Integrated Transportation and Energy Activity-Based Model

by

Anwar Ghauche

Bachelor of Engineering in Civil and Environmental Engineering, 2008
American University of Beirut

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Signature of Author..
Department of Civil and Environmental Engineering
January 22, 2010

Certified by..
Moshe Ben-Akiva
Edmund K. Turner Professor of Civil and Environmental Engineering
Thesis Supervisor

Certified by..
P. Christopher Zegras
Ford Career Development Assistant Professor of Urban Studies and Planning
Thesis Co-Supervisor

Accepted by..
Daniele Veneziano
Chairman, Departmental Committee for Graduate Studies

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Abstract

There is a long history of projects and regulations that have had limited or even counter-productive results. These unforeseen effects are due to the failure of planners to capture all of the complexity inherent in urban dynamics. With the increasing risks of global warming, policy-makers and planners need to make optimal or close-to-optimal decisions on how to use the available resources in order to reduce energy and fuel consumption.

This thesis develops the framework for an urban model that serves as a decision support tool to inform sustainable policies and investments. The model discussed integrates the modeling of land use, transportation, and energy consumption by micro-simulating the behavior of households and firms in an urban area. This approach derives transport and energy consumption from human activities and includes the two-way feedback between each agent's behavior and the area's overall dynamics. We build upon complex systems theory and make an analogy with epidemiology modeling to derive the properties of heterogeneity-based, organized complex systems. We then translate the properties of these models with respect to the spatial and temporal resolutions of transportation, land market and energy systems' models.

To achieve the integration of the three complex systems with activities in our framework, we present three different extensions to activity-based modeling in the household context. We first expand the scope of activities considered in activity-based modeling to fit the integrated transportation and energy scope. We then present the econometric techniques of latent variable and latent class modeling to capture individual heterogeneity. Third, we formulate the motivation behind activity participation and model the short- and long-term activity dynamics by operationalizing the concept of stress.

We illustrate the potential of iTEAM in modeling different scenarios to demonstrate the role of our integrated transportation and energy model as a decision support tool for sustainable urban planning.

Thesis Supervisor: Moshe E. Ben-Akiva
Title: Edmund K. Turner Professor of Civil and Environmental Engineering

Thesis Co-Supervisor: P. Christopher Zegras
Title: Ford Career Development Assistant Professor of Urban Studies and Planning

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Chapter 1

Introduction

1.1   Context

Concerns about economic viability, social equity, and environmental quality have heightened in the last few decades, intensifying interest in sustainable development. The most widely accepted definition of sustainable development was advanced in 1987 at the World Commission on Environment and Development (WCED) as one that "meets the needs of the present without compromising the ability of future generations to meet their own needs".

Despite the vagueness of this definition, we know that we have not yet achieved sustainable development as indicated by the global climate change risk. In fact, more and more parties of the United Nations Framework Convention on Climate Change (UNFCCC) view "limiting global mean temperature rise to 2 degrees centigrade above pre-industrial levels as being essential to avoid the most dangerous consequences of climate change" (Bongardt et al., 2009).

How to achieve this goal and address the global warming risk is however still subject to heated debate.

The transportation sector is a major consumer of energy and a primary source of greenhouse gas emissions (GHGs). The sector currently accounts for one-quarter of the world's energy-related carbon dioxide (CO_2) emissions and is expected to be the most rapidly growing source over the next 30 years. Any plan to mitigate the global climate risk should therefore address the energy consumption related to the transportation sector.

The transportation sector has witnessed several changes in the past few decades with the introduction of new technologies. Many of these aim for a "greener" and more sustainable transport sector and while some are more successful than others, a final answer to sustainable transport development has yet to be found.

The question becomes even more pressing with the new regulations and new standards that the communities may impose on different factors related to the transport sector.

In the US, since the oil crisis in the 1970s, the government has enforced the Corporate Average Fuel Economy (CAFE) standards requiring automobile fleets in the US market to achieve a certain level of average fuel economy every year. In response to the economic and regulatory pressures, the three US domestic automakers, General Motors, Ford, and Chrysler, successfully introduced a number of small, highly fuel-efficient vehicles in the 1980s and 1990s. Despite this, the US efforts in designing fuel-efficient vehicle fleet have been disputed.

The average US car has been increasing in weight (figure 1-1) and speed (figure 1-2) at a rate faster than technological improvement in fuel efficiency.

Indeed, the effect of these two factors (weight and speed) was so pronounced that despite significant improvements in fuel-combustion engines and materials there was an overall gradual increase in the US's fleet fuel-consumption between 1987 and 2004 (United States Environmental Protection Agency - EPA, 2008).
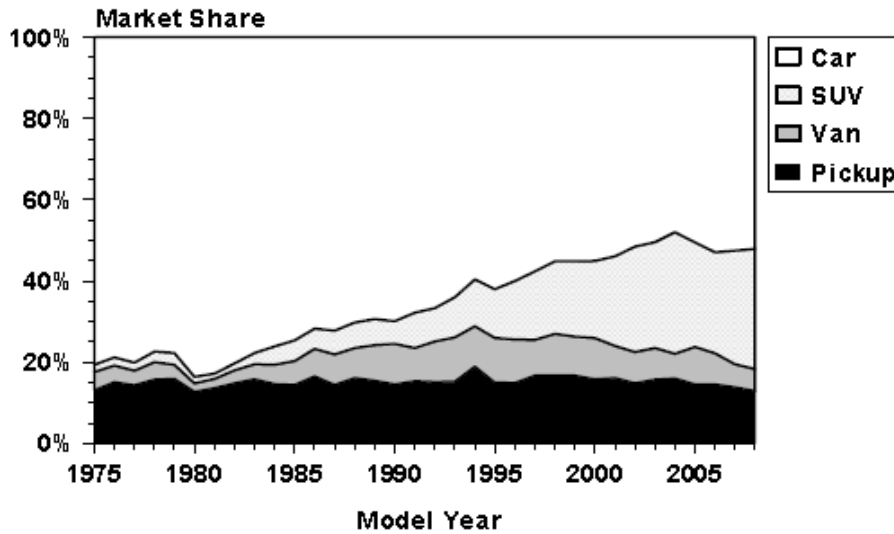
Figure 1-1: Sales Fraction in US by Vehicle type
(EPA, 2008)
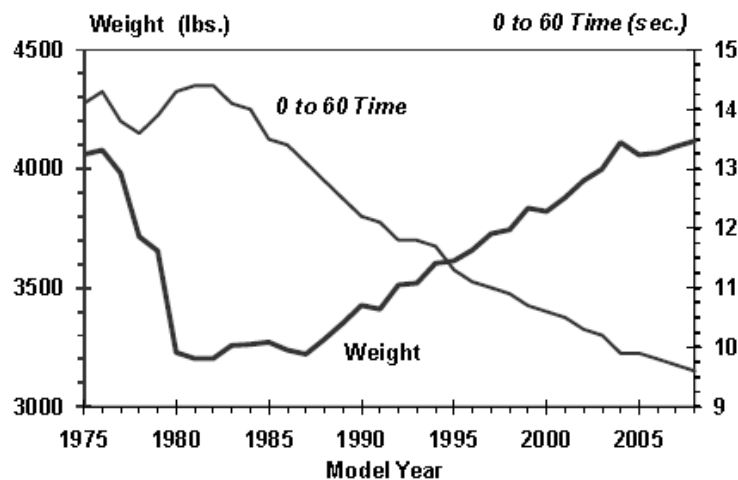
Figure 1-2: Weight and acceleration of US vehicle fleet
(EPA, 2008)

In Europe, regulators have better understood the risk and the role that transportation has to play in the fight against global warming. They moved away from policies that involve increasing the supply of transport network to transportation demand management techniques. These policies aim to reduce automobile travel demand or to redistribute it and spread it over space and time. As the former UK Prime Minister Tony Blair phrased it in the British Government's White Paper on Transport (Secretary of State for Transport, 2004), "We recognize that we cannot simply

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build our way out of the problems we face. It would be environmentally irresponsible - and would not work".

These regulations tackled each of the transport sectors and modes with varying degrees of aggressiveness. For the automobile industry, fuel taxes were sharply increased to deter people from buying low efficiency cars and to motivate people to switch to transit. Furthermore, tax-breaks were provided for energy-efficient cars to encourage potential car owners to adopt greener technologies (Commission of the European Communities, 2001).

In addition, some cities adopted different pricing schemes. Most of these schemes aimed to reduce congestion by charging a fee to vehicles crossing a certain boundary during peak travel periods. Some of the car users switched to transit and others shifted their travel to off-peak periods or to other less congested and non-tolled roads. Milano on the other hand adopted a pricing scheme for direct pollution relief, Ecopass (Rotaris et al., 2009). The city banned a major cordon to very low-efficiency vehicles and charged the other vehicles a fee directly related to their gas emissions.

Other strategies that were adopted or are being considered include parking policies and cap-and-trade (Grubb et al., 2009). In Europe, the cap-and trade policies are regulated by the European Union Emission Trading Scheme (EU ETS) which plans to include some variation of a carbon trading scheme for the aviation and maritime transport sector in 2012. This system would put a cap on the aggregate emission of CO_2 for a specific sector and allow each company to use its carbon credits or trade it on the market.

Overall the different policies implemented turned out to be less effective than expected[1]. This has fueled the innovation of non fuel-combustion technologies such as hydrogen cell-powered and electric cars. Although these technologies may be cleaner (depending on the source of energy), their impact is still limited by their availability and their adoption rates in the different countries and they do not solve the issue of the remaining vehicle stock among other problems.

Thus, in the developed world, active work is being done to achieve more sustainable mobility.

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[1] Still debated. See the discussion by Grubb et al., (2009)

One of the major threats to the environment nowadays comes from the developing countries where the largest wave of cars is expected. In particular, the emergence of a middle class in China and India is driving an increase of 15-20% in motorized vehicles concentrated in the urban areas (Schipper and Ng, 2005).

To cater for this growth, China is investing hundreds of billions of US dollars in its infrastructure, mainly in the housing and transport sectors (Bradsher, 2009). At this early stage of development, any plan for land-use or transportation will set the conditions for future energy consumption.

1.2 Motivation

This context sets the tone for our research and raises the question of how to achieve sustainable development in the transport sector.

Looking back at the history of projects and regulations that have attempted to answer this question, we notice that several of these efforts had limited impact and some of them even resulted in counter-productive outcomes.

To put it in the words of JW Forrester (1969):

> *"It has become clear that complex systems[2] are counterintuitive. That is, they give indications that suggest corrective action which will often be ineffective or even adverse in its results. Very often one finds that the policies that have been adopted for correcting a difficulty are actually intensifying it rather than producing a solution. The intuitive processes will select the wrong solution more often than not"*

The most common case of counter-intuitive results in transportation planning is that of the Braess paradox (Braess et al., 2005). This paradox occurs when the addition of a path in a network results in more overall congestion because of the selfish user-optimal Nash equilibrium that takes place. Such effects were observed in New York (Kolata, 1990) and Stuttgart.

Another example of a transport policy that can have negative long term results is the case where an inprovement of certain modes in one region effectively alienates other regions, creating

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[2] We review complex systems theory and prove that the transport network is a complex system in chapter 3.

isloated pockets in the urban landscape, which fosters crime, deprivation, and ghettoization (Blanchard and Volchenkov, 2009).

While a wide range of policies has been implemented in different areas around the world, significant reduction in GHG emissions has yet to be achieved.

With the increasing risks of global warming, policy-makers and planners need to make optimal or close-to-optimal decisions on how to use the available scarce resources in order to reduce the energy and fuel consumption. Analytical tools that can help in the scenario analysis and forecasting can help to support the process in three ways:

➢ By capturing the long term effects of a policy or investment

➢ By capturing the indirect effects of a policy or investment.

➢ By making the comparison of different scenario outcomes more objective and transparent.

To make the situation even more complex, decision-makers have to tailor their policies and investments to their specific urban region and have to navigate through the different – and sometimes conflicting – agendas of various involved public entities.

To illustrate this point, we present the following example of an emissions trading scheme to be implemented in two regions of similar acreage and population density:

Depending on their economic status, their *Marginal Abatement Cost* (MAC) – the cost of eliminating an additional unit of pollution – will be different and the optimal cap will vary.

Hence, although planners can learn a lot from the efforts done in other regions of the world, they still need tools to develop their own sustainable policies.

Today, most experts and practitioners agree that there is no one silver bullet to achieve sustainable development in the transport sector. Rather, a portfolio of approaches is needed where technological advances, regulations and regional planning all have to contribute to avoid the risks of global warming.

This integrative approach is gaining popularity in the academic, industrial and regulatory circles with several programs including:

• "Sustainable Transportation Energy Pathways (STEPS)" in California.

• "Towards a Sustainable Transport System (TaSTS)" in London

- "Moving on Sustainable Transportation (MOST) program" in Canada
- "The Sustainable Transportation Systems Program (STSP)" in IOWA
- "Urban Energy Systems" in London

These and other programs arose from the need to understand the potential drivers of sustainable mobility in order to better manage them.

1.3 Thesis scope

This thesis focuses on supporting and informing the planning needed to achieve a sustainable development and mitigate the risks of global warming. We develop the framework of a model that can be used as a decision support tool for policy-makers and urban planners to achieve more sustainable planning.

We can a priori detect two levels of complexities in an urban system that create obstacles to this modeling task:

A) A major challenge in modeling the energy consumed in a city is in defining a scope that is broad enough to capture the major indirect and secondary effects of mobility patterns and yet well-defined so that the system is still tractable.

B) Another level of complexity is in representing the different processes with their respective spatial and temporal scales which range as follows:

- *Very slow change: networks, land use*. Large infrastructure that supports urban transport, communications and utility *networks* are the most permanent elements of the physical structure of cities. They require a decade or more to be built, and once in place, shape the other processes profoundly.

- *Slow changes: workplaces, housing.* Buildings have a long life-span and take several years from planning to completion. They usually exist much longer than the firms or households that occupy them.

- *Fast change: employment, population, equipment ownership*. Workers go through different stages in their careers. Similarly, households are created, grow or decline and eventually die out, and in each stage in their respective cycle they adjust their employment, residential location and equipment to their changing needs.

• *Immediate change: goods transport, travel*. People and goods interact in several markets. They can adjust in minutes or hours to changes in congestion or fluctuations in demand, though in reality adjustment may be retarded by habits, obligations and many other factors.

Previously developed urban models presented major flaws; they broke-down cities into component parts, and then studied each component separately (Alberti, 2008). However, cities are the archetype of an integrated system whose individual components interact and cannot hence be fully understood by merely understanding their different parts.

We can readily identify the following sources of complexity in the urban dynamics:

➢ Non-linear behaviors resulting from the two-way interactions between the different agents and systems.

➢ The long term and indirect effects on the urban form and energy sector of a policy or investment affecting the transport sector.

➢ The varying spatial and temporal scales of the different processes at work.

1.4   Research objective

The driving question behind this research is to capture the complexity inherent in the urban dynamics and investigate the relation between the different energy consumption sectors that figure 1-3 outlines.

These four energy sinks account for all the energy consumed in an urban region apart from the system losses for the creation, storage and transfer of the energy in the urban area.
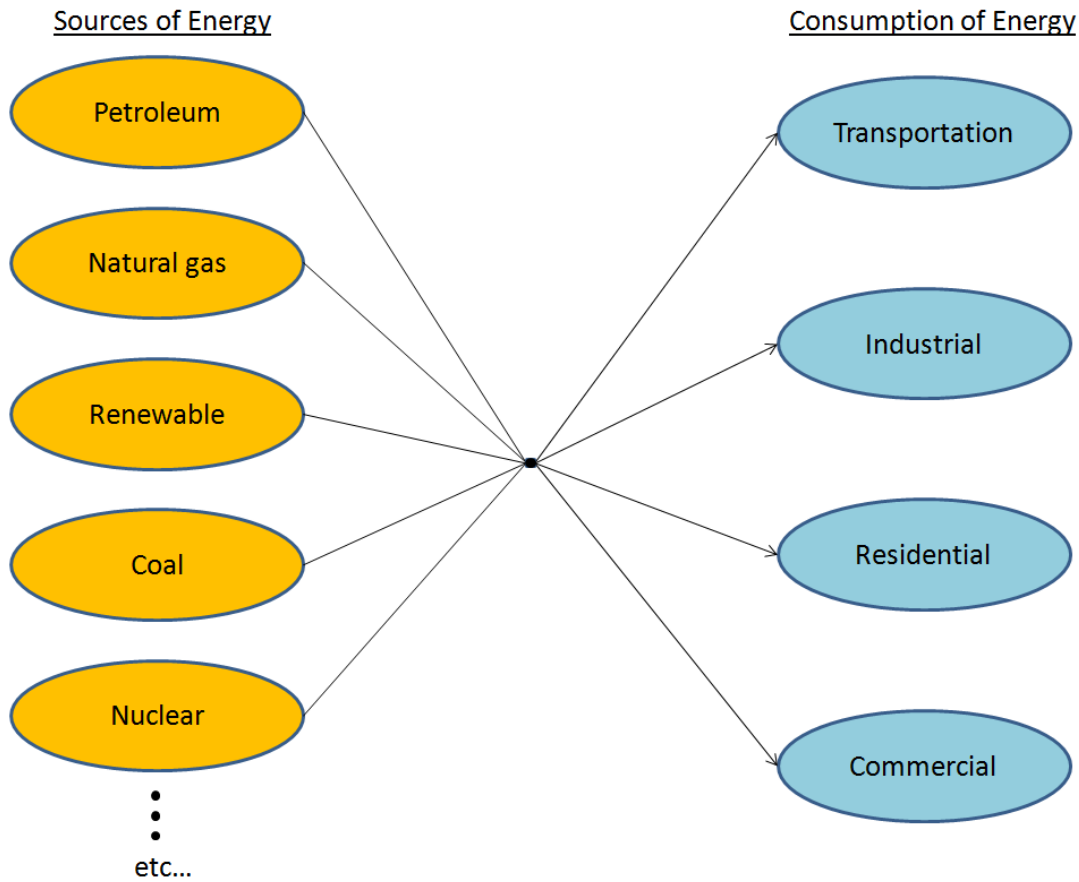
Figure 1-3: Energy production and consumption sectors

Within the context set forth, we aim to provide a framework that integrates the impact of transportation policies on the energy consumption in the transport sector as well as the other related energy consuming sectors.

Thus, the objective of this thesis is to develop the methodology needed to investigate these relations and embed it in a decision support tool for planners.

Specifically, we focus on the interactions of transportation and energy on the demand side and identify the properties of the supply side model for each sector separately.

We go beyond simplistic and sometimes misleading high-level analysis by looking at the actual driver of energy consumption in the transport, residential, commercial and industrial sectors: *human behavior*.

1.5   Research contributions

The main conceptual contributions of this thesis include:

- The derivation from complex systems theory of a formal framework and architecture for an urban model that integrates the transport, land-use, and energy sectors of an urban region. We believe this is the first model that formally addresses the linkage between transport and stationary energy consumption and shows great promise for future research.

- The integration of transport, land-use and energy networks with human activities.

The main methodological contributions of the thesis include:

- The formulation of extensions to activity-based models in the household context. These extensions account for individual heterogeneity and human motivation by capturing the human needs.

- Modeling the short and long term dynamics of human behavior through the operationalization of the stress concept in a utility maximization framework.

1.6   Thesis organization

The thesis is structured as follows:

- Chapter 2 reviews the literature on transportation, land-use and energy modeling. First, we provide a historical background on integrated transportation and land-use models. Second, we present six current integrated transport and land-use models and identify their differences in terms of scopes, approaches and techniques. Third, we review the modeling of energy consumption at the vehicular, residential, and urban levels. We conclude with a summary on the state-of-the-art in modeling transport, land-use and energy.

- Chapter 3 presents the framework and architecture of our proposed urban model. We develop an approach consistent with a set of guidelines obtained from the study of analogous complex systems. We use this approach to present the architecture of our urban model, an integrated transportation and energy activity-based model (iTEAM). Finally, we conclude this chapter by presenting the relations and interactions of the main sub-models of iTEAM.

- Chapter 4 reviews the literature on activity-based modeling. We present the different approaches and techniques for activity-based modeling. We first discuss specific instances of time allocation models and then focus on activity scheduling models, which constitute the backbone of iTEAM.

- In Chapter 5, we formulate three different extensions to current activity-based models. We first identify the activities of interest for our urban model and expand the scope of the activity-based models to meet the needs of iTEAM. We then present the econometric techniques of latent variable and latent class modeling to capture individual heterogeneity. Finally, we formulate a link between the human needs theory and activity theory and model the activity dynamics by operationalizing the concept of stress.

- Chapter 6 outlines the potential capabilities of iTEAM in analyzing different scenarios and policies. We first present the sustainability indicators that can be output from iTEAM and then present some examples of scenarios where an integrated transport and energy model such as iTEAM is need to support decision-making.

- Chapter 7 summarizes the thesis and presents directions for future research.

Chapter 2

Literature Review of Transportation, Land-use and Energy Modeling

"Happy families are all alike; every unhappy family is unique in its own way" Leo Tolstoy

In the context of this thesis, we are interested in reviewing the work previously done that contributes to our research on developing the framework for an integrated transportation and energy activity-based model. Since such a model is non-existent yet, we will review the literature concerning the different areas on which our model will build. We begin this chapter with a review and comparison of integrated transportation and land-use models[3] in sections 2.1 and 2.2. We then go over the literature in energy demand modeling in section 2.3. In section 2.4, we synthesize the state of the art in this extensive body of knowledge to lead the way for presenting our framework for iTEAM in chapter 3.

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[3] Often referred to as urban models

Large-scale urban models are mathematical simulation models that describe urban systems with a certain level of spatial and temporal detail. They adopt different modeling strategies such as state transition models, random utility choice models, rule-based ''computational process'' models, as well as hybrid combinations of these approaches. These types of models emerged in the late 50's in the US and flourished in the 60's and early 70's in the UK with a large number of applications for sub-regional territorial planning (Batty, 1976).

2.1 Historical background

2.1.1 *From 1960s to early 1970s*

With the increase in computational power brought about by the spread of non-military computers, the '60s period witnessed the first systematic effort to study the interrelationship between transport and land use.

Using data from Washington DC, Hansen (1959) demonstrated that locations with high accessibility levels had a higher chance of being developed, and at a higher density, than remote locations.

The recognition that trip and location decisions are interdependent quickly spread among American planners. Hence, the idea to integrate both transport and land use and the 'land-use transport feedback cycle' (see figure 2-1) became commonplace in the American planning literature.
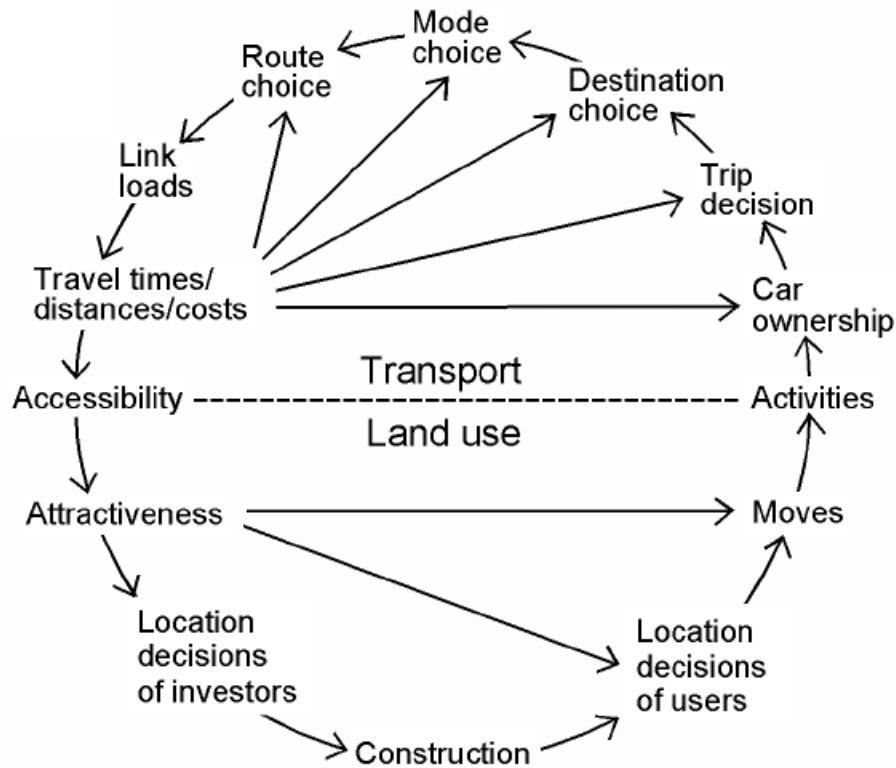
Figure 2-1: The land-use transport feedback cycle
(Wegener, 2004)

The seminal work of Lowry (1964) was the first attempt to implement the urban land-use transport feedback cycle in an operational model. It consisted basically of connecting a residential location choice model and a firm location choice model with a four-step transportation model. This effort was continued by several researchers who built on this idea to develop more complex and more sophisticated models in what is now known as the Lowry model heritage (Goldner, 1971).

2.1.2 *From early 1970s to 1980s*

In 1973, Lee published a paper entitled "Requiem For Large Scale Models" (Lee, 1973) where he heavily criticized the development of large scale urban models. After working himself on this type of urban models, he dismissed them as lacking theoretical basis and impractical for proper planning. To back his point of view he mentioned what he thought were seven inherent flaws to any large scale urban model:

- "Hypercomprehensiveness" or the multiplicity of goals.

- "Grossness" or the coarseness of spatial and temporal detail
- "Hungriness" in terms of data required to run the model
- "Wrongheadedness" or the unrealistic replication of behavior using oversimplified equations
- "Complicatedness" because microscopic behavior is still unexplored
- "Mechanicalness" or limited by computer capacity
- "Expensiveness" financially.

Although these 'flaws' reflect the situation in the 60's and 70's they are still relevant are still just as relevant today as they were back when this paper was written. In particular, the lack of behavioral realism in the replication of behavior has still not been addressed properly (see chapter 5). We will revisit these issues and explain how our proposed framework attempts to address these concerns.

Lee's paper and the disappointing outcome of many of these models helped discourage modelers from moving ahead with large scale urban models. Thus, the impetus to advance the state-of-the-art in urban modeling declined during the 70's and 80's (Wegener, 2004).

However, in the last two decades, the advances in computational power and data collection, coupled with the move towards disaggregate models and microsimulation, have led to renewed efforts in urban modeling. For a detailed review of these models the interested reader is referred to Wegener (2004).

In the next section, we review the more recent urban models either operational or under development.

2.2 Current models: operational or under development

The new found momentum for urban modeling has led both academic researchers and practitioners to take a holistic approach in their designs, an approach that would enable them to consider all the secondary and side-effects of their plans. This movement is both fueled by and faced with the exponentially increasing complexity of the urban reality. Firms' supply chains that were once gathered in one location are becoming more global and scattered all over the world. Households that were once confined to pick a house in a certain residential area and constrained

by cultural, linguistic and financial constraints, have now more choice in choosing their locations then they have time to explore. This growth has made the prevalent models used by urban planners and public agencies unsuited to address the policies and investments.

To overcome these shortcomings, and given the environmental context that we presented in chapter 1, several organizations have started to develop models that integrate land use, transport, and the environment; models that were coined Integrated Urban Models (IUM).

These models include the California Urban Futures Model (CUFM) developed in 1998, DELTA which was developed by Davids Simmons consultancy in 2001, the Transportation and Environment Strategy Impact Simulator (TRESIS) developed in 2001. The reader is referred to Wegener (2004) and Kazuaki (2006) for a more detailed listing of recent urban models.

In this thesis, we present six models that tackle the modeling problem from different perspectives so as to capture the different approaches, obstacles and tradeoffs that modelers face when attempting to capture the different interactions involved in IUMs.

2.2.1 *PROPOLIS*

The PROPOLIS or "Planning and Research of Policies for Land Use and Transport for Increasing Urban Sustainability" is one IUM[4] that was geared towards implementation in the European context. This project took place in 2004 under the 'Energy, Environment and Sustainable Development' group within the European Committee and was built on the plans and land use models that were available in certain European cities (Lautso et al., 2004).

PROPOLIS had a broad scope and combined indicators for the three sustainability pillars as outlined in Figure 2-2.

