity in the sense that these patterns follow an *attractor*: While the patterns of mobility do show fluctuations over time they are seemingly resistant to policy interventions. From a complexity theory perspective, this could be explained in the sense that the attractor will return to its initial pattern even after a perturbation. Other changes in the attractor do have the ability of changing the pattern of the attractor when the sum of incremental changes reaches a critical point. Translating this to a geographic perspective one could see the patterns of mobility as resistant or *robust* to some perturbations. For instance, closing down one highway does not collapse the entire street network; smaller roads provide an alternative to the closed highway. This point of view sheds light on why policy interventions have so far been ineffective. Other developments such as changes in the effectiveness of transport modes or breakthroughs in ICT might have far going implications for the use of transport. For instance, the usage of the mobile phone and laptop might in time lead to a *bifurcation point* and a change in actual mobility patterns.

Furthermore, the way that people use transport mode(s) to get from A to B could be seen as *Good enough strategies*; habits that work adequately but might not be the most ideal solutions. In effect, people in need of transport could be seen as looking at a *fitness landscape* of available transport modes. For instance, one is able to take the train, bus or car to reach the same destination. He or she makes an assertion of the relative fitness of the transport modes available to her or him and pick the mode with the greatest fitness. This is not unlike utility as coined in economics, the difference lies in the position the *fitness landscape* takes in the wider theory of biologic complexity. For instance, biologic complexity does not assume complete rationality or homogenic preferences.

The idea of *fitness landscape* is related to the concept of *co-evolution*. The strategies that people employ in using the mode that is most suited for their particular situation are arguably culturally dependent. For example, within a group of students information about the fastest, most comfortable and dependable way of transport is exchanged. In addition, the students share information on how to make the most of their travel time. The strategies of students are thus changing in way described by Lamarckian evolution. Lamarck argued that physical changes in an organisms form during its lifetime could be inherited by its spouse (Mitchel, 2009A). As opposed to this Lamarckian evolution of strategies, the modes themselves evolve in more Darwinian way; if a certain type of car is more successful on the market, producers will adapt newer designs in way that reflects the merits of the older design. If conceptualized in this way, it could said that the *fitness landscape* of transport modes co-evolves through an interplay of Darwinian and Lamarckian evolution.

In their study, Kolbl and Helbing (2006) provide an example of the interplay between human corporality, bodily constraints and transport mode choice. They show that the bodily energy consumption of humans spent on transport has remained stable over period of 26 years. The left graph in figure 2.7.7 illustrates how the average daily travel time has remained stable. The right hand graph uses the same data to illustrate that the more energy is consumed during a journey, the less journeys are made. The implication of this is next a stable travel time budget, but a stable bodily energy budget which governs human travel behavior. Put differently it is the energy consumption of the human body per transport mode that determines the time spent on using it and consequently the distance traveled while on it.

Figure 2.7.2: Travel time stability and travel energy stability (Kolbl and Helbing, 2006)



The existence of budgets for travel time, money and energy is debated within transport geography (Mokhatarian and Chen, 2004). When linked to complexity theory, one can argue in favor of these budgets by regarding them as *attractors*. The budgets show stability over time but fluctuate from location to location (ibid.). In the sense of complexity theory, this could be explained by the concept of the *attractor*. The budgets could behave similar to an *attractor* and fluctuate over time but still remain on the same long term pattern. So even though significant changes in travel behavior are found, this does not mean that the system itself has changed its course. The *attractor* state is still the same and will return to similar points over time. To influence travel demand, one has to tip over the attractor into a different state so that changes remain over time. The point here is that significant changes in travel behavior might be no accurate indicator of a long term change in modal split or travel behavior in general.

Furthermore, considering *attractors* allows for the identification of *bifurcation points* which indicate a dramatic change in travel behavior. The author believes such dramatic change might be possible under the influence of ICT's. For instance, the use of a laptop while on the move can increase the utility of travel (Buscher and Urry, 2010). This increased utility could potentially result in larger travel time budgets as time spent on travel can simultaneously be used to work, stretching the budget.

In human geography, a common problem in research is the issue of scale (Montello, 2001). Usually it comes down to making an educated decision what to include in a research and what to leave out. For instance, in the study of an urban transport system, what exactly justifies the decision to measure characteristics at the scale of the neighborhood, street, family or individual? All of these entities could be argued to have an influence on travel behavior. In addition, is hard to justify any delineation of space because it violates the first law of geography which was introduced at the beginning of this chapter. It can be argued that complexity theory has the means to overcome these dilemmas:

Firstly, in some cases measurements made on a certain scale can also be valid at other scales because of the *self-similarity* usually present complex systems; in accordance with power laws, what goes for one scale might also be valid for another. Another solution comes from biological complexity theory, from which we can take the idea that systems have a hierarchical structure. For instance, organisms are made from organs, which are made from tissues, which are made from cells. With such an organization, the amount of information required to understand the system is dramatically lower compared to if every cell had to be positioned individually inside the body (Sullivan, 2004). While the second idea might not be completely new to geography, it does provide additional support for arguments in favor of hierarchical structures.

Secondly, the concept of *emergence* provides an explanation for the existence of macro-phenomena. Following this line of argumentation, it can be said that the micro-scale holds the key to understanding geographical phenomena. If we were able to simulate the behavior of individual humans, it could be that neighborhoods and cities would automatically be reproduced by a simulation of such a system. This notion will be returned to in chapter 2.9. It has also been proven that some spatial phenomena also adhere to so-called power laws, which means that they correspond to a certain scale-free distribution.

This chapter has looked into how complexity theory can contribute to transport geography in general. It was shown how concepts from biologic complexity theory can adequately be employed in geographic thinking. The fifth sub question can now be answered: "*To what extent do concepts from (biological) complexity relate to existing literature in human geography?*" It was shown that many idea's from complexity theory resonate within the existing literature in human geography. Some tangents are: the relational nature of both, the idea that some phenomena cannot be understood through reductionism. Complexity theory seems to be suited for dealing with longstanding problems such as the micro-macro link. Furthermore, it could be used to extend existing theories such as ANT and contribute to our understanding of path dependent phenomena such as modal-splits. Finally, complexity theory also fits within the notions of relational space and contextuality, which have been developed recently within human geography.

In relation to the new mobilities paradigm, biologic complexity offers insights that can explain the existence of differing strategies such as differing mode choice. To summarize up, it could be stated that complexity theory and transport geography are suitable candidates for scientific cross-fertilization. In the next chapter, the methodologies associated with complexity will be discussed.

2.8 Complex methodologies

Previous chapters introduced the reader to different strands of complexity theory and the possibilities they offer for transport geographic research. However, little has been said about the research methodologies that could be employed in studying complex adaptive systems within human geography. This chapter introduces the most prominent methods and provides the basis for the empirical research part of this thesis.

2.8.1 Ethnography

Chapter 2.3 and 2.7 show that ethnographic research methods are able to capture complexity. These qualitative accounts allow for the intensive study of one or several subjects and usually try to uncover how certain behavior is performed. Especially when positioned within the framework of Actor-network theory, these accounts try to uncover the meaning behind performed actions and try to uncover how actants play a role in different systems. Ethnographic approaches are valuable and have proven their use in relation to the new mobilities paradigm. Most *mobile methods* are qualitative and since the use of such qualitative methods is already well established, these methods are not discussed here (see chapter 2.1).

2.8.2 Mathematical modeling

Another way of dealing with complex systems empirically is by developing dynamic mathematical models. Wilson (2000) provides several examples of how traditional spatial analytic models can be adapted to deal with complexity. Wilson's approach is to convert the traditional models to discrete zone models. This conversion from continuous to discrete zones allows for the modeling of interaction effects, which are central to complexity theory. This method is applied to the classical examples of amongst others Von Thunen (1826), Christaller (1933) and Hotelling (1929).The adapted dynamic models arguably are to be able to capture complex systems more realistically than the traditional models. From this, it follows that the models have more strength and can be applied more widely.

While these dynamic mathematical models do enhance our understanding and perform better than traditional spatial analytic model, they do not suffice for the aim of this thesis. As was concluded in chapter 2.5 and 2.6, biological complexity is more suited for use within human geography. While the dynamic mathematical models do certainly have their value, it can be argued that they do not capture the complexity of human behavior adequately enough. The main reason for this is the inability of such models to portray adaptive behavior. Furthermore, in relation to the new mobilities paradigm, the discrete model equations do not necessarily qualify as *mobile methods* since they only consider multiple interactions but not what happens "on the move". In other words, the models do not fit well within the new mobilities paradigm introduced in chapter 2.1.

2.8.3 Agent based modeling

Macal and North (2010) argue that agent-based modeling (ABM) is a relatively new approach for modeling complex systems composed of interacting autonomous "agents". The purpose of ABM is to study the properties of complex adaptive systems by simulating them on a computer. Axelrod (1997) even makes the claim that ABM's are the principle research methodology for complexity theory in the social sciences. This claim is supported by Crooks (2010) who adds that agent-based models can be considered to be a "natural method" within the social sciences for the simulation of a system composed of real world entities. ABM seems to become increasingly popular as is evident from the increased number of conferences, workshops and publications on the subject (Macal and North, 2010). This growth in the popularity of ABM seems to be running parallel to the growth of the field of complexity theory (Crooks, 2010).

While the field is growing increasingly popular, it should be noted that there is no general consensus on a definition for agent-based modeling (Crooks, 2010). Axelrod (1997) even suggests that the naming of the field itself is subject to scrutiny, with alternative names being “bottom-up modeling” and “artificial social systems”. Indeed, the field of ABM seems to have things in common with complexity theory, in which the exact definitions of the field itself is also being debated. Regardless of these discussions, most scientists seem to agree on the fact that agent-based modeling is a bottom up approach in which agents are simulated in order to study the workings of complex adaptive systems. Applications of the approach span a broad range of fields, ranging from the stock market to the spread of epidemics and even the threat of bio-warfare (Macal & North, 2010). Agent-based models have also been employed to study urban systems (Crooks, 2010).

Macal and North (2010) suggest that a typical agent-based model consists of three elements:
(i) Agents with attributes and behaviors
(ii) Relationships between agents and methods of interaction between them
(iii) An environment in which the agents interact
Both the agents and the environment can be dynamic in an ABM (Crooks, 2010), allowing for an accurate representation of a system in which the actions of the agents can alter their environment. In the sense of complexity theory, ABM’s thus deal with the idea of a changing fitness landscape illustrated in chapter 2.7.

Agents can be used to simulate different entities ranging from animals to humans or even companies. The single most important characteristic of an agent is its capability to act autonomously referring to its ability to act without human intervention when the simulation is started (Macal & North, 2010). Each agent has internal states and behavioral rules. Some states are fixed for the duration of the agent’s life, while others change through interaction between agents or with the external environment (Axtel and Epstein, 1996). By modeling agents individually, the full effect of the diversity that exists among agents in their attributes and behaviors can be observed as it gives rise to the behavior of the system as a whole (Macal and North, 2010).

ABM is a way of doing experiments (Crooks, 2010). However, it should be contrasted with the two standard methods of induction and deduction. In that sense, it can be thought of as a third way of doing science (Axelrod, 1997). Like the method of deduction, ABM starts with a set of explicit assumptions. As opposed to deduction however, it does not try to prove hypothesis. Instead, an ABM generates data that can then be analyzed by means of induction. Unlike more typical induction, the data comes from a computer simulation rather than from a direct measurement of the world (Axelrod, 1997). This could be seen as opposed to other modeling techniques in which the models represent the real world environment. In ABM a new environment -based upon the real world- is created for the simulation.

There are several features that make ABM an attractive method for studying complex phenomena. Firstly, the approach allows for the simulation of individuals which are situated inside an environment. Agents can both be mobile and move around the environment as well as immobile and stationary. Agents in this sense could thus be humans, but also non-humans or objects like parcels of land. A second advantage is that ABM allows for the portrayal of a heterogeneous population similar to that observed in society. As an effect of this, the use an “homo economicus” or PAX[7] is obsolete. Subsequently, Axelrod (1997) argues that ABM’s are the only viable way to study population who are adaptive rather than fully rational. Thirdly, agents are active and exert influence on the simulation. The agents are capable of exchanging information during the simulation and thus shape the outcome through their interactions (Crooks, 2010).

[7]See “On the move” by Tim Cresswell (2006) Chapter 9: The production of mobilities at Schiphol Airport.

Fourthly, ABM's can effectively be used for explanatory models to explore theories and descriptive models which are concerned with making predictions about a system's state (Crooks, 2010). Fifthly, agent-based models allow for the simulation to represent and test theories which cannot easily described by using mathematical models (Crooks, 2010). Since the modeling of complex systems is arguably very complicated, ABM might be more suitable to simulate them. Furthermore, ABM is getting more and more integrated into geographic information systems. This coupling allows for extensive simulations in the graphic environment of GIS-software, making the analysis not only more visually attractive but also potentially more insightful (Crooks, 2010).

This chapter answered the sixth sub research question: *"Which methodologies can be employed in complexity inspired research?"* Three research methods were introduced: Ethnography, dynamic mathematical models and agent-based modeling. All these three methods have the ability to portray complexity to a certain extent. However, it was argued that ABM has the most merits for the aim of the current thesis. Agent-based modeling allows for the accurate portrayal of human behavior and has the ability to uncover the emergent properties amongst them.

In relation to the new mobilities paradigm, agent-based models seem to be able to cope with both the inherent complexity of human behavior and allow for the simulation of dynamic or adaptive behavior. ABM allows for the simulation of what happens while "on the move"; in that sense, it can be considered a mobile method. In Urry's terms (see chapter 2.1), ABM can be seen as a way of doing qualculation and is thus compatible with the new mobilities paradigm. Furthermore, agent-based modeling has been developed in line with complexity theory and is well suited for studying many of the concepts introduced in chapter 2.6 and 2.7. The next chapter contains a discussion of the theoretical part of this thesis. More specifically it links the built up knowledge of complexity theory to the new mobilties paradigm.

2.9 Putting it together: Complex mobility systems?

The previous chapter introduced several research methods that can be used to study complex adaptive systems. In chapter 2.7 several tangents of complexity theory with transport geography were discussed. This chapter builds on chapter 2.6 and 2.7 to show how complexity theory could be used to extend the use of the new mobilities paradigm.

The introduction of this thesis argued that it is hard to study mobility systems because of their dynamic and unpredictable nature. The new mobilities paradigm developed by Urry (2007) emphasizes these difficulties and argues for a mobilities-turn in the social sciences. Moreover Urry (ibid.) calls for both the extension of his theory and the development of *mobile-methods.* Urry and Buscher (2009) suggest that ethnographic research can be used to study the complex nature of mobility systems. Also, these authors (ibid.) are skeptical of quantitative research methods, since these methods do no justice to the complex nature of mobility systems. This skeptical attitude of the mobilities paradigm towards quantitative methods arguably moves it away from spatial analytics and transport geographical research that aims to predict for instance the volume of transport flows or modal splits.

Scientists generally agree that current mobility systems are unsustainable and that something needs to be done in order to change such mobility patterns. However, policy interventions have so far been ineffective (Prillwitz and Barr, 2007; Goodwin, 2009). This suggests that our understanding of mobility systems is not developed enough or that no effective policy tools exist or that science fails to inspire policy or a combination of these three. Arguably, if the efforts of quantitative researchers and qualitative researchers could be combined, this would increase our understanding of mobility and allow for the development of more effective policy tools (see chapter 2.2). If existing models used in transportation research can be adapted to cope with the dynamic nature of mobility system this would move these models closer to the new mobilities paradigm. In addition, such dynamic models could outperform existing models in terms of their predictive power. At the very least, dynamic models or dynamic quantitative methods can be used to illustrate the uncertainties inherent to the prediction of a complex system to policymakers. Buscher et al (2009) suggest that quantitative data that inspires, supports or combines with qualitative judgment could contribute to our understanding of mobilities.

Because complexity theory has inspired both the new mobilities paradigm and the development of dynamic models, it is possible to link the theories of these qualitative and quantitative strands. By explicitly stating this, cooperation between proponents of both strands could be stimulated. In addition, reflecting on complexity theory could inspire the future development of the new mobilities paradigm. For instance, complexity theoretic vocabulary can be used to describe processes in mobility systems. Some concepts, such as *path-dependency,* are already used in the literature on transport geography. However, these concepts are often used out of the context of complexity theory. Because of this, the meaning of such concepts is not fully employed. By strengthening the link with complexity theory, the new mobilities paradigm can draw upon an extensive existing vocabulary that is developed to describe complex systems.

Next to this conceptual value of the new mobilities paradigm, complexity theory also offers research methodologies which suit the new axiom of dynamism. More specifically, agent-based modeling offers a way to cope with the elusive and dynamic nature of complexity. While still not able to perfectly cope with all the aspects of human behavior, ABM does capture parts of it. The idea that recently developed quantitative methods are better capable of dealing with the complex nature of mobilities and human behavior is supported by Schwanen (2006). He argues that computer models and simulations might never be able to fully capture human behavior but can certainly contribute to our understanding. In line with the critical realist ontology it can be argued that using both quantitative and qualitative methods would yield the best results. Both approaches have their merits and shortcomings, but can equally contribute to inspire change in society.

In concluding this chapter it is possible to answer the seventh subquestion: *"To what extent can biological complexity contribute to the applicability of the new mobilities paradigm in society and research?"* The answer to this is threefold. Firstly, on a conceptual level complexity theory offers the new mobilities paradigm a vocabulary to describe the dynamism and interaction inherent in mobility systems. Secondly, complexity theory provides the foundation to inspire cooperation between proponents of quantitative research and qualitative research. Thirdly, research methods associated with complexity theory can be used in mobility research. These methods allow the researcher to quantitatively study complexity in a way that is impossible with traditional approaches. Agent-based modeling is a prominent method that can be used to study complex systems quantitatively. The results of such simulations can be analyzed in accordance with what Urry terms *qualculation.* By combining quantitative methods and qualitative judgement in this way, agent-based models could be used to assess the impact of measures which are inspired by ethnographic research. This thesis argues that both the existing *mobile methods* and quantitative complex methods can contribute to advancing knowledge and inspiring policy formation. By connecting complexity theory and the new mobilities paradigm policy makers could potentially be convinced to engage in public experiments. Hopefully, the combined efforts of scientists and policymakers can steer society away from the dark futures that Urry (2006) sketches. Part 3 of this thesis explores the applicability of agent-based models to transport geographical research. This exploration builds on the knowledge set out in part 2

3. Case study: Transport mode choice of students in Utrecht

3.1 Exploring the application of complexity theory

Section 2 shows how the literature on complexity theory and the new mobilities paradigm can be related. Furthermore, it indicates that insights from complexity theory seem to be applicable to the field of transport geography. The empirical section of this thesis attempts to study a mobility system – as defined in the new mobilities paradigm – by using insights and methods from complexity theory.

The specific topic for this empiric research is transport mode choice. As was illustrated in the introduction of the thesis (see chapter 1), a shift towards more sustainable modes would have a positive impact on the environment and contribute to negating the adverse effects climate change. Furthermore, information on transport mode choice is considered to be of great importance and interest to planners and policy makers alike (see chapter 2.2).This empirical section starts with an introduction to the existing literature on transport mode choice in chapter 3.2. Chapter 3.3 presents an overview of existing agent-based models. Chapter 3.4 set out the methodology for the empirical research. Chapter 3.5 contains an initial data overview and chapter 3.6 builds an multinomial logistic model. Chapter 3.7 develops an agent-based model

3.2 Insights in transport mode choice

This chapter looks into the existing literature on transport mode choice and introduces the reader to the different factors that are thought to influence mode choice. In addition, this chapter explores which factors are currently used in transport mode choice modeling.

3.2.1 A parsimonious need for speed

Before turning to a discussion of which variables are used in transport mode choice modeling, it is important to discuss which factors are considered to determine transport mode choice. Scheiner (2010) studied the trend of increasing trip distance in travel behavior in Germany from 1976 to 2002. He argues that the built environment has a profound effect on travel behavior. Aspects of the built environment that influence travel behavior are amongst others: density, land-use and distance to the city center. The built environment has a particularly strong impact on travel mode choice (ibid.). Complexity theory defines such interaction between a system and its environment as *co-evolution*. A dense urban structure with diverse land uses allows the population to make short trips because of the proximity of housing to other facilities. Consequentially, most trips in such an urban setting are usually made by non-motorized transport modes. This is an indirect influence; the trip distance in such urban areas is smaller and this influences mode choice.

There is also a direct relation between the built environment and transport mode choice. In dense, mixed-use urban areas public transport use is also high. This is because of two reasons. First, a population density usually goes along with restrictions in car use, such as lack of parking space and low travel speeds. Second, the high population density results in an attractive market -or *fitness landscape*- for public transportation. On the basis of this study Scheiner (2010) concludes that trip distance affects mode choice. Next to this, the research shows that city size influences mode choice. In larger cities, less people use the car for any length of trip. Finally, the research also showed that car use in large cities has shown no increase over the last 30 years. It is suggested that the disadvantageous conditions for car use in densely populated cities could explain this finding.

However, the link between built environment and transport behavior is contested. Some scientists suggest that this link can be explained by the self-selection of people into neighborhoods that fit their mobility preferences (Scheiner and Holz-Rau, 2006). In this context self-selection can be defined as: “the tendency of people to choose locations based on their travel abilities, needs and preferences” (Litman, 2005, p. 6). Cao and Mokhatarian (2008) explore several methods have been used to study such self-selection. However, they conclude that their research cannot provide a solid statement regarding the causality of self-selection. In other words, it remains unsure if people select themselves into certain neighborhoods or the built environment affects the behavior of people.

Income and car ownership are assumed to be primary determinants of mode choice (Scheiner, 2010). These two factors are related; a higher income makes owning and using a car more likely (Buehler, 2011). Next to these two socio-economic factors, research in transport behavior in developed economies suggests that demographics also account for differences in mode choice. For instance, household composition, age and gender have been shown to affect mode choice (ibid.). Other variables that are considered in mode choice studies include: bicycle ownership, distance to public transport stops, the costs of a certain mode, education level and transfer waiting time (See Asenio, 2011; Commins and Nolan, 2008; Pinjari et al, 2011). Recent studies by Saneinejad (2010) and Creemers (2010) suggests that the weather can also influence transport mode choice. Buehler (2011) studied these transport mode choice determinants in the US and Germany. He concludes that after controlling for differences in wealth, motorization-level and distance to public transport stops Germans are still less likely to use the car. This suggests that variables other than socio-economics, demographics and spatial development influence mode choice. For instance, Buehler (ibid.) states that culture could account for the differences in transport mode choice.

Relatedly, Garling and Axhausen (2003) argue that most transport mode choice research ignores the history of people. This history is considered to be of importance because it consists of previous experiences –habits- that are likely to affect future mode choice. In a sense, habits reduce the costs of searching for alternatives by relying on past solutions. Habits are *good enough strategies* that persist in a certain *fitness landscape*. This means that for habitual car users are less likely to switch to alternative modes because of the costs involved in this change. In addition the car user might not even perceive any alternatives because his or her information about alternatives is limited and imperfect. This subjective perception of different modes acts a barrier to behavior change; even when more efficient or attractive alternatives exist an individual might not perceive these alternatives as such (Pillwitz and Barr, 2009). Van Exel and Rietveld (2010) studied the influence of perception on mode choice. They conclude that perception influences peoples estimation of desirability and viability in terms of travel time. Furthermore, they suggest that the overestimation of public transport travel times could be a way of justifying car use. To summarize, perceptions and habits can bias peoples information on transport modes. This view opposes the idea of the homo economicus that is all knowing and rational. This brings us to the discussion of contextual variables in transport mode choice. As was argued in chapter 2.7 recent methodological innovations allow for these “softer” or “latent” contextual variables to be considered in quantitative models.

3.2.2 Attitudes and Lifestyle in modeling

In an introduction to a special issue of Transportation Abou-Zeid and Scott (2011) write about the current issues in mode choice modeling. Firstly, they state that more advanced models, such as the mixed logit model, are increasingly being applied in transport mode choice modeling. These advanced models allow researchers to model the influence of latent factors such as perceptions and attitudes towards a certain mode. Secondly, they (ibid.) argue that new survey techniques that mix revealed and stated preference data have been developed and applied in transport mode choice modeling. While Abou-Zeid and Scott (2011) acknowledge the ongoing progress in the understanding of transport mode choice, they also point at the dynamic nature of travel behavior. Mobility systems themselves change over time as they follow an *attractor* or reach a *bifurcation point* and suddenly change rapidly.Consequentially, they suggest that our understanding of the factors governing mode choice will probably have to be revised in the future.

Models of mode choice was initially focused on socioeconomic factors, time and costs. More recent research also considers other factors such as the effect of travel attitudes and perceptions (Popuri et al, 2011). Attitudinal or “latent” factors can relate to the comfort, convenience and safety of various transportation modes. More specifically, “attitudes refer to the subjective importance which certain attributes have for an individual” (Scheiner and Holz-Rau, 2010). The inclusion of such factors has been problematic in the past because of issues with their quantification. From the 1970’s onwards researchers managed to measure attitudes and consider their effect on transport mode choice. Several studies have shown that attitudes can explain mode choice and some studies even suggest that the explanatory value of these variables is greater than that of the traditional ones such as time and costs (ibid.). Popuri et al’s (2011) research suggests that when both socio-economical and attitudinal factors are considered the goodness-of-fit of a model is improved.

Outwater et al (2011) also suggest that including attitudinal data improves transport mode choice models. In their study, they focused on travelers’ attitudes towards amenities in public transport, such as real-time trip duration information and comfortable seating. The use of attitudinal data in mode choice research is connected to the conception of lifestyles as both focus on latent variables which are hard to measure objectively. This idea developed in the social science in the 1980’s and has found its way into transport studies. Lifestyle can be defined as “the group specific forms of organization of daily life that are expressed symbolically in cultural taste and in activities” (Scheiner and Holz-Rau, 2007).

The influence of these lifestyle determined attitudes for mode choice is confirmed in empirical research (Johanson et al, 2011). It is suggested that differences in people's personality lead to a preference for a certain transport mode. According to the same study, attitudes that affect mode choice are environment-friendliness, safety, comfort, convenience and flexibility. As in other studies, the inclusion of attitudes improved the model significantly.

3.2.3 Trips, tours and activity based approaches

In the past the "four-step model" was used for forecasting future demand and performance of transport systems. This model consists of the following four steps:

1) Trip generation: Generates a specified number of trips
2) Trip distribution: Distributes the trips according to a pre-defined attraction distribution
3) Mode choice: Compares the utility of different trips and selects the best option
4) Route choice: Assigns the trips to mode-specific transport networks.

While the four step model has been criticized extensively it goes beyond the scope of this thesis to discuss all its limitations.[8] The main weakness of the model is that the "trip generation" is done arbitrary; the number of trips has to be input to the model. This is opposed to the view that travel is a derived demand of spatially separated activities. Furthermore, the four step model does not consider the interrelation between trips and based solely on the concept of utility maximizing-behavior.

Recent research suggests that transport modeling can be improved through the use of a tour-based rather than trip-based approach. Tours are also known as chains and link individual trips together. A tour consists of the inbound and outbound trip (viewed from the origin of the trip) and includes all stops made along the way (Frank et al, 2007). For example, a tour could consist of travelling to work and stopping on the way to drop off a child at daycare, then returning home after work and stopping to do some groceries along to way. With regard to mode choice, this means that a person will typically plan his tour ahead of time. It seems highly unlikely that one would take the transit to work and then find out that the transit systems stops running before one has to return home (ibid.). Studies that employ such a tour-based usually assume that travel demand is derived from the need to participate in spatially distributed activities and are therefore often referred to as activity-based approaches (Krygsman et al, 2004).

Within the activity-based framework trips are supposed to be generated by certain activities. For instance, the trip to work is generated by the need to get to the office in order to work. As opposed to previous trip-based approaches, the focus is on the activity that generates the trip instead of the trip itself. In addition activity-based approaches focus not on the individual trip, but on sequences or chains of trips. To summarize, activity based approaches use a "rich, holistic, framework in which travel is analyzed as daily or multi-day patterns of behavior, related to and derived from differences in lifestyles and activity participation among the population" (McNally and Rindt, 2007).

3.2.4 Derived demand?

While activity-based approaches are applauded for their more adequate portrayal of actual behavior, they rely on the assumption that travel is a derived demand (Verhoeven, 2010). This means that people regard travelling as disutility in reaching their destination. Recently however, this view has been questioned. It has been suggested that travelling might have a positive utility; in other words that (some) people enjoy travelling (Paez and Whalen, 2010). Empirical research has confirmed that some people do indeed enjoy commuting. In addition, it has been shown that people do not tend to

---

[8] For a more exhaustive discussion see:
McNally, M.G. and C.RR. Rindt (2007), The activity-based approach in Hensher and Button (eds)."Handbook of Transport Modeling", Pergamon (2007)

minimize their travel time, but instead have an optimal amount of time they preferably would like to spend travelling (ibid.)

Lyons and Urry (2005) point out that people can also use their travel time effectively. For instance, one can read a book while traveling on a train. It is also suggested that different groups of people have different travel time use opportunities. Travel time thus can be considered to be productive instead of being time wasted. Based upon the findings of their research in the travel time use of train passengers Lyons et al (2007) speculate that the opportunity for effective travel time use might be of influence on mode choice. A study by Wester (2011) found that public transport modes do allow for more and more diverse travel time uses than private modes. While the opportunities for travel time use do seem to differ per mode, the current author is not aware of research that examines the link between travel time use and mode choice.

3.2.5 Virtual mobility?

Chapter 2.1 introduced the reader to the new mobilities paradigm and the idea of virtual mobility. To recap, virtual mobility relates to virtual travel or communication at a distance. Urry (2002) argues that even before the invention of the telephone people employed means such as postcards to communicate at a distance. However, modern innovations such as video-calling arguably allow for more efficient communication than their predecessing methods. Therefore, one could question the importance of physical proximity in interaction or even the need for travel in itself. Opponents of this view argue that face-to-face contact is still preferred and necessary for a wide range of interactions. For instance, body language, status and atmosphere are hard to transmit using any modern communication method. Urry (ibid.) states that new communication methods might even stimulate travel because they allow for more efficient scheduling and communication over large distances. For instance, it is possible to schedule a meeting using a text-message. In addition, the possibility to communicate in real time with people on the other side of the world might result in more travel to those far destinations because face-to-face contact is still needed for some purposes. In terms of complexity theory one could argue that the current mobility systems have resisted the perturbations of advanced communication methods. However, this does not mean that continued development of such communication methods could tip over the *attractor* towards a different trajectory.

This chapter has introduced the reader to several factors that are known to influence mode choice. It answers the eight' sub question: *"What factors are known to influence mode choice?"* There are several categories of factors that influence mode choice. First, individual socio-economic and demographic factors influence mode choice. In addition, spatial characteristics can also exert influence on mode choice. Next to these "hard" and easy to measure factors softer factors such as attitudes and lifestyle also influence mode choice. Traditional models of mode choice usually perform best when both hard and soft factors are considered. The next chapter will look at the factors that influence mode choice that have been used in agent-based models.

3.3 Agent based modeling and mode choice

Chapter 2.9 introduced agent based modeling introduced as a research method that aligns with complexity theory. This chapter discusses the current state of agent based modeling of transport mode choice.

3.3.1 Mode choice determinants in agent based models

Several studies use agent-based modeling in the analysis of mobility. The subject of these studies ranges from highway traffic simulation (Khalesion and Delavar, 2008) to the modeling of an entire urban region's transport system (Meister et al, 2010). Rieser (2010) argues that most of these simulations have thus far focused on either the private car or public transport. Rieser (ibid.) elaborates that in reality public transport systems and the private car system are highly entwined. In effect, these mobility systems are marked by *connectivity* and *interaction*. For example, one could see that buses and private cars use the same roads and thus the use of one mode of transport potentially could influence the use of another. The idea that different transport modes are interdependent is supported by Meister et al (2010) who add that the mode chosen by an individual for one trip might affect his or her choice for subsequent trips. For instance, if one takes the car on his home-work trip, he or she is probably less likely to use public transport on the work-home trip. This can be traced back to the idea of habits that was introduced in chapter 3.2.

Since Rieser (2011) recognizes that interdepencies exist between transport modes and argues that these should be a part of any traffic simulation he aims to incorporate this insight in his dissertation. In his study Rieser (ibid.) develops an agent-based model that uses two modes of transport (bi-modal); the private car and public transport. His approach is successful in proving interdependency between modes and that mode choice is dependent on relative location in the urban region. However, Rieser (ibid.) also identifies several shortcomings of his model. For instance, he states that in his implementation of the two modes he only made public transport dependent on private car use, and not the other way around. He suggests that a more dynamic approach for both modes could be subject of further research. An unmentioned possible shortcoming of his model is that it employs a utility maximizing view of human behavior, in which time and costs are considered. As was shown in chapter 2.1 and 3.2, this does not correspond with recent insights from transport geography. In addition, biologic complexity shows the existence of *good enough strategies* that are sub-optimal. To recap, recent insights suggest that feelings, attitudes and habits can all play a role in mode choice.

Sunitinyoso and Matsumoto (2007) also use a bi-modal agent based model. However, in their study they focus on how the sum of individual behavior influences the mode choice of a larger population. In complexity theory terms, they focus on how *emergent* effects affect mode choice. The agent-based model in the study uses three types of agents which all have their own optimizing mechanism. The results of the study suggest that different kinds of people (optimistic, pessimistic and average) have different mode choice preferences. Furthermore, Sunitinyoso and Matsumoto (2007) suggest that intra-group information sharing influences the decision making of all individuals within a group. This study (ibid.) incorporates learning-effects in the agent based model and can arguable be called "advanced" in terms of the way that agents share information and learn to optimize their behavior. However, the study only incorporates two mode choices. In addition, the study only uses socio-economic variables as input for the model. The way these variables are handled by the model is different for each group. The model used in this study (ibid.) also does not consider attitudinal variables such as dispositions towards flexibility and comfort.

Ciari et al's (2008) study incorporates mode choice into a bigger agent based model. In this study five modes are considered; walking, biking, car driver, car passenger and public transport. In addition Ciari et al (ibid.) allow the agents to choose different modes for every trip they make during a day. For example, an agent can take the bus to work, use the bike to get from work to the mall and use the car to get back home from the mall. This model seems to be more exhaustive in terms of realism than Riesers' (2011) model. However, the model presented by Ciari et al (2008) also only incorporates socio-economic and demographic variables. This chapter shows that most agent based models do only include socio-economic and demographic variables, while the literature on mode choice suggests that other variables also play an important role. The aim of this thesis is to attempt to include these variables (see 3.2) in an agent based model.

3.3.2 Factors influencing mode choice

This chapter and the previous one have introduced several determinants of mode choice and their use in (agent-based) models. Figure 3.3.2.1 shows which determinants of mode choice have been used in modeling transport mode choice in previous studies.

Table 3.3.2.1 : Determinants of mode choice used in (agent-based) models

Personal characteristics:	**Spatial characteristics:**	**Transport mode-specific characteristics:**
Demographic variables	**Population density**	***Time***
Age	**Distance to closest public transport stop**	***Costs***
Gender		Transfer waiting time
Household composition		Travel time use opportunity
Socio-economic variables		
Income		
Education		
Car-ownership		
Bike-ownership		
Attitudes		
Lifestyles		

Bold = used in mode choice models
Italic = used in agent based models
Bold/italic = used in both mode choice models as agent based models

From the table it is clear that many of the supposed determinants of transport mode choice have been used in "regular" transport mode choice models. The amount of determinants that have been used in agent-based models is less; only demographic and socio-economic variables have been included in those models. Studies in transport mode choice modeling show that incorporating attitudes includes the quality of such models. Based upon these findings, it can be argued that including attitudinal variables could improve an ABM.

3.4 Methodology

The previous two chapters introduced the reader to the existing literature on transport mode choice and agent based models that deal with mode choice. This chapter sets out the methodology for the present study.

3.4.1 Research design

In the theoretic section of this thesis, much has been said about the use of surveys. Chapter 2.2 suggests that surveys are an outdated research method. The use of other research methods such as ethnography and agent based modeling was suggested as an alternative in chapter 2.8. This study aims to construct an agent based model for transport mode choice. To construct such a model, data is needed to estimate the parameters. While the survey might be an outdated way of doing research "an sich", it does allow for the collection of much data. Therefore, this study uses surveys to generate input for the agent based model. For the initial exploration and analysis of the data SPSS will be used, Excel is the program of choice for running the agent based model.