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[4] PROPOLIS is actually the name of the umbrella program in the European Union under which this model was developed but we will use this name interchangeably for the sake of clear reference
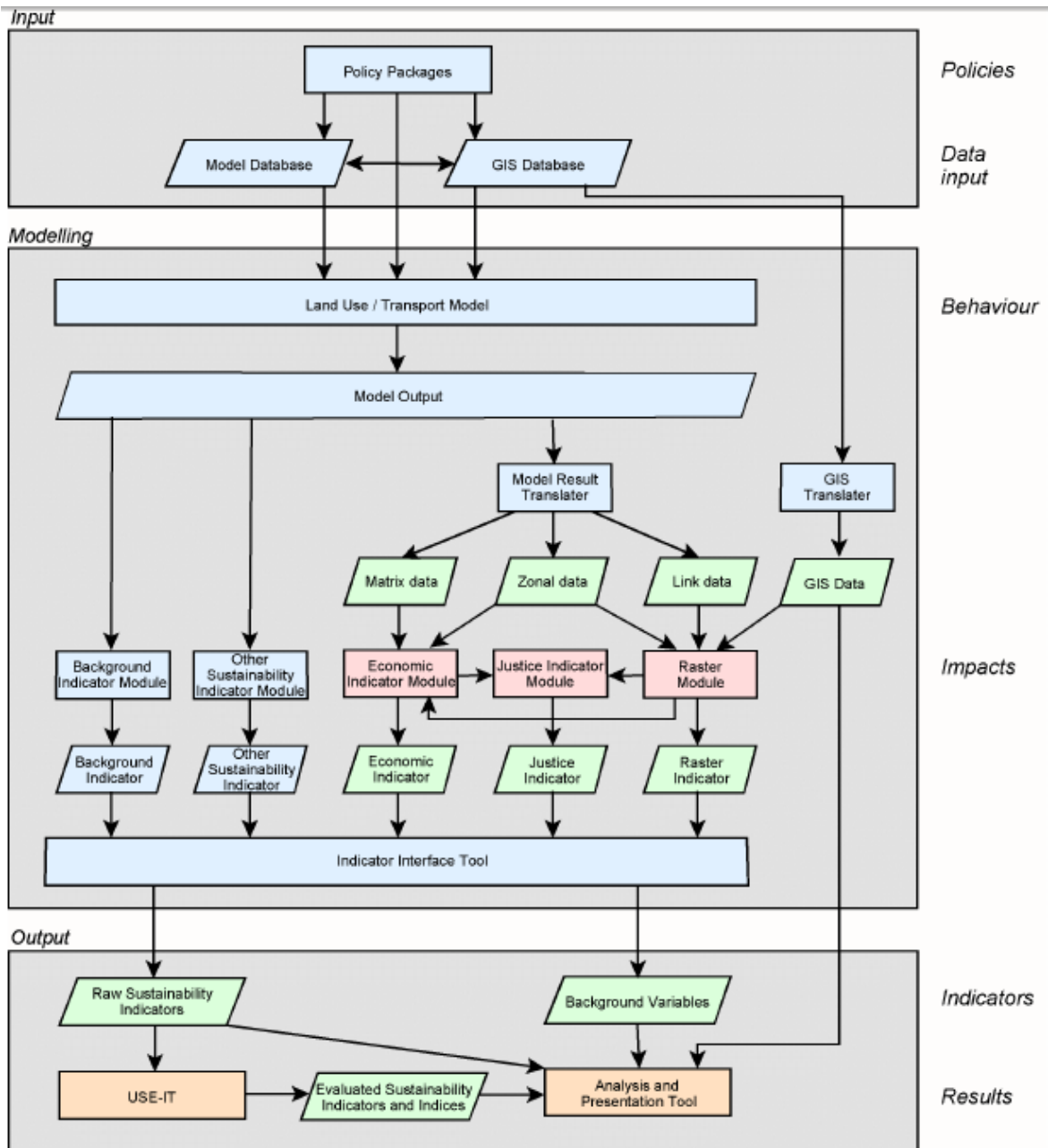
Figure 2-2: PROPOLIS scope
(Lautso et al., 2004)

The result of this work was that *"The PROPOLIS project has shown that it is possible to use urban land use and transport models as a platform for producing urban environmental, social and economic sustainability indicators and indices that can be used in assessing policy options and when searching for new and effective ways to urban sustainability."*

Within this context, the general approach for the Land-use/Transport models used in PROPOLIS is summarized in figure 2-3:
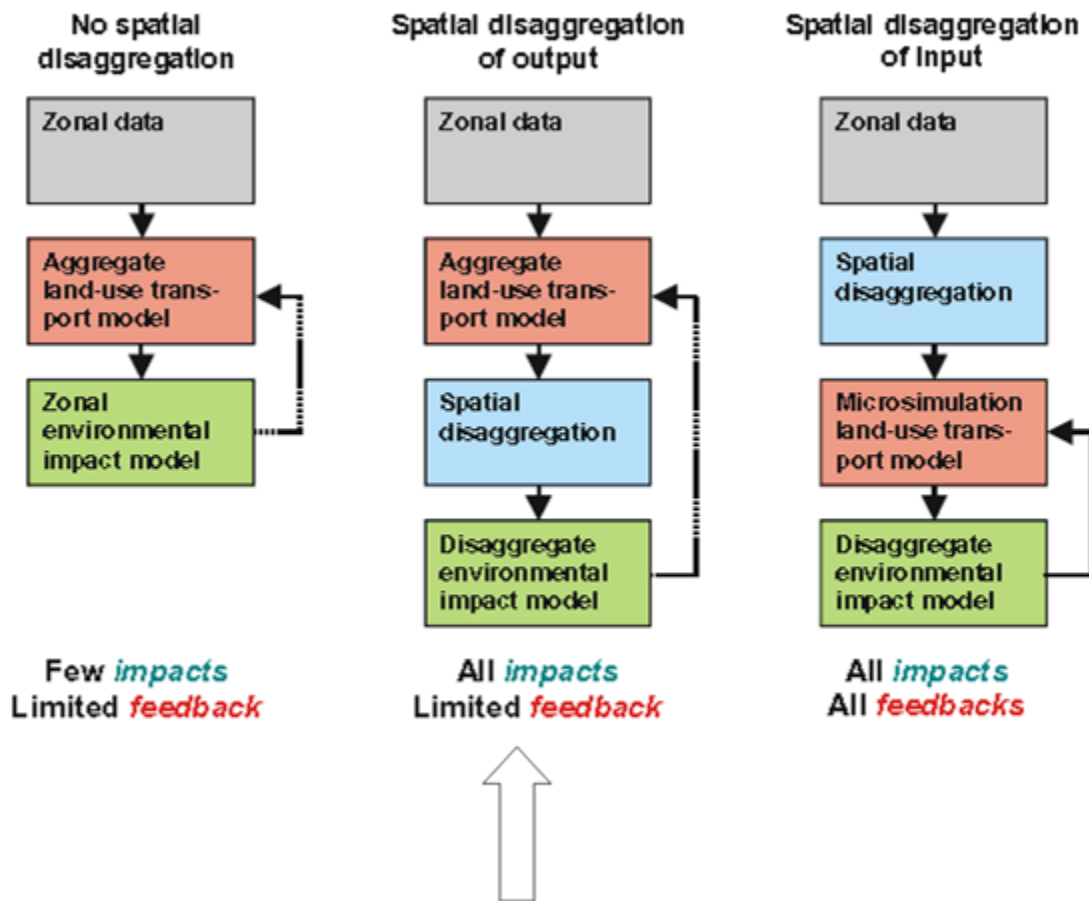
Figure 2-3: PROPOLIS approach
(Lautso et al., 2004)

PROPOLIS opted out of the microsimulation approach in order to make use of the integrated transportation land-use models that were already estimated and calibrated in some of the targeted European cities[5]. These integrated transportation and land-use models, MEPLAN, TRANUS, and IRPUD all use spatial aggregation at the zone level to represent the different parcels of land.

Another major conclusion of the project that is of particular relevance to our thesis was that *"A more radical move towards microsimulation models would bring several benefits, including:*

- *Better presentation of transport and other activities in space and time*

- *New, more detailed policy types could be evaluated*

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[5] MEPLAN was used in Helsinki, Naples, Vicenza and Bilbao. TRANUS was used in Inverness and Brussels. IRPUD was used in Dortmund.

- *Better inputs into environmental models*

- *Better inputs to the exposure models as estimates could be made about where and when people are and what the air quality is there at that time*" (Lautso et al., 2004)

2.2.2 *PRISM*

The framework of PRISM[6] or Puget Sound Regional Integrated Synthesis Model was developed to model the urban development and ecological dynamics in the Puget Sound region (Alberti, 1999; Alberti and Waddell, 2000). This urban model's unique feature is that it recognized the need to model the interactions between the ecological system and the urban dynamics and built on the foundations of urban economics, landscape ecology, and complex system theory.

The PRISM approach is illustrated in figure 2-4 and can be summarized in the following series of steps:

- Model urban dynamics at a disaggregate level

- Link urban dynamics with ecological model

- Feedback the biophysical model into the behavioral model by incorporating the environmental qualities of land parcels and neighborhoods.

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[6] PRISM is actually the name of an initiative undertaken at the University of Washington which this model is part of but we will use this name interchangeably for the sake of clear reference.
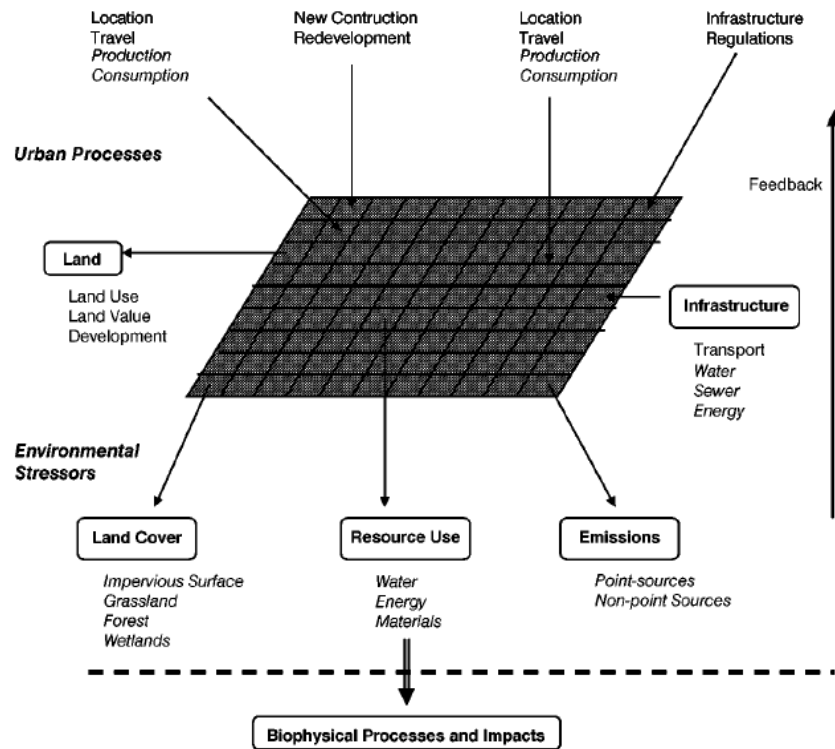
Figure 2-4: PRISM Framework
(Alberti and Waddell, 2000)

PRISM adopts the UrbanSim model (Waddell, 1998) as its urban economic foundation to model the dynamics of land market between residences and businesses and real estate developers. This model builds on Martinez's (1992) 'bid-choice' land-use model that uses a logit formulation to combine the land supply and demand as follows:

$$P_{h|i} = \frac{\exp\left(\Theta_{hi} - b_i\right)}{\sum_j \exp\left(\Theta_{hj} - b_j\right)}$$

Where:

$P_{h|i}$ is the probability that a consumer h will choose lot i;

Θ_{hi} is the willingness of individual h to pay for lot i;

b_i is the market price for lot i.

Although at the time when this framework was being developed UrbanSim still modeled space with a certain aggregation level, the authors quickly realized that a move towards microsimulation was needed. Microsimulation, they found, was necessary in order to accuratly

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capture the different urban processes and to adequately link them with ecological models (Alberti, 1999).

For the urban ecological model, PRISM planned to use the method of Cellular Automata (CA) to forecast the state of the land cover in a particular area, taking into account its previous states, and that of the surrounding cells. However, this method lacks fundamental behavioral realism as it relies on stochastic state transitions without touching upon the actual ecological causes behind these transitions. To put it in the authors' words, "important progress needs to be made, however, with respect to realism before CA can be applied to real urban problems"
This model is still under development today.

2.2.3 *CEMUS*

CEMUS or Comprehensive Econometric Microsimulator for Urban Systems is an urban model under development at the University of Texas at Austin (Bhat and Waller, 2008).

The CEMUS scope favors depth rather than breadth. In other words, although this project only models household behavior and only accounts for their vehicular emissions, CEMUS goes a long way in trying to represent this behavior realistically. For instance, it uses state-of-the-art discrete choice techniques to model joint decision making and activity participation in a household.

Moreover, CEMUS represents the space-time continuum at the individual household level and at fine temporal detail to appropriately capture the different tradeoffs between activities and travel modes. This makes CEMUS an excellent tool for analyzing the short term impact of policies such as road congestion pricing on the transportation network.
This focus is apparent in Figure 2-5 where a big emphasis is placed on modeling the population characteristics and the household travel patterns.
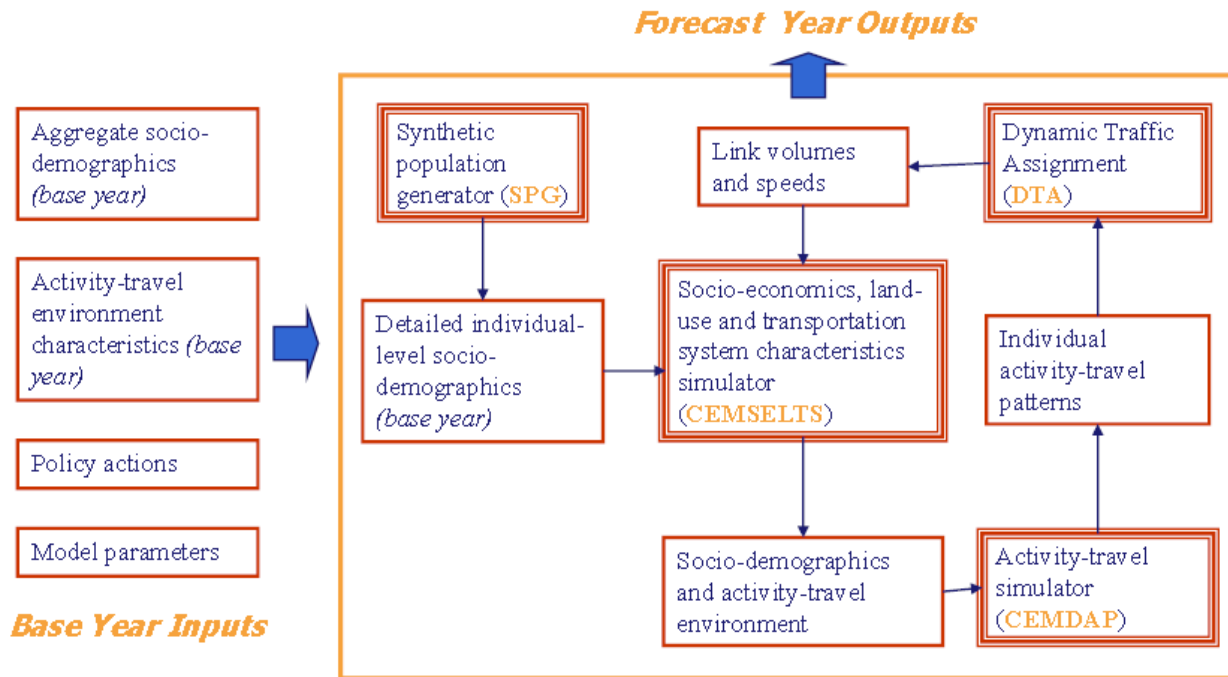
Figure 2-5: CEMUS scope
(Bhat and Waller, 2008)

It is important to note at this point the level of detail that CEMUS puts on accurately modeling and forecasting population characteristics. Not only does the model capture agents at the individual level but it also represents their detailed socio-economic characteristics such as specific education level, marital status, etc. It is therefore a clear advocate for the move toward more disaggregate-level urban modeling and microsimulation.

2.2.4 *ILUMASS*

The ILUMASS project or the 'Integrated Land-Use Modeling and Transportation System Simulation' was under development between 2002 and 2006 in Germany (Strauch et al., 2005). The project had two main highlights:

1) This project was one of the first urban models to identify two different types of agents interacting in the urban context: households and firms. ILUMASS microsimulated households behavior by going through the sequence of steps shown in figure 2-6.

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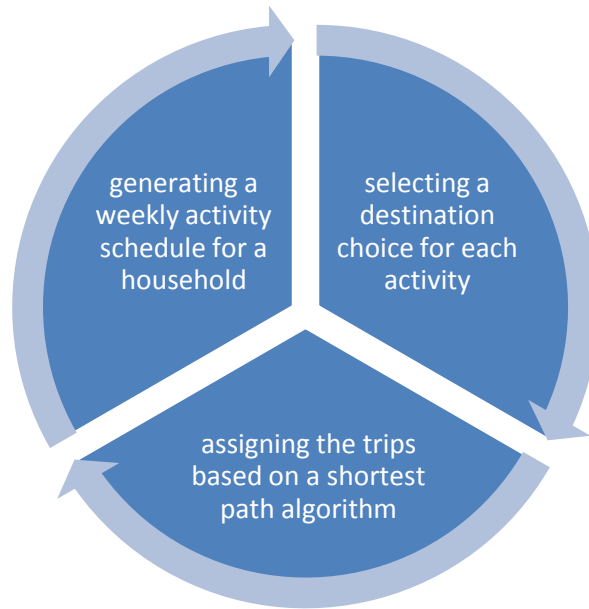
Figure 2-6: ILUMASS household behavior model

On the firm side, the model simulated the firm location and relocation choice but used an Input/Output model to assign the movement of goods onto the traffic network.

In this sense, ILUMASS used a hybrid approach of microsimulation and Input/Output models to cope with the very fine spatial disaggregation level it used.

2) On the other hand, ILUMASS considered a two-way feedback link between transportation, land-use and the environment. It translated the trips into their corresponding environmental impacts such as vehicular emissions, traffic noise and visual impairment. It then reflected these impacts on the land accessibility to capture the effect of the environment on land-use and transportation by making regions with cleaner air and reduced traffic noise more attractive to households and firms in their relocation model.

Under its *environment* module, ILUMASS only considered the direct environmental impacts of transport and land use such as greenhouse gas emissions, air pollution, traffic noise, barrier effects and visual impairment by transport and selected emissions. The model did not include the indirect effects of transportation on energy consumption from households and firms.

Figure 2-7 shows the overall model structure of ILUMASS as divided into the three modules, Land-use, Environment, and Transport with two-way feedback between them.

Although the ILUMASS project greatly advanced the state-of-the-art in integrated urban models, the project ran out of funding before its complete implementation and failed to meet its goals (Wagner and Wegener, 2007).

It is interesting to note here the ILUMASS researcher's reaction about their project and integrated urban model in general: *"Many of these [integrated urban models] projects had to readjust their plans when the project targets proved to be too ambitious."*

Furthermore, the researchers attributed this partial failure to other factors that include:

- Technological issues related to computing power and capabilities

- Attempts to run the whole project without any incremental work process

- Data shortage and data sharing problems

This reminds us that Lee's comment about "hypercomprehensiveness", "hungriness", and "mechanicalness" just as relevant today as they were in 1973.

Even more importantly, it emphasizes the need for a more flexible, incremental development approach to building integrated urban models.
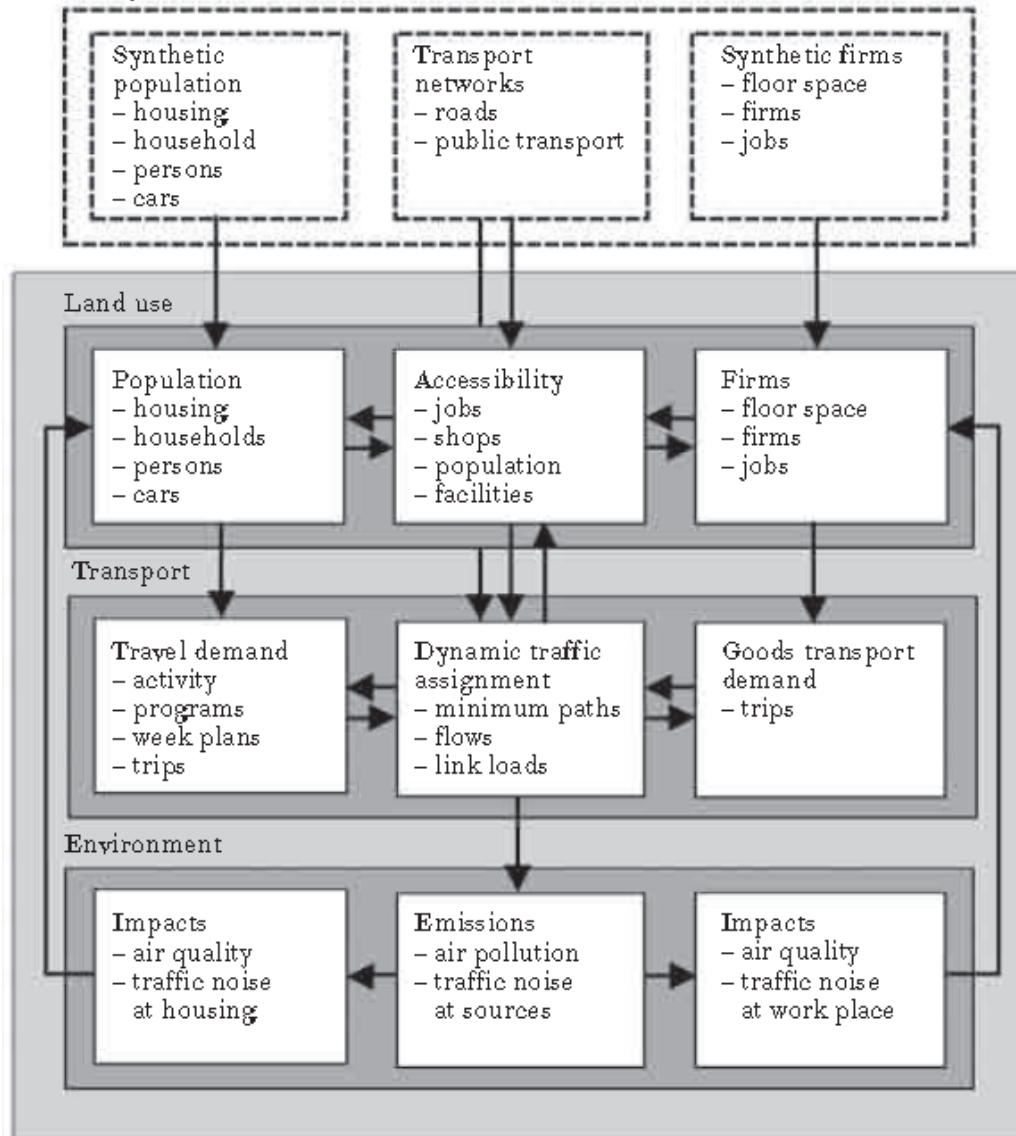
Figure 2-7: ILUMASS structure
(Wagner and Wegener, 2007)

Despite this final outcome, after their experience with ILUMASS, the authors still agree that microsimulation is necessary to:

• Accurately capture societal developments, such as new lifestyles and new tendencies in mobility behavior.

• Forecast the impacts of innovative policies in the fields of travel demand management and transport operation.

• Model the environmental impact of land use and transport policies with the necessary spatial resolution.

2.2.5 *I-PLACE³S*

In 2008, The Sacramento Area Council of Governments (SACOG) adopted a plan to develop and improve its integrated urban modeling capabilities.

The goal cited was to provide "*better information*" and develop "*tools for decision making*", particularly because the "*policy issues are often, and more frequently, interrelated*" (Garry, 2008).

The objective was to improve on the current model of I-PLACE³S and the aggregate transportation model available to obtain a new and improved Internet-PLAnning for Community Energy, Economic and Environmental Sustainability (I-PLACE³S) that accurately models:

- Land use development
- Return on investment
- Transportation
- Energy demand - buildings
- Public health
- Physical activity
- Agriculture/open space
- Infrastructure cost
- Fiscal analysis
- Water demand

The tool would be used to evaluate how alternative development approaches or transportation investments may impact the following indicators:

- Water consumption
- Jobs by sector
- Vehicle trips per household
- Vehicle miles traveled per household
- Transit ridership
- Pedestrian friendliness
- Electricity / natural gas / gasoline demand
- Return on Investment

I-PLACE³S is not a full-fledged integrated urban model but rather a GIS-based land-use mapping/scenario building platform with ongoing development, which makes it difficult to describe. We do note that the project is considering moving towards activity-based transportation modeling (SACOG, 2009) and is currently researching different opportunities for integrating an energy module into the current platform (Czachorski et al., 2008)

It is important to note three key characteristics of I-PLACE³S:

- **Shareable**: As a web-based modeling platform, it is accessible to any party interested developing party

- **Flexible**: it can be "expanded by adding new or updated modules and can be customized to meet the needs of individual organizations. Any new functionality added by any one agency is made available for use or customization for all users, thus enabling synergy and cost savings between the IPLACE³S users."

- **Scalable** to large study areas and large datasets.

These features indicate more than just a modeling approach that might have been convenient at the time, they represent a new mindset that acknowledges the large amount of work needed in this effort and that tackles this problem by making it possible for modelers to pool their efforts in an incremental development process.

2.2.6 *ILUTE*

The ILUTE project is an "Integrated Land-Use, Transportation, Environment" microsimulation modeling system under development by a consortium of researchers in Canada.

As framed by Miller et al. (2004), ILUTE is a long-term research experiment that aims to investigate the extent to which microsimulation can be operationalized within a practical model.

The approach of ILUTE as presented in Figure 2-8 is two-fold:

1) Microsimulate households' residential choice and activity-travel behavior.
2) Use a hybrid approach of firms' location choice microsimulation and aggregate regional economics.
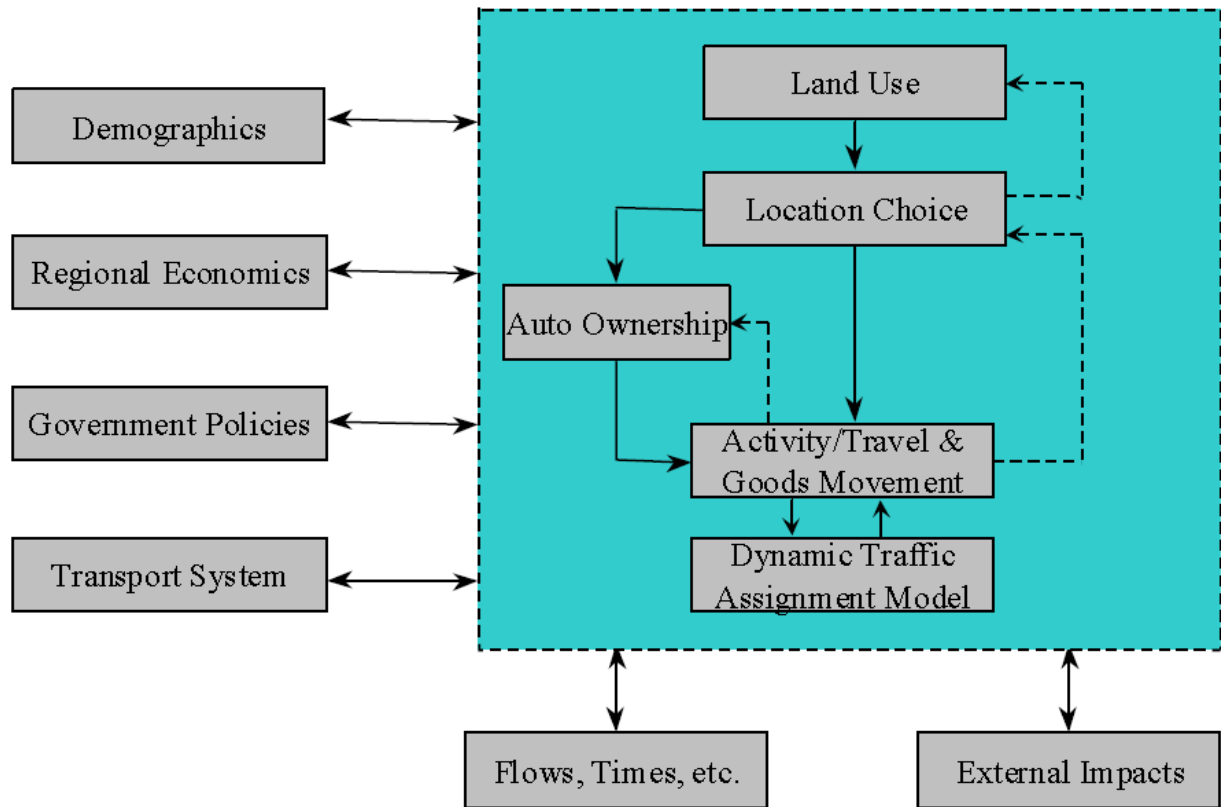
Figure 2-8: ILUTE core model
(Miller, 2008)

It is interesting to note that despite the main research objective behind ILUTE of pushing the limits of microsimulation, Miller (2008) points out that "given current theory and methods, […] a totally disaggregate, reductionist approach is not generally feasible. Rather, a much more aggregate macroeconomic approach to modeling the regional economy is adopted in all current practical applications".