3.4.2 Study focus: students

Much literature is available on working trips but not specifically on student trips (Kiran, 2008). In addition, students make for a convenient subject group because their abundance in the city where the current author lives. Furthermore, students are considered to be more likely to participate in a survey because they understand the difficulties inherent in doing empirical research. It is important to delineate the target group of this study further so that the results can be replicated. In Dutch law (Nieuwenhuizen, 2005) the following definition of students is given: "A participant who is enrolled at a university or college". However, student-subsidies and –loans are only provided to students over 18 and under 30 years of age (IB-Groep, 2011). That suggests that the definition of a student is age-related. This view is supported by considering the average time students take to complete their studies; according to CBS (2011) the average student takes 84 months (7 years) to complete their studies. Subsequently, the average age at which students start their education is 19.7 years (CBS, 2010). Combining these observations from the CBS results in an average study period that spans from 19.7 until 26.7. Based upon this, the average age of students should lie somewhere around 24 years. In this thesis students are considered to be people enrolled in higher education. No limitation is set for a maximum or minimum age.

3.4.3 Location

The study is carried out in the municipality of Utrecht. Utrecht is a medium-sized university town in the center of the Netherlands. The municipality of Utrecht (2010) reports that the city has 307,000 inhabitants and that the population is increasing at a pace of about 10 % per 5 years. Of these 307,000 inhabitants 22.7% is aged between 20 and 30 years. It is estimated that the city houses about 25.000 students. The city is home to the Utrecht University of Applied Sciences (HU) and the University of Utrecht (UU), the former institute has 38,396 enrolled students (HU,2010) the latter institute educates 30,344 students (UU, 2010). From these numbers it is clear that more than half of the students lives outside the municipality and has to commute across municipal borders in order to attend their classes. Seeing as Utrecht has a large amount of resident students and is home to the largest university in the Netherlands (UU, 2010), it is a suitable location for studying the transport mode choice of students.

3.4.4 Survey design and operationalization

As can be seen in appendix B the survey contains a total of 21 questions. Next to age, gender and household composition, participants are also asked to share their nationality. This is done to see if there is a difference in transport mode choice between native and foreign students. Also, the survey contains a question asking for the place of residence of participants, this question was included as an alternate measure of distance.

Besides asking for car-ownership, the survey also contains a question looking into the bike-ownership of the participants. The reason for this is that owning a bike might have a similar predictive value as owning a car, which has been shown in chapter 3.2. The same reasoning lies behind the question asking the participants if they have a transport subscription; having a subscription might influence mode choice.

Question 12 of the survey contains 16 statements that relate to four attitudinal categories, being comfort/convenience, flexibility, travel time and the weather. These categories are based on previous research (see chapter 3.2.2) on attitudes that influence travel mode choice. To recap, these categories are safety, comfort, convenience and flexibility. The comfort and convenience groups were combined because of their overlap in terms of definition. The safety category was dropped because of limited evidence in the literature regarding the influence of the attitude on mode choice.
Flexibility is included as are travel time and several questions regarding attitudes towards the weather, speed and costs. The studies that the individual questions are based on is listed in table 3.4.4.1.

Table 3.4.4.1: Questions used to measure attitudes

Comfort/Convenience

1. I hate getting in a traffic jam (Asensio, 2011)
2. I hate delays in public transport (Asensio, 2011)
3. Privacy is important to me while travelling (Popuri et al, 2011)
4. I hate travelling in a crowded train / bus (Bhat, 1995)
5. I hate transfers (Asensio, 2011)

Flexibility

6. The frequency of public transport service influences my mode choice (Johansen et al, 2006)
7. I like to combine several activities in one trip. For example, going to school and doing groceries afterwards (Johansen et al, 2006)

Travel Time use

8. I try to minimize my travel time (Mokhtarian and Salomon, 2001)
9. I spend my travel time idly
10. I use my travel time to relax
11. I use my travel time to work or study (Holley et al, 2008)
12. I enjoy travelling (Paez and Wahlen, 2006)
13. I spend my travel time less effectively when its crowded

Other

14. The cost of a transport mode is important for my mode choice (Scheiner, 2010)
15. The speed of a transport mode is important for my mode choice (Scheiner, 2010)
16. The weather influences my transport mode choice (Saneinejad, 2010)

The measures of travel time use in questions 9, 10 and 11 are based upon Wester's (2011) study on travel time use. Wester (ibid.) used a wider scope of statements, but the central are employed here. Question 13 is included to provide input for the agent-based model. If crowding has an influence on travel time use and travel time use influences mode choice, this can be modeled in the ABM.

Subsequently, participants are asked to fill in the mode they use most often when travelling to school or university. Five options are given : Walking, bike, bus, train, car. In addition, participants are asked to indicate which mode they use as an alternative for the first one, if applicable. Participants are then asked to rate a series of statements regarding the transport mode(s) they picked. These statements are shown in table 3.4.4.2. Again, the studies that the statements are based on are listed. Questions

9, 10 and 11 are again included to provide input for the agent-based model. It is important to note that these statements relate specifically to the mode(s) that the participant uses.

Table 3.4.4.2: Statements regarding a particular transport mode

1. I use this mode because I own a subscription (Scheiner, 2010)
2. I use this mode in warm/sunny weather (Saneinejad, 2010)
3. I use this mode in cold/rainy weather (Saneinejad, 2010)
4. This mode is comfortable (Popuri et al, 2011)
5. I use this mode because it has a stable travel time (Johansen et al, 2006)
6. I use this mode because it is always available when I need it (Johansen et al, 2006)
7. I use this mode to combine several activities along the way (Johansen et al, 2006)
8. This mode allows me spend my travel time efficiently (Holley et al, 2008)
9. When this mode is crowded, I cannot spent my travel time as efficiently
10. When crowded, this mode is less comfortable
11. I use this mode to avoid congestion/crowding
12. I use this mode because it is the fastest way to reach my destination (Mokhtarian and Salomon, 2001)

In addition, all participants were asked to rate the modes they use on a 1 to 5 scale. Also, there was some space reserved for remarks or comments. Finally respondents could indicate they want to receive the results of this study by providing their email address. Both an English and a Dutch version of the survey are used, in order to accommodate both domestic and foreign students. These surveys can be found in appendix B.

3.4.5 Data collection

To ensure a balanced sample, students were asked to participate in the survey at several different locations. These locations included the buildings of different faculties at the campus “de Uithof”, the inner city university library and the central station. In addition to these paper surveys, a mailing was sent out to different student associations with the request to forward the survey to their members.

3.5 Data overview and sample characteristics

This chapter provides an overview of the data that was collected for this thesis. The aim of this chapter is to introduce the reader to the general characteristics of the dataset. Furthermore, some analysis are performed to identify potential predictor variables of mode choice. Furthermore, the analysis can identify connections between predictor variables. Such connections could be a sign of multicollinearity and should be dealt with in building a model of transport mode choice.

3.5.1 Data set

In total, 154 completely filled-out surveys were collected. The 154 participants that filled out a survey are all students attending university or HBO (university of applied sciences). Figure 3.5.1.1 gives an overview of the amount of surveys collected at different locations. As is clear from the diagram, most surveys were conducted at the grounds of the university. The surveys were collected at different times during the day in order to ensure that no time-related bias could occur. Some surveys were collected in public transport, both at bus-stops and in busses. Finally, some surveys were filled in online. All the surveys were gathered in a two week period in the late autumn of 2011.

Figure 3.5.1.1: Data collection locations

3.5.2 Age

The average age of the participants in the survey is 21.5 years old with a standard deviation of 2.5. This is somewhat below the expected average age posited in paragraph 3.3.3 which was 24 years old. The students in the sample are thus somewhat younger than the general student population. A correlation analysis was executed to check for connections between age and other variables. This analysis showed that there is a connection between age and income ($p < 0.01$ Pearson’s = 0.401), this implies that the older participants have a higher income. In addition, there is a connection between age and the importance of speed ($p < 0.05$ Pearson’s = -0.205), this suggests older students attach less importance to the speed of their transport mode.

3.5.3 Gender

55.5% of the surveys are filled in by women and 43.9% by men. The remaining 0.6% of the participants did not submit their gender. A student’s T-test was performed to investigate any differences between male and female participants in the sample. This test showed several significant differences between the two groups. Firstly, there is a difference in income between the genders; male participants seem to have a higher income per month. The male participants have an average income of 706.95 euro’s per month while the female participants have an incoming cash flow of 557.95 Euros per month. Secondly, female participants attach more value to the speed of their transport mode. They rate this statement higher (4.1) than men do (3.8). Thirdly, female participants indicate that they enjoy travelling more than men do. The former group gave an average grade of 2.9 (slightly negative) and the latter rated the statement with a 2.6. Fourthly, female participants attach more importance to being able to combine several activities in one trip; the rated the corresponding statement with a 3.9, against a 3.5 of the male participants. Fifthly, female participants are more negative regarding congestion and crowding (average rating. of 4.0) than men (average rating of 3.6). The differences between the genders thus should be kept in mind during the further analysis of the data.

3.5.4 Education

The figure below (3.5.4.1) shows the participant's distribution over the different educational levels used in the survey. The bachelor group seems to be the biggest, followed by the HBO and master education levels. Pearson's Chi square was used to look for significant differences between the three groups. Using this method it was found that university bachelor students more often reside ($p < 0.5$) outside of the city of Utrecht than the other groups. No other significant differences between the groups could be identified ($p < 0.05$).

Figure 3.5.4.1: Education of the sample

3.5.5 Nationality

Of the 151 participants 15 did not have the Dutch nationality. To investigate differences between Dutch and non-Dutch students a Mann- Whitney U-test was performed. This test was used because of the small size of the non-Dutch nationality group ($n < 30$). Using this test it is found that non-Dutch students have significantly worse access to a car than Dutch students. Also, foreign students attach more value to minimizing their travel time (4.6) than Dutch students (3.7). Because of the small sample size these findings should be handled with care and their validity outside of the sample is questionable. The small size of the different nationality group makes it unsuited for use in a predictive model.

3.5.6 Household composition

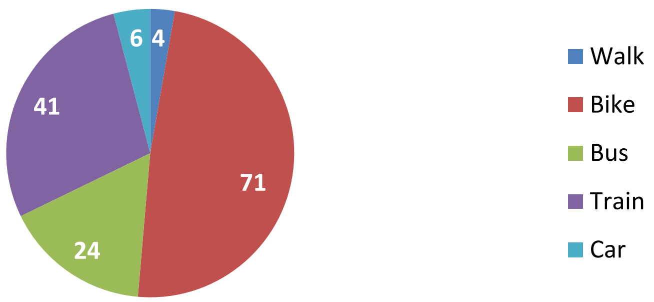
Figure 3.3.6.1 shows the distribution of the participants of the house-hold composition classes used in the survey. The biggest category is student-housing, in which students share a kitchen and bathroom. The other categories are self-explanatory. To test for differences between groups Pearson's chi square was used. This uncovered a connection between age and household composition; older students significantly more often live in apartments and student houses. No other significant differences between the groups could be found at the $p < 0.05$ level.

Figure 3.5.6.1: Household composition of the sample

3.5.7 Primary mode choice

Figure 3.5.7.1 gives an overview of the primary mode choice of all participants. In the context of this study "primary" refers to the mode that the students use most often. In addition, the mode represented in the figure is the mode that the students spent most time in during their total trip. For instance, if one uses the bike to drive to the train-station and then gets on the train to reach Utrecht University the mode selected is the train. From the figure it is clear that the bike is the most common mode used among students in Utrecht, followed by the train and bus. Only a small proportion of the sample indicates the walk or car modes as their primary choice.

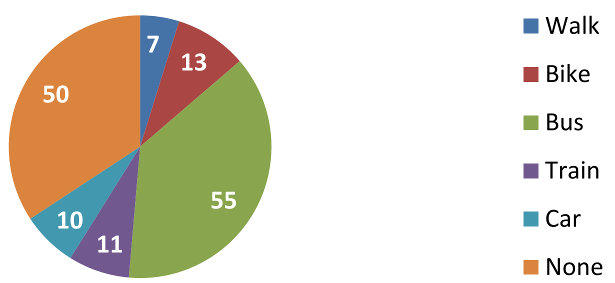
Figure 3.5.7.1: Primary mode choice



3.5.8 Alternative mode choice

Besides asking for their most used mode, the survey also includes a question on the alternative mode the students use to reach their educational institute. The distribution of these modes is presented in figure 3.5.8.1. This figure shows that the bus is the most frequently used alternative. Smaller proportions of the sample indicate the bike, train car and walk modes as their alternative mode. About one thirds of the students stated that they did not use an alternative mode to travel to the university.

Figure 3.5.8.1: Alternative mode choice



3.5.9 Travel duration

The average travel duration in the sample, including both preferred and alternative choices, is 34 minutes. The average travel duration for the preferred mode choices is somewhat lower at 35.7 minutes, for the alternative mode the average travel duration is 31.2 minutes. This difference is tested using a Students' t-test and is not significant. The travel duration for students living in Utrecht (21.7 minutes) differs significantly ($p < 0,01$) from the travel duration for students living outside of Utrecht (53.7 minutes).

3.5.10 Pre-transport

Next to the total travel duration, the participants were asked to indicate how far they live from the closest public transport stop. On average students live 3.54 minutes from the nearest public transport stop. The most frequent mode used for pre-transport is walking ($n = 144$). Only some participants use the bike to get to the nearest public transport stop ($n = 10$). A student t-test shows that students living inside of Utrecht live significantly ($p < 0,01$) closer to public transport stops (2,5) minutes than students from outside of Utrecht (4,3 minutes). A chi-square test shows ($p < 0,05$) that students from outside of Utrecht use the bike more often to get to the closest public transport stop. However, since the amount of pre-transport bike users is very small, pre-transport mode is not suited for use in the predictive model.

3.5.11 Transport mode availability

The participants were asked to indicate if they owned a car, a bike and a public transport subscription. 91.6 % of the students in the sample reported that they own a bike and 87.7 % own a government paid public transport card. Only 8.4% of the participants own a car, with 55.5% having access to a car through family or friends. A small proportion of the participants has a different public transport subscription (6.5 %).

3.5.12 Attitudes

Table 3.5.12.1 provides an overview of the ratings the participants gave to the different statements introduced in paragraph 3.2.4. From the table it is clear that the participants hate getting in a traffic jam and being delayed. Furthermore, they spent their travel time less efficiently when their mode is crowded. In addition, the costs and speed of a transport mode are considered to be of importance. Privacy is regarded as relatively unimportant and not many participants seem to enjoy travelling, as both statements score below the center value of 3. Subsequently, on average students do not seem to spend their travel time idly or working/studying.

Table 3.5.12.1: Attitudes towards travelling

Comfort/Convenience	Mean	Std. Deviation
1. I hate getting in a traffic jam	4.04	1.09
2. I hate delays in public transport	4.29	0.99
3. Privacy is important to me while travelling	2.94	1.06
4. I hate travelling in a crowded train / bus	3.85	1.09
5. I hate transfers	3.20	1.19
Flexibility		
6. The frequency of public transport service influences my mode choice	3.77	0.89
7. I like to combine several activities in one trip	3.70	1.19
Travel Time use		
8. I try to minimize my travel time	3.89	1.09
9. I spend my travel time idly	2.49	1.08
10. I use my travel time to relax	3.36	0.99
11. I use my travel time to work or study	2.86	1.26
12. I enjoy travelling	2.79	1.10
13. I spend my travel time less effectively when its crowded	3.97	1.12
Other		
14. The cost of a transport mode is important for my mode choice	3.91	1.05
15. The speed of a transport mode is important for my mode choice	4.01	1.04
16. The weather influences my transport mode choice	3.60	1.26

3.5.13 Mode characteristics

Table 3.5.12.1 provides an overview of the scores the participants gave to the different modes on several statements. This table includes both the primary and alternative mode's scores. In the table scores above 4.0 and below 3.0 are highlighted. . The mode with the highest grade for attractiveness is the car. The car also has a high score on comfort and usage in bad weather. The participants indicate that they cannot spend their travel time usefully in the car. Furthermore, the scores show that the car is no less comfortable in congestion. However, students indicate that they do not use the car to avoid congestion.

The bus has the lowest grade and the participants state that they use the bus because they own a subscription. In warm and sunny weather they do not use the bus as often as in cold weather. The travel duration of the bus is not stable and it does not allow the passenger to combine several activities along the way. Also, the bus is less comfortable when crowded and it is generally not the fastest way to reach a destination. In the bus the participants do not spend their travel time efficiently and when it is crowded this is worsened.

The walk-mode received a grade of 3.9 and is used more often in good weather. The mode is always available when needed. However, walking does not allow for the efficient usage of travel time. Walking is pretty comfortable but is not used to avoid congestion, nor is it the fastest way to get somewhere. Travelling by bike received an average grade of 3.9 and is also mainly done in good weather. The bike has a stable travel time and is always available when needed. The bike allows its user to combine several activities along the way and is used to avoid crowding or congestion. Finally, the bike has the highest score on statement 12. This suggests that it is often perceived to be the fastest mode to reach a destination.

The train has a high average travel duration and a grade of 3.5. It is used both in warm and cold weather and considered to be pretty comfortable. Aparantly, the train does not allow its user to combine several activities along the way. This suggests that students don't see visiting the small shops at stations as a separate activity. Also, when the train is crowded passenger cannot spend their travel time as efficiently. Also, the train is a lot less comfortable when crowded and is not used because it is the fastest way to reach a destination. Finally, the train is also not used to avoid congestion or crowding.

Table 3.5.12.1: Mode characteristics

Mode	**Walk**	**Bike**	**Bus**	**Train**	**Car**
Travel duration	**14.1**	**19.1**	**31.3**	**67.9**	**30.6**
Grade	**3.9**	**3.9**	**2.9**	**3.5**	**4.3**
1. I use this mode because I own a subscription	**n/a**	**n/a**	**4.0**	**4.4**	**n/a**
2. I use this mode in warm/sunny weather	**4.6**	**4.7**	**2.2**	**4.1**	**3.3**
3. I use this mode in cold/rainy weather	**3.4**	**3.4**	**4.3**	**4.0**	**4.3**
4. This mode is comfortable	**3.9**	**3.7**	**3.4**	**3.6**	**4.5**
5. I use this mode because it has a stable travel time	**3.5**	**4.0**	**2.8**	**3.2**	**3.1**
6. I use this mode because it is always available when I need it	**4.7**	**4.6**	**3.0**	**3.7**	**3.7**
7. I use this mode to combine several activities along the way	**3.2**	**3.9**	**2.3**	**2.7**	**3.0**
8. This mode allows me spend my travel time efficiently	**2.9**	**3.0**	**2.7**	**3.6**	**2.8**
9. When this mode is crowded, I cannot spent my travel time as efficiently	**n/a**	**n/a**	**4.3**	**4.5**	**3.3**
10. When crowded, this mode is less comfortable	**n/a**	**n/a**	**3.8**	**4.2**	**2.9**
11. I use this mode to avoid congestion/crowding	**2.8**	**3.7**	**2.0**	**2.9**	**1.4**
12. I use this mode because it is the fastest way to reach my destination	**2.1**	**3.9**	**2.6**	**3.4**	**3.6**

3.6 Data analysis

3.6.1 Factor analysis

Previous research (see chapter 3.2) suggests that attitudes influence mode choice. In empirical studies a series of statements is usually used to measure a certain attitude. This study uses a similar approach in order to test whether the statements used in the survey are measures of the same concept. If these attitudes can be identified, this also convenient for the regression that will be done in the next chapter as it brings down the number of predictor variables. Because of the small sample size (N =154) and large survey (40+ questions) it is important to consider the maximum amount of predictor variables that can be used. Many rules of thumb exist, but Field (2009) suggests that with a sample size of 150 the maximum amount of predictors is 10 when medium and large effects are expected. In order to analyze if the statements used in the survey measure similar concepts a principal component analysis was conducted.

The analysis is done with oblique rotation using the Direct Oblimin method. This rotation method yields better factor loadings for this sample as compared to Orthogonal rotation. The Kaiser-Meyer-Olkin measure is 0,589, which is above the required 0,5 (Field, 2009). The Barlett's test for sphericity reports a chi square of 346 with a p < 0,0001. This indicates that the correlations between items are sufficiently large to perform a principal component analysis. There are 6 components with an eigenfactor above 1. However, the accompanying Scree-plot shows only one point of inflexion and only justifies using three components. Table 3.6.1.1 bellow shows the three components after rotation. All components that scored above the threshold of 0,4 are highlighted in bold.

The same table (3.6.1.1) shows that the frequency of services, minimizing of travel time, costs, speed and weather all load onto the same component. It seems that these statements all measure the inclination of the participant to reach their destination in a fast, cheap and convenient matter. The inclusion of weather in this component suggests that students consider weather in the same way as they do speed. This component is termed " Need for speed" in reference to the traditional determinants of mode choice listed in paragraph 3.2.1.

The second component is labeled "Aversion to disruptions". All statements regarding the participants attitude towards disruptions, delay and congestion load on this factor. From this it seems that students have a generally negative attitude towards disruptions. It should be noted that the statement " I hate transfers" only loads on this factor with 0,390 which is below the threshold of 0,4.

The last component is called "Travel time use". This factor loading contains all the statements towards travel time use, regardless of the specific activity. Furthermore, it also contains the statement "I enjoy travelling", this suggest that there is a relation between travel time use and the enjoyment of travelling. The statement "I spend my travel time idly" loaded negatively on this component, which suggests that there is an inverse relation between boredom and travel time use and travel enjoyment. This is a logical conclusion since travel time activities seem to be the direct opposite of idling.

The components found in this analysis correspond to those found in the literature of comfort, convenience and flexibility (paragraph 3.3.3). The comfort/convenience category is found in the sample, but privacy did not load well onto the same factor. This indicates that the survey possibly measures aversion to disruptions instead of comfort or convenience. The travel time category can be found back in component three, with the exclusion of statement 8 and 13. Statement 8 seems to load somewhat negatively on the third component, suggesting that this is the opposite of travel time use. Statement 13 does load somewhat on the third component, but loads stronger on the second component and thus is added to that one. The category of flexibility does not load entirely on one component. Only statement 6 on the frequency of transport services was found to load on a component at all. Together with the three statements contained in the category "Other" and statement 8, statement 6 loads onto the Need for speed component.

Table 3.6.1.1 Summary of the factor analysis results (N = 151)

	Rotated factor loadings		
	1. Need for speed	**2.Aversion to disruption**	**3.Travel time use**
6. The frequency of transport services is important	**0.743**	0.087	0.128
15. The speed of a transport mode is important	**0.696**	0.032	-0.049
16. The weather influences my transport mode choice	**0.556**	0.063	-0.071
8. I try to minimize my travel time	**0.539**	0.19	-0.249
14. The costs of a transport mode are important	**0.521**	0.095	0.025
5. I hate transfers	0.060	**0.390**	0.001
2. I hate delays	0.210	**0.785**	-0.163
4. I hate crowding	0.099	**0.686**	0.159
1. I hate traffic jams	0.043	**0.674**	-0.126
13. I spend my travel time less effectively when its crowded	0.035	**0.589**	0.321
3. Privacy is important to me	0.253	0.144	0.288
7. I like to combine several activities along the way	0.214	0.121	0.264
9. I spent my travel time idly	0.117	-0.009	**-0.637**
12. I enjoy travelling	-0.046	-0.132	**0.692**
10. I use my travel time to relax	0.383	-0.177	**0.477**
11. I use my travel time to work	-0.164	0.111	**0.482**
Eigenvalues	**2.374**	**1.755**	**2.312**
% of variance explained	**14.84**	**11.00**	**14.45**

3.6.2 Multinomial logistic regression (MNL)

To predict the preferred transport mode choice of students a multinomial logistic regression analysis is used. Hesner and Button (2000) refer to this type of model as "simple and elegant" (p. 72). Furthermore, they state that the MNL model has been used in a wide variety of travel and transport related studies, including amongst others mode choice. Field (2009) argues that logistic regression is similar to multiple regression with the exception that the former should be used in the case of a categorical dependent variable. Multinomial logistic regression estimates the probability that a case will fall into a certain category. This probability is calculated by relating categories to one reference category. For instance, "a compared to b" and "a compared to c". Mathematically formulated, the model looks as follows:

$$P(Y) = \frac{1}{1 + e^{-(b_0 + b_1 X_{1i} + b_2 X_{2i} + \cdots + b_n X_{ni})}}$$

In this equation P(Y) is the chance of Y occurring, b_0 is a constant, $X_1$is a coefficient attached to predictor variable b_1. The MNL model assumes that there is a linear relationship between the predictor variables and the logit of the dependent. Also, the model assumes that the errors are independent and that the predictors are not correlated too highly. To evaluate the fit of a MNL model the log-likelihood measure is used. Large values of this statistic indicate a poorly fitting model so the lower the log-likelihood the better the model. However, the log-likelihood can be difficult to compare across models, therefore the Cox and Snell's R^2_{cs} and Nagelkerkes R^2_N can be more suitable alternatives. These two statistics can vary between 0 and 1, with a value of 1 being a perfect fit of the model to the data. Of the two statistics Cox and Snell's R never reaches its theoretical value of 1, while Nagelkereke R does do so (Field, 2009). To provide the reader with a clear comparison of the models R^2_{cs} and R^2_N will be provided to evaluate the subsequent models. Only Nagelkerke's R will be discussed. Another important statistic is the Wald-statistic, this indicates whether or not a predictor is significant in explaining the dependent variable. Higher values of the Wald-statistic suggest that a variable is a better predictor of the dependent. Every model is checked for multicollinearity and linearity of the logit. Multicolliniarity is checked by reviewing the variance inflation factor (VIF). VIF's of over 10 are cause for concern, as is an average VIF of over 1 (Field, 2009). Residuals are interpreted using Cook's distance and DFBeta values. On the basis of these statistics, one case was dropped. This case had an income of 3500 euro's per month, which is 5 times the average income. While the definition of students (see chapter 3.4.2) does not include a defined income, the author believes that a student with such a high income cannot be considered a student.

In this analysis of mode choice only three modes will be taken in to account. The reason for this is that the "walking" and "car" modes have very few cases and could thus have an excessive influence over the model. Furthermore, the models is based upon the participants primary mode choice. In the following paragraphs several models will be estimated. Field (2009) suggests that using a stepwise method for estimating the model takes many important considerations out of the hands of the researcher and is thus less desirable when there is previous research available. Previous research can identify the variables that can be entered directly in the model, new variables can then be added in order of importance (ibid.). As there is previous research available on transport mode choice, the model will be based on this, including new variables stepwise.

However, the scope of transport mode choice modeling literature is so wide that many variables could be entered directly into model. Furthermore, there are different types of variables that could be of more or less importance (demographics, socio-economic, attitudes). Therefore, before building the final model it is important to see how these different sets of predictor variables explain mode choice own their own. The results of these models can then be used to determine which variables are entered directly into the final model and which ones stepwise. This method is also necessary because of the sample size, which allows for a maximum of 10 variables to be included into the model.

The first model to be estimated includes only on socio-economic and demographic variables. In paragraph 3.2.1 several socio-economic and demographic variables were introduced that have been shown to influence mode choice in previous research. To recap, these variables are: Income, age, place of residence, gender, household-composition and education. When including all these variables into the model R^2_{CS} is 0.600 and R^2_N is 0.534. However, not all variables are significant predictors of the outcome variable (mode choice). Both age and gender do not significantly predict mode choice. Income negatively influences the odds that a student will choose the bus or train. If a student lives within the municipality of Utrecht, he or she is also less likely to use either public transport mode. Subsequently, students that live with their parents are more likely to use public transport. HBO-students are more likely to use public transport then university students.

Table 3.6.2.1: Model (1) with demographic and socioeconomic variables (Reference category = Bike)

	Parameter	B	Wald
Bus	Intercept	2.341	0.529
	Income(euro's)**	-0.003	5.575
	Age	-0.036	0.165
	Gender (Male)	2.159	1.059
	City of residence (Utrecht)***	-1.868	9.384
	Household composition (parents)	0.398	0.576
	Education (University)**	1.145	3.993
Train	Intercept	-0.834	0.680
	Income(euro's)*	-0.000	2.907
	Age	0.117	0.266
	Gender (Male)	-1.293	0.011
	City of residence (Utrecht)***	-3.412	26.937
	Household composition (parents)**	1.325	5.097
	Education (University)**	1.286	4.137

* p < 0.10 ** p < 0.05 ***p < 0.01 R_N^2 = 0.538 R_{cs}^2 =0.600

The second model uses only attitudinal variables to predict mode choice. Table 3.6.2.2 shows the model with “Need for speed”, “Aversion to disruption”, “Travel time use”, the ability to combine several activities along the way (“combine” from now on) and the need for privacy(“privacy from now on) entered directly. The “combine” and “privacy” variables are entered because these variables do not load sufficiently on any of the three factors. The R_N^2 of this model is 0,308 suggesting that it is a worse fit to the data than the first model. However, only “combine” in the model is a significant predictor of mode choice ,all other variables are not significant. The more value students attach to the possibility to combine activities the lower the odds that they will use either the bus or train. Also, the higher the score on the aversion to disruption factor, the higher the odds that a student will use either public transport mode. This seemingly contradicting result might be explained by the higher frequency of disruptions in public transport. Students that use public transport more often might have a more outspoken attitude towards these disruptions. The same could be said for the attitude towards privacy; public transport users could be more subject to intrusions. Students that value the use of their travel time are less likely to use the bus and more likely to use the train than the bike.

Table 3.6.2.2: Model (2) with attitudinal variables (Reference category = Bike)

	Parameter	B	Wald
Bus	Intercept	0.616	0.219
	Need for speed	0.408	1.576
	Aversion to disruption	0.222	0.472
	Travel time use	-0.022	0.007
	Possibility to combine activities along the way*	-0.334	3.777
	Privacy is important for me	0.003	0.000
Train	Intercept	1.145	1.070
	Need for speed	-0.249	1.126
	Aversion to disruption	0.092	0.138
	Travel time use	0.206	0.819
	Possibility to combine activities along the way*	-0.401	7.299
	Privacy is important for me	0.295	2.544

* p < 0.10 ** p < 0.05 ***p < 0,01 R_N^2 = 0.308 R_{cs}^2 =0.273

Thirdly, a model using only spatial variables is estimated. For this the distance to the closest public transport stop and mode of reaching that public transport stop are used. Table 3.6.2.3 shows the resulting model, which has a $R_N^2 = 0.282$. This model is thus the worst fit to the data so far. However, all predictor variables in the model are significant. As the distance to the public transport increases, students are more likely to use the bus or train. Again, this seems to be a illogical result; one would expect a larger distance to the transport stop to negatively influence the use of the bus and train. However, it is possible that this effect is created by the fact that students that live further away also live in more rural area with less dense public transport networks. This idea is confirmed by looking back to paragraph 3.5.11 in which a significant distance in pre transport time was found for students from inside and outside Utrecht. If students walk to access the closest public transport stop they are less likely to use the bus or train. However, this result can also be explained by the fact (see 3.5.10) that students from outside Utrecht more often use the bike to access public transport. These earlier findings suggest that correcting for place of residence might make both predictor variables in model 3 insignificant.

Table 3.6.2.3: Model (3) with spatial variables (Reference category = Bike)

	Parameter	B	Wald
Bus	Intercept**	-3.625	4.638
	Distance to closest public transport stop (minutes)***	0.337	7.102
	Pretransport mode (walking)***	-2.120	20.305
Train	Intercept	-0.609	0.968
	Distance to closest public transport stop (minutes)***	0.209	3.740
	Pretransport mode (walking)***	-1.259	11.469

* p < 0,10 ** p < 0,05 ***p < 0,01 R_N^2 = 0,282 R_{cs}^2 = 0,251

The fourth model uses only tour characteristics to predict mode choice. The only tour characteristic asked in the survey is travel duration. Table 3.6.2.4 shows that travel duration is a significant predictor only for the train. As trip duration increases students are less likely to use the train. This result suggest that students use the train for longer trips. The R_N^2 value is 0,141 and thus the model is not a good fit of the data.

Table 3.6.2.4: Model (4) with tour variables (Reference category = Bike)

	Parameter	B	Wald
Bus	Intercept***	-4.000	33.430
	Trip duration***	-0.006	0.893
Train	Intercept***	-5.609	34.471
	Trip duration***	0.013	7.833

* p < 0.10 ** p < 0.05 ***p < 0.01 R_N^2 = 0.282 R_{cs}^2 = 0.251

Of all four models shown so far the socio-economic and demographic model (1) is the best fit of the data. However, previous research has shown that incorporating several kinds of variables in a single model improves the model fit. The fifth model builds on the previous four and is built using a stepwise method. All variables that were significant in models 1, 2 and 4 are entered in one block. Model 3 is excluded because it was shown that the variance of the predictor variables in that model can be explained by the participants city of residence. The remaining variables are entered in backward stepwise fashion. Table 3.6.2.5 shows the resulting model. It has a R_N^2 of 0,818 which is higher than each of the separate models. In model 5 income has a negative effect on the odds of using the bus or train. As in the previous models living in Utrecht also lowers the odds for a student to use the public transport modes, attending HBO increases the likelihood of choosing the bus or train. The need for speed attitude negatively influences the odd of choosing for the train. This seems contradictory since the train supposedly has the highest speed. However, it is possible that students that have a “Need for speed” choose to live closer to the university. Consequentially, students living outside of Utrecht might have a lower need for speed than their counterparts; a Student's T-test confirms this hypothesis ($p < 0.05$). This significant difference suggests multicollinearity, but neither the VIF nor the condition-index supports this concern. Finally, a higher trip duration increases the odd for choosing the bus or train. In comparison with model 4 the coefficient for travelling by bus has become positive.

Table 3.6.2.5: Model (5) including all variables (Reference category = Bike)

	Parameter	B	Wald
Bus	Intercept	-0.667	0.252
	Income(euro's)**	-0.005	6.278
	Place of residence (Utrecht)**	-2.136	3.787
	Education (HAVO)	1.247	2.082
	Travel duration (minutes)***	0.116	12.432
	Need for speed	-0.102	0.052
Train	Intercept**	-4.092	5.475
	Income (euro's)	-0.003	1.781
	Place of residence (Utrecht)***	-6.564	15.534
	Education (HAVO)	1.074	-0.990
	Travel duration (minutes)***	0.185	23.446
	Need for speed*	-1.118	3.556

* $p < 0.10$ ** $p < 0.05$ ***$p < 0.01$ R_N^2 = 0.818 R_{cs}^2 = 0.727

Field (2009) suggests that after an initial analysis variables that are statistically redundant should be dropped from the model in order to optimize it. From table 3.6.2.5 it is clear that education is not a significant predictor for mode choice. This variable is thus removed from the directly entered block and added to the stepwise regression. The analysis is repeated and this results in model (6) which is shown in table 3.6.2.6. Model 6 has a slightly decreased R_N^2 (0.812) compared to model 5. All coefficients have maintained their direction with minor changes to the strength of their effects. Most importantly, one variable has been dropped while maintaining a high R_N^2; the efficiency of the model has thus been increased.

Table 3.6.2.6: Model (6) including all variables (Reference category = Bike)

	Parameter	B	Wald
Bus	Intercept	-0.647	0.250
	Income (euro's)***	-0.004	6.278
	Place of residence (Utrecht)*	-1.879	3.787
	Travel duration (minutes)***	0.119	12.432
	Need for speed	-0.100	0.052
Train	Intercept**	-4.105	5.699
	Income (euro's)	-0.003	1.781
	Place of residence (Utrecht)***	-6.400	15.534
	Travel duration (minutes)***	0.188	23.446
	Need for speed**	-1.124	3.556

* $p < 0.10$ ** $p < 0.05$ ***$p < 0.01$ R_N^2 = 0.812 R_{cs}^2 = 0.722

The six models that were introduced in this chapter mostly support what previous studies have also found. Firstly, it was shown that socio-economic and demographic variables play an important role in predicting mode choice behavior. In addition, it was shown that the fit of such a model can be improved by adding attitudinal variables such as the Need for speed component score. However, the spatial variables used in this study did not proof to be significant in predicting the mode choice of students.

These results can also be interpreted from the perspective of complexity theory that was developed in chapter 2. From his perspective the results suggest that the three different modes (bike, bus and train) occupy different positions in the *fitness landscape* of modes. In a sense each mode thus has a specific niche in which it operates and caters to the differing needs of students. The next chapter will build further on this. Because in this study is students were asked for both their primary and alternative mode choice, it is possible to consider the impact of situational variables on mode choice. Such situational variables include the weather or congestion (see chapter 3.2).