On the households' side, ILUTE models human activities and travel patterns though TASHA (an activity-based model that will be reviewed in chapter 4). Having reached an equilibrium assignment of trips and flows throughout the day on the transportation network, ILUTE derives the vehicular gas emissions by coupling the dynamic traffic assignment model with the vehicular emissions factor model MOBILE6.2C (EPA, 2003). The transportation gas emissions are then used as input for CALMET (Scire et al., 2000) and CALPUFF (Scire et al., 2000), a meteorological and a dispersion model, to obtain the concentration of the gases by zone throughout the day (Miller, 2009) (see figure 2-9).

These features allow ILUTE users to study the effect of transportation emitted gases on health issues in an urban region thereby making a big step towards achieving more objective and quantitative sustainability indicators.
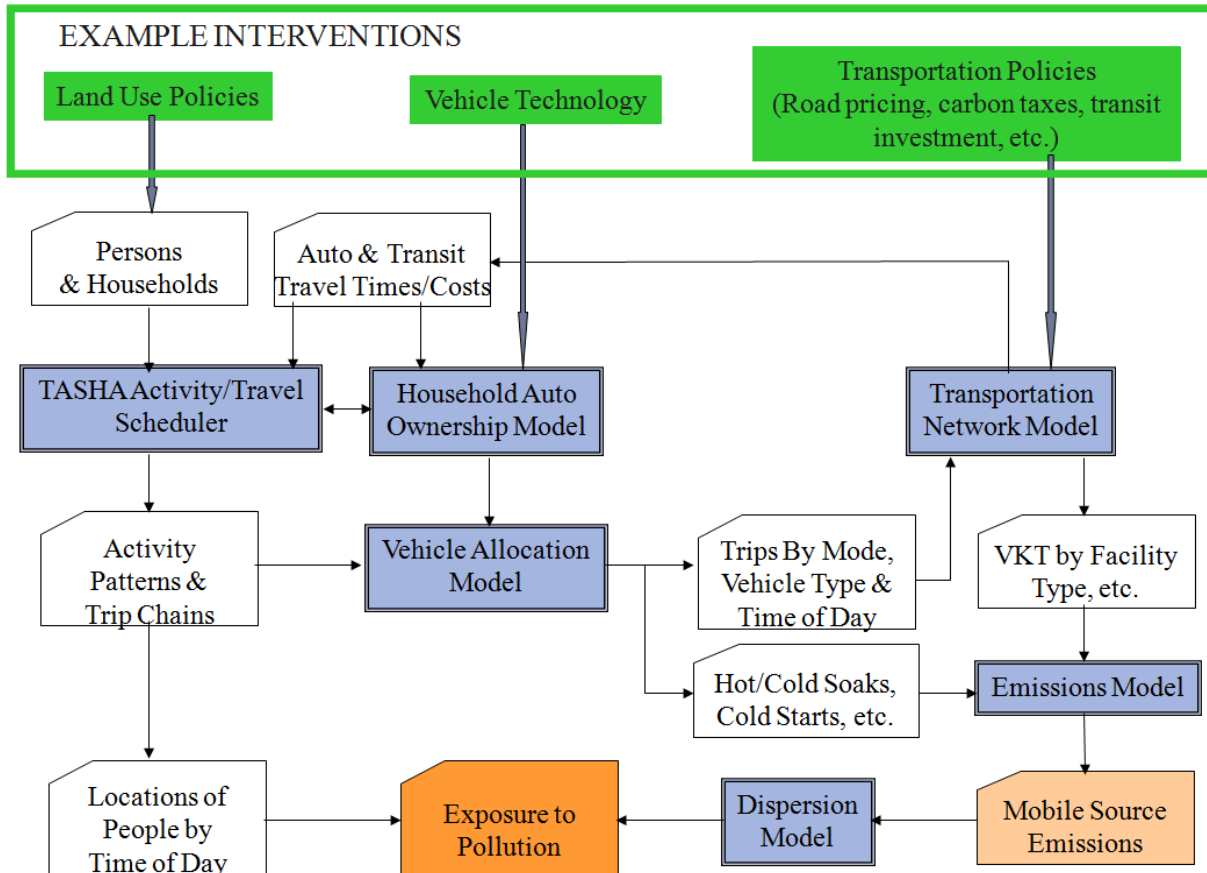
Figure 2-9: ILUTE transportation environmental impact model
(Miller, 2009)

For the household residential location model, ILUTE introduces the concept of stress as defined by the difference between the utility derived from the household's current dwelling unit and the highest utility of the alternative dwelling units.

Consistent with the fact that households do not continually relocate as soon as the marginal utility from relocation becomes positive, a stress threshold value is introduced, whereby if this threshold value is exceeded, the household becomes active on the residential market. After gathering information and conducting a search, the household may or may not decide to relocate

to the alternative residence. This procedure that is generated by an excess in residential stress level is detailed in the diagram below (see Figure 2-10).
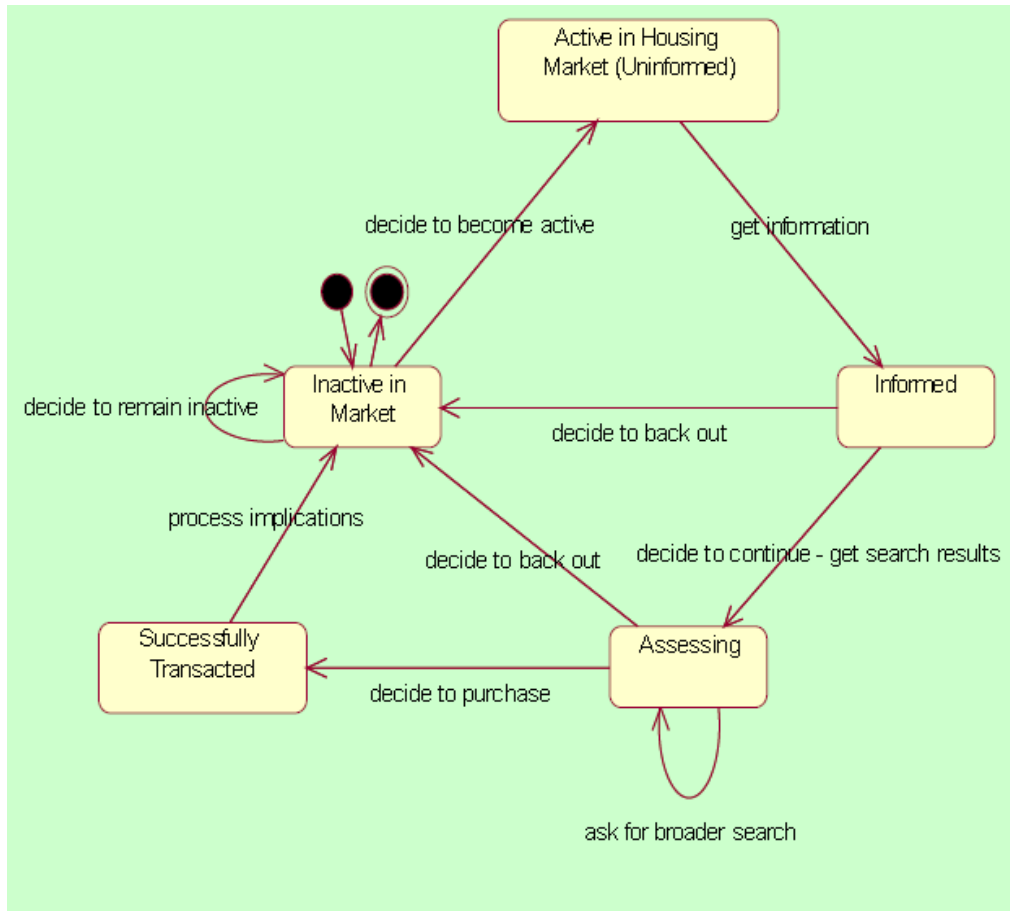
Figure 2-10: ILUTE residential relocation decision model
(Miller, 2009)

The readers interested in more details about this procedure or about the implementation of the stress concept as defined above are referred to Miller (2005a, b) and Roorda et al., (2009).

2.2.7 *Models Comparison*

Six projects were presented in this section for a more in depth review with each of them presenting a unique feature or dimension. In this section, we compare these models and synthesize this information to present a summary on the state-of-the-art in integrated urban modeling (see table 2-1).

From the review of the above models and some others that we have omitted, three main categories of differences between the models exist:

3) Differences in the **scope** of the models.

4) Differences in the **modeling approach** of the models.

5) Differences in the **modeling techniques**

These three categories are expanded into a list of specific different options. The list is not intended to sum up all the dimensions of urban models but rather contains what we think are some essential disparities that affect the use of the model for policy analysis.

Table 2-1: Urban models comparison

		ILUTE	CEMUS	ILUMASS	I-PLACE³S	PROPOLIS	PRISM
Scope	Includes mobile energy and emissions	X	-	X	X	X	X
	Includes land use modifications	X	-	X	X	X	X
	Includes ecological processes	X	-	X	X	X	X
	Includes stationary energy	-	-	-	X	-	X
	Includes impact of environment on transport	-	-	-	-	-	-
	Includes environmental indicators of sustainability	X	-	X	X	-	X
	Includes economic indicators of sustainability	X	-	-	X	X	-
	Includes social indicators of sustainability	X	-	X	-	X	-
Modeling approach	Bottom-up approach	X	X	X	X	-	X
	Includes households	X	X	X	X	-	X
	Includes individual activities	X	X	X	X	-	X
	Includes firms	-	-	X	X	-	-
	Includes activities of firms	-	-	-	-	-	-
	Spatial resolution	high	high	medium	high	low	medium

Modeling techniques							
	Rule-based models	X	-	-	-	-	-
	Utility-based models	-	X	X	X	-	X
	Includes inter-individual interactions	X	X	-	X	-	-
	Includes intra-individual dynamics	-	-	-	-	-	-
	Includes partnerships and competition between firms	-	-	-	-	-	-

We can note from this comparison that there doesn't seem to be an apparent trade-off between the three main categories whereby strength in one modeling aspect is correlated with weakness in another.

This is encouraging and makes use confident that Lee's requiem for large scale urban models was premature.

Nevertheless, we note that most of these models are still in the development stage and that tradeoffs usually start to appear towards the end of the project when researchers aim to produce a functional output.

This reinforces the argument that a modular and incremental development approach is necessary for such large scale models which in turn requires each sub-model to capture behavioral realism so as to serve as a good foundation for later-stage development.

2.3 Background on energy modeling

From our review of integrated transportation land-use models, we conclude that, to the best of our knowledge, there is no single operational or under development urban model that includes the energy demand from households and firms in an integrated urban modeling framework.

It is important to note that there is work underway in the regions of Austin (Tirumalachetty et al., 2009) and Sidney (Boydell et al., 2009) on modeling urban energy demand along with other urban dynamics, such as location choices for households and firms. However, both projects involve models that are developed and estimated from separate datasets and with no linkage between the models making them a set of stand-alone models that relate to different aspects of

the urban dynamic rather than a single integrated urban model. This may be on the verge of change for Austin, with a move towards integrating the land-use and transportation components (Kakaraparthi and Kockelman, 2010).

We dedicate this section to the review of the literature on energy demand modeling. We begin by reviewing models of individual mobile energy consumption (transportation sector). We then review models of stationary energy consumption (residential, commercial, industrial). We subsequently present some models of total urban energy demand.

2.3.1 *Mobile energy demand*

Mobile energy demand includes the energy needed to power transportation on land, on water and by air. Although the energy demand in the maritime, air, and rail sectors is directly related and affected by policies at the urban level, a review of these models is outside the scope of this thesis. This is not to say that these modes are beyond the scope of the iTEAM framework that we outline in Chapter 3; rather, it means that we will adopt an incremental approach where modeling these energy consumption sources is left for future work. We focus in this section on the review of energy demand models for personal vehicles usage.

We can identify two classes of models for vehicular energy demand: (1) vehicle-based models that predict energy consumption based on the result of a traffic assignment model and (2) region-based models that use aggregate energy consumption data to predict vehicular energy consumption with low spatial and temporal resolutions. We will focus in section 2.3.1 on the first class of models as they are more relevant in the context of an integrated transportation and energy model. To a lesser extent, we will go over the region-based models that have been used in an urban energy modeling context in section 2.3.3

Static vehicle-based emission models are also known as emission inventory models. They output emissions over a link (or subset of links) l over which the speed is taken as constant $\bar{v}_l$ and where external factors such as grade and weather are assumed to be uniform. Here is the general form of a static model:

$$E_{l,t}^i = \sum_c VMT_{l,t} \times ER_{l,t}^{i,c}(\bar{v}_l) \times f_c(l,t)$$

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Where $E_{l,t}^i$ is the total emission of pollutant i on link l during period t.

$ER_{l,t}^{i,c}$ is the emission rate of pollutant i on link l during period t for a vehicle of class c. Measured in grams of gas emitted per mile traveled. It is estimated and corrected for different average speeds and factors (cold starts, etc…)

$VMT_{l,t}$ is the vehicle-miles traveled on link l during period t.

$f_c(l,t)$ is the distribution of vehicles on link l during period t between the different classes c.

These models may vary in their sophistication of $ER_{l,t}^{i,c}$ by taking into account more vehicle classes, link grade, the weather impact, vehicle aging, etc. However, applying this type of modeling over an urban network would lose any routing information from an antecedent dynamic traffic assignment model. Furthermore, static vehicle-based emission models tend to misestimate emissions in case of highly dynamic flow regimes (frequent stop-and-go) because they only take into account the average link speed.

This modeling approach has been widely used with macroscopic transportation models. Available applications of it include: EPA's MOBILE 6 (EPA, 2003) and MOVES (EPA, 2009), California's EMFAC (California Air Resources Board, 2006), the EU's COPERT IV (Ntziachristos, 2007; Ntziachristos et al., 2009).

Dynamic vehicle-based models are continuous instantaneous microscopic models of emissions from a single vehicle. They are based on instantaneous vehicle kinematic variables such as speed and acceleration, or on more aggregated modal variables, such as time spent in acceleration mode, in cruise mode, and in idle mode (Cappiello, 2002). Here is the general form of a dynamic model:

$$E_l^i(t) = \sum_j e_j^i(t)$$

$E_l^i(t)$ is the instantaneous vehicular emission of pollutant i on a network or link l from all vehicles j on the network at time t.

$e_j^i(t)$ is the instantaneous vehicular emission of pollutant i from vehicle j at time t.

This factor can be obtained directly from, or through a hybrid combination, of three main methods:

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- Emission maps that relate a {velocity, acceleration} point for a certain vehicle type to an emission level of each pollutant.
- Multivariate regression models.
- Load-based models that capture the emission generation chemical process.

Dynamic models are usually integrated with microscopic traffic assignment models to study emissions over a small number of links or an intersection.

For additional details about these models, the interested reader is referred to Sturm et al., (1998), Barth et al., (1999), Barth et al., (2000), Hausberger (2002), EPA (2002), Ajtay et al., (2005) and Biona et al., (2007).

2.3.2   *Stationary energy demand*

Stationary sources of energy demand include the residential, commercial, and industrial sectors. In section 2.3.2 we review models that have been applied to one such source alone (e.g. one house or one factory).

Although the models that have been applied to predict energy demand for a single household are very different from those that have been applied for a single factory, we can still identify the same classification of models for these stationary sources:

- Household-based/firm-based models are econometric models that forecast the total energy demand for a single dwelling unit/factory based on some observed variables (e.g. price of energy, equipment stock, etc.). Perhaps one of the most well known models in this group is the Fisher-Kaysen residential electricity demand model (Fisher and Kaysen, 1962).

This abstraction has lead to two drawbacks:
   (1) Household/factory-based models have typically been prone to different econometric problems such as heteroskedasticity and endogeneity due to the misspecification of the regression model or due to the model not capturing the simultaneous interaction of stock holding and equipment usage.

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(2) These models have been criticized as lacking behavioral insight for their abstraction of the energy consumption process, which makes them insensitive to different policies.

However, these models are still widely used in practice. For more recent applications of these models, the reader is referred to Holtedahl and Joutz (2004), Reiss and White (2005) and Davis (2008)

Process-based models identify the different energy consuming processes within a household/firm. A typical process may be water-heating for households or running the conveyor belt for factories. These models forecast the energy demand for these different processes before summing them up. These models are more data intensive but allow for testing policies on different appliance types as they make explicit the equipment ownership choice process. One of the most widely used process-based models is the EPRI-REEPS model for residential energy forecasting. For more details on the feedback between household appliance choice and usage, the reader is referred to the seminal works by Cowing and McFadden (1984) and Dubin and McFadden (1984). For more examples on process-based models, the interested reader is referred to Koomey et al., (1995), Energy Efficient Strategies (2006) and Jaccard and Dennis (2006).

We define an activity-based energy model as one that tracks the different activities of an individual (household member, firm worker) and derives his equipment usage and energy consumption. This approach is by far the most complex and has thus only recently received some attention (Tanimoto et al., 2008). We can readily identify the data limitations of such a model because we would need to gather information about each energy consuming activity the agent is performing and we would have to deal with the ambiguous situations of shared equipment usage (who is really watching the television?) and multi-tasking (washer machine is on, while watching TV). Despite these drawbacks, an activity-based energy model creates the potential for analysts to observe the energy substitution effects between the use of different equipments and the participation in different activities.

Hybrid models combine features from the different approaches outlines above. These models represent a tradeoff between the data requirement of lower complexity models and the modeling accuracy of more complex models.

2.3.3 *Urban energy demand modeling*

In this section, we assess the approaches that have been used to model energy demand at the urban level. A recent paper developed at the World Bank (Bhattacharyya and Timilsina, 2009) identifies the following types of urban energy models:

- Econometric models
- Engineering-economy (or end use) models
- Input-output models
- Scenario approaches
- Decomposition models
- System dynamics models
- Artificial neural networks
- Hybrid models

The report provides an extensive and detailed review of several models that have been used in practice.

In this thesis, our objective is not to compare the models that have been applied but their underlying approaches and techniques in order to see what urban energy model would fit better with the integrated framework that we propose.

We can broadly, categorize urban models into top-down models and bottom-up models. In general, top-down approaches allow the modeler to capture the entire urban energy demand and the aggregation pools together the different effects underlying the total energy demand which may be useful in order to reduce the forecasting uncertainty.

However, top-down approaches are not able to capture the complex substitution effects properly that usually accompany policies.

On the other hand, bottom-up approaches suffer from the exact opposite problems. For instance, if we were to only use the models from the mobile and stationary sources, we might end-up neglecting the energy wasted in transmission or production losses.

Theoretically, the benefits of bottom-up energy models have not been clearly shown to outweigh their added complexity although we are witnessing the development of more complex and data intensive models. Moreover, there are voices arguing for simplicity saying that the output results of these sophisticated models are not so different from those of simpler models (Armstrong, 2001; Craig et al., 2002).

Faced with opposing views on the best approach and the best modeling techniques, we use a set of criteria to filter through these models. We adapt these criteria from those suggested by Hartman (1978, pp. 8-11) to ensure the resulting models are useful for a policy support tool in the context of integrated urban modeling. Hartman suggests that for a model to be useful for policy analysis it needs:

- *"Proper identification of major market participants and the level of disaggregation required"*
- *"Proper identification and incorporation into variables in the model of policy issues and technological considerations for the major market participants"*
- *"Proper degree of geographical disaggregation"*
- *"Utilization of the appropriate behavioral models and underlying behavioral assumptions"*
- *"Proper integration of the demand analysis into an overall energy and/or macroeconomic model"*
- *"Utilization of proper data and statistical/econometric techniques"*

Adapted to the context of this thesis, using this set of criteria, our selected model needs to:
➤ Identify households and firms as consuming agents
➤ Link energy demand to activities, taking into account the equipment stock available (appliance usage in households or machine operation in companies)
➤ Include the most relevant factors for the decision making process about appliance usage.
➤ Account for endogeneity and heteroskedasticity problems.

The above criteria direct us towards bottom-up (or engineering-economic) models. Worrell et al., (2002) present an excellent case for adopting bottom-up models[7]. They argue that most new policies do not affect energy demand directly and thus cannot be captured appropriately using simplistic top-down models. They also emphasize the need to capture the behavioral underpinnings of energy demand by adopting a multi-disciplinary perspective and modeling the different interactions surrounding energy demand at the social and technical levels.

Recently, agent-based simulation has been gaining larger acceptance in the field of energy economics and particularly for modeling electricity markets (Koritarov 2004; Sensfub et al., 2007; Weidlich and Veit, 2008; Connolly et al., 2010).

These arguments are even more relevant when testing combinations of policies (no silver bullet) in the fight against climate change in order to properly understand the interactive effect and adequately assess the benefits and value of each of these policies.

2.4   State-of-the-art on integrated urban modeling

We conclude chapter 2 by briefly summarizing the major trends in transportation, land-use and energy modeling and identifying the direction forward in integrated urban modeling.

In retrospect, we can identify a clear trend in the field of urban modeling towards more disaggregate-level modeling and microsimulation and deriving transportation and energy from human activities. This type of modeling is better suited for policy analysis than top-down models as it can capture the substitution effect between different activities. Microsimulation involves a bottom-up approach that recognizes two elementary agents in the city: individuals/households and firms/organizations.

On the household side, the urban models capture residential location, vehicle ownership and daily activity-travel patterns. The advances in the economics of time allocation and mathematical psychology have made this microsimulation possible and there is nowadays an entire field of research dedicated to capturing more realistically households' decision-making and activity-participation (See chapters 4 and 5).

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[7] Although their work was specific to energy demand in the industrial sector, it can be generalized to urban energy demand models.

On the organizations side, the models have so far only captured location choice at the disaggregate level. To date there has been no operationalized model that captures firms location choice, vehicle and equipment stock and mobility patterns at the disaggregate level. Rather, they all use some form of spatial aggregation and predominantly input/output models to model the flows of goods in a city. This is not to say that there is no ongoing research on this specific field. Actually, freight modeling is particularly active with research being undertaken on several of the sub-models that compose firm behavior. We will touch upon this briefly in Chapter 3 hereafter.

We also depict a move towards internalizing more and more factors in the different models.
For instance, CEMUS goes into the details of modeling individuals' education levels, marital status, etc… and the transitions between the different stages.
On the firms' side, ILUTE is moving towards internalizing economic growth by modeling regional economics to provide any growth factor endogenously in the urban models.
Energy modeling is moving towards integrating the equipment stock choice and the equipment usage patterns.

On another level, one of the main lessons that previous modeling attempts such as ILUMASS have shown is that different sub-models require different levels of spatial and temporal disaggregation

Regarding time modeling, the best approach so far has been to adopt a hybrid discretization of time with an order of magnitude on the order of years for transitions on the infrastructure and buildings level, to a time span of 30 minutes - if not less – to capture daily activity-travel patterns.

Similarly, for space modeling, location choice models for organization might need very fine-level detail about the floor plan of a specific building in a specific bloc whereas destination choice models rarely need finer detail than at the bloc or neighborhood level.
This is a direct result of the tradeoff between forecasting accuracy on one hand and computational limitations and data availability on the other and this balance is likely to keep

shifting as technological advances push the barriers of computational power and data gathering methodologies.

Finally, we note striking differences in the scope and techniques of the different models developed for transportation, land use and energy. These differences reveal a gap in the theory of urban modeling. We attempt, in chapter 3, to fill this gap by presenting a theory with clear requirements and properties for modeling transportation, energy and land use as parts of an integrated transportation and energy activity-based model.

Chapter 3
The iTEAM

"We shape our buildings and afterwards, our buildings shape us" Winston Churchill

In this chapter, we present a framework for a 'next generation' integrated urban model: an integrated transportation and energy activity-based model (iTEAM). We leave the discussion of the scenario types where iTEAM can act as a decision support tool for policy and decision making for chapter 6.

Given the varying scopes and modeling techniques of urban modeling reviewed in chapter 2, we build the iTEAM framework based on mathematical properties derived from the theory of complex systems.

We begin by presenting our perspective on the urban dynamics and its characteristics in section 3.1. We present the microsimulation approach of the model in section 3.2, which guides the iTEAM modeling framework of section 3.3. In section 3.4, we briefly review the theory of complex systems and derive mathematical properties for the complex system models within

iTEAM. In section 3.5, we present the behavioral models that integrate transportation, land-use and energy through households' and firms' activities.

3.1   The urban dynamics

We begin present in this section our perspective on urban dynamics to set the tone and define the scope of our urban model.

A *city* is an urban area[8] shaped by the interaction of its people, the movement of its vehicles, and the flows of water, materials, wastewater, energy, and information[9] among others.

We look at city as a complex system, to be more precise as a *system of complex systems* where the transport, energy, etc. form different *complex organized systems*. We will return to this point briefly and define the terminology and implication of these terms that we borrow from complexity theory.

We think of individuals in a city as *agents* in two social constructs: households and firms.

These agents interact in several ways that can be classified in two categories: *direct* and *indirect*. Direct interactions are of three types:

1) Households – Households: friends, extended families, etc.
2) Households – Firms: Employment, consumption, investment, etc.
3) Firms – Firms: competition, partnership, supply-chain, etc.

Indirect interactions are made through the city itself. Households and Firms are constantly interacting due to scarce resources in the land market, transport network, energy market, etc… and shaping (and being shaped by) the invisible hands of demand and supply.

Households and Firms are also interacting more subtly by the creation of information in the form of education, inventions, fashion, etc.

Indirect interactions, although taking place between individual agents, abstract the other individuals from each decision maker. For instance, one doesn't think of every other individual

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[8] the US census bureau defines an urban area as a "densely settled geographical area with a minimum population of 2500 people and a minimum density of 5000 people per square mile"
[9] Includes sensory information, not limited to data flows

on the road when planning his trip schedule but rather thinks of congestion peak or off-peak periods. The definition of this type of abstraction or indirect interactions that take place through the city as opposed to the direct interactions between individuals is a guiding principle for the model structure of iTEAM. The urban modeling problem is thus 'reduced' to the exercise of modeling these two types of direct and indirect interactions.

Therefore, we can caricaturize our understanding of the city in the a-spatial and a-temporal graph of figure 3-1:
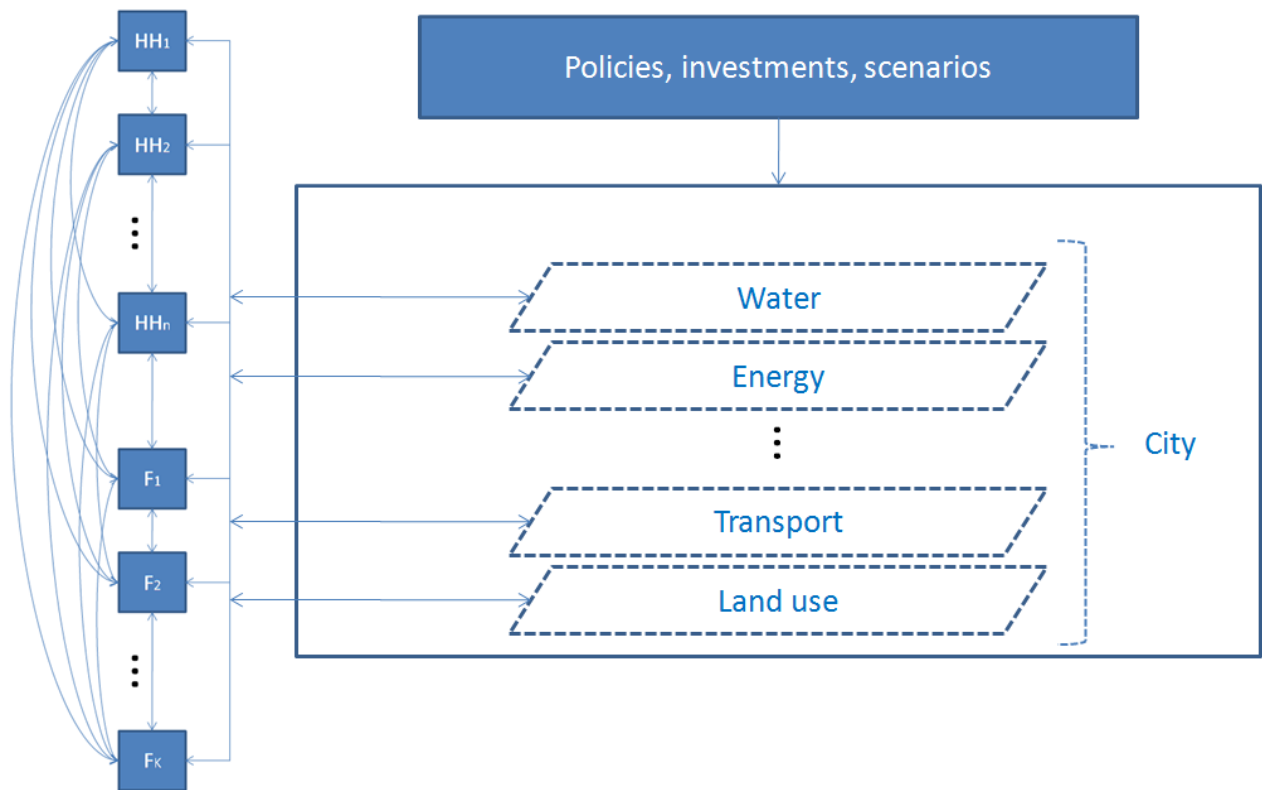
Figure 3-1: Urban Dynamics

The end goal of iTEAM is to output the resources consumed, the agents' activities and interactions, as well as the by-products generated under the different scenarios (policies, investments, etc.) so that objective and transparent sustainability indicators can be used to compare the different scenarios and inform decision-makers.