This chapter has mainly tested ideas that were already present in the literature on transport mode choice. It answers the ninth sub question: *"What factors influence the mode choice of students?"* It is found that both hard and soft factors affect the mode choice of students in Utrecht. Except for age, all socio-economic and demographic factors were found to be significant predictors of mode choice (income, gender, city of residence, household composition, education). Regarding the spatial-characteristics, both distance to the closest transport stop as the pre-transport mode were found to be significant. Subsequently, trip duration is also a significant predictor of students' mode choice. Finally, the students attitude towards combining several activities along the way also determines their mode choice.

The model that is the best fit of the data includes 5 parameters. These are income, place of residence, travel duration and the Need for speed factor score. Based upon this sample mode choice can thus be predicted most accurately by including both hard and soft factors. Spatial characteristics add nothing to the fit of the model to the sample. However, it should be noted that the place of residence could arguably be grouped as an spatial variable if one considers that every city to be a different environment *an sich*.

Tale 3.6.2 summarizes which determinants of mode choice that have previously been studied are also found to be significant in the present study. The next chapter will look into constructing an agent based model that deals with mode choice as a complex adaptive system.

Table 3.6.2 : Significant determinants of mode choice

Personal characteristics:	**Spatial characteristics:**	**Transport mode-specific characteristics:**
Demographic variables	Population density	Time
Age	Distance to closest public transport stop	~~Costs~~
~~Gender~~		~~Transfer waiting time~~
~~Household composition~~		~~Travel time use opportunity~~
Socio-economic variables		
Income		
Education		
~~Car-ownership~~		
~~Bike-ownership~~		
Attitudes		
Lifestyles		

Strikethrough = not significant
Underline = not tested

3.7 An agent based model for mode choice

Chapters 2.1 and 2.9 argue that traditional methods of quantitative data analysis are outdated because they cannot cope with complexity. Chapter 2.8 presents agent-based modeling as one of the alternatives to these traditional models. This chapter aims to formulate an agent-based model for transport mode choice of students in the Utrecht area. It builds on the results of chapter 3.6 and uses model 6 as the starting point. It should be noted that this chapter is experimental. More specifically, the agent-based model moves away further from model 6 with every step of increased sophistication. Chapter 2.8 introduced the three aspects of agent-based models as defined by Macal and North (2010). To recap, an agent-based simulation consists of: (i) agents with attributes and behaviors (ii) relations between agents and methods of interaction between them (iii) an environment in which the agents interact. These three aspects are used to introduce and construct the agent-based model of mode choice.

3.7.1 The agents

First, the attributes of the agents need to be defined. In the case of this thesis, the agents are the students. The attributes of these "student agents" are those variables that are needed to predict their mode choice. Model 6 uses income, place of residence, travel duration and need for speed as predictor variables. In the MNL model these variables are all static; they do not change over time. In order to construct an agent-based model it is necessary to use dynamic variables that can change over time. To clarify, chapter 2.5 shows that a relatively simple equation can produce complex behavior:

(1) $t_{n+1} = rt_n (1-t_n)$

However, this equation presents a time-series in which every new step builds on the previous one. In that fashion complexity is induced. In order to produce a complex model of mode choice it is necessary to identify several dynamic parameters that are subject to change over time, or build on the previous iteration of the model. As model 6 does only include one such variable –travel duration- it needs to be adapted in order to be suited for use in an agent-based model. The survey provides the basis for this alteration. It includes questions regarding the transport mode choice of students in different circumstances or contexts. More specifically, students were asked how the weather, congestion and other scheduled activities influence their mode choice (See chapter 3.4.4 or appendix B). The scores of the participants on these questions are converted from a 5 point Likert-scale to a dummy variable. Scores of 3 and up convert to a value of 1 and scores bellow 3 convert to a value of 0. For example, if a participant strongly agrees (5) with the statement "I use this mode in bad weather" he or she is supposed to use that mode in bad weather (1).

In order to increase the amount of information on the relative attractiveness of the modes, both primary and alternative mode choices are used to estimate model (7). In total 298 cases are used. It should be noted that the inclusion of both primary and alternative modes results in a decreased predictive value for variables measured on the participant level. To clarify, income is measured for every student, but students answered questions about two separate modes. As such, much of the variance in the mode choice of students cannot be explained by demographic or socio-economic variables, but rather by the mode specific variables.

Table 3.7.1.1 shows the result of entering the three dummy variables –weather, combining activities and avoiding congestion- into the existing model 6. As suggested, the entry of these dummies affects the significance of the variables included in model 6. In effect, neither income nor need for speed are significant predictors of mode choice. This means that they are statistically redundant and can be dropped from the model (Field, 2009). Model 7 has a a R_N^2 of 0,659, which is lower than the R_N^2 of model 6. This decrease in model fit can be attributed to the larger number of cases included in model 7 and the decreased predictive power of person-specific variables.

Table 3.7.1.1: Model (7) including all variables (Reference category = Bike)

	Parameter	**B**	**Wald**
Bus	Intercept***	-2.014	8.286
	Place of residence (Utrecht)***	-2.965	9.696
	Travel duration (minutes)***	0.051	9.204
	Avoid congestion (reference category = yes)***	1.519	7.857
	Combine activities (reference category = yes)***	2.280	13.955
	Weather (good)***	-1.923	6.224
Train	Intercept***	-2.882	13.492
	Place of residence (Utrecht)***	-4.828	18.497
	Travel duration (minutes)***	0.086	23.245
	Avoid congestion (reference category = yes)	0.590	1.433
	Combine activities (reference category = yes)***	2.153	6.669
	Weather (good)*	-1.665	3.393

* p < 0.10 ** p < 0.05 ***p < 0.01 R_N^2 = 0.686 R_{cs}^2 =0.659

In model 7 rainy weather conditions make students more likely to use the bus or train. However, students are less inclined towards to use the bus or train to avoid congestion or crowding. In addition, when students plan on combining multiple activities along the way they are also less likely to use either form of public transport. The duration of the trip increases the likelihood that students will pick the bus or train. If students live outside of the Utrecht municipal area, they are also more likely to use public transport. It should be noted that most dynamic parameters have lower scores for the train. This might suggest that train usage is less susceptible to bad weather conditions and the avoiding of crowding or congestion. It is possible that this is caused by a lack of alternatives that train users have because of their larger travel duration.

The simulation uses 1000 generated agents, which are based on the students in the sample. This means that the attributes of the agents correspond to those of the students in the sample. For example, the means and standard deviations found in the sample were entered into Excel's "NORMINV" function in order to create a similar distribution. It should be noted that not all variables were normally distributed. Travel duration was not normally distributed; both a Kolmogorov-Smirnov and Shapiro-Wilk test are significant (p < 0.01). In order to adequately simulate this data, the place of residence was first generated. After this the different means and standard deviations found in the sample for these groups were used to generate the travel duration.

3.7.2 The environment and interaction

The agent based simulation is performed in Microsoft Excel. While many researchers use object oriented programming languages in order to execute their ABM's, this is beyond the scope of a masters' thesis in terms of available time, equipment and money. Furthermore, a simulation in Microsoft Excel allows for the demonstration of the concept behind ABM's and their possible use in transportation research, which is one of the aims of this thesis. Appendix C contains the excel file for reference. In this simulation, the environment does four things. First, it counts the number of agents that choose a particular mode and returns that number. Secondly, it determines the weather; this can done both randomly or manually. Thirdly, it randomly determines if a specific mode breaks down

–this simulates *systems failure*. Fourthly, the environment determines if a mode is congested according to certain thresholds.

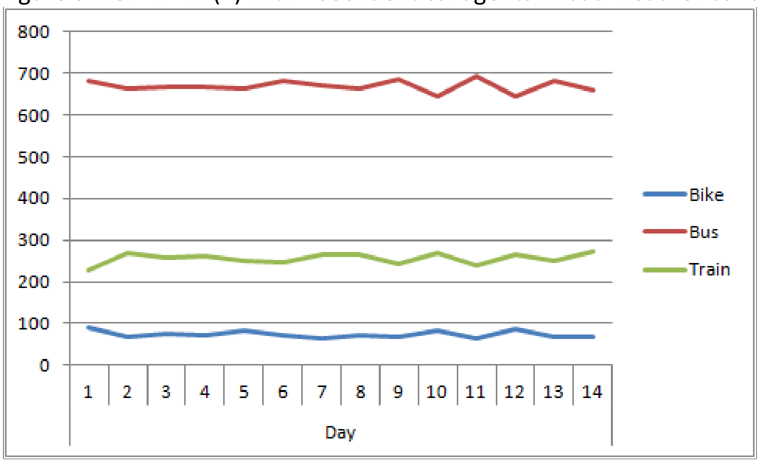
As said, the agents behave according to model 7. They determine their mode choice on their place of residence, travel duration, whether they want to avoid congestion or not, the weather and whether they want to combine several activities. The place of residence and the intercept are fixed for the entire duration of the simulation. The decision to combine activities is made randomly. The decision to avoid congestion is based upon if the mode the agent used the day before was congested. The weather is inherited from the simulation environment. The travel duration is fixed, but can increase due to a mode break down. These interrelations between the environment and the agents are central to the simulation and relate to the second aspect of Macal and North (2010). Each time the simulation is run, the agent based model simulates 14 days of mode choice.

The accuracy of this Excel based model was tested by entering the 151 participants into Excel and evaluating the difference between the predicted outcome category in SPSS and Excel. Depending on the different weather conditions the Excel model predicts the same results as SPSS. Generally, the similarity between the predictions is between 80% and 95%. This indicates that the Excel agent based model performs similar to the model run in SPSS. The differences between the models can be explained by the fact that the weather is considered to be a normal parameter in the Excel model. This means that for a given iteration, the weather is either rainy or not-rainy. In SPSS weather was considered a dummy variable that could be in effect or not, regardless of any inherent logical discrepancies resulting from this (the weather cannot be rainy and not-rainy at the same time).

3.7.3 Running the initial simulation

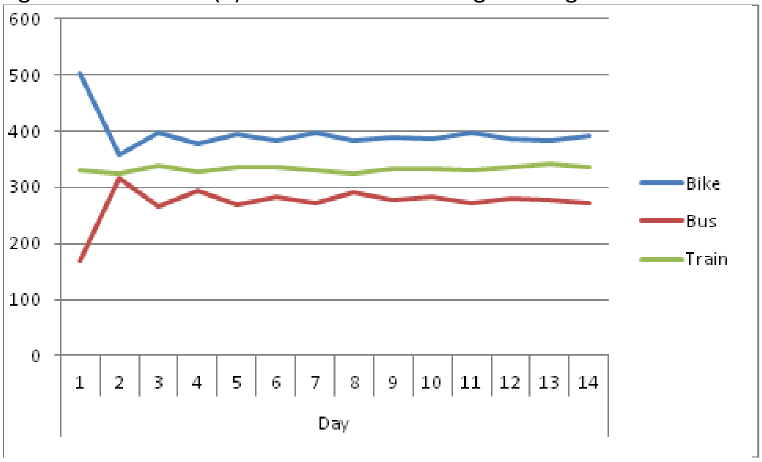
To illustrate the workings of the agent-based model, it is first run with 1000 agents that exhibit the same kind of behavior. All transport modes are considered to be resistant to system failure. Figure 3.7.3.1 shows the result of running the simulation with stable weather conditions. The figure shows that in rainy weather conditions, most agents in the simulation choose to use the bus. The number of bus-users fluctuates between 650 and 680. This fluctuation can be attributed to the random generation of the decision by the agents to combine activities or not. Most agents alternate between choosing the bus and train or bus and bike. Only a few (n < 10) agents switch from train to bike every day. In total, over the 14 days the simulation looks to be relatively stable as if following a kind of *attractor*.

Figure 3.7.3.1 ABM (1) with 1000 identical agents in bad weather conditions



As opposed to figure 3.7.3.1, figure 3.7.3.2 shows how the agents behave in stable good weather conditions. The figure shows that the bike mode is the most popular amongst the agents with just under 400. The train mode remains stable around 330 agents and the bus attracts about 290 agents every day. From the figure, it seems that the simulation needs 2 – 3 days to stabilize itself, with day 1 and day 2 being the most dissonant from the rest of the series. This overture also occurs in figure 3.7.3.1 but is less visible there because of the minor difference with the modal split during the rest of the simulation.

Figure 3.7.3.2 ABM (1) with 1000 identical agents in good weather conditions



The first two figures show that the agent-based model reaches an *attractor* after only a few days if weather conditions are kept stable. Figure 3.7.3.3 shows what happens if the weather turns after a week of stability. On day 7 almost all bike users switch to the bus, some train users do the same. Only a very small amount of agents still chooses to travel by bike. After the initial shock, the system seems to stabilize after 3 – 4 days. Congestion causes agents to return to the bike and train modes. The switch in weather conditions can be thought of as a *bifurcation point*; after the change of weather, the system stabilizes in a new *attractor*.

Figure 3.7.3.3 ABM (1) with 1000 identical agents 7 days of not-rainy followed by 7 rainy days

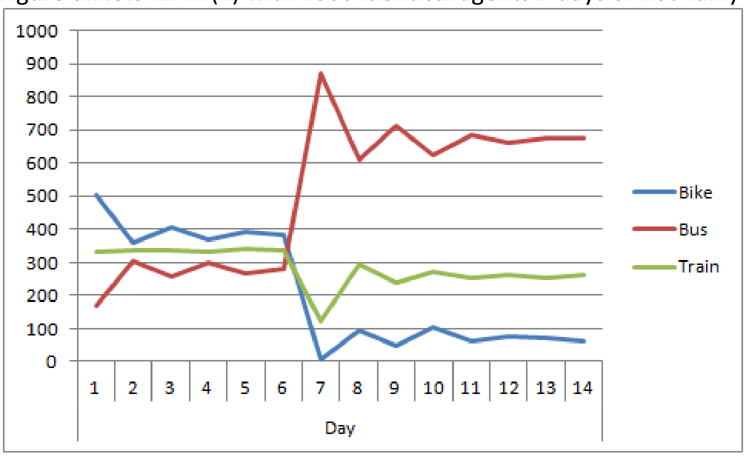
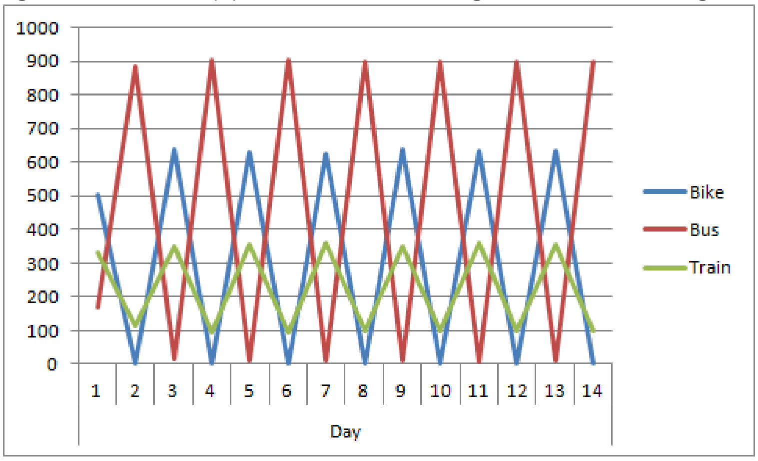


Figure 3.7.3.4 shows what happens when the weather alternates between rainy and not-rainy for 14 days. From the figure, it is apparent that the simulation does not settle, but oscillates between 2 points with only minor deviations. This is caused by the large amount of agents that decide to switch modes when the weather changes; because of this massive switching the system keeps spiking.

Figure 3.7.3.4 ABM (1) with 1000 identical agents with alternating weather conditions



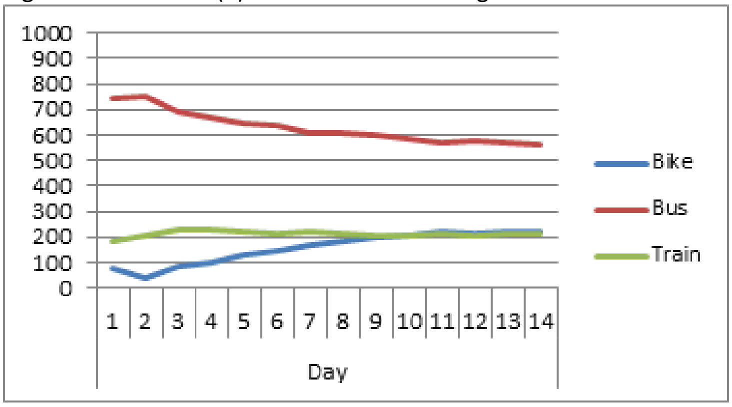
3.7.4 A more advanced agent-based model

In the agent-based model of paragraph 3.7.3 agents decided which mode to take daily. Each decision was made separate from the previous one, so agents did not benefit from their knowledge of their preferred mode. The more advanced agent-based model used in this paragraph does allow for agents to have a "memory". This memory consists of adding up the scores of model (7) for the present and previous day, divided by two. This way, agents use their knowledge of previous iterations of the model in a very basic way. However, agents can only use information of the mode they actually used the day before. For instance, if agent x uses the bus on day one, it does not gather additional knowledge on the train. In addition, the second agent-based model includes variable congestion thresholds for the agents. This means that agents have variable tolerance to congestion. A similar variable threshold is implanted for combining activities. In the second agent-based model all agents have a different probability to combine activities. This reflects differences in lifestyle, as some students might never combine activities in one trip, while others frequently do so.

Another addition to the second agent-based model is that modes can break down. For the simulation this means that modes randomly (p =0,01) get travel duration. This simulates break downs and disruptions in public transport due to extreme weather conditions or material failure. A breakdown of the bus and train mode is considered to be system-wide so all agents using that particular mode are affected. For the purpose of the simulation the bike mode is assumed not to break down. This would require additional processing power as the bike cannot be assumed to break down system-wide and therefore has to break down individually.

Figure 3.7.4.1 shows what happens when agents are given a kind of “memory” that allows them to consider previous days in their mode choice. At first, the amount of agents choosing to travel by bus is similar to figure 3.7.3.1 of ABM (1). However, as time progresses the amount of agents that choose the bike mode increases. This is a direct consequence of introducing memory to the agents and the fact that if an agent decides to combine activities the bike mode becomes more attractive. As days pass an increasing amount of agents will randomly have decided to combine activities at least once. This increases the score of the bike mode relative to that of the bus, so in the long run an *attractor* state is reached just above 200 bike users.

Figure 3.7.4.1 ABM (2) with 1000 identical agents in bad weather conditions



A similar effect is visible when figure 3.7.4.2 and 3.7.3.2 are compared. In figure 3.7.4.2 the amount of bike users gradually increases over time to around 525, while the amount of bus users decreases to about 250. The effect of the memory of agents is also visible when comparing 3.7.3.4 and 3.7.4.3. The oscillations are less pronounced in figure 3.7.4.3 because of the smoothening that occurs by the agents considering the previous day.

Figure 3.7.4.2 ABM (2) with 1000 identical agents in good weather conditions

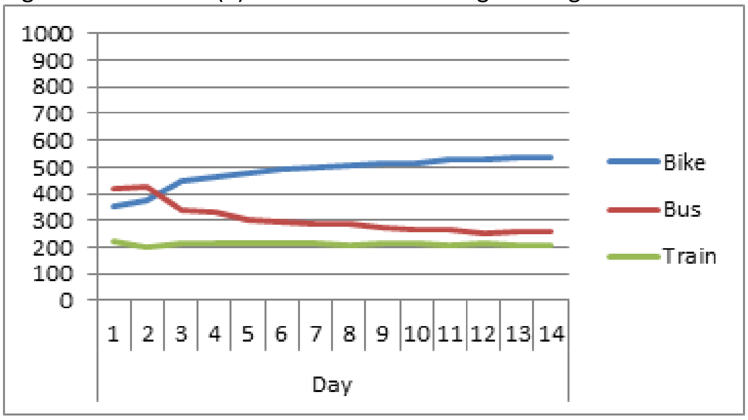
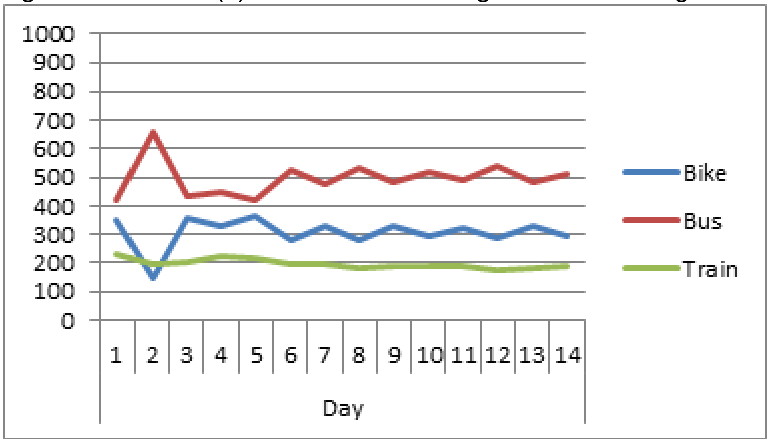


Figure 3.7.4.3 ABM (2) with 1000 identical agents in alternating weather conditions



While the agent based models used in this thesis is very rudimentary in the sense that it only incorporates some aspects of mode choice and because it only uses 1000 agents, it still offers some insights for the study of transport mode choice and transport as a complex adaptive system. First and foremost, the agent based model provides a graphical overview into the workings of complexity. Instead of remaining stable like traditional models, the agent based model shows fluctuations over time. These fluctuations occur both when the simulation is held stable in terms of weather and when the weather changes from day to day. Even when the system seemingly oscillates between two values, the exact number of agents choosing a mode differs every day.

The agent based model illustrates that mode choice is a dynamic phenomenon that is highly dependent on context. The model might be able to illustrate the differences between using equilibrium models and dynamic models. The former would have resulted in a graph with straight horizontal lines, as it would consider mode choice to be a result of either supply and demand or the result of more static supply-side variables. The current ABM shows how minor changes in agent's decisions can cause fluctuations in mode choice. Furthermore, it shows that variables such as the weather can have a major impact on mode choice. In terms of complexity theory, the ABM shows the *non-linearity* and interconnectivity of transport mode choice.

This chapter answers the tenth sub research question: "To what extent can the existing agent-based models on mode choice be improved by including attitudinal parameters? " In terms of the current state of large scale agent based transport simulations, the present simulation shows the importance of adding context variables such as the weather. Most of the current ABM's do not incorporate the effects of weather and therefore overlook a possibly important variable that predicts mode choice. Furthermore, most of the existing ABM's do not incorporate variable thresholds in regard to congestion. Chapter 3.5 shows that students' attitudes towards congestion differ from individual to individual. Some people might be very inclined to avoid any level congestion, while others might never let congestion influence their mode choice. The same line of argument can be made for combining of several activities in one trip. Arguably, the train or bus allows for less flexibility than the car or bike, because the former is marked by timetables and fixed stops while the latter does not have such limitations

Chapter 2.1 presented three guidelines for mobility oriented science. To recap, according to Buscher et al (2011) mobile methods should (i) Highlight how life is woven together by mobility practices, (ii) Study how mobility affects life as a whole, (iii) Consider the way spatial practices become embedded in space and vice versa. When these guidelines are considered, the present agent-based model does not qualify as a *mobile method*. At most, it offers an explanation for how spatial practices become embedded in behavior by including a "memory" in the simulation. However, the agent-based model does provide a look into the workings of mobility systems as complex systems. In the sense of *qualculation* it provides a look into the behavior of students' mode choice that is impossible through direct observation or with traditional models. Moreover, agent-based modelling in general seems a to be a step towards more realistic quantification as it allows for the inclusion of "softer" variables and adaptive behavior. Chapter 4 provides a more thorough evaluation of the use of agent-based modeling in new mobilities paradigm inspired studies.

4. Discussion & Conclusion

4.1 The new mobilities paradigm and complexity theory

In the introduction (chapter 1) of this thesis the aim of this study was presented. To recap, the goal was to contribute to the development of the new mobilities paradigm by lending concepts and tools from the field of complexity theory. The following research question was formulated and can now be answered: ”To what extent do transport geography and subfields from biology relate to each other in terms of complex systems and how can insights from biologic complexity theory be used in improving the applicability of the new mobilities paradigm?”

The new mobilities paradigm and biologic complexity theory have several things in common. Most essentially, both theories aim to understand and describe the behavior of complex systems. Much vocabulary developed within complexity theory can be applied to the study of mobility as proposed by the new mobilities paradigm. Complexity theory jargon offers descriptions of processes that occur in complex systems. This offers the new mobilities paradigm existing conceptualizations for processes that are also observed within mobility. This has the advantage that less new vocabulary has to be developed for the new mobilities paradigm. In addition, the existing conceptualizations of complex systems in complexity theory could be used to expand the understanding of mobility.

Next to the value of complexity theory for the theoretic development of the new mobilities paradigm, complexity theory also offers quantitative empiric methods that can be used to study complex systems. For example, dynamic mathematical models and agent-based models (see chapter 2.8). This is important because the new mobilities paradigm calls for new mobile research methods to be developed. The use of methods that have been developed in complexity theory could contribute to the development of mobile methods. Currently, the new mobilities paradigm adheres to qualitative empiric research methods since quantitative methods are considered to be unable to capture the intricate nature of human behavior. As opposed to traditional quantitative methods, the quantitative methods that have been developed for complexity theory arguably do capture many aspects of human behavior such as intentionality. For instance, Chapter 3 shows that in an agent-based model, agents can learn from their previous decisions.

The persisting importance of predictive models for policymakers makes it important to develop quantitative methods in mobility research. New quantitative methods could be used to develop new – dynamic- models that are more able to capture complex human behavior. This is not to say that complexity theory based quantitative models capture all aspects of human behavior, but arguably are better at this than traditional models. If more accurate models are used in practice, this could lead to better policy formation and more effective policy. Qualitative methods without question are important in order to establish the meaning of mobility in human lives.

The conclusion of the present theoretic study of the new mobilities paradigm and complexity is by no means an exhaustive one. Chapter 2 of this study merely shows that complexity theory and the new mobilities paradigm share many views and provides several possible starting points for the inclusion of complexity theoretic insights in new mobilities paradigm inspired research. This thesis shows that the study of mobility as a dynamic and unpredictable phenomenon advocated by the new mobilities paradigm does not disqualify the use of quantitative methods. Contrariwise, the view that mobility is a complex phenomenon opens the door to quantitative methods that have recently been developed in order to cope which such dynamic and unpredictable behavior.

These methods that can be used to study complex systems have been developed in scientific fields that arguably do not neighbor human geography. For example, agent-based modeling relies heavily on computer simulations and has been developed by computer- and information scientists. Consequentially, the use of these methods requires a venture of most human geographers into new disciplines that are unfamiliar to them. It could be argued that such ventures are not for a human geographer to make and that human geographers should play to their own strengths. However, human geographers have an extensive knowledge on spatial phenomena and can contribute to the future development of these "complex" quantitative research methods. For instance, studies in transport geography (including this one) have shown that choice models can significantly be improved by including soft factors such as attitudes. The experience of human geographers in dealing with space, human behavior and modeling can arguably contribute to the quality of methods such as agent-based modeling.

This thesis has shown that an agent-based model can be used to predict transport mode choice. This has been done before but, to knowledge of the current author, this is the first time that weather and attitudes towards congestion and flexibility are included in such a simulation. Including these soft factors in a simulation of mode choice shows that is possible to use "complex" quantitative methods theory in a study of mobility as a complex system. The agent-based model developed in this thesis illustrates the unpredictability of mode choice on a day to day basis. As such, it shows that the use of static choice models that focus on socio-economic and demographic factors might not provide optimal predictions.

Currently, the current agent-based model might be too inaccurate to be applied, but this type of model could be used in transport mode demand analysis made by transport-companies and –local-governments. Currently, the model can be used to illustrate to students, professionals and policy makers that static prediction of mode choice with traditional models fails to capture several aspects. For example, the agent-based model shows how individual decisions to avoid congestion can affect the total demand for a certain mode. In addition, it shows how the history of an individual with a certain mode influences his or her future mode choice.

4.2 Limitations and shortcomings

While paragraph 4.1 shows that this thesis yields new findings, it is also important to point at the shortcomings and limitations of this study. Future studies can benefit from these insights and built on the experiences of this study.

On a theoretical level this thesis dealt with the similarities between complexity theory and the new mobilities paradigm. While many sources were consulted in order to give the most thorough overview of complexity, it goes beyond the scope of a thesis to give a complete overview of all the literature of complexity theory. Arguably, such an overview would require many years of study, since the complexity theory is all but a well-defined field. As a results of the selection that was made of complexity theory it goes without question that aspects of this theory have been missed or overlooked. Consequentially, this thesis cannot be seen as a complete overview of the similarities and differences between complexity theory and the new mobilities paradigm.

A second theoretical limitation is caused by the wide variety of theories discussed in this thesis. More specifically, while the main objective was a comparison of complexity theory and the new mobilities paradigm, many other theories had to be drawn in to make such a comparison possible. For instance, in order to understand the new mobilities paradigm, one has to have some knowledge of actor-network theory and so on. Because of the wide variety of theories that were included it was not possible to discuss every theory thoroughly. Resultantly, not all theories have been given the attention they deserve in relation to complexity theory and the new mobilities paradigm. In this context, the present thesis should perhaps be seen as a theoretical exploration of the tangents of complexity theory and transport geography.

The empirical study arguably has more severe shortcomings and limitations. To start, an important variable that is known to govern mode choice that has not been addressed directly in this thesis; costs. It should be noted that Dutch students get a free public transport subscription and typically own a bike. Because this study only includes the bike, bus and train modes, it only includes modes that are "free" to use for the students. As such monetary costs are not considered in this study. More fundamentally, the use of the MNL-model in order to predict a categorical outcome has received major criticisms in the past. The main scope of these criticisms focuses on the fact that MNL-models assume independence of irrelevant alternatives. More specifically, this assumption states that the odds of the model predicting a certain outcome do not change if additional options are added. To elaborate, for this thesis this means that adding a fourth mode to model should not alter the odds for the existing four modes. In other words, if alternative C is added to choice set (A,B) resulting in the set (A,B,C) this must not make A preferable to B. The inclusion of C should not influence the preference for A or B; C is irrelevant for the choice between A and B. The literature (Hensher and Button, 2000) suggests that this assumption is often violated by the MNL model in transport mode choice studies. Some alternatives have already been explored and introduced. These could not be used in this thesis because of the technical limitations of the SPSS program. Still, this means that the empirical findings of this thesis could be falsified using newer, more sophisticated, models.

There are also shortcomings in the agent-based model. First and foremost, the construction of the ABM was based upon the MNL model, but was not exactly the same. This means that the significance of the ABM could be questioned. Furthermore, the ABM makes several assumptions about human behavior which were not explicitly tested in the survey. For instance, it seems logical to assume that students avoid congestion, but this is not a fact established above doubt. In addition, the ABM uses 1000 randomly generated agents, which is far less than similar simulations currently in use. These simulations can use up to 20 million agents.

It also possible to criticize the additional value of using an agent-based model in the present study. Much of the effects that were simulated in the agent-based model also have been captured in the MNL model. Weather for instance can be included as a dummy variable in a MNL choice model, and the same goes for avoiding congestion and combining several activities. The only things that are unique to the agent-based model are the memory of the agents, the individual threshold values for avoiding congestion and combing activities and the random breaking down of the modes. In response to such criticisms it could be said that the current agent-based model is a proof-of-concept. More extensive agent-based models could include longer term memories and differing agent behavior. In addition, such simulations could also include more sophisticated learning mechanisms for agents, such as the agents recognizing that it is bad weather and basing their mode choice on their previous experience with each mode in bad weather. The application of agent-based modeling in the present study is thus not representative for the general practice of agent-based modeling. When the possibilities of agent-based models are considered in full, it arguably allows for more sophistication than MNL models. Such agent-based models could be used to estimate transport mode demand in metropolitan regions. More specifically, transport companies could use agent-based models to predict and plan the amount of busses needed on a specific route.

Furthermore, while the agents in the second ABM did have a kind of memory. This memory only included the previous day in the mode choice. Based upon the literature on habitual mode choice, it can be argued that in real life people consider their previous experiences when choosing a mode. Within excel, such memory is hard to achieve. Object oriented programming languages often used in agent-based modeling might be more suitable for this. In addition, some of the effects that were observed in the agent-based model are attributable to random effects (for instance, the decision of agents to combine activities along the way), these effects rely on the quality of the random number generator in excel. The current author has no in depth knowledge of such random number generating algorithms, but it goes without question that the quality of such an algorithm should be evaluated in more sophisticated ABM's. Moreover, the agent-based simulations in this thesis run 14 iterations or days. However, at day 14 it was not always clear whether or not the simulation had already reached a stable state or *attractor*.

4.3 Future research

While the limitations and shortcomings of this thesis are exhaustive, it does provide room for new research in the future. Most of the shortcomings presented above stem from the limited availability of time and resources that are connected to the writing of a master thesis. Larger projects should be able to overcome these constraints in time. The main finding is that subjective variables can be included in an agent based model and that these variables can also improve the fit of an MNL model.

On a theoretical level, the new mobilities paradigm could benefit from the study of complexity theory. Future studies could look deeper into the similarities of the new mobilities paradigm and complexity theory on a more specific level. For instance, the new mobilities paradigm conception of dynamism could be compared to complexity theories concept of dissipation. Furthermore, more theoretical research could uncover deeper going similarities between complexity theory and other theories in the social sciences. For example, this thesis shows how actor-network theory and complexity theory share many insights. Arguably, there are more recently developed theories that deal with complexity that could also be used to advance our understanding of complex systems.

Most importantly, a conception of meaning is seemingly absent from complexity theory. Future research could try to identify or locate such conceptions of meaning within complexity theory as viewed by other authors than the ones used in this thesis. In sum, the analysis of socials systems as complex systems needs a lot of development and is as of yet still far from mainstream. In the future, research could focus on the implications of the “complexity turn” that is taking place within social science (Urry, 2007).

On the applied and empiric level future studies into mode choice agent-based models could develop more sophisticated agent behaviors that better capture human behavior. Furthermore, future studies should look into the performance of agent-based models as compared to traditional models such as MNL modeling. Benchmarking the models with historic figures on mode use could potentially decide if agent-based modeling is the better alternative.

4.4 Concluding remarks

This thesis opened with a brief discussions of the multidisciplinary tendencies of human geographers. It was argued that to contribute to solving contemporary societal problems, scientists need to look across the borders of their disciplines. This thesis argues that in order to advance our understanding of complex systems in society the same combined effort is needed. The point was made that in order to firm our grasp of complexity both theoretical and empirical studies are of importance. In regard to empirical research both quantitative and qualitative methods are likely to contribute towards our understanding of complex systems.

This thesis does not present any new ways of influencing travel behavior. It merely illustrates the difficulties that need to be dealt with in policy formation. Moreover, this thesis suggests that by looking at different disciplines it is possible to gain new insights into phenomena that us human geographers have studied exhaustively. This thesis shows that geography, physics and biology are trying to deal with unpredictable and emergent system behavior. In the opinion of the author the science of human geography could potentially benefit from incorporating ideas of complexity theory. Hopefully, this thesis will contribute something towards the promotion of complexity theory within our field.