3.2 Modeling approach

As we have seen in Chapter 2, most of the current urban models only consider one or two of the layers outlined in the urban dynamics, usually the transport and land use systems. There is nothing wrong with this approach *so long as the direct interactions are fully captured* − which has actually not been the typical the case. In fact, we only propose to study the land, transportation, and energy networks as part of our modular[10] approach.

The main drawback with this 'narrow' focus is that it doesn't allow us to study the impact of a change in (or a policy directed towards) the water or waste 'layers' on the energy and transportation systems.

Alberti (2008), among many others, criticizes previous urban models that break down cities into component parts and study each part separately. She reminds us that cities are complex systems with correlated hybrid phenomena, and as a result, cannot be fully understood by simply understanding each of their individual parts.

We fully agree with such statements and *add* that the linkage between these parts is actually captured by the *direct interactions* that represent human activities (as opposed to purchases of land, equipment or trips that are represented by indirect interactions).

Our review of Chapter 2 revealed that microsimulation and activity-based modeling have almost become the norm in transportation and land-use modeling. Meanwhile, in energy modeling, although this approach has not been performed at a large urban scale yet, it is gaining more and more attention as computational limitations are lifted. Furthermore, we presented some of the arguments made in the literature for microsimulation as a necessary approach for models aimed at policy analysis rather than simple forecasting. Hence, from here onwards, we adopt microsimulation as the approach for developing iTEAM and no longer consider aggregate-level urban modeling approaches[11].

One main axiom for our modeling approach is the premise that energy and transportation demands are derived from the demand for activities. Hence, a behavioral model for human

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[10] Refer to discussion about Lee's paper in chapter 2
[11] Agent microsimulation will be shown as a mathematically necessary requirement for modeling complex systems in section 3.4

activities is pivotal in our approach. To test the impact of different policies or investments accurately, we frame a model that microsimulates individual behavior (within the constructs of households and firms) in connection with the associated mobility and energy consumption patterns. The model converts these patterns into their appropriate resource consumption and aggregates these impacts over the entire population to generate the overall effect of the policy. This bottom-up modeling approach is shown in figure 3-2. Once a model run is completed, several indicators can be post-processed from the iTEAM output to evaluate the tested policy or investment (See chapter 6).

This methodology allows us to capture the true relation between transportation and energy in a way that would be abstracted by traditional macro-level models. Furthermore, it permits the identification of the role of each specific variable on the aggregate results thereby allowing allowing the model to serve as a decision support tool for urban planners and policy makers.

Gather aggregate and individual data

Activities, transportation, energy consumption, residential characteristics

Generate population

Generate agents with socio-economic and demographic characteristics

Apply the iTEAM

Model Households and Firms activities, transportation, location, equipment holding and usage

Model Resource consumption and waste generation

Translate transportation and equipment usage into resources consumed

Aggregate impacts

Energy consumption, transportation patterns, GHG emissions, telecommunications

Figure 3-2: Modeling approach

3.3 The iTEAM framework

Our proposed model structure can now be put forth as a hybrid multi-agent-based microsimulation that captures direct interactions through behavioral activity-based models and indirect interactions through organized complex systems.

The resultant integrated activity-based model builds on the two-agent split (households and firms) and explicitly models their direct and indirect interactions to represent the urban dynamics.
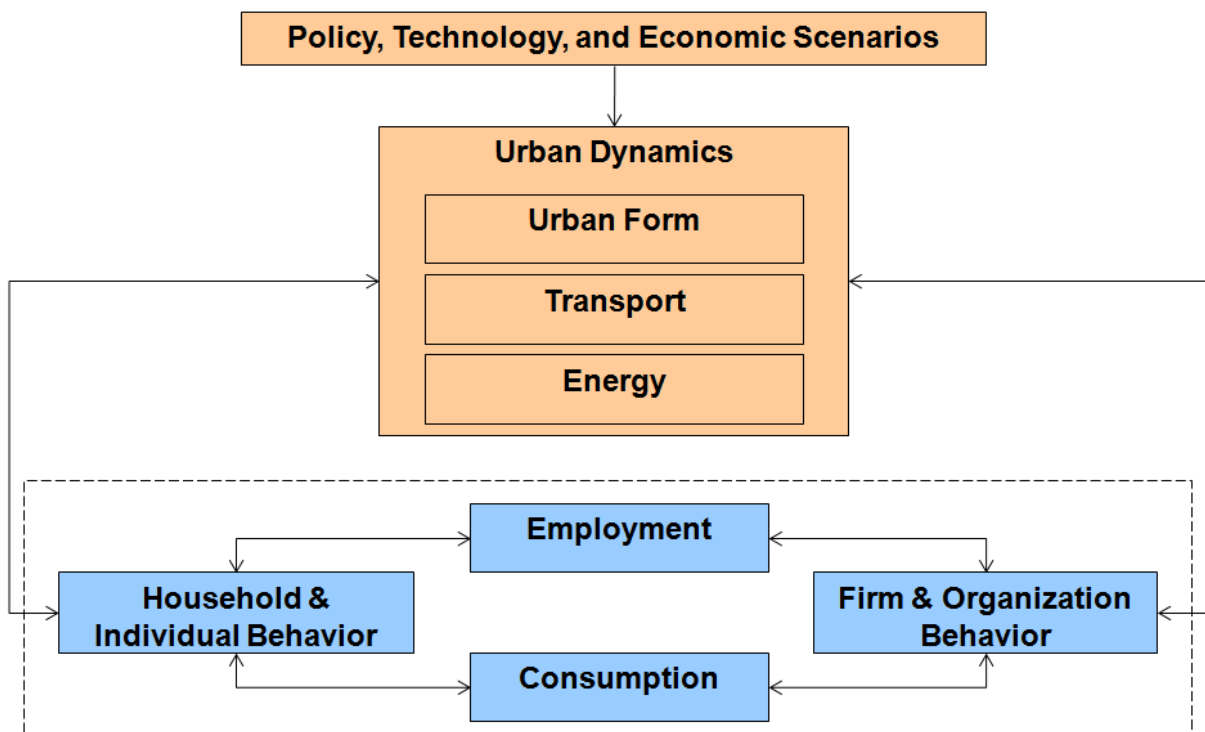
Figure 3-3: iTEAM

The model structure presented in figure 3-3 is directly derived from the urban dynamics presented in section 3.1 and the modeling approach presented is section 3.2.

Direct Household-Firm interactions:

The direct interaction between the households and firms are captured by the employment (or labor market model) and the consumption models. The employment model assigns individuals from households to organizations (also includes students assigned to schools and colleges) while

taking into account the characteristics of the household in terms of demographics and location. The consumption model represents the destination choice model for an individual's activities such as shopping, recreation, seeking the doctor. More details will be provided about the type of activities in the activity model presented in chapter 5.

Direct Household-Household and Firm-Firm interactions

Direct Household-Household and Firm-Firm interactions are included in the 'activities' sub-models shown in figures 3-5 and 3-6 respectively. In the household context, they represent individuals from different households meeting to perform a joint activity. The intra-households are also captured in the activity models in terms of joint activity participation, resource sharing and joint decision making (see chapter 5). In the firm context, they represent the partnerships and competition between firms and draw on the techniques of cooperative and non-cooperative game theory as well as operations research. A detailed study of these interactions is beyond the scope of this thesis.

Indirect interactions:

The indirect interactions are symbolized by the 'urban dynamics' set of models that capture the complex behavior in the land market, transportation network, and energy network where households and firms interact.

We formulate the models of the urban dynamics based on several fields, including urban economics and complexity theory.

Why economics?

Economics is commonly defined as "the science which studies human behavior as a relationship between ends and scarce means which have alternative uses" (Robbins, 1932)).

We choose to create our urban model around a behavioral core to enable its use as a policy support tool. This is in accordance with Lee's requirement and in opposition to the traditional simplistic perspective that abstracts the behavioral root and only considers the apparent outcomes.

Why complexity and complex systems theory?

We believe that the system-based formulation accurately captures the natural behavior that people demonstrate when they use one of these city-wide systems. For instance, individuals do not explicitly think of the entire electricity grid when they decide to use an appliance. Nor do they think of the other people on the road individually but rather as a continuous flow of cars causing congestion. These are examples of indirect interactions captured in the complex systems models. However, people do think of the company they work for in a unique fashion. This is an example of a direct interaction captured in the activity model.

In the remainder of this chapter, we briefly put forward a non-technical overview of complex systems theory and prove that transportation, energy and land-use in a city exhibit the properties of organized complex systems. We then detail the household and firm behavior by showing the explicit interactions between human activities and each complex network in a city.

3.4 Organized complex systems

Let us begin by defining a system as a collection of interacting elements making up a whole (e.g. a watch).

A dynamic system is a triple $\{X, \Phi, G\}$ where X denotes the state space usually given by a topological space, Φ is the flow of the system (the evolution rule) given by a continuous map from $G \times \mathbb{R}$ into X and $G \subseteq \mathbb{R}$ a semigroup of times.

Discrete dynamical systems are a special case with $G = \mathbb{Z}$. (Balibrea, 2006)

One can distinguish between two types of dynamic systems: simple and complex

While many simple systems may be very complicated, they are not necessarily complex.

There is no precise definition for complex systems, only a general agreement on their essential characteristics: (Boccara, 2004, pp.3)

1) *"Complex systems consist of a large number of interacting agents"*
2) *"They exhibit emergence; that is a self-organizing collective behavior (pattern) difficult to anticipate from the knowledge of the agents' behavior"*
3) *"Their emergent behavior does not result from the existence of a central controller"*

Complex systems can be recognized in several colonies (Reynolds, 1987), in the World Wide Web, in cities, etc. but perhaps the most famous example of a complex system is Conway's game of life (Gardner, 1970).

To illustrate the difference between a complicated simple system and a complex system, we use the same examples presented by Weaver (1948):

➢ We think of the trajectory of a ball on a billiard table as a simple system

➢ As the number of balls increases, to say 25 or 30 balls, the model becomes too cumbersome to compute but is still a simple system.

➢ Interestingly, if we consider the movement of a very large number of balls, we can now predict the movement of the balls but using completely different tools: While we were using deterministic tools for the simple systems, we use stochastic methods for the complex systems. The situation described here is one of disorganized complexity as the balls do not anticipate or react to other ball's movements.

➢ In contrast with disorganized complexity, organized complexity is said of systems that involve a large number of agents (usually not as large as disorganized complexity) and show signs of organization (patterns). They are characterized by an interaction between the agents such as typically found in living organisms.

The concept of emergence as defined above bears little use for the study of urban dynamics as it covers a very large spectrum of patterns and is implicitly subjective, that is, a pattern unexpected to one analyst may be expected to another. (Pessa, 2001)

For our purposes, the more interesting concept is that of *intrinsic emergence* which happens in organized complex systems. Intrinsic emergence is tied to patterns that evolve and become important *within* the system itself. This new characteristic of the whole itself, at the macroscopic level, bears purpose to, and affects, the agents or parts of the complex systems (Crutchfield, 1994; Pessa, 2004).

The standard example of intrinsic emergence in social systems is that of the optimal pricing that evolves from the interactions of the different agents in an efficient market influences in turn their individual behavior (Fama, 1991).

A more detailed review of complexity and complex systems theory is beyond the scope of this thesis and we refer the interested reader to the works we cited along with the references they contain.

In order to understand the implication of complex systems theory on the modeling techniques that should be used, we draw on the analogies between urban dynamics and those of other complex systems. This is not a new approach in this field which has actually been called "transdisciplinary" (Friesz, 2007) as it combines work done that can be applied in different disciplines ranging from quantum theory, cognitive psychology, computational biology, artificial intelligence, operations research, computational sociology, and many more.

We select to build this analogy with the field of epidemiology for the readily defined terminology along with important commonalities between the two systems – mainly the fact that both systems are heterogeneity-based organized systems as opposed to a disorganized homogeneity-based model such as that presented in Quantum Field Theory (Lahiri and Pal, 2001).

Heterogeneity-based organized complex systems exhibit some basic characteristics regardless of the specific context. Pessa (2004) contrasts between this type of systems and ideal or disorganized complex systems.

Table 3-1: Comparison of heterogeneity-based organized complex systems and disorganized complex systems

Heterogeneity-based organized complex systems	Disorganized complex systems
Medium-range correlations	Long-range correlations
Metastable states	Stable ground states
Hierarchical organization	Collective phenomena
Interaction with the environment	Working in the infinite volume limit

Ulanowicz (2005) presents an excellent treatment of the modeling done in complex living organisms and ties back the methodology to its historical context and the scientific movements initiated by Aristotle and Newton.

He elaborates on the ideas set forth by Karl Popper to find the middle ground between "pure stochasticity and strict determinism" and move away from causality to propensity (the tendency for a certain event to occur in a particular context).

This notion of propensity is related (but not equivalent) to conditional probability and can be thought of as the counterpart of a force (which only exists in an isolated universe) in an organized complex system. The intrinsic emergence of new patterns and new phenomena can be thus thought of as the result of interferences among propensities.

Ulanowicz goes on to illustrate how this theory explains the positive and negative feedbacks that we can observe in living organisms while giving special attention to self-reinforcing phenomena as major factors in shaping the growth and selection pressures in an organism.

The impact of this theory on the modeling of complex networks in the city is profound. It necessitates several characteristics of these models, mainly:

1) *The models have to be dynamic.*
2) *The models have to be agent-based.*
3) *Agents' heterogeneity needs to be captured.*
4) *The models have to capture propensities and not be confined to deterministic causality or pure randomness*
5) *The models have to allow for the possibility of intrinsic emergence.*

Furthermore, since the agents (households and firms) in a city are not identical but heterogeneous, if we can prove that a system in a city is a complex organized system, its model will have to present the four properties of heterogeneity-based organized models reiterated below:

1) *Medium-range correlations*
2) *Metastable states*
3) *Hierarchial organization*
4) *Interaction with the environment*

3.5 The city as a system of complex organized systems integrated through activities

We have so far presented our perspective of the city and defined the properties and modeling methodology of organized complex systems.

In this section, we present our approach for modeling the city as a system of complex systems (Peeta et al., 2005) and discuss the theoretical implications of this approach for the integration of each complex system with activities. We detail in this section the modeling needed within each of the three complex systems considered (transport, energy and land-use) to represent the indirect interactions while focusing on the integration with the behavioral models of households and firms. We dedicate chapters 4 and 5 for the detailed discussion of the direct interactions in the household construct (Household-Household, Household-Firm) and the activity modeling at the core of the household behavioral model.

A detailed discussion of the firm-firm interactions such as partnership in a supply chain or price competition is beyond the scope of this thesis. We only show the linkage between a firm's activities and the three complex systems discussed in this section and refer the reader to other resources for further readings.

The linkage between complex systems in a city has been steadily gaining momentum in the literature of complex systems (Maeir, 1998, Keating et al., 2004).

Friesz et al., (2007) identify five main sources of coupling between the complex systems of a city: "physical interdependencies", "budgetary interdependencies", "market interdependencies and spatial economic competition", "information interdependencies", "environmental and congestion externalities".

While we acknowledge the existence of these couplings, we propose to use human behavior as a broader connecting web between these different systems. We realize that the added complexity of modeling human activities but posit that it is outweighed by the added value of capturing activities in terms of analysis and forecasting power. We dedicate chapter 6 to illustrate the types of policies and investment scenarios that can be tested with iTEAM as a decision support tool.

Having identified human activities at the core of iTEAM, we expand the boxes representing household behavior and firm behavior from figure 3-3 as shown in figures 3-4 and 3-5 respectively[12].
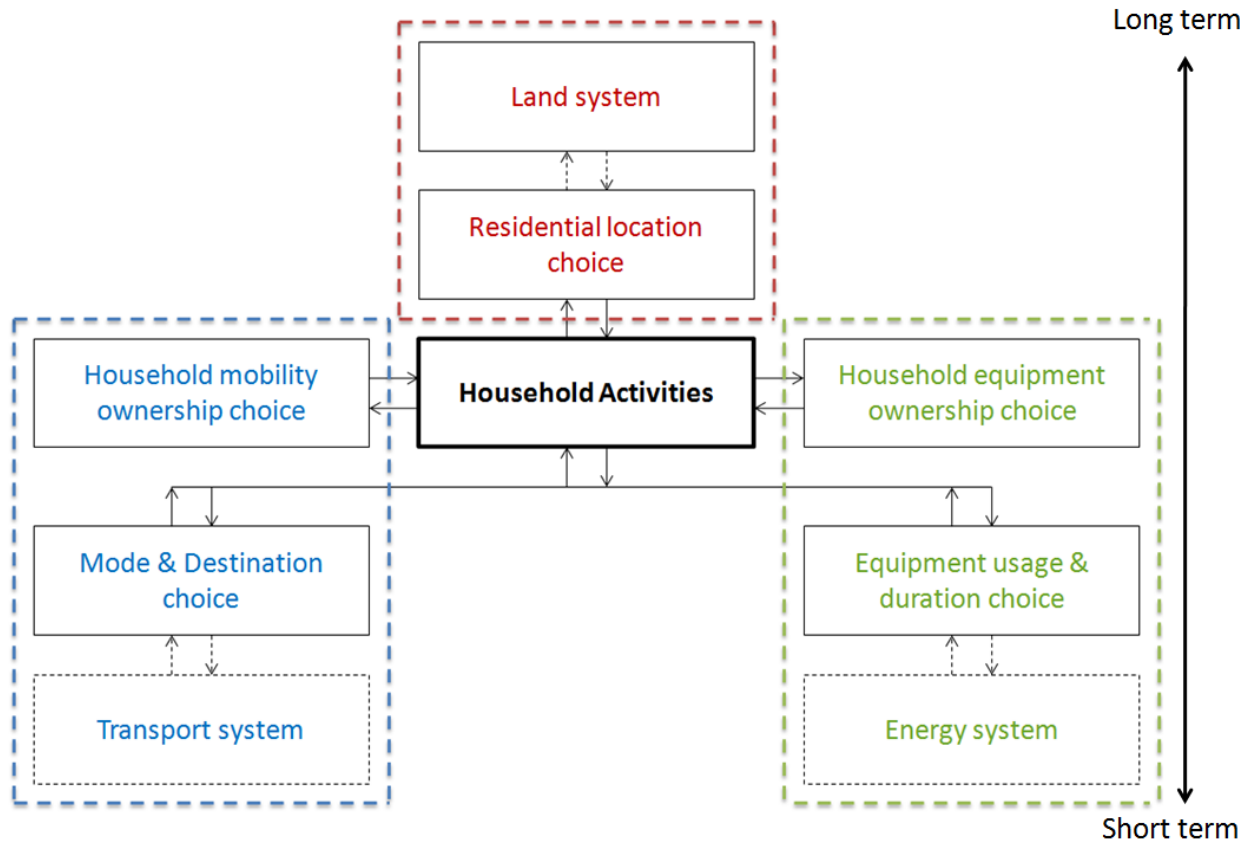
Figure 3-4: Household behavioral model
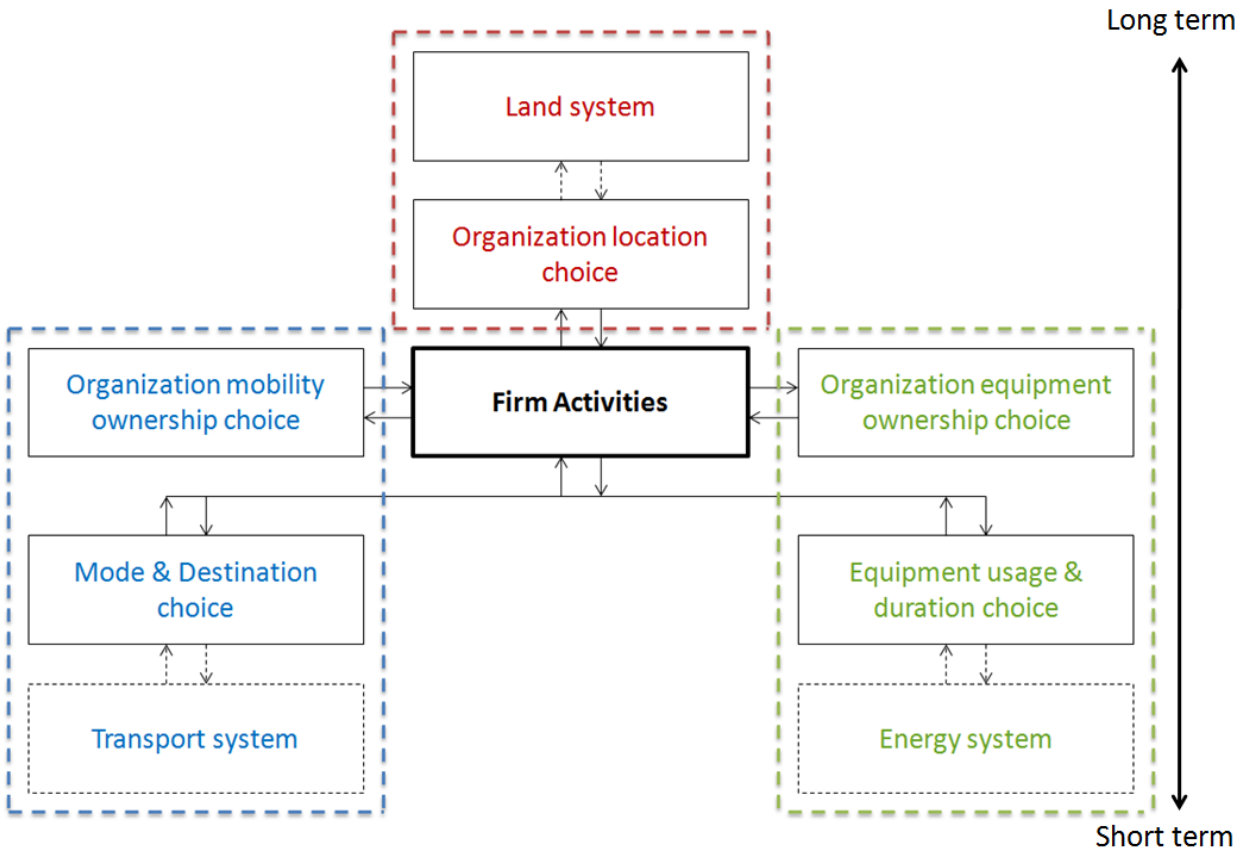
Figure 3-5: Firm behavioral model

The behavioral models shown above closely mimic real human behavior by recognizing that different decisions and processes take place at different temporal and spatial scales:

- In the short term[13], our framework predicts agents' immediate behavior including activity participation, mode use, inventory order, fleet dispatching, etc. These decisions are all conditional on the available location and equipment stocks available to the agents.

- In the medium term, households and firms purchase or upgrade their mobility (vehicles, transit pass, etc.) and equipment stocks (electrical appliances, machines, etc.). These decisions are motivated by the agent's activities at the short term and affected by the agent's location. The integration of the different models here is necessary to capture the endogenous relation between the use and ownership of equipment. That is, an agent will anticipate a certain usage pattern of the specific equipment and, accordingly, make a decision on the best equipment to purchase.

- In the long term, at the individual agent level, the household/firm might select a new location. This decision is motivated by the short term activities and results from the interaction between

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[13] What we referred to as 'immediate term' in chapter 1

the residential/commercial property market and the agent's internal factors, such as finances, accessibility demands, etc.

Spanning across the different spatial and temporal scales, each trip, energy consumption, or relocation decision has an indirect relation with the supply model that represents the dynamics of the city.

We first prove that each of the three systems considered is a heterogeneity-based organized complex system. We then deduce properties that are necessary to model the supply side of the system and the supply/demand interaction.

3.5.1 *Integration of transportation with activities*

Over 24 hours, we notice that certain patterns of free-flow or congestion *emerge* out of the interactions of the different agents on the network. These patterns in return influence the behavior of agents in scheduling their daily trips. This property, along with the lack of centralized control proves that the transport network is an organized complex system. Furthermore, since the agents interacting are heterogeneous, we can talk about transportation as a heterogeneity-based organized complex system. Thus, to accurately capture the details of this system in a model, we need to capture the following defining properties:

1) *Medium-range correlations*
2) *Metastable states*

A transportation model within iTEAM should capture medium-term correlations and dynamic equilibriums. These two criteria imply that in a one day simulation, the model needs to have a certain temporal disaggregation so as to capture the metastable states of congestion or free-flow along with their correlations through the household and firm scheduling processes.

3) *Hierarchical organization*
4) *Interaction with the environment*

These two criteria require the transport model to have a certain level of spatial disaggregation in order to capture the differences in level of service on different parts of the network. When we study a small network, a micro-level transportation model is necessary but when we are studying a larger urban area, this does not preclude the use of meso-level transportation models that work on a link basis.

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Current dynamic traffic assignment (DTA) models suit these criteria and can thus be used in an integrated model of transport and energy. These models represent the supply side of the transport sector by moving each vehicle according to microscopic or macroscopic performance models. Given a fixed network configuration, DTA models represent the demand/supply interaction by solving for the equilibrium where no vehicle has an incentive to switch routes according to his route choice model. In the context of iTEAM where individual heterogeneity is important, the equilibrium can be computed at the disaggregate level using methods such as fixed point formulation as opposed to aggregate network-level properties. For more details on such models, we refer the reader to Kaysi et al., (1995), Ben-Akiva et al., (2007) and Lam et al., (2009).

The question remains of how to integrate the transportation model with a human activity model so as to achieve integration among the different complex systems of the city. As shown in figures 3-4 and 3-5, the trips that we use as input to the dynamic traffic assignment model, result from the activity scheduling process – including the mode and destination choices – which takes into account the mobility stock available to the household or firm.

Roorda et al., (2009) present a model to integrate activities, and vehicle transactions that is based on their definition of the concept of stress (See chapter 2) as the difference between the current utility and the best alternate utility. Regardless of whether we agree or not with this particular way to integrate vehicle transactions with activities, we note that this is the type of model that is needed in iTEAM because it has the property of propensity. The randomness is captured by the stochastic stress threshold that they use and the determinism stems from the rule that is used. However, we argue that to achieve this integration with activities, the model requires variables related to the agents daily activities and lifestyle, that capture the positive and negative feedback loops that we showed in the analogy with complex modeling done in epidemiology. We will propose such a formulation in Chapter 5 that is based on our definition of the concept of stress.

The need to capture the lifestyle and activities impact on vehicle transactions has long been recognized in the modeling of household behavior (Choo and Mokhtarian, 2004) but has not yet been properly integrated in an operationalized urban model.

On the firms side however, the task of vehicle fleet design has a long history, and has been related to firms' logistics through profit maximization, risk minimization or more complex objective functions (e.g. profit maximization with environmental concerns). For the sake of brevity, we will not present specific models that have been used for mode choice, destination choice and vehicle transaction choice models.

3.5.2 *Integration of stationary energy with activities*

For stationary energy demand, the situation is more complex because the supply side has more fluctuations while households and firms usually face fixed energy prices for a certain period of time. Nonetheless, in a deregulated energy market, we can observe similar fluctuations and patterns throughout the day and between different days where the price of energy, whether in crude form (e.g. oil) or electricity form, is affected by the demand from the different agents who in turn adjust their behaviors according to the equilibrium price. Thus, we can see that all the conditions of organized complex systems are satisfied. Regarding the temporal scale of the energy model, we argue that a 24hour simulation is necessary if we want to capture the impact of a change in activities on the energy supply market. Thus the integration of energy and activities is necessary for the energy systems and the model needs to have the four properties:

1) *Medium-range correlations*
2) *Metastable states*

These properties imply that in a one-day simulation of activities, the energy model within iTEAM should capture within day price and demand fluctuations in order to predict the energy supply accurately.

3) *Hierarchical organization*
4) *Interaction with the environment*

The energy model should also capture the energy load in different parts of the city at the disaggregate level so as to adequately represent the energy distribution shifts within the day.

The exact energy model structure depends on the political, regulatory, and actual context of the urban region studied. Agent-based simulation of the players on the supply side of the energy markets fits all of the aforementioned criteria. For the complex case of deregulated electricity markets, agent-based simulation allows the different entities concerned (generators, transmitters, customers, etc.) to interact and evolve in an organized complex system by using dynamic

stochastic optimization as well as different rules to mimic the learning and adaptation that take place in the market.

3.5.3   *Integration of land-use with activities*

There is a fundamental difference between the transportation or energy systems and the land system. Housing, offices or factories are usually seen as necessary constraints that affect an agent's activities. Hence, we cannot draw a parallel structure regarding the land market and simulate it over a 24-hour period with individual activities:

"people don't instantly change their workplaces and residences when circumstances change" (O'Sullivan, 2007). This means not only that the land market changes at a much slower pace, it also means that even after all the circumstances that lead to a change are there, there exists a time lag between when the relocation move is decided and actually implemented.