5. Literature

Abou-Zeid, M. and D.M. Scott (2011), Current issues in mode choice modeling. Transportation, 38(4), pp. 581-585
Adly, P. and D. Bissel (2010), Mobilities, meetings and futures: and interview with John Urry. Environment and Planning D: Society and Space, 28, pp. 1 – 16
Aitken, S.C. and G. Vallentine (2006), Approaches to human geography. Sage: Londen.
Amin, A. and N. Thrift (2001), What kind of economic theory for what kind of economic geography?'' Antipode, 32, 4 – 9
Andersson, C. (2008). Ontogeny and Ontology in complex systems modeling. In S. Albeverio et al. (eds.), The dynamics of complex urban systems: an interdisciplinary approach (pp. 43-58). Heidelberg: Physica
Asensio, J. (2011), Transport Mode Choice by Commuters to Barcelona's CBD
Axelrod, R. (1997), The Complexity of Cooperation: Agent-Based Models of Competition and Collaboration. Princeton University Press, Princeton
Axtel, R.and J.M. Epstein (1996), Growing Artificial Societies: Social Science from the Bottom Up. The Brookings Institution, Washington
Barabasi, A. (2004), Linked: How everything is connected to everything else and what it means for business, science and everyday life. Penguin: New York
Bentham, J. (1791), The Panopticon writings. Edited and introduced by Miran Bozovic (1995). Verso, Londen.
Bertalanffy, L. von (1968), General system theory: foundations, development, applications. George Braziller.
Bhat, C.R. (1995), A heteroscedastic extreme value model of intercity travel mode choice. Transportation Research Part B: Methodological,29(6), pp. 471-483
Buehler, R. (2011), Determinants of transport mode choice: a comparison of Germany and the USA. Journal of Transport Geography, 19, pp. 644 – 657
Buscher, M., J. Urry, K. Witchger (2010), Mobile Methods. Routledge, Londen
Byrne, D.S. (1998), Complexity theory and the social sciences. Routledge: New York.
Bryman, A. (2008), Social research methods. Oxford university press: Oxford.
Brockman, D., L. Huffnagel and T. Geisel (2005), The scaling laws of human travel. Nature, 439, pp. 462- 465
Bosco, F.J. (2005), Actor-Network Theory, Networks, and Relation Approaches in Human Geography. In: Aitken, S.C. and G. Vallentine (eds.) Approaches to human geography. Sage: Londen
Campbell, C. (1995), Does Quantum Theory Add to the Geographic Perspective? The Professional Geographer 47(2), Pages 216 – 217
Cao, X., Mokhtarian, P. L. ,Handy, S. L. (2008) Examining the Impacts of Residential Self-Selection on Travel Behavior: Methodologies and Empirical Findings. Available online: http://pubs.its.ucdavis.edu/ [accessed 14-01-2012]
Capra, F. (2002), The hidden connection: A science for sustainable living. HarperCollins.
Castree (2009), Charles Darwin and the geographers. Environment and Planning A, 41, pp. 2293 – 2298
Castells, M. (2000) The rise of the network society. Blackwell publishers.
Castellani, B. and F.W. Hafferty (2009), Sociology and complexity science: A new field of inquiry. Springer: Berlin.
CBS (2011), Jaarboek onderwijs in cijfers. Beschikbaar online: http://www.cbs.nl/NR/rdonlyres/FC6D3388-0F9E-4129-8F2B-53022BA3F774/0/2011f162pub.pdf [accessed 01-12-11]
CBS Statline (2011), Gemiddelde studieduur van afgestudeerden. Available online: http://statline.cbs.nl/StatWeb/publication/?VW=T&DM=SLNL&PA=71073ned&LA=NL [accessed on 01-12-11]
Changizi, M.A. and M. DeStefano (2009), Common scaling laws for city highway systems and the mammalian neocortex. Available online: http://www.changizi.com/citybrain.pdf [accessed on 15-01-10]

Chappel, J.E. (1995), Geography and Quantum Physics. The Professional Geographer 47(2), pp. 220 – 221

Ciari, F., M. Balmer, K.W. Axhausen. A new mode choice model for a multi-agent transport simulation. Swiss Transport Research Conference Paper. Available online: http://e-collection.library.ethz.ch/eserv/eth:30908/eth-30908-01.pdf [Accessed on 29-12-2011]

Chettiparamb, A. (2006) 'Metaphors in Complexity Theory and Planning' Planning Theory, 5, pp. 71 – 91

Christaller, W. (1933), Christaller, Walter. Die zentralen Orte in Suddeutschland. Gustav Fischer

Coleman, J.S. (1986), Social Theory, Social Research and a Theory of Action. American Journal of Sociology, 91(6), pp. 1309 - 1335

Commins, N. and A. Nolan (2006), The Determinants of Mode of Transport to Work in the Greater Dublin Area. ESRI Papers WP268

Comunian, R. (2010), Rethinking the creative city: The role of complexity, networks and interactions in the urban creative economy. Urban studies, 48(6), pp. 1157 - 1179

Courtney , L. and W.G. Hardwick (1995), Self-Organizing Systems in Geography: A response to Peterman. The Professional Geographer 47(2), pp. 218-220

Creemers, L. (2010), Do weather conditions and weather forecasts trigger changes in our daily travel behavior. Available online: https://uhdspace.uhasselt.be/dspace/bitstream/1942/12530/1/05228112009324.pdf [Accessed on 30-01-2012]

Crooks, T.A. (2010), Using Geo-spatial Agent-Based-Models for Studying cities. Working paper, available online at: http://www.casa.ucl.ac.uk/working_papers/paper160.pdf [Accessed on 04-01-2012]

Danowski, J.A. and D.W. Park (2009), Networks of the dead or alive in cyberspace: public intellectuals in the mass and internet media. New media society, 11, pp. 337 – 356

Desprez, N. (2007), Poisson Saturne attractor. Available online: http://www.chaoscope.org/gallery.htm [Accessed on 04-07-2011]

Driscoll, C. (2008), On our best behavior: optimality models in human behavioral ecology. Studies in History and Philosophy of Biological and Biomedical Sciences, 40, pp. 33–141

Driver (2010), Charles Darwin and the geographers: unnatural selection'' Environment and Planning A, 42, 1 – 4

Finnegan (2010), Darwin, dead and buried? Environment and Planning A, 42, pp. 259 - 261

Flyvbjerg, B. (2001), Making Social Science Matter. Cambridge University Press, Cambridge.

Frank, L., M. Bradley, S. Kavage, J. Chapman, K. Lawton (2007), Urban form, travel time, and cost relationships with tour complexity and mode choice. Transportation, 35(1), pp. 37-54

Frenken, K. (2006), Innovation, evolution and complexity theory, Cheltenham: Elgar

Garling, T. and K.W. Axhausen (2003), Introduction: Habitual travel choice. Transportation 30(1), pp. 1 - 11

Goodwin (2003), How easy is it to change behavior? In: Fifty years of transport policy, proceedings of the European Conference of Ministers of Transport. OECD Publishing. Paris.

Geyer, R. and S. Rihani (2010), Complexity and Public Policy: A new approach to 21st century politics, policy and society. Routledge, New York.

Harisson, S., D. Massey, K. Richards (2006), Complexity and emergence (another conversation). Area, Volume 38, Issue 4, pages 465 – 471.

Hogeschool Utrecht (2010), Jaarverslag 2010. Available online: http://www.hu.nl/~/media/HU-JAARVERSLAG/Docs/jaarverslag%20%20HU%202010%2015-6.ashx [Accessed on 10-12-11]

Hotelling, Harold (1929), "Stability in Competition", Economic Journal 39(153). pp. 41–57

Holley, D., J. Jain, G. Lyons (2008), Understanding business travel time use and its place in the working day. Time Society, 17(1), pp. 27-46

IBG (2011), Voorwaarden studiefinanciering. Available online: http://www.ib-groep.nl/particulieren/studiefinanciering/sfho/voorwaarden.asp [Accessed on 01-12-11]

Johansson, M.V., T. Heldt, P. Johansson (2006), The effect of attitudes and personality traits on mode choice. Transportation Research Part A, 40, pp. 507 - 525

Johnson, J. (2010), The future of the social sciences and humanities in the science of complex systems. Innovation: The European Journal of Social Science Research, 23(2), pp. 114 – 134

Kallis, G. and R.B. NorGaard (2009), Coevolutionary ecological economics. Ecological Economics, 69, pp. 690 – 699

Kaufman, V. (2000), Modal practices: from the rationales behind car and public transport use to coherent transport policies. World Transport Policy and Practice, 6, pp. 8 - 17

Kearns (2009), The descent of Darwin. Environment and Planning A, 42, pp. 257 – 258

Khalesian,M. and R. Delavar (2008), A Multi-agent based traffic network micro simulation using spatio-temporal GIS. The international archives of the photogrammetry, Remote Sensing and Spatial Information Sciences, 37, pp. 31 - 36

Kolbl, R. and D. Helbing (2003), Energy laws in human travel behavior. New journal of physics, 5, pp. 1 – 12

Krygsman, S., Dijst, M., Arentze, T., 2004. Multimodal public transport: an analysis of travel time elements and the catchment ratio. Transport Policy, 11(3), pp. 265–275

Latour, B. (2005), Reassembling the social: An introduction to Actor-Network-Theory. Oxford, Oxford university publishing.

Latour, B. (2010), On actor network theory: A few clarification pluse more than a few complications. Available online: http://www.cours.fse.ulaval.ca/edc-65804/latour-clarifications.pdf [Accessed on 30-03-2011]

Latour, B. (2010A), Tarde's idea of quantification. Chapter in M. Candea The social after Gabrial Tarde: Debates and assessments. Routledge, London, pp. 145 - 162.

Laurier, E. (2002), The region as a socio-technical accomplishment of mobile workers. In: B. Brown, N. Green and R. Harper (eds.), Wireless World: Social and Interactional Aspects of the Mobile Age (pp. 46-61). London: Springer Verlag,

Leary, M.E. (2009), The Production of Space through a Shrine and Vendetta in Manchester: Lefebvre's Spatial Triad and the Regeneration of a Place Renamed Castlefield. Planning Theory & Practice 10(2), pp. 189- 212

Litman T. (2005) Land use impacts on transport: how land use factors affect travel behavior. Available online: http://www.vtpi.org/landtravel.pdf [Accessed 21-12-2011]

Lyons, G., J. Jain and D. Holley (2007), The use of travel time by rail passengers in Great Britain. Transportation Research A, Policy and Practice, 41, pp. 107 – 120.

Lyons, G. and Urry, J. (2005). Travel time use in the information age. Transportation Research A, 39, pp. 257-276

Macal, C.M. and North M.J. (2010), Tutorial on agent-based modeling and simulation. Journal of Simulation 4, pp. 151–162.

Mackenzie, M. (2005), The Problem of the Attractor: A singular Generality between Sciences and Social Theory. Theory, Culture & Society, 22(5), pp. 45 – 65.

May, R.M. (1976), Simple mathematical models with very complicated dynamics. Nature 261, pp. 459 – 467

Martin, R. en P. Sunley (2006), Path dependence and regional economic evolution. Papers in evolutionary economic geography. Available online: http://econ.geo.uu.nl/peeg/peeg0606.pdf [Accessed 24-10-2011]

McNally, M.G. and C. Rindt (2008), The Activity-Based Approach in: Heshner and Button (eds.) Handbook of Transport Modelling. Pergamon.

McGlade, J. and E. Garnsey (2006), Complexity and co-evolution. Edward Elgar: Londen.
Meister, K., M. Balmer, F. Ciari, A. Horni, M. Rieser, R.A. Waraich, K.W. Axhausen (2010) Large-scale agent-based travel demand optimization applied to Switzerland, including mode choice. Available online: http://www.matsim.org/node/507 [Accesed 12-12-2011]
Mitchel, M. (2009[a]), Complexity: A guided tour. Oxford university press.
Mitchel, S.D. (2009), Unsimple truths: Science, Complexity and Policy. University of Chicago Press, Chicago.
Mokhtarian, P.L. and C. Chen (2004), TTB or not TTB, that is the question: a review and analysis of the empirical literature on travel time (and money) budgets. Transportation Research Part A, 38, pp. 643 – 675
Mokhtarian, P.L. and I. Salomon (2001), How derived is the demand for travel? Some conceptual and measurement considerations. Transportation Research Part A, 35, pp. 695 - 719
Montello, D.R. (2001), Scale in Geography. In N.J. Smelser & P.B. Baltes (Eds.) International Encyclopedia of the Social & Behavioral Sciences (pp. 135001 - 13504). Oxford: Pergamon Press
Murdoch, J. (1998), The spaces of Actor-Network Theory. Geoforum, 29(4), pp. 357- 374
Murdoch, J. (2006), Post-Structuralist Geography, chapter 3. London: Sage, 56-77.
Nieuwenhuizen, T. (2005), Het Campuscontract. Available online: http://www.ngnb.nl/data///artikelcampuscontract.pdf [Accessed on 01-12-11]
Nowotny, H. (2005) The increase of complexity and its reduction: Emergent interfaces between the natural sciences humanities and social sciences. Theory, Culture and Society, 22(15), pp. 15 – 31
Outwater et al (2011), Characteristics of premium transit services that affect mode choice. Transportation, 38(4), pp. 605-623
'OSullivan, D. (2003), Complexity science and human geography. Transactions of the Institute of British Geographers, 29 (3) pp. 23 - 49
Paez, A. and K. Whalen (2010), Enjoyment of commute: A comparison of different transportation modes. Transportation Research Part A , 44, pp. 537-549
Pajunen, K. en M. Maunula (2008), Internationalisation: A co-evolutionary perspective. Scandinavian Journal of Management, 24, pp. 247-258
Park, R. And E. Burgess (1925), The City. Chicago: University of Chicago press.
Pater, B. de (2005), Het geografisch huis. Couthino: Amsterdam.
Peterman, W. (1994), Quantum Theory and Geography: What Can Dr. Bertlmann Teach Us? The Professional Geographer, 46(1), Pages 1 – 9
Pinjari, A.R., R.M. Pendyala, C.R. Bhat, P.A. Waddel (2011), Modeling the choice continuum: an integrated model of residential location, auto ownership, bicycle ownership and commute tour mode choice decisions. Transportation, 38, pp. 933-958.
Popuri, Y., K. Proussaloglou, C. Ayvalik, F. Koppelman, A. Lee (2011), Importance of traveler attitudes in the choice of public transportation to work: finding from the Regional Transportation Authority Attitudinal Survey. Tranportation, 38(5), pp. 581-585
Potts, J. S. Cunningham, J. Hartley, P. Ormerod (2008), Social network markets: A new definition of the creative industries. Journal of cultural economics, 32(3), pp. 167 – 185
Portugali, J., H. Meyer, E. Stolk, E.Tan (2006), Complexity Theories of Cities Have Come of Age: An Overview with Implications to Urban Planning and Design. Springer Heidelberg, London.
Prigogine, I. and G. Nocolis (1989), Exploring complexity: An introduction. Freeman: New York.
Prillwitz, J. and S. Barr (2009), Working paper: Motivations and Barriers to adopting sustainable travel behavior. Available online: http://geography.exeter.ac.uk/prost/Downloads/WP2- Motivations-Barrierers.pdf [Accessed on 17-01-11]
Ratter, B.M.W. (2006), Komplexitätstheorie und Geographie – ein Beitrag zur Begründung einer anderen Sicht auf Systeme. In: Mitteilungen der Österreichischen Geographischen

Gesellschaft, 148, pp. 109 - 124.
Rai, V. and W.M. Schaffer (2001), Chaos in ecology. Chaos, Solitons and Fractals 12 197 – 203
Rieser, M. (2010) Adding Transit to an Agent-Based Transportation Simulation: Concepts and Implementation, PhD thesis. Available online: http://www.matsim.org/node/564 [Accessed on 13-011-2011]
Ryan, A. (2008), What is a systems approach? Available online: http://arxiv.org/pdf/0809.1698.pdf [Accessed on 11-05-2011]
Saneinejad, S. (2010), Master thesis: Modelling the impact of weather conditions on active transportion travel behavior. Available online: https://tspace.library.utoronto.ca/bitstream/1807/25793/6/Saneinejad_Sheyda_201011_MASc_thesis.pdf [Accessed on 11-12-2-11]
Scheiner, J. (2010), Interrelations between travel mode choice and trip distance: trends in Germany 1976 to 2002. Journal of Transport Geography, 18(1), pp. 75-84
Scheiner, J. and C. Holz-Rau (2006), Travel mode choice: affected by objective or subjective determinants. Transportation, 34(3), pp. 487-511
Schwanen, T. and M.P. Kwam (2009), Critical quantitative geographies. Environment and Planning, A, 41(2): pp. 261-264.
Scoones, I. (1999), New ecology and the social sciences: What prospects for a fruitfull engagement? Annual Revision of Anthropology, 28, pp. 479.507
Smith, J. and C. Jenks (2005), Complexity, ecology and the materiality of information. Theory, Culture & Society 20, pp. 142-163
Sokal, A. D. (1996), Transgressing the Boundaries: Towards a Transformative Hermeneutics of Quantum Gravity. Social text, 46, pp. 217 – 252
Springerimages (2011), Bifurcation diagram. Available online: http://www.springerimages.com/Images/Education/1-10.1007_s10758-010-9166-6-0 [Accessed 04-06-2011]
Strathern, M. and Baldwin, J.S. (2006), Evolutionary drive: New understanding of change in socio-economic systems. Emergence: complexity and organization, 8(2), pp. 22 – 39.
Strokes, P. (2000), Philosophy: 100 essential thinkers. Arcturus Publishing.
Sui (2010), On Darwin, geography, and biology: another tale of the lions and the butterflies –episode 2? Environment and Planning A, 42, pp. 1775 – 1781
Sunitiyoso, Y. and S. Matsumoto (2009), Modelling a social dilemma of mode choice based on commuters' expectations and social learning. European journal of operational research, 193, pp. 904-914
Springerimages (2011), Bifurcation diagram. Available online: http://www.springerimages.com/Images/Education/1-10.1007_s10649-009-9228-7-0 [Accessed on 29-06-2011]
Summerfield (2010), Observations on Darwin and geography. Environment and Planning A 2010, 42, pp. 262 – 264
Tarde, G. (1895), Monadologue et socialogie. Paris, Les empecheurs de penser en rond.
Temme, D., M. Paulssen, T. Dannewald (2008), Incorperating latent variables into discrete mode choice models. A simultaneous estimation approach using SEM Software. Business research, 1(2), pp. 220-237
Thrift, N. (1999), The place of complexity. Theory, Culture and society, 16(3), pp. 31 -69
Tobbler, W.R. (2007), A Computer Movie Simulating Urban Growth in the Detroit Region. Economic Geography, 45, pp. 234 – 240
Torrens, P.M. (2010), Geography and computational social science. Geojournal, 75(2), pp. 133 – 148.
Tredinnick, L.(2009) "Complexity theory and the web", Journal of Documentation, 65(5), pp.797 – 816

Universiteit Utrecht (2010), Jaarverslag 2010. Available online: http://www.uu.nl/university/utrecht/NL/Profielenmissie/Documents/UU_JVsl_2010_web.pdf [Accessed on 10-12-11]
Urry, J. (2002), Mobility and proximity. Sociology, 36, pp. 255-274
Urry, J. (2005), The complexity turn. Theory, Culture and Society, 22(5), pp. 1 - 14
Urry, J. (2007), Mobilities. Cambridge, Malden: Polity Press
Urry, J. And Buescher, M. (2009), Mobile methods and the empirical. European Journal of Social Theory 12, pp. 99 – 116
van Exel, N.J.A. and P. Rietveld. A note on perceptions of public transport travel time and their effect on choice sets among car drivers. Journal of Transport and Land Use, 2(3), pp. 75–86
Verhoeven, M. (2010), Modelling life trajectories and mode choice using Bayesian belief networks. Technische Universiteit, Eindhoven
Von Thunen, J.H. (1826), Der Isolierte Staat in Beziehung auf Landwirtschaft und Nationalokonomie. Gustav Fischer
Weber, M. (1904), The Protestant Ethic and the Spirit of Capitalism. New York, Scribner
Wester, S.J. (2011), Master thesis: The Positive Utilities of Performing Mobilities.
Wolfram, S. (2002), A new kind of science. Wolfram Media.
Wilson, A.G. (2006), Ecological and urban systems models: some explorations of similarities in the context of complexity theory. Environment and planning A, 38, pp. 633 - 646
Zimmerer, K.S. (1994), Human Geography and the “New Ecology”: The prospect and promise of integration. Annals of the Association of American Geographers, 84(1), pp. 108-125.