We propose a two-stage model for this:

> 1) *Relocation decision:* this model is based on the lifestyle and daily activities of agents. It is affected by the characteristic of the current and alternative dwelling units as well as by characteristics of the agents:

> - In a household: change in demographics (e.g. marriage, divorce or new child), change in employment (college, work), etc.

> - In a firm: change in square footage per employee, new product line, etc…

We develop and formulate this link between activities and the relocation decision model in the context of household activity-based modeling in section 5.3.3.[14]

We capture the propensity of households to relocate or acquire a new location by operationalizing the concept of lifestyle stress. This decision would result from the household seeking an increase in accessibility, an increase in room space, or of a lower rent.

> 2) Relocation: this model is based on the state of the new household or firm (whether they have to build it, renovate it, purchase it, rent it, etc.) and characteristics of the agent in the period of time once the relocation decision has been made, (e.g. if there are other purchases that are competing with the relocation with respect to resources).

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[14] We leave out the discussion of firms' relocation models.

This entire process takes place in the land market where households and firms interact.

We can observe the same properties of organized complex systems in the land market with different patterns emerging such as neighborhood average prices, industrial or residential zones, accessibility, etc…

The land use model within iTEAM should thus capture:

1) *Medium-range correlations*

2) *Metastable states*

These imply that over the desired simulation period, the land use model within iTEAM should capture price and demand fluctuations. Therefore any 'equilibrium price' is dynamic and changing as a result of the interaction of the urban form and the agents desire to relocate.

This implies that parameters of the models do not change with respect to time but only as a result of demand and supply factors.

3) *Hierarchical organization*

4) *Interaction with the environment*

These properties require that in an agent location choice model, the neighborhood characteristics should be taken into account whether explicitly or through some hybrid neighborhood measure (e.g. accessibility) along with characteristics of the alternative houses in the choice set.

Furthermore, modeling the interaction with the environment property means more than simply finding the equilibrium price set by the demand and supply; it also means that a firm should take into consideration any regulation that affects its operations such as the cap-and-trade system.

Unfortunately, on the land-use supply side, a real estate model with all of these properties has not yet been developed. Nonetheless, the bid-rent and hedonic price theories and the random utility maximization framework offer the tools necessary to develop a microsimulation real estate model with the four properties of organized complex systems. We note here that there is still a large need for improvement on the current techniques especially for capturing the real estate agent's heterogeneity, their learning and adaptation processes, as well as the access to information in the supply/demand interaction.

3.6   The iTEAM structure

We present in this section a simplified model structure for iTEAM that only shows the indirect interactions in an urban region between the transport, energy, and land-use systems.

The structure, as presented in figure 3-6, is modular and builds on the iTEAM framework and the behavioral models for households and firms.
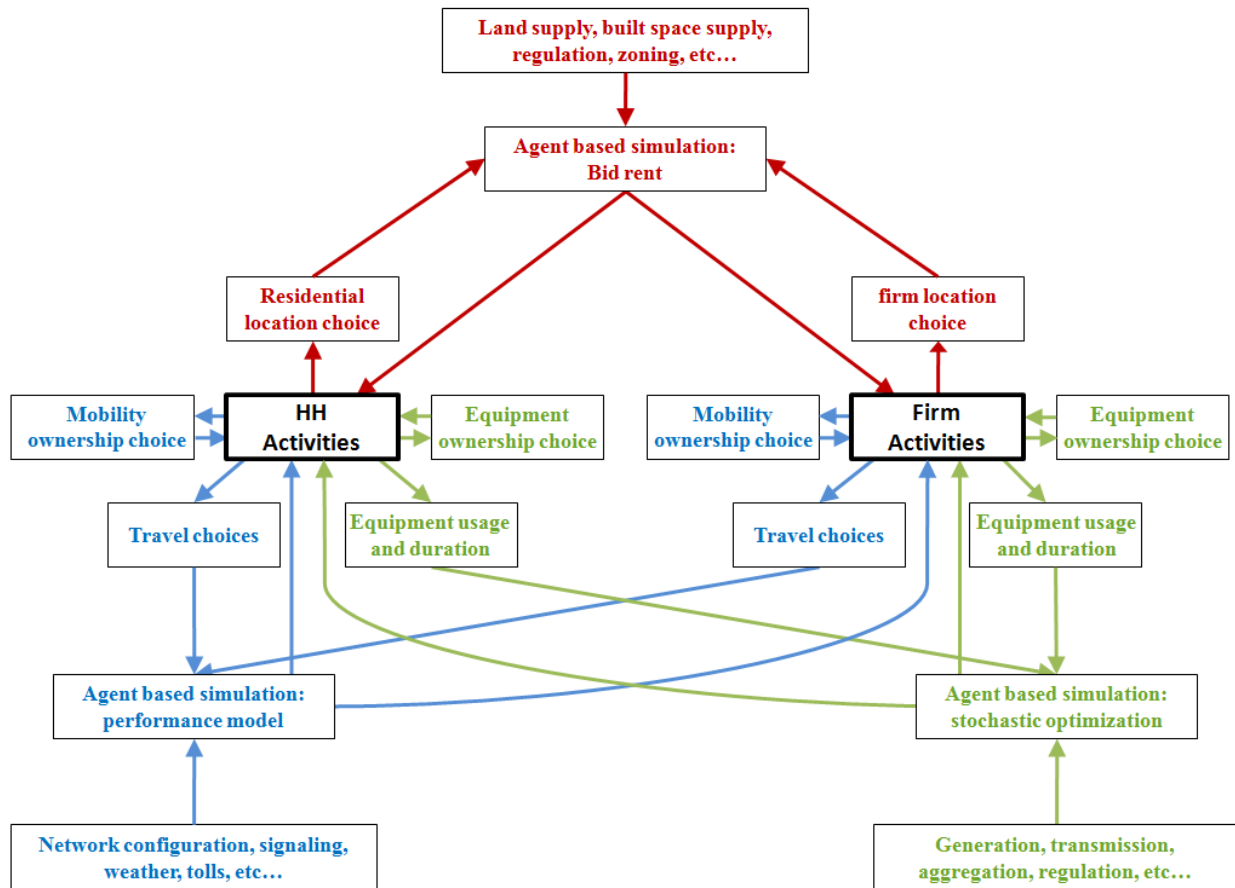
Figure 3-6: Model structure

On the transportation side, the activities of households and firms will output the timing and purpose of the trips; this will be converted into an origin/destination node by the travel choice models. Each O/D will be input into the dynamic traffic assignment model and assigned to a route according to the traffic performance model. This procedure will be iterated until equilibrium between the transport demand and supply is reached. As a result of the demand/supply interaction, the dynamic traffic assignment model will output the trips' exact route and duration. This in turn will affect the agents' subsequent activities.

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On the energy side, the activities of households and firms will output the timing and purpose of the appliance or machine used; this will be converted into an energy demand by the equipment usage & duration models. The usage of appliances will generate an energy demand (e.g. electricity, gas, oil). For the case of publicly offered utilities where demand has to be met, the supply will be modified to match the demand. This optimization procedure will reflect the regulatory context for that urban region (e.g. regulated or deregulated electricity and gas markets). As a result of the supply/demand interaction, the energy supply may be modified (energy prices may fluctuate; different plants may be activated or shut-down). This will output the stationary energy consumption for households and firms.

In the medium and long term, we show in figure 3-6 how households and firms may decide to modify their mobility stock, equipment stock or relocate to a new location. We detail and formulate these decisions for households in chapter 5. The real estate market demand modifies the price of existing real estate and available land according to the bid-rent model. This may trigger real estate agents to acquire and develop new land. The urban form is thus the dynamic equilibrium between the supply and demand.

3.7   Conclusion

In this chapter we have presented our view of the urban dynamics as a system of complex organized systems connected through human activities.

We first showed how the transportation, energy, and land-use 'layers' of a city have the properties of organized complex systems. By relying on analogies with other models of organized complex systems we then derived a set of requirements for modeling each of these systems. Finally, we showed how each of these systems is integrated with human behavior in the context of the household and firm agents.

We hereafter review the literature on activity-based modeling in the household context in chapter 4, and present in chapter 5 different extensions to activity-based models to satisfy the properties that we put forth in this chapter. Mainly we focus on the scope of activities covered and go beyond deterministic or stochastic models to models that capture the actual propensity of activities. We model activities propensity by including stress in the activity utility and use these

variables to model the short and long term dynamics of human behavior in the context of iTEAM.

Chapter 4

Background on Activity-Based Modeling and Current Applications

"Economy of time, to this all economy ultimately reduces itself" *Karl Marx*

In this chapter, we go into the details of the activity model that is at the core of the household behavioral model in iTEAM. We begin by defining the nature and scope of activity-based modeling in section 4.1 and select to focus on a specific class of activity-based model that is based on random utility theory which we briefly review in section 4.2. In sections 4.3 and 4.4 we review the literature on time allocation and activity scheduling models and present different examples for each of these two approaches to activity-based modeling.

4.1 Fundamentals of activity-based models

Broadly stated, activity-based models are mathematical or qualitative formulations of individuals' activity participation. They model the response to the common questions that each

individual faces on a daily basis: 'what activity will I perform?', 'with whom?', 'when?', 'for how long?', 'how do I get there?' and so on.

The interest in modeling human behavior in terms of activity participation originated in different disciplines: psychology, sociology, economics, geography, urban planning, artificial intelligence, and transportation. This has resulted in a plethora of activity-based models with different scopes, focal points and modeling techniques.

For instance, activity-based models originating in urban planning circles focused on the linkage between activities and urban form leading to detailed models of land use dynamics. On the other hand, models originating in transportation research focused on the linkage between activities and travel patterns leading to detailed models of trip, mode and route choice. Even within the single discipline of transportation research, there is no single cohesive body of knowledge that all researchers agree and build upon.

In the context of this thesis, we are interested in models that can be implemented in the iTEAM framework developed in chapter 3. Thus, we will only focus on activity-based models that can mathematically forecast individuals and households activity participation. We do nonetheless visit qualitative models of human activity participation done by psychologists and sociologists in chapter 5 in an effort to provide our model with a strong behavioral foundation.

Under the topic of mathematical activity-based models, we can identify two broad classes of activity-based models.

- The first class is based on Markov models, where the schedule is composed of a sequence of states. Each state represents a different activity and the transition between the states indicates the mobility patterns (if any) between the activities.

Although this method might be mathematically appealing, it doesn't capture the fundamental behavioral mechanism behind the choice of activity participation and transport decision. Furthermore, it is based on pure randomness with doesn't conform to our requirement of propensity. This reduces its efficacy as an analysis and policy decision support tool.

- The second class is based on random utility theory which is rooted in the microeconomic theory of consumer behavior. In the remainder of this thesis, we will focus on this second set of models. For that, we begin by presenting the basics of random utility theory in section 4.2

4.2 Random utility theory

Utility theory originated in consumer behavior modeling where goods are assumed to be homogeneous and continuous, and behavior to be deterministic.

A utility function $U(.)$ is a function that captures the value that an individual derives from consuming a bundle X of goods. This function covers the entire $\mathbb{R}$ domain with negative values of the utility function representing the value that an individual would be willing to forgo in order to avoid this bundle.

Utility theory states that if a bundle X_1 is viewed as inferior to bundle X_2, then $U(X_1) < U(X_2)$. This implies rationality, which can be defined in terms of three major assumptions about rational human cognitive behavior:

(A) Completeness: The ability to determine his preference between two bundles.

(B) Transitivity: If bundle X_1 is preferred to bundle X_2 and bundle X_2 is preferred to bundle X_3, then bundle X_1 is preferred to bundle X_3

(C) Continuity: If bundle X_1 is preferred to bundle X_2 and bundle X_3 is sufficiently close to bundle X_1, then X_3 is preferred to X_2.

An individual is assumed to choose the bundle that maximizes his utility under a certain generalized budget constraint. We refer the reader to Nicholson (2004) as a reference textbook on microeconomics for further details.

This theory of decision making has been contested by several cognitive scientists and economists (Edwards, 1954, Simon, 1955, Ariely, 2008) that refuted utility maximization theory and proposed other theories such as Prospect Theory[15] (Kahneman and Tversky, 1979). However, there is evidence that individuals are capable of rational decision making in daily activities they are familiar with.

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[15] Takes into account individual's biases such as loss aversion and general inability to correctly value stochastic events

For instance, the experiments presented by Griffiths and Tenenbaum (2006) clearly showed that people's predictions of 'standard' events closely approach the prediction of an optimal Bayesian model.

Utility theory was extended to random utility theory and applied in the context of decision-making, not confined to consumer behavior, by Thurstone (1927) and Luce (1959) among others. In random utility theory, the apparent unpredictability in human behavior is assumed to be a shortcoming on the modeler's side and not of the individual himself. Individuals are still assumed to make "rational" choices but randomness is introduced into the model to reflect the fact that the modeler/analyst does not have all of the information that is available to the decision-maker.

This randomness captures four main types of modeling errors: unobserved variables, measurement errors, unobserved taste heterogeneity, and instrumental of proxy variables (Manski, 1977).

Random utility is the basis of the discrete choice framework, which considers choices between discrete alternatives rather than quantities of a certain homogeneous good. A discrete choice model represents the decision making protocol as the selection of the alternative with the highest utility among a universe of alternatives $\mathbb{C}$ available to the individual:

Mathematically, we represent the choice of individual n with the dummy variable y_{in}:

$$y_{in} = \begin{cases} 1, & if\ U_{in} = \max_{j} U_{jn} \\ 0, & otherwise \end{cases} for\ i,j \in \mathbb{C}$$

The utility that individual n derives from an alternative i is formulated as:

$$U_{in} = V_{in} + \varepsilon_{in}, \qquad i \in C_n$$

Where V_{in} is the systematic component of utility expressed as a function of observable variables and ε_{in} is the random component of utility that captures the imperfect information available to the modeler.

Therefore, the probability that individual n chooses alternative i is

$$P(i|C_n) = P\left(U_{in} \geq U_{jn}, \qquad \forall j \in C_n \right)$$

$$P(i|C_n) = P\left(V_{in} + \varepsilon_{in} \geq V_{jn} + \varepsilon_{jn}, \qquad \forall j \in C_n \right)$$

$$P(i|C_n) = P\left(\varepsilon_{jn} - \varepsilon_{in} \leq V_{in} - V_{jn}, \qquad \forall j \in C_n \right)$$

The choice of the distributions of the error (random) terms is left to the analyst.

McFadden (1974) made the assumption of independent and identically distributed Gumbel random terms with scale μ which leads to:

$$P(i|C_n) = \frac{\exp(\mu V_{in})}{\sum_{j \in C_n} \exp(\mu V_{jn})}$$

This is known as the multinomial logit model (MNL) that has the advantage of having a closed form.

Other researchers have assumed a normal distribution for the error terms which leads to the following J-1 dimension integral for the probability where J is the size of the choice set.

$$P(i|C_n) = \int_{-\infty}^{V_{in}-V_{1n}} \int_{-\infty}^{V_{in}-V_{2n}} \int_{-\infty}^{V_{in}-V_{(i-1)n}} \int_{-\infty}^{V_{in}-V_{(i+1)n}} \dots \int_{-\infty}^{V_{in}-V_{Jn}} n(\varepsilon; 0; \Sigma) d\varepsilon$$

Where $n(\varepsilon; 0; \Sigma)$ denotes the multivariate normal density with 0 mean and Σ variance-covariance matrix.

The main limitation of this model is the computational burden it imposes on the modeler.

For more details on the subject, the interested reader is referred to Ben-Akiva and Lerman (1985).

It is important to note here that this approach is limited by the fact that a decision-maker can only make a single choice from the universe of alternatives. However, individuals are constantly making complex decisions that involve bundles of choices. Consider, for instance, the typical case where an individual may decide to take his car to go shopping at a far place on a rainy day while he might choose to go walking to the corner convenience store on a sunnier day. In this example, the individual linked the two decisions of mode and destination choice and chose a specific combination depending on an exogenous factor (e.g. the weather). What may seem as a simple outcome actually stems from a complex decision-making protocol that we humans use unconsciously.

Classic discrete choice models have tackled the issue of multi-dimensional choice by identifying all the possible combinations in the choice set as composite alternatives. It is easily noticeable that with the different types of activities, the different household equipments, transportation modes, and especially with the different times available throughout the day, it is impossible to

even generate all of these different combinations let alone estimate a decision model with all of these alternatives in the choice set.

4.3 Time allocation models

In this section we refer to time allocation models as mathematical formulations of the task that individuals and households face when allocating the 24 hours in a day to different activities. The research behind these models is more focused on forecasting the time allocated to each activity during the day and less on the sequencing and decision-making process that leads to a specific allocation.

4.3.1 *Budget-constrained consumer approach*

Time allocation models were initiated by economists who have modeled household behavior using a budget-constrained consumer approach. This approach was originated by Becker who presented one of the earliest operational formulations of human behavior that included the value of time in the budget of households. In his "revised theory of choice" Becker (1965) formulated the allocation of time in a household as an optimization problem where the objective is to maximize the utility derived from the different activities subject to budget and time constraints. DeSerpa (1971) developed this approach by modeling goods and activities as direct sources of satisfaction and introducing a constraint to capture the minimum amount of time to be spent on a certain activity.

This work enabled the distinction between two basic categories of activities: leisure activities where people may spend more than the minimum time required and non-leisure where people will only spend the minimum amount required. There is nowadays an entire branch of literature on the value of time that distinguishes between the value of saving time, the value of time as a personal resource and the value of time as a commodity. The reader is referred to Bruzelius (1979) for details on the differences in time valuation and to Jara-Diaz (2008) for a time allocation formulation that separates goods-consumption from activity participation. This work allowed for the estimation of the value of time for different activities and different individuals thus capturing taste heterogeneity. Furthermore, it captured intra-day interactions by separating between the periods of time when a person has an approaching deadline (i.e meeting, or work) from when a person has a more flexible agenda.

4.3.2 *Discrete-continuous models*

Discrete-continuous choice models (Hanneman, 1984) were devised specifically to handle the explosion in the number of alternatives in the choice set brought by a continuous variable such as quantity or time. They do so by introducing a continuous variable into the discrete choice random utility maximization framework.

Bhat (2005, 2008) presented the following multiple discrete continuous extreme value model to simulate individual activity participation:

$$U(x) = \sum_{k=1}^{K} \frac{\gamma_k}{\alpha_k} \varphi_k \left[\left(\frac{x_k}{\gamma_k} + 1 \right)^{\alpha_k} - 1 \right]$$

Where $\forall k \in K, \varphi_k > 0, \alpha_k \leq 1, x_k \geq 0$

x_k is the quantity of units consumed of item k

φ_k represents the baseline utility derived from the participation in activity k

γ_k and α_k capture the satiation effect from the consumption of x_k. The higher the value of γ_k, the lower the satiation effect.

This utility form was used in a random utility framework with the stochasticity introduced in the baseline utility:

$$\varphi_k = \varphi(z_k) . e^{\varepsilon_k} = exp(\beta' z_k + \varepsilon_k)$$

Where z_k is a vector of attributes for the good k and of individual characteristics for the decision-maker.

The optimization can be then framed as:

$$max \sum_{k=1}^{K} \frac{\gamma_k}{\alpha_k} exp(\beta' z_k + \varepsilon_k) . \left[\left(\frac{x_k}{\gamma_k} + 1 \right)^{\alpha_k} - 1 \right]$$

Subject to:

$$\sum_{k=1}^{K} p_k x_k \leq E$$

Where p_k is the unit price of good k and E is the budget available to the decision-maker.

A general form of the MDCEV model is obtained using a Generalized Extreme Value (GEV) error structure which gives the advantages of a closed-form model while not imposing any restrictions on the correlation of the error terms.

To account taste variations, modelers have resorted to the use of a mixing distribution.

In the Mixed MDCEV, the error term ε_k is divided into two parts. The first part assumed to be independently and identically Gumbel distributed (i.i.d) while the second part captures the correlation structure.

Other researchers have explicitly included the time budget constraint in their formulations. (Anas and Xu, 1999, Kockelman, 2001, Anas, 2007)

Meloni et al. (2004) proposed a Nested tobit formulation for household time allocation. Their work incorporates some aspects of the decision-making process by using a two-stage allocation process (see figure 4-1).
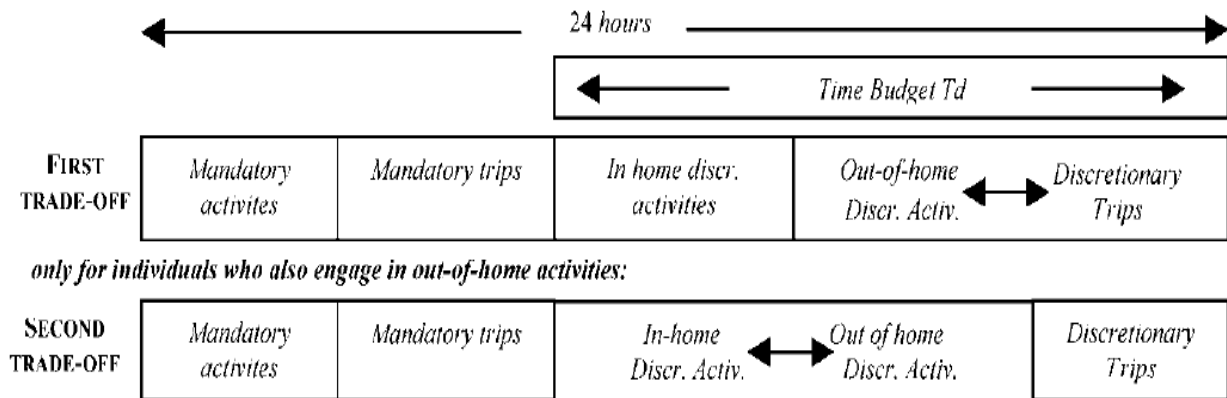
Figure 4-1: Nested tobit time allocation model
(Meloni et al., 2004)

Lee et al., (2007) used simultaneous doubly-censored tobit models to model time-use behavior within the context of household activity participation.

The main drawback of this method is the computational burden it imposes as the multivariate normally distributed errors make it computationally inhibiting to model a large number of activities in the choice set of individuals.

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Ye and Pendyala (2005) proposed the fractional logit methodology.

This method is intuitively appealing when we think of time allocation as it literally consists of allocating fractions of the 24 hours in a day to different activities as follows:

$0 \leq y_{qi} \leq 1$ and $\sum_{i=1}^{I} y_{qi} = 1$ for a single individual q where i represents a specific activity from the choice set I of potential activities.

This method is appealing as it allows for diminishing marginal utility (as does the MDCEV) and it ensures that all of the 24 hours of the day are allocated.

In this section we have reviewed several examples of time allocation models that have been used in different contexts each developed with a different research perspective but all of them attempting to forecast time allocation to activities by individuals. Despite the different advantages that each of these methods possesses, they all share a common characteristic: None of them truly captures the behavioral process behind the observed time allocation. Although they do capture the substitution effects between the activities performed, they do not account for the motive behind those activities. This makes them good mathematical techniques to be embedded in a broader framework that is in tighter connection with time-use research or some theory of human motivation that can explain the root cause of the time allocation and activity participation of individuals. We will revisit this idea in detail in chapter 5. Even more importantly in the iTEAM context, time allocation models do not capture the trips or trip chains, therefore, they do not in themselves fully capture the impact of transportation policies on mode and route choice.

4.4 Activity-scheduling models

In this section we will visit activity-scheduling models. The research behind these models aims to understand the location and timing of human activities and it has been typically driven by researchers interested in modeling the urban form and mobility patterns in a city.

This was a large step for transportation and urban modelers from the traditional trip-based and tour-based four-step models. Although these traditional transportation models are still in use and are sometimes used in conjunction with activity-based models (Pendyala et al., 2004), their review is outside of the scope of this thesis. We refer the interested reader to Daganzo and Sheffi (1977), Manheim (1979), Anas (1981), Gomez-Ibanez et al., (1999), Ben-Akiva and Bierlaire (2003) Small and Verhoef (2007) and the references within these resources.

For activity-scheduling models, the premise that demand for transportation is derived from the demand for activities implies a decision framework where travel decisions are components of a broader activity scheduling decision, and therefore calls for modeling activity demand explicitly.

The main obstacle to model activity demand in a random utility maximization framework using discrete choice models is the inhibitive large number of alternatives in the decision-maker's choice set for the multi-dimensional choice that accompanies activity participation. As mentioned above, a model for activity demand has to take into account choices of timing, destination, mode, route, etc.

Modelers have tackled this computational limitation in two different ways that have lead to two distinct classes of activity-scheduling models:

The first class of models focuses on the choice set generation at the expense of capturing the true decision protocol. These models rely on a variety of decision theories such as dominance, satisfaction, or even a set of rules that the modelers pre-enter. These rules are simulated and applied in a sequential manner as constraints to eliminate alternatives from the choice set of activities that an individual can participate in. A classic utility maximization discrete choice model is sometimes run on a restricted choice set for each decision. Usually, the choice set generation and the choice making steps are iterated until the simulated activity schedule matches the estimation data.

These models accurately capture the universal choice set and the situational, timing and spatial constraints and they do have a computational advantage. However, they suffer from two main drawbacks:

1) The sequential scheduling of activities omits the fact that individuals plan ahead and that some activities may have a priority over others.

2) The use of exogenous rules limits the effectiveness of the model because the decision protocol is oversimplified.

This weakens these models use for policy analysis especially in the context of an integrated transportation, land use, and energy model since the rules cannot capture all of these variables.

It becomes an art to balance the 'tightness' of these rules and the forecasting power of the model so that the model still accounts for a large enough number of exogenous variables and interactions to be reasonably realistic and robust.

The other class of models focuses on the decision-making protocol at the expense of generating a restricted choice set for decision-makers. This is done by aggregating the time component to coarse intervals, by aggregating the spatial component into analysis zones, and even by aggregating the activities into activity types (e.g. leisure activities). The main drawback of these models is the alternative aggregation, which may cause problems in the case of integrated models by not going into the details of the activity participation. However, the increase in computational power made available by technological advances and parallel processing makes these models more attractive.

It is important to note at this point that the division between these two model classes is not necessary apparent and there exists several hybrid models that propose different tradeoffs between choice set generation and behavioral realism.

For a review of the features and limitations of each of these classes of activity-scheduling models, the reader is referred to Bowman (1998) and Timmermans (2001).

We will review in this section three models that place a strong focus on capturing the behavioral processes behind decision-making. This is by no means an extensive review, but these models were purposely selected because each presents a distinct advantage that we deem useful for the development of the activity-based component of iTEAM.

4.4.1 *Prism-constrained activity-travel simulator*

The activity-travel simulator generates the daily activity pattern for an individual by decomposing the day into a series of activity-travel bundles.

PCATS begins by "blocking" certain periods of time at a specific location for "blocked" activities such as work, sleep, etc. that can be obtained from surveys.

PCATS uses the notion of Hagerstrand's time-space prisms (Hagerstrand, 1970) that represent the spatio-temporal constraints for any activity to occur during the open periods given the maximum mobility speed available to the decision maker (figure 4-2).
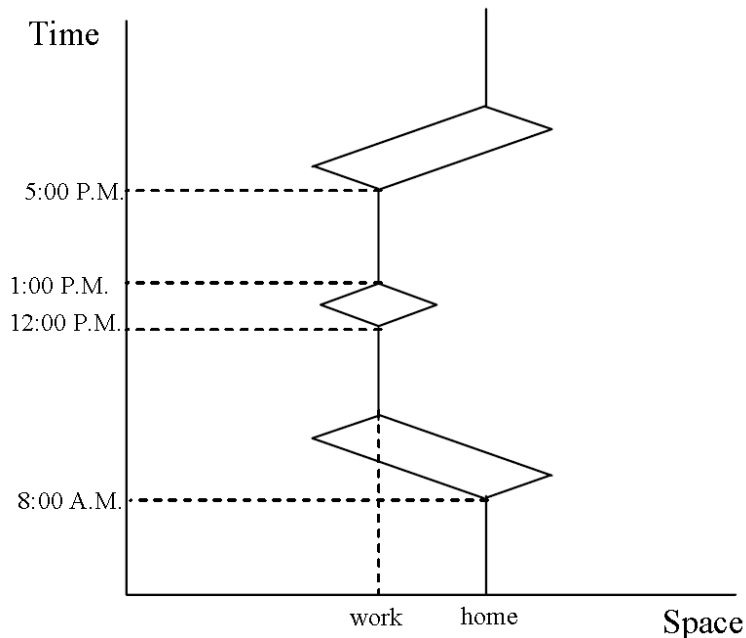
Figure 4-2: Time-space prisms
(Pendyala et al., 2002)

In order to model the prism vertices, Pendyala et al. (2002) use the stochastic frontier model (Aigner et al., 1977) whose general form is:

$$Y_i = \beta' X_i + v_i - \mu_i$$

Where Y_i represents the trip beginning or ending time for observation I, Xi is a vector of observable explanatory variables, v_i is an unbounded random variable and μ_i is non-negative random variable – typically a truncated normal. Since $Y_i \leq \beta' X_i + v_i$, $\beta' X_i + v_i$ is used as an estimator of the unobserved prism starting and ending times.