6. Appendices

Appendix A: Glossary

A.1 General Complexity

(i) Interaction
The separate parts of a complex system influence one another constantly.

(ii) Connectivity
The separate parts of a complex systems are related.

(iii) Sensitivity to initial conditions
Complex systems are sensitive to the initial conditions in which they start. This aspect makes them hard to predict, as the initial conditions are usually unknown.

(iv) Non-compressibility
Complex systems can not be reduced to their parts, since through this reduction one obscures the interactions of the separate parts.

(v) Dissipative nature
Complex systems are open and dissipative. This means that they need the energy or influence of other systems or their environment to maintain their organization.

(vi) Far-from-equilibrium state
The dissipative nature of complex systems makes them operate in a state that is far from equilibrium. If a complex system is in equilibrium, it is essentially dead.

(vii) Non-linearity
Because of their many interactions complex systems frequently exert non-linear behavior.

(viii) Attractor
Complex systems operate in a far-from equilibrium state. Still, they often have some kind of stability over time. The pattern of this stability can be conceptualized as an attractor.

(ix) Phase space
Phase space is the space in which all possible states of a complex system can be portrayed. The attractor is therefore a pattern in this phase space.

(x) Bifurcation points
A bifurcation point refers to the switch from one attractor state to another.

(xi) Feigenbaum constants
These constants refer to the intervals at which bifurcations commonly occur within complex systems.

(xii) Self-similarity
This is a property of some complex systems. It means that regardless of what scale the system is observed on it looks the same.

A.2 Biologic Complexity

(i) Emergence
Emergence refers to the spontaneous formation of order in complex adaptive systems.

(ii) "Good enough" strategies
These strategies are well enough adapted to survive, but might not be the most ideal ones.

(iii) Frozen accidents
This aspect refers to path dependency. Frozen accidents might rely on chance but exert a great influence on a complex system because of sensitivity to initial conditions.

(iv) Redundancy
Many complex adaptive systems have built in fail-safes consisting of back-up parts.

(v) Robustness
This form of fail-safe does not consist of a back-up but rather the ability of different parts to take on the role of the failed part.

(vi) Fitness landscape
A fitness landscape is similar to phase space. It portrays the possible states of a complex adaptive system and adds to this the competitiveness of those states.

Appendix B: Surveys

B.1 English Survey

Location:	…………………………………………………………………………………	English
Survey number:	…………………………………………………………………………………	

General

1. **What is your age?**

   …….. years old

2. **What is your nationality?**

   …………………………………………………

3. **What is your gender?**
   Male / Female

4. **What is your city of residence?**

   …………………………………………………

5. **Where do you live?**
   0 Student-house 0 Apartment
   0 Parents 0 Other, …………………………………………………

6. **What is your income?**

   ………………………. per month

7. **What is your current level of education?**
   0 HBO 0 University – Master
   0 University – Bachelor 0 Other, …………………………………………………

<u>Transport mode availability</u>

8. **Do you own a bike?**
   0 Yes
   0 No

9. **Do you have access to a car?**
   0 I own a car
   0 I have access to car through a family member or friend
   0 I do not have access to a car

10. **Do you have a public transport subscription?**
    0 I have an OV-students chip card
    0 I have a different public transport subscription, …………………………………………………
    0 I do not have a public transport subscription

11. **How far do you live from the closest public transport stop?**

…………….. minutes (walk / bike ride)

Preferences

12. Please rate the following statements on a scale from 1 (strongly disagree) to 5 (strongly agree)

The cost of a transport mode is important for my mode choice	**1**	**2**	**3**	**4**	**5**	**n/a**
The speed of a transport mode is important for my mode choice	**1**	**2**	**3**	**4**	**5**	**n/a**
The weather influences my transport mode choice	**1**	**2**	**3**	**4**	**5**	**n/a**
The frequency of public transport service influences my mode choice	**1**	**2**	**3**	**4**	**5**	**n/a**
I hate transfers	**1**	**2**	**3**	**4**	**5**	**n/a**
I try to minimize my travel time	**1**	**2**	**3**	**4**	**5**	**n/a**
I spend my travel time idly	**1**	**2**	**3**	**4**	**5**	**n/a**
I use my travel time to work or study	**1**	**2**	**3**	**4**	**5**	**n/a**
I use my travel time to relax	**1**	**2**	**3**	**4**	**5**	**n/a**
I enjoy travelling	**1**	**2**	**3**	**4**	**5**	**n/a**
I spend my travel time less effectively when its crowded	**1**	**2**	**3**	**4**	**5**	**n/a**
I hate getting in a traffic jam	**1**	**2**	**3**	**4**	**5**	**n/a**
I hate delays in public transport	**1**	**2**	**3**	**4**	**5**	**n/a**
I like to combine several activities in one trip. For example, going to school and doing groceries afterwards	**1**	**2**	**3**	**4**	**5**	**n/a**
Privacy is important to me while travelling	**1**	**2**	**3**	**4**	**5**	**n/a**
I hate travelling in a crowded train / bus	**1**	**2**	**3**	**4**	**5**	**n/a**

13. Which mode do you use <u>most frequently</u> to travel to school/university? (1 answer)

0 Walking
0 Bike
0 Bus
0 Train
0 Car

14. How long does it take to reach your school/university using this mode?

………………. minutes

15. Rate this mode on a scale from 1 (not attractive) to 5 (very attractive):

……….

16. Please rate the following statements on a scale from 1 (strongly disagree) tot 5 (strongly agree)

I use this mode because I own a subscription	**1**	**2**	**3**	**4**	**5**	**n/a**
I use this mode in warm/sunny weather	**1**	**2**	**3**	**4**	**5**	**n/a**
I use this mode in cold/rainy weather	**1**	**2**	**3**	**4**	**5**	**n/a**
This mode is comfortable	**1**	**2**	**3**	**4**	**5**	**n/a**
I use this mode because it has a stable travel time	**1**	**2**	**3**	**4**	**5**	**n/a**
I use this mode because it is always available when I need it	**1**	**2**	**3**	**4**	**5**	**n/a**
I use this mode to combine several activities along the way	**1**	**2**	**3**	**4**	**5**	**n/a**
This mode allows me spend my travel time efficiently	**1**	**2**	**3**	**4**	**5**	**n/a**
When crowded, this mode is less comfortable	**1**	**2**	**3**	**4**	**5**	**n/a**
When this mode is crowded, I cannot spent my travel time as efficiently	**1**	**2**	**3**	**4**	**5**	**n/a**
I use this mode to avoid congestion/crowding	**1**	**2**	**3**	**4**	**5**	**n/a**
I use this mode because it is the fastest way to reach my destination	**1**	**2**	**3**	**4**	**5**	**n/a**

17. Which mode do you <u>occasionally</u> use to travel to school/university? (1 answer)

0 Walking
0 Bike
0 Bus
0 Train
0 Car
0 I never use a different mode → **skip questions 17,18 and 19**

18. How long does it take to reach your school/university using this alternative mode?

………………. Minutes

19. Rate this mode on a scale from 1 (not attractive) to 5 (very attractive):

……….

20. Please rate the following statements on a scale from 1 (strongly disagree) tot 5 (strongly agree)

I use this mode because I own a subscription	**1**	**2**	**3**	**4**	**5**	**n/a**
I use this mode in warm/sunny weather	**1**	**2**	**3**	**4**	**5**	**n/a**
I use this mode in cold/rainy weather	**1**	**2**	**3**	**4**	**5**	**n/a**
This mode is comfortable	**1**	**2**	**3**	**4**	**5**	**n/a**
I use this mode because it has a stable travel time	**1**	**2**	**3**	**4**	**5**	**n/a**
I use this mode because it is always available when I need it	**1**	**2**	**3**	**4**	**5**	**n/a**
I use this mode to combine several activities along the way	**1**	**2**	**3**	**4**	**5**	**n/a**
This mode allows me spend my travel time efficiently	**1**	**2**	**3**	**4**	**5**	**n/a**
When crowded, this mode is less comfortable	**1**	**2**	**3**	**4**	**5**	**n/a**
When this mode is crowded, I cannot spent my travel time as efficiently	**1**	**2**	**3**	**4**	**5**	**n/a**
I use this mode to avoid congestion/crowding	**1**	**2**	**3**	**4**	**5**	**n/a**
I use this mode because it is the fastest way to reach my destination	**1**	**2**	**3**	**4**	**5**	**n/a**

21. Please fill in your email address if you want to receive the results of this study:

…….

B.2 Dutch Survey

Locatie:	……………………………………………………………………………… Nederlands
Enquêtenummer:	………………………………………………………………………………

Algemeen

1. **Wat is je leeftijd?**

   …….. jaar oud

2. **Wat is je nationaliteit?**

   …………………………………………………

3. **Wat is je geslacht?**

   Man / Vrouw

4. **In welke plaats woon je?**

   …………………………………………………

5. **Wat is je woonsituatie**

   0 Studentenhuis 0 Appartement
   0 Ouders 0 Anders, …………………………………………………

6. **Wat is je maandinkomen (Inclusief ouderbijdrage, studiefinanciering, etc.)**

   ………………………. per maand

7. **Wat voor opleiding volg je op dit moment**

   0 HBO 0 Universiteit – Master
   0 Universiteit – Bachelor 0 Anders, …………………………………………………

Beschikbaarheid

8. **Heb je een fiets?**

   0 Ja
   0 Nee

9. **Heb je beschikking over een auto?**

   0 Ik heb een auto
   0 Ik heb beschikking over een auto via mijn ouders en/of vrienden
   0 Ik heb geen beschikking over een auto

10. **Heb je een abonnement op het openbaar vervoer?**

    0 Ik heb een OV studenten chipkaart
    0 Ik heb een ander abonnement, …………………………………………………
    0 Ik heb geen abonnement op het openbaar vervoer

11. **Hoe ver woon je van de dichtstbijzijnde openbaar vervoer halte?**

    …………….. minuten (lopen / fietsen)

Voorkeuren

12. Beoordeel de volgende stellingen op een schaal van 1 (geheel mee oneens) tot 5 (geheel mee eens)

De kosten van een vervoerswijze zijn van belang voor mijn keuze	**1**	**2**	**3**	**4**	**5**	**n.v.t.**
De snelheid van een vervoerswijze is van belang voor mijn keuze	**1**	**2**	**3**	**4**	**5**	**n.v.t.**
Het weer is van invloed op mijn transportkeuze	**1**	**2**	**3**	**4**	**5**	**n.v.t.**
De frequentie van openbaar vervoersverbinding is van belang voor mijn transportkeuze	**1**	**2**	**3**	**4**	**5**	**n.v.t.**
Ik heb een hekel aan overstappen	**1**	**2**	**3**	**4**	**5**	**n.v.t.**
Ik beperk mijn reistijd tot het minimum	**1**	**2**	**3**	**4**	**5**	**n.v.t.**
Tijdens het reizen verveel ik me	**1**	**2**	**3**	**4**	**5**	**n.v.t.**
Ik gebruik mijn reistijd om te werken / studeren	**1**	**2**	**3**	**4**	**5**	**n.v.t.**
Ik gebruik mijn reistijd om te ontspannen	**1**	**2**	**3**	**4**	**5**	**n.v.t.**
Ik vind reizen leuk	**1**	**2**	**3**	**4**	**5**	**n.v.t.**
Wanneer het druk is, gebruik ik mijn reistijd minder nuttig	**1**	**2**	**3**	**4**	**5**	**n.v.t.**
Ik heb een hekel aan files	**1**	**2**	**3**	**4**	**5**	**n.v.t.**
Ik heb een hekel aan vertragingen	**1**	**2**	**3**	**4**	**5**	**n.v.t.**
Ik combineer vaak verschillende activiteiten in dezelfde trip. Bijvoorbeeld, boodschappen doen op weg terug van de universiteit	**1**	**2**	**3**	**4**	**5**	**n.v.t.**
Privacy is belangrijk voor mij wanneer ik reis	**1**	**2**	**3**	**4**	**5**	**n.v.t.**
Ik heb een hekel aan drukte in het openbaar vervoer	**1**	**2**	**3**	**4**	**5**	**n.v.t.**

13. Welk vervoersmiddel gebruik je doorgaans om naar de universiteit/hogeschool te reizen?

0 Ik ga te voet
0 Fiets
0 Bus
0 Trein
0 Auto

14. Hoe lang duurt het om op deze manier naar de universiteit / hogeschool te komen?

………………. minuten

15. Geef dit vervoersmiddel (ingevuld bij vraag 13) een cijfer van 1 (onaantrekkelijk) tot 5 (aantrekkelijk):

……….

16. Beoordeel de volgende stellingen van 1 (sterk mee oneens) tot 5 (sterk mee eens)

Ik gebruik dit vervoersmiddel omdat ik een abonnement heb	**1**	**2**	**3**	**4**	**5**	**n.v.t.**
Ik gebruik dit vervoersmiddel in warm / zonnig weer	**1**	**2**	**3**	**4**	**5**	**n.v.t.**
Ik gebruik dit vervoersmiddel in koud / regenachtig weer	**1**	**2**	**3**	**4**	**5**	**n.v.t.**
Dit vervoersmiddel is comfortabel	**1**	**2**	**3**	**4**	**5**	**n.v.t.**
Ik gebruik dit vervoersmiddel omdat de reistijd altijd hetzelfde is	**1**	**2**	**3**	**4**	**5**	**n.v.t.**
Ik gebruik dit vervoersmiddel omdat het beschikbaar is wanneer ik het nodig heb	**1**	**2**	**3**	**4**	**5**	**n.v.t.**
Ik gebruik dit vervoersmiddel omdat het mij in staat stelt om verschillende activiteiten te combineren	**1**	**2**	**3**	**4**	**5**	**n.v.t.**
Dit vervoersmiddel stelt mij in staat om mijn reistijd effectief te gebruiken	**1**	**2**	**3**	**4**	**5**	**n.v.t.**
Dit vervoersmiddel is minder comfortabel wanneer het druk is	**1**	**2**	**3**	**4**	**5**	**n.v.t.**
Wanneer het druk is, kan ik mijn reistijd in dit vervoersmiddel minder goed gebruiken	**1**	**2**	**3**	**4**	**5**	**n.v.t.**
Ik gebruik dit vervoersmiddel om files en drukte te vermijden	**1**	**2**	**3**	**4**	**5**	**n.v.t.**
Ik gebruik dit vervoersmiddel omdat het de snelste manier is om mijn bestemming te bereiken	**1**	**2**	**3**	**4**	**5**	**n.v.t.**

17. Welk vervoersmiddel gebruik je als alternatief om naar de universiteit/hogeschool te reizen?

0 Ik ga te voet
0 Fiets
0 Bus
0 Trein
0 Auto
0 Ik gebruik nooit een ander vervoersmiddel → **sla vraag 18,19 en 20 over**

18. Hoe lang duurt het om op deze manier naar de universiteit / hogeschool te komen?

………………. minuten

19. Geef dit vervoersmiddel (ingevuld bij vraag 17) een cijfer van 1 (onaantrekkelijk) tot 5 (aantrekkelijk):

……….

20. Beoordeel de volgende stellingen van 1 (sterk mee oneens) tot 5 (sterk mee eens)

Ik gebruik dit vervoersmiddel omdat ik een abonnement heb	**1**	**2**	**3**	**4**	**5**	**n.v.t.**
Ik gebruik dit vervoersmiddel in warm / zonnig weer	**1**	**2**	**3**	**4**	**5**	**n.v.t.**
Ik gebruik dit vervoersmiddel in koud / regenachtig weer	**1**	**2**	**3**	**4**	**5**	**n.v.t.**
Dit vervoersmiddel is comfortabel	**1**	**2**	**3**	**4**	**5**	**n.v.t.**
Ik gebruik dit vervoersmiddel omdat de reistijd altijd hetzelfde is	**1**	**2**	**3**	**4**	**5**	**n.v.t.**
Ik gebruik dit vervoersmiddel omdat het beschikbaar is wanneer ik het nodig heb	**1**	**2**	**3**	**4**	**5**	**n.v.t.**
Ik gebruik dit vervoersmiddel omdat het mij in staat stelt om verschillende activiteiten te combineren	**1**	**2**	**3**	**4**	**5**	**n.v.t.**
Dit vervoersmiddel stelt mij in staat om mijn reistijd effectief te gebruiken	**1**	**2**	**3**	**4**	**5**	**n.v.t.**
Dit vervoersmiddel is minder comfortabel wanneer het druk is	**1**	**2**	**3**	**4**	**5**	**n.v.t.**
Wanneer het druk is, kan ik mijn reistijd in dit vervoersmiddel minder goed gebruiken	**1**	**2**	**3**	**4**	**5**	**n.v.t.**
Ik gebruik dit vervoersmiddel om files en drukte te vermijden	**1**	**2**	**3**	**4**	**5**	**n.v.t.**
Ik gebruik dit vervoersmiddel omdat het de snelste manier is om mijn bestemming te bereiken	**1**	**2**	**3**	**4**	**5**	**n.v.t.**

21. Vul je email adres als je de resultaten van deze enquête wil ontvangen

…….

22. Opmerkingen:

Appendix C: DVD

Contents:

- Digital version of the thesis
- Excel file that contains the simulation
- SPSS datasets