Having determined the open time-space prisms, PCATS uses a sequential scheduling algorithm to determine the activities and travel decisions of the decision-maker.

For each activity-trip bundle, PCATS models the activity type choice, the destination choice of this activity and the mode choice conditional on the destination, and the activity duration model as a hazard-based, split population survival model. This scheduling structure is represented in figure 4-3:
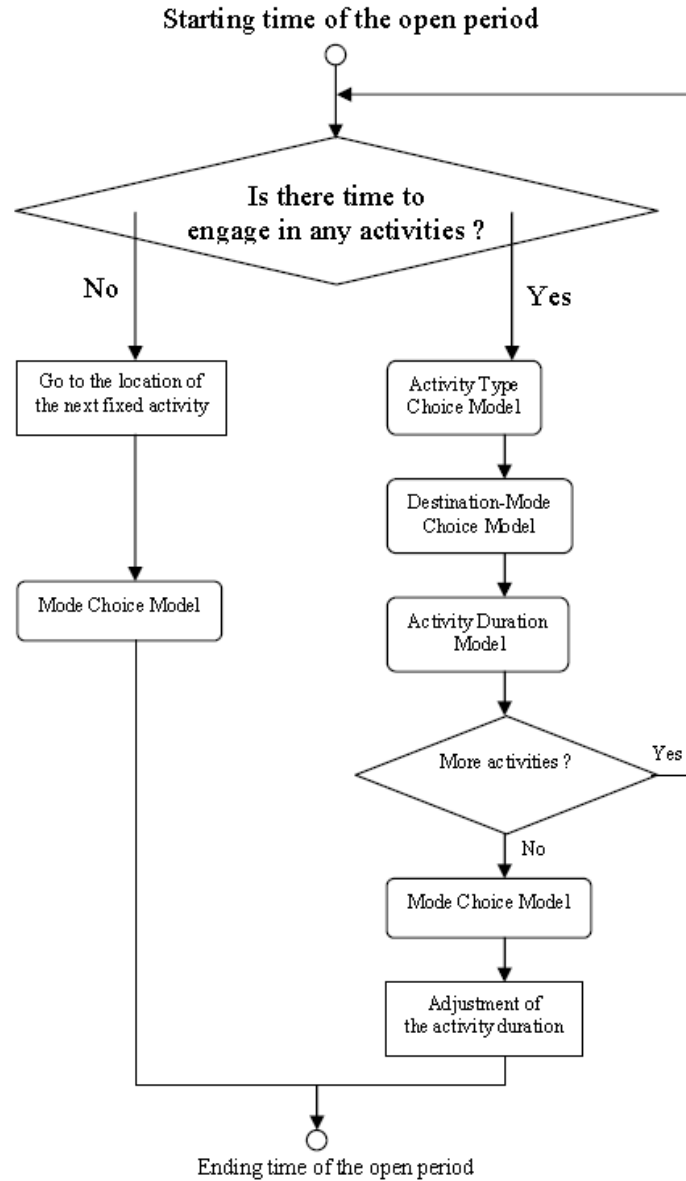
Figure 4-3: PCATS structure
(Pendyala et al., 2004)

4.4.2 *Activity-schedule approach*

The activity-schedule approach recognizes the day's primary importance in regulating activity engagement and travel behavior. This method captures the intra-day interactions but doesn't consider the inter-day interactions to ease the computational power.

The activity schedule approach is built on the premise that decision-makers plan ahead during the day. Instead of using the simpler chronological sequential planning approach, it models the

individual tours and activities conditional on an overarching day pattern. The day pattern represents the fact that decision-makers have a higher priority task in mind for the day that they decide on ahead of time and the rest of the activities are conditioned or constrained by the resulting daily pattern. Hence the probability of a particular schedule is expressed as the product of the marginal pattern probability and the conditional tours probability:

prob(*schedule*) = *prob*(*pattern*) . *prob*(*tour attributes|pattern*)

This activity schedule model has been widely applied by different planning organizations in the US and different applications of the model have included variations on the definitions of the day pattern.

In its original formulation by Bowman (1995, 1998) a pattern was defined by:

1) The primary activity of the day

2) The location of the primary activity (home or away)

3) The type of tour for the primary activity, including the number, purpose and sequence of activity stops.

4) The number and purpose of secondary tours.

5) Purpose-specific participation in at-home activities.

The conditional tour choice affected the pattern choice by including a measure of their expected utility in the pattern model through a nested logit formulation. The resulting model structure is presented in Figure 4-4.

Thus, the activity-schedule approach captures the substitution effect between in-home and out-of home activities through the pattern choice.
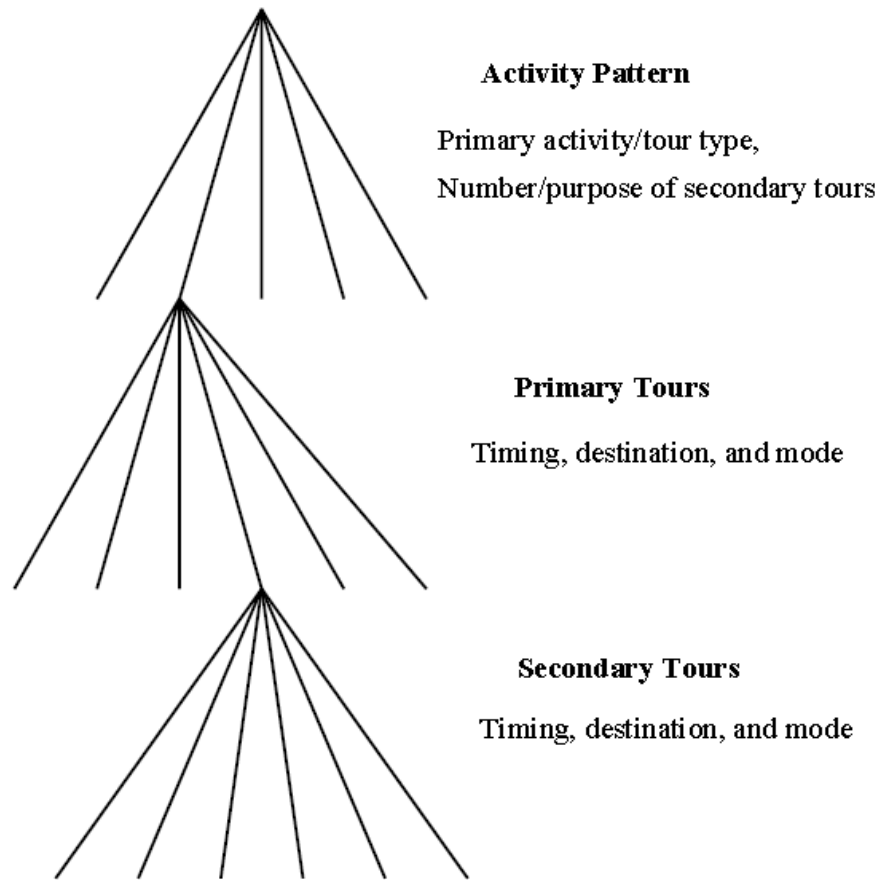
Figure 4-4: Activity-schedule model structure
(Ben-Akiva et al., 1996) and (Bowman, 1998)

The mathematical interpretation of this nested structure is captured in a nested logit discrete choice formulation.

We present here Bowman's (1998) first formulation of the model:

The utility U_p of a pattern p is a function of its systematic utility V_p and of a random component ε_p that is Gumbel distributed independently across different patterns p.

$$U_p = V_p + \varepsilon_p , \qquad p \in P$$

The utility U_{c_t} of a tour t, where c_t is a vector of characteristics of tour t, is a function of its systematic utility V_{c_t} and of a random component ε_{c_t} that is Gumbel distributed independently across different tours t from the set of tours available in pattern p.

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$$U_{c_t} = V_{c_t} + \varepsilon_{c_t}, \quad c_t \in C_t, t \in T_p, p \in P$$

For the pattern choice:

The probability of a pattern p being observed is:

$$P(p) = \frac{\exp(\mu_p V_p)}{\sum_{\acute{p} \in P} \exp(\mu_p V_{\acute{p}})}, \quad p \in P$$

Where μ_p is the scale parameter and V_p is the systematic utility of pattern p defined as:

$$V_p = \tilde{V}_p + \sum_{a \in A_p} V_a + \sum_{t \in T_p} V_t$$

V_a being the utility derived from the participation in activity a

$\tilde{V}_p$ being the utility derived from the pattern organization such as activity sequencing.

V_t being the utility derived from travel tour t. Since V_t is the expected utility of the chosen tour for pattern p,

$$V_t = E\left[\max_{c_t \in C_t} U_{c_t}\right] = \frac{1}{\mu_t} ln\left(\sum_{c_t \in C_t} \exp(\mu_t V_{c_t})\right) + \frac{\gamma}{\mu_t}$$

Where γ is Euler's constant: (~ 0.577)

For the tour choice:

The probability of choosing tour t conditional on the choice of pattern p is:

$$P(c_t|p) = \frac{\exp(\mu_t V_{c_t})}{\sum_{\acute{c}_t \in C_t} \exp(\mu_t V_{\acute{c}_t})}, \quad c_t \in C_t, t \in T_p, p \in P$$

Where μ_t is the scale parameter and V_{c_t} can follow the specification of a standard tour model.

Hence, assuming conditional independence of the tours, the activity schedule model predicts a probability of observing a specific schedule s as:

$$P(s) = P(p) . \prod_{t \in T_p} P(c_t|p), \quad s \in S$$

$$P(s) = \frac{\exp(\mu_p V_p)}{\sum_{\acute{p} \in P} \exp(\mu_p V_{\acute{p}})} . \prod_{t \in T_p} \frac{\exp(\mu_t V_{c_t})}{\sum_{\acute{c}_t \in C_t} \exp(\mu_t V_{\acute{c}_t})}$$

4.4.3 *TASHA*

The Toronto Area Scheduling model with Household Agents (TASHA) is the activity model used in the ILUTE urban model presented in chapter 3.

TASHA is a rule-based model that builds on the concept of activity *projects* (Axhausen, 1998) and schedules activities sequentially to predict an individual's daily schedule (Miller and Roorda, 2003). Briefly stated, a project is a collection of activity *episodes* that combine to achieve one goal. (i.e a "dinner at home" project involves the activity episodes of shopping, cooking, eating and cleaning among others). TASHA microsimulates the behavior of every individual by going through the steps outlined below as shown in Figure 4-5:

Step 1:

Within TASHA, all individuals have a pre-specified set of projects (e.g. work, school, shopping, in-home activities). At the onset of every day, the model selects random activity episodes (e.g. type, timing, duration and location) based on the frequency of this episode in an observed sample. This agenda constitutes the pool of activities that are likely to be done each day.

Step 2:

These episodes are sequentially "scheduled" using a set of rules according to a pre-specified priority order while making sure that spatio-temporal constraints are respected.

Step3:

Associated with each activity episode is a travel episode that may or may not materialize depending on the location of the sequential activities. The scheduling of a travel episode includes a mode choice model given the household's vehicle resources and situational constraints (e.g. if an individual left home without a car to go to work, he may not use his car for work-based trip during the day).

TASHA captures intra-household interactions in two ways:

In case of vehicle allocation conflict between two individuals, the car is allocated to a person so as to maximize the additive utilities of these two household members.

By creating an ad hoc household decision making unit (Salvini and Miller, 2005) that has its own set of activity projects such as child care and home-maintenance, TASHA adds the activity episodes within these pools to the pool of potential activities for each individual.

For more details on the intricacies of this model, the reader is referred to the papers referenced above along with Miller et al., (2004), Roorda and Miller, (2008) and Roorda et al., (2009).
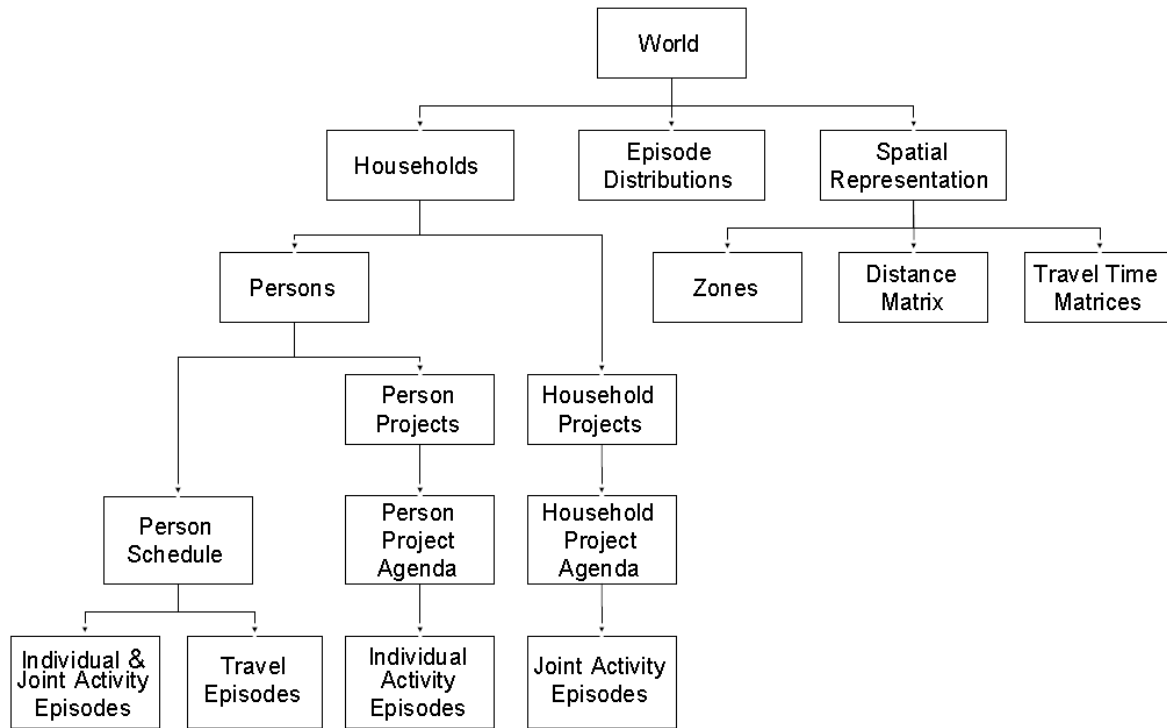
Figure 4-5: TASHA
(Miller and Roorda, 2003)

4.5   State-of-the-art in activity-based modeling

In this chapter, we reviewed the literature on activity and activity-based modeling in the context of households. We identified two main approaches to activity-based modeling:

- Markov chains models that are purely stochastic and thus not fit for policy analysis and utility based models.

- Utility theory has been used in time allocation models that abstract different aspects of the activity participation and activity scheduling models.

Activity scheduling models are plagued with the multi-dimensionality challenge that arises when attempting to model human behavior at different points in time and modelers have resulted to using rules, either to ease the computational burden or to reduce the choice set of individuals. We have shown three models that cover the range between these two possibilities and outlined the strength of each one of these models.

The activity-based models that we have selected to review also cover the full spectrum of human's ability to plan ahead:

- TASHA's sequential approach assumes that individuals are only capable of making immediate decisions with no ability to plan ahead of time or schedule their day around an important activity.

- The activity-schedule approach represents the other extreme. It assumes that people are able to plan ahead for their entire day and do so when they select a 'pattern' for the day.

- The PCATS model represents a middle ground whereby it acknowledges that people can plan ahead and schedule their day around some major activities, as represented by the blocked periods, but do no schedule their entire day from its onset.

There is clear evidence that people are able to plan ahead and do reschedule their activities throughout the day. There is a large body of literature in transportation modeling that discusses this particular question of plan-action and the scheduling-rescheduling process. We will not address this topic in this thesis as it is less important in the context of modeling activities for policy analysis.

More importantly, all activity scheduling models developed to date lack a component to explain why agents are engaging in these different activities. This reduces their use in policy analysis as it limits the substitution between activities captured by the models. We will address this limitation in chapter 5, along with other extensions to activity scheduling models that are necessary for the activity model to serve as the core of the household behavioral model in iTEAM.

Chapter 5
Extending Activity-Based Models

"Everything should be made as simple as possible but not simpler" Albert Einstein

Given the state of activity-based models just presented, the aim of this chapter is threefold. First, we expand the scope of activity-based models to include a broad range of human activities. We deem this broader set of activities necessary in order to accurately capture the urban form, transport patterns and energy consumptions that arise from human behavior in the context of the integrated model presented in chapter 3. Second, we present different modeling extensions for utility-based activity models. These extensions should improve the forecasting power of activity-based models by capturing individual heterogeneity and capturing the drivers of activity participation that has so far been missing to ground activity-based modeling in the theoretical foundation of human behavior.

5.1 Scope of activities

The range and detail level of activities considered varies from one activity-based model to another depending on the model's scope, intended application and computational power available. While earlier transportation activity-based models focused more on out-of-home activities and aggregated all the activities in a few categories, some time-use models identified hundreds of activities.

To use iTEAM for policies aimed at sustainable transportation and urban development in the way presented in chapter 3, we need to detail human activities. Detailed in-home activities allow the link between activities and stationary energy demand while detailed out-of-home activities can capture the substitution between different activities and the scheduling flexibility. This level of activity specification – as opposed to using just a few groups of activities – is necessary to integrate the three complex systems of land, transportation, and energy. Thus, even for transportation policy testing, we still need to move beyond simple locations of activities into their actual scheduling mechanism and the different dynamics they involve.

To build our activity choice set for each individual, we rely on models and surveys for transportation, time use, consumer expenditure, and residential energy consumption. We lump together activities that share the following characteristics:

- Similar scheduling patterns:
    - o Similar potential number of people involved
    - o Similar financial costs
    - o Similar duration and location space
- Similar activity role or similar need satisfied
- Similar equipment usage

The grouping of some activities into meta-activities in this way reduces the computational burden of the model without much affecting the policy analysis efficacy of the model.

While the exact activity list considered may vary depending on the available resources and the cultural context of the model, the idea here is to carry out a paradigm shift in transportation activity-scheduling models. The shift consists of moving away from a definition of activities based on their location (1) and duration (2) only towards a definition based on the location (1),

duration (2), equipment used (3), other individuals involved (4) and the need satisfied by the activity (5).

Although this is the more common way of determining the activities of interest, it is not unique. Other modelers have defined activities in terms of the duration they occupied in discrete time periods (e.g each 15 minutes is a new activity). This definition of activities is useful because it removes the need for time duration modeling which greatly reduces the computational burden of the model. Furthermore, if the time is discretized into small enough periods of time, it theoretically allows the modeler to capture small events such as stopping for coffee or stopping to greet a person. In this sense this definition of activities is more flexible than the one we propose. However, this method limits the behavioral realism of the activity model and is usually used in Markov chain models.

In sections 5.2 and 5.3 we will present different extensions to the current state-of-the art on activity-based modeling to better capture the activities performed.

5.2 Capturing individual heterogeneity

One of the main properties that we identified for our organized complex models of land use, transportation and energy is capturing agents' heterogeneity (see chapter 3). The fact that people behave differently needs little examination. It is equally clear that people behave differently even when faced with apparently similar situations due to individual heterogeneity.

In this section, we present different econometric techniques that can be applied to utility-based activity-scheduling models along with other discrete choice models used to predict the household behavior in iTEAM (see chapter 3).

Individual heterogeneity results from three factors that influence the decision-makers' choices:

Differences in attitudes: a*ttitudes* relate to latent characteristics of the decision-maker such as sensitivity to reliability or sensitivity to noise.

Differences in perceptions: *perceptions* refer to the individuals' pre-conceived beliefs or estimates about the attributes of the alternatives considered such as expected mode reliability or expected mode speed.

Differences in preferences: *preferences* refer to the desirability of the different alternatives considered in the choice set and are captured by the concept of utility. Regardless of the decision-making protocol which might be satisfaction, dominance, or utility maximization.

These preferences exist and the main way to infer them is through observing the actual choice. However, we may be able to get some additional insight about into utility and preferences in general by gathering other indicators about these preferences using psychometric variables

In this section, we explore how individual heterogeneity can be captured within the discrete choice random utility maximization framework so that we can make use of these methods in the activity-based modeling context.

The motivation for this section is to increase the behavioral realism of the discrete choice models classically used in activity-based models by reducing the gap between the actual human decision-making behavior and the model decision prediction process as depicted in figure 5-1.
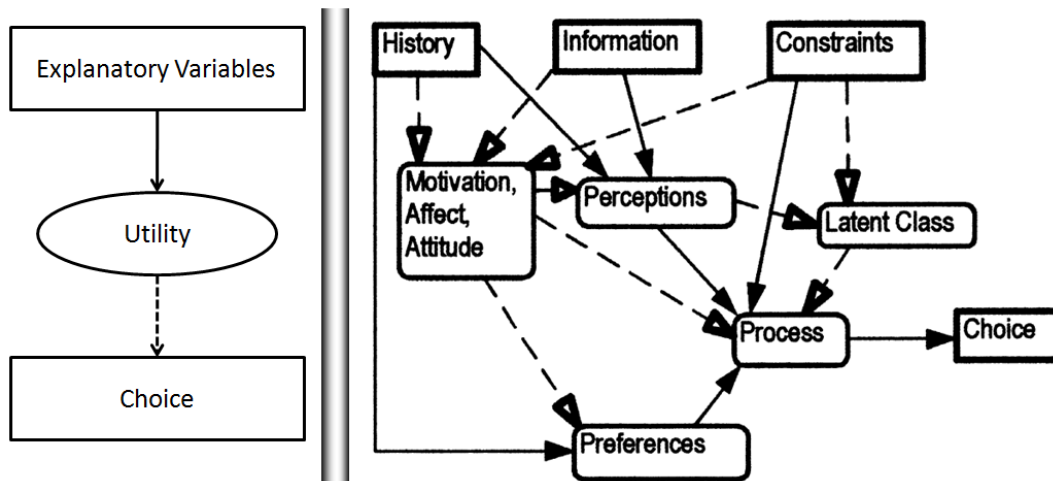
Figure 5-1: Gap between discrete choice models and human decision-making behavior
Adapted from McFadden (2001)

We present a quick overview of the literature on the topic beginning with the simplest methods of capturing individual taste heterogeneity and progress to the more sophisticated methods used. Our goal here is not to focus on the details of the identification and estimation of these models, but rather to shed light on their ability to capture the heterogeneity of the individual decision-maker.

5.2.1 *Multinomial logit models*

In this first section, we focus on models that follow the earliest random utility maximization framework depicted in figure 5-2[16].
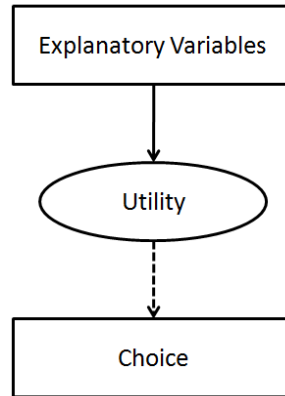
Figure 5-2: Utility maximization choice model

Within this framework, Multinomial Logit models are the simplest of those models belonging to the Generalized Extreme Value family that was introduced by McFadden (1981) and are of the form:

$$U_{in} = \beta' X_{in} + \varepsilon_{in}$$

In the simplest applications of discrete choice models, socio-economic characteristics are not taken into account in the systematic component.

Let us take for instance the following utility specification:

$$U_{in} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k \ldots + \varepsilon_{in}, \qquad for \; k \in K - \{3\}$$

Where X_3 represents as socio-economic characteristic of the decision maker and

X_k for $k \in K - \{3\}$ represent attributes of the alternatives that are independent from the decision-maker.

$$\frac{\partial U_{in}}{\partial X_3} = 0$$

Here, individual heterogeneity, or lack thereof, is "captured" by the stochastic component of the utility specification while the systematic component is independent of the individual decision-

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[16] In this section, we represent observed variables by rectangular boxes, latent variables by ovals, structural or behavioral relationship by solid arrows, and measurement relationship by dashed arrows.

maker's characteristics. This leads to biased estimators and overall to models with weak explanatory power.

As the theory behind discrete choice modeling evolved, variables representing socio-economic characteristics of the decision maker were introduced in the systematic specification to avoid the problem. These variables capture what we term observed heterogeneity and aim to segment the population of observed decision makers into different segments having similar socio-economic characteristics. For examples of such specifications in the context of transportation modeling, the reader is referred Domencich and McFadden (1975) and Ruiter and Ben-Akiva (1978).

These models capture heterogeneity in two pre-determined deterministic manners:

- By introducing a separate observable coefficient for each socio-economic segment:

$$U_{in} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_{3n} \ldots + \varepsilon_{in}$$

$$\frac{\partial U_{in}}{\partial X_{3n}} = \beta_3$$

- By introducing a non-linear variable that combines a taste coefficient with a specific socio-economic characteristic (gender, age, etc.).

$$U_{in} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 X_{3n} \ldots + \varepsilon_{in}$$

$$\frac{\partial U_{in}}{\partial X_{3n}} = \beta_2 X_2$$

This creates a continuous interaction between the taste coefficient and the socio-economic characteristic and more importantly between the observed socio-economic variable and the marginal utility of the decision makers.

There have been several advances in the specification of discrete choice models targeting both the systematic and random components structures to better capture the substitution effect between alternatives but we will not go into the details of these models as the models presented in the next sections do a better job of capturing individual taste heterogeneity and have a more solid behavioral foundation. The interested reader is referred to Train (2003), Hess et al., (2005) and Greene et al., (2006).

5.2.2 GEV with latent variables

It became quickly apparent that not all of the relevant individual characteristics that are important in the decision-making process are observable in the choice process.

This lead to two efforts:

➤ An effort to place individuals in hypothetical situations where they are asked to make a choice in a controlled environment. The data collected from this type of surveys that is now commonly termed stated preference survey serves to enrich the data observed in the actual choice or revealed preference survey to get more insight into the individual's decision making process. Ben-Akiva and Morikawa (1990) present in detail the theory and estimation process behind this method.

➤ On a separate effort level, researchers attempt to quantify the unobserved mechanisms of the choice process. Indicators of attitudes, perceptions and preferences are collected and used in the estimation of the choice model to quantify the latent variables that influence the choice process. For more details about the theory behind this type of modeling or the estimation process, the interested reader is referred to McFadden (1986), Ben-Akiva & Boccara (1995) and Ben-Akiva et al. (1999)

Both of these efforts are shown in the framework of figure 5-3.
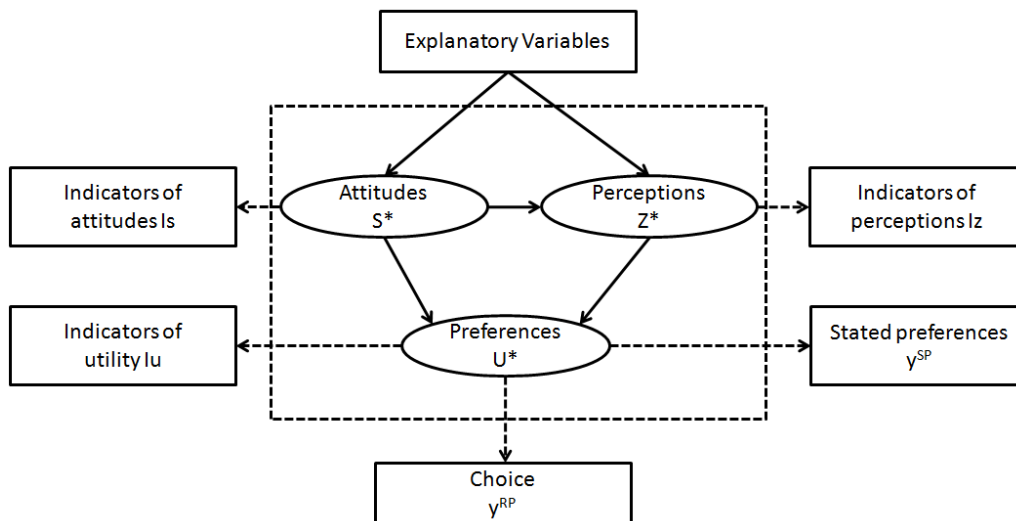
Figure 5-3: GEV with latent variables choice model
Adapted from (Walker, 2001)

The output probability of such combined (structural and measurement equations) models is the choice probability of the core GEV multiplied by the density function of the indicators and integrated over the distribution of the latent variables.

The computational aspect of these models is more complex involving simulation to solve the integrals.

5.2.3 *GEV with latent class models*

The main idea behind latent class models is that individual tastes do not vary randomly across individuals in a society. Rather, this heterogeneity which is due to unobserved attributes, preferences or perceptions occurs between different classes or categories of individuals. Basically, latent class models discretize the notion behind GEV with latent variables models that we presented in section 5.2.2 into K separate classes of individuals.

Latent class models operate in the integrated fashion depicted by figure 5-4:
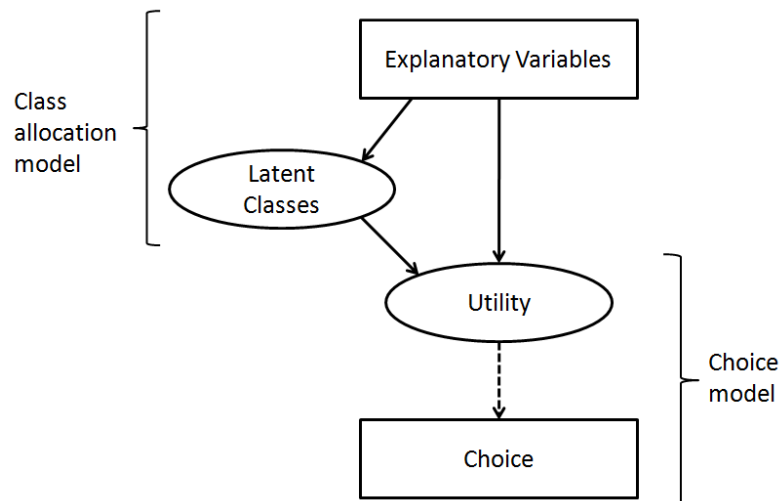
Figure 5-4: Integrated latent class model
(Walker, 2001)

1) They stochastically allocate individual n into class k with probability $\pi_{n,k}$

The allocation model probability has the form of a standard GEV model probability, (typically a Multinomial Logit Model is used):

$$\pi_{n,k} = \frac{\exp(\alpha_k + g(\gamma_k, z_n))}{\sum_{l=1}^{K} \exp(\alpha_l + g(\gamma_l, z_n))}$$

Where:

γ_k is a vector of parameters to be estimated

z_n is the vector of characteristics related individual n that we use to allocate him to class k

α_k is a class specific constant

g (.) gives the functional form of the utility function

2) The core choice probability given by the GEV model is the probability of individual n choosing alternative i conditional on n being in class k.

Thus, combining the two steps, the unconditional choice probability of individual n choosing alternative i is simply the sum of the conditional probabilities from the GEV model over the K classes, or:

$$P_n(i|\varphi_1, \dots, \varphi_K) = \sum_{k=1}^{K} \pi_{n,k} \, P_n(i|\varphi_k)$$

Where $P_n(i|\varphi_k)$ is the conditional probability obtained from the core GEV model.

For a more in-depth review of latent class modeling, the interested reader is referred to Gopinath (1995), Walker (2001) and Hess et al., (2009).

Hence, Latent Class models account for individual heterogeneity through the class allocation process that is stochastic but not random. This gives the models the ability to capture the heterogeneity distributions from the data without forcing a specific pre-assumed distribution in the population, except for the number of classes K.

In conclusion, we have presented in section 5.2 different mechanisms to capture individual heterogeneity in discrete choice models that are readily available for use in activity-based modeling. Capturing the agents' heterogeneity is crucial to the definition of the iTEAM framework since it relies on the properties of heterogeneity-based organized complex models.

5.3 Capturing activities motivation and dynamics

We showed in chapter 3 that models of complex systems have to capture the propensities of human behavior to allow for intrinsic emergence. This propensity that is visible in the transportation, land-use and energy systems is derived from the propensity in activity

participation, which thus needs to be captured in the iTEAM activity-based models. Thus, only an activity-based model that captures the dynamics of activity participation can lead to an urban model that accurately analyzes and forecasts the effects of a policy in an urban setting.

Despite all the techniques outlined or referenced to so far, the theory behind activity models has yet to tackle the real motivation behind activity engagement. On one hand, deterministic rule-based models are too rigid and insensitive to policies since they don't allow for any new behavior to emerge. On the other hand, purely stochastic models that only consider the observed behavior do not properly capture the substitution effects between activities. Even utility-based models that attempted to capture part of the behavioral process have yet to capture the most important part of activities: their drivers[17]. The reality of the matter is that individuals and households do not 'aim' to minimize a certain generalized cost or maximize a certain utility but have a certain set of needs and drivers that motivate their activity engagement. Random utility models have so far been unable to capture this concept and have only focused on the decision-making process that takes place once a household has decided to participate in a given activity. While this shortcoming has been outlined by several researchers – from both proponents and antagonists of activity-based models – it has yet to be addressed thoroughly.

We emphasize at this point that discrete choice models and utility theory in general is still an appropriate framework because we are modeling the choice of selecting which activity to engage in. Thus, the question here is not how to replace utility theory but rather how to extend utility-based activity-scheduling models to capture the motivation and dynamics behind the choices that individuals make in the household construct. The abstraction of this step is justified in discrete choice models where the alternatives all fall in the same category. For instance, it is acceptable to make an abstraction of the need to eat if we are comparing different meal options since they share the same underlying objective.

However, ordering food to be delivered from a restaurant and going with friends to a restaurant are not actually exactly similar activities. Although they both satisfy the need to eat, one might be staying at home with a partner to satisfy the need for security and intimacy, while the other

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[17] This strongly reminds us of Lee's 'flaw' of "wrongheadedness" (see chapter 2)

might satisfy the need for relatedness and social interaction. Such tradeoffs become even harder to capture using traditional activity-based models when the individual is deciding between two unrelated activities such as going out and going to sleep although people make such decisions on a daily basis.

Hence, it becomes important to understand and model the motive behind people's activities in order to capture the substitution effects between activities in response to policies and infrastructure investments. We formulate this extension to activity-scheduling models based on the theoretical work done by sociologists and psychologists on motivation theory in the context of time-use research.

5.3.1 *Motivation theory and time-use research*

Time-use research is an interdisciplinary field dedicated to understanding what activities people perform and how much time they allocate to them. It is often identified as the field that analyzes time-use data to understand the drivers of human activities and the value of the time allocated to different activity types (Gershuny, 2000). Time-use researchers look for long term political, cultural or sociological underlying changes that drive changes in observed human behavior in order to understand its true motives. There are several schools of thought that discuss the true motivation of human behavior and a complete review of motivation theory lies outside of the scope of this thesis. However, we will present some work done within the "Needs theories"[18] which lends itself most amenable to our goal of understanding and modeling human behavior. Within this broad school of thought, and probably the most famous work done on the drivers of human behavior, is Abraham Maslow's work on the hierarchy of human needs (Maslow, 1943).

In his seminal paper on human motivation, Maslow stresses the requirement for a theory of human motivation to focus on ultimate ends rather than superficial goals or means. He concludes that paper by presenting his view on five basic levels of human needs "physiological, safety, love, esteem, and self-actualization". In addition, Malsow suggests that individuals are "motivated by the desire to achieve or maintain the various conditions upon which these basic satisfactions rest and by certain more intellectual desires." His work is often summarized by a variation on the following pyramid (see figure 5-5) where one can only achieve the 'higher' needs after satisfying the bottom or "inferior" needs.

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[18] A subset and particular case of motivational theory.
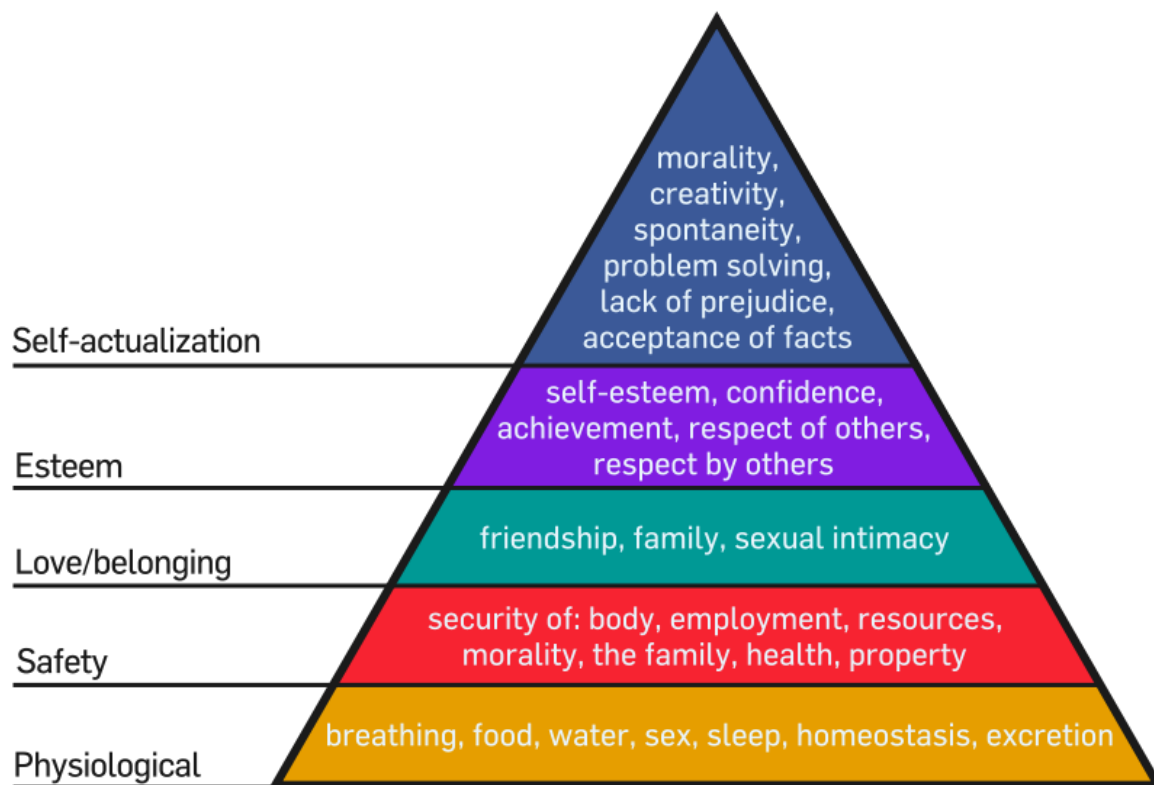
Figure 5-5: Maslow's theory of human motivation
Adapted from (Maslow, 1943)

Maslow contrasts the four bottom physiological needs or deficit needs (D-needs) with the top psychological growth need or benefit need (B-need). He argues that D-needs are only obstacles in the way of individuals on the path to engage in B-needs.

This theory was later on revised by Clayton Alderfer in his Existence Relatedness Growth (ERG) theory (Alderfer, 1972) and by the work on Self-Determination Theory (SDT). These theories allow for the coexistence of needs at the same time for the same individual and identify the transition processes between them.

Our objective in this thesis is not to make an argument for one theory of human needs over another nor to compare these different theories. Our main take-away from this area of study is the simple fact that human activities are driven by a set of different and distinct needs. Thus, we

are motivated to incorporate these needs into activity-based models to capture the true drivers of human behavior, and not resort to interpreting each single action as driven by its associated time or cost characteristics as has so far been the case.

We can summarize the need-activity relation as follows:

1) *Whether we agree on three need categories such as the one presented in ERG theory or five need categories such as the one presented by Maslow, there is an implicit agreement on a discrete number K of basic innate human needs.*

2) *These needs are not explicitly observed but rather latent.*

3) *One activity can satisfy different needs*

4) *Different activities can satisfy one need.*

Latent needs k
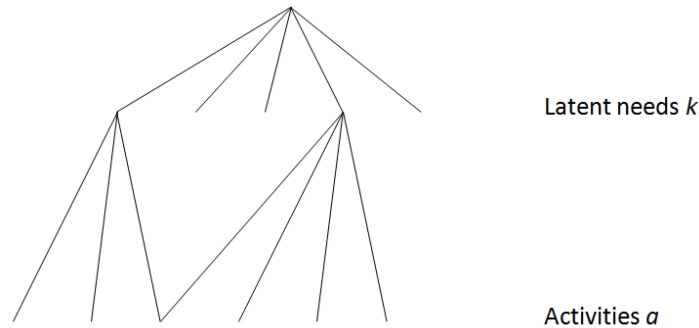
Activities a

Figure 5-6: Need-activity relation

This structure is not to be confused with a cross-nested logit formulation that is used to capture the correlation between the activities. Rather, it implies a two-stage choice that individuals perform when selecting an activity:

$$P(activity) = P(need) \times P(activity|need)$$

Where $P(activity|need)$ is a GEV model that we apply over the choice set of activities a_k that answer need k.

Having formulated the need-activity relation as an extension of activity choices in activity-based modeling, we tackle in section 5.3.2 the question of how to model the need that individuals are seeking to satisfy.

5.3.2   *Activity and need dynamics*

For Maslow, the B-needs could only be reached once the D-needs are satisfied. This is not necessarily the case in real life and some of the common counterarguments given are that of the 'starving artist' that seeks to satisfy higher growth needs even though basic existence needs are not completely satisfied or of Trachtenberg who developed a new way of doing arithmetic in a concentration camp.

ERG theory on the other hand postulates that people are motivated by three needs (Existence, Relatedness, Growth) and at any point in time, an individual may be motivated by more than one need. It argues that if a lower need is satisfied (even partially) an individual may progress to higher needs. Whereas if a higher need is frustrated, the individual may regress to lower needs that are easier to satisfy.

This leads us to the main question of this section: how can we capture the transitions or *dynamics* of the need and activities?

In the transportation literature, there have been several attempts to capture these dynamics in an activity-based model but only few actually implemented these dynamics.

Arentze and Timmermans (2006, 2009) implement such a model in a utility maximization framework. Their model resembles inventory replenishment models commonly used in supply chain management whereby an individual's needs vary with time (similar to inventory) and engaging in an activity replenishes the inventory of this need (similar to replenishing inventory stock). This method provides an excellent first step to extend traditional activity-based models and include dynamics because the time element approximates closely the different physical and biological processes that factor in human decisions. However, this method lacks psychological factors that influence behavior. By linking the needs variation to time only, this method doesn't incorporate the complex interaction effects between activities. For instance, this method doesn't capture the effect that some activities may tire the individual and make him seek more pleasant and less stressful activities.

For example, think of the traditional case where an individual who just delivered a big project seeks to engage in activities that satisfy his lower needs of existence and relatedness by going out with his friends or relaxing at home while this same individual seeks to engage in higher need

activities after a long period of vacation. Note that we are not talking about the financial motivation for work in this example but about the positive or negative feedback that one activity creates over another.

The implementation of these feedbacks is necessary given the framework and properties of organized complex models that we discussed in chapter 3. The sequencing and occurrence of a specific activity cannot be accurately modeled as a purely stochastic process – based upon the observed frequency of occurrence – nor as a completely deterministic process – based on specific rules of the sequencing.

The concept of stress is a good mediator between the different types of needs in which individuals engage. Stress was coined by Selye in the 1930's as a response to a stimulus – a stressor.

Miller (2005a) and Roorda et al., (2009) operationalize this concept in activity modeling as the difference between the utility of a current state and that of the optimal alternative accessible state. Although this definition is quite attractive for its simple implementation in a utility maximization framework, it doesn't capture the propensity and feedback mechanisms that are in place in complex organized systems. To build upon this concept, we go back to the roots of stress in psychology and then reformulate stress as a mediator between needs.

Selye (1975) later revised his work and identified two types of stress reactions:

- Eustress – stress that enhances and motivates physical and psychological reactions
- Distress – stress that is not resolved through coping or adaptation, which may lead to anxiety and regression.

The difference between the two reactions, Selye proposed, depended on the activity type, the personal expectations of the individual and the resources available.

It is important to note here that the two types of stresses can coexist thereby creating a complex dynamic.

This more elaborate definition of stress possesses the properties of the mediator required in our iTEAM behavioral framework because it captures both the individual heterogeneity and the complex dynamics of positive and negative feedback that one need imposes upon another.

Although we realize that this is a simplification of the actual affective and cognitive processes that underlie behavior motivation, we believe that this is a progress over the current state-of-the art in activity modeling as it fills the required properties that we set forth in chapter 3.

We formulate this extension of activity models by using a new activity systematic utility:

$$V'_{an} = V_{an} + \beta^+_{an} v^+_{an} + \beta^-_{an} v^-_{an}, \qquad for\ activity\ a \in A_n, and\ individual\ n$$

Where v^+_{an} represents the eustress derived from this activity for individual n
And v^-_{an} represents the distress derived from this activity for individual n.

These two variables are then used in the model that outputs other needs to be satisfied. Basically, a high level of eustress and a low level of distress create the propensity for an individual to satisfy a higher level need whereas a low level of eustress and a high level of distress create the propensity for a lower level need. Despite the simplicity of this formulation, it still captures the complex positive and negative loops that are required of activity models in a complex organized system context.

- In a sequential planning model, the stresses from activity *a* are used in the need model for activity *a+1* to represent the limited planning behavior.
- In the case of the activity-schedule approach, these stresses appear in the pattern systematic utility as well as in the need model for each of the needs met during the day to represent the full ability to plan ahead.
- In more behaviorally complex where the individual is planning ahead for some activities, these two variables have to be introduced accordingly by taking into account the stress of the 'blocked periods' activities.

We advise that the values of the two stressors for each activity and individual not be taken from generic tables (Holmes and Rahe, 1967) but rather derived from psychometric indicators retrieved from surveys and estimated through measurement latent variable models as shown in section 5.2.2

5.3.3 *Activities, lifestyle and long term changes: closing the loop with iTEAM*

We have thus far identified the link between needs and activities in section 5.3.1 and formulated the dynamics of this link in section 5.3.2. This enables activity-scheduling models to capture the inter-activities substitution and the activity propensity in the short term. In this section, we present the link between the daily activities and the long term choices of mobility stock, home appliance stock, and household location for individuals in the household context. This will enable the activity-scheduling model to drive the behavioral models presented in figure 3-4 and thus close the loop between individual activities and the complex urban networks captured in iTEAM.

In the context of urban modeling, the ILUTE model has presented a model that formulates this link (See chapter 2). We develop a different model that is based on the concept of lifestyle and the need-activity relation that we have formulated thus far. We propose a formulation that links an individual's short-term activities to his long term choices though his lifestyle.

The lifestyle concept originated in market research and has been given many definitions in transportation and urban planning (Salomon and Ben-Akiva, 1983; Axhausen et al., 2001, Scheiner and Holz-Rau, 2007). We refer to it as the bundle defined by the watershed events[19] of an individual's life with coarse temporal and spatial resolutions (1); his dwelling unit's location (2); his mobility (3) and appliance (4) holding.
This definition stems from the fact that individuals are capable of planning certain major events with accuracy over a long period of time without planning their detailed activities over this period of time.

We define the lifestyle stress of an individual as the stress from the *anticipated detailed activities* to be performed over a period Ω.
The positive lifestyle stress $\Upsilon_{n,t}^+$ and negative lifestyle stress $\Upsilon_{n,t}^-$ for individual n at period t can be formulated as:

$$\Upsilon_{n,t}^+ = \sum_{t}^{t+\Omega} \beta_{a,n,t} v_{an}^+ , \quad \text{and} \quad \Upsilon_{n,t}^- = \sum_{t}^{t+\Omega} \beta_{a,n,t} v_{an}^-$$

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[19] Events that significantly alter a household's social, economic, or demographic characteristics.

The parameters $\beta_{a,n,t}$ reflect the fact that different individuals deal differently with anticipated stress:

- The subscript n indicates that some people are more susceptible than others to future stress.

- The subscript a indicates the fact that different future activities are anticipated more vividly and with more ease, thus affecting strongly the individual's lifestyle stress.

- The subscript t, indicates the time of occurrence of the anticipated activity. It reflects the fact that people generally value differently the stress from the same event occurring at different times.

Higher levels of lifestyle stresses trigger the individual to consider and compare different coping mechanisms to decrease his stress levels[20]. The lifestyle coping mechanisms[21] include changes in the social, economic, or demographic status of an individual (1); changes in the equipment (2) and mobility (3) stocks; or a change in the household location (4); or combinations of these (4).

Coping mechanisms (2,3,4) are reflected by the equipment choice model, mobility choice model, and household choice model captured in the iTEAM household behavioral model (figure 3-4).

For example, a household may purchase new appliances in anticipation of a new-born. We model this as a lifestyle stress-reduction mechanism to ease the stress induced by the anticipated new activities. Thus the anticipation of a higher level of stress in the daily activities is captured and reflected in an increased lifestyle stress and met with the purchase of different household appliances.

5.4   Conclusion

5.4.1   *Summary*

In this chapter, we presented two behavioral extensions to traditional activity-based models to use them within the iTEAM framework presented in chapter 3.

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[20] We note here that regarding the implementation of the urban model, this formulation imposes very serious performance constraints. These could be alleviated by a number of techniques such as using statistical models to select when and for whom the look-ahead will be done or using a simplified look-ahead model.

[21] As opposed to the short-term coping mechanisms of a change in the activity or need. These would be already captured by the short-term dynamic model.

In chapter 3, we built the framework for the model based on the view of a city as a system of complex organized systems. For each of the land use, transport, and energy networks, we used the properties of heterogeneity-based organized systems and framed their integration with households' and firms' behavioral models. We reviewed the state-of-the-art in household activity modeling in chapter 4 and noticed that the models under use do not fit the properties needed. Thus, we provided three extensions to activity-based models in this chapter.

Section 5.1 expanded the scope of activity models by introducing more specific in-home and out-of-home activities to better link the activity model with the three complex networks of iTEAM. In section 5.2, we provided different techniques to capture individual heterogeneity in utility based models. These techniques are necessary to ensure the behavioral model fits the properties of heterogeneity-based models. In section 5.3 we extended activity-based models in order to capture the motivation and drivers of activities. We formulated the link between the activities and the basic human needs as provided from motivational theory. For short-term behavior, we formulated the dynamics of human needs and activities by using the concept of stress in its eustress and distress forms to capture the effect of one activity on the next need. For long-term behavior, we formulated the concept of lifestyle stresses and linked it with equipment choice models, mobility choice models and residential choice models for households.

While some of these extensions have already been incorporated into some activity-scheduling models, no single model to date includes all three of them. Furthermore, we deem these extensions as necessary but insufficient for the activity model to be used in the iTEAM framework because they still do not tackle the issue of inter-individual interactions. This topic has been outlined since the beginning of activity-based modeling and has recently been studied by many researchers. Thus, we will only briefly define these interactions hereafter and refer the interested reader to appropriate resources.

5.4.2   *Inter-individual interactions*

In this section, we present some of the work done in activity-based modeling to cover the inter-individual interactions *within* the households and *between* the households.

- Interactions within a household, or intra-household interactions, cover the joint decision making and joint activity participation of members within a household. The strength and impact of these interactions are the reason of the definition of the household as a basic agent of society in the iTEAM framework. We refer the reader to Zhang and Fujiwara (2006), Bhat and Pendyala (2005), Gliebe and Koppelman (2002), Zhang et al., (2007), Kim (2008), Timmermans (2009) and Arentze and Timmermans (2009) for detailed information concerning this topic.

- Interactions between households, or inter-household interactions, cover the influences of an individual's social group on his behavior and joint activity participation with different individuals of the social group. These represent the *direct* interactions that we referred to in our definition of the urban dynamics. We refer the reader to Rose and Hensher (2004), Dugundji and Walker (2005), Arentze and Timmermans (2007) and Fukuda and Morichi (2007).

Chapter 6

Scenario Analysis

We illustrate in this chapter the capacity of the iTEAM framework to act as a decision support tool for scenario analysis. Section 6.1 discusses the general usage that we envision for this model and the different scenarios that iTEAM can capture. In section 6.2, we elaborate on the type of sustainability indicators that can be output from the model. In section 6.3, we present different examples of policies that can be studied with the iTEAM model. Finally, section 6.4 concludes this chapter and sheds light upon new types of urban policies.

6.1   Model use

The goal behind the development of iTEAM is the development of an objective and transparent tool to act as a decision support system for transport-related policies and investments that affect an urban region's sustainability. We can identify three types of transport policies and investments that iTEAM can handle.

6.1.1 *Direct transport-vehicular energy consumption*

iTEAM can readily account for the impact of changes in transport patterns in a city on the vehicular energy consumption and gas emissions.

The microscopic dynamic traffic assignment model can accurately capture the transportation patterns and the distribution of vehicles in the network. The individual agent activity model capture the timing and substitutions of activities.

The household and firm behavioral models also capture the vehicle stock ownership which makes the model capable of analyzing the penetration and usage of new vehicles and new vehicular fuels.

This would make iTEAM a useful tool to analyze the effects of a range of scenarios and policies that includes mode pricing and taxation, vehicle/road operational improvement and vehicle/fuel technological changes.

A simple but highly debated example of direct transport-vehicular energy consumption scenario is carbon taxation. iTEAM could readily capture the short term effect of a carbon tax by capturing potential shifts in vehicle usage patterns. iTEAM could also capture the long term changes induced by taxation though mobility stock change and agent relocation. These shifts can be observed at any spatial resolution (including an agent based one) and analyzed to observe any systematic differences in the effect of carbon tax between agents of different socio-economic strata. Thus, the iTEAM would allow policy-makers to forecast the response to different carbon tax levels in an urban region and to output sustainability indicators that would provide an objective and transparent tool to compare the carbon tax effect from one region to another.

6.1.2 *2nd order transport - stationary energy consumption*

The iTEAM would go beyond the models currently operational or under development by integrating transport patterns with stationary energy consumption from households and firms. This would enable analyzing the changes in stationary energy demand (residential, commercial, or industrial) that may accompany transportation policies. Furthermore, iTEAM would enable the comparison of effects from transport-related policies with effects from policies affecting

other sectors. We believe this area to hold significant potential and will give an example of a hypothetical investment scenario where a new transport infrastructure leads to major implications on industrial energy consumption in section 6.3

6.1.3 *3rd order transport - urban form - energy*

From the very beginning of this thesis, we argued that different processes take place at different time scales in the city so that urban form only changes at the *very slow* and *slow* time scales as opposed to the *fast* and *immediate* changes of other processes. Since many transport polices and investments operate at these longer time frames, we included the impact of transport and energy on land use in iTEAM. This makes the model able to handle such long term scenarios to unravel the long term impact of these policies and investments (e.g. new transport infrastructure, new pedestrian/bicycle infrastructure, or new transit mode).

The ability of iTEAM to include the effect of urban form changes on energy consumption takes on additional importance in the context of developing urban areas. It has been argued by many that the impact of transport infrastructure on urban form decreases with life of a settlement because households and organizations have a high sunk cost once they locate in a region. Thus, in the case of evaluating alternatives for transport infrastructure investments, iTEAM's ability to forecast the agents' location while taking into account the accessibility of a neighborhood should be important for accurate policy analysis in developing urban regions.

6.1.4 *Combination scenarios*

Finally, the iTEAM framework is able to handle combinations of these policies and investments in the same scenario run. We agree with the approach of a portfolio of policies rather than the silver bullet approach and thus iTEAM can go beyond simplistic single equation models to capture the effect and interactions of different policies. This is particularly useful to study whether different policies and investments reinforce or cannibalize each other so that decision-makers are able to accurately valuate the cost of each policy or investment.

6.1.5 *Limitations*

We do not refer in this section to the limitations of the modeling techniques used but rather to the fact that the framework that we have developed is limited to the transport-energy interaction categories that we have mentioned above. Although the iTEAM framework includes the water usage, the waste generation, and the telecommunication patterns derived from the activities of the urban area's agents, it doesn't capture the 3rd order effect of transportation on energy consumption through one of these networks. For example, one can imagine a transportation policy that affects the waste generated throughout the day. While this impact is captured, the long term changes on structural waste disposal costs (new trucks or new disposal factory) are not endogenous to the model. Thus iTEAM doesn't include the impacts of these changes on the transportation patterns and energy usage in the long run.

6.2 Sustainability indicators

The vast amount of data that can be output from a model such as iTEAM can be overwhelming for policy-makers and regulators. Thus, a set of indicators is needed to monitor the effect of policies and investments in an urban area and develop a benchmarking system to compare these scenarios. We began our discussion of sustainable development in this thesis with the definition advanced by the Bruntland commission. However, while this definition may have achieved a political consensus around itself, it is difficult to convert it to a set of operational sustainability principles or indicators. (Giddings et al., 2002). Moreover, it is now accepted that there is no unique set of indicators that needs to be observed in every case but rather that this set of indicators is case- and context-sensitive (INECE Expert Working Group on ECE Indicators, 2003). Effective urban sustainability indicators are those that balance the practical needs of practitioners with the theoretical foundation of iTEAM while being neutral, objective, and technically proficient (Keirstead and Leach, 2008; Astleithner et al., 2004)

There is a vast literature on sustainability indicators providing a wide array of indicators to choose from and a complete review of these is beyond the scope of this section. The reader is referred to Jeon and Amekudzi (2005) and the included references for a thorough review of the topic; to Feitelson (2002) on environmental equity indicators; to Steg and Gifford (2005) and Poortinga et al., (2004) on quality of life indicators; to Bertolini et al., (2005) on 'sustainable

accessibility'[22] . While most of the studies have aimed at developing 'descriptive indicators', there are only a few developed 'performance indicator' sets that can be estimated from models (Hatzopoulou, 2008) with the PROPOLIS project being one of the very few to combine the indicators with an urban model (Lautso et al., 2004).

The Sustainable Transportation Indicators Subcommittee of the Transportation Research Board (2008) presented a set of performance indicators classified in nine categories: travel activity, air pollution emissions, noise pollution, traffic risk, economic productivity, overall accessibility, land use impacts, equity, transport policy and planning. This set is only useful for analyzing the direct impact of transportation on vehicular emissions. In the case of iTEAM, the performance indicator set should contain indicators that relate to the overall behavior of household and firm agents. Since the detailed elaboration of this set could be the result of a thesis on its own, we will only mention that this set should include economic, social, and environmental indicators that convey the changes on the entire urban region for these agents while being neutral, objective, and technically proficient.

It is important to note at this point that many of the currently widely used indicators such as Gross Domestic Product (GDP) for economic sustainability are actually misleading and should be reexamined as repeatedly argued by Nobel laureates Joseph Stiglitz and Amartya Sen.

6.3   Transport-stationary energy scenario example

In this section, we provide a hypothetical scenario of a transportation policy that affects firm energy demand to show how iTEAM is able to handle the impact of transportation policy on stationary energy.

6.3.1   *The base case*

Let us take the case of the region ABCD shown in figure 6.1-A below:

The flow of vehicles between regions A and C is restricted to paths 1 and 2 initially (see figure 6.1-B). Assume that the road from C to B is a very long and winding road, thus most individuals traveling from C to A will take path 1 leading to congestion and a high level of emissions. The split between the two paths can be modeled through a classical discrete route choice model.

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[22] Includes qualities of transportation and land-use network, economic, social and environmental goals

6.3.2 *The policy*

Suppose the infrastructure investment under study is that of a 3rd path alternative linking C to A directly. Any currently available transportation model can estimate a route choice model for drivers and forecast the new split between paths 1, 2 and 3 (see figure 6.1-C).

Assume that under the conditions stated above; this will result in an increase in the speed on link D-A which will reduce emissions by a certain amount. If the benefits of time saving and gas reductions on the network are not sufficient as is often the case, this will result in the new road not being built[23].

Thus, by looking solely at the environmental indicators that could be output from the current integrated urban models, decision-makers would opt not to build the new link.

6.3.3 *The iTEAM difference*

iTEAM is able to consider an additional level of analysis in parallel with transportation that pertains to the agents activities:

In iTEAM, there is information about the agents in the region, namely that locations B, C and D are mostly residential areas and that A is an area of high industrial activity concentration.

Suppose now, that most factories in region A are currently using coal as a primary source of energy while region D is a region that is currently practicing the illegal process of dumping untreated sewage into the sea.

Since iTEAM framework includes an equipment choice model for the factories, the systematic utility of biomass fueled equipment for a factory in region A is increased because of the increased accessibility of biomass from region D caused by lower transportation costs.

Now the benefits of the infrastructure project include the environmental benefits of a reduced untreated sewage dump at location D and a reduced coal burning at region A.

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[23] The same could have been argued for a transit infrastructure.

These additional benefits, which could not be captured in traditional transport assessment studies, would be reflected in the emissions parameters and indicators of iTEAM. Thus, using iTEAM in this case would have informed the decision-makers to go forth with path 3.
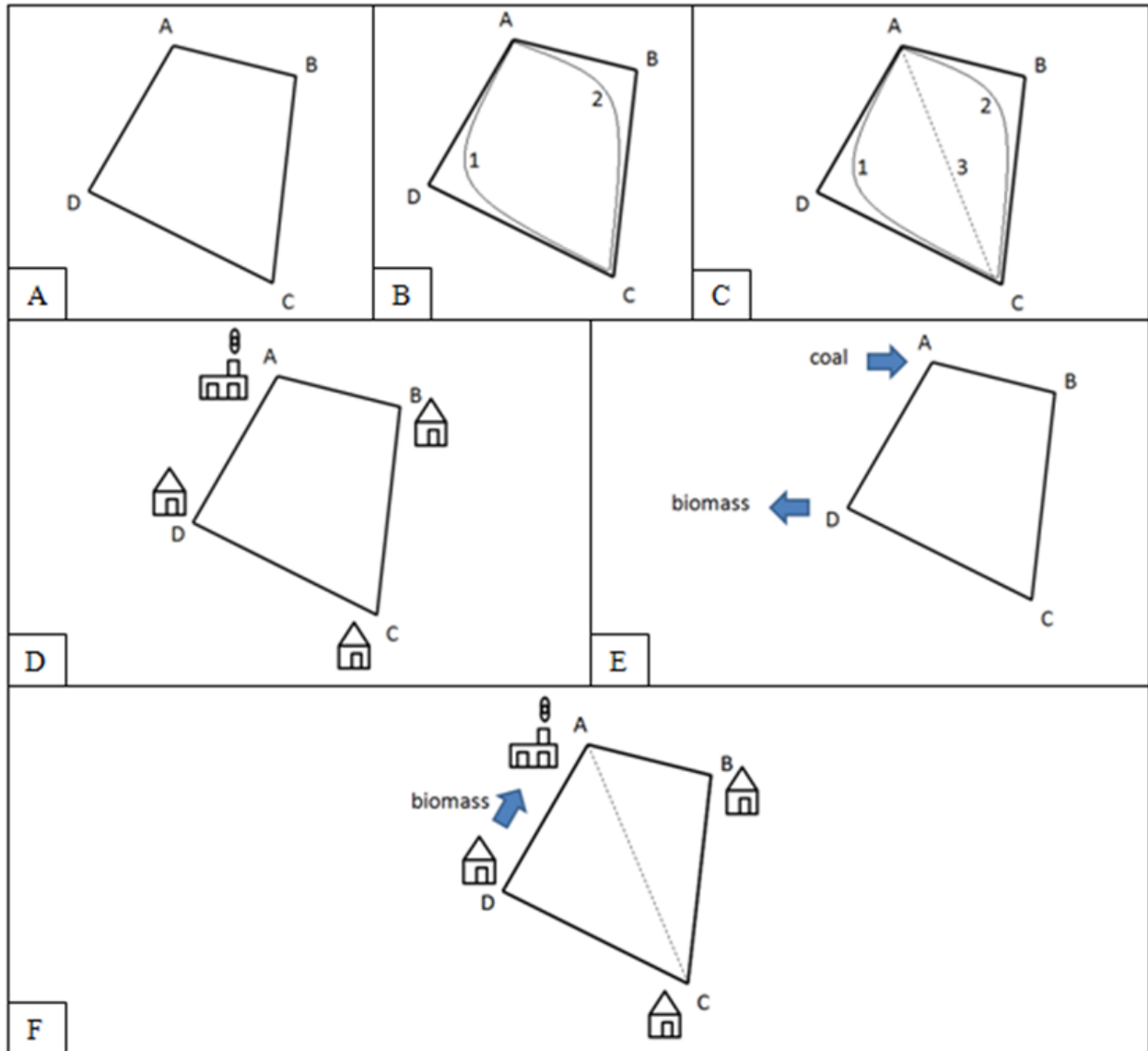
Figure 6-1: Transport-stationary energy case study

This example illustrates a scenario where the integration of transport and stationary energy can unravel new and more sustainable Nash equilibriums that were hidden to transport policy makers.

Our objective behind this example is not to shed light on this particular case but rather to give our main motive for developing iTEAM and to demonstrate how a narrow view of transportation sustainability can be misleading and counter-productive in some cases. This is

why we believe that there is a true need for a decision support tool to handle all of the complex chain of reactions that a policy or an investment can have that may not be readily identifiable to the observer.

6.4 Directions forward

In this chapter, we have presented three categories of transportation scenarios that can be handled by iTEAM to analyze their impacts on sustainability:

- The simplest form of transportation policies/investments that affect energy consumption are those where the energy consumption from the vehicle ownership and usage change. These policies are the ones usually tackled by transportation modelers and practitioners.

- The 2nd order effect of transportation on stationary energy demand is an untapped pool of interactions that reveal more connections between these two networks. The main driver behind our thesis was to develop a framework that could capture these interactions to inform decision-makers about the impacts of their choices.

- The 3rd order effect of transportation on energy demand through urban form changes is a field of research that has had its fair share of attention in the literature but has still a long way to go before being fully implemented. By this, we mean that, to date, the transport-urban form emissions cycle has been studied but the cycle of transport-urban form-stationary energy demand has not been analyzed yet.

These are not the only types of policies that can be considered in the iTEAM framework. In fact, we did not mention the many land-use related policies that can be analyzed such as zoning and land pricing. However, we believe that there is still a big pool of policies and investments that have yet to be developed and tested but that are showing great promises. We are referring here to policies that adopt the approach of nudging or influencing human behavior by building on insights gained from hedonic psychology and behavioral economics. These insights are established on quirks that appear in human behavior and that can be the appropriate place for a 'choice architect' to intervene for the betterment of society. The idea behind nudging, choice architecture or libertarian paternalism is to alter the setup of different situations while giving people the freedom to make their selection (Thaler and Sunstein, 2009).

An example of such an intervention recently took place in the utilities sector in the US where two large field experiments showed that peer comparison feedback can reduce residential energy usage (Ayres et al., 2009).

We strongly believe that the movement towards transportation sustainability will have such policies in its arsenal and will probably build upon one of the powerful trends of the new era: social media – especially that we are currently witnessing contests such as Defense Advanced Research Projects Agency DARPA's Red Balloon Challenge (MIT Media Relations, 2009).

Thus the iTEAM agent based approach and utility based discrete choice models that can be extended with different inter-individual interactions that we presented in chapters 3 and 5, place iTEAM in a unique position to be the tool of choice for decision makers to analyze such policies and investments.

Chapter 7
Conclusion

7.1   Summary

Fueled by the growing interest in combating the global warming risks, this thesis tackles the problem of sustainability in the transportation sector. Given the modest and often counter-productive effects of previous policies, we developed the framework for a model to support and inform regulators and policy makers in their decision.

From the onset, we recognized the complexity inherent in the urban dynamics that was behind these negative results and aimed to capture in our formulation the following sources of complexity:

➢ Non-linear behaviors resulting from the two-way interactions between the different agents and systems.

➢ The long term and indirect effects on the urban form and energy sector of a policy or investment affecting the transport sector.

➢ The varying spatial and temporal scales of the different processes at work.

After reviewing the literature on transportation, land use and energy modeling, we noticed that different urban modeling attempts had different scopes, approaches and techniques which revealed a gap in the theoretical foundations of urban modeling.

Nonetheless, there is a growing consensus around the need for agent-based microsimulation as the adequate approach to capture the non-linear behavior and the two-way interactions between the agents and systems of an urban region. This microsimulation was based on the recognition of two fundamental agents in a city: households and firms.

We began our modeling effort by answering the question of which scope is needed to capture the long term and indirect effects of transportation policies and investments on urban form and stationary energy.

After identifying the main types of interactions, both direct and indirect, between households and firms, we put forth the following modeling framework for our urban model: an integrated transportation and energy activity-based model, iTEAM.
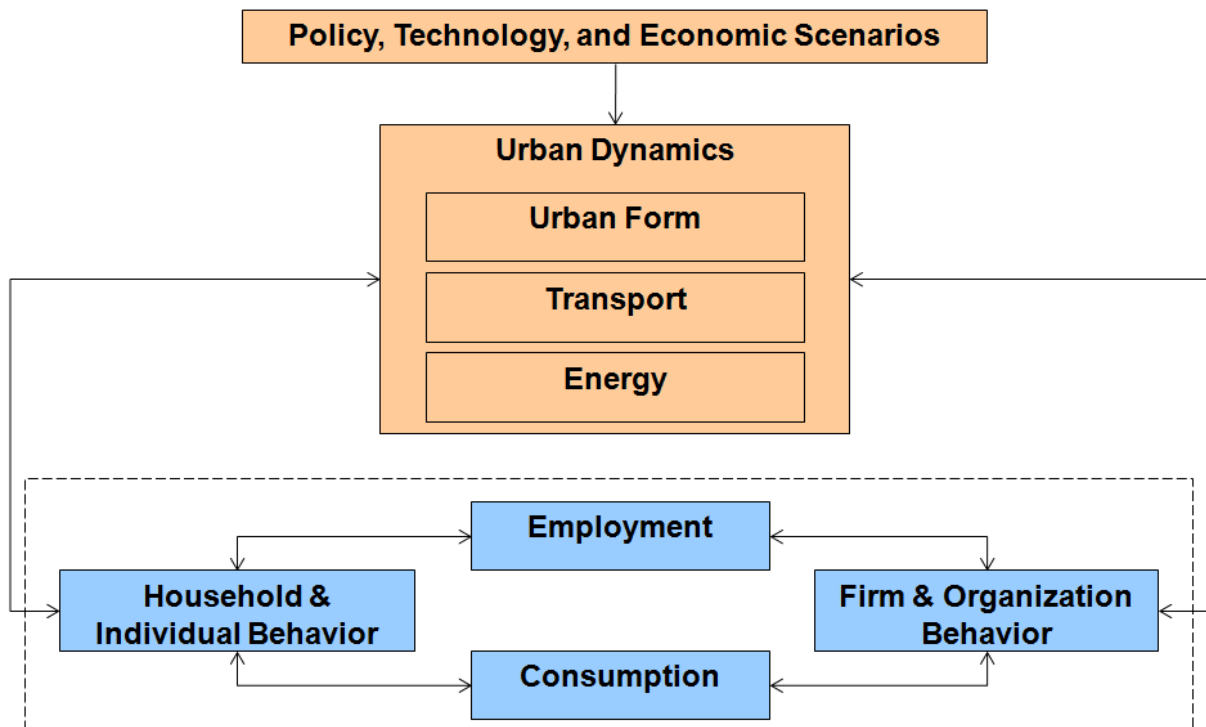
Figure 7-1: iTEAM

The direct interactions are of three types: household-household, household-firm and firm-firm.

- Household-firm interactions are captured by the employment and consumption models.

- Household-household interactions are captured in the household activity model which is the core of the household/individual behavioral model (see figure 7-2).

- Firm-firm interactions are captured in the firm activity model which is the core of the firm/organization behavioral model (see figure 7-3).

The indirect interactions between the agents within each of the transportation, land use and energy systems are captured through specific system-level models.

To answer the question of the techniques needed to capture the two-way feedback between agents and systems in a city, we looked at the literature in complex systems theory.

We showed how the transportation, land market and energy systems of a city each demonstrate the properties of heterogeneity-based, organized complex systems.

By making an analogy with similar systems in epidemiology and biology, we derived different properties of the modeling techniques needed for such systems to form the following theoretical foundation of urban modeling.

Regarding the structure of the models:

1) They are dynamic.
2) They are agent-based.
3) They capture agents' heterogeneity.
4) They capture behavior propensity and are not be confined to deterministic causality or pure randomness
5) They models allow for the possibility of intrinsic emergence.

Regarding the spatial and temporal resolution, the models capture:

1) Medium-range correlations
2) Metastable states
3) Hierarchical organization
4) Interaction with the environment

After demonstrating that each of the three systems considered in iTEAM was a complex system, we presented the integration of these systems with agents' behavior. We expanded the behavioral models of households (see figure 7-2) and firms (see figure 7-3) and illustrated the integration of each of the three systems with agents activities.
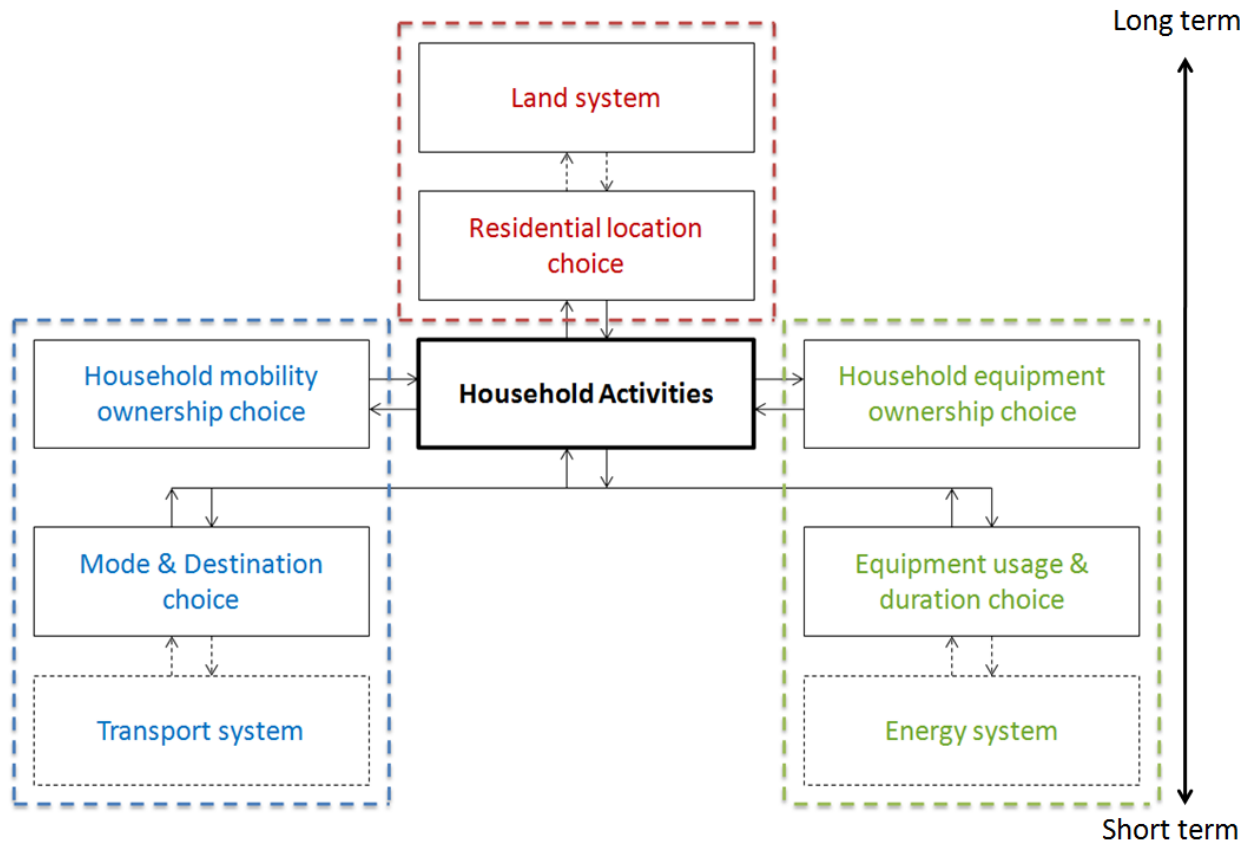
Figure 7-2: Household behavioral model
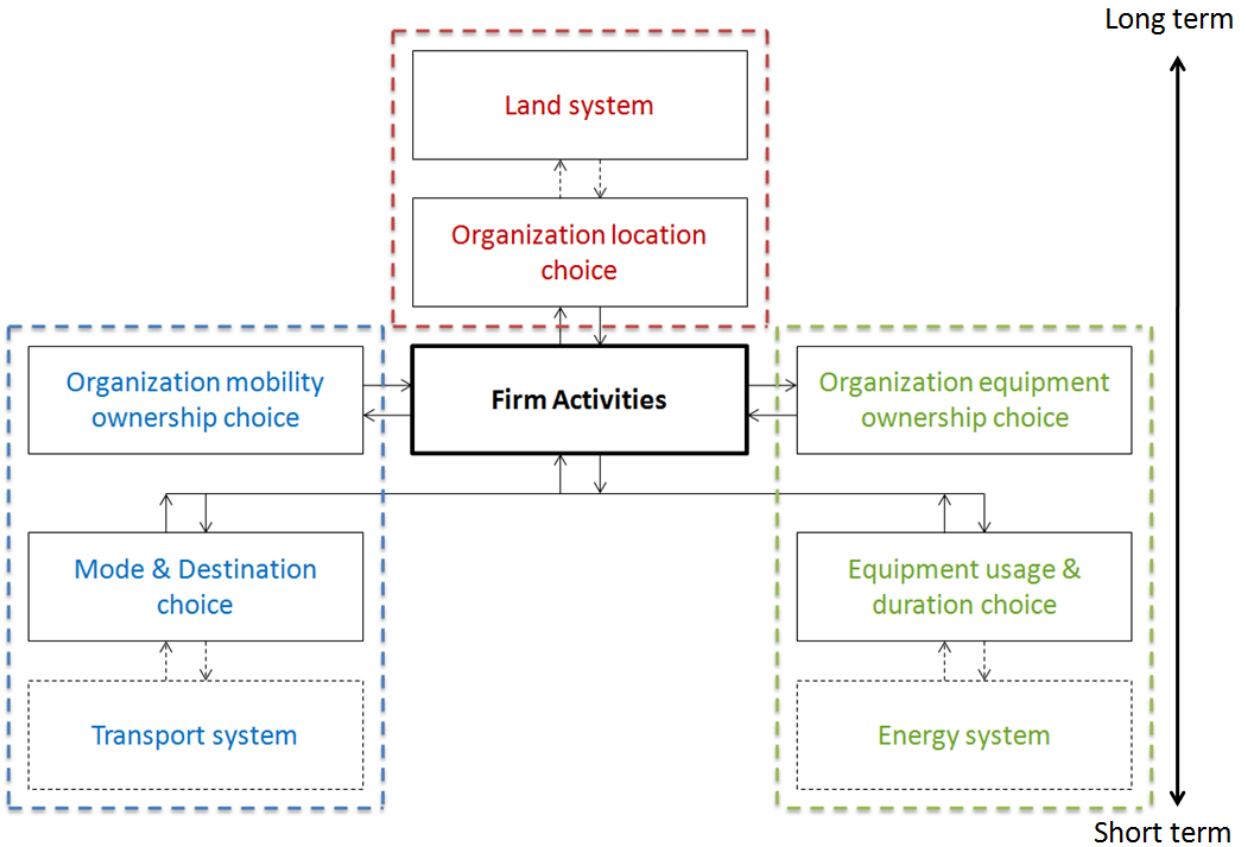
Figure 7-3: Firm behavioral model

We then reviewed and presented three extensions to the state-of-the-art in activity-based modeling. These extensions are necessary to integrate activity-based models with the household behavioral models in iTEAM.

➢ We first expanded the range of activities considered to feature the detailed in-home and out-of-home activities. This allowed the model to better capture inter-activity substitution and appliance usage.

➢ We second presented different extensions to discrete choice models to capture the individuals' heterogeneity.

➢ We third reviewed the theory behind activity participation in time-use research and motivational theory and modeled the need-activity relation. We formulated this relation in a dynamic model to capture the propensity for a new activity in a utility maximization framework.

We demonstrated the capability of iTEAM to serve as a decision support tool and inform sustainable urban planning by illustrating its analysis and forecasting power in the following three categories of scenarios:

- Direct transport-vehicular energy consumption scenarios such as carbon taxation, congestion pricing, etc…

- 2nd order transport-stationary energy consumption scenarios in a hypothetical case study where a new highway decreased the energy consumption in factories by driving a switch from coal to biomass fueled equipment

- 3rd order transport - urban form - energy consumption scenarios that consider the long term changes in the urban form induced by new transport infrastructure.

7.2   The model in practice

It is important to note at this point that while the objective of iTEAM is to support and inform the decision making process, it does not replace the decision makers' role.

The iTEAM model could in theory output a wealth of information about each scenario which can be summarized and wrapped in sustainability indicators. However, the tradeoff evaluation between different advantages and benefits of each policy or investment is left to the decision maker.

Besides the fact that these indicators need to be agreed upon (which is not always an easy process), on many occasions, different sustainability indicators might be 'competing'[24]. In these instances, standard techniques of benefit-cost analysis and multi-criteria judgment are still needed.

Nonetheless, we believe that iTEAM can inform this process by making it more objective and transparent. After all, we have literally shown that land-use, transportation, and energy are complex systems that by definition are difficult to anticipate from the simple knowledge of the behavior of the individual agents. This reinforces our conviction that a tool such as iTEAM is needed for regulators and policy-makers to steer us in the right direction with the many urban problems that we are facing today.

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[24] Many proponents argue that true sustainable development should have the three pillars, environment, economic and social, that reinforce each other. We leave it to the practitioners to use iTEAM according to their own sustainable development perspectives.

7.3 Data collection

Thus far in this thesis, we have outlined the framework for an integrated transportation and energy activity-based model and given special focus to human behavior in the household context. It should be clear by now that the data requirements for such a model are very large and cannot be readily gathered through standard paper-based surveys. Rather, new methodologies that make use of the advances in social media and ubiquitous sensing methodologies are needed to gather the necessary data for the estimation and calibration of the proposed models. Fortunately, surprising amounts of detailed information can be gathered from individuals (see figure 7-4) or from public social media websites such as Facebook, Flikr, Twitter, Myspace, blogs, etc…
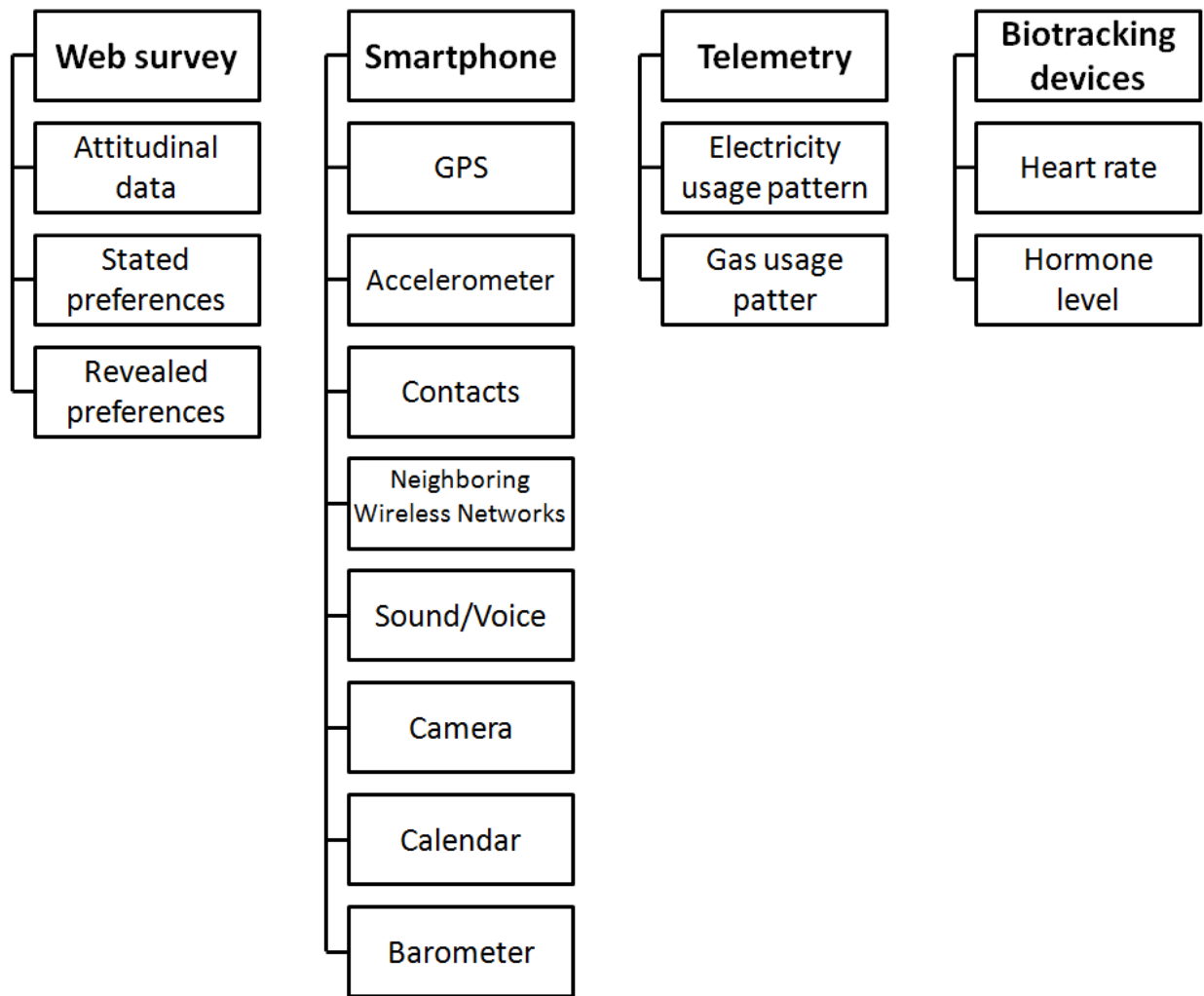
Figure 7-4: Data sources

The data can be processed using different types of algorithms (statistical, genetic, evolutionary, fuzzy logic, etc…) to potentially obtain the information needed about individuals' in-home and out-of home activities, transportation mode and appliance usage, attitudes, etc…

7.4 Future work

This thesis has outlined some important research topics that need to be addressed in future research. There is still a lack of consensus on the modeling techniques needed for activity-based modeling. This should be addressed in an empirical case study to assess the advantages and disadvantages of each approach in terms of forecasting power especially in light of the advances in computational technology.

On another point, the work on firm logistics and supply chain management in operations research and game theory should be enhanced to handle the scale and variation level encountered in urban modeling. Lastly, the coding of iTEAM is bound to shed light on many additional interesting research topics.

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